OFFSHORING AND THE SHIFTING SKILL COMPOSITION OF THE IT WORKFORCE

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ABSTRACT

We use new offshoring data and new workforce micro-data with occupational classifications to investigate how an increase in the global supply of IT workers has affected the occupational composition of the US IT workforce. Our estimates suggest that when firms open offshore captive centers for IT employment, domestic IT employment skews towards occupations requiring more "personal" inputs, such as network administration, project management, or sales, and away from jobs such as computer programming in which work output can be easily transferred over computer networks. At firms with offshore captive centers, the fraction of domestic workers employed in occupations requiring little personal input fell by over 8% during the last decade, although mean employment levels for these occupations was steady in firms that were not offshoring. We discuss implications for workers, policy makers, educators, and managers.

Contact: tambe@stern.nyu.edu. Comments are welcome. We are grateful for valuable feedback from seminar participants at New York University and the INFORMS conference.

Introduction

Globalization has raised a number of labor market concerns for US policy makers. In this study, we investigate how offshore employment is affecting occupational demand within the US information technology (IT) workforce. Our interest in this question is motivated by concerns among the public, academic researchers, educators and policy makers about the effects of globalization on the US labor market. Although globalization is expected to impact workers in a wide variety of occupations, IT workers are a particularly interesting test case because they have so far been more impacted by offshoring than most other types of workers (Tambe & Hitt, 2009), and patterns observed in this population may be applicable in the future to other groups, such as financial analysts, who are beginning to face offshore competition (Deloitte, 2007).

We rely heavily in this analysis on the classification of different IT occupations by their "offshorability", based on a literature that argues that employees who produce services that can easily be delivered through computer networks are most vulnerable to offshoring (Apte & Mason, 1995; Jensen & Kletzer, 2005; Blinder, 2007). By contrast, employees who produce "high-touch" or "personally" delivered services are more costly to offshore because the delivery of these services (e.g. a haircut or a restaurant meal), is substantially degraded if delivered over a computer network. The goal of this study is to demonstrate an empirical link between offshoring and a shift towards a domestic IT workforce that produces more "personal" services.

Empirically, these shifts may be somewhat difficult to detect in data because unlike manufacturing, where industry level import figures are regularly collected, there is no definitive data source on service imports by category or on workforce composition.[1] Therefore, data on levels of imported IT services cannot be tied to changes in occupational employment at the industry level in a straightforward way. Even if imports data were available, there would still be significant challenges with using industry-level data. Aggregate levels of offshoring-related job volatility are likely to be small

[1] A report issued by the Government Accountability Office in 2004 was entitled "Current Government Data Provide Limited Insight Into Offshoring of Services" (Government Accountability Office, 2004)

compared to normal levels of job churn, and if displaced workers primarily move within sectors, these movements will be invisible in aggregate industry data. There is potentially significant value, therefore, in obtaining and analyzing new, fine-grained data through which to investigate how offshoring affects labor demand.

The principal contribution of this paper is that we bring two new data sources to this question, each of which addresses a limitation of prior empirical research on offshoring and labor demand. To measure IT offshoring levels, we use a new data set on the self-reported employment of a very large sample of offshore IT workers. This measure captures offshore IT employment through captive centers (i.e. foreign affiliates), rather than contracts executed with third party offshore contractors. However, our focus on multinational overseas employment is consistent with a prior literature on offshoring and domestic employment at the firm level (Brainard & Riker, 1997; Harrison, Mcmillan, & Null, 2007). Furthermore, 1) most of the current discussion about how offshoring affects labor demand has been focused on geography rather than organizational form, and 2) in other work we showed that captive center employment and third party outsourcing are highly correlated. The effects we observe using captive center measures, therefore, should be a good first-order representation of the effects of offshoring on domestic occupational employment in the IT sector.

Our second data source describes employers and occupations for a very large sample of the US IT workforce. These data are unique because they include both occupational data and employer identifiers. No other workforce data sets of which we are aware include both of these attributes. Access to employer identifiers allows us to connect these data to external data sets on economic variables and offshore employment. Furthermore, if occupational skill content rather than education or experience levels determine offshoring vulnerability, firm-level workforce databases that describe education or experience levels but not skill content may not be particularly useful. By aggregating the workers in our sample by firm, we can construct employer-level measures of the distribution of IT occupations, which provides a unique opportunity to analyze how IT offshoring is associated with labor demand at the firm level. Furthermore, beyond workforce composition, access to micro-data on the mobility patterns of the individual IT workers allows us to explore the dynamics of labor reorganization that lead to changes in workforce mix.

Our analysis is a relatively straightforward exploration of how IT offshoring is affecting the skill content of the domestic IT workforce. Our results indicate that the fraction of domestic IT workers involved in the production of services that can easily be transmitted over computer networks (e.g. computer programmers, data entry clerks, systems analysts and software engineers), dropped by about 8% at multinationals that opened captive centers in India in the 1990's. These effects are particularly notable because the fraction of workers producing these types of services was steady during the same period at firms without offshore captive centers, suggesting that the changes observed in offshoring firms were not due to secular trends in skill demand. These effects are observable in both cross-sections and in panel regressions and are robust to IV regressions and other tests we conduct to eliminate some potential sources of unobserved heterogeneity.

In terms of employment dynamics, we find that this reorganization primarily occurred through hiring changes in the five-year span after these centers were opened. Between 1995 and 2000, as firms opened captive centers abroad, they became less likely to hire domestic IT workers than their US counterparts. Our analysis suggests four key findings: 1) that offshoring firms are rebalancing their US-based IT workforces towards jobs requiring greater personal interaction, 2) that the adverse impact of offshoring on workers, thus far, has been somewhat tempered by a shift of workers from firms that offshore to those that have not, 3) that this reorganization appears to have occurred primarily through a change in the composition of new hires at offshoring firms over a five-year span, and 4) that there may be complementarities between offshored IT workers and US-based IT workers employed in occupations that are difficult to move offshore.

These findings have implications for policy makers, managers, IT workers, and educators. A potential employment shift of this magnitude calls for a reassessment of a wide array of government policies, directed at trade, social insurance, and worker retraining. However, these types of policy initiatives require evidence of the nature and scope of the shift, evidence that has so far been largely missing from the offshoring debate. Our paper is among the first to provide evidence for this type of employment shift. For managers, changes in the skill content of the domestic workforce may have important implications for workforce management. Finally, a shift in the skill basis for the IT workforce has clear implications for IT workers and for curriculum design. Offshoring levels are likely to continue to rise, so IT workers based in the US may want to choose to invest in skills with an eye towards how demand within the US is being impacted by offshoring, and educators and policy makers should adjust training programs to emphasize skills that will be in high-demand in the future.

In the next section, we describe the theoretical perspectives that we use to guide our analysis, as well as the limitations of existing empirical work. In Section 3, we describe the data and methods we use to investigate the effects of offshoring on workforce structure. Section 4 describes our results. The final section includes a discussion of our findings, and addresses their implications for workers, policy makers, and managers.

Framework

The term “offshoring” is generally used to describe either offshore “captive center” employment, in which multinational firms directly hire offshore workers, or “offshore outsourcing”, in which firms outsource work to third party vendors located offshore. These trends have attracted interest because they signal a dramatic increase in the size of the labor pool available to corporations, and therefore have the potential to significantly impact labor market outcomes for US workers. Although offshoring of various forms has been occurring for decades, services offshoring became relatively common only in the early to mid 1990’s. The boom in services offshoring was initially characterized by the establishment of captive centers abroad by multinational firms, because few third party offshore vendors had the capabilities to handle the complex requirements of multinational firms. However, as third party offshoring firms have continued to build their capabilities, corporations have shifted much of this captive center work to offshore vendors (Overby, 2009).

In this study, we focus on some of the labor market effects of captive center offshoring. However, in many respects, captive centers and third party offshoring, should have similar effects on US labor markets. Theoretical research on the potential domestic labor market effects of offshoring has placed emphasis on the geographic location of work, not on the organizational form. Theoretically, cost-minimizing employers offshore jobs for which net gains are positive, where gains can be estimated by comparing wage savings with the costs required to provide these services from a distance, such as possible degradation of service quality. When the costs of offshore delivery are sufficiently high, the net gains from moving a job offshore will be negative, even when the wage differential is substantial. Thus, the benefits from offshoring are increasing in domestic wages and the ease of remote delivery. Empirically, although data describing offshoring is relatively scarce, results from a 2007 survey indicate a very high correlation between captive center offshoring and third party offshoring at the firm level (Tambe & Hitt, 2009).

The concern about how offshoring might affect domestic labor markets has motivated studies that classify jobs into those that can be cost-effectively delivered remotely, such as call-center services and computer programming, and those that require rich personal interaction such as waitressing, nursing, or hairdressing, which would be relatively costly to send offshore (Apte & Mason, 1995; Bardhan & Kroll, 2003; Jensen & Kletzer, 2005; Blinder, 2007; Mithas & Whitaker, 2007). A number of criteria, such as the need for face-to-face customer communication or the need to work with an object in a particular fixed location, have been used to determine whether a job can reasonably be offshored. Applying these distinctions to the distribution of occupations in the US, researchers have generated a wide range of estimates of the number of US jobs that are potentially offshorable. For example, Blinder uses a subjectively derived index based on job task and content indicators from the O*Net database, and characterizes the vulnerability of jobs to offshoring depending on whether the services provided by that job must be "personally delivered". He estimates that 30-40% of US jobs are ultimately potentially vulnerable to offshoring (Blinder, 2007).

These predictions have attracted much interest, but to date, have received little empirical support. Evidence on services offshoring and labor demand remains scarce because of difficulties in obtaining reliable, fine-grained data describing services trade (Government Accountability Office, 2004). The predominant approach in the literature on offshoring and employment has been to relate levels of imports of goods and services to employment changes, at the country, firm, or industry level. Feenstra and Hanson used this approach for manufacturing imports in the 1990's, and found that materials imports were linked to an increase in the demand for non-production workers relative to production workers (Feenstra & Hanson, 1996, 1999). Some country level studies have associated foreign direct investment with an increase in domestic employment (Amiti & Wei, 2005; Desai, Foley, & Hines, 2005). Firm-level survey data available from the Bureau of Economic Analysis (BEA) has been used to show that the expansion of offshore employment substitutes for domestic jobs (Brainard & Riker, 2001; Riker & Brainard, 1997), and that these effects are moderated by whether offshore workers are employed in high-wage or low-wage countries (Harrison, McMillan, & Null, 2007).

These studies provide insights into the nature of the relationship between offshoring and aggregate employment levels, but are somewhat limited by the resolution of the available data. Offshoring levels are currently small compared to the normal movement of labor among firms, and when labor demand is high, employee flows among firms in the same industry may be lost entirely when examining industry data. For example, small changes in industry-level workforce composition may be masking significant heterogeneity in workforce composition across firms within the same industry. Most importantly, however, the data used in these studies do not identify workers' occupations or skill sets, which is critical if the impact of offshoring on the workforce is associated with skills rather than more traditionally collected data such as education. For example, although some offshoring studies have focused on changes in the relative demand for educated workers, Blinder reports that the correlation between the offshore index based on personal delivery that he creates and educational attainment in his data set is .08, which indicates 1) that offshorability is not closely correlated with education, and 2) to the extent that they are correlated, increased education is associated with more not less, risk of being offshored (Blinder, 2007). Thus, traditional data sources that describe education or experience may be insufficient to cleanly identify the effects of services offshoring on US workers.

Our data describe IT offshoring and employment at the firm level and allow us to overcome some of these limitations. Because both offshoring and employment decisions occur at the firm-level, data describing economic activity at these levels makes it easier to test hypotheses, and to capture within-industry shifts in workforce composition. Firm-level identifiers also allow us to control for other factors associated with offshoring levels. Furthermore, the combination of fine-grained occupation and human capital information available in the workforce data are useful because occupational skills may be correlated with other human capital variables. If these workforce attributes are omitted, correlations between skills and employment outcomes erroneously reflect the effects of other workforce characteristics.

We use the classification advanced by Blinder, categorizing IT workers in our sample according to whether they produce services requiring "personal delivery". Blinder's broad classification scheme for putting occupations into categories is visually described in Figure 1. The main criteria used to determine which jobs are most affected by offshoring are whether the job needs to be in a fixed work location, and whether that location needs to be located within the US. These attributes for each job are determined by examining the textual detail in the Department of Labor's O-NET database, which contains occupational information for over 950 occupational classifications. Beyond placing jobs into the four high-level categories shown in Figure 1, Blinder uses the details provided for each job to rank order the jobs according to offshorability on a scale from 1 to 100. A ranking towards the upper end of the spectrum, closer to 100, indicates that a job is more easily offshored, while a score towards the lower end of the spectrum indicates that a job is unlikely to be offshored. Examples of some occupations and the indices assigned to them by Blinder are shown in Table 1.[2] Within the IT workforce, programmers and systems analysts are more easily offshored, while IT sales personnel, managers, and network administrators are

[2] Category IV jobs are not ranked and are therefore omitted in this list.

less easily offshored. This theoretical framework predicts that offshoring will eventually increase the demand for network administrators and sales personnel relative to programmers and systems analysts.

This type of shift in relative demand has implications for the IT workforce. Over the last two decades, researchers have documented a steady shift away from the employment of IT workers who have only technical strengths, towards business facing professionals who are able to successfully interact with and interface with others across the organization. The changes in the demand for skills implied by theoretical offshoring research would suggest that this trend will continue. This shift in relative demand, however, has ambiguous implications for absolute demand levels in each of these categories. If offshore employment directly substitutes for domestic IT employment, offshoring would increase displacement levels or reduce hiring levels for some occupations. However, economic theory suggests that as the prices of some skills fall, complementarities between these and other skills raise the demand for other, less easily offshorable skills. Therefore, a shift in workforce composition towards more personal skills could also reflect rising demand for domestic jobs that require interpersonal skills. For instance, if sales positions for domestic markets are easier to fill locally, complementarities between programmers and software sales positions will create some new jobs domestically. The aggregate change in the number of jobs, therefore, will depend on the cross elasticities across different occupations and the numbers of workers required for each of these occupations. The net effects of offshoring on IT hiring and IT employment, therefore, are ultimately empirical questions.

Some preliminary evidence regarding broad changes in occupational demand levels can be found in the administrative occupational employment data, published annually by the Bureau of Labor Statistics (BLS). Table 2 shows Blinder's offshoring index for different computer occupations along-side employment shifts from 2001 to 2006. Aggregate employment in occupations with a high offshoring index appears to have fallen significantly, while employment in job categories associated either with hands-on analysis or personal interaction, such as database administrators, and network analysts, has risen. While this is consistent with the hypothesis that globalization raises the relative demand in occupations requiring personal interaction, evidence from aggregate employment data is not sufficient to identify these effects because other trends relating to new technologies, organizational change, and worker attributes may also be influencing aggregate employment numbers. In the next section, we describe new data that we use to more precisely address this question.

Data

IT Workforce Composition

We measure the distribution of IT occupations at the firm level through micro-data that describes the employment histories of a very large sample of US workers. The data were obtained through a research partnership with a leading online careers site, and for each employee in the data set, includes employer name, employment dates, and job title. We also have human capital variables for each worker, including education and experience. From these data, we extracted the approximately 500,000 workers who appeared in the data set between 1995 and 2006 and identified themselves as IT workers. Because these data indicate when employees enter and exit firms, we can use them to build annual measures of the occupational composition of a firm's IT workforce by aggregating employees to the firm level for each year.

A potential criticism of this data source is that selection bias is likely to be significant for workers who participate on an online careers web site. For example, "job-hoppers" are more likely to register on an online careers site than other types of workers. However, there are a number of reasons to believe that our estimates will be reasonably robust to selection issues. First, our large sample size mitigates the severity of many potential selection problems. Secondly, because IT workers are known to use online sites extensively, IT workers who post information online are less likely to differ from the "average" IT worker. Third, in our regression models, we control for education, time in the labor market, managerial experience, number of prior jobs, wages, and a variety of other human capital variables to adjust for differences among workers. Fourth, in our analysis, we perform sensitivity tests to ensure that our findings are not being driven by particular categories of workers. A final potential concern is that displaced IT workers may be over-represented in the data. However, if our hypotheses are correct, this will introduce a liberal bias into our estimates because departing programmers and systems analysts will appear to form a disproportionately large, not small, fraction of the workforce.

Summary statistics for these workers are reported in Column (1) of Table 3. Most workers have at least a four-year college degree, and average job tenure for a worker in our sample is slightly over five years. In column (2), we include comparable statistics, where available, for IT workers in the 2006 Current Population Survey (CPS), an administrative sample of workers randomly selected from the US population. There is a slightly higher concentration in our data set of workers with vocational training or a two-year degree, and a slightly lower concentration of workers with four-year college degrees. Otherwise, the educational distribution of workers in the CPS looks similar to the distribution in our data. Job tenure for the IT workers in the CPS sample is slightly lower than the average job tenure for workers in our sample, reflecting the tendency of the workers in our sample to be job hoppers.

Finally, in Table 4, we report correlations reproduced from earlier work that compare the number of IT workers in each firm in our sample with other sources of IT employment data, including ComputerWorld, InformationWeek, and MIT surveys (Tambe & Hitt, 2008). The correlations between these data sources and our firm-level IT employment figures are quite high, over .6 in the most recent surveys. Finally, in Table 5, we compare the occupational distribution of the IT workers in this data set against the occupational distribution reported in the Occupational Employment Survey (OES) for 2006. A comparison of these statistics indicates that our data set contains a larger number of computer support workers and a smaller number of computer programmers. However, Figure 2, which shows the 2000 distribution of "offshorability" across the IT workers in our data set, illustrates the considerable variation in this variable within the IT worker set.

Offshore IT Employment

Our offshoring measures are created from data obtained in late 2006 from a leading online database through which over ten million workers have posted employment information, including occupation, primary industry affiliation and geographic location, as well as information for each professional position that they have held, employer name, job title, years spent at the firm, and for public companies, a ticker symbol. This data set is particularly useful for investigating offshoring because it is international in scope and rich in IT workers. From this service, we obtained a random sample of about one million workers. These data include information for about 156,000 IT workers employed at about 7,500 US public firms. Of these IT workers, about 92,000 are located in the United States, with the remainder located offshore. The employers listed for these offshore IT employees provide information about the offshore IT employment activities of US firms.

These data provide a number of advantages over alternative potential data sources, such as surveys. Offshoring data collected from managerial responses may contain substantial response error if managers are hesitant to reveal information about offshoring activity, or because of the difficulty that managers face in accurately estimating the numbers of IT workers located in other establishments. Self reported data at the employee level raises some sampling concerns which we address below, but potentially contains less measurement error from other sources. Furthermore, in earlier work we show that offshoring can have very different implications for the US workforce depending upon the type of occupation being offshored or the specific offshoring location (Tambe & Hitt, 2009). For example, the domestic labor market effects of hiring sales staff in Europe may be very different than hiring technical workers in India. Therefore, the ability to narrow our sample to IT workers, specific offshore locations, and industries is useful for conducting fine-grained analyses that avoid the possible confounding effects of broader measures such as foreign direct investment or offshore employment aggregated across occupations.

To construct our IT offshoring measures, we focus specifically on IT workers in India, of which there are about 2,500 in our sample. We pay particular attention to offshoring in India because although firms may offshore for a number of reasons, the labor market substitution that has raised concerns in the public domain primarily occurs when firms offshore for lower costs or for access to skills, rather than when firms hire offshore employees to service overseas markets. For instance, a retail salesman hired in Australia to staff a US firm’s Austrialian stores, which technically counts as “offshore employment” for

US firms, is unlikely to affect domestic employment levels. Among offshore destinations, India appears to have the most significant share of cost or skills based IT offshoring by a substantial margin (Tambe & Hitt, 2009). In our recent survey, 76% of firms that offshore programming work offshore work to India, and cost savings or access to skills was the most common reason provided for sending offshore work to India. The second most popular destination for offshoring computer programming was China, at only 18%, and other countries were cited by less than 5% of the respondents. In the robustness section of our analysis below, however, we also test offshoring measures computed using offshore IT workers in other destinations.

Of the firms in the Compustat database, about 6.1% had at least one offshore IT worker in India in 2006. By comparison, our 2007 survey results indicated that about 6.2% of employers send IT jobs offshore to foreign affiliates, so the rate of offshoring to foreign affiliates is very similar in the two data sets. In Figure 3, we show how the fraction of firms with offshore captive centers has increased over time, from close to zero in the early 1980's to over 6% in 2006, with the steepest increases coming between 1995 and 2005. The red line indicates the fraction of IT workers employed by US firms in our data who are located offshore, which rises from zero to about 3% in 2006, which is consistent in magnitude with the findings produced by other research reports (Aspray, et al, 2006). In Figure 4, we compare the types of workers being offshored within the IT sector. Although technical workers were the last to be offshored, by the mid 1990's, they appear to have experienced the highest offshoring rates.

In Table 6, we explore the industry distribution of our offshoring measure. We compare the composition of offshore employment to data collected through a 2007 survey. In Columns 1 and 2, the distribution of offshore employees are categorized by 4 and 3 digit SIC industry. In Column 3, we compare the industry distribution from the survey data where the level of aggregation is somewhere in between a 3 and 4 digit SIC industry classification. A comparison of these columns suggests that the distribution appears to broadly track across the two data sources. Captive centers appear to be most common in technology industries, such as computer programming, business services, and semiconductor design, and in financial sectors, such as banking and insurance.

Within industry, however, the offshoring data raise some sampling concerns. If the online site from which these data were generated is more popular in some firms than in others, or with some groups than others, than the offshoring measures that we construct from these data will include some error. There is little theoretical guidance available on how online participation might differ among firms. However, it is reasonable to expect that biases among workers in India in the sample would also exist among US based employees that participate on the site. Therefore, we compare firm-level counts of the US based IT workers in the networking data with measures of US firm level IT employment from the job search data described above. The correlation coefficient between the two sets of measures is 0.57, and a Spearman test firmly rejects the hypothesis that the two measures are independent ($p<0.00$).

We believe, therefore, that these data are a reasonably good representation of captive center IT employment by US firms. Our survey data indicate that by 2007, third party offshoring was more common than captive center offshoring. However, this reflects a gradual change from the 1990's, when more offshoring activity occurred through captive center employment (Oshri, Kotlarsky, & Liew, 2008). More recently, however, firms struggling to justify the costs associated with captive center establishment have divested themselves of offshore captive center operations (Overby, 2009). Therefore, many firms engaged with offshore contractors once had captive centers -- the correlation between offshore outsourcing and captive center employment in our 2007 survey data is 0.47.

In the next section, we describe how we use these offshoring measures, along with the workforce composition variables and supplementary Compustat data to examine how offshoring has affected the composition of the US IT workforce.

Methods

Our primary models test how offshoring, measured through captive center IT employment, affects IT workforce composition. We classify workers according to whether they produce "personal" or "impersonal" services. To assign IT workers to one of these categories, we match self-reported job titles to standard occupational codes in the O*Net database[3] using third party software, and then use these codes to assign workers to an index of "offshorability" developed by Blinder, which ranks occupational codes according to their vulnerability to offshoring (Blinder, 2007). For most of our analysis, we categorize workers as producing "impersonal" services if they have an index value less than 92.[4] We choose this value based on anecdotes of what jobs are currently being offshored, but similar results are obtained when using a cutoff value of 70 or 85. Aggregating these workers to the firm level generates a variable describing the percentage of a firm's IT workforce that produces services requiring little personal input. We refer to this percentage as the "impersonal task intensity" of a firm's IT workforce.

We relate this workforce variable to the intensity of a firm's offshoring efforts. Offshoring intensity is measured as the fraction of a firm's IT workers located in India. Offshore IT employment measures are extracted from the captive center data described above--we extracted individuals from these data who list computer services or IT as their primary industry[5], are located in India, and are employed by public US firms. US firms are defined as those that have headquarters located in the United States, where headquarter locations are obtained from the Compustat Database. We also include *firm size*, measured as the log of the number of employees, which may influence offshoring propensity and internal labor market structure. We also include measures of IT employment levels (*IT*), because large IT departments may have different organizational structures. Both offshoring and employee turnover are also potentially influenced by firm health. Therefore, we include *percentage sales growth (PCTSALES)*, measured as the year-on-year difference in sales, normalized by total sales.

Finally, a key contribution of our study is that we also include IT workforce human capital measures such as *education (EDUC)*, *experience (EXP)*, and *job tenure (TENURE)* to ensure that our skill composition measure does not reflect correlations with other unobserved human capital. Our complete specification is:

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[3] http://online.onetcenter.org

[4] In our analysis, we discuss sensitivity to this cutoff.

[5] Specifically individuals who identify "Information Technology and Services", "Computer Software", "Internet", "Computer Networking", "Computer and Network Security", "Computer Hardware", "Telecommunications", or "Semiconductors" as their primary job affiliation.

(1) $IMP_{it} = O_{it} + EMP_{it} + IT_{it} + GROWTH_{it} + EDUC_{it} + EXP_{it} + TENURE_{it} + controls_{it} + u_{it}$

IMP_{it} is impersonal task intensity at firm *i* in year *t*. We also include controls for year and industry at the two-digit level to account for time and industry-specific trends. In several regressions, we include firm fixed-effects to eliminate biases potentially caused by unobserved firm heterogeneity. In our cross-sectional analyses, error terms will be correlated across firms, so we use Huber-White robust (clustered) standard errors for panel data models.

One concern with estimating (1) is that the coefficient estimates on our offshoring variable may reflect correlations with other unobserved organizational factors that are also associated with workforce mix. Therefore, we also present some results from a two-step estimator (2SLS), where we choose instruments that vary the relative "costs" of offshoring, but are unlikely to have a serious effect on IT workforce composition. Our first instrument is the number of *non-IT offshore workers* employed by a firm, and the second is *foreign income*. Firms with offshore financial analysts, for example, are more likely to offshore IT work because they have already incurred the fixed costs associated with opening an offshore center. Hiring financial analysts abroad, however, should have little impact on domestic IT workforce mix, other than through correlations with IT offshoring. Firms with higher levels of foreign income, conditional on size, have developed the capabilities to take advantage of offshore labor pools, and may already have the necessary infrastructure in place to establish offshore captive centers.

Descriptive Statistics

Table 7 shows statistics for the variables used in our firm-level analyses. In the average firm, 59% of IT workers are employed in the production of services requiring some personal interaction, such as sales support or network administration. This compares with about 51% of "Computer and Mathematical Science Occupation" workers in the 2006 Occupational Employment Survey who are employed in the production of services requiring some personal interaction. The higher fraction of workers of this type in our sample is probably because our sample includes a number of workers, such as computer and information systems managers and sales workers, who are classified in non-IT categories in the OES data. If computer and information systems managers are included in the OES data, the fraction of workers producing personal services rises to 53%. Including sales personnel would increase this fraction further, but sales for IT products and services are not separately classified in the OES data.

The average level of experience for workers in firms in our sample is 15 years, and most workers have at least four years of college education. Average tenure with the current employer is slightly over 5 years. The average firm in our sample is large, with about 19,000 employees and 5 billion dollars in sales. In Table 8, we report correlations between these and other firm-level variables.

Figure 5 is a graphical description of how the IT workforce has been changing in offshoring firms, relative to other firms. Workforce composition for these firms was similar in 1995, but begins to diverge thereafter. Workforce mix in non-offshoring firms is stable, but the fraction of workers producing services requiring little personal interaction drops by about 8% in offshoring firms before leveling off. In Table 9, we report statistics from these trends in 1992 and 2006. The fraction of workers producing impersonal services was steady in non-offshoring firms, but fell by almost 8% in offshoring firms, and a t-test firmly rejects the hypothesis that the mean difference between these two sets of firms is the same (t=-7.61). Figure 5 also shows that the workforce mix at both types of firms was similar in the early 1990's, suggesting that our results are probably not being driven by pre-existing factors that influence workforce mix and offshoring. In our regression results, we attempt to disentangle these stories further, and to more rigorously isolate the impact of offshoring on changes in IT workforce composition.

Regression Results

In Table 10, we use linear regression methods to test how offshoring levels are associated with changes in IT workforce mix. The dependent variable is the impersonal task intensity of the IT workforce. The primary independent variable in Column 1 is our offshoring measure, which is a dummy variable indicating whether or not a firm has a offshore captive IT labor pool, but we also include other firm-level variables such as total employment, IT employment, industry, sales growth, and workforce human capital measures such as education, experience, and average job tenure. The results shown in

Column (1) indicate that offshore hiring is associated with lower levels of impersonal task intensity in the domestic IT workforce. The point estimates from this regression indicate that after controlling for other factors, the difference in impersonal task intensity in offshoring and non-offshoring firms is about 3%. Similar results are observed in the fixed effect estimates shown in Column (2), but the point estimates are slightly lower, and indicate only a 1-2% difference in impersonal task intensity after controlling for other factors. In Column (3), we present the results of our IV regressions, where non-IT offshore workers and foreign income are used as instruments for the IT offshoring decision. These regression estimates indicate that the difference in impersonal task intensity between offshoring and non-offshoring firms is about 8% after controlling for other factors. In Columns (4) and (5), we use offshore intensity, rather than a dummy variable, as our primary independent variable. The point estimates in column (4) are negative and significant, and the magnitude of the estimate indicates that doubling the size of the existing offshore IT workforce would further decrease the impersonal task intensity of the domestic IT workforce by about 2%.

In Table 11, we present some sub-sample regressions. The effects observed in Table 10 appear to be particularly pronounced in software and financial industries, the industries in which offshoring intensity is generally the highest. Impersonal task intensity is about 6% lower in offshoring firms in the software industry, and about 3% in financial industries. In other industries, there is little correlation between offshoring and workforce composition, perhaps because offshoring levels in other industries may be too low to have a measurable impact. In Columns (4) and (5), we present results by firm size, where the set of firms in (4) are firms that have ever during this panel been in the Fortune 1000, and firms in Column (5) are all other firms. The effects observed in Table 10 appear to primarily be driven by the smaller class of firms, and there does not appear to be a measurable association between offshoring and impersonal task intensity in Fortune 1000 firms.

In Table 12, we present the results of some robustness tests, using some of the detail available in the offshoring data. In Column (1), we also include a second "offshoring" measure comprised of IT workers who are located offshore, in countries other than India. As described earlier, IT offshoring destinations other than India are more likely to be associated with geographic expansion and therefore should have less of an impact on the domestic labor market. The point estimate on our initial offshoring measure remains unchanged after controlling for IT offshoring in other locations. Furthermore, including the second offshoring measure in this model addresses some endogeneity concerns. In Column (2), we present results when the offshoring measure is divided by offshore IT worker type, where workers are classified as technical, managerial, or other, depending on their two digit occupational codes. The number of workers in each of these divisions is roughly the same, so our results are not driven by measurement error or sample size. The results indicate that this change in impersonal task intensity is solely driven by offshoring of technical workers, rather than workers of other types. The point estimate on the technical worker measure is similar to our initial estimated elasticity in Table 10, and indicates that doubling the size of the current captive offshore IT workforce lowers impersonal task intensity by about 2% in the domestic IT workforce.

Discussion

We use new microeconomic data to test how offshoring affects IT occupational composition in the US. The level of data aggregation in prior studies, along with the complexity of labor flows in multinational organizations, has made it difficult to directly relate aggregate changes in employment to foreign affiliate activity. Our results, using finer-grained data, provide support for the argument that offshoring reduces relative demand for workers who provide services that can be easily delivered through computer networks, and increases levels of hiring for other IT workers who produce services that are superior when delivered domestically.

We also find that most workforce reorganization appears to have been achieved through hiring patterns. Turnover rates do not appear to be systematically related to offshoring--offshoring firms adjust workforce composition by hiring offshore instead of domestically, leading to a net flow of IT workers with these skills from offshoring to non-offshoring firms. Although the proportion of the domestic IT workforce comprised of workers in offshorable occupations has been steady in non-offshoring firms over the last decade, it has dropped about 3% in offshoring firms over the same time period.

Our analysis suggests that any proposed policy interventions that are intended to reduce the adverse effects of offshoring, such as worker retraining or government compensation to offset wage losses associated with moving to new industries, could productively be focused on specific worker classes. For managers, a workforce shift of this type has a number of implications. Our results suggest that the types of IT jobs that remain in the US will have a greater component of tacit work, and may require more firm-specific capital. This has implications for IT retention rates, which has been an important issue for IT managers in the past. IT managers may be able to divert some of their domestic personnel resources from hiring and retention to job redesign and internal development. These changes may also have implications for human resource strategy. IT labor mobility has been identified as an important mechanism for knowledge transfer in environments where the technological frontier is rapidly shifting. If the jobs in which this knowledge is encapsulated are located offshore, these spillovers will be captured outside the US, and managers should therefore be cognizant of how the location of captive centers affects access to new technologies and methods.

These results are also a useful lens through which to examine educational policies. Our findings suggest that US-based IT workers in jobs requiring complex communication (e.g. persuasion, negotiation, teamwork) are less likely to be adversely affected by globalization trends than other workers. These findings are consistent with recommendations from education scholars who advocate shifting some emphasis in the US educational system to “softer” skills such as creativity and complex communication (Levy & Murnane, 1996). It also suggests that US-based IT workers may find it productive to add business and communication skills to an existing technical portfolio, as some have begun to do (Lohr, 2009).

Finally, there are a number of notable limitations to this research. First, our offshoring measures only include captive center employment. This is important if the types of IT workers firms hire through captive centers differ from the types of workers hired through third parties. However, the basic assertion, that jobs are easier to offshore if the service being produced can easily be delivered over computer networks, should hold true regardless of organizational form. Secondly, our results describe the labor market effects of captive center employment in the late 1990's. As technology and offshore capabilities evolve, US corporations may choose to offshore broader categories of IT work. Research relating offshoring to the structure of US employment is still in its infancy, and there are a number of topics that deserve further consideration. Our classification was motivated by existing theoretical research in this stream. However, as more detailed offshoring and workforce measures become available, it will be useful to develop a more fine-grained understanding of how offshoring of various types is affecting the organization of domestic work at a more detailed level.

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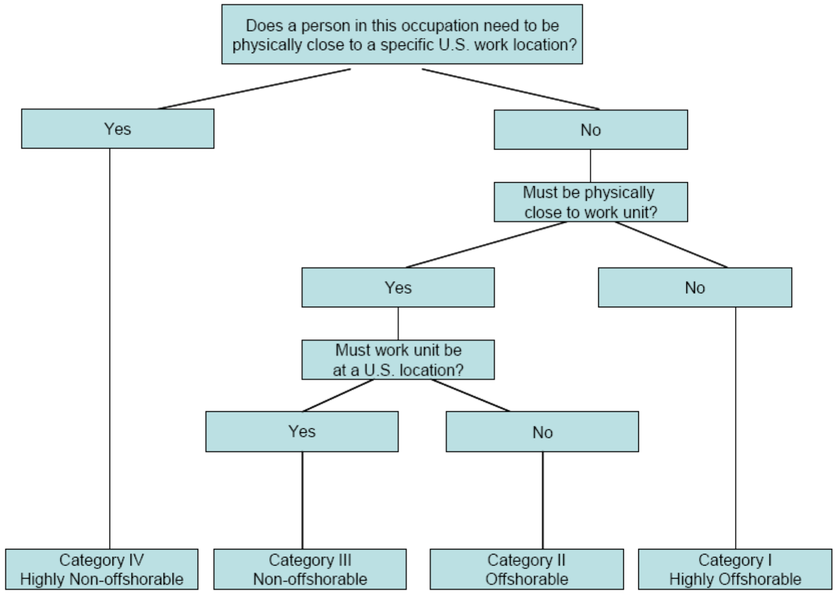
Figure 1
Broad Occupational Categories*



*Reproduced from Blinder (2007)

Table 1
Common Occupations and Impersonal Task Ratings[a]

Job Title	Offshorability Index
Computer Programmers	100
Data Entry Keyers	100
Computer Scientist, Research	96
Computer Systems Analyst	93
Computer Support Specialist	92
Graphic Designer	86
Database Administrator	75
Software Engineer	74
Hardware Engineer	73
General Managers	55
Marketing Managers	53
Financial Specialists	50
Systems Administrators	50
HR Managers	49
Sales Managers	26
Sales Agents	25

[a]Index Values reproduced from Blinder (2007), Minimum value is 25 and maximum value is 100. Occupations with values closer to 100 are predicted to be more easily offshorable.

Table 2
Change in U.S. Employment in Computer Related Jobs Between 2001 and 2006
BLS Statistics

Occupation	Impersonal Task Input	2001 Employment	2006 Employment	Percentage Change
Data Entry Keyers	100	405,000	295,650	-27.0
Computer Programmers	100	501,550	396,020	-21.0
Computer Systems Analysts	92	448,270	446,460	-0.40
Database Administrators	74	104,250	109,840	5.36
Network Administrators	50	126,060	203,710	61.60

Table 3
Summary Statistics for IT Worker Sample

Variable	IT Worker Sample	CPS, 2006
Total Worker-Year Observations	xxx	1,489
Education		
High School Degree or Less	24.7	25.1
Vocational Degree	2.8	.81
Two Year Degree	14.3	10.8
Four Year Degree	38.8	42.8
Graduate Degree	18.6	18.9
Doctorate	0.7	1.7
Job Tenure	5.18	6.33

Table 4
Comparison of Resume Based Measures with External IT Employment Measures*

	ComputerWorld[a]	**InformationWeek**[c]	**MIT**[c]
Years	**1988-1992**	**1994-1995**	**2001**
Geometric Mean			
External Sample	27.1	639.0	106.7
Matched Sample	376.2	399.4	96.5
Coefficient of Variation			
External Sample	.14	.01	.06
Matched Sample	.01	.01	.05
Correlations			
Correlation	.63	.46	.62
Corr. of Logs	.58	.54	.73
Spearman	.62	.29	.74
Firm size controls	.19	.48	.60
N	706	321	88

[a]Measured in millions of dollars of IT labor expenses.
[c]Measured in number of IT employees.
All correlations with multi-year samples include year dummies.
*Reproduced from Tambe & Hitt (2008)

Table 5
Comparison of Occupational Distribution in Sample of Domestic Workers with 2006 Occupational Employment Survey

Occupation	IT Worker Sample	OES
Computer & IS Managers	.11	.10
Computer Support Specialists	.30	.20
Systems Analysts & Programming	.38	.50
Network and Data Communications	.21	.20

Figure 2
Distribution of IT Occupations by Offshorability

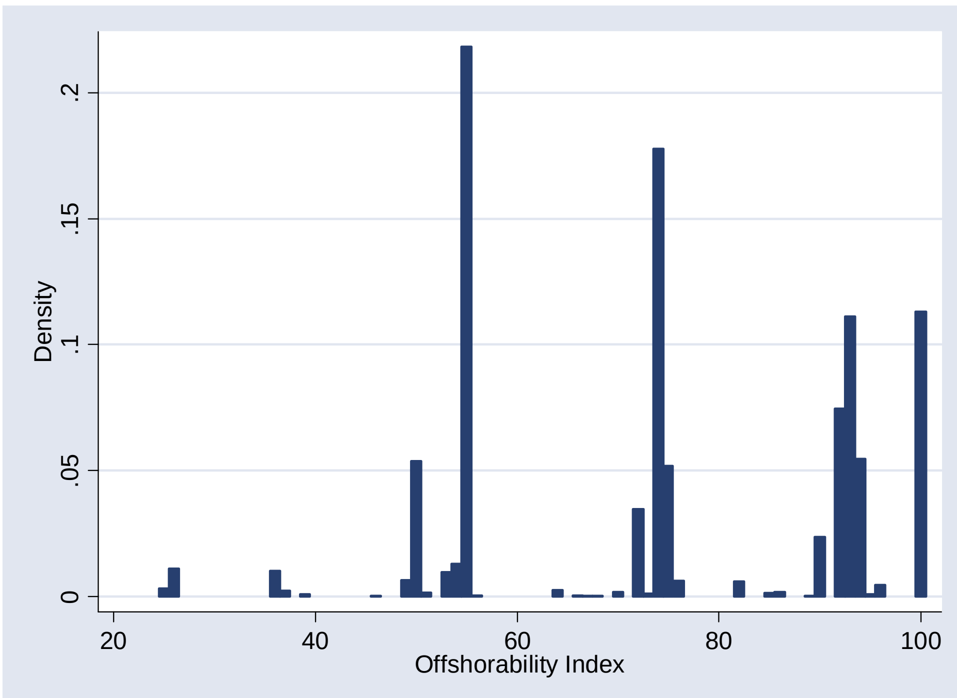


Figure 3
Rate of IT Offshoring through Captive Centers

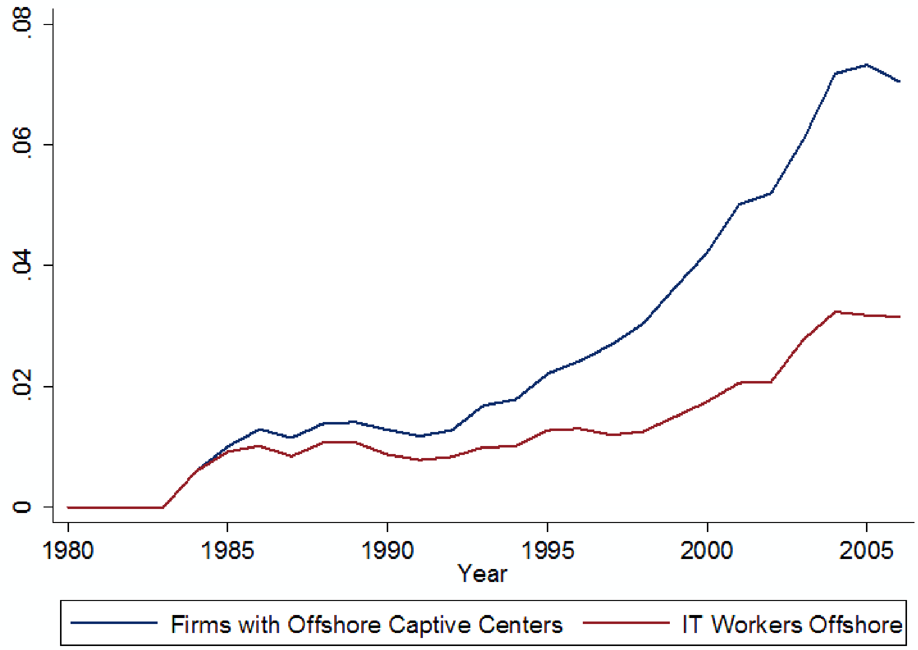


Figure 4
Types of IT Workers Offshore

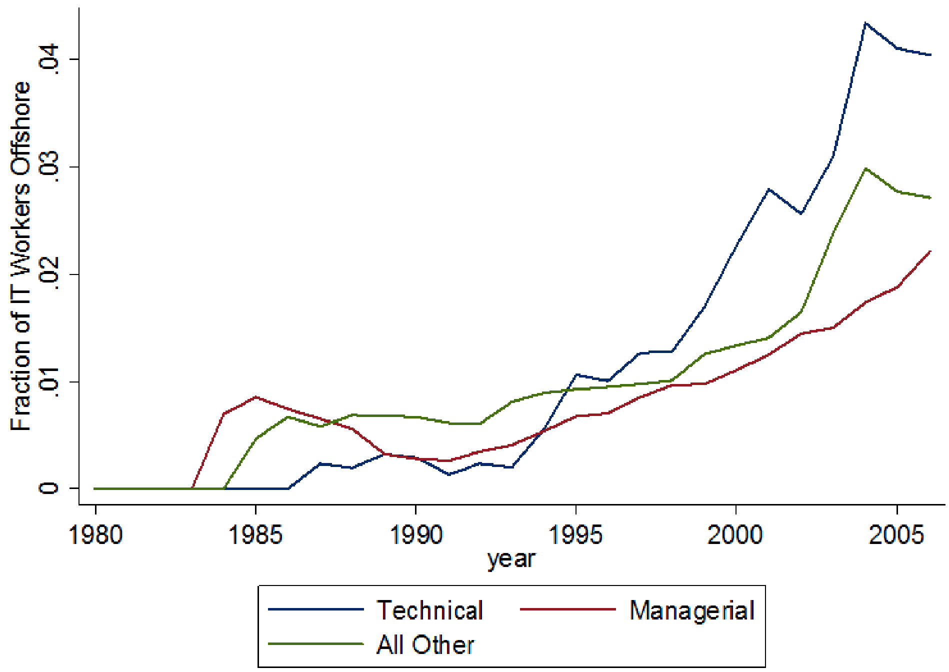


Table 6
Comparison of Offshoring Data With Offshoring Survey Data (Tambe & Hitt, 2009)

By 4 Digit SIC	%	By 3 Digit SIC	%	Survey Data*	%
Computer Programming	35.7	Management Services	20.0	Technology Services	29.4
Printed Circuit Boards	30.0	Misc. Business Services	18.8	Manufacturing	19.0
Advertising	30.0	Computer and Data Processing	16.7	Engineering Services	17.1
Other Business Svcs	37.2	Life Insurance	15.0	Telecommunications	16.3
Management Consulting	22.2	Advertising	14.3	Insurance	11.8
Electronic Computers	21.4	Motor Vehicles and Equipment	13.6	Banking & Finance	11.1
Computer System Design	18.9	Electronic Components	13.1	Oil	11.1
Prepackaged Software	17.0	Computer and Office Equipment	10.7	Advertising	9.8
Life Insurance	15.0	Security Brokers, Dealers	10.6	Travel	9.1
Data Processing	13.8	Investment Offices	10.0	Automotive	8.9
Semiconductors	13.5	Commercial Banks	10.0	Administrative Support	8.9

*Survey data was collected from the responses of over 3000 HR managers and is described in further detail in Tambe & Hitt, 2009. Reported percentages are managers who responded that they offshore work to foreign affiliates.

Table 7
Means and Standard Deviations for Firm-Level Variables (2006 Levels)

Variable	N	Mean	Std. Dev.	Offshoring mean	Non-Offshoring mean
Offshore Y/N	491	.073	.261	1	0
Impersonal Task Intensity	491	.37	.17	.30	.37
Experience (Years)	491	12.9	9.79	14.5	12.8
Education	491	4.24	.516	4.45	4.23
Job Tenure (Years)	491	3.12	1.17	2.94	3.14
Sales (x 1,000,000)	491	14223.9	31027.4	22471.5	13571.3
Employment (x 1,000)	491	45.7	111.2	54.9	45.0
IT Employment	491	301.5	543.7	955.1	249.8
Foreign Income	491	533.9	2879.0	1290.8	474.0

Table 8
Correlations for Variables Used in Firm-Level Analyses (2006 Levels)

	1	2	3	4	5	6	7	8
1. Offshore	1.00							
2. Impersonal Task Intensity	-.12	1.00						
3. Log(Experience)	-.01	-.06	1.00					
4. Education	.11	-.26	-.09	1.00				
5. Log(Tenure)	-.04	-.13	.27	.13	1.00			
6. Log(Employment)	.09	.10	.04	.05	.14	1.00		
7. Log(IT Employment)	.25	.10	.15	.02	.04	.52	1.00	
8. Log(Foreign Income)	.07	.02	.01	.02	.06	.18	.16	1.00

Figure 5
Impersonal Task Intensity in the Domestic IT Workforce, 1992-2006

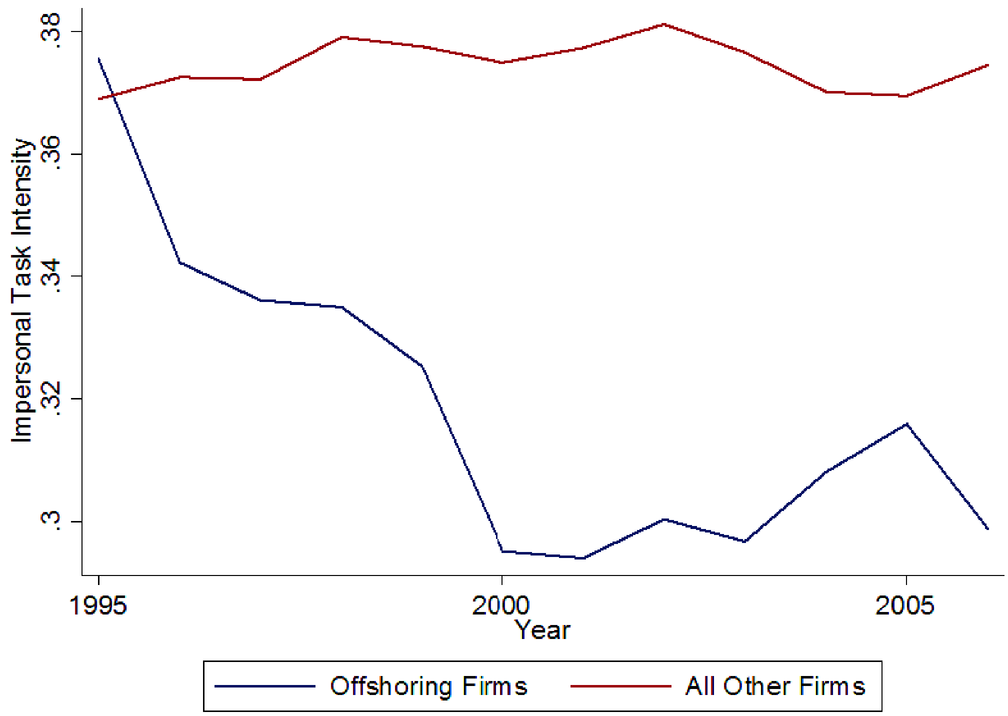


Table 9
Impersonal Task Intensity in the Domestic IT Workforce

	1995	**2006**	**Difference**
In firms that are Offshoring	.37	.29	**-.08**
In firms that are not Offshoring	.37	.37	**.00**
Difference			**-.08**
A t-test of the hypothesis that the difference between the mean differences is zero is rejected at the .01 level (t = -7.61)			

Table 10
Linear Regression Tests of Offshoring on Impersonal Task Intensity in the Domestic IT Workforce

DV: Impersonal Task Intensity	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	OLS	FE	2SLS	OLS	FE
	All	All	All		
Offshore (Y/N)	-.033	-.015	-.080		
	(.011)**	(.006)*	(.029)**		
Offshore Share				-.488	-.161
				(.174)**	(.114)
Log(Employment)	.008	-.003	.010	.008	-.003
	(.004)**	(.004)	(.004)**	(.004)*	(.004)
Log(IT Employment)	.007	.025	.009	.005	.026
	(.005)	(.006)**	(.006)	(.005)	(.006)**
Sales Growth	-.002	.001	-.001	-.002	.001
	(.000)**	(.002)	(.000)**	(.000)**	(.002)
Education	-.047	-.019	-.040	-.049	-.021
	(.008)**	(.004)**	(.008)**	(.008)**	(.004)**
Log(Experience)	-.036	.009	-.042	-.035	.009
	(.024)	(.007)	(.026)	(.025)	(.007)
Log(Job Tenure)	-.069	-.034	-.056	-.071	-.032
	(.016)**	(.010)**	(.016)**	(.016)**	(.010)
Controls	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	5193	5204	4816	5153	5153
R-squared	0.19	0.01	0.17	0.18	.03
Standard errors are robust, clustered on firm. *p<.10, **p<.05					

Table 11
OLS Subsample Regressions

DV: Impersonal Task Intensity	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Software Industries	Financial Industries	All Other Industries	F-1000 Firms	All Other Firms
Offshore Y/N	-.057	-.041	-.012	-.017	-.070
	(.020)**	(.020)*	(.017)	(.017)	(.024)
N	1378	843	2983	2553	2600
R^2	0.21	0.17	0.19	0.22	.26
Standard errors are robust, clustered on firm. *p<.10, **p<.05. Regressions are from baseline model used in Table 10, Column 1.					

Table 12
Regressions by Offshore Worker Composition

DV: Impersonal Task Intensity			
By Location		**By IT Worker Type**	
India	-.490	Technical	-.518
	(.174)**		(.190)**
All Other	.005	Managerial	-.355
	(.018)		(.329)
		All Other	-.312
			(.256)
R^2	0.19		0.19
Standard errors are robust, clustered on firm. *p<.10, **p<.05. Regressions are from baseline model used in Table 10, Column 1.			