Essays on International Trade, Offshoring, and FDI

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Abstract

With globalization, offshoring and foreign direct investment (FDI) have been growing dramatically in recent decades. This dissertation studies the effects of offshoring and FDI on labor market outcomes and living standards. Chapter 1 focuses on estimating the effect of material and service offshoring on wages in South Korea. Chapter 2 investigates the effect of inward FDI on income distribution and absolute living standards in Vietnam. Chapter 3 contributes to the empirical trade and offshoring literature by estimating the effects of the negative employment shock of offshoring on individual wages across local labor markets. Below, I discuss each chapter in detail.

Chapter 1 is an empirical-oriented study on offshoring and wages in South Korea. Using disaggregated Input-Output tables with detailed import matrices for South Korea between 2005 and 2014, I measure offshoring directly, free of the erroneous proportionality assumption. I estimate the effect of both material and service offshoring on wages in South Korea. The results show no statistically-significant effect of offshoring on wages at the industry level. However, at the occupation level, the effect is statistically and economically significant. An instrumental variable approach indicates that a one percent increase in material offshoring results in a wage increase by 0.083 percent. This finding is driven by the workers in service sector who had not switched sector of employment. Material offshoring appears to increase wage inequality among the workers who perform routine tasks and non-routine tasks in South Korea.

Chapter 2, coauthored with John McLaren, investigates the effects of inward FDI on income distribution and absolute living standards in Vietnam using the Census data from 1989-2009. We compute the number of employees of foreign establishments

in each of Vietnam's provinces for each year, and use that as a measure of local FDI. We estimate the effects of FDI on local households' living standards as reported in the data, broken down by educational background to allow us to analyze effects on inequality. Estimates based on the repeated cross section indicate that rising FDI in a province is associated with a slight decline in living standards for households there if they do not have a member employed by the foreign enterprises, with only modest gains for households who do have a member employed by the foreign enterprises. These estimates may reflect selection effects, however, since we find large movements of people toward the provinces receiving the FDI. The findings show that measuring the effect of FDI on household welfare is more difficult than measuring the effect of trade policy, and may pose a difficulty for the view of FDI as a general anti-poverty strategy.

Chapter 3 examines the effect of offshoring-induced employment shock on wages of U.S. workers across local labor markets, joint with Hyejoon Im and Yang Shen. Using a dataset of petitions from the U.S. Trade Adjustment Assistance (TAA) program, we identify the offshoring-induced layoffs by commuting zone and by industry. We construct a measure which captures the negative employment effect of offshoring. The measure is defined as the share of offshoring-induced layoffs out of the total employment in a commuting zone or industry. With this measure, we estimate the effect of offshoring-induced layoffs on wages and find that among the observations exposed to negative employment shocks of offshoring, a one-percentage-point increase in the share of offshoring-induced layoffs at the commuting-zone level is associated with a 1.024% decrease in individual wages.

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Chapter 1

Effects of Material and Service Offshoring on Wages: Evidence from South Korea

1.1 Introduction

Offshoring, a fragmentation of the production process in which a subset of the production process is performed overseas, has received great attention as it is now ubiquitous for multinational firms all over the world. A growing number of studies examine the consequences of an increase in offshoring on labor market outcomes in developed countries.[1] In addition, studies have shown that offshoring has been increasing in the last two decades for a number of industrialized economies.[2] As shown in the right panel of Figure 1.1, South Korea is not an exception. Both material and service offshoring have been generally growing since 2005, except during the period of the Great Recession.[3] How does an increase in offshoring of materials and services affect domestic wages in South Korea? While Feenstra and Hanson (1996a) and Grossman and Rossi-Hansberg (2008) provide theories for understanding the mechanism of offshoring and its implications on wages, the implication of Grossman and Rossi-Hansberg (2008) makes the effect on wages ambiguous.

There has been an extensive work on material offshoring, while studies on service offshoring is relatively scarce.[4] There are two main reasons why service offshoring has not been widely studied empirically. First, many perceived non-tradable services have only recently, over the last decade or so, become tradable. Second, more generally, there are severe data limitations. Not only does there exist scarce data on how much

[1] For example, Feenstra and Hanson (1996a,b), Amiti et al. (2005); Amiti and Wei (2009), Liu and Trefler (2011), Ebenstein et al. (2014), Hummels et al. (2014), and Boehm et al. (2017).

[2] Feenstra and Hanson (1996b), Yeats (1998), and Hummels et al. (2014) show increases in offshoring in the U.S., the U.K., Australia, Canada, France, and Japan.

[3] Although "manufacturing offshoring" is a widely-used term, I use material offshoring throughout this paper instead, to distinguish from the manufacturing sector. However, I use the term service offshoring as is. Service offshoring means the producer's import of service inputs, whether the producer belongs to a manufacturing industry or a service industry.

[4] Liu and Trefler (2011) note that "only six papers have examined the impacts of service trade."

domestic firms offshores (even at the industry level), but it is also difficult to find a good measure of offshoring.[5] Thus, much of the focus has been put on the study of material offshoring, which is measured by the imported intermediate inputs in the manufacturing sector.

Empirical studies that focus on material offshoring in the manufacturing sector overlook the non-negligible fractions of workers switching from manufacturing sectors to non-manufacturing sectors. More importantly, when constructing offshoring measures, most previous studies rely on an assumption proposed by Feenstra and Hanson (1996a), which is known as the proportionality assumption. Specifically, each industry is assumed to import a commodity (material or service) in the same proportion as its economy-wide import share of the commodity. The proportionality assumption circumvents the data limitation problem, but under this assumption, cross-sectional industry variation is solely determined by the input share of production. The proportionality assumption is an erroneous assumption since it ignores the heterogeneity in import shares across industries, which could have differential effects on industry-level wages and employment.

Studies of offshoring mostly concentrate in the advanced countries such as the U.S., the U.K, and Germany. This paper contributes to the empirical offshoring literature by investigating unexplored South Korean data. I examine the effects of both material and service offshoring on domestic wages across all industries in South Korea from 2005 to 2015. The rich data I gather allow me to measure offshoring directly, free of the proportionality assumption. Moreover, I analyze the wage effect not only

[5]Recently, two alternative offshoring measures have been introduced. Monarch et al. (2017) and Kondo (2018) measure offshoring from certified Trade Adjustment Assistant (TAA) petitions, which laid-off workers file due to offshoring in the U.S. Bernard et al. (2018) use Danish firm-level survey data in which each firm is asked whether any production process has been relocated overseas.

induced by the industry exposure of offshoring but also induced by the occupation exposure. Due to the endogeneity problem arising from a firm's simultaneous decisions on offshoring and wages, I employ an instrumental variable approach. I instrument material and service offshoring by global material export and global service export, respectively. To examine the heterogeneous wage effect of offshoring, I extract two sub-samples: individuals in the manufacturing sector and in the service sector. I also divide workers into groups based on occupation characteristics and skills in order to analyze the differential effects of occupation exposure of offshoring on wages of workers in different groups. I measure workers' skills by level of education.

The results show that there is no statistically-significant effect of material and service offshoring on wages at the industry level. However, at the occupation level, the effect is statistically and economically significant. With the instrumental variable approach, I find that a one percent increase in material offshoring results in a wage increase by 0.083 percent. This effect is largely driven by the workers employed in the service sector who had never switched sectors. Moreover, production and blue-collar workers experience a decrease in wages from material offshoring, whereas non-production and white-collar workers experience an increase in wages. The regression results also show that unskilled workers experience an increase in wages from both material and service offshoring while skilled workers' wages decline due to service offshoring.

The contribution of this paper is two-fold. First, I use unexplored South Korean data of disaggregated Input-Output (I-O) tables with detailed import matrices to directly measure both material and service offshoring. I show that the Feenstra and Hanson (1996a) measure is significantly different from the true measure of offshoring. The two measures are correlated only on average across industries. I confirm that the proportionality assumption is an inappropriate assumption, as the data reveals that the Feenstra and Hanson (1996a) measure ignores a source of variation across industries that varies over time.[6]

Second, owing to the level of disaggregation of the I-O tables containing about 400 commodities, I construct an industry-level dataset, including 29 private service industries. This number is much larger than the number of service industries in the previous papers regarding service offshoring.[7] In addition, I analyze the effect of both material and service offshoring for every industry in South Korea. Previous studies have focused on only a limited number of industries in manufacturing and/or service sectors, let alone other sectors in the economy.

Related literature. This paper is largely related to a growing body of literature on assessing the effect of offshoring on labor market outcomes. Since Feenstra and Hanson (1996a) introduce the idea of offshoring as imported material inputs by manufacturing industries, studies in the literature have mainly focused on the effect of (i) material offshoring within manufacturing sector (e.g. Feenstra and Hanson (1996a,b, 1999)), (ii) offshoring in manufacturing sector (e.g. Harrison and McMillan (2011) and Boehm et al. (2017)), and (iii) material offshoring in both manufacturing and service sectors (e.g. Hummels et al. (2014)). Amiti et al. (2005) first adapt the measure of offshoring proposed by Feenstra and Hanson (1996a) and apply to service offshoring. Since then, only a few studies have investigated service offshoring (e.g. Amiti and Wei (2009), Crino (2010), Liu and Trefler (2011)).

[6]Crino (2010)'s offshoring measure also relies on the import matrix to compute the industry share of the import, but only for one year. The author assumes that the import share does not change over time, and that the cross-sectional variation is kept constant at the year in which the import matrix is available.

[7]For example, Amiti et al. (2005); Amiti and Wei (2009) have nine and five service industries, respectively, Crino (2010) has thirteen, and Liu and Trefler (2011) study ten service industries.

I differ from these studies by considering both material and service offshoring across all industries, including manufacturing and service industries, in the South Korean economy. In addition, I examine the occupation exposure of both material and service offshoring following the spirit of Ebenstein et al. (2014). The authors find that a one percent increase in occupation-level offshoring to low-wage countries is associated with a 0.04 percent wage decline from 1984 to 2002. For workers in the most routine occupations, a one percent increase in offshoring to low-wage countries is associated with a 0.07 percent decline in domestic wages. They found no evidence in the industry-level analysis. Another closely-related paper, Hummels et al. (2014), use Danish matched worker-firm data in manufacturing firms and exploit exogenous variations in imports and exports. They report that a one percent increase in offshoring induces a wage increase by 0.03 percent for skilled labor and a wage decrease by 0.022 percent for unskilled labor.[8]

A few recent studies in the empirical offshoring literature introduce novel measures of offshoring. Monarch et al. (2017) measure offshoring from the Trade Adjustment Assistant program by identifying layoffs pertaining to (i) increased imports of final goods or services, (ii) increased imports of intermediate goods or services, or (iii) shift of production location. Using difference-in-difference and propensity matching techniques, they found declines in employment, output, and capital due to import competition, but no significant change in average wages at the firm level. A recent working paper by Bernard et al. (2018) uses a Danish firm-level survey dataset in which firms report whether they have relocated their core business function to a

[8]The measure of offshoring used in Hummels et al. (2014) is based on imports of manufacturing firms, utilizing the distinction between manufacturing firms and service firms in that service firms re-sell a large fraction of their import purchases. Nonetheless, it is still a proxy measure since the data on imported inputs are not available.

foreign location. The authors report that firms reallocate labor from production work to technology and R&D occupations, which increases product development and R&D spending. Also in a recent working paper by Boehm et al. (2017), the authors investigate the effect of offshoring on U.S. manufacturing employment and find that offshoring substitutes for manufacturing employment. In the study, they introduce a novel procedure for classifying firm-level imports into intermediate inputs, combining with a number of restricted Census datasets that make a substantial improvement on measuring imported intermediates inputs. My paper, unlike the previous studies, provides a direct measure of offshoring using disaggregated I-O tables with import matrices that have never exploited before.

The rest of the paper proceeds as follows. In section 2, I describe the data. Section 3 presents the theoretical motivation and empirical strategy of the analysis. Section 4 reports the ordinary-least-squares (OLS) and instrumental-variable (IV) estimation results at the industry and occupation level. The last section concludes.

1.2 Data

In this section, I first describe the institutional background of the data sources, with a particular focus on the South Korean data as, to the my best knowledge, they have never been explored in the literature. Then, I present summary statistics of the data.

1.2.1 Data Sources

I gather data from four different data sources: the Bank of Korea, Korea Labor Institute, UN COMTRADE, and OECD Statistics. Below, I describe each dataset with brief institutional information.

Input-Output Tables

The Bank of Korea maintains and provides Input-Output tables (henceforth I-O tables) at the commodity level. The most disaggregated level of I-O tables at which they initially have surveyed the firms, however, are not released to the public. In addition, the public version does not include the import matrices, which indicate how much of a commodity is imported and used as an input in each commodity-level output. The dataset I obtain and use in this paper is a non-public version of the disaggregated I-O tables, which contains the import matrices that play a crucial role in measuring offshoring intensity.

I-O tables are directly constructed every five years (years ending in 0 and 5) since 1970. From 1986, annually extended tables are available using statistical inferences based on the directly measured data. The I-O tables use the Korean Standard Industrial Classification (KSIC)[9] system, which is based on International Standard Industrial Classification (ISIC). There are 403 commodities in the I-O tables between 2005 and 2009, and 384 commodities in the I-O tables between 2010 and 2014.[10] I use the I-O tables in basic price rather than producer's price so that production taxes would not distort the values in the tables.

Relying on the concordance table provided by the Bank of Korea, I merge the two versions of the I-O tables with aggregations to some extent. However, in order to match the COMTRADE data, more aggregations are necessary. It results in 67

[9]KSIC classifies industries into 5-digit codes. KSIC is revised in 2000 (8th version) and in 2007 (9th version). 2005 I-O tables and its annually extended tables (2006 - 2009) use the 8th version, and 2010 I-O tables and its annually extended tables (2011 - 2014) use the 9th version of the KSIC.

[10]The most disaggregated data available online are 168 commodities for I-O 2005 version and 161 commodities for I-O 2010 version.

industries of which five industries are in agriculture and mining sectors, 32 industries are in the manufacturing sector, 29 industries are in the service sector, and one in the public sector.

These detailed I-O tables help me construct material and service offshoring intensities at the industry level between 2005 and 2014. The crucial element in the construction is the import matrices associated with the I-O tables. They are structured in the same way as the I-O tables but only with the import values. Thus, each element represents how much commodity x is imported and used as an input to produce commodity y. This allows me to directly measure offshoring intensities, which are free of the assumption of proportionality proposed by Feenstra and Hanson (1996a).[11]

Korea Labor and Income Panel Study

The Korea Labor Institute (KLI) is a government-affiliated institution that focuses on labor-related issues and facilitates the government in its policy-making process. It also collects and maintains the only Korean labor panel data called the Korean Labor and Income Panel Study (KLIPS). The surveys that KLI conducts are very similar to NLS, NLSY, and PSID in the U.S., SLID in Canada, BHPS in the U.K., and GSEP in Germany. The first survey began in 1998, including 5,000 households who resided in non-rural areas. As of today, there are 19 years (waves) of data available. KLIPS has a relatively high attrition rate: 74.2% of the original sample remained in the 11th wave, and currently, slightly over 70% remains.[12] In the 12th wave in 2009, 1,415

[11] The proportionality assumes that each industry imports a commodity (material or service) in the same proportion as its economy-wide import share of the commodity. For more details, see Section 1.3.2.

[12] As a comparison, in the 11th wave, attrition rates in other benchmark datasets are: 67% for PSID, 77.7% for GSEP, and 68.4% for BHPS.

new households, including rural households, were added into the sample for better representation of the labor market.

I retrieve individual-level data from the 8th wave in 2005 to the 18th wave in 2015 for the analysis. The sample sizes are 11,580 in 2005 and 14,011 in 2015. Workers are linked to industry and occupation in which they are employed. Industry is coded using the Korean Standard Industrial Classification (KSIC) in three digits. KLIPS also provides 3-digit Korean Standard Classification of Occupations (KSCO) codes. In addition, I observe individual-level characteristics such as wage, age, education attainment, and province.

UN COMTRADE

The UN COMTRADE is one of the most commonly-used public depository of international trade data. It consists of bilateral trade statistics by commodities and services for over 170 reporter countries. The value of a commodity is converted into US dollars. I use trade in goods data to construct an instrument for manufacturing offshoring from 2005 to 2014. The data are reported in International Standard Industry Classification (ISIC), rev. 3.

OECD Statistics

The Organization for Economic Co-operation and Development (OECD) is an international organization comprising 36 countries, most of which are high-income and developed economies. The OECD publishes statistics on a wide number of subjects, including bilateral international trade statistics, called the "OECD.Stat." I gather international trade data in services in the 2010 Extended Balance of Payments Services Classification (EBOPS 2010) from OECD.Stat to construct an instrument for service offshoring variable in 2005 - 2014.[13]

1.2.2 Summary Statistics

Before describing the data, clarifying terminology should be in order. Although "manufacturing offshoring" is a widely-used term, I use material offshoring throughout this paper instead, to distinguish from the manufacturing sector. However, I use the term service offshoring as is. Service offshoring means the producer's import of service inputs, whether the producer belongs to a manufacturing industry or a service industry.

The right panel in Figure 1.1 shows the time-series industry-average offshoring intensities in South Korea for material and service, respectively, weighted by the industry output. MOS denotes material offshoring, and SOS denotes service offshoring. On average, 14% of the input purchase out of total non-energy input purchase was imported in 2005 and about 16% of inputs were imported in 2014. The general trend is increasing with two troughs, notably one in the period of the Great Recessions. Service offshoring intensities are much smaller in magnitude comparing to material offshoring intensities but has grown rapidly and consistently over time. On average, about 3.2% of service inputs were purchased from abroad out of the total non-energy inputs in 2005, and 4.2% of inputs were imported in 2014. Table 1.1 provides the list of industries that are aggregated from the I-O commodities using the concordance table provided by the Bank of Korea. The aggregation is mostly based on the 2-digit KSIC 2000 while matching with the UN COMTRADE data is also taken into consideration.

Table 1.2 reports the unweighted raw summary statistics of material and service

[13] Although UN COMTRADE also has data on trade in services, the quality of the dataset is much less satisfactory as it has many missing values and is less consistent.

offshoring intensities in 2005 and 2014. Industry means are slightly lower than the weighted means shown in Figure 1.1. It is quite surprising that the differences between the minimum and the maximum are fairly large. Table 1.3 reports the list of industries with the highest and lowest offshoring intensities in 2014. In general, service industries tend to purchase inputs from abroad less compared to industries that require sophisticated machineries and equipments. Water transport and Air transport stand out in service offshoring as these industries include services provided by foreign carriers.

Table 1.4 presents summary statistics of the individual-level data for the years 2005 - 2015. I limit the sample to the individuals whose ages are between 16 and 65, with full-time jobs and regular wages. Individuals in the sample belong to 67 industries and 159 distinct occupations. Mean age is about 40 years old, and 40% of the sample is female. Each worker on average earns 2,130,000 Korean Won per month, which is about 1,900 U.S. Dollars. There are 21.9% of workers working in the manufacturing sector and 64.5% of workers working in the service sector. A close look at the data reveals that 22.4% and 29.7% of the workers work in production occupations and blue-collar occupations, respectively. Skilled-workers, defined as workers holding bachelor's degree or higher, constitute about 30% of the sample.

1.3 Theoretical motivation and empirical approach

In this section, I first describe the potential theoretical channels through which offshoring affects wages based on two seminal papers: Feenstra and Hanson (1996a) and Grossman and Rossi-Hansberg (2008). The latter model of offshoring shows that there are opposing forces, which lead to the conclusion that the effect of offshoring on wages is ambiguous. Thus, to examine the effect of offshoring on wages using South Korean data, I present an empirical strategy later in the section.

1.3.1 Theoretical Motivation

There are two prevailing theories of offshoring that provide the insights of the benefits and the costs of offshoring. First, Feenstra and Hanson (1996a) consider a two-country model (North and South) with the production process in which there is a unit continuum of intermediate inputs indexed by z, using unskilled labor, skilled labor, and capital to produce a manufacturing output. Unit-input requirements are denoted as $a_L(z)$ and $a_H(z)$ for unskilled and skilled labor, respectively. Sort z such that $\frac{a_H(z)}{a_L(z)}$ is increasing in z, and assume that the skill premium is higher in North. In equilibrium, there exists a cutoff z^* such that South produces $0 \leq z < z*$, which is offshored from North due to lower cost, and north produces $z* \leq z \leq 1$. As offshoring costs fall, it gets cheaper to produce in South, which implies that the cut off z^* increases to $z^{*'}$.[14]

The inputs that are offshored more in response to a decrease in offshoring costs are the least skill-intensive tasks in North while being the most skill-intensive tasks in South. As the relative demand for skilled labor increases in both countries, skill premium rises. Consequently, wage inequality grows in both countries as a response to an increase in offshoring.

Second, Grossman and Rossi-Hansberg (2008) emphasize that offshoring induces a productivity effect that benefits low-skilled workers whose tasks are more easily

[14] Originally, Feenstra and Hanson (1996a) model capital flows from North (U.S.) to South (Mexico), but the core idea of offshoring is incorporated.

moved across the border. They assume that there are two goods (x and y) produced with a continuum of low-skilled tasks and a continuum of high-skilled tasks in a small open economy. When Home offshores some low-skilled tasks to Foreign, good x requires $a_{L_x}\beta t(i)$ units of labor, where a_{L_x} the labor requirements for good x at Home and $\beta t(i) > 1$ is the task-specific multiplier associated with offshoring low-skilled task i. $t(i)$ is an increasing function of i. Assuming that Foreign low-skilled wage w_L^* is lower than in Home low-skilled wage w_L, Home will offshore the range of low-skilled tasks $0 \leq i \leq I$ to Foreign if $w_L^* \beta t(i) \leq w_L$. This leads to a decrease in the cost of low-skilled labor for producing both goods in the equilibrium. Offshoring is operating as if Home low-skilled labor experiences productivity increase, resulting in an increase in the wage w_L.

This increase occurs because the rent from the reduction in costs is completely captured by the Home low-skilled workers. However, the productivity effect would be offset, and could even be reversed, in a large open economy by the terms-of-trade effect as the relative supply of the low-skilled intensive good increases. As a result, the relative price of the low-skilled intensive good decreases. It is important to note that in a large open economy, high-skilled workers unambiguously gain from the productivity effect since the terms of trade effect does not play a role for the high-skilled workers. The question of which effect, the productivity effect or the terms-of-trade effect, dominates for low-skilled workers is an empirical matter.[15]

[15] There is also a labor supply effect, but the result depends on the parameter of the model. Nonetheless, the implication on wages is the same.

1.3.2 Empirical Approach

In this subsection, I discuss the proportionality assumption, delineate the empirical specification, and lay out the construction of the variables I instrument for the material and service offshoring intensities.

Proportionality Assumption

Feenstra and Hanson (1996a) propose a measure of offshoring (henceforth the F-H measure) using the share of imported materials in total non-energy input purchases. The underlying idea of this measure is that once a subset of the production process is offshored, it has to be imported back to the country for the final good production. With this logic, the higher the imported input share is, the higher the offshoring intensity is. When measuring offshoring intensity, Feenstra and Hanson (1996a) impose the proportionality assumption due to data unavailability. That is, each industry is assumed to import a commodity (material or service) in the same proportion as its economy-wide import share of the commodity. As a consequence, cross-sectional variation is solely determined by the input-induced variation. This is an erroneous assumption since it ignores the heterogeneity in import shares across industries, which could have differential effects on the industry-level wages.

The F-H measure of material and service offshoring intensities are defined as follows. Let t denote time in years, i denote industry, m denote material commodities and s denote service commodities. Then, material offshoring intensity MOS_FH_{it} is:

$$MOS\_FH_{it} = \sum_m \left[\frac{\text{input purchases}_m}{\text{total non-energy inputs purchases}}\right]_{it} \times \left[\frac{\text{imports}_m}{\text{absorption}_m}\right]_t, \quad (1.1)$$

and service offshoring intensity SOS_FH_{it} is:

$$SOS\_FH_{it} = \sum_{s} \left[\frac{\text{input purchases}_s}{\text{total non-energy inputs purchases}} \right]_{it} \times \left[\frac{\text{imports}_s}{\text{absorption}_s} \right]_t , \quad (1.2)$$

where absorption of commodity $j \in \{m, s\}$ is defined as the sum of gross output and net imports: $\text{absorption}_j = Y_j + IM_j - EX_j$.

The first term in equations (1.1) and (1.2) is the input share of commodity j out of the total non-energy inputs in industry i in year t. It indicates the intensity of input j in industry i's production. The second term is the nation-wide import share of commodity j out of the absorption, i.e., the total amount of commodity j available in the domestic market. To compute MOS_FH_{it}, I aggregate the product of the two terms over all material commodities used in industry i in year t. SOS_FH_{it} is computed in the same manner except that the summation is over all service commodities.

The proportionality assumption is manifested in the second term in equations (1.1) and (1.2). The import share of absorption does not vary by industry; it is at the national import share of j. It implies that each industry uses the same proportion of the imported inputs. Thus, the proportionality assumption neglects the industry heterogeneity in imported input composition. As a result, industry variation only comes from differences in input intensity.

To illustrate, consider Computer Management Services as an input for two industries: Motor Vehicles and Parts, and Accommodation and Food Services. Under the proportionality assumption, Motor Vehicles and Parts industry imports Computer Management Services in the same share of absorption as the Accommodation and Food Services industry, which is the import share of absorption for Computer Management Services at the nation-wide level.

However, according to the South Korean data, the Motor Vehicles and Parts industry's import share of absorption for Computer Management Services, 68.9%, is very different from that of the Accommodation and Food Services industry's, 2.5%. With the proportionality assumption, we would assume that both industries' import shares are the same at the nation-wide level at 7.0%, which is clearly far from being correct.

With the South Korean data, I am able to measure offshoring intensities directly from the detailed I-O tables with import matrices. I call these measures the direct measures:

$$MOS_{it} = \sum_{m} \left[\frac{\text{imported input purchases of } m}{\text{total non-energy inputs purchased}} \right]_{it} \tag{1.3}$$

$$SOS_{it} = \sum_{s} \left[\frac{\text{imported input purchases of } s}{\text{total non-energy inputs purchased}} \right]_{it}. \tag{1.4}$$

The direct measures have only one term, the imported input j share of total non-energy inputs in industry i in year t. I then aggregate the share over all commodities in j to construct industry-level offshoring intensities. Given the definition of offshoring in Feenstra and Hanson (1996a) - importing of materials and services as inputs - equations (1.3) and (1.4) are the correct expression of the intensities of material and service offshoring in the absence of the proportionality assumption.

Figure 1.1 depicts the time series of both material and service offshoring intensities (average across industries), weighted by industry's output, for F-H measures (left panel) and the Direct measures (right panel). Even at the national average, F-H measures discernibly differ from the direct measures.

The discrepancies are even larger at the industry level. The level differences in year 2014 range from -0.1770 to 0.1601 for material offshoring and from -0.0621 to

0.2159 for service offshoring.[16] Figure 1.2 presents the proportional discrepancies across industries in year 2014. The largest proportional discrepancy is close to 800%. Generally, F-H measures over-measure the true offshoring intensities. Hence, proportionality assumption may be justified at a very aggregate level of analyses. However, it is an inappropriate assumption when conducting analyses at more disaggregated level.

Empirical Specification

I study the effect of offshoring on wages in two dimensions: industry-level exposure of offshoring and occupation-level exposure of offshoring.

Industry exposure of offshoring: To investigate the effect of material and service offshoring on wages, the empirical strategy is to regress log wages of worker k in industry i in year t, lnw_{kit}, on one-year lagged log offshoring intensities, $lnMOS_{it-1}$ and $lnSOS_{it-1}$. I use lagged measures of offshoring intensities since offshoring takes time to be fully functional, and wages do not adjust instantaneously.

In an attempt to identify the effect of offshoring on wages, I consider a few fixed effects and individual characteristics in the estimating equation. First, common macro shocks to the economy may affect wages and offshoring decisions simultaneously. To address this issue, I include time fixed effects (δ_t). In addition, some industries offshore tasks relatively more easily than others due to industry-specific characteristics that do not vary over time. I control these by adding industry fixed effects (γ_i). With the panel data, I observe the same individuals over time. This allows me to control for unobserved worker characteristics, for instance, IQs, abilities, and social skills, by

[16] Water supply, Air transport, and Storage and Support Activities for Transportation are the industries with the biggest discrepancies.

including individual fixed effects (α_k). Lastly, as Mincer's earnings function suggests, I control for time-varying individual characteristics: age^2, education, and province (Σ_{kt}).[17] Therefore, the baseline estimating equation of log wages:

$$lnw_{kit} = \beta_1 lnMOS_{i,t-1} + \beta_2 lnSOS_{i,t-1} + \alpha_k + \gamma_i + \delta_t + \Sigma_{kt} + \varepsilon_{kit} \tag{1.5}$$

Occupation exposure of offshoring: To analyze the effect of offshoring on wages at the occupation level, I use the same setup as the industry exposure analysis in equation (3.3) with modified offshoring intensities at the occupation level. The initial material and service offshoring intensities vary by industry and time. I apply the Bartik-type transformation to generate the occupation-level exposure of both material and service offshoring.[18] Specifically, I compute each occupation's exposure to the industry-level offshoring using the distribution of workers employed in each occupation across industries in the pre-sample year in 1998.[19] Choosing a pre-sample year allows me to sidestep any endogenous employment composition changes in response to wage changes. That is, for each occupation o and industry i, the distribution of workers is $\lambda_{oi,98} = \frac{L_{oi,98}}{L_{o,98}}$. Then, I interact the distribution with the offshoring intensities, and sum up over all industries:

$$MOS_{ot} = \sum_i \lambda_{oi,98} \times MOS_{it}. \tag{1.6}$$

Occupation exposure of service offshoring is constructed in the same manner as above.

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[17] Age-squared is included instead of age due to multicollinearity between age and the two fixed effects: individual fixed effect and year fixed effect.

[18] Autor et al. (2013) uses this approach to generate the import competition at the local labor market level, and Ebenstein et al. (2014) adopts the same approach for offshoring exposure at the occupation level.

[19] The 1998 data is the first wave of the worker-level data in KLIPS.

The occupation-level estimating equation is:

$$lnw_{koit} = \beta_1 lnMOS_{o,t-1} + \beta_2 lnSOS_{o,t-1} + \alpha_k + \zeta_o + \gamma_i + \delta_t + \Sigma_{kt} + \varepsilon_{kit}. \tag{1.7}$$

I include occupation fixed effects in equation (1.7) to control for time-invariant occupational characteristics, such as occupational offshorability.

Instrumental Variables Approach

There are a few reasons why OLS cannot identify the causal effect of offshoring on wages, due to the endogeneity problem. First, when producing final goods, firms could either produce intermediate inputs in-house or source them from international suppliers. It implies that firms decide how much to spend on workers and how much to offshore simultaneously. Second, trade literature on heterogeneous firms initiated by Bernard and Jensen (1999) and Melitz (2003) suggests that firms with higher productivity pay more to workers and imported inputs. I do not observe the firm-level productivity as well as the industry-level aggregate productivity, which may cause an omitted variable bias. Third, there might be a reverse causality problem such that an increase in offshoring may be the result of a change in the domestic labor market. One can postulate that wages in South Korea have been rising, which may have led firms to switch from in-house production to intermediate inputs purchases from abroad.

To tackle the endogeneity problem, I consider an instrumental variable (IV) approach. The instruments must be correlated with the offshoring intensities while being uncorrelated with other confounding variables that affect domestic wages. In this analysis, I propose two instruments: global material export for material offshoring and global service export for service offshoring. These instruments intend to capture the changes in world's comparative advantage of the material or service commodity relative to South Korea, arising from changes in costs, quality, variety, etc.[20]

Global material export is the exports of a material to the world, aggregated across all countries, subtracting South Korea's import of the material:

$$GME_{mt} = \sum_{c} EX_{cmt} - IM_{KOR,mt}, \tag{1.8}$$

where EX_{cmt} denotes country c's exports of material m in year t, and $IM_{KOR,mt}$ denotes South Korea's imports of material m in year t. I construct GME_{mt} from UN COMTRADE bilateral trade data at ISIC Rev.3 4-digit level, aggregated and matched to the defined industries using the concordance tables discussed in Section 1.2. To construct the IV for material offshoring at the industry level, I then interact GME_{mt} with South Korea's material input share at the industry level. Industries that rely heavily on material inputs are more likely to respond to changes in worlds' export supply of materials. To avoid endogenous compositional changes over time in the material input shares, I use the material input shares in 2005, which is the initial year in the commodity sample. The IV for material offshoring is given by:

$$IV\_MOS_{it} = \sum_{m \in i} \left\{ GME_{mt} \times \left[\frac{\text{input}_m}{\text{total non-energy material inputs}} \right]_{i,05} \right\}, \tag{1.9}$$

where GME_{mt} is global material export for material m in year t, and i denotes industry.

The construction of the instrument for service offshoring follows the same idea as

[20] Hummels et al. (2014) has similar an idea. Their instrument, world export supply, is at the product level for all commodities.

the one for material offshoring. Global service export is the export of a service to the world, aggregated across all countries, subtracting South Korea's import of the service:

$$GSE_{st} = \sum_{c} EX_{cst} - IM_{KOR,st}, \tag{1.10}$$

where EX_{cst} denotes country c's export of service s in year t, and $IM_{KOR,st}$ denotes South Korea's imports of service s in year t. I construct GSE_{st} from OECD Bilateral Trade in Services Statistics in EBOPS 2010 classification, aggregated and matched to the defined industries.[21] Then, I interact GSE_{st} with the initial year's service input share of South Korea at the industry level. This yields:

$$IV\_SOS_{it} = \sum_{s \in i} \left\{ GSE_{st} \times \left[\frac{\text{input}_s}{\text{total service inputs}} \right]_{i,05} \right\}. \tag{1.11}$$

To summarize, I construct two instruments for two endogenous offshoring variables: global material export for material offshoring and global service export for service offshoring. These shocks are external to South Korea's industries and vary by industry and time.

To utilize the IVs to the occupation exposure of material and service offshoring, I apply the same Bartik-type transformation as in Section 1.3.2. by interacting the pre-sample distribution of workers on the aforementioned instruments and aggregating over industries in each occupation. That is:

$$IV\_MOS_{ot} = \sum_{i} \lambda_{oi,98} \times IV\_MOS_{it}. \tag{1.12}$$

[21] There does not exist an official concordance table for EBOPS 2010 and I-O 2005. I manually match the two datasets based on commodity names.

Same approach applies to the IV for service offshoring, which generates:

$$IV\_SOS_{ot} = \sum_i \lambda_{oi,98} \times IV\_SOS_{it}. \tag{1.13}$$

The instrumental variable approach is an attempt to identify the causal effect of offshoring on the wages when firms engage more in offshoring at the industry level. The IV approach identifies that firms in each industry increase offshoring when the material or service export to the world net of South Korea increases. The key identification assumption is that an increase in material or service offshoring is due to the increase in world's comparative advantage. The exclusion restriction requires that changes in world supply of material or service affect South Korea's wages only through each industry's offshoring responses.

1.4 Results

In this section, I first present the OLS and IV estimates for the industry and occupation exposure of offshoring. To examine the heterogeneous wage effect of offshoring, I extract two sub-samples: individuals in the manufacturing sector and in the service sector. I also divide workers into groups based on occupation characteristics and skills to analyze the differential effects of occupation exposure of offshoring.

1.4.1 Effects of Offshoring on Wages at the Industry vs. Occupation level

Recall that the baseline regression equation (3.3) is:

$$lnw_{kit} = \beta_1 lnMOS_{i,t-1} + \beta_2 lnSOS_{i,t-1} + \alpha_k + \gamma_i + \delta_t + \Sigma_{kt} + \varepsilon_{kit}.$$

In Table 1.5, I present the OLS and TSLS results showing the effect of material and service offshoring on wages at the industry level for all workers in the sample. Column (1) shows the OLS estimates for equation (3.3), which is the baseline one-year lagged estimating equation. Columns (2) and (3) show the result of the same regression, except that I replace the offshoring measures with contemporaneous and two-year lagged measures, respectively. Columns (4) through (6) show the Two-Stage Least Squares (TSLS) estimates using the instruments I construct in Section 1.3.2. Standard errors are clustered at the industry level for all columns. All specifications include worker, industry, and year fixed effects. The regression is weighted by the sample weights across all specifications.

OLS results in Table 1.5 suggest that there is no statistically significant wage effects of both material and service offshoring with lags. Only contemporaneous service offshoring has a positive effect on wages. A one percent increase in service offshoring is associated with a 0.02 percent increase in wages of South Korean workers on average.

Before turning into the TSLS results, a discussion of the instruments is in order. There are two endogenous variables and two instruments, thus it is exactly identified. The first-stage F-statistic under the baseline specification with respect to MOS is 7.04

and with respect to SOS is 9.62. An under-identification test reveals that Kleibergen-Paap rk LM statistic has a p-value of .038. Hence, I can reject the null of under-identification at the 5% level. Regarding weak identification test, Stock and Yogo (2005) provide a table of critical values with which we can compare the Cragg-Donald statistic. The Cragg-Donald statistic is calculated based on the assumption that errors are i.i.d. However, in my analysis, the errors are clustered by construction, which renders the Cragg-Donald statistic not applicable. Therefore, I rely on the first-stage F-statistics for the weak identification test.[22]

By looking at the TSLS results in columns (4) through (6), I find that only the service offshoring measure with one-year lag has a statistical significance at the 10% level. Comparing to the OLS result, the sign of the point estimate has changed. It suggests that a one percent increase in service offshoring in the year before leads to a 0.20 percent decrease in wages. Table 1.6 presents the results of the same regressions of Table 1.5 but with occupation fixed effect included. The statistical significance and the size of the point estimates are very similar. Thus, even controlling for occupation characteristics, such as occupational offshorability, the results do not change by much. These findings are consistent with what Ebenstein et al. (2014) find in the U.S.

Recall the baseline regression equation with occupation exposure of offshoring in equation (1.7) is:

$$lnw_{koit} = \beta_1 lnMOS_{o,t-1} + \beta_2 lnSOS_{o,t-1} + \alpha_k + \zeta_o + \gamma_i + \delta_t + \Sigma_{kt} + \varepsilon_{kit}.$$

[22]Staiger and Stock (1997) suggest the rule of thumb that instruments are considered weak if the first-stage F-statistic is less than ten. However, Stock and Yogo (2005) argue that it is a very specific case of i.i.d. errors with one endogenous variable. According to them, the critical value of a case with two endogenous variables and four instruments is 7.56, and the critical values increase as the number of instruments increases.

Table 1.7 shows the results for this regression. Columns (1) through (3) present the OLS estimates with different lags as in Tables 1.5 and 1.6. Columns (4) through (6) present the TSLS estimates using the instruments I construct in Section 1.3.2 with the transformation. All three columns include worker, industry, year, and occupation fixed effects. The standard errors are clustered at the occupation level in this analysis. The regression is also weighted by the sample weights across all specifications.

The OLS results in Table 1.7 show that material offshoring is statistically significant at the 1% level under the baseline specification. The point estimate suggests that a one percent increase in material offshoring is associated with a 0.02 percent increase in wages for South Korean workers on average. Column (3) shows very similar results as column (1).

As with the OLS results, TSLS results show that material offshoring has a significant effect on wages, at the 5% significance level (column (4)). The point estimate quadruples compared to the OLS estimate, which implies that the OLS estimate suffers from a downward bias. A one percent increase of material offshoring leads to a 0.083 percent wage increase. Despite that I cannot compare point estimate to point estimate, the results show qualitatively somewhat different with what Ebenstein et al. (2014) find. Generally, material offshoring can be thought of as offshoring to low-income countries. If so, I find a positive wage effect as opposed to their finding.

Columns (5) and (6) show that the point estimates of the contemporaneous and two-year lagged measures are not statistically significant. Therefore, for the rest of the analysis, I focus on the baseline specification of occupation exposure, using a one-year lagged measure of offshoring.[23]

[23] Amiti and Wei (2009), Liu and Trefler (2011), and Ebenstein et al. (2014) also look at the one-year lagged measure of offshoring.

1.4.2 Manufacturing Sector vs. Service Sector

To examine the differential wage effects of offshoring, I extract two sub-samples: workers in the manufacturing sector and workers in the service sector.[24] To be more precise, the manufacturing sector sample contains workers whose industries of employment are in the manufacturing sector, and likewise, the service sector sample contains workers whose employment industries are in the service sector.

Table 1.8 presents both the OLS and TSLS estimates for the samples of manufacturing sector and service sector. For workers in the manufacturing sector, OLS result suggests that an increase in material offshoring at the occupation level is associated with a wage decline while an increase in service offshoring is associated with a wage increase. The magnitudes of the two effects are similar at about 0.04 percent. For workers in the service sector, OLS result indicate that wages increase with material offshoring, significantly at the 1% level. On the other hand, TSLS estimates show that the effects are not statistically significant for both the manufacturing and service sectors.

To further disentangle the wage effects of offshoring, I run regressions for the workers who switched sectors and the ones who stayed in the same sector. Table 1.9 shows that there are no significant effects for the workers who switched from the manufacturing sector to the service sector. On the contrary, OLS results indicate that a one percent increase in material offshoring at the occupation level leads to a wage decrease by 0.047 percent for workers who stayed in the manufacturing sector. It also shows that a one percent increase in service offshoring at the occupation level leads

[24] The industries that are not categorized as either manufacturing or service sector are: 1) Crops, 2) Animals, 3) Forest goods, 4) Fishery goods, 6) Mined and quarried goods and natural gas, and 67) Public administration and defense.

to a wage increase by 0.039 percent for non-switchers. The manufacturing sample results are driven by the ones who did not switch their sector of employment.

The service sector results reveal a different case. Table 1.10 suggests that workers experience a wage increase as material offshoring increases at the occupation level, regardless of sector switching. For those who switched from service to manufacturing sector, the wage effect is about four times larger than the ones who did not switch. The TSLS results indicate that material offshoring at the occupation level induces a statistically-significant wage increase for workers who stayed in the service sector.

Note that since the sample sizes in this exercise are not sufficiently large, coefficients may not be precisely estimated. That being said, it provides evidence that the baseline result is driven by the workers who did not switch sector of employment.

1.4.3 Occupation Characteristics and Skills

Autor et al. (2003) document the importance of the task content of occupations by distinguishing routine and non-routine tasks as routine tasks are easier to be automated. Thus, automation could replace workers who perform routine-intensive tasks. This has a very crucial implication on offshoring since, if tasks are easier to be automated, then they are more likely to be offshored and completed by unskilled labor with low wages. Ebenstein et al. (2014) uses the same logic to analyze the effect of offshoring by the degree of the routine-ness of occupations. In the absence of data containing information on task contents of occupations, such as O*NET in the U.S., I contemplate the following methodology to divide occupations into groups for the South Korean data. To begin with, I categorize occupations into six groups as in Bernard et al. (2018): (i) managers, (ii) high-skill, R&D and technicians, (iii) support activities, (iv) sales activities, (v) line workers 1 - involved in transport and warehousing, and (vi) line workers 2 - other activities, mostly production.

Then, I define production workers as the workers in category (vi) and non-production workers as the workers in the other categories. Similarly, a worker is defined as a blue-collar worker, if he or she falls into categories (v) and (vi). Using this categorization, I attempt to capture the routine-ness of occupations as the tasks performed by production and blue-collar workers are considered more routine than the others.

The last categorization of workers I entertain is the traditional skilled and unskilled workers, measured by years of educational attainment. Skilled workers are defined as the individuals with at least a bachelor's degree, i.e., years of education greater than or equal to 16. Accordingly, unskilled workers are defined as the ones with lower than a bachelor's degree.

To examine the differential effects of offshoring with respect to skills and occupation characteristics, I interact the aforementioned three dummy variables with material and service offshoring intensities and estimate the following equation:

$$\begin{aligned} lnw_{koit} = {} & \beta_1 D \times lnMOS_{ot-1} + \beta_2 D \times lnSOS_{ot-1} + lnMOS_{ot-1} + lnSOS_{ot-1} \\ & + \alpha_k + \zeta_o + \gamma_i + \delta_t + \Sigma_{kt} + \varepsilon_{kit}, \end{aligned} \tag{1.14}$$

where D is a dummy variable for production workers, blue-collar workers, or skilled-workers.

Table 1.11 reports the OLS and TSLS results of equation (1.14). Column (1) suggests that a one percent increase in material offshoring is associated with a 0.024 percent increase in wages for non-production workers. However, for production workers, a one percent increase in material offshoring leads to a 0.057 percent decrease in wages. These results are statistically significant at the 1% significance level. As for service offshoring, there is no statistically-significant effect on non-production workers, but I find a positive and significant effect on production workers. For blue-collar workers, the result is similar to the one for production workers, but the decline in blue-collar wages due to material offshoring is more moderate than the decline in production worker wages. The findings are qualitatively and quantitatively similar to the the results by Ebenstein et al. (2014) on rountine-ness of occupation.

Column (3) has a different result. Both material and service offshoring raise wages of unskilled workers, while there is no support that material offshoring causes skilled workers to lose relative to unskilled workers. This can be seen from the point estimate of the interaction term of skilled workers and $lnMOS$ being negative but small and statistically insignificant. Service offshoring seems to have a strong effect, with coefficient being 0.0325 for the unskilled workers and -0.0264 for the skilled workers, both of which are statistically significant. It is suggestive that service offshoring could explain a decrease in wage inequality across different skill groups among South Korean workers.

Columns (4) through (6) present the TSLS results. Since two interaction terms are added in each specification compared to the baseline model, I generate two additional instruments, by interacting the occupation group dummies and the instruments described in Section 1.3.2. The results imply that there are no heterogeneous effects across occupation groups, as the statistical significance disappears for material offshoring of non-production and white-collar workers. Note that the first-stage F-statistic of the term $Occ\ Group \times SOS$ is about two in columns (4) and (5). It is dubious that the two additional instruments are valid. Note also that the P-value of the under-identification test in column (6) is 0.5661, which suggests that we cannot reject to the null hypothesis of the under-identification. Thus, I would not reply too much on the interpretation of the TSLS results in Table 1.11.

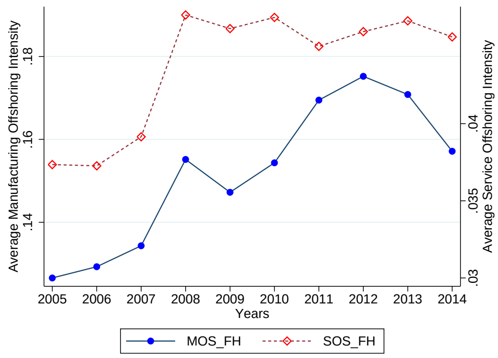
The two canonical theories of offshoring by Feenstra and Hanson (1996a) and Grossman and Rossi-Hansberg (2008) neither have a prediction at the occupation level nor the distinction between manufacturing offshoring and service offshoring. However, Table 1.11 provides another piece of evidence that routine component of occupation is an important aspect of offshoring. In line with Ebenstein et al. (2014), the workers who get hurt by offshoring in South Korea are the ones who perform routine-heavy tasks, i.e., production workers and blue-collar workers.

1.5 Conclusion

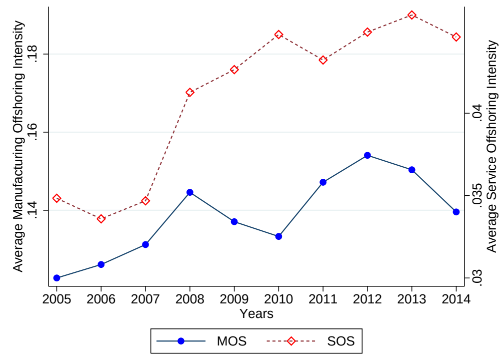
In this paper, I study the effect of material and service offshoring on wages in South Korea for the period 2005-2015. Using unexplored South Korean disaggregated Input-Output tables with detailed import matrices, I measure offshoring intensities directly as the imported input purchases over the total non-energy input purchases. This measure is free of the erroneous proportionality assumption, which has been widely used in the empirical offshoring literature due to data limitation.

Using an instrumental variable approach, I find evidence that material and service offshoring have no significant effects on wages at the industry level. However, occupation exposure of material offshoring has a significant effect on wages: a one percent increase in material offshoring results in a wage increase by 0.083 percent. This finding is driven by the workers in the service sector who did not switch sector of employment. Workers who perform routine tasks, such as production workers and blue-collar workers, experience a decrease in their wages due to material offshoring. On the contrary, workers working in non-routine-task-intensive occupations, such as non-production workers and white-collar workers, experience an increase in wages. Material offshoring appears to increase wage inequality between workers who perform routine tasks and non-routine tasks in South Korea.

Figure 1.1: Time Series of Offshoring intensities: F-H Measure vs. Direct Measure



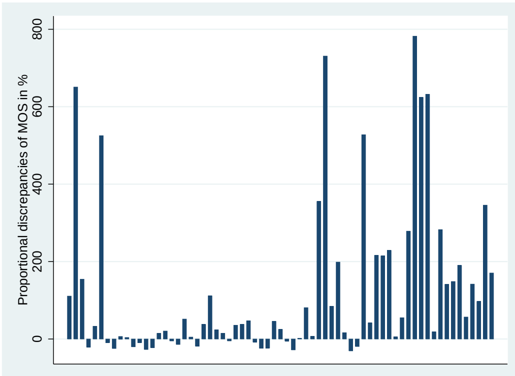
Material offshoring intensities, 2005



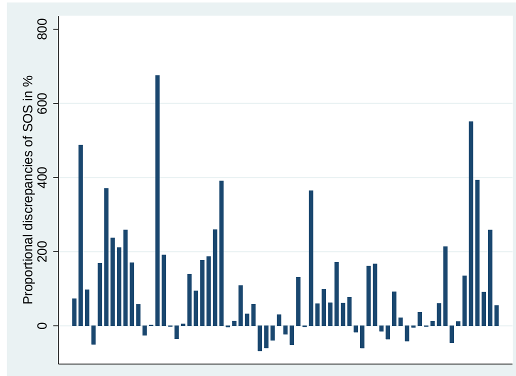
Material offshoring intensities, 2014

Note that above figures are weighted averages across industries, weighted by industry output.

Figure 1.2: Proportional Discrepancies between Direct Measure and F-H Measure on Offshoring Intensities, 2014



Material offshoring intensities



Service offshoring intensities

Note: Proportional discrepancies in percentage terms for material offshoring intensities are computed as $\{(MOS_{FH} - MOS) * 100\}/MOS$ and likewise for service offshoring intensities.

Table 1.1: List of Constructed Industries based on 2-digit KSIC 2000

Code	Industry	Code	Industry
1	Crops	32	TV, video, and audio equipment
2	Animals	33	Household electrical appliances
3	Forest goods	34	Precision instruments
4	Fishery goods	35	Motor vehicles
5	Agriculture, forestry and fishing	36	Ships
	related services	37	Other transportation equipment
6	Mined and quarried goods	38	Other manufactured products
	and natural gas	39	Electricity, gas, steam supply
7	Food: Meat, dairy, seafood	40	Water supply
	fruit, vegetable	41	Waste/remediation services
8	Grains, flour, sugars	42	Construction, civil engineering
9	Bakery, confectionery, other foods	43	Wholesale and retail trade
10	Beverages	44	Land transport
11	Tobacco products	45	Water transport
12	Fiber yarn, fabrics, textile, apparels	46	Air transport
13	Leather and fur products, footwear	47	Transportation support activities
14	Wood and wooden products	48	Food services and accommodation
15	Pulp and paper, printing and	49	Communications
	reproduction of recoded media	50	Broadcasting
16	Coke and hard-coal, petroleum products	51	Information services
17	Organic/inorganic chemical products	52	Software development, computer
	and Medicaments		related services
18	Fertilizer and pesticides, other	53	Publishing
	chemical products	54	Video/audio production and
19	Plastic products		distribution
20	Rubber products	55	Financial services
21	Glass products	56	Insurance
22	Ceramic wares	57	Residential building rental services
23	Cement and concrete products	58	Research and development
24	Other non-metallic mineral products	59	Business professional services
25	Primary fabricated iron/steel products	60	Scientific and technical services
26	Non-ferrous metal ingots and products	61	Business support services
27	Fabricated metal products, except	62	Educational services
	machinery and furniture	63	Medical and health care services
28	General machinery and equipment	64	Social work activities
29	Special machinery and equipment	65	Cultural services, repair and
30	Electronic equipment and components,		other personal services
	semiconductor, computer equipment	66	Social organizations
31	Telecommunication and broadcasting	67	Public administration and defense
32	equipment		

Table 1.2: Summary Statistics of Offshoring Intensities in 2005 and 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
Year: 2005					
MOS	67	.12267	.12765	.00008	.4458
SOS	67	.03484	.10705	.00146	.83491
Year: 2014					
MOS	67	.13957	.14501	.00225	.82802
SOS	67	.04462	.11006	.00042	.83035

Note: MOS and SOS above are based on direct measures. They are unweighted simple summary statistics.

Table 1.3: Most and Least Offshoring Intensive Industries in 2014

Year: 2014			
Lowest industries	MOS	Lowest industries	SOS
Financial Services	.0022529	Animal	.0004164
Insurance	.0024551	Wood and wooden products	.0017988
Building rental	.0027025	Medical and health care	.0024335
Business professional services	.0038607	Crops	.0025881
Animals	.004159	Grains, flour, sugars	.0026151
Highest industries	MOS	Highest industries	SOS
Air transport	.8280236	Water transport	.8303487
Chemical products	.4766761	Air transport	.3603218
Glass products	.4095162	Scientific and tech serv	.1351569
Telecomm. and broadcasting	.3992023	Fishery goods	.1180905
Electricity, gas supply	.3324691	Broadcasting	.1038656

Note: MOS and SOS above are based on direct measures.

Table 1.4: Summary Statistics of Workers: 2005 - 2015

Variable	Obs	Mean	Std. Dev.	Min	Max	Distinct
Industry	46751	46.702	15.561	1	67	67
Occupation	46751	492.772	279.434	11	982	159
Gender	46751	.399	.490	0	1	2
Age	46751	40.604	10.801	16	65	50
Province	46751	6.409	4.521	1	19	17
Wage per Month	46751	213.307	150.800	6	5500	642
Workers in Manufacturing	46751	.219	.408	0	1	2
Workers in Service	46751	.645	.478	0	1	2
Production Workers	46751	.224	.417	0	1	2
Blue-collar Workers	46751	.297	.457	0	1	2
Skilled-Workers	46751	.299	.458	0	1	2

Note: Gender takes the value 0 if male and 1 if female. The two missing values for Province are "North Korea" and "Abroad." Wage per month is for "(main job) wage earner - amount of average monthly pay (unit: 10,000 KRW)." 10,000 KRW is roughly 9,000 USD. Production Workers takes value 1 if occupation is in "Group L2, Line Workers (mostly production)" from Occupation Group. Likewise, Blue-collar workers takes value 1 if Production Workers or "Group L1, Line workers, involved in transport and warehousing." Skilled workers are defined based on the level of education: Skilled workers variable is 1 if education is greater than 16 (bachelor's degree).

Table 1.5: OLS and TSLS Estimates with Industry Exposure of Offshoring

Dep. Var:	OLS			Two-Stage Least Squares		
ln(wage)	(1)	(2)	(3)	(4)	(5)	(6)
lnMOS_lag1	0.0106			0.00281		
	(0.00733)			(0.0626)		
lnSOS_lag1	0.0149			-0.198*		
	(0.0108)			(0.109)		
lnMOS		0.00854			-0.0195	
		(0.00631)			(0.0635)	
lnSOS		0.0201**			-0.216	
		(0.00971)			(0.141)	
lnMOS_lag2			0.00629			0.0246
			(0.00783)			(0.0382)
lnSOS_lag2			0.00461			-0.0788
			(0.0109)			(0.0667)
Age^2	-0.00097***	-0.00099***	-0.00096***	-0.00094***	-0.00096***	-0.00095***
	(8.52e-05)	(7.22e-05)	(8.48e-05)	(0.000121)	(0.000122)	(9.23e-05)
Education	0.0343**	0.0338***	0.0304**	0.0348**	0.0359***	0.0296**
	(0.0142)	(0.0123)	(0.0134)	(0.0149)	(0.0127)	(0.0138)
Province	0.00201	0.00176	0.000895	0.00205	0.00216	0.000747
	(0.00225)	(0.00256)	(0.00251)	(0.00259)	(0.00279)	(0.00274)
Observations	41,308	40,910	37,195	41,308	40,910	37,195
R-squared	0.868	0.869	0.874	0.015	0.027	0.028
1st Stage F-Stat						
w.r.t. MOS				7.04	5.87	6.25
w.r.t. SOS				9.62	9.09	8.31
Underidentification test:						
Kleibergen-Paap rk LM Stat				4.59	3.59	3.07
P-value				0.0380	0.0582	0.0797

Robust standard errors in parentheses and are clustered at the industry level. All classifications include worker, industry, and year fixed effects. The regression is weighted by the sample weights for every specification.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: OLS and TSLS Estimates with Industry Exposure of Offshoring with Occupation Fixed Effects

Dep. Var:	OLS			Two-Stage Least Squares		
ln(wage)	(1)	(2)	(3)	(4)	(5)	(6)
lnMOS_lag1	0.0106			-0.000614		
	(0.00674)			(0.0610)		
lnSOS_lag1	0.0148			-0.191*		
	(0.0103)			(0.109)		
lnMOS		0.00796			-0.0239	
		(0.00602)			(0.0637)	
lnSOS		0.0193*			-0.209	
		(0.00984)			(0.143)	
lnMOS_lag2			0.00577			0.0216
			(0.00668)			(0.0360)
lnSOS_lag2			0.00324			-0.0716
			(0.0104)			(0.0632)
Age^2	-0.00086***	-0.00089***	-0.00086***	-0.00083***	-0.00086***	-0.00084***
	(8.52e-05)	(7.56e-05)	(8.24e-05)	(0.000121)	(0.000125)	(8.96e-05)
Education	0.0293**	0.0306***	0.0243*	0.0295**	0.0321**	0.0236*
	(0.0129)	(0.0113)	(0.0127)	(0.0138)	(0.0122)	(0.0129)
Province	0.00184	0.00181	0.00102	0.00192	0.00221	0.000873
	(0.00225)	(0.00255)	(0.00248)	(0.00256)	(0.00274)	(0.00270)
Observations	41,306	40,910	37,193	41,306	40,910	37,193
R-squared	0.873	0.874	0.880	0.022	0.034	0.022
1st Stage F-Stat						
w.r.t. MOS				6.13	5.84	6.42
w.r.t. SOS				8.53	8.96	8.21
Underidentification test:						
Kleibergen-Paap rk LM Stat				4.64	3.59	3.09
P-value				0.0364	0.0581	0.0789

Robust standard errors in parentheses and are clustered at the industry level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: OLS and TSLS Estimates with Occupation Exposure of Offshoring

Dep. Var:	OLS			Two-Stage Least Squares		
ln(wage)	(1)	(2)	(3)	(4)	(5)	(6)
lnMOS_Occ_lag1	0.0212***			0.0828**		
	(0.00527)			(0.0398)		
lnSOS_Occ_lag1	0.0165			-0.0645		
	(0.0108)			(0.0634)		
lnMOS_Occ		0.00865			0.2378	
		(0.00553)			(0.2220)	
lnSOS_Occ		0.0137			-0.3343	
		(0.0106)			(0.3662)	
lnMOS_Occ_lag2			0.0212***			0.0569
			(0.00653)			(0.0599)
lnSOS_Occ_lag2			0.00524			-0.0509
			(0.0102)			(0.0695)
Age^2	-0.00085***	-0.00088***	-0.00086***	-0.00083***	-0.00079***	-0.00084***
	(7.75e-05)	(7.06e-05)	(8.59e-05)	(8.08e-05)	(0.000128)	(9.41e-05)
Education	0.0290***	0.0307***	0.0229**	0.0263***	0.0191	0.0219*
	(0.0102)	(0.00885)	(0.0111)	(0.00983)	(0.0151)	(0.0114)
Province	0.00156	0.00214	0.000932	0.00144	0.00220	0.000745
	(0.00204)	(0.00207)	(0.00235)	(0.00206)	(0.00221)	(0.00236)
Observations	40,642	40,308	36,556	40,642	40,308	36,556
R-squared	0.874	0.874	0.880	0.022	0.174	0.026
1st Stage F-Stat						
w.r.t. MOS				22.77	20.77	21.18
w.r.t. SOS				20.60	23.27	25.77
Underidentification test:						
Kleibergen-Paap rk LM Stat				7.23	1.48	3.91
P-value				0.0072	0.2240	0.0479

Robust standard errors in parentheses and are clustered at the occupation level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Manufacturing and Service Sector Sample: Occupation Exposure of Offshoring

Dep. Var:	Manufacturing sample		Service Sample	
ln(wage)	OLS	TSLS	OLS	TSLS
lnMOS	-0.0456**	0.1677	0.0296***	0.1778
	(0.0211)	(0.3473)	(0.00982)	(0.1272)
lnSOS	0.0397**	-0.2060	0.00963	-0.1835
	(0.0190)	(0.3892)	(0.0147)	(0.2244)
Age^2	-0.00081***	-0.00068***	-0.00092***	-0.00085***
	(0.000105)	(0.000230)	(9.70e-05)	(0.000139)
Education	0.00612	0.000295	0.0401***	0.0336**
	(0.00606)	(0.00986)	(0.0138)	(0.0144)
Province	0.00537	0.00451	0.000681	-0.000574
	(0.00389)	(0.00459)	(0.00292)	(0.00298)
Observations	8,394	8,394	25,659	25,659
R-squared	0.910	0.065	0.876	0.034
1st Stage F-Stat				
w.r.t. MOS		49.52		13.18
w.r.t. SOS		10.86		8.55
Underidentification test:				
Kleibergen-Paap rk LM Stat		0.74		1.93
P-value		0.3900		0.1653

Robust standard errors in parentheses and are clustered at the occupation level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification. Offshoring measures are at the occupation level and lagged by one year.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.9: Switchers - Manufacturing to Service vs. Non-switchers - Manufacturing: Occupation Exposure of Offshoring

Dep. Var:	Switchers: Manuf. to Service		Non-switchers: Manufacturing	
ln(wage)	OLS	TSLS	OLS	TSLS
lnMOS	0.0191	0.137	-0.0468**	0.220
	(0.0254)	(0.154)	(0.0230)	(0.558)
lnSOS	-0.00226	0.0224	0.0392*	-0.258
	(0.0524)	(0.102)	(0.0210)	(0.595)
Age^2	-0.00078***	-0.00079***	-0.00085***	-0.00069**
	(0.000133)	(0.000137)	(0.000114)	(0.000318)
Education	-0.0188	-0.0167	0.00516	-0.00125
	(0.0219)	(0.0217)	(0.00646)	(0.0135)
Province	-0.00173	-0.00123	0.00528	0.00409
	(0.00681)	(0.00675)	(0.00410)	(0.00541)
Observations	2,978	2,978	7,452	7,452
R-squared	0.825	0.015	0.911	0.115
1st Stage F-Stat				
w.r.t. MOS		10.29		43.12
w.r.t. SOS		6.51		10.60
Underidentification test:				
Kleibergen-Paap rk LM Stat		8.28		0.41
P-value		0.0040		0.5234

Robust standard errors in parentheses and are clustered at the occupation level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification. Offshoring measures are at the occupation level and lagged by one year.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.10: Switchers - Service to Manufacturing vs. Non-switchers - Service: Occupation Exposure of Offshoring

Dep. Var:	Switchers: Service to Manuf.		Non-switchers: Service	
ln(wage)	OLS	TSLS	OLS	TSLS
lnMOS	0.102***	0.184	0.0286***	0.0889*
	(0.0373)	(0.135)	(0.00913)	(0.0512)
lnSOS	-0.00944	-0.0588	0.00540	-0.0519
	(0.0476)	(0.156)	(0.0143)	(0.0751)
Age^2	-0.00099***	-0.00099***	-0.00090***	-0.00087***
	(0.000132)	(0.000132)	(0.000101)	(0.000109)
Education	0.0505**	0.0489**	0.0398***	0.0371***
	(0.0200)	(0.0201)	(0.0136)	(0.0134)
Province	0.00867	0.00920	0.000831	0.000247
	(0.00659)	(0.00621)	(0.00302)	(0.00298)
Observations	3,137	3,137	24,433	24,433
R-squared	0.811	0.049	0.878	0.026
1st Stage F-Stat				
w.r.t. MOS		12.91		11.24
w.r.t. SOS		6.18		16.92
Underidentification test:				
Kleibergen-Paap rk LM Stat		7.66		6.13
P-value		0.0057		0.0133

Robust standard errors in parentheses and are clustered at the occupation level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification. Offshoring measures are at the occupation level and lagged by one year.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.11: OLS Estimates of differential effects with respect to occupation groups: Occupation Exposure of Offshoring

Dep. Var:	OLS			Two-Stage Least Squares		
ln(wage)	(1)	(2)	(3)	(4)	(5)	(6)
Prod × lnMOS	-0.0807***			-0.0474		
	(0.0253)			(0.0673)		
Prod × lnSOS	0.0375**			0.160		
	(0.0165)			(0.0988)		
Bcollar × lnMOS		-0.0582**			-0.0876	
		(0.0247)			(0.0951)	
Bcollar × lnSOS		0.0374**			0.183	
		(0.0162)			(0.144)	
Skill × lnMOS			-0.00233			-0.0605
			(0.0104)			(0.377)
Skill × lnSOS			-0.0589***			-0.0217
			(0.0112)			(0.304)
lnMOS	0.0239***	0.0239***	0.0205***	0.0808*	0.0918**	0.0996
	(0.00571)	(0.00579)	(0.00695)	(0.0430)	(0.0464)	(0.163)
lnSOS	0.00541	0.00366	0.0325***	-0.0737	-0.106	-0.0480
	(0.0115)	(0.0120)	(0.0108)	(0.0695)	(0.0927)	(0.131)
Age^2	-0.00085***	-0.00085***	-0.00084***	-0.00084***	-0.00084***	-0.00081***
	(7.58e-05)	(7.63e-05)	(7.57e-05)	(7.67e-05)	(7.89e-05)	(0.000110)
Education	0.0292***	0.0292***	-0.00416	0.0282***	0.0283***	-0.0112
	(0.0102)	(0.0102)	(0.00837)	(0.00991)	(0.0101)	(0.00958)
Province	0.00158	0.00161	0.00171	0.00150	0.00157	0.00152
	(0.00204)	(0.00204)	(0.00206)	(0.00206)	(0.00206)	(0.00226)
Observations	40,642	40,642	40,642	40,642	40,642	40,642
R-squared	0.874	0.874	0.874	0.024	0.019	0.025
1st Stage F-Stat						
w.r.t Occ Group × MOS				11.68	13.85	41.44
w.r.t Occ Group × SOS				1.97	2.25	43.33
w.r.t MOS				22.93	18.05	12.91
w.r.t SOS				10.70	10.47	11.80
Underidentification test:						
Kleibergen-Paap rk LM Stat				6.77	4.67	0.33
P-value				0.0093	0.0306	0.5661

Robust standard errors in parentheses and are clustered at the occupation level. All classifications include worker, industry, year, and occupation fixed effects. The regression is weighted by the sample weights for every specification. Offshoring measures are at the occupation level and lagged by one year.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 2

FDI and Inequality in Vietnam: An Approach with Census Data (with John McLaren)

2.1 Introduction

OECD countries, and not least both the US and Japan, have embraced FDI as a primary tool of economic development in low-wage economies, and even perhaps as a more important tool than Official Development Aid. However, there has been much debate over the effects of FDI on the host economies, and particularly its effects on income inequality. Perhaps the most important channel by which FDI can affect income inequality is by shifting the demand for labor. In principle, FDI could either raise or lower income inequality in this way.

This paper attempts to measure this effect in the case of Vietnam. Vietnam is an extremely interesting one for measuring the effects of trade and foreign investment because of its rapid transition from a relatively closed centrally-planned economy to a very open market-based economy. McCaig and Pavcnik (2013) document the dramatic restructuring of the economy from the late 1980's to 2008 following the Doi Moi market reforms of 1986, with a large drop in the share of agriculture in employment and GDP and increases in the share of manufacturing and especially services. The share of State-Owned Enterprises (SOE's) has fallen as SOE's have lost subsidies and failing SOE's have been allowed to exit, and the role of foreign enterprises has increased rapidly as restrictions on foreign ownership have been relaxed. At the same time, increases in labor productivity in each sector combined with movements away from the lowest-productivity sector (agriculture) have resulted in a doubling of income per capita. The Vietnamese economy has been the recipient of a large volume of Japanese FDI, with smaller flows from the US to date, but that is likely to change given the close trade ties between the US and Vietnam, and particularly if the Trans-Pacific Partnership is ratified, which would provide for free trade between

Vietnam and several other top trade partners including the United States.

To address the effect of FDI on income inequality in Vietnam, we use data from the 1989 to 2009 Population and Housing Census (hereafter, the 'Census'), each of which records the industry and province of employment for each worker, as well as an unusual piece of information that is crucial for the question at hand: whether the worker is employed in a private entity, state enterprise, or foreign-owned enterprise. The amount of FDI into each industry and province can be computed by adding up the number of workers in foreign-owned entities. This is available for 1999 and 2009, so our regressions focus on those years (using some information from 1989 for initial conditions).

If the Census also provided wage data, a Mincer wage regression could then be used to establish whether or not the skilled wage premium has moved systematically together with FDI inflows either by industry or by province, and in what direction. Specifically, controlling for all available personal characteristics, a measure of the worker's skill level could be interacted with the number of foreign-owned enterprise jobs in the province. This would allow us to test for the possibility that a hiring surge by multinationals in a particular location has an effect on skill premia, and we could estimate it both for those actually employed in the foreign sector and for those outside of it.

Unfortunately, wage data were not collected by the Census, so indirect methods are required. The Census does ask a wide variety of questions that can be used to gauge a household's standard of living. Does the household have access to piped water? Is it piped into the household's dwelling? Does the household have access to electricity? Does it own a radio? A television? What is the rate of child mortality? These can be observed over time to see if people living in a province that saw a greater

FDI inflow also were more likely to see a measurable improvement in living standards as measured in these basic amenities. In addition, we can look for a differential effect by education: Were households with more high-school-educated adults, for example, more likely to see an improvement in their living conditions, in provinces with a large FDI inflow, compared to those with less education? Is there any educational class that saw a *worsening* in living conditions, or a slower improvement relative to other groups, when more FDI is present?

This allows us to measure the pure general-equilibrium effect of FDI on local income inequality operating through its effect on labor demand. This approach can also be used to examine the effect of FDI on the absolute level of local real income, assuming that all of the amenities in question are normal goods.

Before turning to our approach in detail, we will review some of the main theoretical ideas and existing literature.

2.1.1 Theoretical ideas

There are many reasons inward FDI could increase income inequality and many reasons it could have the opposite effect. Here we mention three different mechanisms as examples.

(i) *Inward FDI could compete with domestic capital for domestic workers, pushing down the income of domestic capitalists and raising the incomes of domestic workers.* This is the idea behind the political argument of Pandya (2013) that the median voter should typically be in favor of policies to welcome FDI. One simple model in which this outcome emerges is as follows. Home is a small open economy with multiple industries, each producing some tradable output by combining labor and capital with constant returns to scale. The capital for each industry is sector-specific, meaning that it can be used only for that industry, and it is available in a fixed amount. There is an exogenous supply of homogeneous workers, who can switch from one industry to another costlessly. Each citizen has one unit of labor, but some in addition own some capital, creating income inequality. An increase in inward FDI to any of the industries raises the marginal product of labor in that industry, raising aggregate labor demand and the equilibrium wage. This decreases income per unit of capital in each industry (since output prices are determined on world markets and remain unchanged). As a result, incomes of low-income citizens (who have only labor income) rise proportionally more than the incomes of higher-income citizens (who receive income gains on their labor but income reductions on their capital). In this model, inward FDI unambiguously reduces income inequality.

(ii) *Inward FDI could shift the mix of tasks performed in the economy in the direction of increase skill intensity.* This mechanism is developed in detail in Feenstra and Hanson (1996a) (a similar story with a slightly different mechanism emerges in Zhu and Trefler (2005); and Raveh and Reshef (2016)). In that model, there is one manufactured good that requires a continuum of inputs to produce. Each input requires high-skilled labor, low-skilled labor and capital to produce, and can be produced either in North or in South. Each country has an exogenous endowment of all three factors, and the ratio of high-skilled to low-skilled labor is higher in North. The inputs differ in the ratio of high-skilled and low-skilled labor required to produce them.

In equilibrium, the ratio of high-skilled to low-skilled wages is higher in South, so it is more expensive to produce very skilled-labor intensive inputs in the South than in the North, and *vice versa* for very low-skilled-labor intensive inputs. Therefore, there is a cutoff input such that inputs that are more skilled-labor-intensive than the cutoff are produced in North and less skilled-labor-intensive inputs are produced in South. Now, if FDI transfers some capital from North to South, the cutoff input changes: The increased productivity of Southern labor expands the range of inputs produced in the South, so that the new cutoff is more skill-labor intensive than the old one. Consequently, the least skilled-labor intensive inputs that had previously been produced in North are now produced in South, where they become the most skilled-labor intensive inputs produced in South. As a result, the relative demand for skilled labor goes up in both countries, increasing wage inequality.

The result is that in this model, inward FDI reduces the income of South's capitalists, which in and of itself lowers inequality; but it increases wage inequality, which pushes in the other direction.

(iii) *Inward FDI could be more or less skill intensive than domestic businesses in its own demand for labor.* Consider the following illustrative model. Home is a small open economy, with a range of industries, each producing a traded good combining skilled and unskilled labor with constant returns to scale. To keep the argument as simple as possible, suppose that all of these industries have the same production function.[1] In addition, there is a sector that requires foreign capital to produce, in combination with both kinds of labor. Think, for example, of an oil field that requires foreign technology to exploit, or an assembly operation that will use foreign machines plus local labor to produce products for export. For simplicity, suppose that the foreign-capital-using sector uses skilled workers in a fixed ratio, S^F, to unskilled, and

[1] This is not essential to make the point. If different industries differ in their skilled-labor intensities, then analyzing labor demand is complicated by the fact that the mix of products produced will be endogenous, as varying the skilled-wage-to-unskilled-wage ratio will move the economy from one cone of specialization to another. However, this is only a complication and does not affect the main point under discussion.

that all capital is foreign-owned.

Suppose that initially there is no foreign capital at all, and the economy's exogenous ratio of skilled to unskilled labor is $\bar{S}$. Now, allow a small amount of inward FDI, so that the foreign-capital-using sector begins hiring local workers, S^F skilled workers for each unskilled worker. If $S^F > \bar{S}$, the labor left over for the domestic industries has a lower ratio of skilled to unskilled workers than $\bar{S}$, and so the skilled-to-unskilled wage ratio must rise to induce domestic employers to substitute toward unskilled workers and restore labor-market clearing. The result is a rise in wage inequality (which in this illustrative model is also a rise in overall inequality). In this case, FDI reduces the absolute wages of the unskilled workers as well, since in each domestic firm the ratio of skilled to unskilled workers, and hence the marginal product of unskilled labor, will fall. If $S^F < \bar{S}$, inequality is reduced, and real incomes of unskilled workers are increased, due to FDI, following the same logic.

The former case could be quite plausible in the case of extractive industries; perhaps a new oil well will require 1 engineer, 1 supervisor, and 20 manual workers; but if the typical domestic employer has 1 supervisor for 100 manual workers, the oil well removes from the domestic economy skilled workers who would normally employ 200 manual workers, while providing new jobs in the foreign-capital-using sector for only 20 of them. The resulting net decrease in unskilled labor demand requires a drop in unskilled wages to restore equilibrium. The opposite outcome is more likely for an assembly operation, where the skilled-unskilled ratio might be comparable to or even below the domestic-sector average.

These three examples are by no means exhaustive. Indeed, there is now a rich theoretical literature on the relationship between trade and inequality (Harrison et al. (2010)), and any one of those models would have its own implications for the effect of FDI on inequality. These examples merely illustrate the point that there can be no theoretical presumption regarding whether inward FDI will raise or lower income inequality, whether it will raise or lower the real incomes of low-skilled workers, or whether it will raise or lower poverty rates. Only empirical enquiry can answer these questions.

2.1.2 Literature review

A broad literature investigates the relationship between FDI and income inequality. Macro approaches are exemplified by Jaumotte et al. (2013), who use panel data for 51 countries over 1981-2003 and find a positive effect of FDI on income inequality but a negative effect of trade. Im and McLaren (2015) suggest that such findings may be due to the endogeneity of FDI, and find a negative effect on inequality, once FDI inflows are instrumented by a range of variables. Raveh and Reshef (2016) examine the effects of capital imports on the skill premium in wage data for a wide panel of countries, using changes in unit prices of different types of capital as instruments. They find that the *composition* of capital imports is more important than the *quantity* of capital imports, with more R&D intensive capital imports promoting increased skilled-wage premia.

Micro studies tend to examine the effect of FDI on wages in the host country. Lipsey (2004) surveys a wide range of studies, finding robust evidence that multinationals raise incomes for the workers whom they hire, but little evidence either way on the effects of multinationals on the income of other workers in the same labor market. We provide some evidence on that question.

A small number of studies based on micro data investigate the effects of FDI on outcomes of living standards in a manner somewhat analogous to what we are attempting here. Atkin (2009) uses the height of a worker's children as a measure of economic outcomes in response to local hiring by multinationals in Mexico. Apart from FDI, Young (2012) uses a range of tangible variables quite similar to what we use here (ownership of a television, access to electricity, various health measures) from the Demographic and Health Surveys of USAID to assess economic growth trends in Africa.

This study is also related to the literature that assesses the effects of globalization by exploiting intra-national geographic variation in its effects. Edmonds and Pavcnik (2002) studied the effect of the mid-1990's liberalization of rice exports in Vietnam on child labor, by using variation in the effect on rice prices across different locations within the country. Topalova (2007) studied the poverty effects of the Indian trade liberalization of the early 1990's by using differences in the intensity of the shock across districts. Many studies have followed in this vein. Particularly relevant for our present purposes is Hanson (2007), who used geographic variation in FDI in Mexico to investigate the effect on income inequality there, finding modest evidence in Census data that FDI (and trade) raise inequality.

The rapid changes in Vietnam have provided the setting for a number of studies focussed on income effects of globalization in that country in particular. Aside from Edmonds and Pavcnik (2002) mentioned above, McCaig (2011) finds that the reduction of US tariffs on Vietnamese goods following the 2000 bilateral agreement significantly reduced poverty, with the most-affected provinces showing the largest reductions in poverty. McCaig and Pavcnik (2013) show that the same tariff reductions led to a large reallocation within affected industries from informal production to the formal enterprise sector. Brambilla et al. (2012) show that US protectionist actions limiting exports of Vietnamese catfish lowered incomes of affected households. Although in this study we use variation in international shocks at the level of the province analogously to McCaig (2011), this appears to be the first study to look at the effects of FDI on welfare of Vietnamese households in a similar way.

2.2 Empirical Approach

Our outcome variables are observed at the household level, so all of our individual-level data needs to be aggregated to the household level. Given a household h living in province i in year t, consider an outcome variable y_h. This could be a dummy variable for the presence of a television in the household, for example. Once we condition on h, we do not need to condition on i or t, because each household in the sample is observed in only one year of the data, and of course lives in only one province. It will be useful to write $i(h)$ and $t(h)$ for the location and year of observation, respectively, of household h.

Given that we have no income variables, the simplest way to measure the effect of FDI in the local labor market would be through a regression of the following sort:

$$y_h = \beta_0 + \beta_1 n_h + \sum_j \beta_2^j n_h^j + \beta_3 n_h^{FOR} + \beta_4 FOR_{i(h),t(h)} + \beta_5^{i(h)} + \beta_6^{t(h)} + \epsilon_h. \qquad (2.1)$$

Here, n_h is the number of members in the household; n_h^j is the number of adult members of educational class j, where j takes one of four values, indicating that the highest level of education achieved is either 'less than primary,' 'primary,' 'secondary,' or 'university;' n_h^{FOR} is the number of adult household members employed by a foreign employer; $FOR_{i,t}$ is the number of workers employed by foreign employers in province

i in year t, normalized by the initial population of province i;[2] and β_5^i and β_6^t are province and year fixed effects respectively. The n_h^j are controls for the human capital endowment of the household. This last variable, $FOR_{i,t}$, is the main variable of interest. If its coefficient β_4 is positive, then that implies that households living in provinces with a greater increase in FDI during the period under study saw a greater increase in the probability of owning a television, or whatever the particular outcome variable is. Note that we are controlling for whether or not the household has members who are themselves employed by foreign enterprises through n_h^{FOR}, so this would demonstrate that even those who are not themselves hired by foreign firms nonetheless benefit from the increased local demand for labor that the foreign firms create.

A comment on how to interpret the demographic coefficients may be in order. Increasing n_h^j, holding n_h constant, implies exchanging one working-age adult with education j for one child or senior citizen. Therefore, each of the β_2^j coefficients measures the effect of a reduction in the household's dependency ratio, with higher values of j implying higher levels of education for the working-age member in question. On the other hand, an increase in n_h, holding the n_h^j variables constant, implies addition of one non-working-age dependent to the household, whose effect is measured by β_1.

Now, equation (2.1) is framed as if an increase in FDI will have the same effect for all households in the same province, but of course that may not be the case, and indeed the discussion above indicates that there are many reasons FDI might affect the real incomes of households with different human capital to different degrees, or

[2] More precisely, this is the number of foreign-employed workers in province i at date t, divided by the population of province i in 1989, unless that population figure is not available, in which case we use the population in 1999.

even in different directions. We can investigate such differences with the modified equation as follows:

$$y_h = \beta_0 + \beta_1 n_h + \sum_j \beta_2^j n_h^j + \beta_3 n_h^{FOR} + \sum_j \beta_4^j n_h^j FOR_{i(h),t(h)} + \beta_5^{i(h)} + \beta_6^{t(h)} + \epsilon_h. \quad (2.2)$$

The difference from (2.1) is in the fourth term, which interacts the household human-capital variables with the provincial foreign-hiring variable. If $\beta_4^j > 0$ for all j, then a rise in local foreign hiring improves living conditions for households of all human capital levels. However if, for example, $\beta_4^1 < 0$ while $\beta_4^4 > 0$, then local foreign investment improves living standards for highly-educated households, while worsening things for lower-education households.

An obvious problem with this approach is the possible endogeneity of foreign hiring. This could arise for many reasons. For example, if a province receives a new highway or an improved electrical grid, that could increase incomes and living standards throughout the province, and at the same time make the province more attractive for foreign investment. If there are enough shocks of that sort, a spurious positive correlation between foreign hiring and living standards will be induced, and regressions of the sort we are using will overstate any benefit from the foreign hiring. On the other hand, during this period the State-Owned Enterprise (SOE) sector contracted very rapidly as market reforms proceeded (McCaig and Pavcnik (2013, pp. 13-14)). In a province with a heavy concentration of SOE's, the reduction in labor demand from that sector could in and of itself reduce wages and living standards, but that same reduction in wages would also make the province more attractive to foreign enterprises. If there are enough shocks of that sort, a spurious *negative* correlation between foreign hiring and living standards will be induced, and regressions of the sort we are using will *understate* any benefit from the foreign hiring. Many such possible correlations between foreign hiring and omitted variables can be contemplated.

To deal with this issue, we have explore two different instrumental variable strategies as follows.

(i) A shift-share approach. We can construct a simple instrumental variable as follows. For each industry k, we construct from the Census data the share θ_i^k of that industry's total jobs nationwide that are located in province i as of 1989.[3] Then, for year $t = \{1999, 2009\}$, we sum up the total foreign employment nationwide in industry k for year t, $foreign\_empl_t^k$. Our instrument for $FOR_{i,t}$ is then $IV_{i,t}^{SS} \equiv \sum_k \theta_i^k foreign\_empl_t^k$. This is analogous to a standard instrument, variously called a 'shift-share' or 'supply-push' instrument, used in the immigration literature to deal with the endogeneity of immigrant inflows as popularized by Card (2001). It should be uncorrelated with local productivity and labor-demand shocks subsequent to 1989, but correlated with local foreign hiring to the extent that a multinational enterprise will prefer to hire, other things equal, in locations where that firm's industry has already established itself.

(ii) An approach based on foreign supply of FDI. An alternative approach is based on data from foreign FDI outflows. For countries that are major suppliers of FDI, we can define $outflow_t^k$ as the outflow of FDI worldwide in industry k and year t. We can then define $IV_{i,t}^{FS} \equiv \sum_k \theta_i^k outflow_t^k$. This can be called a 'foreign supply' instrument, and is analogous to the instrument used by Hummels et al. (2014) for offshoring by Danish firms.

A difficulty that has plagued both approaches is that for most specifications the

[3] As in footnote 2, for provinces in which the 1989 value is not available we substitute the 1999 value.

IV's produced tend to be weak, with first-stage F-statistics well below 10. Trial and error has led us to use the 'foreign-supply' specification constructed from outward FDI from Japan, lagged 2 years. It is not surprising that this is the strongest instrument, since Japan has been by far the largest source of FDI to Vietnam (although Vietnam makes up a small share of Japan's FDI). Our only criterion has been to find the IV method that produces the strongest first stage, as measured by the first-stage F-statistic. As reported at the bottom of our results tables, the F-statistic tends to range from just over 3 to 7 with this approach.

2.2.1 Data

We use the 1989, 1999 and 2009 Vietnam Population and Housing Census, from which we have an anonymized 5%, 3% and 15% sample respectively, taken from the Integrated Public Use Micro Samples system (IPUMS) (Ruggles et al. (2010)).[4] As Table 2.1 presents, we have 19,172,742 individuals in our sample, divided into 4,226,009 households, with an average of 3.914 members per household. The data are divided into 43 provinces.[5] A fraction 60.19% of the individuals are adults, defined as the ages between 18 to 65. On average, there are 0.038 adult workers per household who are employed by the foreign firms – about one foreign-employed worker for every 26 households. The average household has 0.703 adults with less than primary education and 1.19 adults with only primary education completed. About one in three households has a high-school graduate, and about one in eight a college graduate. The

[4] The data are available through IPUMS - International: https://international.ipums.org/international/

[5] In the Census raw data, there were originally 79 distinctive provinces in terms of their names. Brain McCaig pointed out that there was a provincial boundary reform between 1989 and 1999. We are very grateful that Brain McCaig shared his code for constructing time-consistent provinces for our sample periods from 1989 to 2009.

number of Adult FDI workers in each province in each year is scaled by the person weights so that we have correct representation from each sample.[6] On average, there are 3,088 adult workers employed in the foreign sector in a given province in year 1999 and 38,433 workers in year 2009, which, as shown in Table 1, amounts to about half a percent and 4.8% of the initial provincial population respectively.

The census records the 'foreign enterprise' indicator, which is our means of keeping track of trends in FDI employment, for all three years. However, in 1989, no worker is recorded as employed by a foreign entity (to be precise, not a single worker in the entire economy). This is clearly an error. For example, the Foreign Investment Law of 1987 opened up almost the entire economy to foreign firms, allowing for 100% foreign ownership in most cases, and provided generous tax incentives. In 1990, FDI was 2.8% of GDP (McCaig and Pavcnik, 2013, pp. 12-13). Consequently, we take the zeros for 1989 as a coding error, and use only the foreign-employment data from 1999 and 2009.

Our data include a wide range of standard-of-living variables at the household level, which we will use as the outcome variables in question. The summary statistics are provided in Table 2.2. Most of these are dummy variables, i.e., whether the household has an access to electricity, etc. However, 'Living area in square meters' and 'Child deaths' are integers. We define these briefly: *(i) Electricity.* Indicates whether or not the household has access to electricity. *(ii) Water supply.* Indicates whether or not the household has access to piped water. *(iii) Private water supply.* Indicates whether or not the household has access to water that is piped right into the household's dwelling. *(iv) Television set.* Indicates ownership of at least one tele-

[6]This is a correction required when working with IPUMS samples, as the samples intentionally oversample some demographic groups.

vision, either color or black and white. *(v) Radio in household.* Indicates ownership of a radio. *(vi) Toilet.* Indicates that the household has a toilet of any kind, including flush toilets and latrine-type toilets. *(vii) Flush toilet.* Indicates the flushable subset of the previous indicator. *(viii) Living area in square meters.* Indicates total area of the household's dwelling. *(ix) Child deaths.* Indicates the number of children ever born alive to a woman in the household who are no longer living (including from fathers not in the household but excluding still births).

We have had to omit data on a number of other interesting living-standard variables because they are not available for both 1999 and 2009. These include: access to a sewage system or septic tank; presence of a telephone within the dwelling; air conditioning; personal computer; clothes-washing machine; refrigerator; number of rooms; and number of bedrooms.

These amenities vary widely in the breadth of their availability. For example, in our data, 94% of households have access to electricity, while 23.6% have a radio. Only 21% have access to piped water, but 81.6% have a television. The average dwelling is 67 square meters (about 710 square feet) in size.

2.3 Results

The results from equation (2.1) estimated with OLS are shown in Table 3. Each column presents results from a regression with a different dependent variable. Each row lists estimated coefficients from a different regressor, which are in order: *Foreign-employed in province*, the number of adults employed by foreign enterprises in the province and year in which the household is located (*FOR_i(h),t(h)* above); *Size of household*, the number of people of any age in the household (n_h above); *Adults with-*

out primary education, the number of adults with less than primary education (n_h^{LTP} above); *Adults with primary school*, the number of adults with primary education (n_h^{Pri} above); *High-school graduates*, the number of adults with secondary education (n_h^{Sec} above); *College graduates*, the number of adults with university education (n_h^{Univ} above); *Foreign-employed in household*, the number of adults in the household employed by a foreign enterprise (n_h^{FOR} above); and $Urban$, a dummy variable indicating that the household lives in an urban location. Each regression has year and province fixed effects, and all standard errors are clustered at the province level.

Note that in controlling for the regressors in rows 3 through 6, we are controlling for the number of working-age adults in the household, so the second row shows the effect of an increase in the number of non-working age household members, holding the number of working-age adults constant. Looking at the results in the second row, we see that an increase in the size of the household is associated with a small increase in living area (about three square meters, perhaps the size of a closet), but otherwise is associated with reduced living standards suggesting that the household budget needs to be stretched further to accommodate the additional dependent. For example, one more non-working-age member is associated with a one-percentage-point reduction in the probability of a toilet in the house. The one exception to this pattern is a small increase in the probability that the household has a radio or TV.

Turning to the human-capital variables, note that the coefficient on n_h^j implies the effect of one more working-age adult of education class j, holding household-size fixed. This effect is in most cases positive for all four educational classes except for the first one, indicating that, holding household size constant, one more working-age adult tends to improve living standards, unless that adult has less than primary education. The coefficients mostly increase as one moves down the column, indicating that having more education has a bigger impact on the living standard. One more uneducated adult is associated with a 1.7 percentage point reduction in the probability that the household has electricity, and a 5 percentage-point reduction in the probability of having a flush toilet. On the other hand, one more university-educated adult is associated with an increased living space of 16 square meters, enough for an extra bedroom, and is associated with a 14.5 percentage-point increase in the probability that the household has a flush toilet. Importantly, adding high-school or college-educated adults to the household reduces child mortality, by approximately 1 percentage point (in other words, one less child death with a probability of 1%).

The $Urban$ variable is correlated with improvements in living standards along all fronts. Controlling for all other factors, an urban household is 6.6 percentage points more likely to have electricity, 40 percentage points more likely to have private, piped water, 6.8 percentage points more likely to have a toilet and 33 percentage points more likely to have a flush toilet, and has 9 square meters of additional living space. This last point is striking in light of the likelihood that space is more expensive in urban areas. Finally, child mortality is 2.2 percentage points lower for urban households.

The overall pattern of the control variables is consistent with a story in which one more dependent causes the household to spend a bit more on housing but to sacrifice living standards along other dimensions, while one more working-age adult tends to be associated with improvements along all dimensions as long as the adult has some education, and dramatically so if he or she has university education, as does urban status.

We turn now to the main variable of interest, the foreign employment in the household's province, which recall is normalized by the province's 1989 population. There is a great deal of variance in the number of people employed by foreign enterprises, both across provinces and across time. For our purposes, the time-series variation is the most important, which we can measure as the standard deviation across provinces of the first difference in the foreign employment in a given province. This standard deviation is 0.14. We will interpret regression results in terms of this standard deviation. For example, in the first regression, with ownership of a television as the dependent variable, the coefficient on the normalized number of foreign-employed workers in the province is -0.102. Multiplying this by the standard deviation of the right-hand side variable gives $-0.102 \times 0.14 = -0.014$. This implies that a one-standard deviation increase in foreign employment on average is associated with a 1.4-percentage-point reduction in the fraction of local households who own a television, holding all controls constant.

Going through the regressions, there are five statistically significant coefficients. A one-standard-deviation increase in local hiring by multinationals lowers the probability of TV and radio ownership by 1.1 and 1.4 percentage points respectively (that is, -0.102×0.14 and -0.0773×0.14), and reduces living space by 1.5 square meters. On the other hand, the same change raises the probability of a flush toilet by 5.2 percentage points and lowers expected child mortality by a third of a percentage point. We see a mix of good and bad news, in other words. The picture is similarly mixed for a household that actually has an employee at one of the foreign enterprises, as the seventh row of the table shows.

We do not wish to pin too much on the OLS regressions because of the endogeneity problem. Table 4 reports the results for the IV version of the regression. Clearly, the negative findings for the number of foreign jobs in the province are greatly strengthened. Three variables are now statistically significant, two of which indicate a worsening of living standards when foreign hiring increases. The exception is living space, which increases by 8.4 square meters when foreign hiring goes up by one standard deviation – perhaps enough space for one small room. Access to electricity and a TV fall by about 23 and 12 percentage points respectively with a one-standard-deviation increase in foreign hiring. For households who have a member who gets one of the foreign-enterprise jobs, there are two bright spots – an increased probability of a flush toilet and a drop in child mortality – but the magnitudes are negligible, and there is no increase in living space. (It is possible that this is due to people moving into a dormitory to take a foreign-sector job. The results are essentially unchanged when households with a foreign-sector employee are removed from the sample). Note that the worsening of the estimates of the effect of foreign hiring on household welfare suggests that the first endogeneity story discussed in Section 2 fits better – omitted variables that improve living standards also attract FDI.

To sum up, *a rise in local hiring by multinationals is associated with slightly reduced living standards, even if the household itself has a member who takes one of the foreign jobs.*

We turn now to the results from estimation of equation (2.2), to see if we can infer anything about inequality. These results are reported for OLS in Table 5 and for the IV regression in Table 6, which are set up exactly as Tables 3 and 4, but the rows 8 through 11 are the interaction terms between the human capital measures and the province's foreign employment (*Foreign employed in province* $\times$ *adults w/o primary* is the interaction with the number of adults with less than primary education, and so forth). Once again, all regressions have province and year fixed effects and standard errors clustered at the province level.

The control variables have coefficients similar to their counterparts in equation (2.1). More non-working-age members cause the household to allocate resources toward living area and away from other uses. More education and living in the city both improve living standards including reducing child mortality. The effect of having a household member employed by a foreign employer has mixed effects on living standards, and is correlated with reduced living area.

In this case, it is more difficult to find any appreciable effect on living standards due to foreign hiring. In the OLS results, there is a small negative effect on access to electricity, significant only for workers with a primary education, and very small in magnitude (a one-standard-deviation increase in foreign hiring is associated with about a third of a percentage point decrease). For toilets, there is a minuscule increase in access for uneducated workers, and a similarly-sized drop for educated workers. There is a significant rise in probability of a flush toilet ($0.431 \times 0.14 = 0.09$), of 9 percentage points per standard-deviation increase in foreign hiring, which disappears in households who have one university graduate – perhaps because those households already have a flush toilet regardless of foreign hiring. There are very small reductions in child mortality. However, most of these effects become insignificant in the IV regressions.

The effect of having a household member employed by a foreign enterprise, recorded in row 7, is very similar to what it was for equation (2.1); very small, and a mixed bag. Foreign employment improves access to a flush toilet by about half a percentage point.

To sum up, *a rise in local hiring by multinationals is associated with slightly reduced living standards, slightly less so for a household with very low education, and with small improvements if the household itself has a member who takes one of the foreign jobs.*

2.4 Allowing for heterogeneous effects

The effects of foreign hiring estimated above were almost uniformly quite small. Note that this cannot be because the data are simply noisy and uninformative, since a number of strong effects came through for other variables, such as household size, education, and urban location. Here we look more closely at some forms of heterogeneity that may have been obscuring the effects.

(i) Gender. We have not to this point paid any attention to gender. However, it is quite conceivable that male-led households and female-led households respond differently to the presence of foreign hiring. We do not have any meaningful indicator of household leader in our Census data, but we do have both the gender and the education level of each household member. In Table 7, we extend equation (2.2) to allow for a count of both male and female family members at each education level. The second row shows the effect of the number of male household members, and the third row the number of female household members. Similarly, each subsequent row corresponds to a row from Tables 5 and 6, but with the count of male members first and the corresponding count of female members next. As before, the table is estimated by IV, with province and year fixed effects and clustering at the provincial level.

Two striking points emerge. First, the variables for the two genders appear to have very similar effects. Almost throughout, the sign of the variables for men and women is the same and the magnitudes are similar. For example, one more boy in the household increases child mortality by 0.3 percentage points, and one more girl by 0.5 percentage points. One more man with a university degree reduces child mortality by 0.7 percentage points, and one more woman with the degree reduces it by 0.9

percentage points. Second, the effects of foreign hiring in the province are once again very weak. The only significant effects are very small increases in the probability of having a television, and reductions in living area. These do not differ by gender in any interesting way.

(ii) The average effect. In our main regressions, we controlled for the number of workers each household had who were employed by foreign employers, in order to isolate the direct effect of foreign employment from its indirect effect on the local labor market. However, if we wish to identify the *average* effect, it is desirable to do the estimation without controlling for the household's own foreign employment. It is also possible that trying to estimate the direct and indirect effect at the same time diluted the identification, resulting in only very small effects being observed. To address these issues, we also have performed the estimation without controlling for the household's own foreign-employed members. The results, for equation (2.1) with the IV and clustering as before, are reported in the first panel of Table 8, with only the right-hand-side variables of interest included.

The results show much the same story as before: Modest effects, indicating a slight drop in living standards. We find a 22 percentage-point reduction in access to electricity for the average household, and a small increase in living space of about 8 square meters, associated with a one-standard-deviation increase in foreign hiring. There is also a small drop in television ownership.

(iii) The urban-rural divide. Throughout, we have controlled for urban residence, but we have not allowed for the possibility that the *response* of an urban household to foreign hiring may be different from the response of a rural one. This could be crucial: Given that foreign hiring is concentrated in the urban areas, it may well be that all of the response in concentrated in the urban areas, and by pooling all households we

have obscured the effect. The two remaining panels of Table 8 show, respectively, the estimation results for the sample of rural households only, and urban households only. Once again, this is equation (2.1), with IV and clustering as before, and the other regressors suppressed to save space.

The urban results are indeed stronger than the rural ones, but, perhaps surprisingly, they are stronger in a negative direction. Most strikingly, the probability of having a flush toilet rises by 41 percentage points for a rural household with a one-standard-deviation increase in the province's foreign hiring, while for an urban household the same probability falls by 28 percentage points. For an urban household, the probability of connection to electricity falls by 6 percentage points, while the effect for a rural household is very imprecisely estimated.

The results are surprising and somewhat enigmatic, but they certainly show that the failure to find beneficial effects of foreign hiring is not due to pooling of rural and urban households.

2.5 Migration

As a final exercise, we look at the effect of FDI on the movement of people. If FDI raises living standards in a province, and mobility is not prohibitively costly, it is likely that the population of the province will respond as a result, as people move to that province to take advantage of the new opportunities. This can be an alternative test for living standards effects; if people vote with their feet, they may reveal living-standards effects indirectly that are difficult to measure directly.

Table 9 shows the results of regressing the change in province i's population between 1999 and 2009 on the increase in foreign employment in province i between the same two years. The first two columns show the results from OLS, while the remaining two show IV regressions. In each case, we control for the first differences of provincial characteristics. which are merely the province-wide means of the variables in equations (2.1) and (2.2): average household size; average number of members of each educational group per household; average number of foreign-employed members per household; and (for columns 2 and 4) the interactions between the educational means and the aggregate foreign employment. In this case, the first-stage F-statistic is well above 10. In all four regressions, the coefficient on aggregate foreign hiring is strongly significant, ranging from about 5 to about 8. The implication is that each 1,000 people hired by foreign firms in province i results in at least $5,000$ people moving to province i from other locations.[7]

This can be taken as indirect evidence of strong beneficial effects on local welfare from the foreign hiring, in contrast to the micro evidence we have seen to this point. An alternative interpretation is that this finding is a possible *explanation* for the absence of beneficial effects in the main regressions: If people are sufficiently mobile across provinces, any difference in real incomes across locations can be arbitraged away by mobility.

To see how in principle the positive migration findings could be consistent with the negative living-standards findings of the preceding sections, consider the following simple model. Suppose that there are two industries, X and Y, located in two different provinces. There are a continuum of workers, with a total mass of 2, indexed by $z \in [0, 2]$. Each worker z can supply $a^{z,i}$ units of effective labor in industry i. Production in each industry requires labor and industry-specific capital; labor is

[7]For some perspective on these magnitudes, it may be useful to note that Moretti (2010) estimated that each local tradable-sector job in the US leads to an increase of 1.5 local non-tradable-sector jobs.

endogenously allocated across industries, but capital is in fixed and exogenous supply in each industry. Output of industry i is given by $F^i(L^i, K^i)$, where L^i is total effective labor allocated to industry i, or the integral of the $a^{z,i}$ terms of all workers employed there; K^i is the industry's capital; and F^i is a concave constant-returns-to-scale production function. The price p^i of industry i output is fixed on world markets and can be taken as given. With competitive markets, the price of effective labor in each industry is the marginal value product of effective labor, $r^i \equiv p^i F_1^i(L^i, K^i)$, where a subscript denotes partial differentiation, and so the wage of a worker in i is equal to $w^{z,i} = a^{z,i} r^i = a^{z,i} p^i F_1^i(L^i, K^i)$. Each worker chooses the industry i that pays that worker the highest wage $w^{z,i}$, and all of these individual decisions together determine L^i and r^i for $i = X, Y$. Equilibrium is an (r^X, r^Y) pair that generates in this way values of L^X and L^Y that are consistent with that (r^X, r^Y) pair, clearing the labor market.[8]

Suppose now that FDI exogenously increases the stock of capital in industry X. It is easy to verify that this will increase r^X, r^Y, and $\frac{r^X}{r^Y}$, as well as causing some workers who otherwise would have chosen sector Y to switch to X, raising L^X and lowering L^Y.[9] One consequence is a reduction in the average productivity of workers in the X industry, in the sense of $a^{z,X}$, as workers with a weaker comparative advantage in

[8]This formulation is an example of what are sometimes called 'assignment models,' which are becoming broadly used in international trade to analyze the income-distribution effects of trade policy (Costinot and Vogel (2015)).

[9]A worker z will choose sector X if $\frac{a^{z,Y}}{a^{z,X}} < \frac{r^X}{r^Y}$ and Y otherwise. Consequently the whole allocation of labor is determined by the value of $\frac{r^X}{r^Y}$. We can show by contradiction that the FDI increases $\frac{r^X}{r^Y}$. First, if this ratio is unchanged after the FDI, the labor allocation will be unchanged, but this is a contradiction since in that case $r^X = p^X F_1^X(L^X, K^X)$ will have increased due to the rise in K^X while $r^Y = p^Y F_1^Y(L^Y, K^Y)$ will be unchanged. If $\frac{r^X}{r^Y}$ falls, labor will move from X to Y, but that will imply, due to the effect on the marginal products of labor, that r^X rises and r^Y falls, providing a contradiction. The only possibility is that $\frac{r^X}{r^Y}$ rises and labor flows from Y to X. The reduction in L^Y that this implies must cause a rise in $F_1^Y(L^Y, K^Y)$ and hence r^Y; but since $\frac{r^X}{r^Y}$ rises, that implies a rise in r^X as well.

that industry choose employment in it.[10] The rise in r^X tends to pull wages in X up, but the fall in average $a^{z,X}$ works in the opposite direction.

It is easy to construct examples in which average wages in X *fall* in equilibrium as a result of the FDI, because the selection effect of lower average $a^{z,X}$ values overwhelms the labor-demand effect of the rise in r^X. For example, consider the case in which industry Y does not use capital and the production functions are $F^X(L^X, K^K) = 2(L^X K^X)^{1/2}$ and $F^Y(L^Y) = L^Y$. Let $K^X = 10$, and suppose that there are two types of worker. 'Ordinary' workers have $a^{z,X} = a^{z,Y} = 1$, while 'talented' workers have $a^{z,X} = 10$ and $a^{z,Y} = 1$. The prices are $p^X = p^Y = 1$. Each type of worker makes up half of the population. In the initial equilibrium, $r^X = r^Y = 1$, and labor is evenly divided between the industries. 'Ordinary' workers all are employed in Y (so $L^Y = 1$), while 'talented' workers are all employed in X (so $L^X = 10$). Now, if the FDI raises K^X to 11, the equilibrium will have all workers in X. The effective units of labor in X will be 10 units due to the 'talented' workers plus 1 unit due to the 'ordinary' workers for a total of $L^X = 11$. The marginal product of labor will be unchanged in both industries, but the average value of $a^{z,X}$ in the X industry will have fallen from 10 to 5.5, and so the average real wage in X will have fallen sharply. (Before and after the FDI, 'ordinary' workers are indifferent between the two industries.)

Now, consider a slightly larger infusion of FDI, which leaves K^X at a value slightly above 11. Now, all workers strictly prefer industry X. It is still the case that average wages in X have fallen due to the FDI. However, note that in this case, as in all cases

[10] Note that conditional on any value of $a^{z,Y}$, the worker who is indifferent between the two industries is the worker whose value of $a^{z,X}$ is the greatest lower bound to the set of $a^{z,X}$ values for workers who choose X. Consequently, when $\frac{r^X}{r^Y}$ rises, the workers who switch from Y to X are the lowest-$a^{z,X}$ workers for each value of $a^{z,Y}$. They thus bring down the average value of $a^{z,X}$ conditional on $a^{z,Y}$ for each value of $a^{z,Y}$. Therefore, the unconditional average value of $a^{z,X}$ for workers employed in X also falls.

with this sort of model, the FDI *raises the real wage for every worker.*

This sort of equilibrium story could rationalize the finding from Sections 3 and 4 that average living conditions in a province fall slightly when more FDI flows in, with the finding from this section that FDI in a province induces a very rapid inflow of workers to that province. It would also allow for a very optimistic interpretation of the effect of FDI on welfare in Vietnam. However, this interpretation is not terribly plausible; it would fly in the face of large differences in real income effects across provinces due to trade shocks as measured by McCaig (2011), for example. If the reallocation of people in response to FDI in a province is really strong enough to overwhelm the effect of FDI on average living standards in that province, it seems that there should be a similar movement of people into a province whose industries get a boost from reduced barriers to export to the US, overwhelming the effect of the trade shock on average living standards in the province. However, McCaig (2011) shows large improvements in living standards (measured by poverty rates) on provinces that receive this beneficial trade shock (as do other studies of similar changes for other countries - for example, see Kovak (2013) for a similar case in Brazil). For now, we are left with a paradox.

2.6 Concluding Remarks

We have investigated the effect of FDI, measured by hiring by foreign enterprises, on standards of living and inequality in Vietnam. Our sample is a random draw from the Vietnamese decennial census, which gives us a series of cross sections of the population. Using the full, repeated cross-section sample, after correcting for the endogeneity of FDI, we find consistently that increased foreign hiring in a province is associated with small reductions in living standards for households whose members are not employees of the foreign firms. In particular, once endogeneity of FDI is controlled for, access to electricity falls by more than 20 percentage points when local foreign hiring rises by one standard deviation. Whether this reflects extra strain on the local power grid due to extra demand for power by multinationals, or some other mechanism, is a question beyond our ability to answer within this study. Workers hired by the foreign firms see very minor increases in living standards. The results are changed in details but not in their broad contours when we allow for heterogeneous response by education level, gender, or rural/urban status.

However, the failure to find benefits for the local population from FDI could stem from a number of sources. In our main regressions, our instrumental variables are on the weak side at best. We are limited in our geographic detail to the province only; it would be desirable to have metropolitan areas or commuting zones, but these are not available in the Vietnamese Census. This may mask crucial geographic variation and stymie identification. (However, McCaig (2011) found large effects of trade shocks at the provincial level). In addition, we find large changes in provincial population associated with increases in foreign hiring, which suggest that there may be welfare benefits that we are failing to measure.

A number of studies of the effects of globalization on Vietnamese workers and families have found great benefits. Edmonds and Pavcnik (2002), McCaig (2011), Brambilla et al. (2012) all show tangible benefits to Vietnamese households from increased export opportunities. This paper is an attempt to see if similar benefits extend to inward FDI. One lesson from the exercise is that effects of FDI are harder to measure than the effects of those trade policies, because of the endogeneity of FDI flows and the difficulty of finding effective instruments. Another is that the welfare benefits of trade openness found in those studies may well not be replicated by an infusion of FDI. This could be offered as a word of caution to policy makers who would hope that opening the door to increased FDI would in and of itself be a powerful anti-poverty program in Vietnam.

Table 2.1: Summary Statistics of Households and Province

	Mean	Std. Dev.	Min	Max	Obs.
Household level					
Number of people	3.914	1.734	1	20	4,226,009
Number of adult	2.356	1.221	0	20	4,226,009
Adult FDI workers	0.038	0.252	0	19	4,226,009
Less than primary education	0.703	1.021	0	16	4,226,009
Primary education	1.190	1.083	0	17	4,226,009
Secondary education	0.332	0.659	0	16	4,226,009
University education	0.130	0.454	0	15	4,226,009
Province level					
Normalized FDI workers in 1999	0.006	0.018	0	0.107	43
Normalized FDI workers in 2009	0.063	0.150	0.0003	0.875	43
Employment in initial year	579,178	408,505	50,153	2,024,101	43
Employment in 1999	4,330	14,717	0	80,554.98	43
Employment in 2009	37,104	86,117	41.65	399,008	43

Table 2.2: Summary Statistics of Households' Living Standards

Living Standards	Mean	Std. Dev.	Min	Max	Obs
Electricity	0.9401	0.2371	0	1	4,222,136
Water supply	0.2126	0.4091	0	1	4,222,627
Private water supply	0.2063	0.4047	0	1	4,222,627
Television set	0.8162	0.3873	0	1	4,223,687
Radio	0.2356	0.4244	0	1	4,212,082
Toilet	0.8872	0.3163	0	1	4,205,940
Flush toilet	0.4404	0.4964	0	1	4,205,940
Living area in square meters	66.797	44.995	3	998	4,105,128
Number of children dead	0.0525	0.2924	0	9	451,861

Table 2.3: OLS (1): Effect of FDI on Living Standards

VARIABLES	(1) Elec	(2) Water	(3) Water_priv	(4) TV	(5) Radio	(6) Toilet	(7) Toilet_flush	(8) Livearea	(9) Chdead
Foreign-employed in province	0.0620	0.0374	0.0419	-0.102**	-0.0773***	0.00725	0.369***	-11.03***	-0.0252*
	(0.0851)	(0.0356)	(0.0344)	(0.0449)	(0.0190)	(0.0241)	(0.0437)	(3.223)	(0.0149)
Size of household	-0.00751***	-0.00394***	-0.00322**	0.0241***	0.0105***	-0.0144***	-0.00937***	3.223***	0.00400**
	(0.00218)	(0.00130)	(0.00128)	(0.00356)	(0.00129)	(0.00306)	(0.00134)	(0.283)	(0.00181)
Adults without primary education	-0.0171***	-0.0130***	-0.0136***	-0.0316***	-0.00383*	-0.0310***	-0.0477***	-1.275***	0.0336***
	(0.00276)	(0.00221)	(0.00216)	(0.00492)	(0.00218)	(0.00606)	(0.00330)	(0.394)	(0.00296)
Adults with primary school	0.0249***	-0.000249	-0.000334	0.0533***	0.0170***	0.0395***	0.0233***	2.793***	0.00205
	(0.00390)	(0.00219)	(0.00222)	(0.00581)	(0.00272)	(0.00585)	(0.00485)	(0.427)	(0.00220)
High-school graduates	0.0268***	0.0390***	0.0386***	0.0518***	0.0352***	0.0436***	0.0783***	6.359***	-0.00798***
	(0.00448)	(0.00362)	(0.00365)	(0.00880)	(0.00322)	(0.00631)	(0.00706)	(0.513)	(0.00190)
College graduates	0.0146***	0.0975***	0.0972***	0.0601***	0.0786***	0.0451***	0.145***	15.58***	-0.00954***
	(0.00359)	(0.00606)	(0.00597)	(0.00866)	(0.00456)	(0.00795)	(0.0200)	(0.609)	(0.00249)
Foreign-employed in household	-0.00117	-0.00296	-0.00383	-0.0720***	-0.0270***	-0.00864***	0.0342**	-5.476*	-0.00482**
	(0.00439)	(0.0182)	(0.0183)	(0.0109)	(0.00428)	(0.00312)	(0.0145)	(2.951)	(0.00211)
Urban	0.0660***	0.406***	0.403***	0.0843***	0.0163**	0.0677***	0.328***	8.960***	-0.0221***
	(0.00902)	(0.0247)	(0.0246)	(0.00887)	(0.00792)	(0.0124)	(0.0107)	(0.932)	(0.00295)
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
R-squared	0.141	0.362	0.364	0.155	0.077	0.199	0.338	0.127	0.020
Prov & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at the province level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: IV (1): Effect of FDI on Living Standards

VARIABLES	(1) Elec	(2) Water	(3) Water_priv	(4) TV	(5) Radio	(6) Toilet	(7) Toilet_flush	(8) Livearea	(9) Chdead
Foreign-employed in province	-1.617*	0.398	0.405	-0.848***	0.173	-0.109	-0.383	59.95**	-0.0185
	(0.981)	(0.440)	(0.441)	(0.327)	(0.581)	(0.421)	(0.427)	(26.58)	(0.0878)
Size of household	-0.00781***	-0.00388***	-0.00316***	0.0239***	0.0105***	-0.0144***	-0.00949***	3.238***	0.00400**
	(0.00221)	(0.00120)	(0.00118)	(0.00349)	(0.00123)	(0.00301)	(0.00139)	(0.285)	(0.00179)
Adults without primary education	-0.0185***	-0.0128***	-0.0133***	-0.0322***	-0.00363	-0.0311***	-0.0483***	-1.219***	0.0336***
	(0.00321)	(0.00215)	(0.00210)	(0.00489)	(0.00247)	(0.00593)	(0.00317)	(0.390)	(0.00296)
Adults with primary school	0.0244***	-0.000145	-0.000229	0.0531***	0.0171***	0.0395***	0.0231***	2.806***	0.00205
	(0.00388)	(0.00220)	(0.00223)	(0.00578)	(0.00277)	(0.00581)	(0.00478)	(0.423)	(0.00217)
High-school graduates	0.0274***	0.0389***	0.0385***	0.0521***	0.0351***	0.0436***	0.0786***	6.335***	-0.00799***
	(0.00456)	(0.00357)	(0.00360)	(0.00869)	(0.00309)	(0.00617)	(0.00692)	(0.504)	(0.00189)
College graduates	0.0143***	0.0976***	0.0973***	0.0600***	0.0786***	0.0450***	0.144***	15.59***	-0.00953***
	(0.00350)	(0.00608)	(0.00598)	(0.00853)	(0.00451)	(0.00789)	(0.0198)	(0.607)	(0.00245)
Foreign-employed in household	0.0184	-0.00718	-0.00807	-0.0633***	-0.0299***	-0.00728	0.0430**	-6.092*	-0.00492**
	(0.0239)	(0.0128)	(0.0128)	(0.00559)	(0.00818)	(0.00550)	(0.0199)	(3.323)	(0.00236)
Urban	0.0681***	0.406***	0.403***	0.0852***	0.0159**	0.0679***	0.329***	8.902***	-0.0221***
	(0.00883)	(0.0244)	(0.0243)	(0.00863)	(0.00799)	(0.0121)	(0.0104)	(0.921)	(0.00300)
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
Prov & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-stat	6.999	6.999	6.999	6.990	6.998	7.014	7.014	6.523	14.06
P-value	0.0114	0.0114	0.0114	0.0115	0.0114	0.0113	0.0113	0.0144	0.000536

Robust standard errors clustered at the province level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: OLS (2): Effect of FDI on Living Standards, Heterogeneous Effect with respect to Education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Elec	Water	Water_priv	TV	Radio	Toilet	Toilet_flush	Livearea	Chdead
Foreign-employed in province	0.0997	0.0325	0.0396	-0.0120	-0.0453	0.0377	0.431***	-13.93	0.00408
	(0.0661)	(0.0343)	(0.0335)	(0.0497)	(0.0376)	(0.0278)	(0.0662)	(14.53)	(0.0149)
Size of household	-0.00730***	-0.00376***	-0.00304**	0.0246***	0.0104***	-0.0140***	-0.00887***	3.219***	0.00384**
	(0.00214)	(0.00137)	(0.00135)	(0.00342)	(0.00130)	(0.00296)	(0.00129)	(0.274)	(0.00176)
Adults without primary education	-0.0187***	-0.0145***	-0.0150***	-0.0350***	-0.00290	-0.0346***	-0.0479***	-1.312***	0.0375***
	(0.00309)	(0.00229)	(0.00226)	(0.00559)	(0.00196)	(0.00680)	(0.00329)	(0.474)	(0.00338)
Adults with primary school	0.0264***	-0.000708	-0.000705	0.0562***	0.0179***	0.0411***	0.0224***	2.691***	0.00253
	(0.00401)	(0.00239)	(0.00242)	(0.00534)	(0.00255)	(0.00601)	(0.00523)	(0.448)	(0.00229)
High-school graduates	0.0301***	0.0408***	0.0403***	0.0611***	0.0360***	0.0480***	0.0852***	6.359***	-0.00886***
	(0.00465)	(0.00423)	(0.00429)	(0.00771)	(0.00311)	(0.00645)	(0.00581)	(0.505)	(0.00187)
College graduates	0.0175***	0.106***	0.106***	0.0688***	0.0765***	0.0531***	0.174***	15.52***	-0.0110***
	(0.00404)	(0.00528)	(0.00540)	(0.00787)	(0.00541)	(0.00831)	(0.0145)	(0.442)	(0.00229)
Foreign-employed in household	0.00281	-0.00192	-0.00278	-0.0628***	-0.0261***	-0.00310	0.0367***	-5.569*	-0.00494**
	(0.00382)	(0.0182)	(0.0183)	(0.0128)	(0.00445)	(0.00204)	(0.0116)	(3.196)	(0.00212)
Foreign employed in province	0.0302	0.0271	0.0251	0.0636***	-0.0183	0.0676*	0.000661	0.719	-0.0495**
× adults w/o primary	(0.0220)	(0.0203)	(0.0188)	(0.0223)	(0.0212)	(0.0365)	(0.0224)	(6.036)	(0.0219)
Foreign employed in province	-0.0310**	0.00500	0.00355	-0.0627	-0.0149	-0.0359*	0.00787	1.829	-0.00533*
× adults with primary	(0.0149)	(0.00559)	(0.00595)	(0.0463)	(0.0164)	(0.0203)	(0.0127)	(4.930)	(0.00301)
Foreign employed in province	-0.0543	-0.0263*	-0.0251	-0.148*	-0.0137	-0.0712*	-0.104	0.163	0.0138**
× high-school graduates	(0.0325)	(0.0146)	(0.0153)	(0.0764)	(0.0185)	(0.0364)	(0.0741)	(3.900)	(0.00589)
Foreign employed in province	-0.0416	-0.115***	-0.112***	-0.122	0.0257	-0.109**	-0.399**	1.095	0.0193
× college graduates	(0.0283)	(0.0141)	(0.0142)	(0.0799)	(0.0165)	(0.0495)	(0.188)	(6.962)	(0.0146)
Urban	0.0654***	0.406***	0.402***	0.0829***	0.0165**	0.0666***	0.326***	8.957***	-0.0215***
	(0.00904)	(0.0246)	(0.0246)	(0.00889)	(0.00786)	(0.0122)	(0.0114)	(0.927)	(0.00283)
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
R-squared	0.142	0.363	0.364	0.158	0.077	0.201	0.341	0.127	0.021
Prov & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at the province level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: IV (2): Effect of FDI on Living Standards, Heterogeneous Effect with respect to Education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Elec	Water	Water_priv	TV	Radio	Toilet	Toilet_flush	Livearea	Chdead
Foreign-employed in province	-2.763	0.761	0.767	-1.117	0.380	-0.0243	-0.577	96.75**	-0.00928
	(2.090)	(0.862)	(0.865)	(0.716)	(1.011)	(0.708)	(0.794)	(47.81)	(0.162)
Size of household	-0.00869***	-0.00341***	-0.00269**	0.0240***	0.0107***	-0.0140***	-0.00936***	3.274***	0.00383**
	(0.00253)	(0.00113)	(0.00111)	(0.00327)	(0.00113)	(0.00287)	(0.00168)	(0.273)	(0.00175)
Adults without primary school	-0.0418*	-0.00864	-0.00911	-0.0439***	0.000525	-0.0351***	-0.0560***	-0.521	0.0373***
	(0.0219)	(0.00805)	(0.00805)	(0.0101)	(0.00904)	(0.00847)	(0.00822)	(0.592)	(0.00482)
Adults with primary school	0.00135	0.00567	0.00567	0.0466***	0.0216**	0.0406***	0.0135	3.524***	0.00233
	(0.0240)	(0.00880)	(0.00882)	(0.0120)	(0.00981)	(0.00945)	(0.0102)	(0.709)	(0.00284)
High-school graduates	0.00869	0.0462***	0.0457***	0.0528***	0.0392***	0.0475***	0.0776***	7.064***	-0.00902***
	(0.0210)	(0.00852)	(0.00854)	(0.0121)	(0.00868)	(0.00912)	(0.0107)	(0.774)	(0.00236)
College graduates	-0.0106	0.113***	0.113***	0.0580***	0.0807***	0.0525***	0.164***	16.45***	-0.0112***
	(0.0272)	(0.0115)	(0.0116)	(0.0141)	(0.0113)	(0.0113)	(0.0208)	(0.719)	(0.00309)
Foreign-employed in household	-0.00317	-0.000398	-0.00127	-0.0651***	-0.0252***	-0.00323	0.0346***	-5.345*	-0.00500**
	(0.00532)	(0.0191)	(0.0192)	(0.0123)	(0.00542)	(0.00242)	(0.0120)	(3.175)	(0.00220)
Foreign employed in province	0.458	-0.0817	-0.0837	0.229**	-0.0819	0.0769	0.151	-13.38**	-0.0467
× adults w/o primary	(0.356)	(0.157)	(0.156)	(0.109)	(0.151)	(0.113)	(0.120)	(6.743)	(0.0419)
Foreign employed in province	0.422	-0.110	-0.112	0.112	-0.0823	-0.0261	0.168	-13.01*	-0.00265
× adults with primary	(0.405)	(0.149)	(0.149)	(0.163)	(0.159)	(0.111)	(0.137)	(7.464)	(0.0309)
Foreign employed in province	0.330	-0.124	-0.123	-0.000219	-0.0708	-0.0628	0.0314	-12.38	0.0160
× high-school graduates	(0.371)	(0.136)	(0.137)	(0.175)	(0.133)	(0.0937)	(0.164)	(7.643)	(0.0261)
Foreign employed in province	0.404	-0.228	-0.225	0.0501	-0.0406	-0.0996	-0.242	-13.54	0.0222
× college graduates	(0.421)	(0.146)	(0.149)	(0.194)	(0.159)	(0.111)	(0.280)	(8.411)	(0.0364)
Urban	0.0676***	0.405***	0.402***	0.0837***	0.0161**	0.0666***	0.327***	8.908***	-0.0215***
	(0.00891)	(0.0243)	(0.0243)	(0.00857)	(0.00795)	(0.0120)	(0.0111)	(0.916)	(0.00293)
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
Prov & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-stat	3.652	3.653	3.653	3.649	3.649	3.655	3.655	3.981	5.410
P-value	0.0629	0.0628	0.0628	0.0629	0.0629	0.0627	0.0627	0.0525	0.0249

Robust standard errors clustered at the province level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: IV (2): Effect of FDI on Living Standards with Gender Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Elec	Water	Water_priv	TV	Radio	Toilet	Toilet_flush	Livearea	Chdead
Foreign-employed in province	-2.784	0.775	0.783	-1.119	0.382	-0.0178	-0.572	97.42**	-0.00257
Size of household - male	-0.01000***	-0.00430***	-0.00358***	0.0290***	0.0133***	-0.0155***	-0.0100***	3.338***	0.00305*
Size of household - female	-0.00784***	-0.00345***	-0.00276**	0.0193***	0.00844***	-0.0133***	-0.00969***	3.230***	0.00488***
Adults without primary school - male	-0.0428**	-0.0114	-0.0121*	-0.0512***	-0.00764	-0.0354***	-0.0603***	-1.734***	0.0195***
Adults without primary school - female	-0.0406	-0.00310	-0.00324	-0.0366***	0.00752	-0.0329***	-0.0493***	0.546	0.0525***
Adults with primary school - male	0.00253	-0.000621	-0.000987	0.0375***	0.0185**	0.0370***	0.00783	3.392***	-0.000428
Adults with primary school - female	0.000467	0.0155	0.0160	0.0562***	0.0241**	0.0464***	0.0225*	3.606***	0.00875*
High-school graduates - male	0.00935	0.0295***	0.0286***	0.0466***	0.0380***	0.0451***	0.0648***	7.000***	-0.00866***
High-school graduates - female	0.00841	0.0663***	0.0664***	0.0591***	0.0396***	0.0515***	0.0937***	7.072***	-0.00518
College graduates - male	-0.00417	0.111***	0.110***	0.0479***	0.0828***	0.0473***	0.151***	17.04***	-0.00705***
College graduates - female	-0.0172	0.117***	0.118***	0.0683***	0.0777***	0.0593***	0.180***	15.81***	-0.00884*
Foreign-employed in household	-0.00605	-0.00226	-0.00321	-0.0661***	-0.0248***	-0.00414	0.0320***	-5.251*	-0.00606**
Foreign employed in province × adults w/o primary - male	0.396	-0.0717	-0.0735	0.190**	-0.0751	0.0684	0.118	-12.37**	-0.0281
Foreign employed in province × adults w/o primary - female	0.530	-0.0980	-0.100	0.267**	-0.0898	0.0818	0.182	-14.73*	-0.0604
Foreign employed in province × adults with primary - male	0.367	-0.0973	-0.0985	0.101	-0.0732	-0.0214	0.153	-10.95*	-0.00230
Foreign employed in province × adults with primary - female	0.488	-0.130	-0.132	0.124	-0.0924	-0.0343	0.179	-15.39*	-0.00736
Foreign employed in province × high-school graduates - male	0.318	-0.105	-0.104	0.0146	-0.0778	-0.0539	0.0599	-11.98*	0.0143
Foreign employed in province × high-school graduates - female	0.344	-0.150	-0.149	-0.0159	-0.0634	-0.0745	-0.00316	-12.83	0.0109
Foreign employed in province × college graduates - male	0.374	-0.220*	-0.216*	0.0486	-0.0676	-0.0858	-0.219	-13.53	0.0164
Foreign employed in province × college graduates - female	0.443	-0.241	-0.239	0.0516	-0.0128	-0.117	-0.268	-13.61	0.0176
Urban	0.0674***	0.404***	0.400***	0.0835***	0.0163**	0.0662***	0.326***	8.932***	-0.0203***
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
Prov & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-stat	3.603	3.605	3.605	3.601	3.601	3.607	3.607	3.935	4.585
P-value	0.0646	0.0645	0.0645	0.0646	0.0646	0.0644	0.0644	0.0538	0.0381

Robust standard errors clustered at the province level. They are omitted due to space issue.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Heterogenous Effects: Average Effect and Urban-Rural Divide

VARIABLES	(1) Elec	(2) Water	(3) Water_priv	(4) TV	(5) Radio	(6) Toilet	(7) Toilet_flush	(8) Livearea	(9) Chdead
Average Effect									
Foreign-employed in province	-1.607*	0.395	0.401	-0.881***	0.157	-0.113	-0.360	56.76**	-0.0202
	(0.969)	(0.444)	(0.445)	(0.328)	(0.575)	(0.418)	(0.424)	(25.98)	(0.0874)
Observations	4,222,136	4,222,627	4,222,627	4,223,687	4,212,082	4,205,940	4,205,940	4,105,128	451,861
1st stage F-stat	7.129	7.129	7.129	7.120	7.129	7.144	7.144	6.604	14.35
P-value	0.0107	0.0107	0.0107	0.0108	0.0107	0.0107	0.0107	0.0138	0.000477
Urban Sample									
Foreign-employed in province	-0.396*	-0.163	-0.132	-0.667**	-0.0476	-0.337	-2.025***	50.19*	-0.133**
	(0.236)	(0.397)	(0.398)	(0.338)	(0.395)	(0.209)	(0.620)	(26.32)	(0.0517)
Observations	1,273,098	1,273,322	1,273,322	1,273,614	1,269,085	1,270,779	1,270,779	1,234,713	208,280
1st stage F-stat	9.215	9.220	9.220	9.225	9.220	9.245	9.245	10.27	18.43
P-value	0.00411	0.00410	0.00410	0.00409	0.00410	0.00406	0.00406	0.00258	0.000102
Rural Sample									
Foreign-employed in province	-3.169	0.917	0.846	-0.897**	0.638	0.0471	2.925**	98.20*	0.271
	(2.635)	(0.833)	(0.815)	(0.376)	(0.975)	(0.488)	(1.416)	(55.45)	(0.270)
Observations	2,949,038	2,949,305	2,949,305	2,950,073	2,942,997	2,935,161	2,935,161	2,870,415	243,581
1st stage F-stat	3.959	3.955	3.955	3.941	3.956	3.962	3.962	2.913	7.199
P-value	0.0532	0.0533	0.0533	0.0537	0.0533	0.0531	0.0531	0.0952	0.0104

Robust standard errors clustered at the province level in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.9: Effects of FDI on Inter-provincial Migration, first-differenced between 1999 and 2009

VARIABLES	(1) OLS (1)	(2) OLS (2)	(3) IV (1)	(4) IV (2)
Number of foreign-employed in province	4.804***	8.039***	5.105***	7.092**
	(0.911)	(1.916)	(1.495)	(3.203)
Mean size of household	103,700	38,603	89,731	91,206
	(382,921)	(418,970)	(345,977)	(383,607)
Mean adults without primary education	103,834	350,945	117,768	262,701
	(574,482)	(636,100)	(514,941)	(592,674)
Mean adults with primary education	19,616	170,370	11,958	125,561
	(468,006)	(455,295)	(418,045)	(403,722)
Mean high-school graduates	633,268	893,741	591,380	914,568*
	(608,354)	(609,347)	(569,245)	(514,659)
Mean college graduates	2.409e+06	1.555e+06	2.242e+06	1.672e+06
	(1.567e+06)	(1.565e+06)	(1.560e+06)	(1.356e+06)
Mean foreign-employed in household	-3.255e+06**	-4.486e+06***	-3.616e+06*	-4.082e+06**
	(1.266e+06)	(1.589e+06)	(1.883e+06)	(1.782e+06)
Mean foreign employed in province		-1.147e+06		-1.165e+06
× adults without primary school		(2.685e+06)		(2.252e+06)
Mean foreign employed in province		6.062e+06*		5.514e+06*
× adults with primary school		(3.508e+06)		(3.350e+06)
Mean foreign employed in province		-3.568e+07**		-3.210e+07*
× high-school graduates		(1.556e+07)		(1.672e+07)
Mean foreign employed in province		2.930e+07*		2.810e+07**
× college graduates		(1.487e+07)		(1.295e+07)
Mean urban	150,513	543,075	175,586	412,144
	(432,472)	(484,559)	(399,095)	(558,489)
Observations	43	43	43	43
R-squared	0.858	0.890	0.858	0.889
1st stage F-stat			14.20	10.08
P-value			0.000625	0.00345

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Offshoring and Local Labor Market Outcomes: Evidence from the U.S. Trade Adjustment Assistance Program (with Hyejoon Im and Yang Shen)

3.1 Introduction

Offshoring, also known as the importing of intermediate inputs, has grown rapidly in most developed countries over the last three decades. A number of empirical studies in the trade and offshoring literature have attempted to estimate the effect of offshoring on labor market outcomes.[1] However, it is challenging to identify such an effect because of the poor measurement of offshoring. Data on imported inputs at the firm level or even the industry level are scarce. Empirical research has thus mostly, if not entirely, adopted a proxy measure of offshoring proposed by Feenstra and Hanson (1996b), which relies on the "proportionality assumption." Under this assumption, each industry imports an input of material or service in the same proportion as the economy-wide imports of the input. This measure has received many critiques since it ignores the heterogeneity in import shares across industries, which could generate differential effects on industry-level wages and employment.

In this paper, using a dataset of petitions from the U.S. Trade Adjustment Assistance (TAA) program, we construct a measure which captures the negative employment effect of offshoring by commuting zone and industry. The TAA program, which is administered by the U.S. Department of Labor, aims at fostering reemployment of trade-induced displaced workers. A group of workers can file a petition at the plant level. Once filed, an investigator determines whether the layoffs are due to increased imports of final goods or services, increased imports of intermediate goods or services, shift in production sites, or none of the above. If the cause of layoffs is one of the first three, then the petition is certified, and the displaced workers in this plant could receive benefits provided by the program. The TAA petitions dataset allows us to

[1] For example, Feenstra and Hanson (1996a,b), Amiti et al. (2005), Amiti and Wei (2009), Ebenstein et al. (2014), and Hummels et al. (2014).

identify offshoring-induced layoffs across local labor markets (defined as commuting zone, CZ) and industries by examining the number of certified workers. Formally, our measure of the negative employment effect of offshoring, *offshoring-induced layoffs weighted by employment (OL)*, is defined as the share of offshoring-induced layoffs out of the total employment in a CZ-by-time cell or an industry-by-time cell.

We obtain a sample of workers from the American Community Survey (ACS) and map the measure of offshoring-induced layoffs to workers either by industry of employment or by commuting zone of residence. We then estimate the effect of the weighted offshoring-induced layoffs on individual wages, controlling for a set of worker characteristics, fixed effects, and time-varying demographic and labor market characteristics. We find that among the observations exposed to negative employment shocks of offshoring, a one-percentage-point increase in the share of offshoring-induced layoffs at the commuting-zone level is associated with a 1.024% decrease in individual wages. This result remains statistically significant and robust under alternative specifications. However, we do not find a significant effect of service-offshoring-induced layoffs.

The effect of offshoring-induced layoffs on individual wages is insignificant across all specifications at the industry level. This indicates that wages seem to be unaffected by the industry-level offshoring-induced layoffs, which is consistent with the findings in Ebenstein et al. (2014).

These results may support the idea that when an employment shock hits, it is relatively easy to switch the industry of employment than relocating to a different commuting zone due to migration costs.

Related Literature. This paper contributes to the empirical literature on the effects of offshoring on local labor markets. Broadly speaking, it relates to three avenues of research: offshoring effects on wages, import competition and local labor market outcomes, and TAA.

There exists a handful number of papers on offshoring effects on labor market outcomes. Ebenstein et al. (2014) use individual worker data from the Current Population Surveys to examine the effects of trade and offshoring on wages. They use foreign affiliates employment of U.S. multinational firms as a measure of offshoring and examine the wage effects of offshoring at the industry level and at the occupation level. Hummels et al. (2014) use matched worker-firm level data for Denmark along with data on trade flows to study the wage effects of offshoring. Following Feenstra and Hanson (1996b), the authors measure offshoring as imported intermediate inputs at the firm level. Crinò (2010) looks at the effects of offshoring on post-displacement wages. Using the Feenstra and Hanson (1996b) offshoring measure and the data on U.S. displaced workers from the Displaced Workers Supplements, the author examines the wage effects of offshoring for displaced workers. However, the aforementioned studies do not consider offshoring effects in terms of local labor market outcomes, which is the focus of this paper.

On the other hand, only a couple of studies specifically examine the effects of service offshoring on wages. Using imports data of computing (including computer software designs) and other business services (including accounting and other back-office operations), Amiti et al. (2005) find that service offshoring has no significant effects on employment. Geishecker and Görg (2011) follow Feenstra and Hanson (1996b) to measure service offshoring in the U.K. and find that service offshoring leads to the wage decrease in unskilled workers but the increase in the skilled workers, resulting in a skill premium increase. The current study adds to these studies by looking at not only material offshoring but also service offshoring.

The current study also contributes to a large body of recent literature on trade effects on local labor markets. Autor et al. (2013) investigate the effects of Chinese imports on employment and wages in U.S. local labor markets (represented by commuting zones). Autor et al. (2014) use worker-level data from U.S. Social Security Administration and examine how individual workers respond to Chinese import competition for the last two decades. Hakobyan and McLaren (2016) look at the effects of NAFTA on local labor markets using individual workers data from U.S. Census. Unlike these studies, we focus on offshoring activities rather than trade exposure.

As described earlier, this paper uses TAA data to investigate offshoring effects. Recently, some authors use TAA data to examine various aspects of globalization. By linking firms that are TAA certified due to offshoring activities to firm-level data, Monarch et al. (2017) investigate how offshoring affects firms performances such as employment, output, capital intensity, wage, and productivity. In a similar vein, Uysal et al. (2015) use firm-level data and trade-induced layoffs recorded in the TAA data to investigate whether the relationship between trade-induced layoffs and firm productivity differs between non-exporting firms and exporting firms.

Kondo (2018) is closely related to our study in that he uses TAA data to examine effects of import competition on local labor markets. To motivate his theory of job creation and job destruction in local labor markets, he uses TAA data and shows that the elasticity of local employment to TAA trade-induced displacements is about two both at state and at the commuting zone level. That is, one extra TAA trade-displaced worker is associated with local employment falling by about two workers. Unlike his study, we focus on the relationship between offshoring and wage.

The rest of the paper proceeds as follows. Section 3.2 describes the TAA program and the TAA petitions dataset with descriptive statistics. Section 3.3 describes the dataset of individual workers, construction of the explanatory variable of interest, and provides summary statistics. Section 3.4 presents empirical specification and regression results. Section 3.5 concludes.

3.2 TAA Petitions Data

In Section 3.2.1, we provide an overview of the benefits, eligibility, and petition process of the TAA program. We then describe the details of the TAA petitions dataset in Section 3.2.2, followed by descriptive statistics in Section 3.2.3.

3.2.1 The TAA Program

The Trade Adjustment Assistance (TAA) program, administered by the U.S. Department of Labor (DOL), was first established in early 1960s and later formalized under the Trade Act of 1974. The program has been modified several times in the past. The most recent changes were influenced by the 2002 Trade Act and the 2009 Trade Globalization and Adjustment Assistance Act. The TAA program seeks to help displaced workers affected by import competition and offshoring in goods and services.[2] The TAA program provides participants with a variety of reemployment services (for up to two years), such as job training, job search and relocation allowances, income support, and assistance with healthcare premium costs.

[2] According to the DOL, displaced workers are defined as "persons 20 years of age and older who lost or left jobs because their plant or company closed or moved, there was insufficient work for them to do, or their position or shift was abolished."

To participate in the program, a petition must be filed with the DOL, by or on behalf of a group of workers.[3] These workers claim that they either have lost (or may lose) their jobs or have experienced a reduction in wages as a result of increased imports or shifts in production outside the United States. A petition is filed at the plant level. Each petition contains plant-level information, including company name, plant location, industry, main products or services, estimated number of workers affected, and so on. Once a petition is filed, the DOL initiates an investigation of the claimed layoffs. The purpose of the investigation is to determine whether the group of displaced workers meets the eligibility criteria, depending on which a petition is deemed certified, declined, or terminated. Specifically, an investigator certifies a petition if the cause of job displacement is one of the following: (i) import competition, which results in a decline in the company's production and sales, (ii) a shift in production to a foreign country with which the U.S. has a trade agreement, and (iii) the company is an upstream supplier or a downstream buyer of another company that has been certified under the TAA program. A petition is typically processed within one to two months. Workers with certified petitions can apply to the State Workforce Agency to receive TAA benefits and services.

3.2.2 The Dataset

The TAA petition dataset contains information on over 80,000 petitions dating back to mid 1970s. For each petition, the dataset contains its company name, address (state, city, ZIP code, and street address), main products or services that the worker

[3]Petitions can be filed by companies, unions, state employment agencies, or groups of three or more workers.

group produces, industry code (4-digit SIC code and/or 6-digit NAICS code), determination date and code, impact date (the start of eligibility for a certification, typically one year before the petition is filed), expiration date (typically two years after certification), estimated number of workers, and worker group (production, service, or mixed).

Each petition is assigned a determination code, which encrypts investigation result and the corresponding reasons. These codes were modified in 2002 and 2009, to reflect offshoring and further, service offshoring. Tables 3.1 and 3.2 present the determination codes under the 2002 and 2009 laws, respectively. According the the 2002 Law, certified petitions (under primary reasons) fall into five categories, among which two are related to imports of final goods (C-2 and C-3), and three are related to imports of intermediate inputs, i.e., offshoring (C-1, C-4, and C-5).[4] Determination codes under the 2009 Law are more disaggregated, as products are categorized into materials and services. Under the 2009 Law, we identify petitions with determination codes C-1, C-2, CSP-1, CSP-2, CSS-1, CSS-2 as certified offshoring petitions, among which we further separately identify petitions related to material offshoring (C-1, CSP-1, and CSP-2) and service offshoring (C-2, CSS-1, and CSS-2).[5]

The rich dataset of TAA petitions allows us to compute the number of workers exposed to negative employment shock of offshoring, by geography and by industry.

[4]Reasons for certification are classified into primary reasons (the plant itself is affected by import competition or offshoring) and secondary reasons (the upstream supplier or downstream buyer of the plant is affected by import competition or offshoring). Given the determination codes, it is difficult to identify job displacement caused by imports of final goods or intermediate inputs for petitions under secondary reasons. For this reason, we only consider petitions under primary reasons in this paper.

[5]Another way to identify service offshoring petitions is by using information on worker group (production, service, or mixed). We find that this method does not alter our results. In fact, the number of certified service offshoring petitions differs only slightly under the two methods (3,620 versus 3,480).

In addition, for petitions certified under the 2009 Law, we can separately examine the effect of material offshoring and service offshoring on local labor market outcomes. In this paper, we use petitions with impact year in 2005-2017 as our baseline sample.[6] For analysis that focuses on service offshoring, we restrict to a subsample between 2008 and 2017, for which the 2009 Law is applied.

3.2.3 Descriptive Statistics

Table 3.3 provides descriptive statistics of the TAA petition dataset. Over the period 2005-2017, there are a total of 24,416 petitions filed with the Department of Labor. Less than one-third of these petitions are either denied or terminated. Among the remaining petitions that are certified, about one-fourths are certified under imports of final goods and services, and three-fourths are certified under imports of intermediate inputs or shift in production sites (henceforth offshoring). There are a total of 1.64 million certified displaced workers in this period, among which roughly one-third are affected by imports of final goods and services and two-thirds are affected by offshoring. Using the 2008-2017 sample, we further break down the certified offshoring petitions into material offshoring and service offshoring. As shown in column (2) of Table 3.3, out of the 11,851 petitions certified during this period, nearly 73 percent are offshoring-related. Furthermore, about 55 percent of the certified offshoring petitions are material offshoring, and 45 percent are service offshoring. During this period, there are a total of 1,155,359 displaced workers, among which 30 percent are affected by imports of final goods and services and 70 percent are affected by offshoring.

[6] Instead of looking at the year in which the petition is filed, we use the impact year as the time of interest. The impact year identifies the start of eligibility for a certification, which provides a more accurate timing of the offshoring shock.

Within the offshoring sample, about one-fourth of workers are affected by service offshoring. These descriptive statistics indicate that in the past decade, there are at least as many offshoring-induced layoffs as those induced by imports of final goods and services. Offshoring has become a primary cause of job displacement resulting from globalization. In addition, petitions pertaining to service offshoring account for a considerable share of the certified offshoring petitions.

Using the plant-level industry information in the TAA petition dataset, we report statistics regarding offshoring at the industry level. For each plant, the dataset provides an industry code for the industry that the company belongs to. The industry codes consist of 4-digit Standard Industrial Classification (SIC) codes from 1974 to 2011 and 6-digit North American Industry Classification System (NAICS) codes from 2007 onwards. Since our sample period coincides with the transitional period, we convert the 6-digit NAICS codes to the 4-digit SIC codes for petitions with NAICS codes only, using a weighted crosswalk provided by David Dorn (Autor et al. (2013)).[7] The resulting dataset contains an SIC industry code for every plant.

In Table 3.4, we show the distributions of certified offshoring petitions and offshoring-induced layoffs by sector. Sectors are aggregated SIC industries. Unsurprisingly, *Manufacturing* is the sector accounting for the largest share of certified offshoring petitions (67.2 percent) and offshoring-induced layoffs (80 percent). *Service* sector and *Finance, Insurance, and Real Estate* sector are also highly exposed to the negative employment shock of offshoring, with a combined share of 27.4 percent of certified offshoring petitions and 14.7 percent of offshoring-induced displaced workers. The two measures produce almost identical rankings of sectors.

[7] For each observation, we compute the weighted number of displaced workers. The weights are taken directly from Dorn's crosswalk, which indicate the share of a NAICS industry's employment that maps to a given SIC code.

3.3 Individual Data and Explanatory Variable of Interest

In this section, we begin with descriptions of the individual-level data for the local labor market analysis. Then, we define the explanatory variable of interest of the analysis and layout the crosswalk we use to construct the variable of interest. Lastly, we present statistics of the variable.

3.3.1 Individual Data

The individual sample is drawn from the American Community Survey (ACS, annual sample 2005-2017).[8] We select individuals from age 16 to 65 who earn wage and salary income. The individual characteristics we gather include age, gender, race, educational attainment, marital status, industry of employment, occupation, wage and salary income, and county of residence.

3.3.2 Explanatory Variable of Interest

In empirical analysis, we first examine the effect of offshoring-induced negative employment shock on local labor market outcomes. This negative employment shock is captured by certified offshoring-induced layoffs in the TAA petitions dataset. For local labor market analysis, a commonly used geographic unit is a commuting zone (CZ).[9] It is well accepted that a commuting zone is a good representation of a local labor market, because it is a cluster of U.S. counties that are characterized by strong

[8] Available at https://usa.ipums.org/usa/.

[9] For example, Autor et al. (2013) conduct analysis at the commuting zone level to investigate the "China shock" on local labor markets in the United States.

within-cluster and weak between-cluster commuting ties. Thus, our explanatory variable of interest for the local labor market analysis is at the commuting zone by year (CZ $\times$ year) level. Second, we are also interested in exploring the wage effect of the industry-level exposure to the negative employment shock of offshoring. For this exercise, we construct our explanatory variable of interest at industry by year (IND $\times$ year) level.

We define the explanatory variable of interest, offshoring-induced layoffs weighted by employment (OL), as follows:

$$OL_{ut} = \frac{\text{Number of offshoring-induced layoffs}_{ut}}{\text{Total employment}_{ut}}, \tag{3.1}$$

where $u = c$ in the CZ analysis and $u = j$ in the IND analysis, and c and j denote CZ and IND, respectively.

The TAA dataset contains plant-level geography information including state, city, ZIP code, and street address. To construct CZ level offshoring-induced layoffs, we first extract ZIP code information from the dataset, and then apply crosswalks and matching methods described in Chetty et al. (2014) and Chetty and Hendren (2018) to map ZIP codes to CZs. Total employment by CZ is constructed using the ACS individual dataset. In particular, we first match a worker's county to CZ with existing crosswalk, as in Autor and Dorn (2013), then we compute the weighted number of workers residing in that CZ, using the personal weight provided by the survey.

To compute the total employment by industry, we rely on information regarding worker's industry of employment in the ACS dataset. The ACS reports an individual's industry of employment using Census 1990 Industrial Classification System (IND1990). For each IND1990 industry, we sum up the weighted number of individuals working in that industry, applying the personal weight available in the dataset. For consistency of industry classification, we map the SIC codes in the TAA petitions dataset to the IND1990 codes using the match approach proposed by Autor et al. (2018).

3.3.3 Summary Statistics

For each CZ × year unit and each IND × year unit, we compute the OL measure as in equation (3.1). We now present summary statistics of the variable by CZ and by IND.

By Commuting Zone

We first consider variation in the OL variable by CZ. Figure 3.1 depicts TAA-certified offshoring-induced layoffs (per thousand employment) across CZs, averaging 2005-2017. The white CZs are the ones without any certified offshoring-induced layoffs during our sample period. This group contains a mixture of CZs that are (i) truly not affected by offshoring, (ii) claim to have experienced job displacement from offshoring but the petition is denied or terminated, and (iii) positively affected by offshoring, i.e., benefiting from job creation, increased labor demand, or wage increase. Since it is hard to tell whether (and how) offshoring has affected these CZs, we exclude the white CZs from our analysis. In other words, we only focus on the shaded CZs in Figure 3.1, for which we are certain that offshoring has led to job losses. We present the five quintiles of the shaded CZs, based on their employment adjusted layoffs. It is evident from the map that the CZs most intensively exposed to the negative employment shock of offshoring are concentrated near the Rust Belt and the Southeast. We also produce a map for the 2008-2014 sample of certified service offshoring petitions. As shown in Figure 3.2, the negative employment shock of service offshoring is less concentrated. A comparison of the two maps reveals that CZs near the Rust Belt and the Southeast are relatively more vulnerable to material offshoring, whereas CZs located on the west coast, especially the ones in the State of Oregon, are relatively more vulnerable to service offshoring.

By Industry

Next, we proceed by examining the intensiveness of the negative offshoring-induced employment shock across industries. In Table 3.5, we present the top ten industries (according to the 2-digit IND1990 codes) ranked by the average share of offshoring-induced layoffs out of industry employment in 2005-2017. Eight manufacturing industries are on the top ten list. Over 2005 to 2017, on average 1.4 percent of workers in the *Motor vehicles and motor vehicle equipment* industry lost jobs due to offshoring.

3.4 Empirical Approach and Results

In this section, we describe the empirical specification we use to estimate the effect of offshoring-induced layoffs on workers' wages and the regression results.

3.4.1 Local Labor Market Analysis

Empirical Specification

Our empirical model for the local labor market analysis is motivated by Autor et al. (2013). In their seminal work of the "China Syndrome," Autor et al. (2013) develop a model of import competition and show that positive shocks to China's export supply decrease wages in the U.S. locality which imports from China. Following their logic, we postulate that an exogenous technology shock that reduces costs of offshoring from the U.S. to China can be thought of as a positive shock to China's export supply, since the offshored intermediate inputs would eventually be imported back to the U.S. Therefore, if migration is costly across CZs, we expect that the offshoring-induced layoffs leads to a wage decrease in a CZ.

The model has an implication that the CZ-level wage would decrease as the China competition rises. As for the employment, it would decrease in the traded sector while increasing in the non-traded sector. Given that we do not have positive employment effects measured in our variable, it would mean that the workers who would have switched from traded sector to non-traded sector would be reabsorbed in the traded sector by the labor market clearing condition. It implies that the wage would be pushed down further. Thus, we anticipate that our analysis may have overestimated the true wage effect. Nevertheless, we expect that the sign would stay unchanged.

To estimate the effect of offshoring-induced layoffs on wages at the local labor market level, we fit the following estimating equation:

$$ln(w_{ict}) = \alpha + \beta OL_{c,t-1} + \gamma X_i + \theta_c + \theta_t + \Omega_{c,t-1} + \varepsilon_{ict}, \qquad (3.2)$$

where $ln(w_{ict})$ is the (log) wage income of worker i in commuting zone c in year t, $OL_{c,t-1}$ is the (lagged) offshoring-induced layoffs weighted by employment, X_i are personal characteristics of worker i (age, age squared, dummies for male, white, married, and educational attainment), θ_c and θ_t are CZ and year fixed effects, respectively, and $\Omega_{c,t-1}$ is a set of time-varying CZ characteristics (percentage of employment in manufacturing, percentage of college-educated workers, percentage of foreign-born workers, and percentage of female workers).

Wages do not respond instantaneously to offshoring shocks. Considering this fact, most existing studies use a lagged measure of offshoring to capture the delay of wage adjustment. It is worth to point out once more that the OL measure is constructed using a petition's impact year, not petition year, to provide a more accurate picture of the timing of the offshoring shock. Thus, if we take $t = 2006$, then $OL_{c,t-1}$ reflects the offshoring shock in 2005, i.e., petitions with impact year of 2005, regardless of when they were filed.

In the regression, we also control for other variables that could explain variation in wages. The Mincerian model of return to education suggests that individual characteristics, such as age, gender, race, education level, are important in explaining individual-level wages. CZ fixed effect controls for unobserved time-invariant CZ characteristics that affect wages. Year fixed effect eliminates any variation in wages and offshoring due to common macroeconomic shocks. In addition, inspired by Autor et al. (2013), we control for a set of CZ-specific demographic and labor market measures which varies over time to account for potential confounding effects.

A discussion of endogeneity is in order. As offshoring shocks hit, firms choose to offshore a part of their production process for cost reduction opportunities. It implies that there is a change in the firms demand for inputs, which results in the decision of how much to offshore and how much to pay for the labor input being simultaneously made. In this paper, the endogeneity of the offshoring-induced layoffs variable is a bit less of a problem than other offshoring measure variables used in the literature. The variable in use is the people who have been certified by the U.S. government to have lost their jobs due to offshoring, rather than due to domestic shocks.

Results

We present the weighted OLS regression results of the local labor market analysis in columns (1)-(3) of Table 3.6, where weights are personal weights. To address the concern that error terms are correlated within a CZ, we cluster the standard errors by commuting zone. Across all regression results, the coefficients of individual controls are all statistically significant at the 1% level. In addition, they all appear to have expected signs. For example, wage increases with age but at a decreasing rate, married white males earn higher wages, and there is a wage premium from education.

The coefficient of our variable of interest, OL_{ct}, is negative and statistically significant at the 5% level in column (1). The regression result suggests that among the observations exposed to negative employment shocks of offshoring, a one-percentage-point increase in the share of offshoring-induced layoffs is associated with a 1.024% decrease in individual wages.

Columns (2)-(3) in Table 3.6 report regression results of alternative specifications. In particular, column (2) includes a set of CZ-specific demographic and labor market measures. Among these controls, the coefficient of percentage of female employment is negative and statistically significant at the 1% level. The point estimate of the OL variable differs only slightly from column (1), but the statistical significance drops to 10%. In column (3), we further control for occupation fixed effect to address routiness and offshorability of an occupation, as suggested by Autor et al. (2013).[10] The regression result is robust to the inclusion of the occupation fixed effect.

In columns (4)-(6), we present the results of a similar set of regressions, but restricting to the service-offshoring sample in 2008-2017. This means that the OL measure is defined as the share of service-offshoring-induced layoffs out of the total employment. In contrast to the full offshoring sample, we do not find evidence of the wage effect resulting from service-offshoring-induced layoffs.

Table 3.7 shows the heterogeneous wage effect by educational attainment. Specifically, we construct an indicator for college education, which equals one if the individual has at least one year of college education. We interact the college indicator with the $OL_{c,t-1}$ measure to capture the differential effect of offshoring-induced layoffs on individuals with different levels of educational attainment. We also include the college indicator by itself to allow for level difference. Columns (1) and (2) show that workers with college experience earn more but suffer more from the adverse shock of offshoring. In column (3), we further control for occupational characteristics by including occupation fixed effects. Both the direct and the interaction effects are weakened as compared to columns (1) and (2). However, the effects remain statistically significant at the 1% level.

The results in Table 3.7 suggest that offshoring-induced layoffs have opposite wage effects on individuals with and without college education. While the less-educated workers experience an increase in wages associated with the negative employment

[10] Autor et al. (2003) emphasizes the importance of the task content of occupations by distinguishing routine and non-routine tasks. Routine tasks are easier to be automated, and are more likely to be offshored and completed by unskilled labor with low wages. Ebenstein et al. (2014) applies the same logic to analyze the effect of offshoring on wages by the degree of routineness of occupations.

shock of offshoring, the educated workers suffer heavily. The negative wage effect on educated workers dominates, driving an average wage decrease from offshoring-induced layoffs, as shown in the baseline results in Table 3.6.

3.4.2 Industry Analysis

For industry analysis, we follow the idea of Ebenstein et al. (2014). The authors regress individual wages on an industry-level measure of offshoring with an extensive set of controls.

To estimate the effect of offshoring-induced layoffs on wages at the industry level, we fit the following estimating equation:

$$ln(w_{ijt}) = \alpha + \beta OL_{j,t-1} + \gamma X_i + \theta_j + \theta_t + \Omega_{j,t-1} + \varepsilon_{ijt}, \quad (3.3)$$

where all variables bear similar definitions as those in equation (3.2), except that we denote j for industries. $\Omega_{c,t-1}$ is a limited set of time-varying industry characteristics (percentage of college-educated workers, percentage of foreign-born workers, and percentage of female workers). We acknowledge that this set of controls is far from ideal, as we do not have key variables such as TFP and capital-labor ratio. However, the current exercise would be our first attempt to detect any evidence of the wage effect at the industry level.

Table 3.8 shows the industry-level results. Across all specifications, coefficients of the individual controls are significant with expected signs. However, the coefficient of the OL measure is insignificant in all columns. This indicates that wages seem to be unaffected by the industry-level offshoring-induced layoffs, which is consistent with the findings in Ebenstein et al. (2014).

3.4.3 CZ by Industry Analysis

Given the rich structure of the data, we further disaggregate the level of analysis to CZ $\times$ IND $\times$ year.

We extend the estimating equation to the following:

$$ln(w_{icjt}) = \alpha + \beta OL_{cj,t-1} + \gamma X_i + \theta_{jt} + \theta_c + \Omega_{cj,t-1} + \varepsilon_{icjt}, \quad (3.4)$$

where all variables bear similar definitions as those in equations (3.2) and (3.3). In this specification, we are now able to control for the time-varying industry characteristics such as TFP and capital-labor ratio, by including industry-time fixed effects θ_{jt}.

As shown in Table 3.9, the coefficients of $OL_{cj,t-1}$ are negative and statistically significant at the 1% level across all specifications. Column (4) presents the result with the most comprehensive set of controls, which suggests that a one-percentage-point increase in the share of offshoring-induced layoffs at the CZ-by-IND level is associated with a 0.305% decrease in individual wages. Note that this result should be taken with caution, as the sample size decrease significantly when we disaggregate the level of analysis.

3.5 Concluding Remarks

In this paper, using a dataset of petitions from the U.S. TAA program, we construct a measure which captures the negative employment effect of offshoring by commuting zone and industry. This measure is defined as the share of offshoring-induced layoffs out of the total employment in a commuting zone or industry. We estimate the effect of offshoring-induced layoffs on individual wages, controlling for a set of worker characteristics, fixed effects, and time-varying demographic and labor market characteristics.

The regression result at the commuting-zone level suggests that among the observations exposed to negative employment shocks of offshoring, a one-percentage-point increase in the share of offshoring-induced layoffs at the commuting-zone level is associated with a 1.024% decrease in individual wages. However, we do not find a significant effect of service-offshoring-induced layoffs. The effect of offshoring-induced layoffs on individual wages is insignificant across all specifications at the industry level. This indicates that wages seem to be unaffected by the industry-level offshoring-induced layoffs, which is consistent with the findings in Ebenstein et al. (2014). We further disaggregate the level of analysis to CZ $\times$ IND $\times$ year. With the most comprehensive set of controls, the result suggests that a one-percentage-point increase in the share of offshoring-induced layoffs at the CZ-by-IND level is associated with a 0.305% decrease in individual wages.

These results may support the idea that when an employment shock hits, it is relatively easy to switch the industry of employment than relocating to a different commuting zone due to migration costs.

Table 3.1: Determination Codes under the 2002 Law

PRIMARY			
Certifications		Denials	
C-1	Increased company imports	D-1	No employment decline
C-2	Increased customer imports	D-2	No sales or production decline/shift in production (domestic transfer)
C-3	Increased aggregate imports	D-3	No import increase and/or production shift abroad
C-4	Shift in production to country with a free trade agreement/beneficiary	D-4	Predominant cause of layoffs unrelated to imports, shift in production to beneficiary country, or increase in imports following a shift
C-5	Actual/likely increase in imports following a shift abroad	D-5	Workers do not produce an article
SECONDARY			
Certifications		Denials	
CS-1	Upstream supplier of trade certified primary firm	DS-1	No secondary upstream supplier impact
CS-2	Downstream producer of trade certified primary firm impacted by shift in production to/increase in imports from Canada or Mexico	DS-2	No secondary downstream producer impact

Notes: This table contains the determination codes and descriptions under the 2002 Law, for certified petitions (left) and denied petitions (right), subject to primary reasons (top) and secondary reasons (bottom). "PRIMARY" reasons: the plant itself is affected by import competition or offshoring; "SEONDARY" reasons: the upstream supplier or downstream buyer of the plant is affected by import competition or offshoring.

Table 3.2: Determination Codes under the 2009 Law

PRIMARY			
Certifications		Denials	
C-1	Company imports of articles	D-1	No employment decline or threat of separation
C-2	Company imports of services	D-2	No sales or production decline
C-3	Customer imports of articles	D-3	No sales or service decline
C-4	Customer imports of services	D-4	No shift in production/ no company or customer imports
C-5	Imports of finished articles containing like or directly competitive components	D-5	No shift in services/ no company or customer imports
C-6	Imports of finished articles containing foreign components	D-6	No import increase of finished articles containing foreign components
C-7	Imports of articles produced using worker services	D-7	No import increase of finished articles containing foreign services
C-8	Increased aggregate imports	D-PA	Public agency separation not related to shift import of services
CSP-1	Shift in production		
CSP-2	Acquisition of articles from a foreign country		
CSS-1	Shift in services		
CSS-2	Acquisition of services from a foreign country		
C-PA	Public agency		
C-ITC	ITC Determination		
SECONDARY			
Certifications		Denials	
CSS	Secondary component supplier	DSC	No secondary upstream supplier impact - component
SSS-2	Secondary service supplier	DSS	No secondary downstream supplier impact - service
CDP	Downstream producer	DDP	No secondary downstream producer impact

Notes: This table contains the determination codes and descriptions under the 2009 Law, for certified petitions (left) and denied petitions (right), subject to primary reasons (top) and secondary reasons (bottom). "PRIMARY" reasons: the plant itself is affected by import competition or offshoring; "SEONDARY" reasons: the upstream supplier or downstream buyer of the plant is affected by import competition or offshoring.

Table 3.3: Sample Statistics of TAA Petitions

	(1) 2005-2017 Sample	(2) 2008-2017 Sample
Number of petitions	24,416	17,326
Denied/Terminated	7,962	5,475
Certified	16,454	11,851
Imports of final goods and services	4,800	3,177
Offshoring	11,654	8,674
Material offshoring		4,782
Service offshoring		3,892
Number of certified displaced workers	1,643,467	1,155,359
Imports of final goods and services	500,392	349,180
Offshoring	1,093,075	806,179
Material offshoring		592,440
Service offshoring		213,739

Notes: "Offshoring" refers to imports of intermediate inputs or shift in production sites. Data for "Number of displaced workers" is available for certified petitions only.

Table 3.4: TAA Offshoring Statistics by Sector

		Certified offshoring petitions		Offshoring-induced layoffs	
		(1)	(2)	(3)	(4)
		Number	%	Number	%
1	Manufacturing	8,998	67.2	799,140	80.0
2	Services	2,522	18.8	114,743	11.5
3	Finance, Insurance and Real Estate	1,150	8.59	32,366	3.24
4	Transportation and Public Utilities	391	2.92	29,231	2.92
5	Wholesale Trade	146	1.09	11,035	1.11
6	Retail Trade	135	1.00	7,633	0.76
7	Mining	26	0.19	2,882	0.29
8	Construction	14	0.10	641	0.06
9	Agriculture, Forestry, and Fishing	9	0.07	819	0.08

Notes: Sectors are aggregated SIC industries. Entries in column (2) are the shares of certified offshoring petitions by sector. Entries in column (4) are the shares of offshoring-induced displaced workers by sector. Sample period is 2005-2017.

Table 3.5: Industries Most Intensively Exposed to Negative Employment Shock of Offshoring

		Sector	Average share of offshoring layoffs out of industry employment (%)
1	Motor vehicles and motor vehicle equipment	M	1.40
2	Food preparations and misc. food industries	M	1.11
3	Tobacco manufactures	M	0.51
4	Plastic and leather products	M	0.43
5	Metal and screw machine products	M	0.39
6	Chemicals	M	0.35
7	Cement and concrete products	M	0.34
8	Logistic services	T	0.28
9	Pottery products	M	0.27
10	Wholesale trade of non-durable goods	W	0.26

Notes: Sample period is 2005-2017. Under "Sector", M stands for *Manufacturing* sector, T stands for *Transportation Utilities* sector, and W stands for *Wholesale Trade* sector.

Table 3.6: CZ-level Regression Results

Dependent Variable: ln(wage)	Full Offshoring Sample			Service Offshoring Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
OL	-1.024**	-1.053*	-0.941*	-0.833	-0.309	-0.619
	(0.498)	(0.620)	(0.514)	(0.853)	(1.105)	(0.873)
Male	0.384***	0.384***	0.268***	0.370***	0.370***	0.257***
	(0.00769)	(0.00769)	(0.00539)	(0.00836)	(0.00836)	(0.00599)
Age	0.202***	0.202***	0.166***	0.201***	0.201***	0.166***
	(0.00215)	(0.00215)	(0.00170)	(0.00230)	(0.00230)	(0.00184)
Age^2	-0.00214***	-0.00214***	-0.00175***	-0.00212***	-0.00212***	-0.00174***
	(2.36e-05)	(2.36e-05)	(1.79e-05)	(2.52e-05)	(2.52e-05)	(1.95e-05)
Education	0.154***	0.154***	0.0805***	0.157***	0.157***	0.0817***
	(0.00181)	(0.00181)	(0.00109)	(0.00198)	(0.00198)	(0.00121)
White	0.135***	0.135***	0.0826***	0.135***	0.135***	0.0845***
	(0.00765)	(0.00762)	(0.00454)	(0.00853)	(0.00852)	(0.00487)
Married	0.185***	0.185***	0.115***	0.186***	0.186***	0.116***
	(0.00629)	(0.00629)	(0.00421)	(0.00660)	(0.00661)	(0.00433)
Manufacturing		0.154	0.145		0.379	0.267
Emp. Share		(0.208)	(0.175)		(0.270)	(0.217)
College Share		-0.139	-0.122		0.0649	0.00987
		(0.0932)	(0.0883)		(0.0953)	(0.0974)
Women Share		-0.965***	-0.800***		-0.740***	-0.629***
		(0.214)	(0.180)		(0.276)	(0.237)
Foreign-born		0.269	0.169		0.129	0.0337
Share		(0.180)	(0.133)		(0.128)	(0.0958)
Observations	8,687,659	8,687,659	8,687,659	5,763,676	5,763,676	5,763,676
R-squared	0.377	0.377	0.464	0.374	0.374	0.462
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
OCC FE	No	No	Yes	No	No	Yes

Notes: "OL" is the share of offshoring-induced layoffs out of the total employment at the CZ $\times$ year level. "OCC" indicates occupation. Regressions are weighted by personal weights. Coefficients of the constant are not reported. Robust standard errors in parentheses are clustered by CZ. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3.7: Heterogeneous Effects by Education Attainment

Dependent Variable: ln(wage)			
	(1)	(2)	(3)
College	0.579***	0.579***	0.228***
	(0.0144)	(0.0144)	(0.00643)
College × OL	-10.05***	-10.03***	-4.730***
	(3.108)	(3.102)	(1.674)
OL	4.479***	4.586***	1.699*
	(1.696)	(1.584)	(0.937)
Male	0.372***	0.372***	0.273***
	(0.00825)	(0.00825)	(0.00590)
Age	0.210***	0.210***	0.169***
	(0.00281)	(0.00281)	(0.00194)
Age^2	-0.00223***	-0.00223***	-0.00178***
	(3.11e-05)	(3.10e-05)	(2.07e-05)
White	0.172***	0.172***	0.0928***
	(0.0117)	(0.0117)	(0.00594)
Married	0.217***	0.217***	0.121***
	(0.00801)	(0.00802)	(0.00459)
Manufacturing		0.0823	0.118
Emp. Share		(0.218)	(0.177)
College Share		-0.0774	-0.0993
		(0.107)	(0.0930)
Women Share		-0.944***	-0.792***
		(0.225)	(0.182)
Foreign-born		0.267	0.155
Share		(0.182)	(0.130)
Observations	8,687,659	8,687,659	8,687,659
R-squared	0.346	0.346	0.457
CZ FE	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes
OCC FE	No	No	Yes

Notes: "OL" is the share of offshoring-induced layoffs out of the total employment at the CZ × year level. "OCC" indicates occupation. Regressions are weighted by personal weights. Coefficients of the constant are not reported. Robust standard errors in parentheses are clustered by CZ. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3.8: Industry-level Regression Results

Dependent Variable: ln(wage)			
	(1)	(2)	(3)
OL	-0.299	-0.347	-0.409
	(0.356)	(0.395)	(0.396)
Male	0.327***	0.327***	0.324***
	(0.0129)	(0.0129)	(0.0129)
Age	0.164***	0.164***	0.164***
	(0.00616)	(0.00616)	(0.00609)
Age^2	-0.00173***	-0.00173***	-0.00172***
	(6.88e-05)	(6.88e-05)	(6.78e-05)
Education	0.145***	0.145***	0.143***
	(0.00591)	(0.00590)	(0.00573)
White	0.0992***	0.0992***	0.130***
	(0.00875)	(0.00874)	(0.00847)
Married	0.189***	0.189***	0.194***
	(0.0157)	(0.0157)	(0.0152)
College Share		0.102	0.0849
		(0.127)	(0.126)
Women Share		-0.404*	-0.411*
		(0.216)	(0.217)
Foreign-born		0.118	0.101
Share		(0.219)	(0.219)
Observations	6,023,423	6,023,423	6,023,423
R-squared	0.396	0.396	0.401
IND FE	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes
STATE FE	No	No	Yes

Notes: "OL" is the share of offshoring-induced layoffs out of the total employment at the IND × year level. Regressions are weighted by personal weights. Coefficients of the constant are not reported. Robust standard errors in parentheses are clustered by IND. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3.9: CZ-IND-level Regression Results

Dependent Variable: ln(wage)				
	(1)	(2)	(3)	(4)
OL	-0.408***	-0.354***	-0.342***	-0.305***
	(0.112)	(0.109)	(0.106)	(0.103)
Male	0.288***	0.237***	0.287***	0.236***
	(0.00871)	(0.00935)	(0.00854)	(0.00933)
Age	0.160***	0.144***	0.160***	0.144***
	(0.00483)	(0.00435)	(0.00487)	(0.00437)
Age^2	-0.00167***	-0.00150***	-0.00167***	-0.00150***
	(5.64e-05)	(5.23e-05)	(5.68e-05)	(5.26e-05)
Educ	0.151***	0.0901***	0.150***	0.0895***
	(0.00514)	(0.00425)	(0.00485)	(0.00421)
White	0.186***	0.132***	0.186***	0.133***
	(0.0158)	(0.0137)	(0.0162)	(0.0140)
Married	0.161***	0.124***	0.161***	0.124***
	(0.00848)	(0.00845)	(0.00860)	(0.00857)
College Share			0.516***	0.382***
			(0.0640)	(0.0664)
Women Share			-0.183***	-0.148***
			(0.0621)	(0.0562)
Foreign-born Share			0.139**	0.117
			(0.0695)	(0.0820)
Observations	502,919	502,917	502,919	502,917
R-squared	0.396	0.449	0.397	0.449
IND X YEAR FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
OCC FE	No	Yes	No	Yes

Notes: "OL" is the share of offshoring-induced layoffs out of the total employment at the CZ $\times$ IND $\times$ year level. "OCC" indicates occupation. Regressions are weighted by personal weights. Coefficients of the constant are not reported. Robust standard errors in parentheses are clustered by CZ and by IND. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

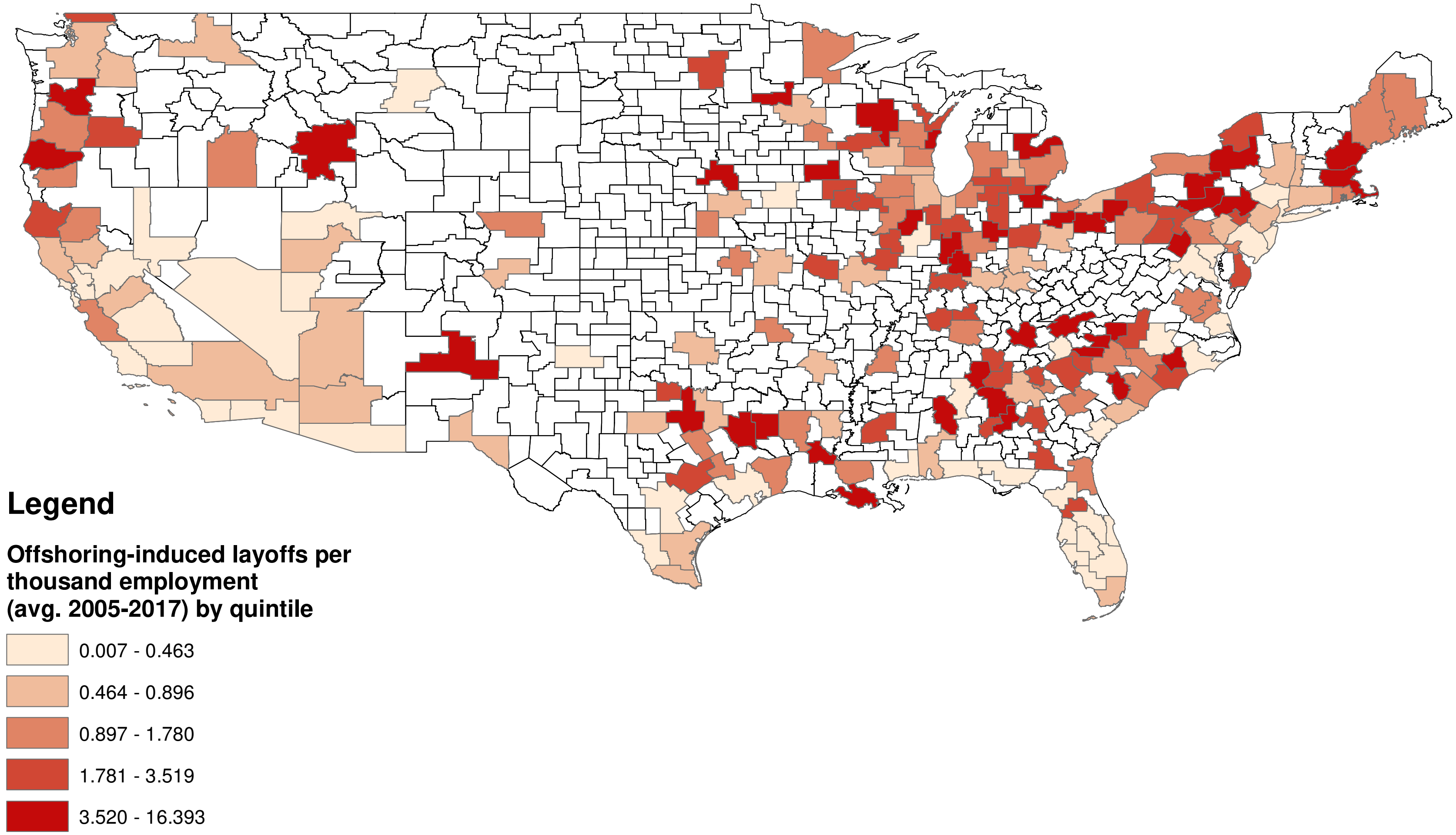


Figure 3.1: TAA-Certified Offshoring-induced Layoffs across Commuting Zones, 2005-2017

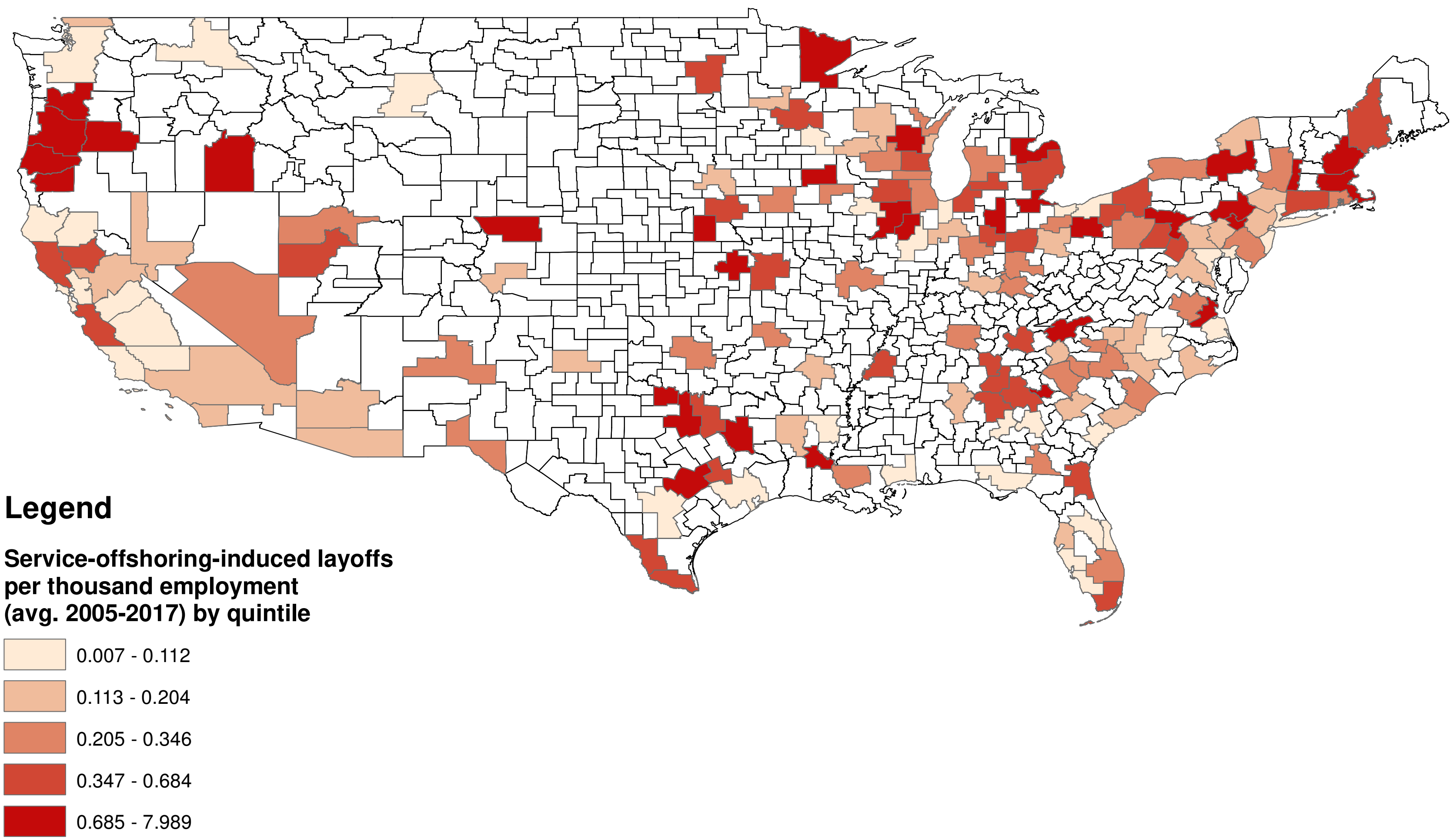


Figure 3.2: TAA-Certified Service-Offshoring-induced Layoffs across Commuting Zones, 2008-2017

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