Offshoring and U.S. Wages: Evidence from Individual-Level Data

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Abstract

This paper develops a new measure for skill to investigate the effects of offshoring on wages of three types of workers: high-skilled, medium-skilled, and low-skilled. I use proxies for both material and service offshoring at industry-level and link them with individual-level worker data from the Current Population Survey March Supplement from 1999-2009. I also look at the effect of offshoring on wages of offshorable occupations. Although the previous literature emphasizes the impact of offshoring on skill premium, I find that the job characteristics such as offshorability is critical in explaining the wage effect.

JEL Classification: F16, J23, J24

1 Introduction

In recent years, falling transportation costs and advancements in information technology has allowed firms to fragment their production process and to increase their offshoring activities. The inclusion of developing countries with low labor costs in the global market allows firms to shift its highly labor intensive production from the North to the South. This has led many market research companies to predict that offshoring would lead to a massive job loss in developed nations (McCarthy et al., 2002; Parker et al., 2004). As a result, offshoring has received a great deal of attention in policy discussions in the US.

A large number of studies have well-documented the change in wage structure and increase in skill-premium for the U.S.[1] The general consensus of the literature is that before the 1980's, the growth rates at different parts of the wage distribution were similar and the wage differences were relatively stable. However, since the late 80's, the wage gap between various groups has been widening. Goldin and Katz (2007) show that a large part of the increase in wage dispersion can be explained by the educational wage differential. Their study shows that the period before the 1980's saw an increase in both the demand for skilled labor and supply of skilled labor that allowed for a stable wage differential. Since the early 80's, using various data sources, Katz and Autor (1999) find an increase in skill premium for educated workers. The study estimates that real wages of those with less than 12 years of education fell by 13.4%, while real wages fell by 20.2% for workers with 12 years of education between 1979 and 1995. During the same period, wages of workers with a college degree or more rose by 3.4%.

There has been a considerable debate on whether the increase in skill premium is a result of technological change or growth in international trade and offshoring. Feenstra and Hanson (1996, 1999) argue that although technological change is an important factor in explaining the wage differential, focusing solely on technological change would obscure more fundamental questions regarding how firms respond to import competition and how these

[1] See Burkhauser et al. (2011) Van Reenen (2011) Levy and Murnane (1992) Katz and Murphy (1992)

responses, in turn, affect the labor market.

Initial studies that looked at the effect of trade in final goods on skill-premium could not find empirical evidence to support the theory of factor abundance.[2] New theories were developed to understand the mechanism through which trade would affect wages, which increased theoretical literature on offshoring. Offshoring can lead to within-industry wage differential because when an industry relocates the unskill-intensive stages of its production process abroad, it expands the skill intensity of production at home. This increases the relative demand for skilled workers widening the wage differential between skilled and unskilled workers.

The data for direct measure of offshoring activities by firms, however, are only limited to a few subset of countries and are mostly confidential and not publicly available. Trade literature has used different measures to proxy offshoring, such as total employment of foreign affiliates among multinational U.S. firms, import penetration, and trade in intermediate inputs. One of the most widely used measure of offshoring was developed by Feenstra and Hanson (1996) that defines offshoring as the share of non-energy inputs that are imported. I will use this measure as a proxy for offshoring.

Initially, the above proxy was used to measure material offshoring for manufacturing industries, but was later modified to include service offshoring to reflect the fast growth of offshoring in services. Although early studies mainly focused on industry-level wage differential, a new wave of literature looks at the effect of offshoring activities of industries at individual-level wages. Individual level data allows us to control observable demographic characteristics that may affect wages.

In this paper, I investigate the effect of both material and service offshoring of manufacturing industries in the U.S. from 1999-2009 on individual wages obtained from the CPS March Supplement. Only a handful of studies so far have looked at the effect at an indi-

[2] Stolper and Samuelson (1941) predicted that high skilled workers wage would rise in the North but fall in the South. Many studies (Berman et al., 1994; Belkman et al., 1998) found empirical evidence contradicting the theory

vidual level. For instance, Egger et al. (2007), Ebenstein et al. (2014) look at individual data but only consider the effect of material offshoring. Liu and Trefler (2008) study service offshoring, but only those offshored to India and China. Geishecker and Görg (2013) look at the effect of both material and service offshoring on individual wages for the U.K. Tempesti (2015) looks at the effect on individual wages for the U.S; however, he only looks at material offshoring. Moreover, like Geishecker and Görg (2013), the study uses educational attainment as a proxy for skill.

I contribute to this growing literature by defining a novel measure for skill as a composite set of skill indicators using the O*NET database to look at the effects of material and service offshoring on skill premium. This measure captures the skill-set workers have acquired on the job without any formal education.[3] In addition, I also look at the effects of offshoring on wages for occupation that are offshorable.[4] My analysis finds that both material and service offshoring increases the skill premium for high-skill and medium-skill workers. I find that a 10 percentage point increase in material offshoring increases the skill premium by about 3 percent. I also find that material and service offshoring has a negative impact on wages of offshorable occupations. Offshorable occupations are primarily defined as those that require low face-to-face interaction, minimal decision-making, and are easily automated.

The remainder of the paper is structured as follows: Section 2 defines the measure for offshoring and discusses the trend in service and material offshoring. Section 3 reviews the literature on the effect of offshoring on wages. Section 4 discusses the data and empirical methodology, and Section 5 presents the results. Section 6 includes robustness checks and Section 7 concludes.

[3]Most studies use level of education as a measure of skill. However, such a measure would not account for skills learned on the job. Thus, my measure of skill attempts to account for skills that are learned without formal education.

[4]I use Firpo et al. (2011) measure of classifying the occupation into offshorable jobs. Their study only looks at the return to occupational tasks, and do not specifically look at the direct effect of offshoring on the wages of these offshorable jobs.

2 Offshoring

When firms relocate parts of its production process outside the firm, it is called outsourcing. The fragmentation may include both material and immaterial (service) stages of production. Further, outsourcing can be either domestic or foreign. When a firm in the U.S. contracts parts of its production process to a different firm within the U.S., it is called domestic outsourcing. If a firm in the U.S. contracts parts of its production process to a location outside the U.S., it is called foreign outsourcing. This paper will focus on foreign outsourcing, also called offshoring.

Offshoring includes both the procurement of inputs from foreign firms owned by the U.S. firm and the arm's length production by a foreign firm not affiliated with the U.S. firm. Material outsourcing takes the form of imported physical goods that are used as intermediate inputs in the production and assembly process. Likewise, service offshoring takes the form of customer call centers, business services, accountancy and tax services, and financial services.

2.1 Measuring Offshoring

It is difficult to get a direct measure of offshoring because consistent data on offshoring activities by U.S. firms are not easily available. As a result, trade literature has used different measures for offshoring, such as total employment of foreign affiliates of multinational U.S. firms, import penetration and trade in intermediate inputs. One of the most widely used measure of offshoring was developed by Feenstra and Hanson (1996) (FH hereafter) that defines offshoring as the share of non-energy inputs that are imported.

I measure offshoring using the methodology introduced by FH for material offshoring and the method developed by Amiti and Wei (2009) to calculate service offshoring. The services included are 1) finance, 2) insurance, 3) telecommunication, computer and information services, and 4) business services.[5]

[5] I exclude other service imports such as travel and education because of minimal trade in these sectors.

For a given industry i at time t, material offshoring OSM_{it} is defined as the share of the industry's total non-energy inputs that are imported. Mathematically, it is calculated as:

$$OSM_{it} = \sum_j \left[\frac{M_{jit}}{N_{it}}\right] \times \left[\frac{I_{jt}}{Y_{jt}}\right] \qquad (1)$$

where, M_{jit} is the purchases of input j by industry i at time t, N_{it} is the total non-energy inputs used by industry i at time t, I_{jt} is the imports of inputs j at time t, and Y_{jt} is the total domestic supply of input j at time t.[6]

The first term represents the share of input j as a proportion of the total non-energy inputs. The second term represents the share of good or service j that was imported nationally.Similarly, I can calculate the measure for service offshoring, OSS_{it}, if goods j that represent service inputs. Further, as the data on trade of each input is not available at an industry level, I cannot tell the amount of those imports used by a certain industry. Therefore, as in the literature, I rely on the "proportionality assumption" such that every industry that uses input j, uses the input in the same proportion. Data on input purchases is calculated using the annual input-output table constructed by the Bureau of Labor Statistics (BLS) based on the 2002 benchmark table of Bureau of Economic Analysis (BEA). Data on trade of materials comes from Schott (2008), and data on trade of services are obtained from the BEA International Economic Accounts.

However, there are a few potential problems with the offshoring measure used in this paper(Amiti and Wei, 2005; Houseman et al., 2011; Feenstra and Jensen, 2012). First, the measure has the "proportionality assumption" due to the lack of data on imports by individual industry. Studies for Germany (Milberg and Winkler, 2010) and Asia (Puzzello, 2012) show that this assumption does not hold well. Second, I can not ascertain whether the imported goods are intermediate inputs or final use commodities. Third, imports from affiliated foreign firms are cheaper than importing from independent firms; but I cannot differentiate the two types of imports and will use the same producers value for both. Despite

[6]Total domestic supply is calculated as the total production plus net imports.

its problems, the measure has been frequently used in the literature as a reasonable proxy of offshoring.

2.2 Trends in Offshoring

Recent economic literature has well-documented the tremendous rise in offshoring by U.S. firms starting from the 1970's. FH measure offshoring as defined in equation 1 and find that imported material inputs has risen from 6.5% in 1972 to 11.6% in 1990. Shocks in exogenous factors in the 90s has led to a faster pace of globalization which has facilitated offshoring activities by firms. Bottini et al. (2007) point out three such factors: 1) reduction in trade barriers, 2) reduction in transportation cost, and 3) technological change.

First, regional free-trade agreements such as NAFTA eliminated red tapes allowing firms to relocate their production process. Yi (2003) shows the non-linear response of trade volumes to tariff reduction; thus, even a small decrease in tariff rates leads to a large increase in trade volume. Baier and Bergstrand (2001) studied the relationship between transportation costs and trade volume for industrialized nations. They estimate that the reduction in transportation costs explains about 8% increase in the trade volume post World War II until the late 80s. However, the impact of falling transportation cost, plays a minor role in facilitating trade than the reduction in trade barriers (Hummels, 1999). Lastly, in the past few decades, the advances in computer, network technology, and access to internet has expanded service offshoring in the form of call centers, tax and accountancy services, and financial services.

In addition, as economies have converged in economic size, multinational firms have become more vertically specialized, which has increased trade in intermediate goods (Feenstra et al., 1998). More importantly, rapid globalization has introduced large developing economies such as China and India with different factor endowments in the global market, thus providing further opportunities for offshoring.

Initially, most offshoring activities comprised of material offshoring. This phenomenon was mainly led by labor intensive industries that had an incentive to fragment their relatively unskilled-intensive production process internationally to exploit the lower wages of unskilled labor in developing economies. Recently, however, the advancements in technology has increased service offshoring. However, it comprises only a tiny fraction compared to material offshoring. Figure 1 shows the average trend in both material and service offshoring from 1999-2009. Material offshoring has risen from about 14.5% in 1999 to 19.07% in 2008. Likewise, although service offshoring is a small part of manufacturing industries, it has risen at an average annual rate of 6.8%.

Figure 2 presents a clearer picture of the trend at the 3-digit NAICS industry level.[7] Electronic manufacturing sector's material offshoring has risen by more than 44% during the sample period. Within the sector, the sharp rise can be attributed to audio and video equipment manufacturing. Their offshoring has risen from 32.3% in 1999 to 39.7% in 2004 and to 48.4% in 2009. We see similar increase in the appliance manufacturing industry and primary metal manufacturing, where material offshoring has risen by more than 36% and 31% , respectively. An industry that hasn't been affected as much is the food manufacturing industry, where material offshoring still stands below 5%. However, within the food manufacturing industry, offshoring by grain and oilseed industry has increased by about 3 percentage point from 4.5% in 1999 to 7.1% in 2009. Likewise, the figure also shows the increase in service offshoring. Although service offshoring remains below 1% of the total production process, there's been a sharp increase in service offshoring activities. For instance, in wood product manufacturing, service offshoring has risen by over 200% from 1999-2009. Similarly, such sharp increases can be seen in the non-metallic mineral industry, transportation industry and chemical industry. Within the chemical industry, one of the fastest growing service offshoring industry is the pharmaceutical and medicine manufacturing, which has seen its offshoring increased from about 0.4% to 0.9% during the period.

[7] In my analysis, I use industry at the 4-digit NAICS level to merge with the CPS industry classification. The graph shows it at the 3-digit industry level to see a trend at an aggregated industry level.

3 Literature Review

3.1 Conceptual Framework

Traditionally, the effect of trade on wages has been empirically tested from the Stolper and Samuelson (1941) theory that predicts trade will lead in an increase in wages for factors used intensively in the production of that good. The North is relatively abundant in skilled labor, whereas the South is relatively abundant in unskilled labor. Thus, the theory implies that the skill-premium for North would increase while the skill-premium for the South would decrease. However, empirical studies found that skill premium in both the North and South was increasing (Belkman et al., 1998). Furthermore, studies also found that there was an increase in the skill-intensity within industry and not an expansion of skill-intensive industries. This led to finding new mechanisms through which trade affects wage and skill premium. Therefore, rather than focusing on the trade in final goods, recent theories have looked at trade affecting wages through trade in intermediate good. Thus, there is an increasing focus on the effect of offshoring on skill premium.

In seminal papers, Feenstra and Hanson (1996, 1999) emphasized the role of trade in intermediate goods within an industry. Their model had a single final goods sector that used a continuum of tradable inputs to produce the good. The production of these inputs differed in their skill-intensity. In the model, when capital share in production cost is the same across inputs and the trade costs are zero, then in equilibrium, countries that are skill-abundant specialized in the production of skill-intensive inputs, whereas countries that are unskill-abundant specialized in unskilled-intensive inputs. Hence, as the trade costs have fallen, it has shifted the production of less-skill intensive inputs from the North to South. Further, the production process shifted to the South are more skill-intensive than the previous productions in the South. As a result, the fragmentation of the production process increases the relative demand for skilled labor in both North and South and thus increases the skill premium of the workers.

However, more recently, Grossman and Rossi-Hansberg (2008) propose the production process that mainly focuses on tasks that are tradable rather than focusing on the goods. Therefore, as it becomes easier to move tasks offshore, it will have a productivity effect, such that all factors can share the gains from the trade in tasks.

3.2 Empirical Literature

Initial literature that looked at the effect of material offshoring on skill premium focused on industry-level aggregates, where the relative demand for skilled workers was measured by the skill labor share of the wage bill. Feenstra and Hanson (1999) (FH hereafter) used the offshoring proxy as defined in equation 1 and found that for the period during 1979-1990, offshoring explained 15-40% of the increase in the skilled workers' share in wage bill for the U.S. Yan (2006) employed the same measures as FH and studied the case for Canada by analyzing 84 manufacturing industries from 1981-1996 and found that offshoring increased the non-production share of wage bill by 0.12 percent annually. Likewise, Hsieh and Woo (2005) studied how offshoring to China affected the relative demand for skilled workers in Hong-Kong from 1971-1996. China opened up its market for foreign investors in 1980, which allowed Hong Kong to easily offshore its production process due to its close proximity. They concluded that offshoring to China accounted for about 40% - 50% increase in the relative demand for skilled labor in Hong Kong.

More recently, offshoring literatures have started to focus not just on material offshoring, but also on service offshoring. Although service offshoring accounts for a very small percentage of the total offshoring activities, it is increasing at a fast rate as shown in section 2.2. Like material offshoring, the direct data on service offshoring is hard to find. Therefore, Amiti and Wei (2005) employ a similar method as FH to proxy for offshoring in service inputs. They study the effects on service offshoring on labor productivity in the U.S. manufacturing industry from 1992-2000 by looking at the value-added per worker. Due to data constraints, they limit their measure for service offshoring to telecommunication, information technology, financial and insurance services. Apart from using industry fixed effects in their analysis, they also use the lagged value of offshoring to address the problem of endogeneity of offshoring decisions. However, unlike the previous studies, they find that the effects of material offshoring are insignificant, but service offshoring increases labor productivity by about 10%.

There are a few drawbacks in using industry-level aggregates to measure the impact of offshoring. First, there may be compositional changes in the workforce of industries in response to offshoring shocks so that it will change the average wages. Second, it doesn't account for worker heterogeneity within each industry. Therefore, using individual level data can control for observable individual characteristics that affect wages. Lovely and Richardson (2000) study the effect on individual wages by looking at the data from the Panel Study of Income Dynamics (PSID) for the 1981-1992 period. They define skilled workers based on the years of education. Further, they focus only on the effects of imports and exports and not on the measure of offshoring discussed above. They find that trade with newly industrialized countries increases the premium for skilled workers. Kosteas (2008) uses the National Longitudinal Survey of Youth (NLSY) for the period of 1979-1996 to look at the impact of imports from low-wage countries. He separates the workers into white-collars and blue-collars arbitrarily based on their occupation, and finds that rising imports from low-wage countries drives down the wages for all workers, but the effects are stronger for blue-collar wages. The study finds that a one-percentage-point increase in the low-wage import share results in a 2.8% decline in blue-collar wages. However, he doesn't interact offshoring and white-collar dummy to get a clear picture of the effect of offshoring on wages. Furthermore, a problem with using data from the PSID and NLSY is the limited sample size. For instance, Kosteas (2008) sample is limited to workers who were between ages of 14-21 in 1979, thus failing to account for the effect of workers who were older than that during the period.

As a result, recent literature has focused on the individual data from Current Population Survey (CPS) because of the availability of a larger sample. Liu and Trefler (2008) use this data to look at the effect of service offshoring to China and India from 1995-2006 on industry and occupation switching. They only look at the transactions that take place between unaffiliated parties. To look at occupation switching, they match workers in consecutive years. They find that offshoring to China and India has small effects on occupation and industry switching. Other studies asks a more subtle question of whether offshoring affects wages through occupation switching or industry switching. Ebenstein et al. (2014) create a measure of occupation exposure and industry exposure to look at the effect of offshoring.Their analysis finds that occupational exposure to globalization has significant wage effects, whereas industry exposure has no significant impact.

A more closely related paper is Tempesti (2015) who uses CPS March supplement data to look at the effect of offshoring on skill premium from 1979-1990. The study looks at industry at a more aggregated level (SIC 2 digits) and only looks at the effect of material offshoring and doesn't consider the effect of service offshoring. In my analysis, I study the effect of service offshoring and material offshoring. Further, in his paper, skill is based on the education level of workers, whereas I develop a new proxy to include the skills that may have been learned on the job and not necessarily acquired through education.

4 Empirical Methodology

4.1 Data

My sample links individual level workers' data with industrial measures of offshoring and occupational measure of offshorability. Individual level data is collected from the Current Population Survey (CPS) March Supplement for the years 1999-2009. CPS randomly samples addresses in the US, where residents in the address are surveyed for four consecutive months, dropped for the next eight months and then surveyed again for four more months. The March supplement has additional questions about labor market activities and are assigned a classification for their industry and occupation. I restrict the sample to civilian population aged 16-65, who worked at least one week during the past year. Hourly wage is calculated from earnings using the weeks worked last year and the usual hours worked per week. The wages are then converted to 2009 real dollars. I further restrict my sample to workers who earned at least 10 cents an hour and dropped workers who earned more than a 1000 dollars an hour. As I am only able to construct material and service offshoring for manufacturing industries, I only look at workers in manufacturing industries.

Data to calculate the measure for material offshoring comes from the annual input-output table constructed by the Bureau of Labor Statistics (BLS) based on the 2002 benchmark table of Bureau of Economic Analysis (BEA). Data for imports and exports of material goods are obtained from Schott (2008) and data for trade in services comes from BEA International Economic Accounts. The industry level data on total factor productivity comes from NBER's calculations provided by Wayne Gary.

The proxy for skills and occupation offshorability comes from the Occupation Information Network (O*NET), a successor to the Department of Occupation Titles (DOT). O*NET collects data on standardized occupation-specific descriptors by surveying a broad range of workers from each occupation. The O*NET content model identifies six major domains that specify key attributes and characteristics of workers and occupations. These are: worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics and occupation-specific information. Skill index uses information from worker requirements and the information for occupation offshorability comes from worker characteristics and occupational requirements.

My final sample consists of 81,107 cross-section samples of manufacturing workers from 1999-2009. Table 1 provides the descriptive statistics of the variables. The sample mainly consists of married, white, citizens and full-time workers. About 16% of the workers in the sample are high-skilled, 40% are medium skilled and the rest are low-skilled. The average of lag material offshoring is 17.5% and 0.28% for service offshoring. .

4.2 Skill Index

In the literature, a worker is usually classified into different skill-level based on either education level (college graduates vs non-college graduates) or years of experience. However, classifying skills based on only a single criteria like education does not account for skill-sets that workers learn and master on the job without any formal education. Therefore, by defining skills as a composite set of skill indicators such as critical thinking and complex problem solving skills, we can better classify individuals into different skill-levels.

O*NET collects data on skill requirements, among others, for more than 800 occupations. These skills are further characterized as Basic Skills and Cross-Functional Skills. Basic skills are defined as "developed capacities that facilitates learning or the more rapid acquisition of knowledge" and cross-functional skills are defined as "developed capacities that facilitates performance of activities that occur across jobs." To define my skill index, I combine two aspects of basic skills: reading comprehension and critical thinking, and two aspects of cross-functional skills: complex problem solving and judgment and decision-making. For each of these skills, the dataset provides a measure of "importance" based on how important the skill is to the job responsibilities and a value of "level" that shows the proficiency in the skill. The importance measure ranges from 0 to 5 (0 being least important and 5 being very important) and the level value ranges from 0 to 7 (0 being less proficient and 7 being highly proficient). To calculate the skill index, I arbitrarily assign Cobb-Douglas weights of two thirds to "importance" and one third to "level"[8]

Mathematically, the skill index can be written as

$$SI_o = \sum_{k \in S_p} I_{ok}^{2/3} * L_{ok}^{1/3} \tag{2}$$

where S_p is the skills elements.

Table 2 shows the occupations that receive high and low scores in the normalized mea-

[8]Blinder et al. (2009) assigns a similar Cobb-Douglas measure to create offshorability index for occupation using O*NET database

sure.[9] The results agree with the general consensus of high-skill and low-skill occupations as presented in other studies. For instance, lawyers and chief executives have the highest scores in the index, whereas graders and sorters of agricultural products and cleaner of vehicles and equipments score low on the index. I then use this index to classify individuals into three different categories of skill: high, medium and low. I classify individuals to high skill if their skill index is above 75 percentile, to medium skill if the index ranges from 25 percentile to 75 percentile, and to low skill if the index is below 25 percentile.

4.3 Occupation Offshorability

I follow Firpo et al. (2011) to look at the potential offshorability of occupation by constructing an index based on three categories: automation, face-to-face, and decision-making. The data comes from the work activities and work context criteria of occupational requirements domain of the O*NET database.

The "automation" category is constructed to reflect the degree of potential automation of the job. It includes five elements from the work context criteria. They are: "degree of automation", "importance of repeating same tasks", "structures versus unstructured work", "pace determined by speed of equipment", and "spend time making repetitive motions". In contrast, "face-to-face" category reflects the need for the workers to interact with other colleagues so that these occupations are not easily offshorable to a different location. The category includes four work-activity elements and one work-context element. The work-activity elements are: "coaching and developing others", "establishing and maintaining interpersonal relationships", "assisting and caring for others", and "performing for or working directly with the public". It also adds the "face-to-face discussion" element from work-context. Likewise, the "decision-making" category reflects the responsibilities and creativity of the occupation. It is constructed using "making decision and solving problems", "thinking creatively", and

[9] Since the absolute value of the index has no particular meaning, I normalize the index by dividing them by the maximum value of the skill observed over all occupation. The normalized measure is useful in ranking the skill-level, whereas the absolute value have no particular meaning

"developing objectives and strategies" elements from the work-activities and "responsibility for outcomes and results" and "frequency of decision making" elements from work-context.

Similarly to the elements used to create the skill index, all the above elements of O*NET has information on the "level" and "importance" of the required work-activity and has the value of level and the frequency of five categorical levels of work-context.[10] The work-activity elements are arbitrarily assigned a Cobb-Douglas weight of two-thirds to "importance" and one-third to "level" for a weighed sum, and multiply the frequency (F) with the value of the level (V) for the work-context elements.

Matematically, the total composite score, CS_m, for occupation j in category m is computed as

$$OFF_o = \sum_{m \in A_p} I_{ok}^{2/3} L_{ok}^{1/3} + \sum_{l \in C_p} F_{ol} * V_{ol} \tag{3}$$

where A_p is the work activity elements, and C_p is the work context elements in the category OFF_o. [11]

Using the above measures, I define "not face-to-face" and "not decision-making" categories as the reverse of "face-to-face" and "decision-making". I then combine the three categories: automation, not face-to-face and not decision-making into a single measure to look at the likelihood of offshorability. I hypothesize that occupations that are more likely to be offshorable will suffer a higher wage loss compared to other occupations as a result of material and service offshoring.

Table 3 shows the different occupations that score high on the the different categories calculated above. I use the normalized score to rank each worker in one of the categories based on its index score. For instance, if the score is above the mean in not-face-to-face category, the worker will be classified as not requiring to have many face-to-face interactions.

[10] For instance, for "face-to-face discussion", the frequency is classified into five categories: a) never, b)once a year or more but not every month, c)once a month or more but not every week, d)once a week or more but not every day, e) everyday.

[11] Since the absolute value of the index has no particular meaning, I normalize the index by dividing them by the maximum value of the skill observed over all occupation. The normalized measure is useful in ranking the skill-level, whereas the absolute value have no particular meaning

Likewise, after I combine the three categories into a single offshorability category, if a worker scores above the mean, he is placed under the likelihood of his job being offshored. If the score is below the mean, the chances of the job being offshored falls. Under automation, computer control programmers and operators rank high, whereas teachers and clergy rank low. Likewise, for not face-to-face, telephone operators and pressers in the textile and garment industry rank high, whereas managers rank low. A similar result is seen in the not-decision-making as graders and sorters rank high and production managers rank low. Combining all three into a single measure, it shows that textile knitting and weaving occupations have a higher chance of being offshored compared to medical technicians and dentists.

4.4 Econometric Specification

I use the Mincer human capital wage equation to measure the effect of offshoring on individual wages. I regress the log wages of workers i in industry j in period t on the lagged measure of service and material offshoring at the industry level and individual skill-level while controlling for individual observable characteristics such as age, sex, marital status and race. I regress lagged measure of offshoring for two reasons. First, simultaneous shocks may affect both wage and offshoring in a given year. Second, the effect of offshoring decision will not affect wages in the same year as it takes time for the firms to implement them.

In addition, as Ebenstein et al. (2014) point out, there are further challenges in estimating the casual effect of offshoring on wages. Industries that are more likely to involve in offshoring activities are may be those that pay lower wages. I, therefore, include industry fixed-effects I_j to control for these. Also, there may be common time-varying shocks such as business-cycles that may affect both offshoring and wages. To address this concern, I include the time fixed-effects δ_t. In addition, I control for the lagged of total factor productivity at the industry level, TFP_{jt-1}, to account for any changes in productivity that would affect the relative demand for labor.

The basic regression model takes the following form:

$$ln(w_{zt}^{oi}) = \alpha + \beta_1 OSM_{i,t-1} + \beta_2 OSS_{i,t-1} + \beta_3 SI_o + \gamma X_{zt} + \delta_t + I_i + \epsilon_{zt} \tag{4}$$

where $ln(w)_{zoit}$ is the log of hourly wage of worker z in industry i and occupation o at time t. OSM_{it-1} and OSS_{it-1} is the measure for material and serving offshoring in industry i and time t, respectively. SI_o denotes the skill of the workers, X_{ot} is a vector of standard demographic variables like age, sex, and dummies for marriage, race and full-time/part-time status.

In addition, I also examine the effect of offshoring on the wages of different occupation based on their offshorability. To look at the effect, my specification becomes,

$$ln(w_{zt}^{oi}) = \alpha + \beta_1 OSM_{i,t-1} + \beta_2 OSS_{i,t-1} + \beta_3 OFF_o + \gamma X_{zt} + \delta_t + I_i + \epsilon_{zt} \tag{5}$$

where OFF_o represents the occupational offshorability of worker z at time t. I will also interact the offshorability of occupation with offshoring measures to see the effect of offshoring on the wage of workers whose jobs are offshorable.

5 Results

I first look at the effect of material offshoring and service offshoring on individual wages. The result is reported in table 4. In column 1, I regress wages on only the demographic control variables and find that all the controls have the expected correlation. In columns 2-3, I regress log of hourly wage on material offshoring, service offshoring, and both measures of offshoring, respectively, while controlling for individual demographic characteristics and industry-specific measures. Consistent with labor literature, compared to low-skill workers, I find that high-skill workers earned 40 percent more and medium-skill workers earned 18 percent more. Likewise, workers with college degree and some college classes earn more than high-school graduates. In the first column, when I only include material offshoring, I find a negative insignificant effect. Service offshoring has a positive effect on wages as seen on column 2. However, when I include both the measures in column 3, they are qualitatively the same, but are statistically insignificant.

A more interesting question to explore would be the effect of service and material outsourcing on individuals with different skill-level. If an industry is more likely to offshore mainly activities performed by a certain skill group to a foreign firm, then we can expect it to have a negative effect on wages of that skill group. In table 5, I look at the effect of both material and service offshoring on workers of different skill levels. The first column shows that a 10 percentage-point increase in material offshoring will increase the high-skill wage by 2.2 percentage and the medium skill wages by 2.4 percentage. In the second column, including interaction terms with service offshoring, I find that both high-skill and medium skill workers earn a higher statistically significant wages than low-skilled workers. Further, when I include all the interaction terms together, I find that material offshoring negatively affects low-skilled workers, whereas a 10 percentage point increase in material offshoring increases the wages of high-skilled workers by 2.9 percent and medium skilled workers by 3 percent. This result is consistent with the idea that if low-skilled intensive part of the production process is offshored, it will reduce the relative demand for unskilled workers, thus negatively impacting their wages.

In addition, apart from the skill-level of the workers, recent theories show that the offshoring may have significant effect on workers who perform tasks that are easily offshorable. Therefore, first, I will look at the wages of workers on different task spectrum and then look at the effect of offshoring on wages of these workers. In table 6, I look at the wages for workers under automation, not decision-making, and not face-to-face. I anticipate that since the task performed by workers on these classifications to be easily offshored, they should have a negative effect on their wages. In the first three columns, when I control for these tasks separately, I find that workers in all three tasks earn less than their counterparts. Further, when I regress all three together, I find that all three occupational tasks have negative effect on wages, but occupations with low requirements for face-to-face interactions suffer the most. Workers in automation category earn 7.7 percent less than workers with low risk of automation. Similarly, workers who do not require much decision-making earn 6.7 percent less and workers with few face-to-face interaction tasks earn 11 percent less.

I then combine the three measures of occupational task into a single measure of offshorability to look at the effect of material and service offshoring on these occupations. In table 7, column 1 shows the results for offshorability and the subsequent column adds the interaction term with material offshoring, service offshoring, and both the offshoring together. I find that people whose occupation have a higher chance of being offshored earn 17 percent less. However, when I interact with material offshoring, I find a negative effect but it is insignificant. However, it does show a statistically negative effect as a result of service offshoring. In the last column, I find that a 10 percentage point increase in material offshoring will result in lowering the wages of offshorable occupations by 0.8 percent. Similarly, a 10 percentage point increase in service offshoring will decrease their wages by 1.5 percent. This result is consistent with the idea that if the occupation requires low face-to-face interactions, can easily be automated and does not involve significant decision making, then these tasks can be easily monitored offshore than more complex tasks, thus negatively impacting the wages for these workers.

6 Robustness Checks

In this section, I'll look at a different classification of skill for workers. In my main analysis, I classified workers who were above the 75th percentile as high-skill, between 25 to 75 percentile as medium skill and workers below the 25th percentile as low-skill. For a robustness check, I assign workers above 66 percentile to high-skill, between 33 and 66 percentile to medium skill and below 33 percentile to low skill. I run a regression using the same specification as my main analysis and present the result in table 8. Although the results differ slightly in their quantitative magnitude, they're qualitatively the same and statistically significant. I find that high-skill workers and medium-skilled workers earn 27 to 28 percent more than low-skill workers as a result of material offshoring. Likewise, the result for service offshoring are also similar to my main analysis and statistically significant.

7 Conclusion

This paper looks at the effect of material and service offshoring on individual workers wages based on two criteria: workers skill-level and the offshorability of their occupation. I examine the effect by combining the individual level data from the March Supplement of the CPS and the industry-level measures of service and material outsourcing for the period 1999-2009. For my analysis, I developed a new measure for skill using the O*NET database. Previous literature has focused only on education as a measure for skill; however, by using a singular measure for skill may overlook the new skills that workers have learned on the job without any formal education. Therefore, I utilize the information on the important and level of skills they perform on the job to create a skill-index to classify workers into three types of skill-level. Further, in my analysis, I also used Firpo et al. (2011) classification of occupation offshorability to study the effect of material and service offshoring on the wages of workers in occupations that had a higher chance of being offshored.

My results showed that workers with high and medium skill earn about 3 percent more than workers with low skill as a result of a 10 percentage point increase in material offshoring. A greater impact if found for service offshoring, where high skill workers earned 3.2 percent more and medium-skilled workers earn 2.2 percent more for one percentage point increase in service offshoring. However, it is important to note that the current level of service offshoring stands well below 1 percent of the total production process. This result is consistent with the previous literature and theory that shows that offshoring of less skill-intensive part of the production process will negatively impact the wages of workers involved in low-skill intensive production process. This result was robust to a different classification of skill-level based on the skill index I created.

I also looked at the effect of on wages of occupations that have a higher probability of being offshored. I found that occupations that required less decision-making, low face-to-face interaction and a higher possibility of being automated earn less than their counterparts. Combining all these three measures into a single measure of offshoring, I found that workers in occupation with higher chances of being offshored earned 0.8 percent less with a 10 percentage point increase in material offshoring. The result represented that it would be easier for firms to monitor the performance of these occupations in an offshore location relatively easily compared to occupations with complex tasks thus having a downward pressure on their wages.

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Figure 1: Trends in Overall Material and Service Offshoring

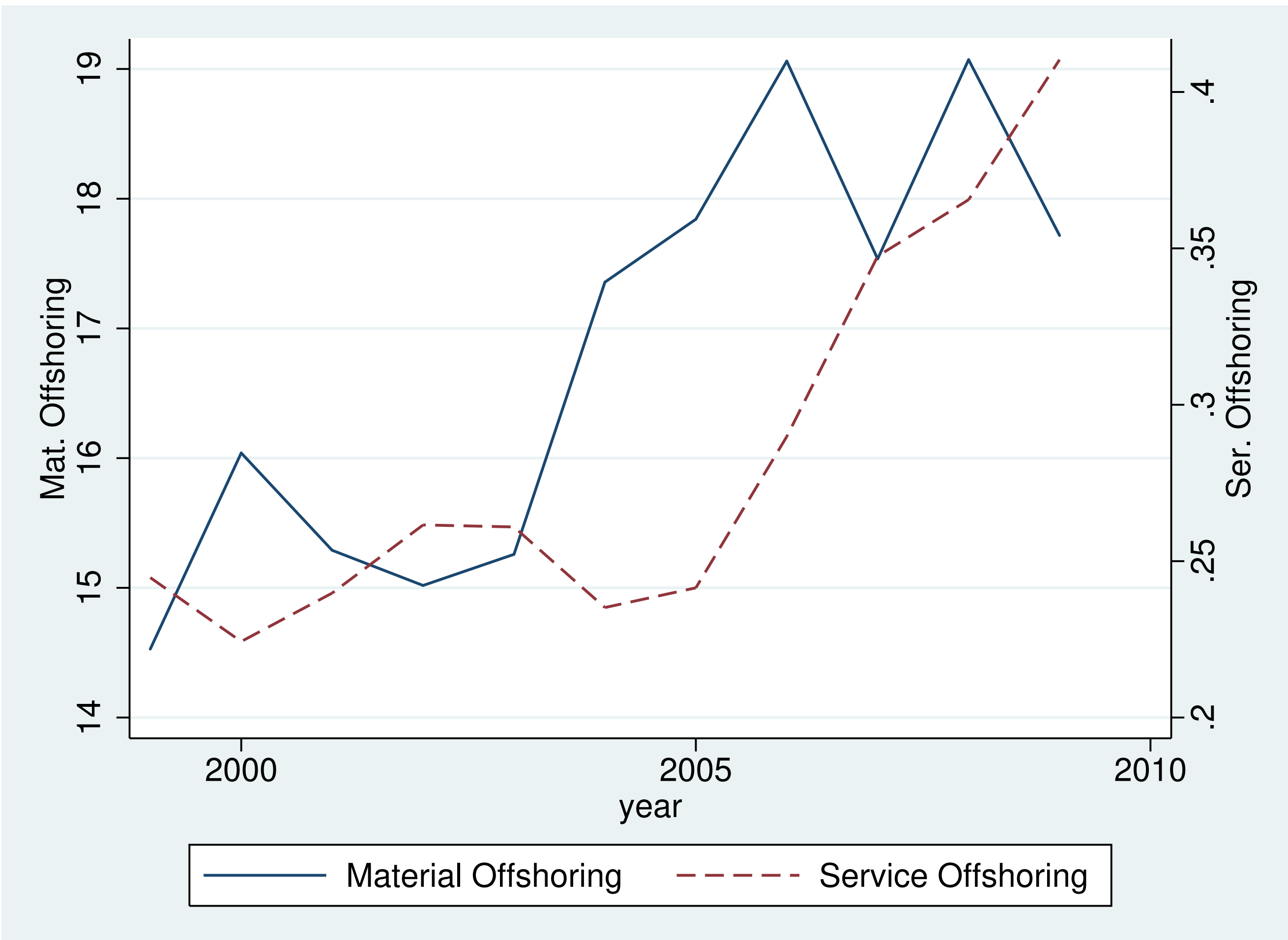

Figure 2: Trends in Sectoral Material and Service Offshoring

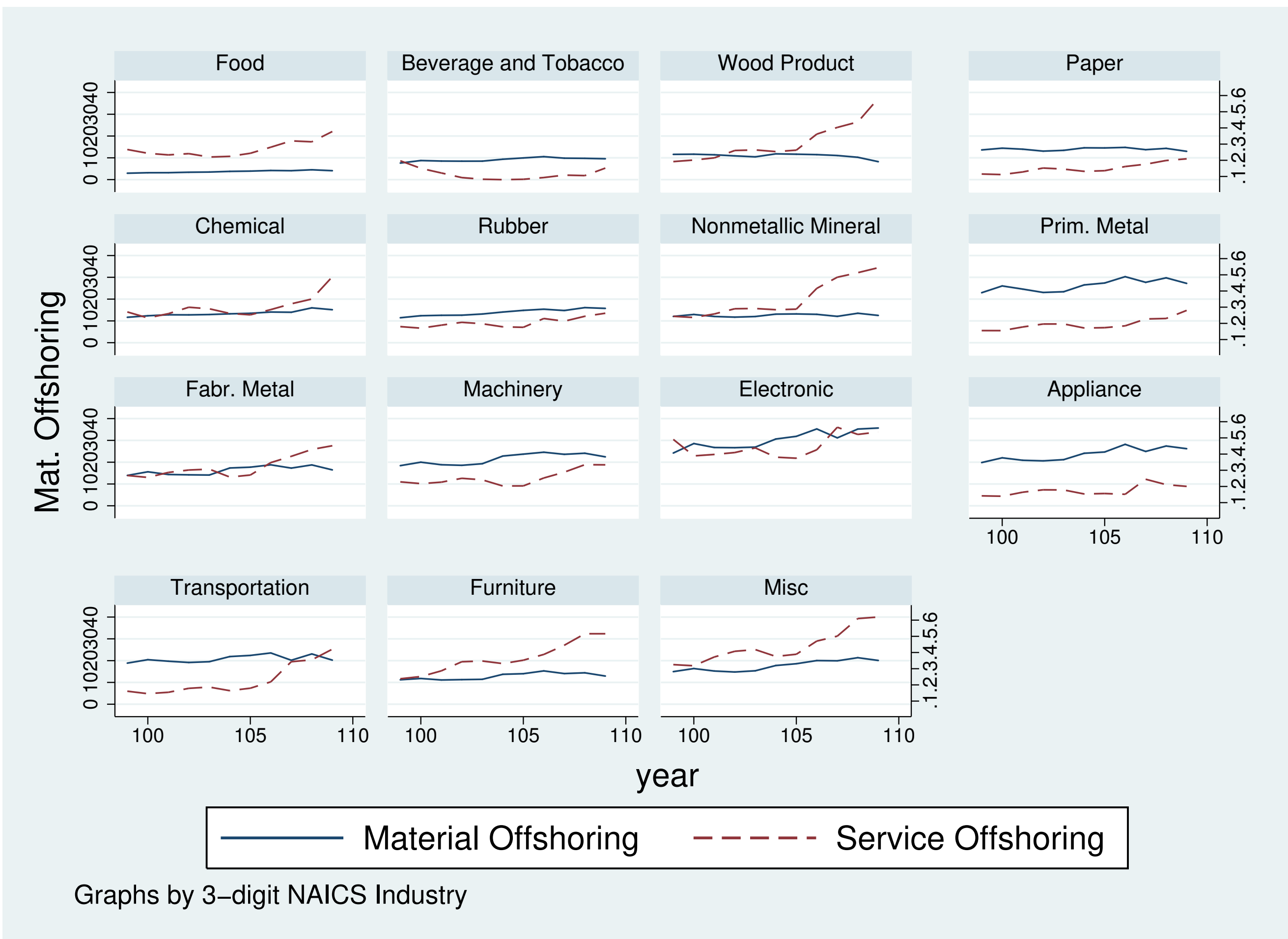

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**
LnWage	2.896	0.666
Lag Mat. Offshoring	17.542	9.106
Lag Ser. Offshoring	0.285	0.16
Age1624	0.075	0.263
Age2539	0.356	0.479
High Skill	0.165	0.372
Med Skill	0.409	0.492
College	0.237	0.425
SomeCollege	0.262	0.439
lagTFP	1.014	0.254
Married	0.815	0.388
Male	0.699	0.459
Union	0.028	0.164
Full-Time	0.959	0.199
Citizen	0.827	0.378
White	0.838	0.369
N	81107	

Table 2: Occupation Skill Rank

Occupation Title	Skill Index
A: Occupation with High Skill Index	
Lawyers	1.000
Biomedical Engineers	0.995
Actuaries	0.994
Chief Executives	0.992
Physicans and Surgeons	0.976
Medical Scientist	0.963
Research Analyst	0.963
B: Occupation with Low Skill Index	
Janitors and Building Cleaners	0.524
Pressers, Textile, Garments and Related Materials	0.522
Food Preparation Workers	0.516
Dishwashers	0.512
Cafeteria Attendants	0.499
Cleaner of Vehicles and Equipments	0.418
Graders and Sorters, Agricultural Products	0.453

Table 3: Occupation Task Rank

Occupation Title	**Occupation with High Score**	**Occupation with Low Score**
Automation	Tire Builders, Hoist and Winch Operators, Etchers and Engravers, Computer Control Programmers and Operators	Models and Demonstrators, Teachers, Actors, Clergy
not Face To Face	Tire Builders, Pressers (Textile and Garments), Reinforcing Iron and Rebar Workers, Telephone Operators	Social and Community Service Managers, Public Relation Managers, Dentists, Physical Therapists
not Decision Making	Graders and Sorters (Agricultural Products), Lobby Attendants, Extraction Workers, Pressers(Textile and Garment)	Dentists, Pharmacists, Veterinarians, Production Managers
Offshorability	Tire Builders, Pressers (Textiles and Garments), Textile Knitting and Weaving, Paper Goods Machine Setters	Veterinarians, Clergy, Emergency Medican Technician, Dentists

Table 4: OLS Estimates of Offshoring on Skill-Premium

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring		-0.166		-0.0729
		(0.105)		(0.122)
Lag Ser. Offshoring			0.0938**	0.0800
			(0.0420)	(0.0487)
HighSkillOccOne		0.400***	0.400***	0.400***
		(0.00639)	(0.00639)	(0.00639)
Med Skill Occupation		0.183***	0.183***	0.183***
		(0.00408)	(0.00408)	(0.00408)
lagTFP	0.0345***	0.0235*	0.0215*	0.0232*
	(0.0126)	(0.0126)	(0.0123)	(0.0126)
Constant	1.957***	2.001***	1.993***	1.994***
	(0.0313)	(0.0306)	(0.0308)	(0.0309)
Observations	81,107	81,107	81,107	81,107
R-squared	0.368	0.403	0.403	0.403
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 5: OLS Estimates of Skill and Offshoring Interaction

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage
Lag Mat. Offshoring	-0.183	-0.0330	-0.224*
	(0.126)	(0.122)	(0.126)
Lag Ser. Offshoring	0.0810*	-0.0808	-0.0936*
	(0.0487)	(0.0516)	(0.0516)
High Skill Occupation	0.395***	0.347***	0.291***
	(0.0150)	(0.0122)	(0.0186)
Med Skill Occupation	0.180***	0.169***	0.112***
	(0.00925)	(0.00799)	(0.0120)
Lag Mat. Off * High Skill	0.221***		0.290***
	(0.0687)		(0.0686)
Lag Mat. Off * Med. Skill	0.248***		0.301***
	(0.0476)		(0.0477)
lagSerOut * High Skill		0.304***	0.324***
		(0.0354)	(0.0355)
lagSerOut * Med. Skill		0.200***	0.220***
		(0.0254)	(0.0255)
lagTFP	0.0307**	0.0309**	0.0272**
	(0.0127)	(0.0127)	(0.0127)
Constant	1.996***	2.011***	2.046***
	(0.0312)	(0.0312)	(0.0315)
Observations	81,107	81,107	81,107
R-squared	0.404	0.405	0.405
Demographic Controls	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 6: OLS Estimates on Occupational Measure of Offshorability

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring	0.0556	-0.0406	0.00396	-0.00263
	(0.125)	(0.125)	(0.125)	(0.124)
Lag Ser. Offshoring	0.129***	0.104**	0.131***	0.123**
	(0.0500)	(0.0499)	(0.0498)	(0.0496)
AutomationOne	-0.0979***			-0.0778***
	(0.00444)			(0.00450)
notDecisionMakingOne		-0.106***		-0.0673***
		(0.00387)		(0.00405)
notFaceToFaceOne			-0.149***	-0.112***
			(0.00392)	(0.00419)
lagTFP	0.0338***	0.0392***	0.0341***	0.0334***
	(0.0128)	(0.0129)	(0.0130)	(0.0128)
Constant	2.027***	2.046***	2.095***	2.187***
	(0.0318)	(0.0318)	(0.0317)	(0.0320)
Observations	81,048	81,048	81,048	81,048
R-squared	0.372	0.374	0.379	0.383
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 7: OLS Estimates on Offshoring and Offshorability Interaction

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring	0.0133	0.0481	-0.0197	0.0252
	(0.124)	(0.127)	(0.124)	(0.127)
Lag Ser. Offshoring	0.113**	0.112**	0.186***	0.187***
	(0.0496)	(0.0496)	(0.0511)	(0.0511)
Offshorability	-0.172***	-0.160***	-0.127***	-0.111***
	(0.00410)	(0.00912)	(0.00783)	(0.0116)
Lag Mat. Off. * Offshorability		-0.0658		-0.0863*
		(0.0448)		(0.0449)
Lag Ser. Off. * Offshorability			-0.153***	-0.157***
			(0.0242)	(0.0243)
lagTFP	0.0344***	0.0334***	0.0342***	0.0329**
	(0.0129)	(0.0129)	(0.0129)	(0.0129)
Constant	2.127***	2.121***	2.103***	2.095***
	(0.0318)	(0.0321)	(0.0320)	(0.0324)
Observations	81,048	81,048	81,048	81,048
R-squared	0.382	0.382	0.382	0.382
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 8: Robustness Check based on Skill Classification

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage
Lag Mat. Offshoring	-0.204	-0.0709	-0.249**
	(0.126)	(0.121)	(0.125)
Lag Ser. Offshoring	0.0785	-0.0859*	-0.0977*
	(0.0486)	(0.0514)	(0.0515)
HighSkillOccOne	0.418***	0.358***	0.305***
	(0.0140)	(0.0117)	(0.0176)
MedSkillOccOne	0.178***	0.169***	0.116***
	(0.00945)	(0.00811)	(0.0121)
lagMatOutHighSkillOne	0.201***		0.272***
	(0.0639)		(0.0640)
lagMatOutMedSkillOne	0.231***		0.283***
	(0.0486)		(0.0486)
lagSerOutHighSkillOne		0.325***	0.344***
		(0.0330)	(0.0332)
lagSerOutMedSkillOne		0.185***	0.203***
		(0.0260)	(0.0261)
lagTFP	0.0247*	0.0243*	0.0209*
	(0.0127)	(0.0126)	(0.0126)
Constant	2.011***	2.028***	2.060***
	(0.0312)	(0.0311)	(0.0315)
Observations	81,107	81,107	81,107
R-squared	0.407	0.408	0.408
Demographic Controls	Yes	Yes	Yes

All regression has demographic control and time and industry fixed effect

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%