Offshoring and Skills Demand*

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Abstract

This paper studies how offshoring-related layoff events change the mix of skills that are demanded by trade-affected firms. Our analysis relies on a novel data set which combines the universe of Trade Adjustment Assistance (TAA) petitions filed by US firms during 2010-2015 with detailed information on online job vacancies. TAA petitions allow us to precisely identify the timing of layoff events, the number of affected workers, and the type of offshoring resulting in the layoff (materials versus service). Utilizing within firm variation in the timing of filing a TAA petition, we find little evidence that TAA petitions lead to a change in the monthly number of vacancies a firm posts online. In contrast, we find that both materials and service offshoring events lead to an increase in the share of vacancies requiring soft skills (such as communication and teamwork). Service offshoring events are also associated with an increase in the demand for hard skills (such as math and problem solving).

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1 Introduction

The relocation of U.S. jobs to foreign countries over the past few decades continues to reshape the U.S. labor market, with some measures suggesting that roughly 25% of U.S. jobs are offshorable (Blinder and Krueger 2013).[1] A large body of literature has focused on identifying which jobs and what tasks are likely to be offshored and the implications of such processes on the employment and wages of affected workers (Blinder 2006; Blinder 2009; Bhagwati and Blinder 2009). In particular, several studies have found that offshoring is linked to the recent phenomenon of job polarization in which the demand for labor in middle-skill routine tasks has declined (Autor, Levy and Murnane 2003; Autor, Katz and Kearney 2006, 2008; Goos and Manning 2007; Autor and Dorn 2013; Goos et al. 2014).

It is far less clear, however, how firms reorganize their domestic operations following a decision to offshore production and how that impacts the composition of their domestic demand for labor and the demand for specific skills (Hummels et al. 2016). Under one scenario, the firm simply offshores some tasks abroad, substituting part of its domestic workers with foreign ones. Under a different scenario, the firm offshores some tasks abroad while changing the type of tasks performed at home and, as a result, the type of skills it demands. The main contribution of this paper is to show exactly which skills are made redundant or scarce following an offshoring-related layoff event, and how trade-affected firms reorganize their production and their broader demand for labor following a decision to offshore the tasks performed in one of their establishments.

We utilize a newly constructed data set to study how firms adjust their demand for domestic labor following a decision to layoff workers and offshore their jobs abroad. The demand for labor at a given firm is measured by the number of vacancy postings they advertise and by the change in the mix of skills and type of workers they desire to hire. Importantly, we differentiate a firm's labor demand adjustment by whether the layoff

[1] Following Grossman and Rossi-Hansberg (2008a, b), offshoring occurs when a firm sends part of its production process to a different country, whether the production is kept "in-house" or outsourced to a different firm.

event was a result of material or service offshoring as they could have different effects on domestic labor demand (Amiti and Wei 2006).

The novel data set we use for the analysis is constructed by linking two administrative data sets. The first includes the universe of Trade Adjustment Assistance (TAA) petitions for the period 2010-2015. It allows us to identify the exact timing a firm experienced an offshoring-related layoff event, whether the layoff was related to material or service offshoring, and the number of workers who require assistance. The second data set, made available to us by Burning Glass Technologies (BGT), contains the near-universe of online job postings by U.S. establishments for the same time period and is unique in three important dimensions. First, information on the inflow of new vacancies allows us to identify changes in the demand for new types of labor with high temporal detail, eliminating sample selection issues associated with differential fill rates for vacancies. Second, job vacancies can be identified at the establishment- and firm-levels, allowing us to examine the spillover effects of offshoring at a single establishment across the entire firm. Third, in addition to information on education and experience, the data include detailed descriptions of other skills required in each vacancy such as cognitive, character, computer, or social skills. In addition, the data include job titles which can provide more granular and economically-relevant characterizations of skills than even six-digit ONET-SOC codes (Marinescu and Wolthoff 2016).

Our empirical strategy relies on variation in the timing a firm files an ultimately approved TAA petition to the government. The identifying assumption is that, controlling for firm and calendar month fixed effects, the filing of a petition can be treated as if randomly assigned. We provide support for this assumption using an event study approach and show that pre-TAA vacancy postings and skill composition trends are unrelated to the timing a petition was filed. Unlike previous studies which have primarily focused on the effects of materials offshoring on labor market outcomes, we also examine how service offshoring-related layoffs impact the type of domestic workers a firm hires after deciding to offshore parts of its operations.

Following the work of Heckman and Kautz (2012), Borghans et al. (2014), Demming (2017), and Deming and Kahn (Forthcoming) we classify skills into three main categories: Hard skills (such as cognitive and critical thinking skills), soft skills (such as character and workforce management skills), and specific skills (such as computer software skills).[2]

Focusing initially on the number of vacancy postings by skill category, we find no evidence that layoff events, whether due to materials or service offshoring, are associated with a change in the overall number of vacancies a firm posts online or the number of vacancies requiring hard, soft, or specific skills. This is an important finding as it suggests that, on average, relocating part of the production process abroad does not cause the firm to downsize its overall domestic demand for labor. It also suggests that changes in the share of vacancies requiring a given type of skill is the result of a change in the demand for such skills.

We provide several novel findings on how offshoring-related layoff events impact the composition of skills required by firms. First, we find evidence that the share of vacancies requiring at least one hard skill increases in the period following a decision to offshore some operations abroad. Interestingly, this effect is driven by firms who offshore service operations and not by those who engage in materials offshoring. Second, we find that both materials and service offshoring events are associated with an increase in the average number of vacancies requiring soft skills . Importantly, the change in the share of soft skills following a materials offshoring event is driven by an increase in the number of required soft skills among vacancies requiring at least one soft skill (the intensive margin). In contrast, service offshoring-layoff events are associated with an increase in the share of vacancies requiring at least one soft skill (the extensive margin) and in the number of required soft skills among vacancies requiring at least one soft skill. We also find some

[2] Details on the construction of these skills are provided in the data section.

evidence that service offshoring events lead to an increase in the share of vacancies which require specific skills.

More broadly, the results are consistent with recent research suggesting that the returns to social skills have increased substantially in the past decade (Demming 2017; Demming and Kahn, Forthcoming) and highlights the contribution of offshoring to this change. Given the rapid growth in offshoring of service jobs, these results are of paramount importance to both U.S. workers who are deciding which skills to acquire, and to policy makers tasked with designing training and compensation programs for displaced workers.

The paper proceeds as follows. Section 2 describes our data sources and the construction of the analysis sample. Section 3 outlines the empirical strategy and we discuss the results in section 4. We conclude in section 5.

2 Data

2.1 Trade Adjustment Assistance Petitions

Under the Trade Expansion Act of 1962 and defined further under the Trade Act of 1974, U.S. workers are eligible for Trade Adjustment Assistance if a significant proportion of workers in an establishment are partially or totally separated from their jobs or under threat of separation. Importantly, the cause of the separation must be trade related. Specifically, separation must be caused by i) an absolute decline in sales due to increased imports, ii) outsourcing of production or services to foreign countries, iii) outsourcing of production or services to foreign countries and a high likelihood of increased imports of the outsourced good or service, and iv) lower output due to a loss of business as a supplier of parts or finisher for a TAA certified firm. Failure to meet one of the criteria above indicates that the firm did not experience a significant layoff event or that it was not able to provide evidence that the layoff event is trade related. The TAA program is the largest federal program designed to aid workers impacted by trade exposure (Monarch et al. 2016). Workers who meet one of these criteria are eligible to receive benefits such as job search and relocation assistance, subsidized health care insurance, and extended unemployment benefits.[3] Importantly, workers and not firms are those who receive the benefits associated with the program.

Workers or any entity that represents them (company, union, or state) may file a petition on the workers behalf with the Department of Labor. The petitions are filed at the establishment level, and TAA certification applies to layoffs at that establishment. Petitions must be filed within 60 days from when the injury occurred providing us with information about when the specific shock occurred and variation in the timing of injury across establishments and firms. For instance, in 2010, 1,281 unique firms experienced trade exposure covered by TAA program and at those firms 2,718 petitions were certified covering an estimated 280,873 workers for which over $975 million in federal funds were allocated to states to provide benefits and services to impacted workers (Monarch et al. 2016).[4] We have obtained every TAA petition filed from 1975-2015 through a Freedom of Information Act request. This data includes the name and industry affiliation of the firm, the address of the establishment, the number of affected workers, the reason for filing (including material or service offshoring), the date of the filing, and whether the petition was accepted or denied. Figure 1 plots the quarterly number of approved offshoring petitions by type and the number of denied petitions for 2010-2015. According to the 2015 TAA fiscal report, approved petitions disproportionately affect lower skilled workers whose jobs are threatened because of exposure to foreign competition.[5]

Although TAA petitions do not capture all forms of exposure to trade and outsourcing, they provide a very precise and temporally detailed indicator of a layoff event related to offshoring. Previous research has shown that petitions related to foreign import competition

[3] Generally, workers are required to enroll in job training programs to receive the unemployment benefits. Alternately, some workers 50 years and older can receive wage insurance for up to two years if they are reemployed in lower paying jobs.

[4] Historically, most petitions were led by labor unions, but more recently, companies have been the main source of petitions: between 1999 and 2015, just over half of all petitions were led by companies.

[5] https://www.doleta.gov/tradeact/docs/AnnualReport15.pdf

are associated with reductions in the wages of local economies (Kondo 2013) and that they have heterogeneous effects depending on firm productivity (Uysal et al. 2015). TAA-related material offshoring events have also been shown to have long run effects on employment, skill intensity, and output (Monarch et al. 2016). No previous research, however, has analyzed the impact of offshoring-related layoff events on the firm's demand for specific skills. Examining the impact of an offshoring decision on the demand for labor across establishments and geography will shed light on how firms re-organize their operations following a decision to relocate certain tasks or production processes abroad.

2.2 Burning Glass Technologies Database

The data set collected by BGT includes more than 60 million electronic job vacancies in the U.S. for 2010-2015, which BGT obtains by examining over 40,000 job boards and company websites, resulting in a data set which captures a near-universe of all online job ads (Hershbein and Kahn 2016). The BGT provides vacancy-posting data covering the vast majority of occupations, industries and geographic areas. During the period 2010-2015 we observe vacancy postings within 99 percent of all counties. For each vacancy, BGT creates about 70 possible job characteristics such as the job posting date, job title, detailed occupational classification, education and experience credentials, and other job attributes and skill requirements (such as problem solving, knowledge of specific computer programs, communication, and teamwork skills) which have been standardized from open text in each job posting.

Detailed skills information, collected for the vast majority of all BGT vacancies, is unique to this data set and of paramount importance to our research design. From these requirements, we will construct harmonized measures of skill intensity of vacancies posted by firms. We classify skills into three broad categories: hard, soft, ad specific skills. Each category includes a number of related requirements as detailed in Table 1 and the source for the classification. For example, hard skills include 9 different requirements such as research, math, problem solving and writing. Soft skills include 25 different requirements such as multi-tasking, teamwork, leadership, and mentoring. Specific skills include 35 different requirements such as knowledge in excel, powerpoint, Java, inventory, and materials management. Using similar skills and wage information from the BGT data set, Deming and Kahn (2017) find a positive correlation between wages and required cognitive and non-cognitive skills even after controlling for occupation, industry, and geographical fixed effects. This finding suggests that these job skills can explain variation in wages beyond what is available in other commonly-used labor market data.

A clear advantage of the BGT data is that they do not rely on information about vacancies from a single job board such as Monster.com, thus providing a broader coverage of the flow of vacancies in the U.S. while standardizing vacancy postings and removing duplicate vacancies posted on more than one job board. Moreover, compared to the sample of vacancies obtained from JOLTS, the BGT data allow us to track vacancies and associated demand for different skills within a firm over time. Importantly, the BGT data include vacancies for jobs in the service industry which enable us to study the effects of offshoring on these occupations, whereas most previous studies focused on the impacts on manufacturing jobs.

A disadvantage of the BGT data is that they only cover vacancies posted on the Internet, and it is possible that the types of vacancies posted online are different from job posts in more traditional outlets, such as newspapers. Hershbein and Kahn (2016) conducted an extensive analysis describing the industry-occupation mix of job vacancies in the BGT. They find that the industry composition of the BGT vacancies is relatively similar to the industrial composition in JOLTS. In Figure 2 we demonstrate that the comparability of the BGT and JOLTS also holds for our sample window of 2010-2015. Moreover, the vacancy data does not measure hires, separations, or total employment.

2.3 TAA/BGT Matched Sample

Our analysis sample is constructed by combining the TAA petition dataset with the BGT vacancy data. The match is based on the firm's name and the address of the establishment that filed a petition in any given year. During 2010-2015, the BGT database contains information on about 60 million unique vacancies posted by about 6 million unique establishments belonging to 349,805 firms. We exclude from this sample all public administration vacancies (federal and local government jobs), vacancies without a firm name, and vacancies at firms who post less than 10 vacancies within the entire sample period.

During our sample there were 6,241 total petitions accepted for any type of trade exposure. Of those, 3,453 were filed in zip codes and calendar months in which we also observe vacancy posting data. Of those potential matches, using name and address matching, we are able to match 1,011 establishments observed in both the TAA and BGT database. 733 of those matches are perfect, meaning the firm name and location are identical across both datasets. The remaining 278 were less than perfect matches and were verified by visual inspection. We observe 316 materials offshoring events (i.e. relocation of input production to abroad) and 416 service offshoring events (i.e. relocation of services to abroad). We limit our analysis to the firms that only experience one offshoring event. We define an offshoring event as a single type of offshoring petition (materials or service) filed within a firm-month-year pair. It is possible that multiple establishments within the same firm file an approved petition in the same month. In this case, we treat these multiple petitions as one event at the firm level. As an example, in May 2014 Souther California Edison offshored its information technology operations to two firms in India. As a result approximately 4,000 employees were laid off across 29 different establishments. In our TAA dataset, we observe 29 separate petitions, all of which were filed on May 2nd, 2014. However, by collapsing information at the firm-level, we consider them to be one large layoff event which the firm experienced. In addition, we exclude from the sample firms who experienced an offshoring event in the five years prior to 2010. This is intended to ensure that the vacancy postings we observe were not affected by a major offshoring-related layoff event before the start of our sample period.

Our final sample contains 87,196 establishments belonging to 298 firms which had an approved TAA petition. The median firm in the analysis sample has about 50 establishments while the average number of establishments per firm is 303. While the unmatched BGT is quite comparable to the distribution of vacancies as measured by JOLTS, our final sample over represents industries that one might expect to be more impacted by trade. In Figure 3 we plot the share of vacancies accounted for by each sector in our sample relative to both the full BGT sample as well as JOLTS. As one might expect, industries such as manufacturing, information and finance and insurance are over represented in our sample, while industries like health care are under represented. Comparing our sample to the full BGT sample across occupations in Figure 4, we find that our sample contains more "Computer and Mathematical" vacancies and less "Health Practitioner" vacancies, which seems consistent with our representation across industries.

Finally, Figure 5 depicts the distribution of affected workers by materials versus service offshoring events. We are unable to calculate the share of workers affected by offshoring relative to the number of workers the firm employs. Instead, we proxy for the pre-treatment size of the firm by the average number of vacancies per month during the year before the petition was filed. The distribution of affected workers per average number of vacancies for materials and service offshoring events is depicted in Figure 6. As can be seen, the number of affected workers as a share of monthly vacancies is similar between materials and service offshoring evidence. Thus, differences between materials and service offshoring events do not reflect difference in the magnitude of the layoffs.

2.4 Measuring Skills Demand Intensity

Having matched TAA petitions to vacancies at the establishment level we then utilize the detailed vacancy information in the BGT to construct our primary outcomes of interest. In addition to analyzing the relationship between an offshoring-related layoff event and the number of vacancies posted by petitioning firms, we are also interested in how offshoring might impact the skill and occupational composition of posted vacancies. We construct three measures of skill composition. The first measure simply calculates the average number of skill requirements as a share of vacancies posted by the firm:

$$\bar{S}_{jt}^{tot} = \frac{\sum_k (\sum_l S_l^k)}{v_{jt}}. \tag{1}$$

where j represents a firm, t is a calendar month, v is total vacancies posted by a given firm, k represents a job vacancy, and l represents one of three skill categories. Equation (1) measures the unconditional average number of skills required by a firm, therefore variation in this measure can come from either a change in the number of vacancies requiring any such skills or a change in number of skills demanded per vacancy.

The second measure calculates the share of vacancies that require at least one hard, soft, or specific skill as follows:

$$\bar{S}_{jt}^{ext} = \frac{\sum_k 1_k (\sum_l S_l^k > 0)}{v_{jt}} \tag{2}$$

Thus, equation 2 identifies the extensive margin of skill demand, as it captures changes in the number of vacancies requiring any particular skill but does not measure the intensity of the demand (i.e. the number of hard soft or specific skills demanded).

The third measure is intended to capture the intensity of demand for those vacancies that require skills. This measure is equal to the average number of skills required for each vacancy, conditional on requiring at least one skill. For example, as reported in Table 1, soft skills contain 25 different types of skills. As a result, conditional on requiring a soft skill, a vacancy could require 1-25 soft skills. We define this measure more formally as follows:

$$\bar{S}_{jt}^{int} = \frac{\sum_k 1_k(\sum_l S_l^k > 0) \times (\sum_l S_l^k)}{v_{jt}} \tag{3}$$

Variation in this measure identify changes in the intensity of demand for hard, soft and specific skills.

Having constructed our sample of firms filing TAA petitions and our measures of skills demand based on detailed information from the BGT, we now describe our empirical strategy for identifying the effect of offshoring related layoff events on the demand for skills.

3 Empirical Strategy

3.1 Offshoring Petitions and Labor Demand

We begin by investigating the effect of offshoring-related layoff events on the total number of vacancies a petitioning firm posts online, and the total number of vacancies requiring a hard, soft, or specific skills. This is important as it will provide evidence on whether TAA petitions lead to an absolute decline in the demand for any particular category of skills. We limit our sample to firms who filed one approved petition and use within-firm variation in job vacancies.[6] The underlying assumption is that, conditional on firm and calendar month fixed effects, the exact month in which a petition was filed can be thought of as randomly assigned. This assumption would be violated if petitioning firms were already in the process of downsizing by laying off workers before filing the petition. However, as described in the results section, we conduct a series of event-studies which provide little

[6]This sample selection excludes 23 firms who filed more than one petition during the sample period. Including firms who filed more than one petition in the sample, and considering changes in the number of vacancies in response to their first approved petition, does not change the results. Results with and without these firms can be found in tables A2 and A3 in the appendix.

evidence that such pre-trends are present at the affected establishment or the firm as a whole. Formally, we estimate the following OLS equation:

$$V_{jt} = \alpha + \beta post_{jt} + \bar{X}_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{4}$$

where V_{jt} is the number of online vacancies by skill category posted by firm j in calendar month t. $post_jt$ is an indicator variable which takes the value of 1 starting the month when the petition was filed through the remaining sample month and zero otherwise. $\bar{X}_{jt}$ is the average time-varying local economic conditions within all counties in which firm j operates.[7] δ_j and δ_t are firm and calendar month fixed effects, respectively, and ϵ_{jt} is the error term. We cluster the standard errors at the firm level.[8]

The specification in equation 4 estimates the effect of an approved petition on the firm's subsequent number of vacancies but does not allow the effect to vary by the number of affected workers or the firm size. Because firms vary substantially by size, equation 4 could mask substantial heterogeneity in the effect of filing a petition on labor demand. To address this concern, we estimate a version of equation 4 where we multiply the *post* indicator by the number of affected workers as specified in the petition. Thus, *post* is equal to the number of affected workers starting the month when the petition was filed through the remaining sample month and zero otherwise.

3.2 Offshoring Petitions and Skill Composition

Having estimated the effect of offshoring petitions on the firm's number of vacancy postings, we proceed by examining whether offshoring-related layoff events lead to a a change in the composition of skills demanded by the firm. As discussed earlier, we classify skills into three broad categories: hard skills, soft skills, and specific skills. For each type of skill we

[7]The average time-varying local economic conditions is calculated as the average number of vacancies posted by establishments in all counties in which firm i operates that are **not** owned by firm i. This is meant to proxy for time-varying local labor demand.

[8]Appendix Table A1 reports results of estimating a Poisson model.

consider the effect of a TAA petition on the average number of required skills, the share of vacancies requiring at least one skill (the extensive margin), and the average number of skills conditioning on vacancies requiring at least one such skill (the intensive margin). Specifically, we estimate the following OLS equation:

$$y_{jt} = \alpha + \beta post_{jt} + \bar{X}_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{5}$$

where y_{jt} is a measure of skill composition of vacancies posted in calendar month t by firm j. All other variables are defined as in equation 4. We weight equation 5 by the number of vacancies posted by the firm in a given month. The coefficient of interest β is interpreted as the effect of filing a TAA petition on the skill demand by petitioning firms. Standard errors are clustered at the firm-level.

4 Empirical Results

4.1 Event-Study Approach

We start our empirical analysis by providing evidence in support of the underlying identification assumption that the timing of filing a TAA petition can be thought of as randomly assigned with respect to firms labor demand. Figure 7 depicts coefficient estimates from a simple event-study design in which we estimate the relationship between filing a petition and overall number of vacancies.[9] We normalize the quarter prior to a TAA petition being filed to equal zero and follow vacancy posting behavior in the 10 quarters prior and 10 quarters after filing a petition, controlling for calendar month and establishment fixed effects.

[9] All event studies are estimated using a Poisson model since the dependent variable is the count of number of vacancies. Because the distribution of vacancy postings has a long right tail we expect that a linear OLS model may not fit the data well. We test this hypothesis by performing a RESET test, which confirms that an OLS specification results in considerable remaining heteroskedasticity. See Silva and Tenreyro (2011) for details regarding the RESET test and the bias generated by heteroskedasticity. Despite this potential source of bias our results are quite similar using an OLS model.

Panel A of Figure 7 depicts the number of vacancies posted by affected establishments separately for materials and service offshoring events. It is important to notice that for both materials and service offshoring events, there is little evidence to suggest that the filing of a TAA petition was preceded by significant changes in vacancy postings. The flat pre-trends suggest that the timing of filing a petition was not a result of a declining trend in vacancy postings. Interestingly, a materials-related layoff event is associated with a sharp decline in the number of vacancies an establishment posts. In contrast, an establishment seem to not change or even increase the number of vacancies it posts after a service-related layoff event.

Panel B of Figure 7 repeats the same exercise at the firm level. In these specifications, quarter zero indicates the quarter in which the first TAA petition by an establishment within the firm was filed. As for the results in Panel A, there is little evidence to suggest that the timing of filing a petition was preceded by a decline in the activity of the firm–as measured by vacancy postings. Moreover, at the firm level, we see no indication that the filing of a TAA petition of either type led to changes in the number of job vacancies a firm posts. Our sample implicitly conditions on establishments which continue to operate after filing a petition. However, it is possible that filing a petition could have impacted the survival of the affected establishment or other establishments within the firm. We explore this possibility in Panel C of Figure 7 where we replace the dependent variable with the number of active establishments per firm 10 quarters prior and 10 quarters after filing a petition. The results provide little evidence that filing a TAA petition is associated with a change in the composition of existing establishments within the firm.[10]

4.2 Effect of Offshoring on Labor Demand

Estimating the effect of offshoring-related layoff events on the total number of vacancies by skill category is important to the interpretation of our results on skill composition.

[10]We conduct the same event-study style analysis for the composition of skills demand as well and find similarly little evidence of pre-trends. These results can be found in Figure A1.

For example, if firms reduce their demand for hard skills following a TAA-approved layoff event, then the share of soft skills from all required skills will mechanically increase even if the firm does change its demand for soft skills.

Panel A of Table 2 provide no evidence that filing a TAA petition leads to a change in the number of vacancies posted by a firm (column 1). Importantly, TAA petitions also do not change the total number of vacancies requiring any skill, or the total number of vacancies requiring hard, soft, or specific skills. Panel B of Table 2 uses TAA petitions related to materials offshoring layoff events. The results, although statistically insignificant, suggest that materials offshoring is associated with a decrease in the number of job vacancies, and that they are present for all skill categories. In Panel C of Table 2 we use TAA petitions related to service offshoring layoff events and again find no evidence that TAA petitions lead to a statistically significant change in the number of job vacancies across the different types of skills. Table 3 presents results of estimating equation 4 where we replace the *post* indicator by the number of workers who were laid off. The results suggest that laying off an additional workers does not impact the firm's number of job vacancies or the number of skill-specific vacancies. Based on the results in Tables 2 and 3, we conclude that an approved TAA petition does not change the firm's overall number of job vacancies or the number of skill-specific job vacancies.

4.3 Effect of Offshoring on Skill Composition

We present results of estimating equation 5 for the different measures of skill composition in Tables 4-6. The results in Table 4 (Panel A, column 1) indicate that filing a TAA petition is associated with a 10.5 percentage point increase in the average number of hard skills required per vacancy, or about a 14.5 percent relative to the mean share of hard skills vacancies. This effect is driven by an increase in the share of vacancies requiring at least one hard skill (column 2) and not through an increase in the number of hard skills among vacancies that require them. Although not statistically significant at conventional levels, the results in Panels B and C of Table 4 suggest that service offshoring is driving the effects of TAA petitions on the share of hard skills.

The results on the demand for soft skills presented in Table 5 indicate that TAA petitions are associated with about a 29 percentage point increase in the average number of soft skills required per vacancy, or about a 12 percent increase relative to a mean of 2.32. In contrast to the results on hard skills, this effect is driven by an increase in the number of soft skills as a share of vacancies that required at least one such skill. This is not surprising since, on average, 73 percent of vacancies require at least one soft skill. Interestingly, this effect is present for both materials and service offshoring as is shown in Panels B and C.

Table 6 presents the results for specific skills. Although the results in Panel A are positive in columns 1 and 2, they are not statistically significant at conventional levels. These positive coefficients are driven by the effects of service offshoring events (Panel C), but also cannot be distinguished from zero. Based on the results in Tables 4-6, we conclude that service offshoring events lead to a broader re-organization in the firm's activities and to an increase in its demand for hard and soft skills. Similarly, but to a lesser extent, materials offshoring leads to an increase in the demand for soft skills.

4.4 Effect over Different Time Horizons

To explore how the effects of offshoring vary over time, we replace the *post* indicator in equation 5 with 4 different indicators and estimate the effects of filing a TAA petition over the period of 4 years. The first indicator is equal to 1 during the one year period following the filing of a petition and zero otherwise, the second indicator is equal to 1 during the 2 year period following a petition and zero otherwise, the third indicator is equal to 1 during the 3 year period following a petition and zero otherwise, and the fourth indicator takes the value of 1 during the 4 year period following a petition and zero otherwise.

The results in Table 7 indicate that the share of vacancies requiring at least one hard skill increases immediately in the year following a TAA petition and the coefficients remain positive and significant throughout the 4 year period we observe (columns 5-8). The increase in the share of vacancies requiring at least one hard skill is observed for both material and service offshoring, although the results by type of offshoring are not precisely estimated. The effects on the demand for soft skills presented in Table 8 also provides evidence that filing a TAA petition leads to an increase in the share of vacancies requiring soft skills that persists during the 4 year window we observe. Unlike the effects on hard skills, the results suggest that the increase in the demand for soft skills is caused by an increase in the number of soft skills required as a share of vacancies that require at least one soft skill. Moreover, the results on soft skills are primarily driven by service offshoring. There is also some evidence (Table 9, Panel C) that the demand for specific skills increases in the medium- to long-run in response to service offshoring events.

Because petitions were filed at different points in time, the number of post-TAA months used in the analysis vary by petition and calendar month. As a robustness check, we limit our post-TAA period to 38 months which is the median number of post-TAA months in the sample. Although the sample size decreases, the impact of filing a petition on the number of vacancies (Table 10) and on the skill composition of vacancies (Tables 11-13) remains unchanged.

5 Conclusion

This paper studies how offshoring-related layoff events change the mix of skills that are demanded by trade-affected firms, as measured by highly detailed skill requirements in online job posts. The analysis is based on a newly constructed data set which combines information on Trade Adjustment Assistance (TAA) petitions with information on job vacancies posted by the petitioning firm for the period 2010-2015. As a result, we are able to examine the broader spillover effects of offshoring on the firm's hiring practices across many establishments. Importantly, the analysis is conducted separately for materials and service offshoring events which are likely to have fundamentally different effects on the mix of skills demanded by trade-affected firms (Amiti and Wei 2006).

The results suggest that offshoring-related layoff events do not impact the monthly number of vacancies an affected firm posts online, and does not affect the number of vacancies by skill category. However, we find strong evidence that service offshoring events increases the share of vacancies requiring both hard and soft skills, while having a smaller impact on the demand for specific skills. In contrast, materials offshoring layoff events only increases the share of vacancies requiring soft skills. For example, following a service-related offshoring event, the average number of vacancies requiring soft skills increases by about 14 percent.

The results provide additional support for the rising importance of social skills in the past decade (Demming 2017; Demming and Kahn, Forthcoming) and highlights the contribution of offshoring to this change. Given the role offshoring has played in reshaping the U.S. labor market, these results are of paramount importance to understand the broader implications of offshoring on the allocation of tasks not only within affected local labor markets but across other seemingly non-affected labor markets. The results should also guide vulnerable workers who are deciding which skills to acquire in order to mitigate the effects of offshoring, and to policy makers tasked with designing training and compensation programs for displaced workers.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, March 1999, *67* (2), 251–334.

Alexander, Katie Genadek Ronald Goeken Matthew B. Schroeder Steven Ruggles Trent and Matthew Sobek, "Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]," Technical Report, Minneapolis: University of Minnesota 2010.

Amiti, Mary and Shang-Jin Wei, "Service Offshoring and Productivity: Evidence from the US," *World Economy*, 2009, *32* (2), 203–220.

Arai, Mahmood, "Wages, Profits and Capital Intensity: Evidence from Matched Worker-Firm Data," Research Papers in Economics 1999:3, Stockholm University, Department of Economics April 1999.

Autor, David H., Frank Levy, and Richard J. Murnane, "The skill content of recent technological change: an empirical exploration," *Proceedings*, 2003, (Nov).

___, Lawrence F. Katz, and Melissa S. Kearney, "The Polarization of the U.S. Labor Market," *American Economic Review*, May 2006, *96* (2), 189–194.

Beaudry, Paul, David A. Green, and Benjamin M. Sand, "The Great Reversal in the Demand for Skill and Cognitive Tasks," *Journal of Labor Economics*, 2016, *34* (S1), S199–S247.

Bhagwati, J.N., A.S. Blinder, and B.M. Friedman, *Offshoring of American Jobs: What Response from U.S. Economic Policy?* Alvin Hansen Symposium Series on Public Policy, MIT Press, 2009.

Blinder, Alan S., "The Challenge of High Unemployment," *American Economic Review*, 1988, *78*, 131–139.

___ and Alan B. Krueger, "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics*, 2013, *31* (S1), S97–S128.

Bustos, Paula, "The Impact of Trade Liberalization on Skill Upgrading Evidence from Argentina," Working Papers 559, Barcelona Graduate School of Economics April 2011.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Robust Inference with Multi-way Clustering," Working Paper 327, National Bureau of Economic Research September 2006.

Castex, Gonzalo and Evgenia Kogan Dechter, "The Changing Roles of Education and Ability in Wage Determination," *Journal of Labor Economics*, 2014, *32* (4), 685–710.

Davidson, Carl, Lawrence Martin, and Steven Matusz, "Trade and search generated unemployment," *Journal of International Economics*, August 1999, *48* (2), 271–299.

Deming, David and Lisa B. Kahn, "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals," Working Paper 23328, National Bureau of Economic Research 2017, month =.

Deming, David J., "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics*, forthcoming.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips, "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys," *The Review of Economics and Statistics*, 2014, *96* (4), 581–595.

Feenstra, Robert C. and Bradford Jensen, "Evaluating Estimates of Materials Offshoring from U.S. Manufacturing," UC Davis Working Paper, University of California, Davis 2009.

Frigant, Vincent and Yannick Lung, "Geographical proximity and supplying relationships in modular production," *International Journal of Urban and Regional Research*, 2002, *26* (4), 742–755.

Goos, Maarten, Alan Manning, and Anna Salomons, "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 2014, *104* (8), 2509–26.

Hamermesh, Daniel S., "Fun with Matched Firm-Employee Data: Progress and Road Maps," IZA Discussion Papers 2580, Institute for the Study of Labor (IZA) January 2007.

Heckman, James J. and Tim Kautz, "Hard evidence on soft skills," *Labour Economics*, 2012, *19* (4), 451–464.

Hershbein, Brad and Lisa B. Kahn, "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," Working Paper 22762, National Bureau of Economic Research October 2016.

Hummels, David, Rasmus Jrgensen, Jakob Munch, and Chong Xiang, "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, June 2014, *104* (6), 1597–1629.

Jensen, J. Bradford and Lori G. Kletzer, *Measuring Tradable Services and the Task Content of Offshorable Services Jobs*, University of Chicago Press, October

Levine, David, "Production Chains," *Review of Economic Dynamics*, July 2012, *15* (3), 271–282.

Marinescu, Ioana E. and Ronald P. Wolthoff, "Opening the Black Box of the Matching Function: The Power of Words," IZA Discussion Papers 9071, Institute for the Study of Labor (IZA) May 2015.

Martins, Pedro S. and Luca David Opromolla, "Exports, Imports and Wages: Evidence from Matched Firm-Worker-Product Panels," Working Papers 4646, Institute for the Study of Labor 2009.

Monarch, Ryan, Jooyoun Park, and Jagadeesh Sivadasan, "Domestic gains from offshoring? Evidence from TAA-linked U.S. microdata," *Journal of International Economics*, 2017, *105* (C), 150–173.

Montgomery, James D, "Equilibrium Wage Dispersion and Interindustry Wage Differentials," *The Quarterly Journal of Economics*, February 1991, *106* (1), 163–79.

S., R. Lanz Miroudot and A. Ragoussis, "Trade in Intermediate Goods and Services," 2009.

Silva, J.M.C. Santos and Silvana Tenreyro, "Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator," *Economics Letters*, August 2011, *112* (2), 220–222.

Tomiura, Eiichi, "Foreign outsourcing, exporting, and FDI: A productivity comparison at the firm level," *Journal of International Economics*, 2007, *72* (1), 113 – 127.

Trends in U.S. Wage Inequality: Revising the Revisionists, *Review of Economics and Statistics*, 2008, *90* (2), 300–323. Data and Replication Files.

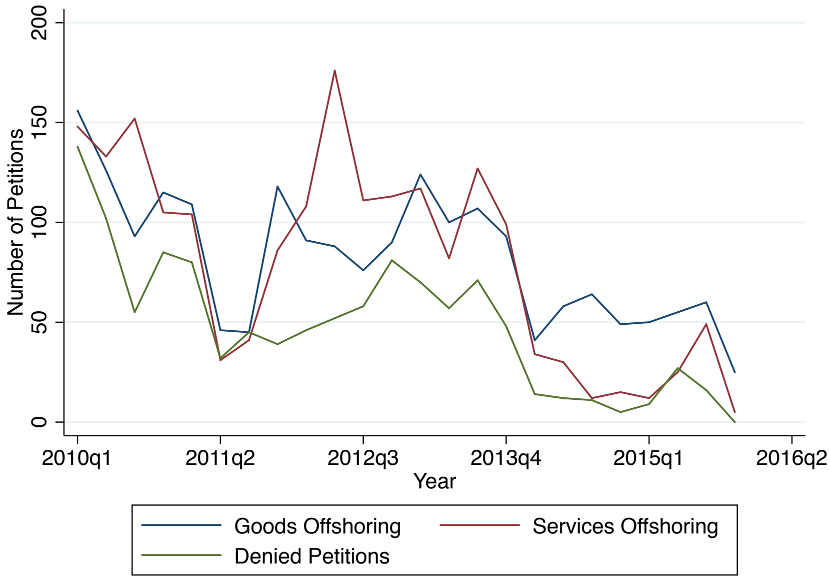
Uysal, Pinar, Yoto Yotov, and Thomas Zylkin, "Firm Heterogeneity and Trade-Induced Layoffs: An Empirical Investigation," School of Economics Working Paper Series 2014-6, LeBow College of Business, Drexel University 2015.

Voigtländer, Nico, "Skill Bias Magnified: Intersectoral Linkages and White-Collar Labor Demand in U.S. Manufacturing," *Review of Economics and Statistics*, 2013.

Yeaple, Stephen Ross, "Offshoring, Foreign Direct Investment, and the Structure of U.S. Trade," *Journal of the European Economic Association*, 04-05 2006, *4* (2-3), 602–611.

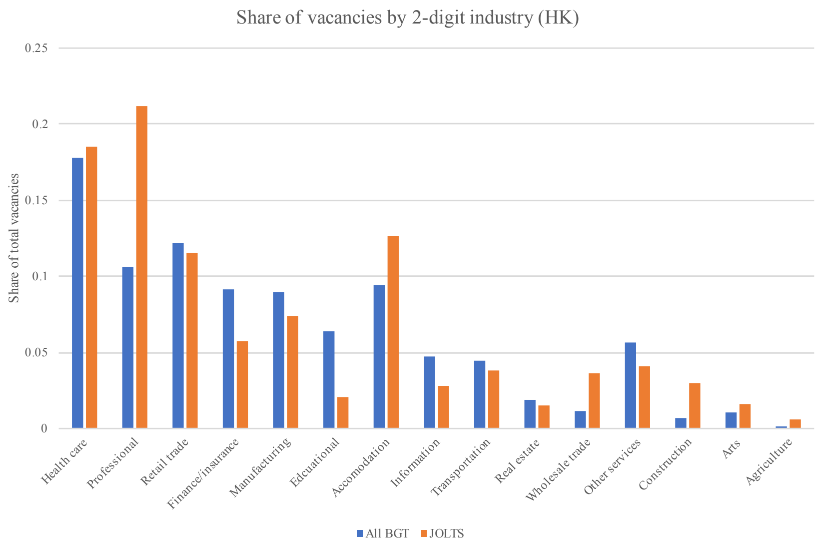
6 Figures

Figure 1: TAA Petition Filing Over Time



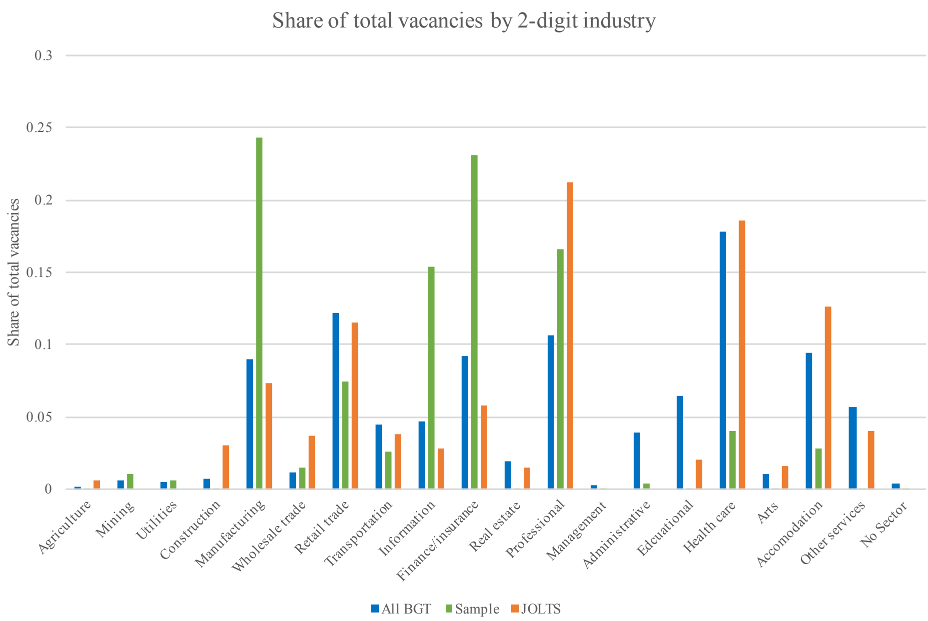
Notes:This figure plots total number of petitions filed and approved quarterly for both Materials and Service offshoring as well as the total number of denied petitions between 2010-2015.

Figure 2: BGT vs. JOLTS



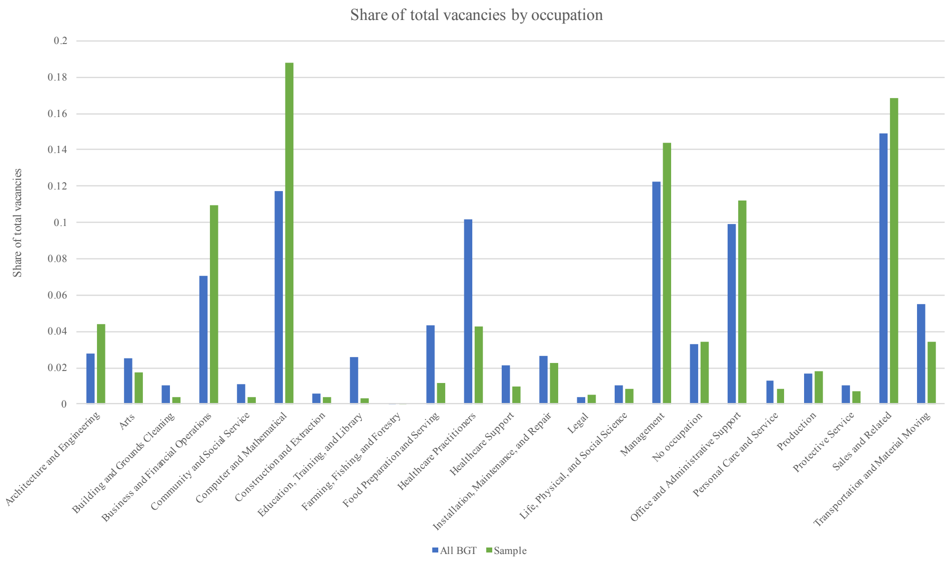
Notes: The above figure plots the share of total vacancies by industry for both the BGT and for JOLTS.

Figure 3: Full BGT vs. TAA/BGT sample across Industries



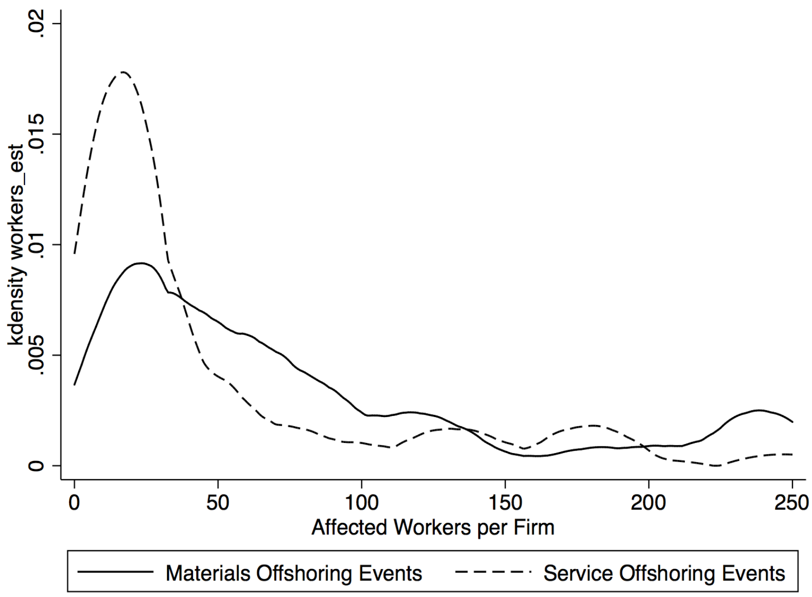
Notes: The above figure plots share of total vacancies across industries in the JOLTS, the full BGT and our sample.

Figure 4: Full BGT vs. TAA/BGT sample across Occupations



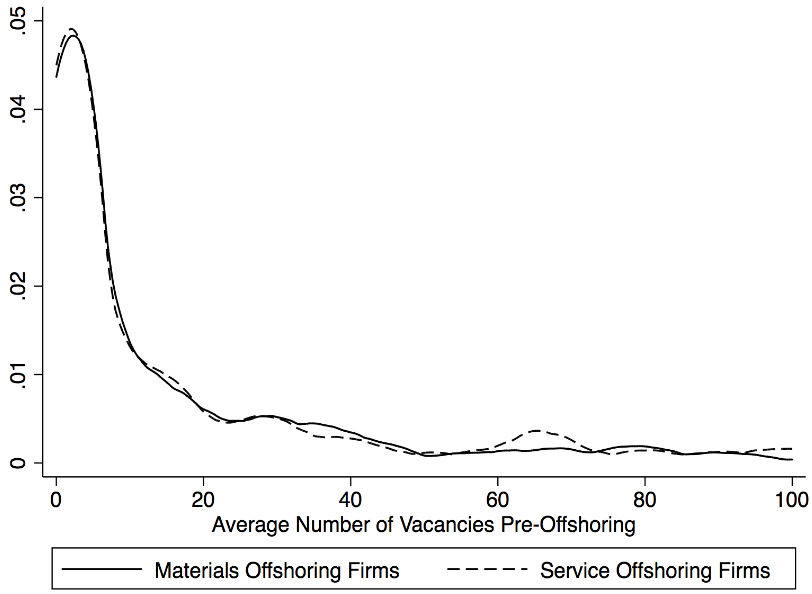
Notes: The above figure plots share of total vacancies across occupations in the JOLTS, the full BGT and our sample.

Figure 5: Distribution of Number of Affected Workers for Offshoring Firms



Notes:This figure plots total number of petitions filed and approved quarterly for both Materials and Service offshoring as well as the total number of denied petitions between 2010-2015.

Figure 6: Distribution of Workers per Average Number of Vacancies for Offshoring Firms

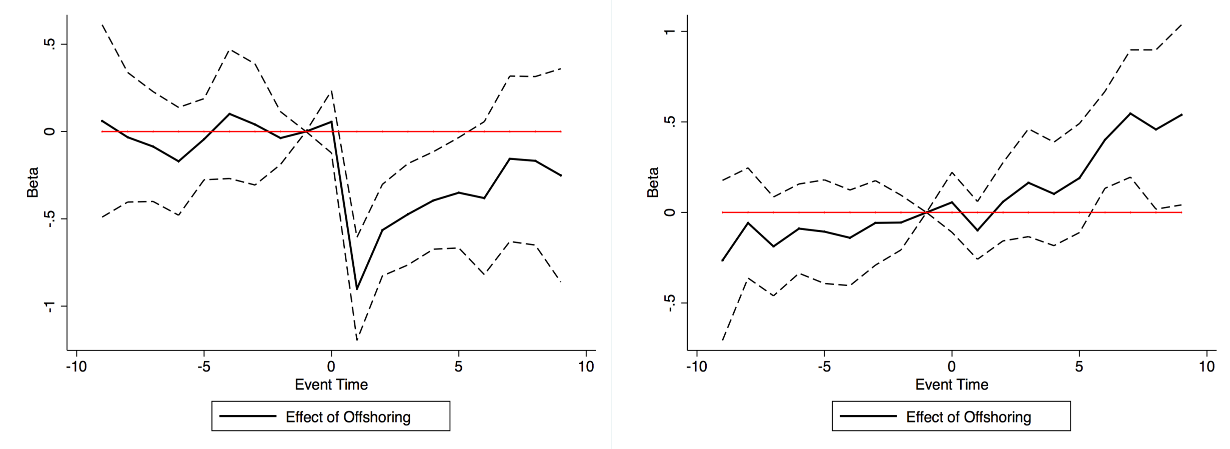


Notes:This figure plots total number of petitions filed and approved quarterly for both Materials and Service offshoring as well as the total number of denied petitions between 2010-2015.

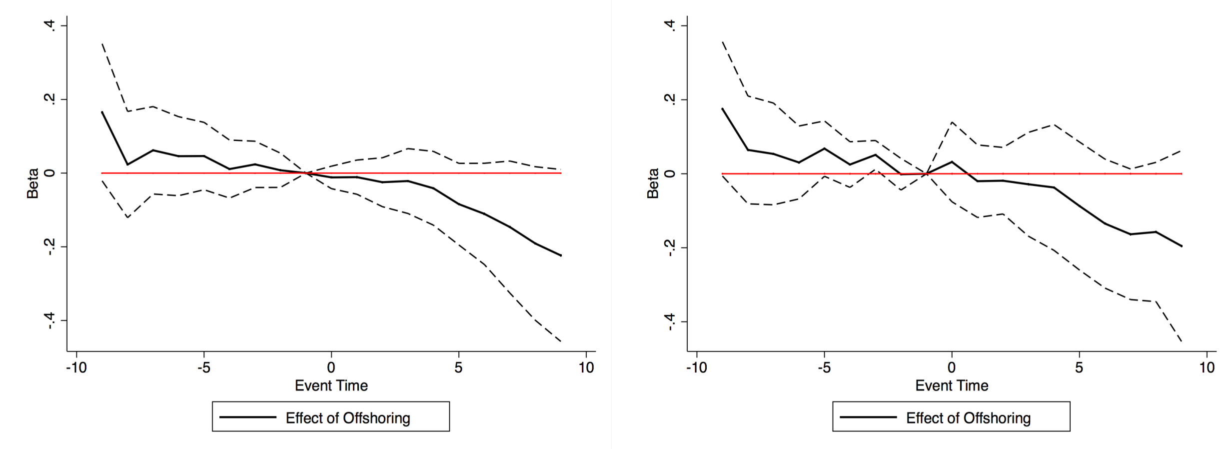
Figure 7: Effect of Offshoring on Establishment, Firm-level Vacancy and Number of Active Establishments

Materials	Service

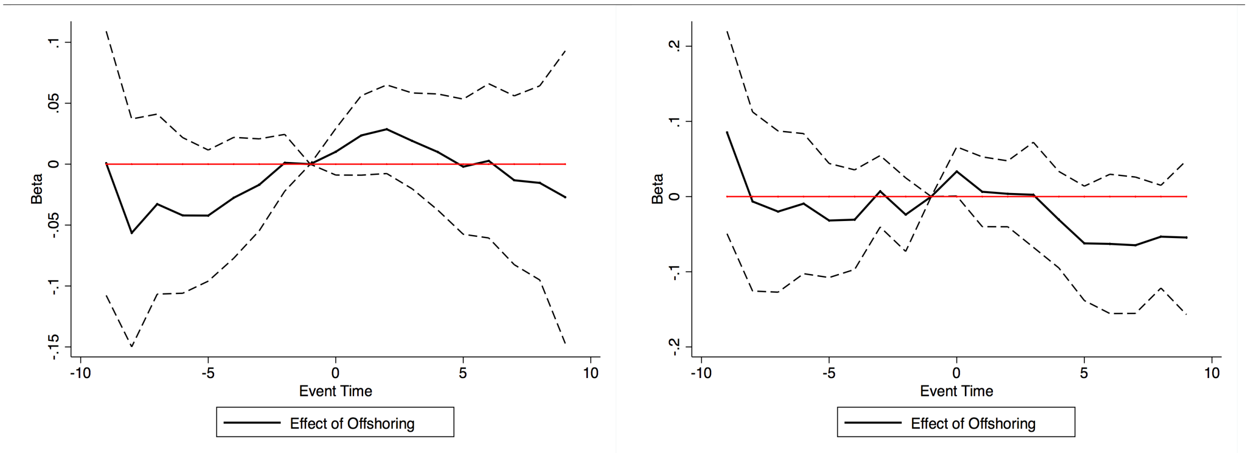
Panel A: Total Establishment Level Vacancies



Panel B: Total Firm Level Vacancies



Panel C: Establishments Per Firm



Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero. Event time is measured in quarters. Total vacancies at the establishment and firm-level are measured in levesl and our model is estimated as a Poisson. An in panel C an an establishment is considered active at time t if it posts a vacancy within 6 months after t.

7 Tables

Table 1: Defining Skill Categories Using Vacancy Posting Requirements

Skill Group	Skill	Requirements	Skill Measure Source
Hard	Cognitive	Research, analytics, math, statistics, data analysis	Based on DK (2016)
Hard	Critical Thinking	Problem solving, critical thinking, strategist thinkings	Our Measure
Hard	Writing	Writing	DK (2016)
Soft	Character	Organized, detail oriented, multi-tasking, time management, meeting deadlines, energetic, communication skills	DK (2016)
Soft	Customer Service	Customer, sales, client, patient, retail sales, up-selling	DK (2016)
Soft	Social	Communication, teamwork, collaboration, negotiation, presentation, listening	DK (2016)
Soft	Workforce Management	Supervisory, Leadership, management, mentoring, staff project manager	Based on DK (2016)
Specific	Automation Support	Robot, robotics, automation machine operation, machinery	Our Measure
Specific	Computer	Computer, spreadsheet, Microsoft, excel, powerpoint	DK (2016)
Specific	Financial	Budgeting, accounting, finance, cost, financial analysis, financial analysis, cost, financial analysis	Based on DK (2016)
Specific	Offshoring Support	Supply chain, logistics, inventory, international, import, export, material flow, materials management, purchase management, warehouse	Our Measure
Specific	Software	JAVA, SQL, Python, C++, CAD, LexisNexus, Visual Basic	DK (2016)

Notes: Most of our measures are based on categories developed by Deming and Kahn (2016), which in the above table are listed as sourced from DK (2016). For several of our measures we have revised their definition slightly, these measures are listed as "based on DK (2016)". For example, Deming and Kahn (2016) define Cognitive skills as requiring one of the following: Problem Solving, Research, Analytical, Critical Thinking, Math, Statistics. In order to define an additional skill we call Critical thinking we have updated our measure of Cognitive skills as described above. Workforce management is based on a combination of two measures proposed by Deming and Kahn, workforce management and Project management. Financial skills are based on Deming and Kahn's measure by the same name, which defined this still as requiring one of the following: budgeting, accounting, finance, or cost. Lastly, both Automation support and Offshoring support are measures created by us and are meant to capture skills which are complementary to trade and automation, two possible drivers of changes in skills demand.

Table 2: Effect of All Offshoring on Total Labor Demand OLS

	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
A: Total Offshoring					
β : *Post*	14.359	24.524	11.523	25.455	16.382
	(41.315)	(40.152)	(23.603)	(38.616)	(22.376)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	111.69	104.25	50.42	87.25	52.39
Reset p-val	0.03	0.04	0.27	0.06	0.06
Observations	19512	19512	19512	19512	19512
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
B: Materials Offshoring					
β : *Post*	-24.960	-25.421	-18.619	-27.164	-15.606
	(35.466)	(35.344)	(25.517)	(33.503)	(19.515)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	61.74	59.90	33.87	49.14	34.66
Reset p-val	0.01	0.01	0.03	0.02	0.01
Observations	12024	12024	12024	12024	12024
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
C: Service Offshoring					
β : *Post*	68.888	90.893	47.982	93.376	57.794
	(73.681)	(70.857)	(36.202)	(68.301)	(39.777)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	186.36	172.41	81.88	147.31	83.43
Reset p-val	0.04	0.05	0.06	0.06	0.06
Observations	9432	9432	9432	9432	9432

Notes: The dependent variable is the share of vacancy postings across the the occupational routineness distribution. The dependent variable in column 1 is the number of vacancies in occupation from the lowest quartile of routineness (i.e. the least routine occupatoins) as a share of all vacancies. The dependent variable in column 4 is the number of vacancies in occupation from the highest quartile of routineness (i.e. the most routine occupations). Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of All Offshoring on Total Labor Demand OLS (Treatment $Post \times W$)

	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
$\beta : Post \times Workers$	-4.048	1.860	0.824	-1.669	2.548
	(24.060)	(25.165)	(14.815)	(22.656)	(15.394)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	111.69	104.25	50.42	87.25	52.39
Reset p-val	0.07	0.02	0.01	0.01	0.01
Observations	19512	19512	19512	19512	19512
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
$\beta : Post \times Workers$	-1.060	13.097	14.731	-3.118	16.547
	(81.204)	(79.939)	(46.864)	(74.768)	(48.044)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	111.69	104.25	50.42	87.25	52.39
Reset p-val	0.00	0.13	0.01	0.01	0.05
Observations	19512	19512	19512	19512	19512
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
$\beta : Post \times Workers$	5.065	10.282	-6.319	10.138	4.518
	(18.698)	(22.043)	(8.889)	(21.403)	(11.424)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	111.69	104.25	50.42	87.25	52.39
Reset p-val	0.02	0.65	0.01	0.17	0.01
Observations	19512	19512	19512	19512	19512

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 4: Effect of All Offshoring on Hard Skills Demand OLS

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
$\beta : Post$	0.105*	0.052**	0.016
	(0.053)	(0.025)	(0.030)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.72	0.47	1.31
Reset p-val	0.80	0.34	0.00
Observations	12987	12987	12987
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
$\beta : Post$	0.009	0.009	-0.005
	(0.055)	(0.039)	(0.025)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.71	0.47	1.27
Reset p-val	0.20	0.23	0.50
Observations	6763	6763	6763
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
$\beta : Post$	0.082	0.035	0.009
	(0.071)	(0.036)	(0.037)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.73	0.47	1.36
Reset p-val	0.97	0.32	0.00
Observations	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 5: Effect of All Offshoring on Soft Skills Demand OLS

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
$\beta : Post$	0.287**	0.066	0.163***
	(0.113)	(0.045)	(0.061)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	2.32	0.73	2.87
Reset p-val	0.77	0.54	0.64
Observations	12987	12987	12987
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
$\beta : Post$	0.116	-0.015	0.195**
	(0.086)	(0.013)	(0.080)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	2.14	0.70	2.70
Reset p-val	0.26	0.41	0.06
Observations	6763	6763	6763
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
$\beta : Post$	0.357**	0.110*	0.104
	(0.159)	(0.066)	(0.086)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	2.51	0.77	3.04
Reset p-val	0.88	0.76	0.52
Observations	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 6: Effect of All Offshoring on Specific Demand OLS

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
$\beta : Post$	0.081	0.024	-0.006
	(0.065)	(0.016)	(0.071)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.45	0.56	2.29
Reset p-val	0.24	0.51	0.02
Observations	12987	12987	12987
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
$\beta : Post$	-0.043	-0.001	-0.074
	(0.057)	(0.020)	(0.048)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.52	0.59	2.30
Reset p-val	0.65	1.00	0.57
Observations	6763	6763	6763
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
$\beta : Post$	0.110	0.024	0.017
	(0.071)	(0.020)	(0.094)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.37	0.54	2.27
Reset p-val	0.35	0.54	0.02
Observations	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 7: Effect of All Offshoring on Hard Skills Demand OLS

	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Total Offshoring												
β : *Post* ($\leq$ 1 yr)	0.026				0.016*				-0.008			
	(0.022)				(0.009)				(0.018)			
β : *Post* ($\leq$ 2 yr)		0.049				0.022*				0.007		
		(0.031)				(0.013)				(0.016)		
β : *Post* ($\leq$ 3 yr)			0.058**				0.026**				0.015	
			(0.027)				(0.013)				(0.021)	
β : *Post* ($\leq$ 4 yr)				0.046				0.026*				-0.010
				(0.028)				(0.014)				(0.027)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	0.71	0.71	0.71	0.71	0.47	0.47	0.47	0.47	1.31	1.31	1.31	1.31
Reset p-val												
$SR = LR$												
Observations	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
B: Materials Offshoring												
β : *Post* ($\leq$ 1 yr)	0.012				0.014				-0.013			
	(0.020)				(0.014)				(0.011)			
β : *Post* ($\leq$ 2 yr)		0.019				0.016				-0.012		
		(0.029)				(0.021)				(0.010)		
β : *Post* ($\leq$ 3 yr)			0.033				0.022				0.000	
			(0.038)				(0.029)				(0.015)	
β : *Post* ($\leq$ 4 yr)				0.035				0.020				0.009
				(0.032)				(0.027)				(0.025)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	0.71	0.71	0.71	0.71	0.47	0.47	0.47	0.47	1.27	1.27	1.27	1.27
Reset p-val												
$SR = LR$												
Observations	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
C: Service Offshoring												
β : *Post* ($\leq$ 1 yr)	0.026				0.015				-0.015			
	(0.030)				(0.011)				(0.024)			
β : *Post* ($\leq$ 2 yr)		0.046				0.019				0.007		
		(0.040)				(0.019)				(0.018)		
β : *Post* ($\leq$ 3 yr)			0.056				0.022				0.016	
			(0.041)				(0.023)				(0.024)	
β : *Post* ($\leq$ 4 yr)				0.041				0.021				-0.018
				(0.039)				(0.022)				(0.032)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	0.73	0.73	0.73	0.73	0.47	0.47	0.47	0.47	1.36	1.36	1.36	1.36
Reset p-val												
$SR = LR$												
Observations	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 8: Effect of All Offshoring on Soft Skills Demand OLS

	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Total Offshoring												
β : *Post* ($\leq$ 1 yr)	0.081				0.025				0.026			
	(0.073)				(0.019)				(0.044)			
β : *Post* ($\leq$ 2 yr)		0.167***				0.028*				0.110**		
		(0.064)				(0.017)				(0.047)		
β : *Post* ($\leq$ 3 yr)			0.202**				0.047				0.106**	
			(0.080)				(0.035)				(0.041)	
β : *Post* ($\leq$ 4 yr)				0.161**				0.048				0.071*
				(0.081)				(0.036)				(0.037)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	2.30	2.30	2.30	2.30	0.73	0.73	0.73	0.73	2.85	2.85	2.85	2.85
Reset p-val												
$SR = LR$												
Observations	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
B: Materials Offshoring												
β : *Post* ($\leq$ 1 yr)	0.033				-0.006				0.080			
	(0.075)				(0.012)				(0.054)			
β : *Post* ($\leq$ 2 yr)		0.023				-0.008				0.072		
		(0.065)				(0.009)				(0.057)		
β : *Post* ($\leq$ 3 yr)			0.095*				-0.003				0.134***	
			(0.051)				(0.008)				(0.051)	
β : *Post* ($\leq$ 4 yr)				0.135***				-0.005				0.179***
				(0.051)				(0.009)				(0.059)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	2.14	2.14	2.14	2.14	0.70	0.70	0.70	0.70	2.70	2.70	2.70	2.70
Reset p-val												
$SR = LR$												
Observations	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
C: Service Offshoring												
β : *Post* ($\leq$ 1 yr)	0.093				0.043				-0.017			
	(0.101)				(0.028)				(0.060)			
β : *Post* ($\leq$ 2 yr)		0.201**				0.043*				0.099*		
		(0.082)				(0.024)				(0.060)		
β : *Post* ($\leq$ 3 yr)			0.236**				0.067				0.083	
			(0.109)				(0.046)				(0.067)	
β : *Post* ($\leq$ 4 yr)				0.198*				0.070				0.045
				(0.107)				(0.048)				(0.056)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	2.51	2.51	2.51	2.51	0.77	0.77	0.77	0.77	3.04	3.04	3.04	3.04
Reset p-val												
$SR = LR$												
Observations	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 9: Effect of All Offshoring on Specific Demand OLS

	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Total Offshoring												
β : *Post* ($\leq$ 1 yr)	-0.015				-0.003				-0.040			
	(0.033)				(0.009)				(0.036)			
β : *Post* ($\leq$ 2 yr)		0.037				0.008				0.015		
		(0.032)				(0.010)				(0.039)		
β : *Post* ($\leq$ 3 yr)			0.077**				0.022**				0.011	
			(0.038)				(0.010)				(0.055)	
β : *Post* ($\leq$ 4 yr)				0.052				0.018*				-0.018
				(0.037)				(0.010)				(0.049)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	1.44	1.44	1.44	1.44	0.56	0.56	0.56	0.56	2.28	2.28	2.28	2.28
Reset p-val												
$SR = LR$												
Observations	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987	12987
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
B: Materials Offshoring												
β : *Post* ($\leq$ 1 yr)	-0.032				-0.005				-0.043			
	(0.036)				(0.012)				(0.027)			
β : *Post* ($\leq$ 2 yr)		-0.022				0.001				-0.046*		
		(0.031)				(0.010)				(0.023)		
β : *Post* ($\leq$ 3 yr)			0.012				0.016				-0.043	
			(0.032)				(0.011)				(0.027)	
β : *Post* ($\leq$ 4 yr)				0.021				0.017				-0.029
				(0.036)				(0.012)				(0.040)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	1.52	1.52	1.52	1.52	0.59	0.59	0.59	0.59	2.30	2.30	2.30	2.30
Reset p-val												
$SR = LR$												
Observations	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763	6763
	Total: $\bar{S}^{tot}$				**Extensive Margin:** $\bar{S}^{ext}$				**Intensive Margin:** $\bar{S}^{int}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
C: Service Offshoring												
β : *Post* ($\leq$ 1 yr)	-0.005				-0.003				-0.038			
	(0.044)				(0.013)				(0.050)			
β : *Post* ($\leq$ 2 yr)		0.059*				0.009				0.043		
		(0.035)				(0.013)				(0.052)		
β : *Post* ($\leq$ 3 yr)			0.103***				0.024**				0.032	
			(0.038)				(0.011)				(0.072)	
β : *Post* ($\leq$ 4 yr)				0.068*				0.019				-0.018
				(0.040)				(0.012)				(0.062)
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X	X	X
Y mean	1.37	1.37	1.37	1.37	0.54	0.54	0.54	0.54	2.27	2.27	2.27	2.27
Reset p-val												
$SR = LR$												
Observations	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734	6734

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 10: Effect of All Offshoring on Total Labor Demand OLS, limiting post period to 38 months

	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
A: Total Offshoring					
$\beta : Post$	27.183	29.657	18.495	30.822	18.598
	(27.864)	(27.171)	(13.980)	(25.803)	(13.962)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	97.70	93.33	44.52	78.26	47.26
Reset p-val	0.04	0.05	0.04	0.06	0.05
Observations	16984	16984	16984	16984	16984
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
B: Materials Offshoring					
$\beta : Post$	10.942	10.323	4.298	5.824	3.445
	(7.864)	(7.713)	(4.688)	(6.122)	(4.090)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	43.26	41.72	22.61	32.89	24.56
Reset p-val	0.00	0.00	0.20	0.12	0.70
Observations	10544	10544	10544	10544	10544
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
C: Service Offshoring					
$\beta : Post$	64.887	70.801	43.221	75.068	46.805
	(62.734)	(61.321)	(31.168)	(58.595)	(32.779)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	165.56	157.67	73.89	134.92	77.04
Reset p-val	0.07	0.08	0.07	0.09	0.09
Observations	8167	8167	8167	8167	8167

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 11: Effect of All Offshoring on Hard Skills Demand OLS, limiting post period to 38 months

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
$\beta : Post$	0.111*	0.047**	0.049
	(0.058)	(0.022)	(0.038)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.72	0.47	1.31
Reset p-val	0.08	0.33	0.21
Observations	6345	6345	6345
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
$\beta : Post$	0.003	0.006	-0.010
	(0.020)	(0.012)	(0.019)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.68	0.46	1.22
Reset p-val	0.65	0.88	0.18
Observations	3514	3514	3514
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
$\beta : Post$	0.144**	0.060**	0.067
	(0.070)	(0.027)	(0.044)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	0.75	0.48	1.40
Reset p-val	0.01	0.25	0.08
Observations	2875	2875	2875

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Table 12: Effect of All Offshoring on Soft Skills Demand OLS, limiting post period to 38 months

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
β : *Post*	0.271*	0.063**	0.078
	(0.149)	(0.027)	(0.098)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	2.26	0.73	2.80
Reset p-val	0.25	0.65	0.01
Observations	6345	6345	6345
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
β : *Post*	0.017	0.000	-0.024
	(0.069)	(0.016)	(0.066)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.95	0.69	2.53
Reset p-val	0.90	0.91	0.65
Observations	3514	3514	3514
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
β : *Post*	0.352*	0.083**	0.109
	(0.179)	(0.032)	(0.117)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	2.55	0.77	3.07
Reset p-val	0.00	0.38	0.00
Observations	2875	2875	2875

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 13: Effect of All Offshoring on Specific Demand OLS, limiting post period to 38 months

	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
A: Total Offshoring			
β : *Post*	0.041	-0.006	0.048
	(0.071)	(0.022)	(0.049)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.50	0.57	2.33
Reset p-val	0.02	0.00	0.45
Observations	6345	6345	6345
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
B: Materials Offshoring			
β : *Post*	-0.097	-0.042	0.008
	(0.064)	(0.029)	(0.043)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.52	0.59	2.27
Reset p-val	0.31	0.06	0.31
Observations	3514	3514	3514
	$\bar{S}^{tot}$	$\bar{S}^{ext}$	$\bar{S}^{int}$
	(1)	(2)	(3)
C: Service Offshoring			
β : *Post*	0.084	0.002	0.080
	(0.080)	(0.026)	(0.063)
Time FE	X	X	X
Firm FE	X	X	X
County-Time Controls	X	X	X
Y mean	1.41	0.54	2.35
Reset p-val	0.02	0.00	0.53
Observations	2875	2875	2875

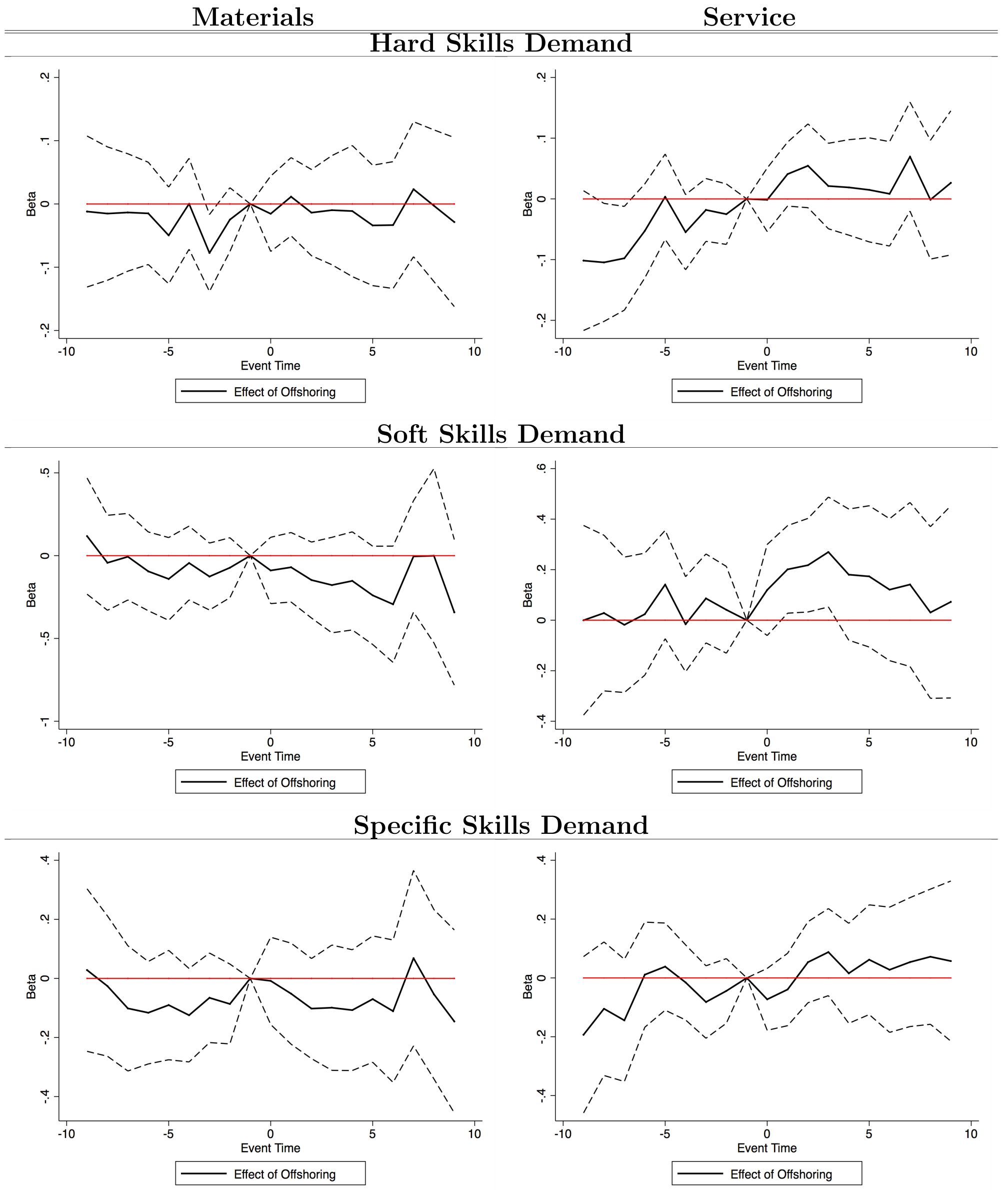
Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* p<0.10, ** p<0.05, *** p<0.01

Appendix

The following reports empirical results for alternative specifications as well as the underlying skill categories which compose our hard, soft and specific skill groups.

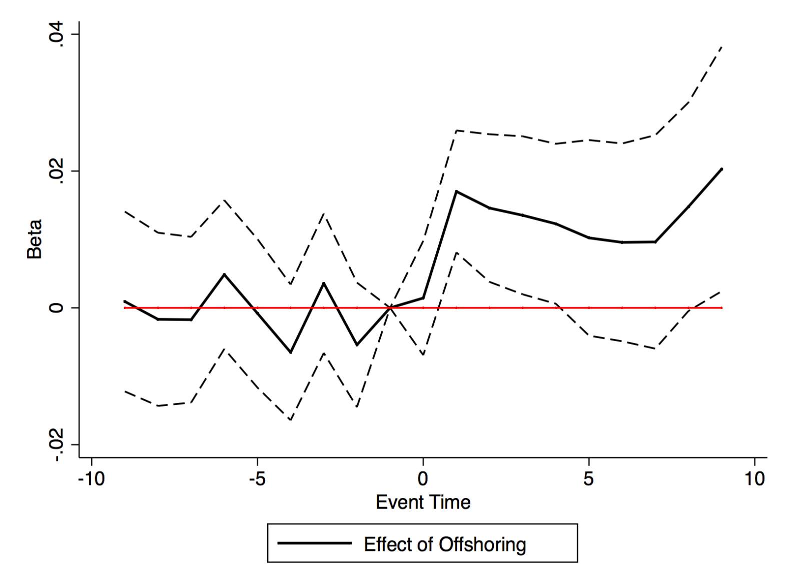
A Figurues

Figure A1: Effect of Offshoring on Skills Demand at Firm Level



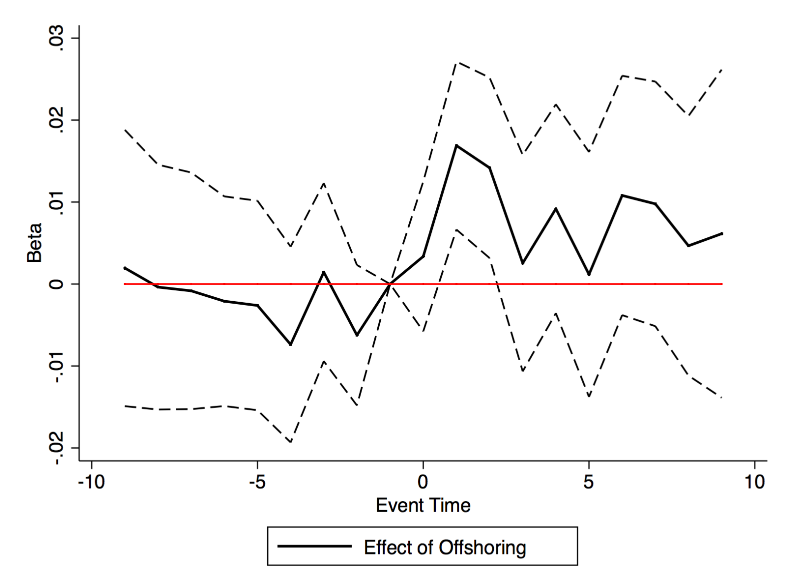
Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

Figure A2: Effect of Service Offshoring on Workforce Management Skill Intensity at Firm Level



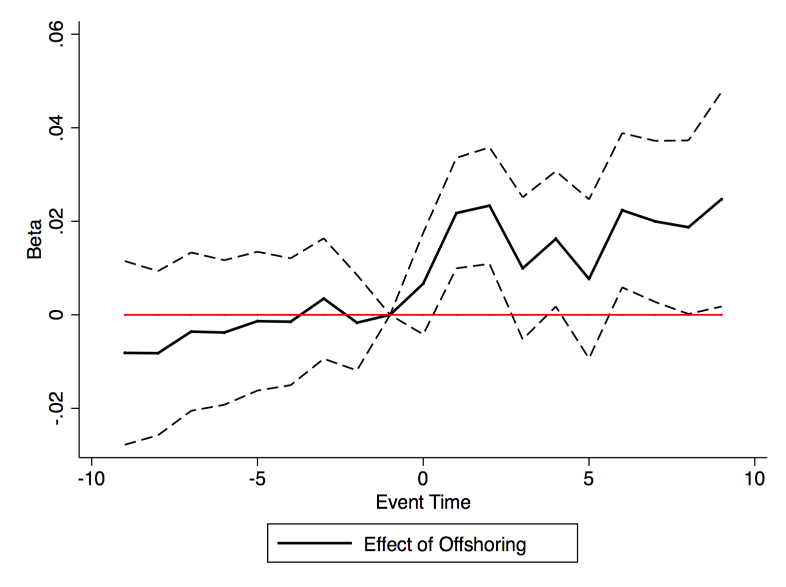
Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

Figure A3: Effect of Service Offshoring on Social Skill Intensity at Firm Level



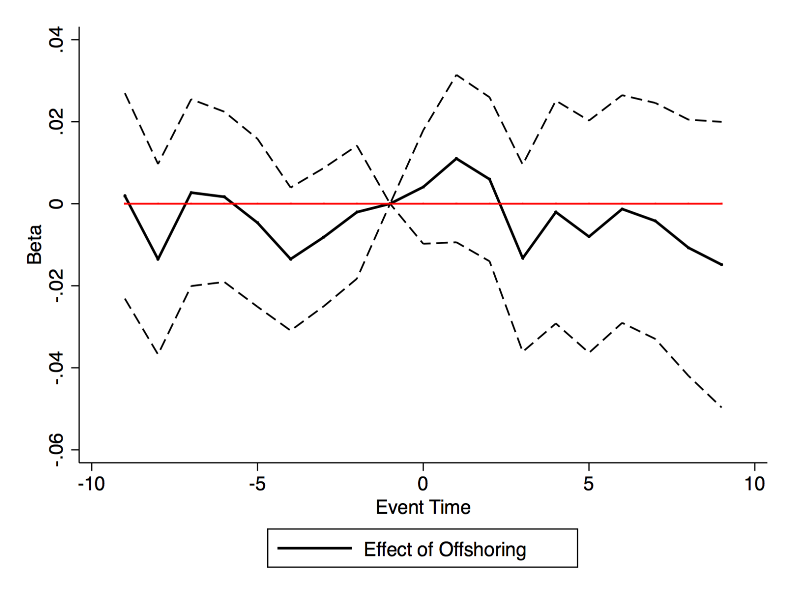
Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

Figure A4: Effect of Service Offshoring on Character Skills Intensity at Firm Level



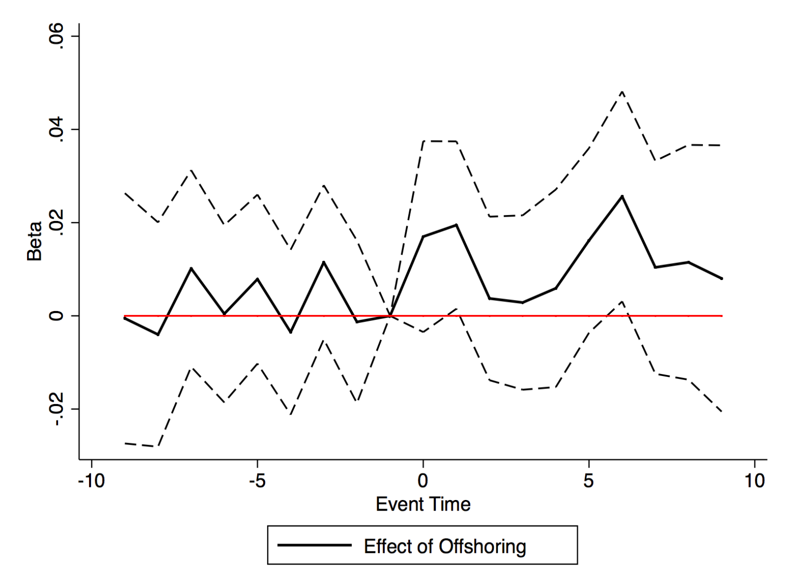
Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

Figure A5: Effect of Service Offshoring on Critical Thinking Skills Intensity at Firm Level



Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

Figure A6: Effect of Service Offshoring on Cognitive Skills Intensity at Firm Level



Notes: The above figure plots marginal effects for an event study regression where an offshoring petition is filed at time zero.

B Tables

Table A1: Effect of Offshoring on Skills Demand Poisson

	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
A: Total Offshoring					
$\beta : Post$	0.373	0.435	0.419	0.479	0.458
	(0.282)	(0.301)	(0.336)	(0.334)	(0.290)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	111.69	104.25	50.42	87.25	52.39
Reset p-val	0.50	0.53	0.45	0.43	0.22
Observations	19512	19512	19152	19368	19296
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
B: Materials Offshoring					
$\beta : Post$	0.223	0.170	0.042	-0.301	0.061
	(1.128)	(1.177)	(1.336)	(2.292)	(1.140)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	61.74	59.90	33.87	49.14	34.66
Reset p-val	0.42	0.33	0.75	0.31	0.25
Observations	12024	12024	11736	11952	11808
	Total	Any Skill	Hard	Soft	Specific
	(1)	(2)	(3)	(4)	(5)
B: Service Offshoring					
$\beta : Post$	1.088	1.135	1.302	1.383	1.358
	(0.975)	(1.019)	(0.969)	(0.996)	(0.956)
Time FE	X	X	X	X	X
Firm FE	X	X	X	X	X
County-Time Controls	X	X	X	X	X
Y mean	186.36	172.41	81.88	147.31	83.43
Reset p-val	0.75	0.50	0.73	0.56	0.70
Observations	9432	9432	9360	9360	9432

Notes: Petitions and vacancies are measured at the firm level. Standard errors are clustered at the firm level are reported in parenthesis.* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A2: Effect of Offshoring on Workforce Management Demand with various Measures of Treatment within the Affected Firm

	Materials					Service				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β : Post × Workers	-0.008*	-0.008				0.013**	0.012**			
	(0.005)	(0.005)				(0.005)	(0.005)			
β : Post			-0.031	-0.030				0.058**	0.057**	
			(0.027)	(0.028)				(0.024)	(0.024)	
β : Post × Count					-0.012					0.000
					(0.012)					(0.005)
Reset p-val	0.782	0.748	0.995	0.941	0.989	0.595	0.543	0.653	0.593	0.979
One Petition Firms		X		X			X		X	
Time FE	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X
Observations	26396	26036	28286	27926	28286	26396	26036	28286	27926	28286

Notes: The dependent variable is the share of vacancies that specify a requirement for the above skill. The measure of trade exposure in columns 1, 2 and 6 and 7 is 1 in the month of a petition being filed within a firm scaled by the number of displaced workers in columns 3, 4, 8 and 9 the treatment is a simple post indicator equal to 1 after the firm files a petition. In column 5 and 10 the treatment is a continuous measure of the number of petitions filed within a firm. Petitions and vacancies are measured at the establishment level. Standard errors are clustered by state and standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A3: Effect of Offshoring on Soft Skills Demand with various Measures of Treatment within the Affected Firm

	Materials					Service				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β : Post × Workers	-0.006	-0.006				0.011***	0.011***			
	(0.004)	(0.004)				(0.004)	(0.004)			
β : Post			-0.021	-0.019				0.051***	0.051***	
			(0.022)	(0.022)				(0.017)	(0.017)	
β : Post × Count					-0.007					0.001
					(0.009)					(0.003)
Reset p-val	0.576	0.595	0.339	0.360	0.276	0.761	0.788	0.552	0.578	0.300
One Petition Firms		X		X			X		X	
Time FE	X	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X	X
County-Time Controls	X	X	X	X	X	X	X	X	X	X
Observations	26438	26078	28328	27968	28328	26438	26078	28328	27968	28328

Notes: The dependent variable is the share of vacancies that specify a requirement for the above skill. The measure of trade exposure in columns 1, 2 and 6 and 7 is 1 in the month of a petition being filed within a firm scaled by the number of displaced workers in columns 3, 4, 8 and 9 the treatment is a simple post indicator equal to 1 after the firm files a petition. In column 5 and 10 the treatment is a continuous measure of the number of petitions filed within a firm. Petitions and vacancies are measured at the establishment level. Standard errors are clustered by state and standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01