Trade, Internal Migration, and Human Capital

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Abstract

Investments in education and infrastructure are the two most important drivers of economic development: About a fifth of world GDP is spent on just these two categories.[1] As the world is becoming increasingly global with the growth rate of exports exceeding that of GDP, studying the links between trade and investments in human and physical capital has become more important than ever.[2] The three chapters of my dissertation focus on understanding these links: The first two chapters analyze how trade affects investments in human capital and the consequent changes in welfare, and the third chapter studies the links between investments in infrastructure capital in the form of highway expansion, internal trade, and regional development.

In the first chapter, using an external demand shock in the Indian Information Technology (IT) sector, data on the IT sector that I assemble and confidential internal migration data from India, I document that both IT employment and engineering enrollment increased in response to the rise in IT exports across regions in the late 1990s, and this response was heterogeneous across regions.

In the second chapter, I develop a structural spatial model featuring two new channels compared to the existing spatial models: the option to choose education and the option to move for education. I estimate the model using the external IT demand shock and detailed internal migration data from India. Using this framework, I then quantify the aggregate and distributional effects, and perform counterfactuals. I find that without any of these channels, estimated aggregate welfare gains from the IT boom would be halved and estimated regional inequality would be a third higher. Shutting down the second channel alone (not allowing migration for education) reduces the estimated aggregate welfare gains marginally but increases regional inequality by 15%. Sector specific trade shocks, such as the Indian IT boom, change the relative returns to occupations across locations depending on two factors: the location's comparative advantage in that sector and its connectivity to other locations. The changes in the relative returns to occupations affect an individual's incentives to invest in different skill types. Skill investments are constrained by the local availability of higher education and the costs of moving to regions with colleges.

[1] Source: World Bank Indicators, 2017, McKinsey Global Institute Analysis.
https://data.worldbank.org/indicator/se.xpd.totl.gb.zs accessed 3/21/2019
https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/bridging-infrastructure-gaps-has-the-world-made-progress

[2] Source: WTO, International Trade Statistics, 2015.
https://www.wto.org/english/res_e/statis_e/its2015_e/its15_highlights_e.pdf accessed 3/21/2019

The key ingredient of my model is that individuals make education and work decisions in two stages. In the first stage, they decide what and where to study taking access to higher education and job opportunities into account. In the second stage, individuals choose the sector and location of work.

The first two chapters of my dissertation make three contributions. First, I introduce human capital acquisition decisions in a general equilibrium economic geography model. The general equilibrium aspect is important, since human capital takes time to respond to employment opportunities, during which both people and goods can move. Second, in the model, people face differential migration costs when they move for education or for work. I develop a framework to estimate these two costs separately and find that the mobility costs for education are 7 percentage points higher than those for work. Individuals born in districts with greater access to education and jobs gained as much as 2.63%, while those in remote districts experienced gains as low as 0.67%. Third, the framework is well-suited for analyzing the effects of policy-induced spatial frictions to moving for higher education, such as in-state quotas at colleges. Reducing these barriers would increase aggregate welfare marginally but substantially decrease the impact of the export shock on regional inequality. The results underscore the potential for education policies to distribute the gains from globalization more equally.

In the third part of my dissertation, in joint work with Kerem Cosar, Banu Demir and Nate Young,[3] we study how investments in infrastructure improvements, specifically, the expansion of highway networks, affect short-run and long-run distributions of welfare by improving internal trade between regions. In this paper, we examine the benefits that a major capacity upgrade to existing transport infrastructure can have in middle-income economies by looking at the case of Turkey, which expanded highways from divided two lanes to four lanes during the 2000s. We do this by measuring the impact of reduced travel times between Turkish provinces and then linking changes in travel times to changes in intranational trade as well as regional sales, employment, and productivity. Our results suggest that travel time reductions due to the ambitious investment program boosted intranational trade in Turkey, increased output, and generated employment. The results are robust to a number of robustness checks, including a falsification test that investigates whether changes in do-

[3]Kerem Cosar, Associate Professor, University of Virginia. Banu Demir, Assistant Professor, Bilkent University. Nate Young, Principal Economist, European Bank for Reconstruction and Development

mestic interprovincial trade flows during the 2006-2011 period can be explained by travel time reductions over the 2010-2015 period.

But how large are gains in welfare from road development, especially when there are various types or stages of investments that are possible? Arguably, constructing a new road from scratch or paving a dirt road would have a different effect than constructing a highway or expanding the lane capacity of existing roads. In a quantitative exercise using a workhorse model of spatial equilibrium, we find a rate of return on investment around 70%. In the long run, when people can move across regions, this translates into a welfare gain of 2%. In the short run when people cannot move, the welfare gains are more unequal: Already well-connected cities like Istanbul do not gain substantially while more remote places gain a lot.

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Contents

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1 The Indian IT Boom: Some Stylized Facts

1.1 Introduction

New economic opportunities that arise from globalization are often accompanied by a rising demand for different types of skills. Inequalities in local access to education and jobs, along with mobility frictions, make it costly for individuals in some regions to acquire education or pursue better job opportunities. These frictions could be particularly large in developing countries. To what extent do these frictions limit the gains from trade and exacerbate inequality? What policies can help reduce these inequalities? The main challenge in answering these questions is disentangling the different ways in which individuals respond to these opportunities, such as choosing the sector and the locations of work and education, and the interdependence between these decisions.

In this paper, I analyze the effects of trade on welfare and inequality when education choice is endogenous and when there are mobility frictions to access both education and work. Combining detailed spatial and migration data, I document that IT employment and engineering enrollment responded to the rise in Indian IT exports in the late 1990s, and this response was heterogeneous across regions. Consistent with these stylized facts, I develop and quantify a spatial equilibrium model that adds two new margins of response relative to the existing economic geography literature: first, agents can acquire new skills and second, they can migrate internally to acquire these skills. I find that without higher education choice, estimated aggregate welfare gains from the IT boom would be halved and estimated regional inequality would be a third higher. Restricting individuals to go to college only in their home districts (i.e., not allowing for mobility for education), reduces the estimated aggregate welfare gains marginally but increases regional inequality by 15%.

The paper begins by providing a set of stylized facts about the labor market consequences of the IT boom using spatially granular sectoral labor and education data that I compiled and a unique census dataset tracking migration flows between Indian districts, disaggregated by reason for migration. From 1998 to 2008, while Indian IT as a fraction of total service exports increased from 15% to 40%, engineering enrollment as a fraction of total enrollment more than doubled, and total college enrollment increased three-fold. I document two salient stylized facts: 1) IT employment and engineering enrollment positively respond to IT exports, with IT employment responding more when nearby regions have higher engineering enrollment and exports; and 2) distance affects migration, and individuals migrate more for work than for education. State borders restrict migration flows for education more than that for work, reflecting state-level barriers to mobility for education, such as in-state quotas for students at higher education institutes.

Consistent with these stylized facts, I develop a quantitative spatial equilibrium model that allows individuals to make education and work decisions in two stages. In the first stage, they decide what and where to study, accounting for access to higher education and job opportunities. In the second stage, individuals choose the sector and location of work. The first and second stage decisions generate the education and employment responses respectively, documented by stylized fact 1. To my knowledge, this is the first paper to allow for and estimate differential mobility costs for work and education to find that the mobility cost estimates are consistent with stylized fact 2.

In the model, sector specific trade shocks, such as the Indian IT boom, change the relative returns to occupations across locations depending on two factors: 1) the location's comparative advantage in that sector and 2) its connectivity to other locations. The changes in the relative returns to occupations affect an individual's incentives to invest in different skill types. Skill investments are constrained by the local availability of higher education and the costs of moving to regions with colleges. Thus, regions differ in how much skilled labor they can access and consequently, by how much they can expand IT production. To the extent that the external demand shock and historical regional differences in comparative advantage are not correlated with unobserved productivities that are determined from the supply side, I can leverage the IT boom to estimate the structural model parameters, such as the elasticity of software exports to software prices. Differences in local access to jobs and education, along with differential moving costs for work and education, generate regional inequalities in welfare gains from the IT boom.

People face differential migration costs when they move for education or for work. The dependence of job opportunities on skill levels makes it challenging to separately estimate work mobility costs using migration data that do not track the skill level of the migrant. I use the two stage structure of the model to explicitly account for such dependence and use the unique census data that track why people move, to estimate these two costs separately.[4] I find that the mobility costs across districts, measured as the dis-utility from moving, for education are 7 percentage points higher than those for work. Estimated state border effects are large: being in the same state increases migration between neighboring districts by 269% for education and 59% for work. There are several reasons why the mobility cost of education could differ from that of work, such as policy-induced mobility barriers and language barriers that could have a differential effect depending on an individual's age. In India (as in many other countries like the U.S. and China), there are state quotas in higher education institutes for in-state students. This policy could result in higher costs of crossing state borders for education than for work.

Compared to a benchmark quantitative model with fixed skill types, I find significantly different aggregate and distributional consequences of trade across regions after incorporating the mechanism of endogenous education choice. Almost half of the gains in average welfare are driven by the ability to change skills: without endogenous education, the average individual would have benefited by 0.67% compared with an average gain of 1.12% in the endogenous education case. Even though inequality in the distribution of employment is reduced, the rise in inter-regional welfare inequality due to the IT boom, measured as the coefficient of variation in regional

[4]To my knowledge, this is only the second project to use this highly confidential data and the first that uses it to estimate migration costs. Kone et al. (2018) were the first to use this data to show how migration flows relate to geographic and cultural distances in India

welfare at the origin district, is 37% more in the fixed-skills model than in the model with endogenous education choice. The key mechanisms leading to higher aggregate welfare and lower welfare inequality in the endogenous education model, compared with the fixed-skills model are the ability to acquire skills and to move across regions for education.

How important is this mobility cost for education that I introduce in a spatial equilibrium model? To quantify the importance of mobility costs for education, I restrict individuals to attend college in their home districts. This counterfactual increases regional inequality by 15%. The gap between the welfare gains of the worst off and the best district increases by 63%.

The question of how to reduce inequality across both regions and skill groups lies at the heart of many policy debates. This paper suggests policy interventions in the education market that can reduce trade-driven regional inequality, but not by moving jobs directly. The policy of reducing in-state quotas for students at colleges can reduce the migration costs for education relative to work. In the model, this is implemented by restricting the effect of state borders on migration for education to be exactly the same as that for work. I find that the rise in average welfare would have been 1% higher compared with the rise in the actual model and regional inequality, measured by the coefficient of variation, would have been 27% lower. Reducing inter-state barriers to education can significantly increase access to education for out-of-state students. This can increase the opportunity for people from remote regions to gain access to education and migrate to areas with more high-skilled jobs. Although this policy does not reduce inequality in the distribution of employment, it reduces inequality in the distribution of welfare by increasing access to education. This underscores the importance of general equilibrium effects induced by the expansion of exports, which requires us to give more consideration to the interactions of trade, education, and labor markets.

This paper makes three contributions. First, I introduce human capital acquisition decisions in a general equilibrium economic geography model. The general equilibrium aspect is important, since human capital takes time to respond to employment opportunities, during which both people and goods can move. Second, to my knowledge, this is the first paper to estimate the mobility costs for work and education separately and show that these costs are quantitatively different. The unique Census data tracking migration flows disaggregated by reason, obtained through an agreement with the Indian government, made this estimation possible. I show that access to both jobs and education are individually important for determining the spatial dispersion in the gains from trade. Third, the framework is well-suited for analyzing the effects of policy-induced spatial frictions to moving for higher education, such as in-state quotas at colleges. Reducing these barriers would increase aggregate welfare marginally but substantially decrease the impact of the export shock on regional inequality. The results underscore the potential for education policies to distribute the gains from globalization more equally.

The model builds on a large theoretical literature in the fields of international trade, economic geography, labor, and migration. Similarly to Caliendo et al. (2019), Fuchs (2018), and Kucheryavyy et al. (2016) the model features multiple sectors. Like Allen et al. (2018) and Tsivanidis (2018), the model features agents with heterogeneous skill types. However, unlike the above models, the theory developed here endogenizes the formation of skills across space.

Costly labor mobility relates this paper to the class of gravity migration models, such as those by Allen et al. (2018), Tombe and Zhu (2019), Fan (2019), and Bryan and Morten (2019) that feature multiple sectors with costly mobility of goods and people. Kone et al. (2018) use the Indian migration data to provide evidence of how migrations flows relate to distance and cultural differences. Differently from these papers, I provide separate estimates for mobility costs by reasons for migration.

A few structural trade models study endogenous human capital acquisition in trade. Khanna and Morales (2017) studies how US immigration policy and the internet boom affected aggregate welfare in both the US and India in a dynamic setting with international migration. In contrast, this paper studies the regional distributional consequences of the IT boom, quantifying how costs of migration contributed to regional inequality induced by the IT boom. Compared to Ferriere et al. (2018), who build a dynamic multi-region model of international trade with heterogeneous households, incomplete credit markets, and costly endogenous skill acquisition, this paper, in a static setting, additionally features costly mobility for education. A few other theoretical works in this literature focus on quantifying the overall response of endogenous education to trade, without considering regional differences, such as Danziger (2017). Seminal works on the dynamic Heckscher-Ohlin (HO) model, which embeds endogenous factor formation in response to trade in the classic HO framework, include Stiglitz (1970), Findlay and Kierzkowski (1983), and Borsook (1987). Consistent with this literature, I demonstrate trade can strengthen a country's initial comparative advantage and how this endogenous response can reduce regional inequality in the gains from trade.

Endogenizing education relates my model to the class of human capital accumulation models prominent in the education and labor literature. In these models, forward-looking individuals make education decisions based on labor market returns and costs of tuitions (Jones and Kellogg (2014), Johnson (2013), and Lee (2005)). Compared to this class of models which requires keeping track of a large number of state spaces, I use a simpler two-stage model that allows me to tractably incorporate many regions and bilateral migration flows between these regions.

Given the emphasis in the trade literature on the effect of exports and trade liberalization on skill premium, there has been relatively little research on the effect of trade on skill acquisition. A number of empirical studies such as Atkin (2016), Blanchard and Olney (2017), Edmonds et al. (2010), Greenland and Lopresti (2016), Shastry (2012), Liu (2017), and Oster and Steinberg (2013) focus on the impact of trade on primary and secondary education. Exceptions to these are Li (2018) and Khanna and Morales (2017) which study the response of college enrollment to high-skill export shocks. More evidence has emerged recently (Li (2019), Hou and Karayalcin (2019), Ma et al. (2019)). Complementing this literature, I provide reduced form evidence about the response of tertiary enrollment to shocks in the high-tech sector in a large developing country, and I document regional heterogeneity in this response.

1.2 Data

A major constraint in studying the effects of IT export growth on human capital acquisition in the presence of costly migration is the lack of employment and education data, disaggregated at the sector of work and field of education level, combined with the absence of detailed migration data. To this end, I use three sources to collect data on India's IT sector and access confidential Indian Census data to obtain district-to-district migration flows by reasons for migration.

1.2.1 Data on the Indian IT sector

I use three rounds of Economic Census data (1998, 2005, and 2013) to obtain data on total IT employment across all regions of India. While the advantage of the Census data is that it covers the entirety of all Indian firms and hence reports total employment, the data are not disaggregated by level of education. To supplement this information, I use data from the National Sample Survey (NSS) rounds 50, 55, 60, 61, 62, 64, 66, and 68. These surveys record information on the sector and location of occupation as well as the field of study. The drawback of the NSS data is that it represents only a small sample, and hence does not contain a lot of important sector-level information. However, it does report multipliers on each unit of observation, which, in the NSS, is an individual. This allows me to obtain the unbiased ratios of engineers and both college-educated and non-college-educated individuals in each sector of employment. By multiplying these ratios with total employment from the Economic Census, one can recover the distribution of the population by field of study and employment in each region.

Data on wages by sector of occupation and field of education are also obtained from the NSS. However, due to the small sample representation of the NSS data, there are several observations in which employment is positive, according to the Economic Census data, but for which no NSS data on wages and employment exist. For these observations, I impute the missing values using machine learning techniques, such as including the K-nearest neighbors. See appendix A.3 for further details.

As an additional source, I supplement the IT employment and wage data with data on IT exports from NASSCOM (the leading trade association of the software industry in India) directories 1992, 1995, 1998, 1999, 2002, and 2003. The strength of the NASSCOM dataset is that it contains data on "95% of all registered IT firms in India" [5]. NASSCOM also contains data on IT employment, and this information is divided according to whether employees are technical employees (that is, associated directly with the provision and deliverance of IT services) or non-technical employees (all other employees). Several papers have used the NASSCOM data, which is the most comprehensive source of data on Indian IT firms; among these, Tharakan et al. (2005) and Shastry (2012) are notable.[6]

1.2.2 Data on internal migration

The National Census of India for 2001 is the main data source for internal migration in India. An individual is a migrant, according to the Census,"if the place in which he is enumerated during the census is other than his place of immediate last residence" (Census, 2001). The Census includes additional questions based on the last residence criteria. These questions include reason for migration, such as marriage, education, or employment; the urban/rural status of the last residence's location; and the duration of stay in the current residence since migration. This level of disaggregation is crucial for separately estimating the costs of migration due to education and work. Publicly available Census data only report the destination district and whether the migrant's origin is in the same state or out-side the state, aggregated over all reasons

[5] Source: NASSCOM

[6] Tharakan et al. (2005) cross-checked the quality of NASSCOM software exports data by comparing yearly aggregate software exports from India from International Data Corporation with the figures obtained from NASSCOM data and claim that they are of comparable magnitude.

for migration. I obtain the more disaggregated data through a special agreement with the Census of India.

1.2.3 Other data

Data on the linguistic distance of each Indian district from Hindi was obtained from Gauri Kartini Shastry who constructed the linguistic distance measures for Shastry (2012). Construction of the index, which is key to my empirical strategy, is detailed in Shastry's paper and in appendix A.2. The linguistic distance I use is calculated by ethno-linguistics based on the similarity of grammar and cognates. For example, daughter in English is "dokhtar" in Perisan and "nuer" in Mandarin Chinese. While Persian and English are both part of the Indo-European language family, Chinese is derived from the Sino-Tibetan language family. Linguistic distance between Persian and English is therefore lower than between Chinese and English or Chinese and Persian. In India, languages differ across regions. The 1961 Census of India documented speakers of 1652 languages from five language families. There can be wide linguistic diversity between districts, and most people adopt a second language that is a widely accepted speaking medium across districts. Of all multilingual people who were not native speakers, 60 percent chose to learn Hindi and 56 percent chose English (Shastry (2012)).

Shastry (2012) proxies English-learning costs as linguistic distance from Hindi relative to English. She shows that since a necessary condition for employment in the IT industry is fluency in English, IT firms locate more in districts that have a higher proportion of English speakers, as proxied by linguistic distance of that district to English relative to Hindi.

Data on the college-age population, college enrollment, and literacy are collected from the decadal Census data of 2001 and 2011. Summary statistics for the employment and enrollment are reported in tables 15, 16, and 17 in the appendix. The most notable is the rise in engineering enrollment. Between the pre and the post boom period, the proportion of engineers in total college enrollment more than doubled from 5% to 11%. During this time, the total number of people enrolled in college also increased by three-fold. Thus, the total number of students studying engineering also increased in absolute numbers.

1.3 Background of India's IT growth

While the last two decades have witnessed a world-wide expansion of IT and consequent increase in demand for computing skills, this expansion has been disproportionately larger for India than for any other country in the world (International Trade Center (2017)). Figure 1 plots the growth in IT exports over time, where the value of IT exports in 1993 has been normalized to one. This figure shows that IT exports from India have been steadily increasing since 1993, but a large jump occurred in the late 1990s and early 2000, when normalized software exports increased by more than 76% in one year. Figure 2 shows that during this period, IT employment as a fraction of total employment was also rising. From 1998 to 2000, IT employment as a fraction of total employment almost doubled. Engineering as a fraction of total enrollment was also generally increasing, but the largest jump occurred after 2000.

While many factors are responsible for the growth of IT in India, the lack of domestic demand for IT means that the sector's growth is constrained by the growth in world demand for Indian IT. This constraint was eased during the late 1990s and early 2000s, when several major events suddenly escalated demand for Indian IT. The Y2K phenomenon dominated from 1998 to 2000, along with the earlier dot-com boom and, later on, the dot-com bust. In order to solve Y2K-related computer problems, commonly known as the "Y2K bugs", IT firms started offshoring large parts of their work to developing countries such as India.[7] The dot-com boom was a historic

[7] Before 2000, all computers stored dates using only the last two digits of a year. The Y2K problem refers to the problem that can occur in computer systems as the year 1900 becomes indistinguishable from 2000. The majority of programs with Y2K problems were business applications written in a 40-year-old language called COBOL (UC Berkeley (1999)). While COBOL programming was already obsolete in US universities, in India it was still a part of the regular course curriculum. (Mathur (2006)).

economic bubble and period of excessive speculation that occurred from roughly 1995 to 2000; it was marked by extreme growth in the use and adaptation of the Internet. The dot-com bust caused many firms in the US (two-thirds of India's IT market) and elsewhere to slash their IT budgets, prompting even more outsourcing to India. (Economist (2003))

Most notably, technological progress in the worldwide Internet which had been underway for some time, was responsible for bringing world outsourcing demand to Indian firms. As Khanna and Morales (2017) notes:

> The absence of world-wide Internet during the 1980s meant that on-site work ("body-shopping") dominated, because otherwise software had to be transported on tapes that faced heavy import duties. But in 1992, satellite links were set up in Software Technology Parks (STP), negating the need for some kinds of on-site work, and this boosted the offshoring of work to India. In 1993, the shift from B-1 to H-1 visas in the US further lowered the incentives to hire Indian engineers for on-site work, as they were to be paid the prevailing market wage.

While world-wide events such as the Y2K shock, the dot-com boom and bust, and changes in US H-1B visa policies provided considerable external stimuli for the growth of the Indian IT sector, certain factors inherent to India are responsible for this exceptional expansion of Indian IT exports. It is generally agreed that the availability of low-cost, high-skill human resources has given India a comparative advantage in the IT sector over its competitor nations (Kapur (2002)). Moreover, much of the population (over 60%) is under 25, and India has one of the largest pools of technical graduates in the world. India also has a large English-speaking population due to its British legacy, and this fact is considered one of the key ingredients in the success of IT. As Shastry (2012) has shown, IT firms in India are located mostly in regions with a larger English-speaking population. A natural advantage of India is its time difference with the US, which is one of India's biggest customers for IT services; this enables India to offer overnight services to the US, effectively creating round-the-clock working hours for outsourcing firms (Carmel and Tjia (2005)).

The growth of Indian IT is the result of much more than a single transitory demand shock that temporarily catapulted the sector upward. With the expansion in Indian IT exports, Indian IT employment continued to increase. Wages peaked during the sudden expansion of the late 1990s and early 2000s. Arguably, in response to rising IT employment opportunities, engineering enrollment started to respond after 2000, as shown in Figure 2.

1.4 Reduced-form facts

In this section, I present four facts about internal migration, the relationships between IT exports, regional employment, and enrollment over the short-run and the long-run in India. I use the expansion of IT during 1998-2002, largely driven by external demand shocks as described in section 1.3, to study the labor market effects in the long-run, that is, between 2005-2011. The choice of this time frame is dictated by the fact that an engineering degree takes at-least four years to complete and thus any effect on the labor market related to skill acquisition will occur after 2004-2005.

Fact 1: *IT employment and engineering enrollment positively respond to exports.*

To understand how IT employment and engineering enrollment changed across regions after the IT boom, I estimate the following event study specification:

$$Y_{dt} = \alpha_t + \gamma_d + \chi_d * t + \beta_t Exports_{d,1995} + \epsilon_{dt} \tag{1}$$

where Y_{dt} is IT employment or engineering enrollment in district d at time t. $Exports_{d,1995}$ is the proportion of software exports from district d in the year 1995 out of total Indian IT exports in 1995. α_t are time fixed effects that capture any factors that are common to all districts at time t. γ_d are district fixed effects that capture any factors that are fixed over-time in district d. $\chi_d * t$ is a district-level time-trend capturing any linear trend in the outcome variable at the district level. Standard errors are clustered at the state-year level, with alternative clustering assumptions at the state and district levels explored in appendix B, table 19.

The idea is that districts which initially had higher connections with the rest of the world, as measured by the proportion of software exports in 1995, will gain more from the expansion in world demand for Indian IT than districts that had little or no connection with the rest of the world. In alternative specifications reported in appendix B, following Shastry (2012), I instrument the initial software exports with the historical linguistic distance of a district from English.

In figure 3, I plot the estimated coefficients along with the confidence intervals for the years 1995-2013. From this figure, we can see that post-1998, IT employment increased more in districts that had a higher level of software exports in 1995. This effect is significant in all years available in the data from 1999-2013. The insignificant coefficients for 1995 and 1998, the pre-boom years, indicates the absence of pre-trends.

In figure 4, I plot the response of engineering enrollment at ten year intervals, as the available census data allows. As the graph shows, engineering enrollment has also been rising since 2001.

Since the Census data is available at decadal intervals, I cannot show the pre-trend estimates for enrollment.

Fact 2: *The effects are heterogeneous. Employment responds more when nearby regions have higher engineering enrollment and higher IT exports. The heterogeneous effects are stronger in the long run.*

In equation 2 below, I add an interaction term between the number of students enrolled in engineering in 1991 and the proportion of software exports from district d in 1995. Estimated coefficient δ_t is plotted in figure 5. δ_t measures the differential response of IT employment between the pre and post boom periods depending on the historical level of engineering college enrollment in 1991, in districts that already had prior software exports in 1995.

$$\begin{aligned} Y_{dt} = \alpha_t + \gamma_d + \beta_t * Exports_{d,1995} + \chi_t Enrollment_{d,1991} + \\ \delta_t Exports_{d,1995} * Enrollment_{d,1991} + \epsilon_{dt} \end{aligned} \tag{2}$$

Figure 5 shows that, conditional on the level of software exports, post 1998, IT employment responds more in districts that, in 1991, had more enrolled engineering students in same-state, nearby districts. The intuition, formalized in the model, is that in these districts, it is easier to expand future IT production due to having more college-educated, engineering program graduates in close proximity. Regression results are reported in appendix B in table 21.

Both IT employment and engineering enrollment thus respond more in districts that had prior IT exports compared to districts that did not. Figure 6 shows the spatial distribution of IT employment as a proportion of total employment and engineering enrollment as a proportion of total enrollment in 2011.

The graph shows that there is a positive correlation between the percentage of people employed in the IT sector and the proportion of people enrolled in engineering. While the contemporaneous correlation in 2011 is 0.38, the corresponding correlation between the proportion of IT employment in 2005 and the proportion of engineering enrollment in 2011 is 0.43. Districts in the south have a higher proportion of both, districts in the north and northeast are relatively deprived of both.

The presence of migration costs could be one reason why we would observe this spatial correlation of IT employment and engineering enrollment. I use detailed data on district-to-district bilateral migration flows, disaggregated by reason for migration to study whether geographic and cultural distance affect migration flows.

Fact 3: *Migration reduces over distance. In addition, state borders negatively affect migration and this effect is significantly larger when people migrate for education than when they migrate for work or for any other reason.*

Using the Poisson pseudo maximum likelihood procedure (PPML), I estimate (3), similar to Kone et al. (2018). [8] PPML is a non-linear estimation procedure which performs better than a log-log estimation in the presence of zeros and has been traditionally used in the estimation of migration gravity equations (Santos Silva and Tenreyro (2006)).

$$\begin{aligned} l_{oj} = C + f_j + f_o + \beta_1 ln(Dist_{oj}) + \beta_2 lang_{oj} + \\ \gamma_1 Diff_{oj}^{diff-NBR} + \gamma_2 D_{oj}^{same-NBR} + \gamma_3 D_{oj}^{same-notNBR} + \epsilon_{oj} \end{aligned} \tag{3}$$

where l_{oj} is the stock of migrants migrating for education (column 1 in Table 1), for work (column 2) or for other reasons (column 3) from district o to district j, $Dist_{oj}$ is a measure of geographic distance between two districts.[9] For bilateral distance between any two districts, I use the geodesic (flight) distance between the geographic centers of districts i and j. All these variables included in the gravity specification are obtained from the calculations by Kone et al. (2018). [10]

$lang_{oj}$ denotes the likelihood of any two individuals from districts i and j being able to communicate in a common language. This is given by:

$$CommonLanguage = \sum_l s_i^l . s_j^l$$

where s_i^l is the share of people from district i having mother tongue l.

There are three contiguity variables: $diff-NBR_{ij}$ is a dummy variable that takes the value of 1 if districts i and j are in different states but are neighbors; $same - NBR_{ij}$

[8]Kone et al. (2018) ran this specification for 585* 584 districts, excluding the own district. Following the literature on gravity estimation, for e.g., see Bryan and Morten (2019)), I estimate it on a 585*585 sample, including own district.

[9]Other reasons include marriage, business and other unclassified reasons

[10]geodesic distance is the length of the shortest curve between two points along the surface of a mathematical model of the earth—between the districts' geographical centers, denoted as distance centroids.

is a dummy variable that is equal to 1 if the districts i and j are in the same state and are neighbors; $same-notNBR_{ij}$ is a dummy variable that is equal to 1 if the districts i and j are in the same state but are not neighbors. The base group is 'not in the same state and not neighbors'. The difference between γ_1 and γ_2 gauges the role of the state borders.

Table 1 shows that the coefficient for same-state-neighbor dummy is larger than the different-state-neighbor coefficient in every column, and this difference is statistically significant. For two districts that are neighbors, being in the same state increases migration by 217% when people migrate for education. [11] This effect is about 30% when people migrate for work and for other reasons.

This shows that the effect of state borders differ substantially depending on the reason for migration. One reason why the state border dummy is so important when people migrate for education is the policy of reserving a large proportion of seats in public as well as private colleges for in-state students. Most state colleges have home state quotas of 50 % with such limits being as high as 85% for some states.[12] While such quotas also exist for jobs and thus create significant hurdles for moving across states, the employment quotas are more specific and less ubiquitous than the in-state education quotas.

Fact 4: *Individuals migrate more for work than for education and the distributions of flows for work and for migration across districts differ accordingly.*

Figure 7 shows the histogram of migration flows by reason for migration. The x-axis plots the percentage of people who migrated for work and for education out of the total number of migrants at the destination district. The y-axis plots the number of destination districts with the corresponding percentages. As is clear from the plots of these very different and almost non-overlapping distributions, out of the total migrant population in most destination districts, a much higher percentage had migrated for

[11] This effect is calculated by $(e^{3.577-2.422} - 1) * 100$

[12] Support for the 85% reservation policy started in Maharashtra from the year 2011 with the backing of nationalist state parties

work compared to that for education.

Facts 3 and 4 are also borne out by Table 2 below. Reading off column 3, out of all migrants who migrated out of their district of past residence in the last 10 years, 48% migrated for work, but only 3% migrated for education. Column 6 shows that out of all individuals who migrated for education, only 31% crossed state borders, while over half of those migrating for work did so.

Informed by these four facts, the next section presents a general equilibrium model featuring many locations, costs of movement of people and goods between locations, and costly human capital acquisition decisions.

2 Trade, Internal Migration, and Human Capital: Who Gains from India's IT Boom?

2.1 A Quantitative spatial equilibrium model with endogenous education choice

There are discrete locations $d \in D$ where D includes the many regions within a country. There is also the Rest of the World (RoW) that these many regions trade with. The small open economy assumption holds. The regions differ from each other in their distances to other regions and the RoW and in the distribution of population eligible to attend college, that is, individuals who have already completed high school. There are individuals in each region who make decisions in two stages. In the first stage, they decide whether or not to go to college, and if they go to college, what field to study and in what location. There are F fields individuals can choose to study, such as engineering. In the second stage, given their education decisions, individuals decide where and in which sector to work. There is a representative firm of each sector in each location, and within each sector the firm in each location produces a different variety which is costly to trade across locations, in an Armington set up. Each worker is endowed with an unit of labor which they supply inelastically. There are S sectors in the economy.

Individuals

Utility of an individual i who attained college education in field f from region o_2 and then works in sector S in region d depends on wages, amenities, migration costs, prices indices and idiosyncratic productivity shocks and is given by: (suppressing individual subscript i from utility for expositional clarity)

$$V_{o_2 f,dS} = \left(\frac{w_{f,dS}}{P_d}\right) \cdot u_{f,dS} \cdot \eta_i \cdot \mu_{o_2 d}^2 \tag{4}$$

where $w_{f,dS}$ is the wage of a worker in region d with a degree in field f who is working in sector S, $u_{f,dS}$ is the amenity of living in region d for a worker with degree f working in S, henceforth referred to as type (f, S) worker. P_d is the cost of living in region d, which is endogenously determined as described in section 2.1. $(1 - \mu^2_{o_2d})$ is the utility cost of migrating from o to work in d.

The idiosyncratic productivity shocks for each individual i, $\eta_{io_2f,dS}$ are drawn from a Frechet distribution where

$$F(\eta_{io_2f,dS}) = exp(-\eta_{io_2f,dS}{}^{-\theta})$$

θ determines the dispersion of the Frechet productivity shocks.

Utility cost of education

The above formation of utility ignores the utility cost of education. To add workers' education choice, I introduce an utility cost of education. Let a_{o_2f} denote the amenity of studying f in o_2, which includes the unobserved preferences for studying f in o_2 and the time and money cost of education. In other words, it is the fraction of utility lost in order to study field f in region o_2. People who choose not to go to school earn income $w_{u,dS}$ and people who go to school earn a normalized stipend 1. Let ζ_{iof} denote the idiosyncratic preference shock of individual i for his field of choice f in location o_2, where

$$G(\zeta_{io_2f}) = exp(-\zeta_{io_2f}^{-\gamma})$$

γ again determines the dispersion of amenities of studying f in o_2. There is also a migration cost incurred due to moving from one's location of birth o_1 to one's location of study o_2 denoted by $(1 - \mu^1_{o_1o_2})$. Thus utility of an individual i born in o_1 who chooses to study field f in location o_2 and then decides to work in sector S in region d is given by: (suppressing individual subscript i in utility for expositional clarity)

$$U_{o_1o_2f,dS} = \left(\mu^1_{o_1o_2} \cdot \frac{a_{o_2f} w_{u,o_2S}}{P_{o_2}} \cdot \zeta_i\right)^{IU} \left(\left(\frac{w_{f,dS}}{P_d}\right) \cdot u_{f,dS} \cdot \eta_i \cdot \mu^2_{o_2d}\right)^{(1-IU)} \tag{5}$$

where IU is the weight placed on period 1 utility. [13] w_{u,o_2} is the wage earned by unskilled workers in stage 1 in region o_2. w_{u,o_2} is 1 if the person is not employed in stage 1. In other words, people who are not working in stage 1 earn a normalized stipend of just one. Derivation of this utility is given in appendix C.1

Migration decisions for education and work

When choosing the location and field of education in stage 1, the individual takes into account his expected utility from stage 2 . He does not know the exact utility in stage 2 since the idiosyncratic productivity shock is not yet observed. We thus solve the individual's problem backwards. In stage 2, given the choice of location and field of education (sector of work for an unskilled person), the individual makes his choice of sector of occupation (S) and location (d): Now,

$$argMax_{d,S}\left(\mu^1_{o_1o_2}\cdot\frac{a_{o_2f}w_{u,o_2}}{P_{o_2}}\cdot\zeta_i\cdot\right)^{IU}\left(\left(\frac{w_{f,dS}}{P_d}\right)\cdot u_{f,dS}\cdot\eta_i\cdot\mu^2_{o_2d}\right)^{(1-IU)}|o_1,o_2,f$$
$$=argMax_{d,S}\left(\left(\frac{w_{f,dS}}{P_d}\right)\cdot u_{f,dS}\cdot\eta_i\cdot\mu^2_{o_2d}\right)|o_1,o_2,f$$

Given the Frechet distribution of the idiosyncratic productivity shock, the proportion of people with degree in f from region o_2 who goes to region d to work in sector S is given by:

$$m_{o_2f,dS}=\frac{\left(\left(\frac{w_{f,dS}}{P_d}\right)\cdot u_{f,dS}\cdot\mu^2_{o_2d}\right)^{(\theta)}}{\Phi_{o_2f}}\tag{6}$$

where $\Phi_{o_2f}=\sum_{d''S''}\left(\left(\frac{w_{fd''S''}}{P''_d}\right)\cdot u_{fd''S''}\cdot\mu^2_{o_2d''}\right)^{(\theta)}$

In stage 1, the individual maximizes $E(U_{io_1o_2f,dS})$ by choosing (o_2,f) .

Proposition 1: If $\eta\sim Frechet(\theta)$, then $\eta^\alpha\sim Frechet(\frac{\theta}{\alpha})$

Proof: See appendix C.5

[13] Here, being born in o_1 is equivalent to completing non-tertiary education in o_1.

Proposition 2: If $\eta_i \sim Frechet(\theta)$, then $E(max_i(a_i \times \eta_i)) = (\sum_i a_i^{\theta})^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta})$

Proof: See appendix C.5

Using propositions 1 and 2, the results of the maximization problem of an individual in stage 1, described by the left-hand side, is given by:

$$Max_{o_2,f}((\frac{a_{o_2f}w_{u,o_2}}{P_{o_2}}\mu^1_{o_1o_2}\zeta_{io_2f})^{IU}E\Big(max_{d,S}\Big((\frac{w_{f,dS}}{P_d}\Big)\cdot u_{f,dS}\cdot\eta_i\cdot\mu^2_{o_2d}\Big)^{(1-IU)}|o_1,o_2,f\Big)$$
$$= Max_{o_2,f}(\frac{a_{o_2f}}{P_{o_2}}\cdot\mu^1_{o_1o_2}\cdot\zeta_{io_2f})^{IU}\Phi_{o_2f}^{\frac{(1-IU)}{\theta}}$$

where $E\Big(max_{d,S}\Big((\frac{w_{f,dS}}{P_d}\Big)\cdot u_{f,dS}\cdot\eta_i\cdot\mu^2_{o_2d}\Big)^{(1-IU)}|o_1,o_2,f\Big) = \Phi_{o_2f}^{\frac{(1-IU)}{\theta}}\Gamma(1-\frac{\theta}{(1-IU)})$ is the expected income prior to drawing match productivities for workers trained in field f at location o_2

The proportion of people living in o_1 who go to study f in region o_2 is then given by:

$$l_{o_1o_2f} = \frac{\Big((\frac{a_{o_2f}w_{u,o_2}\mu^1_{o_1o_2}}{P_{o_2}})^{\beta}\Phi_{o_2f}^{\frac{(1-\beta)}{\theta}}\Big)^{\frac{\gamma}{\beta}}}{\Phi_{o_1}} \tag{7}$$

where $\Phi_{o_1} = \sum_{o_2',f'}\Big((a_{o_2'f'}\mu^1_{o_1o_2'})^{IU}\Phi_{o_2'f'}^{\frac{(1-IU)}{\theta}}\Big)^{\frac{\gamma}{IU}}$.

Firms

There is perfect competition in the production of each variety. The representative firm of sector S in location d produce a variety of the sector S good using both high-skilled L_{hdS} and low-skilled labor L_{ldS}, combined in a nested CES constant returns to scale production function:

$$Q_{dS} = (Q_{hdS}^{\frac{\rho_S-1}{\rho_S}} + Q_{ldS}^{\frac{\rho_S-1}{\rho_S}})^{\frac{\rho_S}{\rho_S-1}} \tag{8}$$

where

$$Q_{hdS} = (\sum_{f \in college} A_{f,dS}(\tilde{L}_{f,dS})^{\frac{\rho_{hS}-1}{\rho_{hS}}})^{\frac{\rho_{hS}}{\rho_{hS}-1}} \tag{9}$$

and

$$Q_{ldS} = (\sum_{f \in nocollege} A_{f,dS}(\tilde{L}_{f,dS})^{\frac{\rho_{lS}-1}{\rho_{lS}}})^{\frac{\rho_{lS}}{\rho_{lS}-1}}$$

where $\tilde{L}_{f,dS} = \overline{\eta}_{f,dS} L_{f,dS} = \Gamma(1 - \frac{1}{\theta}) L_{f,dS}$ is the effective labor supply.

The Armington structure of the model delivers a cost of living index P_d for each region, where $P_d = \Pi_S P_{dS}^{\alpha_S}$ and $(P_{dS})^{1-\sigma_S} = \sum_j (\tau_{jdS} p_{dS})^{1-\sigma_S}$.

External trade

The domestic country exports a tradeable good to the RoW where each region of the domestic country produces a variety of the tradeable good, and, in turn, imports an importable good from the RoW. The domestic country is a price-taker in the world market so the price of the importable good is given. The income of the RoW is also exogenously given. [14] Gravity determines the level of trade between each region of the domestic country and the RoW. There are only movements of the importable and the exportable goods between the RoW and the domestic country. People can move within the country but not outside the country. The demand for IT exports from district d ($E_{d,IT}$) is given by:

$$E_{d,IT} = \underbrace{\left[\frac{\tau_{d,IT} p_{d,IT}}{\sum_{d'} (\tau_{d',IT} p_{d',IT})^{1-\sigma_{IT}}}\right]^{(1-\sigma_{IT})}}_{\text{gravity}} E_{IT} \tag{10}$$

where $p_{d,IT}$ is the price of IT variety from district d, $\tau_{d,IT}$ are the costs of exporting IT to the RoW, mostly consisting of communication and management costs, E_{IT} is

[14] In theory, the income of the RoW consists of income from sales to itself, the domestic country, and all other countries. In this particular empirical setting, given that US exports to India consists of a negligible proportion of total US income, this assumption is tenable.

the RoW's income spent on the IT sector. Using equation 10, we can solve for IT prices in each district:

$$p_{d,IT} = (\frac{E_{d,IT}}{E_{IT}})^{\frac{1}{1-\sigma_{IT}}} \frac{(\sum_{d'}(\tau_{d',IT}P_{d',IT})^{1-\sigma_{IT}}).^{\frac{1}{1-\sigma_{IT}}}}{\tau_{d,IT}} \tag{11}$$

Internal trade

The sectors other than IT and the importable goods sector are all internally traded. The gravity equations determining the flows of these internally traded sectors are given by:

$$Y_{dS} = \sum_j X_{djS} = \sum_j \tau_{dj}^{1-\sigma_S} p_{dS}^{1-\sigma_S} P_j^{\sigma_S-1} E_{jS} \tag{12}$$

$$E_{jS} = \sum_k X_{jkS} = \sum_k \tau_{jk}^{1-\sigma_S} p_{kS}^{1-\sigma_S} P_j^{\sigma_S-1} E_{jS} \tag{13}$$

Equation 12 states that the income of sector S in district d equals the sum of exports from sector S in district d to all other districts. Equation 13 states that the expenditure of district j on sector S good must equal the sum of imports of good S from all other districts.

Equilibrium

For each region, equilibrium in the steady-state is defined as a set of sectoral employment according to field of study ($L_{f,dS}$), field-wise college enrollment (L_{o_2f}), wages ($w_{f,dS}$), prices (P_d), and quantities (Q_{dS}). For each district, the equilibrium takes into account population, amenities and bilateral migration costs of studying and working according to their fields and sectors, trade costs between domestic districts and between domestic districts and the RoW. It also takes as given the parameters governing the dispersion of productivity shocks (θ) and amenity shocks (γ), the proportion of income spent on goods ,the elasticity of substitution between goods from each sector (ρ_S) and between different types of high-skilled workers (ρ_{hS}), as well as between high-skilled and low-skilled workers (ρ_S).

The steady-state equilibrium is governed by the following equations describing goods and labor market clearance:

1. Given productivities and the initial distribution of population, the quantity produced in each location is determined by the production functions.

2. Given quantities produced in each location and trade costs, exogenously given world income spent on IT, from equation 11 the price of the tradeable good is given by the market clearing for the tradeable good S' in each region d:

$$p_{S',d} = \frac{1}{Q_{S',d}} \frac{(p_{S',d}\tau_{S',d,RoW})^{1-\sigma_{S'}}}{\sum_{d'}(p_{S',d'}\tau_{S',d',RoW})^{1-\sigma_{S'}}}(Y_{RoW}) \tag{14}$$

3. Given quantities produced in each location and trade costs, price of the tradeable good, from equations 12 and 13 prices of the externally non-tradeable goods S is given by market clearing of the non-tradeable goods:

$$p_{S,d} = \frac{1}{Q_{s,d}} \sum_j \tau_{dj}^{1-\sigma_S} p_{S,d}^{1-\sigma_S} P_j^{\sigma_S - 1} \alpha(\sum_S p_{S,j} Q_{S,j}) \tag{15}$$

where the price index $P_d^{1-\sigma_S} == \sum_j \tau_{jd}^{1-\sigma_S} p_{S,j}^{1-\sigma_S}$, $(\sum_S p_{S,j} Q_{S,j})$ is the income of region j, and α is the proportion of income spent on the non-tradeable good. [15]

4. Given prices of both tradeable and non-tradeable goods, the wages of workers with skill level f working in industry S in region d are given by:

[15] Note that, conditions 2 and 3 automatically ensure that the trade balance condition is maintained. Summing over d in condition 2, one can easily see that the sales from IT in the domestic country is the same as the amount of income spent on IT goods in the foreign country. Now, for balanced trade, the amount of income spent on IT in the foreign country also has to be equal to the amount of income spent on imports by the domestic country. (3) uses the condition that the income spent on Non-IT goods by each region is α proportion of its income, that is, $\alpha(p_{IT}qIT + p_{NonIT}q_{NonIT})$. This implies that $(1-\alpha)(p_{IT}qIT + p_{NonIT}q_{NonIT})$ is spent on imports. Since condition 2 ensures that sum of imports is equal to value of sales from IT, trade balance is maintained.

$$w_{f,dS} = p_S A_{f,dS} Q_{Sd}^{\frac{1}{\rho_S}} Q_{hSd}^{\frac{1}{\rho_{hS}} - \frac{1}{\rho_S}} (L_{f,dS} \Gamma(1 - \frac{1}{\theta}))^{\frac{1}{\rho_{hS}}} \tag{16}$$

5. Given wages and prices, migration flows for education determine the population distribution of skill at each location. The proportion of people from o migrating to j to seek education in field s is given by:

$$L_{o_2 f} = \sum_{o_1} l_{o_1, o_2 f} L_{o_1} \tag{17}$$

where L_{o_1} is the college eligible population in o

6. Given wages, prices, and the distribution of skill in each region, the distribution of people with skill f working in industry S in region d is given by:

$$L_{f,dS} = \sum_{o_2} m_{o_2 f, dS} L_{o_2 f}$$

7. In the steady-state, the initial distribution of population working in different industries with different skill levels is equal to the final distribution.

This completes the description of equilibrium in this model. In appendix C.4 , I show that a competitive general equilibrium exists.

Summary of the mechanics of the model

This section describes how a rise in the demand for the externally traded good, in this case IT, affects employment, education, and ultimately welfare of individuals in different regions within the country. The rise in IT export demand translates into differential changes in IT real wages across regions, depending on the region's geographic location that determines how difficult it is to migrate there and the regions comparative advantage in IT that I discussed before. People start moving into regions where the real wages rise faster. This is the place where the mobility costs for work matter. This part of the model is like a specific factors model in that engineers are more required in the IT sector. This is a standard spatial model with no changes in skills. But then the rise in real wages changes the incentives for higher education, specially engineering. Individuals who are closer to skilled jobs or who are closer to good education facilities are more likely to get educated. Thus, enrollment rises. This is where the mobility costs for education matter and this is the new component that I add to existing spatial models. This generates a Heckscher- Ohlin (HO) type response to changes in skilled wages.

2.2 Identification and estimation

In this section, I estimate the structural parameters that determine the migration and IT trade costs and measure the expenditure shares on goods using available expenditure data. I then use the estimated parameters and the measured quantities, along with the available data on employment, wages, migration and enrollment, to back out the unknown amenities and productivities consistent with the model. Adapting the model for estimation, I assume F=3, where $f \in F$. f can be college degree in engineering, college degree in any other field, henceforth referred to as non-engineering, or no college degree at all. There are two types of high-skilled workers: those who complete a college degree in engineering and those who complete a college degree but not in engineering. There is only one type of low-skilled worker, those who do not go to college. There are 7 sectors in the economy (S=7), where these sectors are: agriculture and allied activities, manufacturing, wholesale trade, low-skill services, skilled services except IT, the IT sector and an importable sector.

IT is only consumed by the RoW and only produced domestically. There is an importable sector: goods in this sector are not produced domestically but are consumed domestically. Goods in the other sectors are all traded internally.

2.2.1 Estimation of migration costs

Estimation of migration costs due to education:

In this section, the migration costs of people moving to acquire education are estimated. Taking the logarithm on both sides of equation 57, the ideal gravity equation of flows of workers from o_1 to o_2 who move to study field f would be estimated by:

$$\ln(l_{o_1 o_2 f}) = \gamma \ln(\mu^1_{o_1 o_2}) + \gamma \frac{(1-IU)}{IU\theta} \ln(\Phi_{o_2 f}) - \ln(\Phi_{o2}) + a'_{o_1 o_2 f} \tag{18}$$

where f is engineering, non-engineering, or no college. The equation states that the the proportion of people who move from o_1 to o_2 to study field f depends on

i) The expected return from studying f in o_2 ($\ln(\Phi_{o_2 f})$)

ii) The bilateral migration costs of moving from o_1 to o_2, given by $\mu^1_{o_1 o_2}$

iii) The geographic advantage of the origin district, determined by its proximity to regions with good job and education opportunities (Φ_{o_1})

iv) $a'_{o_1 o_2 f}$ is an error term which captures any field of education f, origin and destination specific factors such as the time and money cost of education and unobserved preferences for education.

However, flows of people disaggregated by reason for migration, origin, destination, and field of study are not available. Instead, the data informs us of the number of people migrating for education from every origin district o_1 to every destination district o_2, aggregated across all fields of education f that they chose to study. Aggregating equation 18 across all fields of education and taking the logarithm on both sides, one gets the following equation:

$$\ln(l_{o_1 o_2}) = \gamma \ln(\mu^1_{o_1 o_2}) - \ln(\Phi_{o1}) + \gamma(\sum_f (a_{o_2 f})^{IU} (\Phi_{o_2 f}^{\frac{(1-IU)}{\theta}})) \tag{19}$$

Following the migration gravity literature, I parameterize the costs of migration in equation 18 where the migration costs depend on geographic and cultural distances:

$$\ln\left(\mu^{1}_{o_1o_2}\right) = \lambda_1^{'}\ln\left(DistCentroid_{o_1o_2}\right) + \lambda_2^{'}lang_{o_1o_2} + \lambda_3^{'}Diff^{diff-NBR}_{o_1o_2} + \lambda_4^{'}D^{same-NBR}_{o_1o_2} + \lambda_5^{'}D^{same-notNBR}_{o_1o_2} \tag{20}$$

where $DistCentroid_{o_1o_2}$ measures the distance between district-centroids and $(lang_{o_1o_2})$ measures the proportion of people speaking the common language in districts o_1 and o_2. If two districts belong to different states but share the same border, $diff-NBR$=1. If two districts belong to the same state and also share a border, $same-NBR$=1. If two districts belong to the same state and are not neighbors, $same-notNBR$=1.

The estimating equation becomes:

$$log(l_{o_1o_2}) = f_{o_1} + f_{o_2} - \lambda lndist_{o_1o_2} + \epsilon_{o_1o_2} \tag{21}$$

, where $f_{o_1} = \gamma log(\sum_f (a_{o_2f})^{IU}(\Phi_{o_2f}^{\frac{(1-IU)}{\theta}})$, $f_{o_1} = log\Phi_{o_1}$, $\lambda' = (\lambda_1^{'}, \lambda_2^{'}, \lambda_3^{'}, \lambda_4^{'}, \lambda_5^{'})$ and $\lambda = \gamma\lambda^{'}$ is a combination of elasticity of migration flows to migration costs, and the elasticity of migration costs to distance. $\epsilon_{o_1o_2}$ includes any measurement error or random factors not correlated with the distance measures. ${\mu^{1}_{o_1o_2}}^{\gamma}$ can be estimated using equations 20 and 21 in the usual gravity estimation framework using origin, destination fixed effects and bilateral measures of distances.

Given bilateral migration data on the number of people moving from district o_1 to district o_2 to acquire education, bilateral geographic and cultural distances, the composite parameter λ is identified in the cross-section by the elasticity of migration flows to distances. The key assumption required for the identification of λ is that the unobserved error term $\epsilon_{o_1o_2}$ which is not derived from the model and does not represent any structural object, is random measurement error and is uncorrelated with bilateral district to district cultural and geographic distances.

Regression 21 thus gives an estimate of

$\mu^{1}_{o_1o_2}{}^{\gamma} = exp(\lambda'_1 ln(DistCentroid_{o_1o_2}) + \lambda'_2 lang_{o_1o_2} + \lambda'_3 Diff^{diff-NBR}_{o_1o_2} + \lambda'_4 D^{same-NBR}_{o_1o_2} + \lambda'_5 D^{same-notNBR}_{o_1o_2})$

The results of the estimation are given in table 3.

Joint estimation of migration due to work and amenities

To estimate the migration costs for work, the ideal regression would be estimating the log of 6, the migration flow equation:

$$log(m_{o_2f,dS}) = \theta log(w_{f,dS}) + \theta log\mu^2_{o_2d} - \theta log(P_d) + \theta log u_{f,dS} - \theta log\Phi_{o_2f} + \epsilon_{o_2f,dS} \quad (22)$$

This relates the proportion of people from o_2 with degree f who move to d to work in sector S, $(m_{o_2f,dS})$, to the wages of workers with degree f working in sector S in location d $(w_{f,dS})$, bilateral migration costs $(\mu^2_{o_2d})$, destination-specific prices (P_d), and the option value of a degree from location o_2 in field f, (Φ_{o_2f}). The option value summarizes the job opportunities available to a person who has completed degree f in location o_2. The error term, ϵ_{o_2fdS}, is uncorrelated to migration costs by assumption, and represent random measurement errors.

However, the available data does not inform us of bilateral migration flows disaggregated according to degree of education and sector of work. The data give information on the number of people who moved from district o_2 to district d for work, aggregated across all levels of education and sectors of work. Summing across all fields f and sectors S, the estimable regression equation is given by:

$$ln(m_{o_2d}) = \theta log(\sum_{f,S} \frac{w_{f,dS}}{\Phi_{o_2f}}) + \theta log(\mu^2_{o_2d}) - \theta log P_d + \theta(log \sum_{f,S} u_{f,dS}) + \epsilon_{o_2d} \quad (23)$$

This relates the flow of people who move from location o_2 to location d for work to the average wage in location d in field f weighted by the option value of studying f (Φ_{o_2f}). Since the option value of education varies by origin (o_2) and field of education (f), the relative attractiveness of a destination is no longer separable in just the origin and destination fixed effects. The problem is that the option value of education contains the unobserved migration costs $\mu^2_{o_2d}$ and amenities $(u_{f,dS})$, and so this relative attractiveness is not known. If we treat this relative attractiveness of a destination as unknown, the existence of unobserved migration costs in the error will bias the estimate of θ.

First, for a relatively remote district o_2, a rise in bilateral migration cost to d will reduce migration to d but by not as much compared to a district that is relatively well-connected to regions with employment opportunities, since people from the remote district have fewer options. Even this effect will differ according to an individual's skill level depending on how valuable destination d is for that skill group. Thus, the existence of this unaccounted for and unknown remoteness measure in the error term will bias the estimate of the elasticity of migration costs downward.

On the other hand, for people in well-connected locations, if the migration cost to a particular district falls, they can more easily turn to other districts compared to their more remote counterparts and this effect varies according to their field of training f. For districts in well-connected locations, the elasticity of migration to migration costs are thus over-estimated.

On the aggregate, it remains an empirical question as to which effect dominates.

The costs of migration depend on distance:

$$\begin{aligned} log\mu^2_{o_2d} = \zeta_1^{'} log(DistCentroid_{o_2d}) + \zeta_2^{'} loglang_{o_2d} + \zeta_3^{'} Diff^{diff-NBR}_{o_2d} + \\ \zeta_4^{'} D^{same-NBR}_{o_2d} + \zeta_5^{'} D^{same-notNBR}_{jd} \end{aligned} \tag{24}$$

Rewriting the estimating equation by inserting the migration cost in terms of distance,

$$ln(m_{o_2d}) = \theta log(\sum_{f,S} \frac{w_{f,dS}}{\Phi_{o_2f}}) - \zeta logdist_{o_2d} - \theta log P_d + \theta(log \sum_{f,S} u_{f,dS}) + \epsilon_{o_2d} \tag{25}$$

where $logdist_{o_2d}$ is the vector of distances mentioned above, and $\zeta = -\theta\zeta^{'}$ and $\zeta^{'} = (\zeta_1^{'}, \zeta_2^{'}, \zeta_3^{'}, \zeta_4^{'}, \zeta_5^{'})$

I use a nested nonlinear least squares approach to estimate ζ. The idea is to explicitly account for the effect of the unobserved option value of education by location and degree, thereby correcting the source of the bias in traditional gravity estimation. After accounting for the unobserved option value of education as I will describe below, the moment condition that identifies ζ is:

$$E(\epsilon_{o_2d}|lndist_{o_2d}) = 0$$

The assumption is that after accounting for the unobserved attractiveness of the destination region relative to the origin region, the remaining unobserved term is white noise, uncorrelated with migration costs.

Since the option value of education contains the unobserved amenities, in practice, for estimation, I use a nested non-linear least squares procedure where I make a guess of migration costs and use labor market data on workers across fields, sectors of occupation and locations to back out the unknown amenities as shown in equation 26.[16] Using the equations governing the distribution of workers across fields, sectors of occupation and locations and the option value of education across locations and fields of education, the unique district and field of education amenities are given by: (See equations 52 and 53 in appendix for more detailed derivations)

[16]The data provided by the Census shows bilateral migration separately by reason for migration and by education level but does not show the cross-tabulation between the two. To infer how many college-eligible people choose to remain unskilled and seek employment, I subtract the total number of people who migrate for education from the total number of people with a higher secondary or equivalent degree who migrate. The assumption is that males with higher secondary degree either migrate for work or for education.In .03% of the sample, this subtraction yields negative values which I topcode to zero

$$
\begin{aligned}
L_{f,dS} &= \sum_{o_2} \frac{{\mu^2_{o_2 d}}^{\theta} (\frac{W_{f,dS} u_{f,dS}}{P_d})^{\theta}_{f}}{\sum_{o''_2 S''} {\mu^2_{o_2 d''}}^{\theta} (\frac{W_{f,d''S''} u_{f,d''S''}}{P''_d})^{\theta}} L_{f o_2 j} \\
&= u^{\theta}_{f,dS} \sum_k \sum_{o_2} \frac{{\mu^2_{o_2 ds}}^{\theta} (\frac{W_{f,dS}}{P_d})^{\theta}_{s}}{\sum_{d''S''} {\mu^2_{o_2 d''}}^{\theta} (\frac{W_{f,d''S''} u_{f,d''S''}}{P''_d})^{\theta}} L_{f o_2} \\
u_{f,dS} &= \frac{(L_{f,dS} / (\sum_k \sum_{o_2} \frac{{\mu^2_{o_2 d}}^{\theta} (\frac{W_{f,dS}}{P_d})^{\theta}}{\sum_{d''S''} {\mu^2_{o_2 d''}}^{\theta} (\frac{W_{f,d''S''} u_{f,d''S''}}{P''_d})^{\theta}} L_{f o_2}))^{\frac{1}{\theta}}}{\frac{W_{f,dS}}{P_d}}
\end{aligned}
\tag{26}
$$

In the outer loop, I choose migration cost parameters to minimize the distance between bilateral migration flows predicted by the model and observed in the data in 2001, the only year for which such detailed migration data is available. Given the assumption that migration costs do not change during the period under study, I use the estimated migration costs and the distribution of employment post-2004 to recover unknown amenities. As unknown amenities are recovered in the last step from the distribution of population in each location, I update the amenities and re-estimate equation 25 until the migration costs converge. Note that the estimation of unknown amenities requires an estimate of θ, which is described in section 2.2.1.

In the same way, given estimated migration costs for education and the option value of education, one can use population with and without college degrees in each location to solve for unknown quantities $a_{o_2 f}$, which includes the time and money cost of education as well as unobserved preferences for education.

The results of the estimation procedure are given in table 3. Columns 1 and 2 report the estimation results of the traditional PPML gravity regression where the reasons for migration are education and work, respectively. In the third column, I report the estimates for work using the non-linear least squares method.

The notable point from table 3 is that in contrast to the effect of state borders, geographical distance does not affect migration flows very differently by reason for migration. Many state-level policies, such as quotas for in-state students, create barriers to mobility that differ according to the reason for migration. These estimates suggest that there could be scope for policy interventions in reducing the mobility costs across state borders. Reading off columns 1 and 3 of table 2, a 1% increase in distance reduces migration by 0.60% when the reason for migration is education and by 0.65% when the reason for migration is work. These estimates are comparable with findings in the traditional gravity literature. For example, Bryan and Morten (2019) finds that a 1% increase in distance leads to a 0.7% reduction in the proportion migrating. [17]

The effect of state borders is large: being in the same state increases migration between neighboring districts by about 269% when the reason for migration is education and by 59% when the reason for migration is work.

Figure 10 and 11 display estimated average migration costs for non-neighboring districts in different states, and for those within the same state, respectively. On the x-axis, the bilateral distances between district centers are plotted and on the y-axis, the estimated costs of migration are plotted. Note that since migration costs also differ by cultural distances and state borders, multiple values of estimated migration costs appear for each value of distance centroid.

With these estimates, the average iceberg cost of migration when people migrate for education and for work turns out to be 0.95 and 0.89 on average. This means that migrants on average lose 95% and 89% of their utility, and this loss includes many different factors such as cultural differences, loss of home network, and transportation costs. In the literature, only combined estimates of migration costs aggregated across reasons for migration are available, and these estimates vary across countries. For example, Tombe and Zhu (2019) finds that migrants, on average, have to be compensated 82% more than non-migrants in China in 2000, and this cost is almost 1.75 times larger when workers migrate across provinces than when they stay within their own province. Bryan and Morten (2019) finds that in Indonesia, on average, migrant workers have to be paid 38% more if they were to receive the same wage

[17] They do not separately account for cultural differences. As long as geographic distances are positively correlated with cultural distances, their estimates would be over-stating the effect of physical distance

as non-migrant workers. They estimate a much lower cost, only 15%, for the US. It would be interesting to compare the finding of substantially larger migration cost for education relative to that for work for India with other countries if such data are available for other countries.

Estimation of elasticity of migration flows to migration Costs

The elasticity of migration flows to migration costs is the dispersion parameter θ that governs the variance of the idiosyncratic component of workers' productivity draws. The higher the value of θ, the lower is the variance in productivity, and thus workers are more identical. This means that workers tend to respond more similarly to changes in migration costs compared to when they are more heterogeneous in their productivities. Thus, for a given rise in migration cost, the higher is θ, the larger is the fall in migration.

Following Fan (2019), I use the variance in the wage distribution of stayers, that is, the wage distribution of people who do not migrate for work, to identify θ. Using the properties of the Frechet distribution, it can be shown that the productivity distribution of stayers also follows a Frechet distribution where the mean varies by field of education, sector of work, and location of degree. For any (f, d, S) combination, the wage observed in the data is the effective wage ($\tilde{w}_{f,dS}$), where

$$\tilde{w}_{if,dS} = w_{f,dS}\eta_{if,dS}$$

Taking logs on both sides,

$$\ln(\tilde{w}_{if,dS}) = F_{f,dS} + \ln\left(\eta_{if,dS}\right)$$

where $F_{f,dS}$ is a sector of job, field of education and district fixed effect which is a combination of average wage per effective unit of labor and the average productivity of stayers. θ is matched to its data counterpart, the variance of exponentiated residuals 2.61. The assumption is that after controlling for field of education, sector, and location of work, the remaining variation in individual wages for those who stay back in the same location is due to variation in the idiosyncratic component, which can include factors such as ability, talent, and family background.

Given the estimate of θ (elasticity of migration flows to migration costs for work) and γ (elasticity of migration flows to distance for work) from section 2.2.1, it is possible to separately identify the elasticity of migration flows to migration costs for education (ζ). The assumption required for this identification is the following: the elasticity of migration costs to geographic distance is the same irrespective of the reason for migration, once institutional boundaries such as state borders and neighboring districts dummies have been accounted for.

Note that this assumption does not require the elasticity of migration flows to distance to be the same. In fact, these elasticities are very different, as we estimated before. It only requires the costs of migration to respond to geographic distances in exactly the same way, once we have accounted for state-specific institutional barriers such as differential quotas for work and for education. An example of a violation of this assumption would be any factor that increases or decreases the migration costs for education relative to work over the same geographic distance. For example, one such factor would be the provision of special transportation for students.

By assumption, $\zeta_1^{'} = \lambda_1^{'}$ Thus,

$$\frac{\lambda}{\gamma} = \frac{\zeta}{\theta}$$

Given $\theta = 2.61$, $\zeta = .648$, $\lambda = .602$, the above identity yields $\gamma = 2.42$.

This completes the description of my estimation strategy for migration costs.

2.2.2 Trade costs

Trade costs in the IT sector: In this model, IT is the only good traded with the RoW and it is not consumed domestically. Taking the logarithm on both sides of 11, the gravity equation expressing IT trade flows as a function of IT prices and comparative advantage, and getting rid of IT in the notation, I get the following estimating equation:

$$\ln(\frac{E_{d,t}}{E,t}) = C + (1-\sigma_{IT})\ln(\tau_d) + (1-\sigma_{IT})\ln(p_{d,t}) \tag{27}$$

where C$=-(1-\sigma_{IT})\ln(\sum_{d'}(\tau_{d'}p_{d'})^{1-\sigma_{IT}})$ is a quantity that is constant across districts. $(1-\sigma_{IT})\ln(\tau_d) = \kappa_{IT}\ln(dist_d)$. τ_d is the comparative advantage of district d in IT which depends on the linguistic distance of d from English and the prior software exports in 1995. The historical comparative advantage of a district in this sector depends on the prior links of a district to the RoW, measured by the proportion of software exports historically exported from that district. Prior connections, through building reputation, play an important role in determining the volume of transactions in this sector (Banerjee and Duflo (2000)). Shastry (2012) showed that linguistic distance of each regional language, spoken in a district, from English determines the cost of learning English for individuals in that district. Since English proficiency is a necessary skill in this industry, the comparative advantage of a district also depends on the linguistic distance of the district from English. Let $\vec{dist}_{d,IT}$ be the vector denoting the linguistic distance of each district from English and the proportion of historical software exports from d.

Note that price is unobserved since it includes the unobserved productivities. Using the structure of the production function, price can be log-linearly decomposed into its known and unknown components. Using marginal cost pricing,

$$\begin{aligned}(p_{d,IT})^{1-\rho_{IT}} &= ((A_{e,d,IT}^{\rho_{h,IT}} w_{e,d,IT}^{(1-\rho_{h,IT})} + A_{ne,d,IT}^{\rho_{h,IT}} w_{ne,d,IT}^{(1-\rho_{h,IT})}))^{\frac{1-\rho_{IT}}{1-\rho_{h,IT}}} + (A_{l,d,IT}^{-1} w_{l,d,IT})^{(1-\rho_{IT})} \\ &= A_{ne,d,IT}^{\frac{-\rho_{h,IT}(\rho_{IT}-1)}{1-\rho_{h,IT}}} (\tilde{p}_{d,IT}^{h}{}^{1-\rho_{IT}} + \tilde{x}_{l,d,IT}^{(-\rho_{IT})} (w_{l,d,IT})^{1-\rho_{IT}})\end{aligned} \tag{28}$$

where $\tilde{x}_{l,d,IT} = \frac{A_{ne,d,IT}^{(\frac{\rho_{h,IT}}{\rho_{h,IT}-1})(\frac{1}{\rho_{IT}}-1)}}{A_{l,d,IT}^{\frac{1}{\rho_{IT}}-1}} = \frac{W_{l,d,IT}(L_{l,d,IT})^{\frac{1}{\rho_{IT}}}}{\tilde{p}^h_{S,IT}(\tilde{Q}_{h,d,IT})^{\frac{1}{\rho_{IT}}}}$

and ${\tilde{p}^h_{d,IT}}^{1-\rho_{IT}} = ((\frac{A_{e,d,IT}}{A_{ne,d,IT}})^{\rho_{h,IT}} w_{e,d,IT}^{1-\rho_{h,IT}} + w_{ne,d,IT}^{1-\rho_{h,IT}})^{\frac{1}{1-\rho_{h,IT}}}$

Due to the firm's first order conditions, the ratio of productivities is a function of known wages and employment, and therefore, both ${\tilde{p}^h_{d,IT}}^{1-\rho_{IT}}$ and $\tilde{x}_{l,d,IT}$ are also functions of observables. For derivation see appendix C.2

Substituting this, the estimating equation becomes:

$$\ln(\frac{E_{d,t}}{E_t}) = C + \kappa_{IT}\ln(dist_{d,RoW,IT}) + \frac{(\sigma_{IT}-1)}{(\rho_{IT}-1)}\ln(({\tilde{p}^h_{d,t}}^{1-\rho_{IT}} + \tilde{x}_{l,d,t}^{(-\rho_{IT})}(w_{l,d,t})^{1-\rho_{IT}})) - \frac{(\sigma_{IT}-1)}{(\rho_{IT}-1)}\frac{\rho_{h,IT}(\rho_{IT}-1)}{1-\rho_{h,IT}}\ln(A_{ne,d,t})$$

Taking first differences,

$$\Delta\ln(\frac{E_{d,t}}{E_{RoW,t}}) = \tilde{\sigma_{IT}}\Delta\ln(({\tilde{p}^h_{d,t}}^{1-\rho_{IT}} + \tilde{x}_{l,d,t}^{(-\rho_{IT})}(w_{l,d,t})^{1-\rho_{IT}})) + \Delta\ln(\tilde{A}_{ne,d,t}) \tag{29}$$

where $\frac{(\sigma_{IT}-1)}{(\rho_{IT}-1)} = \tilde{\sigma}_{IT}$ and $\Delta\ln(\tilde{A}_{ne,d,t}) = \Delta\frac{(1-\sigma_{IT})}{(1-\rho_{IT})}\frac{\rho_{h,IT}(\rho_{IT}-1)}{1-\rho_{h,IT}}\ln A_{ne,d,t}$

Intuitively, in equilibrium, how responsive IT exports are to changes in marginal costs depends on two parameters:

i) **Demand side parameter**: The elasticity of substitution between different varieties of IT products (σ_{IT}), where each variety corresponds to a region. The lower the elasticity of substitution, the more difficult it is to switch to a different variety as the price of a particular variety rises.

ii) **Supply side parameter:** The elasticity of substitution between high and low-skill workers. This determines the responsiveness of equilibrium prices to changes in marginal costs. If a sudden exogenous increase in wages increases the marginal cost, that is, the independent variable in equation 29 falls, the higher the elasticity of substitution between high-skilled and low-skilled workers, the easier it is to substitute the costly input for the relatively cheaper input. This implies a lower increase in the price of IT and subsequently a lower fall in the demand for IT products. Thus, a higher elasticity of substitution implies a lower responsiveness of IT exports to changes in marginal costs.

Since in general equilibrium the unobserved district specific productivities determine the marginal cost of production, σ_{IT} cannot be recovered through a linear regression of IT exports on the observed part of marginal cost. I construct an instrument by leveraging the IT boom of the late 1990s and early 2000. As demand for IT increased, the prices of IT increased in all regions that produce IT. However, the capacities of IT production differ across regions. In particular, regions that are better connected geographically to other populous regions could expand supply more because people can migrate more easily into these regions and thus the supply of labor in these regions is more elastic. Also, regions with a historical comparative advantage in IT production gained more. I summarize this comparative advantage by two measures: first, linguistic distance of each district from English, which summarizes the cost of learning this language, the vehicular mode of communication in the IT industry. Second, the historical connection of each district to the RoW in the IT industry, measured by the proportion of software exports from each district out of the total Indian IT exports in 1995.

This estimation requires the assumption that changes in the productivity of non-engineers in the IT sector, in the pre and post-2000 boom periods are uncorrelated with the pre-period exports, historical linguistic distance, and the remoteness of a region during the period of the IT boom. The unobserved productivities, by model construction, do not depend on historical software exports, historical linguistic distance, and the historical distribution of college educated workers. These productivities are the residual quantities that explain the deviation of predicted output from actual output, after these known quantities are taken into account. These historical factors, in turn, are not affected by future changes in productivities.

To summarize, the three instruments I use are:

1. A measure of labor supply access for each region, summarized by

$$LMA_d = \sum_o L_o(\frac{1}{distance_{o,d}})^{-1}$$

2. The share of historical software exports from a region, measured in the year 1995.

3. The historical linguistic distance of each district from English, estimated using the 1991 population Census.

The first stage is reported in C.6.2. The instruments pass the Sargan test for validity and the model is identified as per the Anderson Canon LM test for under identification and the instruments are jointly significant (Anderson Rubin Wald Test and Stock-wright LM test).

To recapitulate the above discussion, I regress the log changes in the proportion of IT exports from district d on log changes in the observable marginal cost

$$\Delta ln(\frac{E_{d,t}}{E_{RoW,t}}) = \tilde{\sigma_{IT}} \Delta ObservableMC_t + \Delta ln(\tilde{A}_{ne,d,t}) \tag{30}$$

where $\Delta ObservableMC_t = \Delta ln((\tilde{p}^h_{d,t}{}^{1-\rho_{IT}} + \tilde{x}^{(-\rho_{IT})}_{l,d,t}(w_{l,d,t})^{1-\rho_{IT}}))$

Table 4 shows the result of estimating equation 30. Column 1 reports the OLS results. Column 2 reports the results where observable price is instrumented with linguistic distance and historical software exports of a region. In column 3, in addition, I use remoteness of a district as an instrument. In column 4, I repeat the results adding state-level time trend.

This yields a value of elasticity of substitution between different IT products (σ_{IT}) as 1.27, since $\sigma_{IT} = \tilde{\sigma}_{IT} + 1$. This value is pretty low compared to elasticities of substitution between different varieties that the literature has estimated (between 3 and 5). There are a couple of caveats when comparing σ_{IT} to the estimates from the literature. First, the literature has mostly estimated the elasticities of substitution between varieties traded internationally. Second, my estimate is specifically for the IT industry, for which we do not have any known estimate in the literature. The low value of elasticity of substitution between the IT varieties of different regions could be justified on the ground that these regions specialize in very different types of tasks, such as, data processing, software development, multimedia graphics, as is reported in the NASSCOM software data.

Trade costs in the non-IT sector

The iceberg transport cost is taken to be, $\tau_{od} = distance_{od}^{1}$, calibrating the distance elasticity to the canonical value of -1 (Head and Mayer (2014)).[18]

Sector-specific productivities

Using the expression for equation (31) determining prices,

$$(p_{d,IT})^{1-\rho_{IT}} = A_{ne,d,IT}^{\frac{-\rho_{h,IT}(\rho_{IT}-1)}{1-\rho_{h,IT}}}({\tilde{p}^{h}_{d,IT}}^{1-\rho_{IT}} + \tilde{x}_{l,d,IT}^{(-\rho_{IT})}(w_{l,d,IT})^{1-\rho_S}) \tag{31}$$

Since $(p_{d,IT})^{1-\rho_{IT}}$, ${\tilde{p}^{h}_{d,IT}}^{1-\rho_{IT}}$, $\tilde{x}_{l,d,IT}^{(-\rho_{IT})}$, $(w_{l,d,IT})^{1-\rho_{IT}})$, $\rho_{h,IT}$ are all known, we can recover $A_{ne,d,IT}$ using

$$A_{ne,d,IT} = \left(\frac{({\tilde{p}^{h}_{d,IT}}^{1-\rho_{IT}} + \tilde{x}_{l,d,IT}^{(-\rho_{IT})}(w_{l,d,IT})^{1-\rho_{IT}})^{\frac{1}{1-\rho_{IT}}}}{p_{d,IT}}\right)^{\frac{\rho_{h,IT}-1}{\rho_{h,IT}}} \tag{32}$$

Intuitively, how the magnitude of estimated prices differ from that of the observed components of marginal cost consisting of the information on wages and employment, helps determine productivities. Note that $(p_{d,IT})$ is known by recovering it from equation 11, given estimated trade costs σ_{IT} and exports. ${\tilde{p}^{h}_{d,IT}}^{1-\rho_{IT}}$ and $\tilde{x}_{l,d,IT}^{(-\rho_{IT})}$ are known as they are functions of observables.

Finally we recover the productivity of low-skilled workers in the IT sector $A_{l,d,IT}$

[18] The only estimate for India is from Donaldson (2018) who estimate it to be -1.69 from Colonial India. Since connectivity has much improved since then, taking the classic estimate seems more appropriate in this case

in all locations by using

$$\tilde{x}_{l,d,IT} = \frac{A_{ne,d,IT}^{(\frac{\rho_{h,IT}}{\rho_{h,IT}-1})(\frac{1}{\rho_{IT}}-1)}}{A_{l,d,IT}^{\frac{1}{\rho_{IT}}-1}} = \frac{W_{l,d,IT}(L_{l,d,IT})^{\frac{1}{\rho_{IT}}}}{\tilde{p}^{h}_{d,IT}(\tilde{Q}_{h,d,IT})^{\frac{1}{\rho_{IT}}}}$$

and then $A_{e,d,IT}$ by using the firm's first order conditions.

To recover prices in the internally traded sectors, use equations 12 and 13, the identities that state that the income of sector S in district d equals the sum of exports from sector S in district d to all other districts, and the expenditure of district d on sector S good must equal the sum of imports of good S from all other districts, respectively. Combining these two equations, prices can be expressed as:

$$p_{d,S}^{1-\sigma_S} = \sum_j (\tau_{dj})^{1-\sigma_S} (\sum_k \tau_{kj}^{1-\sigma_S} p_{kS}^{1-\sigma_S})^{-1} \frac{E_{jS}}{Y_{dS}} \tag{33}$$

where S is any sector other than IT and the importable goods sector.

Income of each region Y_{dS} is obtained by summing wage bill and employment. Expenditure of each region on sector S goods E_{dS} is calculated given share of GDP spent on sector S good. Internal trade costs τ_{jdS} are calculated given distances between districts and σ_S from the literature. Productivities in the internally traded sector can be recovered in exactly the same way as in the IT sector described above.

2.2.3 Calibration from the literature

The elasticity of substitution between engineers and non-engineers is calibrated to 2 across all sectors Ryoo and Rosen (2004). The elasticity of substitution between high and low skilled labor (college and non-college graduates) is taken to be 1.7 from Khanna and Morales (2017) which apply Card and Lemieux (2001) methodology to Indian data and find the estimate to be consistent with the literature (such as in Katz and Murphy (1992), Card and Lemieux (2001) and Goldin and Katz (2007)). The elasticity of substitution σ between different types of goods traded internally within India is taken to be 5 following Simonovska and Waugh (2014b). Several other papers estimate elasticities of substitution that are close. For example, Van Leemput (2016) estimate an elasticity of substitution between different types of agricultural goods in India as 5.6. The weight on current period utility (IU) is taken as 0.53, which corresponds to an intertemporal elasticity of substitution of 0.9, which is standard in the literature. Share of consumption expenditure on agriculture $\alpha_2 = 0.38$, share of consumption expenditure on manufacturing $\alpha_3 = 0.16$, share of consumption expenditure on non-traded goods $\alpha_s = 0.37$, share of consumption expenditure on high-skill services $\alpha_1 = 0.07$, share of consumption expenditure on imports $(1 - \alpha_1 - \alpha_2 - \alpha_3 - \alpha_s) = 0.02$ are all obtained from official government reports. The price of US imports is normalized to be 1. Table 5 summarizes the parameter values:

2.2.4 Model validity

Given model parameters and the exogenous amenities and productivities, the model makes predictions about the equilibrium wages, employment, and enrollment across districts, all of which are observable quantities in the data. In this section, I validate the model by first showing that the model generated data can replicate the reduced form facts established in section 5.

2.2.5 Replication of reduced form facts

Reduced form fact 1: IT employment and engineering enrollment positively respond to software exports

Using the model generated data, I repeat the reduced form regression and plot the coefficients β_t in figure 9

$$Y_{dt} = \alpha_t + \gamma_d + \chi_d * t + \beta_t Exports_{d,1995} + \epsilon_{dt} \tag{34}$$

where Y_{dt} is IT employment or engineering enrollment in district d at time t. $Exports_{d,1995}$ is the proportion of software exports from district d in the year 1995 out of total Indian IT exports in 1995. α_t are time fixed effects that capture any factors that are common to all districts at time t. γ_d are district fixed effects that capture any factors that are fixed over-time in district d. $\chi_d * t$ is a district-level time-trend capturing any linear trend in the outcome variable at the district level.

From this figure, just like in the data, we can see that post-1998, IT employment increased more in districts that had a higher level of software exports in 1995.

In figure 12, I plot the response of engineering enrollment and here also the reduced form results are replicated: post 2000, engineering enrollment increased in districts with higher level of software exports.

Fact 2: The effects are heterogeneous. Employment responds more when nearby regions have higher engineering enrollment and higher IT exports. The heterogeneous effects are stronger in the long run.

In equation 2 below, I add an interaction term between the number of students enrolled in engineering in 1991 and the proportion of software exports from district d in 1995. Estimated coefficient δ_t is plotted in figure 8.

$$\begin{aligned} Y_{dt} = \alpha_t + \gamma_d + \beta_t * Exports_{d,1995} + \chi_t Enrollment_{d,1991} + \\ \delta_t Exports_{d,1995} * Enrollment_{d,1991} + \epsilon_{dt} \end{aligned} \tag{35}$$

As in the reduced form counterpart, figure 13 shows that, conditional on the level of software exports, post 1998, IT employment responds more in districts that, in 1991, had more enrolled engineering students in same-state, nearby districts. The intuition, formalized in the model, is that in these districts, it is easier to expand future IT production due to having more college-educated, engineering program graduates in close proximity.

2.2.6 Non-targeted moments

In figures 13 and 14 below, I plot the percentage changes in log engineering enrollment over the periods 1991-2001 and 1991-2011, respectively, and compare with the data. Both figures show a positive relationship with a correlation coefficient of 0.28.

2.3 Quantification and counterfactuals

I first use the model to quantify the effect of the IT boom on the Indian economy. To do that, I use data on the changes in IT exports between 1995 and 2001, holding the estimated parameters and the model fundamentals (i.e., the exogenous amenities and productivities) constant between the pre- and post-boom periods. This is the period during which major international demand shocks led IT exports to expand by more than 50% annually, whereas secular growth in the post boom period averaged about 26%. Between 1995 and 2001, the share of IT in total GDP rises from 1.2% to 3.2% in the data (in the model, the same targeted moment increases from 1.2% to 3.2%). The IT boom also partly explains the reorientation of production in the Indian economy, away from manufacturing and towards the service sector. According to the model, the Indian IT boom explains 49% of the decline in manufacturing from about 18% to 16% between 1995 to 2001. The IT boom also explains 67% of the rise services as a fraction of GDP from about 37% in 1995 to 44% in 2001. These number takes into account the general equilibrium effects of the IT boom on other sectors of the economy.

The short-run is defined as the period during which people cannot change their skills. Since it takes at-least four years of college and two years of pre- college to complete an engineering degree, the long-run changes in skill composition will not be visible in the labor market until 2001. The long-run is defined as the period from 2001 to 2007 [19]. In the long-run, welfare is defined as:

[19] The model fundamentals, ie, the amenities and productivities, are estimated using the post period data since the post period data is better available across regions

$$\Gamma(1 - \frac{1}{\gamma})(\Phi_{o_1})^{\frac{1}{\gamma}}$$

where Φ_{o_1} measures the access to higher education for college-eligible individuals from o_1.

$\Phi_{o_1} = \sum_{o_1',f'}((a_{o_2'f'}\mu^1_{o_1o_2'})^{IU}\Phi_{o_2'f'}^{\frac{(1-IU)}{\theta}})^{\frac{\gamma}{IU}}$, where access to education, in turn, depends on education amenities, connectivity of region, and the job opportunities available from that region.

When skill levels are fixed, regional welfare depends on the access to jobs for each skill-group, weighted by the distribution of skills. In this case, welfare is defined as:

$$\Gamma(1 - \frac{1}{\theta})({\Phi_{Eng}}^{\frac{1}{\theta}} propEng + {\Phi_{NonEng}}^{\frac{1}{\theta}} propNonEng + {\Phi_{Un}}^{\frac{1}{\theta}} propUn)$$

where Φ_s measures access to jobs for skill-group s, $s =$ engineers, non-engineers, and unskilled.

With fixed skill-level, welfare increases on average by 0.61%, with the regional gains ranging from 0.17% to 2%.

Using the full general equilibrium model with endogenous skill acquisition, costs of human mobility for both education and work, and costs of moving goods internally, I find that the IT boom increased the average welfare of an individual by 1.12%. The average masks substantial variation across districts, with individuals born in districts with good access to jobs and education gaining as much as 2.63% while their counterparts in remote districts experienced gains as low as 0.67%.

Figure 16 below plots the histogram of regional welfare gains from the IT boom in the short and long-run. The long-run distribution of regional welfare gains lies to the right of the short-run distribution and the welfare gains are pareto improving.

The gains are positively correlated with the amenities for education, productivities in the IT sector, and the geographical connectivity of a district d, roughly approximated by the sum of inverse distances of d from all other districts. Districts in large states with good facilities for engineering education and connectivity to regions with jobs experienced the largest gains. This underscores the importance of accounting for endogenous skill acquisition in a general equilibrium setting.

To quantify the importance of mobility for education, I run a counterfactual where the option to move for education is shut off. I find that regional inequality increases by 15% and the gap between the welfare gains of the worst off and the best district increases by 63%. The gains in aggregate welfare would have been 1.79% lower if there were no education mobility. These numbers, especially the changes in regional welfare, are large despite the fact that the estimated migration costs for education are quite high. A high migration cost for education makes it more difficult to migrate across districts for education, undermining the importance of the endogenous education channel compared to a situation with no mobility frictions for education. However, since zero mobility frictions are not possible in reality, I conduct a counterfactual experiment where I reduce the costs of migrating for education across states.

Counterfactual policy: Reducing state quotas for education:

In the particular case of India, the widespread prevalence of in-state student quotas for higher educational institutions, reflected in the significantly higher costs of crossing state borders for education relative to that for work, increases the potential for districts in larger states with good educational facilities to gain more from the IT boom. Given that migration costs in India are one of the highest compared to available migration costs for other countries, the geographical connectivity of the district also plays an important role in determining the welfare gains of the district. [20] There seems to be an obvious policy intervention in the education market – the reduction of state quotas for education – that is easier to implement than labor market policies that aim to move jobs. In the counterfactual, this is achieved by reducing the effect of state borders on migration costs for education to the same level as that for work.

The existing magnitude of quotas in higher education institutes in India is huge: most

[20] For example, many districts in Uttar Pradesh, the largest state of India in terms of land area and also the number of colleges, gained more than the average district

state colleges have home state quotas of 50%, with some being as high as 85 % . [21] The size of the state quota varies by state and by whether the university in question is public or private, but in general, it is a substantial proportion of the total class size (Kone et al. (2018)). [22] These domicile quotas, legally defined as quotas pertaining to the "place of living" or permanent residence, create huge costs of migrating to a different state. While such quotas also exist for jobs and thus create significant hurdles for moving across states, the employment quotas are more specific and less ubiquitous than the in-state education quotas. Such quotas are in no way unique to India, and exist in many other countries, including the US and China.

One way of looking at the effect of reduction in state quotas for education on the aggregate and distributional consequences of the IT boom is to reduce the effect of state border on migration for education to be the same as that for work. The reduction of migration costs has the effect of increasing aggregate welfare due to the IT boom by 1% and reducing regional inequality by 27%, compared to the equilibrium change with full migration costs. An interesting point to note is that the reduction in state quotas increases aggregate welfare by very little since not all districts gain from such a measure. A little less than a third of districts actually gain less from the IT boom in this case compared to the case with the current levels of higher education quotas. In fact, the gains are negatively correlated with the initial education amenities in a district, implying that districts that gained the most from this policy are those that did not initially have good education facilities. Figure 15 shows that the histogram of welfare gains with reduced education quotas has a lower spread than that with education quotas.

It is also clear from the histograms that reducing in-state quotas is not a Pareto improving measure and is likely to meet with political resistance from districts which

[21] Support for the 85% reservation policy started in Maharashtra from the year 2011 with the backing of nationalist state parties

[22] Reservation policy in India is a contentious issue. The magnitude of reservation at private institutions varies hugely from state to state and is still a matter of legal debate. For example, some private universities reserve seats following the state laws under which they were established. For example, in Haryana, private universities also have to reserve 25% of it's seats for students domiciled in Haryana.

benefit from the quota policy. In 2016, when the Chinese government announced a policy of reducing provincial quotas to increase opportunities for students from poorer provinces to study in elite colleges, mostly located in the more prosperous provinces, there were wide spread protests in Beijing and Shanghai, fueled by the fear that this will hurt local students. [23] In the mid- 2000s, the Haryana state government invested land and money to build a hub for higher learning and a center for research, at the same time implementing a policy that reserves 25% seats for in-state students in all colleges across the state. [24]

2.4 Conclusion

This paper assesses the aggregate and distributional consequences of human capital response to trade for the spatial distribution of welfare. In answering this question, the paper makes three contributions: first, it introduces human capital acquisition decisions in a general equilibrium model with multiple locations. It shows that studying the effects of trade on the labor market without taking into account endogenous skill acquisition can underestimate the aggregate welfare gains from trade. Second, a key innovation of this paper compared to the existing literature on migration is that people can move either for work or for education. Using confidential and unique district-to-district Indian migration data disaggregated by reasons for migration, this paper provides the first separate estimates of mobility costs by reasons for migration. I show that quantifying both of these costs separately is important as these costs can significantly alter the welfare gains from trade depending on their relative magnitudes. Third, as a result of studying the interaction of education and labor market choices in the presence of changes in export-driven employment opportunities, this paper is able to suggest new forms of policy intervention to reduce inequality in regional welfare gains from trade.

Despite a lot of interest surrounding the IT boom and its effect on geographic in-

[23]Source: South China Morning Post, 15th May 2016
[24]Source: Scroll in, 27th July, 2019

equality in India, the lack of disaggregated data made it challenging to quantify its effect on overall economic growth. This paper also takes the first step in collecting district-level data and building a general equilibrium model to quantify the effect of IT boom on skill acquisition and the regional distribution of welfare gains in India. Using the model, it finds that between 1995 and 2005, the IT boom in India increased the average individual welfare by 1.116%, with individuals born in districts with good access to jobs and education gaining as much as 2.36% while those in remote districts experienced gains as low as .67%. These gains are attenuated by high costs of mobility for education and for work across Indian districts, leaving scope for policy interventions in both the education and labor markets that have the potential to reduce regional inequality as well as increase aggregate welfare. There is scope for future work to further the research agenda presented in this paper by studying the regional welfare implications of endogenous education choice with trade in a dynamic framework, which can trace how welfare changes during the transition period from short to long run. The challenge will be to devise a way to tackle the large number of state spaces as people migrate across regions and over time for work and for education.

3 Road Capacity, Domestic Trade and Regional Outcomes (Joint with A. Kerem Cosar, Banu Demir Pakel, and Nate Young)

3.1 Introduction

Transport is one of the largest contributors to infrastructure investment in the world. It plays a vital role in modern market economies, enabling domestic and international trade. High transport costs impede market access in isolated regions, both in terms of firms' ability to sell goods and in terms of their ability to buy the required inputs. Investment in transport infrastructure can reduce these frictions and improve growth prospects by facilitating trade. But how large are these gains, especially when there are various types or stages of investments that are possible? Arguably, constructing a new road from scratch or paving a dirt road would have a different effect than constructing a highway or expanding the lane capacity of existing roads. Previous empirical work has focused on cross-country analysis Limao and Venables (2001); Yeaple and Golub (2007), on the impact of the US interstate highway system Duranton et al. (2014); Allen and Arkolakis (2014), and the construction or paving of new roads in low- or lower-middle income countries, such as Faber (2014) on the highway network in China, Asturias et al. (2018) on the Golden Quadrilateral highway in India, and Kebede (2019) on improved village roads in Ethiopia. In this paper, we examine the benefits that a major capacity upgrade to existing transport infrastructure can have in middle-income economies by looking at the case of Turkey, which undertook major public investment in roads during the 2000s. We do so by providing reduced-form empirical evidence as well as by quantifying a structural model of economic geography.

The empirical exercise first measures the impact of road construction on reduced travel times, then links travel time reductions to changes in intra-national trade as well as regional sales, employment and productivity. We leverage a new dataset on within-country trade across the 81 provinces in Turkey. The data span a time period during which intensive road construction took place (2006-2015) and can be broken down by industry to analyze heterogenous effects as well as to control for compositional changes.

The nature and the quality of data improves upon Coşar and Demir (2016) who have examined the effect of the same investment program on the external trade of Turkish provinces between 2003-2012 using provincial shares of upgraded roads in the road stock. In contrast, this paper uses province-to-province trade, which captures a larger fraction of total economic activity, and GIS-based province-to-province travel times, a more precise measure of transportation costs. Our results suggest that travel time savings due to the investment program boosted intra-national trade in Turkey, increased output and generated employment. The results are robust to a number of checks, including a falsification test that investigates whether changes in domestic inter-provincial trade flows during the 2006-2011 period can be explained by travel time reductions over the 2010-2015 period.

The quantitative exercise adapts a workhorse model of economic geography Allen and Arkolakis (2014) to the case at hand. The framework allows labor mobility within a standard Armington trade model, capturing the spatial equilibrium within a country in the long-run. We calibrate provinces' productivities and amenities from their 2005 population shares and nominal wages. The quantified model helps us to gauge welfare changes across provinces through market access shifts in the short run when labor is immobile. We find a substantial increase in inter-provincial inequality: at conventional parameter values, the largest and smallest welfare gains across 81 provinces are 10.3 percent and 0.8 percent, respectively. In the long run, when labor is perfectly mobile across regions, the implied aggregate welfare increase is around 3 percent, implying a 70 percent rate of return on the road investment program.

3.2 Background

Turkey is an upper-middle-income country according to the World Bank classification, with a GDP per capita of USD 14,117 (in constant 2010 dollars) and a population of 79.8 million as of 2016. The dominance of roads as a mode of transportation in Turkey, accounting for about 90 percent of domestic freight (by tonne-km) and passenger traffic, motivated the country to undertake a major public investment in its transportation infrastructure during the 2000s. The road network was already extensive prior to this investment: in 2005, a paved road network already connected Turkey's 81 provincial centers (see thin grey lines in Panel A of Figure 17).[25] However, the lack of dual carriageways for most network segments resulted in limited capacity, long considered inadequate (see the thick green lines indicating dived multi-lane highways or expressways).

Consequently, the Turkish government launched a large-scale transportation investment program in 2002. The investment resulted in a significant percentage of existing single carriageways (undivided two-lane roads) being turned into dual carriageways.[26] By 2015, numerous arterial routes had been upgraded (see Panel B of Figure 17), with dual carriageways accounting for 35 per cent of inter-provincial roads, up from 10 per cent in 2002 (see Figure 18). The increase in capacity allowed vehicles to travel more reliably at higher speeds, making arrival times more predictable and reducing accident rates, with the number of fatalities per kilometer travelled declining by 57 per cent between 2002-2014.[27]

The objectives and design of the investment mitigate some concerns related to the selection of province pairs for domestic trade-related outcomes. First, policy documents

[25] Provinces correspond to the NUTS 3 (Nomenclature of Territorial Units for Statistics) level in the Eurostat classification of regions.

[26] According to the World Bank, Turkish public expenditures on transport have almost doubled from 1.06 percent of Gross Domestic Product (GDP) in 2004 to 1.92 percent in 2010, and the transport sector accounted for the bulk of the increase in total public investments over this period (http://bit.ly/2Aw0XX4).

[27] See the second column from right in table 1 in Murat and Zorlu (2018). Since the reporting criteria was changed in 2015 from "fatality on impact" to "fatality within 30 days of the accident," we report the change until 2014.

explicitly emphasize the long-term goal as the improvement of connections between all provincial centers to form a comprehensive grid network spanning the country, rather than boosting trade between particular regions. The General Directorate of Highways policy describes the criteria as "ensuring the integrity of the international and national networks, and addressing capacity constraints that lead to road traffic accidents." GDH (2014). Second, the extent of road upgrading shows considerable variation across provinces, without any visible sign of concentration in particular regions. Finally, the investment was centrally planned and financed from the central government's budget with no direct involvement of local administrations. Additional details about the investment program and discussion of external evidence on its contribution to the improvement of road transport quality in Turkey are available in Coşar and Demir (2016).

3.3 Data

A distinguishing feature of our study is the availability of high-quality data on domestic trade flows within Turkey during a time period when the country undertook a significant upgrading of its road network. The source of the domestic trade data is the administrative firm-to-firm transaction data provided by the Turkish Ministry of Science, Industry and Technology. Since 2006, Turkish firms have been legally required to report all purchases and sales exceeding a certain threshold (≈USD 3,300 in 2010) to the Ministry of Finance. The objective of this requirement is to reduce tax evasion and increase value-added tax (VAT) collection. Each transaction report is cross-checked and in case of inconsistencies, both firms are audited to retrieve the correct information.

In this paper, we use annual bilateral trade flows between provinces at the 2-digit industry level (according to the NACE Rev.2 classification) constructed by aggregating the firm-to-firm transaction data described above. The agricultural sector is excluded since it is dominated by unincorporated small farmers whose transactions tend to fall under the reporting threshold. We group remaining industries into two groups: manufacturing and other non-agricultural/non-manufacturing. The latter includes wholesale, retail and services other than finance, insurance and utilities.[28] The dataset covers the 2006-2016 period. Data on provincial employment is collected by the Social Security Institution (SGK) and made available by the Ministry of Industry, while data on provincial population come from the Turkish Statistical Institute. Table 6 provides summary statistics for the data. As a benchmark, it also reports the value of nominal GDP and total non-agricultural employment obtained from the Turkish Statistical Institute.[29]

To measure the impact of the road upgrades, we calculate the decadal change in inter-provincial travel times. To do so, we digitized the official maps of the road network published by the General Directorate of Highways for 2005, 2010 and 2015. Figure 17 shows the first and last year's rendered maps. Using geographic information system (GIS) software, we then calculated the fastest possible travel times between the 81 provincial centers in each year.[30] Figure 19 plots the reduction in travel times between province pairs from 2005 to 2015 against their time-invariant geodesic distances. The average travel time between any two provinces has been reduced by 1.4 hours, relative to the average of 6.5 hours in 2005. Time savings increase the further apart cities are, reaching five hours in the case of cities that are 1,500 km or more apart.

[28] Since the data are not at the establishment level, transactions of multi-establishment firms are accounted for at the headquarter province. The ensuing mismeasurement is most severe in utilities and financial services with numerous bank branches.

[29] It is worth noting that our data cover formal workers only while the aggregate employment statistics presented in Table 6 include both formal and informal workers.

[30] Average speeds are calculated for trucks using a representative sample of road segments on the basis of data from the General Directorate of Highways. While the maps in Figure 17 show both divided expressways and highways as dual carriageways, travel times assume a speed of 90 km/h on expressways and 110 km/h on highways. The speed on single carriageways is assumed to be 65 km/h. For each pair of provincial centers in Figure 17, ArcMap software is used to calculate the shortest possible travel time for both years on the basis of the above assumptions regarding speeds.

3.4 Results

3.4.1 Baseline results on travel time reductions

We start our analysis by checking whether the reduced travel times resulting from the road improvements between 2005 and 2015 increased bilateral domestic trade flows between Turkish provinces. Aggregating the data up to the level of province pairs, there are 6,561 pairs (81×81) that can potentially trade with each other as buyers or sellers. In 2006, only 3,704 of these pairs were trading with each other. In 2016, this number increased to 6,379. To account for this sizable extensive margin increase, we let the dependent variable $\Delta Trade_{ij}$ between source province i and destination province j to be the mid-point growth defined as

$$\Delta Trade_{ij} \;=\; 2 \cdot \frac{trade_{ij}^{2016} - trade_{ij}^{2006}}{trade_{ij}^{2016} + trade_{ij}^{2006}},$$

which ranges between -2 and 2, and approximates percentage change for pairs trading in both the initial and terminal years. Letting

$$\Delta TravelTime_{ij} \;=\; TravelTime_{ij}^{2015} - TravelTime_{ij}^{2005},$$

we estimate

$$\Delta Trade_{ij} \;=\; \alpha_i + \alpha_j + \beta \cdot \left|\Delta TravelTime_{ij}\right| + \epsilon_{ij}, \tag{36}$$

where source and destination province fixed effects control for province-level characteristics that affect domestic sales and purchases of each province. Since travel times decreased for all pairs between the two periods, the absolute value can be directly interpreted as travel time savings. We thus expect $\beta > 0$. We use two-way clustered standard errors by source and destination provinces. Columns (1) and (3) of Table 7 report the results for manufacturing and the non-agricultural/non-manufacturing sector separately for three samples: full sample (panel A), sample excluding Istanbul as destination (panel B), and sample Istanbul as source province (panel C). For all samples, we find economically and statistically significant results for manufacturing but not the other. The estimate presented in the first column of panel A implies that a one-hour reduction in travel times between two provincial centers increases bilateral trade between those provinces by around 5.3 percent. This effect is highly statistically significant and translates into a USD 2.6 million increase in trade flows in manufacturing over 10 years for a typical pair of cities. Results obtained for the alternative samples are qualitatively and quantitatively very similar.

By using a back-of-the-envelope calculation, we can quantify the effect in monetary terms. Suppose that there is a hypothetical route with length equal to the mean bilateral distance in 2006 (755 km), and it is entirely two-lane undivided. Given the assumptions we make about travel speeds on different types of roads, travel time on this route would be approximately 11.6 hours. To reduce travel time by one hour, about 30 percent of the route (234 km) needs to be transformed into four-lane divided roads, which would cost USD 25.7 million (per annum) based on the investment costs reported by Turkish authorities. Given that the value of domestic trade generated by such investment is USD 2.6 million, the value of domestic trade generated by a one USD investment in roads is USD 0.10.

To further examine the extensive margin effect of reduced travel times on the establishment of new trade links, we estimate a linear probability model in which the dependent variable equals 1 for province pairs with positive trade in 2016 conditional on zero trade in 2006, and 0 otherwise. The result in Column (2) of Table 7 suggests that an average province pair with zero trade in manufacturing in 2006 had a probability of 7 per cent to start trading in 2016, calculated by multiplying the estimated coefficient with 1.85 hours, the average time saving between two provinces at that quintile. The result obtained for services industries is even stronger. The estimated coefficient on $|\Delta TravelTime_{ij}|$ presented in the last column of Table 7 implies that an average province pair with zero trade in services in 2006 had a probability of 18 per cent to start trading in 2016. There exist two channels through which improvements in domestic transport infrastructure affect inter-provincial trade: first, by reducing the cost of transporting goods between the source and destination provinces, and second, by reducing the cost of finding new suppliers/buyers (i.e. establishing new trade relationships). While both channels matter for trade in manufacturing, one would expect the second channel to be more relevant for trade in services. Consider legal and accounting services. Even if work is completed in a firm?s office and transmitted electronically, lower travel times reduce the cost of recruiting new clients or holding initial face-to-face meetings. The message from Table 7 is consistent with this hypothesis. Manufacturing flows are affected by both the intensive and extensive margins, while services flows are only affected at the extensive margin and that effect has a larger magnitude.

Next, we use the industry dimension of the data to control for potential compositional effects. That is, depending on the covariance of industries' input-output linkages with their spatial distribution, the aggregate province-level estimates could be over- or under-stating the true effect. For instance, if industries widely used as intermediate inputs with low elasticity of substitution are located in provinces with good market access to begin with, while more substitutable final goods are produced in initially isolated locations, the differential response between such provinces will be inflated. Columns (1) and (2) of Table 8 present the results for all industries from estimating the same specifications with origin province-industry is and destination province-industry js' fixed effects clustered at origin-destination level. Both the the extensive margin effect in Column (2) and the combined effect in Column (1) remain close to the respective estimates obtained in Table 7. In particular, a one-hour reduction in travel times between two provincial centers increases inter-industry bilateral trade by about 4.9 per cent, implying about USD 9.3 million worth of additional trade flows over 10 years for an average origin-destination pair in the data.[31]

[31]This estimate assumes positive trade in 14 2-digit NACE industries for an average source-destination pair, which is the average number of active industries for a given province in 2006. As it is estimated that a one-hour reduction in travel times creates USD 47,600 worth of additional trade flows over 10 years for an average industry pair between two provinces, the value of aggregate trade over all industries becomes approximately USD 9.3 million for an average source-destination province.

Next, we consider the possibility that provinces benefiting most from improved connectivity may be the ones with the greatest potential for new trade due to low initial levels. To address this concern, we include the initial share of each source province in its destinations, $TradeShare_{ij}^{2006}$, as an additional control in the specification where inter-industry bilateral trade changes is the dependent variable. Columns (3) and (4) of Table 8 confirm the importance of this channel: coefficients of travel time reduction shrink considerably with the difference being picked up by provinces' initial shares. The effect of road improvements, however, still remain statistically significant in this most demanding specification.

In Table 9, we present results from estimating the most demanding specifications in Table 8 for manufacturing and services industries separately. The coefficient on travel time savings for changes in inter-industry bilateral trade flows is estimated to be statistically significant for both sectors. The result for services highlights the importance of accounting for industry composition across provinces since the aggregate province-level estimate obtained for services is not statistically significant in Table 7. Controlling for industry composition of trade also matters for the extensive margin effect of reduced travel times as the estimates presented in Table 9 are smaller in size than the respective estimates presented in Table 7.

3.4.2 Robustness checks

We conclude this section by subjecting the baseline results to two robustness checks. These involve splitting the sample into sub-periods and estimating a placebo test.

Replicating the baseline specification for inter-industry bilateral trade estimated from decadal changes —presented in Column (3) of Table 8—first column of Table 10 presents the results for the 2006-2011 sub-period. Similarly, the main variable of interest, $|\Delta TravelTime_{ij}|$, measures travel time savings between 2005 and 2010. The results confirm that the effect is positive and highly significant in the first sub-period. The coefficient estimate is actually higher than the baseline presented in Column (3) of Table 8 from the entire sample period. This implies that most of the increase in bilateral trade took place in the first sub-period. In other words, initial road improvements starting from a low level can have a greater impact on inter-provincial trade than subsequent investments, consistent with diminishing returns to infrastructure investment.

Column (2) reports the results from a placebo test which regresses changes in trade flows in the 2006-2011 period on travel time reductions in both the preceding 2005-2010 and the succeeding 2010-2015 periods. The main variable of interest, reduction in travel times in the preceding period, remains positive and highly significant while further improvements in the succeeding period are statistically insignificant, which strengthens the validity of our identification.

Finally, Figure 20 presents the distribution of the estimate of β in equation (36) on 500 random drawn samples of size 2,000. Both the mean and median of the distribution is almost identical to our baseline estimate. This robustness check alleviates potential concerns about dominance of certain provinces or province pairs, as well as selection of the location of road upgrades by the authorities.

3.4.3 Results on various regional economic outcomes

Beyond its impact on trade, did the reduction in domestic travel times affect other key regional economic outcomes such as industry employment and productivity? To address this question, we construct a variable capturing improved domestic market access at the provincial level. In particular, weighting each province's time savings on the basis of destination provinces' population for 2005,

$$\left|\Delta \overline{TravelTime_i}\right| = \sum_{j=1}^{81} \left(\frac{population_j}{\Sigma_{k=1}^{81} population_k} \right) \cdot \Delta TravelTime_{ij},$$

calculates the average connectivity improvement experienced by a province when selling goods to other provinces. We will report the results from estimating various specifications of

$$\Delta \ln(Outcome_{is}) \;=\; \alpha_s + \beta \cdot \left|\Delta \overline{TravelTime_i}\right| + \epsilon_{is},$$

where $Outcome_{is}$ is origin province-industry sales (Y_{is}), employment (L_{is}) or labor productivity (Y_{is}/L_{is}) depending on specification. Aggregate industry-wide effects are controlled by α_s and standard errors are clustered at the province level.

The outcome of interest in the upper panel of Table 11 is total industry sales, further disaggregated into domestic and export sales in the middle and lower panels. In the first column, the coefficient on $\overline{TravelTime_i}$ is estimated to be positive and statistically significant, implying that improvements in domestic market access had a positive effect on industry-level sales. We subject this result to two robustness checks. In Column (2), we add initial population share of provinces (as of 2005) as an additional control to address the potential concern that larger provinces in terms of population attracted more investment. The coefficient of interest remains positive and highly significant. In Column (3), we also add the initial per capita GDP to control for the possibility that initially lagging regions posted greater sales growth, or they also attracted other public investment during the period under consideration. The coefficient estimate becomes significantly smaller in size and becomes statistical significant only at the 15 percent level. The middle panel presents the results for domestic sales. In Column (3), which presents the results from estimating the most demanding specification, the coefficient of interest remains statistically significant at the 10 per cent level. Consistent with the results in Coşar and Demir (2016), we find a positive impact on export sales (lower panel).

Upper panel of Table 12 confirms that the effect of improvements in domestic market access on sales were large enough to show an impact on employment, as opposed to increasing production and sales through increased capacity utilization alone. The estimated coefficient on $|\Delta\overline{TravelTime_i}|$ presented in Column (3) implies that a one-hour reduction in travel time increases average industry-level employment by 15.7 per cent. Given that about two-thirds of provinces experienced time-savings of an hour or more, the effect on regional job opportunities is non-negligible. At a population-weighted average time savings of 90 minutes, the mean of the $|\Delta \overline{TravelTime_i}|$ variable, the effect equals a 23.6 percent increase in industry-level employment.

In the lower panel of Table 12, we let the outcome of interest be the province-industry level labor productivity, Y_{is}/L_{is}. While the coefficient has the expected positive sign in the first two columns, improved market access does not seem to be associated with productivity gains at conventional levels of statistical significance. The coefficient of interest reverses its sign in Column (3) but remains statistically insignificant.

3.5 Quantifying the welfare effects

3.5.1 Model

In this section, we use a workhorse spatial equilibrium model Allen and Arkolakis (2014) to quantify the short-run regional and long-run aggregate welfare effects from the expansion and upgrading of expressways in Turkey.

Each province produces a differentiated Armington variety linearly and competitively with L_i workers and productivity A_i. An exogenous aggregate labor supply $\overline{L}$, normalized to unity, is freely mobile between 81 provinces of the country.

Productivity of a province has an exogenous component $\overline{A}_i$, augmented by its labor force: $A_i = \overline{A}_i L_i^{\alpha}$. Production displays external increasing returns to scale due to agglomeration forces if $\alpha > 0$. Similarly, each province has an exogenous amenity level $\overline{u}_i$, augmented by its labor force: $u_i = \overline{u}_i L_i^{\beta}$. Amenities display decreasing returns to scale due to congestion forces if $\beta < 0$. We note that the (α, β) used in the model notation is completely unrelated to the reduced form coefficients used in previous sections.

The cost of trade between two provinces k, i is of iceberg type: $\tau_{ij} = \tau_{ji} > 1$ if $i \neq j$, and $\tau_{ii} = 1$. That is, province-i variety with an origin price p_i costs $\tau_{ij} p_i$ in province

j. CES demand with elasticity $\sigma > 1$ implies trade flows from i to j equal to

$$X_{ij} = \left(\frac{\tau_{ij} p_i}{P_j}\right)^{1-\sigma} w_j L_j, \tag{37}$$

where w_j is the equilibrium nominal wage prevailing in province j, and P_j is the price index given by

$$P_j^{1-\sigma} = \sum_{i=1}^{81} \tau_{ij}^{1-\sigma} p_i^{\sigma-1}. \tag{38}$$

Since production is linear and competitive in each province, prices are $p_i = w_i/A_i$ at the origin. Utility of a worker living in province i is given by

$$W_i = \frac{w_i}{P_i} u_i.$$

Spatial long-run equilibrium holds when wages and labor allocations $\{w_i, L_i\}_{i=1}^{81}$ are such that

- welfare is equalized across provinces: $W_i = W$ for all i,
- aggregate labor demand equals aggregate labor supply: $\sum_i L_i = 1$,
- provinces' expenditures equal their total sales: $w_i L_i = \sum_j X_{ij}$.

Allen and Arkolakis (2014) characterize the conditions on (α, β, σ) that ensure the existence of an equilibrium. In particular, regardless of the magnitude of σ, a unique and stable equilibrium exists if $\alpha + \beta \leq 0$. Under this assumption on parameter values, which we maintain, there is a one-to-one relationships between the set of exogenous productivities and amenities, $\{\overline{A}_i, \overline{u}_i\}$, and the set of endogenous wage and population levels $\{w_i, L_i\}$. Thus, given the empirical levels of $\{w_i, L_i\}$ and the function of trade costs between provinces $\tau_{ki}^{1-\sigma}$, the following system of equations can be solved to back out composite amenities $u_i^{1-\sigma}$ and productivities $A_i^{1-\sigma}$ up to a scale W:

$$u_i^{1-\sigma} = W^{1-\sigma} \sum_{j=1}^{81} \tau_{ji}^{1-\sigma} w_i^{\sigma-1} w_j^{1-\sigma} \cdot A_j^{\sigma-1}, \tag{39}$$

and

$$A_i^{1-\sigma} = W^{1-\sigma} \sum_{j=1}^{81} \tau_{ji}^{1-\sigma} L_i^{-1} w_i^{-\sigma} L_j w_j^{\sigma} \cdot u_j^{\sigma-1}. \tag{40}$$

With values of $\{A_i^{1-\sigma}, u_i^{1-\sigma}\}$ at hand, exogenous components $\{\overline{A}_i, \overline{u}_i\}$ can be backed out for given values of (α, β, σ).

Given the calibrated exogenous productivities and amenities, the following set of 81 equations implied by spatial utility equalization, together with the national labor market clearance condition, help to solve for the level of welfare W and labor allocations $\{L_i\}$:

$$L_i^{\tilde{\sigma}\gamma_1} = W^{(1-\sigma)} \overline{u}_i^{(1-\tilde{\sigma})(\sigma-1)} \overline{A}_i^{\tilde{\sigma}(\sigma-1)} \sum_j \tau_{ji}^{(1-\sigma)} \overline{A}_j^{(1-\tilde{\sigma})(\sigma-1)} \overline{u}_j^{\tilde{\sigma}(\sigma-1)} L_j^{\tilde{\sigma}\gamma_2}. \tag{41}$$

Here, $(\tilde{\sigma}, \gamma_1, \gamma_2)$ are functions of the parameters (σ, α, β).[32] We refer the reader to Allen and Arkolakis (2014) for the proofs and the description of the solution algorithm.

To quantify the welfare impact of the road program, we need a measure of trade costs τ_{ki} before and after the upgrades, as well as values for the parameters $\{\alpha, \beta, \sigma\}$. In what follows, we first estimate trade costs as a function of travel times in 2005. We then use these trade cost estimates together with the empirical level of wages and urban populations in the same year to back out composite amenities and productivities $\{A_i^{1-\sigma}, u_i^{1-\sigma}\}$. We then tease out exogenous amenity and productivity components $\{\overline{A}_i, \overline{u}_i\}$ at various values for the parameters $\{\alpha, \beta, \sigma\}$. To attain our main objective—evaluating the welfare effect of the transport infrastructure investment—we fix these exogenous components at their calibrated values and solve the model using the reduced travel times in the upgraded 2015 network. This gives us an estimate of the long-run increase in aggregate welfare W, and a prediction on the associated population shifts across provinces. We now explain each step in detail.

Trade costs Taking the logarithm of equation (37), trade flows between provinces are given by the gravity equation

$$\ln(trade_{ij}) \;=\; \mu_i + \mu_j + (1-\sigma)\ln(\tau_{ij}), \tag{42}$$

[32] In particular, $\gamma_1 = 1 - \alpha(\sigma-1) - \beta\sigma$, $\gamma_2 = 1 + \alpha\sigma + (\sigma-1)\beta$ and $\tilde{\sigma} = (\sigma-1)/(2\sigma-1)$.

where μ's are origin and destination fixed effects. We specify trade costs as a function of travel times, $\tau_{ij} = TravelTime_{ij}^{\theta}$, and estimate the following equation for $i \neq j$:[33]

$$\ln(trade_{ij}) \;=\; \mu_i + \mu_j + \underbrace{(1-\sigma)\theta}_{\delta} \cdot \ln(TravelTime_{ij}) + \epsilon_{ij}. \tag{43}$$

As standard in the literature, this estimation cannot separately identify the elasticity of trade to trade costs $(\sigma - 1)$ from the elasticity of trade costs to travel times θ. The results in Table 13 therefore report $\hat{\delta} = (1-\sigma)\theta$. The estimate in Column (1) using 2006 trade flows and 2005 travel times before the upgrades equals -1.461, a number consistent with the gravity literature. In Column (2), we use the 2015 trade flows and travel times in the upgraded road network for the set of provinces that had positive trade in 2006. This sample yields a close but slightly higher estimate. We continue with the conservative $\hat{\delta}$ value from Column (1).[34]

Solving for amenities and productivities Given trade costs, and the empirical levels of provincial wages and populations, we solve the system of 162 equations captured by equations (39)-(40) for the 162 unknowns $\{A_i^{1-\sigma}, u_i^{1-\sigma}\}$, normalizing the baseline welfare to $W = 1$. In order to purge out the exogenous components $\overline{A}_i = A_i/L_i^{\alpha}$ and $\overline{u}_i = u_i/L_i^{\beta}$, we need values for (α, β, σ).

To calibrate β, the parameter capturing congestion forces, we use the isomorphism of the model to one that features residential land/housing in consumption Allen and Arkolakis (2014). In that version of the model, the price of the immobile fixed factor (land) is increasing in population, thereby decreasing the utility of residents. The isomorphism holds if land has a Cobb-Douglas expenditure share of $-\beta/(1-\beta)$. According to the Household Budget Survey of the Turkish Statistical Institute, housing

[33] The calculation of travel times has been described in Section 3.3, and the levels before and after the road upgrades plotted in Figure 19. In order to make the travel time units irrelevant, we take the lowest level of τ_{ki} for $k \neq i$ in the combined 2005 and 2015 data, and normalize all other τ_{ki}'s by that level. We set $\tau_{ii} = 1$.

[34] Note that in the model described above, trade costs only appear as $\tau^{1-\sigma}$, which equals $TravelTime_{ij}^{(1-\sigma)\theta}$. This implies that to get a measure of trade costs, we can simply use the estimated gravity coefficient $TravelTime_{ij}^{\hat{\delta}}$ without the need to make an assumption on the value of σ.

has a stable expenditure share around 25 percent across the relevant data period.[35] We set $\beta = -1/3$ to match that value. This is very close to the value of $\beta = -0.3$ in Allen and Arkolakis (2014) who use the US housing expenditure share as the calibration target.

We consider a range of values for α satisfying the constraint $\alpha \in [0, -\beta]$ to ensure existence and uniqueness of equilibrium. In particular, we report results for when there are no agglomeration economies ($\alpha = 0$), when agglomeration economies are as strong as permissible ($\alpha = -\beta = 1/3$), and for the intermediate value $\alpha = 1/6 \approx 0.167$. The estimates of this parameter in the literature range between 0.04 and 0.1 Rosenthal and Strange (2004). Finally, we take a baseline value of $\sigma = 5$ to attain a trade elasticity of $\sigma - 1 = 4$ Simonovska and Waugh (2014a), and report results for upper and lower bounds of $\sigma = 3$ and $\sigma = 7$.

In Figure 21, we plot the exogenous amenities ($\overline{A}$) and productivities ($\overline{u}$) of provinces against the data from which they were backed out: population shares and wages (normalized around the average) in 2006. Evidently, amenities are the main driver of city sizes while productivities correlate with nominal wages.

3.5.2 Results

When labor is immobile, road upgrades generate spatial inequality between provinces through changes in market access. To solve for the short-run equilibrium, we keep the population vector $\{L_i\}$ in its 2005 level, change trade costs τ to its 2015 level, and find market clearing wages w_i for each province. We then calculate provincial price indices P_i as defined by equation (38) using the lower trade costs. Since labor is fixed, amenities enjoyed by residents do not change. The only variation in welfare comes from the real wage component of utility, that is, from the response of w_i/P_i to the change in trade costs.

Note that in principle, some provinces can incur welfare losses through trade diversion

[35] http://www.tuik.gov.tr/MicroVeri/HBA_TH_14-15-16/english/index.html

in the short run. For the parameter values we consider, that is not the case, i.e., all locations experience a real wage increase. There is, however, a substantial increase in inter-provincial inequality: for the baseline value of $\sigma = 5$, the largest and smallest welfare gains are 10.3 percent and 0.8 percent, respectively.[36] Weighted by population, aggregate welfare increase is 2.84 percent.

To demonstrate the mechanism through which real incomes are affected with immobile labor, we calculate for each province a reduced-form measure of change in market access:

$$\Delta MarketAccess_i = \frac{\sum_{j=1}^{81}(w_j^{2015}L_j)/\tau_{ij}^{2015}}{\sum_{j=1}^{81}(w_j^{2005}L_j)/\tau_{ij}^{2005}}.$$

The scatter plot of percentage real wage changes against this measure in Figure 22 visualizes the variation in welfare in response to the heterogenous shift in market access across provinces. The correlation between the two variables is 0.51. The maps in Figure 23 display the spatial distribution of this relationship, confirming that provinces with larger improvements in market access tend to experience higher welfare gains in the short run.

The long run effect on aggregate welfare is calculated by jointly solving the system in equation (41) with the national labor market constraint $\sum_i L_i = 1$. In Table 14, we present the percentage welfare increase resulting from the travel time reductions for various parameter combinations. The response is larger when the differentiated varieties produced by provinces are less substitutable. This is expected, since a lower elasticity of substitution in demand increases the welfare impact of trade costs. Stronger agglomeration economies imply larger welfare gains, although the variation within the permissible range of α values is limited. Depending on the parameter combinations, welfare gains vary between 1.89 percent and 6.25 percent. For the baseline value of $\sigma = 5$, the gains range between 2.86 percent and 3.08 percent. The long-run gains are only slightly higher than the population weighted aggregate welfare gain in the short run, which implies that market access rather than the reallocation of labor is the primary driver of the overall welfare impact.

[36] Short-run welfare responses are invariant to (α, β) values.

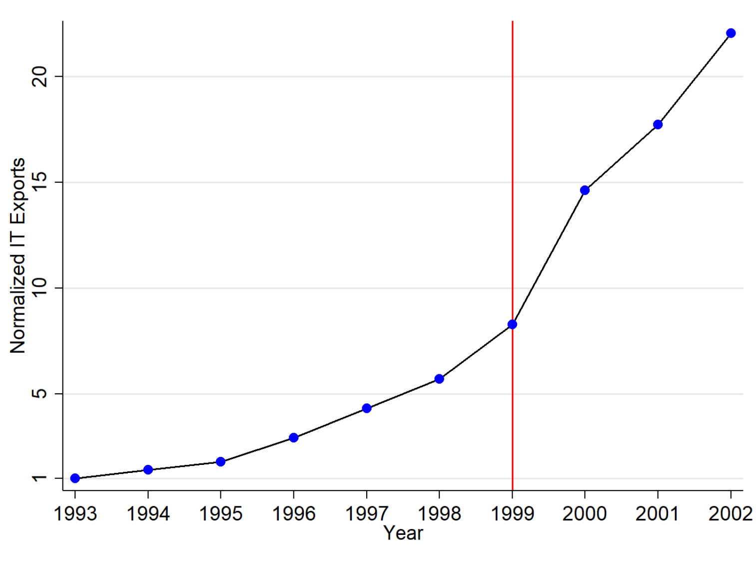
We finish by calculating the rate of return for the investment program. The investment cost was around 1.7 percent of GDP per year. An annual welfare increase of 2.9 percent implies a rate of return equal to $(2.9 - 1.7)/1.7 = 70$ percent.

3.6 Conclusion

Developing countries need large investments in transport infrastructure EBRD (2017). Yet, evidence on the rates of return for various types of road projects—paving dirt roads, expanding the capacity of existing paved roads, constructing highways—is still scant. We make a contribution to filling this gap by providing an empirical analysis of the lane-capacity expansion to Turkey's national road network during the past decade and a half. Our results suggest that travel time reductions due to the ambitious public investment program undertaken by Turkey boosted its intranational trade and yielded a sizable return on investment. In particular, a one-hour reduction in travel times between two provincial centers increases bilateral trade by about 4.9 percent. To gauge the long-run welfare impact, we quantify a workhorse spatial equilibrium model with labor mobility and find an aggregate real income gain around 3 percent.

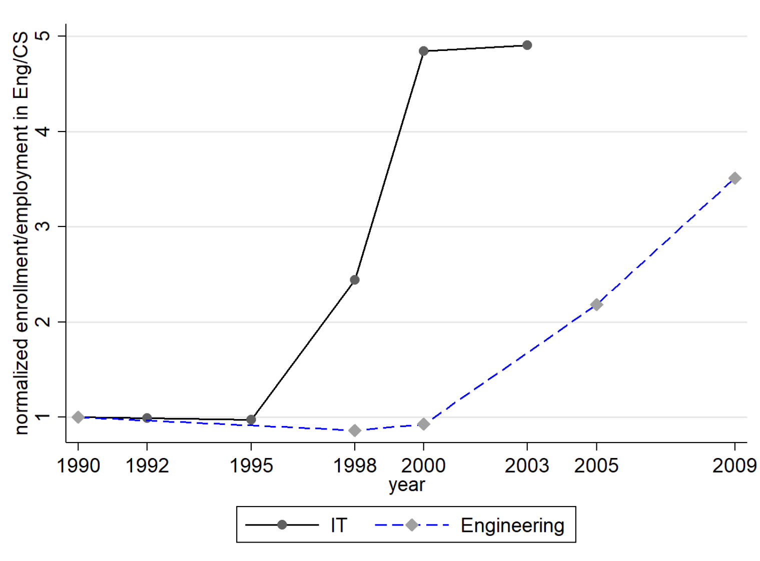
4 Tables and Figures

Figure 1: Growth in Software Exports over Time, normalized to 1993



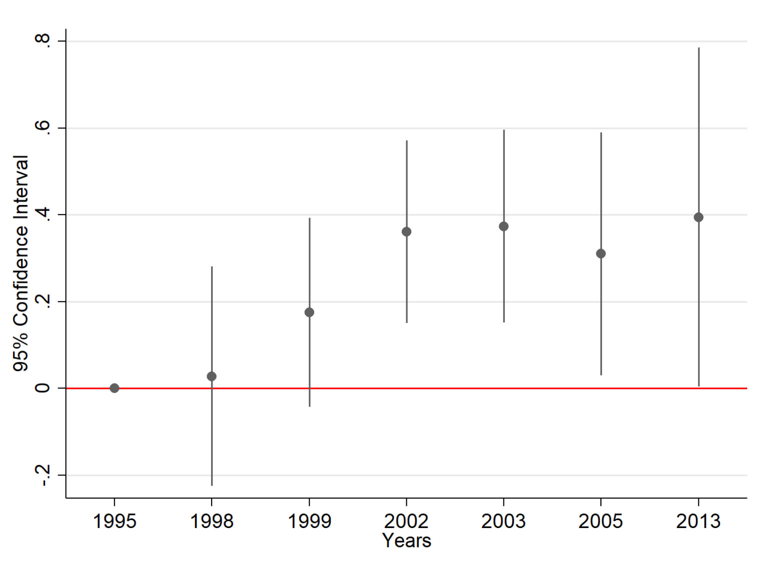
NOTE: This graph shows the growth in IT exports over time, with IT exports normalized to their 1993 levels. This was generated using data on software exports compiled by Richards Heeks

Figure 2: growth in IT Employment and Enrollment over Time, Normalized to 1990.



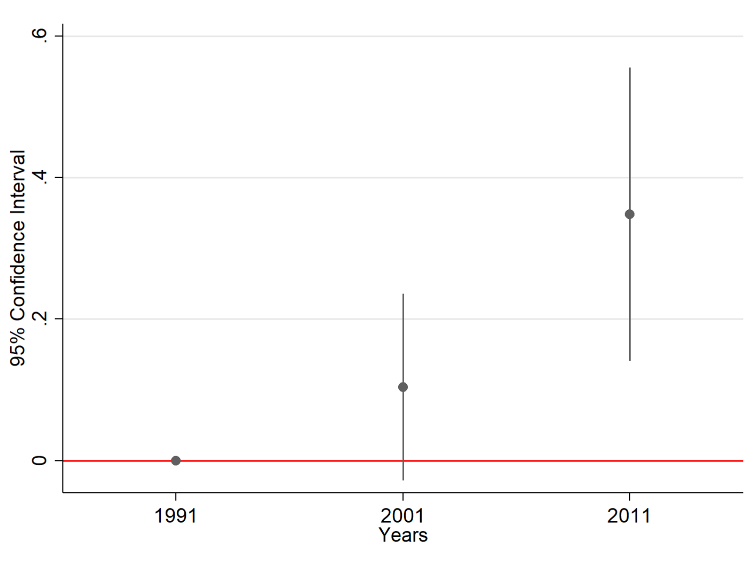
NOTE: This graph shows the growth in IT employment and engineering enrollment over time, with both IT employment and engineering enrollment normalized to their 1990-1991 levels. This was generated using IT employment data from NSSO, NASSCOM, Economic Census and engineering enrollment data from the Population Census.

Figure 3: Response of IT Employment across Regions with Different Levels of Software Exports



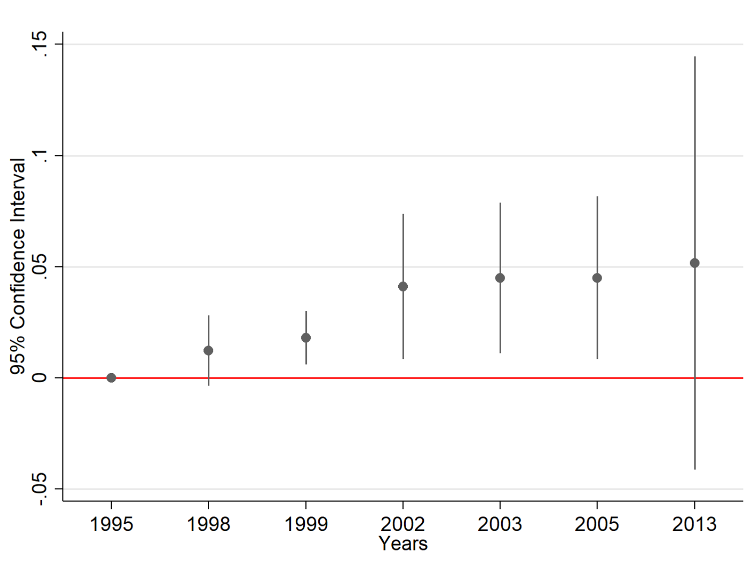
NOTE: This graph plots the confidence intervals for the year by year response of standardized IT employment over the pre and the post boom periods in districts that had any IT exports in 1995 compared to districts that did not.

Figure 4: Response of Engineering Enrollment across Regions with Different Levels of Software Exports



NOTE: This graph plots the confidence intervals for the year by year response of standardized engineering employment over the pre and the post boom periods in districts that had any IT exports in 1995 compared to districts that did not

Figure 5: Heterogeneous Response of IT Employment



NOTE: This graph plots the confidence intervals for the year by year heterogeneous response of IT employment to differences in historical college enrollment among districts that had any existing level of IT exports over the pre and the post boom periods. The unit is denoted as per '000 engineering students.

Figure 6: Spatial Distribution of IT Employment and Engineering Enrollment in 2011

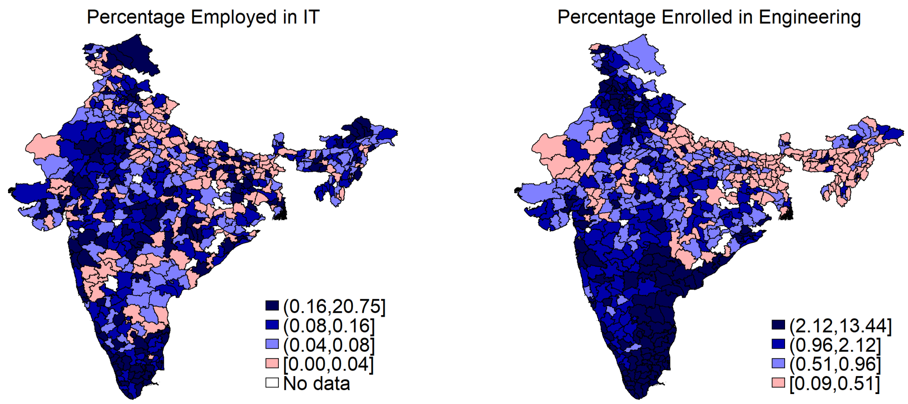
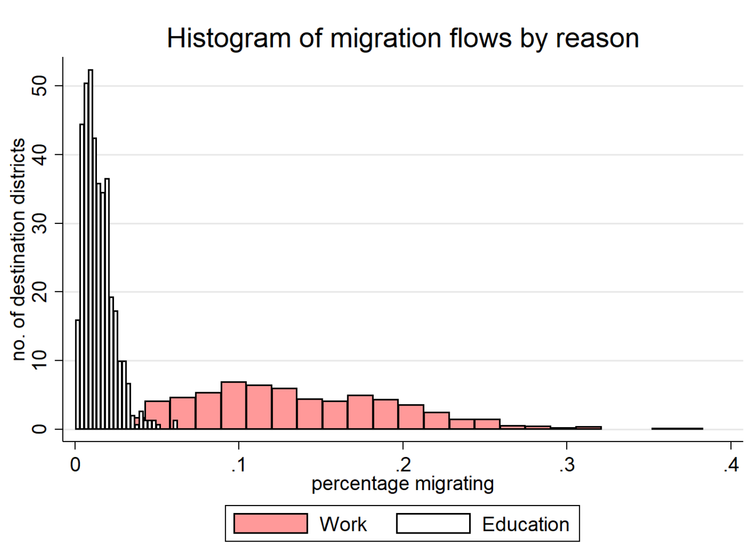
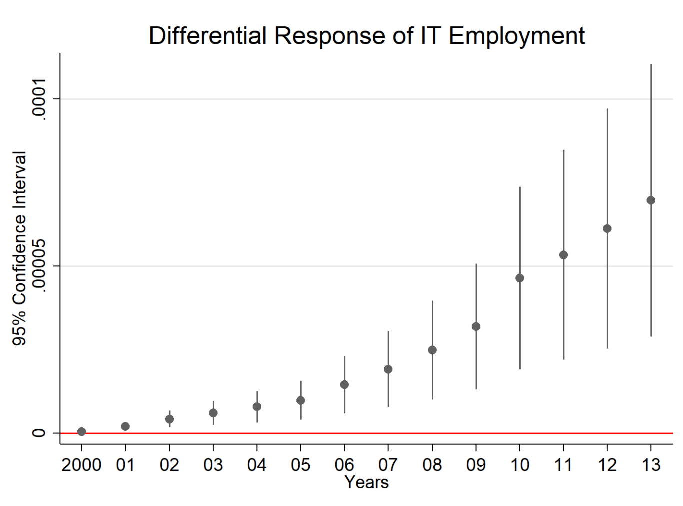


Figure 7: Histogram of Work-flows by Reason for Migration.



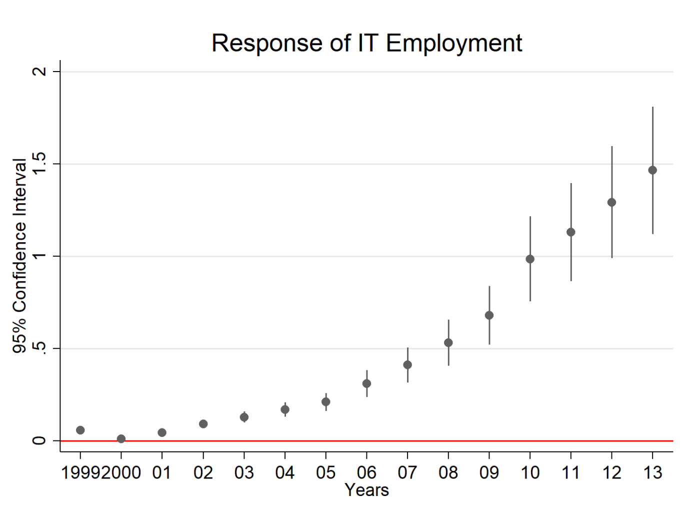
NOTE: On the x-axis, this histogram plots the proportion of migrants in a district that migrated for work and education respectively as shown by the pink and blue colors. On the y-axis, the number of destination districts with the corresponding proportions of migrants for work and education are plotted. Data source is the 2001 Census migration data.

Figure 8: Heterogeneous Response of IT Employment. *Units: Per '000 engineering students in own and neighboring districts(own state)*



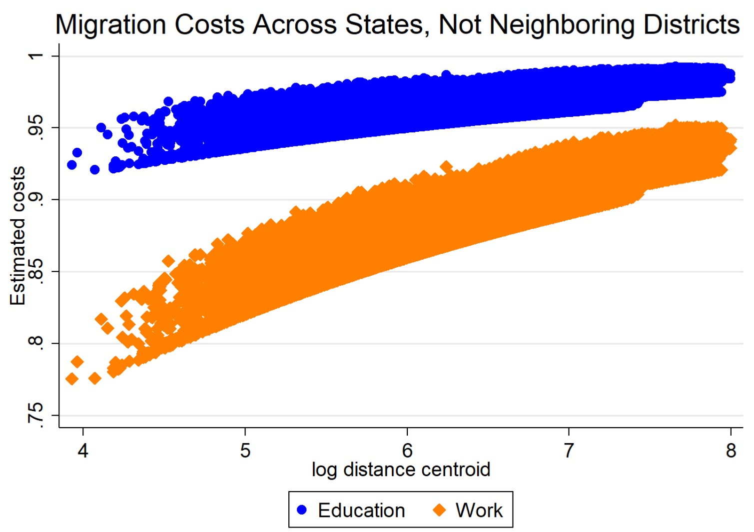
NOTE: This graph plots the confidence intervals for the year by year heterogeneous response of IT employment to differences in historical college enrollment among districts that had any existing level of IT exports over the pre and the post boom periods. The unit is denoted as per '000 engineering students.

Figure 9: Response of IT Employment Across Regions with Different Levels of Software Exports



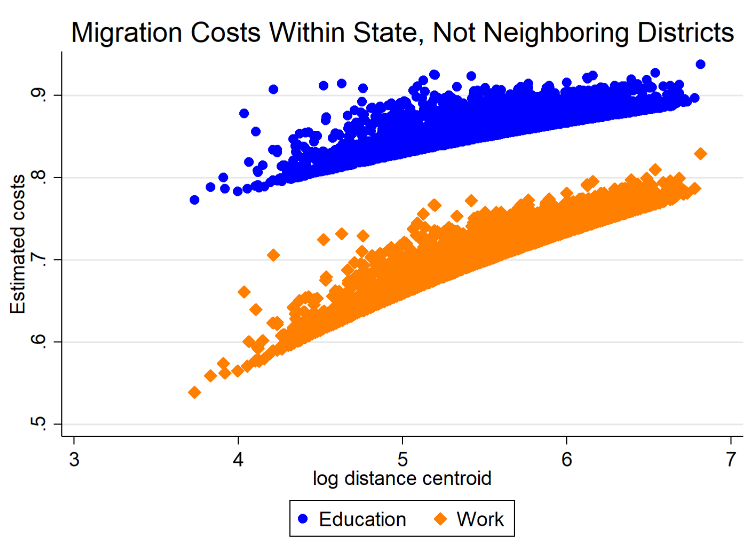
NOTE: This graph plots the confidence intervals for the year by year response of standardized IT employment over the pre and the post boom periods in districts that had any IT exports in 1995 compared to districts that did not using model generated data.

Figure 10: Estimated migration costs for non-neighboring districts in different states



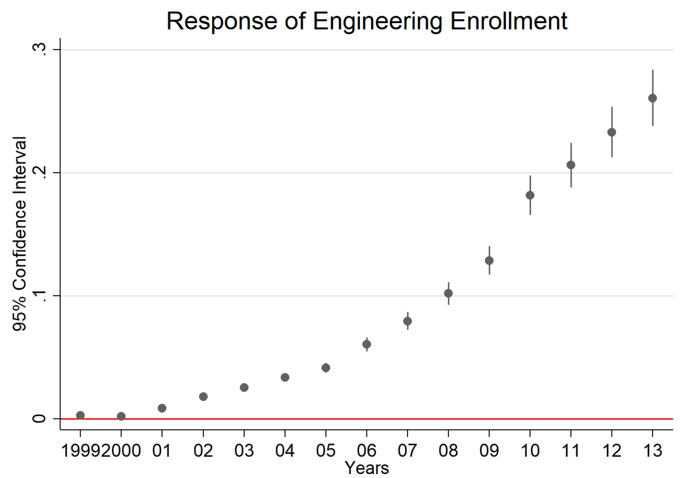
NOTE: This graph plots the log distance between district centers on the x-axis and the estimated costs by reason for migration on the y-axis for non-neighboring districts that fall in different states.

Figure 11: Estimated migration costs for non-neighboring districts in the same state



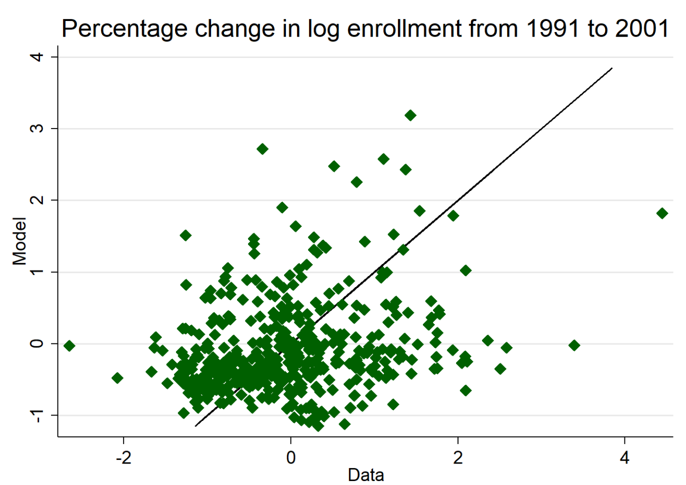
NOTE: This graph plots the log distance between district centers on the x-axis and the estimated costs by reason for migration on the y-axis for non-neighboring districts that fall in different states.

Figure 12: Response of Engineering Enrollment Across Regions with Different Levels of Software Exports



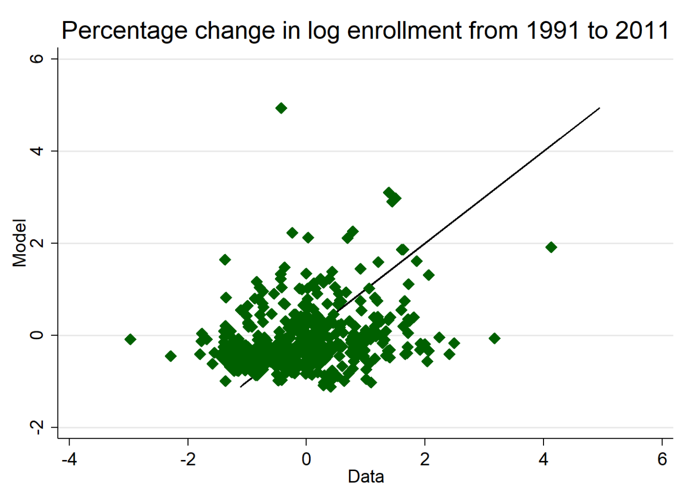
NOTE: This graph plots the confidence intervals for the year by year response of standardized engineering employment over the pre and the post boom periods in districts that had any IT exports in 1995 compared to districts that did not using model generated data

Figure 13: Percentage rise in log Engineering Enrollment from 1991 to 2001, standardized



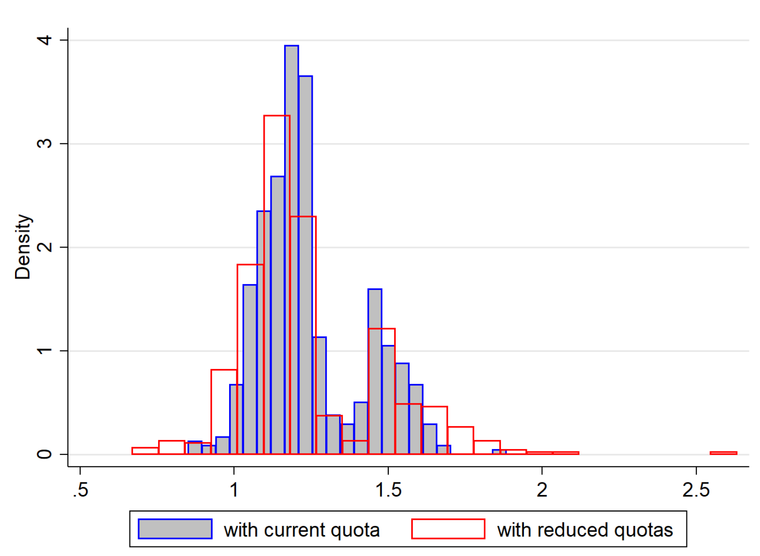
NOTE: This graph plots the percentage change in log engineering enrollment from 1991 to 2001 in the data on the x-axis and the percentage change in log engineering enrollment predicted by the model on the y-axis.

Figure 14: Percentage rise in log Engineering Enrollment from 1991 to 2011, standardized



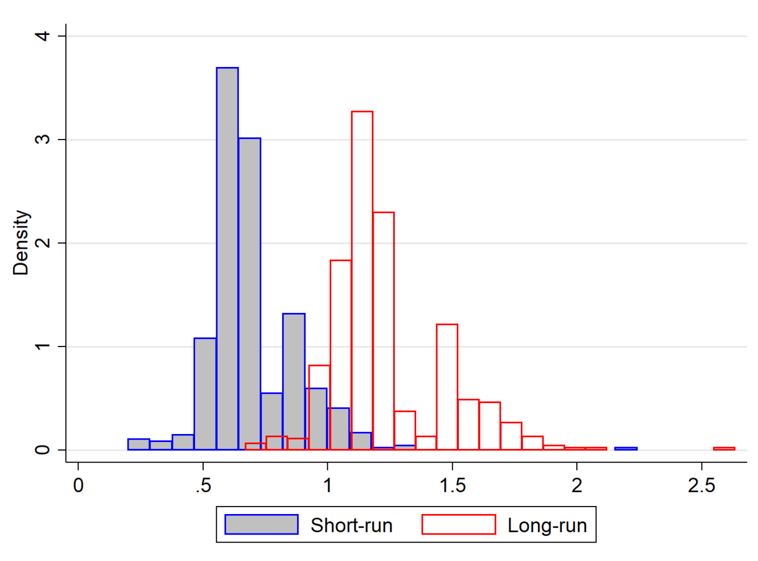
NOTE: This graph plots the percentage change in log engineering enrollment from 1991 to 2011 in the data on the x-axis and the percentage change in log engineering enrollment predicted by the model on the y-axis.

Figure 15: Distribution of Welfare Gains from the IT Boom



NOTE: The histograms show the distributions of welfare gains from the IT boom in the short and the long run. In the short run education choice is fixed and in the long run education choice is endogenous

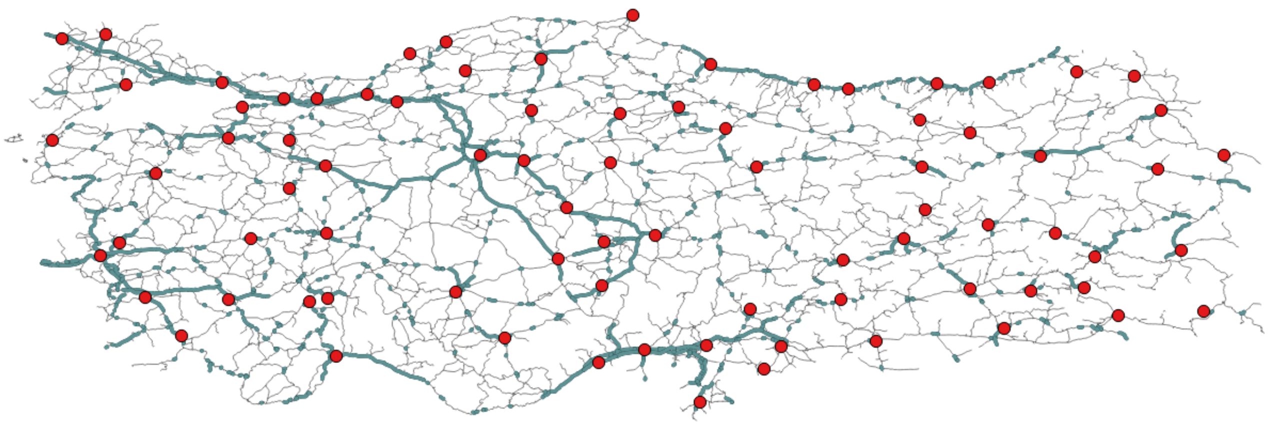
Figure 16: Distribution of Short-run and Long-run Welfare Gains from the IT Boom



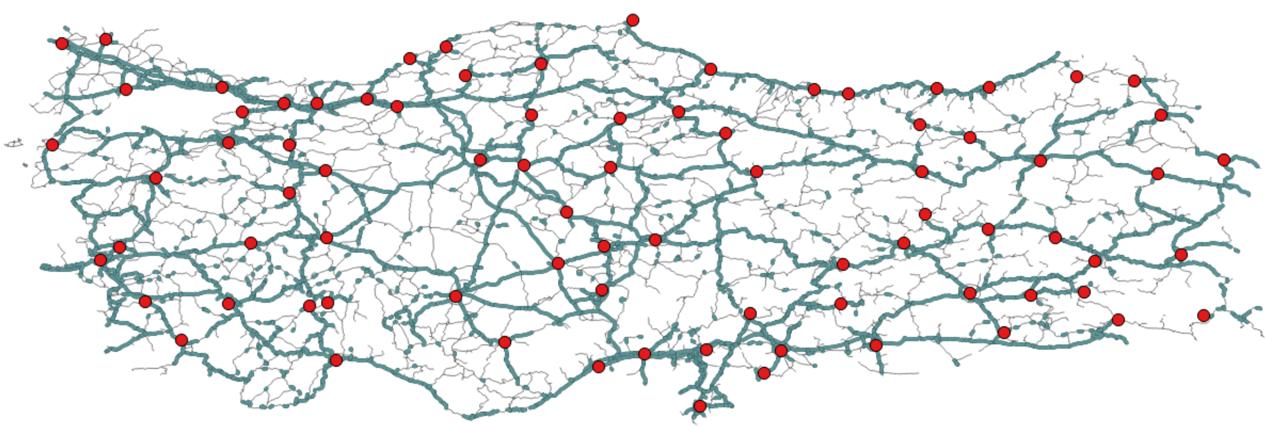
NOTE: The histograms show the distributions of welfare gains from the IT boom in the short and the long run. In the short run education is fixed and in the long run education choice is endogenous

Figure 17: **Turkish Provinces and Roads**

*Panel A: Road Network in 2005

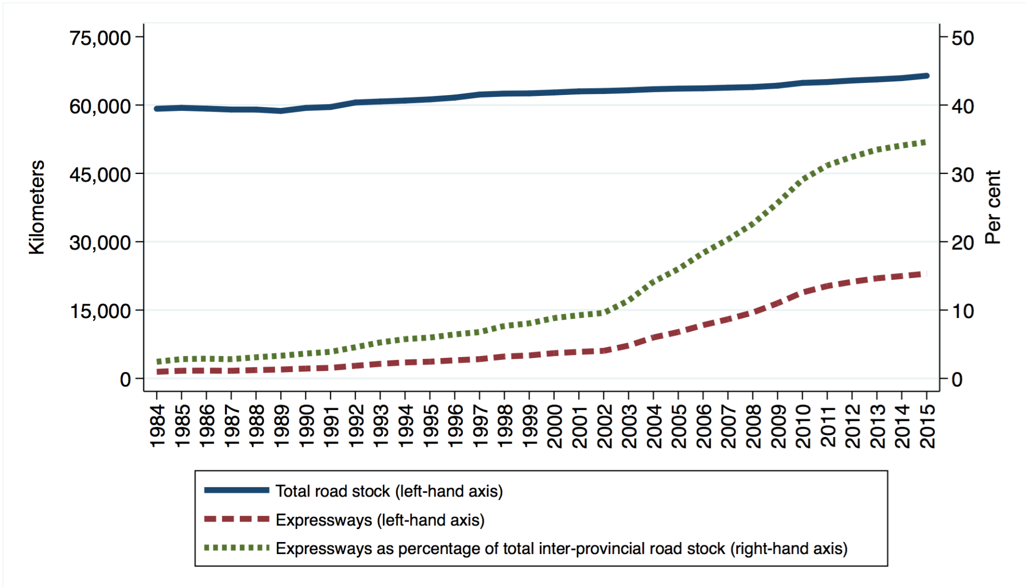


*Panel B: Road Network in 2015



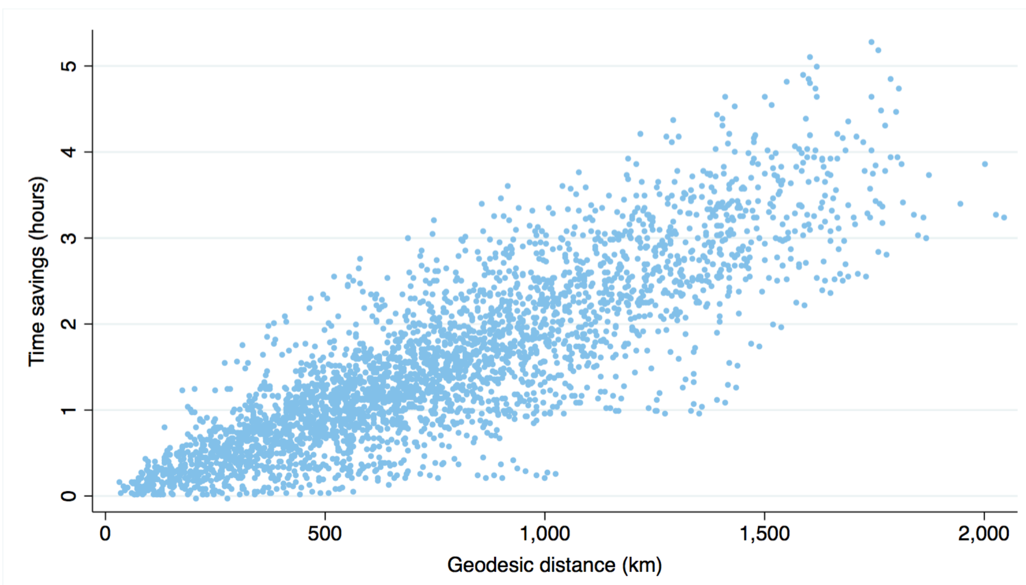
Notes: Data source is Turkish General Directorate of Highways. Red nodes denote provincial centers, thin grey lines represent single-carriageway roads, and thick green lines represent dual-carriageway roads (highways and expressways).

Figure 18: **Turkish Roads over Time**



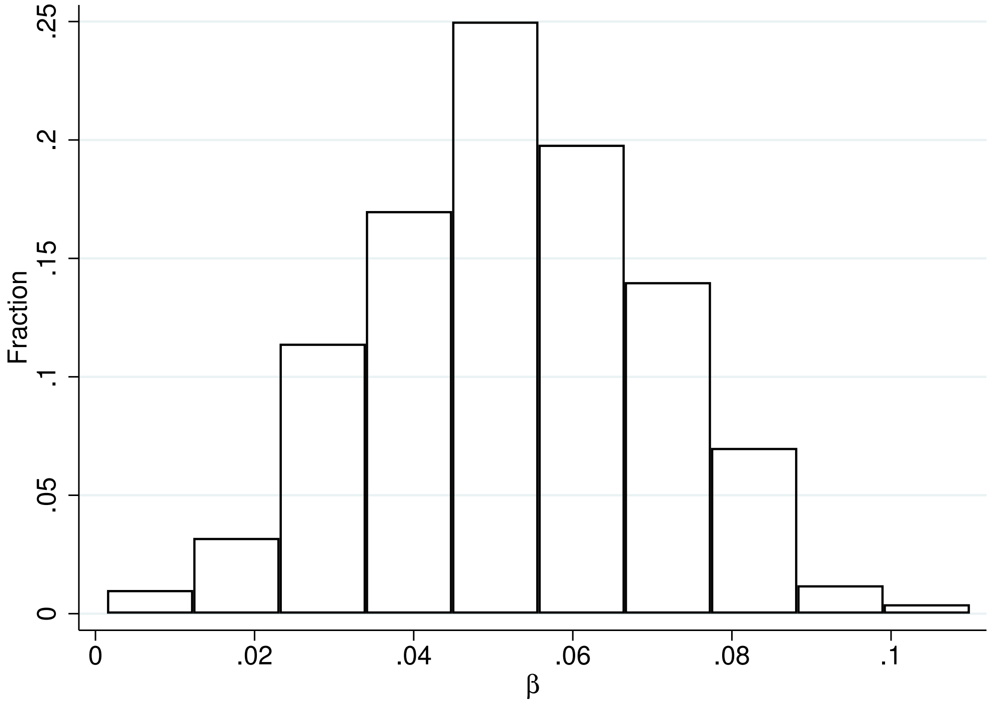
Notes: Data source is Turkish Statistical Institute and General Directorate of Highways. Data downloaded from http://bit.ly/2E3Qh4m, accessed on January 2018.

Figure 19: **Time Savings on Inter-Provincial Travel from 2005 to 2015**



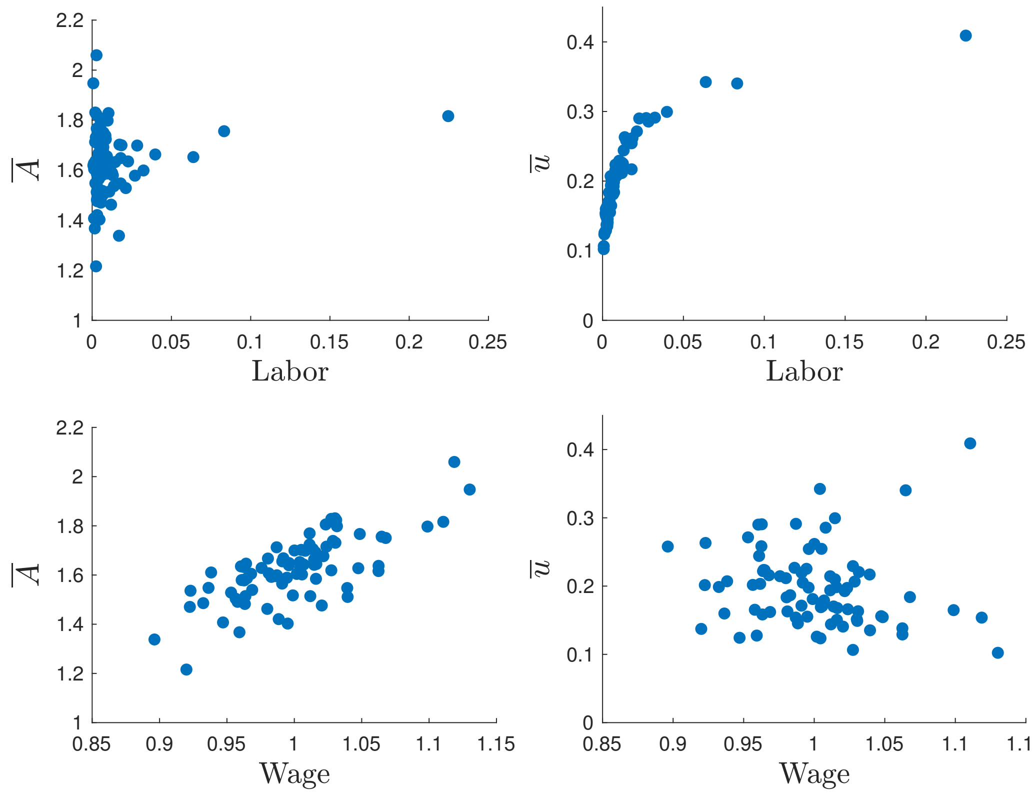
Notes: This chart plots declines in the fastest province-to-province travel times from 2005 to 2015 against the time-invariant distances as the crow flies. Each observation represents a pair of provinces. With 81 provinces, there are $(81 \times 80)/2 = 3,240$ unique pairs.

Figure 20: **Distribution of** β



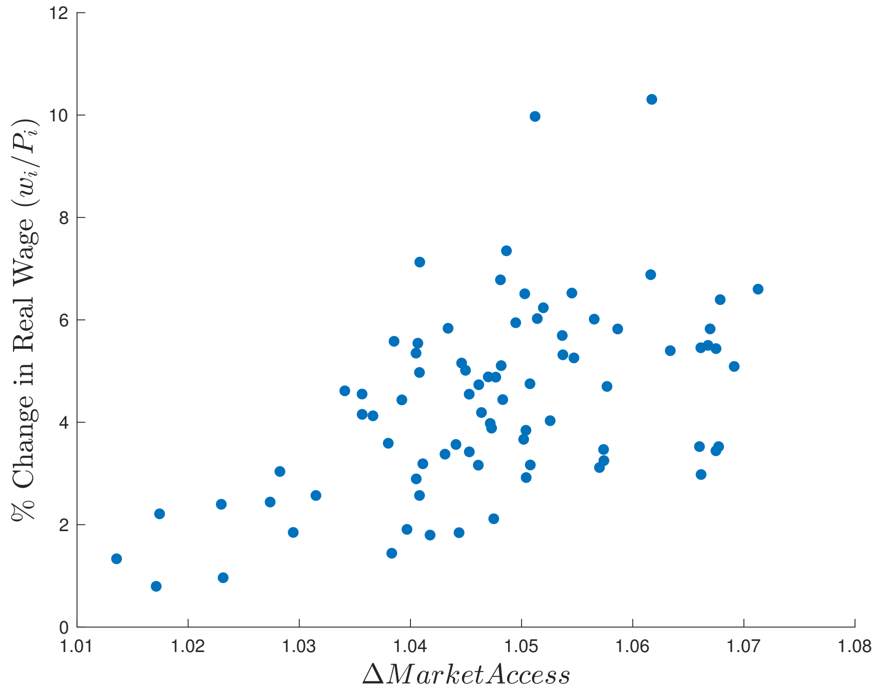
Notes: This figure plots the distribution of the estimate of β in equation (36), obtained from estimating the equation on 500 randomly drawn samples of province pairs of size 2000.

Figure 21: **Calibrated Exogenous Characteristics of Provinces**



Notes: Each observation is a province. Labor and wages are provinces' employment shares and normalized wages in 2006. $\overline{A}$ and $\overline{u}$ are the exogenous productivities and amenities, respectively. For their calibration, see Section 3.5.1.

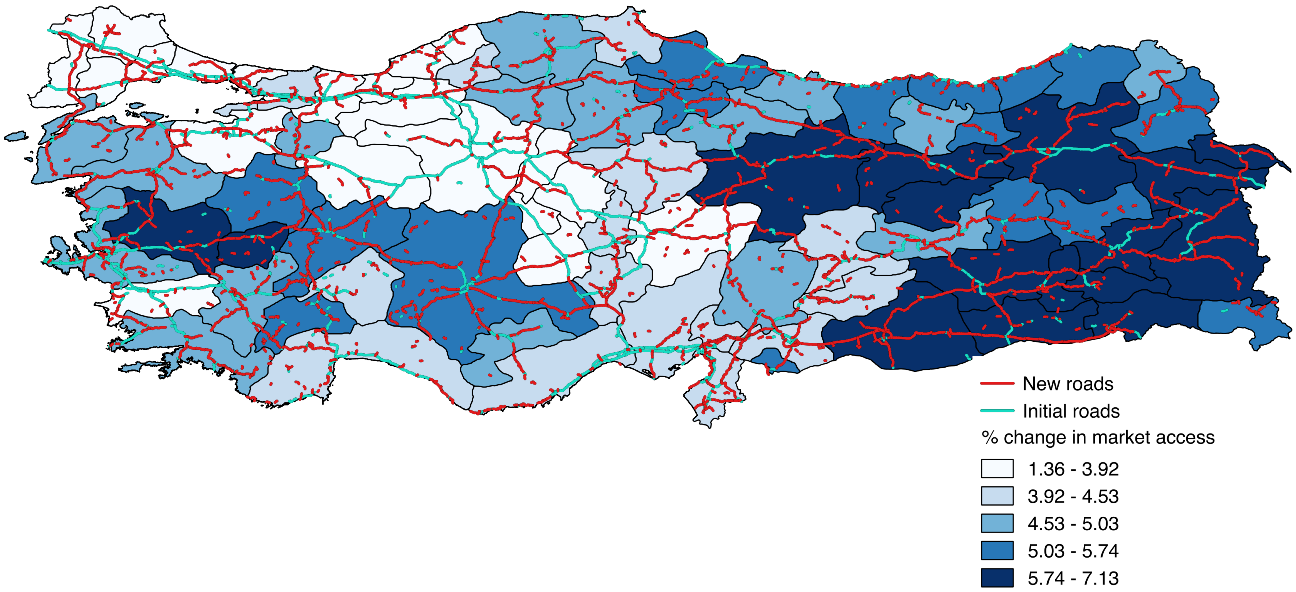
Figure 22: **Short-run Changes in Market Access and Real Wage**



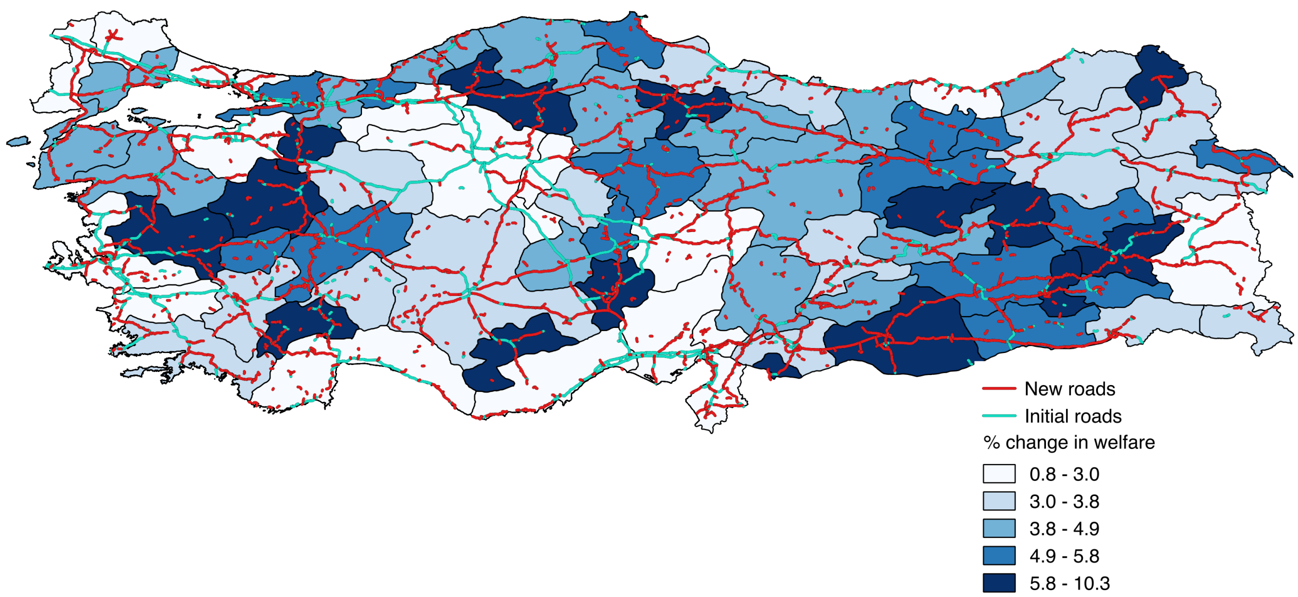
Notes: Each observation is a province. The y-axis is the percentage change in real wage (w/p) when labor is immobile in the short-run. The x-axis is a measure of market access change defined in Section 3.5.2.

Figure 23: **Short-run Changes in Market Access and Real Wage**

*Panel A: Change in Market Access



*Panel B: Change in Welfare



Notes: In both panels, initial roads in light green represent roads that were dual carriageways in 2005 (corresponding to the green roads in Panel A of Figure 1), and new roads in red represent the additions to the dual carriageway network in 2015. Short-run welfare results are changes in real wage w/P assuming labor is immobile.

Table 1: **PPML gravity estimation on district to district migration by reason for migration**

	(1) Education	(2) Work	(3) Other reasons
log distance between district centers	-0.585***	-0.567***	-0.752***
	(-71.67)	(-48.87)	(-60.02)
common language	0.656***	0.478***	0.335***
	(8.05)	(5.11)	(4.52)
Same state; neighboring districts	3.577***	3.002***	3.126***
	(64.25)	(39.58)	(35.16)
Same state; not neighboring districts	2.559***	2.088***	1.935***
	(47.51)	(29.10)	(25.72)
Different state, neighboring districts	2.422***	2.737***	2.845***
	(32.31)	(37.56)	(33.66)
N	342225	342225	342225

NOTE: The table shows the PPML estimation results, differentiated by reason for migration. t-statistics are reported in parenthesis.

Table 2: Migration Flows by Reason for Migration.

Reason for Migration	**No. of Migrants**	**Percentage**	**Out of State**	**Percentage**
Work	18,901,992	48	9,771,841	52
Education	11,507,98	3	3,59,029	31
Other	19,746,588	49	72,00,884	36
Total	39,799,378	100	17,331,754	44

NOTE: Column 1 lists the reason for migration. Column 2 lists the number of people migrating out of their district of previous residence by reason for migration in 2001. Column 3 shows the percentage distribution of migrants by reason for migration. Column 4 shows the number of people who migrated out of their own state of birth by reason for migration. Column 5 shows the percentage of people migrating out of their state of birth among the total number of migrants by reason for migration. Data source is the 2001 Census migration data.

Table 3: **Estimation of response of district to district migration flows to distances by reason for migration**

	(1) Education	(2) Work: Traditional	(3) Work:NLS
log distance between district centers	-.602***	-.554***	-.648***
	(-62.04)	(-55.55)	(-11.32)
common language	.307 ***	.393 ***	.14
	(17.77)	(3.00)	(0.90)
Same state; neighbors	3.646***	3.158***	1.235***
	(45.48)	(36.13)	(3.99)
Same state; not neighbors	2.379***	2.125***	1.673***
	(27.49)	(23.39)	(3.015)
Different state, neighbors	2.339***	2.737***	.7703***
	(17.16)	(35.17)	(3.74)
N	280900	280900	280900

NOTE: The table shows the PPML estimation results, differentiated by reason for migration. t-statistics are reported in parenthesis. Columns 1 and 2 reports the traditional PPML estimation results. Column 3 reports the results for work migration estimation using non linear least squares.

Table 4: **Trade Cost Estimation**

	(1) Exports OLS	(2) Exports IV1	(3) Exports IV2	(4) Exports State-level trend
Observable MC	-0.076***	-0.24***	-.21*	-.27***
	(-4.61)	(-6.87)	(-5.30)	(-2.64)
Constant	-0.066	-0.049	-.045	.259***
	(-1.48)	(-1.16)	(-1.20)	(4.87)
State-time Trend	Yes	No	No	Yes
IV	No	Remoteness, Hist Software Exp	+linguistic distance	Same
First Stage F-stat:		164.24***	86.34***	14.28***
N	523	523	523	523

Robust standard errors are used. t statistics are reported in parenthesis.

Table 5: **Summary of estimated parameter values**

Parameter	**Value**	**Source**
Productivity dispersion (θ)	2.61	Estimated
Education amenity dispersion (ζ)	2.42	Estimated
IT trade elasticity (σ_{IT})	1.27	Estimated
$\rho_S{}^*$	1.41	Katz and Murphy (1992)
$\rho_{hS}{}^*$	2	Ryoo and Rosen (2004)
Internal trade elasticity (σ_S)	5	Simonovska and Waugh (2014)
Agriculture share	.38	Ministry of Statistics, Govt of India
Manufacturing share	.16	-
High-skill services	.07	-
Other services	.37	-

Table 6: **Summary Statistics**

	2006	2016
Trade value	4.6	5.2
	(150.7)	(284.3)
Employment	1,385.4	2,247.4
	(8,787.2)	(14,824.0)
Domestic sales	161.4	525.7
	(2,350)	(7,785.7)
Time savings (hours)		1.4
		0.9
Total non-agriculture employment	15,516	21,900
Nominal GDP	46,011	115,218

Notes: Table shows the mean and standard error (in parentheses) of the main outcome variables at the industry-province level (industry-province pair level for trade values) used in the regressions. All values are in million USD, calculated using the average within-year TL/USD exchange rate in 2006 (1USD=1.4TL). Aggregate statistics (last two rows) are obtained from Turkish Statistics Institute.

Table 7: **Changes in Travel Times and Inter-provincial Trade by Sector**

	(1)	(2)	(3)	(4)
	Manufacturing		Non-agri./non-manuf.	
	Panel A: All provinces			
	$\Delta Trade_{ij}$	$NewTrade_{ij}$	$\Delta Trade_{ij}$	$NewTrade_{ij}$
$\left\|\Delta TravelTime_{ij}\right\|$	0.0527*	0.0367**	0.0009	0.0957***
	(0.030)	(0.014)	(0.021)	(0.015)
N	3,995	4,977	4,725	4,977
R^2	0.218	0.187	0.133	0.294
	Panel B: Excluding Istanbul as destination			
	$\Delta Trade_{ij}$	$NewTrade_{ij}$	$\Delta Trade_{ij}$	$NewTrade_{ij}$
$\left\|\Delta TravelTime_{ij}\right\|$	0.0542*	0.0361**	0.0005	0.0978***
	(0.031)	(0.015)	(0.022)	(0.015)
N	3,914	4,896	4,644	4,896
R^2	0.215	0.186	0.133	0.293
	Panel C: Excluding Istanbul as source			
	$\Delta Trade_{ij}$	$NewTrade_{ij}$	$\Delta Trade_{ij}$	$NewTrade_{ij}$
$\left\|\Delta TravelTime_{ij}\right\|$	0.0527*	0.0368**	0.00105	0.0961***
	(0.030)	(0.014)	(0.021)	(0.015)
N	3,962	4,944	4,692	4,944
R^2	0.217	0.185	0.130	0.292
Origin FE	Y	Y	Y	Y
Destination FE	Y	Y	Y	Y

Notes: Robust standard errors clustered at the source and destination provinces (two-way) are in parentheses. Non-agri./non-manuf. includes wholesale, retail trade and services other than finance and utilities. Significance: *10%, **5%, ***1%.

Table 8: **Changes in Travel Times and Inter-provincial Industry-level Trade**

	(1)	(2)	(3)	(4)
	$\Delta Trade_{is,js'}$	$NewTrade_{is,js'}$	$\Delta Trade_{is,js'}$	$NewTrade_{is,js'}$
$\lvert\Delta TravelTime_{ij}\rvert$	0.0493***	0.0512***	0.0338***	0.0292***
	(0.005)	(0.007)	(0.004)	(0.003)
$TradeShare_{ij}^{2006}$			-0.307***	-0.464***
			(0.049)	(0.065)
N	436093	529897	436093	529897
R^2	0.168	0.146	0.169	0.150
Origin-Ind. FE	Y	Y	Y	Y
Dest.-Ind. FE	Y	Y	Y	Y

Notes: Robust standard errors clustered at the source-destination pairs are in parentheses. Significance: *10%, **5%, ***1%.

Table 9: **Changes in Travel Times and Inter-provincial Industry-level Trade by Sector**

	(1)	(2)	(3)	(4)
	Manufacturing		Non-agri./non-manuf.	
	$\Delta Trade_{is,js'}$	$NewTrade_{is,js'}$	$\Delta Trade_{is,js'}$	$NewTrade_{is,js'}$
$\lvert\Delta TravelTime_{ij}\rvert$	0.0272***	0.0213***	0.0374***	0.0336***
	(0.006)	(0.004)	(0.005)	(0.003)
$TradeShare_{ij}^{2006}$	-0.211***	-0.274***	-0.361***	-0.532***
	(0.041)	(0.044)	(0.035)	(0.061)
N	173884	213819	262209	316078
R^2	0.189	0.167	0.162	0.156
Origin-Ind. FE	Y	Y	Y	Y
Dest.-Ind. FE	Y	Y	Y	Y

Notes: Robust standard errors clustered at the source-destination pairs are in parentheses. Non-agri./non-manuf. includes wholesale, retail trade and services other than finance and utilities. Significance: *10%, **5%, ***1%.

Table 10: **Robustness Checks**

	(1) $\Delta Trade_{is,js'}^{2006-2011}$	(2) $\Delta Trade_{is,js'}^{2006-2011}$
$\left\|\Delta TravelTime_{ij}^{2005-2010}\right\|$	0.0357***	0.0350***
	(0.005)	(0.006)
$TradeShare_{ij}^{2006}$	-0.459***	-0.458****
	(0.051)	(0.051)
$\left\|\Delta TravelTime_{ij}^{2010-2015}\right\|$		0.00879
		(0.031)
N	354289	354289
R^2	0.151	0.151
Origin-Ind. FE	Y	Y
Dest.-Ind. FE	Y	Y

Notes: Robust standard errors clustered at the source-destination pairs are in parentheses. Significance: *10%, **5%, ***1%.

Table 11: **Impact of Travel Times on Regional Sales**

	(1)	(2)	(3)
Panel A:		$\Delta \ln(Y_{is})$	
$\left\|\Delta \overline{TravelTime_i}\right\|$	0.239***	0.221***	0.114+
	(0.048)	(0.049)	(0.076)
$PopShare_i^{2005}$		-2.994***	-1.624
		(0.912)	(1.127)
$\ln GDPpc_i^{2005}$			-0.303*
			(0.170)
N	4174	4174	4174
R^2	0.168	0.170	0.171
Panel B:		$\Delta \ln(Y_{is}^{dom})$	
$\left\|\Delta \overline{TravelTime_i}\right\|$	0.234***	0.216***	0.118*
	(0.044)	(0.045)	(0.069)
$PopShare_i^{2005}$		-2.771***	-1.508+
		(0.827)	(0.975)
$\ln GDPpc_i^{2005}$			-0.279*
			(0.150)
N	4139	4139	4139
R^2	0.171	0.173	0.174
Panel C:		$\Delta \ln(Y_{is}^{exp})$	
$\left\|\Delta \overline{TravelTime_i}\right\|$	0.227**	0.235*	0.407**
	(0.114)	(0.119)	(0.201)
$PopShare_i^{2005}$		0.736	-0.901
		(1.296)	(1.974)
$\ln GDPpc_i^{2005}$			0.446
			(0.420)
N	1574	1574	1574
R^2	0.107	0.107	0.108
Industry FE	Y	Y	Y

Notes: Robust standard errors clustered at the province level are in parentheses. Significance: +15%, *10%, **5%, ***1%. Dependent variables in Panel A, B and C are the logarithms of total sales of province p's industry i, its domestic sales and export sales, respectively.

Table 12: **Impact of Travel Times on Regional Employment and Labor Productivity**

	(1)	(2)	(3)
Panel A:		$\Delta \ln(L_{is})$	
$\left\lvert\Delta \overline{TravelTime_i}\right\rvert$	0.203***	0.202***	0.157***
	(0.032)	(0.033)	(0.047)
$PopShare_i^{2005}$		-0.125	0.452
		(0.412)	(0.732)
$\ln GDPpc_i^{2005}$			-0.128
			(0.122)
N	4139	4139	4139
R^2	0.215	0.215	0.216
Panel B:		$\Delta \ln\left(\frac{Y_{is}}{L_{is}}\right)$	
$\left\lvert\Delta \overline{TravelTime_i}\right\rvert$	0.0411	0.0232	-0.0236
	(0.052)	(0.053)	(0.073)
$PopShare_i^{2005}$		-2.843***	-2.246**
		(0.826)	(0.875)
$\ln GDPpc_i^{2005}$			-0.133
			(0.121)
N	4047	4047	4047
R^2	0.0994	0.102	0.103
Industry FE	Y	Y	Y

Notes: Robust standard errors clustered at the province level are in parentheses. Significance: *10%, **5%, ***1%.

Table 13: **Estimation of Trade Costs**

	(1)	(2)
	$\ln(Trade_{ij})$	
$\ln(TravelTime_{ij})$	-1.461***	-1.537***
	(0.026)	(0.025)
Observations	3704	3704
Year	2006	2015
R^2	0.781	0.816

Notes: $TravelTime_{ij}$ is travel times divided by the minimum travel time in the data. Within-province travel times are set to $TravelTime_{ii} = 1$. See section 3.5.1 for details. Robust standard errors are in parentheses. Significance: *10%, **5%, ***1%.

Table 14: **Long-run Aggregate Welfare Effects**

		σ		
		3	5	7
2pt2-5	0	5.86%	2.86%	1.89%
α	1/6	5.92%	2.89%	1.9%
	1/3	6.25%	3.08%	2.04%

Notes: This table reports the aggregate percentage welfare gains for combinations of values for the elasticity of substitution σ and strength of agglomeration economies α.

References

Allen, T. and C. Arkolakis (2014). Trade and the topography of the spatial economy. *Quarterly Journal of Economics*.

Allen, T., C. d. C. Dobbin, and M. Morten (2018, nov). Border Walls. Technical report, National Bureau of Economic Research, Cambridge, MA.

Asturias, J., R. Ramos, and M. G. Santana (2018). Competition and the welfare gains from transportation infrastructure: Evidence from the golden quadrilateral in india. *Journal of the European Economic Association*.

Atkin, D. (2016, aug). Endogenous skill acquisition and export manufacturing in Mexico. *American Economic Review 106*(8), 2046–2085.

Banerjee, A. V. and E. Duflo (2000). Reputation effects and the limits of contracting: A study of the Indian software industry. *Quarterly Journal of Economics 115*(3), 989–1017.

Blanchard, E. J. and W. W. Olney (2017, may). Globalization and human capital investment: Export composition drives educational attainment. *Journal of International Economics 106*, 165–183.

Borsook, I. (1987). Earnings, ability and international trade. *Journal of International Economics 22*(3-4), 281–295.

Bryan, G. and M. Morten (2019, jul). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy*, 000–000.

Caliendo, L., M. Dvorkin, and F. Parro (2019). Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *Econometrica 87*(3), 741–835.

Card, D. and T. Lemieux (2001). Can falling supply explain the rising return to college for younger men? A cohort-based analysis. *Quarterly Journal of Economics 116*(2), 705–746.

Carmel, E. and P. Tjia (2005). *Offshoring Information Sourcing and Outsourcing to a Global Workforce*. Cambridge University Press.

Coşar, A. K. and B. Demir (2016). Domestic road infrastructure and international trade: Evidence from turkey. *Journal of Development Economics 118*.

Danziger, E. (2017, jul). Skill acquisition and the dynamics of trade-induced inequality. *Journal of International Economics 107*, 60–74.

Donaldson, D. (2018, apr). Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review 108*(4-5), 899–934.

Duranton, G., P. Morrow, and M. A. Turner (2014). Roads and trade: Evidence from the us. *The Review of Economic Studies*.

EBRD (2017). Chapter 3 of transition report 2017/2018: Infrastructure and growth. Report Transition Report 2017/2018, European Bank for Reconstruction and Development, London.

Economist (2003). America's pain, India's gain.

Edmonds, E. V., N. Pavcnik, and P. Topalova (2010, oct). Trade adjustment and human capital investments: Evidence from indian tariff reform. *American Economic Journal: Applied Economics 2*(4), 42–75.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from china's national trunk highway system. *The Review of Economic Studies*.

Fan, J. (2019, jul). Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics 11*(3), 252–288.

Ferriere, A., G. Navarro, and R. Reyes-Heroles (2018). Escaping the Losses from Trade: The Impact of Heterogeneity on Skill Acquisition *. Technical report.

Findlay, R. and H. Kierzkowski (1983, dec). International Trade and Human Capital: A Simple General Equilibrium Model. *Journal of Political Economy 91*(6), 957–978.

Fuchs, S. (2018). The Spoils of War: Trade Shocks during WWI and Spain's Regional Development Job Market Paper *. Technical report.

GDH (2014). Turkish general directorate of highways, divided highway projects. Website. http://translate.google.com/translate?hl=en&sl=tr&tl=en&u=http://www.kgm.gov.tr/Sayfalar/KGM/SiteTr/Projeler/Projeler-BolunmusYol.aspx.

Goldin, C. and L. Katz (2007, nov). Long-Run Changes in the U.S. Wage Structure: Narrowing, Widening, Polarizing. Technical report, National Bureau of Economic Research, Cambridge, MA.

Greenland, A. and J. Lopresti (2016, may). Import exposure and human capital adjustment: Evidence from the U.S. *Journal of International Economics 100*, 50–60.

Head, K. and T. Mayer (2014). Gravity Equations: Workhorse,Toolkit, and Cookbook. In *Handbook of International Economics*, Volume 4, pp. 131–195. Elsevier B.V.

Hou, Y. and C. Karayalcin (2019, aug). Exports of primary goods and human capital accumulation. *Review of International Economics*.

International Trade Center (2017). TRADE IMPACT FOR GOOD BRICS COUNTRIES: EMERGING PLAYERS IN GLOBAL SERVICES TRADE. Technical report.

Johnson, M. T. (2013, oct). Borrowing constraints, college enrollment, and delayed entry. *Journal of Labor Economics 31*(4), 669–725.

Jones, B. F. and . Kellogg (2014). The Human Capital Stock: A Generalized Approach †. *American Economic Review 104*(11), 3752–3777.

Kapur, D. (2002). India Review The causes and consequences of India's IT boom.

Katz, L. F. and K. M. Murphy (1992, feb). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics 107*(1), 35–78.

Kebede, H. (2019). The gains from market integration: The welfare effects of rural roads in ethiopia. *University of Virginia mimeo*.

Khanna, G. and N. Morales (2017, sep). The it Boom and Other Unintended Consequences of Chasing the American Dream. *SSRN Electronic Journal*.

Kone, Z. L., M. Y. Liu, A. Mattoo, C. Ozden, and S. Sharma (2018, jul). Internal borders and migration in India. *Journal of Economic Geography 18*(4), 729–759.

Kucheryavyy, K., G. Lyn, and A. Rodríguez-Clare (2016, aug). Grounded by Gravity: A Well-Behaved Trade Model with Industry-Level Economies of Scale. Technical report, National Bureau of Economic Research, Cambridge, MA.

Lee, C. (2005). Labor Market Status of Older Males in the United States, 1880-1940. *Social Science History 29*(1), 77–105.

Li, B. (2018, sep). Export expansion, skill acquisition and industry specialization: evidence from china. *Journal of International Economics 114*, 346–361.

Li, L. (2019). Skill-biased Imports, Human Capital Accumulation, and the Allocation of Talent *. Technical report.

Limao, N. and A. J. Venables (2001). Infrastructure, geographical disadvantage, transport costs, and trade. *The World Bank Economic Review 15*(3), 451–479.

Liu, M. Y. (2017). How does globalization affect educational attainment? Evidence from China *. Technical report.

Ma, S., Y. Liu, and M. Zhou (2019, aug). Trade, educational costs, and skill acquisition. *Review of International Economics*.

Mathur, S. K. (2006). Indian Information Technology Industry: Past, Present and Future& A Tool for National Development. Technical Report 2.

Murat, O. and F. Zorlu (2018). Türkiye'de devlet karayollarında kaza oranlarının ve kaza örüntüsünün analizi. *Teknik Dergi 29*(5), 8589–8604. https://dergipark.org.tr/tr/download/article-file/529673.

Oster, E. and B. M. Steinberg (2013, sep). Do IT service centers promote school enrollment? Evidence from India. *Journal of Development Economics 104*, 123–135.

Rosenthal, S. S. and W. C. Strange (2004). Evidence on the nature and sources of agglomeration economies. In *Handbook of regional and urban economics*, Volume 4, pp. 2119–2171. Elsevier.

Ryoo, J. and S. Rosen (2004, feb). The engineering labor market. *Journal of Political Economy 112*(1).

Santos Silva, J. M. and S. Tenreyro (2006, nov). The log of gravity. *Review of Economics and Statistics 88*(4), 641–658.

Shastry, G. K. (2012). Human capital response to globalization: Education and information technology in India. *Journal of Human Resources 47*(2), 287–330.

Simonovska, I. and M. Waugh (2014a). The elasticity of trade: Estimates and evidence,. *Journal of International Economics*.

Simonovska, I. and M. E. Waugh (2014b, jan). The elasticity of trade: Estimates and evidence. *Journal of International Economics 92*(1), 34–50.

Stiglitz, J. E. (1970, may). Factor Price Equalization in a Dynamic Economy. *Journal of Political Economy 78*(3), 456–488.

Tharakan, P. K., I. Van Beveren, and T. Van Ourti (2005, nov). Determinants of India's software exports and goods exports. *Review of Economics and Statistics 87*(4), 776–780.

Tombe, T. and X. Zhu (2019). Trade, migration, and productivity: A quantitative analysis of China. In *American Economic Review*, Volume 109, pp. 1843–1872. American Economic Association.

Tsivanidis, N. (2018). The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio . Technical report.

UC Berkeley (1999). 8.02.99 - UC Berkeley computer scientists attack Y2K bug with new program to find millennium glitches in C applications.

Van Leemput, E. (2016, dec). A Passage to India: Quantifying Internal and External Barriers to Trade. *International Finance Discussion Paper 2016*(1185), 1–65.

Yeaple, S. and S. Golub (2007). International productivity differences, infrastructure, and comparative advantage. *Review of International Economics 15*(2), 223–242.

A Data

A.1 Education and labor market data

Table 15: Summary statistics of education

Education	Pre Boom	Post Boom
Engineers/college enrollment	5.10%	11.45%
College enrollment	12,404	32,632

Table 16: Summary statistics of wages

	Pre Boom		Post Boom	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev**
Labor market: Wages				
High-skill services				
College-educated	363.64	336.98	467.18	243.15
Non college-educated	171.02	80.28	275.17	235.45
Manufacturing				
College-educated	324.25	570.00	307.96	209.08
Non college-educated	115.08	111.37	152.21	104.28

Table 17: Summary statistics of employment

	Pre Boom		Post Boom	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev**
Labor market: Employment				
High-skill services				
College-educated	7256	16526	9664	16125
Non college-educated	7574	13553	11750	204375
Manufacturing				
College-educated	25276	43491	30799	49503
Non college-educated	34231	61375	44380	66592

A.2 Linguistic distance

I summarize the way Shastry (2012) described the construction of this index in her paper. The 1961 Census of India documented speakers of 1652 languages from five language families. Much linguistic diversity is between districts. A district's primary language is native to 83 percent of residents on average, ranging from 22 percent to 100 percent. Most people thus adopt a second language that is a widely accepted speaking medium across districts. Of all multi-linguals who were not native speakers, 60 percent chose to learn Hindi and 56 percent chose English. Think of an individual who is not a native Hindi speaker. Given everything else, whether this individual learns Hindi or English as a second language depends on the relative costs of learning that language, which in turn depends on her mother tongue. Someone whose mother tongue is similar (not similar) to Hindi will find Hindi easier (more difficult) to learn relative to English. To quantify what is the relative cost of learning Hindi or English , Shastry constructed three measures of linguistic distance of each native language from Hindi.The first measure classifies languages into five "degrees" of linguistic distance from Hindi based on cognates, grammar, and syntax (see Table 2). The second measure is the percent of words from a core list that are cognates of Hindi words. The third measure is based on language family trees from the Ethnologue database. These measures are highly correlated: 0.935 between degrees and percent cognates and 0.903 between degrees and nodes.

Table 18: Measures of linguistic distance to hindi

Sample Language	**Degrees**	**% Cognates**	**Nodes**	**% Native Speakers**
0 Degrees	0	100	0	.456
Hindi, Urdu				
1 Degree	1	67.1	5	0.084
Gujarati, Punjabi, Rajasthani				
2 Degrees	2	56.4	6.5	.076
Konkani, Marathi				
3 Degrees	3	64.1	7	.133
Assamese, Bengali, Bihari, Oriya				
4 Degrees	4	53.3	7.3	0.005
Kashmiri, Sindhi, Sinhalese				
5 Degrees	5	5	12.5	.244
All non-Indo European Languages				

Source: Gauri Kartini Shashtry, 2012

From the 1991 census of India, Shastry calculates a district's linguistic distance from

Hindi in two ways-1) the population weighted average distance of all native languages from Hindi and 2) the population share of languages at least 3 degrees away from Hindi. All my analysis that follows is conducted with measure 2) but the analysis are robust to using measure 1) instead. Shastry proxies English-learning costs as linguistic distance from Hindi. One may think the natural proxy is linguistic distance from English, but it is the relative costs of learning Hindi and English that should determine which language one learns. A native Hindi speaker can choose to learn English as a second language at a much lower cost than a non-native speaker whose language is close to Hindi. So there is a non-monotonicity in the relationship- native Hindi speakers are more likely to learn English but speakers of languages close to Hindi learn Hindi rather than English. Then as distance to Hindi rises, the probability of learning English as a second language rises except for at distance 0. Shastry (2012) shows that such a relation holds. From now on, I would use linguistically distant to Hindi and linguistically closer to English interchangeably.

A.3 Missing value imputation

The NSS is a sample as opposed to the Census which is a complete enumeration. In the NSS, individuals are included in the sample so that it is representative. However, there are many observations in the NSS where no individual working in sector S, having a degree in s in district d has been interviewed, even though according to the Census there are individuals working in sector S, having a degree in s in district d. I use a weighted knn where the weights can be uniform, ie, only the reciprocal of the distance or the weights could be Gaussian Kernel, Epanechnikov, Cosine etc (isotropic Kernels) to impute missing values. This machine learning technique involves using a training data to choose the value of "k" that minimizes the sum of squared distances between the actual and predicted values, where the predicted values are obtained by taking a weighted average of the variables values of the "k" nearest neighbors. I have used the uniform Kernel as weight here.

B Reduced Form Facts

B.1 Stylized facts 1 and 2

The table below reports the regression results for total IT employment graph reported in the reduced form facts section.

	(1)
	Standardized Employment
year=1995 × Standardized Historical Export	0.000
	(.)
year=1998 × Standardized Historical Export	0.028
	(0.22)
year=1999 × Standardized Historical Export	0.175
	(1.58)
year=2002 × Standardized Historical Export	0.361***
	(3.37)
year=2003 × Standardized Historical Export	0.373***
	(3.31)
year=2005 × Standardized Historical Export	0.310**
	(2.18)
year=2013 × Standardized Historical Export	0.395**
	(1.99)
Constant	-0.071***
	(-3.57)
N	3880.000

Table 19: **Response of the IT sector**

	(1)	(2)	(3)	(4)
	total employment	total employment	total employment	total employment
1998 × Software Exports 1995	0.028			0.028***
	(0.22)			(5.73)
1999 × Software Exports 1995	0.175			0.175***
	(1.58)			(4.28)
2002 × Software Exports 1995	0.361***			0.361***
	(3.37)			(3.10)
2003 × Software Exports 1995	0.373***			0.373***
	(3.31)			(2.79)
2005 × Software Exports 1995	0.310**			0.310
	(2.18)			(1.54)
2013 × Software Exports 1995	0.395**			0.395
	(1.99)			(1.63)
1998 × AnyExports		0.129**	0.129**	
		(2.40)	(2.14)	
year=1999 × AnyExports		0.932***	0.932***	
		(3.11)	(3.25)	
year=2002 × AnyExports		1.858***	1.858***	
		(2.81)	(2.91)	
year=2003 × AnyExports		1.823***	1.823**	
		(2.61)	(2.65)	
year=2005 × AnyExports		1.773**	1.773**	
		(2.31)	(2.59)	
year=2013 × AnyExports		3.849**	3.849**	
		(2.19)	(2.42)	
Clustering	District	District	State	State
Observations	3880	3880	3880	3880

Table 20: **Response of the Education Sector**

	(1) Engineers	(2) Engineers	(3) Engineers	(4) Proportion of Engineers	(5) Proportion	(6) Proportion
AnyExports	0.000	0.000	0.000			
	(.)	(.)	(.)			
2001 × Any Exports	1.449	1.449**	1.449**			
	(1.40)	(2.43)	(2.23)			
2011 × Any Exports	4.998***	4.998**	4.998**			
	(3.08)	(2.51)	(2.18)			
Historical Software Exports				0.000	0.000	0.000
				(.)	(.)	(.)
2001 × Historical Software Exports				0.104	0.104**	0.104**
				(1.56)	(2.39)	(2.43)
2011 × Historical Software Exports				0.348***	0.348**	0.348**
				(3.33)	(2.23)	(2.36)
N	1726	1726	1726	1724	1724	1724

Table 21: **Heterogeneous Response of IT Employment**

	(1) total employment	(2) total employment	(3) total employment	(4) total employment	(5) total employment	(6) total employment
year=1998 × AnyExports × Engineers 1991	0.012*	0.012	0.012*			
	(1.85)	(1.51)	(1.84)			
year=1999 × AnyExports × Engineers 1991	0.018***	0.018***	0.018***			
	(3.00)	(2.95)	(2.97)			
year=2002 × AnyExports × Engineers 1991	0.041***	0.041**	0.041**			
	(2.76)	(2.47)	(2.50)			
year=2003 × AnyExports × Engineers 1991	0.045***	0.045***	0.045**			
	(2.75)	(2.60)	(2.65)			
year=2005 × AnyExports × Engineers 1991	0.045***	0.045**	0.045**			
	(2.76)	(2.41)	(2.51)			
year=2013 × AnyExports × Engineers 1991	0.052	0.052	0.052			
	(1.25)	(1.09)	(1.29)			
year=1998 × Historical Software Exports × Engineers 1991				0.000	0.000	0.000**
				(0.92)	(0.41)	(2.28)
year=1999 × Historical Software Exports × Engineers 1991				0.001**	0.001**	0.001**
				(2.26)	(2.53)	(2.24)
year=2002 × Historical Software Exports × Engineers 1991				0.004***	0.004***	0.004***
				(4.70)	(6.56)	(6.09)
year=2003 × Historical Software Exports × Engineers 1991				0.005***	0.005***	0.005***
				(5.53)	(7.79)	(7.39)
year=2005 × Historical Software Exports × Engineers 1991				0.005***	0.005***	0.005***
				(3.95)	(2.95)	(3.68)
year=2013 × Historical Software Exports × Engineers 1991				-0.002	-0.002	-0.002
				(-0.93)	(-0.62)	(-0.77)
Clustering	State time	District	State	State time	District	State
N	3838	3838	3838	3838	3838	3838

Table 22: **Response of IT employment, with historical software exports predicted by linguistic distances**

	(1) Standardized Employment
year=1995 × Standardized Historical Export	0.000
	(.)
year=1998 × Standardized Historical Export	0.033
	(0.08)
year=1999 × Standardized Historical Export	0.318
	(0.97)
year=2002 × Standardized Historical Export	0.645**
	(1.91)
year=2003 × Standardized Historical Export	0.667*
	(1.88)
year=2005 × Standardized Historical Export	0.665**
	(1.92)
year=2013 × Standardized Historical Export	0.955
	(1.58)
Constant	-0.08***
	(-3.47)
N	3880.000

Table 23: **Predicting historical software exports**

	(1) Standardized Employment
Hindi speakers	0.115***
	(2.62)
English speakers	1020.29***
	(23.46)
linguistic distance	0.007
	(0.614)
Constant	-0.18***
	(-3.30)
N	2731
F(3,2727)	184.29
Adjusted R-squared	.167

Table 24: **Gravity estimation by reason for migration, replicating table 8 from Kone et al**

	(1) Marriage	(2) Work or Business	(3) Move with Family	(4) Education
log distance_centroid	-1.626***	-1.481***	-1.454***	-1.207***
	(-48.78)	(-50.19)	(-44.60)	(-47.62)
common	1.077***	0.499***	0.941***	1.338***
	(15.65)	(7.01)	(15.40)	(19.14)
Same state,; neighbors	2.265***	1.508***	1.681***	2.359***
	(40.98)	(24.20)	(24.41)	(43.37)
Same state; not neighbors	0.881***	1.226***	1.148***	1.777***
	(19.09)	(22.52)	(20.72)	(38.25)
Different state; neighbors	2.167***	1.054***	1.368***	1.036***
	(34.24)	(14.27)	(18.39)	(12.86)
N	341640	341640	341640	341640

t-stats reported in parenthesis

C Model Derivations

C.1 Worker's problem

Problem of worker i educated in o_2 in field f who goes to work in d in sector S is given by: Max $\Pi_S C_S^{\alpha_S}$ where $C_S = (\sum_k c_{kdS}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$

s.t $\sum_k \sum_{S'} p_{kdS'} c_{kdS'} = W_{f,dS} \eta_{io_2f,dS} \mu_{o_2d}$

This yields : Consumption of variety k of good S' for an individual who got his degree in o_2 and moved to d to work in occupation S is given by:

$$c_{ikf,dS'} = (p_{kdS'})^{-\sigma} P_{dS'}^{\sigma-1} (\alpha_{S'} W_{f,dS'} \eta_{ikf,dS'} \mu_{o_2d})$$

Assuming ice-berg transportation cost:

$$p_{kdS'} = \tau_{kdS'} p_{kS'}$$

Consumption of variety k of good S' for an individual who got his degree in o_2 and moved to d is given by:

$$c_{ikf,dS'} = (\tau_{kdS'}p_{kS'})^{-\sigma}P_{dS}^{\sigma-1}(\alpha_{S'}W_{f,dS}\eta_{if,dS}\mu_{o_2d})$$

Using the above quantities, worker indirect utility in stage 2 is derived as:

$$U_{io_2f,dS} = \frac{W_{f,dS}u_d\eta_{if,dS}\mu_{o_2d}}{\Pi_S P_{dS}^{\alpha_S}} \tag{44}$$

We can derive the indirect utility for stage 1 very similarly and this gives a combined stage 1 and stage 2 utility of the following form:

$$U_{io_2f,dS} = \Big(\mu_{o_2d}a_{o_2s}\zeta_{io_2s}\Big)\Big(\frac{W_{f,dS}u_d\eta_{if,dS}\mu_{o_2d}}{\Pi_S P_{dS}^{\alpha_S}}\Big) \tag{45}$$

where $P_{dS} = \sum_d \tau_{kdS}p_{kS}$

C.2 Firm's problem

The firm profit maximization condition for sector S is given by:

$$max_{L_{sdS}\forall d,s}P_{dS}Q_{dS} - \sum_s w_{sdS}\tilde{L}_{sdS} - w_{sdS}\tilde{L}_{sdS}$$

where $Q_{dS} = (Q_{hdS}^{\frac{\rho_S-1}{\rho_S}} + Q_{ldS}^{\frac{\rho_S-1}{\rho_S}})^{\frac{\rho_S}{\rho_S-1}}$

$Q_{hdS} = (\sum_{s\in college,k} A_{sdS}(\tilde{L}_{sdS})^{\frac{\rho_{hS}-1}{\rho_{hS}}})^{\frac{\rho_{hS}}{\rho_{hS}-1}}$
and in theory we can have, $Q_{ldS} = (\sum_{s\in nocollege} A_{sdS}(\tilde{L}_{sdS})^{\frac{\rho_{lS}-1}{\rho_{lS}}})^{\frac{\rho_{lS}}{\rho_{lS}-1}}$

For this paper, I use only one type of unskilled labor. And thus, here $Q_{ldS} =$

$(A_{ldS}\tilde{L}_{ldS})$

Differentiating with respect to $\tilde{L}_{s,S,k'}$ where s=e or ne,

$P_{dS}\frac{\rho_S}{\rho_S-1}Q_{dS}^{\frac{1}{\rho_S}}\frac{\rho_S-1}{\rho}Q_{hdS}^{\frac{-1}{\rho_S}}\frac{\rho_{h,S}}{\rho_{h,S}-1}(\sum_{s\in college,k}A_{sdS}(\tilde{L}_{sdS})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{\rho_{h,S}-1}-1}A_{sdS}\frac{\rho_{h,S}-1}{\rho_{h,S}}(\tilde{L}_{sdS})^{\frac{-1}{\rho_h}}$
$= w_{k',s,S}$

Simplifying ,

$P_{dS}Q_{dS}^{\frac{1}{\rho_S}}Q_{hdS}^{\frac{-1}{\rho_S}}(\sum_{s\in college,k}A_{sdS}(\tilde{L}_{sdS})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{1}{\rho_{h,S}-1}}A_{sdS}(\tilde{L}_{sdS})^{\frac{-1}{\rho_h}}$
$= w_{sdS}$

Simplifying further, $P_{dS}Q_{dS}^{\frac{1}{\rho_S}}Q_{hdS}^{\frac{1}{\rho_{h,S}}-\frac{1}{\rho_S}}A_{sdS}(\tilde{L}_{sdS})^{\frac{-1}{\rho_h}} = w_{sdS}$ In the empirical model, we use engineers and non-engineers as two types of skilled labor. Denoting s=e and s=ne for engineers and non-engineers respectively, one can derive the following foc:

$$\frac{A_{e,d,S}L_{e,d,S}^{\frac{-1}{\rho_{h,S}}}}{A_{ne,d,S}L_{ne,d,S}^{\frac{-1}{\rho_{h,S}}}} = \frac{w_{e,d,S}}{w_{ne,d,S}} \tag{46}$$

Under the assumption that all productivities are drawn from the same Frechet distribution, and firms do not know worker productivities,the foc does not contain effective labor, only labor. We thus get the following estimating equation:

$\frac{A_{e,d,S}L_{e,d,S}^{\frac{-1}{\rho_{h,S}}}}{A_{ne,d,S}L_{ne,d,S}^{\frac{-1}{\rho_{h,S}}}} = \frac{w_{e,d,S}}{w_{ne,d,S}}$

Denote $(p_{dS}^h)^{1-\rho_S} = (p_{dS}^h)^{1-\rho_S} + (p_{dS}^l)^{1-\rho_S}$

where, $p^l_{dS} = A_{ldS} w_{ldS}$

where, $p^h_{dS}{}^{(1-\rho_{hS})} = \sum_s A^{\rho_{h,S}}_{sdS} w^{(1-\rho_{h,S})}_{sdS}$

From firm first order condition for high-skilled labor, we can rewrite it as:

$$
\begin{aligned}
p^h_{dS}{}^{(1-\rho_{h,S})} &= \sum_s A^{\rho_{h,S}}_{sdS} (P_{dS} Q^{\frac{1}{\rho_S}}_{dS} Q^{\frac{1}{\rho_{h,S}} - \frac{1}{\rho_S}}_{hdS} A_{sdS} (\tilde{L}_{sdS})^{\frac{-1}{\rho_h}})^{(1-\rho_{h,S})} \\
&= (P_{dS} Q^{\frac{1}{\rho_S}}_{dS} Q^{\frac{1}{\rho_{h,S}} - \frac{1}{\rho_{h,S}}}_{hdS})^{(1-\rho_{h,S})} (\sum_s A^{\rho_{h,S}}_{sdS} (A_{sdS} (\tilde{L}_{sdS})^{\frac{-1}{\rho_{h,S}}})^{(1-\rho_{h,S})}) \\
&= (P_{dS} Q^{\frac{1}{\rho_S}}_{dS} Q^{\frac{1}{\rho_{h,S}} - \frac{1}{\rho_S}}_{hdS})^{(1-\rho_{h,S})} \sum_s (A_{sdS} \tilde{L}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}}_{sdS}) \\
&= (P_{dS} Q^{\frac{1}{\rho_S}}_{dS} Q^{\frac{1}{\rho_{h,S}} - \frac{1}{\rho_S}}_{hdS} Q^{\frac{-1}{\rho_{h,S}}}_{hdS})^{(1-\rho_{h,S})} \\
&= (P_{dS} Q^{\frac{1}{\rho_S}}_{dS} Q^{-\frac{1}{\rho_S}}_{hdS})^{(1-\rho_{h,S})}
\end{aligned}
$$

Thus we get the following equation for high-skilled,

$$p^h_{dS} = P_{dS} (Q^{\frac{1}{\rho_S}}_{dS} Q^{-\frac{1}{\rho_S}}_{hdS}) \tag{47}$$

I now solve the foc for low skilled workers.

$\text{Max}_{L_{ldS}}\ P_{dS} (Q^{\frac{\rho_S - 1}{\rho_S}}_{hdS} + (A_{k',S,l} L_{k',S,l})^{\frac{\rho_S - 1}{\rho_S}})^{\frac{\rho_S}{\rho_S - 1}} - \sum_s w_{s,S,k'} \tilde{L}_{s,S,k'} - w_{l,S,k'} \tilde{L}_{l,S,k'}$

For low-skilled, taking the first order condition, we get,

$$
\begin{aligned}
w_{ldS} &= P_{dS}\frac{\rho_S}{\rho_S-1}(Q_{hdS}^{\frac{\rho_S-1}{\rho_S}}+(A_{ldS}L_{ldS})^{\frac{\rho_S-1}{\rho_S}})^{\frac{1}{\rho_S-1}}\frac{\rho_S-1}{\rho_S}(A_{ldS}L_{ldS})^{\frac{-1}{\rho_S}}A_{ldS}\\
&= P_{dS}Q_{dS}^{\frac{1}{\rho_S}}(A_{ldS}L_{ldS})^{\frac{-1}{\rho_S}}A_{ldS}\\
&= P_{dS}Q_{dS}^{\frac{1}{\rho_S}}Q_{ldS}^{\frac{-1}{\rho_S}}A_{ldS}
\end{aligned}
$$

Since $p^l_{dS} = \frac{w_{ldS}}{A_{ldS}}$

Thus, $p^l_{dS} = P_{dS}Q_{dS}^{\frac{1}{\rho_S}}Q_{ldS}^{\frac{-1}{\rho_S}}$ Combining the two, we get the following equation:

$$
\frac{p^h_{dS}}{p^l_{dS}} = \frac{Q_{hdS}^{\frac{-1}{\rho_S}}}{Q_{ldS}^{\frac{-1}{\rho_S}}} \tag{48}
$$

Thus,

$$
ln(\frac{p^h_{dS}}{p^l_{dS}}) = \frac{-1}{\rho_S}ln(\frac{Q_{hdS}}{Q_{ldS}}) \tag{49}
$$

Note however, that these are not observable quantities due to the presence of unobserved productivity.

$$
ln(\frac{(\sum_s A_{sdS}^{\rho_{h,S}}w_{sdS}^{(1-\rho_{hS})})^{\frac{1}{(1-\rho_{h,S})}}}{(A_{ldS}^{\rho_l}w_{ldS})}) = \frac{-1}{\rho_S}ln(\frac{(\sum_{s\in college,k}A_{sdS}(\tilde{L}_{sdS})^{\frac{\rho_{hS}-1}{\rho_{hS}}})^{\frac{\rho_{hS}}{\rho_{hS}-1}}}{A_{ldS}\tilde{L}_{ldS}}) \tag{50}
$$

For ease of notation, I now use s=e and s=ne for engineers and non-engineers respectively.

$$
\begin{aligned}
&ln(\frac{(A_{ne,d,S})^{\frac{-\rho_{h,S}}{\rho_{h,S}-1}}((\frac{A_{e,d,S}}{A_{ne,d,S}})^{\rho_{h,S}}(w_{e,d,S})^{1-\rho_{h,S}}+w_{ne,d,S}^{1-\rho_{h,S}})^{\frac{1}{1-\rho_{h,S}}}}{(A_{ldS}^{-1}w_{ldS})})\\
&= ln(\frac{(A_{ne,d,S})^{\frac{\rho_{h,S}}{\rho_{h,S}-1}}((\frac{A_{e,d,S}}{A_{ne,d,S}})(\tilde{L}_{e,d,S})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}}+\tilde{L}_{ne,d,S}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{1-\rho_{h,S}}}}{(A_{l,d,S}\tilde{L}_{l,d,S})})
\end{aligned} \tag{51}
$$

This implies,

$$ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})^{\rho_{h,S}}(w_{e,d,S})^{1-\rho_{h,S}} + w_{ne,d,S}^{1-\rho_{h,S}})^{\frac{1}{1-\rho_{h,S}}}}{(w_{l,s,k'})}) - \frac{\rho_{h,S}}{\rho_{h,S}-1}ln(A_{ne,S,k'}) - ln(A_{l,S,k'})$$

$$= (\frac{-1}{\rho_S})ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})(\tilde{L}_{e,d,S})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}} + \tilde{L}_{ne,d,S}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{1-\rho_{h,S}}}}{\tilde{L}_{ldS}}) - \frac{1}{\rho_S}ln(A_{ldS}) - \frac{1}{\rho_S}(\frac{\rho_{h,S}}{\rho_{h,S}-1})ln(A_{ne,d,S})$$

Thus,

$$\begin{aligned}
&ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})^{\rho_{h,S}}(w_{e,d,S})^{1-\rho_{h,S}} + w_{ne,d,S}^{1-\rho_{h,S}})^{\frac{1}{1-\rho_{h,S}}}}{(w_{ldS})}) \\
&= (\frac{-1}{\rho_S})ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})(\tilde{L}_{e,d,S})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}} + \tilde{L}_{ne,d,S}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{1-\rho_{h,S}}}}{\tilde{L}_{ldS}}) \\
&- \frac{1}{\rho_S}ln(A_{ldS}) - \frac{1}{\rho_S}(\frac{\rho_{h,S}}{\rho_{h,S}-1})ln(A_{ne,d,S}) \\
&+ \frac{\rho_{h,S}}{\rho_{h,S}-1}ln(A_{ne,d,S}) - ln(A_{ldS}) \\
&= (\frac{-1}{\rho_S})ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})(\tilde{L}_{e,d,S})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}} + \tilde{L}_{ne,d,S}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{1-\rho_{h,S}}}}{\tilde{L}_{ldS}}) \\
&+ (\frac{\rho_{h,S}}{\rho_{h,S}-1})(1-\frac{1}{\rho_S})ln(A_{ne,d,S}) + (1-\frac{1}{\rho_S})ln(A_{ldS}) \\
&= (\frac{-1}{\rho_S})ln(\frac{((\frac{A_{e,d,S}}{A_{ne,d,S}})(\tilde{L}_{e,d,S})^{\frac{\rho_{h,S}-1}{\rho_{h,S}}} + \tilde{L}_{ne,d,S}^{\frac{\rho_{h,S}-1}{\rho_{h,S}}})^{\frac{\rho_{h,S}}{1-\rho_{h,S}}}}{\tilde{L}_{ldS}}) \\
&+ (1-\frac{1}{\rho_S})\frac{\frac{\rho_{hS}}{1-\rho_{hS}}A_{ne,d,S}}{A_{ldS}}
\end{aligned}$$

Note that, all the quantities in this equation are observable. If we plugin the first order condition 46, this is a regression of known quantities with the unobserved productivities as residuals.

Recover IT prices then non-IT Use the following equation for S=IT $(p_{S,k'})^{1-\rho_S} = (p^h_{S,k'})^{1-\rho_S} + (p^l_{S,k'})^{1-\rho_S}$

where $p^h_{S,k'}{}^{(1-\rho_h)} = \sum_s A^{\rho_{h,S}}_{k',s,S} w^{(1-\rho_{h,S})}_{k',s,S}$

and $p_{S,k'} = A_{u,l} w_{l,S,k'}$

Thus we can write price as:

$$
\begin{aligned}
(p_{S,k'})^{1-\rho_S} &= ((A^{\rho_{h,S}}_{k',e,S} w^{(1-\rho_{h,S})}_{k',e,S} + A^{\rho_{h,S}}_{k',ne,S} w^{(1-\rho_{h,S})}_{k',ne,S}))^{\frac{1-\rho_S}{1-\rho_{h,S}}} + (A^{-1}_{k',l,S} w_{l,S,k'})^{(1-\rho_S)} \\
&= A_{k',ne,S}^{\frac{\rho_{h,S}(1-\rho_S)}{1-\rho_{h,S}}} ((\frac{A^{\rho_{h,S}}_{k',e,S}}{A^{\rho_{h,S}}_{k',ne,S}} w^{(1-\rho_{h,S})}_{k',e,S} + w^{(1-\rho_{h,S})}_{k',ne,S})^{\frac{1-\rho_S}{1-\rho_{h,S}}} + (\frac{A_{k',ne,S}^{\frac{\rho_{h,S}(\rho_S-1)}{\rho_{h,S}-1}}}{A_{k',l,S}} w_{l,S,k'})^{1-\rho_S}) \\
&= A_{k',ne,S}^{\frac{-\rho_{h,S}(\rho_S-1)}{1-\rho_{h,S}}} (\tilde{p}^h_{S,k'}{}^{1-\rho_S} + (\frac{A_{k',ne,S}^{\frac{\rho_{h,S}}{\rho_{h,S}-1}}}{A_{k',l,S}} w_{l,S,k'})^{1-\rho_S}) \\
&= A_{k',ne,S}^{\frac{-\rho_{h,S}(\rho_S-1)}{1-\rho_{h,S}}} (\tilde{p}^h_{S,k'}{}^{1-\rho_S} + (\tilde{x}_{l,S,k'}^{(\frac{\rho_S}{\rho_S-1})} w_{l,S,k'})^{1-\rho_S}) \\
&= A_{k',ne,S}^{\frac{-\rho_{h,S}(\rho_S-1)}{1-\rho_{h,S}}} (\tilde{p}^h_{S,k'}{}^{1-\rho_S} + \tilde{x}^{-\rho_S}_{l,S,k'} (w_{l,S,k'})^{1-\rho_S})
\end{aligned}
$$

The term in the bracket is a function of known quantities. How?

$\tilde{p}^h_{S,k'}{}^{1-\rho_S} = ((\frac{A_{e,S,k'}}{A_{ne,S,k'}})^{\rho_{h,S}} w^{1-\rho_{h,S}}_{e,S,k'} + w^{1-\rho_{h,S}}_{ne,S,k'})^{\frac{1}{1-\rho_{h,S}}}$ is known from 46.

and

$$
\tilde{x}_{S,l,k'} = \frac{A_{k',ne,S}^{(\frac{\rho_{h,S}}{\rho_{h,S}-1})(\frac{1}{\rho_S}-1)}}{A_{l,S,k'}^{\frac{1}{\rho_S}-1}}
$$

From 48, we get:

$$
p^h_{S,k'} Q^{\frac{1}{\rho_S}}_{k',S,h} = p^l_{S,k'} Q^{\frac{1}{\rho_S}}_{k',S,l}
$$

Or, substituting prices and quantities in terms of their observable components,

$$\tilde{p}^h_{S,k'}(\tilde{Q}_{k',S,h})^{\frac{1}{\rho_S}}A_{k',ne,S}^{(\frac{\rho_{h,S}}{\rho_{h,S}-1})(\frac{1}{\rho_S}-1)} = \frac{W_{l,S,k'}}{A_{l,S,k'}}(A_{l,S,k'}L_{l,S,k'})^{\frac{1}{\rho_S}}$$

Thus,

$$\frac{A_{k',ne,S}^{(\frac{\rho_{h,S}}{\rho_{h,S}-1})(\frac{1}{\rho_S}-1)}}{A_{l,S,k'}^{\frac{1}{\rho_S}-1}} = \frac{W_{l,S,k'}(L_{l,S,k'})^{\frac{1}{\rho_S}}}{\tilde{p}^h_{S,k'}(\tilde{Q}_{k',S,h})^{\frac{1}{\rho_S}}}$$

Denote

$$\tilde{x}_{S,l,k'} = \frac{A_{k',ne,S}^{(\frac{\rho_{h,S}}{\rho_{h,S}-1})(\frac{1}{\rho_S}-1)}}{A_{l,S,k'}^{\frac{1}{\rho_S}-1}}$$

C.3 Unknown amenities

Given the distribution of population in each region, estimated migration costs and real wages, unknown region, field of education and sector specific amenities are backed out. The equilibrium population in location d of workers with degree in s working in sector S is given by:

$$L_{sdS} = \sum_j \mu^{\theta}_{jdss}(\frac{W_{sdS}u_{sdS}}{P_d})^{\theta_s}\Phi^{-1}_{sj}L_{sj} \tag{52}$$

And

$$\Phi_{sj} = \sum_{d'S'} \mu^{\theta}_{ojs}(\frac{W_{sd'S'}u_{sdS}}{P_d})^{\theta_s} \tag{53}$$

Equations 52 and 53 have $D*s*S+D*s$ unknowns and $D*s*S+D*s$ equations. We can solve these uniquely for the unknowns Φ_{sj} and $(\frac{W_{sdS}u_{sdS}}{P_d})^{\theta_s}$. Using the obtained values, I run the following regression:

$$(\frac{W_{sdS}u_{sdS}}{P_d})^{\theta_s} = \theta_s ln(\frac{W_{sdS}}{P_d}) + \theta_s u_{sdS}$$

Since wages are given from data and the sequence of regional prices P_d have already been estimated, one can run this regression to recover θ_s. Now local amenities are correlated with real wages in general equilibrium. I can again use the same instrument here by using a long-difference equation and using model predicted wages, holding amenities constant at old values, as an instrument.

To estimate the elasticity of movement for education, I use the population of people with degrees in field s in each location:

$$L_{js} = \sum_{o} l_{ojs} L_o = \sum_{o} \frac{(a_{js}\mu_{oj}E(V^{ijs}))^{\gamma}}{\Phi_o} L_0 \tag{54}$$

$$\Phi_o = \sum_{s,j} (a_{js}\mu_{oj}E(V^{ijs}))^{\gamma} \tag{55}$$

In the same way, I can solve for unknown quantities a_{js} and Φ_o. The utility cost of education has two components:

C.4 Existence of equilibrium proof

To show the existence of equilibrium I use the following theorem, proved in Allen et al (2019).

Theorem 1: Consider any $N \times K$ system of equations $F : R_{++}^{N\times K} R_{++}^{N\times K}$:

$$F(x)_{ik} \equiv \sum_{j} K_{ij,k} \prod_{l=1}^{K} (x_{j,l})^{\alpha_{k,l}} \prod_{l=1}^{K} (x_{i,l})^{\lambda_{k,l}} \prod_{m=1}^{M} Q_m(x_j)^{\gamma_{k,m}} \prod_{m=1}^{M} Q_m(x_i)^{\kappa_{k,m}}$$

where $Q_m(.)$ are nested CES aggregating functions:

$$Q_m(x_j) \equiv \left(\sum_{l\in S_m} \frac{1}{\mid S_m \mid} \left(\left(\sum_{n\in T_l} \frac{1}{\mid T_n \mid} (x_{j,n})^{\delta_{m,l}} \right)^{\frac{1}{\delta_{m,l}}} \right)^{\beta_m} \right)^{\frac{1}{\beta_m}}$$

where $\delta_{m,l} > 0$ and $\beta_m > 0$ for all m and l, $K_{ijk}, U_l, T_{j,n}$ are all strictly positive parameter values; S_m and $T_{l,m}$ are (weak) subsets of $1, ..., K$; and $\{\alpha_{k,l}, \lambda_{k,l}, \gamma_{k,m}, \kappa_{k,p}\}$ are all real-valued.

If $max_{k\in\{1,...,K\}}$ $(\sum_{m=1}^{M} \mid \gamma_{k,m} \mid + \sum_{l=1}^{K} \mid \alpha_{k,l} \mid + \sum_{m=1}^{M} \mid \lambda_{k,m} \mid + \sum_{m=1}^{M} \mid \kappa_{k,m} \mid) < 1$, then there exists an unique fixed point $F(x*) = x*$

I can show that the equilibrium system of equations in my model falls into the framework considered by theorem 1.

The equilibrium conditions that govern enrollment are:

$$L_{o_2} = \sum_{o_1,f} l_{o_1 o_2 f} L_{o_1}$$

$$L_{o_2} = \sum_{o_1,f} \frac{\left((\frac{a_{o_2 f}\mu^1_{o_1 o_2}}{P_{o_2}})^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}}}{\Phi_{o_1}^{\frac{\gamma}{IU}}} L_{o_1}$$

$$L_{o_2}\left((\frac{a_{o_2 f}}{P_{o_2}})^{IU} \right)^{\frac{-\gamma}{IU}} = \sum_{o_1,f} \frac{\left((\mu^1_{o_1 o_2})^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}}}{\Phi_{o_1}^{\frac{\gamma}{IU}}} L_{o_1}$$

$$\Phi_{o_1}^{\frac{\gamma}{IU}} = \sum_{o_2',f'} \left(\left(\frac{(a_{o_2' f'}\mu^1_{o_1 o_2'})}{P_{o_2'}} \right)^{IU} \Phi_{o_2' f'}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}}$$

Let the following hold for some value of κ

$$L_{o_2}\left((\frac{a_{o_2 f}}{P_{o_2}})^{IU} \right)^{\frac{-\gamma}{IU}} = \kappa_f (\Phi_{o_2})^{\frac{\gamma}{IU}}$$

Thus, we get,

$$\kappa_f (\Phi_{o_2})^{\frac{\gamma}{IU}} = \sum_{o_1,f} \frac{\left((\mu^1_{o_1 o_2})^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}}}{\Phi_{o_1}^{\frac{\gamma}{IU}}} L_{o_1}$$

$$= \sum_{o_1,f} \frac{\left((\mu^1_{o_1 o_2})^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}}}{\Phi_{o_1}^{\frac{\gamma}{IU}}} L_{o_1}$$

$$= \sum_{o_1,f} \left((\mu^1_{o_1 o_2})^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}} \right)^{\frac{\gamma}{IU}} \kappa_f L_{o_1}^{-1} (\frac{a_{o_1,f}}{P_{o_1}}^{\gamma}) L_{o_1}$$

Simplifying,

$$\Phi_{o_2}^{\frac{\gamma}{IU}} = \sum_{o_1,f} \Big(\Big(\frac{(a_{o_1 f}\mu^1_{o_1 o_2})}{P_{o_1}}\Big)^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}}\Big)^{\frac{\gamma}{IU}}$$

The two equations then just boil down to one.

This allows us to consider a single non linear equation:

$$L_{o_2} = \kappa_f \Big((\frac{a_{o_2 f}}{P_{o_2}})^{IU}\Big)^{\frac{-\gamma}{IU}} \sum_{o_1,f} \Big(\Big(\frac{(a_{o_1 f}\mu^1_{o_1 o_2})}{P_{o_1}}\Big)^{IU} \Phi_{o_2 f}^{\frac{(1-IU)}{\theta}}\Big)^{\frac{\gamma}{IU}} \tag{56}$$

Substitute

$$(\Phi_{o_2 f}) = \sum_{d'' f''} \mu^{\theta}_{o_2 d''} (\frac{W_{fd''S''} u_{fd''S''}}{P''_d})^{\theta}$$

$$L_{o_2} = \kappa_f \Big((\frac{a_{o_2 f}}{P_{o_2}})^{IU}\Big)^{\frac{-\gamma}{IU}} \sum_{o_1,f,d'',f''} \Big(\Big(\frac{(a_{o_1 f}\mu^1_{o_1 o_2})}{P_{o_1}}\Big)^{IU} (\mu^{\theta}_{o_2 d''}(\frac{W_{fd''S''} u_{fd''S''}}{P''_d})^{\theta})^{\frac{(1-IU)}{\theta}}\Big)^{\frac{\gamma}{IU}}$$

The equilibrium condition in the internally traded sector is given by:

$$Y_{dS}^{\sigma_S} Q_{dS}^{1-\sigma_S} = \sum_j \tau_{dj}^{1-\sigma_S} P_j^{\sigma_S - 1} Y_j$$

We can rewrite the internal gravity equation 12 as:

$$Y_{dS} = \sum_j \tau_{dj}^{1-\sigma} p_{dS}^{1-\sigma} P_J^{\sigma-1} (\alpha_j Y_j)$$

Multiplying both sides by $Q_{dS}^{1-\sigma}$, we get,

$$\begin{aligned} Y_{dS} Q_{dS}^{1-\sigma} &= \sum_j \tau_{dj}^{1-\sigma} p_{dS}^{1-\sigma} P_j^{\sigma-1} Q_{dS}^{1-\sigma} (\alpha_S Y_j) \\ &= \sum_j \tau_{dj}^{1-\sigma} P_j^{\sigma-1} Y_{dS}^{1-\sigma} (\alpha_S Y_j) \end{aligned}$$

Simplifying, the above:

$$Y_{dSS}^{\sigma} Q_{dS}^{1-\sigma} = \sum_{j} \tau_{dj}^{1-\sigma} P_j^{\sigma-1} (\alpha_S Y_j)$$

We can rewrite 13,

$$\begin{aligned} P_j^{1-\sigma} &= \sum_k \tau_{jk}^{1-\sigma} p_{kS}^{1-\sigma} Q_{kS}^{1-\sigma_S} Q_{kS}^{\sigma_S - 1} \\ &= \sum_k \tau_{jk}^{1-\sigma} Y_{kS}^{1-\sigma} Q_{kS}^{\sigma-1} \end{aligned}$$

Suppose that the following relationship holds true for some scalar κ

$$Y_{dS}^{\sigma} Q_{dS}^{1-\sigma} = \kappa P_d^{1-\sigma}$$

In that case, as I show below, I can express equations 12 and 13 as a single equation. Equation 12 is given below:

$$Y_{dS}^{\sigma} Q_{dS}^{1-\sigma} = \sum_{j} \tau_{dj}^{1-\sigma} P_j^{\sigma-1} (\alpha_S y_j)$$

Substituting $Y_{dS}^{\sigma} Q_{dS}^{1-\sigma} = \kappa P_d^{1-\sigma}$ in the above we get back equation 13

$$P_d^{1-\sigma} = \sum_j \tau_{dj}^{1-\sigma} (Y_{jS}^{1-\sigma}) Q_{jS}^{\sigma-1}$$

This allows us to consider a single non-linear equation:

$$Y_{dS}^{\sigma} Q_{dS}^{1-\sigma} = \kappa \sum_{j \in N} \tau_{dj}^{1-\sigma} (Y_{jS}^{1-\sigma}) Q_{jS}^{\sigma-1}$$

Now substitute the price index

$$P_d = (\kappa)^{\frac{-1}{1-\sigma}} Y_{dS}^{\frac{\sigma}{1-\sigma}} Q_{dS}$$

in 56

$$L_{o_2} = \kappa_f \Big(\big(\frac{a_{o_2 f}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_2 S}^{\frac{\sigma}{1-\sigma}} Q_{o_2 S}} \big)^{IU} \Big)^{\frac{-\gamma}{IU}} \sum_{o_1,f} \Big(\big(\frac{(a_{o_1 f} \mu^1_{o_1 o_2})}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_1 S}^{\frac{\sigma}{1-\sigma}} Q_{o_1 S}} \big)^{IU} \\ (\sum_{d'' f''} \mu^\theta_{o_2 d''} \big(\frac{W_{fd''S''} u_{fd''S''}}{P''_d} \big)^\theta)^{\frac{(1-IU)}{\theta}} \Big)^{\frac{\gamma}{IU}}$$

Simplifying,

$$L_{o_2} = \kappa_f \Big((\frac{a_{o_2 f}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_2 S}^{\frac{\sigma}{1-\sigma}} Q_{o_2 S}})^{IU} \Big)^{\frac{-\gamma}{IU}} \sum_{o_1,f} \Big(\big(\frac{(a_{o_1 f} \mu^1_{o_1 o_2})}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_1 S}^{\frac{\sigma}{1-\sigma}} Q_{o_1 S}} \big)^{IU} \\ (\sum_{d'' f''} \mu^\theta_{o_2 d''} (\frac{W_{fd''S''} u_{fd''S''}}{P''_d})^\theta)^{\frac{(1-IU)}{\theta}} \Big)^{\frac{\gamma}{IU}} \\ = \sum_{o_1,f,d'',f''} \kappa_f \Big((\frac{a_{o_2 f}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_2 S}^{\frac{\sigma}{1-\sigma}} Q_{o_2 S}})^{IU} \Big)^{\frac{-\gamma}{IU}} \Big(\big(\frac{(a_{o_1 f} \mu^1_{o_1 o_2})}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_1 S}^{\frac{\sigma}{1-\sigma}} Q_{o_1 S}} \big)^{IU} \\ (\mu^\theta_{o_2 d''} (\frac{W_{fd''S''} u_{fd''S''}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{d''S}^{\frac{\sigma}{1-\sigma}} Q_{d''S}})^\theta)^{\frac{(1-IU)}{\theta}} \Big)^{\frac{\gamma}{IU}}$$

Finally, substitute the expression for wages,
$W_{fd''S''} = Y_{d''S''} Q_{d''S''}^{\frac{1-\rho_f}{\rho_f}} Q_{hd''S''}^{\frac{1}{\rho_{h,S''}} - \frac{1}{\rho''_S}} A_{fd''S''} (\tilde{L}_{fd''S''})^{\frac{-1}{\rho_h}}$

$$L_{o_2} = \sum_{o_1,f,d'',f''} \kappa_f \Big((\frac{a_{o_2 f}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_2 S}^{\frac{\sigma}{1-\sigma}} Q_{o_2 S}})^{IU} \Big)^{\frac{-\gamma}{IU}} \Big(\big(\frac{(a_{o_1 f} \mu^1_{o_1 o_2})}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{o_1 S}^{\frac{\sigma}{1-\sigma}} Q_{o_1 S}} \big)^{IU} \\ (\mu^\theta_{o_2 d''} (\frac{Y_{d''S''} Q_{d''S''}^{\frac{1-\rho_f}{\rho_f}} Q_{hd''S''}^{\frac{1}{\rho_{h,S''}} - \frac{1}{\rho''_S}} A_{fd''S''} (\tilde{L}_{fd''S''})^{\frac{-1}{\rho_h}} u_{fd''S''}}{(\kappa)^{\frac{-1}{1-\sigma}} Y_{d''S}^{\frac{\sigma}{1-\sigma}} Q_{d''S}})^\theta)^{\frac{(1-IU)}{\theta}} \Big)^{\frac{\gamma}{IU}}$$

We are thus able to express the equilibrium conditions in the form required for theorem 1. An equilibrium thus exists by the contraction mapping theorem.

C.5 Proofs of propositions

Proposition 1: If $\eta \sim Frechet(\theta)$, then $\eta^{\alpha} \sim Frechet(\frac{\theta}{\alpha})$

Proof:

Since $\eta \sim Frechet(\theta)$, thus

$$F_{\eta}(x) = P(\eta \leq x) = (exp(-x^{-\theta}))$$

Let $z = \eta^{\alpha}$

$$\begin{aligned} F_z(x) = P(z \leq x) &= P(\eta^{\alpha} \leq x) \\ &= P(\eta \leq (x)^{\frac{1}{\alpha}}) \\ &= exp(-(x^{\frac{1}{\alpha}})^{-\theta}) \\ &= exp(-(x^{\frac{-\theta}{\alpha}})) \end{aligned}$$

Thus z follows Frechet with dispersion parameter $\frac{-\theta}{\alpha}$

Proposition 2: If $\eta_i \sim Frechet(\theta)$, then $E(max_i(a_i \times \eta_i)) = (\sum_i a_i^{\theta})^{\frac{1}{\theta}}\Gamma(1 - \frac{1}{\theta})$

Proof:

Let $z_i = max_i(a_i\eta_i)$

$$
\begin{aligned}
F_{Z_i}(z) &= Pr(Z_i \leq z) \\
&= Pr(a_i\eta_i \leq z\forall i) \\
&= Pr(\eta_i \leq \frac{z}{a_i}, \forall i) \\
&= \Pi_i F(\frac{z}{a_i}) \\
&= \Pi_i exp(-\frac{z}{a_i})^{-\theta} \\
&= exp(-z^{-\theta}(\sum_i (\frac{1}{a_i})^{-\theta})) \\
&= exp(-(\sum_i a_i^{\theta}))z^{-\theta}
\end{aligned}
$$

$z = max_i(a_i\eta_i)$ thus follows a Frechet distribution with dispersion parameter θ and position parameter $(\sum_i a_i^{\theta})$

According to the properties of the Frechet distribution, the mean of z will thus be

$E(z) = E(max_i(a_i\eta_i)) = (\sum_i a_i^{\theta})^{\frac{1}{\theta}}\Gamma(1 - \frac{1}{\theta})$

To understand how the propositions apply to the maximization problem at hand, consider $(1 - IU) = \alpha$, $a_i = (w_{f,dS} \cdot P_d \cdot u_{f,dS} \cdot \mu^2_{o_2d})^{1-IU}$

C.6 Identification and estimation

C.6.1 Migration cost estimation

In column 1, I report the results from the PPML estimation, the same one reported in the main text of the paper. In column 2, I report the results from regressing the log flows of people migrating for education on the relevant distance measures, where zeros are replaced by the minimum across all migration flows. In column 3, I repeat the same estimation as in column 2, but with zeros excluded. In column 4, I follow a more traditional estimation where the combinations of same state and neighbor

Table 25: **Gravity estimation on district to district migration when reason for migration is work**

	(1)	(2)	(3)	(4)
	migration flows	log migration flows	log migration flows	migration flows
log distance centroid	-0.548***	-1.294***	-1.006***	-0.722***
	(-75.44)	(-217.22)	(-171.13)	(-135.72)
log common	0.332***	0.164***	0.194***	0.342***
	(39.70)	(63.88)	(65.24)	(36.47)
Same state, neighbors	3.025***	2.663***	2.320***	
	(64.04)	(78.82)	(82.73)	
Same state,not neighbors	1.773***	2.112***	1.342***	
	(50.17)	(142.09)	(104.13)	
Not same state, neighbors	2.629***	2.702***	2.059***	
	(42.00)	(46.72)	(44.81)	
Same state				1.751***
				(44.21)
Clustering	State-year	District	State	State-year
District	State			
N	280900	280900	127709	280900

dummies have been replaced with just a same state dummy. Across all specifications, the effect of state borders is huge: the effect is 269.5%, 481%, 293.5% and 1039% in specifications 1,2,3 and 4 respectively. Specification 1 is the preferred specification. In specification 2 pairs of districts that do not record any migration flows receive a small value in order to avoid getting thRoWn out of the sample, which induces downward bias in the estimated cost. In specification 3, the pairs of districts with zero values have been ignored which introduces the selection problem. In specification 4, the estimated state border effects are huge because districts in different states share a border with less frequency than districts in the same state, which was previously accounted for by the neighborhood dummy and now gets loaded on to the state dummy.

Table 26: **Gravity estimation on district to district migration when reason for migration is education**

	(1) migration flows	(2) log migration flows	(3) log migrationflows	(4) migration flows
log distance centroid	-0.603***	-0.616***	-0.620***	-0.771***
	(-91.50)	(-136.98)	(-87.57)	(-159.26)
log common	0.307***	0.044***	0.106***	0.323***
	(25.39)	(22.86)	(24.60)	(25.04)
Same state, neighbors	3.647***	4.898***	2.686***	
	(75.31)	(192.11)	(95.61)	
Same state, not neighbors	2.380***	2.014***	1.057***	
	(59.10)	(179.62)	(67.88)	
Not same state, neighbors	2.340***	3.138***	1.316***	
	(25.27)	(71.90)	(30.78)	
Same state				2.433***
				(56.23)
N	280900	280900	45362	280900

In table 7 above, the same specifications are repeated when people migrate for work.

Table 27: **Gravity estimation on district to district migration when reason for migration is education**

	(1) migrationflows2	(2) logmigrationflowsNoZero	(3) logmigrationflowsWithZero	(4) migrationflows2
logdistance_centroid	-0.609***	-0.614***	-0.617***	-0.777***
	(-92.37)	(-137.31)	(-87.89)	(-162.01)
log common	0.303***	0.044***	0.106***	0.317***
	(25.05)	(23.03)	(24.64)	(24.94)
Same state, neighbors	3.611***	4.893***	2.685***	
	(74.11)	(191.91)	(95.67)	
Same state, not neighbors	2.364***	2.010***	1.051***	
	(58.61)	(179.22)	(67.49)	
Not same state, neighbors	2.315***	3.155***	1.329***	
	(24.76)	(72.34)	(31.13)	
Same state				2.408***
				(55.75)
N	280900	280900	45362	280900

Table 28: **Gravity estimation on district to district migration when reason for migration is work**

	(1) migrationflows2	(2) logmigrationflowsNoZero	(3) logmigrationflowsWithZero	(4) migrationflows2
logdistance econcenter	-0.553***	-1.284***	-0.995***	-0.727***
	(-76.85)	(-216.57)	(-170.23)	(-138.81)
log common	0.331***	0.166***	0.195***	0.340***
	(39.11)	(64.70)	(65.87)	(35.75)
Same state, neighbors	2.992***	2.669***	2.331***	
	(63.82)	(78.96)	(83.06)	
Same state, not neighbors	1.753***	2.107***	1.339***	
	(49.89)	(141.68)	(103.77)	
Not same state, neighbors	2.611***	2.750***	2.099***	
	(39.89)	(47.55)	(45.67)	
Same state				1.723***
				(44.13)
N	280900	280900	127709	280900

Table 29: **Gravity estimation on district to district migration when reason for migration is education, clustering at origin level**

	(1) migrationflows2 b/t	(2) logmigrationflowsNoZero b/t	(3) logmigrationflowsWithZero b/t	(4) migrationflows2 b/t
logdistance_centroid	-0.603***	-0.616***	-0.620***	-0.771***
	(-68.52)	(-41.63)	(-46.61)	(-67.15)
logcommon	0.307***	0.044***	0.106***	0.323***
	(15.40)	(9.52)	(19.19)	(15.53)
Same state, neighbors	3.647***	4.898***	2.686***	
	(53.89)	(72.24)	(83.06)	
Same state, not neighbors	2.380***	2.014***	1.057***	
	(34.12)	(28.98)	(41.89)	
Not same state, neighbors	2.340***	3.138***	1.316***	
	(19.69)	(34.73)	(21.09)	
Same state				2.433***
				(35.48)
N	280900.000	280900.000	45362.000	280900.000

Table 30: **Gravity estimation on district to district migration when reason for migration is work, clustering at origin level**

	(1) migration flows b/t	(2) log migration flows no zero b/t	(3) log migrationflows With Zero b/t	(4) migrationflows2 b/t
logdistance_centroid	-0.548***	-1.294***	-1.006***	-0.722***
	(-52.50)	(-56.99)	(-54.57)	(-65.96)
logcommon	0.332***	0.164***	0.194***	0.342***
	(26.63)	(16.79)	(25.63)	(22.91)
(mean) one_one	3.025***	2.663***	2.320***	
	(43.02)	(30.25)	(43.16)	
(mean) one_zero	1.773***	2.112***	1.342***	
	(36.95)	(45.09)	(42.27)	
(mean) zero_one	2.629***	2.702***	2.059***	
	(22.46)	(32.15)	(27.26)	
(mean) same_state				1.751***
				(31.88)
N	280900.000	280900.000	127709.000	280900.000

Table 31: **Gravity estimation on district to district migration when reason for migration is education, clustering at destination level**

	(1) migrationflows b/t	(2) logmigrationflowsNoZero b/t	(3) logmigrationflowsWithZero b/t	(4) migrationflows b/t
logdistance_centroid	-0.603***	-0.616***	-0.620***	-0.771***
	(-62.04)	(-25.21)	(-36.35)	(-81.47)
logcommon	0.307***	0.044***	0.106***	0.323***
	(17.77)	(5.81)	(8.61)	(18.82)
Same state, neighbors	3.647***	4.898***	2.686***	
	(45.48)	(66.78)	(61.44)	
Same state, not neighbors	2.380***	2.014***	1.057***	
	(27.49)	(24.07)	(21.56)	
Not same state, neighbors	2.340***	3.138***	1.316***	
	(17.16)	(34.00)	(24.02)	
same_state				2.433***
				(27.58)
N	280900.000	280900.000	45362.000	280900.000

Table 32: **Gravity estimation on district to district migration when reason for migration is work, clustering at destination level**

	(1) migration _ lows	(2) log_ migration_flows_no_zero	(3) log_migration_flows_with_zero	(4) migration_flows
logdistance_centroid	-0.548***	-1.294***	-1.006***	-0.722***
	(-46.73)	(-73.33)	(-64.70)	(-70.47)
logcommon	0.332***	0.164***	0.194***	0.342***
	(23.27)	(20.08)	(24.11)	(23.00)
Same state, neighbors	3.025***	2.663***	2.320***	
	(37.83)	(31.91)	(41.97)	
Same state, not neighbors	1.773***	2.112***	1.342***	
	(23.00)	(47.22)	(40.93)	
Not Same state, neighbors	2.629***	2.702***	2.059***	
	(28.49)	(33.42)	(30.45)	
Same_state				1.751***
				(22.66)
N	280900.000	280900.000	127709.000	280900.000

C.6.2 Trade cost estimation

Table 33: **First Stage Regression**

	(1) Observable price
Hisorical Software exports	-6.139***
	(-2.83)
Remoteness	-0.0000135
	(-1.36)
log English to hindi speakers	0.213***
	(3.31)
linguistic distance	-390.901**
	(-2.39)
Constant	-10.088*
	(-1.83)
N	482.000

Robust Standard errors are used. t statistics reported in parenthesis

C.6.3 Model extensions

1. Quality differences in education: Let the idiosyncratic preference shock be drawn from a Frechet distribution with mean T_{o_2}, where T_{o_2} depends on regional average quality of education.

   $$G(\zeta_{io_2f}) = exp(-T_{o_2}\zeta_{io_2f}^{-\gamma})$$

   Given this, the proportion of people migrating for education is given by:

   $$l_{o_1o_2f} = \frac{T_{o_2}\left((\frac{a_{o_2f}\mu^1_{o_1o_2}}{P_{o_2}})^{\beta}\Phi_{o_2f}^{\frac{(1-\beta)}{\theta}}\right)^{\frac{\gamma}{\beta}}}{\Phi_{o_1}} \tag{57}$$

   The new Φ_{o_1} is scaled by T_{o_2}. The destination fixed effects capture the average quality of education in that region. It therefore behaves in the exact same manner as amenities for education. Note that, this does not change the migration equation for work.

2. International migration: International migration is introduced in the model by

adding one region where people can migrate to but from where people cannot migrate out. This region is closer to some regions of India and further from others. Education facilities and job opportunities are both better in this region than in any region of India. The introduction of this region increases both the aggregate welfare as well as the regional inequality.

3. Endogenous agglomeration and congestion:

$$A = \overline{A}L^{\alpha}$$

$$U = \overline{U}L^{-\beta}$$

I take $\alpha = .3$ and $\beta = -.2$. For this parametric configuration, overall inequality as a result of the IT boom increases.

4. Differential mobility costs for skilled and unskilled workers: In this extension, the migration costs for unskilled workers are taken to be double that of skilled workers, with the average migration costs being the same as the original estimated migration costs. In this extension, unskilled workers lose in about a third of Indian districts. This is because skilled and unskilled workers are complements in the production function. As skilled workers start migrating out of certain districts that did not see much of the IT boom, this brings down the marginal productivity of unskilled workers as skilled and unskilled workers are complements in the production function.