THREE ESSAYS ON DEVELOPMENT ECONOMICS

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ABSTRACT

My dissertation consists of three independent yet thematically related chapters on development economics. The first two chapters focus on the digital economy. The first chapter examines gender gaps in the gig economy, while the second investigates how firms respond to digitalization opportunities in developing countries. The third chapter continues to study firm behaviors; specifically, it analyzes how firms leverage political connections to increase resilience during economic crises.

In the first chapter, “Does the Gig Economy Discriminate against Women? Evidence from Physicians in China,” I examine gender disparities in the burgeoning gig economy. Using novel data from a major Chinese online healthcare platform, I show that female physicians charge 2.3% lower prices and provide 11.0% fewer consultations than males. Patients appear to discriminate against female physicians despite them having identical observable productive characteristics to those of male physicians. The differential responses of patients to quality signals from female physicians suggest that a portion of this discrimination is statistical in nature. I further find that the platform’s design, particularly its ranking algorithm, plays an important role in enlarging gender gaps. The ranking algorithm amplifies and perpetuates the gaps by using past patient behavior (and thus pre-existing discrimination) as a key predictor of future patient behavior, thereby placing fewer females at the top of search results. Additionally, I cast doubt on several other alternative explanations and conducted a series of robustness checks.

In the second chapter, “Digitalization as a Double-Edged Sword: Winning Services and Losing Manufacturing in India,” I explore the impacts of digitalization on firms. While digitalization can increase firm productivity, in developing countries with labor market frictions, not all firms are able to capitalize on digitalization opportunities. I use data from India–where a demonetization policy led to a large increase in digital payments–to examine the impacts of digitalization on firms across sectors in a

developing country, identifying winners and losers in the short run. I find that service firms experienced growth in income and productivity while manufacturing firms witnessed a decline. I then explore the mechanisms driving this divergence. The results show that service firms invested more in information and communications technology (ICT) capital and hired more complementary skilled ICT labor, whereas manufacturing firms did not. Notably, this influx of skilled ICT workers into the service sector was drawn from the manufacturing sector due to limited spatial labor mobility. During this short-run transitional phase, wages for ICT labor were driven up while remaining stagnant for other workers. These findings underscore how digitalization, in the presence of labor market constraints, can exacerbate short-term sectoral divergence in productivity growth and shed light on its impacts on the growth trajectories of developing countries.

In the third chapter, “How Do Political Connections of Firms Matter During An Economic Crisis?”, we use a new machine learning-enabled, *social network based* measurement technique to assemble a novel dataset of firms’ political connections in India. Combining it with a long panel of detailed financial transactions of firms, we study *how* firms leverage these connections during an economic downturn. Using a synthetic difference-in-differences framework, we find that connected firms had 8-10% higher income, sales, and TFPR gains that were persistent for over a three-year period following the crisis. We unpack various novel mechanisms and show that connected firms were able to delay their short-term payments to suppliers and creditors, delay debt and interest payments, decrease expensive long-term borrowings from banks in favor of short-term non-collateral ones, and increase investments in productive assets such as computers and software. Our method to determine political connections is portable to other applications and contexts.

Dedication

This dissertation is dedicated to my parents, my husband, and my dog, Molly.

Acknowledgments

Pursuing a PhD is like a journey across the boundless Sahara Desert, yet, thankfully, I encountered my guiding stars.

I believe everyone who embarks on the PhD journey is brave, and no one can ultimately survive it without the help of countless people.

I would like to begin by expressing my deepest gratitude to my advisors, Sheetal Sekhri, Amalia Miller, and Gaurav Chiplunka. About half of my PhD journey unfolded during COVID-19, a time when many graduate students experienced a lack of personal interaction with their advisors. I feel incredibly fortunate to have maintained weekly Zoom discussions about my research progress with my advisors. I also recall moments of sitting in their offices, overwhelmed with emotion about my research, fearing that I could not address the referees' questions or that my research was at a standstill. They provided me with insightful advice and unwavering support, reminding me that I should stand confidently behind my work. They played such a crucial role in my transition from a student to a researcher. Without them, it would be impossible for me to overcome all these challenges in the past years.

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I am profoundly fortunate to have received unconditional love and support from my parents, both mentally and financially. This dissertation could not have been realized without the companionship of my husband, Jiafeng Wu, and my dog, Molly. Jiafeng has consistently been my most enthusiastic supporter, providing a sympathetic ear and invaluable advice. On numerous occasions, when I doubt my work, he is there to uplift me, reminding me to persevere in my passions. Molly has been a constant, comforting presence through numerous days and nights of worry, offering her silent support and bringing joy into my moments of despair. I am eternally thankful for their love and confidence in me.

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Chapter 1

Does the Gig Economy Discriminate against Women? Evidence from Physicians in China

1.1 Introduction

The gig economy has expanded rapidly since 2015, especially in developing countries like China and India. It is driven by online platforms that connect gig workers with prospective employers who post short-term or temporary tasks they need to be completed. In recent years, researchers have argued that the gig economy has the potential to reduce persistent gender pay gaps because of the flexibility it offers workers (Weinberg and Kapelner, 2018; Churchill and Craig, 2019). Flexibility in working arrangements is thought to be beneficial for women because it allows women to customize their working schedules in accordance with time constraints imposed by family responsibilities. However, the gig economy may exacerbate any existing discrimination by employers and/or customers against female workers if it is easy to identify workers' genders (e.g., by names and headshots) and avoid women or offer less for their services. Moreover, the algorithmic systems used by platforms in the gig economy could reinforce gender inequality if the input data being used are affected by social biases. Understanding gender gaps in online markets is therefore important and empirically relevant.

This paper investigates gender gaps in the gig economy in a major developing country. To this end, I examine the skilled labor market for physicians in China. I analyze data from Spring Rain Doctor (SRD), one of the largest e-consultation medical platforms in China. I quantify gender differences in price per consultation (henceforth, gender price gaps) and in the number of consultations provided (henceforth, gender quantity gaps). After quantifying these gaps, I investigate if patients discriminate against female physicians on the online healthcare platform and examine the role of the platform's design.

China's gig economy provides a pertinent context. It is massive: about 15% of the country's workforce was involved in the gig economy in 2018. The mobile medical market is a substantial segment of the Chinese gig economy, comprising 12.7% of its total.[1] The sector has also experienced rapid growth, expanding 35-fold between 2011 and 2020. Gender pay gaps in China's mobile medical market are also large: female physicians earned only 79% of male physicians' annual income in 2017. It is not clear, a priori, whether this gap is a result of discrimination or if female physicians spend less time on the mobile medical market. Although online healthcare platforms allow physicians to freely adjust their working times, they can also exacerbate gender discrimination because they allow patients to select a particular doctor. In contrast, when people go to hospitals for general outpatient visits, they cannot choose their physician.

In this paper, I use novel data from the SRD to study price differences between male and female physicians as well as differences in patient demand between male and female physicians. I conducted two rounds of data collection, one in March-June 2020 and the other in February-April 2023. I constructed a cross-sectional dataset by combining data collected in 2020 with supplementary data from 2023. I chose this platform because it was founded in 2011 and is well-established in the online medical market. In addition, its design is representative of a large class of e-consultation healthcare services, such as *Pingan Good Doctor*, *WeDoctor*, and *Dingxiang Doctor*. Moreover, SRD has a large number of active users, patients, and physicians in China. My sample consists of 13,472 unique physicians who were available at least once on the platform between March 26 and June 30, 2020. In addition to collecting physician profiles, I also recorded each physician's rank in search results under the platform's default settings. While about 38% of physicians in the sample are female, only 30% of physicians displayed in the first 50 search results are women. Compared to male

[1]The gig economy scale was ¥2.5 million in 2019. The data was sourced here. The size of the mobile medical market was ¥321.4 billion in 2019. Data on the size of the mobile medical market is from *2020-2021 China Internet Medical Industry Development White Paper* published by iiMedia Research.

physicians, female physicians in the sample are less likely to hold a senior professional title or an advanced degree in medicine.

I find that female physicians set lower prices; however, despite this, they receive fewer consultations compared to their male counterparts on the platform. The within-specialty raw gender price gap and raw gender quantity gap between men and women among all physicians are 3.6% and 17.6%, respectively. After controlling for physician characteristics such as professional title, education, work experience, and availability, the gaps persist: the unexplained gender price gap is 2.3% and the unexplained gender quantity gap is 11.0%. The combined effect of the gender price gap and gender quantity gap results in female physicians earning 13.0% less than male physicians on average per month.

After conditioning on a latent measure of physicians' quality, constructed by comparing physicians' profiles in 2023 with those from 2020, both gender price and quantity gaps persist at similar levels to those observed without including this measure. This provides supportive evidence of patient discrimination on the SRD. I also explore whether some of the discrimination is attributable to statistical discrimination, following the framework proposed by Phelps (1972).[2] Specifically, I assume that patients interpret signals from female physicians differently than those from male physicians. I find that patients penalize female physicians more for negative signals and reward them more for positive signals, which is consistent with my model of statistical discrimination.

Given the presence of discrimination on the platform, I next explore the platform's design. Using the Gelbach decomposition method (Gelbach, 2016), I find that displaying physicians' headshots in the search results and the platform's ranking algorithm together accounts for 23.3% of the raw gender quantity gap, making the platform's design the largest contributor to the gap. Displaying physicians' profile photos lowers patients' search costs and indulges patients' discriminatory preferences by making gender more salient. The platform's ranking algorithm, which predicts a physician's likelihood of being chosen by future patients using past patient demand data, can

[2] I acknowledge the fact that the observations on prices and labor demand are equilibrium outcomes and I am limited by the scraped data to isolate variation coming from the demand (or patient) side. I address this data limitation by developing a theoretical model that includes the behaviors of physicians and patients and their interactions in the market. This model delivers implications for equilibrium outcomes that I can test empirically.

exacerbate and *perpetuate* gender gaps.

The ranking algorithm, supposedly free of gender bias, is based in part on the past volume of consultations, which amplifies the impact of patient discrimination by placing fewer female physicians at the top of default search results. Since patients are less likely to consult physicians listed at the end of the search results, their behavior will impact future patients' decisions and the future rankings of physicians. This vicious feedback loop is self-reinforcing and thus *exacerbates* gender gaps. I also find suggestive evidence that patients continue to rely on default sorting, even when more efficient filtering and sorting options are introduced. As a result, female physicians experience a persistent low ranking over time. This highlights the potential of the ranking algorithm to *perpetuate* gender gaps.

I examine three alternative mechanisms that may contribute to the observed gender gaps and cast doubt on them. First, I demonstrate that gender quantity gaps are not attributed to lower supply by female physicians, as females are equally available on the platform compared to males. Next, by utilizing both cross-sectional and panel data, I cast doubt on the concern that price is positively related to unobserved quality and the estimated quantity differences may be related to quality rather than discrimination. Lastly, I show that it is unlikely the case that female physicians set a lower price due to lower confidence.

To further bolster confidence in the findings, I conduct four robustness checks. I first validate the reliability of the gender prediction algorithm used in this study by cross-checking its accuracy rate with another widely used algorithm. I then re-estimate the gender gaps on sub-samples that drop physicians without profile photos. The estimated gender gaps are robust. To provide additional support for the presence of gender-based discrimination indicated by gender-oriented names and profile photos, I conducted a placebo test utilizing name neutrality. The results show that neutral names have no impact on gender gaps. Lastly, I use data scraped from another popular online healthcare platform, *WeDoctor*, to examine external validity. And I also find a gender price gap on this platform.

This paper is broadly related to the emerging literature on provider choice in low- and middle-income countries. It has been shown the choice of healthcare providers is influenced by various factors, including patients' and physicians' characteristics, as well as the characteristics of healthcare facilities (Thuan et al., 2008; Victoor et al., 2012; Mohammad Mosadeghrad, 2014; Y. Liu et al., 2018). And patients gather information from multiple sources, such as word of mouth and physician referrals, before making a decision. J. Das et al. (2016) compare the quality of public and private healthcare providers in India and find that patients may benefit from seeking healthcare from private providers, particularly when public providers demonstrate a low level of effort. This paper explores patients' decisions on an *online* healthcare platform in a developing country, China, and provides suggestive evidence that patients do not tend to seek additional information beyond the online platform.

The results of this paper complement the literature that studies gender pay gaps among employees. Gender pay gaps, precipitated by factors like occupational segregation (Meara, Pastore, and Webster, 2020; Maldonado, 2021) and labor market discrimination (Chi and Bo Li, 2008; Ahmed and McGillivray, 2015), have been widely found across developed and developing countries (Blau and Kahn, 2003) including in the U.S. (Antonie, Gatto, and Plesca, 2020), in countries in Europe (Arulampalam, Booth, and Bryan, 2007), in India (Jong-Wha and Wie, 2017; Poddar and Mukhopadhyay, 2019; Ara, 2021), and in China (Chi and Bo Li, 2008; Jong-Wha and Wie, 2017; Hare, 2019; Zhao et al., 2019; Iwasaki and Ma, 2020). A growing literature also documents a pay gap between male and female physicians. Jena, Olenski, and Blumenthal (2016), using salary data on academic physicians, find that female physicians in the U.S. earn 8% less per year after adjusting for various physicians' characteristics. And Sarsons (2017) provides evidence that this pay gap can be explained by how people interpret signals of ability differently depending on a physician's gender. Some analysts also argue that the wage gap is inversely correlated with flexibility as women's value of time for non-paid housework is higher than men's (Goldin, 2014; Goldin and Katz, 2016; Mas and Pallais, 2017; Bolotnyy and Emanuel, 2022). I extend this work to an area of high-skilled workers in an online labor market in a large developing country, China, where sexism could be more salient (Xiaoyan and Wenfang, 2020).[3]

My work also adds evidence to the growing literature on the gig economy. Women are found to be relatively more attached to gig work than men because gig work

[3] There is a growing literature on the gender differences in negotiation/bargaining: Babcock et al. (2003), Bowles, Babcock, and McGinn (2005), Abrahm (2008), Roussille (2022), and Biasi and Sarsons (2022). Yet, in my setting, physicians do not engage in price negotiations with patients; rather, they simply set a price and await inquiries.

provides a flexible schedule (Churchill and Craig, 2019). But, the flexibility that the gig economy provides does not eliminate gender pay gaps. Studies of Upwork (Foong et al., 2018), Amazon Mechanical Turk (Litman et al., 2020; Adams-Prassl et al., 2023), and Uber (Cook et al., 2021) show that women still earn less than men. Moreover, many platforms in the gig economy employ algorithms that, although intended to be unbiased, can favor one group over another (e.g., men over women) (Hannák et al., 2017; Lambrecht and C. Tucker, 2019; Cowgill and C. E. Tucker, 2020; J. Chen et al., 2023). Relative to the existing literature, in this paper, I study a platform in which participants are able to adjust both the margin of labor supply and price. In particular, on the SRD, I can observe physicians' availability and infer from this their labor supply. And, in contrast to platforms such as Uber and Lyft, on this platform prices are self-determined. Thus, I can examine gender gaps among workers, specifically physicians, who can adjust both the margin of labor supply and prices. More importantly, to the best of my knowledge, this is the first paper that studies how a platform's algorithm can amplify existing gender gaps. In my setting, women set lower prices but still receive fewer consultations than men, and the gaps are enlarged by the platform's ranking algorithm which disadvantages female physicians. My results highlight the fact that the flexibility offered by the gig economy alone is not sufficient to eliminate the impact of factors such as consumer discrimination, which is usually more severe in developing countries, and eliminate gender gaps in earnings.

This paper also relates to narrower literature on gender discrimination in the gig economy that underlines discrimination as a potential source of gender pay gaps (Adams and Berg, 2017; Lesner, 2018; Aderemi and Alley, 2019; Gharehgozli and Atal, 2020; Vyas, 2021).[4] Most of these studies, which use decomposition or regression methods, attribute the unexplained part of gender pay gaps to discrimination. (Heshmati and Su, 2017; Jong-Wha and Wie, 2017; Poddar and Mukhopadhyay, 2019; Galperin, 2019). One study (Hannák et al., 2017) closely related to this work examines discrimination against female gig workers on TaskRabbit and Fiverr, but does not identify the source of discrimination. Hannák et al. (2017) finds that online customers have a bias against workers who they believe to be women. The perceived female workers tend to

[4] There is also a growing literature that studies racial/ethnic discrimination in the online marketplaces: Doleac and Stein (2013), Zussman (2013), Ayres, Banaji, and Jolls (2015), Edelman, Luca, and Svirsky (2017), and Laouénan and Rathelot (2022).

get lower ratings and worse positions in search rankings. In this study, I identify the true gender of most physicians and specifically test for statistical discrimination. I apply the 1972 discrimination framework by Phelps (1972), assuming different variances of signal in the model. My findings conform to statistical discrimination.

The rest of the paper is organized as follows. Section 1.2 provides details of the online healthcare markets and the setting of SRD. Section 1.3 describes the data. Section 1.4 provides empirical results on gender gaps and patient discrimination and Section 1.5 examines the role of the platform. Section 1.6 investigates three alternative mechanisms that may contribute to gender gaps, while Section 1.7 conducts a series of robustness checks. Finally, Section 1.8 provides the conclusion of the study.

1.2 Background

1.2.1 The E-consultation Healthcare Market in China

The demand for healthcare e-consultation in China primarily arises from a scarcity of quality medical services. As of 2010, there were only 1.4 physicians per 1,000 persons in China, which was 45.6% lower than the average of OECD countries. This shortage often leads to overcrowded hospitals, resulting in long queues, extended waiting times, and subsequently, brief screening sessions. Online healthcare platforms, starting with *Haodaifu.com* in 2006, followed by *WeDoctor* in 2010 and SRD in 2011, offer a practical solution that helps reduce hospital crowding. Specifically, they enable patients with mild symptoms to choose online inquiry services as an alternative to in-person hospital visits. Reflecting this need, the e-consultation sector has experienced significant growth: as of 2019, more than 30 healthcare inquiry apps were widely used, with over six million combined daily uses in 2020. Additionally, the number of monthly active users grew from 46.9 million in November 2019 to 54.8 million one year later.

The e-consultation healthcare market is a nationwide market comprising various two-sided platforms. Physicians with practicing licenses from all over the country can register to provide services on these platforms and decide their working hours and prices. Patients seeking e-consultations on these platforms can check a physician's availability for consultation based on whether or not they have a price listed on a platform like SRD.[5] A listed price indicates that the physician is "available" to offer consultation services and respond to patients' queries within a specified time frame, which is communicated to the patients. For example, on the SRD, while physicians may not be able to reply immediately, they are required to reply within 48 hours. If they fail to do so, a refund will be issued to the patient. Patients can select any "available" physicians on these platforms.

1.2.2 Spring Rain Doctor

I study the SRD because it is one of the earliest-founded platforms and one of the most downloaded teleconsultation apps. The core business of the platform is its online inquiry service, which includes text inquiry, telephone inquiry, and urgent inquiry. The platform takes a percentage commission on prices not covered by universal medical insurance.[6] The SRD has a large number of monthly active users. As of October 2021, more than 650,000 physicians had registered on the platform, or about 19.1% of the total number of physicians licensed in 2020. To give a rough picture of the type of physicians who were active on the online healthcare platform in 2020, I compare the sample of SRD physicians to the national statistics in Appendix Table A.21. Compared to national averages, physicians on the SRD exhibit a higher likelihood of holding advanced education degrees (such as master's and M.D.), working at the highest-tier hospitals, and having relatively less work experience. Yet, the distribution of professional titles is broadly comparable between the national average and the SRD.

Although patients' information cannot be observed on the platform,[7] I use the Baidu Index, which is similar to Google Trends, to provide basic characteristics of the poten-

[5]This was true of SRD at the time of crawling in 2020. After 2023, it became unlikely to see unavailable physicians on the list.

[6]In China, a patient who goes to the hospital for an outpatient visit needs to pay the outpatient registration fee, *Zhen Liao Fei*, which is similar to the online inquiry fee. The fee is not covered by universal medical insurance. See this website for details.

[7]Patients' information is not publicly available on the platform. If patients decide to leave reviews after the consultation, then other patients and researchers could observe their gender and age but no other information. Moreover, researchers could only read the most recent 600 reviews on the website and less than 600 reviews on the app or the WeChat mini-program in 2021.

tial user population in 2020 in Appendix Figure A.14.[8] As shown, there was a minor difference in the gender composition of potential users, which suggests that users of a particular gender are not more or less inclined to use the platform. The majority of potential users (hereafter patients) were aged between 20 and 39, who tend to exhibit greater familiarity and comfort with digital platforms compared to the older population. In terms of spatial distribution, the east and northern regions have a larger share of users than other regions as presented in Appendix Figure A.15a. The distribution of demand is similar to the spatial distribution of physicians on the SRD platform displayed in Appendix Figure A.15b. The darker areas in the two figures are also the most densely populated regions of China, so the distributions are intuitive.

1.2.3 Text Inquiry Process in 2020

I focus on the text inquiry service on the SRD, which is the earliest-developed and most popular type of consultation service. Below, I discuss the process patients use to inquire about a physician in 2020. I also provide an overview of the process in Appendix Figure A.3a.[9]

A patient first selects a specialty. Then, s/he sees a list of doctors with photos and information about the doctor's hospital affiliation, professional titles, specializations, prices, and the total number of consultations provided by the doctor in the past. "Unavailable" physicians, those without a listed price, may be listed on the list of doctors, but patients could not purchase their services. Patients could click a physician's photo or name that links to the physician's profile page (Appendix Figure A.16), where they could explore further details, such as education, work experience, patient ratings, and peer ratings.[10] While physicians are required to disclose their professional titles and

[8]Baidu collects data about user searches and generates the Baidu Index to show the search intensity of keywords over time. People can check some characteristics of the user population, such as geographic region, gender, and age, within a custom time range.

[9]Patients can access the SRD platform via its mobile app, its website, and its mini-program on WeChat, China's most popular social media platform. The process of searching for a physician was the same for patients who use PCs and phones in 2020. However, a patient using a PC to select a physician must scan the physician's QR code and then communicate with the physician on their cell phone using WeChat's mini-program.

[10]On the platform, physicians can rate the answers provided by other physicians to patients' questions. If physicians disagree with a specific response, such as when they believe it does not benefit the patient or contains incorrect analysis, they have the option to give it a low rating. The platform then aggregates these ratings and provides a final peer rating for patients' reference. A

the hospitals they work at, they can voluntarily provide information on work experience and education.[11] After selecting a physician, the patient proceeds to make the payment and then types his/her questions and uploads relevant pictures if necessary. After the consultation, the patient has the opportunity to write a review and rate the physician.[12]

1.2.4 The SRD's Ranking Algorithm in 2020 and 2023

In 2020, patients on the SRD platform were only presented with a list of doctors sorted by "featured," the default setting.[13] Patients could not sort or filter physicians by specific attributes, such as professional titles or patient ratings, on either the webpage or the WeChat mini-program. The rightmost part of Appendix Figure A.3a displays this fact: patients had limited options and were only able to select regions and departments without the ability to sort or filter the search results. However, in 2023, as shown in the rightmost part of Appendix Figure A.3b, patients gained more flexibility. Apart from the default sorting, they could now sort physicians based on patient rating, total number of consultations, and response rate. Additionally, filtering options by price and professional titles also became available. Appendix Figure A.5 displays a complete list of filtering options available in 2023. I discuss the changes to the platform in more detail in Appendix A.1.3. This paper focuses on the default rankings of physicians.

The SRD takes a certain percentage of the commission from each consultation provided by a physician, so its objective is to maximize profit. To achieve this, the

high peer rating thus serves as a strong indicator of recognition for one's professional knowledge within the medical community.

[11] Upon joining the platform, a physician is required to submit photographic evidence of his/her qualification, which includes the name of the hospital and his/her professional title. The platform then verifies this information to ensure its authenticity. Physicians can only provide services after the platform has verified the information. Because of this, I use the date on which a physician's qualification was endorsed by the platform as his/her joining date.

[12] In 2020, the rating scale ranged from one star to five stars. The system then added the rating to the cumulative patient rating, which the system re-scaled from 0% to 100%. The rating system changed between 2020 and 2023. It first moved to a simplified "thumbs-up, thumbs-down" system in 2021. Then, in 2023, the system evolved again and offered three options: satisfied, average, and not satisfied.

[13] It should be noted that in 2020, the list of doctors was the same regardless of whether patients accessed the platform via PC or the WeChat mini-program.

platform's default physician ranking algorithm, henceforth called the ranking algorithm, is designed to *predict* and display physicians in a way that maximizes the likelihood of their services being purchased. Similar to other machine learning-based algorithms, the ranking algorithm uses a set of features to predict an outcome and aims to achieve *goodness of fit* in a test set (i.e., future patient behaviors) by minimizing deviations between actual outcomes (i.e., future patient behaviors) and predicted outcomes. According to the SRD in 2020, the ranking algorithm considers four key features: the physician's professional title, their affiliated hospital, their availability, and the number of consultations they have provided. Therefore, it is expected that a chief physician, who works at a prestigious hospital, is available most of the time, and has served many patients, is more likely to be placed toward the top of the search results.

1.3 Data & Descriptive Statistics

1.3.1 Data Collection & Sample Construction

I collected two rounds of data from the SRD website and its mini-program on WeChat. The first round spanned from March 26 to June 30, 2020, and the second round was conducted between February and April 2023. The SRD platform provides comprehensive information on registered physicians, such as their educational background, work experience, professional title, and the date of joining the platform. I discuss the details of the data collection process in 2020 and 2023 in Appendix A.1.1 and A.1.2, respectively.

In the first round, I crawled the SRD 24 distinct times and obtained information on 43,744 unique physicians. I then restricted my sample to physicians who were "available" or provided a price at least once between March 26 and June 30, 2020. Here, I use availability for a consultation as a proxy for physicians' labor supply on the online platform. However, this might overestimate their labor supply, since they may simply be waiting for patients rather than actively providing services. Among 43,733 physicians, 14,195 met the criterion. After trimming outliers (i.e., those below the 1st percentile or above the 99th percentile) of prices and the total number of consultations provided, I was left with 13,472 physicians. In February-April 2023, I conducted a follow-up round of data collection for the 13,472 physicians. The main analysis of this paper uses the constructed cross-sectional data from 2020. I supplement the 2020 data with additional information (e.g., gender) gathered in 2023.[14]

1.3.2 Variables

I provide detailed definitions of variables in Appendix Table A.22. I categorize physicians' education into three groups: "not known degree" (those without provided educational background in 2020), "bachelor and below" (those with a degree from junior college or a bachelor's degree), and "master or M.D."[15] I classify professional titles into two groups: junior, comprising general physicians, and senior, including attending physicians, associate chief physicians, and chief physicians. As for years of work experience, I divide them into three groups: "not known years" (those who do not report information on their years of work experience in 2020), "less than 10 years," and "more than 10 years."[16] In China, hospitals are categorized into three tiers: I, II, and III, with three levels, A, B, and C, within each tier. The ranking, from highest to lowest, is IIIA, IIIB, IIIC, IIA, IIB, IIC, IA, IB, and IC. I create an indicator variable, "IIIA hospitals," that takes the value of one if physicians work at IIIA hospitals and zero otherwise. In addition to these variables, I derived several other variables from the collected data.

"Available time" is the number of times a physician appears in the 2020 data with a price. I normalize it by the number of times the physician appears in the 24 instances of the 2020 data and I call this the "share of available time."[17] The average price per service is the sum of prices listed in March-June 2020 divided by the number of

[14]The SRD platform underwent several design changes between 2020 and 2023, resulting in less direct comparability of the outcomes. I discuss the changes in Appendix A.1.3. Because of this, I use the cross-sectional 2020 data in the main analysis.

[15]Unlike in the U.S., students can obtain a bachelor's degree in medicine in China. Some junior colleges are also allowed to award a medical degree. After graduation, students can become physicians if they pass the examination of medical practitioners.

[16]I use 10 years as the cutoff point because some physicians mentioned having less than 10 years of experience while others reported over 10 years.

[17]During the crawling process in 2020, physicians had the possibility of being listed in the first 30 pages, irrespective of their availability or whether they posted a price. For physicians listed beyond the initial 30 pages who did provide prices, the share of available times served as the lower bound estimate for their labor supply.

available times in the 2020 data.[18] The average monthly consultations offered are the difference between the total number of inquiries observed in the last instance in the 2020 data and the number observed in the first instance in 2020 divided by the number of months between the two instances.[19] Since patients can see how many past consultations a physician has provided, I also construct a variable called "past consultations provided." The total number of past consultations provided is the cumulative number of inquiries observed in a physician's first instance in 2020.

The patient rating employed a scale ranging from 0 to 100 in 2020. The average patient rating is calculated as the sum of patient ratings observed in the 2020 data divided by the total number of times a physician appeared in the 2020 data. Since a physician's patient rating relative to physicians in other specialties is unlikely to be relevant to his/her probability of being selected in his/her specialty, I convert it into a standard score using the within-specialty mean and variance and call it the "relative patient rating."[20] The "relative peer rating" is constructed using the same approach as the relative patient rating.

I recorded the default ranking of each physician on the list of doctors within a specialty in 2020. A physician who ranked 20th on the list of doctors was more likely to be viewed by a patient than a physician who ranked 100th. The method used to calculate a physician's "average default ranking" is the same as that used for average prices.[21] "Displayed in the first 50" is an indicator equal to one if a physician's average default ranking in 2020 is less than 50 within the specialty.[22] I also constructed a variable

[18] In the sample, 78.97% (10,639) of physicians did not change their prices during March-June 2020. Most of the physicians who had set different prices were general physicians in 2020. I display the trend of average prices for physicians who did not set the same price over time in 2020 in Appendix Figure A.17. On average, male physicians consistently set a higher price than females. And both genders tend to raise prices over time. So, it is unlikely the case that female physicians lower their prices over time in order to attract patients.

[19] At the time of data-scraping in 2020, text consultation was the dominant type of service. So, the total number of text inquiry services a physician has provided approximates the total number of a physician's consultations.

[20] In the 2020 sample, out of 13,472 physicians, 1,350 did not receive a patient rating. Among them, 897 physicians joined the platform after 2019, and 38.5% joined in 2020. For these physicians, I assume zero relative patient ratings.

[21] In the 2020 data, the first observed ranking of a physician is highly correlated with a physician's average default ranking (correlation coefficient=0.865). Thus, I use the average displayed ranking instead of the first observed rank.

[22] I display the distribution of average default ranking in 2020 in Appendix Figure A.18. For male physicians, the distribution peaks at around 50. For female physicians, one can see a relatively flat distribution between 50 and 200. So, I use 50 as the cutoff.

called "first-week average ranking" for physicians who joined the platform between March 25 and June 30, 2020. This variable represents a physician's average ranking in the first week after joining the platform.

Gender is either identified from a physician's headshot or predicted by his/her name. 83.1% (11,195) of physicians in the sample provided photos in 2020. Among the 2,277 physicians who did not upload their headshots in 2020, 1,667 of them updated their profile photos in 2023. For the 610 physicians without photos, I predict their gender on the basis of their full names. I use a prediction algorithm, *Ngender*, to predict a physician's gender. For physicians without headshots, I assign their gender as female if they are predicted as female by *Ngender* and as male otherwise.

1.3.3 Summary Statistics

The sample consists of 13,472 registered physicians employed in 4,370 hospitals.[23] I provide descriptive statistics of the sample in 2020 in Table 1.1. Over half of these physicians were working at IIIA hospitals, the highest class of hospitals in China. Women comprised 38.39% of the sample. Female physicians clustered in gynecology and obstetrics while males were more likely to work in surgical departments, such as orthopedics and neurosurgery. Physicians, on average, set a price of ¥19.47 and provided 34.45 consultations per month. The majority (84.06%) were general physicians and attending physicians. Physicians were highly educated. 91.75% of them had at least a bachelor's degree and 44.37% had at least a master's degree. About one-sixth of them had less than 10 years of work experience and 44.02% of them have more than 10 years of work experience. In the sample, 1,112 (8.25%) physicians did not provide information about their education and 5,343 (39.66%) did not list years of work experience.

Compared to male physicians, female physicians were on average less educated and more likely to hold a junior professional title. There was also a smaller percentage of female physicians who worked at the most prestigious hospitals (i.e., IIIA hospitals). Furthermore, female physicians were less likely than males to provide information

[23] *Dingxiang Doctor*, another popular e-consultation healthcare platform, has over 2,000,000 registered physicians, or three times the number listed by SRD. Yet, the former only had about 15 thousand physicians who were active in 2019. Data is from this website. Therefore, 13 thousand active physicians on the SRD was conventional and was not a small number in this market in 2020.

Table 1.1: Descriptive Statistics for Physicians on the Spring Rain Doctor in 2020

	(1) All	(2) Male	(3) Female	(4) Diff. ((2)-(3))	(5) S.E. of Diff.
Observations	13,472	8,300	5,172		
Avg. prices (¥)	19.467	20.037	18.551	1.487***	(0.318)
Avg. monthly consultations	34.450	32.154	38.134	-5.980***	(1.084)
Past consultations	2286.122	2110.761	2567.541	-456.780***	(96.362)
Share of available times	0.970	0.966	0.977	-0.011***	(0.002)
IIIA hospitals	0.565	0.582	0.539	0.043***	(0.009)
Relative patient ratings	0.171	0.196	0.132	0.064***	(0.017)
Relative peer ratings	0.621	0.685	0.518	0.167***	(0.021)
Entry year	2017.420	2017.304	2017.605	-0.300***	(0.035)
Professional titles					
Junior	0.467	0.451	0.492	-0.042***	(0.009)
Senior	0.533	0.549	0.508	0.042***	(0.009)
Education					
Not known degree	0.083	0.078	0.090	-0.012**	(0.005)
Bachelor and below	0.474	0.467	0.485	-0.017**	(0.009)
Master/M.D.	0.444	0.455	0.426	0.029***	(0.009)
Years of work experience					
Not known years	0.397	0.388	0.410	-0.021**	(0.009)
$\leq$ 10 years	0.163	0.163	0.164	-0.002	(0.007)
$>$ 10 years	0.440	0.449	0.426	0.023***	(0.009)
Platform					
Have photo	0.831	0.848	0.804	0.044***	(0.007)
Avg. default ranking	232.754	221.461	250.878	-29.417***	(2.830)
Displayed in the first 50	0.124	0.140	0.098	0.042***	(0.006)

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. "Have patient ratings" is a dummy equal to 1 if a physician has a patient rating. "Have photos" is a dummy equal to one if a physician has a profile photo. "Displayed in the first 50" is a dummy equal to 1 if a physician's average displayed rank is smaller than 50 within a specialty. "Avg. default ranking" is a continuous variable of physicians' default ranking in 2020. The junior professional title means general physician. Senior professional titles include attending physicians, associate chief physicians, and chief physicians. Column 4 reports the differences between male and female physicians and column 5 provides the corresponding standard errors. I test the differences between male and female physicians using a t-test with equal variance. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

regarding their education and work experience to potential patients in 2020. In terms of ratings, female physicians tend to have lower relative patient ratings and peer ratings than male physicians.[24]

[24] Although female physicians receive lower patient ratings than males, it should be noted that the patient ratings could suffer from selection bias and subjectivity (Boring, 2017; Cecchi-Dimeglio, 2017; Duberstein et al., 2007; Mitchell and Martin, 2018; Tadelis, 2016). When it comes to peer ratings,

A notable point from Table 1.1 is that the mean average displayed ranking for female physicians was higher than that of male physicians. It means that female physicians are more likely to be listed towards the lower end of patients' search results. The share of female physicians displayed in the first 50 physicians was 10%, which was 4 percentage points smaller than the share of male physicians. This suggests a potential bias in the ranking algorithm. In Section 1.5.2, I delve deeper into the role of the ranking algorithm and shed light on its effects on gender gaps.

1.4 Empirical Results on Gender Gaps

1.4.1 Lower Price, Fewer Consultations?

Table 1.1 shows that, on average, female physicians charge a lower average price and provide more average monthly consultations compared to their male counterparts. This would seem to suggest that female physicians set their prices lower to attract more patients. However, this is not the case if we compare female and male physicians within the same specialty. I estimate the raw gender price gap and the raw gender quantity gap in Table 1.2. After conditioning on entry year, province, and specialty, female physicians, on average, set their prices 3.59% lower and provided 17.60% fewer consultations compared to their male counterparts. Male physicians charged an average of ¥20.04 per consultation and provided an average of 32.15 consultations per month, earning an average of ¥644.27 on the platform. In contrast, female physicians earned 20.55% (calculated as $1-(1-3.59\%)(1-17.60\%)$) or ¥132.42 less than their male counterparts on the platform in 2020. This gap is similar to the average gap of 23.23% reported by Hoff and D. R. Lee (2021)[25] though is smaller than the one (30%) found by Gravelle, Hole, and Santos (2011) among general practitioners in the English National Health Service. The importance of the quantity dimension is a key feature of the gig economy setting for contract jobs and is analogous to the hiring decision in long-term employment relationships that are more commonly studied in

female physicians are equally qualified as their male counterparts. A more detailed discussion of the two ratings is provided in Appendix A.4.2.

[25] Hoff and D. R. Lee (2021) compare the mean unadjusted physician income by gender in 22 studies in Table 2, and the average unadjusted gender gap in income across the 22 studies was 23.23%.

the discrimination literature.

Table 1.2: Raw Gender Gaps: Spring Rain Doctor

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Ln(Avg. prices in 2020)					
Female	-0.033**	-0.003	-0.022*	-0.080***	-0.036**
	(0.013)	(0.013)	(0.013)	(0.015)	(0.014)
Control Mean	3.362	3.362	3.362	3.362	3.362
R^2	0.000	0.076	0.075	0.060	0.192
Panel B. Dependent Variable: Ln(Avg. monthly consultations in 2020)					
Female	0.198***	0.218***	0.181***	-0.142***	-0.176***
	(0.039)	(0.038)	(0.039)	(0.043)	(0.042)
Control Mean	2.096	2.096	2.096	2.096	2.096
R^2	0.002	0.057	0.015	0.090	0.154
Entry year FE	No	Yes	No	No	Yes
Province FE	No	No	Yes	No	Yes
Specialty FE	No	No	No	Yes	Yes
Observations	13,472	13,472	13,472	13,472	13,472

Notes: The "Control Mean" is the average for male physicians in all columns. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

1.4.2 Unexplained Gender Gaps

Next, following the previous literature, I estimate the unexplained gender gap in this regression:

$$\ln(Y_{jspt}) = \alpha + \beta_0 g_{jspt} + \gamma X_{jspt} + \delta_s + \delta_p + \delta_t + u_{jspt}, \tag{1.1}$$

where Y_{jspt} is the outcome variable, price or the number of average monthly consultations provided by physician j who is from province p, joined the platform in year t, and is working in specialty s. g_{jspt} is an indicator of gender that takes the value of one if physician j is female. The controls X_{jspt} are physicians' characteristics discussed in Section 1.3 such as relative patient ratings and relative peer ratings.[26] δ_s is

[26]Previous research demonstrates the importance of online ratings as an important information source for potential customers when making purchase decisions (Moe and Trusov, 2011; Godes and Silva, 2012; Tadelis, 2016; A. Chen, Y. Lu, and B. Wang, 2017; Vana and Lambrecht, 2021). Because of this, I include the relative patient ratings, as well as relative peer ratings, as controls in

the specialty fixed effects; δ_p is the province fixed effects;[27] δ_t is the entry year fixed effects;[28] and u_{jspt} is the error term. The coefficient β_0, the parameter of interest, is the estimate of the gender gap after controlling for observable characteristics that may be correlated with gender and affect demand.

Table 1.3 reports the results of the estimation of equation (1.1). In column 1, I include physicians' characteristics such as education, professional titles, and work experience. In column 2, I further control for two variables related to the platform's design: whether a physician has a profile photo and whether a physician is displayed among the first 50 on the list of doctors. The gender price gap does not change much with added controls, decreasing from 3.59% in column 5 of panel A in Table 1.2 to 2.25% ($p < 0.10$) in column 2 of panel A in Table 1.3. Panel B of Table 1.3 documents both statistically and economically significant quantity disparities between female and male physicians on the platform. The gender quantity gap in column 2 reduces by 37.63 percent (from 17.60% to 10.98%) after adjusting a series of physician characteristics, as compared to the gap in column 5 of panel B in Table 1.2.

I provide details on how physicians' characteristics affect the price and quantities in Appendix Table A.23 and Table A.24. As expected, working at IIIA hospitals, having a higher patient rating, having a senior professional title, and working for more years have positive effects on both prices and quantities.[29] In Appendix Table A.25, I also control for price and past consultations provided in the regression of quantity and the estimates are similar to the ones in Appendix Table A.24.[30] Specifically, neither

the regression analysis.

[27] The province fixed effect would capture unobserved patient preference in the same province. For example, as discussed in Q. Chen et al. (2022), patients display "home bias," preferring to consult physicians located in the same province, on the online healthcare platform.

[28] The entry year fixed effects will account for physicians' experience with the SRD platform.

[29] The negative effect of having a headshot on quantity could be driven by physicians who use selfies. I display two types of photos in Appendix Figure A.12, selfie and passport-type photos. The passport-type photo is professional while the selfie is not. And this will influence patients' purchase behavior. For example, as shown by Athey et al. (2022), online borrowers' profile photos have impacts on online lenders' decisions. In Appendix Figure A.19, I display the cumulative distribution function of quantity for physicians who have photos. The quantity distribution for physicians using selfies is statistically significantly different from that for physicians using passport-type photos. Physicians using selfies provide fewer consultations than physicians using professional photos.

[30] Here, I control the price for two reasons: 1) price affects demand directly; and 2) to investigate if patients are less likely to hire women at the same price as men. Price is endogenous to quantity. But if price and gender are uncorrelated, then it is better to leave price out of my regression altogether, because in that case, it does not bias my estimate of β_0, no matter how many variations in quantity are explained by price. I assume that the price is dependent on the physician's quantity rather than

Table 1.3: Unexplained Gender Gaps: Spring Rain Doctor

	(1)	(2)	(3)
Panel A. Dependent Variable: Ln(Avg. prices in 2020)			
Female	-0.023***	-0.023*	-0.020^{+}
	(0.013)	(0.013)	(0.013)
Platform			
Have photo		0.109***	0.109***
		(0.016)	(0.015)
Displayed in the first 50		0.149***	0.146***
		(0.020)	(0.020)
Latent Measure of Productivity			
Promotion			0.085***
			(0.016)
Control Mean	3.362	3.362	3.362
R^2	0.300	0.305	0.306
Panel B. Dependent Variable: Ln(Avg. monthly consultations in 2020)			
Female	-0.136***	-0.110***	-0.101***
	(0.039)	(0.038)	(0.038)
Platform			
Have photo		-0.372***	-0.370***
		(0.049)	(0.049)
Displayed in the first 50		1.758***	1.747***
		(0.056)	(0.056)
Latent Measure of Productivity			
Promotion			0.366***
			(0.044)
Control Mean	2.096	2.096	2.096
R^2	0.280	0.328	0.332
Other characteristics	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes
Observations	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, education, professional titles, and years of work experience. The "Control Mean" refers to the average value for male physicians. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

price nor past consultations changes the magnitude or significance of the coefficient on $Female$ in Appendix Table A.25. These two variables are not included in the following regression analysis.

gender. In the main specification, I do not include the price. In terms of past consultations, while it can be due to past discrimination, I control for it because new patients can observe this information and use it as a signal of experience and quality without acting discriminatorily. Since the log of past consultations does not alter the estimates much, I do not include it in the main specifications.

1.4.3 Discrimination?

Is the observed pattern of "lower price and fewer consultations for women" attributed to patient discrimination against female physicians? Discrimination occurs when members of one group (i.e., female physicians) are treated less favorably than members of another group (i.e., male physicians), despite having identical productive characteristics. As shown in column 2 of Table 1.3, gender gaps persist even after accounting for physicians' observable characteristics on the platform, indicating discrimination.

Yet, one may be concerned that observed gender gaps could suffer from omitted variables bias if there are unobserved gender differences in physician quality that patients can infer or if patients possess the sophistication to make such inferences. To alleviate this concern, I leverage the promotion information available by comparing physicians' profiles in 2023 to the ones in 2020 as the latent measure of physicians' quality. The idea is that physicians who are promoted in their main hospital jobs in the future (in 2023 relative to 2020), conditional on their current rank, are already of higher quality in 2020 compared to physicians who are not promoted later on. The variable "promotion" is equal to 1 if a physician has either been promoted to a more senior professional title (e.g., from attending physician to associate chief physician) or gone to a higher rank hospital (e.g., from an IIB hospital to an IIIC hospital) by 2023 and 0 otherwise.[31] In total, 1,839 physicians have been promoted in either form by 2023. It should be noted that, under this definition, chief physicians in IIIA hospitals have no further opportunities for promotion. So, I also assign a value of one to these physicians, of whom there are 280.[32] This variable captures a portion of the physician's true quality that was unobserved by patients in 2020 but observed by econometricians.

I test whether gender price and quantity gaps persist after conditioning on whether physicians were promoted by 2023. If this is the case, then it casts doubt on the con-

[31] I define a physician as having exited the market by 2023 if his/her information cannot be found on the platform in 2023. Details can be found in Appendix Section A.1.2. About 25% of 13,472 physicians exited the market by 2023. For these exited physicians, a value of zero is assigned to the "promotion" variable. In Appendix Table A.26, I show that the results remain after excluding the exited physicians.

[32] I also generate a variable called "Promotion (Exclude)" for a robustness check. For "Promotion (Exclude)", I assign a value of 0 to the 280 chief physicians in IIIA hospitals.

cern that the observed gaps in column 2 of Table 1.3 are due to unobserved gender differences in physician quality and supports discrimination. I include *Promotion* in equation (1.1) and report the result in column 3 of Table 1.3. The positive estimated coefficients for *Promotion* indicate that physicians who would be promoted by 2023 (i.e., have a higher quality) charged a higher price and provided more consultations than those who would not be promoted by 2023. Comparing column 3 to column 2, one can see that female physicians still set lower prices and provide fewer consultation services than their male counterparts after conditioning on their observable characteristics and a latent measure of physicians' actual productivity or quality.[33] More importantly, the estimated unexplained gender gaps in column 3 are both statistically and economically similar to those in column 2. This finding provides supportive evidence that there is discrimination in favor of male physicians on the SRD.

I further examine whether some of the discrimination is statistical in nature. in Appendix A.2, I provide a detailed discussion on testing for statistical discrimination within the context of information asymmetry, based on the statistical discrimination framework by Phelps (1972). I assume that the quality of both female and male physicians is drawn from a common distribution.[34] However, patients interpret signals differently based on a physician's gender. I find that patients penalize female physicians more for not providing information about work experience (a negative sig-

[33]The result in column 3 of Table 1.3 still persists after incorporating an interaction term between professional titles and types of hospitals. The estimated coefficient for *Female* stands at -0.02 ($p = 0.13$) when the dependent variable is the log of average prices in 2020, and -0.10 ($p < 0.01$) when it is the log of average monthly consultations provided in 2020. The result in column 3 of Table 1.3 also persists when I replace "Promotion" with "Promotion (Exclude)." The result is reported in column 4 of Appendix Table A.27. Additionally, I augment equation (1.1) with the interaction term of *Female* and *Promotion* to examine if patients possess the capability to obtain additional information beyond the platform and are sufficiently knowledgeable to deduce the actual quality of physicians. By Implication 2, discussed in Appendix A.2.2, if patients possess additional information on physicians' quality beyond what is provided by the platform, then they would significantly increase inquiries for female physicians who would be promoted by 2023. The result is displayed in column 3 of Appendix Table A.27. As shown, the estimated coefficient for *Female* $\times$ *Promotion* is statistically insignificant at conventional levels. The estimated coefficient for the interaction term becomes negligible and remains statistically insignificant when "Promotion" is replaced with "Promotion (Exclude)" (column 5 of Appendix Table A.27). These results suggest that patients did not treat female physicians who would be promoted by 2023 differently from their male counterparts. In short, it is unlikely that patients are that knowledgeable or able to distinguish high-quality female physicians from low-quality ones using information beyond the SRD.

[34]In Appendix A.2.4, I examine the scenario in which patients believe that female physicians have a lower average quality than male physicians, following the method proposed by Foster and Rosenzweig (1993) and Foster and Rosenzweig (1996).

nal of quality) and reward them more for having a senior professional title (a positive signal of quality). Over time, the revelation of work experience by physicians leads to the elimination of the gender penalty. These provide supportive evidence of patients statistically discriminating against female physicians. in Appendix A.3, I further investigate whether patients treat female physicians differently by specialty and find suggestive evidence of homophilic preferences—a form of taste-based discrimination—on the online healthcare platform.

1.5 The Platform Design

Regardless of the source of discrimination, there are gender gaps. In this section, I delve deeper into the potential role of the platform, specifically examining if it has the potential to intensify patient discrimination and widen gender disparities. As discussed in Section 1.3, the platform displays physicians' pictures on the list of doctors and uses an algorithm to determine a physician's position on the list. In column 2 of Table 1.3, I include the two attributes and the unexplained gender quantity gap decreases from 13.62% to 10.98% (or by 19.42 percent). This indicates that the platform's design plays an important role in perpetuating gender gaps. To determine the contributions of a physician's profile photo, ranking, professional title, education, and work experience to the gender quantity gap, I conduct a Gelbach decomposition as these variables are likely to be correlated (Gelbach, 2016). Table 1.4 displays the results. The platform's design contributes 23.43% to the raw gender quantity gap in total. A physician's headshot and his/her position on the list of doctors account for 5.65% and 56.60% of the explained part of the gender quantity gap, respectively. The combined effect of these two factors surpasses the contribution made by other characteristics of the physician.

1.5.1 Profile Photos

Although physicians' profile photos make a small contribution (2.13%) to gender quantity gaps, it has the potential to make discrimination easier. While patients can use a physician's first name to predict their gender, photos make gender more salient and facilitate discrimination, thereby exacerbating gender gaps. To assess the

Table 1.4: Contributions to the Gender Quantity Gaps

	Raw	Unexplained	Explained	Contribution: Professional Title, Education, Work Exp.	Photo	Rank (Dummy)	Other Controls
Quantity gap	-0.176	-0.110	-0.066	-0.008	-0.004	-0.037	-0.017
p-value				(0.004)	(0.171)	(0.001)	(0.160)
Contributions (Explained)				(12.16%)	(5.65%)	(56.60%)	(25.59%)
Contributions [Raw]		[62.37%]	[37.63%]	[4.57%]	[2.13%]	[21.30%]	[9.63%]

Notes: Work Exp. = Work experience. Other controls include a physician's share of availability, class of working hospital, relative patient ratings, relative peer ratings, and a dummy of promotion. The explained part of the gender gap is the difference between the raw gender gap and the unexplained part of the gender gap. I calculate the contributions (as a percentage) of the three factors to the explained part of the gender quantity gap in the round brackets and the contributions to the raw gender quantity gap in the square brackets.

contribution of physician headshots to the gender quantity gap, an ideal approach would be to compare the demand gap among physicians with neutral names (i.e., names that do not directly indicate gender) who have profile photos versus those who do not. In the sample, I identify 1,044 physicians with neutral names. The identification of neutral names will be discussed in detail in Section 1.7.3. I regress the log of average monthly consultations provided in 2020 on $Female$, $Have\ photo$, and their interaction term on this small sub-sample. The results are displayed in Appendix Table A.28. In columns 1-3, I include specialty, entry year, and province fixed effects progressively. The estimated coefficients on $Female$ and the interaction term are all negative in columns 1-3 though measured imprecisely. While female physicians receive fewer consultations than males, profile photos further exacerbate the disadvantage faced by female physicians. The results thus suggest that photos can make discrimination easier, and removing physicians' pictures from the search results could be a potential measure to mitigate gender gaps.[35]

1.5.2 The Ranking Algorithm

As presented in Table 1.4, a physician's ranking contributes the most (21.30%) to the raw gender quantity gap, with female physicians being less likely to be placed at the top of the doctor list. Previous research (Barocas and Selbst, 2016; Kleinberg et al., 2018; Mayson, 2019; Rambachan, Kleinberg, et al., 2020) has highlighted that there

[35]The platform may still display a physician's headshot on his/her homepage so that patients would not know a physician's gender exactly unless they visit a physician's homepage. It will increase patients' cost of discrimination as it requires more steps to determine a physician's actual gender.

is growing concern about algorithmic fairness due to the increasing use of algorithms in various fields, particularly if the algorithm is trained on data generated by biased human decision-makers. Studies (Cowgill, 2018; Cowgill and C. E. Tucker, 2020) have shown that algorithms may *exacerbate* and *perpetuate* existing disparities. In light of these concerns, I further explore the platform's ranking algorithm, especially its potential to prevent female physicians from receiving fair treatment.

The platform's problem

Let $A_j(X_j)$ represent physician j's position on the list of doctors, where a smaller A_j indicates a higher, more desirable position. X_j is a vector of four features discussed in Section 1.2.4. For simplicity, let's assume that the algorithm does not allow for ties.[36] I define the ranking algorithm as unbiased if

$$\Delta A^* = E[A|g = F] - E[A|g = M] = 0, \tag{1.2}$$

and conditionally unbiased if

$$\Delta A = E[A|g = F, X] - E[A|g = M, X] = 0. \tag{1.3}$$

g represents a physician's gender, with $g \in \{M = 0, F = 1\}$, where M denotes male and F denotes female. The algorithm is (conditionally) biased towards female physicians if $\Delta A^* < 0$ ($\Delta A < 0$).

As outlined in Section 1.2.4, the platform's objective is to maximize its profit by altering physicians' rankings, $A(X)$, with the ranking algorithm designed to maximize sales. In other words, the ranking algorithm is trying to predict future patient demand for a physician's services, using past patient behaviors, including discrimination (whether statistical or taste-based), as an important predictor. In this case, those who are more frequently consulted by patients are more likely to be displayed at the top, regardless of their actual quality.[37] In the following, I will first show that the

[36] For physicians who have the same set of characteristics, the algorithm may rank them by their last name.

[37] One might wonder if the platform would display physicians according to their true quality if it could develop a complex model to determine the actual quality of physicians. This could be possible in two scenarios: 1) the same objective applies, but the platform operates under perfect information without any taste-based discrimination; and 2) the platform's goal is to showcase the

ranking algorithm is biased and determine if it is conditionally unbiased. Then, I will examine the persistence of default rankings over time.

Biased ranking algorithm

I employ the conditioning-on-observables approach and conduct two tests to determine if the ranking is (conditionally) unbiased. In the first test, I regress the average default ranking (a smaller value means a better position) on gender and include the four main features used by the platform's ranking algorithm progressively. The results are presented in panel A of Table 1.5. Two points can be inferred. First, as indicated by column 1, the ranking algorithm is biased. Second, after adjusting for the average number of monthly consultations in 2020, the estimated coefficient for $Female$ becomes small and statistically insignificant, suggesting that the ranking algorithm is conditionally unbiased. I also implement a Gelbach decomposition to examine the contribution of each of the four factors and report the results in Appendix Table A.29. The table shows that the number of average monthly consultations in 2020 explains most of the variation in physicians' default rankings. It accounts for 55.16% of the raw gender gap in the average default ranking.

In the second test, I restricted the sample to 992 physicians who joined the platform between March 25 and June 30, 2020. For these physicians, the platform does not have prior information on patient demand during the initial days. Given this, if one does not identify a lower default ranking for female physicians than their male counterparts, then it suggests that the ranking algorithm would not rank female physicians lower than male physicians in the absence of biased data on patient behaviors. I regress the first-week average ranking on gender and progressively include three factors except for patient demand. The results are provided in panel B of Table 1.5. In column 1, the estimated coefficient for $Female$ (13.16) is economically similar to the one (11.19) in column 1 of panel B though measured imprecisely. In column 4, one can see that after accounting for physicians' availability, the algorithm is not biased towards male physicians. The estimated coefficient (-2.83) is neither statistically nor economically significant, whereas it (9.88) remains positive and statistically significant in column 4 of panel A.

most productive physicians. However, neither condition is met on the SRD.

Table 1.5: Results on the Ranking Algorithm

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent variable: Average Default Ranking					
Female	11.194***	8.943***	9.632***	9.881***	3.531
	(3.039)	(2.973)	(2.863)	(2.858)	(2.457)
Senior professional title		-60.683***	-63.117***	-63.024***	-55.665***
		(2.638)	(2.569)	(2.565)	(2.212)
IIIA hospitals			-77.638***	-78.664***	-54.937***
			(2.555)	(2.553)	(2.244)
Share of available times				-71.015***	-7.744
				(8.602)	(8.524)
Ln(Avg. monthly consultations in 2020)					-35.088***
					(0.485)
Entry year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
R^2	0.186	0.217	0.268	0.272	0.462
Observations	13,472	13,472	13,472	13,472	13,472
Panel B. Dependent variable: First-Week Average Ranking					
Female	13.159	12.285	13.208	-2.833	
	(9.919)	(9.954)	(9.946)	(5.635)	
Senior professional title		-16.759*	-17.204**	-17.140***	
		(8.689)	(8.683)	(5.400)	
IIIA hospitals			-20.416**	-7.775	
			(9.220)	(6.370)	
Share of available times in that week				-270.097***	
				(10.39)	
Entry Month FE	Yes	Yes	Yes	Yes	
Province FE	Yes	Yes	Yes	Yes	
Specialty FE	Yes	Yes	Yes	Yes	
R^2	0.422	0.424	0.427	0.770	
Observations	992	992	992	992	

Notes: "Share of available times in that week" = The number of times a physician appeared on the SRD with a listed price during their first week on the platform, divided by the total number of times the physician appeared in the data during that same week. Robust standard errors are reported in parentheses. In panel B, I restrict the sample to physicians who joined the platform between March 25 and June 30, 2020. In panel A, I incorporate entry year, province, and specialty fixed effects in all regressions; and in panel B, I include entry month, province, and specialty fixed effects in all regressions. "Control Mean" is the average of the outcome variables for male physicians. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

The results in Table 1.5 show that the ranking algorithm does not systematically rank female physicians lower than male physicians when lacking information on patient demand and relies on the three other factors to maximize purchase likelihood. However, once information on (biased) patient demand becomes available, the algorithm exhibits an unconditional gender bias. It prioritizes physicians, especially male physicians, who receive more patient inquiries per month. Therefore, despite the fact that the algorithm is gender-neutral conditional on the four features, it has the potential to *amplify* gender gaps. This occurs through a feedback loop, where the algorithm uses past patient behaviors, including discrimination, to predict future patient behavior.[38] For example, when *some* patients discriminate against female physicians and intend not to buy their services, this would harm their rankings. The negative impact on female physicians' rankings would then influence future patients' decisions since it takes time and effort for patients to explore all the listed physicians.[39] This, in turn, feeds back into the platform's data used for future rankings, creating a vicious feedback loop. Figure 1.1 displays this process. As a result, discrimination by some patients could lead to female physicians as a whole being ranked lower, thus further *exacerbating* the gender gaps.

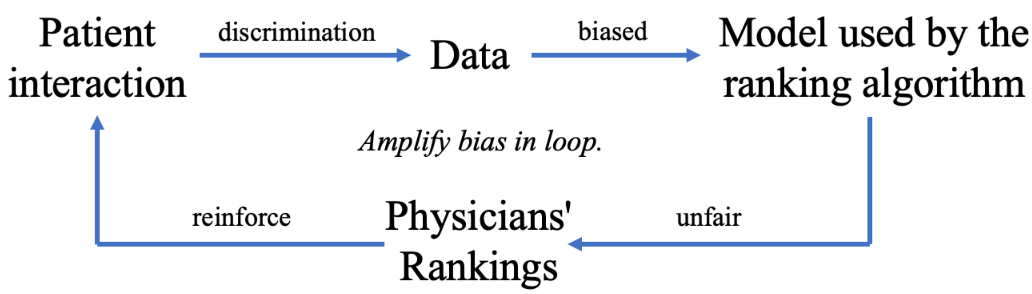


Figure 1.1: Platform's Ranking Algorithm: Feedback Loop

Note: If patients discriminate against female physicians, it will generate biased data that the ranking algorithm is trained on, which then produces unfair ranking and affects future patients' decisions.

Sticky default rankings

Next, I compare physicians' default rankings in 2020 with those in 2023 to investigate the *persistence* of physicians' default rankings. As discussed in Section 1.2.4, in 2023, patients can sort and filter physicians based on various characteristics (excluding gender), which was not an option in 2020. It means that patients can now search for physicians more efficiently, and as a result, the default rankings in 2020 and 2023 are expected to be weakly positively or even negatively correlated. This is because if patients are no longer restricted by the default ranking, they can improve their

[38] Rambachan and Roth (2019) show that using the algorithm trained on data generated by human decision-makers to predict human decisions could lead to the "bias in, bias out" outcome. And biased training data is the most common reason for biased predictions (Cowgill, Dell'Acqua, et al., 2020).

[39] An item's position on the search results page is correlated with customers' purchase decisions and buyers are more likely to select the item listed on the top of the results (Ghose, Ipeirotis, and Beibei Li, 2014; Ursu, 2018; Derakhshan et al., 2022).

search efficiency, which leads to an increase in consultations with female physicians compared to before. This increased demand for female physicians, in turn, improves their default rankings. If a moderate or strong positive correlation is observed, then it provides suggestive evidence that: (1) patients rely on the default ranking; and (2) the ranking algorithm has the potential to *perpetuate* gender gaps by consistently placing female physicians in lower positions.

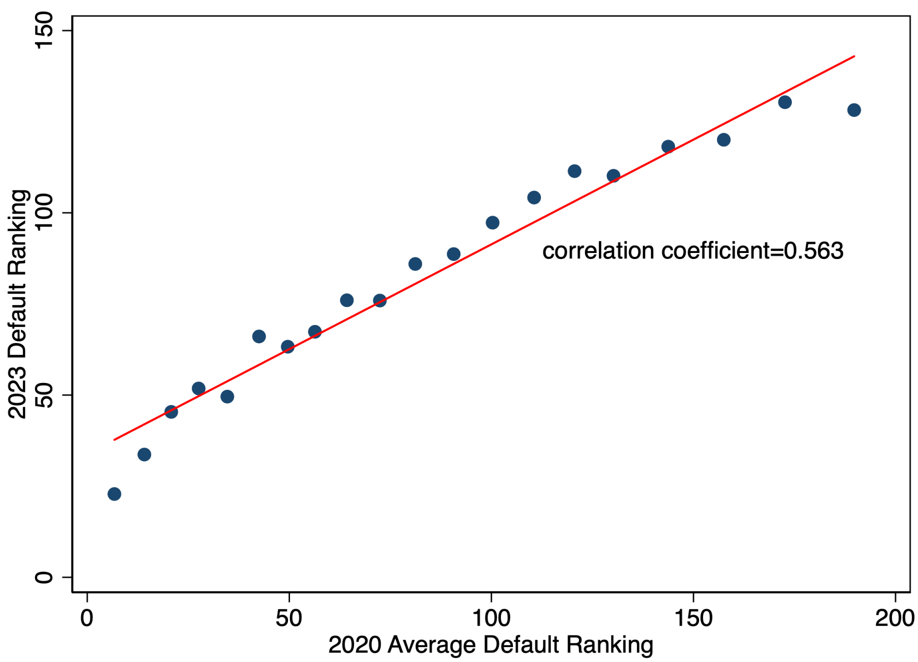


Figure 1.2: Binscatter Plot of Relationship between Physicians' Default Ranking in 2020 and 2023

Note: The figure plots the default ranking in 2023 against the average default ranking in 2020. Due to crawling restrictions, I could only access the information of the first 200 physicians in each specialty in 2023. 5,124 physicians who continued to be on the platform in 2023 were displayed in the top 200 on the list of doctors within a specialty in 2020. Among those physicians, 61.6% were also displayed in the first 200 on the list of doctors within a specialty in 2023. I restrict the sample to these 3,155 physicians. The red line is the fitted line, which has an estimated coefficient of 0.575. The correlation coefficient is 0.563.

In Figure 1.2, I plot physicians' default ranking in 2023 against their average default ranking in 2020, based on a sub-sample of physicians who were displayed in the top 200 in both years. As shown, there is a positive correlation (correlation coefficient = 0.563) between physicians' rankings in 2023 and their rankings in 2020. I then calculate the correlation coefficients of displaying in the top 50, between 51 and 100, between 101 and 150, between 151 and 200, and after 200 in 2020 and 2023.[40] This complements the result presented Figure 1.2, as it enables the inclusion of physicians ranked outside the top 200. Appendix Table A.30 displays the results, which further support that physicians who ranked higher (lower) in 2020 tended to maintain their default rankings in 2023. For example, the correlation coefficient for displaying in the top 50 in both 2020 and 2023 is 0.48, and the coefficient for displaying beyond the top 200 in 2020 and 2023 is 0.50. Besides, it is unlikely that physicians who ranked low in 2020 (e.g., after the top 200) would be ranked high in 2023 (e.g., in the top 50). The results thus provide support for the idea that patients rely on the default sorting, which enables the ranking algorithm to *perpetuate* gender gaps by consistently positioning female physicians, even those with high quality, in lower rankings.

1.6 Alternative Mechanisms

In this section, I examine three plausible alternative mechanisms: lower supply by female physicians due to household responsibilities, lower pricing by female physicians associated with lower quality, and lower pricing by female physicians as a result of lower self-confidence. But, I do not find support for the proposed mechanisms.

1.6.1 Lower Supply by Female Physicians?

One may be concerned that the lower number of consultations provided by female physicians is attributed to their lower supply rather than a lower demand for their services. For example, according to the *2018 National Time Use Survey Bulletin* published by the National Bureau of Statistics, the average daily working hours are 7.9 for men and 7.4 for women and the average daily hours spent on household duties are 0.75 for men and 2.1 for women. As women dedicate nearly three times more time to domestic responsibilities than men, it can restrict the availability of female physicians to allocate time for providing online consultation services. However, it is worth noting that the online platform offers greater flexibility compared to in-person

[40]Here, I calculate the correlation coefficients between two dummy variables. For example, "Average default ranking in 2020 is between 101 and 150" is a dummy variable equal to one if the ranking is larger than 101 and smaller than 150.

options, which aligns with the preferences of women (Goldin, 2014; Goldin, 2015). This increased flexibility can be particularly appealing to female physicians, which can result in an increased supply of their time to the online platform. For example, Barzilay and Ben-David (2016) find that women work for more hours than men on a global online platform.

To further examine the potential supply-side effect (i.e., female physicians are less available on the platform), I document the differences between women's and men's availability on the healthcare platform. I first constructed the share of physicians by gender who were available among all observed physicians on that day by gender. I plot the shares over time in Appendix Figure A.11. The availability share of female physicians was consistently higher than the share of male physicians. Next, I regress the share of available times on *Female*. Appendix Table A.8 displays the results. From column 1 to column 3, I progressively include fixed effects (i.e., entry year, province, and specialty) and physicians' characteristics. The estimated coefficients on *Female* are consistently positive across all three columns and statistically significant at a 15% level in column 3. Thus, conditional on appearing on the platform, female physicians are not less available than males. This also alleviates the concern that household responsibilities might crowd out female physicians' time for providing online consultations.[41]

1.6.2 Lower Quality, Lower Price?

One may be concerned that female physicians charge lower prices due to lower quality but not lower expected demand, and patients associate lower prices specifically with female physicians as an indication of lower quality. In other words, price captures some expected unobserved quality of physicians which is correlative with female physicians. This is a valid concern if there is an element of quality that is observable to patients and not to the econometrician. Yet, this seems unlikely, as patients seem to have a limited tendency to seek information from external sources. If quality is equally unobservable to patients as to the econometrician, then additional conditions would be needed for a higher price to be a credible signal of quality in equilibrium. In

[41] While these findings alleviate much of the concern that household responsibilities might crowd out female physicians' time for providing online consultations, it is important to note that the measure used here is a rough proxy based solely on the times when the data was scraped in 2020.

that case, price is positively related to unobserved quality, and the estimated quantity differences may be related to quality rather than discrimination. Based on this concern, I conducted three tests to investigate the possibility of unobserved quality driving the gender gaps. First, I investigate whether female physicians receive lower relative peer ratings than their male counterparts, given that these ratings are generally more objective than patient ratings and are indicative of physicians' quality. Next, I check if patients increase their demand from physicians who raise their prices by leveraging both the cross-sectional and the panel data. But, I find no support for this probability. I discuss the details of the three tests in Appendix A.4.2.

1.6.3 Lower Self-Confidence, Lower Price?

Lastly, I examine if female physicians undervalue their services because they are less confident than their male counterparts and thus set a lower price. Previous research has shown that women are often less aggressive/confident (Bengtsson, Persson, and Willenhag, 2005; Buser, Niederle, and Oosterbeek, 2014; Buser, Peter, and Wolter, 2017; Haeckl, 2022), and thus the price differences may reflect gender differentials in self-confidence. To examine whether gender differences in self-confidence can explain gender price gaps, I use the type of photo posted by a physician as a proxy of confidence. Previous studies note that people who use selfies are more likely to be less confident (Albury, 2015; Fox and Rooney, 2015; Richa, Nidhi, and Chhavi, 2020). A physician's photo type is a dummy equal to one if it is a passport-type photo and zero if it is a selfie (Appendix Figure A.12). I restrict the analysis to 11,195 physicians who uploaded headshots in 2020. In this sub-sample, females are more likely to use selfies, with 50.6% of them using this type of photo, which is 11.4 percentage points higher than male physicians.

In column 1 of Appendix Table A.14, I estimate equation (1.1) on the restricted sample. The gender price gap is 3.1% ($p < 0.05$). In column 2, I control for *Photo type*, the gender price gap decreases by 0.6 percentage points but remains statistically significant at a 10% level. In column 3, I augment the equation with an interaction term of *Female* and *Photo type*. The estimated coefficient for *Female* is -0.029. Although measured imprecisely, its magnitude is similar to -0.031 in column 1 and -0.025 in column 2. The estimated coefficient for *Female* $\times$ *Photo type* is 0.008 and is statistically insignificant at conventional levels. It implies that there is no gender differential impact of photo types on prices. In short, the results suggest that the channel of self-confidence is unlikely.

1.7 Robustness of Results

In this section, I conduct four additional exercises to enhance the robustness of the findings and strengthen confidence in the observed gender gaps and the presence of discrimination.

1.7.1 Gender Prediction Algorithm

One may be concerned that the prediction algorithm, *Ngender*, used in this study is not reliable. To address the concern and to strengthen the confidence in my results, I employ another gender prediction algorithm, *Namsor* to cross-check correctness. First, when using the names of 13,472 physicians, approximately 85% of the gender predictions made by the two algorithms matched. Among the 610 physicians without profile photos, around 96% of those predicted as female by *Ngender* were also predicted as female by *Namsor*. Second, using a sub-sample of 12,862 physicians with photos, the probability that a physician predicted to be (fe)male is, in fact, (fe)male is (72%) 90% using *Namsor*. And the probability that a physician predicted to be (fe)male is, in fact (fe)male is (85%) 86% using *Ngender*. The overall accuracy rate is 82% for *Namsor* and 86% for *Ngender*. So, *Ngender* is superior to *Namsor* in terms of both the overall accuracy rate and the accuracy rate for predicting females. Based on these findings, the gender predictions made by *Ngender* are reliable.

1.7.2 Sample Restrictions

To bolster the confidence in the results of gender disparities and to further alleviate the concern regarding the gender prediction algorithm, I estimate equation (1.1) on two sub-samples. The first sub-sample consists of physicians with profile photos in 2020. And the second sub-sample is composed of physicians in the first sub-sample and physicians who updated their profile photos in 2023. The results are displayed in Appendix Table A.15 and Table A.16, and show that the coefficients remain robust despite these restrictions. Moreover, as expected, the gender gaps observed in the first sub-sample are larger than in the analysis sample of 13,472 physicians (3.13% in column 4 of Appendix Table A.15 panel A versus 2.25% in column 2 of Table 1.3 panel A; 12.44% in column 4 of Appendix A.15 panel B versus 10.98% in column 2 of Table 1.3 panel B). This finding supports the notion that photos make gender more salient, lower the cost of discrimination, and thus contribute to the widening of gender gaps.

1.7.3 Placebo Test: Neutral Name

Next, I conduct a placebo test using variations in physicians' name neutrality. A neutral name can be considered exogenously determined as it is usually given to a child by their parents. By not indicating the gender of a physician, a neutral name is expected to have no influence on prices or services provided. If this holds true, it will reinforce the evidence that discrimination based on gender, as inferred through gender-oriented names or profile pictures, exists.

I define neutral names as names whose predicted gender, either from *Ngender* or *Namsor*, differs from one's actual gender or where the predicted gender from *Ngender* does not align with the predicted gender from *Namsor*. I further restrict neutral names to those whose probability of being a specific gender is below the average probability among names with conflicting gender assignments.[42] This restriction is applied because names associated with higher probabilities are considered unlikely to be neutral.

I include the dummy variable "Neutral name" and re-estimate equations (1.1). Appendix Table A.17 displays the results. Comparing Appendix Table A.17 to Table 1.3, one can observe two points.[43] First, both gender price and quantity gaps remain after the inclusion of *Neutral name*. Second, the estimated coefficients for *Neutral name* are small and statistically insignificant at conventional levels in both panel A

[42] The average probability among names with conflicting gender assignments is 73% by *Ngender* and 52% by *Namsor*.

[43] Column 1 in Table 1.3 corresponds to column 3 in Appendix Table A.17; and column 2 in Table 1.3 corresponds to column 5 in Appendix Table A.17.

and panel B. These results thus provide supportive evidence that profile photos and gender-specific names make discrimination easier.

1.7.4 External Validity: *WeDoctor*

Lastly, to assess the external validity of the results obtained from the SRD platform, I replicated the regression analysis on another platform, *WeDoctor*. I crawled *WeDoctor* 24 times between October 2020 and January 2021 and collected data on 30,042 physicians. Despite differences in the distribution of physicians working at *WeDoctor* concerning professional title, education, and work experience compared to SRD, the analysis still shows that on average, female physicians set lower prices than their male counterparts, even after controlling for physicians' characteristics. Thus, gender gaps widely exist in the gig economy, indicating the robustness of the results presented in this paper. I provide a detailed discussion of the platform and the results in Appendix A.5.3.

1.8 Conclusion

This paper examines novel data from a leading online healthcare platform in a major developing country. I document a 2.25% unexplained gender price gap (column 2 in panel A of Table 1.3) and a 10.98% unexplained gender quantity gap (column 2 in panel B of Table 1.3) between men and women for a sample of highly-skilled workers, specifically physicians, in the medical industry. The gaps are statistically significant and economically meaningful. After adjustment, female physicians, on average, earn ¥83.64 (12.98%) less per month than their male counterparts, an amount equivalent to the cost of four decent Big Mac Meals.

Patient discrimination plays an important role in the observed gender gaps. After accounting for a latent measure of physicians' true quality, female physicians still charge prices 2.04% lower and offer 10.08% fewer consultations than their equally productive male counterparts. Under the assumption of identical quality distributions but different signal distributions for female and male physicians, I find supportive evidence for statistical discrimination. Specifically, patients penalize female physicians more for not providing information on work experience (a negative signal) but reward female physicians more when they observe senior professional titles (a positive signal).

Although the platform offers flexibility, which is valued by female workers, its design does not address the discrimination that is prevalent in developing countries. Instead, the platform's design has the potential to *amplify* and *perpetuate* gender gaps. Displaying physicians' headshots on the list of doctors makes discrimination easier and disadvantages female physicians further. The ranking algorithm contributes 21.30% to the raw gender gaps. It predicts future patient behavior and determines physicians' positions based on past patient behaviors, including discrimination, which then circles back as training data for the algorithm. This feedback loop intensifies biases over time. Furthermore, although the platform introduced more efficient filtering and sorting options, which, in theory, should benefit female physicians and narrow gender gaps, patients continue to rely on the default sorting option, leading to the persistent low ranking of female physicians. These findings highlight the significance of improving mechanism design, such as debiasing data and models, as sexism is always more severe in developing countries.

In summary, this paper shows that algorithms could undermine the gig economy's potential to narrow gender gaps. An important policy implication of this study is the need to regulate the algorithmic designs of burgeoning online platforms, with a particular focus on ensuring algorithmic fairness.

Chapter 2

Digitalization as a Double-Edged Sword: Winning Services and Losing Manufacturing in India

2.1 Introduction

Digitalization is a transformative force reshaping economies.[1] It alters the dynamics between consumers and firms, and affects competition and coordination across firms. This transformation is evident in the rapid growth of e-commerce platforms such as Amazon and Alibaba.[2] Besides, businesses are increasingly harnessing digital platforms like Amazon Web Services to enhance efficiency and lower costs. Previous research finds a positive relationship between digitalization and economic growth in developed countries (S. Agarwal, Qian, Yeung, et al., 2019; Bakhshi and Larsen, 2005; Colecchia and Schreyer, 2002; Kolko, 2012; Oulton, 2002). Yet, in developing countries, the implications of digitalization for firms remain unclear. Missing credit markets can hinder capital adoption if firms need to make lumpy investments. Similarly, labor market frictions can also impede adoption. There is a paucity of research about the consequences for firms in developing countries.

This paper explores whether firms can universally capitalize on digitalization opportunities and, if not, examines the mechanisms driving these transitional dynamics across sectors in developing countries in the short term. To answer these questions, I

[1]Digitization is the process of converting information into digital format. An illustrative example of digitization is the transition from physical currency to digital payment methods. Digitalization refers to the adoption and application of digital technology, spurred by digitization, to change a business model and create new revenue opportunities (Ritter and Pedersen, 2020).

[2]For example, Alibaba has revolutionized China's retail sector, not just by simplifying online shopping but also by integrating digital payments and providing innovative financial services.

analyze firms' behavior during a period in which there was a significant and sudden push toward digitizing the economy in India.

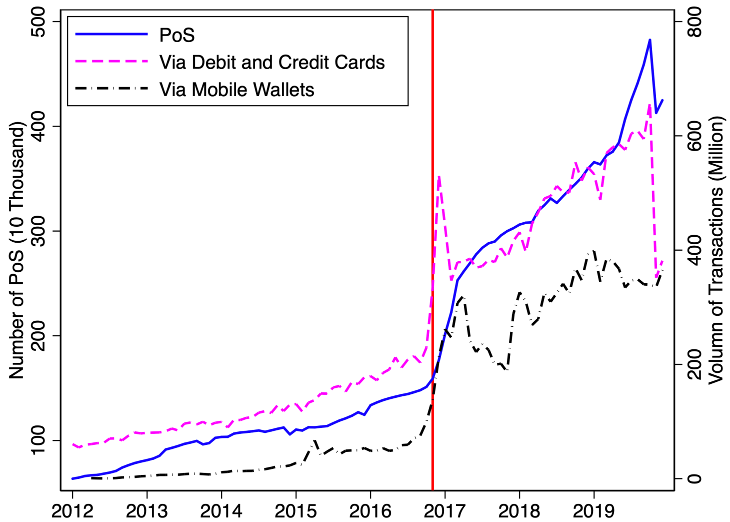
India provides a pertinent and important setting for this analysis. The Indian government initiated a series of policies to digitize the economy and promote digitalization;[3] however, the results fell short of expectations. For example, as shown in Figure 2.1, the use of electronic payment methods and the number of point of sale (PoS) terminals that facilitate these methods remained relatively low up until late 2016. This slow adoption hindered the country's digitization progress. Additionally, integrating digitalization into business operations requires specialized skills. Yet, as reported by ManpowerGroup, the share of Indian employers facing challenges in filling vacant positions increased from 48% in 2012 to 63% in 2019 and further surged to 80% by 2023.

I use two main data sources to answer my research questions. First, I employ a comprehensive panel of firm-level data, covering over 30,000 firms in the formal sector from 2012 to 2019. This data was obtained from the Prowess Database, collected by the Center for Monitoring the Indian Economy (CMIE). It contains annual financial statements, which provide statistics on income, expenses, and both asset and liability portfolios. Most importantly, it allows me to observe firms' expenditures on ICT-related services like internet subscriptions and to generate a variable called "ICT assets," which includes software, computers, and IT systems, serving as a proxy variable for digitalization and aiming to capture digital technology adoption and application. Second, to investigate labor market changes between 2014 and 2019, I use the Consumer Pyramids Household Survey, also collected by the CMIE, as the Prowess data does not contain information on labor.[4] The data includes individual-level information on wages, education, and degree disciplines, enabling me to identify "ICT labor" as individuals who possess degrees in computer science or engineering.

The identification strategy relies on two sources of variation. First, I exploit the temporal variation caused by a surge in digital payment usage following the unex-

[3]For example, the government launched the National e-Governance Plan in May 2006 aiming to facilitate online delivery of government services to citizens. In January 2009, the Aadhaar program was introduced to foster the development of digital payment and e-governance services. The Bharat-Net program, initiated in October 2011, sought to provide high-speed internet connectivity to all villages. Additionally, the Digital India campaign, launched in July 2015, focused on developing digital infrastructure, promoting digital literacy, and offering digital government services.

[4]The Consumer Pyramids Household Survey was initiated in 2014.



Notes: Data is from the Monthly RBI Bulletin published by the Reserve Bank of India. The frequency of the data is monthly. In Figure 2.1, the blue solid line represents the number of point of sale (PoS) terminals, scaled by 10,000; the purple dashed line represents the monthly number of transactions made by debit and credit cards; and the black dash-dotted line represents the monthly number of transactions made by mobile wallets. A PoS terminal is an electronic device that enables customers to pay merchants for goods or services using various methods, such as debit, credit, or prepaid cards or QR scanning. The red vertical line is November 2016.

Figure 2.1: Trends in Card Transactions, Mobile Wallet Transactions, and Point-of-Sale Terminals

pected demonetization policy in 2016.[5] The policy caused a nationwide cash shortage, thereby prompting the transition from paper currency to digital payment methods and accelerating the digitization process (Chodorow-Reich et al., 2020; Crouzet, Gupta, and Mezzanotti, 2023). This shift subsequently increased firms' incentive to adopt digital technology. The second source of variation is spatial differences in the digital environment that facilitated the adoption of digital technology. Upon being hit by the cash crunch, firms in districts with more favorable digital environments (e.g., stable public Wi-Fi and more data centers) were, as was expected, able to transition to digital platforms more smoothly and effortlessly, allowing them to perform relatively better than those in less advanced digital settings. I construct a district-level e-Readiness Index (*e-Index*) to measure a district's preparedness for digitalization, with a higher value indicating a more favorable digital environment.

I employ the difference-in-differences framework to estimate the impacts of digitalization on firms. This strategy compares firms in districts with a high *e-Index* to those

[5]Several other countries have also implemented demonetization policies in the 2000s, including North Korea in 2010, Nigeria in 2022, the Philippines in 2015, and Zimbabwe in 2009.

in districts with a low *e-Index*, before and after a positive digital shock in 2016. The strategy relies on there having been no other shocks occurring around the same time in 2016 that are correlated with districts' digital environments, as well as that firms in more e-Ready districts exhibit similar trends to those in less e-Ready districts before the policy shock. In the baseline regression concerning firms, I incorporate the firm and industry-year fixed effects. This accounts for both the time-invariant characteristics of a firm and a district, as well as time-varying industry attributes.

I begin by examining firms' outcomes in terms of income, sales, and total factor revenue productivity (TFPR). To estimate TFPR, I use the method proposed by Grieco, S. Li, and H. Zhang (2016). It accommodates the endogenous productivity assumption and obviates the need for real output or real intermediate input data, which are not available in the Prowess data. Two results are observed. First, there are no differential effects in income, sales, or TFPR between firms in more e-Ready districts compared to those in less e-Ready areas. Second, surprisingly, the overall null effects mask contrasting impacts on service and manufacturing firms. In districts with one standard deviation higher *e-Index*, service firms reported a 1.3% increase in income, a 1.0% rise in sales, and an 8.4% surge in TFPR. On the other hand, manufacturing firms reported a 2.5% decline in income, a 2.5% drop in sales, and an 8.1% reduction in TFPR.[6] The finding concerning manufacturing firms is contrary to previous research, which shows that digitalization opportunities enhance the performance of manufacturing firms in developing countries (Fernandes et al., 2019; Zhou, Wen, and C.-C. Lee, 2022).

To rationalize the divergent growth trajectories in the service and manufacturing sectors, I provide a simple static conceptual framework of technology adoption, building upon the framework proposed by Doraszelski and Jaumandreu (2013) and Harrigan, Reshef, and Toubal (2023). I assume that the adoption of digital technology, encompassing ICT labor employment and ICT capital investment, affects only Hicks-neutral

[6]The level of the estimates in this study is comparable to those found in related pieces of literature (S. Agarwal, Qian, Yeung, et al., 2019; Aralica and Škrinjarić, 2021; Fernandes et al., 2019; Kogan et al., 2017). For instance, Fernandes et al. (2019) demonstrate that a one standard deviation increase in per capita internet users within a province is associated with a 3.6% rise in the output of firms; Aralica and Škrinjarić (2021) find that in service industries, adopting digital technology is associated with a 13.3% increase in TFP when using a random effect model; S. Agarwal, Qian, Yeung, et al. (2019) document a 3.3% increase in total sales following the introduction of the QR code payment method in Singapore.

productivity. The shock (i.e., a cash crunch) decreases the revenue firms can earn without adopting digital technology, affecting service firms more due to their more direct business-to-customer interactions, compared to manufacturing ones. However, if firms adopt digital technology, then the extent of this reduction also depends on the *e-Index*: it is smaller in more e-Ready areas. Thus, in those areas, the shock more strongly incentivizes firms–especially service firms–to embrace digital technology. With a fixed amount of ICT labor, the higher demand for ICT professionals subsequently drives up their wage rates. In these areas, under the new market equilibrium, the service sector expands its employment of ICT labor and investment in ICT capital. Meanwhile, the manufacturing sector suffers a loss of ICT labor and reduces its investment in ICT capital, owing to the complementary nature of these two factors. As a result, average productivity is likely to increase in the service sector but will fall in the manufacturing sector, which is observed in the data.

Next, I empirically test the mechanisms derived from the framework that are responsible for the divergent trajectories seen in the two sectors. I first find that service firms in more e-Ready districts increased investments in ICT assets and allocated more resources to services like communications and ICT-related outsourced professional services. Yet, manufacturing firms did not do these. Given the complementary nature of ICT assets and ICT labor, in districts with one standard deviation higher *e-Index*, I observe two notable effects. First, wages for ICT professionals increased by 10.2%, whereas wages for all other workers saw no statistically significant change, highlighting a rising ICT skill premium and widening wage inequality. Second, following the shock, there was a sectoral reallocation of ICT professionals in these districts: ICT workers became 2.6% more inclined to join the service sector and 2.4% less likely to work in the manufacturing sector. The expanded use of digital technology in service firms, partially facilitated by increased loans from banks, contributed to their growth. Meanwhile, manufacturing firms reduced these investments and expenditures, opting to substitute low-skill labor for capital, resulting in a decline in productivity. These findings highlight the important role the labor market plays in shaping the transitional dynamics observed in the two sectors.

Put together, the results are consistent with the predictions derived from the conceptual model. I demonstrate that in a developing country grappling with a pronounced skill shortage and limited spatial labor mobility, a sudden push for digitalization can result in distributional consequences for firms and workers in the short run. While the service sector experienced productivity growth due to expanded digital technology adoption, it came at the expense of the manufacturing sector. These transitional dynamics could accelerate a structural shift toward services, potentially leading to premature deindustrialization. Apart from this, wage inequality between ICT professionals and other workers widened. The welfare gains were concentrated among the already high-wage group of workers.[7]

This work relates to two strands of literature. First, I contribute to a growing literature on digitalization. Goldfarb and C. Tucker (2019) provide an overview of the digital economy and its influence on productivity. Recent research has focused on digital payment methods (or Fintech) and has shown their positive effects on both enterprise growth (S. Agarwal, Qian, Yeung, et al., 2019; S. Agarwal, Qian, Ren, et al., 2020) and household financial well-being (Mbiti and Weil, 2015; Suri, Bharadwaj, and Jack, 2021). Previous studies have found positive impacts of ICT on the service and manufacturing sectors separately. Eckert, Ganapati, and Walsh (2022) and Hsieh and Rossi-Hansberg (2023) find that ICT is one of the major drivers of growth in the U.S. service sector and benefits urban areas more than rural ones. Both Fernandes et al. (2019) and R. Khanna and Sharma (2021) find that ICT enhances manufacturing firms' productivity and boosts their exports in developing countries like China and India. This paper complements previous work in two respects. First, I leverage a quasi-experimental shock to analyze the causal impacts of digitalization on both the service and manufacturing sectors, rather than focusing solely on one sector. Second, I demonstrate that in developing countries with labor market frictions and limited digital resources, digitalization can yield divergent effects on firms and result in distributional consequences for workers. Notably, the service sector experienced growth while the manufacturing sector faced challenges.

This paper also augments a small body of literature focused on understanding the impacts of demonetization on the Indian economy. Lahiri (2020) provides an in-depth overview of this episode. Chodorow-Reich et al. (2020) explore the aggregate impacts of the demonetization on the economy, showing reduced economic activities in a cash-dependent context. The shock also had great impacts from various perspectives.

[7] In the Consumer Pyramids Household Survey data, the monthly average wage for ICT workers was ₹18,756, compared to ₹9,841 for all other workers in the wave of May–August 2016.

Karmakar and Narayanan (2020) and Zhu et al. (2018) document the negative effects on household income, while Bajaj and Damodaran (2022) and Wadhwa (2019) report a decline in consumption. This monetary policy adversely affected the ruling party's electoral support in regions with limited access to banking institutions (Bhavnani and Copelovitch, 2018; G. Khanna and Mukherjee, 2020), and Y. Chen et al. (2023) find that political connections mattered for firms during this economic crisis. A growing amount of literature has been focused on the adoption of digital payment methods (S. Agarwal, Basu, et al., 2018; S. Agarwal, Ghosh, et al., 2022; Crouzet, Gupta, and Mezzanotti, 2023; Sivathanu, 2019). To the best of my knowledge, this is the first paper to study the transitional dynamics concerning changes in the relative importance of sectors following the demonetization shock in India. Additionally, I show that the unintended divergent trajectories resulting from the demonetization policy did not align with the government's goal to boost manufacturing.[8]

The paper is structured as follows: Section 2.2 provides the empirical context, Section 2.3 details the datasets used, Section 2.4 discusses the empirical approach, and Section 2.5 presents two key results regarding firm performance. Section 2.6 first introduces a conceptual framework of technology adoption to explain the results observed in section 2.5, followed by empirical testing of the proposed mechanisms. Section 2.8 examines an alternative mechanism. Section 2.9 conducts a series of robustness checks, and section 2.10 concludes.

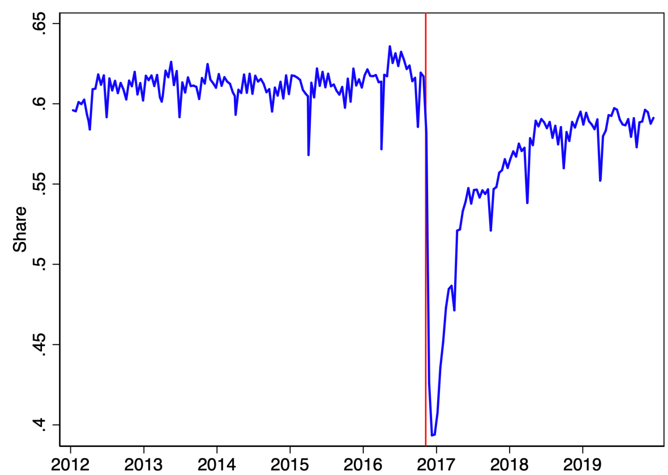
2.2 Background

2.2.1 Cash Crunch & Expansion of Digital Payments

On November 8, 2016, the Prime Minister of India *unexpectedly* announced that from midnight onwards ₹500 (US$7.5) and ₹1,000 (US$15) would become invalid.

[8] Despite the 2011 National Manufacturing Policy and the 2014 *Make in India* plan initially setting a target of a 25% GDP contribution from manufacturing by 2022, the sector achieved only 13% in that year. It should also be noted that the manufacturing sector usually tends to generate more job opportunities compared to the service sector, thereby helping to reduce unemployment and poverty. For instance, in 2015, the service sector accounted for 48% of the GDP but employed only 30% of the total workforce. In contrast, the manufacturing sector contributed 16% to the GDP while employing a comparable share of the total workforce.

The two notes are the largest ones accounting for about 86% of the currency in circulation before the policy shock. The deadline for the public to deposit old notes was set for December 31, 2016. Although the Reserve Bank of India (RBI) began circulating new notes (₹500 and ₹2,000) two days after the announcement, the process was slow.[9] Additionally, the government imposed limits on ATM withdrawals, which were gradually relaxed and eventually lifted in early 2017. As displayed in Figure 2.2, there was a substantial decline in the amount of currency held by the public as a share of narrow money (M1), dropping from 62% in October 2016 to 39% in December 2016.



Notes: Data is from the Monthly RBI Bulletin published by the Reserve Bank of India. The frequency of the data is monthly. The figure plots the trend of currency with the public as a share of narrow money. Currency with the public is the amount of currency in circulation minus the amount of cash with banks. Narrow money (M1) is the money supply composed of currency with the public, demand deposits, and other deposits with the Reserve Bank of India. This share measures liquidity. The red line is November 2016.

Figure 2.2: Currency with the Public as A Share of Narrow Money

The sudden measure, despite being transient, changed the digital landscape of the country. For example, the percentage of India's total population using the Internet underwent a modest increase, from 11% to 15% between 2012 and 2015, and then surged by 76% from 17% to 30% between 2016 and 2019. Prior to 2016, the usage of electronic payment methods was low, with cash being the predominant mode of payment, accounting for 87% (90%) of all transactions in 2012 (2008). For example, firms often handle salaries, supplier payments, utility bills, and customer transactions in cash.[10] But, a large uptake in electronic payments, including debit and credit

[9] Refer to Lahiri (2020) for detailed information on demonetization, such as inadequate bank preparation and the RBI's under-preparedness in printing enough new notes on time.

[10] If firms had not relied on cash in transactions before 2016, then the demonetization policy

cards and digital wallets, was observed after 2016 (S. Agarwal, Basu, et al., 2018; Aggarwal, Kulkarni, and Ritadhi, 2023; Chodorow-Reich et al., 2020; Crouzet, Gupta, and Mezzanotti, 2023). Figure B.16 shows a sharp increase in the monthly volume of debit and credit card transactions attributed to the intensive margin; and Figure B.17 displays a surge in mobile wallet transactions and an exponential growth in mobile banking transactions.

The cash crunch is likely to impact service firms more significantly than manufacturing firms due to their business-to-consumer (B2C) nature.[11] This immediate and direct effect gives them a stronger incentive to transition to digital platforms. On the other hand, manufacturing firms, while not immune to the cash crunch, were somewhat insulated owing to their less direct engagement with individual consumers and the utilization of alternative payment methods like commercial papers and trade credit. The nuanced impacts of the shock on firms are important for this analysis. Ex-ante, one would expect a small impact of the demonetization shock on manufacturing firms.

In short, the demonetization policy introduced *temporal variation* in economic conditions. Temporary restricted access to cash pushed people to transition to digital payments. This shift generated greater digital footprints, including real-time data on business operations such as cash flow timing and buyers' purchasing habits, which, in turn, motivated firms to embrace digitalization.

would not have incentivized them to embrace digitalization. To provide some insights, I conducted a survey on 99 Indian firms between October 19 and November 3, 2023, regarding their usage of cash in transactions in 2015. The survey results show that cash was the primary method of transactions for firms in 2015. I provide more details about the survey in Appendix B.1.

[11] It should be noted that both service and manufacturing firms can operate under a variety of business models, such as B2C, B2B (Business-to-Business), or a hybrid of both. Conventionally, service firms are more commonly associated with the B2C model, while manufacturing firms are linked more with the B2B model. According to the 2015 Input-Output Table, the average share of service goods consumed by households across all service industries was 44%, while the average share of manufacturing goods consumed by households across all manufacturing industries was 19%. If one excluded the industries of food, beverages, tobacco, textiles, and leather, the average share across other manufacturing industries was only 12%. In this paper, for simplicity and clarity, service firms are broadly categorized as B2C, and manufacturing firms as B2B.

2.2.2 Digital Environment

The second source of variation stems from *spatial differences* in districts' digital environments, affecting digital technology adoption. Although the demonetization shock was universal, its impact varied based on each district's digital readiness and infrastructure. As stated by Lahiri (2020),

> The likelihood of demonetization having the desired positive effect on digitization and formalization of the economy depended crucially on the extent of formalization and digitization of the economy *already*.

In other words, in response to the cash shortage caused by demonetization, individuals and firms can transition to digital platforms more effortlessly in areas with better digital environments, such as high-speed internet connectivity, widespread mobile networks, and greater internet penetration, than in areas with poor digital settings. The fixed cost of adopting digital technology is likely to be lower in these advanced areas. For example, as shown by *crouzet2019shocks, there was a higher adoption rate of digital wallets among retailers in districts closer to an electronic payment hub, which also tends to have a better digital environment.[12] Therefore, firms in areas with more favorable digital environments were likely to perform relatively better, as was expected, than those in areas with less advanced digital settings after the 2016 demonetization shock.[13]

2.3 Data

This paper uses several data sources, including firm outcome data and household survey data. I list the used datasets and describe them in Table 2.1.

[12] *crouzet2019shocks define a district as an electronic payment hub if over 500 active firms utilized electronic payments in September 2016. When regressing a dummy variable for being an electronic payment hub against a district-level e-Readiness Index (discussed in detail in Section 2.3.1), the estimated coefficient is 0.49. This is statistically significant at the 1% level when standard errors are clustered at the state level.

[13] It should be noted that even in areas that were most well-prepared for digitalization firms were not immune to the effects of the shock. Before 2016, cash played a significant role in transactions, both between firms and between firms and consumers.

Table 2.1: Data Sets

Data Source	Variables
Prowess	Firm-level outcome variables such as income, expense, assets, and liabilities.
Consumer Pyramids	Individual-level variables such as education, employment status, industry of occupation, and wage.
VIIRS-V.2	Nighttime light intensity.
Reserve Bank of India (RBI)	District-wise deployment of functioning commercial bank offices and state-wise deployment of ATMs.
2011 Population Census	Variables used to construct district-level e-Readiness index such as ICT employees per 1,000 population.
2013 Economic Census	Variables used to construct district-level e-Readiness index such as the share of businesses engaged in wireless telecommunications activities and ICT employees per 1,000 population.

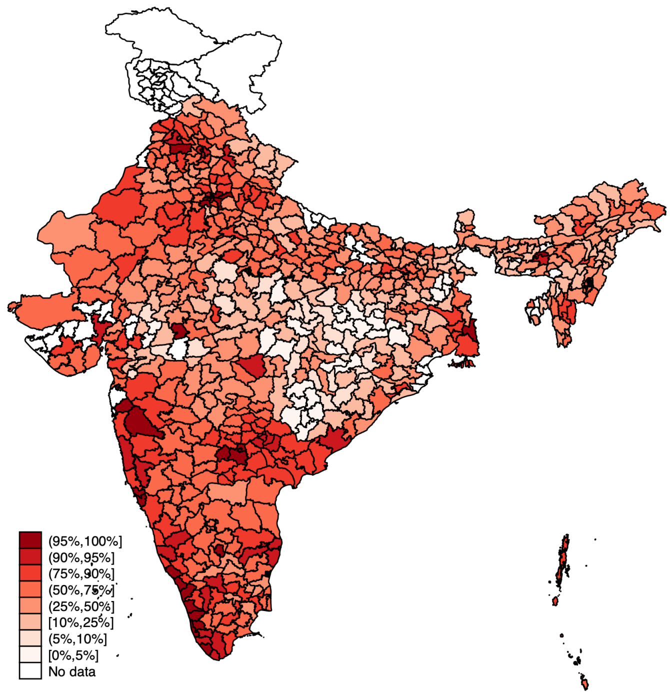
Notes: "VIIRS-V.2" = NASA/NOAA Visible Infrared Imaging Radiometer Suite (Version 2). Data regarding the district-wise deployment of ATMs is not publicly accessible from the Reserve Bank of India (RBI).

2.3.1 Measure of the Digital Environment: e-Readiness Index

The empirical analysis relies on the measure of an area's digital environment. I constructed an e-Readiness Index at the district level using data from the 2011 Population Census and the 2013 Economic Census. I follow the framework developed by the National Council of Applied Economic Research and the Department of Electronics and Information Technology in the Government of India (GoI).[14] This index assesses the ability of a district to participate in the increasingly networked world and its preparedness for digitalization before 2016. It is a composite indicator derived from two main categories: an ICT-friendly environment, which includes infrastructure and market environments that promote ICT adoption, and stakeholder preparedness, which involves the readiness of both businesses and individuals to engage with digital technology. Examples of variables used to compose the index include the population's mobile phone coverage, the proportion of firms engaged in telecommunication activities, and the percentage of households with computers. A detailed discussion of the methodology is provided in Appendix B.2. I display the spatial distribution of the constructed district-level e-Readiness Index (hereafter *e-Index*) in Figure 2.3. As

[14]The DIT-NCAER's e-Readiness Index is only available at the state level. Although it provides a broad assessment of digital readiness across states and union territories in India, it masks variations at more granular levels.

depicted, it is evident that there is considerable variation at the district level.[15]



Notes: Figure 2.3 plots a map of the constructed district-level normalized weighted e-Readiness Index used in this analysis. The percentages in the legend are the percentiles of the normalized weighted e-Readiness Index. The deeper the color, the higher the index is (i.e. the more well-prepared a district is for digitalization).

Figure 2.3: Map of e-Readiness Index (District Level)

2.3.2 Data on Firm Outcome

The main data I use in the analysis is firm-level annual data from the Prowess Database, which is collected by the CMIE.[16] This database includes information on

[15]Comparing Figure 2.3 to Appendix Figure B.18 which displays the spatial distribution of the DIT-NCAER's state-level e-Readiness Index, one can see that there is a significant variation in digital preparedness among districts within the same state. For example, while Maharashtra and West Bengal have the highest value of DIT-NCAER's index, several districts in these states, such as Uttar Dinajpur and Birbhum in West Bengal and Gadchiroli and Yavatmal in Maharashtra, possess an *e-Index* that falls below the 25th percentile. For example, there are 33 districts whose value of the *e-Index* is above the 95th percentile. The 33 districts are in the east (West Bengal), south (Karnataka, Kerala, Tamil Nadu, Telangana), north-east (Assam), north (Uttar Pradesh), central (Madhya Pradesh), north-west (Chandigarh, Delhi, Haryana, Punjab), and west (Goa, Maharashtra) India.

[16]The Annual Survey of Industries (ASI) is another commonly used data on firms in India. While both the ASI and the Prowess data are limited in coverage as they only collect data on formal sector firms, in this analysis, I prefer the Prowess data over the ASI data for two reasons. First,

over 40,000 firms, including those traded on both the Bombay Stock Exchange and the National Stock Exchange, as well as numerous private companies.[17] The companies in the Prowess data contribute to nearly 75% of the total corporate taxes and more than 95% of the excise duty collected by the Government of India (De and Nagaraj, 2014). The study period spans from 2012 to 2019, four years prior to and four years following the demonetization shock. The analysis concludes in 2019 because of the COVID-19 pandemic in 2020.

I retrieve data from Prowess on firms' identities (e.g., name, type, and address) and history of classification (e.g., name, year, and the main economic activity). I use a company's registered office address to identify the district in which a firm is located.[18] The CMIE assigns the National Industrial Classification (NIC) code to each firm, which reflects its main economic activity. I classify a firm's industry by its two-digit NIC code.[19] I obtain firms' financial statistics from their annual financial statements. The statements provide information not only on different kinds of income and expenses but also on their portfolios of assets and liabilities.

ICT capital Although the Prowess data does not offer direct insights into firms' adoption of digital technology or the specific types of digital technologies they use, it does reveal information about firms' investments in software, computers, and IT

the ASI data only covers manufacturing units and not service units but the Prowess data includes both. Second, the ASI data does not reveal firms' located districts, which is crucial for this analysis. Therefore, the Prowess data is a more suitable choice for this study.

[17]These firms operate in the formal sector, and their annual financial statements are required to be audited, which helps prevent discrepancies such as the underreporting of income. Therefore, it is unlikely that the results presented in Section 2.5 are due to increased tax compliance, as shown in S. Das et al. (2023). Furthermore, S. Das et al. (2023) analyzed data from the universe of firms in West Bengal, encompassing over 47,000 firms. In contrast, the Prowess data includes information on about 4,000 firms in West Bengal.

[18]The Prowess data has information on registered offices, corporate offices, and head office addresses. However, not every firm reports its corporate and/or head office location. About 16% of firms provide corporate office addresses while 7% provide head office addresses. I cross-check the three addresses to pinpoint a firm's location.

[19]I use the "History of Classification" in Prowess to check if a firm's two-digit NIC code has ever changed. About 74% of firms had the same two-digit NIC codes between 2012 and 2019 and only about 16% of firms had a different two-digit NIC code for less than two years between 2012 and 2019. That is, about 90% of firms have the same two-digit NIC code for at least six years out of the eight-year period. In the data, less than 5% of firms had ever switched from one sector to another sector (e.g., switching from the service sector to the manufacturing sector). Thus, between 2012 and 2019, most of the firms produce the same kind of products over time. I use the most commonly appeared two-digit NIC code to classify a firm's belonging industry.

systems as recorded in their financial statements. Additionally, the data includes expenditure details on outsourced professional services that support these investments, along with expenses related to communication services like internet subscriptions and services provided by data centers.

TFPR I provide a comprehensive discussion of the estimation of total factor revenue productivity (TFPR) in Appendix B.3. I apply the method proposed by Grieco, S. Li, and H. Zhang (2016) (GLZ) for estimation instead of the control function approach developed by Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), and Ackerberg, Caves, and Frazer (2015) (ACF). This is because the OP, LP, and ACF methods assume an exogenous evolution of productivity, whereas the GLZ method is not subject to such a constraint. The GLZ method also eliminates the need for data on output price, output quantity, and intermediate input quantities, which are unavailable in the Prowess data.

Study Sample The final sample consists of 31,551 firms observed between 2012 and 2019 from 22 major states and union territories in India.[20] 19,921 firms are in the service sector and the rest are in the manufacturing sector. The spatial distribution of service and manufacturing firms, as depicted in Figure B.20a and Figure B.20b respectively, shows a broadly comparable pattern, suggesting that manufacturing firms are not more likely to locate in districts that are less preferred by service firms. I offer detailed definitions for all the variables used in the analysis in Appendix C.2.[21]

[20]The following states are excluded from the study: Andaman and Nicobar Islands, Arunachal Pradesh, Dadra and Nagar Haveli and Daman and Diu, Jammu and Kashmir, Ladakh, Lakshadweep, Manipur, Mizoram, Nagaland, Puducherry, Sikkim, and Tripura. A total of 419 firms located in these 12 states or union territories are excluded from the analysis. In total, there are 347 districts in the sample. The average value of the *e-Index* of these districts is 0.35 with a standard deviation of 0.18.

[21]In the analysis, I take the inverse hyperbolic transformation of variables in money value to retain zero-valued observations but not the common logarithm transformation (i.e., log(number+1)). This is because the unit of these variables is USD million, using the common logarithm transformation would result in unrealistic increases of 1 million USD for each observation.

2.3.3 Data on Labor Market

I use the Consumer Pyramids Household Survey (CPHS), a household-level longitudinal survey conducted by the CMIE, to examine changes in India's labor market over time. The survey is executed every four months (January-April, May-August, and September-December) starting in January-April 2014. It covers approximately 160,000 households from all major states in each wave. The household response rate is consistently high, over 80%, across waves before 2020. The CPHS data is divided into four sections, each containing information on different aspects of households in India. For this analysis, I use data from two of the four sections: the People of India (PoI) section, which focuses on individual demographic characteristics, and the Income Pyramids (InP) section, which tracks the incomes and wages of household members.

The CMIE surveys each individual in a household as part of its PoI section in every wave. It asks questions about people's education, employment status, and industry of occupation. I use 16 waves of PoI from September-December 2014 to September-December 2019.[22] The InP section is conducted monthly and collects monthly income data from each household member. I calculate the average wage for each individual over a four-month period and then aggregate the data to the wave level. I merged the PoI and InP datasets and restricted the sample to individuals who are located in districts that appeared in the Prowess data. I then further restricted my sample to individuals who first appeared in the data between the ages of 15 and 65. This age range is chosen because it represents the typical working-age population. In total, I was left with 236,244 individuals, of whom 23.3% hold at least a bachelor's degree, diploma, or certificate.

ICT Labor To identify ICT labor, I utilize an individual's educational background. The CMIE collects information from respondents regarding both their highest level of education attained and their specific discipline of study. If the respondents have obtained at least a bachelor's degree or have completed a diploma or certificate course, then their discipline of study is known. I generate a variable named "related disciplines" which is assigned a value of one if an individual's field of study falls within

[22] I exclude the first two waves (January-April 2014 and May-August 2014) because the CMIE did not collect information on the industry of occupation or employment status in these two waves.

engineering or computer science, and zero otherwise.[23] Workers possessing degrees in these "related disciplines" are classified as ICT professionals. In the wave of May-August 2016, about 68% of ICT professionals worked in the service sector and 29% worked in the manufacturing sector.

2.3.4 Other Data

I obtain bank penetration data from the RBI. The quarterly data on the number of functioning offices of commercial banks at the district level is from Bank Branch Statistics and the number of automated teller machines (ATMs) at the state level is from State-wise and Region-wise Deployment of ATMs. The district-wise deployment of ATMs is not publicly available at the RBI. I calculate the annual average number of commercial bank branches in a district and the annual average number of ATMs in a state. In Figure B.19, I plot the two variables at the national level in 2012-2019. As is shown, the number of ATMs quickly went up before 2014, which was mainly driven by the off-site ATMs. Yet, after November 2016, the two trends exhibited similar patterns.

I also obtain data on nighttime light intensity from the Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Lights collected by the National Oceanic and Atmospheric Administration (NOAA). The VIIRS data is generated using monthly cloud-free radiance averages. The version that I use is produced with the V.2 method which is discussed in detail in Elvidge et al. (2021). I use this data to calculate the average annual nightlight intensity in each district.

2.4 Empirical Stratgey

In this section, I discuss the empirical strategy I employ to examine the impacts of digitalization on firms. For brevity, only the terms of interest are displayed in the specifications.

[23] One might be concerned that categorizing workers with an engineering degree could lead to an overestimation of the number of ICT professionals, arguing that some engineers work in fields unrelated to ICT. In India, many academic institutions, including the India Institute of Technology, combine computer science and engineering into one department. And the department offers the same set of courses to all students, whether they are pursuing a degree in engineering or computer science. This alleviates the concern engineers might lack ICT knowledge.

I estimate the following difference-in-differences model to examine firm performance:

$$Y_{ijdt} = \alpha_i + \alpha_{jt} + \beta \; Post_{1,t} \times e\text{-}Index_d + X + \varepsilon_{ijdt} \tag{2.1}$$

where Y_{ijdt} is a set of outcome variables (e.g., income, sales, and TFPR) for firm i in industry j, district d, and year t. $e\text{-}Index_d$ is a continuous variable and measures district d's digital environment before 2016. I pool the pre- and post-demonetization years and generate a binary variable, $Post_{1,t}$, with a value of 1 for the years 2016-2019 and 0 for the years 2012-2015. I control for the firm (α_i) and industry-year (α_{jt}) fixed effects in equation (2.1). The firm fixed effects capture all observed and unobserved time-invariant characteristics of a firm, including those that influence firm location decisions in the first place.[24] α_i also accounts for district attributes, such as population and literacy rate. The industry-year fixed effects account for all characteristics of industries over time such as the time-variant common shocks at the industry level, and thus addresses the concern that the effects might be driven by any other contemporaneous changes at the industry level. I cluster standard errors at the district level, which is the level of the treatment, for statistical inference.[25]

X is a vector of control variables, which includes the number of functioning commercial bank branches in a district per 1,000 population, the number of ATMs in a state per 1,000 population, and the average nightlight intensity of a district. The presence of these controls is important. First, people who live in areas with more bank branches and/or ATMs usually deposit old notes and withdraw new ones more easily than those living in areas without as many financial institutions. So, the first two variables allow me to control for the impacts of bank availability on household consumption behavior. Second, the nighttime lights can be used as a proxy for infrastructure, urbanization, and economic activities in developing countries such as India (Chodorow-Reich et al., 2020; Beyer, Franco-Bedoya, and Galdo, 2021) and China (X.

[24] For example, a firm's location decision could be affected by local policies (e.g., Special Economic Zones policies), size of the cities (Deichmann et al., 2008; Sridhar and Wan, 2010), and infrastructure environment (N. K. Ramaul and P. Ramaul, 2016). The Special Economic Zone (SEZ) policy was introduced in 2005 with the objective of promoting exports, attracting foreign investment, and creating economic opportunities. The policy offers a range of benefits to companies that set up their business in SEZs including tax exemption, infrastructure support, and simplified administrative procedures. Most of the SEZs were approved in the 2000s. Such local policies will be incorporated into the firm fixed effects.

[25] In Table B.26, I demonstrate that the statistical inference remains unchanged when clustering standard errors at the firm level, as compared to the results in Table 2.3.

Li et al., 2013; Hu and Yao, 2022), especially in areas where regional official statistics are not available on a regular basis. It is indicative of local unobserved aggregate changes, such as households conserving energy to save money and the establishment of new digital infrastructure. Thus, the average nightlight intensity allows me to account for the local unobserved conditions and isolate the specific impacts of the demonetization policy-induced positive digital shock on firm performance.[26]

2.5 Main Results

In this section, I present two main findings regarding firm performance in more e-Ready districts compared to those in less e-Ready districts using the Prowess data.

Finding 1: *On average, firms in more e-Ready districts did not outperform their counterparts in less e-Ready districts in terms of income and TFPR after the shock.*

Table 2.2: Impacts on Income & TFPR

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(Sales)	Ln(Fin. Serv. Inc.)	Return on Assets	Ln(TFPR)
Post × *e-Index*	-0.026	-0.034	-0.014	0.019	-0.004
	(0.030)	(0.037)	(0.012)	(0.016)	(0.160)
Control Mean	2.38	2.16	0.42	1.00	4.65
R^2	0.94	0.94	0.89	0.82	0.89
No. of firms	28,669	28,669	28,669	28,669	24,992
N	172,328	172,328	172,328	172,328	144,115
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). Details are discussed in Appendix B.3. All regressions control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. I incorporate the firm and industry-year fixed effects. The control mean is the average value of the outcome variable in the pre-treatment periods. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

I begin by analyzing the effects of a positive digital shock on various aspects of firms'

[26] In Table B.27, I show that when excluding the control for average nightlight intensity in the regression, both the magnitudes and statistical inference of the estimated coefficients are similar to those in Table 2.3, specifically for the log of total income (column 1) and the log of TFPR (column 5).

outcomes, including income, sales, income from financial services, return on assets (ROA), and TFPR. The ROA measures the efficiency of a firm's use of assets to generate earnings and thus its profitability. The estimated coefficients ($\hat{\beta}$) from equation (2.1) are presented in Table 2.2 for a pooled sample of service and manufacturing firms. On average, there are no statistically or economically significant impacts on firms located in more e-Ready areas compared to those in less e-Ready areas following the shock. These average null effects are inconsistent with the initial expectation that firms in districts with more favorable digital environments would be able to improve performance relatively more. Besides, it remains unclear whether all firms benefit equally.

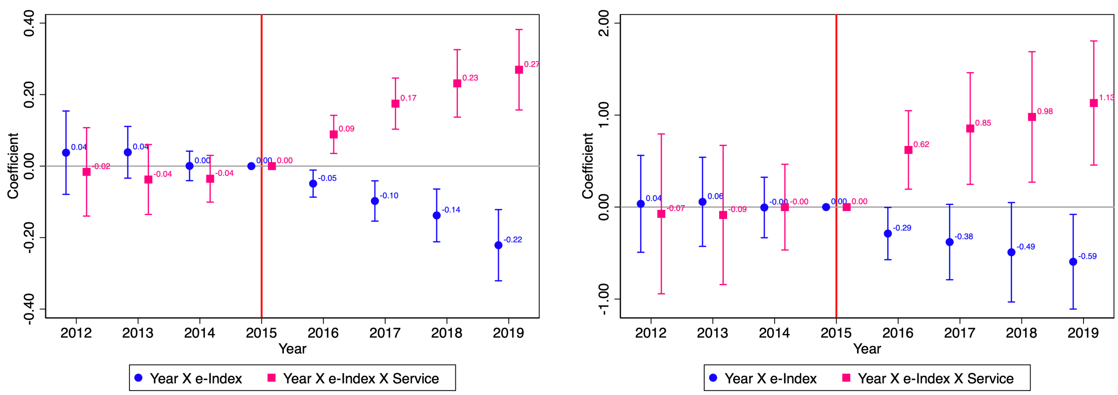
Finding 2: *Service firms in more e-Ready districts experienced a growth in income and TFPR while manufacturing firms saw a decline.*

Table 2.3: Impacts on Income & TFPR by Sector

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Fin. Serv. Inc.)	(4) ROA	(5) Ln(TFPR)
Post × *e-Index* (PeI)	-0.137***	-0.138***	-0.024	-0.036*	-0.450**
	(0.035)	(0.038)	(0.023)	(0.020)	(0.212)
Post × *e-Index*× Services	0.209***	0.195***	0.019	0.103***	0.913***
(PeIS)	(0.041)	(0.036)	(0.041)	(0.023)	(0.272)
PeI+PeIS	0.072*	0.057	-0.005	0.068***	0.464**
p-value	(0.060)	(0.208)	(0.838)	(0.001)	(0.029)
Control Mean (Manu.)	3.34	3.31	0.32	1.29	10.62
Control Mean (Services)	1.79	1.45	0.48	0.82	0.29
R^2	0.94	0.94	0.89	0.82	0.89
No. of firms	28,669	28,669	28,669	28,669	24,992
N	172,328	172,328	172,328	172,328	144,115
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The "Control Mean (Manu.)" is the average value of the outcome variable for manufacturing firms in the pre-treatment periods. The "Control Mean (Services)" is the average value of the outcome variable for service firms in the pre-treatment periods. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Next, I explore the effects by sector to examine whether the average null impacts conceal contrasting effects across different sectors. I add a triple interaction term, *Post* × *e-Index* × *Services*, into equation (2.1). Here, *Services* is a dummy variable set to 1 if the firm is in the service sector and 0 otherwise. I present the results in Table 2.3. Column 1 shows that after 2016, service firms experienced increased income while manufacturing firms saw a decline in more e-Ready districts. Both effects are statistically significant at conventional levels. Specifically, in districts with one standard deviation higher *e-Index*, service firms saw a 1.3% income increase, while manufacturing firms faced a 2.5% decrease. Compared to manufacturing firms, service firms in these districts experienced a 3.8% larger increase in income after 2016. The dynamics of the effects are plotted in Figure 2.4a. It shows that the results are not driven by differential trends between districts with a high *e-Index* and those with a low *e-Index*. Besides, these effects persisted for years after the shock.



(a) Ln(Income) (b) Ln(TFPR)

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. TFPR is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). A detailed discussion is provided in Appendix B.3. I conduct an F-test on the three pre-period coefficients, which are jointly insignificant at the conventional levels in all regressions. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 2.4: Event Study Graphs: Income & TFPR

In columns 2-3, I show that the increase or decrease in income is primarily due to changes in sales rather than income from financial services. It alleviates the concern that the positive outcomes for service firms are driven by financial service firms, which offer digital financial services and are the primary beneficiaries of the widespread adoption of digital payment methods. In column 4, I assess firms' profitability using ROA. As demonstrated, service (manufacturing) firms in districts with a higher *e-Index* become more (less) capable of generating revenue after 2016.

In column 5, I show that service firms located in districts with one standard deviation higher *e-Index*, on average, experienced an 8.4% increase in TFPR. Conversely, manufacturing firms saw an 8.1% decline in TFPR. Similarly, I plot the event study graphs of the log of TFPR in Figure 2.4b. The graph shows that: (1) there were no pre-trends; (2) there was an immediate statistically significant decrease in TFPR for manufacturing firms in higher *e-Index* districts in 2016; (3) compared to manufacturing in more e-Ready districts, service firms exhibited a rising trend in TFPR growth.

In summary, the puzzle of why firms in more e-Ready districts did not outperform those in less e-Ready districts is attributed to the contrasting effects on the service and manufacturing sectors.[27] While one might expect minor impacts on manufacturing firms, significant negative effects are observed for manufacturing firms in more e-Ready areas. In Section 2.6, I first present a simple conceptual framework to reconcile the two findings, and then test the mechanisms empirically.

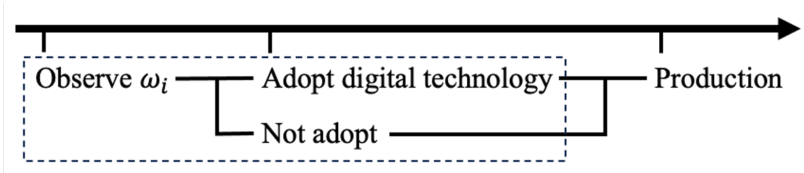
2.6 Mechanisms

2.6.1 Conceptual Framework

In this subsection, I describe a simple static economic framework to analyze the technology adoption behavior of firms within a two-sector economy, comprising both the service and manufacturing sectors ($j = s, m$). There is a fixed mass of firms in each sector. Firms observe their initial draw of productivity from a common distribution and decide whether to adopt digital technology before starting production. This adoption encompasses the employment of ICT labor and investment in ICT assets. The two factors are complements. Following Doraszelski and Jaumandreu (2013) and Harrigan, Reshef, and Toubal (2023), I assume that digital technology only affects Hicks-neutral productivity. Firms will only adopt digital technology if it yields a higher profit than not adopt it. Figure 2.5 summarizes the process. I provide more

[27] I also conduct a heterogeneity analysis by firm size to examine whether the results are driven by medium- or large-sized firms. The results on income and TFPR are displayed in columns 1-2 of Table B.28. As shown, it cannot be stated that only medium and large service firms benefited in terms of income and TFPR, nor can it be said that only micro- and small-sized manufacturing firms faced greater adverse effects. Therefore, the divergent patterns observed between the two sectors are not driven by firms of a particular size.

details of the framework in Appendix B.5.



Notes: I present a firm's decision-making process in the figure. After a firm observes its initial level of productivity ω_i, it determines whether to adopt digital technology or not before initiating production.

Figure 2.5: Illustration: A Firm's Decision-Making Process

A key assumption of the framework is that the supply of ICT labor is fixed and these workers are spatially immobile. This is a reasonable assumption in the short run for two reasons. First, to obtain a bachelor's degree in engineering or computer science in India, students must choose the science stream in their 11th and 12th grades, followed by an additional four years of study. This means that to have more supply in year t, more students should have chosen science six years earlier.[28] Thus, the shock is not likely to trigger a short-term surge in supply. Second, previous research underscores the limited labor mobility in India (Luke and Munshi, 2011; Topalova, 2010). For example, Kone et al. (2018) documents a cross-district migration rate of 2.8% in India in 2001. The 2011 Population Census of India finds that only 0.7% of the workforce migrated for economic reasons (e.g., work, employment, and business) in 2010 (Government of India, 2017).[29]

A firm's decision to adopt digital technology is determined by its initial productivity level, the cost of adoption, and the effective revenue from adopting versus not adopting. The adoption cost comprises two components: the wage rate for ICT labor and the rental rate for ICT capital.[30] The effective share of revenue a firm can earn is

[28] According to All India Council for Technical Education, total enrollment in engineering and technology remained stable from 2012 to 2019. In Appendix Figure B.22, I present the annual percentage change in total enrollment in engineering and technology from the academic year 2012-2013 to 2019-2020. The data is publicly available after 2012-2013. As depicted, the absolute annual changes consistently remained below 5%. Although statistics from previous years are not available, the trend still gives a sense that the supply of ICT labor remains relatively stable over time.

[29] In the 2011 Population Census, of the migrants aged 15 to 64 who had migrated within the previous five years, less than one-fifth did so for economic reasons. This subgroup represents only 5.8% of the total population within the 15 to 64 age range. Additionally, only 8.0% of migrants aged 15 to 64 who moved within the last five years hold at least a bachelor's degree. These educated migrants constitute a mere 4.1% of the total population aged 15 to 64 and 11.6% of the population holding at least a bachelor's degree.

[30] I assume that the rental rate for ICT capital is given and stable over time. I use the wholesale

$1-\tau_j$ when not adopting, and $1-\tau_j x$ when adopting. Here, τ_j represents the revenue wedge for firms in sector j, with $\tau_j \in [0,1)$. Additionally, x is inversely related to an area's *e-Index*, with $x \in [0,1]$. In the absence of shocks, $\tau_j = 0$, indicating that firms can receive the full amount of revenue. Therefore, in the case of no shock (i.e., $\tau_j = 0$), a firm is more likely to adopt digital technology if it has higher initial productivity and/or a lower wage rate for ICT labor.

In the event of a shock, one has $\tau_j > 0$. A shock like a cash crunch, which makes some cash transactions unfeasible, affects firms in different sectors differently. Due to its B2C nature, the service sector would face more severe impacts from such a shock compared to the manufacturing sector, $\tau_s > \tau_m$. It also indicates that service firms face a higher marginal cost of acquiring non-digital technology users as customers. If a firm adopts digital technology, then the share of revenue, $1-\tau_j x$, is also influenced by an area's digital environment. For instance, in a high *e-Index* area (i.e., $x = 0$), firms can secure the full amount of revenue, whereas in a low *e-Index* area (i.e., $x = 1$), they can only receive a $1-\tau_j$ portion of the revenue. Therefore, when $\tau_j > 0$, a firm is also more likely to adopt digital technology if its sector is more severely affected by the shock and/or if its digital environment is more favorable.

Next, I analyze how firms across different sectors respond differently to a shock or a change in τ_j from zero to a positive value. The presence of the shock effectively lowers the profit a firm can earn without adopting digital technology. Firms in more e-Ready areas are more likely to find digital technology adoption profitable compared to those in less e-Ready areas. Specifically, in more e-Ready areas, firms with lower initial productivity, which might not have considered adopting digital technology in the absence of a shock, now find it profitable to do so. As a result, in these areas, firms across both sectors tend to increase their demand for ICT labor and invest more in ICT capital. Given the fixed amount of ICT labor, this will drive up their wage rates. The reallocation of ICT labor will favor the service sector over the manufacturing sector because the service sector benefits more (or loses less) from adopting digital

price index of computers and peripheral equipment as an example to show that the rental rate of ICT capital is relatively stable over the study period. Appendix Figure B.21 displays that the wholesale price index exhibits minimal fluctuations within a narrow range of 126.9 to 127.3 between August 2014 and July 2018. Here, I abstract away from the fixed cost of digital technology adoption, as its presence does not affect the derivation of the model's predictions. It should be noted a firm is more likely to adopt digital technology when the fixed cost is lower. That is, at the baseline, there will be more firms adopting digital technology in a high *e-Index* area than in a low *e-Index* area.

technology. In the new market equilibrium, the wage rate for ICT professionals rises. The service sector will employ a larger share of ICT labor and increase its investment in ICT capital compared to a no-shock case, while the manufacturing sector will see a reduction in both.

Prediction 1. *In a more e-Ready area, compared to the case of no shock (i.e., $\tau_j = 0$), the wage rate for ICT labor, w, is higher when the shock is present (i.e., $\tau_j > 0$).*

Prediction 2. *In a more e-Ready area, compared to the case of no shock (i.e., $\tau_j = 0$), the service sector employs more ICT labor and invests more in ICT capital when the shock is present (i.e., $\tau_j > 0$), while the manufacturing sector employs fewer ICT labor and invests less in ICT capital.*

The two preceding predictions give rise to the last prediction: in a more e-Ready area, compared to the case of no shock, the presence of a shock is likely to lead to an increase in average productivity in the service sector, while causing a decrease in the manufacturing sector. This prediction is corroborated by the finding in Section 2.5, where service firms in more e-Ready districts experienced an increase in TFPR, while manufacturing firms saw a decline after the 2016 demonetization shock. A detailed discussion of the predictions is provided in Appendix B.5.3.

2.6.2 Empirical Test

In Section 2.5, I demonstrate that firms in more e-Ready areas did not outperform those in less e-Ready areas due to contrasting effects in the service and manufacturing sectors. In this subsection, I employ detailed expenditure information and asset portfolio data from the Prowess data, along with labor market information from the CPHS data, to empirically test the mechanisms, as derived from the conceptual framework, that contribute to these divergent outcomes.

Mechanism 1: ICT-related Investment & Expenses

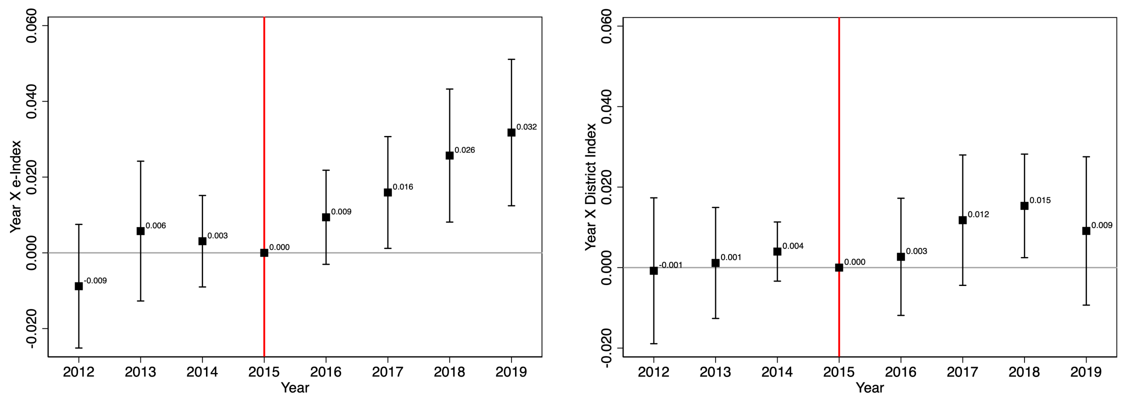
I start by examining firms' investments, estimating equation (2.1) separately for the two sectors. I present the results in Table 2.4. In columns 1-4 of panel A, one can

Table 2.4: Impacts on Assets by Sector

	(1)	(2)	(3)	(4)	(5)
	Ln(Assets)	Ln(Fixed Assets)	Ln(Intangible$_e$)	Ln(PPE$_e$)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.042	0.004	-0.018	-0.012	0.019*
	(0.034)	(0.030)	(0.016)	(0.026)	(0.010)
Control Mean	2.48	0.90	0.10	0.80	0.11
R^2	0.95	0.91	0.79	0.92	0.86
No. of firms	19,037	19,037	19,037	19,037	19,037
N	117,240	117,240	117,240	117,240	117,240
Panel B. Manufacturing					
Post × *e-Index*	-0.073***	-0.046*	0.016$^+$	-0.049*	0.008
	(0.026)	(0.026)	(0.010)	(0.026)	(0.008)
Control Mean	3.17	2.02	0.10	2.00	0.08
R^2	0.97	0.95	0.79	0.95	0.85
No. of firms	11,247	11,247	11,247	11,247	11,247
N	72,185	72,185	72,185	72,185	72,185
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Assets" = Total assets are composed of non-current assets and current assets. "Fixed Assets" = Fixed assets are a type of non-current asset, which includes intangible assets, property, plant, and equipment, and other fixed assets. "Intangible$_e$" = Intangible assets excluding software. "PPE$_e$" = Property, plant, and equipment excluding computers and IT systems. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The "Control Mean (Manu.)" is the average value of the outcome variable for manufacturing firms in the pre-treatment periods. The "Control Mean (Services)" is the average value of the outcome variable for service firms in the pre-treatment periods. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

observe that service firms did not hold statistically significantly more assets after the shock in terms of total assets, fixed assets (a type of non-current assets that cannot be converted into cash within 12 months), intangible assets excluding software, and property, plant, and equipment (PPE) excluding computers and IT systems. However, they did show a statistically significantly higher investment in ICT assets, which include software, computers, and IT systems (column 5). Specifically, service firms in the most e-Ready districts increased their investment in ICT assets by 1.9%, equivalent to 17.3% of the control mean, compared to those in the least e-Ready districts. The results suggest that service firms altered their asset portfolio by allocating more to ICT capital. On the other hand, manufacturing firms in districts with one standard deviation higher *e-Index* decreased their total assets by 1.3% after the shock (column 1) and did not statistically significantly increase their investment in ICT assets (column 5). Figure 2.6a and Figure 2.6b display the event study graphs of the log of ICT assets for the service and manufacturing sectors, respectively. An upward trend in ICT asset investment is evident among service firms in districts with a higher *e-Index*, which is not observed among manufacturing firms. Although there was a tendency for manufacturing firms to increase their investments in 2018, it was reversed in 2019.



(a) Ln(ICT Assets), Service (b) Ln(ICT Assets), Manufacturing

<u>*Notes:*</u> "e-Index" = The normalized district-level e-Readiness Index. "ICT Assets" = Software, computers, and IT systems. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. I conduct an F-test on the three pre-period coefficients, which are jointly insignificant at the conventional levels in all regressions. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 2.6: Event Study Graphs: ICT Assets

I next investigate whether firms spent more or less on services that supplement ICT assets. The results are reported in Table 2.5. In column 1, service (manufacturing) firms in higher *e-Index* districts incurred more (less) expenses than those in lower *e-Index* districts after the shock.[31] As shown in columns 4-5, part of the increase (decrease) in expenses among service (manufacturing) firms was attributed to expenses on communication, such as internet services, data center services, and outsourced software and ICT-related professional services. Additionally, there was a change in the extensive margin regarding outsourced software and ICT-related professional services (column 6). Compared to service (manufacturing) firms in the least e-Ready districts, there are 2.2% more service (1.7% fewer manufacturing) firms in the most

[31] The reduction in total expenditure for manufacturing firms is mainly driven by expenses on raw materials. The estimated coefficient ($\hat{\beta}$) on the log of expenses on raw materials is -0.189 ($p = 0.00$) for manufacturing firms. However, for service firms, the estimated coefficient is 0.001 ($p = 0.97$), indicating that they did not experience a change in expenses on raw materials.

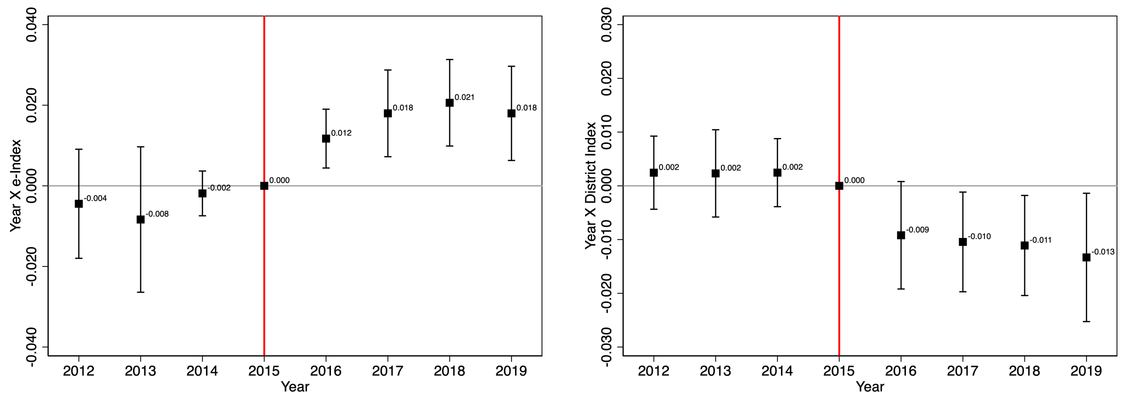
e-Ready districts that started purchasing this kind of service after the shock. This represents a 23.7% increase (25.1% decrease) compared to the average portion of service (manufacturing) firms that purchased this service in the pre-shock periods. Figure 2.7 displays the event study graphs depicting the log of communication expenses for the two sectors. As shown, there were no differential trends in the pre-periods. The figures also demonstrate a consistent increase in expenditure on communication services for service firms during the post-shock years, whereas a tendency of decrease is observed for manufacturing firms.

Table 2.5: Impacts on Expenses by Sector

	(1)	(2)	(3)	(4)	(5)
	Ln(Expenses)	Ln(Compensation)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Any Outsourced: Software & ICT
Panel A. Services					
Post × *e-Index*	0.100**	0.037^{+}	0.019***	0.004**	0.022**
	(0.041)	(0.025)	(0.006)	(0.002)	(0.009)
Control Mean	1.82	0.58	0.05	0.01	0.09
R^2	0.92	0.92	0.85	0.61	0.63
No. of firms	17,526	17,526	17,526	17,526	17,526
N	99,280	99,280	99,280	99,280	99,280
Panel B. Manufacturing					
Post × *e-Index*	-0.140***	-0.017	-0.012**	-0.001	-0.017^{+}
	(0.033)	(0.028)	(0.005)	(0.002)	(0.012)
Control Mean	3.24	0.93	0.04	0.00	0.07
R^2	0.94	0.92	0.81	0.64	0.57
No. of firms	10,176	10,176	10,176	10,176	10,176
N	61,980	61,980	61,980	61,980	61,980
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Compensation" = Compensation to employees. "Communications" = Communications expenses include costs incurred by the company on the telephone, telegram, postage, fax, data center, satellite, and internet services. "Outsourced: Software & ICT" = Expenses on ICT-related outsourced professional services including software development, ICT, and IT-enabled services. "Any Outsourced: Software & ICT" = A binary indicator equal to 1 if a firm spends on ICT-related outsourced professional services and 0 otherwise. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The "Control Mean (Manu.)" is the average value of the outcome variable for manufacturing firms in the pre-treatment periods. The "Control Mean (Services)" is the average value of the outcome variable for service firms in the pre-treatment periods. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In short, the findings align with Predication 2 regarding the investment in ICT capital. One of the mechanisms through which service firms boosted their income and productivity in districts with a higher *e-Index* was by acquiring additional ICT assets



(a) Ln(Communications), Service (b) Ln(Communications), Manu.

Notes: "Manu." = Manufacturing. "e-Index" = The normalized district-level e-Readiness Index. "Communications" = Communications expenses include costs incurred by the company on the telephone, telegram, postage, fax, data center, satellite, and internet services. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. I conduct an F-test on the three pre-period coefficients, which are jointly insignificant at the conventional levels in all regressions. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 2.7: Event Study Graphs: Expenses on Communication Services

and spending more on ICT-related services that complemented these assets. These increases were facilitated, in part, by securing increased loans from banks.[32] Manufacturing firms, on the other hand, did not increase their investment in ICT capital and reduced their spending on communication services.

Mechanism 2: Labor & ICT Labor

In column 2 of panel A in Table 2.5, service firms in more e-Ready districts experienced a slight increase in their labor expenditure compared to those in less e-Ready districts. Conversely, manufacturing firms did not show a noticeable change in labor expenditure following the shock. I first analyze wage changes in the labor market, followed by an examination of labor reallocation between the two sectors.

Wage Due to the lack of information on labor composition in the Prowess data, I now turn to the CPHS data to analyze the impacts on the labor market. Prediction

[32] In Appendix Table B.29, I show the changes in firms' borrowing from banks. Panel A shows that in more e-Ready districts, service firms increased their borrowings from banks, specifically short-term borrowings, whereas manufacturing firms reduced their borrowings.

1 states that the wage rate for ICT professionals would rise after the shock due to increased demand. To investigate the changes in wages, I estimate the following specifications:

$$\ln(Wage_{ijdt}) = \gamma_i + \gamma_t + \gamma_{jt} + \beta \;\; e\text{-}Index_d \times Post_{2,t} + X + \varepsilon_{ijdt} \tag{2.2}$$

$$\ln(Wage_{ijdt}) = \gamma_i + \gamma_t + \gamma_{jt} + \beta \;\; e\text{-}Index_d \times Post_{2,t} \times \text{Related Disciplines}_i + X + \varepsilon_{ijdt}, \tag{2.3}$$

where $\ln(Wage_{ijdt})$ is the log of the average monthly wage for individual i in industry j, district d, and wave t. $Post_{2,t}$ is a dummy variable that takes the value of 1 for the waves of January-April 2017 to September-December 2019 and 0 for the waves of September-December 2014 to September-December 2016. Related Disciplines$_i$ is a binary indicator that takes the value of 1 if individual i majors in computer applications or engineering and 0 otherwise. I incorporate the individual (γ_i) and wave (γ_t) fixed effects to account for time-invariant individual characteristics and common shocks, respectively. I also include the industry-year fixed effects (γ_{jt}). Standard errors are clustered at the district level.

I present the result of equations (2.2) and (2.3) in Table 2.6. As observed in columns 1, 2, and 4, during the post-shock periods, neither high-skill nor low-skill workers experienced statistically significant wage increases in more-Ready districts compared to less e-Ready districts.[33] However, as shown in column 3, in districts with one standard deviation higher *e-Index*, workers with at least a bachelor's degree (high-skill workers) and a degree in ICT-related fields received, on average, a 9.4% higher wage after the shock, compared to those with degrees in other fields. In column 5, I compare the wage rate of ICT labor to all other workers. ICT professionals enjoyed an 8.7% higher increase in wage compared to all other workers in districts with one standard deviation higher *e-Index*. These findings are consistent with Prediction 1. Only high-skilled workers possessing ICT-related skills witnessed a wage increase, while workers of other types did not attain such gains. The results also imply a widening wage inequality among workers due to the rise in ICT skill premiums.

[33]Column 2 suggests that wage rates for high-skill workers increased by 1.4% in districts with one standard deviation higher *e-Index*, and column 4 shows that wages rates for low-skill workers rose by 1.7% in districts with one standard deviation higher *e-Index*. Both are statistically insignificant at conventional levels.

Table 2.6: Impacts on Wage: Employed Individuals

	(1) All	(2) ≥Bachelor (High-Skill)	(3) ≥Bachelor (High-Skill)	(4) ≤Higher Secondary (Low-Skill)	(5) All
Dependent Variable: Ln(Wage)					
Post × *e-Index* (PeI)	0.102	0.076	-0.028	0.094	0.082
	(0.271)	(0.294)	(0.306)	(0.282)	(0.273)
Post × *e-Index* × Related Disciplines (PeIR)			0.553*		0.486*
			(0.290)		(0.295)
PeI + PeIR			0.524^{+}		0.568^{+}
p-value			(0.133)		(0.113)
Control Mean	9.69	10.27	10.26	9.55	9.67
R^2	0.44	0.51	0.51	0.43	0.43
No. of individuals	236,067	54,808	54,808	183,480	236,067
N	2,062,179	433,634	433,634	1,626,749	2,062,179
Individual FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: I restrict the sample to employed individuals residing in districts that are included in the Prowess data. "All" = The regression is estimated on a sample of employed individuals. "≥Bachelor" = The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of employed individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. The "Control Mean" refers to the average log of wages among employed individuals during the pre-periods in column 1, the average log of wages among individuals with diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees in column 2, the average log of wages among individuals in the non-service sector who have diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees, excluding those with a background in computer application or engineering, in column 3, and the average log of wages among employed individuals who either lack any formal education or have completed only primary, middle, secondary, or higher secondary schooling in column 4. All regressions include individual, wave, and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Reallocation of ICT Labor Next, I examine whether workers, especially ICT professionals, became more inclined to move to the service sector after the shock in more e-Ready districts. To do so, I estimate the following specifications:

$$Work_{idt} = \gamma_i + \gamma_t + \beta \ \textit{e-Index}_d \times Post_{2,t} + X + \varepsilon_{idt}, \tag{2.4}$$

$$Work_{idt} = \gamma_i + \gamma_t + \beta \ \textit{e-Index}_d \times Post_{2,t} \times \text{Related Disciplines}_i + X + \varepsilon_{idt}, \tag{2.5}$$

where $Work_{idt}$ is a dummy variable that takes the value of 1 if individual i is working in the service (or manufacturing) sector in district d and wave t and 0 if individual i is working in other sectors. In both equations, I include the individual (γ_i) and wave

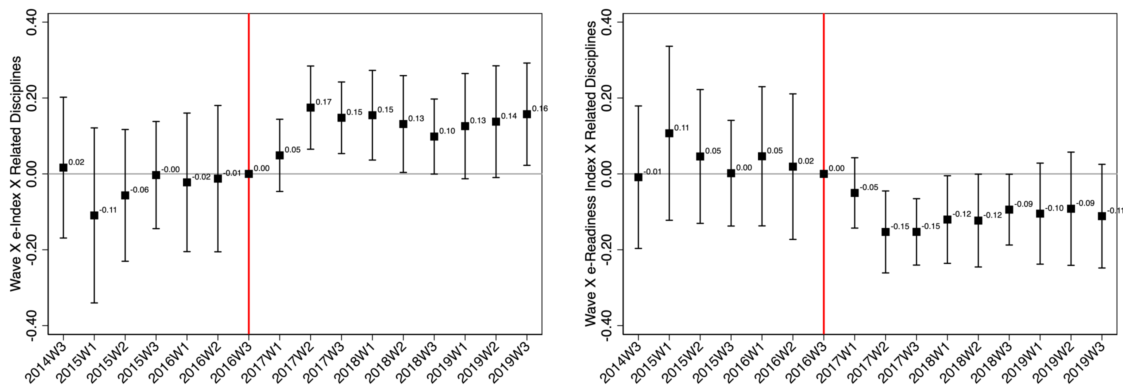
(γ_t) fixed effects and cluster the standard errors at the district level. The results of equations (2.4) and (2.5) are reported in Table 2.7.

Table 2.7: Impacts on Probability of Working in a Specific Sector

	(1) All	(2) ≥Bachelor (High-Skill)	(3) ≥Bachelor (High-Skill)	(4) ≤Higher Secondary (Low-Skill)
Panel A. Dependent Variable: Work in the service sector				
Post × *e-Index*	0.053*	0.058^{+}	0.031	0.046
	(0.030)	(0.036)	(0.030)	(0.033)
Post × *e-Index* × Related Disciplines			0.143*	
			(0.073)	
Control Mean	0.61	0.75	0.76	0.57
R^2	0.58	0.54	0.54	0.58
Panel B. Dependent Variable: Work in the manufacturing sector				
Post × *e-Index*	0.036*	-0.018	0.008	0.046**
	(0.021)	(0.033)	(0.026)	(0.023)
Post × *e-Index* × Related Disciplines			-0.133*	
			(0.075)	
Control Mean	0.21	0.19	0.18	0.21
R^2	0.46	0.45	0.45	0.46
No. of individuals	236,244	54,964	54,964	183,510
N	2,083,714	449,398	449,398	1,632,518
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: I restrict the sample to employed individuals residing in districts that are included in the Prowess data. "Work in the Service Sector" = A dummy variable equal to one if an employed individual is working in the service sector and zero if is working in other sectors. "Work in the Manufacturing Sector" = A dummy variable equal to one if an employed individual is working in the manufacturing sector and zero if is working in other sectors. "All" = The regression is estimated on a sample of employed individuals. "≥Bachelor" = The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of employed individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. All regressions include individual and wave fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In column 1 of both panels, workers in more e-Ready districts were observed to be more likely to work in both the service and manufacturing sectors. This shift implies a migration of workers away from industries such as agriculture and forestry. However, the increased likelihood in the two sectors was primarily driven by workers with different educational backgrounds. In the manufacturing sector, the likelihood of joining increased only for workers with at most a degree from higher secondary school (low-skill workers), as indicated in column 4 of panel B. On the other hand, service firms employed more high-skill workers, but this increase was specifically observed for those with a degree in computer application or engineering that is related to the development and application of ICT (column 3 of panel A).[34] In districts with one standard deviation higher *e-Index*, high-skill workers with ICT-related degrees were 2.6% more likely to join the service sector and 2.4% less likely to work in the manufacturing sector compared to those with degrees in other fields after 2016. The departure of ICT professionals who could operate and maintain the programming of machines also compelled manufacturing firms to scale down capital (column 1 of panel B in Table 2.4) and opt to substitute with low-skill workers.



(a) Work in the Service Sector (b) Work in the Manufacturing Sector

Notes: The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. "Work in the Service Sector" = A dummy variable equal to one if an individual is working in the service sector and zero otherwise. "Work in the Manufacturing Sector" = A dummy variable equal to one if an individual is working in the manufacturing sector and zero otherwise. All regressions include individual and wave fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 2.8: Event Study Graphs: Coefficients on *Wave* × *e-Index* × *Related Disciplines*

In Figure 2.8, I plot the dynamics of the effects on high-skill workers with ICT-related degrees. One can observe that there were no differential trends between districts with a high *e-Index* and those with a low *e-Index* before the 2016 demonetization shock.

[34]As shown in column 4 of Table 2.7, low-skill workers were 0.8% more likely to enter the service and manufacturing sectors in districts with one standard deviation higher *e-Index*, although the estimated coefficient for the service sector is statistically insignificant.

In the post-shock period, the redistribution of ICT labor between the service and manufacturing sectors, with service firms hiring more ICT labor and manufacturing firms employing less, persisted for years. These findings are consistent with Prediction 2 concerning the reallocation of ICT labor between the two sectors.

2.7 Firm Entry and Exit

As discussed in Section 2.5, the manufacturing sector in more e-Ready districts witnessed a decline in income and productivity after the demonetization shock, suggesting that manufacturing firms in those areas were struggling to grow. This raises a natural question: Was the manufacturing sector undergoing contraction? Specifically, were there fewer entrants into manufacturing, and were there more exits from manufacturing?

In Appendix B.6, I provide an analysis of firm entry and exit patterns. I first demonstrate that, after 2016, manufacturing firms were not less likely to enter the market in more e-Ready districts compared to service firms. I then show that firms in both the service and manufacturing sectors were less likely to exit the market in districts with a higher *e-Index*. However, manufacturing firms demonstrate a relatively higher likelihood of exit compared to service firms.[35] I also compare the productivity of firms that exited the market after 2016 with those that remained in the market from 2012 to 2019 in 2015. The average TFPR of exited firms was lower than the average of ongoing firms in 2015.[36]

In summary, although the manufacturing sector in districts with a higher *e-Index* encountered challenges in sales and productivity growth, it was not experiencing a contraction in terms of both employment (column 1 of panel B in Table 2.7) and entry (column 2 of Table B.7) during the post-shock period. Yet, in the long run, as the service sector continues to gain strength, one would anticipate an accelerated shift away from manufacturing toward services.

[35] It is important to note that due to the missing exit date for approximately 69% of the exited firms in the MCA registration data, the results should be interpreted with caution.

[36] An ideal approach would involve comparing the TFPR of new entrants and new exits within the same year. However, due to data limitations on new entrants, I have fewer than 30 observations of TFPR for new entrants in each year after 2016. It is thus unclear whether firms with higher productivity are replacing those with lower productivity, limiting my ability to speak to efficiency.

2.8 Alternative Mechanism: A Pure Demand-Side Story?

As discussed in Section 2.6.1, firms in areas with better digital environments (or a smaller x) were more incentivized to adopt digital technology. Section 2.5 and Section 2.6.2 empirically validate the model's predictions, providing supportive evidence that an area's digital environment plays an important role. Yet, one may still argue that it is a pure demand story: regardless of the *e-Index*, firms are more inclined to adopt digital technology and perform better in areas where a larger number of consumers and firms are utilizing it.

To test this alternative mechanism, I utilize the demonetization shock intensity measure developed by Crouzet, Gupta, and Mezzanotti (2023). This measure is constructed based on the distribution of currency chests, which handle local currency distribution. A higher value indicates areas more severely impacted by the cash crunch and thus a higher demand for digital payment. As shown by Crouzet, Gupta, and Mezzanotti (2023), districts that were more severely impacted experienced a higher total amount of transactions via electronic payment systems and saw a greater number of establishments adopting these systems. Therefore, if driven solely by demand, one would anticipate that firms, especially service ones, would exhibit better performance in areas with a heightened demand for digital payment.

I examine the impact of the demonetization shock intensity on firms' sales, categorized by their *e-Index*. Firms in each sector are divided into two groups: those with an *e-Index* above the median and those below it. I regress the log of sales on the interaction term of *Post* and the severity of the demonetization shock, and the results are displayed in Table B.30. In more e-Ready districts, a firm's sales showed no variation with the severity of the demonetization shock (columns 1 and 3), and this effect also held for manufacturing firms in less e-Ready districts (column 4). However, in less e-Ready districts, the sales of service firms decreased with the severity of the demonetization shock (column 2). These results do not align with a pure demand story, which would anticipate positive estimates for the interaction terms in both more and less e-Ready districts. This is because firms in districts with advanced digital environments were better equipped to meet the demands that shifted towards digital payment methods. In contrast, in less e-Ready districts, despite firms' willingness to adapt, poor digital infrastructure hindered their transition to digitalization. Consequently, a higher demand in these districts led to a more negative estimate, casting doubt on a pure demand story.

2.9 Robustness of the Results

In this section, I conduct a series of robustness checks to strengthen confidence in the findings discussed in Section 2.5 and Section 2.6.2.

2.9.1 Estimates Based on Restricted Sample (Entrants Excluded)

In the Prowess data, about 92.4% of firms were established before 2012, and 98.8% of firms were established before 2016. One may thus be concerned that the results are driven by firms that entered more e-ready districts disproportionately after 2012 or the shock in 2016. To alleviate this concern, I perform regression analysis on two sub-samples: one excluding firms established after 2012 and another excluding firms established after 2016. In Table B.10 and Table B.11, I present the results on five main outcome variables using firms founded before 2012 and 2016, respectively. The five dependent variables are income, TFPR, expenses on communication, expenses on ICT-related outsourced professional services, and investment in ICT capital. These results are comparable to the main findings discussed in Section 2.5 and Section 2.6.2 without such restrictions. Thus, it is unlikely that the outcomes are driven by firms entering after 2012 or 2016. Furthermore, the fact that the results persist even after excluding new entrants provides further support for the notion that the decreased TFPR in manufacturing firms is primarily driven by the reallocation of ICT labor, rather than the entry of manufacturing firms with possibly lower productivity.

2.9.2 Estimates Based on Full Sample (All Observations Used)

In the main analysis, I use consistent samples of firms across outcome variables within the same category. Yet, it should be noted that there are some variations in the availability of outcome variables across firms. For example, there are 112,501 available observations on income for service firms, while there are only 109,805 on sales. So, to account for this limitation and to assess the sensitivity of the findings in Section 2.5 and Section 2.6.2, I redo the analysis using all observations that an outcome variable has. The results, as presented in Tables B.12-B.14, were found to be qualitatively and quantitatively similar to those shown in Tables 2.3-2.5.

2.9.3 Including State-Year Fixed Effects

One may be concerned that the results are influenced by other contemporaneous changes at the state level, such as the implementation of policies that specifically favor the service sector (e.g., Software Technology Parks and Special Economic Zones). To address this concern, I control for state-year fixed effects. This will capture state-level fixed and time-varying unobservable factors. I display the results on firms' outcomes, labor market, and business creation in Appendix B.7.3. As shown, the results remain consistent and robust after incorporating the state-year fixed effects. It thus reinforces the reliability and validity of the analysis.

2.9.4 Temporal Placebo Tests

I conducted two temporal placebo tests to further examine if the results can be attributed to other policy shocks, such as the "Make in India" campaign in 2014 and the "Digital India" campaign in 2015. In the first test, I designate the treatment year as 2014 and treat 2014 and 2015 as the post-treatment years. The results are presented in Table B.20, where the estimated coefficients on income, TFPR, expenses on communication, expenses on ICT-related outsourced professional services, and investment in ICT capital are small and statistically insignificant. In the second test, I set the treatment year as 2015, with only 2015 as the post-treatment year. The results are displayed in Table B.21, and similarly, they are also small and statistically insignificant. The outcomes of both tests further bolster the robustness of the findings discussed in Section 2.5 and Section 2.6.2.

2.9.5 Excluding One Industry

Some may worry that the results are driven by a particular industry in the service or manufacturing sector. As a further robustness check, I re-estimate the parameter of interest (β) in equation (2.1) excluding one industry at a time. The estimations are conducted for the five key outcome variables (i.e., income, TFPR, expenses on communication, expenses on ICT-related outsourced professional services, and investment in ICT capital). I display the distributions of the estimated coefficient on *Post* $\times$ *e-Index* in Figure B.14 for the service sector and in Figure B.15 for the manufacturing sector. As shown, the effects remain stable and cluster around the effect observed in the main analysis when excluding any one of the industries from the analysis.

2.9.6 Labor: Remote Working

One might be concerned about remote working, where labor in one district works from home for an employer in another district. This concern is particularly relevant for ICT labor, as they can transition to remote work more seamlessly compared to other types of workers. However, this was unlikely in India before 2020. As shown by Chakravorti and Chaturvedi (2020), India was the least prepared country for remote working among 42 developed and developing countries. While the preparedness of the U.S. was above the median, only 6% of employed workers worked remotely in 2019. This statistic implies that the proportion of workers who practiced remote work in India prior to 2019 would be even smaller than 6%, thus alleviating this concern.

2.9.7 Labor: Migration & Supply

In Section 2.6.1, I assume that the supply of labor remains relatively stable in the short run. Specifically, I abstract away from factors such as the migration of ICT labor and any sudden surge in the supply of ICT labor. Here, I utilize the CPHS data to examine whether the results presented in Table 2.7 are affected when excluding migrated workers and whether there was an increase in labor supply to the service and manufacturing sectors after 2016.

In the first test, I re-estimate equations (2.4) and (2.5) on a sub-sample of employed individuals excluding those who were migrants. I classify individuals as migrated individuals if their migration status is ‘Yes’ or if their state of origin is different from their current state in any round of the survey.[37] In total, I exclude 11.7% of individuals who had ever been identified as migrants between 2014 and 2019.[38] I present the results in Table B.22, which are similar to the ones in Table 2.7. It provides supportive evidence that changes in the labor market are not driven by migrant labor, specifically not by high-skilled ICT labor.

In the second test, I re-estimate equations (2.4) and (2.5) using two new dependent variables. The first dependent variable is “In the Labor Market,” which is a binary variable equal to one if an individual is either employed or unemployed and looking for a job, and zero if an individual is out of the labor market. The second dependent variable is a binary indicator that takes the value of one if an individual is employed either in the service or manufacturing sector and zero if the individual is employed in other sectors, unemployed, or out of the labor market.[39] I conduct the estimation on a sample of individuals who are employed, unemployed, or out of the labor market. In panel A of Table B.23, I display the results on the first dependent variable, which show that individuals did not exhibit an increased likelihood of entering the labor market following the 2016 demonetization shock in more e-Ready districts. This supports the assumption that the local labor market remains relatively stable in the short run. Moving to panel B, I show that both the service and manufacturing sectors did not experience an expansion in their labor size. This finding further supports that there was no change in the extensive margin, but rather a reallocation of labor between

[37]The CPHS has been collecting information on an individual’s state of origin and current state of residence since 2014. However, data on individuals’ migration status was only collected after the wave of May-August 2018. Additionally, the survey started including inquiries about the specific state and district to which they had immigrated from 2020 onwards, which falls beyond the scope of the study period. The migration status I used encompasses all reasons for migration, including marriage, education, and employment. Therefore, the number will overestimate the count of migrants who moved for economic reasons. It is also important to note that comparing an individual’s state of origin and current state of residence may lead to a potential overestimation of the actual number of individuals who have migrated, as some may have relocated to another state before 2014. Conversely, it may also result in underestimation, as it does not account for those who have moved to a different district within the same state.

[38]The proportion (11.7%) is comparable to the share (10.5%) of the workforce migrating for economic reasons as reported in the 2011 Population Census of India, as presented in Table 1 of Government of India (2017).

[39]The CPHS data does not provide identification of the industry to which unemployed individuals belong or the specific industry they are seeking jobs in. Therefore, I can only examine if individuals are more likely to be employed by service or manufacturing firms.

sectors. Moreover, column 3 of both panels demonstrates that there was no surge in the supply of ICT labor in more e-Ready districts.

2.9.8 Placebo Test: ICT or Management?

One may argue that firms employed more ICT labor not because of digital technology adoption but as a complementary part of firm management and labor re-organization. If this is the case, then one would expect the following: (1) individuals with a degree in commerce or management also exhibited an increased likelihood of joining service firms; and (2) service firms spent more on bonuses, which serve as supplementary payments specifically targeted towards those in management positions.

I first augment equation (2.5) with the interaction term of *Post*, *Related Disciplines*, and *Management*, where *Management* is a binary variable equal to one if an individual's discipline falls under commerce or management and zero otherwise. The results are presented in Table B.24. Column 3 indicates workers with a degree in commerce or management did not become more or less likely to work in the service or manufacturing sector after the shock in more e-Ready districts. I next estimate equation (2.1) on firms' labor expenses, and the results are displayed in Table B.25. In panel A, one can see that the increase in compensation to employees among service firms in more e-Ready districts after the shock is attributed to the rise in salaries, rather than bonuses. In short, I do not find support for the concern that firms employ more ICT labor due to management improvement rather than digital technology adoption. The above results also suggest that there might not be a complementary organizational change among service firms, which is consistent with the findings in Commander, Harrison, and Menezes-Filho (2011) concerning Indian firms.

2.10 Conclusion

This study examines the distributional consequences of digitalization across sectors and firms and its implications for growth trajectories in a developing country with labor market constraints such as skill shortage and limited spatial labor mobility. To answer these questions, I use a quasi-experimental shock–the 2016 demonetization policy that resulted in a massive expansion in digital payments–and spatial variations in the digital environments. Using firm-level panel data, I demonstrate that in districts with more favorable digital environments, the shock disproportionately benefited service firms. Service firms experienced growth in income and productivity by embracing digital technology. They were willing to pay higher wages for the limited supply of ICT labor, thereby expanding their ICT workforce. This led to a widening wage inequality between ICT labor and all other types of workers. Conversely, the manufacturing sector in more e-Ready districts experienced negative spillover effects through ICT labor reallocation across sectors. Manufacturing firms underwent a drain in ICT labor and a reduction in ICT investment and services, resulting in a decline in productivity.

My analysis delivers three main messages. First, the infrastructural and institutional environment matters. As shown, without adequate digital infrastructure and supportive policies, firms are less incentivized or less able to embrace digitalization. Second, a push for digitalization further strengthens service-led growth in India, as identified by fan2023growing, and has unequal welfare implications for workers. It disproportionately benefited ICT professionals in more e-Ready districts, which also tend to be more well-developed areas, while not statistically significantly improving wage rates for all other workers. Third, during this short-run transitional phase, the manufacturing sector paid the price. Despite the government's vision of transforming India into a global manufacturing hub, as outlined in the 2014 *Make in India* plan, the manufacturing sector was declining. Policymakers thus face the challenge of balancing the promotion of digitalization to further boost the service sector with the necessity of ensuring inclusive economic growth. The analysis also highlights an important policy implication, suggesting that the government should increase digital infrastructure investments in less developed regions and address the factors affecting spatial labor mobility.

This study has some limitations that future research should address. First, it is crucial to understand changes in overall efficiency, particularly for policy guidance on choosing the optimal economic path. However, this study is constrained by the lack of data on the productivity of new entrants, making it challenging to assess whether overall efficiency improved in the post-demonetization period. Second, the current data (i.e., Prowess data) does not encompass firms in the informal sector, which represents a significant segment of the Indian economy. Bringing the informal sector into the analysis would offer a fuller picture of the role digitalization plays in economic growth.

Chapter 3

How Do Political Connections of Firms Matter During An Economic Crisis?

Yutong Chen Gaurav Chiplunkar Sheetal Sekhri Anirban Sen Aaditeshwar Seth

3.1 Introduction

The role of political connections in running businesses has been widely acknowledged and politically connected firms operate in all countries across the world, including those with strong institutions and low levels of corruption.[1] This nexus between business and government however has always been an area of active policy interest and debate. The economic literature has documented the benefits of having a political connection, either through access to better finance, taxation benefits, public contracts, lower regulatory oversight, etc., and its resulting impact on firm survival, valuation, profits, and growth.[2]

There is little empirical evidence, however, on how these political connections matter during economic downturns when resources available in the economy are scarce.

[1]Faccio, Masulis, and McConnell (2006), Tihanyi et al. (2019), Amore and Bennedsen (2013), and Acemoglu et al. (2016).

[2]De Soto (1989), Stiglitz and Dasgupta (1971), Fisman (2001), Sapienza (2004), Khwaja and Mian (2005), Dinç (2005), Faccio, Masulis, and McConnell (2006), Goldman, Rocholl, and So (2008), Akcigit, Baslandze, and Lotti (2023), Choi, Penciakova, and Saffie (2021), and Heitz, Y. Wang, and Z. Wang (2021).

Understanding the role of political connections during a crisis has become especially relevant, given that the world has experienced two of the worst economic downturns since the Great Depression in a span of a decade–the Global Financial Crisis and more recently, the Covid-19 pandemic. In theory, political connections could help firms exert their influence over the bureaucratic machinery during a crisis and divert scarce resources toward them. Alternately, the political system could leverage these connections to drain resources from firms instead, as rent-seeking incentives become more acute during an economic downturn (Shleifer and Vishny, 1994). In addition to this, a second question that has received even lesser attention–primarily due to data constraints–is the mechanisms through which political connections impact firm performance. For example, do connected firms systematically alter their borrowings and liabilities portfolio during a crisis, and use it to invest in assets? Does it lead to differential changes in firm performance and growth after the crisis? Using a long panel of firms, with detailed data on their sales, income, and expenses, as well as their portfolio of assets, liabilities, and borrowings, this paper provides answers to both of these questions in the context of an unexpected macroeconomic shock in India in 2016.

A central novel contribution of this study is the construction of a new *social network based* measure of firms' political connections, using a new dataset that we assemble. This measurement relies on machine learning algorithms and can be adapted to other settings. In our context, the creation of the data is based on the following steps: First, we collect comprehensive information on not only politicians who have ever contested elections but also the universe of active and retired bureaucrats in the Indian Administrative Services (IAS). Second, we obtain data on the universe of registered firms (and their Boards of Directors) from the Ministry of Corporate Affairs. Third, we use over 5 million news articles from seven leading media outlets in India and Wikipedia pages for these individuals. We then implement sophisticated machine learning algorithms and entity resolution mechanisms to search and curate their interviews, announcements, and appearances at personal and professional events. This allows us to ascertain if politicians and bureaucrats themselves, or their kin, friends, or social contacts have ever served as Directors in any of these firms.

Our measurement of political connections therefore, improves on some of the most common ones in the literature (such as co-ethnicity, relatives, from the same region, etc.) in two significant ways: first, as opposed to coarse measures of political connections (such as regional associations, social or gender identities, etc.), we observe a more direct connection to the government–politicians and bureaucrats who are Directors. In addition to this, we are also able to capture *indirect* connections between politicians/bureaucrats and Directors through their personal, professional, and social networks such as friendships, meetings, and social appearances as reported in the media. A firm is therefore politically connected if one or more of its Directors: (i) is or ever was a politician/bureaucrat; (ii) is a kin or relative of a politician/bureaucrat; (iii) connected through friendships as well as professional and social interactions reported in the media (Section 3.3 provides a more detailed discussion). For our empirical analysis, we define a time-invariant binary variable that takes the value 1 if a firm in the pre-crisis period (discussed below) is politically connected and 0 otherwise.[3] By this definition, 2.75% of firms in our sample are politically connected.[4]

The empirical context is India's Demonetization episode of 2016. In a completely surprising announcement, India's Prime Minister demonetized 86% of India's currency overnight in November 2016. This led to massive cash and credit shortages across the country, as the banking system grappled with replenishing the economy with the new currency bills gradually over time (Chodorow-Reich et al., 2020). The resulting disruptions and delays severely impacted both households and firms, and economic recovery was slow even a couple of years after this episode (Lahiri, 2020; Karmakar and Narayanan, 2020). It is in this context that our study examines how politically connected firms, as compared to their non-connected counterparts, systematically differed in their response to the crisis and the potential role of these connections in altering the portfolio of assets, liabilities, and operational decisions of a firm.

We use rich data on a panel of over 30,000 formal sector firms across all major Indian states between 2012 and 2019. These data are obtained from the Prowess Data of the Center for Monitoring the Indian Economy (CMIE). Even though the data covers large firms in the formal sector, a unique feature is that it harmonizes detailed information on firm operations by using their Annual Reports, Quarterly Financial Statements, and other publicly available sources. We can therefore observe the composition of asset, liability, and borrowing portfolios of a firm, along with the

[3] It is possible that firms form political connections after the crisis, which we rule out by definition.

[4] This is similar to Faccio (2010), who examines firms' political connections in 47 countries, including India.

more aggregate categories like income, sales, and expenses. We use this information to examine various channels through which firms leverage their political connections in response to a macroeconomic crisis.

It is important to note that politically connected firms in our sample are older and larger in size as compared to their non-connected counterparts (Table 3.1). Consequently, they have higher income, sales, expenses (wage and capital bills) as well as assets and liabilities even before the crisis. While this pattern is consistent for India as well as across countries (Faccio, 2010; Bhalla et al., 2022), it raises the concern on whether firms' response to the crisis can be explained by the *selection* of firms who acquire political connections (such as those with higher entrepreneurial ability, better resilience to shocks, etc.), or political connections themselves. In order to address this, our identification strategy implements a Synthetic Difference-in-Differences (SDID) methodology. Recently developed by Arkhangelsky et al. (2021), SDID combines insights from Difference-in-Differences (DID) and Synthetic Control (SC) methods (Abadie, Diamond, and Hainmueller, 2010) by: (i) re-weighting and matching pre-exposure *trends* between the treated and control units on the outcome variables (similar to SC); and (ii) allowing for the additive unit- and time-specific *selection* into the treatment (similar to DID). These fixed effects, therefore, control for all observable and unobservable time-invariant differences in *levels* across connected (treated) and non-connected (control) firms (such as the entrepreneurial ability for example). Moreover, by construction, we generate a "synthetic control" group of firms that have similar *trends* to the treated (connected) firms in the years prior to the crisis (pre-period).[5] In a nutshell, therefore, firm fixed effects absorb all time in-variant differences that influence firms' *selection* into acquiring political connections, while creating synthetic control units alleviates concerns about time-varying unobservables that could bias our results. In addition to this, a long panel of firms allows us to also control for district×year and industry×year fixed effects in our analysis. These control for all observable and unobservable time-varying changes across districts and industries that could impact firm outcomes, or be correlated with the demonetization shock (such as district- or industry-specific changes in prices and wages, supply and credit disruptions, etc). In what follows, we first discuss the results, followed by mechanisms, and finally, multiple additional robustness tests that reaffirm the role

[5] Using event studies, we show that there are no differential trends in income, sales, and expenses in the pre-period for the treated and the synthetic control units.

of firms' political connections in driving the results.

To begin, we find that politically connected firms (as compared to their non-connected counterparts) reported 8-11% higher income, sales, and expenses in response to the macroeconomic crisis. Moreover, these effects persisted over three years following demonetization. It is unclear just from these estimates whether connected firms were more *robust* to the crisis i.e., firm outcomes (sales, for example) were impacted less due to the crisis; or were more *resilient* as well i.e., were impacted less, but also recovered faster (G. Khanna, Morales, and Pandalai-Nayar, 2022). By examining the trends in firm sales, Appendix Figure C.2 finds evidence in favor of the latter–the decline in sales after the crisis was lower for connected firms as compared to non-connected ones; and while both connected and non-connected firms grew after the crisis, the growth (in sales) was much faster for connected firms.

Politically connected firms also exhibited around a 5% higher TFPR as compared to non-connected ones.[6] A large literature discusses the source of these productivity gains (TFPR), predominantly along three dimensions: (i) gains in the quantity efficiency as measured by TFPQ (De Loecker, 2011; Katayama, S. Lu, and Tybout, 2009); (ii) price markups; (iii) change in firm capability as measured by product quality and scope (Atkin, Khandelwal, and Osman, 2019). While these channels are important, the key lies in being able to measure them using standard data (like ours).[7] Moreover, Atkin, Khandelwal, and Osman (2019) argue that TFPR, as opposed to TFPQ, might anyway be a better proxy for measuring the broader firm capabilities, given these measurement challenges and the fact that TFPR captures firms' ability to produce both quality and quantity. Nevertheless, we make progress on measuring the sources of these TFPR gains to the extent possible in our setting. First, we follow Bau and Matray (2023) and with some caveats (see Section 3.6.2), construct measures of TFPQ. We find, at best, no differences in TFPQ between politically connected and non-connected firms after demonetization. Instead, politically connected firms reported a larger product scope, which suggests that the source of the

[6]A long panel of firms allows us to construct measures of TFP using standard methods from the literature. In particular, we first calculate Revenue Total Factor Productivity (TFPR) measures using the method proposed by Levinsohn and Petrin (2003).

[7]For example, the measurement of TFPQ requires observing prices directly across all products within a firm and then adjusting it for the quality and specification of these products. Both of these are challenging in standard administrative data (like ours) and can lead to TFPQ being a poor proxy of a firm's capabilities.

TFPR gains came from firms adjusting the products they manufactured as opposed to efficiency gains coming from TFPQ, which is reasonable given the nature of the demonetization shock.

A key question that naturally arises from the above analysis is: what did connected firms do differently to be able to realize these gains? Most data is limited in being able to answer this question, but the richness of our data allows us to unpack the mechanisms driving these results.[8] One of the most common channels documented in the literature of how firms' political connections matter is access to credit.[9] Consistent with this literature, we find that politically connected firms reported lower borrowings as compared to their non-connected counterparts (by 5%), especially reducing their long-term borrowing in favor of more short-term ones. This was mainly driven by a substantial reduction in long-term bank borrowings and secured borrowings (i.e., loans requiring collateral, largely reflecting borrowings from formal institutions)[10], driven by commercial banks charging higher interest rates on these long-term loans. Connected firms increased unsecured borrowings instead i.e., borrowings that did not require collateral, though the estimated coefficient is statistically insignificant at conventional levels.

We further harness our data to uncover other novel channels that have not been documented in the literature. In particular, we find that politically connected firms (compared to their non-connected counterparts) increased their liabilities (by 5.5%) after demonetization, and in particular, increased short-term liabilities (expected to be repaid within a year) as opposed to longer-term ones. This increase in short-term liabilities was driven by delaying payments to suppliers and vendors, as well as interest and debt payments to creditors due within the next year.

How did these differential changes in borrowings and liabilities impact the portfolio of assets? We find that as compared to their non-connected counterparts, connected firms were able to expand both the size and composition of their asset portfolio after demonetization. In particular, connected firms (relative to non-connected ones) reported a 4.1% increase in total assets, with a comparable increase in both their

[8] We provide detailed definitions of all variables used in our analysis in Appendix Section C.2.

[9] See Khwaja and Mian (2005), Charumilind, Kali, and Wiwattanakantang (2006), Claessens, Feijen, and Laeven (2008), and Faccio, Masulis, and McConnell (2006)

[10] Our data does not allow us to examine borrowings from public and private sector banks separately.

short-term and long-term assets.[11] Despite the large macroeconomic shock, these connected firms were able to increase both their short and long-term investments as well as incur higher expenditure on intangible commodities (such as computer software, patents, marketing rights, etc.), which is consistent with the productivity gains we documented earlier. On the other hand, we find no relative difference in changes to short-term inventories, bank balance, expenditure on fixed assets, or on plant, property, and machinery between connected and non-connected firms. Put together, our results suggest that firms used political connections to get access to scarce (potentially uncollateralized) credit, delay their short-term payments to creditors and suppliers, and accumulate productive assets, leading to better resilience after the crisis.

In addition to the identification strategy outlined above, we undertake multiple additional analyses to further increase our confidence in the causal interpretation of our results. First, we find no evidence that connected firms had prior knowledge about the government's plan to demonetize. Differences between these firms only appear (and are persistent) after demonetization. Second, we take advantage of our rich data and create alternate, broader measures of a firm's connections through its Board of Directors (see Appendix Section C.5 for details). In particular, for each firm, we calculate the average number of other firms their Directors are on the Board of, as well as other Directors that they would know through them. We find that while being "connected" more generally matters for firms' resilience to the crisis, the impact of having a *political* connection is very robust and an order of magnitude more important (see Section 3.8.3 for a detailed discussion).[12] Third, following the literature (Faccio, Masulis, and McConnell, 2006; Deng, Wu, and Xu, 2020), we show that recent, newer connections matter more than older ones. If firm or Director characteristics were driving our results (as opposed to the political connections themselves), the duration of connections should not matter–firms with older and newer connections would have been equally resilient to the shock. Lastly, we check whether politically connected

[11] Short-term or current assets are those assets that can be easily converted to cash within 12 months, while long-term or non-current assets cannot be converted to cash within 12 months. They include capital work, fixed assets, etc. Please see Appendix C.2 for detailed definitions of all variables.

[12] This mitigates concerns around politically connected firms appointing certain types of Directors on their Board (who might be more connected themselves, for example) to deal with adverse economic situations. In fact, we show that it is not so much about connections in general, but specifically political connections that drive the results.

firms were located in areas with less severe shocks, which could rationalize the results, but find no evidence in support of this either.

Our paper complements and extends rich literature that studies the impact of political connections on firm performance. While some studies (Faccio, Masulis, and McConnell, 2006; Faccio, 2010; Niessen and Ruenzi, 2010; Bertrand et al., 2018) show that politically connected firms underperform compared to non-connected firms and political connections are costly, others (Acemoglu et al., 2016; Goldman, Rocholl, and So, 2009; Boubakri, Cosset, and Saffar, 2012; Amore and Bennedsen, 2013; Houston et al., 2014; Brown and Huang, 2020) argue that firms benefit from political connections. Most of the literature has focused on channels through which firms might benefit from acquiring political connections, such as a higher likelihood of receiving credit loans (Khwaja and Mian, 2005; Charumilind, Kali, and Wiwattanakantang, 2006; Claessens, Feijen, and Laeven, 2008; H. Li et al., 2008), getting corporate bailouts (Faccio, Masulis, and McConnell, 2006), winning public contracts (Goldman, Rocholl, and So, 2008), and facing lower regulatory enforcement (Houston et al., 2014).

We extend this literature in a number of ways. First, unlike previous work that focuses on how political connection matters, we determine how firms leverage political connections to increase their resilience in the presence of a macroeconomic policy-driven economic crisis. In that sense, our paper is closest to Choi, Penciakova, and Saffie (2021), who examine how connected firms in the US are able to access government relief funds during hurricanes. Second, the richness of our data allows us to uncover various channels, such as the portfolio of short and long-term borrowings, assets, and liabilities, through which these connected firms perform better when faced with a crisis. Lastly, we innovate and capture political connections in a more comprehensive way by harnessing a newly developed sophisticated machine-learning method. Both data on political connections of Indian firms as well as the method for measuring political connections more precisely can be used in a wide array of applications and contexts beyond the one we study here.

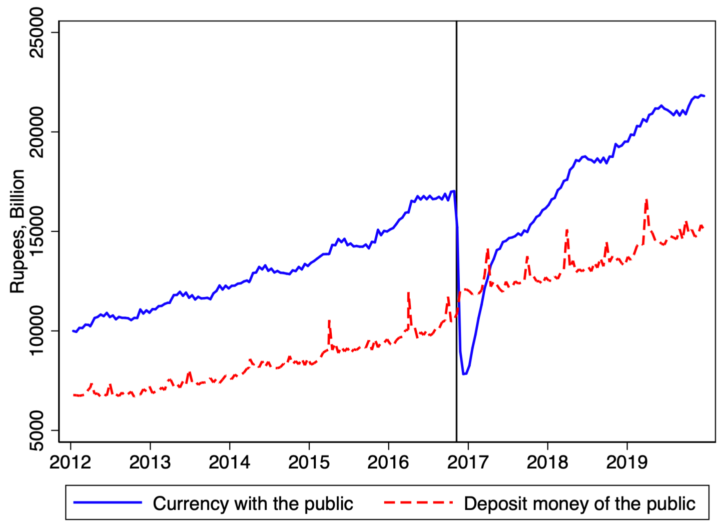
The rest of the paper is organized as follows. Section 3.2 provides a background of the empirical context, while Section 3.3 describes how we measure political connections. Section 3.4 describes the firm data in detail, while Section 3.5 describes our empirical strategy. Sections 3.6 and 3.7 present the empirical results on how political connections played a role during demonetization, and Section 3.8 conducts a number of robustness checks. Finally, Section 3.9 offers a short conclusion.

3.2 Demonetization in India

In a sudden and unexpected televised address to the nation on the evening of *November 8, 2016*, the Prime Minister of India announced that the two largest denomination notes–INR 500 ($7) and INR 1,000 ($15), would cease to be legal tender at midnight and would be replaced by new INR 500 and INR 2,000 rupee notes instead. These old notes, accounting for 86% of the pre-demonetization currency, could be deposited in banks before December 31, 2016, in exchange for new ones, but could not be used for any monetary transactions. The intended objective of this exercise, as emphasized by the Prime Minister, was to curtail corruption and eradicate black money and counterfeit currency notes from the economy. To maintain the secrecy of this policy, the Reserve Bank of India did not print and distribute a large quantity of these new notes, which unsurprisingly led to severe shortages and delays in replacing the old notes with new ones. This caused a lot of chaos and as shown in Figure 3.1, the total currency declined by 75% overnight and recovered very slowly after that over the course of the next year (Chodorow-Reich et al., 2020; Lahiri, 2020).

While the government was able to recover 99% of the demonetized currency, The episode had an adverse impact on a cash-dependent Indian economy.[13] Estimates suggest a 3-4 p.p. decline in output and employment and a 2 p.p. decline in growth in the quarter of demonetization. Moreover, despite a large increase in bank deposits, bank lending remained constrained and while the currency in circulation recovered over the next year, economic recovery was slow even a couple of years after (Chodorow-Reich et al., 2020; Karmakar and Narayanan, 2020; Lahiri, 2020). This episode was a sharp, unexpected change in the economic conditions, resulting in a significant economic downturn and a severe cash crisis.

[13]Currency outside banks as a share of GDP was 12.5% in 2015 for India, as compared to 7.4% in the U.S. and 9.3% in China (Rogoff, 2016).



Notes: Data is from the Database on the Indian Economy published by the Reserve Bank of India. The units are in billions of Rupees and the frequency is fortnightly. The graph shows the time series of currency with the public (the blue solid line) and deposit money of the public (the red dashed line). Currency with the public is the currency in circulation less cash held by banks. Deposit money of the public is the sum of demand deposits with the banks and other deposits with the RBI. The black solid line is November 8, 2016.

Figure 3.1: Steep Fall in Cash

3.3 Innovation in Measuring Political Connections

3.3.1 Political Connections Measurements in Existing Literature

Previous literature has used a variety of ways to define political connections. In Appendix C.1, we list the various ways that political connections have been measured in the literature (Table C.1). In highly cited studies, connections with some principal politicians have been leveraged. For example, Fisman (2001) identifies connections based on the Suharto Dependency Index, developed by the Castle Group, a leading economic consultant in Indonesia. The index ranges from one (least dependent) to five (most dependent). Companies affiliated with Suharto's children or allies have a high index. Likewise, Mobarak and Purbasari (2006) use connections to President Suharto. Khwaja and Mian (2005) consider a firm politically connected if its directors contest elections. A number of papers (Agrawal and Knoeber, 2001; Boubakri, Cosset, and Saffar, 2012; Amore and Bennedsen, 2013; Bertrand et al., 2018) use politician CEOs and/or directors as the definition of political connection. Some papers (Claessens, Feijen, and Laeven, 2008; Brown and Huang, 2020; Choi, Penciakova, and Saffie, 2021) use campaign contributions for measurement.

Faccio, Masulis, and McConnell (2006) advances the measurement of political connections significantly. Politically connected firms include firms where a major shareholder (controlling at least 10 percent of voting shares) or top officer (CEO, president, vice president, chairman, or secretary) is a politician, a former head of a state, foreign politician, member of a political party or a friend of a politician. It relies on many studies (Agrawal and Knoeber, 2001; Backman, 2001; Gomez and Jomo, 1999; S. Johnson and Mitton, 2003; Fisman, 2001) to identify the political connections. All of these studies have a variety of different methods for classifying political connections and there is no harmonization.

3.3.2 Our Measure and Its Innovation

We now discuss how we create our measure of firms' political connections. This measure taps into various datasets and uses sophisticated machine-learning algorithms to link them together. Moreover, while we consider the Indian setting for this paper, the technique we demonstrate can be used more generally for other settings as well, with technical details on the data organization and the algorithm discussed in Sen et al. (2018).

Measuring political connections First, we collate a comprehensive dataset of: (i) around 20,000 politicians who have held political office and/or contested in national and state elections from 2004 onwards[14]; (ii) universe of more than 11,000 retired and current bureaucrats in the Indian Administrative Services across all State and Central Government departments and ministries since 1961.

Second, we collect information on the universe of around 65,000 Directors on the Board of publicly listed companies on the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) from 1980 onwards. Since these Directors could be mem-

[14]A ruling by the Supreme Court in November 2003 around citizens' Right to Information mandated all candidates contesting for public office to disclose information on assets and criminal records. We used these records and also leveraged information from `www.indiavote.com` and `www.persmin.gov.in`.

bers of multiple Boards, we complement it with information on all subsidiaries of these firms and the universe of firms registered with the Ministry of Corporate Affairs from 1980 onwards.

Third, we then train ML algorithms to identify relatives, friends, and social contacts of these individuals from over 5 million news articles (crawled daily) from seven leading media outlets in India: *The Hindu, The Times of India, Indian Express, The New Indian Express, Telegraph, Deccan Herald,* and *Hindustan Times* between 2011 and 2016. We augment this by crawling Wikipedia pages as well as curating interviews, announcements, and appearances at personal and professional events. An entity resolution algorithm (see Sen et al. (2018) for the technical details) is then used to merge information on connections from different sources.

Lastly, we determine if any politician, bureaucrat, or their kin and *social network* served as a Director for any of the firms described above, using a network graph (for up to 3 nodes) of kinship, interactions, and friendships between various entities (bureaucrats, politicians, their kin, and social network).

Definition of a politically connected firm For the purpose of this paper, we define a firm as politically connected *before 2016* if: (i) one or more of its Directors is either a politician or bureaucrat; (ii) kin or close relative of a politician or bureaucrat; (iii) connected through friendships and social interactions as reported in the media. Our measure, therefore, improves on the precision of measuring political connections, as compared to other commonly used measures in the literature (such as proximity by social groups, regions, identity, etc.) as discussed previously and reported in Table C.1, by combining machine learning techniques to measure friendships, meetings, and social appearances reported in the media, which are usually difficult to measure and quantify. Moreover, this method could be applied to any country or setting more generally.

Example of a politically connected firm We provide an example to highlight the intuition behind this method. From a news article published by the *Indian Express* (a large national daily) in 2017 (Figure 3.2), we establish that Mr. Sadanand Sule is the son-in-law of prominent politician Mr. Sharad Pawar. We also locate Mr. Sule from the Master Data of Directors maintained by the Ministry of Corporate Affairs and hence obtain the list of companies where Mr. Sule currently serves (or has ever served) as a Director. Figure 3.3 displays this information. As shown, we know both a company's name and its unique Corporate Identification Number (CIN). These firms are then tagged as "politically connected" and the CIN is used to match them to the data on firms' outcomes described in Section 3.4 below.

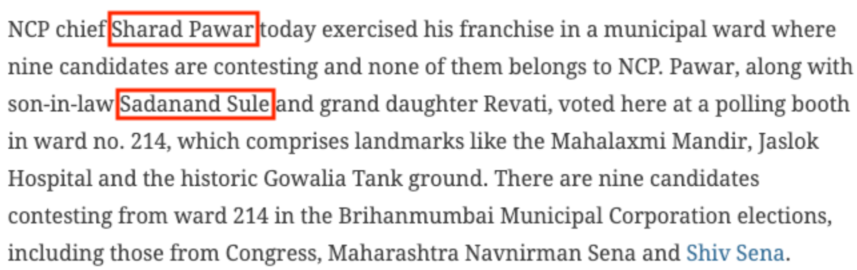
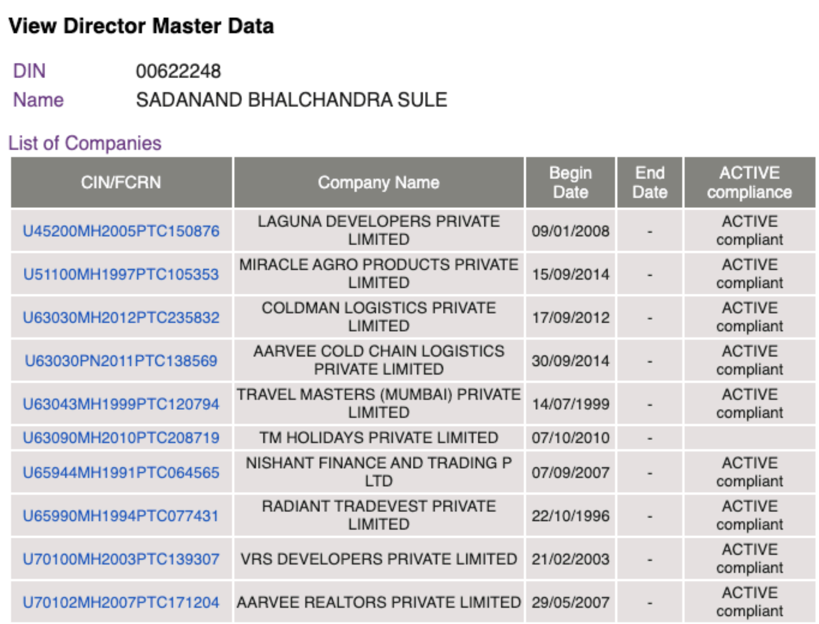

NCP chief Sharad Pawar today exercised his franchise in a municipal ward where nine candidates are contesting and none of them belongs to NCP. Pawar, along with son-in-law Sadanand Sule and grand daughter Revati, voted here at a polling booth in ward no. 214, which comprises landmarks like the Mahalaxmi Mandir, Jaslok Hospital and the historic Gowalia Tank ground. There are nine candidates contesting from ward 214 in the Brihanmumbai Municipal Corporation elections, including those from Congress, Maharashtra Navnirman Sena and Shiv Sena.

Figure 3.2: The Indian Express: Mr. Sharad Pawar & Mr. Sadanand Sule


View Director Master Data

DIN 00622248
Name SADANAND BHALCHANDRA SULE

List of Companies

CIN/FCRN	Company Name	Begin Date	End Date	ACTIVE compliance
U45200MH2005PTC150876	LAGUNA DEVELOPERS PRIVATE LIMITED	09/01/2008	-	ACTIVE compliant
U51100MH1997PTC105353	MIRACLE AGRO PRODUCTS PRIVATE LIMITED	15/09/2014	-	ACTIVE compliant
U63030MH2012PTC235832	COLDMAN LOGISTICS PRIVATE LIMITED	17/09/2012	-	ACTIVE compliant
U63030PN2011PTC138569	AARVEE COLD CHAIN LOGISTICS PRIVATE LIMITED	30/09/2014	-	ACTIVE compliant
U63043MH1999PTC120794	TRAVEL MASTERS (MUMBAI) PRIVATE LIMITED	14/07/1999	-	ACTIVE compliant
U63090MH2010PTC208719	TM HOLIDAYS PRIVATE LIMITED	07/10/2010	-	
U65944MH1991PTC064565	NISHANT FINANCE AND TRADING P LTD	07/09/2007	-	ACTIVE compliant
U65990MH1994PTC077431	RADIANT TRADEVEST PRIVATE LIMITED	22/10/1996	-	ACTIVE compliant
U70100MH2003PTC139307	VRS DEVELOPERS PRIVATE LIMITED	21/02/2003	-	ACTIVE compliant
U70102MH2007PTC171204	AARVEE REALTORS PRIVATE LIMITED	29/05/2007	-	ACTIVE compliant

Figure 3.3: List of Firms where Mr. Sadanand Sule is a Director

3.4 Data

3.4.1 Data on Firm Outcomes

Data on firm outcomes is obtained from the Prowess Data of the Centre for Monitoring of the Indian Economy (CMIE). Prowess is a database of over 40,000 firms that includes all firms traded on the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), and thousands of unlisted Public and Private Limited Companies. Data on these firms is collated and harmonized from Annual Reports, Quarterly Financial Statements, Stock Exchange feeds, and other publicly available sources. While the Prowess covers large registered firms in India's formal sector, it provides granular data on a large set of economic and financial outcomes of a firm. For example, the data provides information not only on output, income, capital, and labor but also on the portfolio of assets, liabilities, and borrowings. The data is a panel of firms going back to 1989 (though the coverage has improved significantly over time). Of particular relevance for this study is that the Prowess contains information on the CIN of a firm (that is unique to a firm) and information on the Board of Directors that includes their names and Director Identification Number (DIN). Both the CIN and DIN are provided by the Ministry of Corporate Affairs and are unique to a firm and Director. Using these, we can then match the Prowess firms with the data on their political connections.

Lastly, while the Annual Survey of Industries (ASI) and the Prowess data are the most commonly used data on firms in India, we prefer using the Prowess primarily because the ASI does not provide information on the Board of Directors of a firm, making it impossible to measure its political connections. Moreover, unlike the Prowess, the ASI has limited information on firm assets and liabilities, which are particularly useful in our context to study the mechanisms underlying how politically connected firms systematically differ in their responses as compared to non-connected ones. Lastly, like the ASI, the Prowess is limited in its coverage since it collects data only on formal sector firms.

3.4.2 Sample Characteristics

Our final sample consists of 31,492 firms that we observe from 2012-2019.[15] For each firm in our sample, we define a time-invariant dummy variable that takes the value 1 if the firm is politically connected before 2016 (based on the details in Section 3.3) and 0 otherwise. 867 firms in our sample (2.75%) are politically connected. This is similar in magnitude to Faccio, Masulis, and McConnell (2006) and Faccio (2010), who use a similar definition and find that on average 2.8% of firms in their sample spanning 47 countries, and 3.1% in India are politically connected. Financial services (17.5%), electricity, gas, steam, and air conditioning supply (9.11%), wholesale trade (8.4%), warehousing and transportation (4.7%), and chemicals and chemical products (4.7%) are the five industries with the largest share of politically connected firms (44.5%) (Appendix Table C.4). Table 3.1 summarizes basic characteristics and differences between politically connected and non-connected firms between 2012 and 2015 i.e., before demonetization. Section C.2 in the Appendix provides detailed definitions for all the variables used in the analysis. As is clear from the table, connected firms are larger than non-connected firms in terms of their size (employees and capital stock), assets and liabilities, income, sales, and expenses. These patterns are again very consistent with Faccio (2010), which studies the differences in politically connected and non-connected firms across 47 countries.

3.5 Empirical Strategy

We define a firm as 'politically connected' based on *politically connected social network of directors* prior to 2016, the year in which demonetization occurred. As is clear from the previous section, political connections are not randomly allocated across firms (i.e., politically connected firms systematically differ from their non-connected counterparts). For example, even in the pre-period (before 2016), connected firms are larger and more productive than non-connected ones. One may thus be concerned

[15] While our results are robust to including previous years (2010 onwards) as well, the impact of the global financial crisis in 2008, large industrial policy reforms implemented in India in 2005-2006, and their aftermath could systematically differ based on political connections of a firm, affecting our interpretation of the pre-period. We, therefore, restrict our panel from 2012 onwards. We end our panel in 2019 to avoid contaminating the post-period with the impact of COVID-19 in India starting March 2020.

Table 3.1: Summary Statistics (2012∼2015)

	(1) Unconnected		(2) Connected		t-test Difference
	N/Firms	Mean/SD	N/Firms	Mean/SD	(1)-(2)/SE
Total Income (USD Million)	81,655	31.348	2,886	119.050	-87.702***
	(28,171)	(0.300)	(834)	(3.667)	(1.740)
Sales (USD Million)	81,655	28.717	2,886	102.308	-73.591***
	(28,171)	(0.281)	(834)	(3.345)	(1.622)
Total Expenses (USD Million)	81,655	31.120	2,886	113.570	-82.450***
	(28,171)	(0.294)	(834)	(3.423)	(1.693)
Ln(TFPR1)	69,399	0.775	2,012	0.877	-0.111***
	(25,602)	(0.004)	(630)	(0.025)	(0.023)
Ln(TFPR2)	69,399	0.630	2,012	0.835	-0.205***
	(25,602)	(0.005)	(630)	(0.031)	(0.031)
Firm's age	81,655	21.516	2,886	26.820	-5.304***
	(28,171)	(0.058)	(834)	(0.348)	(0.317)
Listed on BSE/NSE	81,655	0.157	2,886	0.278	-0.122***
	(28,171)	(0.001)	(834)	(0.008)	(0.007)
Annual avg. value of total	81,655	20.122	2,886	158.498	-138.376***
transactions in BSE (USD Million)	(28,171)	(1.439)	(834)	(21.840)	(8.688)
Annual avg. value of total	81,655	55.935	2,886	487.435	-431.499***
transactions in NSE (USD Million)	(28,171)	(3.816)	(834)	(60.635)	(23.279)
Value added tax (USD Million)	81,655	0.013	2,886	0.024	-0.011*
	(28,171)	(0.001)	(834)	(0.005)	(0.006)
rK (USD Million)	81,410	30.264	2,869	230.804	-200.540***
	(28,111)	(0.692)	(830)	(11.448)	(4.266)
wL (USD Million)	81,166	2.557	2,878	11.746	-9.188***
	(28,075)	(0.041)	(833)	(0.462)	(0.235)
Financial Statistics					
Total assets (USD Million)	81,638	57.595	2,886	375.139	-317.544***
	(28,167)	(1.029)	(834)	(16.962)	(6.334)
Total Liabilities (USD Million)	81,655	56.955	2,886	370.355	-313.400***
	(28,171)	(0.998)	(834)	(16.469)	(6.145)
Total Borrowings (USD Million)	79,583	22.231	2,880	154.145	-131.913***
	(27,749)	(0.559)	(834)	(8.497)	(3.352)

Notes: wL = Compensations to employees. TFPR = Total factor revenue productivity. rK = Non-current assets. CL = Current liabilities. See Section C.2 in the Appendix for detailed definitions of variables. India introduced a goods and services tax in 2017, so it is not included in the summary statistics table above. In the last column, we test the differences between politically non-connected and connected firms using a t-test with equal variance. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

about separately identifying the role of political connections from the role of unobserved firm characteristics in understanding how they respond to a macroeconomic shock. Our identification strategy mitigates these concerns.

All our empirical specifications include a firm fixed effect that controls for all observable and unobservable time-invariant *level* differences across connected and non-connected firms (such as entrepreneurial ability for example). However, time-varying differences (such as pre-period trends) are not captured. We, therefore, employ a new methodology developed by Arkhangelsky et al. (2021)–the Synthetic Difference-in-Differences method (or SDID). This method relies on constructing a synthetic control unit with similar pre-period *trends*. This counterfactual, by construction, rules out differential secular *trends* between treated and (synthetic) control units in the pre-period for various firm outcomes (like income, sales, and other firm characteristics). We describe the method briefly below.

Synthetic Difference-in-Differences method (Arkhangelsky et al., 2021) is a new causal inference estimator that combines attractive features of both the Difference-in-Differences (DID) and the Synthetic Control (SC) methods (Abadie, Diamond, and Hainmueller, 2010). To elaborate, DID relies on a "parallel trends" assumption between the treated and non-treated units, which implies that additive unit-specific and time-specific fixed effects control for selection. In contrast, SC methods (usually applied when a small number of units are treated) re-weight units to match pre-exposure trends between the treated and control units. Combining the insights from the two methods, SDID: (i) re-weights and matches pre-exposure trends on the outcome variables; and (ii) allows for additive unit and time-specific selection into the treatment, thus allowing for valid large-panel inference which is similar to DID (Arkhangelsky et al., 2021). Therefore, in our setting, it allows us to mitigate concerns that the *selection* of firms who acquire political connections (like those with higher entrepreneurial ability, better resilience, etc.) rather than the political connections themselves can explain how they respond to a macroeconomic shock.

We use the unit weights and time weights derived from SDID to re-weight our panel data in the regressions.[16] For a firm i (in industry j and district d) in year t, we then estimate the following regression specifications:

$$Y_{it} = \alpha_i + \alpha_{dt} + \alpha_{jt} + \sum_{t=2012}^{2019} \beta_t \ Connected_i \times 1(Year = t) + \gamma X_{it} + \varepsilon_{it} \tag{3.1}$$

$$Y_{it} = \alpha_i + \alpha_{dt} + \alpha_{jt} + \beta \ Connected_i \times Post_t + \gamma X_{it} + \varepsilon_{it} \tag{3.2}$$

[16]For calculating the weights, we use an R package developed by Arkhangelsky et al. (2021), and match firms on the outcome variables while controlling for their age, whether the firm is listed on the stock market or not, log of value of total transactions on BSE or NSE, and log of value-add tax. SDID requires strongly balanced data. We, therefore, assign a small weight to observations that are not used in SDID but show that the results are robust to relax this requirement later in the paper.

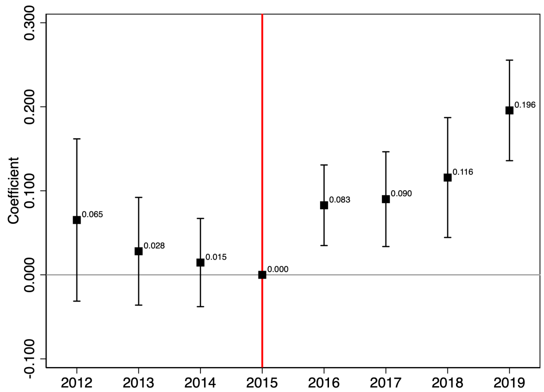
where Y_{it} are a set of outcome variables of a firm i in year t (such as sales, income, expenditure, etc.). Connected$_i$ is a time-invariant definition that takes the value 1 if a firm was ever politically connected in the pre-period, and 0 otherwise. Equation (3.1) is a standard event-study design where $1(Year = t)$ takes the value 1 in year t and 0 otherwise. We take 2015 (the year before demonetization) as the base year. In Equation (3.2), we pool the pre and post-policy years together and define a variable Post$_t$ that takes the value 1 for the years 2016-2019 and 0 otherwise. α_i are firm fixed effects that control for all observed and unobserved time-invariant characteristics of a firm, including those that allow them to become politically connected in the first place. α_{dt} and α_{jt} are district×year and industry×year fixed effects. These control for all characteristics of districts and industries over time that could influence the outcomes of a firm and be correlated with the demonetization shock, such as aggregate changes at the district level (price and wage changes) as well as industry-specific impacts of the shock over time.[17] Lastly, we cluster standard errors at the district level for statistical inference. In Table C.10, we show that our inference does not change when we cluster standard errors at the firm level instead.

3.6 Results

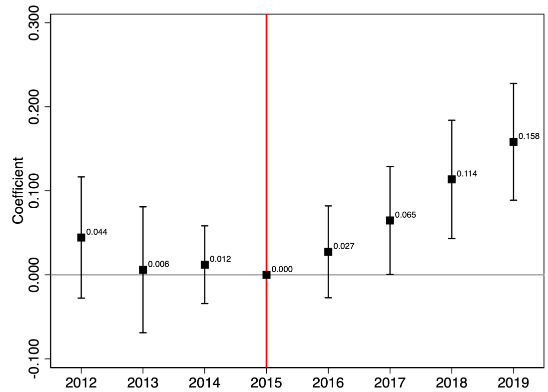
3.6.1 Impact on Firm Income, Sales, and Expenses

We begin by examining the impact of demonetization on the income, sales, and expenses of firms. Appendix Section C.2 provides definitions of all the firm variables that are used in our analysis. We report the estimated coefficients $\hat{\beta}_t$ from the event-study specification (Equation (3.1)) in Figure 3.4. By construction, there is no difference in income, sales, and expenses between politically connected firms and their (synthetic) non-connected counterparts before demonetization. Both the estimated coefficients are small, and they are statistically insignificant at conventional levels. However, we see a substantial difference between the two groups after demonetization, which is both increasing and persistent over the three years that follow. Politically

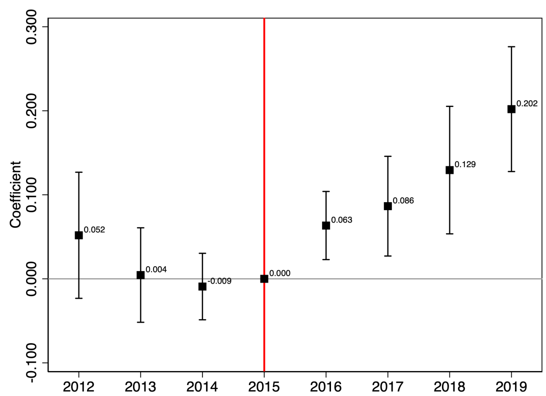
[17] India introduced the Goods and Services Tax (GST) in 2017, which varied across products and industries. Therefore, in addition to controlling for industry×year fixed effects, we also control for the amount of GST tax paid by a firm as well.



(a) Ln(Income)



(b) Ln(Sales)



(c) ln(Expenses)

Notes: The above graphs plot the regression coefficients from Equation (3.1) and estimate the relative difference between connected and non-connected firms for a set of outcome variables. 2015, the year before demonetization, is taken to be the base year. Figures (a)-(c) use Log Income, Sales, and Expenses as outcome variables. Section C.2 in the Appendix provides detailed descriptions of all outcome variables. All regressions include firm, district-year, and industry-year fixed effects, as well as control for the log of Goods and Service Tax payments. Each observation is weighted using weights calculated in the SDID. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 3.4: Event Study: Impact on Income, Sales, and Expenses of Firms

connected firms report 8-20 log-points (8.7-21.7%) higher income, 3-15 log-points (2.7-16.9%) higher sales, and 6-20 log-points (6.5-22.4%) higher expenses compared to their non-connected counterparts. Table 3.2 then reports these effects in a standard difference-in-differences specification (Equation (3.2)). From Columns 1-3, politically connected firms have around 8.7-11.9 log-points (9.1-12.6%) higher income, sales, and expenses relative to the non-connected firms.

Given the difference-in-differences specification, our estimates capture the changes reported by politically connected firms *relative* to non-connected ones. Therefore, it is unclear just from these estimates whether firm outcomes (sales, for example) recovered quickly after the crisis, or actually grew when compared to the pre-crisis period. This is particularly important when we (in subsequent sections) examine changes in firms' assets and investments and the resulting changes in productivity and TFP. In Appendix Figures C.2 and C.3, we report the trends in sales for connected and non-connected firms respectively. These figures show two patterns: first, the decline in sales was lower for connected firms as compared to non-connected ones i.e., they were more robust to the crisis; and second, both connected and non-connected firms experienced a growth in sales after the crisis, but growth was much faster for connected firms i.e., these firms were more resilient as well (G. Khanna, Morales, and Pandalai-Nayar, 2022).

Table 3.2: Impacts on Income, Sales, Expenses and TFPR

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Expense)	(4) Ln(TFPR1)	(5) Ln(TFPR2)
Connected × Post	0.118***	0.087***	0.119***	0.053***	0.050***
	(0.027)	(0.030)	(0.029)	(0.020)	(0.019)
Control Mean	2.32	2.14	2.35	0.85	0.70
R^2	0.95	0.96	0.96	0.88	0.94
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
No. of firms	31,333	31,333	31,333	28,622	28,622
N	186,937	186,937	186,937	161,777	161,777

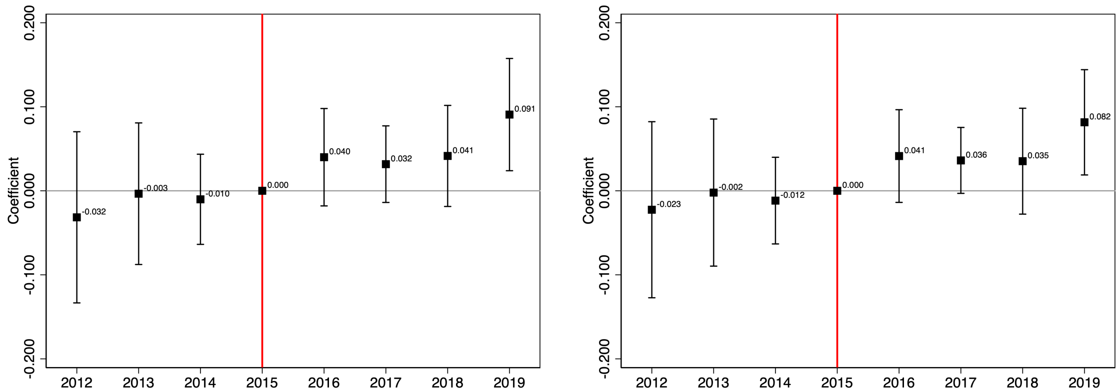
Notes: Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns 4 and 5 are a firm's Total Factor Revenue Productivity calculated based on the method proposed by Levinsohn and Petrin, 2003. In Column 4, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 5, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

3.6.2 Impact on Firm Productivity

We now turn to examine whether the demonetization shock differentially affected firm productivity. A long panel of firms in our data allows us to construct a commonly used measure of productivity in the literature, namely: Revenue Total Factor Productivity or TFPR. Specifically, we construct two measures of TFPR for a firm using the method proposed by Levinsohn and Petrin (2003).[18] For the first measure (denoted by TFPR1), we use the wage bill and raw material expenses as free variables with expenditure on power, fuel, and water as a proxy variable. For the second measure (denoted by TFPR2), we use the wage bill as a free variable and the consumption of raw material expenses and expenditure on power, fuel, and water as a proxy variable instead. As reported in Table 3.1, politically connected firms have around 11-20 log-points (11.7%-22.7%) *higher* TFPR as compared to non-connected ones in the pre-period. Similar to the event study results discussed previously, we see that after demonetization, connected firms exhibit a 3-9% higher increase in their TFPR as compared to non-connected ones (Figure 3.5). Consequently, as reported in Columns 4 and 5 of Table 3.2, this translates into connected firms having an average of 5.2%-5.4% higher TFPR relative to their non-connected counterparts after demonetization. While the magnitude of these coefficients is non-trivial, Figure 3.5 suggests a potential lag in firms' ability to improve their capabilities.

A large literature discusses the source of these productivity gains (TFPR), predominantly along three dimensions: (i) gains in the quantity efficiency as measured by TFPQ (De Loecker, 2011; Katayama, S. Lu, and Tybout, 2009); (ii) price markups; (iii) change in firm capability as measured by product quality and scope. Using tailored primary surveys of firms, Atkin, Khandelwal, and Osman (2019) show that TFPR is actually a better proxy for measuring the broader capabilities of firms as opposed to TFPQ. This is because the measurement of TFPQ requires observing prices directly across all products within a firm and then adjusting it for the quality and specification of these products. Both of these are challenging in standard administrative data (like ours) and can lead to TFPQ being a poor proxy of a firm's capabilities. Moreover, if firms' capabilities come from their ability to produce both quality and quantity, TFPR may indeed be the primary object of interest.

[18]The Levinsohn-Petrin approach uses expenditure on intermediate inputs of firms as a proxy for the free variables. In general, we use income, fixed assets, compensation to employees, raw material expenses, and expenditure on power, fuel, and water for the estimation of the production function, along with a package developed by Rovigatti and Mollisi (2018) that allows us to incorporate systematic firm attrition as well. It should be noted, however, that the Prowess is not well suited for understanding firm entry and exit because it is not mandatory for firms to report their status to the data collecting agency.



(a) Ln(TFPR1) (b) Ln(TFPR2)

Notes: The above graphs plot the regression coefficients from Equation (3.1) and estimate the relative difference between connected and non-connected firms for a set of outcome variables. 2015, the year before demonetization, is taken to be the base year. Figures (a) and (b) use TFPR estimated by the method of Levinsohn and Petrin (2003). In Figure 3.5a, the free variables are compensation to employees and raw material expenses, and the proxy variable is power, fuel, and water charges; in Figure 3.5b, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. In Figure 3.5b, the 2016 coefficient is statistically significant at a 10% level. Section C.2 in the Appendix provides detailed descriptions of all outcome variables. All regressions include firm, district-year, and industry-year fixed effects, as well as control for the log of Goods and Service Tax payments. Each observation is weighted using weights calculated in the SDID. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure 3.5: Event Study: Impact on TFPR of Firms

Nevertheless, we try to make progress on measuring the sources of these TFPR gains to the extent possible in our setting. First, we do not observe prices directly for each product across all firms in our sample. However, we do observe the quantity and value of sales for each product for around a third of the firms in our sample, mostly operating in the agriculture and manufacturing sectors. While on the one hand, it allows us to examine TFPQ changes for these firms, it presents additional challenges in measurement and inference (in line with the previous discussion). We discuss these in detail in Appendix C.6 and follow Bau and Matray (2023) who use the same data to construct TFPQ measures. We find no differential improvement in TFPQ for politically connected firms relative to their non-connected counterparts after demonetization (Table C.8).

Turning to the other sources of TFPR changes, Kisat and Phan (2020) document that adjustment in markups was an important channel in explaining firm responses to the shock after demonetization, though given the data limitations, we are unable to examine differentially for connected and non-connected firms. In line with Atkin, Khandelwal, and Osman (2019) however, we find that politically connected firms (as compared to non-connected ones) expand their product scope after the shock (Column 5 of Table C.8).[19]

Put together, the above analysis suggests that politically connected firms, as compared to their non-connected counterparts, may have enhanced their capabilities after demonetization, as measured by a higher TFPR and wider scope of products, with no discernible difference in TFPQ.

3.7 How Do Political Connections Matter?

With detailed data on the portfolio of assets and liabilities, we now turn our attention to examining the mechanisms through which politically connected firms perform better as compared to their non-connected counterparts. We define all variables in detail in Appendix C.2. Section 3.7.1 discusses firm borrowings and access to credit, including those from banks. Sections 3.7.2 and 3.7.3 then discuss firm liabilities more broadly, along with firm assets. Finally, Section 3.7.4 offers a short discussion to synthesize these results.

3.7.1 Firm Borrowings

As discussed previously, a large literature has documented how firms use their political connections to get access to credit. We therefore begin by examining the change in the amount and composition of firm borrowings, one of the most important components of liabilities, of politically connected firms (as compared to non-connected ones). In particular, we consider three types of borrowings: (i) short-term and long-term borrowings; (ii) secured and unsecured borrowings; (iii) borrowings from banks.

Short-term and Long-term Borrowings: In Panel A of Table 3.3, we find that the total borrowings of connected firms are 4.9 log-points (5%) lower as compared to their non-connected counterparts (Column 1). However, there is a distinct shift in the nature of their borrowings– connected firms decrease long-term borrowings (expected

[19] Goldberg et al. (2010) show that multi-product firms, for example, tend to have a higher TFP compared to single-product firms.

Table 3.3: Impacts on the Portfolio of Borrowings

	(1)	(2)	(3)	(4)
Panel A. Long and Short-term Borrowings				
	Ln(Total Borr.)	Ln(Short-Term Borr.)	Ln(Long-Term Borr.)	Short-Term/Total
Connected × Post	-0.049^{+}	0.063	-0.141***	0.028**
	(0.033)	(0.052)	(0.051)	(0.012)
Control Mean	2.13	1.48	1.31	0.56
R^2	0.95	0.89	0.92	0.82
Panel B. Borrowings from Banks				
	Ln(Total Bank Borr.)	Ln(Short-Term Bank Borr.)	Ln(Long-Term Bank Borr.)	Short-Term/Total
Connected × Post	-0.087***	0.032	-0.090*	0.025***
	(0.028)	(0.043)	(0.047)	(0.010)
Control Mean	1.73	1.21	0.92	0.63
R^2	0.92	0.89	0.90	0.80
Panel C. Secured and Unsecured Borrowings				
	Ln(Total Borr.)	Ln(Secured Borr.)	Ln(Unsecured Borr.)	Unsecured/Total
Connected × Post	-0.049^{+}	-0.085***	0.047	0.009
	(0.033)	(0.028)	(0.065)	(0.011)
Control Mean	2.13	1.81	0.86	0.25
R^2	0.95	0.93	0.83	0.73
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	19,536	19,536	19,536	19,536
N	103,838	103,838	103,838	103,838

Notes: "Borr." = Borrowings. Short-term Borrowings are those that have to be repaid within a year whereas Long-term Borrowings do not have to be repaid within a year. Secured Borrowings are those where the borrower pledges some assets with the lender as collateral and in case of default, the lender has the authority to sell the pledged assets and recover the due. Short-Term Bank Borrowings are those borrowings taken from a bank and have to be repaid within a year. Long-Term Bank Borrowings, on the other hand, do not have to be repaid within a year. In Appendix C.2, we provide the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

to be repaid beyond a year) for a potential increase in short-term borrowing (expected to be paid within a year). In particular, long-term borrowings decrease by 14.1 log-points (15.1%, Column 3), while short-term ones increase by 6.3 log-points (6.5%, Column 2), though (like previously) this is not statistically significant at conventional levels. However, the share of short-term borrowings increases by 2.8 p.p. or 5% (Column 4).

In order to shed light on the relevance of these results, we explore the portfolio of borrowing, especially from banks.

Firm Borrowings from Banks: Bank borrowings of firms are of specific interest given the nature of the demonetization episode, which severely affected the cash holdings and lending capacity of banks. Figure C.4a in the Appendix uses quarterly data from the Reserve Bank of India to plot the total value of loans issued by all scheduled commercial banks of India. As is clear from the figure, bank loans were not severely impacted after demonetization.[20] However, from Figure C.4b, the composition of these loans changed–banks were more likely to issue long-term loans as opposed to short-term ones i.e., there was a small decline in the value of short-term loans as a fraction of total loans.[21] From Figure C.5 however, these long-term loans were also issued at higher interest rates, thus increasing the long-term cost of firm borrowing.

With this context, Table 3.3 examines the borrowings of politically connected firms from banks, as compared to non-connected ones. In line with the higher (long-term) cost of borrowing, we see an 8.7 log-points (9.1%) decline in total bank borrowings (Column 1), which is driven largely by a 9 log-point (9.4%) decrease in long-term bank borrowings (Column 3). Therefore, short-term bank borrowings as a share of total bank borrowings increased by 2.5 p.p. (4%) for connected (relative to non-connected) firms (Column 4).

Secured and Unsecured Borrowings: Another important dimension of firm borrowings, especially through formal channels (such as banks) is whether they are secured or unsecured borrowings. The primary difference between them is that secured borrowings are made on the security of an asset whose market value is no less than the borrowing amount (collateral for example). On the other hand, unsecured borrowings require no such collateral, but usually also attract higher interest rates. As reported in Panel C of Table 3.3, connected firms (as compared to their non-connected counterparts) shifted their portfolio away from secured borrowings (Column 2) and towards unsecured borrowings (Column 3). Connected firms (as compared to non-connected ones) decreased their secured borrowing by 8.5 log-points (8.8%) and increased unsecured borrowings by 4.7 log-points (4.8%). The latter, though large in magnitude, is not statistically significant at conventional levels.

[20] This is consistent with Lahiri (2020), who documents no sharp changes in bank lending after demonetization, despite the substantial increase in bank deposits during this period.

[21] Refer to Section C.7 for information on the source of the data and the methodology used to calculate the share of short-term loans over total loans.

Put together, the results so far indicate that connected firms were more likely (than their non-connected counterparts) to be able to reduce expensive, long-term borrowings, secure short-term (potentially non-collateral) loans, and delay payments to their creditors and suppliers as well as debt and interest payments.

3.7.2 Firm Liabilities

We now examine how politically connected firms differentially altered their liabilities more broadly, as compared to their non-connected counterparts after demonetization. From Panel A in Table 3.4, politically connected firms (as compared to their non-connected counterparts) report a 5.5 log-points increase in their total liabilities (Column 1). We then examine whether these liabilities are driven by changes in short-term (Current) or long-term (Non-Current) liabilities. Current liabilities represent all liabilities or debts that a firm owes its suppliers, vendors, banks, etc., and must be paid within a year, while non-current liabilities are longer-term liabilities that are not expected to be settled within a year. From Columns 2-4, we find that the increase in total liabilities is driven by an 8.2 log-points increase in the current liabilities of a firm. Current liabilities as a fraction of the total liabilities also increase by 1.5 pp or 3.8% (Column 4). On the other hand, there is no differential change in non-current (or longer-term) liabilities.

In Panel B, we then examine various components of current liabilities in greater detail, namely: short-term borrowings, payables, advances, and other liabilities. Short-term borrowings are liabilities a firm is expected to pay within a year. Short-term payables are liabilities that a firm owes its suppliers, creditors, and lenders for purchases of goods and services that are expected to mature within a year. Short-term advances are deposits and advances taken from customers and employees. From Panel B of Table 3.4, politically connected firms report a 6.7 log-points (6.9%) increase in short-term payables (Column 2) as compared to non-connected ones. The changes in short-term borrowings (Column 1) and advances (Column 3) are smaller in magnitude (3-4%), but not statistically significant at conventional levels. Lastly, connected firms report 11.8 log-points (12.5%) higher than other current liabilities (such as maturities, debt, interest accrued, etc.) than their non-connected counterparts (Column 4). Put together, connected firms are able to increase their short-term liabilities, particularly what they owe their creditors and suppliers, as well as delay immediate debt and interest payments.

Table 3.4: Impacts on the Portfolio of Liabilities

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Liabilities				
	Ln(Total Liabilities)	Ln(Non-Current Liabilities)	Ln(Current Liabilities)	Current/Total
Connected × Post	0.055***	0.010	0.082***	0.015*
	(0.019)	(0.025)	(0.015)	(0.008)
Control Mean	2.79	1.19	1.79	0.40
R^2	0.98	0.93	0.94	0.83
Panel B. Components of Current Liabilities				
	Ln(Short-Term Borrowings)	Ln(Short-Term Payables)	Ln(Short-Term Advances)	Ln(Other Current Liabilities)
Connected × Post	0.042	0.067***	0.029	0.118***
	(0.036)	(0.023)	(0.021)	(0.026)
Control Mean	1.00	1.02	0.31	0.66
R^2	0.87	0.93	0.84	0.89
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	29,989	29,989	29,989	29,989
N	173,296	173,296	173,296	173,296

Notes: Current Liabilities of a firm are those liabilities or debts that must be paid within a year whereas Non-Current Liabilities are longer-term debts that need not be paid within a year. Short-term Borrowings are those which have to be repaid within a year. Short-Term Payables are liabilities owed to suppliers, vendors, and creditors for goods and services received that will mature within a year. Short-term advances are deposits and advances received from customers and employees. Other current liabilities include current maturities of long-term debt and lease, interest accrued but not due (short term), and unclaimed and unpaid dividends. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

3.7.3 Firm Assets

Given the changes in connected firms' liabilities and borrowings, we now turn to examine how they systematically altered their asset portfolio.

In Panel A of Table 3.5, we see that connected firms have 4 log-points (4.1%) more assets as compared to non-connected firms after demonetization (Column 1), with a

5 log-points (5.1%) and 6.4 log-points (6.6%) increase in their short-term (current) and long-term (non-current) assets respectively (Columns 2 and 3).[22] As noted in Column 4, the share of current (and hence non-current) assets as a fraction of total assets does not change.

In Panel B of Table 3.5, we then examine the different components of current assets, namely current (short-term) investments, inventories, bank balance, and other assets. Short-term investments of a firm are those that are expected to mature within a year. Current inventories are materials held to be consumed in the production process or for sale, while bank balances capture the deposits that a firm has in a bank. Other current assets include all other short-term assets held by a firm such as trade and bill receivables, assets held for sale and short-term transfer, etc. We find that connected firms report a 5.3 log-points (5.4%) increase in short-term (current) investments (Column 1) as well as a 7.7 log-points (8%) increase in other current assets relative to their non-connected counterparts after demonetization. There is no differential change in short-term inventories and bank balances between these groups of firms (Columns 2 and 3).

In Panel C of Table 3.5, we then examine the components of non-current (long-term) assets. From Columns 1 and 2, we find that connected firms report 9.3 log-points (9.7%) higher non-current investments (i.e., long-term investments) and 5 log-points (5.1%) higher expenditure on intangible goods (such as software, rights, etc.) as compared to their non-connected counterparts after demonetization. From Columns 3 and 4, we do not find any statistically significant difference in fixed assets (such as buildings, land, etc.) as well as expenditure on property, plant, and equipment.

3.7.4 Discussion

The above analysis is helpful in uncovering key channels through which politically connected firms were able to increase their income, sales, expenses, and TFP relative to non-connected firms after demonetization, despite the fact that the demonetiza-

[22] Current assets are defined as those assets that can be easily converted into cash within 12 months (for example, cash balances, short-term investments, and inventory, etc.). Non-current assets on the other hand include more long-term fixed assets and investments that cannot be liquidated within a year (for example, intangible and fixed assets, property, plant, and PPE equipment, etc.). See Appendix C.2 for the definitions of these variables.

Table 3.5: Impacts on the Portfolio of Assets

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Assets				
	Ln(Total Assets)	Ln(Non-Current) Assets)	Ln(Current Assets)	Non-Current/Total
Connected × Post	0.040**	0.050*	0.064***	0.002
	(0.015)	(0.029)	(0.020)	(0.005)
Control Mean	2.66	1.84	2.02	0.44
R^2	0.98	0.97	0.96	0.88
Panel B. Components of Current Assets				
	Ln(Current Investments)	Ln(Current Inventories)	Ln(Bank Bal.)	Ln(Other Current Assets)
Connected × Post	0.053*	-0.005	-0.035	0.077**
	(0.028)	(0.023)	(0.025)	(0.031)
Control Mean	0.12	0.96	0.55	1.22
R^2	0.74	0.95	0.88	0.93
Panel C. Components of Non-Current Assets				
	Ln(Non-Current Investments)	Ln(Exptd. on Intangibles)	Ln(Exptd. on Fixed Assets)	Ln(Exptd. on PPE)
Connected × Post	0.093*	0.050***	0.018	-0.018
	(0.047)	(0.016)	(0.031)	(0.031)
Control Mean	0.48	0.09	1.27	1.23
R^2	0.92	0.84	0.96	0.96
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	30,231	30,231	30,231	30,231
N	175,709	175,709	175,709	175,709

Notes: Current Assets (and their components) are those assets held by the firm that can be easily converted to cash by the firm within 12 months. Non-current assets (and their components) cannot be converted to cash within 12 months. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

tion resulted in a transitory economic downturn. First, politically connected firms cut down on more costly long-term borrowings and shifted the composition of their borrowings towards more short-term, unsecured bank borrowings. Second, politically connected firms were able to delay the payment of their short-term liabilities, and in particular, payments made to creditors and suppliers as well as short-term interest and debt payments. Lastly, there was a clear increase in the total assets held by politically connected firms (relative to non-connected ones). This increase was reported both for short and long-term investments of these firms, as well as investments in acquiring intangible assets (such as computer software, patents, marketing rights, etc.). Hence, our analysis sheds light on multiple channels through which connected firms were able to react to a macroeconomic shock by adjusting the composition of their assets, liabilities, and borrowings. Of special note is how these firms were able to get access to credit within the banking system during a time when the economy was depleted of 86% of its cash.

3.8 Robustness of Results

We now examine the robustness of our results and report the results in Appendix C.8.

3.8.1 Full Sample Estimates

First, we use a consistent sample of firms across outcome variables in our regressions. However, there is some variation in the availability of outcome variables across firms i.e., some outcome variables are reported for some firms, but not others. We, therefore, redo our analysis (estimating Equation (3.2)) using all firms for which an outcome variable is reported. As reported in Table C.11 to Table C.14, our results are qualitatively and quantitatively similar to the ones reported in Tables 3.2-3.5.

3.8.2 Did Connected Firms Anticipate Demonetization?

It is theoretically possible that politically connected firms had prior knowledge about the government's plans to demonetize the currency. However, all anecdotal evidence as well as articles in the media point to the contrary and strongly suggest demonetization plan was kept very confidential.[23] Nevertheless, in order to rule this possibility

[23]As reported in a Right To Information (RTI) reply: *"The demonetization decision was taken in the RBI board meeting at 5:30 pm on November 8, 2016, ... highly placed sources within the government has revealed how apart from a select few, even senior Cabinet ministers had no clue why a meeting had been called. In fact, to stop any leak of this sensitive information before Prime*

out, in Appendix Section C.8.3, we conduct a placebo analysis in the pre-period (2012-2015), where we move the 'treatment year' back in time. If firms had prior knowledge, we would detect effects in the years leading up to the policy change. To do this, we first define the treatment year to be 2013 so that the Post dummy takes a value of 1 for all years after 2013. Similarly in a second regression, we define the treatment year (and corresponding Post dummy) in 2014. As reported in Panel A (for 2013) and B (for 2014) of Table C.15, we see no differential effects between politically connected and unconnected firms in prior years. Both the estimated magnitudes are small and they are statistically insignificant at conventional levels.

3.8.3 Political Connections or Firm Characteristics?

A primary concern for our causal identification is that more productive firms, more resilient firms, or firms with some unobserved characteristics such as entrepreneurial ability that make them stronger during a crisis, are able to attract politicians to their boards. Another possibility is that dynamic, entrepreneurial directors of firms are able to make social connections that attract both political ties as well as help them navigate a crisis better. In financial economics, these would be the *high-type* firms. As discussed in Section 3.5, our empirical strategy mitigates many of these concerns with the help of firm fixed effects as well as the synthetic difference-in-differences strategy. Nevertheless, to further bolster our confidence, we conduct two additional tests.

First, we take advantage of our rich data and create alternate measures of firms' connections since we can observe whether a firm has Directors who are on the board of multiple firms, and hence might know other Directors and entrepreneurs through these connections. More formally, as described in Appendix Section C.5, for each firm i and Director d of this firm, we calculate two measures: (i) the number of other firms that Director d is on the board of; and (ii) the number of other directors that d would know through being on their board. Using these, we then calculate a firm-level measure (averaging across its Directors) on the average number of other firms their Directors are on, the average number of Directors they know, along with the

Minister Narendra Modi announced it to the nation at 8 pm, all cabinet ministers and officials were asked to switch off their mobile phones before entering the meeting." Source: Outlook India Article, Nov 2021.

number of "above-median" connected Directors that a firm has based on these two measures. We then re-estimate Equation (3.2) with these measures of firm connections (political and directorial) and find two insights, as reported in Tables C.6 and C.7. First, the impact of political connections on firm performance after the crisis is very robust (in both magnitude and direction) to controlling for the impact of firms being more connected more broadly through their board of directors. Moreover, political connections are an order of a magnitude more important than just having a more connected set of Directors. This increases confidence in our results that it is indeed firms' political connections, as opposed to just more connections, which make them more resilient to the crisis.

For a second test, we turn to a robust finding in the prior literature, which shows that the impact of political connections on influencing firm outcomes weakens with connections that are made farther back in time, as compared to more recent ones (Faccio, Masulis, and McConnell, 2006; Deng, Wu, and Xu, 2020). In Appendix C.8.6, we test for this in our sample as well and find evidence consistent with this. In Panel A of Table C.17, we utilize the date of the first political connection and define a binary indicator that takes the value 1 for firms having "recently" established political connections i.e., those firms having a political below the median years (4 years), and 0 otherwise. The coefficients for interaction with *recently-established* firms are large and positive whereas those for the interaction with *farther-off* are much smaller. In Panel B, we use the timing of the latest political connection, which is *short-established* if it is less than the median (3 years prior to demonetization), and *long-established* if it is greater than the median. Here again, the short-established political connections matter more (Columns 1 and 3). If firms' entrepreneurial ability or any other firm characteristics instead of political connections were protecting the firms, the firms with father-off or long connections would be just as likely to protect themselves as the firms with more recently formed connections.

3.8.4 Correlation Between Spatial Location of Politically Connected Firms and Severity of the Demonetization Shock?

One may be concerned that the politically connected firms are located in districts/areas with less severe shocks. We therefore examine whether the share of politically connected firms in a district (before demonetization) is correlated with the severity of the shock, by calculating the share of politically connected firms in 2015 (the year before demonetization) and regressing it on the standardized value of shock severity of a district.[24] We cluster standard errors at the district level. As reported in Table C.18, we find no correlation. Both the estimated magnitude is small, and it is statistically insignificant at conventional levels.

3.8.5 Randomization Inference

We examine the robustness of our inference using a Randomization Inference (RI) procedure. This test, originally proposed by Fisher (1935) and developed by Heß (2017) and Young (2019), allows for statistical inference by comparing the realized treatment effect with multiple (100) placebo assignments. This procedure, therefore, has the advantage of providing inference with the correct size, regardless of the sample and cluster size. We report the results in Table C.16 across all our outcome variables. In particular, Columns 1 and 2 of Table C.16 report the SDID coefficient and its associated p-value from our main analysis respectively. The p-values from the RI procedure (Column 3) are similar to those in Column 2, indicating the robustness of our statistical inference. For some variables such as the log of short-term borrowings, we see a smaller p-value which bolsters our confidence that connected firms have more access to scarce short-term credits.

3.9 Conclusion

We highlight a new method for determining the political connection of firms based on the *social network* of politicians. We use this method to construct a novel dataset of political connections for Indian firms. Leveraging this data, we show that politically connected firms were more resilient after a large macroeconomic crisis in India. In

[24]We use Figure V from Chodorow-Reich et al. (2020), reproduced as Appendix Figure C.6, to classify districts into more severely shocked and less severely shocked areas based on whether they had an above or below median demonetization shock index. Chodorow-Reich et al. (2020) define the demonetization shock in a district in the post-demonetization period as the value of legal tenders in the post-demonetization period divided by the total value of cash in that district before demonetization. They construct this shock indicator using currency chest records maintained by the Reserve Bank of India.

light of the recent financial crisis of 2008 and the Covid-19 pandemic-induced crisis of 2020, this sheds light on how these connections can play an important role in responding to the crisis.

Another innovation of our analysis is that it sheds light on the channels through which political connections can play a central role in altering the operational decisions of firms during an economic downturn. In the context of India's demonetization episode, we find that politically connected firms were able to get access to short-term credit, especially from the banking system that was already reeling under a substantial depletion of cash and credit. Moreover, they were able to delay their payments owed to their suppliers, vendors, and creditors, along with delaying short-term interest and debt payments as well. We think of our analysis as a helpful step in not only providing additional empirical evidence on understanding the role of political connections, but the mechanisms through which they can help firms increase resilience to an economic downturn. Further explorations on the interactions with different stakeholders through requests, reputation, threats, future reciprocation, etc., are beyond the scope of this study, but a very promising avenue for future research.

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Appendices

Appendix A

Does the Gig Economy Discriminate against Women? Evidence from Physicians in China

A.1 Data Collection

I gathered the data by scraping information from both the Spring Rain Doctor (SRD) website and its mini-program on WeChat. I conducted two rounds of data collection, one in 2020 and another in 2023. I constructed cross-sectional data using the information gathered in 2020 and then supplemented it with the additional data obtained in 2023. I discuss the data collection process in 2020 in Appendix A.1.1 and the process in 2023, which differed from that of 2020, in Appendix A.1.2. In Appendix A.1.3, I elaborate on the major changes that occurred on the SRD platform between 2020 and 2023.

A.1.1 Data Scraping in 2020

I collected the first round of SRD data from March 26 to June 30, 2020. Because the design of the SRD website and its mini-program on WeChat is the same (i.e., no sorting or filtering options available), I only scrape data from the SRD website. In total, I crawled the SRD website 24 distinct times and obtained information about 43,744 unique physicians. The 24 crawled dates and the number of physicians collected each time are listed in Table A.1. In 2020, it took 24 to 48 hours to collect physicians' information in all specialties from the SRD website each time as there was no daily access limit in 2020.

Table A.1: Dates of Data Collection

Date	Day	Starting Time	No. of Observations
03/26/2020	Thursday	11:30PM	27,658
04/08/2020	Wednesday	03:30AM	28,304
04/12/2020	Sunday	03:00AM	28,613
04/14/2020	Tuesday	09:30PM	28,870
04/20/2020	Monday	09:00PM	28,210
04/26/2020	Sunday	08:00AM	29,328
05/02/2020	Saturday	09:30PM	29,351
05/05/2020	Tuesday	09:30PM	28,962
05/08/2020	Friday	09:00AM	28,788
05/13/2020	Wednesday	09:00AM	28,497
05/18/2020	Monday	08:00AM	28,302
05/20/2020	Wednesday	08:30PM	28,508
05/22/2020	Friday	09:00PM	29,222
05/24/2020	Sunday	09:00AM	28,465
05/27/2020	Wednesday	09:00AM	28,508
05/29/2020	Friday	09:00PM	28,622
06/01/2020	Monday	08:00AM	28,631
06/06/2020	Saturday	08:00AM	28,603
06/10/2020	Wednesday	08:00PM	29,214
06/15/2020	Monday	09:00AM	28,638
06/19/2020	Friday	08:00AM	28,468
06/23/2020	Tuesday	07:00AM	28,886
06/27/2020	Saturday	08:00AM	29,423
06/30/2020	Tuesday	11:00AM	28,711

Notes: Starting time is Beijing Time. I was able to collect information from about 28,000 physicians each time. In total, there were 43,744 *unique* physicians collected in 2020.

The data collection procedure followed the steps outlined in Figure A.1. First, I accessed the platform's website and navigated to the "Find Doctors by Clinical Departments" section. From there, I selected a clinical specialty and kept the region setting as "nationwide," which was the default option. Next, I obtained the data of every physician within the chosen specialty. Detailed information about each physician was accessible on their respective homepage, which could be accessed by clicking on their profile photo or name in the list of physicians (refer to Figure A.16). This process was repeated until data for all specialties had been collected.

It's important to note that the scraping process had a limitation: it only displayed physicians listed on the first 30 pages for each specialty, with 20 physicians per page. Therefore, I could gather information for approximately *600* physicians per specialty.

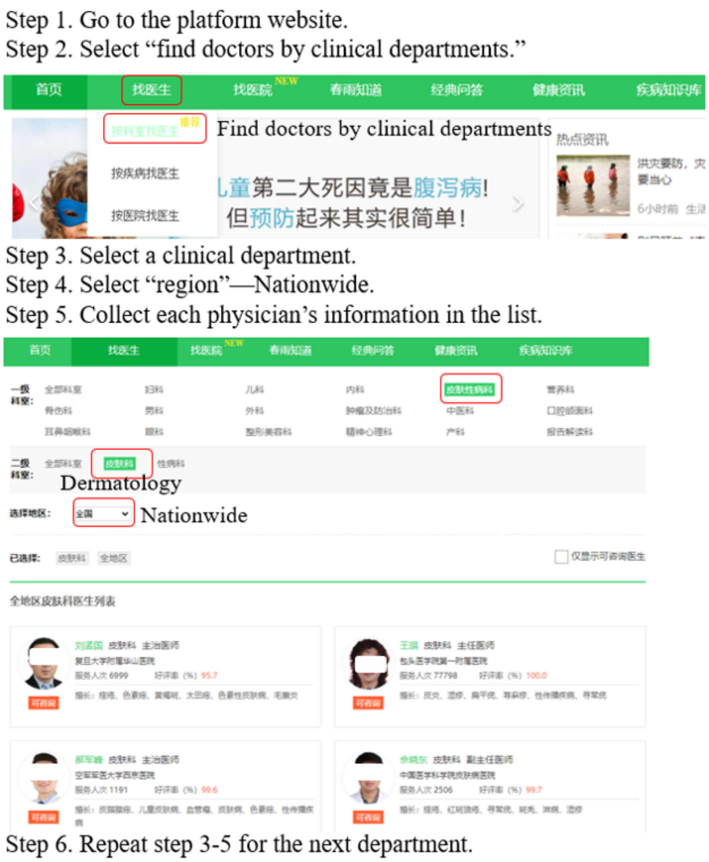


Figure A.1: Data Collection Procedure in 2020

Note: The screenshots were taken in April 2020. There were six steps to complete the data crawling process each time.

Each time I carried out the scraping process, I found new information to enter into my data. For example, 80% of physicians collected on June 30 were also collected on March 26. An example illustrating this limitation is presented in Figure A.2. As there were no daily access limits in 2020, I was able to collect data 24 times between March 26 and June 30, 2020. In total, the data included information for 43,744 unique physicians. As discussed in Section 1.3.1, the study sample consists of *13,472* physicians who had posted a price between March and June 2020 and met specific criteria.

March 26	April 8		June 30
Physician 1	Physician 1		Physician 1
Physician 2	Physician 2		Physician 2
Physician 3			Physician 3
Physician 4	Physician 4		Physician 4
Physician 5	Physician 5	....	Physician 5
Physician 6	Physician 6		
Physician 7	Physician 7		Physician 7
Physician 8	Physician 8		Physician 8
Physician 9	Physician 9		Physician 9
Physician 10	Physician 10		
	Physician 11		Physician 11
			Physician 12
			Physician 13

Figure A.2: Data Collection

Note: Assuming that I am able to collect 10 physicians' information each time. Nine out of ten physicians collected on April 8 can be matched to physicians collected on March 26. On June 30, I still collect 10 physicians, but only eight are matched to physicians on March 26. So, there are new physicians entering my data every time.

A.1.2 Data Scraping in 2023

In 2023, the design of the SRD website has remained unchanged (i.e., no sorting or filtering options available). But, updates have been made to its mini-program on WeChat between 2020 and 2023. Figure A.3 displays the screenshots of the inquiry process on the mini-program in 2020 and in 2023. Comparing the screenshots from April 2020 (Figure A.3a) to those from April 2023 (Figure A.3b), one can see that patients now have access to additional features that allow them to sort and filter physicians more effectively. For example, patients can now sort physicians by the total number of consultations a physician has provided and patient ratings. Patients can also filter physicians by the type of services (i.e., text inquiry, phone inquiry, private doctor, and appointment for offline visits), price range, professional titles, hospital class (i.e., IIIA hospitals or not), and physician status (i.e., physicians are currently available or not). Due to these changes, in the main analysis, I supplement the 2020 data with physicians' information collected in 2023. In Appendix A.1.3, I provide a detailed discussion of the reasons for not conducting a within-doctor analysis using panel data in the main analysis.

Between 2020 and 2023, the platform made several changes to its website and mini-

(a) Inquiry Process in 2020

(b) Inquiry Process in 2023

Figure A.3: Inquiry Process Displayed on the WeChat mini-program

Note: Figure A.3a displays the screenshots of the SRD mini-program on WeChat taken in April 2020. As shown in the right-most image, patients were only able to filter physicians based on their location and clinical department. They could not sort or filter physicians on characteristics such as price or patient rating. Figure A.3b displays the screenshot taken in April 2023. The right-most image depicted that patients can sort physicians by various features, including the default setting, total number of consultations provided, patient ratings, and response rate in 2023. Apart from that, they can also filter physicians by the type of services, price range, professional titles, hospital class, and physician status.

program settings. First, one could only scrape no more than *200* physicians in each specialty on its mini-program. But, there is no daily access limit on the mini-program. The mini-program displays nearly identical information to the website, although it differs in a few ways: it displays 5-scale patient ratings and an approximate number (not an exact number) of consultations provided if the number is over 1,000, and it *does not provide* information on a physician's verification time (*joining date*). The joining date is one of the most important variables that I use to match data from 2020 and 2023. Hence, in addition to scraping data from the SRD mini-program, it is necessary for me to extract physicians' information from the SRD website, specifically to obtain the precise number of consultations provided and their joining date. Second, the SRD platform imposes a daily access limit on its website, allowing users to browse fewer than 1,000 physicians' websites per day. Once this limit is reached, the website will no longer redirect users to the correct physician's homepage.

The aforementioned changes impose challenges on scraping data from the SRD in 2023. In order to get comprehensive information from the SRD platform, I employ two methods to scrape the data. In the first method, I scrape physicians' information based on their default raking on the mini-program. I then scrape the same set of physicians' data from the SRD website to obtain their joining date and the exact number of consultations provided. In February 2023, I was able to scrape about 10,000 physicians using the first method, out of which 3,829 physicians were matched with the 2020 data. For any physicians that could not be matched, they have a default ranking beyond 200 in each specialty.

In the second method, I search for physicians based on their names on both the SRD website and the mini-program. Although this method does not allow me to track a physician's ranking, the first method indicates whether a physician is ranked above or below 200. This is another reason why I use both methods for data scraping. Despite a number of physicians sharing the same names, their joining dates allow me to differentiate them. Because of the daily access limit imposed by the SRD website, it took more time to get a complete list of physicians. I collected information on around 20,000 physicians in March-April 2023. Out of these, 6,314 unique physicians were matched to the 2020 data. Overall, 10,143 physicians were successfully matched between the 2020 and 2023 data sets.

Among these 10,143 physicians, 4,784 posted a text inquiry price or were available to receive text inquiries, while 5,291 were available to provide phone inquiry service. It is worth noting that 3,329 physicians present in the 2020 data were not found on the SRD platform in 2023. An example illustrating this scenario can be found in Figure A.4. I classify a physician as having exited the platform if their information cannot be found on the platform in 2023. As of April 2023, approximately 24.7% of physicians who appeared in the 2020 data have exited the platform.

Figure A.4: An Example of An Exited Physician

Note: The figure illustrates a case in which a physician's information is not accessible in 2023. Yinan Liu was present in the 2020 data, but as of 2023, he is no longer available on the platform.

A.1.3 Major Changes of the SRD between 2020 and 2023

The SRD platform has undergone significant changes between 2020 and 2023, resulting in less direct comparability of the outcomes. While I utilize panel data in Appendix A.2.5 and Appendix A.4.2 to assess the robustness of the results, they serve as *suggestive evidence*. In the main analysis, I rely on cross-sectional data, supplementing the 2020 dataset with the additional information from the 2023 data. Below, I list the three major changes that have been made to the SRD mini-program on WeChat.

1. By 2023, text inquiry is no longer the primary type of service available on the SRD platform. Physicians now offer a range of services including text inquiry, phone inquiry, private doctor service, and offline appointments. Consequently, the total number of consultations provided by a physician is now a combination of these four service types. In the 2023 data, 4,785 physicians have posted text prices, 5,291 physicians have posted phone prices, and 459 physicians have posted offline appointment prices.

2. Patients can sort physicians by the total number of consultations provided, patient rating, and response rate. Additionally, patients can apply filters to narrow down their searches, such as filtering physicians by service type, price

range, professional titles, hospital class, and physician status. The screenshots of the filter options are presented in Figure A.5. These features allow patients to effectively search for physicians based on their specific preferences.

3. In 2023, the SRD platform introduces a feature to "advertise" certain physicians, utilizing three methods. First, the platform makes a list of "Leading Experts" who are affiliated with IIIA hospitals, which are the highest-ranked hospitals in China. Figure A.6 shows this option (accessible after clicking "Finding Doctor") and the list of physicians. Patients can sort these leading physicians by hospital ranking and by price. Second, the platform distinguishes leading experts by attaching orange labels to their profiles, indicating prestigious designations such as "famous expert," "top 100 hospitals," or "top 10 department ranking." At the bottom of the middle graph in Figure A.6, one can see that the physician has two orange labels: "famous expert" and "Department Ranking No. 4 in China." Lastly, after a patient purchases text inquiry service from a physician, the platform will automatically recommend 3 to 5 additional physicians to that patient. The patient has the option to send the same questions to these recommended physicians at an additional charge. Figure A.7 provides an example, where a patient purchases text inquiry service from a female general physician in the Dermatology & S.T.D department, and the platform suggests three male physicians from the same department. By paying the price listed by the recommended physicians, the platform automatically sends the same questions to those physicians.

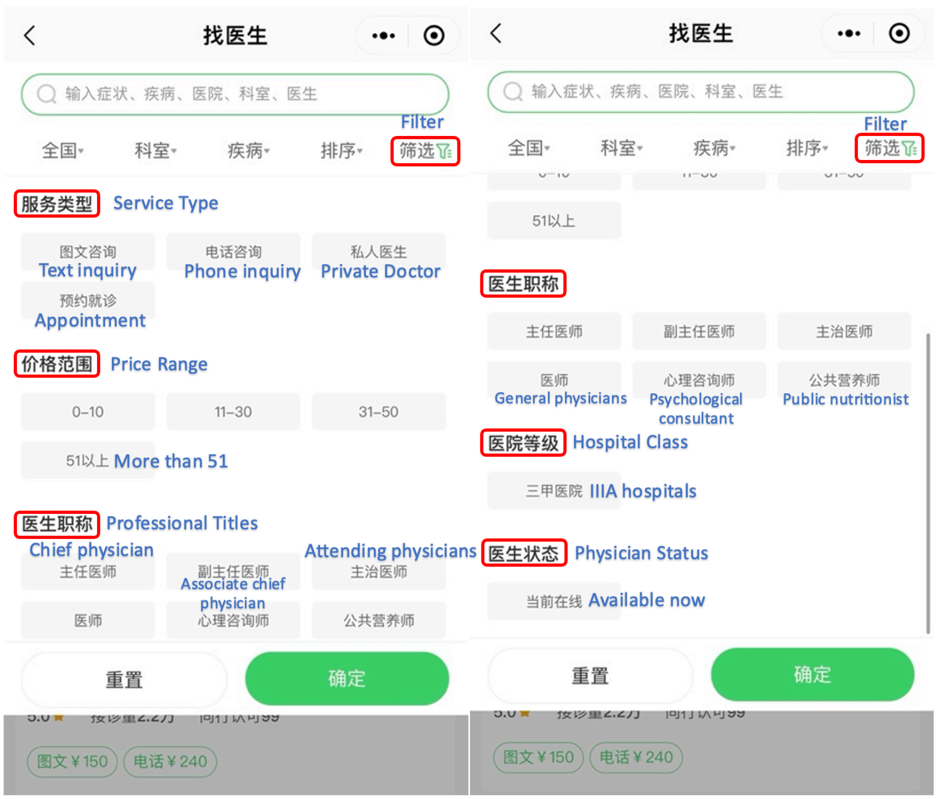


Figure A.5: Options of Filtering in 2023 (mini-program on WeChat)

Note: The screenshots were taken in April 2023. The figure displays the filtering options available on the SRD's mini-program in 2023. As shown, patients have the ability to filter physicians based on various criteria, including service type, price range, professional title, hospital class, and availability.

Figure A.6: Leading Experts

*Note:*The screenshots were taken in April 2023. The figure displays the list of physicians who are affiliated with IIIA hospitals. Within the "Leading Experts" section, patients have the option to sort physicians based on hospital ranking and price.

Figure A.7: Physicians Recommended by the SRD

Note: The screenshot was taken in April 2023. It displays an example scenario, where a patient purchases text inquiry service from a female general physician in the Dermatology & S.T.D department, and the platform suggests three male physicians from the same department. By paying the price listed by the recommended physicians, the platform automatically sends the same questions to those physicians.

A.2 Test for Statistical Discrimination

The source of discrimination can be classified as either taste-based, which occurs when patients experience disutility from interacting with physicians of a certain group identity (Becker, 1957), or statistical, when patients use group identity (e.g., gender) as a proxy for unobserved quality (Arrow, 1971; Phelps, 1972). In this section, I develop a model to test for statistical discrimination on the online healthcare platform based on the framework proposed by Phelps (1972).[1] In the following, I first describe the setup of the model. Then, I discuss two implications of statistical discrimination and empirically test them.

A.2.1 Setup

In the online healthcare platform, there are a number of physicians who have various qualities and a number of patients who will purchase text inquiry services from physicians. The online platform presents *information asymmetry*. Physicians know their qualities and provide optimal information, but patients are uninformed. Patients have prior beliefs about gender-based quality and they update priors after observing physicians' quality signals.

Physicians. Physicians have an observable group identity $g \in \{M = 0, F = 1\}$, where M refers to male and F refers to female. Physician j has private information about his/her true quality q_j. On the platform, physicians make a report about their quality to otherwise uninformed patients, which generates a signal of productivity I_i. Let $I_i = q + \epsilon_{ig}$ where $i = \{c, o\}$ and $\epsilon_{ig} \sim N(0, \sigma^2_{ig})$. c denotes compulsory information, including the professional title that physicians are required to provide. o represents optional information, such as work experience, which physicians may choose to disclose voluntarily.[2]

[1]In this paper, I focus on accurate statistical discrimination, wherein patients treat male and female physicians differently due to unobserved productivity and differences in the perceived distribution of signal between the two groups.

[2]The platform verifies the compulsory information but not the optional information. Physicians lack the incentive to provide false information about work experience or education, as this information is easily verifiable on the official websites of their affiliated hospitals.

Assumption: A physician's quality is drawn from a normal distribution with a mean of $\bar{q}$ and a variance of σ^2.

One might be concerned that the quality distribution for female physicians differs from that of male physicians, particularly with the worry that the quality distribution for female physicians may skew towards lower values. Three things alleviate this concern. First, the National College Entrance Examination (NCEE) sets a common minimum score requirement for all students to qualify for university enrollment.[3] While each university sets its own minimum scores for medical programs, these thresholds are identical for both male and female students. This ensures that male and female students must possess equal qualifications at the very least to gain admission to a medical program. Second, it is widely acknowledged that female students often have the same or sometimes even higher average scores on the NCEE than male students.[4] Third, I examine the distribution of test scores of the National Preliminary Entrance Exam for graduate schools.[5] Figure A.8 displays the preliminary exam score distribution of admitted female and male medical students. I conduct a Kolmogorov-Smirnov test and fail to reject the null hypothesis that the two distributions are equal ($p = 0.389$), which supports the assumption of equal variance. The difference in average test scores between female and male admitted students is -2.44, which is small (0.7% of the average for male physicians) and not statistically significant at conventional levels. In Appendix A.2.4, I further explore the scenario where $\bar{q}_F < \bar{q}_M$.

Patients. I assume that patients are rational and risk-neutral, with accurate prior beliefs about the distribution of physicians' quality. I also assume that patients are *maximally skeptical* (Milgrom, 2008).[6] That is, patients will react to any missing

[3] A bunch of research has used test scores as a measure of productivity. For example, Neal and W. R. Johnson (1996) and Altonji and Pierret (2001) utilize AFQT test scores. The NCEE is one of the most important institutions in China and its scores have been used as a measure of cognitive performance (Zivin, T. Liu, et al., 2020; Zivin, Song, et al., 2020).

[4] News articles from various sources, including *Sohu*, *Sina*, and *The Paper*, have reported the related statistics.

[5] The entrance exam for graduate schools consists of two parts: the preliminary (or first round) exam, which is conducted nationally, and the secondary exam, which varies depending on the university. I obtained the test score data of master students admitted in 2023 from Sun Yat-Sen University, which was publicly available between May 14 and May 25, 2023.

[6] Milgrom (2008) argues that buyers are maximally skeptical. Customers believe that the actual quality of the good is equal to the minimum quality reported by the seller. This assumption is corroborated by the results in Table A.23 and Table A.24. The estimates of not reporting years of

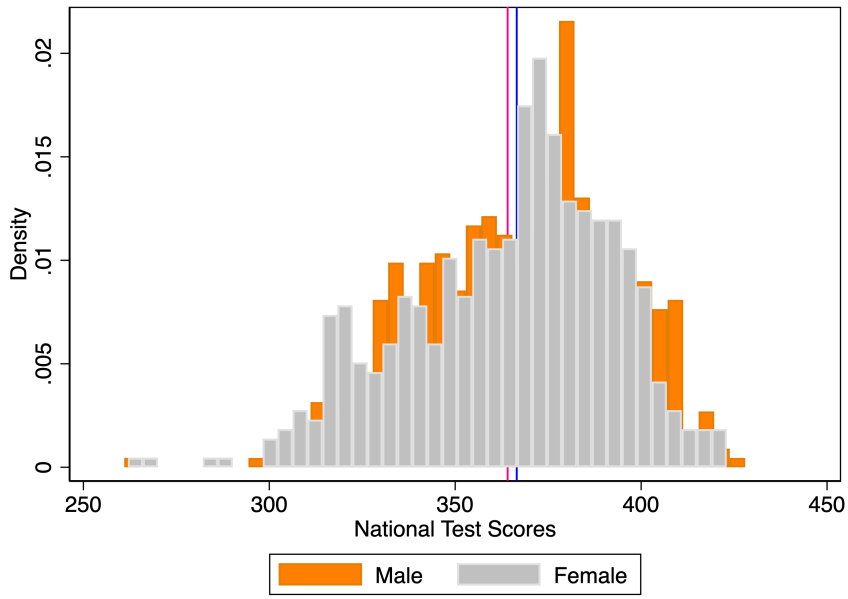


Figure A.8: Distributions of Test Scores by Gender

Note: The figure displays the test score distributions for female and male medical students admitted to Sun Yat-Sen University in 2023. The test is the 2023 National Preliminary Entrance Exam for graduate schools. The gray bars represent the score distribution for female admitted students to Sun Yat-Sen University. The orange bars represent the score distribution for male admitted students to Sun Yat-Sen Univesity. The sample consists of 1,073 students, with 532 of them being male. The pink line is the average test score (364.10) for female students and the blue line is the average test score (366.54) for male students. The difference is -2.44 and is not statistically significant at conventional levels. The Kolmogorov-Smirnov test p-value is 0.389.

information by reducing their purchases to the extent they would if they were to learn that a physician is of low quality. Thus, physicians who have low quality will be indifferent between reporting and not reporting.

work experience are not statistically significantly different from the estimates of having less than 10 years of work experience. To further support the assumption of patients being maximally skeptical, I examine physicians' years of work experience using the 2023 data. Among 13,472 physicians, 5,343 did not provide information on work experience in 2020. Of those, 3,858 (72.21%) continued to be on the platform in 2023. Among these continuing physicians, 2,195 updated their work experience before or in 2023. Notably, 84.56% of them had 10 to 13 years of experience in 2023, indicating they had 7 to 10 years of experience in 2020. This implies that they would be considered less experienced physicians if they had revealed their work experience. To the extent that this can be generalized to the 5,343 physicians, those who did not provide information on work experience in 2020 are more likely to possess fewer years of work experience and therefore would be indifferent between reporting and not reporting it. This aligns with my assumption in the model that patients are maximally skeptical, treating physicians who do not provide years of work experience equal to those who have less than 10 years of work experience.

Patients receive signal I_{ij} from physician j and hold different beliefs about the signal precision of female and male physicians. By construction, the signal is an unbiased estimator of a physician's true quality, $E[I|q] = q$. After observing physicians' error-ridden quality signals, patients update their prior beliefs using the Bayes rule. The posterior distribution of physicians' quality is normally distributed with mean $\frac{\sigma_{ig}^2 \bar{q} + \sigma^2 I}{\sigma_{ig}^2 + \sigma^2}$ and variance $\frac{\sigma_{ig}^2 \sigma^2}{\sigma_{ig}^2 + \sigma^2}$. The smaller σ_{ig}^2 is, the more precise the signal and the more weight patients would assign to the signal rather than the group mean. The conditional expected quality, $\ddot{q}_g$, can be rewritten as:

$$\ddot{q}_g \equiv E[q|I, g] = \frac{\sigma_{iF}^2}{\sigma_{iF}^2 + \sigma^2} \bar{q} + \frac{\sigma^2}{\sigma_{iM}^2 + \sigma^2} I + \Lambda g I \tag{A.1}$$

where $\Lambda = \frac{\sigma^2}{\sigma_{iF}^2 + \sigma^2} - \frac{\sigma^2}{\sigma_{iM}^2 + \sigma^2}$. If $\Lambda > 0$, then we have $\sigma_{iF}^2 < \sigma_{iM}^2$ and the signals of female physicians are more informative than those of males, and vice versa. Patients make their purchase decisions based on physicians' conditional expected quality.

A.2.2 Two Implications for Statistical Discrimination

I utilize the differences in the dispersion of signal between male and female physicians to test for statistical discrimination ($\sigma_{iF}^2 \neq \sigma_{iM}^2$). The main idea is that a strong positive or negative signal of quality serves as a more informative predictor of quality for female physicians. There are two scenarios: In the first scenario, when a negative signal, such as the absence of information on work experience, is present, patients perceive less variability in low quality among female physicians with this negative signal compared to their male counterparts (i.e., $\sigma_{oF}^2 < \sigma_{oM}^2$). In the second scenario, when patients believe that female physicians must surpass a higher threshold to be promoted to a more senior professional title, then a positive signal would be a more precise indicator of high quality for female physicians compared to their male counterparts. Patients will place more weight on strong positive signals from female physicians (i.e., $\sigma_{cF}^2 < \sigma_{cM}^2$).

Implication 1: *In the absence of information on physicians' years of work experience (a strong negative signal), patients apply an additional penalty to female physicians.*

Proof. Years of work experience is optional information. Physicians may not provide it, yet patients value this information because there is a prevalent view that "the older the physician is, the more valuable he is because of a richer experience." The difference in the conditionally expected quality between female and male physicians who do not provide optional information (i.e., work experience), assuming $I_o < 0$, is

$$\ddot{q}_F - \ddot{q}_M = \left[\frac{\sigma^2}{\sigma_{oF}^2 + \sigma^2} - \frac{\sigma^2}{\sigma_{oM}^2 + \sigma^2}\right] I_o = \frac{\sigma^2(\sigma_{oM}^2 - \sigma_{oF}^2)}{(\sigma_{oF}^2 + \sigma^2)(\sigma_{oM}^2 + \sigma^2)} I_o < 0 \tag{A.2}$$

The above inequality holds only if $\sigma_{oM}^2 > \sigma_{oF}^2$. It suggests that negative signals are more indicative or informative of low quality in female physicians compared to male physicians. Therefore, patients are less likely to purchase consultation services from female physicians who do not provide information on work experience than from their male counterparts. □

Empirical results for implication 1. In the data, about 39% of physicians did not provide their years of work experience on their home pages in 2020. I utilize this dispersion to test whether female physicians are penalized more than males in the presence of negative signals (i.e., not providing information on years of work experience) using the following specification

$$\begin{aligned} \ln(Y_{jspt}) =& \alpha + \delta_s + \delta_p + \delta_t + \beta_0 g_{jspt} + \beta_1 \mathbf{1}_{jspt}\{\leq 10 \text{ years}\} + \beta_2 \mathbf{1}_{jspt}\{> 10 \text{ years}\} \\ &+ \gamma_1 g_{jspt} \times \mathbf{1}_{jspt}\{\leq 10 \text{ years}\} + \gamma_2 g_{jspt} \times \mathbf{1}_{jspt}\{> 10 \text{ years}\} + u_{jspt}, \end{aligned} \tag{A.3}$$

where $\mathbf{1}_{jspt}\{\leq 10 \text{ years}\}$ is a dummy equal to one if physician j's work experience is less than 10 years and $\mathbf{1}_{jspt}\{> 10 \text{ years}\}$ is a dummy equal to one if physician j's work experience is more than 10 years. The base group is thus physicians who do not provide information on work experience. In equation (A.3), I also control for other characteristics, such as professional titles and the type of working hospital. β_0 is the unexplained part of gender gaps between female and male physicians who do not report information on years of work experience; $\beta_0 + \gamma_2$ is the unexplained gender gap between female and male physicians with more than 10 years of work experience. The difference between the two gaps, $\beta_0 - (\beta_0 + \gamma_2) = -\gamma_2$, is the additional penalty that patients apply to female physicians over males for not providing information. Table A.2 summarizes the results.

Table A.2: Received vs. Not Received Information on Work Experience

	Ln(Avg. prices in 2020)		Ln(Avg. monthly consultations in 2020)		
	(1)	(2)	(3)	(4)	(5)
Female ($\hat{\beta}_0$)	-0.023*	-0.029$^+$	-0.110***	-0.171***	-0.175***
	(0.013)	(0.019)	(0.038)	(0.054)	(0.054)
Female $\times \leq 10$ years ($\hat{\gamma}_1$)		0.005		-0.099	-0.098
		(0.032)		(0.096)	(0.096)
Female $\times > 10$ years ($\hat{\gamma}_2$)		0.014		0.185**	0.188***
		(0.025)		(0.072)	(0.072)
$\hat{\beta}_0 + \hat{\gamma}_2$		-0.015		0.015	0.012
p-value		(0.438)		(0.792)	(0.824)
Additional Penalty: $-\hat{\gamma}_2$		-0.014		-0.185**	-0.188**
p-value		(0.565)		(0.010)	(0.009)
Ln(Avg. prices in 2020)	No	No	No	No	Yes
Other characteristics	Yes	Yes	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Control Mean	3.362	3.243	2.096	2.096	2.096
R^2	0.305	0.305	0.328	0.329	0.331
Observations	13,472	13,472	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, professional title, education, a dummy of physicians' profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group is physicians not providing information on work experience. The "Control Mean" refers to the average for male physicians in columns 1 and 3 and the average for male physicians who do not provide information on work experience in columns 2, 4, and 5. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

The overall unexplained gender price gap is 2.25% ($p < 0.10$) in column (1) and is 2.94% ($p = 0.11$) in column 2, respectively. But, among physicians with more than 10 years of work experience, the gender price gap reduces to 1.49% and is not statistically significant at conventional levels. The additional penalty that patients imposed on female physicians for not disclosing information on work experience in terms of price is 1.44% though is measured imprecisely. Regarding patient demand, female physicians are on average 17.09% less likely to be inquired about by patients than their male counterparts (column 4). However, the gender quantity gap becomes negligible and statistically insignificant for physicians with more than 10 years of work experience. Female physicians face an additional penalty of 18.54%($p < 0.05$) for not providing information on work experience. The magnitude and significance levels of coefficients remain unchanged after conditioning on physicians' prices (column 5). Comparing columns 4-5 to column 2, the differences in the estimated $-\hat{\gamma}_2$'s indicate that patients adjust more on the margin of service demand than on prices.

To summarize, among physicians who do not report information, females receive fewer consultations than their male counterparts but do not charge lower prices. As a result, female physicians who do not provide information on their work experience earn an average of 19.72% (calculated as $1-(1-1.44\%)(1-18.54\%)$) less income per month from the platform compared to their male counterparts. Meanwhile, holding all else constant, patients pay and inquire about female physicians who have over 10 years of work experience at a comparable rate to male physicians.

Implication 2: *If a strong positive signal (i.e., a senior professional title) is received from both genders, then female physicians are rewarded.*

Proof. The professional title is compulsory information. Patients will update their prior beliefs in favor of women if they receive a strong positive signal of quality: a senior professional title. This stems from patients' belief that female physicians must meet a higher threshold than male physicians to achieve a senior professional title.[7] Because of this, patients' updated beliefs will have a higher mean for women's quality (the purple dashed line in Figure A.9) than for men's quality (the green dashed line in Figure A.9). The variance of the truncated distribution will be smaller for female physicians with a senior professional title than for their male counterparts. That is, a strong positive signal will be more precise or informative for female physicians, $\sigma_{cF}^2 < \sigma_{cM}^2$.

Assuming that $I_c > 0$, a numerical expression for the difference in the conditionally expected quality between female and male physicians with senior professional titles is

$$\ddot{q}_{F,SProf} - \ddot{q}_{M,SProf} = \left[\frac{\sigma^2}{\sigma_{cF}^2+\sigma^2} - \frac{\sigma^2}{\sigma_{cM}^2+\sigma^2}\right] I_c = \frac{\sigma^2(\sigma_{cM}^2-\sigma_{cF}^2)}{(\sigma_{cF}^2+\sigma^2)(\sigma_{cM}^2+\sigma^2)} I_c > 0. \tag{A.4}$$

The above inequality holds only if $\sigma_{cM}^2 > \sigma_{cF}^2$. That is, the positive signal for female physicians is a more reliable predictor of q than it is for male physicians. Patients

[7]Based on administrative data from an IIIA hospital in southeastern China, female physicians, after controlling for age, marital status, education, and specialty, require an average of 227 additional days ($p < 0.15$) to be promoted to more senior professional positions compared to their male counterparts. It provides suggestive evidence that female physicians need to be exceptional to have a senior professional title.

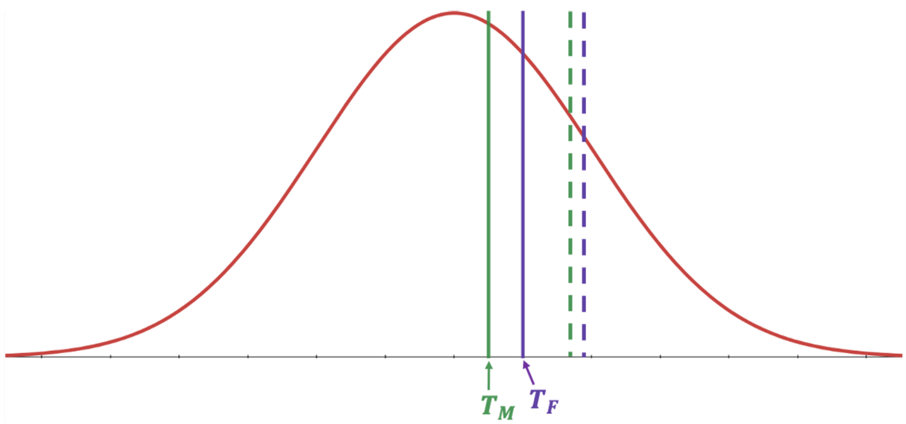


Figure A.9: Physicians' Quality Distribution

Note: The orange curve is the distribution of physicians' true quality q. T_F is the threshold for women to have senior professional titles and T_M is the threshold for men ($T_F > T_M$). The green and the purple dashed lines represent the means of the truncated distributions for men and women, respectively. The truncated mean for women is larger than the one for men.

are more likely to purchase consultation services from female physicians with a strong positive signal (i.e., a senior professional title) than from their male counterparts. □

Empirical results for implication 2. If there is statistical discrimination against women, then patients will construe strong positive signals from female physicians as an indication of positive selection. I employ the dispersion of professional titles in 2020 to test if there is positive discrimination against women with a senior professional title, which is understood by patients to reflect higher quality. In China, the professional title is the most important qualification system among physicians, which measures research acumen and signals a different type of quality from work experience. A senior professional title is conferred upon physicians who publish well.[8]

To identify gender differential dispersion of signals, I estimate the following specifi-

[8] In the U.S., doing research and taking patients are two separate tracks. In China, physicians need to devote time to both scientific research and patients. While publication, such as articles published in prestigious journals like *Nature Cancer* and *American Journal of Obstetrics and Gynecology*, is the most important measure in evaluating professional titles, physicians also need to fulfill other requirements, including meeting the minimum work experience requirement. For example, to be promoted to associate chief physician, an attending physician must possess a minimum of five years of experience in that role. While professional titles and work experience are positively correlated, it should be noted that having more years of experience does not guarantee a physician's promotion to a more senior professional title.

cation:

$$\ln(Y_{jspt}) = \alpha + \beta_0 g_{jspt} + \beta_1 SProf_{jspt} + \beta_2 g_{jspt} \times SProf_{jspt} + \delta_s + \delta_p + \delta_t + u_{jspt}, \tag{A.5}$$

where $SProf_{jspt}$ is a dummy variable equal to one if physician j is of senior title. I also control for physicians' characteristics such as education and work experience. β_0 and β_2 are the parameters of interest. β_0 is the overall unexplained gender gap and β_2 represents the parameter Λ in equation (A.1). If $\beta_2 > 0$, then it implies that $\sigma^2_{cF} < \sigma^2_{cM}$, and patients place more weight on the positive signals. If $\beta_0 + \beta_2 = 0$, then observing a strong signal from female physicians helps patients eliminate discrimination.

Table A.3: Senior Professional Titles as A Strong Signal

	Ln(Avg. prices in 2020)		Ln(Avg. monthly consultations in 2020)		
	(1)	(2)	(3)	(4)	(5)
Female ($\hat{\beta}_0$)	-0.023*	-0.043**	-0.110***	-0.204***	-0.211***
	(0.013)	(0.017)	(0.038)	(0.051)	(0.051)
Female × Senior Professional Title ($\hat{\beta}_2$)		0.040*		0.184***	0.191***
		(0.023)		(0.066)	(0.066)
$\hat{\beta}_0 + \hat{\beta}_2$		-0.003		-0.020	-0.020
p-value		(0.870)		(0.694)	(0.687)
Ln(Avg. prices in 2020)	No	No	No	No	Yes
Other characteristics	Yes	Yes	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Control Mean	3.362	3.196	2.096	1.962	1.962
R^2	0.305	0.305	0.332	0.332	0.334
Observations	13,472	13,472	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, years of work experience, education, a dummy of physicians' profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group is physicians with a junior professional title, general physicians. The "Control Mean" refers to the average for male physicians in columns 1 and 3 and the average for male physicians with junior professional titles in columns 2, 4, and 5. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.3 displays the estimated β's of equation (A.5). The overall gender price gap is 4.31% ($p < 0.05$) in column 2 and the overall gender quantity gap is 20.41% ($p < 0.01$) in column 4. Meanwhile, a senior professional title can boost patients' demand for female physicians by 18.44% ($p < 0.01$) and eliminate the gender quantity gap. The gender price gap also disappears among physicians with a strong positive signal. In column 5, I include the log of average prices in 2020 and it alters neither the magnitude nor significance levels of the estimated coefficients of $\hat{\beta}_0$ and $\hat{\beta}_2$. The findings in columns 2, 4, and 5 are consistent with the idea that patients perceive the distribution of signals differently for female physicians compared to male physicians, and thus provide supportive evidence for statistical discrimination.

A.2.3 Robustness Check of Implications 1 and 2

To bolster the robustness of my findings regarding implications 1 (additional penalties on female physicians for not reporting years of work experience) and 2 (rewarding female physicians more for positive signals), I conduct a regression analysis on gender quantity gaps, incorporating interaction terms between *Female* and both work experience and professional titles. The results are shown in Table A.4. Columns 1 and 2 reproduce the results for implication 1 and implication 2 respectively. In column 3, both interaction terms are included, and the findings remain consistent.

In column 3, the overall unexplained gender quantity gap amounts to 19.79% and is primarily driven by female general physicians who either lack work experience information or have less than 10 years of experience. Specifically, patients would impose an additional demand penalty of 12.36% ($p < 0.15$) on female physicians who do not report their years of work experience. For general physicians with more than 10 years of experience, the quantity gap narrows to 7.44% ($p = 0.39$). Regarding physicians who do not report years of work experience, holding senior professional titles can alleviate the gap by 10.8% ($p = 0.17$), although the estimated coefficient is imprecise. Despite the smaller magnitudes and significance levels of $\hat{\gamma}_2$ and $\hat{\gamma}_3$ in column 3 compared to those in columns 1 and 2, they are jointly statistically significant at a 5% level. Importantly, among physicians with senior professional titles and over 10 years of experience, there is no significant disparity in the average number of consultations between female physicians and their male counterparts. The results provide additional evidence supporting the statistical discrimination against female physicians. Patients tend to penalize female physicians more when they fail to provide information on their years of work experience (a negative signal) and, conversely, reward them more when they demonstrate a strong positive signal.

Table A.4: Results on Combining Implications 1 & 2

	Ln(Avg. monthly consultations in 2020)		
	(1)	(2)	(3)
Female ($\hat{\beta}_0$)	-0.171***	-0.204***	-0.198***
	(0.054)	(0.051)	(0.058)
Female $\times \leq 10$ years ($\hat{\gamma}_1$)	-0.099		-0.111
	(0.096)		(0.097)
Female $\times > 10$ years ($\hat{\gamma}_2$)	0.185**		0.124$^+$
	(0.072)		(0.085)
Female $\times$ Senior Professional Title ($\hat{\gamma}_3$)		0.184***	0.108
		(0.066)	(0.079)
Additional penalty: $-\hat{\gamma}_2$	-0.185**		-0.124$^+$
p-value	(0.010)		(0.147)
$\hat{\beta}_0 + \hat{\gamma}_3$		-0.020	-0.090
p-value		(0.694)	(0.257)
$\hat{\beta}_0 + \hat{\gamma}_2 + \hat{\gamma}_3$			0.033
p-value			(0.557)
Other characteristics	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes
Control Mean	2.096	1.962	2.083
R^2	0.329	0.329	0.329
Observations	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, years of work experience, education, professional title, a dummy of the physician's profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group is physicians with a junior professional title, general physicians. The "Control Mean" refers to the average for male physicians not providing information on work experience in column 1, the average for male physicians with junior professional titles in column 2, and the average for male physicians with junior professional titles and not providing information on work experience in column 3. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

A.2.4 The Case of $\bar{q}_F < \bar{q}_M$

Phelps (1972) discusses two scenarios that can lead to gender inequality: the first scenario involves an identical distribution of quality, but the signals received by patients are interpreted differently; the second scenario is that the signals are equally informative from both groups, but one group has a lower average quality than the other. In this section, I discuss the scenario where patients believe that female physicians have a lower average quality than male physicians (i.e., $\bar{q}_F < \bar{q}_M$). Here, I follow the method proposed by Foster and Rosenzweig (1993) and Foster and Rosenzweig (1996) for examination.

Under this assumption, true quality can be regarded as a noisy measure of expected quality and would be negatively correlated with gender. Let's assume that $\ln(Y) = \beta g + \varepsilon$ is a short regression, where g is equal to 1 if the physician is female and 0 otherwise. A negative β indicates the presence of taste-based discrimination, statistical discrimination, or both. Because patients base their purchase decisions on expected quality, the appropriate method for testing for statistical discrimination is to conduct the regression $\ln(Y) = \ddot{\beta} g + \ddot{\gamma}\ddot{q} + \varepsilon$, where $\ddot{q}$ is the expected quality. If the result yields $\ddot{\beta} = 0$, then it implies that the observed negative β is attributed to statistical discrimination rather than taste-based discrimination. However, information on expected quality is typically not available. So, instead, one runs the long regression $\ln(Y) = \tilde{\beta} g + \tilde{\gamma} q + \tilde{\varepsilon}$. By definition, one has $\tilde{\beta} - \beta = -\tilde{\gamma}\delta$ where δ is obtained from $q = \delta g + e$ with $\delta < 0$. As long as $\tilde{\gamma} > 0$, it results in $\tilde{\beta} > \beta$. If this is not the case, for instance, if $\tilde{\beta} \approx \beta$, then the observed negative β would be consistent with taste-based discrimination.

The results are reported in Table 1.3. Column 2 corresponds to the estimation of the short regression $\ln(Y) = \beta g + \varepsilon$, while column 3 corresponds to estimating the long regression $\ln(Y) = \tilde{\beta} g + \tilde{\gamma} q + \tilde{\varepsilon}$. As shown, after accounting for a latent measure of physicians' true quality, *Promotion*, the estimated coefficient for *Female* does not become statistically significantly more or less negative compared to the model where it is not controlled for. This is consistent with taste-based discrimination but not statistical discrimination. However, if this were the case, it would imply that patients do not perceive signals from female physicians differently than from male physicians, which is not supported by Table A.2 and Table A.3.[9] Therefore, the results cast doubt on the assumption that $\bar{q}_F < \bar{q}_M$ and lend support to the assumption that $\bar{q}_F = \bar{q}_M$ but $\sigma^2_{iF} \neq \sigma^2_{iM}$.

A.2.5 Additional Test: Dynamic Patient Learning

I conduct an additional test to examine statistical discrimination following the method proposed by Altonji and Pierret (2001). The main idea is that statistically discriminating patients would use gender along with work experience and other information

[9]The estimated coefficients in Table A.2 and Table A.3 remain similar after including the variable *Promotion*.

to predict the productivity of physicians. Over time, as more information becomes available, the productivity of physicians would become more apparent, and so patients would make their decisions based on the updated set of information. I use constructed panel data to investigate whether patients revise their beliefs about the productivity of physicians as additional information on years of work experience becomes available. If patients increase their purchases or are willing to pay a higher price to female physicians after observing the updated information, then it supports that patients statistically discriminate on the basis of gender.

I constructed panel data using two rounds of data collected in 2020 and 2023. Each physician who remained on the platform until 2023 is observed twice in the panel data, once in 2020 and again in 2023. As discussed in Appendix A.1, 10,146 out of 13,472 physicians stay on the platform. Among these physicians, 4,785 physicians posted a text inquiry price and the rest were unavailable for text inquiry service at the time of scraping in 2023. 5,343 physicians did not provide information on years of work experience in 2020 and 2,195 reported it in 2023. I utilize the fact that some physicians did not report their years of work experience in 2020 but updated this information in 2023. As patients hold a stronger belief that female physicians who do not provide information on years of work experience are of low quality, once this information becomes available and if they update their beliefs accordingly, then it serves as supportive evidence for statistical discrimination.

I restrict the sample to physicians who provided text inquiry prices in both 2020 and 2023, excluding those who reported their years of work experience in 2020. This restriction results in a remaining sample size of 1,750 physicians, with 978 of them reporting their years of work experience in 2023. In the sub-sample, 600 (1,150) physicians are female (male), and among them, 54% (57%) report work experience.

The two outcome variables that I examine are the log of price and the log of quantity. The variable "price" takes the value of the average price in 2020 if the year is 2020 and is equal to the observed text inquiry price in 2023 if the year is 2023. The variable "quantity" takes the value of the average monthly consultations in 2020 if the year is 2020 and is equal to the average monthly consultations in 2023 if the year is 2023. The number of average monthly consultations in 2023 is calculated as the difference between the total number of inquiries observed in 2023 and the total number of inquiries observed in the last instance in 2020 divided by the number of months between the two instances. For example, a physician last appeared in the 2020 data on June 30 with 1,000 consultations provided and was observed with 2000 consultations provided on February 30, 2023. Then, the number of average monthly consultations in 2023 is equal to $\frac{2000-1000}{32} = 31.25$. I also generate a variable called "Report Work Experience", which takes a value of one if the physicians report years of work experience in that year, and zero otherwise.

Table A.5: Effects of Additional Information on Gender Gaps

	Ln(Price)		Ln(Quantity)	
	(1)	(2)	(3)	(4)
Female	-0.025	-0.028	-0.278**	-0.262**
	(0.041)	(0.040)	(0.113)	(0.112)
Female × Report Work Experience	0.098*	0.090*	0.197^{+}	0.184^{+}
	(0.052)	(0.051)	(0.126)	(0.124)
Other characteristics	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Control Mean	3.276	3.276	1.954	1.954
R^2	0.133	0.193	0.141	0.185
Number of physicians	1,750	1,750	1,750	1,750
Observations	3,500	3,500	3,500	3,500

Notes: I restrict the sample to physicians who posted text inquiry prices in both 2020 and 2023 but did not report years of work experience in 2020. Other characteristics include a physician's type of working hospital, professional title, education, and work experience. The "Control Mean" is the average for male physicians who still do not report years of work experience in 2023. Standard errors are clustered at the physician level and are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In the regression, I include *Female*, *Report Work Experience*, and their interaction term, as well as control for the year and specialty fixed effects. The results are displayed in Table A.5. In columns 1 and 3, I do not include physicians' characteristics such as education and professional titles. In columns 2 and 4, these characteristics are included. As shown, the estimated coefficients on *Female* are negative in columns 1-4 and are statistically significant in columns 3-4. So, on average, patients pay less (though measured imprecisely) and purchase fewer consultations from female physicians. However, once patients observe the additional information regarding years of work experience provided by female physicians, they update their beliefs and adjust their behavior accordingly. Patients are willing to pay female physicians who now report their years of work experience more and purchase consultations from them as much as they do from male physicians. This piece of suggestive evidence further bolsters confidence in the results of statistical discrimination.[10]

A.3 Specialty Heterogeneity & Homophily

In this section, I investigate if patients treat female physicians differently by specialty. Previous studies of taste-based discrimination suggest that homophily, or same-gender preference, could be particularly pronounced in the case of intimate issues (Reyes, 2006; Makam, Saroja, and Edwards, 2010; Janssen and Lagro-Janssen, 2012; Groutz et al., 2016; G. Alyahya et al., 2019; Miller and Segal, 2019). For example, Reyes (2006) finds that female patients prefer to seek care from a female obstetrician or gynecologist, and male patients may prefer to consult a male urinary surgeon.

I categorize specialties into two groups: female-dominant specialties (FDSs) and male-dominant specialties (MDSs). I define an FDS as one in which more than 50% of physicians are women. 14 specialties are classified as FDSs, while 31 are MDSs. Figure A.10 displays the list of specialties and their corresponding shares of female physicians. As is evident, FDSs tend to be female-typed work, such as gynecology and obstetrics, which are widely regarded as suitable for women.[11] Most of the surgical specialties are classified as MDSs, reflecting people's expectations that male-typed work should be reserved for men, who are thought to be more biologically capable. In the sample, about 52.5% (37.5%) of female (male) physicians are working at one of the FDSs.

I first augment equation (1.1) with an interaction term of $Female$ and $FDSs$. The results are displayed in Table A.6. Female physicians, on average, set their price 4.95% (column 1) lower and provide 14.38% (column 3) fewer consultations compared to their male counterparts. But, the price gap goes away and the quantity gap (6.82%) becomes statistically insignificant in FDSs. In columns 2 and 4, I also include $Promotion$. As shown, including this variable does not alter the estimated coefficients

[10] I acknowledge that the limitation of this test is that the platform changed its design between 2020 and 2023. So, at best this is suggestive evidence of statistical discrimination: patients make their purchase decisions on *easily observable* characteristics such as gender.

[11] It is reasonable to assume that the majority of patients who visit FDSs are women. On one hand, only women will visit obstetricians and gynecologists. On the other hand, women do more childcare and thus are more likely to take their children to visit a pediatrician (S. E. Rhoads and C. H. Rhoads, 2012; Fetterolf and Rudman, 2014).

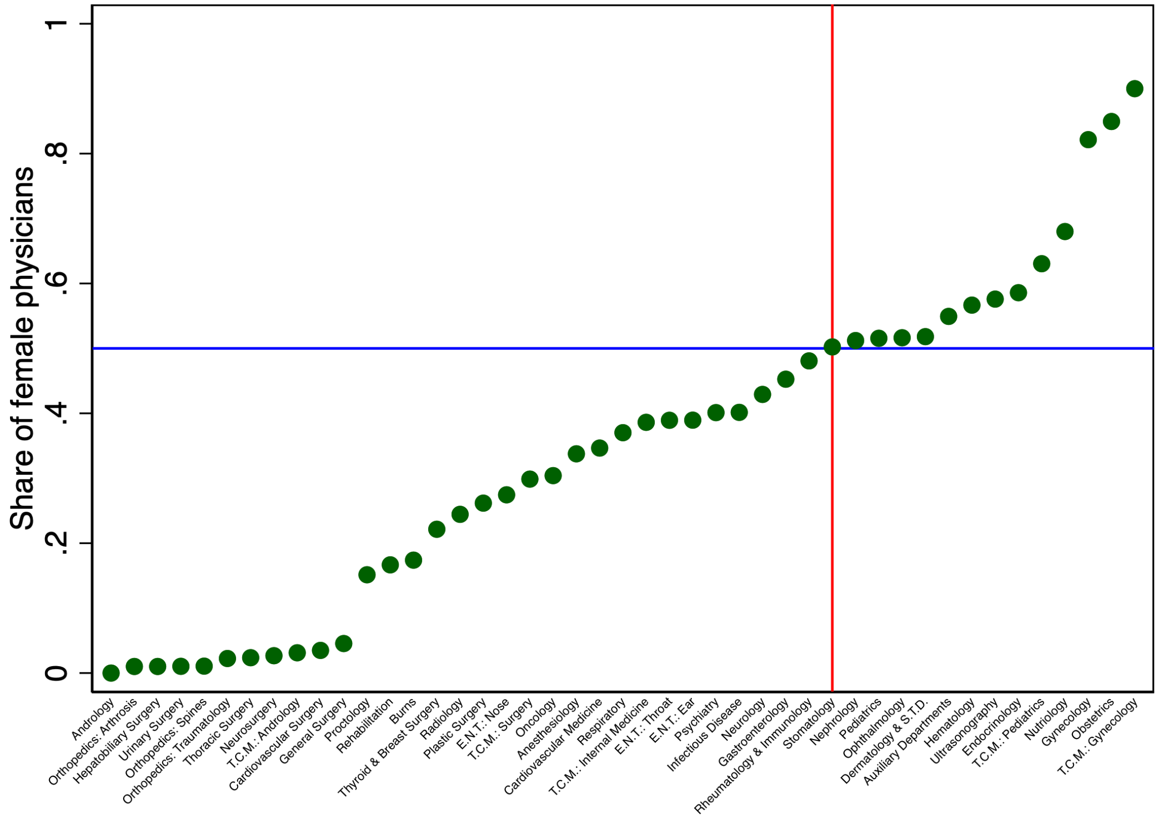


Figure A.10: Share of Female Physicians by specialty

Note: There are 45 specialties listed in the graph. T.C.M. is Traditional Chinese Medicine. S.T.D. is Sexually Transmitted Diseases. E.N.T. is ear, nose, and throat.

for either *Female* or *Female* $\times$ *FDSs*. These results are in line with homophily, wherein women prefer to consult women and men prefer to consult men.

One may argue that the estimates could also be driven by context-dependent statistical discrimination (or context-dependent stereotypes); that is, patients believe that female physicians have the same threshold as male physicians for achieving a senior professional title in FDSs (i.e., $\sigma^2_{cF} = \sigma^2_{cM}$ in FDSs but $\sigma^2_{cF} < \sigma^2_{cM}$ in MDSs). To test this probability, I apply implication 2. If this stereotype holds, then one would expect $\beta_2 = 0$ in equation (A.5) for physicians in FDSs. I estimate equation (A.5) on physicians working at MDSs and at FDSs separately. Table A.7 shows the results on gender quantity gaps. Having a senior professional title helps female physicians attract patients and provide as many consultations as males enjoy in both FDSs and

Table A.6: Gender Gaps: MDSs vs. FDSs

	Ln(Avg. prices in 2020)		Ln(Avg. monthly consultations in 2020)	
	(1)	(2)	(3)	(4)
Female ($\hat{\beta}_0$)	-0.050***	-0.048***	-0.144***	-0.135***
	(0.018)	(0.018)	(0.049)	(0.048)
Female × FDSs ($\hat{\beta}_1$)	0.060**	0.060**	0.076	0.076
	(0.026)	(0.026)	(0.076)	(0.076)
Promotion		0.085***		0.366***
		(0.016)		(0.044)
$\hat{\beta}_0 + \hat{\beta}_1$	0.010	0.013	-0.068	-0.059
p-value	(0.593)	(0.518)	(0.249)	(0.319)
Other characteristics	Yes	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Control Mean	3.358	3.358	1.935	1.935
R^2	0.305	0.307	0.328	0.332
Observations	13,472	13,472	13,472	13,472

Notes: Other physicians' characteristics include a physician's education, work experience, relative patient ratings, relative peer ratings, a dummy of the type of working hospital, the share of available times, a dummy of physicians' profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. The omitted group is physicians with junior professional titles, the general physician. The "Control Mean" refers to the average for male physicians in MDSs. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

MDSs. The positive estimated coefficient on the interaction term ($\hat{\beta}_2$) is large and statistically significant at a 5% level in FDSs (column 2), which is inconsistent with the context-dependent stereotypes. For those who have junior professional titles, women offer statistically significantly fewer consultations than males both in MDSs and FDSs.

In short, I find supportive evidence that patients display homophilic preferences., which helps reduce the relative gender disparities in FDSs. But, the relative improvement for female physicians in FDSs does not mean any bias in favor of women by patients. In fact, female physicians continue to experience statistical discrimination across all specialties.

A.4 Results on Alternative Mechanisms

A.4.1 Results on Lower Supply by Female Physicians

Table A.7: Homophily or Context-Dependent Stereotype: Using Implication 2

	Ln(Avg. monthly consultations in 2020)	
	MDSs	FDSs
	(1)	(2)
Female ($\hat{\beta}_0$)	-0.199***	-0.210**
	(0.065)	(0.088)
Female × Senior professional title ($\hat{\beta}_2$)	0.116	0.243**
	(0.089)	(0.116)
$\hat{\beta}_0 + \hat{\beta}_2$	-0.083	0.033
p-value	(0.214)	(0.680)
Other physicians' characteristics	Yes	Yes
Entry Year FE	Yes	Yes
Province FE	Yes	Yes
Specialty FE	Yes	Yes
Control Mean	1.821	2.476
R^2	0.345	0.284
Observations	8,443	5,028

Notes: Other physicians' characteristics include a physician's education, work experience, relative patient ratings, relative peer ratings, a dummy of the type of working hospital, the share of available times, a dummy of physicians' profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. The omitted group is physicians with junior professional titles, the general physician. The "Control Mean" refers to the average for male physicians with junior professional titles in MDSs in column 1 and the average for male physicians with junior professional titles in FDSs in column 2. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.8: Gender Gaps in Share of Availability

	Share of available times		
	(1)	(2)	(3)
Female	0.011***	0.003	0.004^{+}
	(0.002)	(0.003)	(0.003)
Other characteristics	No	No	Yes
Entry year FE	No	Yes	Yes
Province FE	No	Yes	Yes
Specialty FE	No	Yes	Yes
Control Mean	0.966	0.966	0.966
R^2	0.002	0.020	0.023
Observations	13,472	13,472	13,472

Notes: The dependent variable is the share of available times. Other characteristics include a physician's type of working hospital (IIIA or not), relative patient ratings, relative peer ratings, years of work experience, education, and professional title. Columns 2-3 include the entry year, province, and specialty fixed effects. The "Control Mean" refers to the average for male physicians. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

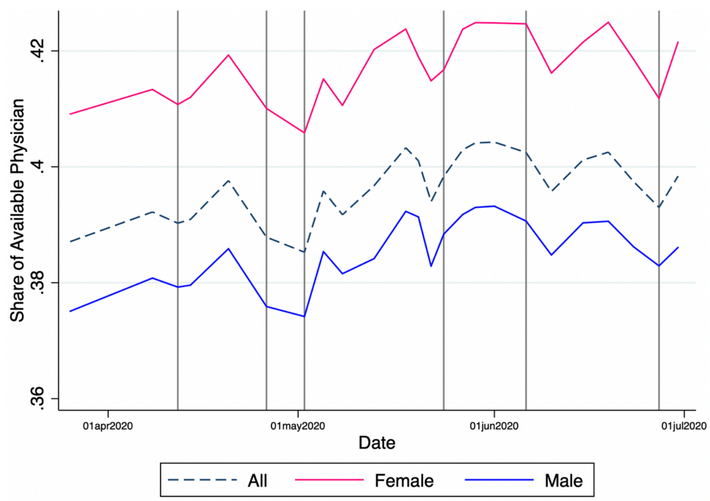


Figure A.11: Share of Available Physicians on Spring Rain Doctor

Note: The full sample has 43,744 unique physicians in total. The number of observations crawled on each date is around 28,000. On each date, about 10,000 subjects are women and 18,000 are men. The pink line is the share of available female physicians in terms of the total number of female physicians observed on that day. And the blue line is the share of available male physicians in terms of the total number of male physicians who appeared on that day. Physicians can appear on the platform while not being available. The dashed line is the share of available doctors in terms of the total number of physicians observed on that day. The vertical gray lines represent weekend dates.

A.4.2 Results on Lower Quality

As discussed in Section 1.6.2, one may be concerned that female physicians set lower prices because of lower quality, and patients are aware of the signaling role of price. Specifically, patients tend to associate lower prices posted by female physicians with lower quality. In the following analysis, I will first demonstrate that female physicians do not appear to have lower average quality than male physicians, as indicated by their relative peer ratings. Next, I conducted two tests to cast doubt on the concern patients use price to infer the unobserved part of expected quality.

Test 1: Relative Patient & Peer Ratings

As shown in Table 1.1, female physicians have lower average relative patient and peer ratings compared to male physicians. One may thus argue that female physicians have lower quality. I conduct a regression analysis to examine this argument. I first regress the relative patient rating on $Female$ and control for other variables. The results are shown in columns 1 and 2 in Table A.9. In column 1, I do not control for physicians' characteristics and female physicians' relative patient ratings are on average 0.06 SD lower than male physicians. After including physicians' characteristics, the gender difference in relative patient ratings between female and male physicians drops to -0.05 SD. The magnitudes of both 0.06 SD and 0.05 SD are relatively small compared to the range of the relative patient ratings $[-2.72, 1.95]$, which is trimmed at the 1st and 99th percentiles. So, despite being statistically significant, the difference is economically insignificant.

It is worth noting that patient ratings are subjective and could themselves reflect gender bias in the perception or reporting of quality, even after having experienced the interactions with the physician. For example, both Boring (2017) and Mitchell and Martin (2018) find that students rate female and male professors differently, specifically female instructors tend to be rated lower in most cases. Furthermore, because ratings are not provided universally after every service, the gender difference in relative patient ratings could be affected by the selection bias of those who left reviews after consultations.

The results in Table A.9 show suggestive evidence of selection bias in patient reviews.

Table A.9: Regression Results on Relative Patient Ratings and Relative Peer Ratings in 2020

	Relative patient ratings		Have patient ratings		Relative peer ratings	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.060***	-0.053***	0.014**	0.018***	-0.021	-0.006
	(0.019)	(0.018)	(0.005)	(0.004)	(0.022)	(0.018)
Other controls	No	Yes	No	Yes	No	Yes
Entry Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.043	0.117	0.181	0.583	0.260	0.502
Observations	13,472	13,472	13,472	13,472	13,472	13,472

Notes: "Have patient ratings" is a dummy variable that takes the value of one if a physician has been rated by patients and zero otherwise. Other characteristics include a physician's share of availability, type of working hospital (IIIA or not), education, work experience, professional titles, and the log of past consultations. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

I created a variable called "Have patient ratings" which is equal to 1 if a physician had been rated by patients in 2020 and 0 otherwise. In the 2020 sample, 1,350 out of 13,472 physicians did not have a patient rating. 854 (63.26%) of them joined the platform after 2019. I first regress *Have patient ratings* on $Female$ controlling the entry year, specialty, and province fixed effects. The estimated difference is 0.014 indicating that female physicians are 1.4% more likely to receive a rating. In column 4, I include physicians' characteristics and the probability of receiving a rating for female physicians increases by 1.8%. Therefore, the missing data in patient ratings are not gender-free: female physicians are more likely to receive a patient rating, which is likely to be negative and subjective. This is supported by previous research: Duberstein et al. (2007) find that patients tend to rate male physicians higher than female physicians in a short treatment period; Cecchi-Dimeglio (2017) finds that female workers are more likely to receive subjective feedback; and Tadelis (2016) summarizes previous research and shows that there are biased in online feedback systems. Although I cannot reject the hypothesis that lower relative patient ratings indicate lower quality, I also cannot rule out the possibility that patients may leave biased reviews which leads to the gender difference in ratings.

Because patient ratings are subjective and may suffer from patients' biases, I examine another rating, relative peer ratings, to check if female physicians are rated lower than males by peers. This rating is given by other physicians. Since physicians have specialized knowledge, they are believed to judge each other more objectively than patients. The results are displayed in columns 5 and 6 of Table A.9. One can see that female physicians are not rated lower than male physicians by other physicians on the platform. The gender difference in relative peer ratings is both economically and statistically insignificant. This finding suggests that female physicians are equally qualified as their male counterparts when it comes to peer ratings.

Test 2: Analysis Using Cross-Sectional Data from 2020

If we assume that lower (higher) prices indicate lower (higher) quality, then this expectation should apply to both female and male physicians, rather than solely to females. In Table A.10, I show the regression results on the gender quantity gaps after controlling for prices and other variables. If prices capture some expected unobserved quality of physicians and patients infer higher prices for higher quality, then one would expect that the estimated coefficient for prices is (at least slightly) positive. Comparing columns 2-7 with column 1, one can see that after conditioning on physicians' characteristics, an increase in prices leads to a decline in demand. So, the results do not support the idea that lower (higher) prices are associated with lower (higher) quality.

To further test if patients solely infer lower (higher) prices for lower (higher) quality from female physicians, I interact *Female* with the log of average prices in 2020 in column 8 of Table A.10. If the coefficient on the interaction term is large and statistically significant, then it does suggest that patients infer higher prices for higher quality exclusively from female physicians. The estimated coefficient for the interaction term is 0.047, which is relatively small in comparison to -0.261 on *Female* and -0.173 on *Ln(Avg. prices in 2020)*. Besides, it is statistically insignificant at conventional levels. Hence, if a female physician raises her log of price by one unit, the decrease in demand is unlikely to differ from that of a male physician increasing his price by the same amount. In other words, patients do not appear to perceive and react differently to price changes from female physicians compared to male physicians.

Table A.10: Gender Quantity Gaps (Price controlled)

	Ln(Avg. monthly consultations in 2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.168***	-0.154***	-0.144***	-0.141***	-0.139***	-0.113***	-0.104***	-0.252*
	(0.042)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)	(0.144)
Ln(Avg. prices in 2020)	0.225***	-0.083***	-0.115***	-0.113***	-0.119***	-0.154***	-0.164***	-0.179***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)
Female × Ln(Avg. prices in 2020)								0.044
								(0.041)
Share of available times		1.817***	1.819***	1.813***	1.811***	1.476***	1.459***	1.460***
		(0.095)	(0.095)	(0.095)	(0.095)	(0.094)	(0.094)	(0.094)
IIIA hospitals		0.738***	0.757***	0.775***	0.786***	0.625***	0.630***	0.629***
		(0.036)	(0.036)	(0.038)	(0.038)	(0.037)	(0.037)	(0.037)
Relative patient ratings		0.520***	0.523***	0.522***	0.524***	0.380***	0.376***	0.376***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Relative peer ratings		0.354***	0.361***	0.360***	0.360***	0.262***	0.260***	0.260***
		(0.020)	(0.020)	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)
Professional Title								
Senior			0.275***	0.272***	0.233***	0.095**	0.130***	0.129***
			(0.035)	(0.035)	(0.040)	(0.039)	(0.039)	(0.039)
Education								
Bachelor and below				0.148**	0.148**	0.137**	0.128**	0.128**
				(0.062)	(0.062)	(0.061)	(0.061)	(0.061)
Master/M.D.				0.080	0.087	0.078	0.054	0.054
				(0.063)	(0.064)	(0.062)	(0.062)	(0.062)
Years of Work Experience								
$\leq$ 10 years					-0.042	-0.042	-0.039	-0.039
					(0.048)	(0.047)	(0.047)	(0.047)
$>$ 10 years					0.079*	0.052	0.037	0.037
					(0.045)	(0.043)	(0.043)	(0.043)
Platform								
Have photo						-0.355***	-0.353***	-0.353***
						(0.049)	(0.049)	(0.049)
Displayed in the first 50						1.781***	1.771***	1.771***
						(0.055)	(0.055)	(0.055)
Latent Measure								
Promotion							0.380***	0.379***
							(0.044)	(0.044)
Entry year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.096	2.096	2.096	2.096	2.096	2.096	2.096	2.096
R^2	0.159	0.277	0.281	0.281	0.281	0.284	0.334	0.334
Observations	13,472	13,472	13,472	13,472	13,472	13,472	13,472	13,472

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. "Have photos" is a dummy equal to one if a physician has a profile photo. "Displayed in the first 50" is a dummy equal to 1 if a physician's average displayed rank is smaller than 50 within a specialty. The omitted groups of professional titles, education, and work experience are junior, unknown education degrees, and unknown years of work experience respectively. Robust standard errors are reported in parentheses. The "Control Mean" is the average for male physicians in all columns. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Test 3: Analysis Using Panel Data

In the last test, I examine whether patients, perceiving lower prices as indicative of lower quality when posted by female physicians, would consult female physicians more frequently after observing higher prices. To this end, I construct panel data using the two rounds of data collected in 2020 and 2023. Each physician who remained on the platform until 2023 is observed twice in the panel data, once in 2020 and again in 2023. As discussed in Appendix A.1, 10,146 out of 13,472 physicians stay on the platform. Among these physicians, 4,785 physicians posted a text inquiry price and the rest were unavailable for text inquiry service at the time of scraping in 2023. In the panel data, the variable "price" takes the value of the average price in 2020 if the year is 2020 and is equal to the observed text inquiry price in 2023 if the year is 2023. The variable "quantity" takes the value of the average monthly consultations in 2020 if the year is 2020 and is equal to the average monthly consultations in 2023 if the year is 2023. The number of average monthly consultations in 2023 is calculated as the difference between the total number of inquiries observed in 2023 and the total number of inquiries observed in the last instance in 2020 divided by the number of months between the two instances. For example, a physician last appeared in the 2020 data on June 30 with 1,000 consultations provided and was observed with 2000 consultations provided on February 30, 2023. Then, the number of average monthly consultations in 2023 is equal to $\frac{2000-1000}{32} = 31.25$. In the following analysis, I restricted the sample to 4,785 physicians who posted inquiry prices in both 2020 and 2023. Among them, 2,552 physicians maintained the same price as they did in 2020, while 1,791 physicians increased their prices, and 442 physicians decreased their prices.

I first check if female physicians are more or less likely than males to decrease or increase prices in 2023 compared to 2020. Table A.11 presents the number and the share of physicians who changed prices by gender. It suggests that there is no statistically significant difference in the propensity of male and female physicians to increase or decrease prices. I then check if such a tendency differs by the professional title (Table A.12). While physicians who raised their prices in 2023 tend to have more senior professional titles in 2020 on average, the distributions are largely similar across different sub-samples.

Next, I perform a regression analysis to examine whether patients, particularly in the case of female physicians, consult them more frequently after observing an increase in price. The dependent variable is the log of quantity (i.e., the average monthly consultations provided) and the results are displayed in Table A.13. In columns 1,

Table A.11: Share of Physicians who Changed Prices by Gender

	(1) Female (1,607)	(2) Male (3,178)	(3) (1)-(2)
Increased prices in 2023	586	1,205	
	(36.47%)	(37.92%)	-1.45%
Same prices	875	1,677	
	(54.45%)	(52.77%)	1.68%
Decreased prices in 2023	146	296	
	(9.09%)	(9.31%)	-0.23%

Notes: In column 3, I test the differences between male and female physicians using a t-test with equal variance. None of the differences in column 3 are statistically significant at conventional levels. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.12: Share of Physicians who Changed Prices by the Professional Title

Professional titles in 2020	(1) Increased Prices	(2) Same Prices	(3) Decreased Prices	(4) Sub-sample	(5) Sample
General physicians	39.25%	46.47%	41.40%	43.40%	46.67%
Attending physicians	41.43%	36.72%	40.72%	38.85%	37.39%
Associate chief physicians	15.41%	13.05%	14.03%	14.02%	12.64%
Chief physicians	3.91%	3.76%	3.85%	3.82%	3.30%
Total	1,791	2,552	442	4,785	13,472

Notes: Column 1 includes physicians who increased prices in 2023; column 2 includes physicians who posted the same prices as they did in 2020; column 3 includes physicians who decreased their prices in 2023; column 4 includes physicians who posted text inquiry prices in both 2020 and 2023; and column 5 includes all physicians appeared in the 2020 sample.

3, and 5, I control for the year and specialty fixed effects; in columns 2, 4, and 6, I also include physicians' characteristics such as professional titles and education. In columns 1 and 2, although the estimated coefficients for the interaction term of *Female* with 2023 are measured imprecisely, their large magnitude implies that female physicians received fewer inquiries after increasing their prices in 2023 than their male counterparts. In columns 3 and 4, among physicians who reduced their prices, there was no difference in patient demand between female and male physicians in 2023. In columns 5 and 6, I run regressions on the sub-sample of 4,785 physicians who posted text inquiry prices in both 2020 and 2023. The base group is physicians who maintained the same prices in both 2020 and 2023. On average, female physicians received a lower number of consultations compared to males in 2023. And patients tend to consult female physicians who lowered their prices more frequently compared to those who increased prices (0.175 vs. 0.026 in column 6) though the difference (0.149) is not statistically significant at conventional levels but is relatively large.

Table A.13: Gender Quantity Gaps among Physicians with Price Changes

	Increased prices		Decreased prices		Posted prices in both years	
	(1)	(2)	(3)	(4)	(5)	(6)
Female × 2023	-0.101	-0.103	-0.011	0.016	-0.142**	-0.134**
	(0.086)	(0.085)	(0.182)	(0.182)	(0.057)	(0.057)
Increased prices × 2023					-0.298***	-0.329***
					(0.056)	(0.056)
Female × Increased prices × 2023					0.041	0.026
					(0.103)	(0.103)
Decreased prices × 2023					0.364***	0.334***
					(0.102)	(0.102)
Female × Decreased prices × 2023					0.130	0.175
					(0.187)	(0.186)
Other characteristics	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.204	3.204	2.920	2.920	1.714	1.714
R^2	0.079	0.096	0.134	0.147	0.210	0.238
Observations	3,582	3,582	884	884	9,570	9,570

Notes: In columns 1 and 2, the sample is restricted to physicians who have increased prices in 2023; in columns 3 and 4, the sample is restricted to physicians who have decreased prices in 2023; in columns 5 and 6, the sample is restricted to physicians who have information on text inquiry prices in both 2020 and 2023. "2023" is a dummy variable equal to 1 if the year is 2023 and 0 if 2020. "Increased prices" is a dummy variable equal to 1 if a physician increased the price in 2023 and 0 otherwise. "Decreased prices" is a dummy variable equal to 1 if a physician decreased the price in 2023 and 0 otherwise. The omitted group is physicians who posted the same prices in 2023. "Other controls" include the type of hospitals (IIIA or not), professional titles, education, and work experience. All regressions include year and specialty fixed effects. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In summary, my findings challenge the notion that lower (or higher) prices are indicative of lower (or higher) quality, as patients do not demonstrate an increased demand for consultations from physicians who raise their prices. Furthermore, my results also cast doubt on the concern that patients associate lower prices with lower quality, particularly in the case of female physicians.

A.4.3 Results on Lower Self-Confidence

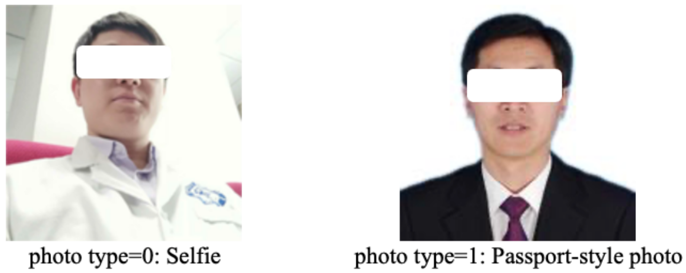


Figure A.12: Photo Type: Selfie vs. Passport-type Photo

Note: The figure gives an example of a selfie (left-hand side) and a passport-type photo (right-hand side) respectively.

Table A.14: Regression Results: Testing Self-Confidence

	Dependent Variable: Ln(Avg. prices in 2020)		
	(1)	(2)	(3)
Female	-0.031**	-0.025*	-0.029
	(0.015)	(0.015)	(0.020)
Photo type		0.063***	0.060***
		(0.013)	(0.017)
Female × Photo type			0.008
			(0.025)
Other characteristics	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes
Control Mean	3.401	3.401	3.278
R^2	0.311	0.312	0.312
Observations	11,195	11,195	11,195

Notes: Other physicians' characteristics include a physician's professional title, education, work experience, relative patient ratings, relative peer ratings, a dummy of the type of working hospital, the share of available times, and a dummy of the displayed rank in the first 50 on the list of doctors. The "Control Mean" refers to the average of male physicians with headshots in columns 1-2 and the average of male physicians with selfies in column 3. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

A.5 Results on Robustness Check

A.5.1 Sample Restrictions

Table A.15: Unexplained Gender Gaps: Spring Rain Doctor (Only Physicians with Headshots in 2020)

	(1)	(2)	(3)	(4)
Panel A. Dependent Variable: Ln(Avg. prices in 2020)				
Female	-0.049***	-0.039***	-0.033**	-0.031**
	(0.015)	(0.015)	(0.015)	(0.015)
Senior professional title		0.249***	0.147***	0.135***
		(0.013)	(0.016)	(0.016)
Years of Work Experience				
$\leq$ 10 years			-0.000	-0.000
			(0.018)	(0.018)
$>$ 10 years			0.211***	0.208***
			(0.018)	(0.018)
Platform				
Displayed in the first 50				0.138***
				(0.022)
Control Mean	3.401	3.401	3.401	3.401
R^2	0.276	0.298	0.309	0.311
Panel B. Dependent Variable: Ln(Avg. monthly consultations in 2020)				
Female	-0.159***	-0.149***	-0.147***	-0.124***
	(0.043)	(0.043)	(0.043)	(0.041)
Senior professional title		0.250***	0.218***	0.055
		(0.038)	(0.044)	(0.042)
Years of Work Experience				
$\leq$ 10 years			-0.046	-0.043
			(0.052)	(0.051)
$>$ 10 years			0.059	0.019
			(0.048)	(0.046)
Platform				
Displayed in the first 50				1.870***
				(0.058)
Control Mean	1.982	1.982	1.982	1.982
R^2	0.278	0.280	0.281	0.337
Other characteristics	Yes	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Observations	11,195	11,195	11,195	11,195

Notes: I drop physicians who did not have headshots in 2020. Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, and education. Robust standard errors are reported in parentheses. The omitted group of professional titles and work experience is the junior professional title and more than 10 years of work experience respectively. The "Control Mean" is the average for male physicians with headshots in 2020. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.16: Unexplained Gender Gaps: Spring Rain Doctor (Only Physicians with Headshots)

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Ln(Avg. prices in 2020)					
Female	-0.041***	-0.030**	-0.025*	-0.026*	-0.024*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Senior professional title		0.238***	0.142***	0.142***	0.131***
		(0.012)	(0.015)	(0.015)	(0.015)
Years of Work Experience					
$\leq$ 10 years			-0.000	-0.001	-0.001
			(0.017)	(0.017)	(0.017)
$>$ 10 years			0.201***	0.200***	0.197***
			(0.017)	(0.017)	(0.017)
Platform					
Have photo				0.106***	0.105***
				(0.018)	(0.018)
Displayed in the first 50					0.139***
					(0.021)
Control Mean	3.372	3.372	3.372	3.372	3.372
R^2	0.270	0.291	0.301	0.303	0.305
Panel B. Dependent Variable: Ln(Avg. monthly consultations in 2020)					
Female	-0.172***	-0.162***	-0.160***	-0.158***	-0.136***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)
Senior professional title		0.241***	0.217***	0.214***	0.068*
		(0.036)	(0.041)	(0.041)	(0.040)
Years of Work Experience					
$\leq$ 10 years			-0.038	-0.037	-0.039
			(0.049)	(0.049)	(0.048)
$>$ 10 years			0.044	0.050	0.014
			(0.046)	(0.046)	(0.044)
Platform					
Have photo				-0.394***	-0.415***
				(0.057)	(0.056)
Displayed in the first 50					1.766***
					(0.056)
Control Mean	2.087	2.087	2.087	2.087	2.087
R^2	0.278	0.281	0.281	0.284	0.331
Other characteristics	Yes	Yes	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Observations	12,858	12,858	12,858	12,858	12,858

Notes: I drop physicians without profile photos. Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, and education. The omitted group of professional titles and work experience is the junior professional title and unknown years of work experience respectively. The "Control Mean" is the average for male physicians with headshots in 2020 or 2023. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

A.5.2 Placebo Test: Neutral Name

Table A.17: Unexplained Gender Gaps: Spring Rain Doctor (Include Variable *Neutral Name*)

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Ln(Avg. prices in 2020)					
Female	-0.037***	-0.029**	-0.024*	-0.025*	-0.023*
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Neutral name	0.016	0.019	0.022	0.020	0.019
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Senior professional title		0.237***	0.140***	0.140***	0.129***
		(0.012)	(0.014)	(0.014)	(0.014)
Years of Work Experience					
$\leq$ 10 years			0.002	0.001	0.001
			(0.016)	(0.016)	(0.016)
> 10 years			0.204***	0.201***	0.197***
			(0.016)	(0.016)	(0.016)
Platform					
Have photo				0.110***	0.108***
				(0.016)	(0.016)
Displayed in the first 50					0.148***
					(0.020)
Control Mean	3.362	3.362	3.362	3.362	3.362
R^2	0.269	0.289	0.300	0.302	0.305
Panel B. Dependent Variable: Ln(Avg. monthly consultations in 2020)					
Female	-0.147***	-0.138***	-0.137***	-0.132***	-0.110***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)
Neutral name	0.008	0.011	0.012	0.016	-0.000
	(0.061)	(0.061)	(0.061)	(0.061)	(0.058)
Senior professional title		0.246***	0.216***	0.214***	0.075*
		(0.035)	(0.040)	(0.040)	(0.039)
Years of Work Experience					
$\leq$ 10 years			-0.042	-0.039	-0.042
			(0.048)	(0.048)	(0.047)
> 10 years			0.055	0.065^{+}	0.021
			(0.045)	(0.045)	(0.043)
Platform					
Have photo				-0.350***	-0.372***
				(0.050)	(0.049)
Displayed in the first 50					1.758***
					(0.056)
Control Mean	2.096	2.096	2.096	2.096	2.096
R^2	0.277	0.280	0.280	0.283	0.328
Other characteristics	Yes	Yes	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Observations	13,472	13,472	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, log of past average monthly consultations provided, and education. The omitted group of professional titles and work experience is the junior professional title and unknown years of work experience respectively. The "Control Mean" refers to the average for male physicians in all columns. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Additionally, I examine the differential impacts of neutral names by work experience and by professional titles on consultations provided. I extend equations (A.3) and (A.5) by incorporating *Neutral name*, along with its interaction terms with work experience and professional titles. The results are presented in Table A.18. Comparing columns 2 and 4 with columns 1 and 3 respectively, one can see that the inclusion of the variable *Neutral name* and its interaction terms does not affect the magnitude or significance of the coefficients on $Female$ and its interaction terms. Furthermore, these additions do not have a statistically significant impact on the number of average monthly consultations provided. Hence, these findings further corroborate that profile photos and gender-specific names facilitate discrimination.

Table A.18: Results on Implication 1 & 2 (Include Variable *Neutral Name*)

	Ln(Avg. monthly consultations in 2020)			
	(1)	(2)	(3)	(4)
Female	-0.171***	-0.170***	-0.204***	-0.204***
	(0.054)	(0.054)	(0.051)	(0.051)
Neutral name	0.003	-0.016	0.002	-0.012
	(0.058)	(0.086)	(0.058)	(0.083)
Female × ≤ 10 years	-0.099	-0.101		
	(0.096)	(0.097)		
Female × > 10 years	0.185**	0.185**		
	(0.072)	(0.072)		
Neutral name × ≤ 10 years		0.041		
		(0.170)		
Neutral name × > 10 years		0.030		
		(0.126)		
Female × Senior professional title			0.184***	0.184***
			(0.066)	(0.066)
Neutral name × Senior professional title				0.027
				(0.116)
Other characteristics	Yes	Yes	Yes	Yes
Entry Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Control Mean	2.096	2.085	1.962	1.953
R^2	0.329	0.329	0.329	0.329
Observations	13,472	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, years of work experience, education, professional title, a dummy of profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group of professional titles and work experience is the junior professional title (columns 3 and 4) and unknown years of work experience (columns 1 and 2) respectively. The "Control Mean" refers to the average for male physicians with unknown years of work experience in column 1, the average for male physicians with neutral names and unknown years of work experience in column 2, the average for male physicians with junior professional titles in column 3, and the average for male physicians with neutral names and junior professional titles in column 4. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

A.5.3 External Validity: ***WeDoctor***

In this section, I examine the external validity of the results on another online healthcare platform, *WeDoctor*. *WeDoctor* is also one of the most popular online healthcare platforms in China. I crawled data 24 times between October 15, 2020, and January 17, 2021. I have 30,042 unique physicians who have posted prices in the analysis sample.[12] *WeDoctor* differs from SRD in five ways: 1) it does not display information about when a physician joined the platform; 2) a posted price does not mean availability;[13] 3) at the time of crawling, the platform provided a variety of services, including a text inquiry service, a video inquiry service, a family doctor package, and an expert team service (the total number of services provided is a sum of all the kinds of service a physician has provided); 4) patients can sort[14] and filter[15] physicians by specific characteristics;[16] and 5) even if a physician does not upload a headshot, the picture (Figure A.13) used by the platform reveals the physician's gender. Given these five differences, I focus on the gender price gap and do not take into account the share of available times and whether a physician has a profile photo. In the regressions, I still control for physicians' displayed ranks (by default sorting) because it serves as a reference for the positions of female physicians in the search results.

I summarize descriptive statistics of *WeDoctor* in Table A.19. Compared to SRD, there are more *WeDoctor* physicians who work at tier III hospitals and fewer of them report information about education (Table A.21). In contrast to SRD physicians, nearly half of whom are general physicians, most (90%) physicians on *WeDoctor* are at least attending physicians. On average, the price of text inquiry services set by physicians on *WeDoctor* is about twice as high as the price set by physicians on the SRD. I estimate equation (1.1) on the *WeDoctor* sample. Table A.20 displays the estimate of the unexplained gender price gap.

The raw gender price gap controlling the specialty and province fixed effect is 3.84% (p = 0.00) between male and female physicians. The gap decreases to 1.96% (p =

[12] The data collection and construction process of *WeDoctor* are similar to SRD.

[13] A price is posted if a physician has registered for that service. It does not guarantee that the physician is available to provide consultation service.

[14] For example, patients can sort physicians by prices or by response rate.

[15] For example, patients can select only looking at physicians working at an IIIA hospital or physicians with a senior professional title.

[16] Sorting and filtering can be done on the website, app, and WeChat. But, patients can not sort or filter physicians by professional title or prices on the SRD's website or its mini-program on WeChat.

Figure A.13: *WeDoctor*: Profile Pictures

Note: The two profile pictures displayed above are pictures that the platform assigns to physicians who do not upload a headshot. The picture on the left-hand side indicates that the physician is a male and the picture on the right-hand side means that the physician is a female.

Table A.19: Descriptive Statistics: *WeDoctor*

	Male	Female	Diff. (Male-Female)	S.E.	Obs.
Avg. prices	44.170	41.190	2.980***	(0.520)	30,042
IIIA hospitals	0.817	0.799	0.018***	(0.005)	30,042
Relative patient rating	0.005	0.019	-0.014	(0.009)	30,042
Displayed in the first 50	0.117	0.118	-0.000	(0.004)	30,042
Professional titles					
Junior	0.095	0.116	-0.021***	(0.004)	30,042
Senior	0.905	0.884	0.021***	(0.004)	30,042
Education					
Not known degree	0.382	0.470	-0.087***	(0.006)	30,042
Bachelor and below	0.191	0.177	0.015***	(0.005)	30,042
Master/M.D.	0.427	0.354	0.073***	(0.006)	30,042
Years of work experience					
Not known years	0.364	0.449	-0.086***	(0.006)	30,042
$\leq$ 10 years	0.074	0.077	-0.003	(0.003)	30,042
$>$ 10 years	0.562	0.473	0.088***	(0.006)	30,042

Notes: The junior professional title includes general physicians and the senior professional title includes attending physicians, associate chief physicians, and chief physicians. In the last column, I test the differences between male and female physicians using a t-test with equal variance. * is $p < 0.1$ ** is $p < 0.05$ and *** is $p < 0.01$.

0.02) after adding relative patient ratings, a dummy of the type of working hospitals, professional titles, education, work experience, and a dummy of the displayed rank at the top. The log of past average monthly services is not controlled since *WeDoctor* does not display information about a physician's join time. Like the results in SRD, a senior professional title, an advanced education degree, and long years of work experience positively affect prices. The unexplained gender price gap in *WeDoctor* stands at 1.96%, which is smaller than the 3.94% gap observed in SRD when controlling for the same set of variables. However, it remains statistically significant at a 5% level. Thus, gender gaps do not exist only in one healthcare platform, instead, are widely spread in the gig economy.

Table A.20: Gender Price Gaps: *WeDoctor*

	Ln(Avg. prices)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8: SRD)
Female	-0.038***	-0.037***	-0.046***	-0.034***	-0.030***	-0.023***	-0.020**	-0.039***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.014)
Relative patient rating		Yes	Yes	Yes	Yes	Yes	Yes	Yes
IIIA hospital			Yes	Yes	Yes	Yes	Yes	Yes
Professional titles				Yes	Yes	Yes	Yes	Yes
Education					Yes	Yes	Yes	Yes
Work experience						Yes	Yes	Yes
Displayed in the first 50							Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.271	0.289	0.319	0.362	0.369	0.391	0.396	0.244
Observations	30,042	30,042	30,042	30,042	30,042	30,042	30,042	13,472

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. Professional titles, education, and work experience are categorical variables. The omitted groups of professional titles, education, and work experience are junior, unknown education degrees, and more than 10 years of work experience, respectively. Displayed in the first 50 is a dummy equal to 1 if a physician's average displayed rank is smaller than 50. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

A.6 Additional Tables

Table A.21: Physician Characteristics: SRD & *WeDoctor* vs. 2020 National Statistics

	(1) SRD	(2) National	(3) *WeDoctor*
Observations	13,472	3,401,672	30,042
Share of female physicians	38.39%	47.30%	39.20%
Education			
Unknown	8.25%	0.00%	41.68%
Junior college and below	1.46%	32.10%	0.72%
Bachelor	45.92%	51.60%	17.81%
Master and above	44.37%	16.30%	39.79%
Professional title			
General physicians	46.67%	47.60%	10.35%
Attending physicians	37.79%	31.20%	37.07%
Associate chief physicians	12.64%	15.20%	31.86%
Chief physicians	3.30%	6.00%	20.72%
Work experience			
Unknown	39.66%	0.00%	39.75%
Less than 10 years	16.32%	35.00%	7.55%
10∼20 years	31.52%	24.00%	30.67%
Over 20 years	12.50%	41.00%	22.03%
Tier of working hospitals			
Tier III	65.52%	56.25%	87.27%
Tier II	33.02%	36.56%	10.54%
Tier I	1.46%	7.19%	2.20%

Notes: The national statistics are from the *2021 China Health Statistical Yearbook*.

Table A.22: Definition of Variables

Variable Name	Definition
Individual Characteristics	
Female	A dummy variable equal to 1 if a physician is female and 0 otherwise.
Junior professional title	A dummy variable equal to 1 if a physician is a general physician and 0 otherwise.

Table A.22 continued from previous page

Variable Name	Definition
Senior professional title	A dummy variable equal to 1 if a physician is an attending physician, an associate chief physician, or a chief physician and 0 otherwise.
IIIA hospital	A dummy variable equal to 1 if the hospital is classified as the highest-class hospital and 0 otherwise.
Not known degree	A dummy variable if a physician does not provide information on his/her education degree and 0 otherwise.
Bachelor and below	A dummy variable if a physician has a bachelor's degree or below and 0 otherwise.
Master/M.D.	A dummy variable if a physician has a master's degree or an M.D. and 0 otherwise.
Not known years	A dummy variable if a physician does not provide information on his/her years of work experience and 0 otherwise.
$\leq$ 10 years	A dummy variable if a physician has less than or equal to 10 years of work experience and 0 otherwise.
$>$ 10 years	A dummy variable if a physician has more than 10 years of work experience and 0 otherwise.
Promotion	A dummy variable equal to 1 if a physician has either been promoted to a more senior professional title (e.g., from attending physician to associate chief physician) or gone to a higher rank hospital (e.g., from an IIB hospital to an IIIC hospital) by 2023 and 0 otherwise.
Individual Features on the Platform	
Entry year	The year when a physician joined the Spring Rain Doctor platform.
Available times	The number of available times is the number of times a physician appears in the 2020 data with a price. For example, a physician may appear in the data 20 times, but only list a price in 18 instances. Then, the number of available times is 18.
Share of available times	The share of available times is the number of available times in 2020 divided by the number of times a physician has appeared in the 2020 data.

Table A.22 continued from previous page

Variable Name	Definition
Average prices (¥)	The average price is the sum of a physician's listed prices observed in the 2020 data divided by available times in 2020. For example, a physician appears in the data 10 times with 3 times having a price. The three listed prices are 7, 7, and 10. Then, the average price for this physician is $\frac{7+7+10}{3} = 8$. I take the inverse hyperbolic transformation of average price. The data contains no zero values for prices.
Average monthly consultations	The average monthly consultations is the difference between the total number of inquiries observed in the last instance in 2020 and in the first instance in 2020 divided by the number of months between the two instances. For example, a physician first appeared in the data on April 14, 2020, with 1,000 consultations provided and last appeared in the data on June 14, 2020, with 1,2000 consultations provided. Then, the number of average monthly consultations is $\frac{1200-1000}{2} = 100$. I take the inverse hyperbolic transformation of average monthly consultations to include physicians with zero monthly consultations.
Past consultations	The number of past consultations is the total number of consultations a physician has provided observed in his/her first instance in the 2020 data. For example, a physician first appeared in the data on April 14, 2020, with 1,000 consultations, then the number of past consultations for this physician is 1,000. I take the inverse hyperbolic transformation of past consultations provided to include physicians with zero past consultations.
Average patient rating	The average patient rating is the sum of patient ratings divided by the total number of times a physician appeared in the 2020 data. For example, a physician appeared in the data 3 times and his/her observed patient ratings were 95, 94, and 96. Then, the average patient rating for this physician is $\frac{95+94+96}{3} = 95$.
Relative patient rating	The equation to calculate the relative patient rating is defined as $\frac{R-\bar{R}_s}{Var(R)_s}$ where R is a physician's average patient rating, $\bar{R}_s$ is the mean of the average patient ratings in specialty s, and $Var(R)_s$ is the variance of physicians' average patient ratings in specialty s.

Table A.22 continued from previous page

Variable Name	Definition
Relative peer rating	The equation to calculate the relative peer rating is defined as $\frac{R_p - \bar{R}_{p,s}}{Var(R)_{p,s}}$ where R_p is a physician's average peer rating, $\bar{R}_{p,s}$ is the mean of the average peer ratings in specialty s, and $Var(R)_{p,s}$ is the variance of physicians' average peer ratings in specialty s.
Variables on the Platform Design	
Have photo	A dummy variable equal to 1 if a physician has a profile photo in the 2020 data and 0 otherwise.
Average default ranking	A physician's average default ranking is the sum of his/her rankings in all instances in 2020 divided by the number of instances. For example, a physician appeared in the 2020 data four times. S/he ranked 15th, 20th, 18th, and 14th in the four instances. Then, the average displayed rank is equal to $\frac{15+20+18+14}{4} = 16.75$.
Displayed in the first 50	A dummy variable equal to 1 if a physician's average displayed rank in 2020 is less than 50 and 0 otherwise.
First-week average ranking	This variable is only for 992 physicians who joined the platform between March 25 and June 30, 2020. It represents the physician's average ranking in the first week after joining the platform. Physicians who did not appear in the data during their first week on the SRD are assigned a value of 601. The results in panel B of Table 1.5 remain robust when a value of 650 or 700 is assigned to these physicians.

Table A.23: Gender Price Gaps: Spring Rain Doctor

	Ln(Avg. prices in 2020)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.036**	-0.033**	-0.024*	-0.028**	-0.023*	-0.024*	-0.023*
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Share of available times	0.135***	0.201***	0.197***	0.204***	0.195***	0.200***	0.173***
	(0.050)	(0.049)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
IIIA hospitals		0.334***	0.341***	0.312***	0.336***	0.334***	0.320***
		(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Relative patient ratings		0.076***	0.077***	0.077***	0.080***	0.078***	0.065***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Relative peer ratings		0.102***	0.105***	0.105***	0.102***	0.100***	0.091***
		(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Professional Title							
Senior			0.237***	0.237***	0.140***	0.140***	0.129***
			(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Education							
Bachelor and below				-0.049**	-0.052**	-0.051**	-0.052**
				(0.022)	(0.021)	(0.021)	(0.021)
Master/M.D.				0.036^{+}	0.053**	0.053**	0.052**
				(0.023)	(0.023)	(0.023)	(0.023)
Years of Work Experience							
$\leq$ 10 years					0.002	0.001	0.001
					(0.016)	(0.016)	(0.016)
$>$ 10 years					0.204***	0.201***	0.197***
					(0.016)	(0.016)	(0.016)
Platform							
Have photo						0.110***	0.109***
						(0.016)	(0.016)
Displayed in the first 50							0.149***
							(0.020)
Entry year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.362	3.362	3.362	3.362	3.362	3.362	3.362
R^2	0.193	0.267	0.287	0.289	0.300	0.302	0.305
Observations	13,472	13,472	13,472	13,472	13,472	13,472	13,472

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. "Have photos" is a dummy equal to one if a physician has a profile photo. "Displayed in the first 50" is a dummy equal to 1 if a physician's average displayed rank is smaller than 50 within a specialty. The omitted groups of professional titles, education, and work experience are junior, unknown education degrees, and unknown years of work experience respectively. The "Control Mean" refers to the average for male physicians in all columns. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.24: Gender Quantity Gaps: Spring Rain Doctor (Price & Past Consultations Not Controlled)

	Ln(Avg. monthly consultations in 2020)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.182***	-0.151***	-0.142***	-0.138***	-0.136***	-0.132***	-0.110***
	(0.042)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)
Share of available times	1.682***	1.800***	1.796***	1.790***	1.787***	1.769***	1.449***
	(0.091)	(0.096)	(0.096)	(0.096)	(0.096)	(0.095)	(0.094)
IIIA hospitals		0.710***	0.717***	0.740***	0.746***	0.751***	0.576***
		(0.035)	(0.035)	(0.037)	(0.038)	(0.037)	(0.037)
Relative patient ratings		0.514***	0.515***	0.513***	0.514***	0.521***	0.370***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Relative peer ratings		0.346***	0.349***	0.349***	0.348***	0.355***	0.248***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)
Professional Title							
Senior			0.247***	0.246***	0.216***	0.214***	0.075*
			(0.035)	(0.035)	(0.040)	(0.040)	(0.039)
Education							
Bachelor and below				0.153**	0.154**	0.151**	0.145**
				(0.062)	(0.062)	(0.063)	(0.061)
Master/M.D.				0.076	0.081	0.080	0.070
				(0.064)	(0.064)	(0.064)	(0.062)
Years of Work Experience							
$\leq$ 10 years					-0.042	-0.039	-0.042
					(0.048)	(0.048)	(0.047)
$>$ 10 years					0.055	0.065+	0.021
					(0.045)	(0.045)	(0.043)
Platform							
Have photo						-0.350***	-0.372***
						(0.050)	(0.049)
Displayed in the first 50							1.758***
							(0.056)
Entry year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.096	2.096	2.096	2.096	2.096	2.096	2.096
R^2	0.164	0.277	0.280	0.280	0.280	0.283	0.328
Observations	13,472	13,472	13,472	13,472	13,472	13,472	13,472

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. "Have photos" is a dummy equal to one if a physician has a profile photo. "Displayed in the first 50" is a dummy equal to 1 if a physician's average displayed rank is smaller than 50 within a specialty. The omitted groups of professional titles, education, and work experience are junior, unknown education degrees, and unknown years of work experience respectively. The "Control Mean" is the average for male physicians in all columns. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.25: Gender Quantity Gaps (Price & Total Past Consultations controlled)

	Ln(Avg. monthly consultations in 2020)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.174***	-0.151***	-0.139***	-0.136***	-0.137***	-0.131***	-0.116***
	(0.042)	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Ln(Avg. prices in 2020)	0.217***	-0.277***	-0.322***	-0.320***	-0.318***	-0.306***	-0.316***
	(0.025)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)
Share of available times	1.653***	1.811***	1.814***	1.809***	1.810***	1.782***	1.565***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.091)
IIIA hospitals		0.746***	0.771***	0.787***	0.780***	0.781***	0.670***
		(0.033)	(0.033)	(0.035)	(0.036)	(0.035)	(0.035)
Relative patient ratings		0.445***	0.448***	0.447***	0.447***	0.453***	0.358***
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Relative peer ratings		-0.079***	-0.076***	-0.076***	-0.076***	-0.076***	-0.098***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Ln(Past consultations)		0.428***	0.434***	0.434***	0.434***	0.441***	0.392***
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Professional Title							
Senior			0.359***	0.357***	0.374***	0.372***	0.263***
			(0.033)	(0.033)	(0.038)	(0.037)	(0.037)
Education							
Bachelor and below				0.110*	0.114**	0.109*	0.108*
				(0.058)	(0.058)	(0.058)	(0.057)
Master/M.D.				0.054	0.052	0.049	0.048
				(0.059)	(0.059)	(0.059)	(0.058)
Years of Work Experience							
$\leq$ 10 years					-0.075*	-0.070^{+}	-0.069^{+}
					(0.045)	(0.045)	(0.045)
$>$ 10 years					-0.049	-0.041	-0.051
					(0.042)	(0.042)	(0.041)
Platform							
Have photo						-0.476***	-0.472***
						(0.049)	(0.048)
Displayed in the first 50							1.236***
							(0.054)
Entry year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.096	2.096	2.096	2.096	2.096	2.096	2.096
R^2	0.169	0.372	0.377	0.377	0.378	0.383	0.404
Observations	13,472	13,472	13,472	13,472	13,472	13,472	13,472

Notes: "IIIA hospital" is a dummy equal to 1 if a physician is working at a tier III grade A hospital. "Have photos" is a dummy equal to one if a physician has a profile photo. "Displayed in the first 50" is a dummy equal to 1 if a physician's average displayed rank is smaller than 50 within a specialty. The omitted groups of professional titles, education, and work experience are junior, unknown education degrees, and unknown years of work experience respectively. The "Control Mean" is the average for male physicians in all columns. Robust standard errors are reported in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.26: Gender Gaps after Adjusting Latent Measure of Physician Quality (Exclude Exited Physicians in 2023)

	Ln(Avg. prices in 2020)		Ln(Avg. monthly services in 2020)	
	(1)	(2)	(3)	(4)
Female	-0.016	-0.013	-0.189***	-0.175***
	(0.015)	(0.015)	(0.044)	(0.044)
Promotion		0.078***		0.364***
		(0.016)		(0.046)
Other characteristics	Yes	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Control Mean	3.361	3.361	2.135	2.135
R^2	0.306	0.308	0.345	0.349
Observations	10,145	10,145	10,145	10,145

Notes: I restrict the sample to physicians who are still using the platform in 2023. Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, years of work experience, education, professional title, a dummy of the physician's profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group is physicians with a junior professional title, general physicians. The "Control Mean" refers to the average for male physicians in columns 1, 2, 4, and 5, and the average for male physicians who were not promoted by 2023 in columns 3 and 6. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.27: Gender Quantity Gaps after Adjusting A Latent Measure of Physician Quality

	Ln(Avg. monthly services in 2020)				
	(1)	(2)	(3)	(4)	(5)
Female	-0.110***	-0.101***	-0.107***	-0.099***	-0.099**
	(0.038)	(0.038)	(0.040)	(0.038)	(0.040)
Promotion		0.366***	0.352***		
		(0.044)	(0.053)		
Female × Promotion			0.040		
			(0.092)		
Promotion (Exclude)				0.375***	0.373***
				(0.047)	(0.056)
Female × Promotion (Exclude)					0.003
					(0.099)
Other characteristics	Yes	Yes	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Control Mean	2.096	2.096	2.010	2.026	2.026
R^2	0.328	0.332	0.332	0.332	0.332
Observations	13,472	13,472	13,472	13,472	13,472

Notes: Other characteristics include a physician's share of availability, type of working hospital, relative patient ratings, relative peer ratings, years of work experience, education, professional title, a dummy of the physician's profile photo, and a dummy of the displayed rank in the first 50 on the list of doctors. All regressions include the entry year, province, and specialty fixed effects. The omitted group is physicians with a junior professional title, general physicians. The "Control Mean" refers to the average for male physicians in columns 1, 2, and 4, and the average for male physicians who were not promoted by 2023 in columns 3 and 5. Robust standard errors are in parentheses. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table A.28: Impacts of Profile Photos on Gender Quantity Gaps (Physicians with Neutral Names)

	Ln(Avg. monthly consultations in 2020)		
	(1)	(2)	(3)
Female	-0.053	-0.060	-0.180
	(0.353)	(0.351)	(0.351)
Female × Have photo	-0.179	-0.156	-0.047
	(0.377)	(0.376)	(0.372)
Specialty FE	Yes	Yes	Yes
Entry year FE	No	Yes	Yes
Province FE	No	No	Yes
Control Mean	2.653	2.653	2.653
R^2	0.123	0.165	0.196
Observations	1,044	1,044	1,044

Notes: I restrict the sample to physicians who have neutral names. The "Control Mean" refers to the average for male physicians who have neutral names and do not have a profile photo. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$..

Table A.29: Contributions to the Gender Ranking Gaps

	Raw	Unexplained	Explained	Contribution			
				Professional Title	Hospital Class	Availability	Quantity
Ranking gap	11.194	3.531	7.663	2.065	-0.551	-0.026	6.175
				(26.95%)	(-7.19%)	(-0.33%)	(80.58%)
		[31.54%]	[68.45%]	[18.45%]	[-4.93%]	[-0.23%]	[55.16%]

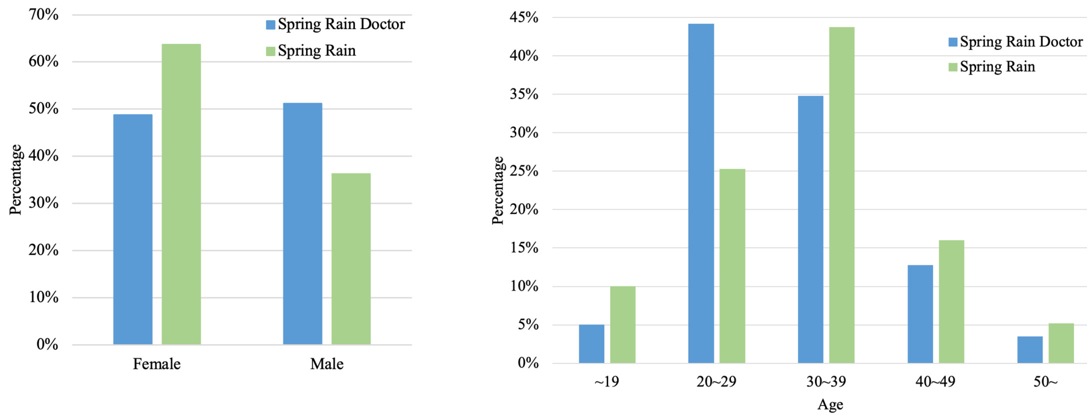
Notes: The explained part of the gender ranking gap is the difference between the raw gender gap and the unexplained part of the gender gap. I calculate the contributions (as a percentage) of the three factors to the explained part of the gender ranking gap in the round brackets and the contributions to the raw gender ranking gap in the square brackets.

Table A.30: Correlation Coefficients of Default Rankings in 2020 and 2023

		Default ranking in 2023				
		[1, 50]	[51, 100]	[101, 150]	[151, 200]	> 200
Average default ranking in 2020	[1, 50]	**0.4795**	0.0885	-0.0437	-0.0542	**-0.3266**
	[51, 100]	0.0758	0.2589	0.0721	-0.0223	-0.2414
	[101, 150]	-0.0561	0.0578	0.2000	0.0615	-0.1423
	[151, 200]	-0.0764	-0.0415	0.0498	0.1443	-0.0275
	> 200	**-0.2897**	-0.2490	-0.1835	-0.0804	**0.4971**

Notes: The variables are dummy variables. For example, "Average default ranking in 2020 $\in [1, 50]$" is equal to one if the average default ranking is less than 50, and "Default ranking in 2023 $\in [51, 100]$" is equal to one if a physician's default ranking is larger than 51 and less than 100.

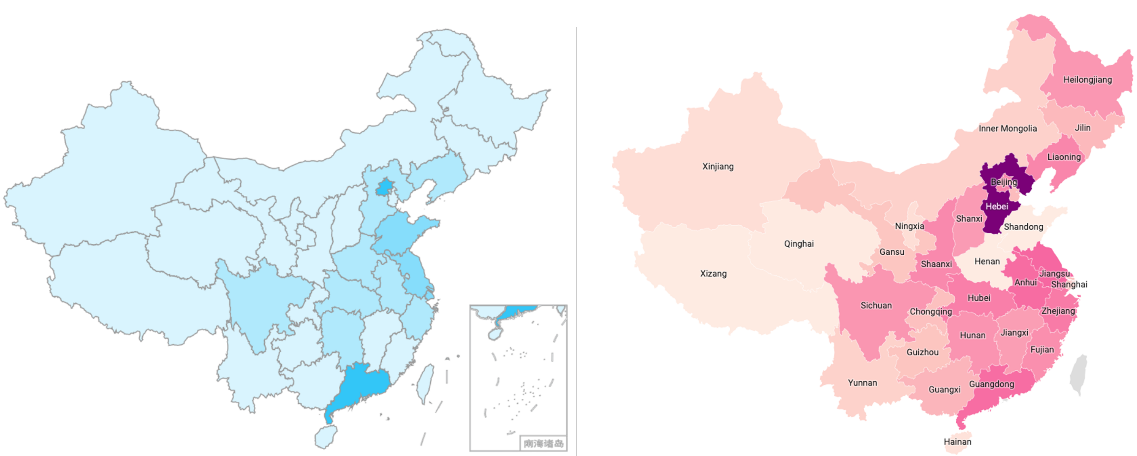
A.7 Additional Figures



(a) Gender (b) Age

Notes: Data is from the Baidu Index and was accessed in January 2021. I use two keywords to capture the user population during the study period, "Spring Rain" (*chun yu*) and "Spring Rain Doctor" (*chun yu yi sheng*).

Figure A.14: Age & Gender Distribution of the User Population



(a) Demand (b) Supply

Notes: Figure A.15a is a screenshot of the Baidu Index in January 2023, which displays the spatial distribution of users during the study period (March-June 2020). I use one keyword to capture the user population, "Spring Rain Doctor" (*chun yu yi sheng*). The deeper the color, the more people have searched for the keyword. Figure A.15b is the spatial distribution of the analysis sample of physicians (13,472 physicians). The deeper the color, the more physicians were on the SRD platform.

Figure A.15: Spatial Distributions of Demand & Supply

Figure A.16: A Physician's Homepage in April 2020

Note: The screenshots in Figure A.16 exhibit a physician's homepage on the WeChat mini-program, captured in April 2020.

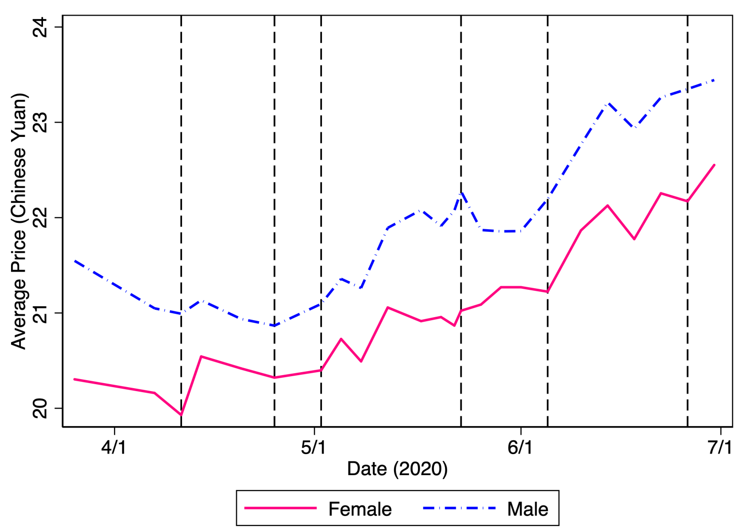


Figure A.17: Average Prices of Physicians who Have Changed Prices

Note: I plot the average prices by gender for physicians who have ever changed prices in 2020 in the figure. The black dashed lines represent weekend dates. The dash-dotted blue line represents male physicians, while the solid pink line represents female physicians.

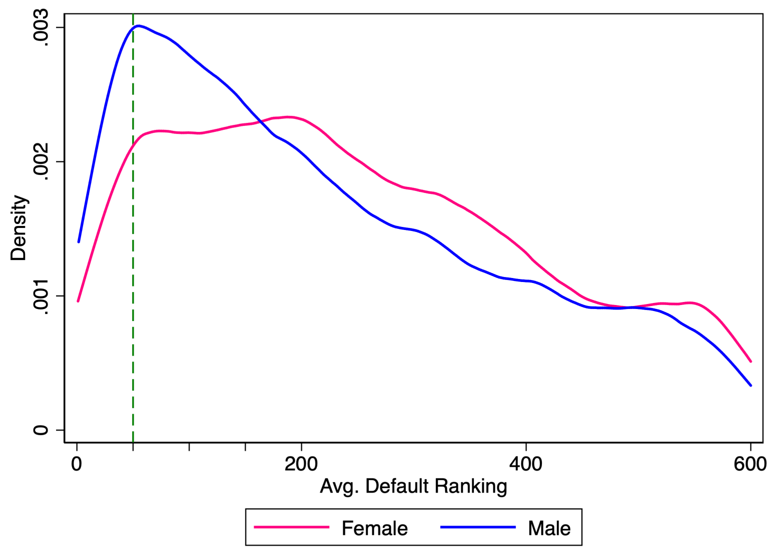


Figure A.18: Distribution of Average Default Ranking by Gender in 2020

Note: The figure plots the distributions of physicians' average default ranking in 2020 by gender. The blue line represents male physicians and the pink line represents female physicians. The green dashed line denotes the rank of 50.

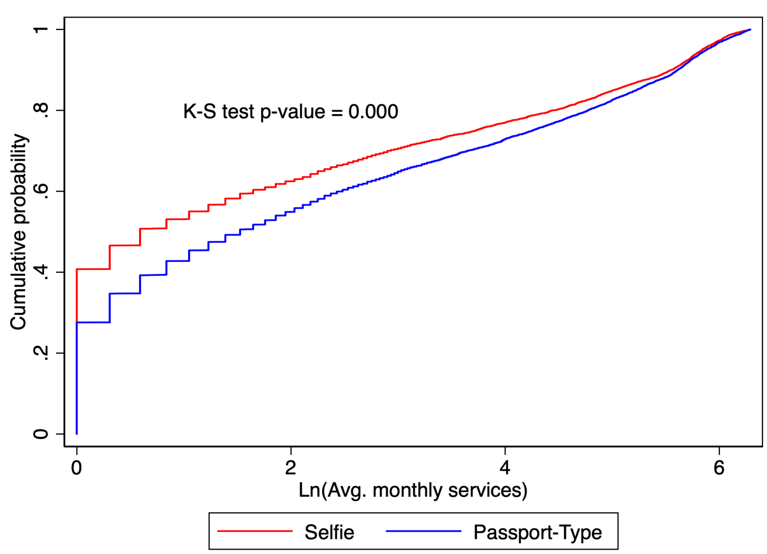


Figure A.19: CDF of Quantity: Selfie vs. Passport-type Photo

Note: I plot the cumulative distribution function of the log of average monthly services provided by the type of a physician's photo. The red line is for physicians who use selfies and the blue line is for physicians who use passport-type photos. The Kolmogorov-Smirnov test p-value is also displayed in the graph.

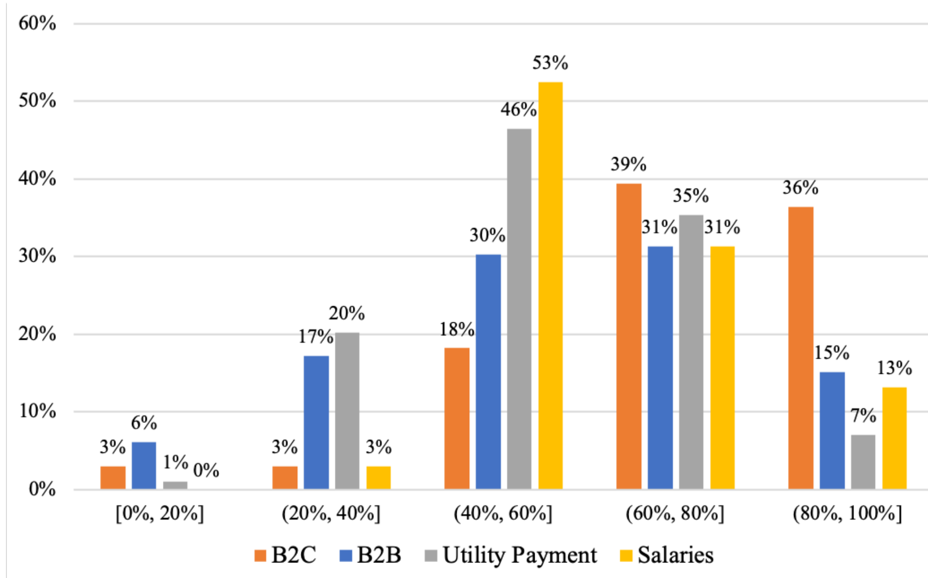
Appendix B

Digitalization as a Double-Edged Sword: Winning Services and Losing Manufacturing in India

B.1 The Prevalence of Cash Transactions in India in 2015

The cash crunch caused by the 2016 demonetization policy could only prompt individuals and firms to shift to digital platforms if they had not already extensively used digital payment methods and relied heavily on cash for transactions before 2016. To investigate this and gain some insights, I surveyed 99 Indian firms between October 19 and November 3, 2023, regarding their cash usage in transactions in 2015. The 99 firms consist of 42 manufacturing and 57 service firms and are located in Delhi, Haryana, Punjab, Rajasthan, and Uttar Pradesh. Of the firms surveyed, 54% have more than 10 employees, and among them, 20% have more than 50 employees.

I asked firms, "What was the share of transactions made via cash in the category of [X] in 2015?" Firms could select from the following options: less than 20%, 21%-40%, 41%-60%, 61%-80%, and 81%-100%. In Figure B.1, I present a breakdown of the reliance on cash payments across four transaction types: transactions with individual consumers (B2C), transactions with other businesses (B2B), utility payments, and salaries. As shown, 75% of firms reported more than 60% of their consumer transactions were cash-based and 76% of firms indicated that over 40% of their business-to-business dealings were executed with cash. When it comes to utility payments, 88% of firms said that over 40% were paid in cash. Lastly, a significant 97% of firms paid over 40% of their salaries in cash. These statistics underscore the important role of cash in various kinds of transactions in 2015.

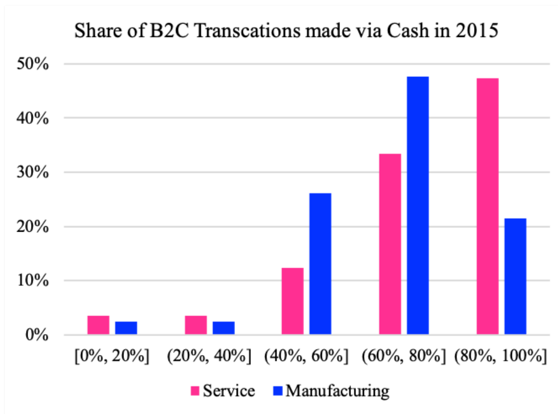


Notes: The y-axis represents the portion of firms, while the x-axis represents the share of transactions in a specific category conducted in cash during 2015. This figure illustrates the distribution of firms' cash transaction extent.

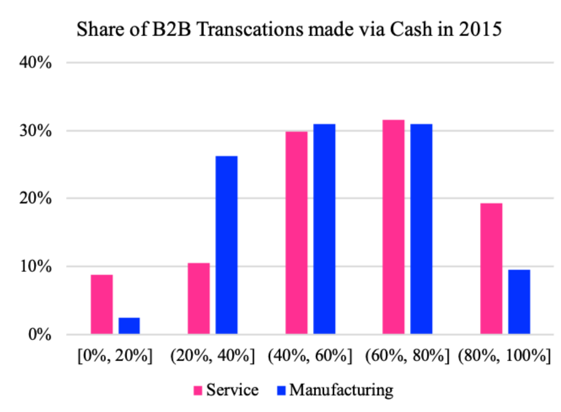
Figure B.1: Share of Transactions Made via Cash in 2015

I then investigate the patterns by sector, specifically examining B2C and B2B transactions. Figure B.2 displays the distributions. One can see that service firms had a higher proportion of B2C transactions made in cash compared to manufacturing firms. 51% of service firms indicated that more than 60% of their consumer transactions were cash-based, as opposed to 41% of manufacturing firms that reported the same. Regarding B2B transactions, the distribution of service and manufacturing firms are broadly comparable. Nearly half of both service and manufacturing firms used cash as their primary method for transactions with other firms in 2015.

In the survey, I also inquired whether firms utilized digital payment methods, such as Paytm, UPI, and NetBanking, in 2015, along with the primary purposes for these transactions. 41% of firms reported not using any digital payment methods that year. Manufacturing firms were more likely to use them compared to service firms, with 71% of manufacturing firms using digital payment methods in 2015, as opposed to 51% of service firms. Regarding the main purpose, 51% of firms selected B2B transactions and only 31% of firms chose B2C transactions. These statistics suggest that manufacturing firms might be less directly affected by cash shortages than service firms, given their lower direct engagement with individual consumers and the fact



(a) B2C Transactions via Cash



(b) B2B Transactions via Cash

Notes: The y-axis represents the portion of firms. The x-axis represents the share of cash transactions in 2015 for B2C and B2B in Figure B.2a and Figure B.2b respectively. The pink bars represent service firms and the blue bars represent manufacturing firms.

Figure B.2: Share of Cash Transactions by Sector

that a considerable proportion had already adopted digital payment methods for transactions.

Additionally, I compare the transaction methods used by firms in more e-Ready districts with those in less e-Ready districts. As shown in Table B.1, there was no statistically significant difference in the likelihood of using paperless payment methods in 2015 between firms in more e-Ready districts and those in less e-Ready districts. However, firms in more e-Ready districts did have a lower average share of both B2C and B2B transactions made via cash compared to those in less e-Ready districts. It should be noted, though, that for firms in more e-Ready districts, over 40% of both B2C and B2B transactions were still conducted in cash on average, indicating that firms extensively used cash across all districts.

In short, this small-sample survey provides insights into the prevalence of cash transactions among firms before the 2016 demonetization policy.

Table B.1: Comparison of Transactions Methods by e-Readiness Index

	(1) Less e-Ready		(2) More e-Ready		t-test Difference
Variable	Obs.	Mean/SD	Obs.	Mean/SD	(1)-(2)/SE
Use digital payment	51	0.57	48	0.63	-0.06
		(0.50)		(0.49)	(0.10)
B2C Transactions	51	4.20	48	3.85	0.34*
		(0.87)		(1.05)	(0.19)
B2B Transactions	51	3.55	48	3.08	0.47**
		(0.97)		(1.22)	(0.22)

Notes: Both "B2C Transactions" and "B2B Transactions" are categorical variables. They are assigned a value of 1 if the share of transactions made via cash is $[0\%, 20\%]$, 2 for $(20\%, 40\%]$, 3 for $(40\%, 60\%]$, 4 for $(60\%, 80\%]$, and 5 for $(80\%, 100\%]$. "Use digital payment" = A dummy variable that takes a value of 1 if the firm utilized any digital payment method (e.g., Paytm, UPI, NetBanking) in 2015, and 0 otherwise. "Less e-Ready" refers to firms located in districts where the *e-Index* is below the median. "More e-Ready" refers to firms located in districts where the *e-Index* is above the median. I test the differences between column 1 and column 2 using a t-test with equal variance. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

B.2 Construction of District-Level e-Readiness Index

B.2.1 Construction of the *e-Index*

The framework of the e-Readiness Index is developed by the National Council of Applied Economic Research (NCAER) and the Department of Electronics and Information Technology (DIT), Ministry of Electronics and Information Technology, Government of India. It is a tool used to measure a state's level of preparedness for digitalization. The index is designed to gauge a state's ability to pursue value-creation opportunities facilitated by information and communications technology (ICT). It is multidimensional and measured based on three major categories: environment, readiness, and usage. The environment category measures the market, political, and infrastructure factors that impact a state's ability to adopt ICT. The readiness category assesses the individual, business, and government factors contributing to ICT readiness. The usage category evaluates individual and government ICT usage. The index is calculated using a comprehensive list of indicators, which can be found on pages 39-41 of this report. The latest publicly available version of the index dates back to

2008. The data used by the DIT-NCAER for index computation is collected from various sources, including the Economic Survey, Population Census, and surveys distributed to state governments. States with policies supporting ICT, better network infrastructure, and greater access to the Internet tend to achieve higher e-Readiness Index scores.

Because the DIT-NCAER's e-Readiness Index is only available at the state level, it is necessary to construct one at the district level to obtain a more granular understanding and to unmask potential variations across districts within the same state. Following DIT-NCAER's framework, I use a similar set of indicators and the same approach—principal component analysis (PCA). Table B.2 lists the variables used in constructing the district-level e-Readiness Index. Table B.3 displays a complete list of variables used by the DIT-NCAER, along with the corresponding district-level variables, if available. It should be noted that government-related indicators are excluded due to data limitations when comparing Table B.2 to Table B.3. The two main sources of data that I use for index construction are the 2011 Population Census and the Sixth Economic Census. The following steps have been used in constructing the district-level e-Readiness Index.

1. After collecting the district-level data, I impute missing values using the distance-weighted average of the three nearest districts. For example, prior to imputation, 576 districts had information on the share of the population with access to common service centers.[1] After imputation, the total number of observations increases to 650.

2. Next, I employ the PCA, which helps to identify the underlying factors that best explain the variation in the data, to condense the minor-category variables, as shown in Table B.2. However, given that there is only one indicator belonging to the minor category of "2.2 Business Readiness," I use all five variables under the major category of Readiness for compression. I retain components with eigenvalues greater than one for the subsequent stage of PCA. In total, four components with eigenvalues larger than one are generated from three categories (one from the market environment category, two from the infrastructure environment category, and one from the readiness category).

[1] Common service centers are locations where the government can provide e-Services to individuals without access to computers or the internet.

3. In this step, I apply the PCA to combine the four derived indices in the previous step to construct the aggregate district-level e-Readiness Index.

4. The state-level e-Readiness Index is modified by DIT-NCAER using two factors: the percentage of rural population to total population and the total population. The DIT-NCAER calculates the modified index using the following equation: $Index_s = 0.8 * OriginalIndex_s + 0.1 \times \frac{Rural_s}{Total_s} + 0.1 \times Total_s$, where the subscript s refers to state s. It inflates the index for states with a higher share of the rural population and a larger population. The DIT-NCAER argues that it is harder to administer ICT-enabled services in states with a larger population. Yet, investing human and material resources in those states is also more cost-effective (i.e., economies of scale). Considering that the effect of the total population can be ambiguous, this study only takes the modifying factor of the share of the rural population into account. The modified district-level e-Readiness Index is calculated as

$$Index_d = 0.8 * OriginalIndex_d + 0.2 \times \left(\frac{Rural_d}{Total_d} - \frac{0.833 \text{ Billion}}{1.21 \text{ Billion}} \right),$$

where $Rural_d$ is the number of the rural population in district d, $Total_d$ is the number of the total population in district d, and $\frac{0.833}{1.21}$ is the national average of the ratio of rural population to population. The modified index for *591* districts has a mean of 0.03, a standard deviation of 0.94, and a range of [-1.62,4.02]. I then conduct unity-based normalization on the modified index. Figure B.3 plots the distribution of the *normalized population-weighted e-Readiness Index*.

B.2.2 Robustness Check: Index Comparison

I conducted three comparisons to evaluate the robustness of the *e-Index* used in this study. First, I compare the *e-Index* with an index generated using three categories of indicators. Due to data limitations, I excluded the major category of "Usage" in constructing the *e-Index*. In this step, I constructed an index that also incorporates information from the minor category of "Individual Usage."[2] That is, I use indicators

[2] There are two minor categories under the major categories of "Usage." Since I do not have data on the minor category of "Government Usage," I only include the indicator under the category of

Table B.2: Variables used in the PCA

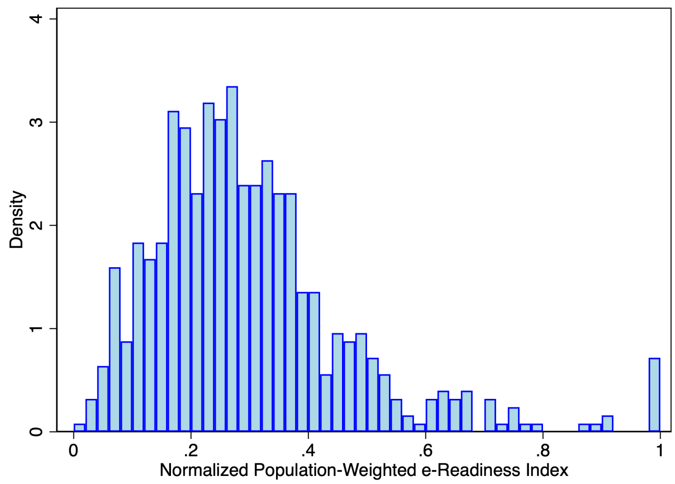
Major category	Minor category	District-level variables	Data Source
1. Environment	1.1 Market Environment	Share of establishments engaged in NIC=611 activity	Sixth Economic Census (2013)
		Share of establishments engaged in NIC=612 activity	Sixth Economic Census (2013)
		Share of establishments engaged in NIC=613 activity	Sixth Economic Census (2013)
	1.2. Infrastructure Environment	Share of rural households having telephones/-cellphones/computers divided by share of urban households having telephones/cellphones/computers	Population Census (2011)
		Share of population having access to common service centers	Population Census (2011)
		Share of population having mobile phone coverage	Population Census (2011)
2. Readiness	2.1 Individual Readiness	Percentage of households with computers	Population Census (2011)
		Percentage of households having computers with internet connection	Population Census (2011)
		Percentage of households with telephone	Population Census (2011)
		Percentage of households with mobile phone	Population Census (2011)
	2.2. Business Readiness	ICT employees per 1,000 population	Sixth Economic Census (2013)

Notes: NIC=611 is wired telecommunications activities; NIC=612 is wireless telecommunications activities; NIC=613 is satellite telecommunications activities. Common service centers are places where the government can deliver e-Service to people without access to computers or the Internet.

from three dimensions to construct this index. I obtained data on monthly expenditure by households on the Internet, telephone, cellphone, and computer from the 2011-12 India Human Development Survey. Only *450* districts have information on the variables listed under "Individual Usage" and thus the index. I then compare the two constructed indices. As shown in Figure B.4, the two indices are highly correlated, with a 0.93 correlation coefficient.

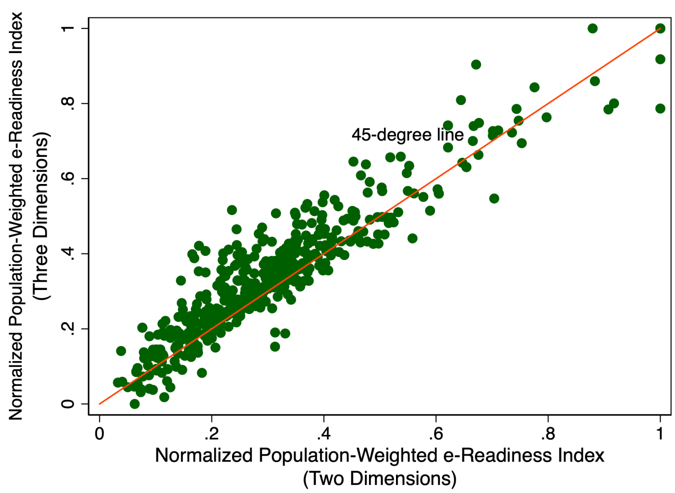
Second, I compare the *e-Index* with an index generated by excluding two indicators from those listed in Table B.2: the percentage of households with mobile phones and the number of ICT employees per 1,000 population. These indicators are omitted

"Individual Usage."



Notes: The figure displays the distribution of the constructed normalized population-weighted district-level e-Readiness Index used in this paper.

Figure B.3: Distribution of Normalized Population-Weighted e-Readiness Index

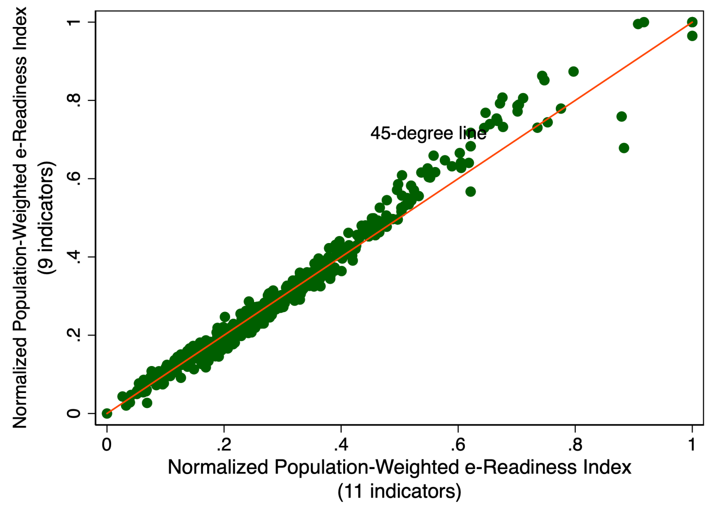


Notes: The figure displays the normalized population-weighted district-level e-Readiness Index using three categories of variables against the one using two categories of variables. I use the normalized population-weighted district-level e-Readiness Index constructed by two categories of variables throughout the analysis. The red line is the 45-degree line.

Figure B.4: Two Types of Normalized Population-Weighted e-Readiness Index

because they may be influenced by the severity of the demonetization shock and are less related to the infrastructural aspect of the *e-Index*. In Figure B.5, the index generated with the remaining nine indicators is plotted against the *e-Index*. As shown, the two indexes are highly correlated with a correlation coefficient of 0.99.

Lastly, I compare the *e-Index* with the state-level DIT-NCAER's e-Readiness In-



Notes: The figure displays the normalized population-weighted district-level e-Readiness Index using nine variables against the one using 11 variables. I use the normalized population-weighted district-level e-Readiness Index constructed by 11 variables throughout the analysis. The red line is the 45-degree line.

Figure B.5: Two Types of Normalized Population-Weighted e-Readiness Index

dex. To do so, I aggregate the district-level *e-Index* to the state-level weighted by district population. The comparison is visualized in Figure B.6, which displays the DIT-NCAER's index alongside the district-population-weighted index that was created from the district-level index. The two indexes are positively correlated. Both Maharashtra and West Bengal have high DIT-NCAER's scores but relatively low population-weighted index scores. This is due to the large variation in the district-level e-Readiness Index in these two states. This example also underscores the importance of utilizing district-level information rather than relying on state-level information because state-level information can mask variations at more granular levels.

Overall, the three comparisons suggest that the *e-Index* is robust, whether new indicators are added or some are excluded. Therefore, throughout the analysis, I utilize the *e-Index* created from 11 variables within two major categories.

Table B.3: Comparison of Indicators used in State-Level and District-Level Index

Major category	Minor category	State-level indicators	District-level variables	Data Source
1. Environment	1.1. Market environment	1.1.1. Competition in the cellular market: Number of players	Share of establishments engaged in NIC=611 activity	Sixth Economic Census (2013)
		1.1.2. Competition in the wireless including WLL(F) market: Number of players	Share of establishments engaged in NIC=612 activity	Sixth Economic Census (2013)

Table B.3 continued from previous page

Major category	Minor category	State-level indicators	District-level variables	Data Source
		1.1.3. Competition in the ISP market: Number of players	Share of establishments engaged in NIC=613 activity	Sixth Economic Census (2013)
	1.2. Political and regulatory environment	1.2.1. Policy Documentation Enabling/Facilitating the ICT Policy	NA	
		1.2.2. Policy implementation	NA	
		1.2.3. Structural policy/government promotion of ICT activity in the private sector	NA	
		1.2.4. Futuristic approach of government	NA	
		1.2.5 Duration of implementation of ICT policy in state	NA	
		1.2.6. How often is the ICT policy amended?	NA	
	1.3. Infrastructure Environment	1.3.1. Rural-urban disparity in teledensity	Share of rural households having telephones/cellphones/computers divided by share of urban households having telephones/cellphones/computers	Population Census (2011)
		1.3.2. School infrastructure	Share of schools having computers*	India Human Development Survey (2011-12)
		1.3.3. ICT infrastructure in State	Share of the population having access to common service centers	Population Census (2011)
		1.3.4. VPN equipment	NA	
		1.3.5. Network availability	Share of the population having mobile phone coverage	Population Census (2011)
		1.3.6. IT security	NA	
2. Readiness	2.1. Individual Readiness	2.1.1 Percentage households with PCs	Percentage of households with computers	Population Census (2011)
		2.1.2 Percentage of households with internet connection	Percentage of households having computers with internet	
		2.1.3 Percentage of households with cell phones	Percentage of households with mobile phones	
		2.1.4 Percentage of households with telephone	Percentage of households with telephone	
	2.2. Business Readiness	2.2.1 IT Park density	NA	
		2.2.2 Employment per IT park	NA	
		2.2.3 IT jobs per million population	ICT employees per 1,000 population	Sixth Economic Census (2013)
	2.3. Government Readiness	2.3.1 Officials trained in ICT	NA	
		2.3.2 Website	NA	
		2.3.3 ICT use by Panchayati Raj institutions (PRIs)	NA	

Table B.3 continued from previous page

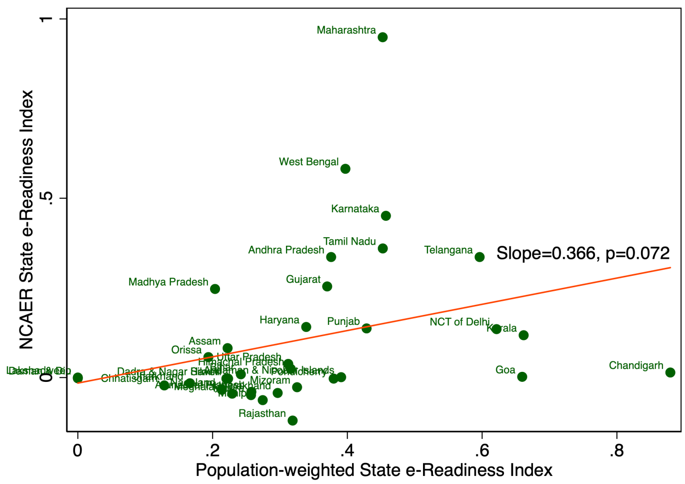
Major category	Minor category	State-level indicators	District-level variables	Data Source
3. Usage	3.1. Individual Usage	3.1.1. Monthly expenditure incurred by households (Rs) on the following: internet access, cellphone, telephone (landline), cable TV connection	*Monthly household expenditures on internet, telephone, cellphone, and computer	India Human Development Survey (2011-12)
	3.2. Government Usage	3.2.1. Has ICT been applied to any of the following fields: agriculture, health services, transportation, energy, trade, others	NA	
		3.2.2. Computerization and its penetration	NA	
		3.2.3. No. of e-Governance projects successfully running for more than one year in the state/UT	NA	
		3.2.4. Use of ICT	NA	

Notes: "*" means that the variable is not included in the principal component analysis due to a smaller number of observations. Only two-thirds of the districts have information on the share of schools having computers and only half of the districts have information on the monthly household expenditures on the internet, telephone, cell phone, and computer.

B.3 TFPR Estimation

In this section, I focus on estimating productivity. Most of the previous research uses the control function approach developed by Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), and Ackerberg, Caves, and Frazer (2015) (ACF). The crucial assumption underlying the OP/LP/ACF method is that productivity evolves exogenously. However, this assumption does not apply to my context as I assume that digital technology affects firms' Hicks-neutral productivity and it only affects future production but not contemporaneous output.

In this study, I apply the method proposed by Grieco, S. Li, and H. Zhang (2016) (hereafter GLZ) to estimate the total factor productivity (TFP). The GLZ method possesses three advantages that render it suitable for this context. First, it can be applied when productivity evolves endogenously, as it relies solely on the first-order profit-maximization conditions to identify the production function. Second, the GLZ method does not necessitate data on output price, output quantity, and intermediate input quantities, which are unavailable in my dataset. Third, productivity can be consistently estimated through the nonlinear least squares (NLLS) method.



Notes: The figure plots the DIT-NCAER's state-level e-Readiness Index against the constructed population-weighted state-level index. The red line is the fitted line with a slope of 0.36 ($p < 0.10$).

Figure B.6: Comparison of State-Level e-Readiness Index

B.3.1 Setup

The production function for firm i in industry j and time t is defined as $Y_{ijt} = e^{\omega_{ijt}}\Gamma_{ijt}$, where $e^{\omega_{ijt}}$ is the Hicks-neutral productivity. Γ_{ijt} represents a CES aggregation of three inputs: non-ICT capital (K_{ijt}), non-ICT labor (L_{ijt}), and materials (M_{ijt}). Γ_{ijt} is expressed as

$$\Gamma_{ijt} = \left(\alpha_{Kj}K_{ijt}^{\gamma_j} + \alpha_{Lj}L_{ijt}^{\gamma_j} + \alpha_{Mj}M_{ijt}^{\gamma_j}\right)^{\frac{1}{\gamma_j}} . \tag{B.1}$$

The production function exhibits constant returns to scale. The distribution parameters are assumed to satisfy $\alpha_{Kj} + \alpha_{Lj} + \alpha_{Mj} = 1$. The elasticity of substitution is expressed as $\frac{1}{1-\gamma_j}$.

In line with the GLZ method, I make the following assumptions. First, firms are considered price takers in input markets. Second, capital is regarded as quasi-fixed in the short run, whereas labor and materials are considered static inputs and are fully flexible. Third, firms strategically select their optimal quantities of labor and materials after observing productivity (ω_{ijt}), non-ICT capital stock (K_{ijt}), and input prices but before observing the revenue shock (u_{ijt}).

A firm's profit maximization problem in time t is

$$\max_{\{L_{ijt}, M_{ijt}\}} P_{ijt}Y_{ijt} - P_{Ljt}L_{ijt} - P_{Mjt}M_{ijt} \tag{B.2}$$

$$\text{subject to } Y_{ijt} = e^{\omega_{ijt}} \left[\alpha_{Kj}K_{ijt}^{\gamma_j} + \alpha_{Lj}L_{ijt}^{\gamma_j} + \alpha_{Mj}M_{ijt}^{\gamma_j}\right]^{\frac{1}{\gamma_j}}, \tag{B.3}$$

$$P_{ijt} = \phi_{jt}Y_{ijt}^{-\frac{1}{\sigma_j}}, \tag{B.4}$$

where $P_{ijt} = \phi_{jt}Y_{ijt}^{-\frac{1}{\sigma_j}}$ is the inverse demand function that the firm faces and ϕ_{jt} is an exogenous demand shifter. The two first-order conditions are

$$\phi_{jt}e^{\frac{(\sigma_j-1)\omega_{ijt}}{\sigma_j}} \left[\alpha_{Kj}K_{ijt}^{\gamma_j} + \alpha_{Lj}L_{ijt}^{\gamma_j} + \alpha_{Mj}M_{ijt}^{\gamma_j}\right]^{\frac{\sigma_j-1-\sigma_j\gamma_j}{\sigma_j\gamma_j}} \frac{(\sigma_j-1)\alpha_{Lj}}{\sigma_j} L_{ijt}^{\gamma_j-1} = P_{Ljt},$$

$$\phi_{jt}e^{\frac{(\sigma_j-1)\omega_{ijt}}{\sigma_j}} \left[\alpha_{Kj}K_{ijt}^{\gamma_j} + \alpha_{Lj}L_{ijt}^{\gamma_j} + \alpha_{Mj}M_{ijt}^{\gamma_j}\right]^{\frac{\sigma_j-1-\sigma_j\gamma_j}{\sigma_j\gamma_j}} \frac{(\sigma_j-1)\alpha_{Mj}}{\sigma_j} M_{ijt}^{\gamma_j-1} = P_{Mjt}.$$

The above two equations yield

$$\frac{E_{Lijt}}{E_{Mijt}} = \frac{P_{Ljt}L_{ijt}}{P_{Mjt}M_{ijt}} = \frac{\alpha_{Lj}}{\alpha_{Mj}} \left(\frac{L_{ijt}}{M_{ijt}}\right)^{\gamma_j}, \tag{B.5}$$

where E_{Lijt} is the expenditure on non-ICT labor and E_{Mijt} is the expenditure on materials for firm i in time t. The equation can be re-written as $M_{ijt} = \left(\frac{\alpha_{Lj}}{\alpha_{Mj}}\frac{E_{Mijt}}{E_{Lijt}}\right)^{\frac{1}{\gamma_j}} L_{ijt}$. One can substitute it into the first-order condition for labor to recover the unobserved productivity term:

$$\begin{aligned} \omega_{ijt} =& \frac{\sigma_j}{\sigma_j-1}\log\left\{\frac{1}{\alpha_{Lj}}\frac{\sigma_j}{\sigma_j-1}\phi_{jt}^{-1}L_{ijt}^{-\gamma_j}E_{Lijt}\left[\alpha_{Lj}\left(1+\frac{E_{Mijt}}{E_{Lijt}}\right)L_{ijt}^{\gamma_j} + \alpha_{Kj}K_{ijt}^{\gamma_j}\right]^{\frac{\sigma_j-1-\sigma_j\gamma_j}{\sigma_j\gamma_j}}\right\} \\ =& \overbrace{\frac{\sigma_j}{\sigma_j-1}\log\left\{\frac{1}{\alpha_{Lj}}\frac{\sigma_j}{\sigma_j-1}L_{ijt}^{-\gamma_j}E_{Lijt}\left[\alpha_{Lj}\left(1+\frac{E_{Mijt}}{E_{Lijt}}\right)L_{ijt}^{\gamma_j} + \alpha_{Kj}K_{ijt}^{\gamma_j}\right]^{\frac{\sigma_j-1-\sigma_j\gamma_j}{\sigma_j\gamma_j}}\right\}}^{\text{1st term}} \underbrace{-\log(\phi_{jt})}_{\text{2nd term}}, \end{aligned} \tag{B.6}$$

where the second term is an unobserved aggregate factor. It should be noted the second term does not matter in the regression analysis because the industry-year fixed effects will account for it.

A firm's revenue function is defined as $R_{ijt} = e^{u_{ijt}} \phi_{jt} Y_{ijt}^{\frac{\sigma_j - 1}{\sigma_j}}$, where u_{ijt} is an error term. By taking the logarithm on both sides and substituting equations (B.3) and (B.6), one can get:

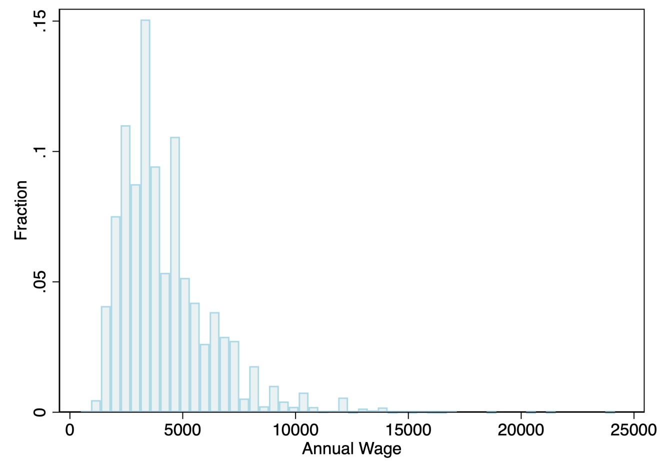
$$\ln R_{ijt} = \ln \frac{\sigma_j}{\sigma_j - 1} + \ln \left[E_{Mijt} + E_{L_{ijt}} \left(1 + \frac{\alpha_{Kj}}{\alpha_{Lj}} \left(\frac{K_{ijt}}{L_{ijt}} \right)^{\gamma_j} \right) \right] + u_{ijt}. \tag{B.7}$$

The above equation is subject to two constraints: 1) $\frac{\alpha_{Mj}}{\alpha_{Lj}} = \frac{\bar{E}_{Mj}}{\bar{E}_{Lj}}$; and 2) $\alpha_{Kj} + \alpha_{Lj} + \alpha_{Mj} = 1$. The two constraints yields $\alpha_{Kj} = 1 - \alpha_{Lj} - \frac{\bar{E}_{Mj}}{\bar{E}_{Lj}} \alpha_{Lj}$. $\bar{E}_{Mj}$ and $\bar{E}_{Lj}$ are the geometric mean of E_{Mijt} and E_{Lijt}, respectively. The parameters that need to be estimated are thus simplified to $\{\sigma_j, \alpha_{Lj}, \gamma_j\}$.

B.3.2 Data

I use the Prowess data, discussed in Section 2.3.2, to estimate firm productivity by leveraging its comprehensive information on firm-level revenue, labor expenditure, material expenditure (including raw materials, energy, fuel, and water consumption), capital stock, and the number of employees. However, it should be noted that less than 10% of firms report their employee count. Among these reporting firms, 95% are public firms, 51% belong to the service sector, and 50% are classified as medium or large firms. To address this limitation, I employ another data set, the Consumer Pyramids (discussed in Section 2.3.3), which contains information on wage and industry of occupation in its Income Pyramids (InP) section. I calculate the average monthly wage at the district-industry-year level.[3] I then match industries in the InP data to the two-digit NIC code in the Prowess data. With the information on the average wage, I am able to estimate the number of employees for firms in each industry j, district d, and time t. Figure B.7 illustrates the distribution of annual wages in US Dollars, with approximately 50% of the annual wages below \$3,000 and 2% exceeding \$10,000.

[3]The wage data is only available for years 2014-2019 because the survey started in 2014. I approximate the average wage for the years 2012 and 2013 by adjusting the 2014 average wage using their respective inflation rates.



Notes: I plot the distribution of annual wages at the district-industry-year level, calculated from the Income Pyramids data. The unit is USD.

Figure B.7: Distribution of Annual Wages (USD)

B.3.3 Results

I first employ the NLLS method to estimate equation (B.7) for each industry j. In this process, I impose a constraint on σ_j, which is $\sigma_j < 2$.[4] This step gives the estimated parameters of $\{\hat{\sigma}_j, \hat{\alpha}_{Lj}, \hat{\gamma}_j\}$. In Table B.4, I present the average of the estimated parameters of $\left\{\hat{\sigma}_j, \hat{\alpha}_{Lj}, \frac{1}{1-\hat{\gamma}_j}\right\}$ for service and manufacturing industries, along with their corresponding standard deviations. The estimated elasticity of substitution ($\hat{\sigma}_j$) across products within an industry is, on average, greater than one in both the service and manufacturing sectors, with the average being larger in the manufacturing sector than in the service sector. This implies that manufacturing goods within the same industry can be more easily substituted for one another. The estimates of the elasticity of substitution in the production function ($\frac{1}{1-\hat{\gamma}_j}$) are larger than one in all industries, with the average being greater in the service sector than in the manufacturing sector. This implies that: 1) non-ICT capital is more substitutable in the service sector than in the manufacturing sector; 2) the production functions are unlikely to be Cobb-Douglas in both the service and manufacturing sectors.

Next, I plug these estimated parameters back into equation (B.6) to calculate the first term of productivity in equation (B.6). I present the distribution of the first term in the service and manufacturing sectors for the years 2015 and 2017, respec-

[4] Refer to Appendix B.5.2 for more details about this constraint.

Table B.4: Estimated Parameters in the Production Function

	Service		Manufacturing	
Parameter	Mean	SD	Mean	SD
$\hat{\sigma}_j$	1.80	0.26	2.00	2.14e-09
$\hat{\alpha}_{Lj}$	0.19	0.14	0.10	0.04
$\frac{1}{1-\hat{\gamma}_j}$	1.69	1.07	1.21	0.30

Notes: I present the averages of the estimated $\left\{\hat{\sigma}_j, \hat{\alpha}_{Lj}, \frac{1}{1-\hat{\gamma}_j}\right\}$ for the service and manufacturing sectors, along with their corresponding standard deviations, in the table. The average value of $\hat{\sigma}_j$ is 1.99999999765 in the manufacturing sector.

tively, in Figure B.8. One should note that due to the inability to estimate ϕ_{jt}, all comparisons below are intended for suggestive purposes only. For the service sector, comparing Figure B.8c to Figure B.8a, one can observe that the distribution in 2017 is generally similar to the distribution in 2015, but with a higher average in 2017. For the manufacturing sector, when comparing Figure B.8d to Figure B.8b, one can see that the distribution in 2017 is less positively skewed (skewed to the right) than the distribution in 2015. And the average is lower in 2017 than in 2015.

In line with the proposition made by Harrigan, Reshef, and Toubal (2023), stating that the simple demand function defined by equation (B.4) can account for some aspects of revenue variation but not all, I consider $e^{\omega_{ijt}}$ as revenue TFP (TFPR).

B.4 Definition of Variables

Table B.5: Definition of Variables

Variable Name	Definition
Data 1. Prowess	
Income	Total income is the sum of all kinds of income generated by a firm.
Sales	Sales are the sum of all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services.

Table B.5 continued from previous page

Variable Name	Definition
Fin. Serv. Inc.	Income from financial services includes income based on providing financial services for a fee (e.g. broking) and income based on providing funds and earning a return (e.g. interest and dividend).
ROA	Return on assets (ROA) is the ratio of total income over total assets. It is a measure of how efficiently a company uses the assets it owns to generate profits (i.e., profitability). It can also be used to evaluate a company's financial health.
TFPR	The total factor revenue productivity ($\hat{\omega}_{ijt}$) is estimated using the method proposed by grieco2016production. A detailed discussion is provided in Appendix B.3.
Assets	Total assets are the sum of all current and non-current assets held by a company as of the last day of an accounting period.
Fixed Assets	Fixed assets are the sum of intangible assets, land and buildings, plant and machinery, computers and electrical installations, transport and communication equipment and infrastructure, furniture, social amenities, and other fixed assets and lease adjustment reserves.
Intangible$_e$	Net intangible assets usually include the gross value of goodwill and software systems. In the analysis, I exclude software systems from the net intangible assets.
PPE$_e$	Net property, plant, and equipment (PPE). PPEs are a company's physical or tangible long-term assets that typically have a life of more than one year, such as buildings, machinery, land, office equipment, furniture, and vehicles. In the analysis, I exclude computers and IT systems from net PPE.
ICT Assets	ICT assets include software, computers, and IT systems.
Expenses	Total expenses are the sum of all revenue expenses incurred by a firm.
Fin. Serv. Exp.	Financial services expenses include fee-based financial services expenses and fund-based financial services expenses.
Compensation	Compensations to employees are the total remuneration in cash or in kind paid by a company to or on behalf of all its employees.
Communications	Communications expenses include costs incurred by the company on the telephone, telegram, postage, fax, data centers, and satellite and internet services.

Table B.5 continued from previous page

Variable Name	Definition
Outsourced: Software & ICT	The sum of the expenses incurred by a company on ICT-related outsourced professional services including software development, IT, and IT-enable services.
Any Outsourced: Software & ICT	A dummy variable equal to 1 if a company spends on ICT-related outsourced professional services and 0 otherwise.
Exits	The log of the number of exited firms plus one in industry j, district d, and year t.
Data 2: Consumer Pyramids	
Work in the service sector	A dummy variable equal to 1 if an employed individual is working in the service sector and 0 otherwise.
Work in the manufacturing sector	A dummy variable equal to 1 if an employed individual is working in the manufacturing sector and 0 otherwise.
$\geq$Bachelor	A sample of individuals holding diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees.
$\leq$ Higher Secondary	A sample of individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling.
Wage	The average monthly wage an individual earns over a four-month period (January-April, May-August, and September-December).
Related Disciplines	A dummy variable equal to one if an individual's discipline is either computer application or engineering and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline.
Management	A dummy variable equal to one if an individual's discipline is either commerce or management and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline.
Data 3: MCA	
Number of entries	The number of firms that entered industry j in district d and year t.
Number of exits	The number of firms that exited industry j in= district d, and year t.
Other Data: Controls	
Avg. nightlight intensity	I calculate the mean value of all pixels within a district to determine the average nightlight intensity.

Table B.5 continued from previous page

Variable Name	Definition
Bank branches per 1M people	The number of functioning offices of commercial banks in a district per one million population.
ATMs per 1M people	The number of ATMs (both off-site and on-site) in a state per one million population.

Notes: In the Prowess data, all monetary values are reported in nominal USD million.

B.5 Conceptual Framework: Mathematical Details

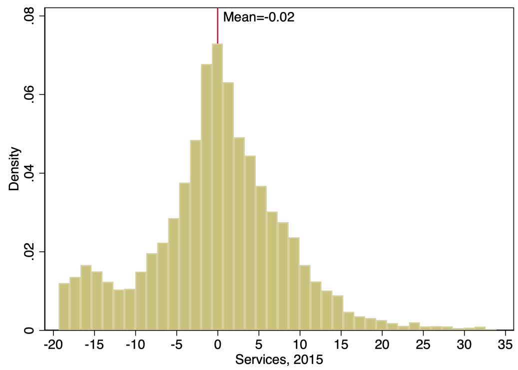
In this section, I describe a simple static model of technology adoption with ICT talent scarcity. The model delivers empirical predictions regarding firms' responses to a cash crunch shock. For simplicity, I consider a two-sector economy ($j = s, m$) comprising the service and manufacturing sectors. There is a fixed mass of firms in both sectors. Firms observe their initial productivity and decide whether to adopt digital technology before starting production.

B.5.1 Productivity

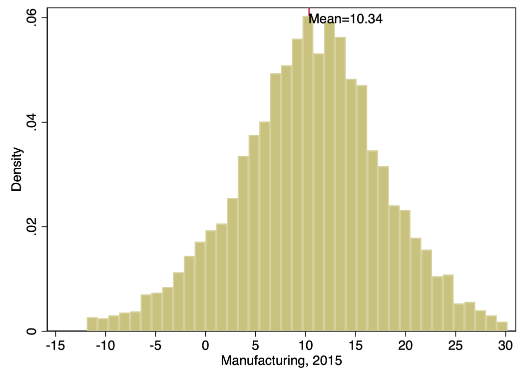
There is a continuum of firms in each sector, each producing a different variety. $A_i \equiv e^{\omega_i}$ is an idiosyncratic productivity level drawn by each firm in sector j from a common distribution $p(\omega)$, where $p(\cdot)$ is a probability density function with $p(\omega > \Omega) = 0$. ω_i is given, but firm i can improve its productivity relative to its initial level (A_i) by adopting digital technology, which encompasses the employment of ICT labor (T_{ij}) and investments in ICT capital (k_{ij}). Specifically, the supply of ICT labor is assumed to be inelastic and fixed, denoted as T. These two factors are established prior to the production stage. Following Doraszelski and Jaumandreu (2013) and Harrigan, Reshef, and Toubal (2023), I assume that both ICT labor and ICT capital affect only Hicks-neutral productivity.

The productivity of firm i in sector j is defined as

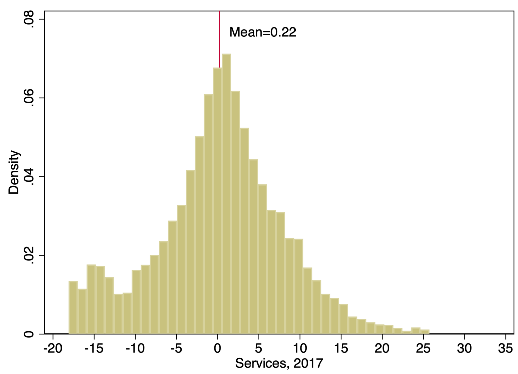
$$\omega_{ij} = \omega_i + \max\left\{\ln\left(\left[T_{ij}^{\eta} + k_{ij}^{\eta}\right]^{\frac{1}{\eta}}\right), 0\right\}. \tag{B.8}$$



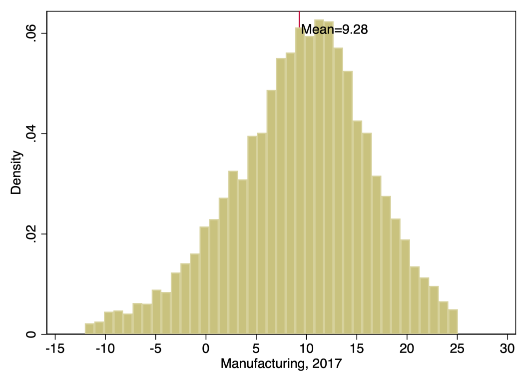
(a) Services, 2015



(b) Manufacturing, 2015



(c) Services, 2017



(d) Manufacturing, 2017

Notes: I display the distribution of the observed part of productivity for the service sector in 2015 in Figure B.8a, for the manufacturing sector in 2015 in Figure B.8b, for the service sector in 2017 in Figure B.8c, and for the manufacturing sector in 2017 in Figure B.8d. The distributions are trimmed at the 1st and 99th percentiles.

Figure B.8: Distribution of the Observed Part of $\hat{\omega}_{ijt}$

η is the substitution parameter which is negative (i.e., ICT labor and ICT capital are complementary). A firm faces two costs when making the adoption decision: the wage rate of ICT professionals (w) and the rental rate of ICT capital (r). The rental rate r is given and is assumed to be stable over time. Thus, in this setup, only w can change endogenously. The total cost associated with digital technology adoption is calculated as $wT_{ij} + rk_{ij}$.[5]

[5]Here, I abstract away from the fixed cost of digital technology adoption, as its presence does not affect the derivation of the model's predictions. It should be noted that a firm is more likely to adopt digital technology when the fixed cost is lower. However, it is possible that a firm will not adopt digital technology, even when the fixed cost is zero, if it has very low initial productivity, or if the wage rate for ICT labor is very high.

B.5.2 Profit Maximization

The production function for firm i in sector j is defined as $Y_{ij} = A_{ij}\Gamma_{ij}$, where $A_{ij} = e^{\omega_{ij}}$ represents Hicks-neutral total factor productivity and Γ_{ij} is a function of the input bundle. Firms in sector j produce differentiated products and face a common constant elasticity of demand, denoted as σ_j, where σ_j is greater than 1. The inverse demand function for firm i in sector j can thus be expressed as $P_{ij} = \phi_j Y_{ij}^{-\frac{1}{\sigma_j}}$, where ϕ_j is an exogenous demand shifter.

In terms of revenue, a firm can earn a $1 - \tau_j$ portion of $P_{ij}Y_{ij}$ when not adopting digital technology, and a $1 - \tau_j x$ portion when adopting digital technology. Here, τ_j represents the revenue wedge for firms in sector j, with $\tau_j \in [0, 1)$. And x is inversely related to an area's *e-Index*, with $x \in [0, 1]$. In the absence of shocks, one has $\tau_j = 0$, indicating that firms can receive the full amount of revenue. There are two cases for the profit maximization problem: one without a shock (i.e., $\tau_j = 0$), denoted by superscript B, and one with a shock (i.e., $\tau_j > 0$), represented by superscript S.

Case 1: No Shock ($\tau_j = 0$) A firm in sector j chooses T_{ij}, k_{ij}, and Γ_{ij} to maximize its profit:

$$\begin{aligned}
\Pi_{ij} =& P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij}) \cdot I(T_{ij} > 0, k_{ij} > 0) \\
=& \phi_j A_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} \Gamma_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} - \mathbf{w}\Gamma_{ij} - (wT_{ij} + rk_{ij}) \cdot I(T_{ij} > 0, k_{ij} > 0), \\
& s.t. \sum_j \left(\int_{\bar{\omega}_j^B}^{\Omega} T_{ij} d\omega \right) = T.
\end{aligned} \tag{B.9}$$

$I(\cdot)$ is an indicator function that takes the value of one when firm i adopts digital technology. $\mathbf{W}_{ij}$ represents the cost of the input bundle and $\mathbf{w}$ denotes the unit cost of the input bundle, which is given. $\bar{\omega}_j^B$ is the threshold initial productivity above which firms in sector j will employ ICT labor and invest in ICT capital. There are two solutions to T_{ij} and k_{ij}, one the corner solution with $T_{ij} = k_{ij} = 0$ and the other an interior optimum with $T_{ij} > 0$ and $k_{ij} > 0$.

When an interior solution exists, the first-order conditions for T_{ij}, k_{ij}, and Γ_{ij} are as follows:

$$\frac{\partial \Pi_{ij}}{\partial T_{ij}} = \phi_j \Gamma_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} e^{\frac{(\sigma_j-1)\omega_i}{\sigma_j}} \frac{(\sigma_j - 1)}{\sigma_j} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{(\sigma_j-1)-\sigma_j\eta}{\sigma_j\eta}} T_{ij}^{\eta-1} - w = 0, \tag{B.10}$$

$$\frac{\partial \Pi_{ij}}{\partial k_{ij}} = \phi_j \Gamma_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} e^{\frac{(\sigma_j-1)\omega_i}{\sigma_j}} \frac{\sigma_j - 1}{\sigma_j} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{(\sigma_j-1)-\sigma_j\eta}{\sigma_j\eta}} k_{ij}^{\eta-1} - r = 0, \tag{B.11}$$

$$\frac{\partial \Pi_{ij}}{\partial \Gamma_{ij}} = \phi_j e^{\frac{(\sigma_j-1)\omega_i}{\sigma_j}} \frac{\sigma_j - 1}{\sigma_j} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{\sigma_j-1}{\sigma_j\eta}} \Gamma_{ij}^{-\frac{1}{\sigma_j}} - \mathbf{w} = 0. \tag{B.12}$$

Rearrange equation (B.12), one can get

$$\Gamma_{ij}^{\frac{\sigma_j-1}{\sigma_j}} = \phi_j^{\sigma_j-1} \left(\frac{\sigma_j - 1}{\sigma_j}\right)^{\sigma_j-1} A_i^{\frac{(\sigma_j-1)^2}{\sigma_j}} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{(\sigma_j-1)^2}{\sigma_j\eta}} \mathbf{w}_{ij}^{1-\sigma_j}. \tag{B.13}$$

By substituting equation (B.13) into equations (B.10) and (B.11) respectively, one can obtain

$$w = \phi_j^{\sigma_j} A_i^{\sigma_j-1} \mathbf{w}_{ij}^{1-\sigma_j} \left(\frac{\sigma_j - 1}{\sigma_j}\right)^{\sigma_j} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{(\sigma_j-1)-\eta}{\eta}} T_{ij}^{\eta-1},$$

$$r = \phi_j^{\sigma_j} A_i^{\sigma_j-1} \mathbf{w}_{ij}^{1-\sigma_j} \left(\frac{\sigma_j - 1}{\sigma_j}\right)^{\sigma_j} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{(\sigma_j-1)-\eta}{\eta}} k_{ij}^{\eta-1}$$

The above two equations yield the ICT-capital-labor ratio, $\frac{k_{ij}}{T_{ij}} = \left(\frac{w}{r}\right)^{\frac{1}{1-\eta}}$. The solutions to T_{ij} and k_{ij} for firm i are characterized as

$$T_{ij}^{B*} = \phi_j^{\frac{\sigma_j}{2-\sigma_j}} A_i^{\frac{\sigma_j-1}{2-\sigma_j}} \mathbf{w}_{ij}^{\frac{1-\sigma_j}{2-\sigma_j}} \left(\frac{\sigma_j - 1}{\sigma_j}\right)^{\frac{\sigma_j}{2-\sigma_j}} w^{\frac{1}{\sigma_j-2}} \left[1 + \left(\frac{w}{r}\right)^{\frac{\eta}{1-\eta}}\right]^{\frac{(\sigma_j-1)-\eta}{\eta(2-\sigma_j)}}, \tag{B.14}$$

$$k_{ij}^{B*} = \phi_j^{\frac{\sigma_j}{2-\sigma_j}} A_i^{\frac{\sigma_j-1}{2-\sigma_j}} \mathbf{w}_{ij}^{\frac{1-\sigma_j}{2-\sigma_j}} \left(\frac{\sigma_j - 1}{\sigma_j}\right)^{\frac{\sigma_j}{2-\sigma_j}} r^{\frac{1}{\sigma_j-2}} \left[1 + \left(\frac{r}{w}\right)^{\frac{\eta}{1-\eta}}\right]^{\frac{(\sigma_j-1)-\eta}{\eta(2-\sigma_j)}}. \tag{B.15}$$

To satisfy the second-order condition, I assume $\sigma_j > 1 + \eta$. The sign of the second derivative of Π_{ij} with respect to T_{ij} depends on $(\eta - 1)(\sigma_j - 1 - \eta)$. Because $\eta < 0$, to guarantee that $\frac{\partial^2 \Pi_{ij}}{\partial T_{ij}^2} \leq 0$, one needs to have $\sigma_j > 1 + \eta$. Similarly, one can derive the second derivative of Π_{ij} with respect to k_{ij} and get the same condition for σ_j. Moreover, I assume that $\sigma_j < 2$, and the following relationships hold between T_{ij}, k_{ij}, and w: $\frac{\partial T_{ij}}{\partial w} < 0$ and $\frac{\partial k_{ij}}{\partial w} < 0$. In essence, σ_j should satisfy the following condition: $1 + \eta < \sigma_j < 2$.

Case 2: With Shock ($\tau_j > 0$) A demonetization shock makes a portion of cash transactions unfeasible, affecting the service sector more than the manufacturing sector due to its business-to-consumer. The profit maximization problem faced by firm j in sector j is now defined as:

$$\Pi_{ij} = \begin{cases} (1-\tau_j)P_{ij}Y_{ij} - \mathbf{W}_{ij} & \text{, if } I(\cdot) = 0 \\ (1-\tau_j x)P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij}) & \text{, if } I(\cdot) = 1 \end{cases} \tag{B.16}$$

$$s.t. \sum_j \left(\int_{\bar{\omega}_j^S}^{\Omega} T_{ij} d\omega \right) = T,$$

where $0 < \tau_m < \tau_s < 1$. A better digital environment corresponds to a lower value of x. Here, $(1-\tau_j)P_{ij}Y_{ij}$ represents the effective revenue firm i can generate either without adopting digital technology or when adopting it in an area with the least favorable digital environment (i.e., $x = 1$). If a firm is located in an area with the highest *e-Index* (i.e., $x = 0$) and adopts digital technology, then it can earn the full amount of revenue (i.e., $P_{ij}Y_{ij}$).

Similarly, one can derive the interior solution for T_{ij} and k_{ij} in this case:

$$T_{ij}^{S*} = (1-\tau_j x)^{\frac{\sigma_j}{2-\sigma_j}} \phi_j^{\frac{\sigma_j}{2-\sigma_j}} A_i^{\frac{\sigma_j - 1}{2-\sigma_j}} \mathbf{w}_{ij}^{\frac{1-\sigma_j}{2-\sigma_j}} \left(\frac{\sigma_j - 1}{\sigma_j} \right)^{\frac{\sigma_j}{2-\sigma_j}} w^{\frac{1}{\sigma_j - 2}} \left[1 + \left(\frac{w}{r} \right)^{\frac{\eta}{1-\eta}} \right]^{\frac{(\sigma_j - 1) - \eta}{\eta(2-\sigma_j)}}, \tag{B.17}$$

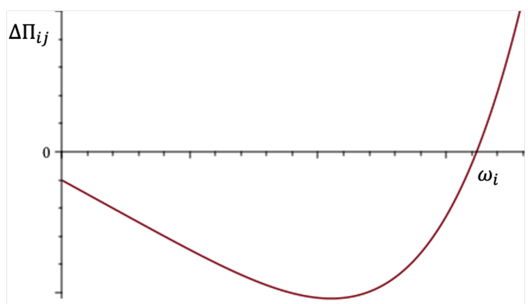
$$k_{ij}^{S*} = (1-\tau_j x)^{\frac{\sigma_j}{2-\sigma_j}} \phi_j^{\frac{\sigma_j}{2-\sigma_j}} A_i^{\frac{\sigma_j - 1}{2-\sigma_j}} \mathbf{w}_{ij}^{\frac{1-\sigma_j}{2-\sigma_j}} \left(\frac{\sigma_j - 1}{\sigma_j} \right)^{\frac{\sigma_j}{2-\sigma_j}} r^{\frac{1}{\sigma_j - 2}} \left[1 + \left(\frac{r}{w} \right)^{\frac{\eta}{1-\eta}} \right]^{\frac{(\sigma_j - 1) - \eta}{\eta(2-\sigma_j)}}. \tag{B.18}$$

Here, as x increases, both the number of employed ICT professionals and the amount of investment in ICT capital decrease. In other words, all else being equal, firms in areas with a higher *e-Index* will employ more ICT labor and invest more in ICT capital compared to those in areas with a lower *e-Index*. The same reasoning applies to τ_j.

Profit Comparisons A firm will opt to employ ICT labor and invest in ICT capital only if it generates higher profits compared to the scenario without any investment (i.e., the corner solution). Let's use superscript 1 to signify the adoption of digital technology and superscript 0 for non-adoption. A firm will adopt digital technology when

$$\Delta\Pi_{ij} = \begin{cases} \Delta\Pi_{ij}^{B} = \Pi_{ij}^{1B} - \Pi_{ij}^{0B} > 0 & \text{, Case 1–No Shock,} \\ \Delta\Pi_{ij}^{S} = \Pi_{ij}^{1S} - \Pi_{ij}^{0S} > 0 & \text{, Case 2–With Shock,} \end{cases}$$

where $\Delta\Pi_{ij}$ represents the profit difference between adopting and not adopting digital technology. Holding all other things constant, higher initial productivity (ω_i) is likely to yield a positive $\Delta\Pi_{ij}$ (Figure B.9) and a higher wage rate for ICT labor tends to lead to a decrease in $\Delta\Pi_{ij}$.



Notes: I plot the variation of $\Delta\Pi_{ij}$ in response to the changes in ω_i holding all other things constant.

Figure B.9: Variations of $\Delta\Pi_{ij}$ with ω_i

For simplicity, I will only compare a firm's profit for $x = 1$ and $x = 0$, considering scenarios both without and with the shock. Here, let's denote $x = 1$ with superscript L and $x = 0$ with superscript H. I present a firm's profits under various conditions in Table B.6, keeping all factors constant except for x.

Table B.6: Profits in Different Cases

	No Shock ($\tau_j = 0$)		With Shock ($\tau_j > 0$)	
	Adopt	Not adopt	Adopt	Not adopt
$x = 1$	$\Pi_{ij}^{1BL} = P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij})$	$\Pi_{ij}^{0B} = P_{ij}Y_{ij} - \mathbf{W}_{ij}$	$\Pi_{ij}^{1SL} = (1-\tau_j)P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij})$	$\Pi_{ij}^{0S} = (1-\tau_j)P_{ij}Y_{ij} - \mathbf{W}_{ij}$
$x = 0$	$\Pi_{ij}^{1BH} = P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij})$		$\Pi_{ij}^{1SH} = P_{ij}Y_{ij} - \mathbf{W}_{ij} - (wT_{ij} + rk_{ij})$	

Notes: Superscript 1 denotes adoption, superscript 0 denotes non-adoption, superscript B denotes the case without a shock, superscript S denotes the case with a shock, superscript L denotes $x = 1$, and superscript H denotes $x = 0$. I hold all factors fixed except for x.

Four key observations emerge from the table. First, a comparison of $\Pi^{1BH}ij$ and

$\Pi^{1BL}ij$ with $\Pi^{0B}ij$ reveals that firms are more likely to adopt digital technology when the wage rate for ICT labor is lower, a pattern that also holds in the presence of a shock. Second, by comparing $\Pi^{1SH}ij$ against $\Pi^{0S}ij$, it is evident that service firms are more likely than manufacturing firms to adopt digital technology in a high e-Index ($x = 0$) area when a shock is present. This is attributed to the greater losses service firms face if they do not adopt digital technology. Third, comparing $\Pi^{1SH}ij$ and $\Pi^{0S}ij$ with $\Pi^{1BH}ij$ and $\Pi^{0B}ij$, one can see that firms are more likely to adopt digital technology in the scenario with a shock than without. Specifically, firms with lower initial productivity, which might not have adopted digital technology in the absence of a shock, are now likely to find adoption profitable. Lastly, a comparison of $\Pi^{1SH}ij$ and $\Pi^{1SL}ij$ with $\Pi^{0S}ij$ indicates that firms are more likely to adopt digital technology in areas that are more e-Ready than in those that are less so.

Proposition B.1. *In the case of no shock (i.e., $\tau_j = 0$), firm i in sector j will adopt digital technology if $\omega_i \geq \bar{\omega}_j^{B*}$, where $\bar{\omega}_j^{B*}$ depends on the value of $\{w\}$.*

Particularly, a firm is more likely to adopt digital technology under the following conditions:

- If the firm's initial productivity (ω_i) is higher,
- If the wage rate for ICT professionals (w) is lower.

When the shock presents, $\Delta\Pi_{ij}$ is also influenced by τ_j and x. Specifically, the larger the value of τ_j, the higher the threshold value of x beyond which a firm will find it unprofitable to adopt digital technology. In other words, service firms in more e-Ready areas are more likely to adopt digital technology compared to those in less e-Ready areas, as well as compared to manufacturing firms in more e-Ready areas.

Proposition B.2. *In the presence of the shock, firm i in sector j will adopt digital technology if $\omega_i \geq \bar{\omega}_j^{S*}$, where $\bar{\omega}_j^{S*}$ depends on the values of $\{w, \tau_j, x\}$.*

Particularly, a firm is more likely to adopt digital technology under the two additional conditions:

- If the sector is hit more severely by the shock, or if τ_j is larger
- If the area's digital environment is more favorable, or if x is smaller.

B.5.3 Responses to the Shock

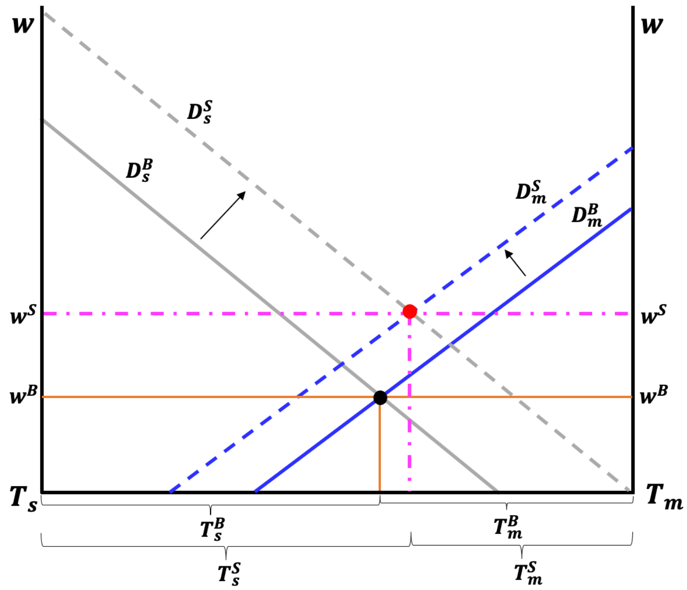
I will now describe how firms' reactions vary to a shock that reduces the effective revenue they can earn without adopting digital technology, compared to a scenario without such a shock. The predictions outlined below are in comparison to the reference group: firms located in areas with a low e-Index ($x = 0$).[6]

Prediction 1. In a more e-Ready area, compared to the case of no shock (i.e., $\tau_j = 0$), the wage rate for ICT labor, w, is higher when the shock is present (i.e., $\tau_j > 0$), $w^S > w^B$.

Prediction 2. In a more e-Ready area, compared to the case of no shock (i.e., $\tau_j = 0$), the service sector employs more ICT labor and invests more in ICT capital when the shock is present (i.e., $\tau_j > 0$), while the manufacturing sector employs fewer ICT labor and invests less in ICT capital ($T_s^S > T_s^B$, $T_m^S < T_m^B$, $k_s^S > k_s^B$, $k_m^S < k_m^B$).

When the shock presents, τ_j will increase from zero (i.e., fully feasible cash transactions) to a positive value less than one (i.e., some portion of cash transactions now becomes unfeasible), which lowers the effective share of revenue a firm can earn without adopting digital technology. This change will motivate firms in more e-Ready areas across both sectors to adopt digital technology, thereby increasing their demand for ICT labor. Conversely, firms in less e-Ready areas will find fewer incentives to make such a transition. In Figure B.10, I present changes in the ICT labor market with a fixed amount of ICT labor in a more e-Ready area. Since the service sector incurs a higher marginal cost of not adopting digital technology ($\tau_s > \tau_m$), there will be a greater demand for ICT labor among service firms. The demand curve (D_s) for the service sector thus shifts outward to a greater extent compared to the demand curve of the manufacturing sector (D_m). As shown, the resulting excess demand pushes the wage rate for ICT professionals from w^B to w^S. ICT labor will move from the manufacturing sector to the service sector until the market clears at the new wage rate, w^S. In the new equilibrium, the wage rate for ICT professionals is higher, and the service sector employs more ICT professionals, while the manufacturing sector experiences

[6] For simplicity, let's assume that the behavior of firms remains consistent (or changes proportionally) regardless of whether a shock is present in an area with a low e-Index ($x = 0$). As previously discussed, the presence of $1 - \tau_j$ suggests that variations in firms' behavior will likely amplify the differences between firms in more e-Ready areas and those in less e-Ready ones. As a result, the predictions are on the conservative side.



Notes: The x-axis represents the total amount of ICT labor and the y-axis is the wage rate for ICT professionals. The solid lines represent the situation before the shock and the dashed lines represent the situation after the shock. The blue solid line, D_m^B, is the demand curve for ICT professionals in the manufacturing sector before the shock. The blue dashed line, D_m^S, is the demand curve for ICT professionals in the manufacturing sector after the shock. The grey solid line, D_s^B, is the demand curve for ICT professionals in the service sector before the shock. The grey dashed line, D_s^S, is the demand curve for ICT professionals in the service sector after the shock. The black dot is the equilibrium before the shock. w^B is the optimal wage rate for ICT professionals to clear the market before the shock. The red dot is the equilibrium after the shock. w^S is the optimal wage rate for ICT professionals to clear the market after the shock. T_m^B (T_m^S) is the optimal amount of employment of ICT labor in the manufacturing sector before (after) the shock. T_s^B (T_s^S) is the optimal amount of employment of ICT labor in the service sector before (after) the shock.

Figure B.10: Demand and Supply of ICT Labor (Small x)

a brain drain.[7] Due to the complementary relationship between ICT labor and ICT capital, one would also expect decreased ICT capital investment in the manufacturing sector. Therefore, the expansion of adoption in the service sector comes at the cost of reducing digital technology adoption in the manufacturing sector.

Prediction 3. In a more e-Ready area, compared to the case with no shock (i.e., $\tau_j = 0$), the presence of a shock is likely to lead to an increase in average productivity in the service sector, while causing a decrease in the manufacturing sector.

I will discuss the changes in average sectoral productivity in a more e-Ready area

[7]In Appendix B.5.4, I discuss two scenarios for the ICT labor supply curve: one with a horizontal supply curve and another with an upward-sloping supply curve. In both cases, manufacturing firms will not lose ICT labor.

below. The average productivity in sector j is defined as

$$\begin{aligned}\bar{A}_j &= \int_{\underline{\omega}_j}^{\Omega} A_{ij} p(\omega) d\omega \\ &= \int_{\underline{\omega}_j}^{\Omega} e^{\omega_i} p(\omega) d\omega + \int_{\bar{\omega}_j}^{\Omega} \left(T_{ij}^{\eta} + k_{ij}^{\eta}\right)^{\frac{1}{\eta}} p(\omega) d\omega. \end{aligned} \tag{B.19}$$

According to this equation, the change in average sector productivity depends only on the average improvement resulting from the adoption of digital technology, represented by the second term in equation (B.19). Holding all other factors constant, an increase in τ_j reduces the threshold of initial productivity at which firms find adopting digital technology more profitable than not adopting it. At this step, one would expect $\bar{\omega}_j^a < \bar{\omega}_j^B$, where the superscript a indicates a decrease in a. Firms in both sectors now tend to increase their demand for ICT labor and ICT capital. As shown in Figure B.10, the excess demand for ICT labor will drive up the wage rate for ICT labor. The higher wage rate will compel some firms with lower initial productivity (e^{ω_i}) to forgo digital technology adoption, which they would have otherwise pursued if there had been only a rise in τ_j without any change in w. However, even with the higher wage rate for ICT professionals, the service sector will still have more new adopters willing to pay this rate compared to the manufacturing sector. Therefore, one would expect $\bar{\omega}_s^S = \bar{\omega}_s^a + \kappa_s < \bar{\omega}_s^B$ and $\bar{\omega}_m^S = \bar{\omega}_s^a + \kappa_m \lesseqgtr \bar{\omega}_m^B$, where $\kappa_j > 0$. For the manufacturing sector, the change in $\bar{\omega}_m$ depends on the change in the wage rate for ICT labor. If w increases by a smaller amount, it is likely that one would have $\bar{\omega}_m^S < \bar{\omega}_m^B$, and vice versa.

Let $\Delta\bar{A}_j = \bar{A}_j^S - \bar{A}_j^B$ denote the difference in average productivity between the cases with and without the shock. The difference in the service sector is calculated as

$$\Delta\bar{A}_s = \underbrace{\int_{\bar{\omega}_s^S}^{\bar{\omega}_s^B} \left(T_{is}^{\eta} + k_{is}^{\eta}\right)^{\frac{1}{\eta}} p(\omega) d\omega}_{\text{1st part}>0} + \overbrace{\Delta IG_s}^{\text{2nd part}<0} . \tag{B.20}$$

The sign of $\Delta\bar{A}_s$ is undetermined. The first part is positive as discussed above. Service firms with $\omega_i \in \left(\bar{\omega}_s^B, \bar{\omega}_s^S\right]$ will now find it profitable to employ ICT labor and to invest in ICT capital. The second part, ΔIG_s, represents the change in average productivity contributed by ICT labor and ICT capital among firms that would have adopted digital technology even without the shock–the incumbent adopters. The second part is negative comparing equation (B.17) to equation (B.14). Overall, in the service sector, one would expect a positive $\Delta\bar{A}_s$ ($\bar{A}_s^S > \bar{A}_s^B$) when the increase in the productivity of new adopters outweighs the changes on the intensive margin.

For the manufacturing sector, the difference in average productivity between the cases with and without the shock is

$$\Delta\bar{A}_m = \underbrace{\int_{\bar{\omega}_m^S}^{\bar{\omega}_m^B} \left(T_{im}^{\eta} + k_{im}^{\eta}\right)^{\frac{1}{\eta}} p(\omega)d\omega}_{\text{1st part}\geq 0} + \overbrace{\Delta IG_m}^{\text{2nd part}<0} < 0, \tag{B.21}$$

if $\bar{\omega}_m^S \leq \bar{\omega}_m^B$ (scenario 1) and is

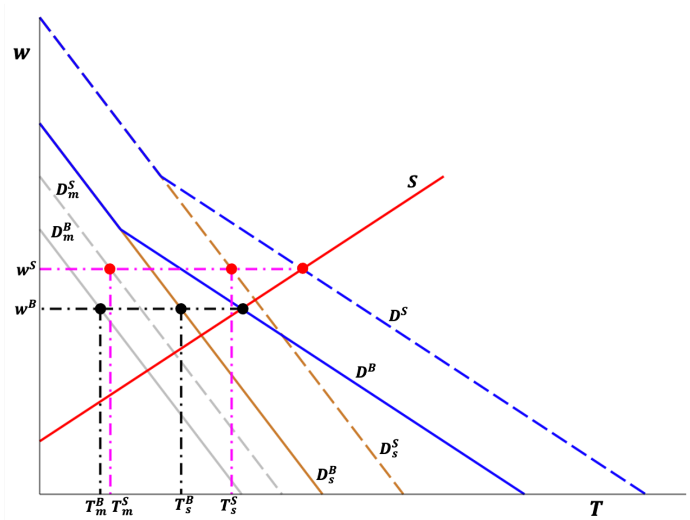
$$\Delta\bar{A}_m = \underbrace{-\int_{\bar{\omega}_m^B}^{\bar{\omega}_m^S} \left(T_{im}^{\eta} + k_{im}^{\eta}\right)^{\frac{1}{\eta}} p(\omega)d\omega}_{\text{1st part}<0} + \overbrace{\Delta IG_m}^{\text{2nd part}<0} < 0, \tag{B.22}$$

if $\bar{\omega}_m^S > \bar{\omega}_m^B$ (scenario 2). In scenario 1, one has $\Delta\bar{A}_m < 0$. Since $T_m^S < T_m^B$ and the number of manufacturing firms adopting digital technology increases, the average number of ICT labor employed by manufacturing firms decreases after the shock. So, the changes in the second part will outweigh the changes in the first part, resulting in $\Delta\bar{A}_m < 0$ in this case. In scenario 2, the first part is negative because firms with $\omega_i \in \left(\bar{\omega}_{mh}^S, \bar{\omega}_{mh}^B\right]$ will no longer find adopting digital technology profitable due to the increased wage rate of ICT professionals. For the second part (the intensive margin), those manufacturing firms that continue to adopt digital technology confront higher wage rates, leading them to cut back on their ICT labor employment. So, in both cases, the manufacturing sector will experience a drop in the average sectoral productivity.

B.5.4 Assumption on the Supply of ICT Labor

One of the key assumptions of this study is that the supply of ICT labor is fixed and inelastic. That is, its supply curve is a vertical line. In this subsection, I explore two alternative scenarios of the supply curve and demonstrate that Prediction

2 only holds true under the condition of a fixed ICT labor supply. The first case is a perfectly elastic ICT labor supply. In this context, heightened demand for ICT professionals would not lead to an increase in wages, and firms in both the service and manufacturing sectors could employ an optimal amount of ICT labor. That is, neither sector would experience losses of ICT labor.



Notes: The x-axis is the number of ICT labor and the y-axis is the wage rate for ICT professionals. The solid lines represent the situation before the shock and the dashed lines represent the situation after the shock. The gray solid line, D_m^B, is the demand curve for ICT professionals in the manufacturing sector before the shock. The gray dashed line, D_m^S, is the demand curve for ICT professionals in the manufacturing sector after the shock. The brown solid line, D_s^B, is the demand curve for ICT professionals in the service sector before the shock. The brown dashed line, D_s^S, is the demand curve for ICT professionals in the service sector after the shock. The blue solid line, D^B, is the demand curve for ICT professionals among all firms before the shock. The blue dashed line, D^S, is the demand curve for ICT professionals among all firms after the shock. The red upward-sloping solid line is the supply curve of ICT professionals. w^B is the optimal wage rate for ICT professionals to clear the market before the shock. w^S is the optimal wage rate for ICT professionals to clear the market after the shock. T_m^B (T_m^S) is the optimal amount of employment of ICT labor in the manufacturing sector before (after) the shock. T_s^B (T_s^S) is the optimal amount of employment of ICT labor in the service sector before (after) the shock.

Figure B.11: Demand and Supply of ICT Labor (Small x): Elastic Supply

The second case is having an elastic ICT labor supply. In this case, excess demand will drive up wages, which in turn will attract more workers to enter the labor market. I display a graph of the changes in the ICT labor market with an upward-sloping ICT labor supply curve in Figure B.11. As shown, the increased demand in both the service and manufacturing sectors will still push up the wage rates for ICT professionals. But, because of the elastic labor supply (or an increasing number of ICT workers entering the market), manufacturing firms will still be able to employ more ICT labor, $T_m^S > T_m^B$.

In summary, when the supply of ICT labor is not fixed or when ICT labor is not scarce, one should not anticipate a decrease in ICT labor employment in the manufacturing or service sector, as proposed in Prediction 2.

B.6 Firm Entry & Exit

In this section, I will first explore the pattern of firm entry and then shift the focus to exits.

B.6.1 Firm Entry

Entry data I obtain data on the universe of firm entries in the formal sector from the Government of India's Ministry of Corporate Affairs (MCA). The publicly available company master data contains information about a firm's registration date, current status, industrial activity codes, as well as address and pin code. I use the registration date to measure a firm's entry time. I classify a firm's industry based on its 2-digit industrial activity codes which are created based on the NIC. I map firms' pin codes to districts using the All India Pincode Directory published by the Department of Posts in the GoI. I aggregate the number of firms created at the industry-district-year level. It should be noted that the Prowess data also contain information on firms' establishment years, but it is not well suited for understanding firm entry because only 7.6% of the firms were established after 2012. For consistency, I keep only the districts that appear in both the Prowess data and the MCA registration data.

Estimation stratgey I estimate the following specification to examine changes in the entry flow:

$$Y_{jdt} = \alpha_d + \alpha_{jt} + \beta \ \textit{e-Index}_d \times Post_{1,t} \times \text{Manufacture}_j + X + \varepsilon_{jdt}, \qquad \text{(B.23)}$$

where Y_{jdt} is the log of the number of newly registered firms for industry j in district d and time t.[8] Manufacture_j is a binary indicator that takes the value of 1 if industry

[8] To avoid an undefined dependent variable when a given industry in a district has no firm created in a given year, I use $\ln(Number + 1)$ as the dependent variable.

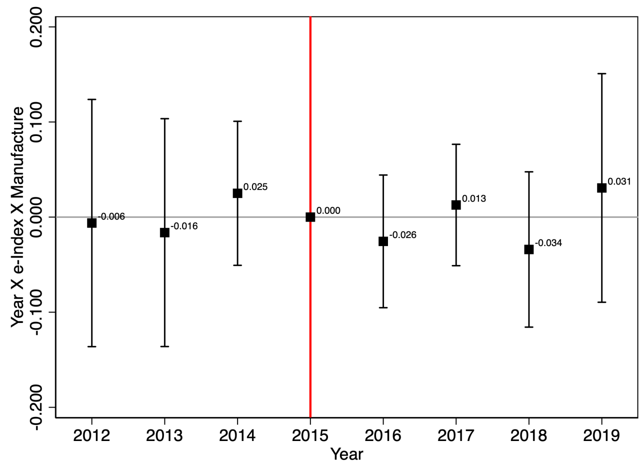
j belongs to the manufacturing sector and 0 if it belongs to the service sector. I incorporate both the district and industry-year (α_{jt}) fixed effects. α_d is the district fixed effect that controls for all time-invariant characteristics of a district including factors that attract firms in the first place. Standard errors are clustered at the district level.

Results Table B.7 reports the results of equation (B.23). The corresponding event study graph for the triple interaction term is Figure B.12, which shows no differential trends between more e-Ready areas and less e-Ready areas in the pre-treatment periods. Column 1 of Table B.7 shows a 2.1% increase in the likelihood of firms entering the market in districts with one standard deviation higher *e-Index* following the demonetization shock. In column 2, no differential effect is observed between the service and manufacturing sectors. In other words, prospective manufacturing firms did not exhibit a reduced likelihood of market entry in districts with a higher *e-Index.* Therefore, these areas experienced an increased influx of both service and manufacturing firms, possibly due to decreased entry barriers. In such districts, the government likely enhanced digital infrastructure investments, such as data centers, and implemented more supportive policies, including streamlined regulations (Carbonara, 2023) and easier access to credit (Bollaert, Lopez-de-Silanes, and Schwienbacher, 2021; X. Zhang et al., 2023), which collectively helped lower entry barriers for new firms.[9]

B.6.2 Firm Exit

Exit data The firm exit data is also derived from the MCA database, which includes information about a company's current status, the date of its last annual general meeting, and the date of the most recent balance sheet. A company's current status,

[9]The reduction in entry barriers does not necessarily imply that new entrants have lower productivity and would not have entered the market without the reduction. Barriers such as the lack of necessary infrastructure, a complicated registration process, and difficulties in acquiring land for business could hinder productive firms from entering the market. Regarding the data centers, I compare the list in 2019 to the list in 2015. There were more data centers established in districts with a higher *e-Index* than others. Regarding policies, local governments in districts with a higher *e-Index* were likely more advanced in promoting digitization. For example, as of 2017, while the government of Bastar district with an index of 0.06 was still advocating the Aadhaar initiative started in 2009, the government in Indore district with an index of 0.92 had progressed to publishing a series of e-Governance guidelines.



Notes: The outcome variable is the log of the number of newly registered firms plus one in industry j, district d, and year t. I plot the estimated coefficient on Year × *e-Index* × Manufacture in the figure. The regression includes district and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level

Figure B.12: Event Study Graph (New Entrants): Year × *e-Index* × Manufacture

Table B.7: Impacts on Firm Entries

	(1)	(2)
Post × *e-Index*	0.117***	0.123***
	(0.030)	(0.028)
Post × *e-Index* × Manufacture		-0.006
		(0.027)
Control Mean	0.30	0.29
R^2	0.57	0.58
No. of districts	347	347
N	194,744	194,744
District FE	Yes	Yes
Industry-Year FE	Yes	Yes

Notes: The outcome variable is the log of the number of newly registered firms plus one in industry j, district d, and year t. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Manufacture" = An indicator variable is set to 1 if the industry belongs to the manufacturing sector and 0 if it pertains to the service sector. All regressions include district and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The control mean is the average of the outcome variable in the pre-treatment periods in column 1. It is the average of the outcome variable in the service sector in the pre-periods in column 2. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

including active, amalgamated, converted to Limited Liability Partnership, dissolved, dormant, liquidated, and strike-off, reveals if a firm has exited the market or not. I define a firm as having exited the market if its status falls into one of the following categories: dissolved, dormant, liquidated, or strike-off. In total, there are 738,590 firms classified as non-active.

Next, I use the most recent date of the last annual general meeting or the latest balance sheet to determine the potential exit year of a firm from the market. This is because it is mandatory for companies in the formal sector to prepare and submit annual financial reports according to the Companies Act 2013. For example, if a non-active firm's latest year of the balance sheet or the general meeting was 2017, then I assume that the firm exited the market in 2018, one year after. But, only about 30.7% of them have information on either the date of the last annual general meeting or the date of the latest balance sheet. Here, I assume that the missing data on the exit year is random and examine this assumption later.[10] In total, I identified 165,703 firms that exited the market between 2012 and 2019. I then aggregate the number of firms that exited at the industry-district-year level. For consistency, I only keep the districts that appear in both the Prowess data and the MCA registration data.

I also construct an industry-district-year panel of exited firms using the Prowess data to complement the MCA one. I define a firm that has not submitted financial statements for three consecutive years (years t, $t+1$, and $t+2$) as one that exits the market in year t. I identify 10,953 firms at best that (may) have exited the market between 2012 and 2019. Among firms in the service (manufacturing) sector, about 27.7% (22.8%) of them exited the market during that period.

Results I estimate equation (B.23) using the outcome variable of the log of the number of firms that exited the industry j, district d, and time t. To prevent issues with undefined variables when the count is zero, I add 1 to the number of exits (i.e., $\ln(\text{Number of exits}_{jdt} + 1)$). The results are presented in Table B.8.

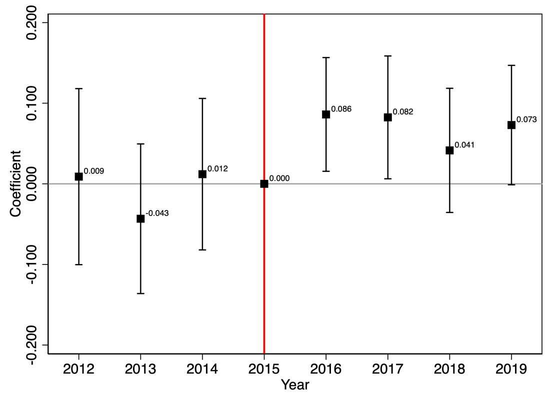
[10] It should be noted that the accumulated company master data is not available on an annual basis. I use the data collected up to March 2021 while the preceding one covers until February 2019. Because the accumulated data is not updated annually, one can not conduct cross-year comparisons to assess changes in companies' status.

Table B.8: Impacts on Firm Exits

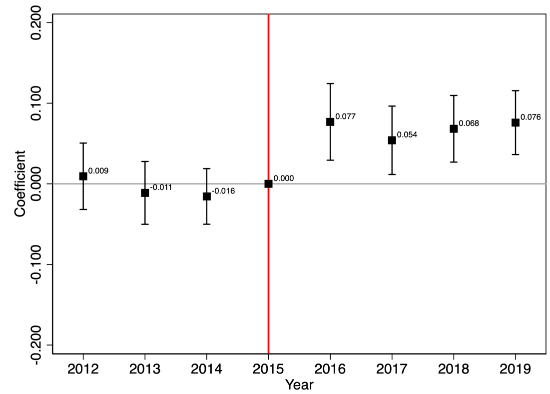
	MCA		Prowess	
	(1)	(2)	(3)	(4)
Post × *e-Index*	-0.158***	-0.187***	-0.137***	-0.165***
	(0.020)	(0.022)	(0.038)	(0.042)
Post × *e-Index* × Manufacture		0.078***		0.073***
		(0.026)		(0.016)
Control Mean	0.11	0.10	0.02	0.02
R^2	0.33	0.33	0.24	0.24
No. of districts	347	347	347	347
N	193,696	193,696	176,080	176,080
District FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: In columns 1 and 2, I use the MCA data; and in columns 3 and 4, I use the Prowess data. The outcome variable is the log of the number of exited firms plus one in industry j, district d, and year t. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The control means in columns 1 and 3 are the average of the outcome variable in the pre-treatment periods; the control means in columns 2 and 4 are the average of the outcome variable in the service sector in the pre-treatment periods. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In columns 1 and 3, both the MCA data and the Prowess data show that there was a decrease in the number of firms exiting the markets in more e-Ready districts after the shock. However, in columns 2 and 4, one can see that manufacturing firms are relatively more likely to exit compared to service firms. For example, in column 2 (4), the MCA (Prowess) data indicates a 1.4% (1.3%) increase in manufacturing firms exiting the markets in districts with an *e-Index* one standard deviation higher than that of service firms. It should be noted the estimates in column 2 are conservative due to the limited ability to identify the exact exit time for only about 30% of the exits. Nevertheless, the similar estimates in column 4 using the Prowess data help alleviate concerns regarding the missing exit year information in the MCA data. In Figure B.13, I display the event study graphs for the log of the number of exits using the MCA data and the Prowess data. As shown, there are no differential trends between districts with a high *e-Index* and those with a low *e-Index*, and these effects persisted over the four-year period. Furthermore, in Table B.9, I compare the log of 2015 TFPR between ongoing firms (those that remained in the market between 2012 and 2019) and firms that exited the market after 2016. As shown, firms destined for exit exhibit lower average TFPR than ongoing firms in both sectors, though the difference in the service sector is measured with imprecision.



(a) Exit, MCA



(b) Exit, Prowess

Notes: In Figure B.13a, I use the MCA data; in Figure B.13b, I use the Prowess data. The outcome variable is the log of the number of exited firms plus one in industry j, district d, and year t. I plot the estimated coefficients on Year $\times$ *e-Index* $\times$ Manufacture in both figures. All regressions include district and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure B.13: Event Study Graphs: Exited Firms

Table B.9: TFPR Comparison: Ongoing Firms vs. New Exited Firms

	(1) Ongoing Firms		(2) Exited Firms after 2016		Difference
Variable	Obs.	Mean/SD	Obs.	Mean/SD	(1)-(2)/SE
Services	8,275	0.634	3,170	0.385	0.249
		(11.520)		(8.232)	(0.224)
Manufacturing	6,246	10.810	2,116	8.911	1.899***
		(8.068)		(8.402)	(0.204)

Notes: "Ongoing Firms" = Firms that did not exit the market between 2012 and 2019. "Exited Firms after 2016" = Firms that exited the market between 2016 and 2019. I test the differences between column 1 and column 2 using a t-test with equal variance. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Missingness of exit dates in the MCA data In the MCA registration data, there are 738,590 firms classified as non-active (e.g. dissolved, dormant, liquidated, and strike-off). I use the most recent date of either the last annual general meeting or the latest balance sheet to determine the exit date of such firms from the market. If a non-active firm's latest year of the balance sheet or the general meeting is t, then I assume that the firm exited the market in year $t+1$, one year after. In the data, only about 30.7% (226,376) of them have information on either the date of the last annual general meeting or the date of the latest balance sheet. I am able to identify 165,703 firms that exited the market between 2012 and 2019. Among these firms, 84.1% are in the manufacturing or service sector. And among firms in the manufacturing or service sector, 29.9% of them have information on the exit year. I assume that the missing data on the exit year is random and examine this assumption in this section.

First, I check if the missing data is random at least in relation to the *e-Index*. That is, firms located in the more e-Ready districts are not more (or less) likely to report the information on the last annual general meeting date or the date of the most recent balance sheet. I construct the ratio of the number of exited firms without information on exit year relative to the total number of exited firms in industry j and district d, $\frac{\text{Number of firms without exit years}_{jd}}{\text{Number of firms exited}_{jd}}$. The correlation coefficient of the ratio and the *e-Index* is -0.070, which indicates a weak negative correlation. I then perform a regression of the ratio on the e-Index. The estimated coefficient on the *e-Index* is -0.093 and is not statistically significant at conventional levels. Therefore, it is unlikely the case that the results in Table B.8 are driven by the disproportionate exit of firms in more or less e-Ready areas.

Another valid concern is that compared to service firms, there may be more or fewer manufacturing firms that exited the market without providing information on their last annual general meeting date or the date of their most recent balance sheet. In other words, the proportion of manufacturing firms is disproportionately higher or lower among the 69.8% of firms without exit year information. I construct the ratio of the number of exited service (manufacturing) firms without information on exit year relative to the total number of exited service (manufacturing) firms in district d, $\frac{\text{Number of services (or manufacturing) firms without exit years}_{d}}{\text{Number of services (or manufacturing) firms}_{d}}$. I then conduct a t-test on the ratio by sector. The difference between the ratio of manufacturing firms and the ratio of service firms is -0.017 with a standard error of 0.011 and is not statistically significant at a 10% level.[11] Thus, it is not the case that manufacturing firms are more or less likely to report the information.

Lastly, I check if the number of exited firms in the Prowess sample is correlated with the number in the MCA sample. I aggregate the annual number of exited firms in

[11] The mean of the ratio for service firms is 0.739 and 0.722 for manufacturing firms. So, among service (manufacturing) firms that have exited in a district, on average, about 74% (72%) did not provide the date of the last annual general meeting or the date of the latest balance sheet. It should be noted that in absolute terms, there are more service firms that exited the market than manufacturing firms in a district. On average, 490 service firms and 183 manufacturing firms exited the market without providing information on the year of exit.

each industry and each district to the sector-district level. That is, I count the number of exited service (or manufacturing) firms in district d and year t. The correlation coefficient between the log of the number of exited firms in the Prowess sample and the log of the number of exited firms in the MCA sample is 0.662, indicating a strong positive correlation between the two datasets.[12] I also regress the log of the number of exited firms in the Prowess sample on the log of the number of exited firms in the MCA sample. I control for district and year fixed effects and cluster the standard errors at the district level. The estimated coefficient is 0.047 with a standard error of 0.014 and is statistically significant at a 5% level.

Overall, the missing information on the exit year in the MCA data seems to be random. The three checks strengthen the analysis of the firm exit patterns.

B.7 Robustness Check

B.7.1 Restricted Sample: Firms Established Before 2012 or 2016

[12] I apply the common logarithm transformation, log(number+1), on the number to retain the zero values.

Table B.10: Impacts on Income, TFPR, ICT-related Expenses & Investment (Firms Established before 2012)

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(TFPR)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.069*	0.524**	0.018***	0.004**	0.020**
	(0.036)	(0.223)	(0.006)	(0.002)	(0.008)
Control Mean	1.81	0.32	0.05	0.01	0.12
R^2	0.93	0.86	0.85	0.61	0.87
No. of firms	16,645	13,862	16,153	16,153	17,493
N	99,981	78,292	93,731	93,731	110,273
Panel B. Manufacturing					
Post × *e-Index*	-0.127***	-0.376*	-0.012**	-0.001	0.007
	(0.035)	(0.202)	(0.005)	(0.002)	(0.008)
Control Mean	3.37	10.77	0.04	0.00	0.09
R^2	0.94	0.88	0.81	0.64	0.85
No. of firms	10,003	9,569	10,228	10,228	10,699
N	63,586	59,448	63,018	63,018	69,548
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: I restrict the sample (Prowess) to firms established before 2012. "e-Index" = The normalized district-level e-Readiness Index. TFPR in Column 2 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). A detailed discussion is provided in Appendix B.3. "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Spend on Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.11: Impacts on Income, TFPR, ICT-related Expenses & Investment (Firms Established before 2016)

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(TFPR)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.064*	0.411*	0.019***	0.004**	0.018*
	(0.039)	(0.229)	(0.006)	(0.002)	(0.010)
Control Mean	1.78	0.29	0.05	0.01	0.11
R^2	0.93	0.86	0.85	0.61	0.86
No. of firms	17,982	14,860	17,355	17,355	18,835
N	106,011	82,419	98,836	98,836	116,660
Panel B. Manufacturing					
Post × *e-Index*	-0.135***	-0.404*	-0.012**	-0.001	0.008
	(0.036)	(0.216)	(0.005)	(0.002)	(0.008)
Control Mean	3.34	10.63	0.04	0.00	0.08
R^2	0.94	0.87	0.81	0.64	0.85
No. of firms	10,455	9,979	10,725	10,725	11,199
N	65,697	61,299	65,332	65,332	72,055
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: I restrict the sample (Prowess) to firms established before 2016. "e-Index" = The normalized district-level e-Readiness Index. TFPR in Column 2 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). A detailed discussion is provided in Appendix B.3. "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Spend on Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

B.7.2 Analysis using All Observations

Table B.12: Impacts on Income & TFPR (All Observations)

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(Sales)	Ln(Fin. Serv. Inc.)	ROA	Ln(TFPR)
Panel A. Services					
Post × *e-Index*	0.084**	0.072$^+$	0.001	0.074***	0.412*
	(0.041)	(0.045)	(0.024)	(0.022)	(0.228)
Control Mean	1.79	1.43	0.46	0.84	0.29
R^2	0.92	0.92	0.89	0.81	0.86
No. of firms	18,575	18,511	18,528	18,242	14,983
N	112,501	109,805	110,418	109,167	82,741
Panel B. Manufacturing					
Post × *e-Index*	-0.147***	-0.144***	-0.019	-0.045**	-0.404*
	(0.039)	(0.041)	(0.023)	(0.022)	(0.216)
Control Mean	3.29	3.26	0.32	1.28	10.62
R^2	0.93	0.93	0.85	0.80	0.87
No. of firms	10,538	10,499	10,503	10,532	10,009
N	68,021	65,900	66,299	68,005	61,374
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). A detailed discussion is provided in Appendix B.3. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.13: Impacts on Assets (All Observations)

	(1)	(2)	(3)	(4)	(5)
	Ln(Assets)	Ln(Fixed Assets)	Ln(Intangible$_e$)	Ln(PPE$_e$)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.051	0.003	-0.017	-0.012	0.020**
	(0.037)	(0.029)	(0.016)	(0.026)	(0.009)
Control Mean	2.33	0.89	0.10	0.80	0.11
R^2	0.94	0.91	0.79	0.92	0.86
No. of firms	19,921	19,078	19,038	19,038	19,042
N	125,317	118,136	117,281	117,274	117,341
Panel B. Manufacturing					
Post × *e-Index*	-0.072**	-0.048*	0.013	-0.049*	0.008
	(0.031)	(0.026)	(0.011)	(0.026)	(0.008)
Control Mean	3.02	1.98	0.10	1.97	0.08
R^2	0.96	0.95	0.79	0.95	0.85
No. of firms	11,612	11,268	11,249	11,247	11,249
N	75,046	72,805	72,227	72,207	72,250
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Assets" = Total assets are composed of non-current assets and current assets. "Fixed Assets" = Fixed assets are a type of non-current asset, which includes intangible assets, property, plant, and equipment, and other fixed assets. "Intangible$_e$" = Intangible assets excluding software. "PPE$_e$" = Property, plant, and equipment excluding computers and IT systems. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.14: Impacts on Expenses (All Observations)

	(1)	(2)	(3)	(4)	(5)
	Ln(Expenses)	Ln(Compensation)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Any Outsourced: Software & ICT
Panel A. Services					
Post × *e-Index*	0.115***	0.050*	0.025***	-0.003	0.021***
	(0.040)	(0.028)	(0.008)	(0.003)	(0.007)
Control Mean	1.73	0.57	0.05	0.02	0.10
R^2	0.92	0.92	0.84	0.63	0.63
No. of firms	19,262	19,184	18,817	19,144	19,144
N	118,918	117,791	111,805	117,110	117,110
Panel B. Manufacturing					
Post × *e-Index*	-0.117***	-0.030	-0.014**	-0.001	-0.015
	(0.036)	(0.027)	(0.006)	(0.002)	(0.011)
Control Mean	3.15	0.97	0.04	0.00	0.07
R^2	0.94	0.93	0.80	0.64	0.58
No. of firms	11,108	11,094	10,813	11,062	11,095
N	71,308	71,101	66,147	70,360	70,837
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Compensation" = Compensation to employees."Fin. Serv. Expenses" = Financial services expenses. "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Any Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

B.7.3 Including State-Year Fixed Effects

Table B.15: Impacts on Income & TFPR by Sector (Include State-Year Fixed Effects)

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Fin. Serv. Inc.)	(4) ROA	(5) Ln(TFPR)
Post × *e-Index* (PeI)	-0.124***	-0.125***	-0.017	-0.058**	-0.546**
	(0.039)	(0.037)	(0.024)	(0.025)	(0.235)
Post × *e-Index*× Services	0.199***	0.197***	0.013	0.105***	0.943***
	(0.043)	(0.040)	(0.041)	(0.024)	(0.282)
PeI+PeIS	0.076*	0.072^{+}	-0.004	0.047*	0.397^{+}
p-value	(0.061)	(0.145)	(0.877)	(0.092)	(0.128)
Control Mean (Manu.)	3.34	3.31	0.32	1.29	10.62
Control Mean (Services)	1.79	1.45	0.48	0.82	0.29
R^2	0.94	0.94	0.89	0.82	0.89
No. of firms	28,669	28,669	28,669	28,669	24,992
N	172,328	172,328	172,328	172,328	144,115
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). All regressions include firm, industry-year, and state-year fixed effects as well as control for the average nightlight intensity of a district and the number of functioning commercial bank branches of a district per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.16: Impacts on Assets by Sector (Include State-Year Fixed Effects)

	(1)	(2)	(3)	(4)	(5)
	Ln(Assets)	Ln(Fixed Assets)	Ln(Intangible$_e$)	Ln(PPE$_e$)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.099**	0.100**	0.035**	0.051	0.021**
	(0.043)	(0.042)	(0.017)	(0.040)	(0.009)
Control Mean	2.32	0.90	0.10	0.80	0.11
R^2	0.94	0.91	0.79	0.92	0.86
No. of firms	19,747	19,037	19,037	19,037	19,037
N	122,936	117,240	117,240	117,240	117,240
Panel B. Manufacturing					
Post × *e-Index*	-0.069**	-0.037	0.025*	-0.038	0.015**
	(0.027)	(0.029)	(0.013)	(0.030)	(0.006)
Control Mean	3.07	2.02	0.10	2.00	0.08
R^2	0.97	0.95	0.79	0.95	0.85
No. of firms	11,612	11,247	11,247	11,247	11,247
N	75,028	72,185	72,185	72,185	72,185
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Assets" = Total assets are composed of non-current assets and current assets. "Fixed Assets" = Fixed assets are a type of non-current asset, which includes intangible assets, property, plant, and equipment, and other fixed assets. "Intangible$_e$" = Intangible assets excluding software. "PPE$_e$" = Property, plant, and equipment excluding computers and IT systems. "ICT Assets" = Software and computers and IT systems. All regressions include firm, industry-year, and State-Year fixed effects as well as control for the average nightlight intensity of a district and the number of functioning commercial bank branches of a district per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.17: Impacts on Expenses by Sector (Include State-Year Fixed Effects)

	(1)	(2)	(3)	(4)	(5)
	Ln(Expenses)	Ln(Compensation)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Any Outsourced: Software & ICT
Panel A. Services					
Post × *e-Index*	0.123**	0.048	0.008	0.003*	0.031***
	(0.053)	(0.043))	(0.009)	(0.002)	(0.011)
Control Mean	1.82	0.58	0.05	0.01	0.09
R^2	0.92	0.92	0.85	0.61	0.63
No. of firms	17,526	17,526	17,526	17,526	17,526
N	99,280	99,280	99,280	99,280	99,280
Panel B. Manufacturing					
Post × *e-Index*	-0.168***	-0.031	-0.017***	-0.005**	-0.037***
	(0.035)	(0.034)	(0.003)	(0.002)	(0.011)
Control Mean	3.24	0.93	0.04	0.00	0.07
R^2	0.94	0.92	0.81	0.64	0.57
No. of firms	10,176	10,176	10,176	10,176	10,176
N	61,980	61,980	61,980	61,980	61,980
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Compensation" = Compensation to employees. "Labor Share" = The ratio of compensation to employees over total income. "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Any Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. All regressions include firm, industry-year, and State-Year fixed effects as well as control for the average nightlight intensity of a district and the number of functioning commercial bank branches of a district per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.18: Impacts on Wage: Employed Individuals (Include State-Year Fixed Effects)

	(1) All	(2) ≥Bachelor	(3) ≥Bachelor	(4) ≤Higher Secondary
Dependent Variable: Ln(Wage)				
Post × *e-Index* (PeI)	-0.002	0.369*	0.304	-0.075
	(0.224)	(0.209)	(0.238)	(0.240)
Post × *e-Index* × Related Disciplines (PeIR)			0.387	
			(0.293)	
PeI+PeIR			0.691***	
p-value			(0.006)	
Control Mean	8.01	7.81	7.73	8.06
R^2	0.45	0.51	0.52	0.44
No. of individuals	236,067	54,808	54,808	183,480
N	2,062,179	433,634	433,634	1,626,749
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Notes: I restrict the sample to employed individuals residing in districts that are included in the Prowess data. "All" = The regression is estimated on a sample of employed individuals. "≥Bachelor" = The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of employed individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. The "Control Mean" refers to the average log of wages among employed individuals during the pre-periods in column 1, the average log of wages among individuals with diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees in column 2, the average log of wages among individuals in the non-service sector who have diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees, excluding those with a background in computer application or engineering, in column 3, and the average log of wages among employed individuals who either lack any formal education or have completed only primary, middle, secondary, or higher secondary schooling in column 4. All regressions include individual, wave, industry-year, and state-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.19: Impacts on Probability of Working in a Specific Sector (Include State-Year Fixed Effects)

	(1) All	(2) ≥Bachelor	(3) ≥Bachelor	(4) ≤Higher Secondary
Panel A. Dependent Variable: Work in the service sector				
Post × *e-Index*	0.052*	0.041	0.018	0.050*
	(0.028)	(0.038)	(0.033)	(0.028)
Post × *e-Index* × Related Disciplines			0.103*	
			(0.058)	
Control Mean	0.61	0.75	0.76	0.57
R^2	0.59	0.55	0.55	0.59
Panel B. Dependent Variable: Work in the manufacturing sector				
Post × *e-Index*	0.012	-0.024	-0.002	0.019
	(0.021)	(0.033)	(0.029)	(0.022)
Post × *e-Index* × Related Disciplines			-0.086^{+}	
			(0.060)	
Control Mean	0.21	0.19	0.18	0.21
R^2	0.46	0.45	0.45	0.47
No. of individuals	236,244	54,964	54,964	183,510
N	2,083,714	449,398	449,398	1,632,518
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Notes: I restrict the sample to employed individuals residing in districts that are included in the Prowess data. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Work in the Service Sector" = A dummy variable equal to one if an employed individual is working in the service sector and zero otherwise. "Work in the Manufacturing Sector" = A dummy variable equal to one if an employed individual is working in the manufacturing sector and zero otherwise. 'All" = The regression is estimated on a sample of employed individuals. "≥Bachelor" = The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of employed individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. All regressions include individual, wave, and State-Year fixed effects as well as control for the average nightlight intensity of a district and the number of functioning commercial bank branches of a district per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

B.7.4 Temporal Placebo Tests

Table B.20: Impacts on Income, TFPR, ICT-related Expenses & Investment (Post-Treatment Years=2014-2015)

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(TFPR)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	-0.001	0.004	0.001	0.000	0.004
	(0.033)	(0.313)	(0.005)	(0.001)	(0.005)
Control Mean	1.72	0.20	0.05	0.01	0.12
R^2	0.96	0.92	0.90	0.74	0.92
No. of firms	14,031	11,033	13,364	13,353	15,360
N	44,132	33,619	42,807	42,738	51,205
Panel B. Manufacturing					
Post × *e-Index*	-0.053	-0.074	0.003	-0.001	0.003
	(0.039)	(0.243)	(0.004)	(0.002)	(0.004)
Control Mean	3.41	10.50	0.04	0.00	0.09
R^2	0.96	0.91	0.92	0.70	0.90
No. of firms	8,640	8,102	8,752	8,752	9,545
N	27,657	25,547	28,597	28,597	32,282
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

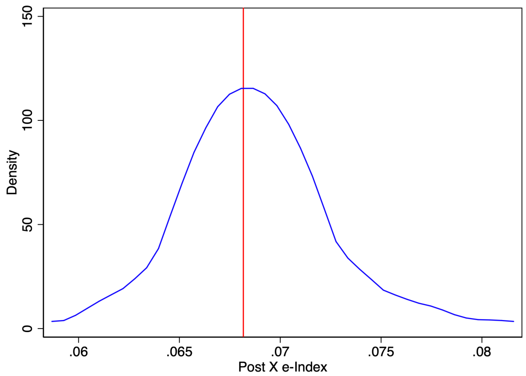
Notes: I restrict the study period to 2012∼2015, assuming 2014 as the treatment year and 2014 and 2015 as the post-treatment years. "e-Index" = The normalized district-level e-Readiness Index. TFPR in column 2 is the Total Factor Revenue Productivity of a firm calculated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Spend on Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.21: Impacts on Income, TFPR, ICT-related Expenses & Investment (Post-Treatment Year=2015)

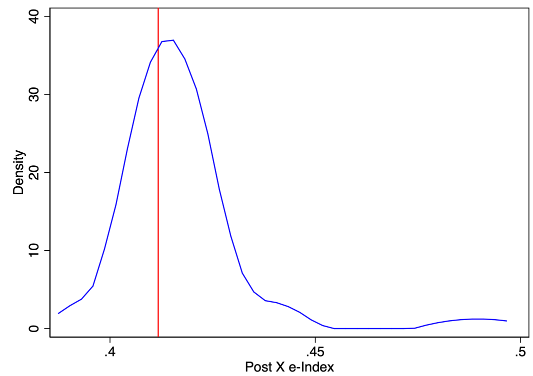
	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(TFPR)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.004	-0.037	-0.001	-0.001	0.001
	(0.034)	(0.264)	(0.004)	(0.001)	(0.007)
Control Mean	1.77	0.17	0.05	0.01	0.12
R^2	0.96	0.93	0.90	0.74	0.92
No. of firms	14,031	11,011	13,364	13,353	15,360
N	44,132	33,538	42,807	42,738	51,205
Panel B. Manufacturing					
Post × *e-Index*	-0.029	0.043	0.000	-0.001	-0.002
	(0.027)	(0.154)	(0.002)	(0.002)	(0.005)
Control Mean	3.39	10.76	0.04	0.00	0.09
R^2	0.96	0.91	0.92	0.70	0.90
No. of firms	8,640	8,102	8,752	8,752	9,545
N	27,657	25,547	28,597	28,597	32,282
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: I restrict the study period to 2012∼2015, assuming 2015 as the treatment year and 2015 as the post-treatment year. "e-Index" = The normalized district-level e-Readiness Index. TFPR in column 2 is the Total Factor Revenue Productivity of a firm calculated based on the method proposed by Grieco, S. Li, and H. Zhang (2016). "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Spend on Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

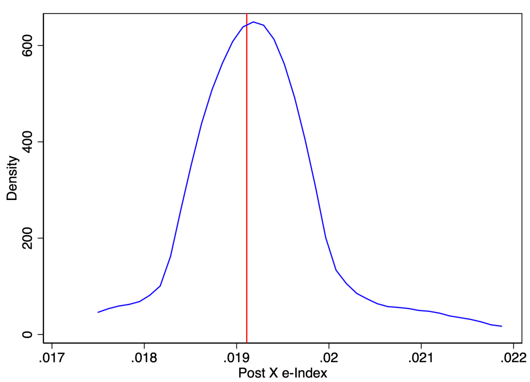
B.7.5 Excluding One Industry



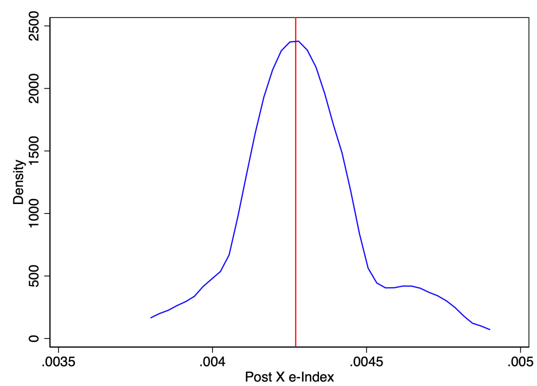
(a) Ln(Income)



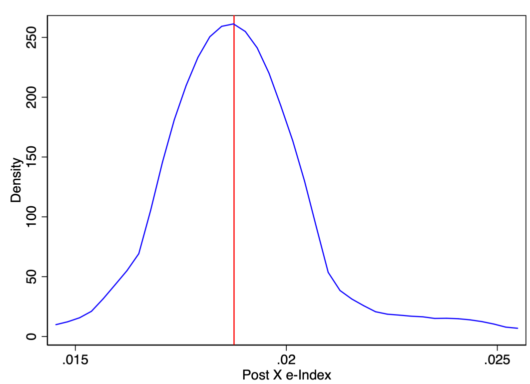
(b) Ln(TFPR)



(c) Ln(Communication)



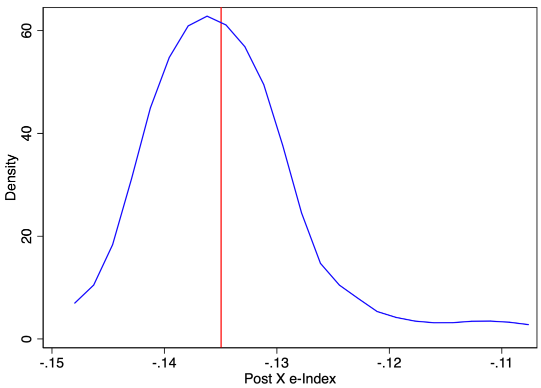
(d) Ln(Outsourced: Software & ICT)



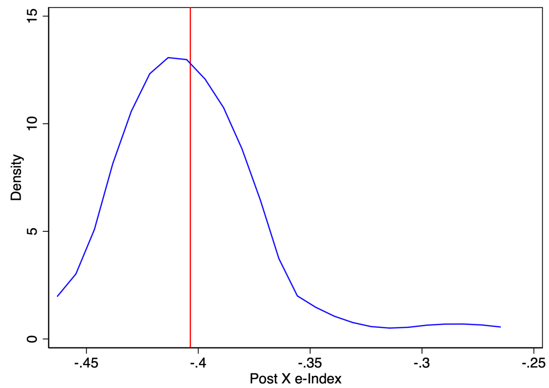
(e) Ln(ICT Assets)

Notes: I re-estimate the parameter of interest (β) in equation (2.1) on service firms excluding one service industry at a time. The estimations are conducted for the five key outcome variables. The distribution of the estimated coefficient of interest is depicted as a blue curve, while the red line represents the main coefficient obtained without excluding any industry.

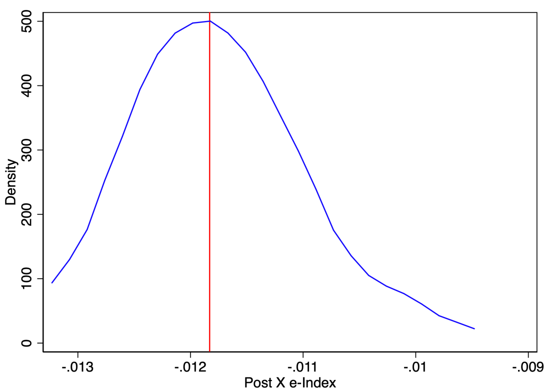
Figure B.14: Distribution of the Estimated *Post* $\times$ *e-Index* (One Service Industry Out)



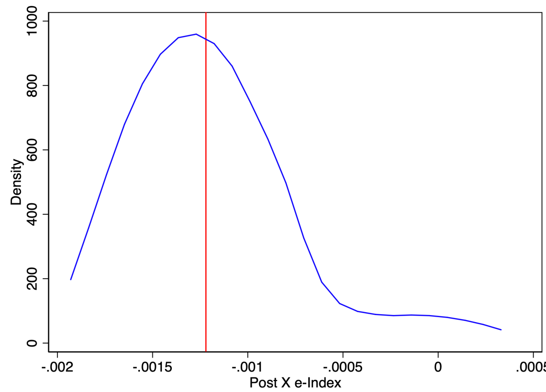
(a) Ln(Income)



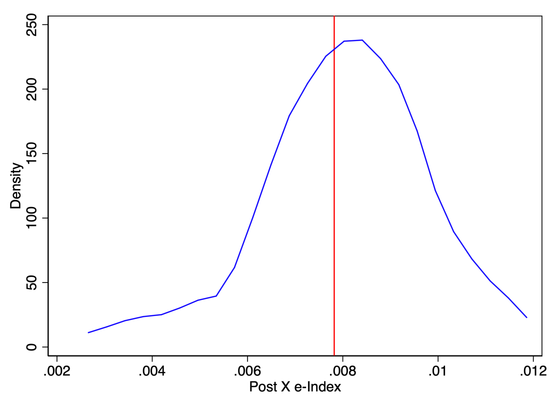
(b) Ln(TFPR)



(c) Ln(Communication)



(d) Ln(Outsourced: Software & ICT)



(e) Ln(ICT Assets)

Notes: I re-estimate the parameter of interest (β) in equation (2.1) on manufacturing firms excluding one manufacturing industry at a time. The estimations are conducted for the five key outcome variables. The distribution of the estimated coefficient of interest is depicted as a blue curve, while the red line represents the main coefficient obtained without excluding any industry.

Figure B.15: Distribution of the Estimated *Post* $\times$ *e-Index* (One Manufacturing Industry Out)

B.7.6 Labor: Migration & Supply

Table B.22: Impacts on Probability of Working in a Specific Sector (Excluding Migrated Individuals)

	(1) All	(2) ≥Bachelor (High-Skill)	(3) ≥Bachelor (High-Skill)	(4) ≤Higher Secondary (Low-Skill)
Panel A. Dependent Variable: Work in the service sector				
Post × *e-Index*	0.058^{+}	0.067^{+}	0.039	0.052
	(0.038)	(0.042)	(0.036)	(0.042)
Post × *e-Index* × Related Disciplines			0.142*	
			(0.081)	
Control Mean	0.61	0.75	0.76	0.57
R^2	0.58	0.54	0.54	0.58
Panel B. Dependent Variable: Work in the manufacturing sector				
Post × *e-Index*	0.028	-0.015	0.012	0.035
	(0.026)	(0.039)	(0.031)	(0.027)
Post × *e-Index* × Related Disciplines			-0.131^{+}	
			(0.082)	
Control Mean	0.21	0.20	0.18	0.21
R^2	0.46	0.45	0.45	0.46
No. of individuals	208,683	48,216	48,216	162,354
N	1,853,131	398,621	398,621	1,453,010
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: I restrict the sample to employed individuals who are not identified as migrated individuals and reside in districts that are included in the Prowess data. "Work in the Service Sector" = A dummy variable equal to one if an employed individual is working in the service sector and zero if is working in other sectors. "Work in the Manufacturing Sector" = A dummy variable equal to one if an employed individual is working in the manufacturing sector and zero if is working in other sectors. 'All" = The regression is estimated on a sample of employed individuals. "≥Bachelor" = The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of employed individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. All regressions include individual and wave fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.23: Impacts on Labor Market Participation

	(1) All	(2) ≥Bachelor (High-Skill)	(3) ≥Bachelor (High-Skill)	(4) ≤Higher Secondary (Low-Skill)
Panel A. Dependent Variable = In the Labor Market				
Post × *e-Index*	-0.013	-0.020	-0.025	-0.018
	(0.023)	(0.017)	(0.018)	(0.025)
Post × *e-Index* × Related Disciplines			0.003	
			(0.025)	
Control Mean	0.59	0.70	0.69	0.57
R^2	0.77	0.73	0.73	0.78
Panel B. Dependent Variable = Employed in the Service or Manufacturing Sector				
Post × *e-Index*	0.015	0.012	0.006	0.017
	(0.013)	(0.014)	(0.015)	(0.015)
Post × *e-Index* × Related Disciplines			-0.013	
			(0.025)	
Control Mean	0.37	0.51	0.50	0.34
R^2	0.72	0.71	0.71	0.72
No. of individuals	448,209	89,812	89,812	368,004
N	4,629,228	837,914	837,914	3,787,483
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: The sample comprises individuals residing in districts included in the Prowess dataset, encompassing those in the labor market (employed or unemployed) as well as those out of the labor market. "In the Labor Market" = A dummy variable equal to one if an individual is employed or unemployed while actively seeking a job and zero otherwise. "Employed in the Service/Manufacturing Sector" = A dummy variable equal to one if an individual is employed in the service or manufacturing sector and zero if the individual is employed in other sectors, unemployed, or out of the labor market. "All" = The regression is estimated on a sample of all individuals (e.g., employed, unemployed, and out of the labor market). "≥Bachelor" = The regression is estimated on a sample of individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees. "≤Higher Secondary" = The regression is estimated on a sample of individuals who have not pursued any formal education or have only completed primary, middle, secondary, or higher secondary schooling. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. All regressions include individual and wave fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

B.7.7 Placebo Test: ICT or Management?

Table B.24: Probability of Working in a Specific Sector: ICT-related Disciplines vs. Management

	≥Bachelor		
	(1)	(2)	(3)
Panel A. Dependent Variable: Work in the service sector			
Post × *e-Index*	0.058^{+}	0.031	0.037
	(0.036)	(0.030)	(0.027)
Post × *e-Index* × Related Disciplines		0.143*	0.144**
		(0.073)	(0.073)
Post × *e-Index* × Management			-0.038
			(0.029)
Control Mean	0.75	0.76	0.76
R^2	0.54	0.54	0.54
Panel B. Dependent Variable: Work in the manufacturing sector			
Post × *e-Index*	-0.018	0.008	-0.002
	(0.033)	(0.026)	(0.023)
Post × *e-Index* × Related Disciplines		-0.133*	-0.130*
		(0.075)	(0.074)
Post × *e-Index* × Management			0.032
			(0.025)
Control Mean	0.19	0.18	0.17
R^2	0.45	0.45	0.45
No. of individuals	54,964	54,964	54,964
N	449,398	449,398	449,398
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes

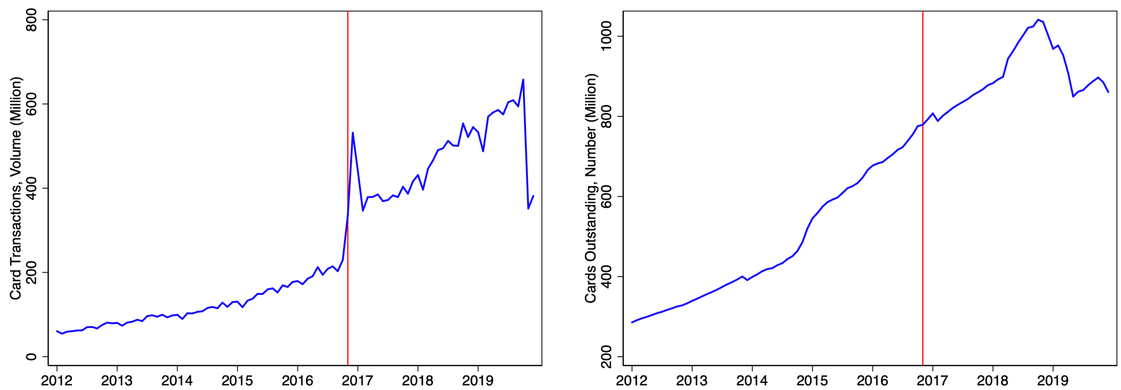
Notes: The regression is estimated on a sample of employed individuals who hold diplomas or certificates, bachelor's degrees, master's degrees, or Ph.D. degrees and reside in districts that are included in the Prowess data. "Work in the Service Sector" = A dummy variable equal to one if an employed individual is working in the service sector and zero otherwise. "Work in the Manufacturing Sector" = A dummy variable equal to one if an employed individual is working in the manufacturing sector and zero otherwise. "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Related Disciplines" = A dummy variable equal to one if an individual's discipline is either computer application or engineering and zero otherwise. "Management" = A dummy variable equal to one if an individual's discipline is either commerce or management and zero otherwise. People who go to primary, middle, secondary, or higher secondary schools do not have a selected discipline. All regressions include individual and wave fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.25: Impacts on Labor Expenses (Prowess)

	(1)	(2)	(3)
	Ln(Compensation)	Ln(Salaries)	Ln(Bonus)
Panel A. Services			
Post × *e-Index*	0.046*	0.044*	-0.001
	(0.024)	(0.024)	(0.001)
Control Mean	0.58	0.53	0.00
R^2	0.92	0.91	0.34
No. of firms	17,504	17,504	17,504
N	98,443	98,443	98,443
Panel B. Manufacturing			
Post × *e-Index*	-0.028	-0.017	-0.002**
	(0.027)	(0.026)	(0.001)
Control Mean	1.02	0.94	0.00
R^2	0.93	0.93	0.32
No. of firms	10,438	10,438	10,438
N	66,364	66,364	66,364
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: "e-Index" = Normalized district-level population-weighted e-Readiness Index. "Compensation" = Compensation to employees. "Salaries" = Salaries and wages encompass periodic payments made to all employees, including workers and managers, in recognition of the services they render. "Bonus" = A bonus is a supplementary payment provided as an incentive or reward to employees, particularly those in management positions. All regressions include firm, industry-year, and State-Year fixed effects as well as control for the average nightlight intensity of a district and the number of functioning commercial bank branches of a district per 1,000 population. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

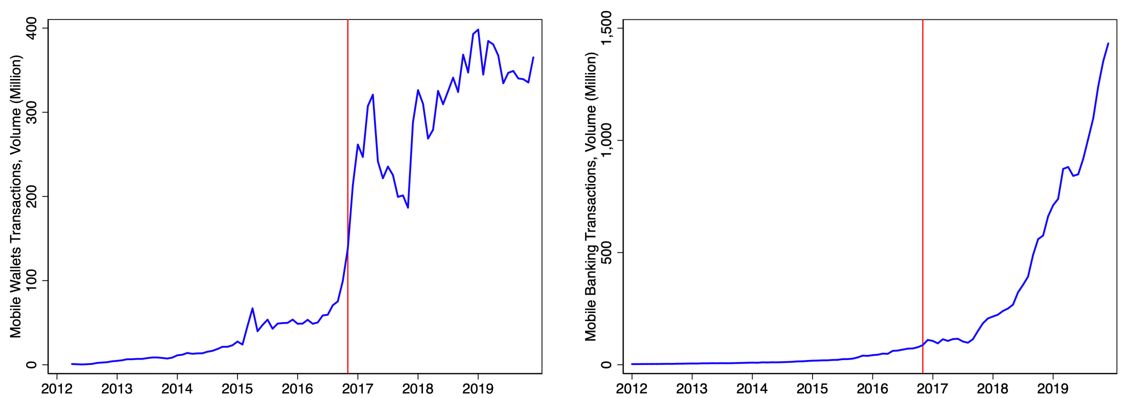
B.8 Additional Figures



(a) Volume of Card Transactions (Million) (b) Number of Cards Outstanding (Million)

Notes: Data is from the Monthly RBI Bulletin published by the Reserve Bank of India. The frequency of the data is monthly. Figure B.16a plots the monthly amount of transactions made by debit and credit cards. Figure B.16b plots the monthly number of outstanding debit and credit cards. The red line is November 2016.

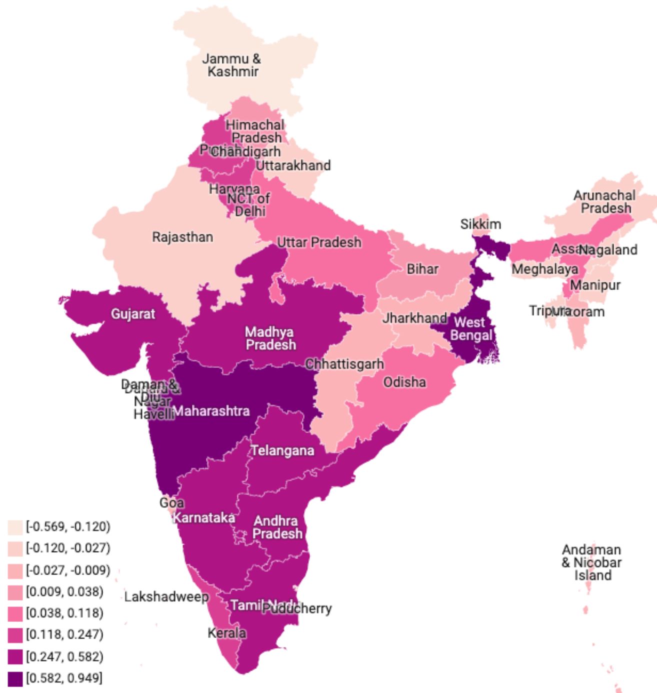
Figure B.16: Trends of Cards & Card Transactions



(a) Volume of Mobile Wallets Transactions (Million) (b) Volume of Mobile Banking Transactions (Million)

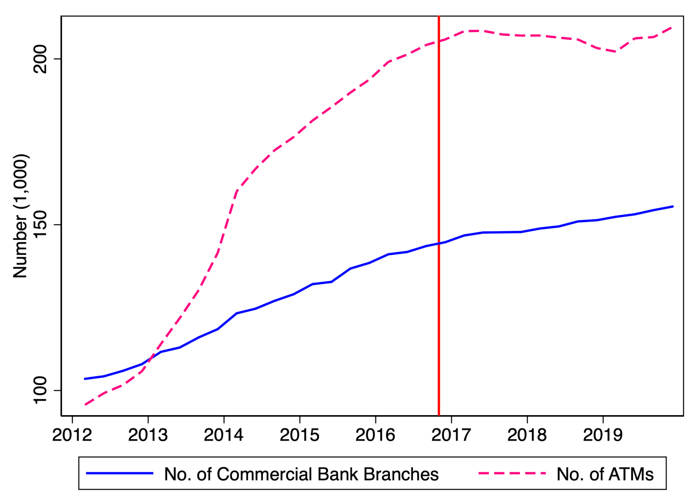
Notes: Data is from the Monthly RBI Bulletin published by the Reserve Bank of India. The frequency of the data is monthly. Figure B.17a plots the monthly amount of transactions made by mobile wallets such as Paytm and Google Pay. Figure B.17b plots the monthly amount of transactions made through mobile-based banking apps. The red line is November 2016.

Figure B.17: Trends of Digital Payments: Mobile Wallets & Mobile Banking



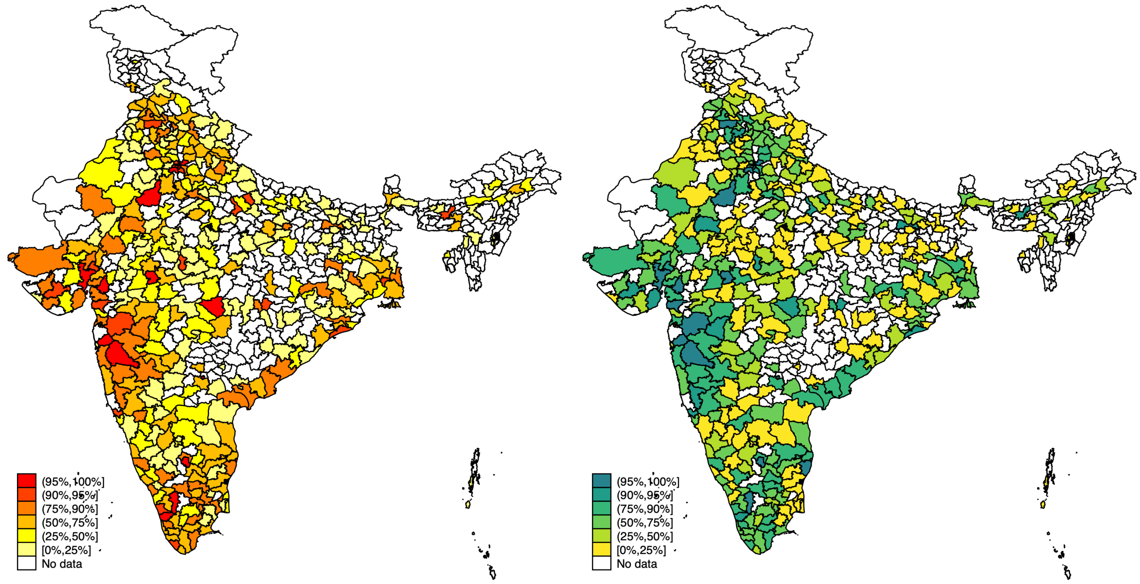
Notes: Figure B.18 plots a map of the DIT-NCAER's state-level e-Readiness Index. Numbers in the legend are the percentiles of the index at 0%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, and 100%. The deeper the color, the higher the index is (i.e. the more well-prepared an area is for digitalization).

Figure B.18: Map of DIT-NCAER's e-Readiness Index (State Level)



Notes: Data on the number of ATMs is from "State-wise and Region-wise Deployment of ATMs" published by the Reserve Bank of India. Data on the number of commercial bank branches is from the Database on Indian Economy published by the Reserve Bank of India. The units are in thousands and the frequency is quarterly (March, June, September, and December). The blue solid line plots the number of functioning commercial bank offices and the pink dashed line plots the number of ATMs (both on-site and off-site) at the national level. The red line is November 2016.

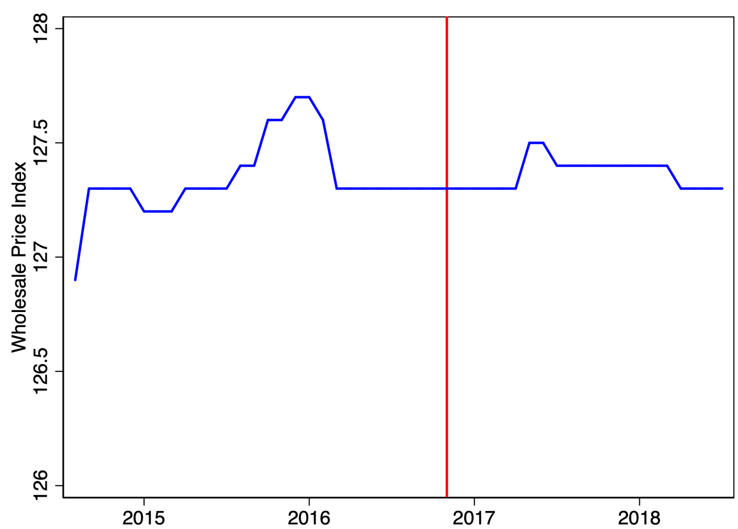
Figure B.19: Trends of Commercial Bank Branches and ATMs



(a) Service Sector (b) Manufacturing Sector

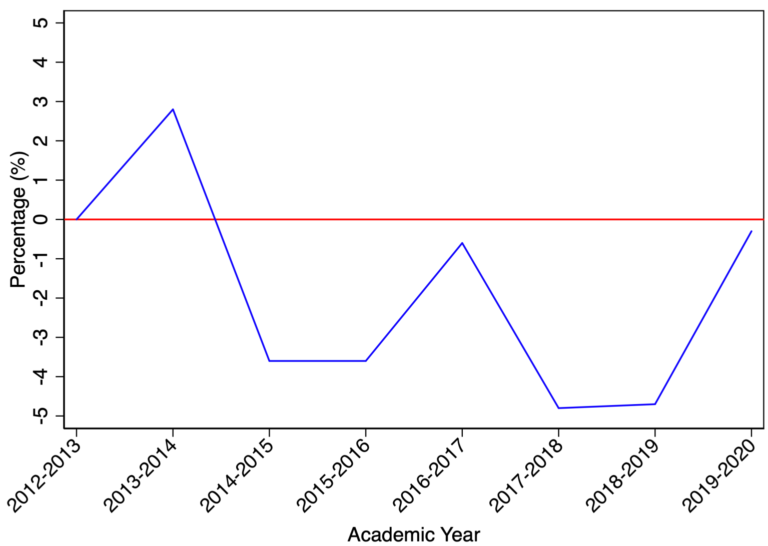
Notes: Figure B.20a plots a map of the number of firms in the service sector and Figure B.20b plots a map of the number of firms in the manufacturing sector. "No data" indicates that the district is either part of the excluded states or union territories or that no company in that district published annual financial statements from 2012 to 2019, according to the CMIE's Prowess data. The percentages in the legend represent the percentiles based on the number of firms. The deeper the color, the more firms are located in that district.

Figure B.20: Spatial Distribution of the Number of Firms



Notes: Data on the wholesale price index of manufacture of computers and peripheral equipment is published by the Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India. The base year for the price index is the financial year 2011-2012. The frequency is monthly. The period is from August 2014 to July 2018. The red line is November 2016.

Figure B.21: Wholesale Price Index: Manufacture of Computers and Peripheral Equipment



Notes: The data on total enrollment in engineering and technology is sourced from the All India Council for Technical Education, available from the academic year 2012-2013 onwards. The x-axis corresponds to the academic year, while the y-axis depicts the percentage change in total enrollment in engineering and technology compared to the preceding academic year.

Figure B.22: Annual Changes in the Total Enrollment in Engineering and Technology

B.9 Additional Tables

Table B.26: Impacts on Income & TFPR (Standard Errors Clustered at the Firm Level)

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Fin. Serv. Inc.)	(4) ROA	(5) Ln(TFPR)
Post × *e-Index* (PeI)	-0.137***	-0.138***	-0.024^{+}	-0.036^{+}	-0.450***
	(0.029)	(0.031)	(0.015)	(0.023)	(0.173)
Post × *e-Index*× Services (PeIS)	0.209***	0.195***	0.019	0.103***	0.913***
	(0.041)	(0.043)	(0.024)	(0.033)	(0.291)
PeI+PeIS	0.072**	0.057**	-0.005	0.068***	0.464*
p-value	(0.016)	(0.055)	(0.784)	(0.006)	(0.055)
Control Mean (Manu.)	3.34	3.31	0.32	1.29	10.62
Control Mean (Services)	1.79	1.45	0.48	0.82	0.29
R^2	0.94	0.94	0.89	0.82	0.89
No. of firms	28,669	28,669	28,669	28,669	24,992
N	172,328	172,328	172,328	172,328	144,115
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by grieco2016production. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The "Control Mean (Manu.)" is the average value of the outcome variable for manufacturing firms in the pre-treatment periods. The "Control Mean (Services)" is the average value of the outcome variable for service firms in the pre-treatment periods. Standard errors are clustered at the firm level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.27: Impacts on Income & TFPR (Exclude Night Light Intensity)

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Fin. Serv. Inc.)	(4) ROA	(5) Ln(TFPR)
Post × *e-Index* (PeI)	-0.144***	-0.147***	-0.024	-0.037*	-0.488**
	(0.035)	(0.038)	(0.022)	(0.020)	(0.216)
Post × *e-Index*× Services (PeIS)	0.208***	0.194***	0.019	0.103***	0.910***
	(0.042)	(0.036)	(0.041)	(0.023)	(0.274)
PeI+PeIS	0.064^{+}	0.047	-0.005	0.066***	0.422**
p-value	(0.111)	(0.316)	(0.828)	(0.001)	(0.048)
Control Mean (Manu.)	3.34	3.31	0.32	1.29	10.62
Control Mean (Services)	1.79	1.45	0.48	0.82	0.29
R^2	0.94	0.94	0.89	0.82	0.89
No. of firms	28,669	28,669	28,669	28,669	24,992
N	172,328	172,328	172,328	172,328	144,115
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Fin. Serv. Inc." = Income from financial services. "ROA" = Return on assets. TFPR in Column 5 is $e^{\hat{\omega}_{ijt}}$ in equation (B.6) estimated based on the method proposed by grieco2016production. All regressions include firm and industry-year fixed effects as well as control for the number of functioning commercial bank branches of a district per 1,000 population and the number of ATMs of a state per 1,000 population. The "Control Mean (Manu.)" is the average value of the outcome variable for manufacturing firms in the pre-treatment periods. The "Control Mean (Services)" is the average value of the outcome variable for service firms in the pre-treatment periods. Standard errors are clustered at the firm level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.28: Impacts on Firms by Firm Size

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(TFPR)	Ln(Communications)	Ln(Outsourced: Software & ICT)	Ln(ICT Assets)
Panel A. Services					
Post × *e-Index*	0.064*	0.375^{+}	0.011**	0.002	0.019***
	(0.037)	(0.259)	(0.005)	(0.002)	(0.005)
Post × *e-Index* × Med./L.	-0.023	0.237	0.022	0.016***	-0.007
	(0.095)	(0.570)	(0.021)	(0.005)	(0.051)
Control Mean	1.78	0.29	0.05	0.01	0.11
R^2	0.93	0.86	0.86	0.61	0.86
No. of firms	17,882	14,967	17,231	17,231	19,037
N	105,300	82,688	98,097	98,097	117,240
Panel B. Manufacturing					
Post × *e-Index*	-0.086^{+}	-0.336	0.001	0.001	-0.008***
	(0.055)	(0.431)	(0.002)	(0.001)	(0.002)
Post × *e-Index* × Med./L.	-0.060	-0.110	-0.017**	-0.003	0.010
	(0.053)	(0.454)	(0.007)	(0.003)	(0.012)
Control Mean	3.34	10.62	0.04	0.00	0.08
R^2	0.94	0.87	0.81	0.64	0.85
No. of firms	10,464	10,004	10,653	10,653	11,247
N	65,714	61,363	65,038	65,038	72,185
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Med./L." = A binary variable that is set to one if the firm is classified as medium- or large-sized, and zero if the firm is categorized as micro- or small-sized. The classification of firm size is based on the provisions of the Micro, Small & Medium Enterprises Development (MSMED) Act, 2006. I rely solely on investment to determine firm size. For manufacturing firms, those with less than 0.6 USD million in plant and machinery are deemed micro- or small-sized, while those exceeding this amount are considered medium- or large-sized. For service firms, the threshold is 0.3 USD million in equipment. TFPR in column 2 is the Total Factor Revenue Productivity of a firm calculated based on the method proposed by grieco2016production. A detailed discussion is provided in Appendix B.3. "Outsourced: Software & ICT" = Expenses on outsourced software and IT-enabled services. "Spend on Outsourced: Software & ICT" = A dummy variable equal to one if a firm has spent on outsourced software and IT-enabled services and zero otherwise. "ICT Assets" = Software and computers and IT systems. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.29: Impacts on Firms' Borrowing

	(1)	(2)	(3)
	Ln(Total Borrowings from Banks)	Ln(Long-term Borrowings from Banks)	Ln(Short-term Borrowings from Banks
Panel A. Services			
Post × *e-Index*	0.045*	0.020	0.029*
	(0.025)	(0.024)	(0.017)
Control Mean	0.63	0.36	0.37
R^2	0.84	0.81	0.81
No. of firms	19,821	19,821	19,821
N	123,663	123,663	123,663
Panel B. Manufacturing			
Post × *e-Index*	-0.100***	-0.086***	-0.078***
	(0.032)	(0.031)	(0.025)
Control Mean	1.48	0.77	1.16
R^2	0.88	0.81	0.86
No. of firms	11,669	11,669	11,669
N	75,561	75,561	75,561
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: "e-Index" = The normalized district-level e-Readiness Index. "Total Borrowings from Banks" = The total amount of borrowings taken by companies from banks, both secured or unsecured. "Long-term Borrowings from Banks" = The total amount of long-term borrowings taken by firms from banks. "Short-term Borrowings from Bank" = The total amount of short-term borrowings taken by firms from banks. All regressions include firm and industry-year fixed effects, as well as control for the log of average night light intensity at the district level, the number of functioning commercial bank branches at the district level, and the number of ATMs per 1,000 people at the state level. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table B.30: Impacts of Demonetization Shock Intensity on Sales by Sector and *e-Index*

	Service		Manufacturing	
	(1) More e-Ready	(2) Less e-Ready	(3) More e-Ready	(4) Less e-Ready
Dependent variable: Ln(Sales)				
Post × Demonetization	0.002	-0.142*	-0.011	0.020
Shock Severity	(0.055)	(0.077)	(0.023)	(0.065)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Control Mean	1.47	1.41	3.49	3.17
R^2	0.93	0.92	0.94	0.93
No. of firms	10,445	7,731	4,590	5,900
N	62,124	44,403	28,901	36,884

Notes: The dependent variable is the log of sales. "More e-Ready" = A firm's constructed normalized district-level e-Readiness Index is above the median. "Less e-Ready" = A firm's constructed normalized district-level e-Readiness Index is below the median. "Demonetization Severity" = The demonetization shock severity developed by crouzet2019shocks with a higher value indicating a more severe cash contraction. All regressions include firm and industry-year fixed effects as well as control for the average nightlight intensity of a district, the number of functioning commercial bank branches of a district per 1,000 population, and the number of ATMs of a state per 1,000 population. The control mean represents the average value of the outcome variable during the pre-treatment periods for a respective sub-sample of firms. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Appendix C

How Do Political Connections of Firms Matter During An Economic Crisis?

C.1 Literature on Political Connections

Table C.1: Related Literature on Political Connections (in chronological order)

	How are political connections measured?
Gomez and Jomo (1999)	The authors define a firm as politically connected if it has officers or major shareholders with close relationships with key government officials—primarily Mahathir, Daim, and Anwar.
Agrawal and Knoeber (2001)	The authors define a firm as politically connected if its outside directors have backgrounds in law (i.e., a degree in law) and/or in politics (i.e., prior employment in government or a political party).
Backman (2001)	The authors define a firm as politically connected if it bribes government officers or employs relatives of government officers.
Fisman (2001)	The author identifies political connections based on the Suharto Dependency Index which is developed by the Castle Group, a leading economic consultant in Indonesia. The index ranges from one (least dependent) to five (most dependent). Companies affiliated with Suharto's children or allies have high indexes.
S. Johnson and Mitton (2003)	The authors follow Gomez and Jomo (1999) and define a firm as politically connected if it has officers or major shareholders with close relationships with key government officials—primarily Mahathir, Daim, and Anwar.
Khwaja and Mian (2005)	The authors define a firm as politically connected if its director participates in an election.

Table C.1 continued from previous page

Literature	How political connections are ascertained?
Charumilind, Kali, and Wiwattanakantang, 2006	The authors assume that the country's richest families that own business empires are well-connected to bankers. They define a firm as having ''close connections'' to banks if the firm is owned by the country's richest families.
Faccio, Masulis, and McConnell (2006)	A company is defined as politically connected if at least one of its top officers (defined as the company's chief executive officer, chairman of the board (COB), president, vice-president, or secretary of the board) or a large shareholder (defined as anyone controlling at least 10% of the company's voting shares) was head of state (i.e., president, king, or prime minister), a government minister (as defined below), or a member of the national parliament, as of the beginning of 1997. The author also defines indirect connections. He 1) classifies a company as indirectly connected if a relative with the same last name as a head of state or minister is a top officer or a large shareholder, as defined above, as of 1997; 2) classifies a company as indirectly connected when a top executive or a large shareholder has been described by The Economist, Forbes, or Fortune as having a "friendship" with a head of state, government minister, or member of parliament during 1997; 3) classifies a company as indirectly connected if a prior study identifies such a relationship as having been in place prior to January 1, 1997.
Mobarak and Purbasari (2006)	The authors define a firm as politically connected if the Suharto health news indicator has a negative coefficient on the firm's stock price which is significantly different from zero at the 95% confidence level. The size of this coefficient is used as a measure of the strength of the connection between this firm and Suharto.
Boubakri, Cosset, and Saffar (2008)	The authors define a firm as politically-connected if at least one member of its board of directors or its supervisory board is or was a politician, that is, a member of parliament, a minister, or any other top-appointed bureaucrat. They track politicians on the board of newly privatized firms over a period of three years after the privatization date.
Claessens, Feijen, and Laeven (2008)	The authors define a listed firm as politically connected if it appears in the official campaign contribution data.
Goldman, Rocholl, and So (2008)	The authors define a firm as politically connected if at least one of its board members at any time prior to 1994 and 2000, respectively, held a position such as Senator, Member of the House of Representatives, Member of the Administration, or was a Director of an organization like the Central Intelligence Agency.
H. Li et al. (2008)	The authors define a firm as politically connected if the private entrepreneurs are a member of the Communist Party.

Table C.1 continued from previous page

Literature	How political connections are ascertained?
Goldman, Rocholl, and So (2009)	The authors define a firm as politically connected if at least one of its board members at any time prior to 1994 and 2000, respectively, held a position such as Senator, Member of the House of Representatives, Member of the Administration, or was a Director of an organization like the Central Intelligence Agency.
Faccio (2010)	The author expands his faccio2006political definition. She adds two new definitions for indirect connections: 4) connections with foreign politicians; and 5) other connections identified in prior studies gomez1999malaysia,johnson2003cronyism. He also includes cases in which a member of parliament serves as a company's CEO, president, vice president, or secretary or controls at least 10% of shareholder votes.
Niessen and Ruenzi (2010)	The authors check whether a member of the Bundestag engaged in any paid job activities besides their governmental mandate such as being a director on the supervisory board or advisory council of a firm and how much that person received as compensation. They then identify those firms as politically connected.
Desai, Olofsgård, et al. (2011)	The authors use perception-based questions about the political influence of firms in shaping national policies affecting their businesses in the World Bank's Enterprise Surveys to evaluate if a firm has political connections.
Boubakri, Cosset, and Saffar (2012)	The authors define a firm as politically connected if at least one of its large shareholders (anyone controlling more than 10% of voting rights, directly or indirectly) or top officers (CEO, chairman of the board, president, vice-president, or secretary) is a member of parliament, is a minister or head of state, or is closely related to a politician or party by friendship, past top corporate or political positions, or other ties identified in prior research. If any supervisory board members had a political affiliation defined as being a candidate for a local and/or state-level elected position, a member of a political party or continuously expressing public support for a given political party.
Amore and Bennedsen (2013)	The authors define a firm as family-related to local politicians if a politician is a CEO or a board director or both, or who is connected by family to a firm's CEO or director. The family relations considered are parent, child, sibling, and current or former spouse(s).
Houston et al. (2014)	The authors define a firm as politically connected if at least one board member and/or director either holds or held an important government or political position. The definition of positions follows Goldman, Rocholl, and So (2009).
Akcigit, Baslandze, and Lotti (2023)	The authors define a firm as politically connected if at least one politician is working in the firm in the same year.

Table C.1 continued from previous page

Literature	How political connections are ascertained?
Bertrand et al. (2018)	The authors define a firm as politically connected if at least one of its CEOs has previously served as a close advisor to a top-raking government official.
Schoenherr (2019)	Lee Myung Bak, former president of South Korea, graduated from Korea University (KU) Business School and served as a CEO at Hyundai Engineering & Construction (HEC), before going into politics. The author then defines a firm as politically connected if its CEO is either a Korea University Business Administration graduate (KU network), or a former Hyundai Engineering & Construction executive (HEC network).
Brown and Huang (2020)	The authors measure political connections by the number of White House visits by corporate executives in a year. They also define a variable, Political access, as an indicator that takes the value of one if the executives of the firm visit the White House at least once in a given year and zero otherwise.
Deng, Wu, and Xu (2020)	If the local official has the same birthplace as one of the top managers of a listed firm located in the official's jurisdiction, then the authors define the firm as politically connected.
Choi, Penciakova, and Saffie (2021)	The authors use campaign contributions in state legislative elections to measure a firm's political connections to state legislators

C.2 Definition of Variables

Table C.2: Definition of Variables

Variable Name	Definition
Income	Total income is the sum of all kinds of income generated by a firm.
Sales	Sales are the sum of all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services.
Expenses	Total expenses are the sum of all revenue expenses incurred by a firm.
Ln(TFPR1)	The log of estimated total factor revenue productivity using Levinsohn and Petrin (2003). Output is total income, capital is fixed assets, inputs are compensation to employees and raw material expenses, and the proxy is power, fuel, and water charges.
Ln(TFPR2)	The log of estimated total factor revenue productivity using Levinsohn and Petrin (2003). Output is total income, capital is fixed assets, input is compensation to employees, and the proxy is the consumption of raw materials and power, fuel, and water.

Table C.2 continued from previous page

Variable Name	Definition
Assets	Total assets are the sum of all current and non-current assets held by a company as of the last day of an accounting period.
Non-Current Assets	Non-current Assets are those assets of a firm that cannot be converted to cash within 12 months. They include tangible and intangible assets. It also includes capital work in progress which refers to fixed assets that are in process of being installed or constructed. The total amount of long-term investments, long-term loans and advances, and other long-term assets of a company are also classified as Non-Current Assets.
Current Assets	Current assets are any assets in the balance sheet which can be easily converted into cash within 12 months.
Current Investments	Short-term investments include all investments made by a company that are due to maturity within 12 months from the date of the balance sheet. Companies often make investments in shares, debentures, bonds, mutual funds, immovable properties, capital of partnership firms, etc.
Current Inventories	Short-term inventories. Inventories are materials held to be consumed in the production process or held for sale.
Bank Balances	Short-term bank balance. It captures the value of a company's deposits in banks, which are short-term/current in nature.
Other Current Assets	Other kinds of current assets include short-term trade receivables and bills receivable, lease rent receivable, accrued income including interest receivables, assets held for sale and transfer (short term), and others.
Non-current investments	Non-current investments include all investments made by a company which are investments not expected to mature within 12 months from the date of the balance sheet.
Exptd. on Intangibles	Net intangible fixed assets which usually include the gross value of goodwill and software systems.
Exptd. on Fixed Assets	Net fixed assets are the net value of the fixed assets of a company after adjusting for additions/(deductions) to gross fixed assets and the cumulative depreciation on gross fixed assets.
Exptd. on PPE	Net property, plant, and equipment (PPE). PPE are a company's physical or tangible long-term assets that typically have a life of more than one year, such as buildings, machinery, land, office equipment, furniture, and vehicles.
Liabilities	Total liabilities. It includes all sums it owes to the shareholders in the form of share capital and reserves and surpluses, all sums it owes to its lenders in the form of secured and unsecured loans, and all current liabilities and provisions. It also includes deferred tax liability.
Non-Current Liabilities	Non-current liabilities are liabilities that are not expected to be settled in the company's normal operating cycle or within 12 months from the balance sheet date.

Table C.2 continued from previous page

Variable Name	Definition
Current Liabilities	Current liabilities are the liabilities or debts a firm owes to its suppliers, vendors, banks, and others, which must be paid within one year.
Short-Term Payables	Short-term trade payables and acceptances. Trade payables are liabilities owed to suppliers, creditors, lenders, or vendors for purchases of goods or services received. Acceptances by a company, which are due to mature within the next 12 months. A trade acceptance is a time draft drawn by the seller of goods on a buyer.
Short-Term Advances	Short-term deposits and advances from customers and employees. It includes deposits in the form of security, a trade deposit, or a dealer's deposit, and advances received from customers for goods and services to be provided by the company.
Other Current Liabilities	Other kinds of current liabilities include current maturities of long-term debt and lease, interest accrued but not due (short term), and unclaimed and unpaid dividend.
Borrowings	Total borrowings. It is the sum of short-term borrowings and long-term borrowings.
Short-Term Borrowings	The number of short-term borrowings taken by a firm, which have to be repaid within a period of 12 months.
Long-Term Borrowings	The number of long-term borrowings taken by a firm, which is not expected to be repaid within the next 12 months from the balance sheet date.
Secured Borrowings	Secured loans are loans made on the security of assets, the market value of which is not at any time less than the amount of such loan.
Unsecured Borrowings	In the case of unsecured loans, the borrower does not have to pledge any assets with the lender as collateral for the loan.
Total Bank Borrowings	Total borrowings from banks. The sum of short-term borrowings from banks and long-term borrowings from banks.
Short-Term Bank Borr.	Short-term borrowings from banks. The number of short-term borrowings taken by the company from banks, whether secured or unsecured. They have to be repaid by the company within a period of 12 months.
Long-Term Bank Borr.	Long-term borrowings from banks. The total amount of long-term borrowings taken by companies from banks, whether secured or unsecured. Money borrowed by companies from banks for a period of more than 12 months is classified as long-term borrowings from banks.
Interest Expenses	Interest expenses include all kinds of company interest payments such as interests on long-term and short-term borrowings, trade payables, and debentures and bonds.
Interest incidence	Interest incidence is an indicator that is expressed as a ratio of a company's interest costs to its borrowings. It serves as an indicator of the effective cost of borrowing of a company by measuring interest paid during the year as a percentage of borrowings.

Table C.2 continued from previous page

Variable Name	Definition
Interest on LTB	Interest on Long-term Borrowings. This is the number of interest paid by a company on long-term loans raised by it.
Interest on STB	Interest on Short-term Borrowings. This is the number of interest paid by a company on short-term loans raised by it.
Firm characteristics:	
Firm age (years)	Years a firm has been operating.
Annual avg. value of total transactions in BSE	The product of weighted average stock price and the total amount of stock transactions in Bombay Stock Exchange (BSE).
Annual avg. value of total transactions in NSE	The product of weighted average stock price and the total amount of stock transactions in the National Stock Exchange (NSE).
Listed on BSE/NSE	Take the value of 1 for firms that are either listed on BSE or NSE and 0 for firms that are not listed.
Goods and service tax	Total amount of goods and service tax levied on the sale/transfer of goods and/or services by a company.
Value-added tax	Total amount of value-added tax paid.

Notes: All monetary values are reported in nominal USD million.

C.3 Data and Construction of Political Connections

C.3.1 Data on Firms

Universe of Firms: We collect the universe of formally registered firms from the Ministry of Corporate Affairs (MCA), Government of India in December 2020. It contains over 1 billion firms and provides basic information about firms such as a company's CIN, business category, date of incorporation, and current status. Specifically, we use the CIN to map firms to the Prowess data (described below) to measure political connections. Figure C.1 provides an example of a firm in the MCA dataset. Note that we do not have access to the firm outcomes from this dataset. hence, we use an alternative source for firm outcomes.

Company/LLP Master Data

CIN	L11101AS1959GOI001148
Company Name	OIL INDIA LIMITED
ROC Code	RoC-Shillong
Registration Number	001148
Company Category	Company limited by Shares
Company SubCategory	Union Govt company
Class of Company	Public
Authorised Capital(Rs)	20000000000
Paid up Capital(Rs)	10844051940
Number of Members(Applicable in case of company without Share Capital)	0
Date of Incorporation	18/02/1959
Registered Address	DULIAJAN DIST: DIBRUGARH DULIAJAN AS 786602 IN
Address other than R/o where all or any books of account and papers are maintained	-
Email Id	ajayasahoo@oilindia.in
Whether Listed or not	Listed
ACTIVE compliance	ACTIVE compliant
Suspended at stock exchange	-
Date of last AGM	29/09/2020
Date of Balance Sheet	31/03/2020
Company Status(for efiling)	Active

Charges

Assets under charge	Charge Amount	Date of Creation	Date of Modification	Status
Book debts; Movable property (not being pledge)	1500000000	16/02/2009	-	CLOSED
	7000000000	17/12/1999	22/11/2013	OPEN
Book debts	3774500000	16/01/2012	-	OPEN

Directors/Signatory Details

DIN/PAN	Name	Begin date	End date	Surrendered DIN
05130108	AMAR NATH	15/10/2018	-	
08245841	ANIL KAUSHAL	09/08/2019	-	
AFVPM5451P	HARISH MADHAV	10/04/2019	-	
08489650	HARISH MADHAV	02/08/2019	-	
08490095	SUSHIL CHANDRA MISHRA	01/10/2019	-	
08516710	GAGANN JAIN	09/08/2019	-	
08516744	TANGOR TAPAK	09/08/2019	-	
08716147	PANKAJ KUMAR GOSWAMI	01/06/2020	-	
09005888	ASHEESH JOSHI	22/12/2020	-	
ALWPS5634D	AJAYA KUMAR SAHOO	11/04/2019	-	

Figure C.1: An Example of Firm Information Available

Data on Firm Outcomes: Data on firm outcomes is from the Prowess data, collected by the Centre for Monitoring of the Indian Economy (CMIE). Prowess is a database of over 40,000 firms that includes all firms traded on the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), and thousands of unlisted Public and Private Limited Companies. Data on these firms is collated and harmonized from Annual Reports, Quarterly Financial Statements, Stock Exchange feeds, and other publicly available sources. It contains: (i) identity information of all firms such as entity type, ownership, industry, and age; (ii) information on the Board of Directors like name and designation; (iii) subsidiaries of each firm and mergers and acquisition deals; (iv) Bombay Stock Exchange (BSE) and National Stock Exchange of India Limited (NSE) stocks trading data; (v) standalone Annual

Financial Statements. We use this data to construct firm outcomes described in the paper, as well as measure political connections.

Table C.3: Data on Firms, Politicians and Bureaucrats

Type of Entity	**Data Source**	**Time Period**	**Count**
(1)	(2)	(3)	(4)
Politicians	Candidates in national elections, Members of National and State Legislative Assemblies	2004 onwards	19,295
Bureaucrats	Indian Administrative Service Records	1961 onwards	11,531
Firms	Listed firms on the Bombay and National Stock Exchanges, Ministry of Corporate Affairs	1980 onwards	64,155
Family information	All Directors, Politicians and Bureaucrats from Wikipedia	All	

Notes: Source: Sen et al. (2018).

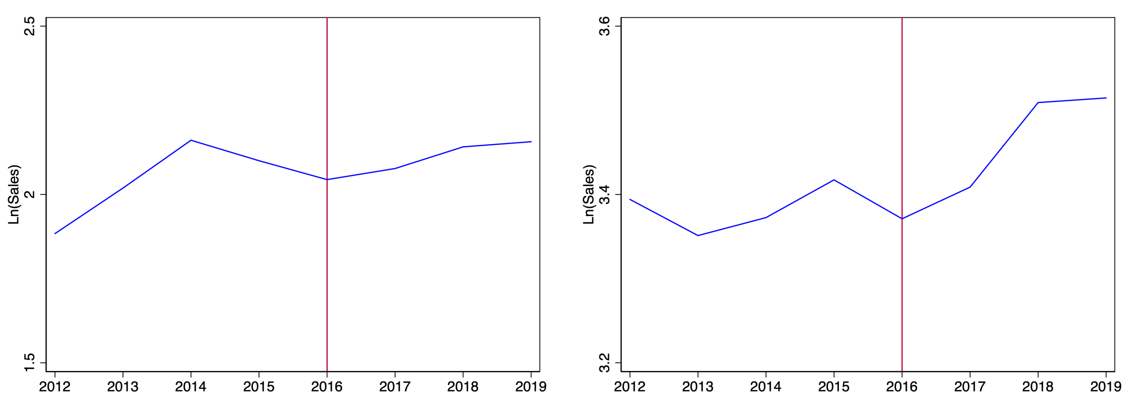
C.3.2 Data on Measuring Political Connections

In Section 3.3.2, we briefly described how the data on political connections is constructed. We refer the reader to Sen et al. (2018) for a detailed discussion of the data and algorithm. In Table C.3 below, we list the entities used in building the political network of firms, the description of entities, time period for which we have the data, and the count of the entities in the network. Table C.4 reports the distribution of politically connected (and non-connected) firms across the most common industries.

Table C.4: Common Industries with Connected and Non-connected Firms

Two-Digit NIC Industry Name	# Firms	Share (%)
	(1)	(2)
Panel A: Politically Connected Firms		
Financial service activities, except insurance and pension funding	152	17.53
Electricity, gas, steam, and air conditioning supply	79	9.11
Wholesale trade, except motor vehicles and motorcycles	73	8.42
Manufacture of chemicals and chemical products	41	4.73
Warehousing and support activities for transportation	41	4.73
Civil engineering	37	4.27
Accommodation	29	3.34
Total	452	52.13
Panel B: Politically Non-connected Firms		
Financial service activities, except insurance and pension funding	5,405	17.65
Wholesale trade, except motor vehicles and motorcycles	4,850	15.84
Manufacture of basic metals	1,102	3.6
Construction of buildings	1,093	3.57
Rental and leasing activities	1,010	3.3
Manufacture of chemicals and chemical products	1,004	3.28
Manufacture of food products	917	2.99
Total	15,381	50.23

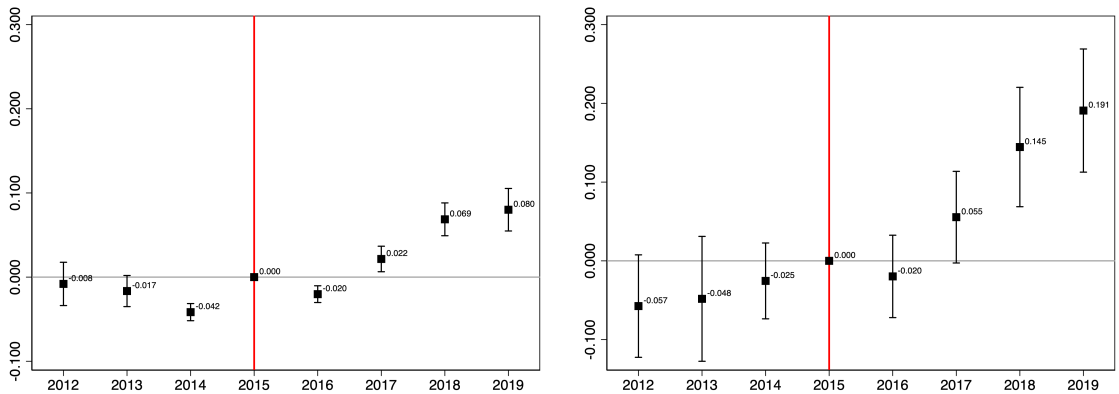
Notes: The above table reports the most common two-digit NIC industries among politically connected (Panel A) and non-connected (Panel B) firms. Column 1 reports the total number of firms in that industry, while Column 2 reports the share of connected (non-connected) firms in that industry. For example, the seven industries reported in Panel A (B) account for 52.1% (50.2%) of all politically connected (non-connected) firms.



(a) Non-connected Firms (b) Politically Connected Firms

Notes: In Figure C.2a, we plot the trend of the average value of the log of sales for non-connected firms; in Figure C.2b, we plot the trend for politically connected firms. The red lines are for the year 2016.

Figure C.2: Descriptive Trends of Log of Sales



(a) Non-connected Firms (b) Politically Connected Firms

Notes: We perform regression analysis of the logarithm of sales on the year indicators with 2015 as the base year, separately for both the samples of non-connected firms and connected firms. The regressions include firm, district-year, and industry-year fixed effects, as well as control for the log of Goods and Service Tax payments. We do not use the weights calculated in the SDID here. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

Figure C.3: Time-Trends in Sales By Political Connections

C.4 Quicker Recovery and/or Growth?

C.5 Broader Firms Connections and Political Connections

In this section, we examine whether it is just firms' connections that help them respond better to a crisis, or whether there is something specific about their political connections. To do this, we take advantage of our rich data where we observe Directors across multiple firms. Hence we can calculate alternate measures of firm connections through their Directors being on the Board of Directors of multiple firms, or through knowing the Directors of these firms that they are on the board of. More formally, for each Director d on the board of firm i, we calculate two measures of her connections:

Measure 1 **Connection through Firms:** we first calculate the total number of firms (excluding i) on which the Director was ever on the Board of Directors i.e., we calculate $M^1_{id} = \sum_{f \neq i} 1(\text{On Board of Directors for firm } f)$ Using this, we also create a binary variable that takes the value 1 if M^1_{id} has an above-median value, and 0 otherwise. Then for each firm i, we calculate the average number of other firms that these Directors are on the board of i.e., $\overline{M_{1i}} = \frac{1}{D}\sum_d M^1_{id}$; and the total number of Directors who are above-median networked.

Measure 2 **Connection through Directors:** we first calculate the total number of Directors who were ever on the Board of Directors that Director d was also on the board of (denoted by M^2_{id}). Similar to the previous measure, we create a binary variable that takes the value 1 if a Director has an above-median value, and 0 otherwise. Then for a firm i, we calculate the average number of other Directors that the Board of Directors is connected with i.e., $\overline{M_{2i}} = \frac{1}{D}\sum_d M^2_{id}$; and the total number of Directors who are above-median networked.

To summarize, apart from just political connections (that we describe in the paper), these measures capture firms' connections more broadly through their Board of Directors being on other boards, or connected to other Directors who are on those boards. We then begin by examining the correlation between a firm having a political connection and the two measures by estimating the following regression specification:

$$1(Pol.Conn.)_i = \alpha_d + \alpha_j + \beta M_{xi} + \varepsilon_i \tag{C.1}$$

where $1(Pol.Conn.)_i$ is a binary variable that takes the value 1 if a firm is politically connected (as described in the paper) and 0 otherwise. M_{xi} is a measure $x \in \{1{,}2\}$ described above. α_d and α_j are district and industry fixed effects respectively.[1]

From the results reported in Table C.6, we see that there is a strong and positive correlation between firms' political connections and Directorial connections defined more broadly. For example, having a Director who is on the board of an additional firm (Column 1) or knows an additional Director on these boards (Column 3) increases the probability of a political connection by 1.8 p.p. and 8.2 p.p. respectively. Similarly, having an additional above-median Director on the board, either connected through firms (Column 2) or Directors (Column 4) increases the probability of being politically connected by 0.2 p.p. and 2.1 p.p. respectively.

In what follows, we turn to examining whether firms' responses after the crisis arise due to their political connections (as we argue in the paper) or whether these firms just have Directors who are better networked. To do so, we estimate Equation (3.2),

[1] Note that all these measures of connections are time-invariant and calculated at the firm level. Hence, we do not have any time subscripts in the regressions.

Table C.5: Correlation between Measures of Firm Connections

Outcome Variable:	Political Connection = 1			
	Conns. Through Firms		Conns. Through Directors	
	Average	Above Med.	Average	Above Med.
	(1)	(2)	(3)	(4)
Measure	0.018***	0.002***	0.082***	0.021***
	(0.001)	(0.001)	(0.003)	(0.003)
Dist. FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
R2	0.19	0.10	0.13	0.10
N	18,439	18,439	18,439	18,439

Notes: The outcome variable in the above regression is a dummy variable that takes the value 1 if the firm ever had a political connection before 2016 and 0 otherwise. Columns (1) and (3) measure firm connections through the average number of firms that a director is on the Board of and the board size of those firms respectively. Columns (2) and (4) are the total number of above-median connected directors in the firm as calculated by each measure in Columns (1) and (3) respectively. Robust standard errors are reported in parentheses. * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

but now incorporate these additional measures of firms' connections. Columns (1), (4) and (7) of Table C.6 replicate the results for the primary outcome variables reported in Table 3.2, where we find that politically connected firms have higher income, sales, and expenses after the crisis, as compared to their non-connected counterparts.[2] In Columns (2), (5), and (8), we instead replace the political connections with connections that Directors have through other firms (Panel A) and other Directors (Panel B) that correspond to the two measures described previously. The results indicate that having additional connected directors does help firms respond better to the crisis, but the magnitude of the coefficient is on average about 10 times lower than firms' political connections, indicating that they matter much less. Therefore, in Columns (3), (6), and (9), we include both political connections and broader directorial connections. There are two insights (from both Panels A and B): first, the magnitude of how much political connections matter is very robust to controlling for other directorial connections more broadly; and second, these directorial connections are substantially less important than political connections. Lastly, in Table C.7, we redo our analysis but now use the number of above-median number of directors as a measure of connections and find that the results are similar.

[2]Note that since we are not able to match all the directorial connections across firms, the sample size is smaller. Nevertheless, it does not affect the direction and magnitude of the result.

To summarize, the above results indicate that firms' political connections are an order of magnitude more important as opposed to other directorial connections more broadly, which provides confidence in the fact that firms' resilience to the demonetization crisis was driven specifically by their political connections, as opposed to directorial connections more broadly.

Table C.6: Broader Firm Connections through Directors

	Ln(Income)			Ln(Sales)			Ln(Expense)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: No. of Connections through Firms									
Conn. Pol. × Post	0.119***		0.114***	0.090***		0.084***	0.117***		0.109***
	(0.029)		(0.027)	(0.032)		(0.030)	(0.033)		(0.031)
Conn. Firms × Post		0.013	0.009		0.015	0.012		0.020*	0.016*
		(0.011)	(0.011)		(0.011)	(0.011)		(0.010)	(0.010)
R^2	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96
Panel B: No. of Connections through Directors									
Conn. Pol. × Post	0.119***		0.098***	0.090***		0.058*	0.117***		0.084**
	(0.029)		(0.036)	(0.032)		(0.033)	(0.033)		(0.038)
Conn. Dirs. × Post		0.009***	0.005*		0.010***	0.008**		0.011***	0.008***
		(0.002)	(0.003)		(0.003)	(0.003)		(0.002)	(0.003)
R^2	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dist/Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of firms	15,050	15,050	15,050	15,050	15,050	15,050	15,050	15,050	15,050
N	95,747	95,747	95,747	95,747	95,747	95,747	95,747	95,747	95,747

Notes: Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. Panel A measures firm connections through the average number of firms that the director is on. Panel B measures firm connections through the number of Directors known to a Director through being on multiple Boards. Conn. Pol. takes the value 1 if a firm is ever politically connected before 2016 and 0 otherwise. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. * is p<0.1 , ** is p<0.05, and *** is p<0.01.

C.6 Measuring the Impact on Firm Productivity (TFPQ)

While we report the impact of the policy on TFPR in the paper, this section focuses on the measurement of TFPQ and how it was differentially affected for politically connected and non-connected firms. To begin, similar to Bau and Matray (2023), we measure TFPQ for a firm i in a year t using the following equation:

$$\ln TFPQ_{it} = \ln TFPR_{it} - \ln \tilde{p}_{it} \tag{C.2}$$

Table C.7: Above Median Firm Connections through Directors

	Ln(Income)			Ln(Sales)			Ln(Expense)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: No. of Connections through Firms									
Conn. Pol. × Post	0.119***		0.117***	0.090***		0.086***	0.117***		0.110***
	(0.029)		(0.027)	(0.032)		(0.030)	(0.033)		(0.032)
Above Med. Conn. Firms × Post		0.028	0.012		0.042	0.031		0.056	0.041
		(0.043)	(0.040)		(0.039)	(0.038)		(0.040)	(0.039)
R^2	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96
Panel B: No. of Connections through Directors									
Conn. Pol. × Post	0.119***		0.117***	0.090***		0.077**	0.117***		0.104***
	(0.029)		(0.034)	(0.032)		(0.032)	(0.033)		(0.035)
Above Med. Conn. Dirs. × Post		0.043	0.008		0.078***	0.055**		0.085**	0.053
		(0.036)	(0.042)		(0.024)	(0.023)		(0.034)	(0.038)
R^2	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dist/Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of firms	15,050	15,050	15,050	15,050	15,050	15,050	15,050	15,050	15,050
N	95,747	95,747	95,747	95,747	95,747	95,747	95,747	95,747	95,747

Notes: Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. Panel A measures firm connections through the average number of firms that the director is on. Panel B measures firm connections through the number of Directors known to a Director through being on multiple Boards. The variable used in the analysis is a dummy that takes the value 1 if a firm has above-median connections through firms (Panel A) and Directors (Panel B) and 0 otherwise. Conn. Pol. takes the value 1 if a firm is ever politically connected before 2016 and 0 otherwise. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. * is p<0.1 , ** is p<0.05, and *** is p<0.01.

$\tilde{p}_{it}$ is the price charged by the firm. However, a typical firm in our sample provides (or manufactures) an average of 4 to 5 products (mostly within the same two-digit NIC industry). The challenge is therefore to construct prices at the firm level. We follow Bau and Matray (2023) to construct a sales-weighted average price of a firm across all its products. However, we do not directly observe product-level prices in our data but have information on the quantity, unit, and value of sales at the product level. We use these to therefore calculate the per-unit price of a product within a firm, which is then averaged (weighted by the fraction of sales of that product in a firm) to generate a price at the firm level. Two important clarifications are in order: first, information on the quantity and value of sales is available only for around a third of the firms in our sample (9,050 firms), and around 80% of these firms are in agriculture and manufacturing. Second, even within these firms, data is available only for some years and not others. We address the latter by linearly interpolating values (weighted by the CPI index) across years and recognize the former as a data limitation that tempers the interpretation of our results below.

With these caveats, we estimate Equation (3.2). The results, reported in Columns 3 and 4 of Table C.8, show no relative difference in TFPQ in connected firms relative to their non-connected counterparts.

We further examine if firms' capabilities play a role. Atkin, Khandelwal, and Osman (2019) show the importance of adjusting varieties and argue that TFPR is a better proxy of firms' capabilities. Producing a wider range of products usually takes longer and imposes higher demands on firms. In Column 5, we estimate Equation (3.2) on the log of the number of products a firm produces in a year. We find that politically connected firms produce more kinds of products than non-connected firms after the shock. It thus suggests that politically connected firms may possess greater capabilities, as they generate a wider range of goods and services at an equivalent pace (i.e. with no discernible difference in TFPQ shown in Columns 3 and 4) when compared to their non-connected counterparts.

Table C.8: Impact on TFPR, TFPQ & Number of Products

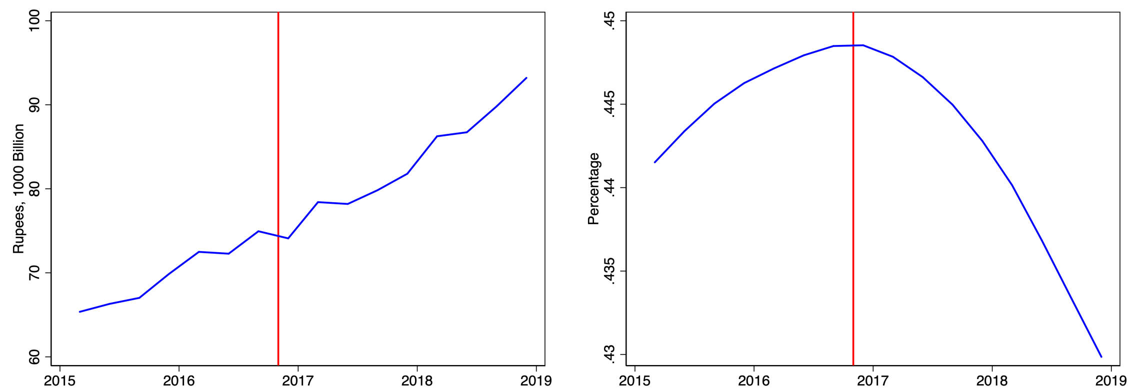
	Ln(TFPR1)	Ln(TFPR2)	Ln(TFPQ1)	Ln(TFPQ2)	Ln(# of Products)
	(1)	(2)	(3)	(4)	(5)
Connected × Post	0.053***	0.050***	-0.001	0.006	0.048**
	(0.020)	(0.019)	(0.022)	(0.022)	(0.021)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.85	0.70	0.62	0.45	1.64
R^2	0.88	0.94	0.95	0.98	0.88
No. of firms	28,622	28,622	9,039	9,119	33,174
N	161,777	161,777	53,083	53,083	208,049

Notes: "# of Products" = The number of products a firm produces or provides. TFPR in Columns 1 and 2 are the TFPR values calculated based on Levinsohn and Petrin (2003), with their corresponding TFPQ values in Columns 3 and 4 respectively. In Column 1, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 2, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

C.7 Cost of Debt

Previous research finds that politically connected firms have a higher likelihood of receiving credit/loans (Khwaja and Mian, 2005; Charumilind, Kali, and Wiwattanakantang, 2006; Claessens, Feijen, and Laeven, 2008; H. Li et al., 2008) with a lower cost of debt (Bliss et al., 2018; Faccio, 2010; Tee, 2018; Khelil, 2023). Yet, in Section

3.7.1, we find that politically connected firms decreased their borrowings and altered their borrowing portfolio by increasing short-term borrowing. To delve deeper into the borrowing behavior of firms, we first examine the lending portfolio of scheduled commercial banks and then investigate the cost of borrowing for firms.



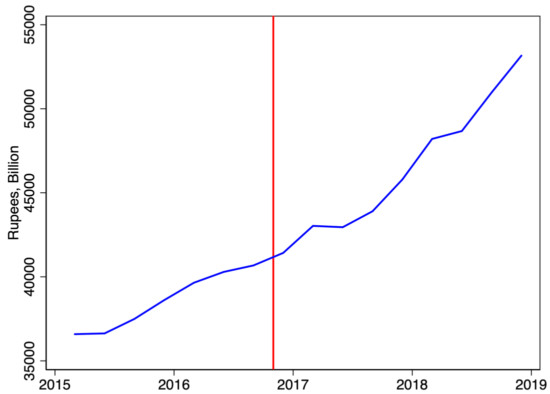
(a) Total Loans (b) Short-Term Loans/Total Loans

Notes: Data is from the Database on the Indian Economy published by the Reserve Bank of India. Figure C.4a plots the loans issued by scheduled commercial banks between 2015 and 2018. To be consistent with Figure C.5a, we only keep data in March, June, September, and December. The graph thus shows the total amount of loans made by all Indian scheduled commercial banks at the end of March, June, September, and December. Figure C.4b plots the share of short-term loans over total loans issued by commercial banks using the LOWESS approach.

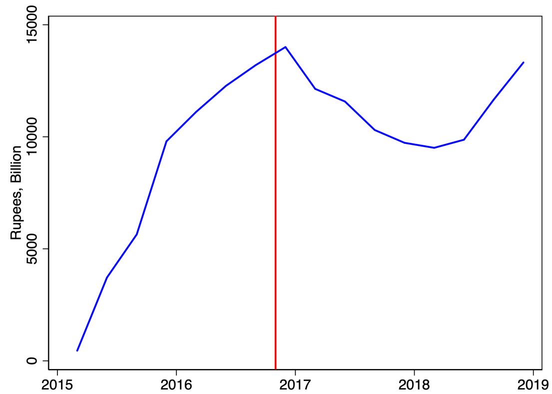
Figure C.4: Outstanding Loans Issued by Scheduled Commercial Banks

Bank lending: We use data from the 'Database on the Indian Economy' published by the *Reserve Bank of India* to analyze the overall credit environment. We get monthly data on the total amount of loans issued by all scheduled commercial banks from "Business in India - All Scheduled Banks and All Scheduled Commercial Banks" in the "Monthly RBI Bulletin." That is, we observe the total amount of loans issued at the end of each month. We also obtain quarterly data on the total amount of medium-term and long-term loans issued by scheduled commercial banks from "Table No 2.6 - Type of Account and Interest Rate Range-Wise Classification of Outstanding Loans and Advances of Scheduled Commercial Banks"[3] in "Banking – Sectoral Statistics." We observe the number of long-term loans issued at the end of March, June, September, and December. We then are able to compute the total amount of short-term

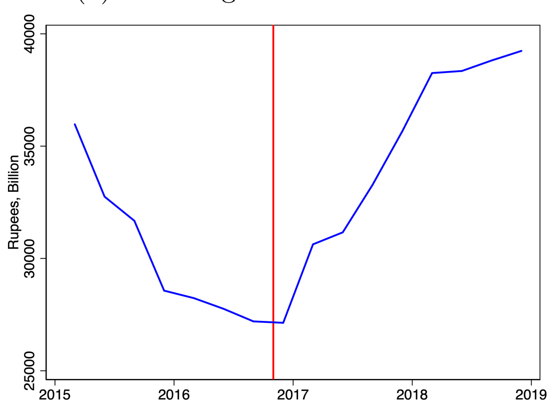
[3]Table No. 26 does not contain information on short-term loans. Scheduled commercial banks define medium-term loans as those that need to be repaid between one and three years. In our analysis, we define long-term loans that do not need to be repaid within one year. Thus, we combine medium-term loans and long-term loans in the data from the RBI for consistency.



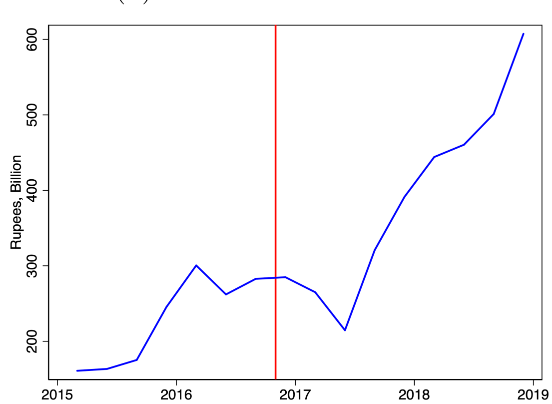
(a) All Ranges of Interest Rate



(b) Interest Rates $< 10\%$



(c) Interest Rates $\in [10\%, 20\%)$



(d) Interest Rates $\geq 20\%$

Notes: Data is from the Database on the Indian Economy published by the Reserve Bank of India. The units are in billions of Rupees and the frequency is quarterly (March, June, September, and December). The graphs plot the descriptive trends of long-term loans, no need to be repaid within a year, issued by scheduled commercial banks between 2015 and 2018 with different ranges of interest rates. The trends of the number of accounts of long-term borrowings are similar to the ones shown in Figure C.5.

Figure C.5: Outstanding Long-Term Loans Issued by Scheduled Commercial Banks

loans issued by scheduled commercial banks and the share of it at the end of March, June, September, and December each year. Figure C.4 displays the trends of the total amount of loans and the shares of short-term and long-term borrowings. While we find a secular increasing trend for the total amount of loans issued by scheduled commercial banks, its composition changed between 2015 and 2018. The scheduled commercial banks issued fewer short-term loans after the demonetization shock. We then further explore the interest rates of long-term credits. We observe that loans with less than 10% interest rates decreased by about 28% (Figure C.5b), loans with interest rates between 10% and 20% increased by 41% (Figure C.5c), and loans with more than 20% interest rates increased by 57% (Figure C.5d) between September

2016 and March 2018.

In summary, long-term bank loans from scheduled commercial banks with interests greater than 10% increased while those with lower interest fell. Short-term bank lending fell though overall lending continued its secular trend.

Firms Interest Incidence: We bolster the cost of long-term borrowing change by examining the interest expenses of firms. Table C.9 documents the results. The interest incidence, an indicator of the effective cost of borrowing of a firm, increased by 1 pp (10%) for politically connected firms after the shock (Column 1), and it is driven by the cost of long-term borrowings (Column 2).[4] Meanwhile, the interest of short-term borrowings (Column 3) dropped by 3.8 pp (or 13.1%) though measured imprecisely.

Table C.9: Impacts on Interest Expenses

	(1)	(2)	(3)
	Interest Incidence	Interests on LTB/LTB	Interests on STB/STB
Connected × Post	0.010***	0.013**	-0.038
	(0.002)	(0.006)	(0.048)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Control Mean	0.10	0.07	0.29
R^2	0.60	0.51	0.48
No. of firms	16,899	16,899	16,899
N	80,978	80,978	80,978

Notes: Interest incidence is an indicator that is expressed as a ratio of a company's interest costs to its borrowings. It serves as an indicator of the effective cost of borrowing of a company by measuring interest paid during the year as a percentage of borrowings. "LTB" = Long-term Borrowings. "STB" = Short-term Borrowings. Short-term Borrowings are those that have to be repaid within a year whereas Long-term Borrowings do not have to be repaid within a year. "Interests on LTB" = Interests on Long-term Borrowings. This is the number of interest paid by a company on long-term loans raised by it. "Interests on STB" = Interests on Short-term Borrowings. This is the number of interest paid by a company on short-term loans raised by it. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

In short, politically connected firms were able to secure scarce short-term loans after the demonetization and resort to other methods like delaying payment to suppliers

[4] We follow the definition of interest incidence to construct the cost of long-term borrowings and the cost of short-term borrowings.

to maintain and even increase their total liabilities to meet their needs in investment.

C.8 Robustness of Results

C.8.1 Standard Errors at the Firm Level

Given that there could be a correlation in the intensity of the demonetization shock across firms within a certain area (districts), our preferred specification clusters the standard errors at the district level. However, in Table C.10, we present the results by clustering standard errors at the firm level instead.

Table C.10: Inference After Clustering Standard Errors at the Firm Level)

	(1) Ln(Income)	(2) Ln(Sales)	(3) Ln(Expense)	(4) Ln(TFPR1)	(5) Ln(TFPR2)
Connected × Post	0.118***	0.087***	0.119***	0.053*	0.050*
	(0.035)	(0.032)	(0.032)	(0.029)	(0.029)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean	2.32	2.14	2.35	0.85	0.70
R^2	0.95	0.96	0.96	0.88	0.94
No. of firms	31,333	31,333	31,333	28,622	28,622
N	186,937	186,937	186,937	161,777	161,777

Notes: We restrict our sample to firms that did not have political/bureaucratic connections before 2016. Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns 4 and 5 are a firm's Total Factor Revenue Productivity calculated based on the method proposed by Levinsohn and Petrin (2003). In Column 4, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 5, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects. Standard errors are clustered at the firm level. + is p<0.15, + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

C.8.2 Analysis Using All Observations

In our preferred specification in the paper, we use a consistent sample of firms across all outcome variables in our regressions. However, there is some variation in the availability of outcome variables across firms i.e., some outcome variables are reported for some firms, but not others. In this section, we, therefore, redo our analysis (estimating Equation (3.2)) using all firms for which an outcome variable is reported, to see whether our results are sensitive to this constraint.

Table C.11: Main Outcome Variables (All Observations)

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(Sales)	Ln(Expense)	Ln(TFPR1)	Ln(TFPR2)
Connected × Post	0.154***	0.143***	0.164***	0.091***	0.083***
	(0.030)	(0.038)	(0.034)	(0.029)	(0.028)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean	2.32	2.05	2.18	0.83	0.68
R^2	0.95	0.96	0.96	0.89	0.95
No. of firms	31,593	31,901	33,951	28,622	28,722
N	193,351	191,208	211,794	161,777	162,777

Notes: Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns 4 and 5 are the Total Factor Revenue Productivity of a firm calculated based on the method proposed by Levinsohn and Petrin (2003). In Column 4, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 5, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

Table C.12: Portfolio of Liabilities (All Observations)

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Liabilities				
	Ln(Total Liabilities)	Ln(Non-Current Liabilities)	Ln(Current Liabilities)	Current/Total
Connected × Post	0.077***	-0.069**	0.113***	0.001
	(0.026)	(0.030)	(0.028)	(0.008)
Control Mean	2.52	1.07	1.61	0.39
R^2	0.98	0.91	0.95	0.86
No. of firms	35,909	36,131	35,937	35,766
N	227,923	229,716	226,189	224,707
Panel B. Components of Current Liabilities				
	Ln(Short-Term Borrowings)	Ln(Short-Term Payables)	Ln(Short-Term Advances)	Ln(Other Current Liabilities)
Connected × Post	0.036	0.111***	0.095***	0.125***
	(0.057)	(0.030)	(0.026)	(0.028)
Control Mean	0.92	0.89	0.28	0.64
R^2	0.86	0.93	0.86	0.90
No. of firms	34,831	35,823	35,833	34,671
N	216,745	224,458	224,244	212,840
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes

Notes: Current Liabilities of a firm are those liabilities or debts that must be paid within a year whereas Non-Current Liabilities are longer-term debts that need not be paid within a year. Short-term Borrowings are those which have to be repaid within a year. Short-Term Payables are liabilities owed to suppliers, vendors, and creditors for goods and services received that will mature within a year. Short-term advances are deposits and advances received from customers and employees. Other current liabilities include current maturities of long-term debt and lease, interest accrued but not due (short term), and unclaimed and unpaid dividends. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

Table C.13: Portfolio of Borrowings (All Observations)

	(1)	(2)	(3)	(4)
Panel A. Long and Short-term Borrowings				
	Ln(Total Borr.)	Ln(Short-Term Borr.)	Ln(Long-Term Borr.)	Short-Term/Total
Connected × Post	0.014	0.036	-0.077*	0.024**
	(0.041)	(0.057)	(0.047)	(0.012)
Control Mean	1.47	0.92	0.91	0.51
R^2	0.93	0.86	0.90	0.83
No. of firms	34,903	34,831	34,800	29,303
N	218,114	216,745	216,690	170,622
Panel B. Secured and Unsecured Borrowings				
	Ln(Total Borr.)	Ln(Secured Borr.)	Ln(Unsecured Borr.)	Unsecured/Total
Connected × Post	0.014	-0.028	-0.011	0.001
	(0.041)	(0.044)	(0.054)	(0.013)
Control Mean	1.47	1.06	0.73	0.45
R^2	0.93	0.90	0.84	0.83
No. of firms	34,903	34,903	34,918	29,395
N	218,114	217,846	218,034	171,703
Panel C. Borrowings from Banks				
	Ln(Total Bank Borr.)	Ln(Short-Term Bank Borr.)	Ln(Long-Term Bank Borr.)	Short-Term/Total
Connected × Post	0.026	0.020	-0.000	0.006
	(0.060)	(0.048)	(0.041)	(0.013)
Control Mean	0.97	0.65	0.51	0.62
R^2	0.88	0.84	0.84	0.81
No. of firms	34,775	34,805	34,784	21,053
N	214,606	214,634	214,553	117,800
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes

Notes: Short-term Borrowings are those that have to be repaid within a year whereas Long-term Borrowings do not have to be repaid within a year. Secured Borrowings are those where the borrower pledges some assets with the lender as collateral and in case of default, the lender has the authority to sell the pledged assets and recover the due. Short-Term Bank Borrowings are those borrowings taken from a bank and have to be repaid within a year. Long-Term Bank Borrowings, on the other hand, do not have to be repaid within a year. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

Table C.14: Portfolio of Assets (All Observations)

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Assets				
	Ln(Total Assets)	Ln(Non-Current) Assets)	Ln(Current Assets)	Non-Current/Total
Connected × Post	0.087***	0.088***	0.135***	0.006
	(0.032)	(0.032)	(0.024)	(0.007)
Control Mean	2.55	1.76	1.84	0.45
R^2	0.98	0.98	0.96	0.91
No. of firms	35,237	35,431	35,456	35,663
N	221,161	221,296	221,311	223,491
Panel B. Components of Current Assets				
	Ln(Current Investments)	Ln(Current Inventories)	Ln(Bank Bal.)	Ln(Other Current Assets)
Connected × Post	0.061**	0.044	-0.045	0.089***
	(0.028)	(0.032)	(0.040)	(0.028)
Control Mean	0.11	0.85	0.53	1.10
R^2	0.72	0.96	0.88	0.93
No. of firms	35,523	35,467	35,495	35,388
N	221,231	221,314	221,269	219,067
Panel C. Components of Non-Current Assets				
	Ln(Non-Current Investments)	Ln(Exptd. on Intangibles)	Ln(Exptd. on Fixed Assets)	Ln(Exptd. on PPE)
Connected × Post	0.171***	0.027*	0.060**	0.036
	(0.059)	(0.016)	(0.030)	(0.026)
Control Mean	0.46	0.09	1.16	1.11
R^2	0.93	0.87	0.95	0.95
No. of firms	35,456	35,546	35,554	35,553
N	221,282	222,059	222,923	222,913
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes

Notes: Current Assets (and their components) are those assets held by the firm that can be easily converted to cash by the firm within 12 months. Non-current assets (and their components) cannot be converted to cash within 12 months. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

C.8.3 Placebo Test Using Prior Years as Post

We conduct a placebo test by restricting our data to the years before the demonetization shock (before 2016), and estimating Equation (3.2) assuming (in a counterfactual case) that the demonetization shock happened in either 2013 (Panel A) or 2014 (Panel B). This implies we estimate Equation (3.2) by defining the binary variable Post to take the value 1 for years between 2013-2015 (Panel A) and 2014-2015 (Panel B).

Table C.15: Placebo Test (2012∼2015): Main Outcome Variables

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(Sales)	Ln(Expenses)	Ln(TFPR1)	Ln(TFPR2)
Panel A. Treatment year is 2013					
Connected × Post 2013	-0.016	0.026	0.033	0.042	0.033
	(0.036)	(0.035)	(0.026)	(0.031)	(0.033)
Control Mean	2.29	2.08	2.30	0.88	0.73
R^2	0.99	0.99	0.98	0.87	0.93
Panel B. Treatment year is 2014					
Connected × Post 2014	-0.001	0.043	0.010	0.019	0.012
	(0.025)	(0.032)	(0.015)	(0.034)	(0.036)
Control Mean	2.28	2.08	2.31	0.87	0.72
R^2	0.99	0.99	0.98	0.87	0.93
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
No. of firms	25,092	25,092	25,092	21,679	21,803
N	80,626	80,626	80,626	73,571	73,571

Notes: Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns 4 and 5 are the Total Factor Revenue Productivity of a firm calculated based on the method proposed by Levinsohn and Petrin (2003). In Column 4, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 5, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section C.2 in the Appendix provides the definition for all variables in detail. We do not control for the log of Goods and Service Tax payments (GST) because GST was started in 2017. We restrict the sample to pre-periods (2012∼2015) and conduct a placebo treatment test assuming that the demonetization happened in 2013 or 2014. Since the Synthetic DID requires at least two pre-periods, we use the same weights in Panel B as in Panel A. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

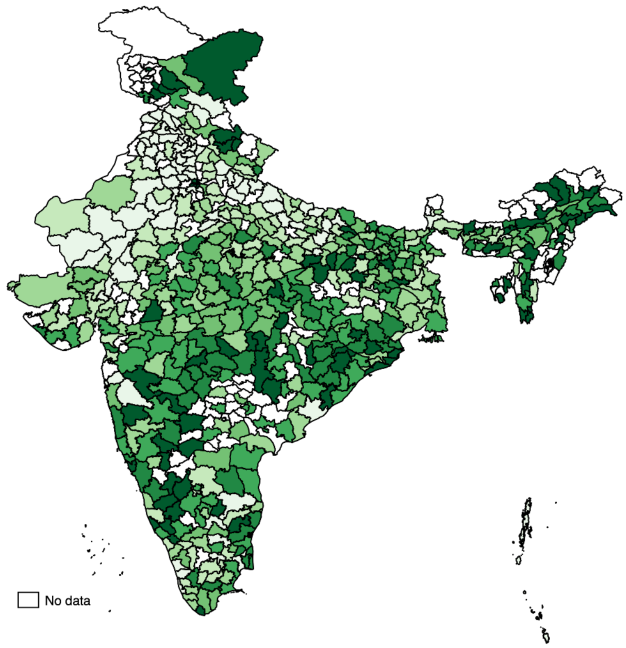
C.8.4 Randomization Inference

Table C.16: Randomization Inference: Main Outcome Variables

Variables	Connected x Post	p-value (SDID)	p-value (RI)
	(1)	(2)	(3)
Main Outcomes:			
Ln(Income)	0.118	0.00	0.00
Ln(Sales)	0.087	0.00	0.01
Ln(Expense)	0.119	0.00	0.00
Ln(TFPR1)	0.053	0.00	0.05
Ln(TFPR2)	0.050	0.01	0.09
Liabilities:			
Ln(Total Liabilities)	0.055	0.00	0.04
Ln(Non-Current Liabilities)	0.010	0.69	0.70
Ln(Current Liabilities)	0.082	0.00	0.00
Current/Total	0.015	0.07	0.26
Ln(Short-Term Borrowings)	0.042	0.24	0.18
Ln(Short-Term Payables)	0.067	0.00	0.00
Ln(Short-Term Advances)	0.029	0.17	0.14
Ln(Other Current Liabilities)	0.118	0.00	0.00
Borrowings:			
Ln(Total Borrowings)	-0.049	0.14	0.09
Ln(Short-Term Borrowings)	0.063	0.23	0.04
Ln(Long-Term Borrowings)	-0.141	0.01	0.00
Short-Term Borr./Total Borr.	0.028	0.03	0.00
Ln(Secured Borrowings)	-0.085	0.00	0.02
Ln(Unsecured Borrowings)	0.047	0.46	0.18
Unsecured Borr./Total Borr.	0.009	0.42	0.39
Ln(Total Bank Borrowings)	-0.087	0.00	0.00
Ln(Short-Term Bank Borr.)	0.032	0.46	0.34
Ln(Long-Term Bank Borr.)	-0.090	0.05	0.02
Short-Term Bank Borr./Total Bank Borr.	0.025	0.01	0.05
Assets:			
Ln(Total Assets)	0.040	0.01	0.05
Ln(Non-Current Assets)	0.050	0.08	0.05
Ln(Current Assets)	0.064	0.00	0.01
Non-Current/Total	0.002	0.67	0.66
Ln(Current Investments)	0.053	0.06	0.00
Ln(Current Inventories)	-0.005	0.83	0.82
Ln(Bank Balance)	-0.035	0.16	0.15
Ln(Other Current Assets)	0.077	0.01	0.00
Ln(Non-Current Investments)	0.093	0.05	0.00
Ln(Exptd. on Intangibles)	0.050	0.00	0.00
Ln(Exptd. On Fixed Assets)	0.018	0.57	0.74
Ln(Exptd. On PPE)	-0.018	0.56	0.60

Notes: Section C.2 in the Appendix provides the definition for all variables in detail. For Randomization Inference, we randomize the assignment of treatment 100 times. Connected × Post in Column 1 and the p-value (SDID) in Column 2 is the estimated coefficient (and the corresponding p-value) from our preferred specification in the paper. p-value (RI) in Column 3 is the p-value associated with the Randomization Inference. Standard errors are clustered at the district level.

C.8.5 Severity of Demonetization Shock



Notes: The figure displays a district-level map of India's 2016 demonetization shock severity constructed from data extracted from Figure V in Chodorow-Reich et al. (2020). It depicts the value of legal tenders in the district in the post-demonetization period divided by the total value of cash in that district before demonetization using currency chest records maintained by the Reserve Bank of India. The deeper the color, the larger the shock a district has experienced.

Figure C.6: Demonetization Shock By District

C.8.6 Recency of Political Connections

Table C.17: Impact of Connection Duration on Income, Sales, Expenses, and TFPR

	(1)	(2)	(3)	(4)	(5)
	Ln(Income)	Ln(Sales)	Ln(Expenses)	Ln(TFPR1)	Ln(TFPR2)
Panel A. The First Connected Year					
Post × Recently-established	0.106*	0.053	0.121**	0.046	0.043
Political Connection ($\hat{\beta}_1$)	(0.061)	(0.066)	(0.051)	(0.044)	(0.043)
Post × Farther off-established	0.048	0.044	0.028	0.076^{+}	0.075
Political Connection ($\hat{\beta}_2$)	(0.042)	(0.051)	(0.041)	(0.046)	(0.051)
p-vale ($\hat{\beta}_1 - \hat{\beta}_2 = 0$)	0.522	0.925	0.196	0.635	0.678
Control Mean	2.32	2.14	2.35	0.85	0.70
R^2	0.95	0.96	0.96	0.88	0.94
Panel B. The Nearest Connected Year					
Post × Short-established	0.156**	0.073	0.151**	0.067	0.058
Political Connection ($\hat{\beta}_2$)	(0.078)	(0.077)	(0.068)	(0.053)	(0.052)
Post × Long-established	0.010	-0.043	-0.004	0.019	0.031
Political Connection ($\hat{\beta}_2$)	(0.050)	(0.053)	(0.045)	(0.032)	(0.037)
p-vale ($\hat{\beta}_1 - \hat{\beta}_2 = 0$)	0.166	0.288	0.104	0.423	0.677
Control Mean	2.32	2.14	2.35	0.85	0.70
R^2	0.95	0.96	0.96	0.88	0.94
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
No. of firms	31,333	31,333	31,333	28,622	28,622
N	186,937	186,937	186,937	161,777	161,777

Notes: In panel A, we use the joining year of the *first* politician/bureaucrat director to calculate how many years a firm has been politically connected. If the connection years are above the median, then we call it a Farther off-established political connection; if the connection years are below the median, then we call it a Recently-established connection. In panel B, we use the joining year of the *latest* politician/bureaucrat director before 2016 to calculate how many years a firm has been politically connected. Income in Column 1 is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column 2 are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column 3 are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns 4 and 5 is a firm's Total Factor Revenue Productivity calculated based on the method proposed by Levinsohn and Petrin (2003). In Column 4, the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column 5, the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section C.2 in the Appendix provides the definition for all variables in detail. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.

C.8.7 Spatial Distribution of Politically Connected Firms

Table C.18: Connected Firms & Shock Severity

	Share of Connected Firms	
	(1)	(2)
Severity	-0.006	-0.006
	(0.010)	(0.009)
N	370	370

Notes: "Share of connected firms" is the percentage of firms that are politically connected in a district in 2015. "Severity" is the standardized value of demonetization shock. Larger values imply larger shock. "N" is the number of districts. We aggregate the unit weights of firms used in the income/sales regression at the district level. In column (1), we apply the aggregated district weights from the income regression; in column (2), we employ the weights from the sales regression. Standard errors are clustered at the district level. + is p<0.15, * is p<0.1 , ** is p<0.05, and *** is p<0.01.