Outsource to India: The Impact of Service Outsourcing to India on the Labor Market in the US

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Abstract

While the impact of outsourcing in manufacturing industries is well-documented, relatively little is known about service outsourcing despite its growing importance in the economy. This paper is one of the few papers studying the effect of service outsourcing on the US's labor market, focusing on India, one of the most popular outsourcing destination countries. I examine whether the increase in service outsourcing to India has reduced the employment of the occupations with greater exposure to Indian service Imports. To account for endogeneity, I instrument for the growth of the US's service import from India exploiting the change in Indian import in European countries. The occupation level analysis gives a mixed result. An increase in service imports reduces the total employment from 2000 to 2007; however, this effect attenuates in the later period of 2007 to 2017. The change is skill-biased: the reduction in employment is smaller for college-educated workers in the first period, and the sign reverses later.

Keywords: Service Outsourcing, Offshore, Employment, India

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I Introduction

Service trade has dramatically increased since the 1980s, thanks to technological advances. A fraction of service imports is considered outsourcing or offshoring. Outsourcing is a common and well-known practice in firms to save costs by transferring certain tasks to a third party that can produce them at cheaper costs. While the impact of outsourcing in manufacturing is studied extensively (Ahmed, Hertel and Walmsley, 2011; Bhagwati, Panagariya and Srinivasan, 2004; Hummels, Munch and Xiang, 2018) studies on service import are still limited and nascent.

Service outsourcing has a different implication to domestic workers than merchandise trade. The traditional outsourcing literature documents the collapse of manufacturing industries in high-income countries as the unskilled domestic workers start to compete with cheaper labor force overseas (Bhagwati, Panagariya and Srinivasan, 2004). For the first time in history, skilled workers in the developed countries are now competing with the skilled labor force in low-income countries, where the skill level is very high with a significantly lower hourly pay (Liu and Trefler, 2019). The technological advances made occupations that traditionally have not been threatened by globalization at risk (Blinder, 2009). At the same time, some people blame service outsourcing for taking jobs away from domestic workers and argue outsourcing is harmful to the labor force. While service outsourcing may improve the productivity of firms (Amiti and Wei, 2009*b*), impact on the labor market is controversial and ambiguous (Amiti and Wei, 2009*a*,*b*; Amiti et al., 2005).

This paper examines the impact of the substantial increase in the US service import from India on the US labor market. In order to estimate the causal effect of the service import, I exploit the substantial increase in the service export from India stimulated by technological advances and expansion of the Business Process Outsourcing (BPO) market since the late 1990s. The growth in service export from India stems from the advance of high-speed internet (broadband) in the early 2000s (Choi, 2010; Freund and Weinhold, 2002) as well as the country's massive effort to promote the BPO sector. I follow Autor, Dorn and Hanson (2013*a*) and instrument for the service trade from India to the US utilizing India's export to the 15 European Union countries in this paper.

I construct an occupation level import penetration measure following Ebenstein et al. (2014); Liu and Trefler (2019), and examine the impact on occupational employment and median wage during 2000-2016. Results in this paper suggest a non-linear and multidirectional impact of service import on employment. The overall effect of service import on occupational employment is negative: a one standard deviation increase in import penetration decreases total employment by 0.25 percent annually during 2000-2016. However, when I break the sample into two periods, 2000-2006 and 2006-2016, the impact is concentrated in the earlier period only. In fact, the point estimate is positive (but statistically insignificant) in the later period.

My results suggest there is a skilled-bias change in employment. The earlier period's negative impact is smaller for college-educated workers (-0.282) than the overall impact (-0.403). More importantly, the employment impact is positive and large in the later period for college-educated workers, increasing the employment by 0.47 percent. The increase in service import changes the composition of workers within occupations toward skilled workers. Skill-biased change is found across occupations as well. The negative impact on employment in the earlier period is stronger for low-skilled (occupations with a lower share of college-educated workers) and high-routine occupations. In fact, the negative impact on these low-skilled and high routine jobs continues to the later period, where the overall impact was small and positive.

I find a positive effect on occupation-level median weekly wages. The impact on wages is consistent over time, without a large difference unlike impact on employment. An increase in import penetration by one standard deviation raises the median weekly wage by 0.13 percent annually. The impact on wage should be interpreted with caution because of the compositional change suggested by the effect on employment. Considering the skill-biased change in employment, the positive impact may represent the compositional change, not an increase in productivity.

This paper contributes to small literature studying the impact of service import on the labor market. Service trade is more difficult to research than merchandise trade because services are not measured at the border like tangible goods. There are very limited harmonic datasets across countries, most of which are available only recently after 2010. Despite the difficulties, there are a few valuable studies. Liu and Trefler (2019) find service import from India and China induces job switching of affected occupation in the US, both upward and downward in terms of average earnings. Crinò (2010*b*) finds a skill-biased change in employment resulting from service import in the US along with his other papers in European countries (Crinò, 2007, 2010*a*, 2012).

The impact on wages is partially supported by Geishecker and Görg (2013). They find service import polarizes the income distribution by rewarding high-skilled workers and penalizing low-skilled with similar import penetration in the UK. If service import from India has a similar impact, the positive impact on wages is amplified by the compositional change toward skilled workers and the positive impact on wages itself.

My paper has three major contributions. First, to my knowledge, this is the first paper studying the impact of service imports from low-income countries on the domestic labor market in the US beyond 2006. Most of the research uses the service trade data in the balance of payment (BOP) from The Bureau of Economic Analysis (BEA); however, the data structure had changed in 2006, making it difficult to study beyond this year. Because the data structure change is not problematic for India as much as in other countries, I overcome this problem by focusing on service import from India.[1] Although I focus on a single country, India's BPO market is the largest globally and accounts for a significant fraction of service outsourcing in the US (Burange, Chaddha and Kapoor, 2010). It is crucial to include beyond 2006 because the service trade has increased significantly since then, with a steeper growth than before.

Second, this paper provides evidence that the impact of service outsourcing on total employment may not be single-directional. I find that the employment of skilled workers even increases in the later period (2006-2016) as the service import grows exponentially. My result supports the existence of skill-biased change in employment, which even increases the total employment in the end. Before 2006, my paper's result is consistent with previous works like Amiti and Wei (2009*a*); Crinò (2007, 2010*a*,*b*); Liu and Trefler (2019), showing a reduction in employment and a skilled-biased change, and I find that this pattern may flip in the later period.

Finally, my paper captures both affiliated and unaffiliated imports from India. Because of the BEA data structure, most of the literature studying the US focus on unaffiliated trade only (Amiti et al., 2005; Crinò, 2010*a*; Liu and Trefler, 2019). Although there is a measurement error caused by ignoring affiliated trade in the late 1990s, I estimate the impact of aggregated service import, unlike other research. Affiliated import accounts for more than 40 percent of total service import in 2006 (Koncz, Mann and Nephew, 2006). Thus, omitting affiliated

[1] BEA has aggregated affiliated and unaffiliated trade together for each country since 2006. Until 2005, information on unaffiliated trade was only available for each country. This structural difference makes it difficult to research beyond 2006 together with the previous years. Because affiliated trade with India was minimal in the late 1990s, I could extend the study period beyond 2006 by ignoring affiliated trade in the earlier period. See Section III for further information.

trade may underestimate the impact of service outsourcing. I attempt to avoid this problem by focusing on a single country.

The remainder of this paper is organized as follows. Section II provides the background of empirical strategy and data sources. In Section III, I explain the importance of India in service outsourcing and the advantage of focusing on India. Section IV presents the results. Section V discusses the results and concludes.

II Empirical Strategy

II.1 Defining Import Penetration

To examine the impact of service import on occupation level employment and wage, I define occupation level import penetration following Acemoglu et al. (2016); Ebenstein et al. (2014); Liu and Trefler (2019). The previous literature uses the industrial composition of each occupation to capture the relevancy to each service. Next, I estimate the industrial composition of each occupation to measure the importance of each service. A large proportion of computer scientists, for example, are working in the computer and information service industry because the service is relevant to the task they perform.

The formal definition is:

$$\Delta IP^{US}_{kt} = \sum_s \omega_{sk,00} \times \frac{\Delta IMP^{IND-US}_{st}}{Y^{US}_{s,96} + IMP^{US}_{s,96} - EXP^{US}_{s,96}}, \tag{1}$$

$$\omega_{sk,00} = \frac{N_{sk,00}}{\sum_s N_{sk,00}},$$

where $\omega_{sk,00}$ is the share of workers of occupation k working in industry s in 2000.[2] In this equation, the change in occupation level import penetration is a weighted average of the change in each service import normalized by the initial size of the sector ($Y^{US}_{s,96} + IMP^{US}_{s,96} - EXP^{US}_{s,96}$).

Table 2 displays the 20 year ΔIP of top 35 occupations. Because growth in computer and information service is the greatest among all tradable services, the top 2 occupations are computer and data related jobs. Scientists and researchers are also on the top list because they are overrepresented in the R&D sector. Note that the top 35 jobs are not necessarily high-skilled

[2]The base year is 2000 because I use decinnial Census to obtain this share.

occupations. For example, data entry keyers (19th), typists (34th), and proofreaders (35th) can be considered a low-skilled service occupation. The full list is available in the Appendix.

II.2 Instrument Variable

Import penetration is endogenous as, in part, it reflects domestic shocks to US industries and occupations. In this section, I explain the instrument variable strategy to address the endogeneity of import penetration. The main idea is coming from Acemoglu et al. (2016); Autor, Dorn and Hanson (2013*b*) that studies the impact of an increase in Chinese import in manufacturing industries on labor market outcomes in the US. In these papers, the authors instrument for the growth in Chinese imports in the US exploiting the Chinese export to other high-income countries in the same period. Analogous to this, I instrument the increase in service import penetration from India with India's export to 15 EU countries (EU member countries before the enlargement in May 2004). The underlying assumption of the identification is that the common rising of Indian service imports comes from the technological shock that made certain services tradable (high-speed internet) and the massive investment in the BPO service industry in India.

The instrument variable is defined as following.

$$\Delta IP^{EU}_{kt} = \sum_{s} \omega_{sk,90} \times \frac{\Delta IMP^{IND-EU}_{st}}{Y^{US}_{s,92} + IMP^{US}_{s,92} - EXP^{US}_{s,92}}. \tag{2}$$

It is similar to the endogenous variable in Equation 1, the numerator replaced with the Indian import of EU. The denominator and industrial share in 2 are constructed using data in the previous period. By using the share defined in the previous decade, the instrument can mitigate the problem coming from the concurrent change in the industrial composition of each occupation.

II.3 Data

I obtain service trade data between the US and India from the Bureau of Economic Analysis (BEA). I use the official balance of payment (BOP) data of the US by combining the Survey of Current Business (SCB) October report from 1997 to 2017. The BOP provides payment and receipt of various services between the US and major countries in dollars.[3] While the exact

[3]Unlike physical goods, service trade is not anchored in any observation of physical movement. Thus, there is no single standard to measure service trade, making the figures vary by the reporting agency. Moreover, the

structure of the reported data varies over time, SCB provides both unaffiliated and affiliated imports of private services.

Similarly, I use Eurostat data on the trade between the European Union (EU) and India. Eurostat reports service trade between India and the entire EU in detail; however, the trade between individual European countries and India is not available at the detailed level until 2010. Using trade between the entire EU and India is problematic because the EU member countries are not consistent during my study period (1997-2017). [4] Fortunately, the countries that joined later to the EU did not actively trade with India. The sum of total Indian service imports of these ten countries accounts for less than 0.5 percent of India's total EU import in 2007. Thus, I consider 15 EU countries equivalent to 25 EU countries in 1997 and 2007.[5]

The outsourcing services I consider in this paper are often called tradable white-collar services, including finance, insurance, telecommunication, computer and information, management and business consulting, research and development, advertisement, construction and architecture, accounting, legal services, and other business professionals, and technical services, following the literature (Amiti and Wei, 2009*a*; Crinò, 2010*b*; Liu and Trefler, 2019).[6] [7] While the BOP data from US BEA and Eurostat is complete at the most detailed level after 2006, each service's exact trade amounts are sometimes ambiguous before then. The aggregate import and export of each service sector are necessary for 1992 and 1996 as they are used in the denominator of the definitions of import penetration. Because the 1992 or earlier trade data is very unreliable, I obtain the total production and trade data using the benchmark Input-Output(I/O) table of 1992.[8]

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measurement in a single agency is often not consistent over time, and it is difficult to expand the study period. Most of the previous research uses BOP data in monetary terms.

[4]The EU had expanded from 15 (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom) to 25 (adding Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia) countries in 2004.

[5]Starting from 2010, detailed trade data at the country level is available. Assuming the trend of trade between the ten countries and India has remained constant from 2007 to 2010, I adjust the values of imports in 2007. For example, if the 15 original countries accounted for 95 percent of legal service imports in 2010, I assume that the share remained the same in 2007.

[6]The name of services is used in BEA and Eurostat. These services are a subset of other private services in BEA classification.

[7]Note that accounting, legal, and management services were reported together as "professional and management consulting services" until 2005. Thus, it is impossible to know the exact amount of trade between the US and India for each service with the official data. To utilize more variation in service trade, I estimate the import of the three services using the share for which each sector accounts for the total unaffiliated professional and management consulting services trade from India to the US. Total unaffiliated trade data is available at the most detailed level. For example, if legal service accounts for 20 percent of total professional and management consulting services, I assume the same share for trade between the US and India. See Appendix A for the details.

[8]The I/O table provides the monetary value of the input and output of the entire economy along with foreign import and export. The advantage of using the benchmark I/O table is that the total output and trade data are

Table 1 shows the change in US import from India by sector. There is a substantial growth in importing all types of services in the table, especially computer and information service by 140,000 percent. In addition, other sectors that are less known, such as accounting (1,000 percent), management (20,225 percent), and R&D (14,133 percent) services, had significantly increased. Telecommunication, one of the most well-known services outsourced to India besides IT service, had not increased much since 1996. In fact, telecommunication outsourcing started in the late 1980s, and outsourcing this service was already prevalent in 1996.

The occupation level data is constructed with the 1990 and 2000 Census and 2007 and 2017 American Community Survey (ACS) IPUMS data Ruggles et al. (2020). To keep the consistent definition of occupations, I use the occupation crosswalk provided by David Dorn used in Autor, Dorn and Hanson (2013*a*), leaving me 330 consistent occupations over time. To define occupation level import penetration in Equation 1, I concord the trade service sectors to industries in the Census. For example, computer and information services in BEA correspond to the "Computer and data processing services" industry (732 in 1990 industry code) in Census. The exact crosswalk is available in Appendix Table A.2.

II.4 Estimation Equation

The main specification has the following form:

$$\Delta \ln(y_{kt}) = \alpha_t + \beta_{1t} \Delta IP^{US}_{kt} + \boldsymbol{X'}_{kt} \Gamma + \varepsilon_{kt}, \tag{3}$$

where $\Delta \ln(y_{kt})$ is the difference of outcome variable of occupation k. The outcome variables examined are the employment and median hourly wage of occupation k. I normalize to the annual change and multiply 100 for interpretation. ΔIP_{kt} represents the annual change in occupation k's import penetration between $t+1$ and t. My data period spans from 2000 to 2016, and I stack the ten-year equivalent first differences for two periods, 2000 to 2006 and 2006 to 2016. I use the Z-score of ΔIP_{kt} for interpretation. $\boldsymbol{X}_{kt}$ is the vector of occupation level controls, including service occupation indicator, employment, college share, weekly wage, average age, sex ratio, and racial composition at the start of the period. The change of IP^{US}_{kt} is instrumented by the variable ΔIP^{EU}_{kt} as described above. Because I use the first difference

available in detail. However, the import is only available if it is used as an intermediate good, so the total amount of import is not available. Fortunately, the tradable services on which this paper focuses are mostly used as input in various industries, not as final goods for consumers. Nonetheless, measurement error exists for the trade data in the benchmark I/O table.

model, the stacked model is similar to the three periods fixed effect model with a less restrictive assumption made on the error term (Autor, Dorn and Hanson, 2013*b*). The standard errors are clustered at the broader classification of occupations.[9]

Figure 2 graphically shows the first stage result. The figure reveals a strong positive correlation between ΔIP^{US}_{kt} and ΔIP^{EU}_{kt}. The coefficient and standard error of the formal first stage regression are denoted in the figure. The F-statistics of the instrument variable is 21.01, which is above the rule of thumb of 10.

III Importance of India in Service Trade

Service import in the US has significantly grown thanks to the development of communication technology since the 1980s. In the interest of expense, countries with relatively low income and a large English-speaking population became popular outsourcing hubs. These include India, Ireland, the Philippines, China, Malaysia, and a couple of Eastern European countries (Amiti et al., 2005).

India is especially famous for IT and BPO services. The increase in India's service export is primarily due to high-speed internet and its massive growth in the BPO market. First, the commercialization of broadband technology around in 2002 made it easier to offshore complicated service. Also, in the same period, the Indian government's support through several laws and investment accelerated the growth of the BPO industry (Thite and Russell, 2007). The BPO market gained a competitive edge by merging small firms into a mega-firm, completed by 2004. The combination of the effort from public and private entities made a synergy effect, and thanks to high-speed internet, the service export has surged in India. This is presented in Figure 1.

In this paper, I focus on the impact of service outsourcing to India. There are three reasons for this. The first reason is relevant to the importance of India, and the other two reasons are to the data issue. To begin with, India has an extensive BPO market: India is best known for its IT consulting and computer programming outsourcing, not limited to those services. Also, India is one of the most popular destinations for outsourcing in the US, accounting for 10 percent of all white-collar service imports and 40 percent of ICT services in the US in 2016

[9] I crosswalk 1990 Census occupations to the 4-digit Standard Occupational Classification (SOC) System. Here, I use the 3-digit SOC codes to cluster the standard errors.

(BEA, 2021). India also exports a large amount of accounting, legal, and financial services. India's BPO market produced 143 billion dollars in 2016, equivalent to about eight percent of India's total GDP (?).

Second, India was not as much engaged in affiliated trade with the US as other countries in the late 1990s. There are two important forms of service trade, trade through affiliated and unaffiliated parties. Affiliated trade is gaining importance over time, especially in the tradable white-collar service sector. Hence, to capture the entire impact of service trade, we must take both affiliated and unaffiliated into account. The BEA trade data had a structural change in 2006. While BEA had reported trade data for each type of service only for unaffiliated trade until 2005, it started to provide the aggregate (affiliated and unaffiliated) trade by type from 2006. This structural change makes it difficult to connect before and after 2006, and most of the previous papers study before 2006. Focusing on India resolves this problem. In 1996, affiliated trade accounted for about 30 percent of the US's total service import; however, less than three percent of Indian service imports came from affiliated trade. Considering that Indian service import was very low in 1996, I assume there was no affiliated import from India in 1996. In this way, I can extend the study period beyond 2006, which is never done in the literature, and where the increase in imports is more rapid.

Third, trade data in both US and EU keep records on India relatively better than other middle- and low-income countries in the 1990s and early 2000s. Although some middle and low-income countries like Ireland and the Philippines are important outsourcing partners, some of the data are limited or confidential in the publicly available BEA trade data. India has relatively complete information both in the US and EU databases, which is a great advantage.

IV Results

IV.1 Main Impact on Employment

In Table 3, I present the main impact on the occupational employment during 2000-2016 using Equation 3. In Panel A, I estimate the impact on total employment by occupation, and in Panel B, I do with the employment of the college-educated workers. Column 1 estimates the impact of import penetration with the OLS model, and columns 2 to 5 use the 2SLS model using the import penetration in the EU countries as the instrument for the US import penetration. In columns 1 to 3, I stack two periods and estimate the impact of import penetration together, while in columns 4 and 5, I do the regressions separately for two periods.

The OLS estimate in Panel A of column 1 shows a minimal correlation between IP and occupation level employment. However, as I switch to the 2SLS model, the point estimates increase by 90 percent, although not statistically significant (column 2). The point estimate becomes statistically significant with control variables in column 3. The most important variable is the share of the college-educated at the beginning of the period. Some of the occupations with high IP are highly educated jobs, such as computer scientists and workers in the R&D sector, so if these occupations have experienced larger growth over time, the point estimate of the impact of IP is underestimated. The point estimate in column 3 implies that a one standard deviation increase in occupational import penetration decreases employment by 0.25 percent.

When I separately estimate the impact of IP in columns 3 and 4, it appears that the negative effect is concentrated on the earlier period. While there is a strong negative impact of IP on occupational employment during 2000-2006 (column 4), the sign of the point estimate reverses and becomes insignificant in the later period of 2006-2016 (column 5). This is notable because the steeper increase in service imports from India started after 2005 (Figure 1).

This result seems to be counterintuitive. However, it may be possible that IP does not work cumulatively. In other words, IP may have hurt employment to a certain point, and the sign of the point estimate reverses after that. When service import first increases, the substitution of tasks happens. The service trade is first concentrated on relatively easier tasks and then progresses to more complicated tasks. After the substitution of task reaches the equilibrium, and together with the technological advance, trade in more complicated tasks begins. If these services are complementary to the service produced domestically, then employment eventually increases. Although not completely comparable, automation has a similar implication. Automation substitutes labor as its intention; however, it also complements labor by increasing output and demand for total labor, leading to the polarization of the workers (Autor and Salomons, 2018; Autor, 2015).

The following results support this hypothesis. In Panel B, I estimate the impact on college-educated workers for all 316 occupations. The overall pattern is similar to columns 4 and 5 in Panel A. While the magnitude (absolute value) of the point estimate in the earlier period is smaller than the main results (-0.282 vs. -0.403), it is larger in the later period (0.467 vs.

0.166). This means that the negative impact on employment in the first period is weaker for college-educated workers, but the positive effect is stronger for them later. The result suggests the employment has moved toward in favor of college-educated workers. It may be true for most occupations considering the increase in college enrollment and graduation in the given period; however, the significant coefficients imply it is stronger for more affected occupations by the Indian service import.

Next, I estimate the impact of IP by age group in Table 4. The table shows there is a clear distinction across age groups. The impact on the youngest (25-34 years old) workers is analogous to the overall result: negative effect during the first period and positive for the later period. The magnitude of the impact is much smaller for middle-aged workers, and especially, the effect in the second period is almost zero. Because the youngest and middle-aged workers constitute as twice as oldest workers, these two groups drive the overall impact. The oldest workers are experiencing a substantial increase in employment in both periods. Especially, the employment effect of IP is positive for these ages, even in the first period, where the overall impact in Table 3 is negative. This table implies a compositional change in employment; switch to the older, experienced, and educated workers.

In Table 5, I divide the occupations into two groups by share of college-educated workers and routine tasks defined by (Autor, Dorn and Hanson, 2013*a*). I separately estimate the impact of import penetration by a period as in the previous tables. Table 5 shows that low-skilled workers were more affected by the increase in import penetration. When comparing columns 1 and 2, there is a much larger decrease in employment of occupations with a low share of college-educated workers. A one standard deviation increase in import penetration results in a 0.9 and -4 percent decline in total employment, for high and low college-educated occupations, respectively, during 2000-2016. While the overall impact on employment disappears in the later period (column 5, table 3), it gets even stronger for low-skilled occupations. The point estimate for 2006-2016 (column 4) is about twice as large as in 2000-2005 (column 2).

Next, I divide the occupations by how much the tasks of occupations are based on routine tasks. Consistent with columns 1-4, the impact of import penetration is much stronger for routine occupations than nonroutine ones. However, the pattern of larger point estimates in the later period, like columns 2 and 4, is not observed. An increase of one standard deviation of import penetration decreases employment of high routine jobs by 1.12 and 0.3 percent during 2000-2006 and 2006-2016, respectively.

IV.2 Impact on Wages

Table 6 presents the impact on the median weekly wages. The wage estimates must be interpreted with caution because of the previous results on employment. If the employment impact is concentrated on a particular group within the occupation, the compositional change in occupation may drive most of the effect on wages. Furthermore, the inconsistent pattern of employment over time complicates the interpretation. The negative impact on the employment of college-educated workers is smaller than the overall effect, in Table 3, suggesting that high-skilled workers within occupation were less vulnerable from Indian service import. Employment of college-educated workers increases in the later period by 0.5 percent, while the overall impact is smaller and statistically insignificant. The pattern observed here suggests the possibility of upward bias caused by compositional change.

The impact on weekly wage is consistent over time, unlike on employment, in Table 6. Overall, a one standard deviation increase in import penetration raises the median weekly wage by 0.13 percent. There is not much difference between the earlier (2000-2006) and later (2006-2016) period, 0.11 and 0.10 percent, respectively. The results here are consistent with my suspicion that the overall wage would increase.

IV.3 Robustness Check: Using Alternative Definition of IP

There is no single way to define occupation level import penetration (IP). In this subsection, I examine whether my results vary by the definition of the occupation level IP. Liu and Trefler (2019)'s IP definition uses the fraction in each service sector as the weight to calculate the occupation level IP. This is very straightforward; however, it may not represent how important the service is as a task. For example, some accountants are hired in different industries than accounting industries but still producing accounting services. If a large fraction of accountants is directly hired in various industries, then the share ($\omega_{sk,90}$ in Equation 1) may not truly reflect how much accounting services matter to accountants.

I emulate Criscuolo and Garicano (2010)'s definition to examine the robustness to the definition of IP. Criscuolo and Garicano (2010) uses the I/O table to define the industry-occupation level exposure to service import. I take a weighted average of this exposure measure similar to Equation 1 to define occupation level exposure. To be specific, I define the IP measures as follows:

$$\xi_{sk} = \sum_j \frac{\omega_{jk}}{\sum_j \omega_{jk}} \times \frac{Y_{sj}}{\sum_s Y_{sj}}, \tag{4}$$
$$\sum_s \xi_{sk} = 1.$$

The first term in Equation 4 is the occupation k's fraction in industry j, which is shown in Equation 1 as well. The second term comes from the I/O table: service sector s's share of production in industry j. This term represents how much the service sector s (as a task) is important in industry j. For example, a great fraction of computer and information services are produced in the same industry, meaning the certain task plays a crucial role in the industry. Using ξ_{sk}'s, I define a weighted average as in Equation 1 to define an alternative IP, and estimate the impact on employment and weekly wages.

Table 7 shows the estimation results using the alternative definition of IP. Columns 1 and 2 are the main specification for comparison. Columns 1 to 4 use the narrowly defined occupation level IP (316 occupations), and 5 to 6 use broadly defined occupations (SOC 3digits, 88 occupations). When comparing columns 1 to 2 and 3 to 4, the overall patterns are consistent regardless of the measure. The results are robust to using broadly defined occupations in columns 5 to 8. The point estimates are larger in this specification (in absolute terms), although not statistically distinguishable.

V Discussion and Conclusion

This paper provides evidence that service imports from India had impacted domestic employment in the US. The direction and magnitude of the impact are not consistent over time, unlike Autor, Dorn and Hanson (2013*a*) who find a consistently strong impact of Chinese import penetration in manufacturing. To be specific, the overall impact on total occupational employment is negative. The employment reduces by 0.25 percent during 2000-2016 with an increase in import penetration by one standard deviation. However, when I split the sample into two periods, the impact is concentrated in the earlier (2000-2006) period and becomes positive but insignificant during 2006-2016.

The paper's subsequent analyses suggest that the Indian service import had had a differential impact over time. The monetary value of imports started to grow exponentially from 2005, with a slower but steady growth rate from the 1990s and early 2000s. If the impact of service import is linear or single-directional, there should be a substantial effect in the later period. This paper clearly shows that this is not the case.

There is no sufficient evidence on substitutability and complementarity of service import and outsourcing. This paper shows that while the service purchase from overseas substitutes the domestic workers at first, the role of service import changes as the skill-biased employment change continues. Initially, firms in the US purchase cheaper services from India and other low-income countries. Firms do not substitute the entire service with a cheaper one because certain services are difficult to import, and in-shoring may be more efficient. As the sorting of service continues, firms become more efficient, and they can now hire high-skilled service inshore. As a result, high-skilled employment increases, as in my analysis.

This implies the task composition within occupation moves toward more complicated and sophisticated tasks, especially for more vulnerable jobs in terms of service import. Further work must be done to prove this hypothesis. The economy would find a way to the new equilibrium by sorting less efficient and skilled workers out of the vulnerable occupations.

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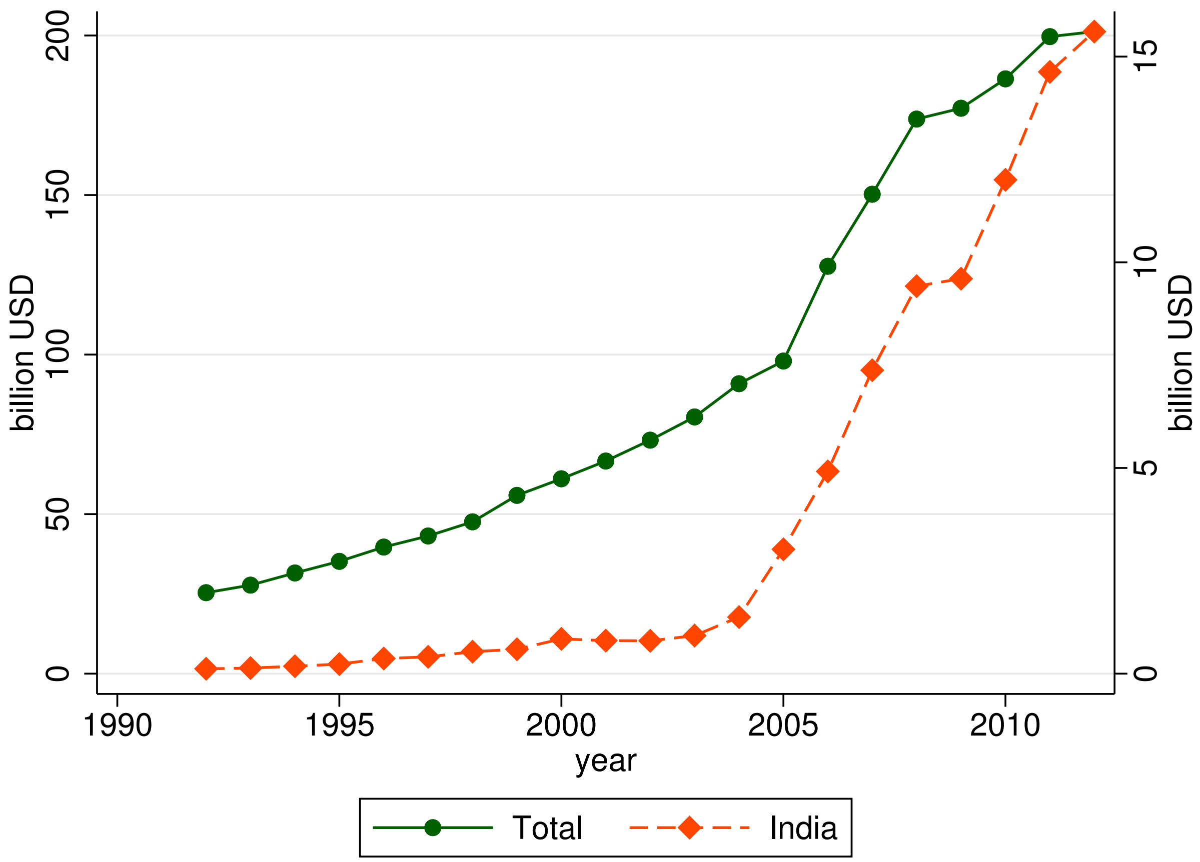
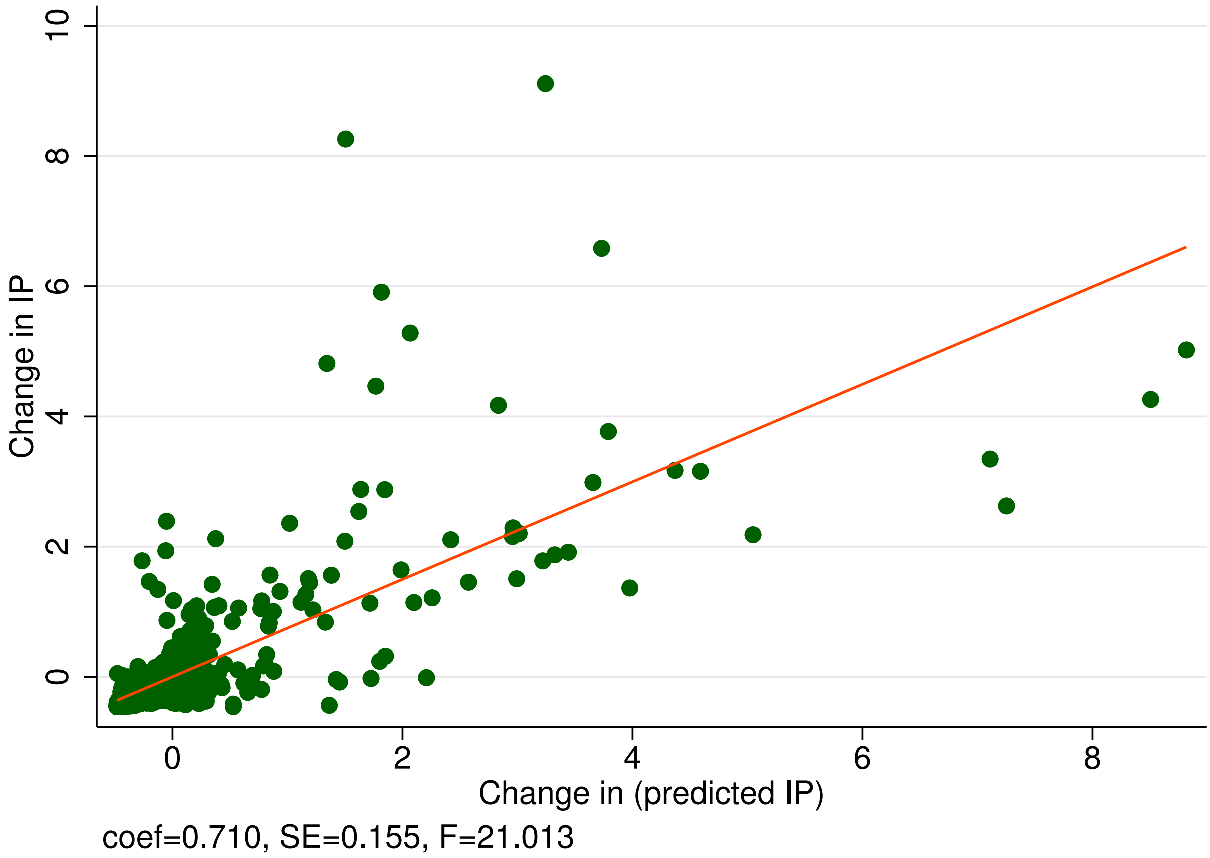
Figures

Figure 1: Import of total other private service



Source: Current Business Survey, Bureau of Economic Analysis. A subset of the total other private service is considered as tradable white-collar service in the literature.

Figure 2: 2SLS first stage, full sample



Notes: N=316 ×2=632. Two periods of 2000-2007 and 2007-2017 are stacked. The IP measures are normalized in each period (to Z-scores). First stage F-statistics is 21.013.

Tables

Table 1: US service import from India (in million USD)

Service type	1996	2006	2011	2016
Advertising	2	17	61	32
Construction	0.5	127	127	181
Financial	15	104	312	543
Insurance	0.98	15	27	84
Accounting	8.1	81	331	483
Legal	5	14	57	82
Management	4	813	1,057	1,275
Computer	2	2,798	9,395	14,235
R&D	3	427	2,165	3,482
Telecommunication	300	399	302	404
Installation	0.5	7	26	47
Industrial Engineering	2	66	83	234
Leasing	0.5	0.5	0.5	0.5
Other tradable service	18	99	401	545

Notes: Data from the balance of payment (BOP) from the Bureau of Economic Analysis (BEA). From 2006 to 2016, the figures include both affiliated and unaffiliated imports from India. In 1996, the figures included only unaffiliated imports; however, affiliated imports comprised a tiny fraction of total service imports. Thus, the unaffiliated imports were almost the same as total imports. See Section II and III for further information.

Table 2: Ranking of ΔIP^{US}_{kt}

Rank	Occupation Title	$\Delta IP^{US}_{kt} \times 100$
1	Computer software developers	67.5502
2	Computer systems analysts and computer scientists	49.3654
3	Technical writers	40.6995
4	Physicists and astronomists	38.7210
5	Technicians, n.e.c.	34.6463
6	Physical scientists, n.e.c.	33.0064
7	Medical scientists	29.2978
8	Repairers of data processing equipment	25.6408
9	Biological scientists	25.3492
10	Social scientists and sociologists, n.e.c.	24.7227
11	Mathematicians and statisticians	21.8731
12	Lawyers and judges	20.4851
13	Computer and peripheral equipment operators	19.8436
14	Atmospheric and space scientists	18.5570
15	Chemists	18.5544
16	Geologists	18.2476
17	Legal assistants and paralegals	17.2559
18	Management analysts	17.0138
19	Data entry keyers	14.3558
20	Operations and systems researchers and analysts	13.7050
21	Biological technicians	13.5794
22	Engineers and other professionals, n.e.c.	12.9407
23	Electrical engineers	11.6488
24	Statistical clerks	11.5795
25	Agricultural and food scientists	11.4366
26	Office machine operators, n.e.c.	11.2605
27	Management support occupations	10.8143
28	Economists, market and survey researchers	10.6534
29	Sales engineers	10.4142
30	Personnel, HR, training, and labor rel. specialists	9.7391
31	Managers and specialists in marketing, advert., PR	8.6551
32	Designers	8.5078
33	Managers and administrators, n.e.c.	8.1676
34	Typists	7.3658
35	Proofreaders	6.7203
⋮	⋮	⋮
303	Barbers	0.0000
303	Mail carriers for postal service	0.0000
303	Primary school teachers	0.0000
303	Air traffic controllers	0.0000
303	Secondary school teachers	0.0000

Notes: This table shows the ranking of change in occupation level import penetration (IP) measure from 2000 to 2016, defined in Equation 1. Occupation titles are defined in the Census. See Appendix Table A.1 for the full list.

Table 3: Impact of import penetration on employment

Dependent variable: Δln(Employment) ×100

	OLS	2SLS			
	All period	All period	All period	2000-2006	2006-2016
	(1)	(2)	(3)	(4)	(5)
Panel A. Total Employment					
Z-score of	-0.0166	-0.110	-0.247**	-0.403**	0.166
ΔIP	(0.114)	(0.137)	(0.111)	(0.171)	(0.159)
First Stage F-Statistics		11.35	14.40	19.46	6.36
Panel B. College Employment					
Z-score of	-0.128	-0.236	-0.0804	-0.282*	0.467***
ΔIP	(0.128)	(0.156)	(0.0942)	(0.152)	(0.159)
First Stage F-Statistics		11.35	14.40	19.46	6.36
Observations	632	632	632	316	316
Controls	No	No	Yes	Yes	Yes

Notes: This table reports the estimates of the impact of occupation level IP on employment using equation 3. Each entry is a coefficient from a separate regression. The coefficients are rescaled to represent the annual change in employment in percentage. I also normalize IP to Z-socre for interpretation. In the 2SLS model, the instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. In column 3, the point estimate is interpreted as the following: a one standard deviation increase in IP reduces employment by 0.25 percent annually. Controls include the log of employment, the fraction of college-educated workers, log of median weekly wage, average age and its square term, percent of female, and the fraction of white and black at the beginning of each period. Regressions are weighted using the size of employment in 2000. Robust standard errors are in parentheses clustered by three-digit SOC codes. * significance at 10%; ** significance at 5%; *** significance at 1%.

Table 4: Impact of import penetration on employment, by age

Dependent variable: Δ*ln(Employment)* $\times$*100*

	Age: 25-34		Age: 35-44		Age: 45-60	
	2000-2006	2006-2016	2000-2006	2006-2016	2000-2006	2006-2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total Employment						
Z-score of	-0.502**	0.413	-0.230	-0.0440	0.266*	0.454***
ΔIP	(0.208)	(0.254)	(0.149)	(0.184)	(0.145)	(0.153)
Panel B. College Employment						
Z-score of	-0.695**	0.841*	0.007	0.215	0.378*	0.766***
ΔIP	(0.317)	(0.432)	(0.255)	(0.294)	(0.195)	(0.258)

Notes: N=316. This table reports the estimates of the impact of occupation level IP on employment using equation 3 separately by age. Each entry is a coefficient from a separate 2SLS regression. The coefficients are rescaled to represent the annual change in employment in percentage. I also normalize IP for interpretation. The instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. All regressions include control variables. See the notes of Table 3 for the details for the controls. Panels A and B present the total and skilled (college-educated) employment, respectively. I separately estimate the impact in each period. Regressions are weighted using the size of employment in 2000. Robust standard errors are in parentheses clustered by three-digit SOC codes. * significance at 10%; ** significance at 5%; *** significance at 1%.

Table 5: Impact on employment by occupation characteristics

Dependent variable: $\Delta ln(Employment)$ ×100

	Share of College-Educated				Routine			
	2000-2006		2006-2016		2000-2006		2006-2016	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Z-score of	-0.905**	-3.961**	-0.194	-7.257**	-1.124**	-0.182	-0.305*	0.159
ΔIP	(0.426)	(2.003)	(0.161)	(2.847)	(0.541)	(0.406)	(0.163)	(0.401)

Notes: This table reports the estimates of the impact of occupation level IP on employment using equation 3 separately by share of college-educated workers and how routine the occupation is. Each entry is a coefficient from a separate 2SLS regression. The coefficients are rescaled to represent the annual change in employment in percentage. I also normalize IP for interpretation. The instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. All regressions include control variables. See the notes of Table 3 for the details for the controls. In columns 1 to 4, I use the share of college-educated workers in 2000 to separate the sample (above and below median). In columns 5 to 8, I separate the occupations by how routine the tasks are. For routine measures, I use the measure defined by (Autor, Dorn and Hanson, 2013*a*). I separately estimate the impact in each period. Regressions are weighted using the size of employment in 2000. Robust standard errors are in parentheses clustered by three-digit SOC codes. * significance at 10%; ** significance at 5%; *** significance at 1%.

Table 6: Impact of import penetration on median weekly wages

Dependent variable: Δ*ln(Median weekly wage)* ×*100*

	OLS	2SLS			
	All period	All period	All period	2000-2006	2006-2016
	(1)	(2)	(3)	(4)	(5)
Z-score of ΔIP	0.141*** (0.0413)	0.180** (0.0698)	0.129*** (0.0410)	0.112* (0.0586)	0.100** (0.0390)
Observations	632	632	632	316	316
Controls	No	No	Yes	Yes	Yes

Notes: This table reports the estimates of the impact of occupation level IP on median weekly wage using equation 3. Each entry is a coefficient from a separate 2SLS regression. The coefficients are rescaled to represent the annual change in employment in percentage. I also normalize IP for interpretation. The instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. All regressions include control variables. See the notes of Table 3 for the details for the controls. Regressions are weighted using the size of employment in 2000. Robust standard errors are in parentheses clustered by three-digit SOC codes. * significance at 10%; ** significance at 5%; *** significance at 1%.

Table 7: Using Alternative Definition of Import Penetration

Dependent variable: Δ*ln(Employment)* $\times$*100*

	Occupation Definition (Narrow)				Occupation Definition (Broad)			
	LT (2019)		CG (2010)		LT (2019)		CG (2010)	
	2000-2006	2006-2016	2000-2006	2006-2016	2000-2006	2006-2016	2000-2006	2006-2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Total Employment								
Z-score of	-0.403**	0.166	-0.515**	0.0939	-0.624**	0.173	-0.545**	0.221*
ΔIP	(0.171)	(0.159)	(0.226)	(0.188)	(0.289)	(0.144)	(0.242)	(0.125)
Panel B. College Employment								
Z-score of	-0.282*	0.467***	-0.337*	0.351**	-0.403**	0.408***	-0.406**	0.492***
ΔIP	(0.152)	(0.159)	(0.173)	(0.172)	(0.191)	(0.151)	(0.186)	(0.161)
Panel C. Median Weekly Wage								
Z-score of	0.112*	0.100**	0.134**	0.0854**	0.154**	0.125***	0.143**	0.129***
ΔIP	(0.0586)	(0.0390)	(0.0663)	(0.0409)	(0.0663)	(0.0389)	(0.0618)	(0.0384)

Notes: This table reports the estimates of the impact of occupation level IP on employment and median weekly wage using equation 3 using alternative IP definitions. Each entry is a coefficient from a separate 2SLS regression. The coefficients are rescaled to represent the annual change in employment in percentage. I also normalize IP for interpretation. The instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. LT (2019) and CG(2010) stand for Liu and Trefler (2019) and Criscuolo and Garicano (2010), respectively. See Equation 1 and 4 for the precise definitions of the IP measures. Narrowly defined occupations are occupation codes used in the Census (and modified by David Dron in Autor, Dorn and Hanson (2013*a*)). Broadly defined occupations are three-digit SOC codes. All regressions include control variables. See the notes of Table 3 for the details for the controls. I separately estimate the impact in each period. Regressions are weighted using the size of employment in 2000. Robust standard errors are in parentheses clustered by three-digit SOC codes. * significance at 10%; ** significance at 5%; *** significance at 1%.

Appendix

A Constructing US's Indian Import Data

The balance of payment (BOP) of the Survey of Current Business (SCB) provides detailed information on service trade between the US and other countries. Unfortunately, the exact amount of trade in 1996 is not available for all service types. The tradable white-collar services are a subset of "other private services" in BEA classification. "Other private services (OPS)" consist of education, finance, insurance, telecommunication, and business, professional, and technical (BPT) services. The total dollar amount of recipient and payment (for all countries) is available for both unaffiliated and affiliated for each sector in 1996. However, at the country level, only unaffiliated trade is available. The trade of OPS is available in Table 5 of the SCB. Fortunately, the total OPS trade (affiliated and unaffiliated) between the US and each country is available through the supplement table. The BPT services are broken into several sectors in Table 7 of the SCB. The BPT services comprise advertising, computer and information, research and development, management, consulting and public relations, legal, construction and architecture, industrial engineering, and installation and maintenance services. In 1996, only unaffiliated BPT trade data is obtainable through SCB for aggregated data and each country.

In Section III, I mention that I ignore affiliated import from India in 1996 as it accounted for only 3 percent of total OPS import. In Tables 5 and 7 of SCB, all types of services are available for India. However, the total import of each sector within BPT services is not available in 1996. Thus, I approximate the total (unaffiliated and affiliated) import and export of each sector of BPT services, assuming that the share of each sector accounting for in the total unaffiliated trade is the same as the share in total affiliated trade. For example, if the unaffiliated import of computer and information services constitutes 10 percent of total unaffiliated import, then this service takes up 10 percent of the total affiliated import as well. This is a strong assumption; however, it seems that this assumption holds well in 2006 when the data is available for the total amount of trade.

B Commuting Zone-Level Analysis

The occupation-level analysis compares the relative change in employment with different levels of import penetration; however, it is difficult to identify the reallocation effects (Acemoglu et al., 2016). This section examines the impact of import penetration on employment in commuting zones (CZ), following Acemoglu et al. (2016); Autor, Dorn and Hanson (2013*a*). The import penetration is defined similarly to equations 1 and 2, with one more weighted average using occupational composition in each CZ. In other words, CZ-level import penetration is defined as follows:

$$\Delta IP_{zt} = \sum_{k} \frac{L_{kz}}{\sum_k L_{kz}} \times \Delta IP_{kt}, \tag{5}$$

where L_{kz} is number of workers in industry k in CZ z. Then, I estimate the impact of trade exposure using a equation similar to Equation 3.

Table A.3 presents the impact of CZ-level import penetration on the fraction of employed among the total working-age population (15-65 years old), the log of the number unemployed, and the fraction in risky occupations in the CZ. Risky occupations here are defined as occupations whose ΔIP is in the top 25th percentile of table A.1. Results in Panels A and B are consistent. In the earlier period, there is a positive impact on total CZ level employment, although small and statistically insignificant. The results seem inconsistent with the main result, showing a decrease in employment of highly affected occupations. It may be that the reduction in employment of high IP occupations is not large enough to affect the total employment in a CZ.

This is not necessarily true when combined with Panel C. Panel C's results display the impact on share in risky occupations. While there is a very small and insignificant impact in the earlier period, a one standard deviation increase in import penetration results in a 2.6 percentage points increase in the share of risky occupations in the later period. This result corresponds to the main result that there is an increase in occupation-level employment.

Overall, although not perfectly, the results here imply there is a sorting effect caused by the increase in Indian service imports. While the employment of certain occupations declines in the earlier period, the total local employment even increases. Liu and Trefler (2019) present people with high import penetration occupations are likely to switch occupations or to unemployed. The results of my paper are in line with the literature.

Appendix Tables

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
1	Computer software developers	67.5502
2	Computer systems analysts and computer scientists	49.3654
3	Technical writers	40.6995
4	Physicists and astronomists	38.7210
5	Technicians, n.e.c.	34.6463
6	Physical scientists, n.e.c.	33.0064
7	Medical scientists	29.2978
8	Repairers of data processing equipment	25.6408
9	Biological scientists	25.3492
10	Social scientists and sociologists, n.e.c.	24.7227
11	Mathematicians and statisticians	21.8731
12	Lawyers and judges	20.4851
13	Computer and peripheral equipment operators	19.8436
14	Atmospheric and space scientists	18.5570
15	Chemists	18.5544
16	Geologists	18.2476
17	Legal assistants and paralegals	17.2559
18	Management analysts	17.0138
19	Data entry keyers	14.3558
20	Operations and systems researchers and analysts	13.7050
21	Biological technicians	13.5794
22	Engineers and other professionals, n.e.c.	12.9407
23	Electrical engineers	11.6488
24	Statistical clerks	11.5795
25	Agricultural and food scientists	11.4366
26	Office machine operators, n.e.c.	11.2605
27	Management support occupations	10.8143
28	Economists, market and survey researchers	10.6534
29	Sales engineers	10.4142
30	Personnel, HR, training, and labor rel. specialists	9.7391
31	Managers and specialists in marketing, advert., PR	8.6551
32	Designers	8.5078
33	Managers and administrators, n.e.c.	8.1676
34	Typists	7.3658
35	Proofreaders	6.7203
36	Human resources and labor relations managers	6.6341
37	Urban and regional planners	6.2050
38	Office supervisors	6.1879
39	Architects	6.0182
40	Mail clerks, outside of post office	5.9978

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
41	Writers and authors	5.9882
42	Bill and account collectors	5.9476
43	Drafters	5.6501
44	Other telecom operators	5.6213
45	Engineering technicians	5.5882
46	Painters, sculptors, craft-artists, and print-makers	5.5765
47	Surveryors, cartographers, mapping scientists/techs	5.3332
48	Inspectors and compliance officers, outside	5.1238
49	Secretaries and stenographers	5.0680
50	Administrative support jobs, n.e.c.	5.0613
51	Purchasing managers, agents, and buyers, n.e.c.	4.9749
52	Accountants and auditors	4.8978
53	Actuaries	4.8825
54	Customer service reps, invest., adjusters, excl. insur.	4.8274
55	Editors and reporters	4.7108
56	Industrial engineers	4.5940
57	Chemical engineers	4.5500
58	Interviewers, enumerators, and surveyors	4.5021
59	Mechanical engineers	4.4394
60	File clerks	4.4030
61	Financial managers	4.3575
62	Broadcast equipment operators	4.2783
63	Aerospace engineers	4.2235
64	Receptionists and other information clerks	3.6779
65	Business and promotion agents	3.6719
66	Records clerks	3.6305
67	Payroll and timekeeping clerks	3.5845
68	Civil engineers	3.5423
69	Clinical laboratory technologies and technicians	3.5300
70	Human resources clerks, excl payroll and timekeeping	3.4523
71	General office clerks	3.4107
72	Retail salespersons and sales clerks	3.3869
73	Airplane pilots and navigators	3.3864
74	Other financial specialists	3.2748
75	Chemical technicians	3.2443
76	Other science technicians	3.1957
77	Bookkeepers and accounting and auditing clerks	3.1789
78	Production checkers, graders, and sorters in	3.1080
79	Actors, directors, and producers	2.9593
80	Sales demonstrators, promoters, and models	2.9106
81	Photographic process workers	2.8248
82	Bank tellers	2.6823
82	Financial service sales occupations	2.6823

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
84	Billing clerks and related financial records processing	2.6745
85	Teachers, n.e.c.	2.6618
86	Psychologists	2.5640
87	Telephone operators	2.5052
88	Material recording, sched., prod., plan., expediting cl.	2.4571
89	Metallurgical and materials engineers	2.4559
90	Messengers	2.4030
91	Machinery maintenance occupations	2.0941
92	Weighers, measurers, and checkers	2.0909
93	Advertising and related sales jobs	2.0341
94	Aircraft mechanics	1.9684
95	Mechanics and repairers, n.e.c.	1.9460
96	Dispatchers	1.9262
97	Supervisors of mechanics and repairers	1.9237
98	Heavy equipement and farm equipment mechanics	1.9078
99	Ship crews and marine engineers	1.8900
100	Art/entertainment performers and related occs	1.8875
101	Crane, derrick, winch, hoist, longshore operators	1.7747
102	Fire fighting, fire prevention, and fire inspection occs	1.7722
103	Correspondence and order clerks	1.7712
104	Police and detectives, public service	1.7635
105	Explosives workers	1.7271
106	Archivists and curators	1.6907
107	Librarians	1.6585
108	Telecom and line installers and repairers	1.6283
109	Miscellanious transportation occupations	1.6274
110	Sales supervisors and proprietors	1.6126
111	Industrial machinery repairers	1.6121
112	Health record technologists and technicians	1.6073
113	Plant and system operators, stationary engineers	1.5842
114	Foresters and conservation scientists	1.5805
115	Printing machine operators, n.e.c.	1.5696
116	Helpers, constructions	1.5483
117	Petroleum, mining, and geological engineers	1.5467
118	Personal service occupations, n.e.c	1.5205
119	Packers and packagers by hand	1.4980
120	Supervisors of guards	1.4882
121	Small engine repairers	1.4874
122	Typesetters and compositors	1.4728
123	Precision makers, repairers, and smiths	1.4042
124	Veterinarians	1.3989
125	Construction inspectors	1.3207
126	Salespersons, n.e.c.	1.2999

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
127	Guards and police, except public service	1.2124
128	Shipping and receiving clerks	1.1564
129	Insulation workers	1.1485
130	Health technologists and technicians, n.e.c.	1.1174
131	Photographers	1.0128
132	Repairers of industrial electrical equipment	0.9723
133	Eligibility clerks for government prog., social welfare	0.9529
134	Hand molders and shapers, except jewelers	0.9384
135	Dressmakers, seamstresses, and tailors	0.9153
136	Repairers of electrical equipment, n.e.c.	0.9130
137	Machine operators, n.e.c.	0.9019
138	Vehicle washers and equipment cleaners	0.8587
139	Insurance underwriters	0.8448
140	Programmers of numerically controlled machine tools	0.8429
141	Insurance adjusters, examiners, and investigators	0.8164
142	Laborers, freight, stock, and material handlers, n.e.c.	0.8087
143	Stock and inventory clerks	0.8013
144	Insurance sales occupations	0.7971
145	Subject instructors, college	0.7834
146	Library assistants	0.7829
147	Separating, filtering, and clarifying machine operators	0.7569
148	Dieticians and nutritionists	0.7558
149	Production helpers	0.7528
150	Other plant and system operators	0.7503
151	Repairers of household appliances and power tools	0.7364
152	Taxi cab drivers and chauffeurs	0.6861
153	Guides	0.6719
154	Production supervisors or foremen	0.6365
155	Bus, truck, and stationary engine mechanics	0.6315
156	Repairers of mechanical controls and valves	0.6311
157	Janitors	0.6276
158	Musicians and composers	0.5973
159	Cementing and gluing machne operators	0.5932
160	Assemblers of electrical equipment	0.5543
161	Vocational and educational counselors	0.5462
162	Machine feeders and offbearers	0.5455
163	Boilermakers	0.5374
164	Licensed practical nurses	0.5339
165	Welders, solderers, and metal cutters	0.5222
166	Motion picture projectionists	0.5126
167	Bookbinders	0.4949
168	Furniture/wood finishers, other prec. wood workers	0.4924
169	Registered nurses	0.4863

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
170	Heating, air conditioning, and refrigeration mechanics	0.4789
171	Operating engineers of construction equipment	0.4779
172	Animal caretakers, except farm	0.4698
173	Water and sewage treatment plant operators	0.4649
174	Truck, delivery, and tractor drivers	0.4643
175	Supervisors of motor vehicle transportation	0.4508
176	Upholsterers	0.4409
177	Stevedores and misc. material moving occupations	0.4389
178	Drillers of earth	0.4373
179	Managers of properties and real estate	0.4359
180	Health and nursing aides	0.4326
181	Shoemakers, other prec. apparel and fabric workers	0.4261
182	Dental laboratory and medical applicance technicians	0.4210
183	Miscellanious textile machine operators	0.4085
184	Social workers	0.4024
185	Drillers of oil wells	0.3995
186	Electric power installers and repairers	0.3927
187	Electricians	0.3838
188	Machinists	0.3837
189	Molders and casting machine operators	0.3822
190	Excavating and loading machine operators	0.3716
191	Mixing and blending machine operators	0.3670
192	Other mining occupations	0.3660
193	Millwrights	0.3571
194	Tool and die makers and die setters	0.3491
195	Garbage and recyclable material collectors	0.3490
196	Graders and sorters of agricultural products	0.3434
197	Extruding and forming machine operators	0.3356
198	Supervisors of cleaning and building service	0.2889
199	Announcers	0.2838
200	Transportation ticket and reservation agents	0.2764
201	Physicians	0.2753
202	Sawing machine operators and sawyers	0.2674
203	Radiologic technologists and technicians	0.2600
204	Slicing, cutting, crushing and grinding machine	0.2595
205	Therapists, n.e.c.	0.2542
206	Packers, fillers, and wrappers	0.2499
207	Physicians' assistants	0.2484
208	Painting and decoration occupations	0.2461
209	Ushers	0.2459
210	Recreation and fitness workers	0.2357
211	Housekeepers, maids, butlers, and cleaners	0.2325
212	Engravers	0.2301

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
213	Gardeners and groundskeepers	0.2218
214	Pharmacists	0.2212
215	Baggage porters, bellhops and concierges	0.2159
216	Textile sewing machine operators	0.2154
217	Garage and service station related occupations	0.2152
218	Clothing pressing machine operators	0.2087
219	Other metal and plastic workers	0.2087
220	Pest control occupations	0.2056
221	Painters, construction and maintenance	0.2031
222	Real estate sales occupations	0.2016
223	Misc. construction and related occupations	0.1991
224	Inspectors of agricultural products	0.1934
225	Nail, tacking, shaping and joining mach ops (wood)	0.1894
226	Plumbers, pipe fitters, and steamfitters	0.1861
227	Helpers, surveyors	0.1790
228	Superv. of landscaping, lawn service, groundskeeping	0.1782
229	Paper folding machine operators	0.1713
230	Construction laborers	0.1709
231	Power plant operators	0.1622
232	Crossing guards	0.1613
233	Managers in education and related fields	0.1607
234	Carpenters	0.1556
235	Textile cutting and dyeing machine operators	0.1502
236	Laundry and dry cleaning workers	0.1456
237	Batch food makers	0.1428
238	Farm workers, incl. nursery farming	0.1425
239	Automobile mechanics and repairers	0.1397
240	Structural metal workers	0.1248
241	Respiratory therapists	0.1227
242	Supervisors of construction work	0.1198
243	Door-to-door sales, street sales, and news vendors	0.1072
244	Dancers	0.1047
245	Locksmiths and safe repairers	0.0993
246	Punching and stamping press operatives	0.0954
247	Other woodworking machine operators	0.0931
248	Athletes, sports instructors, and officials	0.0884
249	Timber, logging, and forestry workers	0.0878
250	Protective service, n.e.c.	0.0866
251	Food preparation workers	0.0851
252	Physical therapists	0.0786
253	Other precision and craft workers	0.0776
254	Recreation facility attendants	0.0766
255	Concrete and cement workers	0.0765

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
256	Speech therapists	0.0740
257	Furnance, kiln, and oven operators, apart from food	0.0726
258	Miscellanious food preparation and service workers	0.0715
259	Supervisors of personal service jobs, n.e.c	0.0712
260	Cashiers	0.0697
261	Parking lot attendants	0.0641
262	Public transportation attendants and inspectors	0.0600
263	Farm managers	0.0558
264	Cabinetmakers and bench carpeters	0.0550
265	Glaziers	0.0548
266	Child care workers	0.0545
267	Dental hygienists	0.0537
268	Welfare service workers	0.0529
269	Cooks	0.0505
270	Supervisors of food preparation and service	0.0477
271	Optical goods workers	0.0453
272	Occupational therapists	0.0409
273	Masons, tilers, and carpet installers	0.0383
274	Kindergarten and earlier school teachers	0.0331
275	Elevator installers and repairers	0.0326
276	Roofers and slaters	0.0325
277	Waiters and waitresses	0.0301
278	Forge and hammer operators	0.0279
279	Plasterers	0.0276
280	Teacher's aides	0.0262
281	Bakers	0.0246
282	Bus drivers	0.0225
283	Butchers and meat cutters	0.0222
284	Bartenders	0.0215
285	Auto body repairers	0.0200
286	Knitters, loopers, and toppers textile operatives	0.0191
287	Other health and therapy occupations	0.0183
288	Railroad conductors and yardmasters	0.0172
289	Paving, surfacing, and tamping equipment operators	0.0172
290	Dental Assistants	0.0169
291	Locomotive operators: engineers and firemen	0.0169
292	Clergy and religious workers	0.0153
293	Fishers, marine life cultivators, hunters, and kindred	0.0150
294	Miners	0.0092
295	Drywall installers	0.0087
296	Funeral directors	0.0084
297	Special education teachers	0.0075
298	Hairdressers and cosmetologists	0.0060

Table A.1: Ranking of ΔIP, all occupations

Rank	Occupation Title	$\Delta IP \times 100$
299	Winding and twisting textile and apparel operatives	0.0058
300	Dentists	0.0056
301	Rollers, roll hands, and finishers of metal	0.0021
302	Optometrists	0.0015
303	Barbers	0.0000
303	Mail carriers for postal service	0.0000
303	Mail and paper handlers	0.0000
303	Hotel clerks	0.0000
303	Air traffic controllers	0.0000
303	Meter readers	0.0000
303	Primary school teachers	0.0000
303	Food roasting and baking machine operators	0.0000
303	Buyers, wholesale and retail trade	0.0000
303	Managers of medicine and health occupations	0.0000
303	Podiatrists	0.0000
303	Postal clerks, exluding mail carriers	0.0000
303	Purchasing agents and buyers of farm products	0.0000
303	Secondary school teachers	0.0000

Notes: Extended version of Table 2.

Table A.2: Crosswalk Between Census Industry and Outsourcing Service Type

Industry Code (1990)	Label	Service Type
721	Advertising	Advertising
882	Engineering, architectural, and surveying services	Construction & Architecture
700	Banking	Finance
701	Savings institutions, including credit unions	Finance
702	Credit agencies, n.e.c.	Finance
710	Security, commodity brokerage, and investment companies	Finance
711	Insurance	Insurance
841	Legal services	Accounting
890	Accounting, auditing, and bookkeeping services	Legal Services
892	Management and public relations services	Management
732	Computer and data processing services	Computer and Information
891	Research, development, and testing services	R&D and testing
441	Telephone communications	telecommunication
442	Telegraph and miscellaneous communications services	telecommunication
752	Electrical repair shops	Installation and maintenance
760	Miscellaneous repair services	Installation and maintenance
782	Shoe repair shops	Installation and maintenance
731	Personnel supply services(Employment)	Other Business Professionals, and Technical Services
741	Business services, n.e.c.	Other Business Professionals, and Technical Services
742	Automotive rental and leasing, without drivers	Leasing and rental

Notes: This table provides a crosswalk between Census industry codes (defined in 1990) and tradable white-collar services used in the paper. I emulate the crosswalk provided by Liu and Trefler (2019).

Table A.3: Impact of import penetration in CZ-level

	OLS	2SLS			
	All period	All period	All period	2000-2006	2006-2016
	(1)	(2)	(3)	(4)	(5)
Panel A. Share Employed					
Z-score of	0.0297***	0.0350***	-0.0129	0.101	-0.0716**
ΔIP	(0.00879)	(0.00993)	(0.0309)	(0.0643)	(0.0347)
Panel B. Ln(Unemployed)					
Z-score of	0.0031***	0.0030***	0.0006	-0.0129*	0.0086**
ΔIP	(0.000683)	(0.000844)	(0.00340)	(0.00666)	(0.00373)
Panel C. Share in risky occupations					
Z-score of	-0.0309***	-0.0332***	-0.0146	-0.0076	0.0264*
ΔIP	(0.00638)	(0.00596)	(0.0161)	(0.0365)	(0.0157)
Observations	1482	1482	1482	741	741
Controls	No	No	Yes	Yes	Yes

Notes: This table reports the estimates of the impact of CZ level IP on the share of the employed population, log of unemployment, and the share of risky occupations. Risky occupations mean that the increase of IP from 2000 to 2016 is greater than the median. Each entry is a coefficient from a separate 2SLS regression. The coefficients are rescaled to represent the annual change in outcome variables. I also normalize IP for interpretation. The instrument is the IP defined with Indian export to 15 EU countries. See the main text for further information. Control variables include the CZ level share of college graduates, foreigners, women, white, and black, population, average offshorability (routine), and average weekly wage at the beginning of each period. Regressions are weighted using the size of the population in 2000. Robust standard errors are in parentheses clustered by state. * significance at 10%; ** significance at 5%; *** significance at 1%.