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Now I.T.'s "Personal": Offshoring and the Shifting Skill Composition of the US Information Technology Workforce

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Completed Research Paper

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Abstract

We combine new offshoring and IT workforce micro-data to investigate how an increase in the offshore supply of IT workers has affected the composition of the US IT workforce. We find that at firms with offshore captive IT centers, the relative demand for onshore IT workers in occupations involving tasks that can be traded over computer networks, such as those requiring little personal communication or hands-on interaction with US-based objects, fell by about 8% over the last decade. By comparison, relative demand for workers in those occupations rose by about 3% in firms that were not offshoring. Our second finding is that hourly IT workers are more likely than full-time workers to be employed in occupations requiring tradable tasks, and that the relative demand for hourly IT workers is about 2-3% lower in offshoring firms. We discuss the implications of our findings for IT workers, policy makers, educators, and managers.

Keywords: offshoring, IT workforce, IT labor markets

Introduction

The impact of globalization on US labor markets continues to be an area of academic interest. In this paper, we investigate how offshore employment has affected the occupation and skill composition of the US information technology (IT) workforce. To organize and frame this analysis, we rely on the classification of different occupations based on a theoretical literature that argues that jobs which primarily involve "tradable" tasks--those that can easily be delivered through computer networks--are highly vulnerable to offshoring-related displacement (Apte and Mason 1995, Jensen and Kletzer 2005, Blinder 2007, Mithas and Whitaker 2007). In contrast, tasks that require "high-touch" or "personally" delivered services (e.g. retail sales) face less offshore competition because the delivery of these services is substantially degraded if delivered over computer networks. The purpose of this study is to empirically link IT offshoring with a shift towards an onshore IT workforce that performs fewer tradable tasks, and correspondingly more personal or interactive tasks.

Task-level employment shifts such as these have been difficult to detect empirically because unlike in manufacturing sectors, where industry level import figures are regularly collected, there are no definitive US data sources on service imports by category[1], and little available data describing changes in IT workforce composition. The principal contribution of the paper is that we introduce new data sources through which we develop 1) firm-level measures of IT offshoring and 2) firm-level measures of changes in onshore IT occupational and task mix. To measure IT offshoring levels, we use self-reported employment data from a very large sample of offshore IT workers employed in captive centers. This unit of analysis, captive center employment, is the same used in existing

[1]For example, 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).

studies of how globalization affects employment (Brainard and Riker 1997, Harrison et al. 2007, Desai et al. 2005), but the occupation and geographic level of detail in our offshoring data allows us to test task-level hypotheses at a higher level of detail. Prior research has shown that the domestic labor market effects of offshoring can vary depending on offshore location (Harrison et al. 2007), so the ability to look at specific locations is useful.

However, these data would be of little use unless they could be connected to changes in domestic IT workforce mix. Our second data source describes employers and occupations for about 15% of the US IT workforce. To the best of our knowledge, these are some of the only US-based workforce data that include both occupations and employer identifiers.[2] By aggregating workers by employer, we can construct firm-level measures of the distribution of IT occupations within the firm, which in conjunction with other human capital variables, provides an opportunity to observe changes in IT occupational composition at the firm level. As described above, we classify occupations within the firm according to how tradable the underlying tasks are in order to analyze firm-level task shifts (Blinder 2007). We choose this approach because offshoring arguably involves trading of tasks rather than finished goods (Grossman and Rossi-Hansberg 2008). Thus, the effects of offshoring are more likely to be seen in changes in task composition, rather than in human capital variables such as education and experience.

This paper, therefore, contributes primarily to a literature on how globalization affects the IT workforce. There has been significant academic interest in factors that influence the demand for different skills within the IT workforce (Lee, Trauth, & Farwell, 1995, Slaughter et al. 2002, Mithas and Krishnan, 2008, Levina and Xin 2008). Existing studies have focused on the human capital and institutional determinants of IT worker supply and demand, but scholars and industry groups have more recently emphasized the need to understand how globalization affects IT workers (Aspray et al. 2004). One of the primary themes in this literature, as well as a reason for the lack of existing evidence on this topic, has been the need for new data collection because existing data sources are insufficient to answer questions about globalization and labor markets (Government Accountability Office 2004). Our study, therefore, is among the first to examine how globalization is affecting IT workforce skills an economy-wide level.

Our regression results indicate that the fraction of domestic IT workers involved in performing tasks where the output can be delivered over computer networks (e.g. computer programmers, data entry clerks, systems analysts and software engineers), fell by about 8% at multinationals operating captive IT centers in India. Firms without offshore IT captive centers increased the share of workers in these occupations by 3% during the same time period, suggesting that the changes observed in offshoring firms were not due to economy-wide trends in IT hiring. These results are robust to controls for workforce and firm performance variables and persist in analyses that address the issue of reverse causality. We also provide evidence that offshoring reduces employers' use of hourly IT employees such as contractors and part-time workers, who are disproportionately employed in the production of tasks that can be delivered over electronic networks. Relative demand for hourly IT workers is about 2-3% lower in offshoring firms than in other firms. Our results, therefore, suggest that: 1) that firms that offshore IT services are readjusting their US-based IT workforces towards occupations requiring greater personal interaction, and 2) that hourly IT workers are disproportionately affected. In the next section, we describe the theoretical perspectives we use to guide our analysis.

Background

Theoretical explorations of how offshoring affects the US labor market have focused on identifying which job characteristics make them most easily tradable over computer networks. Jobs involving tasks that can be cost-effectively *delivered remotely*, such as call-center services and computer programming, are most likely to be moved offshore (Apte and Mason 1995, Bardhan and Kroll 2003, Jensen and Kletzer 2005). At the task level, Blinder classifies non-tradable tasks as those requiring "personal" inputs, including tasks that 1) require extensive interpersonal communication with customers or other workers who must be located in the US, or 2) tasks that require interaction with an object that must remain in the US (2007). According to Blinder's classification,

[2]The difficulty in obtaining human capital measures for US firms has been a notable limitation for researchers examining the relationships between technology and labor. Most workforce data have been obtained through large survey efforts (e.g. see Black and Lynch (2001). Survey efforts have the disadvantage that they are cross-sectional, and it is generally difficult to obtain accurate responses about occupational distributions in very large firms. The Longitudinal Employer Household Dynamics (LEHD) data are a rich resource that include human capital variables (Abowd et al. 2004), but they generally do not include occupation, and are difficult to obtain with firm identifiers, both of which are critical for our study.

computer programmers and software engineers are among the most offshorable occupations because the output of tasks involved in software production can be delivered from remote locations. Software programmers do not need to be located close to consumers to provide a good product, and they do not need to work with machines or capital that must be located in the US. By contrast, the effective delivery of other services, such as network administration or technical sales, requires the producer to be located close to consumers.

This does not imply that tradable tasks do not require interpersonal skills. For example, a significant interpersonal component is required in modern software production because of the extensive teamwork required for large-scale software projects. However, some of this work is potentially offshorable because entire teams, or group of tasks, can be moved offshore. Therefore, even within the IT workforce, there is significant variation in the underlying tradability of the tasks required for different jobs. To the extent that network administrators need to be close to the US-based machines and equipment they maintain, they face less offshore competition. Similarly, client-facing positions and some personnel managers may be difficult to move offshore.

This employment shift has potentially significant implications for the IT workforce. An existing literature on the evolution of IT workforce skills has documented an ongoing shift away from the employment of primarily technical IT employees. Studies using interviews with various IS stakeholders have emphasized the increasing importance of business and interpersonal skills relative to technical skills (Leitheiser 1992, Lee, Trauth, & Farwell, 1995). This shift has emerged because of the emphasis on activities like process reengineering and integration, and because the increasing decentralization of IT activities within the firm has required IT workers to be capable of interfacing with other business stakeholders. Similar shifts have been documented using wage data (Mithas and Krishnan 2008) as well as changes in the skills that appear in classified advertisements for IT jobs (Gallivan et al. 2004). Some of these studies have concluded that IS curricula should be adjusted in response to these changes in skill demand by encouraging the development of both technical and interpersonal skills (Noll and Wilkens 1992). Changes in occupational demand predicted by theoretical offshoring research suggest that this trend towards the increasing importance of interpersonal and business skills in the IT workforce will continue.

The aim of this study is to use new data to address the role of IT offshoring in shaping these trends. We rely on Blinder's theoretical framework. In Blinder's analysis, he rank orders jobs on a scale from 1 to 100, using task level detail from the Department of Labor's O-NET database, which describes the task content of over 950 occupational classifications. A higher score, closer to 100, indicates that a job consists mostly of tradable tasks and is therefore more easily offshored, while a score closer to 0 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.[3] Within the IT workforce, programmers and systems analysts are more easily offshored, while IT sales personnel, managers, and network administrators are less easily offshored. This taxonomy predicts that offshoring will increase the onshore demand for network administrators and sales personnel relative to programmers and systems analysts. Our first hypothesis is:

H1: A lower percentage of domestic IT workers will be employed in jobs comprised of "tradable" tasks at firms that offshore IT workers.

This type of employment shift may also have implications for the use of contractors and part-time workers, who have attracted academic interest because of the use of employment outsourcing for high-skilled, technical work in the IT sector (Gurbaxani 1996, Slaughter and Ang 1996, Barley and Kunda 2004). Hourly workers, a category that includes both contractors and part-time workers (Mellor and Haugen 1986), may differ from full-time workers in ways that may make them more vulnerable to offshoring than full-time workers. For instance, researchers have argued that contractors are often used to create flexibility that allows employers to address changes in work demand (Slaughter and Ang 1996). Contractors are also less likely to work on tasks important for the core business of the firm (Bidwell 2009) and may require less knowledge of the business than full-time IT workers (Ang and Slaughter 2001). From an employment perspective, therefore, it may be easier for employers to reduce employment levels for hourly workers in response to changes in offshore labor supply, rather than to replace full-time workers. Our second hypothesis, therefore, is:

H2: A lower percentage of domestic IT workers will be hourly IT workers at firms that offshore IT workers.

[3] Jobs with an index value lower than 25 are not ranked and therefore omitted from the list.

In the following sections, we describe the data we use to test these two hypotheses.

Table 1
Common Occupations and Impersonal Task Ratings[a]

Job Title	Offshorability Index
Computer Programmers	100
Computer Systems Analyst	93
Computer Support Specialist	92
Graphic Designer	86
Database Administrator	75
Software Engineer	74
Hardware Engineer	73
Marketing Managers	53
Systems Administrators	50
HR Managers	49
Sales Managers	26

[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.

Data

Offshore IT Employment

Our IT offshoring measures are created from data obtained in late 2006 from a leading online career networking service through which over 10 million workers had posted employment information by 2006, including information about occupation, 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 useful for studying offshoring because it is international and particularly 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 US, with the remainder located offshore. The employers reported by these offshore IT employees provide information about the offshore IT employment activities of US firms.

Data of this type provide a number of advantages over alternative potential data sources, such as surveys. Offshoring data collected from managerial responses contain substantial response error if managers are hesitant to reveal information about offshoring, or because of the difficulty that managers face in accurately estimating the numbers of IT workers located in other establishments. Our data contain sampling error, but may contain less measurement error of other types than other sources. Furthermore, other work has shown that offshoring can have very different implications for the US workforce depending upon the types of occupations being offshored (Tambe and Hitt 2010a), and have shown that domestic employment implications can also be different depending on offshoring location (Harrison et al. 2007, Tambe and Hitt 2010a). Harrison and colleagues, for instance, show complementarities with domestic employment when offshoring to high-cost locations, and substitution effects when offshoring to low cost locations. Therefore, narrowing our sample to IT workers, specific offshore locations, and specific industries is useful for conducting fine-grained analyses that avoid the possible confounding effects of using broader measures such as foreign direct investment or offshore employment aggregated across occupations, or across different offshoring locations.

To construct IT offshoring measures, we focus specifically on IT workers in India, of which there are about 2,500 in our sample. A US firm is deemed to have an offshore captive center when they employ IT workers in India. We focus on offshoring to India because we are interested in offshoring for cost or skills rather than geographic expansion, and among offshore destinations, India appears to have the most significant share of cost or skills based

IT offshoring by a substantial margin (Lewin & Couto, 2007; Tambe & Hitt 2010a). In our analysis, however, we also test offshoring measures computed using offshore IT workers in other destinations.

Table 2: Comparison of Offshoring Data With Offshoring Survey Data

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, 2010). Reported percentages are managers who responded that they offshore work to foreign affiliates.

In Table 2, we show comparisons of the offshoring data used in this paper with our earlier survey data. 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. Although the industry boundaries are not harmonized between the two data sources, a comparison suggests that the distribution appears to broadly track. The use of captive centers appears to be most common in technology industries, such as computer programming, business services, and semiconductor design, and in financial services industries, such as banking and insurance. Our figures are also consistent with other research that quantifies offshoring activity. A 2006 study showed that about 9% of offshoring firms were planning to use the captive center model (Hemmerich, 2006).

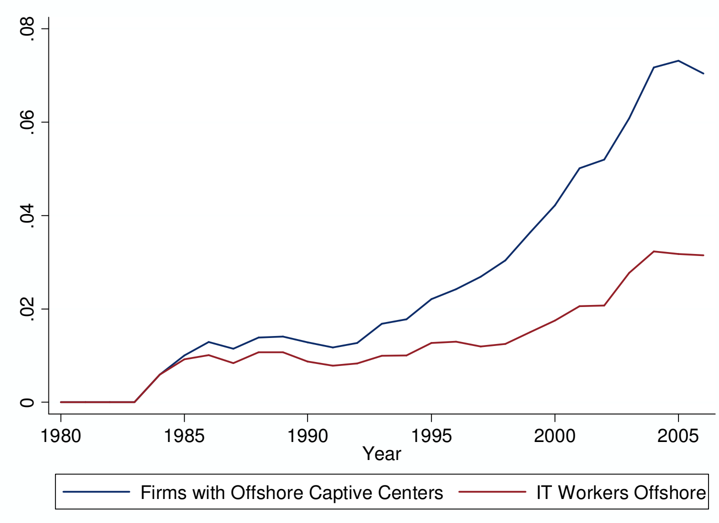
In Figure 1, we show how the fraction of firms with offshore captive centers has increased over time, from close to zero in the early 1980's to over 6% in 2006, with the most rapid rise coming between 1995 and 2005. The red line indicates the fraction of IT workers employed by US firms in our data who are located offshore, which rises from zero to about 3% in 2006, which is roughly consistent in magnitude with the findings produced by other research reports (Aspray et al. 2006).

We believe that these data are a reasonably good representation of captive center IT employment by US firms, and the ability to capture captive center employment by occupation and location is a useful empirical advancement. We do not have comparable data on offshoring to third party offshore vendors, although in our analysis below, we control for aggregate third-party outsourcing (domestic + offshore). However, the move towards third-party offshore outsourcing reflects a gradual change from the 1990's, during which period relatively more offshoring activity occurred through captive center employment (Oshri et al. 2008). As a result, many firms that once had captive centers now also engage third-party offshore contractors–and the correlation between offshore outsourcing and captive center employment in our 2007 survey data is .47. Among firms with captive centers, therefore, our coefficients on captive center offshoring are likely to reflect the effects of both captive center relationships and third-party relationships.

IT Workforce Data

We measure the distribution of IT occupations at the firm level using micro-data describing the employment histories of a large sample of US workers. The data were obtained through an industrial partnership with a leading online jobs site, and for each employee in the data set, includes employer name, employment dates, job title and occupation. 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 which employees are employed at which firms in each year, we can build annual measures of the occupational composition of a firm's IT workforce by aggregating employees to the firm level for each year. Each of the workers that appear in the data set also indicated if they were full-time or hourly workers. However, these classifications are only provided in 2006, and are therefore accurate only for the most recent job. We use these work status data to run cross-sectional regressions testing associations between offshoring and hourly worker usage. Workers also report security clearance and other worker attributes that prove useful for our analysis in ways we describe below.

Figure 1
Rate of IT Offshoring through Captive Centers



We have extensively tested and benchmarked these IT worker data in other work (Tambe & Hitt, 2010b). In Table 3, we report the educational composition of our IT sample compared to IT workers in the administrative CPS sample, which represents a sample randomly drawn from the US IT population. Most workers have at least a four-year college degree, and average job tenure for the workers in our sample is slightly over five years. We also compare the mean wage of the IT workers in our sample, reported in 2006, with the average IT wage in the 2006 Occupational Employment Survey. The two wages are very close—the workers in our sample make just under $74,000, which is only slightly more than the OES average IT worker wage of $72,190. We also compared IT personnel counts in each firm in our sample with other sources of IT employment data, including ComputerWorld, InformationWeek, and MIT surveys. The correlations between the most recent of these data sources and our firm-level IT employment figures is over .6, indicating that the distribution of IT workers across public US firms in our data is an accurate representation of the distribution of IT employment across public firms in the US, and certainly better than any other available IT workforce data.

One concern with this data source is that workers who participate in online career web sites may be atypical. In particular, "job-hoppers" are more likely to register on an online career site than other workers. Indeed, job tenure for the IT workers in the CPS sample is lower than the average job tenure for workers in our sample, reflecting the higher tendency of the workers in our sample to be job hoppers. However, we believe that our estimates will be reasonably robust to selection concerns for several reasons. First, our large sample size mitigates the severity of potential selection problems. Secondly, because IT workers 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 worker categories. A final related concern is that displaced IT workers may be over-represented in the data. However, if our hypotheses are correct, this bias will move in the opposite direction of our predictions (making our results more conservative) since programmers and systems analysts who are more likely to be displaced will appear to be a disproportionately large, not small, fraction of the workforce.

Table 3: Summary Statistics for IT Worker Sample

Variable	IT Worker Sample	CPS*, 2006	OES**, 2006
Total Worker-Year Observations	1,425,859	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	5.82	6.33	
Wage	73,866		72,190

*CPS is the Current Population Survey. Information is available at http://www.census.gov/cps.
**OES is the Occupational Employment Survey. Information is available at http://www.bls.gov/oes.

In the next section, we describe how we use our offshoring measures, workforce composition variables, and supplementary Compustat data to examine how offshoring is affecting the composition of the US IT workforce.

Empirical Implementation

Measures

The primary variables in our analysis are IT offshoring measures, measures of the task composition of the onshore workforce, and the human capital of the onshore workforce. The key variables in the analysis, their data sources, and their construction are summarized in Table 4. Offshore IT employment measures are created from IT captive center data--we extract individuals from these data who list computer services or IT as their primary industry[4], are located in India, and are employed by public US multinational firms. US firms are defined as those that have headquarters in the United States, where headquarters locations are obtained from the Compustat database. We test two different offshoring measures. We use a binary offshoring variable, which indicates whether or not the firm has any offshore IT workers in India, and a continuous measure, which is the fraction of the firm's IT workforce located in India.

Measures of domestic IT workforce task mix are created from the IT workforce data. The tradability of the tasks performed in a particular IT job is quantified by matching job titles to occupational codes in the O*Net database[5] both by hand[6] and using specialized software, and then use Blinder's existing taxonomy to assign workers to an index describing offshoring vulnerability (Blinder, 2007). The relative demand for IT workers who provide tradable task inputs is computed as the percentage of IT workers employed in jobs that exceed a threshold of 92 in Blinder's index, but later in our analysis, we show that our results are similar when using alternate cutoff values. Aggregating workers by employer and year generates a variable describing the percentage of a firm's domestic IT workforce in jobs that involve primarily tradable tasks. We test the hypothesis that IT offshoring is associated with a decrease in this figure. We also use these workforce data to create measures of education and experience for the IT workers in our sample, which are computed as the average educational attainment and experience level of the IT workers that appear in our sample for each firm, where both education and experience levels are self reported by workers. We use these data to test several predictions of the framework discussed above, and in particular, how offshoring affects onshore workforce composition.

[4] 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.

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

[6] We also conducted this matching process using automated software, but found no significant differences. Results produced when using the automated method are shown in our robustness tests.

Table 4: Key Variable Description and Construction

Variable Description	Data Source	Data Source and Construction
IT Offshore Binary	Offshore Emp	Takes value 1 if a firm has IT workers employed in India
IT Offshore Intensity	Offshore Emp	Fraction of the IT workforce located in India
Offshore Non-IT Employment	Offshore Emp	Non-IT Workers employed in India
IT Employment	IT Workforce	Total IT employment from Tambe & Hitt (2010b)
Tradable Task Intensity	IT Workforce	% of workers employed in occupations classified as "tradable"
% Hourly	IT Workforce	% of IT workers who reported hourly employment in 2006
% Security Clearance	IT Workforce	% of IT workers who reported having security clearance in 2006
Education	IT Workforce	Average education level of domestic IT workers
Experience	IT Workforce	Average experience level (years) of domestic IT workers
Job Tenure	IT Workforce	Average job tenure of domestic IT workers
Employment	Compustat	Total employment from Compustat
Sales Growth	Compustat	Year-on-year difference in sales
Foreign Income	Compustat	Annual foreign income
% Outsourced	2008 survey	% of budget spent on IT Outsourcing

Methods

Our main regression models, which connect offshoring to onshore task mix, relate the firm's IT task composition to the offshoring activities of firm *i* in year *t*.

$$(1)\quad TT_{it} = OFF_{it} + X_{it} + Z_{it} + u_{\text{it}}$$

The dependent variable TT is the tradable task intensity of the firm's IT workforce. Our primary independent variable, *OFF*, is a binary variable indicating whether a firm has offshore IT operations in India. *X* is a vector of firm-level variables that includes *total employment*, *IT employment*, and *percent sales growth*. Total employment is obtained from Compustat and measured as the natural logarithm of employees. Percentage growth in sales *(PCTSALES)* is measured as the year-on-year difference in sales, normalized by total sales, and is computed using Compustat data. We also include IT employment levels (*IT*), because large IT departments may have different organizational structures. The characteristics of the IT employment measure have been shown to track well with aggregate IT employment and are correlated with prior measures of IT employment from survey work (Tambe & Hitt, 2010b). *Z* is a vector of IT workforce human capital measures that includes *education*, *experience*, and *job tenure*. We also include dummy variables for year and two-digit industry to control for time and industry-specific trends. Our primary hypothesis is that the coefficient estimate on offshoring will be negative, indicating that onshore IT task mix shifts away from tradable tasks as more tradable tasks are performed offshore. We also test (1) using one-year differences, which eliminates sources of time-invariant heterogeneity across firms. In our cross-sectional analyses, error terms will be correlated across firms, so we use Huber-White robust (clustered) standard errors for all panel data models that we report.

One concern with (1) is that firms' offshoring decisions' may be correlated with the error term in the regression, which would bias the estimates on offshoring. Some of these concerns are removed by including extensive control variables to control for observable differences that might be correlated with offshoring (such as the need or level of human capital), and using difference models to control for unobservable firm-specific factors that are correlated with offshoring (such as variations of skill requirements relative to the firms' industry). However, neither of these approaches can address the problem of endogeneity if there is significant reverse causality. The reverse causal direction is somewhat less intuitive than our primary causal direction, but could arise if firms perceived that a decrease in demand for these skills lead to scale inefficiencies or reduced strategic importance, and therefore made it relatively cost efficient or less risky to manage this smaller number of employees offshore.

One way to check this is to test if historical workforce composition predicts offshoring adoption. If differences in skill requirements are driving offshoring, then firms with a particular skill mix should have been among the first to adopt offshoring. In the longer version of this paper, we present results from an analysis indicating that a firm's skill composition in 1990, which predates most serious offshoring activity, was a relatively poor predictor of 2006 offshoring levels. However, our primary strategy for resolving this potential endogeneity issue is to supplement our cross-sectional and difference results with results from an instrument variables (IV) estimator, where we treat offshoring as endogenous, and use instruments that capture the relative costs or benefits of offshoring across firms but are not related to skill requirements conditional on the other control variables. This estimator removes the correlation between the regressor and the error term, and therefore produces consistent estimates of the effects of offshoring. Therefore, we report results from traditional IV estimators, as well as those that account for the binary nature of the endogenous variable by using a probit model to estimate the first stage.

An instrumental variables estimator requires the identification of variables that are correlated with the endogenous regressor, but not with the error term. The first of these instrumental variables we use is the number of *non-IT offshore workers* employed by the firm. Firms that offshore other types of workers can spread fixed costs associated with opening captive offshore centers across a multitude of worker types, lowering unit costs. The offshoring data described above represent the offshore employment of all worker types, so we can use them to create measures of offshore employment outside the IT sector. The second instrumental variable is *foreign income*, available through Compustat. Firms with greater foreign market exposure already have many of the capabilities in place to take advantage of offshore resources, and may already have some of the necessary infrastructure in place to establish offshore captive centers. The third variable in our instrument set is the fraction of IT workers with *security clearance*. Security clearance affects offshoring activity because it is not granted to offshore workers, so firms cannot offshore work requiring security clearance. We use the fraction of IT workers with security clearance as a proxy for the amount of secure IT work being done in firms. Our first stage regressions suggest that these variables along with the other control variables explain a significant amount of variation in the decision to open a captive center, in contrast to the 1990 skill mix measure, which does little to explain the choice to open a captive center. We see no evidence in our preliminary (or subsequent) analyses that would suggest that the initial decision to offshore is endogenous.

We also test how offshoring affects the use of hourly IT workers by using the following specification.

$$(2)\quad HOURLY_{\mathrm{i}} = OFF_{\mathrm{i}} + X_i + Z_i + u_{\mathrm{i}}$$

The dependent variable is the fraction of IT workers who are paid an hourly instead of annual wage. The right hand side variables are the same as in (1), and we also include dummies for year and industry at the two-digit level to control for time and industry-specific trends. The classification of whether a worker is paid an hourly or an annual wage is only available for workers in 2006. Therefore, we primarily test (2) in cross-sections. However, we also test some differences models by assuming that work status remains relatively fixed over short-time periods. This allows us to test how IT workers in annual and hourly pay categories allocate themselves across different firms depending on the firm's decisions. If workers in this time period switch their work status, this adds error to our dependent variable measure.

Descriptive Statistics and Correlations

Table 5 shows some statistics for the firms in our sample. About 53% of IT workers in firms in our sample are employed in the production of personal services. This compares with about 51% of "Computer and Mathematical Science Occupation" workers in the 2006 Occupational Employment Survey who are employed in comparable occupations. The slightly higher percentage of this category of workers in our sample is partly because computer and information systems managers and sales workers are classified into 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 about 53%. Unfortunately, IT sales workers are not separately identifiable in the OES data. Between 18% and 19% of the IT workers in the firms in our sample report being paid hourly wages in 2006. The average level of experience for IT workers in these firms is 13 years, and most workers have at least four years of college education. Average tenure with the current employer is slightly under 3 years. The firms in our sample are also quite large, with about 19,000 employees and 5 billion dollars in average sales.

We also compare mean values of the main variables in our analysis, based on whether or not firms have offshore IT facilities. Sales and foreign income are higher for offshoring firms, reflecting the scope and size differences of multinational firms. Among workforce variables, the onshore IT workforce in offshoring firms performs significantly fewer tradable tasks and has higher education levels. These differences are consistent with the theory of task tradability discussed earlier, but in the analysis below, we test these relationships more thoroughly.

Table 5: Means and Standard Deviations for Firm-Level Variables (2006 Levels)

Variable	N	Mean	Std. Dev.	Offshoring mean	Non-Offshoring mean	t-stat[a]
Offshore Y/N	864	.073	.261	1	0	
% Tradable Tasks	864	.47	.16	.36	.48	4.47***
Experience (Years)	864	12.8	9.4	15.4	12.6	1.87*
Education	864	4.13	.498	4.38	4.12	3.20***
Job Tenure (Years)	864	2.90	1.16	2.84	2.90	0.331
Sales (x 1,000,000)	864	10026.2	25071.6	20270.6	9528.9	2.66***
Employment (x 1,000)	864	31.0	86.3	30.1	49.6	1.40
IT Employment	864	676.5	1898.6	3183.4	554.8	8.93
Foreign Income	864	356.3	2243.5	1163.6	317.1	2.34**
% With Security Clearance	864	.077	.112	.061	.078	.961
% Hourly Wage	864	.186	.117	.138	.171	1.93*

Correlations are for 2006 values of shown variables. *** p<.01; **p<.05; *p<.10.
[a]t-stat tests the hypothesis that the means in offshoring and non-offshoring firms are equivalent.

The graph in Figure 2 illustrates how IT task composition has been changing over time in offshoring and non-offshoring firms. Task content for these firms was similar in 1995, but diverges thereafter. Tradable task intensity in non-offshoring firms rises slowly between 1995 and 2006, but drops by about 8% in the same period in offshoring firms. The fact that tradable task composition is similar among firms at the beginning of our sample suggests that it does not explain the propensity to offshore. A t-test rejects the hypothesis that the mean difference between these two sets of firms is the same (t=7.61). These preliminary results indicate that offshoring affects IT task mix in a direction consistent with theory.

Figure 2: Tradable Task Intensity in the Domestic IT Workforce, 1995-2006

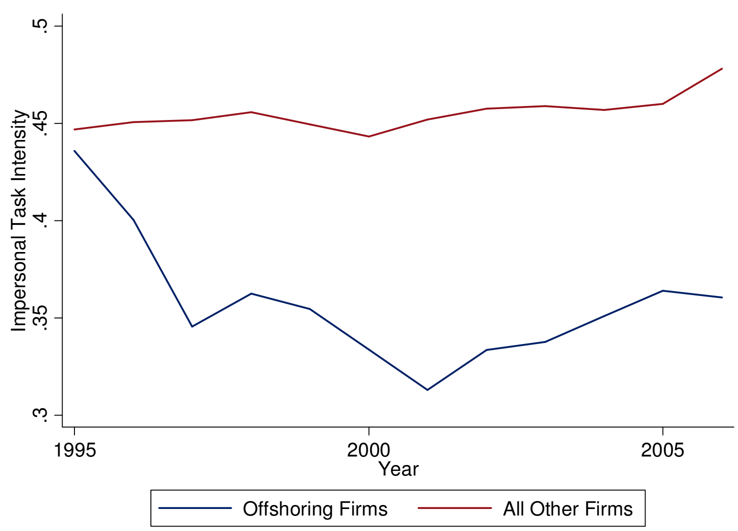


Table 6: Comparing Full Time IT Workers With Hourly IT Workers, 2006 Levels

	Full-Time	Hourly	t-stat
Tradable Task Intensity (Percent)	76.3	82.8	-50.3***
Experience (Years)	20.2	13.2	.678
Education	4.20	3.80	30.9***
Job Tenure (Years)	3.26	1.82	58.4***
Security Clearance (Percent)	11.6	9.6	8.99***

*** p<.01. Tradable task intensity and Security Clearance are in percentages. Experience and Job Tenure are in years. Education is on a scale of 1 (less than high school education) to 7 (Doctorate). A 4 indicates a four-year degree and a 5 indicates some graduate work. The t-statistics in the third column test the hypothesis that the mean values of the variables is the same for full-time and hourly workers.

Finally, in Table 6, we compare human capital measures for the IT workers in our sample, depending on whether they are full-time or hourly workers. Blinder's index values are higher for hourly than for full time IT workers. Full-time workers in this sample are also more educated and have been employed for a longer period of time.

Regression Results

Offshoring and Workforce Composition

The main results of this paper are in Table 7. The dependent variable in all regressions is tradable task intensity (fraction of tradable tasks performed by the firm's IT workforce). We start with the OLS regression in (1) using the pooled sample over all years. The results in (1) indicate lower onshore levels of tradable tasks being performed by firms that have an offshore IT center located in India (t=5.72), which is consistent with Hypothesis 1. The magnitude of the coefficients suggests that after controlling for other factors, the difference in onshore tradable tasks being performed between offshoring and non-offshoring firms is about 8%. In (2), we test differences estimates, which should remove the effects of time-invariant unobserved sources of heterogeneity that are associated with the offshoring indicator. The coefficients from the differences regression indicate that establishment of an offshore captive center is associated with about a 1% one-year drop in tradable tasks onshore after controlling for other factors (t=2.17). If firms in our sample established captive centers in the mid to late 1990's, this 1% difference, compounded over the years in our time span is consistent with the 8% difference estimated in our cross-sectional results.

In Column (3), we show results from our instrumental variable regressions, using non-IT offshore workers, security clearance, and the log of foreign income as instruments for the IT offshoring decision. The estimates from the instrumental variables regression are double the size of the coefficient estimate on offshoring (t=3.14). The R-squared value for the first stage regression is .19, and a Hausman test indicates that we can reject the hypothesis that offshoring is exogenous with respect to onshore workforce mix at the 5% level. The higher IV estimate suggests that unobserved factors tend to bias our offshoring coefficients towards zero. Our use of an IV estimator when the endogenous variable is binary should produce estimates that are consistent, but have decreased statistical power relative to an estimator that predicts binary outcomes in the first stage. Therefore, in (4), we estimate a treatment effects model that estimates the endogenous binary offshoring variable during the first stage using a probit estimator. As expected, the result from the treatment effects model produces an estimate that is similar in magnitude to the estimate in (3), but with greater statistical power (t=7.92).

In Columns (5) and (6), we test if our results differ substantially across industries, using the IV specification in (3). In particular, we focus on SIC 73, which includes IT-producing industries where IT workers are generally production rather than support workers. This industry is also interesting because it has the highest incidence of offshoring. Our offshoring coefficient when restricting the sample to SIC 73 businesses is somewhat higher than our estimate in (3). However, the regression results in (6) indicate that the effects of offshoring are similar for businesses in other industries, where IT workers are more likely to be support workers than production workers. A Chow test does not reject the hypothesis that the offshoring coefficients are equivalent across the two different samples (F(2,1399)=.28, p=.75). The observed effects, therefore, do not appear to be driven solely by offshoring in IT-producing or IT-using industries.

Table 7: Regression Tests of Offshoring on Domestic IT Tradable Task Intensity

DV: % Tradable Tasks	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	All	SIC 73	Other Industries	Outsourcing
	OLS	Differences	IV	Treatment	IV	IV	IV
Offshore (Y/N)	-.079***	-.013**	-.183***	-.190***	-.282***	-.293***	-.120*
	(.015)	(.006)	(.059)	(.024)	(.082)	(.090)	(.069)
Log(Employment)	.030***	-.012	.026***	.029***	.013	.029***	.068***
	(.008)	(.008)	(.007)	(.003)	(.018)	(.008)	(.022)
Log(IT Employ)	-.013	.011	-.007	-.012***	.020	-.012	-.057***
	(.008)	(.007)	(.008)	(.003)	(.019)	(.009)	(.020)
Sales Growth	-.000***	.000	-.000***	-.000	-.001***	.006	-.001
	(.000)	(.000)	(.000)	(.000)	(.000)	(.004)	(.013)
Log(Education)	-.200***	-.109***	-.195***	-.200***	-.339***	-.154***	-.232***
	(.029)	(.019)	(.028)	(.013)	(.064)	(.032)	(.096)
Log(Experience)	-.050**	-.023**	-.045**	-.047***	-.116***	-.030	-.004
	(.020)	(.009)	(.020)	(.008)	(.042)	(.021)	(.031)
Log(Job Tenure)	-.010	-.046***	-.012	-.012**	-.008	-.005	.033
	(.012)	(.011)	(.012)	(.006)	(.026)	(.014)	(.040)
% Outsourced							-.005
							(.008)
First Stage R^2			.19		.22	.18	.50
Hausman Test			p<.05		p<.05	p<.05	p<.10
Observations	8789	7190	8105	8105	1849	6256	526
R-squared	0.21	0.03	0.19		.07	.04	.51

*** p<.01; **p<.05; *p<.10. Standard errors are robust, clustered on firm. All regressions include controls for Industry and Year.

In (7), we include measures of overall IT outsourcing into our regression as a control variable in our instrumental variable regression. Outsourcing levels are a potentially important unobserved variable because they are also likely to impact IT workforce composition, and could be correlated with offshoring levels. However, if offshoring firms have less need for outside domestic IT contractors, then this should work to bias our offshoring coefficients downwards. We directly test this by using IT outsourcing data collected in a recent survey, and available for a subset of the firms in our sample. The point estimate on the offshoring coefficient after controlling for IT outsourcing levels is slightly lower than that in (3), but indicates that offshoring is associated with a significant drop in the percentage of onshore IT work composed of tradable tasks (t=1.74). The reduced significance level is due to a smaller sample from limited availability of our outsourcing measure, not because of bias due to omitting outsourcing as a covariate.

In Table 8, we present estimates using a continuous offshore intensity variable rather than a binary offshoring indicator as our independent variable. Offshore intensity is computed as the fraction of a firm's IT workforce located in India. The offshoring coefficients in Column (1) are negative and significant (t=2.70). The estimates from our differences model in (2) are also negative at the same levels of significance (t=2.26). In (3), we report estimates on offshore intensity, conditional on having offshored some work. These estimates indicate that higher levels of offshoring are observed in firms with higher levels of tradable tasks in the onshore workforce. This result also suggests that the negative estimates in (1) confound the effects of the offshoring decision with a positive association between percent offshore and onshore tradable task composition. This suggests that 1) an IV estimator will have a larger impact on offshore intensity estimates than the offshoring binary variable because offshore intensity is more subject to endogeneity concerns, and 2) that simultaneously including both the offshoring dummy and percent offshored in a regression should produce a larger negative estimate on the offshoring decision variable. These predictions are confirmed in (4) and (5). Use of the IV estimator significantly inflates the estimate and the standard error on offshore share, but the estimate is still negative and significant at the 10% level (t=1.73). The offshoring binary estimate in (5) also confirms that offshoring intensity and the offshoring decision push in opposite directions, and separating the effects of these two variables slightly raises the magnitude of the estimate on the offshoring decision variable. These results provide additional support for the argument that endogeneity is likely to be a larger issue for the rate of offshore employment than for the initial offshoring decision, and that it exerts an upward rather than a downward bias on our estimates of the effects of the offshoring decision on tradable task intensity making our primary results more conservative.

Table 8: Regression Tests of Offshore Share on Domestic IT Tradable Task Intensity

DV: % Tradable Tasks	(1)	(2)	(3)	(4)	(5)
	All	All	Offshoring Only	All	All
	OLS	Differences	OLS	IV	OLS
Offshore Share	-.224***	-.080**	.248*	-1.92*	.109
	(.086)	(.034)	(.147)	(1.11)	(.105)
Offshore (Y/N)					-.091***
					(.019)
Log(Employment)	.031***	-.012	.039	.027***	.030***
	(.008)	(.008)	(.028)	(.008)	(.008)
Log(IT Employ)	-.016**	.011	-.003	-.010	-.013
	(.008)	(.007)	(.028)	(.008)	(.008)
Sales Growth	-.048***	.014	2.92	-.040	-.049***
	(.007)	(.010)	(4.16)	(.008)	(.008)
Log(Education)	-.204***	-.109***	-.317**	-.195***	-.199***
	(.029)	(.020)	(.146)	(.031)	(.029)
Log(Experience)	-.052***	-.023**	-.057**	-.059**	-.049**
	(.020)	(.009)	(.027)	(.023)	(.020)
Log(Job Tenure)	-.010	-.045***	.057	-.009	-.010
	(.012)	(.010)	(.047)	(.013)	(.012)
Controls	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
N	8789	7190	328	8105	8789
R^2	0.21	.03	.39	.09	.21
*** p<.01; **p<.05; *p<.10. Standard errors are robust, clustered on firm.					

Offshoring and Hourly IT Workers

Table 9 shows the relationship between offshoring and the balance of full-time and hourly IT employees hired by organizations. The results in column (1) show that offshoring firms hired 2-3% fewer hourly workers than non-offshoring firms in 2006 (t=1.8), which supports Hypothesis 2. These results are restricted to 2006 because workers in our sample identify themselves as hourly or full-time workers only in 2006. However, we can conduct a quasi-differences test by assuming that most workers retain the same work status over a number of years. Departures from this assumption should introduce noise into our dependent variable, but not in a systematic way that could bias our results. The offshoring coefficient from a regression in one-year differences using the years from 2000 to 2006 indicates an association between offshoring and workforce task mix that is consistent with our prior results, but the estimates are slightly short of significant. Nevertheless, these results provide evidence that part of the workforce shift that we find evidence for in earlier sections may in part be due to a shift away from the use of hourly IT workers, who are more likely than full time IT workers to be performing tradable tasks.

The results in (3) and (4) show that offshoring impacts the task content of work similarly if examining hourly and full-time workers separately. In (5) and (6), we explore how offshoring affects task mix in the overall sample, but we use hourly worker percentage as a control variable to test if the observed changes in task content are explained by the shift away from hourly workers. The results in (5) are the benchmark case that includes only the 2006 sample of firms. In Column (6), we also include the fraction of hourly workers employed by the firm into our model. We find that firms with a higher fraction of hourly workers perform more tradable tasks, which is consistent with the distribution of tasks between hourly and full-time workers, and that conditional on the fraction of hourly workers employed by the firm, offshoring is associated with a shift away from onshore tradable tasks (t=3.29).

Finally, in (7) we report results when restricting the IT workers in our sample to those classified as exempt by the Fair Labor Standards Act. Our interpretation of the hourly wage classification may not be justified for IT support workers, who are often classified as non-exempt employees and paid hourly wages.[7] Furthermore, IT support workers are often offshored to provide 24 hour support. It is useful to check, therefore, whether the associations between offshoring and contractor usage persist after excluding IT support workers and other workers who potentially fall into non-exempt categories, and for whom hourly wages may therefore not reflect contractor status. The estimates from (7) are computed by using only IT managers, programmers, and systems analysts, all of which are exempt occupations. Most notably, this list does not include computer support workers, who comprise a large fraction of the IT workers in our data set, but it also excludes other workers such as network administrators who are sometimes also considered non-exempt. However, the results shown in (7) are similar to those in (1), indicating that our results are probably not driven by measurement issues related to the use of hourly wages. These results suggest that offshoring affects hourly workers disproportionately because of the distribution of tasks between the two types of workers—shifts in employment distribution across these workers appears to primarily be related to differences in work task content, rather than other differences. Offshoring appears to have the same effect on onshore task mix regardless of hourly or full-time status.

Table 9: Regressions of Offshoring on the Use of Hourly IT Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	**% Hourly Workers**	**% Hourly Workers**	**% Tradable Tasks**	**% Tradable Tasks**	**% Tradable Tasks**	**% Tradable Tasks**	**% Hourly Workers**
Sample	All	All	Full-Time	Hourly	All	All	Exempt Workers
	OLS	Differences	OLS	OLS	OLS	OLS	OLS
Offshore Y/N	-.027*	-.007	-.084**	-.096**	-.074**	-.065**	-.031*
	(.015)	(.004)	(.027)	(.047)	(.025)	(.025)	(.017)
% Hourly						.333***	
						(.062)	
Controls	Industry	Industry Year	Industry	Industry	Industry	Industry	Industry
N	863	5685	773	270	863	863	452
R^2	.27	.04	.24	.33	.21	.25	.31

Standard errors are robust, clustered on firm. *p<.10, **p<.05, ***p<.01. Exempt workers in (7) are IT managers, systems analysts, and software engineers.

Robustness Tests

In Table 10, we present the results of some additional robustness tests, in which we use some of the details in the offshoring data to conduct stronger tests of the task-trading hypothesis. In Column (1), we test a model that includes our offshore share measure, as well as a second offshoring measure computed from IT workers who are located in countries other than India. Including the second offshoring measure in this model addresses some endogeneity concerns, because task trading in the IT sector appears to be occurring primarily when offshoring to India—offshoring to other locations is more likely to be associated with growth or expansion patterns. The coefficients indicate that the observed workforce shifts are associated with offshoring to India rather than other destinations, and our offshoring coefficient is probably therefore reflecting the task trading patterns that we are interested in, rather than unobserved factors that might cause firms to expand globally.

In Column (2), we present results when using offshore share measures computed from the offshoring of different types of IT workers, where workers are classified as technical, managerial, or other, depending on their two digit O-NET occupational codes. The results indicate that our task trading results are associated with the offshoring of technical workers, rather than workers of other types, which is consistent with the argument that the division of tasks across countries, rather than other unobserved workforce attributes of offshoring firms, are driving our results. The number of workers in each of these occupational categories is roughly the same, so our results are not driven by measurement error or sample size. We have also conducted a number of additional robustness tests (not shown). We

[7] For a more thorough discussion of the categorization of IT workers under the Fair Labor Standards Act, see http://hrhero.com/hl/articles/2008/10/17/correctly-classifying-it-employees-as-exempt-or-non-exempt/?TOPIC.

tested the sensitivity of our results to the methods used to map job titles to O-Net job codes by running similar tests after hand matching common job titles to O-Net codes. We also test the effects of moving the threshold at which we divide work into tradable categories. By moving this line further to the left, we can broaden the category of jobs consisting primarily of tasks that are tradable and test whether our results are sensitive to this cutoff. Our estimates were not substantially changed in either of these sets of tests, suggesting that they are not sensitive to our method of mapping jobs to tradable tasks.

Table 10: OLS Regressions by Offshore Worker Composition

DV: % Tradable Tasks			
By Location		**By IT Worker Type**	
India	-.487**	Technical	-.485**
	(.233)		(.232)
All Other	-.008	Managerial	-.153
	(.015)		(.242)
		All Other	-.330
			(.288)
N	5616		1625
R^2	0.26		0.19
Standard errors are robust, clustered on firm. *p<.10, **p<.05. Regressions are from baseline model used in Table 8, Column 1.			

Discussion

We used new data to test how offshoring affects IT occupational composition in the US. The level of data aggregation used in prior studies, along with the complexity of labor flows in multinational organizations, has made it difficult to directly relate offshoring to employment shifts. Our results, using fine-grained IT offshoring and IT workforce data, indicate that offshoring shifts workforce composition towards tasks that are not easily tradable across countries. Our estimates suggest that although the fraction of domestic IT workers in offshorable occupations has risen about 3% in non-offshoring firms over the last decade, it has dropped by about 8% in offshoring firms in the same time period. We also find that hourly IT workers are more likely to be performing tradable IT tasks. Our estimates indicate that in offshoring firms, hourly workers comprise about 2-3% less of the total IT workforce than in other firms.

We primarily contribute to a literature on the IT workforce. Earlier studies have found that interpersonal skills are playing an increasingly important role for IT workers. Our study indicates that offshoring will further accelerate the shift towards interpersonal skills for US-based IT workers. Our results, however, also have implications for managers. They indicate that IT jobs that remain in the US will have a greater component of tacit work, and may therefore require more firm-specific capital as personal interaction becomes increasingly valuable. This has implications for IT retention, which has historically been an important issue faced by IT managers (Agarwal and Ferratt 2001). Our findings suggest that IT managers may be able to divert some of their domestic personnel resources away from hiring and retention towards job redesign and internal development. These results are also a useful lens through which to examine educational policies. 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, and our findings therefore are consistent with recommendations from education scholars who advocate shifting some of the emphasis in the US educational system towards "softer" skills such as complex communication (Levy and Murnane 1996). Furthermore, IT workers may find it valuable to add business and communication skills to an existing technical portfolio, as many have already begun to do (Lohr 2009).

Finally, there are some notable limitations to this research. Our results only capture changes at the "extensive" margin—in other words, how offshoring affects task mix as reflected by occupational distribution. Changes at the "intensive" margin--within-occupation changes in task composition—are also likely to be very important. For example, the task content associated with the "computer programmer" job title may shift as firms reallocate tasks among jobs to take advantage of offshoring. Unfortunately, our data are too limited to capture these changes, and offshoring is too new a phenomenon to detect these shifts in administrative task data (see Autor et al. 2003 for a similar exercise with computerization). Similarly, a number of job attributes beyond the ones studied here, such as task modularity, affect offshoring propensity. As more detailed task-level measures become available, and as firms continue to reengineer jobs to maximize the benefits of globalization, we hope researchers will continue to develop a more fine-grained understanding of how offshoring of various types is affecting the organization of work at a task level. Finally, a notable limitation of our offshoring data set is that we do not observe offshore outsourcing. As third party vendors capture a larger share of the offshoring market, it would be useful to integrate data on offshore outsourcing into a similar analysis.

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