



Management Science

Publication details, including instructions for authors and subscription information:
<http://pubsonline.informs.org>

Now IT's Personal: Offshoring and the Shifting Skill Composition of the U.S. Information Technology Workforce

Prasanna Tambe, Lorin M. Hitt,

To cite this article:

Prasanna Tambe, Lorin M. Hitt, (2012) Now IT's Personal: Offshoring and the Shifting Skill Composition of the U.S. Information Technology Workforce. *Management Science* 58(4):678-695. <http://dx.doi.org/10.1287/mnsc.1110.1445>

Full terms and conditions of use: <http://pubsonline.informs.org/page/terms-and-conditions>

This article may be used only for the purposes of research, teaching, and/or private study. Commercial use or systematic downloading (by robots or other automatic processes) is prohibited without explicit Publisher approval, unless otherwise noted. For more information, contact permissions@informs.org.

The Publisher does not warrant or guarantee the article's accuracy, completeness, merchantability, fitness for a particular purpose, or non-infringement. Descriptions of, or references to, products or publications, or inclusion of an advertisement in this article, neither constitutes nor implies a guarantee, endorsement, or support of claims made of that product, publication, or service.

Copyright © 2012, INFORMS

Please scroll down for article—it is on subsequent pages



INFORMS is the largest professional society in the world for professionals in the fields of operations research, management science, and analytics.

For more information on INFORMS, its publications, membership, or meetings visit <http://www.informs.org>

Now IT's Personal: Offshoring and the Shifting Skill Composition of the U.S. Information Technology Workforce

Prasanna Tambe

Stern School of Business, New York University, New York, New York 10012, ptambe@stern.nyu.edu

Lorin M. Hitt

The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104, lhitt@wharton.upenn.edu

We combine new information technology (IT) offshoring and IT workforce microdata to investigate how the use of IT offshore captive centers is affecting the skill composition of the U.S. onshore IT workforce. The analysis is based on the theory that occupations involving tasks that are “tradable,” such as tasks that require little personal communication or hands-on interaction with U.S.-based objects, are vulnerable to being moved offshore. Consistent with this theory, we find that firms that have offshore IT captive centers have 8% less of their onshore IT workforce involved in tradable occupations; those without offshore captive centers have increased the proportion of onshore employment in these same occupations by 3%. In addition, we find that hourly IT workers (e.g., IT contractors) are disproportionately employed in tradable jobs, and their onshore employment is 2%–3% lower in firms with offshore captive centers. These findings persist after considering different measures of employment composition, including controls for human capital, firm performance, domestic outsourcing, and whether firms choose to build or buy software. Instrumental variables and corroborating regressions suggest that our estimates are conservative—the magnitude of the effect generally rises after accounting for reverse causality and measurement error.

Key words: information systems; IT policy and management; management of IT human resources; organizational change; outsourcing; offshoring

History: Received June 1, 2010; accepted June 3, 2011, by Chris Forman, guest department editor, information systems. Published online in *Articles in Advance* January 26, 2012.

1. Introduction

The impact of globalization on information technology (IT) labor markets continues to be an active area of interest for academic researchers. In this paper, we study how offshore IT employment is affecting the occupational and task composition of the U.S. onshore IT workforce. We focus on IT workers because IT has been reported to be among the most widely offshored business functions in recent surveys (Lewin and Couto 2007, Tambe and Hitt 2010), IT workers play a significant role in the growth of modern economies, and employment patterns observed in IT workers may be applicable in the future to other occupations.

To organize and frame our analysis, we rely heavily on a theoretical literature that argues that “tradable” jobs—those that involve routine tasks that can easily be delivered through computer networks—are highly vulnerable to offshoring (Apte and Mason 1995, Jensen and Kletzer 2005, Mithas and Whitaker 2007, Grossman and Rossi-Hansberg 2008, Blinder 2009). In contrast, tasks that require complex, “high-touch”

(e.g., auto mechanics) or “personally” delivered services (e.g., retail sales) face less offshore competition because the delivery of these services is substantially degraded when provided over computer networks. Our study relies on the observation that although IT jobs tend to be more tradable than other jobs, there is considerable variation even within the IT workforce in task composition. Using this variation, we empirically link offshoring with a shift toward an onshore IT workforce that performs fewer tradable tasks and correspondingly more interactive or hands-on tasks. Our data cover the period from 1995 to 2006, which includes a period of rapid growth in IT offshoring.

A principal contribution of this paper is that we introduce new data sources through which we develop firm-level measures of (1) IT offshoring and (2) changes in onshore IT occupational and task mix. Our offshoring data are based on a random sample of 64,000 offshore IT workers with detailed profiles on a global employment networking site. These workers represent about 7,500 U.S. firms. Our data captures employment in captive offshore centers, consistent

with much of the existing literature on offshoring (Brainard and Riker 1997, Harrison et al. 2007, Desai et al. 2009). Our focus is on offshoring to India because prior research suggests India is the most common location for cost-based offshoring, and cost-based offshoring may have the greatest implications for the U.S. domestic IT workforce. We combine offshoring data with detailed occupational data on 500,000 U.S. IT workers from a different source that can be linked to their employers¹ to construct firm-level measures of occupational mix, human capital, and other characteristics of their employer's U.S. workforce. We are therefore able to link offshoring activity to the specific task demand represented by occupations. To the best of our knowledge, no prior work has linked offshoring to U.S. employment mix using firm-level data because there are no U.S. data sources on IT services imports² at the firm level and little data describe firm-level changes in workforce composition.

Rather than absolute employment changes, we consider changes in the skill composition of the IT workforce because our primary interest is in how optimizing firms adjust the skill content of the domestic production of IT services in response to offshore IT labor. The most common way to test for whether technological change such as offshoring favors some skills relative to others (i.e., is "skill biased") has been to examine the sign and significance of right-hand-side factors in a regression that uses the cost share of specific skills as the dependent variable. This approach has the added empirical benefit that it avoids confounding overall changes in IT labor demand with the offshoring decision. Our study is broadly consistent with recent efforts to classify different occupations by vulnerability to offshoring to estimate how much of the U.S. workforce might be vulnerable to offshoring (Blinder 2009). Researchers have applied these classifications to industry-level data. For instance, Crino (2010) used occupational employment and services imports data at the industry level

¹ It is generally difficult to link human capital data on individual employees to employers. Prior work has used surveys, which are limited to a single point in time and may be inaccurate for characterizing large firms, or census data such as the longitudinal employer household dynamics data, which are a rich resource that include human capital variables (Abowd et al. 2004) but do not include occupation and are difficult to obtain with firm identifiers, both of which are critical to our study.

² 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). Even in the manufacturing sector, where there is an extensive body of literature linking cross-border trade and jobs, most data on occupations are aggregated to the industry level. Thus, even if services data were comparable to manufacturing, we would still not capture all the shifts due to offshoring if displaced workers primarily move within the same industry.

to estimate labor-demand elasticities with respect to services offshoring for 100 white-collar occupations, including many IT jobs.

We contribute to this literature by examining how IT offshoring affects IT labor composition at the firm rather than the industry level. Rather than examine aggregate services trade, which has been steadily rising over time, we focus specifically on the IT offshoring phenomenon, which increased rapidly over a relatively short time period in the late 1990s. Furthermore, industry-level data can conceal significant variation in the production choices of individual firms within an industry. For example, an industry-level analysis cannot distinguish whether industry effects reflect the experience of a "typical" firm within the industry or, alternatively, combine changes in a few early adopters with minimal effects or countervailing effects in other firms in the industry that do no IT offshoring.³ Given that offshoring practices are still diffusing among firms, the latter is more likely to characterize the existing data, and distinguishing these alternatives has important implications for measuring the long-term effects of offshoring on IT labor composition—in particular, if average industry effects are driven by a relatively small number of firms within the industry, this may imply a larger long-run effect as an increasing number of firms offshore IT work. Furthermore, an industry-level analysis may understate the effects of offshoring on skill composition to the extent that displaced IT workers move from offshoring firms to nonoffshoring firms within the same industry, or to the extent that offshoring at the industry level is confounded with industry-level differences in labor composition. A firm-level analysis can also control for other firm-level determinants of labor composition, such as firm size, and provides greater flexibility when dealing with issues related to simultaneity between offshoring and workforce composition.

Our analysis suggests that in firms that operate a captive center in India, the percentage of onshore IT workers performing tradable tasks fell by eight points as a proportion of all onshore IT workers, whereas the percentage of workers performing these tasks in firms that do not operate captive centers increased by three points over our time period. These results are robust to a variety of controls for differences across firms, reverse causality, and measurement error. Moreover, the contrasting direction of the offshoring versus nonoffshoring firms in our sample suggests we are not confounding the effects of offshoring with overall changes in skill demand.

³ An industry analysis using our data shows somewhat smaller effects occurring later in the sample period than a firm-level analysis.

Also consistent with our “task-trading” hypotheses, we find that the employment of hourly IT workers, who are disproportionately employed in the provision of tradable tasks, is 2%–3% lower in absolute terms in offshoring firms, a reduction of about one-sixth of all hourly IT employment in these firms. Therefore, our results suggest that (1) firms that offshore IT services are readjusting their U.S.-based IT workforces toward occupations requiring greater personal interaction and (2) that hourly IT workers are disproportionately affected.

Our paper contributes to a literature on factors that influence the demand for IT skills (Lee et al. 1995, Ang et al. 2002, Mithas and Krishnan 2008, Levina and Xin 2007) and an emerging literature on how globalization affects IT labor markets (Aspray et al. 2006). These issues have direct implications for educational policies regarding IT workers and human capital management practices for the acquisition and retention of IT skills.

2. Framework

The IT literature has emphasized the increasing importance of business and interpersonal skills relative to technical skills (Leitheiser 1992, Lee et al. 1995), a shift that has been occurring because of emphasis on activities such as process reengineering and integration, and because the increasing decentralization of the IT function required an IT workforce that could work within business units. Rapid changes in the supply and demand for IT labor during the dot-com boom and bust motivated a number of studies focused on the human capital and institutional factors affecting IT labor demand and IT wages (Ang et al. 2002, Mithas and Krishnan 2008, Levina and Xin 2007). Recent literature has observed that the globalization of IT labor is becoming increasingly important for management of the IT workforce (Aspray et al. 2006). Researchers have examined issues related to the development of a global IT workforce (Bapna et al. 2010) and its effect on the IT function within the firm (Lewin and Couto 2007, Tambe and Hitt 2010), but how managers balance skills across onshore and offshore IT workers remains an open question.

Our analysis of the impact of offshoring on onshore skill composition draws heavily on a theoretical literature linking offshoring to skill demand according to whether task output can be shipped over electronic networks (Apte and Mason 1995, Bardhan and Kroll 2003, Jensen and Kletzer 2005, Blinder 2009). Blinder’s (2009) classification uses personal interaction as the key evaluation criteria in developing a taxonomy of vulnerability to offshoring, and at the task level, he classifies nontradable tasks (personal tasks) as those that (1) require extensive interpersonal communication with customers or other workers located

in the United States or (2) require interaction with a U.S.-based object. He rank orders major U.S. occupations according to their relative tradability along these criteria (Blinder 2009).

Offshoring should affect IT labor markets along similar task-based lines. For instance, many IT tasks such as computer programming can be performed remotely—customers can coordinate with programmers remotely, and computers can be located anywhere in the world. By contrast, project managers or sales people can be difficult to offshore because of the importance of face-to-face contact in those jobs. Other workers, such as network administrators, frequently perform hands-on work with machines and physical networks and therefore also cannot be easily located offshore. This distinction does not imply that tradable tasks do not require interpersonal skills, because most software production is done in teams, and developers must regularly interact with their clients (Gopal et al. 2002). However, even team-based jobs are potentially offshorable because an entire team, or group of tasks, can be moved offshore. Thus, within the IT workforce, programmers and systems analysts are more easily tradable, whereas IT sales personnel, managers, and network administrators are less tradable.

Although the theoretical guidance is consistent on this point, the extent to which IT offshoring has affected onshore skill composition remains an empirical question. Classifications can shed light on the propensity of different skills to be offshored in the long run, but only a subset of jobs that can be offshored has been offshored to date. Furthermore, if tradable and nontradable IT tasks are complements in the production of IT services, an increase in the global supply of IT workers capable of performing tradable tasks may also raise onshore demand for workers who can perform nontradable tasks, which will also affect the composition of onshore skills. Thus, the implications for the relative complementarities (nonsubstitutability) among various task groupings suggests that offshoring favors nontradable skills onshore, but the extent of these changes, which should first become visible at the firm level, is unknown. Therefore, a primary goal of this study is to measure how much IT offshoring shifts domestic skill composition in firms. The underlying hypothesis that is tested is as follows:

HYPOTHESIS 1. Offshoring reduces the employment share of tradable tasks for onshore IT workers.

This type of skill-based shift may affect some segments of the IT workforce more than others because of differing employment relationships. In particular, contract workers, whose employment relationships can be rapidly altered to changing supply and demand conditions (Slaughter and Ang 1996,

Abraham and Taylor 1996), represent an unusually large⁴ and important part of the overall IT workforce (Gurbaxani 1996, Matusik and Hill 1998, Ang and Slaughter 2001, Barley and Kunda 2004). Under a simple adjustment costs story, any effects experienced by the IT workforce because of offshoring are likely to be most pronounced for contract workers because these workers do not have long-term employment relationships, and the cost to the firm of adjusting employment levels of contractors is likely to be small.

In addition to an adjustment cost explanation, contract workers may also be differentially affected by outsourcing because they occupy different roles. Ang and Slaughter (2001), in a series of case studies, found that whereas contractors mostly do computer programming, the tasks required by permanent employees range widely and include user interaction, implementation, system integration, vendor management, project management, and managing contract professionals. Similarly, Bidwell (2009) found that managers tend to use IT contractors more for the technical aspects of work and less for tasks requiring user interaction. Thus, permanent IT employees are more likely to be involved with personal tasks than IT contractors. Furthermore, these studies also provide further support for an adjustment costs story by showing that the lower dismissal costs for IT contractors mean that changes in task requirements may more quickly manifest in changes in the demand for specific skills of contractors. We hypothesize that offshore hiring will shift the IT workforce toward permanent IT employees, because permanent IT employees are more likely to be employed in jobs requiring cross-functional business knowledge and greater face-to-face interaction with customers and vendors.

One limitation of our data is that IT contractors are not explicitly identified. However, a notable distinction between IT contractors and permanent IT employees is that permanent IT professionals are most often salaried, whereas highly skilled IT contractors tend to be paid hourly rates. Ang and Slaughter (2001) found evidence for this empirical regularity across a variety of different domains. Hourly employment can also be common for customer support workers (e.g., helpdesk, technical support, installation technicians), who are often hired by firms on a contingent basis. Therefore, in some of our specifications, we restrict our analyses to certain classes of workers to eliminate this heterogeneity. In our regression analyses, we empirically distinguish IT contractors from permanent IT employees using hourly versus salaried wage data for high-skill IT

occupations, subject to the assumption that hourly wages in the IT sector are more closely associated with contract or contingent work and flexible employment. We test the following hypothesis.

HYPOTHESIS 2. Offshoring reduces the employment share of hourly workers in the IT workforce.

3. Data and Measures

3.1. IT Offshoring Variables

Our IT offshoring measures are created from data obtained in late 2006 from a leading online global career website through which millions of individuals posted employment information, including occupation, primary industry affiliation, geographic location, professional positions, employer name, job title, years spent at the firm, and, for public companies, a ticker symbol. This data set is useful for studying offshore IT employment because it is global in scope and popular among IT workers. We obtained a random sample of about one million workers from this website. These data include information on about 156,000 IT workers employed at about 7,500 U.S. public firms. Of these IT workers, about 92,000 are located in the United States, and 64,000 are located overseas. The self-reported employment of these workers reflects the global IT employment of U.S. firms. Although these data contain some potential error because of nonreporting, they may be more accurate than data generated by surveys because it is possible that managers may be unable or unwilling to provide accurate measures of offshore employment to interviewers.

Using the location of overseas workers, we are able to control for the fact that firms offshore to different locations for different reasons, and these reasons may have direct implications for how offshoring affects the domestic workforce. Prior work has shown that offshoring to high-cost locations may increase domestic employment, whereas offshoring to low-cost locations decreases domestic employment (Harrison et al. 2007). We therefore avoid this potential confound by restricting our sample to India, where offshoring is most often for cost reduction and skill acquisition (Lewin and Couto 2007, Tambe and Hitt 2010). In our robustness analyses, however, we also test offshoring measures computed using offshore IT workers in other destinations.

To create offshore IT employment measures from these data, we extracted individuals who list computer services or IT as their primary industry,⁵ are

⁵ Specifically, we extracted 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.

⁴ Estimates place the proportion of IT workers operating on short term contracts from 10%–30% in large corporations (Ang and Slaughter 2001).

located in India, and are employed by publicly traded firms with their headquarters located in the United States. There are about 2,500 such workers in our sample. From our sample data, we calculate that Indian IT workers are about 3.9% of the global IT workforce outside the United States. This is consistent with other estimates that suggest Indian IT employment is about 4%–5% of the non-U.S. IT workforce (Gokarn et al. 2007, International Data Corporation 2007) at the end of our sample period.

We create two different offshoring measures. The first is a binary offshoring variable that takes the value 1 if a firm has at least one IT worker employed in India and indicates that a firm has established a captive center. Second, we create a variable indicating the percentage of the firm's total IT workforce located in India (Head and Ries 2002 use a similar measure of offshore employment). This measure captures differences in IT offshoring intensity (IT workers in India/total IT workers) among firms that are offshoring but may be more subject to measurement error that is filtered out by the binary variable, such as differences in participation rates on the website that provided our data across a firm's Indian establishments. Therefore, we use both measures in our analysis. We conducted a number of comparisons to ensure that our offshoring measures track well against other available offshoring data—they are similar in both overall incidence as well as cross-industry distribution.⁶

One concern about using captive centers (i.e., multinational overseas employment) as a measure of offshoring, despite the prevalence of this measure in the literature (Brainard and Riker 1997, Desai et al. 2009, Harrison et al. 2007), is that we may understate offshore activity by not including third-party offshore outsourcing. Prior research suggests that captive centers comprise slightly less than half of all offshoring activity and that firms with captive offshore IT centers are likely to engage in third-party offshore outsourcing or hybrid captive-outsourced offshoring approaches (Lewin and Couto 2007, Rajeevan et al. 2007). There are three reasons why we believe that our analysis reflects overall offshoring activity. First, most of the effect we observe is located in the early part of our sample, when captive centers were common but offshore outsourcing was less prevalent. We are therefore capturing offshoring as it appeared at the time. Second, surveys suggest a substantial fraction of firms use either captive centers or both captive centers and offshore outsourcing, so the two types of offshoring are highly correlated (Tambe and Hitt

2010).⁷ Third, we can address this concern econometrically by noting that omitting offshore outsourcing will lead us to *underestimate* the extent of offshoring, making our results conservative under the reasonable assumption that the domestic employment effects of all types of offshoring are similar. Instrumental variables (IVs) and first difference estimates are less subject to this form of measurement error, and we can also repeat this analysis for industry subsamples where we believe this bias is small. Overall, we find little evidence that the omission of offshore outsourcing has substantially affected our estimates or conclusions.

3.2. Onshore IT Skills Measure

We measure onshore IT skills using microdata describing the employment histories of a very large sample of U.S. IT workers from a leading career site. For each employee in the data set, the employer name, employment dates, job title, and occupation are included. We also have human capital variables for each worker, including education and experience. From these data, we extracted the approximately 500,000 IT workers (approximately 10%–15% of the entire U.S.-based IT workforce) who appeared in the data set between 1995 and 2006. Because these data indicate who is employed at each firm in a given year, we can measure the occupational distribution of a firm's IT workforce by aggregating employees' jobs classifications to the firm level for each year. The workers that appear in the data set also indicate whether they were full-time or hourly workers in 2006, whether they have a security clearance, and their level of educational attainment, which allows us to calculate aggregate firm-level averages of these measures for each firm-year in our data set. In other work, we benchmark these IT employment data, and we show that they compare favorably to external data sets with regard to human capital and cross-firm distributions (Tambe and Hitt 2012).

To classify occupations by tradability, we apply the method proposed by Blinder (2009). To the best of our knowledge, only two studies have developed frameworks for ranking jobs by tradability at a detailed occupation level Blinder (2009) and Jensen and Kletzer (2005). We use Blinder's (2009) classification because it has been widely employed in other studies of globalization and employment structure (Becker et al. 2009, Crino 2010). Although there are some differences between the Blinder (2009) and Jensen and Kletzer (2005) classifications generally,

⁷ It is worth noting that firms switching from captive center to hybrid or third-party models will produce positive correlations in levels, but negative correlations in differences as firms substitute captive centers with other organizational forms.

⁶ See Appendix A in the online supplement to this paper (available at <http://ssrn.com/abstract=1837497>).

they are similar within the IT sector. Thus, our classification approach is consistent with essentially all the comparable literature on globalization and jobs.

Blinder 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 easily offshored, whereas a score closer to 0 indicates that a job is unlikely to be offshored. The tradability of the tasks performed in a particular IT job is quantified by matching job titles to occupational codes in the O-NET database⁸ both by hand⁹ and using specialized software, and then assigning workers to the appropriate index value.

Our main dependent variable is IT workforce skill composition—the fraction of IT workers in tradable jobs out of all IT workers at a firm. We use a composition measure for two reasons. Theory and prior empirical research in offshoring generally suggest a relationship between employment share and offshoring—usually a ratio of employment or wages to total costs, variable costs, total employment, or occupational employment—rather than absolute changes in occupational employment. Composition measures are also less likely to be affected by external factors such as changes in the demand for IT labor generally or shifts in the size of individual firms. Finally, a balanced treatment of offshoring and employment levels would require determining the effect of offshoring on non-IT employment as well, which is beyond the scope of our analysis. Our study is limited, therefore, in the sense we cannot make assessments of how offshoring affects the absolute demand for specific IT skills.

The fraction of IT workers in a firm who provide tradable task inputs (*tradable task intensity*) is computed as the percentage of IT workers employed in jobs exceeding a threshold in Blinder's (2009) index. His ranking values are ordinal, so the choice of a particular threshold is subjective. One threshold to consider is 75, which is the boundary marking the Category I jobs that Blinder (2009) describes as "highly offshorable" in the long run. In most of our analysis, however, we instead use a higher threshold of 92 because this is the line at which much of the short-run shift in task share during the years in our panel appears to be occurring. As we show in our analysis, choosing a lower value does not significantly change our results, but reduces the precision at which

⁸ <http://online.onetcenter.org>.

⁹ We conducted this matching process using automated software and by manually coding the titles, but we found no significant differences. Results produced when using manual coding are shown in our robustness tests.

Table 1 Descriptions of Key Variables Used in Study

Key variables	Data source	Construction
<i>Captive center in India (Y/N)</i>	Global IT	Recorded as 1 if at least one IT worker employed in India
<i>% IT workers in India</i>	Global IT	India IT workers/total IT workers in global IT workforce
<i>Tradable task share</i>	Domestic IT	% of IT workers employed in occupations classified as "tradable" ^a
<i>Experience</i>	Domestic IT	Average experience of IT workers in each firm (self-reported)
<i>Education</i>	Domestic IT	Average education level of IT workers in firm (self-reported)
<i>Job tenure</i>	Domestic IT	Average job tenure of IT workers in firm
<i>IT employment</i>	Domestic IT	Firm-level IT employment (construction described by Tambe and Hitt 2012)
<i>% security clearance</i>	Domestic IT	% of IT workers in each firm who report having security clearance
<i>% hourly wage</i>	Domestic IT	% of IT workers in each firm who report being hourly workers.
<i>Sales</i>	Compustat	Annual sales
<i>Employment</i>	Compustat	Total firm employment
<i>Industry</i>	Compustat	Two-digit SIC classification
<i>Domestic outsourcing</i>	2008 survey	% of IT budget spent on outsourced services
<i>Packaged software use</i>	2008 survey	Use of packaged versus build-your-own software for core systems

^aThe classification of occupations as "tradable" varies in this study, but for most of our analyses is determined by using a set threshold in Blinder's (2009) classification of occupations.

we can interpret our estimates. Applying this measure to our panel data on IT employment allows us to calculate the fraction of IT workers at a firm that are tradable for each firm in each year.

3.3. Other Data and Measures

We use Compustat data for standard firm-level measures such as industry and total employment. In addition, we obtained data from a recent survey (2008) of approximately 200 senior IT officers (e.g., CIO, CTO, or vice president) that included questions on the fraction of firmwide information systems expenditure on (domestic) outsourcing and the extent to which the firm builds its own software or buys packaged software, which we will use for robustness tests. All of the measures used in this study and their methods of construction are summarized in Table 1.

4. Empirical Implementation

Our main regression models relating IT skill composition to offshoring activity are consistent with an established literature on outsourcing and skills.¹⁰ The logic

¹⁰ See, e.g., Berman et al. (1994), Feenstra and Hanson (1996), Slaughter (2000), Strauss-Kahn (2004), Head and Reis (2002), Crino (2010), Becker et al. (2009), Hijzen et al. (2010), and Hakkala and Huttunen (2010).

of our model is that there is a trade-off between lower wages from offshore employment and higher coordination costs (or production inefficiencies) arising from managing remote production. Tradable tasks receive the same wage cost benefits, but have fewer coordination cost concerns, so the “price” a firm faces for offshore labor is lower for these tasks. However, the option to use offshore labor only accrues to firms that have sunk the fixed cost needed to establish an offshore center.

To formalize this observation, let production be characterized by a transcendental logarithmic cost function that relates total cost (C) to the prices and quantities of tradable IT labor onshore (L_{itt} with price P_{itt}), tradable IT labor offshore (L_{ito} , P_{ito}), nontradable IT labor (L_{itn} , P_{itn}), ordinary capital and labor (K , L , P_k , P_l), and the level of output (V). Firms that have made an investment in an offshore center (O , where $O = 1$ if the firm has invested offshore and 0 otherwise) can procure tradable labor offshore, whereas other firms cannot. Applying Shepard’s lemma to the cost function yields a factor demand equation for onshore labor:

$$\frac{P_{itt}L_{itt}}{C} = \gamma_0 + \gamma_V \log V + \gamma_{itt} \log P_{itt} + \gamma_{ito} O \log \delta P_{itt} + \gamma_{itn} \log P_{itn} + \gamma_L \log P_L + \gamma_K \log P_K.$$

Using the standard assumption that firms face similar prices for factor inputs in any given year, we can collect all terms that only vary by time (t) into a single intercept and rewrite the outsourcing term:

$$\frac{P_{itt}L_{itt}}{C} = \gamma_t + \gamma_V \log V + \alpha O, \quad \text{where}$$

$$\gamma_t = \gamma_0 + \gamma_{itt} \log P_{itt} + \gamma_{itn} \log P_{itn} + \gamma_L \log P_L + \gamma_K \log P_K \quad \text{and} \quad \alpha = \gamma_{ito} \log \delta P_{itt}.$$

Our focus will be on obtaining estimates of α , which should be negative because offshore and onshore tradable tasks are close substitutes. For our empirical implementation, we estimate the time-varying terms using a dummy variable for each year (see Machin and Van Reenen 1998, Head and Ries 2002) and make two additional approximations. First, although α theoretically should vary over time, the variation is likely to be small, especially in the presence of a time-varying intercept, so we assume it is constant over time. Second, variation in factors other than IT labor are likely to be small (offshore IT labor is on the order of 0.2% of total costs), and price effects on cost share conditional on time are also negligible, so we focus on the share of tradable tasks in total IT labor rather than cost shares. We show that estimates without these assumptions are virtually identical, but we make these two simplifications to make the magnitudes

more easily interpretable. Similar employment-share estimates have informed other studies of offshoring (Anderton and Brenton 1999, Machin and Van Reenen 1998, Strauss-Kahn 2004, Hijzen et al. 2005), and these studies have also found that using employment share produced results similar to when using cost share. Our base estimating equation is thus

$$TTSHARE_{it} = \gamma_t + \gamma_V \log V_{it} + \alpha O_{it} + controls + \varepsilon. \quad (1)$$

The dependent variable in (1), tradable task intensity ($TTSHARE_{it}$) for each firm (i) in each year (t), is the share of tradable tasks in the firm’s IT workforce, O is our offshoring indicator, and V is a measure of firm output. In addition, we include dummy variables for time (represented by γ_t) as well as additional firm controls such as industry (at the two-digit Standard Industrial Classification (SIC) level), the logarithms of total employment (from Compustat) and IT employment (from our workforce data), and sales growth ($PCTSALES$, from Compustat). The two size measures control for organizational differences between smaller and larger firms or IT departments, and sales growth captures potential differences between expanding or shrinking firms that may face different costs of adjusting their labor force. We also control for firm-level characteristics of the IT workforce, including *education*, *experience*, and *job tenure*, averaged across all workers at the firm.

Equation (1) can be estimated using an ordinary least squares (OLS) regression in levels with Huber–White robust standard errors (clustered by firm) or first differences, which removes all time invariant firm effects and is commonly used in employment studies where there might be unobserved firm heterogeneity. The same model is used to conduct our tests of the effect of offshoring on hourly workers, where tradable task share is replaced by hourly worker share in Equation (1).

4.1. Endogeneity

Our model includes controls for detailed characteristics of the IT workforce, and difference estimates mitigate estimation bias due to differences among firms. For instance, our difference estimates should have little bias because firms differ in their composition of tradable skills, and those with more demand for these skills may be more likely to offshore because of the potential for scale economies in an offshore facility. However, our firm controls will have more limited effect in mitigating bias because of time-specific reverse causality. For instance firms may anticipate a change in their need for specific IT tasks and invest in offshoring to reap additional benefits when this occurs. As an initial check, we can test whether

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. We conducted several analyses that indicate that a firm's skill composition in 1990, which predates most serious offshoring activity, was a relatively poor predictor of 2006 offshoring levels.¹¹

Our second (and primary) strategy for resolving the potential endogeneity issue is to supplement our cross-sectional and difference results with results from an IV estimator, where we treat offshoring as endogenous and use instruments that capture factors that influence the ability to engage in offshoring across firms but are not related to skill requirements conditional on the other control variables. We report results from traditional IV estimators, as well as those that account for the binary nature of the potentially endogenous offshoring variable by using a probit model to estimate the first stage.

The benefits and costs of offshoring may vary by firm in ways unrelated to IT task composition, and we have two instruments that capture this variation. First, the number of *non-IT offshore workers* employed by the firm may reflect lower offshoring costs to the extent that firms can share fixed costs for an offshore center across more workers. These data are available from the same source we use for our offshoring measure. Second, we use the fraction of IT workers with a security clearance. Firms that perform secure work cannot shift this work offshore so firms that perform extensive secure work cannot as readily use offshoring.

First-stage regressions suggest that these variables, along with the other control variables, explain a significant amount of 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. Therefore, we see no evidence in our preliminary (or subsequent) analyses that would suggest that the decision to offshore is subject to reverse causality—that is, our data strongly suggest that firms that choose to offshore change their skill mix; we do not find evidence that existing skill mix is a driver of offshoring.

A residual concern with using firm-level instruments is that they may be determined endogenously along with the firm's workforce structure. Therefore, we report estimates from a second set of instruments that are external to the firm and but also affect offshoring propensity. We use two variables to form this instrument set: (1) industry concentration and

(2) offshoring by other firms in the industry. Both variables measure competitive pressures from the firm's environment to lower IT labor costs through offshoring. The R^2 in a first-stage regression using these instruments is comparable to the first-stage regression when using firm-level instruments. In our analysis below, we test these instruments alone and in conjunction with our firm-level instruments.

5. Descriptive Statistics and Correlations

Table 2 shows statistics for the firms in our sample. About 53% of IT workers in our sample are employed in the production of personal services. We find a comparable number of 53% in the 2006 Occupational Employment Survey (OES) by combining workers in the "Computer and Mathematical Science Occupation" and IT management, although the OES may undercount IT sales workers. 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, with a duration of 5 years for a typical employment spell and 3 years at the current employer. Most workers have at least four years of college education. Firms in our sample are also quite large, with about 19,000 employees and 5 billion dollars in sales, on average.

In the fifth and sixth columns of Table 2, we compare mean values of the main variables in our analysis, depending on whether or not the firms have offshore IT facilities. Sales are significantly 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. In Table 3, we report correlations between the firm-level variables. Of particular interest are the correlations in column (1), which suggest that offshoring is positively associated with IT workforce size and negatively associated with the demand for tradable tasks in the onshore IT workforce.

Figure 1 illustrates how the share of tradable IT tasks has been changing over time in offshoring and nonoffshoring firms. Task content for these firms was similar in 1995 but begins to diverge thereafter. The percentage of IT workers performing tradable tasks in nonoffshoring firms rises slowly between 1995 and 2006, but drops by about eight points in the same period in offshoring firms. The fact that tradable task composition is similar among firms at the beginning of our sample also suggests that it does not explain

¹¹ The results of these analyses can be found in the online supplement to this paper.

Table 2 Means and Standard Deviations for Firm-Level Variables (2006 Levels)

Variable	<i>N</i>	Mean	Std. dev.	Offshoring mean	Nonoffshoring mean	<i>t</i> -statistic ^a
<i>Captive center in India</i> (Y/N)	864	0.073	0.261	1	0	
<i>Tradable task share</i>	864	0.47	0.16	0.36	0.48	4.47***
<i>Experience (years)</i>	864	12.8	9.4	15.4	12.6	1.87*
<i>Education</i>	864	4.13	0.498	4.38	4.12	3.20***
<i>Job tenure (years)</i>	864	2.90	1.16	2.84	2.90	0.331
<i>Sales</i> ($\times 1,000,000$)	864	10,026.2	25,071.6	20,270.6	9,528.9	2.66***
<i>Employment</i> ($\times 1,000$)	864	31.0	86.3	49.6	30.1	1.40
<i>IT employment</i>	864	676.5	1,898.6	3,183.4	554.8	8.93
<i>% with security clearance</i>	864	0.077	0.112	0.061	0.078	0.961
<i>% hourly wage</i>	864	0.186	0.117	0.151	0.188	1.93*

Notes. Correlations are for 2006 values of the variables shown. The *t*-statistic tests the hypothesis that the means in offshoring and nonoffshoring firms are equivalent.

* $p < 0.10$; *** $p < 0.01$.

Table 3 Correlations for Variables Used in Firm-Level Analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. <i>Captive center in India</i> (Y/N)	1.0								
2. <i>Tradable task share</i>	-0.14	1.0							
3. <i>Log(experience)</i>	0.04	-0.03	1.0						
4. <i>Log(education)</i>	0.10	-0.25	-0.06	1.0					
5. <i>Log(tenure)</i>	0.01	-0.04	0.26	0.10	1.0				
6. <i>Log(employment)</i>	0.09	0.12	0.09	0.02	0.15	1.0			
7. <i>Log(IT employment)</i>	0.22	0.03	0.11	0.09	0.12	0.89	1.0		
8. <i>Log(foreign income)</i>	0.18	-0.09	0.05	0.15	0.08	0.38	0.43	1.0	
9. <i>% hourly wage</i>	-0.06	0.29	-0.08	-0.20	-0.32	0.15	0.09	0.04	1.0
10. <i>% security clearance</i>	-0.04	-0.02	0.06	0.01	0.00	0.05	0.10	0.02	-0.08

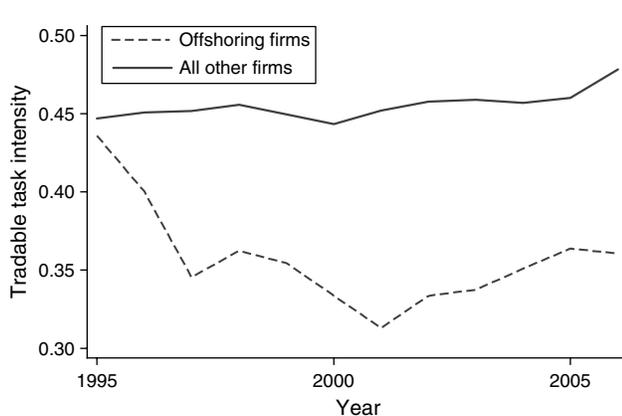
Notes. *N* = 810. Correlations are for 2006 values of the variables shown.

the propensity to offshore (consistent with our causality arguments). In Table 4, we report the comparable statistics from 1995 and 2006. A *t*-test rejects the hypothesis that the mean difference between these two sets of firms is the same ($t = 7.61$). The statistics in Tables 2 and 4 indicate that offshoring affects IT task mix in a direction consistent with theory, but in the next section, we more rigorously test how offshoring affects IT workforce composition.

Table 4 Captive Centers and Tradable Task Share in the Domestic IT Workforce

Tradable task share	1995	2006	Difference
In firms with captive centers in India	0.44	0.36	-0.08
Other firms	0.45	0.48	0.03
Difference			-0.11

Note. A *t*-test of the hypothesis that the difference between the mean differences is zero is rejected at the 1% level ($t = 7.61$).

Figure 1 Tradable Task Share in the Domestic IT Workforce, 1995–2006

6. Regression Results

6.1. Offshoring and IT Workforce Composition

The main results of the paper are in Table 5. The dependent variable in all regressions is the fraction of tradable tasks performed by the firm's IT workforce. We start with an OLS regression using the pooled sample over all years with Huber–White robust standard errors (clustered by firm). The results in column (1) indicate lower onshore levels of tradable tasks being performed by firms that have a captive IT center located in India ($t = 5.72$, $p < 0.001$). The coefficient magnitudes suggest that after controlling for other factors, the difference in the percentage of onshore tradable tasks being performed between offshoring and nonoffshoring firms is about eight points.

Table 5 Main Regression Tests of Offshoring on Domestic IT Tradable Task Intensity

	(1)	(2)	(3)	(4)
	All	All	All	All
Dependent variable: <i>Tradable task share</i>	OLS	Differences	IV	Treatment effects
<i>Captive center in India</i> (Y/N)	-0.079*** (0.015)	-0.013** (0.006)	-0.129** (0.064)	-0.148*** (0.032)
Log(<i>employment</i>)	0.030*** (0.008)	-0.012 (0.008)	0.029*** (0.008)	0.030*** (0.003)
Log(<i>IT employ</i>)	-0.013 (0.008)	0.011 (0.007)	-0.011 (0.008)	-0.013*** (0.003)
<i>Sales growth</i>	-0.048*** (0.008)	0.014 (0.010)	-0.048*** (0.007)	-0.048 (0.039)
Log(<i>education</i>)	-0.200*** (0.029)	-0.109*** (0.019)	-0.196*** (0.029)	-0.199*** (0.013)
Log(<i>experience</i>)	-0.050** (0.020)	-0.023** (0.009)	-0.049** (0.020)	-0.050*** (0.008)
Log(<i>job tenure</i>)	-0.010 (0.012)	-0.046** (0.011)	-0.010 (0.012)	-0.010* (0.006)
First-stage R^2			0.19	0.10
Controls	Industry year	Industry year	Industry year	Industry year
Observations	8,789	7,190	8,789	8,789
R^2	0.21	0.03	0.20	

Notes. Standard errors are robust, clustered on firm. All regressions include controls for year and two-digit SIC industry. A Sargan test for overidentification is not rejected. A Hausman test cannot reject the hypothesis that OLS regressions (column (1)) are consistent.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

In column (2), we test one-year difference estimates, which remove the effects of time-invariant sources of heterogeneity that are associated with the offshoring indicator. The coefficients from the differences regression indicate that establishing a captive center is associated with about a one point per year drop in the percentage of tradable tasks onshore after controlling for other factors ($t = 2.17$, $p < 0.05$). If firms in our sample, established captive centers in the mid to late 1990s, this one percentage point difference, compounded over the years in our time sample, is roughly consistent with the eight percentage point difference estimated in our cross-sectional results.

In column (3), we show results from IV regressions using non-IT offshore workers and security clearance as instruments for the IT offshoring decision. The estimates from the IV regression are larger in magnitude than our original coefficient estimate on offshoring ($t = 2.01$, $p < 0.05$). The R^2 value for the first-stage regression is 0.19, and a Hausman test indicates that we cannot reject the hypothesis that the establishment of a captive center is exogenous with respect to onshore workforce mix. The higher IV estimate suggests that unobserved factors tend to bias our offshoring coefficients toward 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 column (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 column (3), but with smaller standard errors ($t = 4.63$, $p < 0.01$).

6.2. Extensions

In this section, we use various alternative measures of offshore and domestic IT workers to further develop our core result. In Table 6, we present estimates using the percentage of IT workers in captive centers rather than a binary variable indicating the establishment of a captive center, which is the variable we have analyzed thus far. The offshoring coefficients in column (1) are negative and significant ($t = 2.70$). The estimates from our differences model in column (2) are also negative at the same levels of significance ($t = 2.26$). In column (3), we report estimates on the percentage of captive center IT workers, conditional on having a captive center. The estimates indicate that a higher percentage of captive center IT workers is observed in firms with higher levels of tradable tasks in the onshore IT workforce. This result suggests that the negative estimates in column (1) confound the effects of the offshoring decision with a positive association between offshore and onshore tradable task composition. This upward bias disappears after differencing, and the differenced estimate in column (4) is similar to our earlier differenced estimates ($t = 1.9$).

The upward bias in our cross-sectional estimates suggests that (1) an IV estimator will have a larger impact on offshore intensity estimates than the offshoring binary variable because offshore intensity is subject to greater 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 are confirmed in columns (5) and (6). Use of the IV estimator inflates the estimate and the standard error on offshore share, but the estimate is not significant. The offshoring binary estimate in column (5) confirms that offshoring intensity and the offshoring decision push in opposite directions, and

Table 6 Regression Tests of Percentage of Offshore IT Workers on Domestic IT Tradable Task Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Offshoring only	Offshoring only	All	All
Dependent variable: <i>Tradable task share</i>	OLS	Differences	OLS	Differences	IV	OLS
% IT workers in India	-0.224*** (0.086)	-0.080** (0.034)	0.248* (0.147)	-0.095* (0.050)	-1.51 (1.04)	0.109 (0.105)
<i>Captive center in India</i> (Y/N)						-0.091*** (0.019)
Log(<i>employment</i>)	0.031*** (0.008)	-0.012 (0.008)	0.039 (0.028)	-0.076** (0.030)	0.030*** (0.008)	0.030*** (0.008)
Log(<i>IT employ</i>)	-0.016** (0.008)	0.011 (0.007)	-0.003 (0.028)	0.063** (0.028)	-0.013 (0.009)	-0.013 (0.008)
<i>Sales growth</i>	-0.048*** (0.007)	0.014 (0.010)	2.92 (4.16)	0.013 (0.011)	-0.046*** (0.007)	-0.049*** (0.008)
Log(<i>education</i>)	-0.204*** (0.029)	-0.109*** (0.020)	-0.317** (0.146)	-0.501*** (0.131)	-0.195*** (0.030)	-0.199*** (0.029)
Log(<i>experience</i>)	-0.052*** (0.020)	-0.023** (0.009)	-0.057** (0.027)	-0.007 (0.006)	-0.059** (0.022)	-0.049** (0.020)
Log(<i>job tenure</i>)	-0.010 (0.012)	-0.045*** (0.010)	0.057 (0.047)	-0.026 (0.048)	-0.007 (0.013)	-0.010 (0.012)
Controls	Industry year	Industry year	Industry year	Industry year	Industry year	Industry year
<i>N</i>	8,789	7,190	328	299	8,789	8,789
<i>R</i> ²	0.21	0.03	0.39	0.24	0.14	0.21

Notes. Standard errors are robust, clustered on firm. All regressions include controls for year and two-digit SIC industry.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

separating the effects of these two variables slightly raises the magnitude of the estimate on the offshoring decision variable. These results suggest that using an offshoring binary variable as a marker of offshoring activity produces a conservative estimate, and that in firms with high levels of onshore tradable tasks, incurring the fixed costs of an offshore captive center increases offshoring levels of all types. Our interpretation of these results is that once a captive center has been established, offshoring rises with (unobservable) firm-specific demand for tradable tasks, but that this effect is dominated by workforce differences between firms with and without offshore centers. This suggests that the demand for offshoring is likely to be higher for firms with greater demand for tradable tasks, which implies that firm-specific unobservable variables related to skill or task demand will tend to impose a conservative bias on our estimates.

In Table 7, we analyze the relationship between offshoring and the percentage of IT hourly employees hired by organizations. The results in column (1) show that offshoring firms hired 2%–3% fewer hourly workers than nonoffshoring firms in 2006 ($t = 1.8$). These results are restricted to 2006 because workers in our sample identified themselves as hourly or annual salaried workers only in 2006. However, we can conduct a quasi-differences test if we assume that most workers retain the same work status over several years. Departures from this assumption may introduce noise into our dependent variable, but not in a systematic way that could bias our results. The offshoring coefficient from a differenced specification 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

Table 7 Regressions of Offshoring on the Use of IT Hourly Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	% hourly workers	% hourly workers	Tradable task share	Tradable task share	Tradable task share	Tradable task share	% hourly workers
Sample	All	All	Full-time	Hourly	All	All	Exempt workers
	OLS	Differences	OLS	OLS	OLS	OLS	OLS
<i>Captive center in India</i> (Y/N)	-0.027* (0.015)	-0.007 (0.004)	-0.084** (0.027)	-0.096** (0.047)	-0.074** (0.025)	-0.065** (0.025)	-0.031* (0.017)
% hourly						0.333*** (0.062)	
	Industry	Industry year	Industry	Industry	Industry	Industry	Industry
<i>N</i>	863	5,685	773	270	863	863	452
<i>R</i> ²	0.27	0.04	0.24	0.33	0.21	0.25	0.31

Notes. Standard errors are robust, clustered on firm. Exempt workers in column (7) are IT managers, systems analysts, and software engineers. All regressions include controls for year and two-digit SIC industry.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

shift that we find evidence for in earlier sections may in part be due to a shift away from the use of IT workers who are paid hourly and are more likely to be performing tradable tasks.

The results in columns (3) and (4) show that offshoring impacts the task content of work similarly if examining hourly and annual salaried workers separately. The number of observations in columns (3) and (4) are different than in column (1) because some firms have only hourly or salaried IT workers that appear in our sample, so many firms in the full sample are not included when narrowing the focus to only hourly workers or only salaried workers. In columns (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 column (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 a higher fraction of tradable tasks, which is consistent with the distribution of tasks between hourly and salaried workers and that, conditional on the fraction of hourly workers employed by the firm, offshoring is still associated with a shift away from tradable tasks being performed onshore ($t = 3.29$).

Finally, in column (7) we report results when restricting the IT workers in our sample to those classified as exempt by the Fair Labor Standards Act because it is normal for exempt employees to be salaried rather than paid hourly. Our use of the hourly wage classification as a proxy for contractor status may not be justified for IT support workers, who are often classified as nonexempt employees and are paid hourly wages.¹² Furthermore, IT support workers are often offshored to provide 24-hour support. We check, therefore, whether the associations between offshoring and hourly worker usage persist after excluding IT support workers and other workers who potentially fall into nonexempt categories, and for whom hourly wages may not reflect contractor status. The estimates from column (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 nonexempt. However, the results shown in column (7) are similar to those

in column (1), indicating that our results are probably not driven solely by the offshoring of support workers. In other words, our results support not only that hourly workers are more likely to be affected by offshoring, but the stronger statement that these effects may specifically apply to IT contractors. 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 appear to be related primarily to differences in work task content, rather than other differences.

In Table 8, we look at the effects of offshoring to different locations or offshoring technical versus non-technical IT workers. In addition to providing a more nuanced perspective on offshoring and skill composition, these tests address the criticism that our offshoring estimates may reflect unobserved attributes of large, global firms rather than the effects of skill-based offshoring—if this were the case, any observed effects would not be limited to the offshoring of technical workers or offshoring to specific locations. In column (1), we include the percentage of IT workers located in India, as well as a second measure computed from the percentage of IT workers located in countries other than India or the United States. Including the second offshoring measure 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 (Tambe and Hitt 2010). The estimates indicate that the observed workforce shifts are associated with offshoring to India rather than other destinations, and our offshoring coefficient is probably 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 include offshore share measures computed from offshoring different types of IT workers, where workers are classified as technical, managerial, or other, depending on their two-digit

Table 8 OLS Regressions by Offshore Worker Location and Type

Dependent variable: <i>Tradable task share</i>			
By location		By IT worker type	
India	−0.487** (0.233)	Technical	−0.485** (0.232)
All other	−0.008 (0.015)	Managerial	−0.153 (0.242)
		All other	−0.330 (0.288)
<i>N</i>	5,616		1,625
<i>R</i> ²	0.26		0.19

Notes. Standard errors are robust, clustered on firm. Regressions are from the baseline model used in Table 12, column (1). All regressions include controls for year and two-digit SIC industry.

** $p < 0.05$.

¹² For a more thorough discussion of the categorization of IT workers under the Fair Labor Standards Act, see Shea (2008).

Table 9 Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	All	All	All	SIC 73	Other industries	Outsourcing and packaged software	Closures
<i>Tradable task share</i>	External IV set	Full IV set	Differences IV	IV	IV	OLS	Differences
<i>Captive center in India (Y/N)</i>	-0.065* (0.035)	-0.097** (0.038)	-0.017 (0.061)	-0.081 (0.090)	-0.202*** (0.083)	-0.082* (0.046)	-0.026** (0.010)
% <i>outsourced</i>						0.003 (0.008)	
<i>Packaged software</i>						0.015 (0.013)	
First-stage R^2	0.16	0.19	0.02	0.16	0.14		
Controls	Industry year	Industry year	Industry year	Year	Industry year	Industry year	Industry year
Observations	8,176	8,176	6,600	2,090	6,256	559	7,137
R^2	0.20	0.20	0.02	0.07	0.04	0.53	0.03

Notes. Standard errors are robust, clustered on firm. All regressions include controls for year and two-digit SIC industry.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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. The point estimate on the technical worker measure is larger than our initial estimated elasticity when using offshore share as an independent variable in Table 6, perhaps because for the task-level workforce changes of the kind that we are exploring, the offshoring of technical workers is the more accurate measure, rather than the offshoring of all IT workers including the management layer.

6.3. Robustness Tests

In Table 9, we present results from a number of additional regressions that test the robustness of our main results in Table 5. In column (1), we present results from a regression using instruments that are external to the firm: industry concentration measured as a Herfindahl index and the mean of the offshoring variable for other firms in the same two-digit industry. These instruments produce an estimate that is significant and broadly consistent with the IV results from regressions using our firm-level instruments ($t = 2.39$). Including the full set of instruments from both the firm and the industry levels in column (2) produces similar results ($t = 3.66$). Our estimates in most cases indicate that any endogeneity in the offshoring variable is likely to bias our estimates in a conservative direction (downward toward zero). The results from a differences IV regression in column (3) are not significant, perhaps because of the limited power of our firm-level instruments in differences.

However, the direction and magnitude of the estimate are consistent with our expectations.

In columns (4) and (5), we test the extent to which our results may be driven by IT services industries, using the IV specification with our firm-level instruments. IT services offshoring may be fundamentally different because captive centers often serve as offshore development centers that provide IT services to global clients.¹³ We test this assertion by narrowing our sample to SIC 73, which includes industries where IT workers are generally employed in production rather than support and has some of the highest offshoring rates (Tambe and Hitt 2010). Interestingly, the offshoring coefficient in column (4) when restricting the sample to SIC 73 is no longer significant. The regression in column (5) includes firms in all other industries, and indicates that our earlier reported effects of offshoring are driven by IT-using industries, where IT workers are more likely to be support workers than production workers. In IT services offshoring, where firms may need to employ both technical and client-facing personnel, a geographic division of labor within the firm's workforce may not be as viable.

In column (6), we include measures of (1) overall IT outsourcing and (2) packaged software usage as control variables, both of which have experienced tremendous growth, and both of which are likely to have affected IT labor demand. However, if offshoring firms have less need for outside IT contractors, as is suggested by the correlations in Table 3, then this will bias our offshoring coefficients downward. We test whether our results are robust to including measures of outsourcing and packaged software by using data collected in a recent survey on the extent of IT outsourcing and whether firms build or buy the software they use, available for a subset of the firms

¹³ We thank an anonymous reviewer for making this point.

in our sample. The point estimate on the offshoring coefficient after including these variables is comparable to column (1), and indicates that offshoring is associated with a significant drop in the percentage of onshore IT work composed of tradable tasks ($t = 1.80, p < 0.1$). The reduced significance is due to a smaller sample from limited availability of our supplemental survey measures, not because of bias due to omitting these variables as covariates. In column (7), we present differenced results after dropping data points in which firms open new offshore centers—identification, therefore, comes from onshore workforce shifts as firms *exit* captive centers. Interestingly, our effect sizes are larger in this regression, suggesting that firms are faster to reorganize the onshore workforce when they close an offshore establishment.

As discussed earlier, a potentially important variable omitted from our analysis is domestic outsourcing levels, so we also take a closer look at domestic outsourcing. In column (6) of Table 9, we showed that our offshoring coefficients do not change substantially when controlling for domestic outsourcing levels, but we present additional results here. Conditional on size, offshoring and domestic outsourcing should be negatively correlated if firms hire labor through either one or the other of these mechanisms. However, we can explicitly test whether workforce composition in industries that provide domestic outsourcing services is substantially different than that in other industries. In particular, any observed workforce shifts may partially be accounted for by countershifts in the workforce composition of domestic outsourcing firms instead of a countershift in offshore firms, which has very different implications for the U.S. labor market because it indicates a reallocation of tasks among U.S. firms, rather than across countries. However we cannot reject the hypothesis (see Table 10) that IT workforce composition in IT consulting industries (SIC 7370) is the same as that of other industries.

For another perspective on the interrelationship between our offshoring results and domestic outsourcing, we can use the observation that firms that do high-security work cannot offshore but can domestically outsource work. We can test whether our results are affected by domestic outsourcing by looking for differences in tradable task composition between high-security and low-security firms.¹⁴ If domestic outsourcing is causing the skill composition shift we

Table 10 Comparison of Workforce Composition with Domestic Outsourcing Industries

	<i>N</i>	Tradable task intensity
Computer programming and consulting (7370)	8,848	0.43
All other industries	353	0.45
		$t = 0.14, p < 0.89^a$
Firms with high security work (SIC 73)	94	0.47
Other firms (SIC 73)	86	0.38
		$t = 3.62, p < 0.01^b$

^a*t*-test of the hypothesis that tradable task intensity is the same in SIC 7370 as in all other industries.

^b*t*-test of the hypothesis that tradable task intensity in high-security firms in SIC 73 is the same as in other firms in SIC 73.

observe, there should be no difference between high-security and low-security firms. However, we find that IT workforce differences between the two sets of firms (Table 10) are substantial. The differences indicate that the proportion of tradable tasks is higher in high-security firms. Thus, whether or not a firm has the ability to offshore IT work is associated with differences in the task composition of onshore work ($t = 3.62, p < 0.01$).

In Table 11, we test the sensitivity of our results to our model assumptions. In column (1), we test our assumption that price effects on cost share are likely to be negligible by using cost share rather than employment share as a dependent variable. Because we have wage data for the workers in our sample in 2006, we can construct the cost share of IT workers employed in impersonal tasks for that year. The correlation between the cost share and employment share variable in 2006 is 0.94, and using cost share produces an offshoring estimate that is very similar to when using employment share. In column (2), we test the assumption that time-varying effects, which we assume to be constant across firms and absorbed by year dummies, are actually the same between offshoring and nonoffshoring firms by interacting the year dummies with the offshoring variable. A joint significance test of the hypothesis that the year dummy variables interacted with offshoring is significantly different from zero cannot be rejected ($F(10, 1,430) = 0.95$; Prob. $> F = 0.48$).

In columns (3)–(6), we test the sensitivity of our analysis to the methods used to map job titles to O-NET job codes. Our initial categorization of IT workers by job title into O-NET occupational categories was performed using third-party software that is explicitly designed for this purpose and is currently being used by state governments to map reported job titles to skills. However, for robustness, we also performed similar tests after hand matching common job titles to O-NET codes. The size of the sample created through this exercise was smaller than that

¹⁴ The partial correlations between security clearance and outsourcing in our outsourcing data are not significantly different from zero, so it does not appear that of the firms in our sample, security clearance is associated with lower outsourcing levels ($N = 86$). Moreover, a positive correlation between the two suggests that high-security firms are, if anything, outsourcing larger amounts of work.

Table 11 Sensitivity to Model Assumptions and IT Workforce Measurement

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	OLS	OLS	OLS	OLS	OLS	OLS
<i>Tradable task share</i>	<i>Cost share</i>	<i>Offshoring</i> × <i>year</i>	<i>Manual coding</i>	Index threshold ≥ 92	Index threshold ≥ 85	Index threshold ≥ 75
<i>Captive center in India (Y/N)</i>	−0.086** (0.026)	−0.100** (0.019)	−0.050** (0.014)	−0.079** (0.015)	−0.083** (0.015)	−0.090** (0.015)
Controls	Industry year	Industry off × year	Industry year	Industry year	Industry year	Industry year
Observations	579	8,789	5,202	8,789	8,789	8,789
R ²	0.18	0.21	0.19	0.22	0.19	0.22

Notes. Standard errors are robust, clustered on firm. Other independent variables include *employment*, *IT employment*, *sales growth*, *education*, *experience*, and *job tenure*. In column (2), the hypothesis that the *offshoring* × *year* dummy variables are different than zero is not jointly significant: $F(10, 1,430) = 0.95$; Prob. > $F = 0.48$. All regressions include controls for year and two-digit SIC industry.

** $p < 0.05$.

of the original sample because of the labor-intensive nature of this process, so our results are less precisely estimated. However, our results from this approach, shown in (3), are similar, which gives us confidence that our job title mapping methods do not appear to introduce any idiosyncratic errors into our estimates.

We also test the effects of moving the line at which we divide work into tradable categories. The main regressions presented above divide occupations at 92 on Blinder's (2009) scale, which is based upon our observation that this is the margin upon which most IT job substitution occurs. However, by moving this line further to the left, we can broaden the category of jobs consisting of tradable tasks and test how our results respond to moving this cutoff. Our baseline results are reproduced in column (4) of Table 11. In columns (5) and (6), we show results when broadening the jobs composed of tradable tasks, first by moving the index value threshold to 85, and then to 75, which is the value that Blinder (2009) uses to delineate "Category I" jobs, which are those that he deems to be highly offshorable in the long run. The estimates from these regressions are similar to those in column (1) and appear to grow slightly larger as we broaden the category of jobs. Most of the effect size in this time sample, however, appears to be coming from jobs with an index value higher than 92.

Finally, in Table 12, we test the validity of our interpretation of the offshoring variable, as well as the effects of measurement error in the offshoring variable. Some evidence comes from our differences regressions above, which remove the effects of cross-firm differences. However, there are additional contrasts we can use in the data. Industry reports have shown that the rise of third-party offshore outsourcing has been exponential, and economically significant levels of offshore outsourcing are relatively recent. IT services offshoring began with initial waves of multinational captive centers in the mid-1990s, but third-party offshore outsourcing gained in popularity only leading up to the Y2K bug in the late 1990s. As a

result, the total value of all offshore outsourcing contracts to India grew from only \$105 million in 1990 to \$5.3 billion in 2000, and then to \$12.2 billion in 2004 (Dossani 2004). The timing of serious offshore outsourcing spending, therefore, lags the establishment of initial waves of multinational centers, suggesting that any omitted effects of an outsourcing variable should be small in the mid-1990s. In column (1), we show that results are similar when limiting the sample to the mid-1990s, which predates the rise of most offshore outsourcing ($t = 3.33$).

In column (2), we limit our sample to the firms in our survey that reported that less than 5% of their budget was spent on IT outsourcing—any outsourcing levels in these firms, therefore, would have been minor. The expected effects of this restriction on the offshoring estimate, however, are ambiguous, because it not only removes the downward bias caused by firms that engage only in offshore outsourcing, but also lowers the overall offshore footprint of the firms in our sample that use both captive centers and offshore outsourcing. The results from this test are somewhat smaller but significant ($t = 1.9$).

Finally, in columns (3) and (4), we show the results from two different industry subsamples, high-tech industries and financial industries. This contrast is an interesting one because a recent industry report

Table 12 Sensitivity to Measurement of the Offshoring Variable

	(1)	(2)	(3)	(4)
Dependent variable:	Prior to 1998	Outsourcing < 5%	High-tech	Financial services
% <i>tradable tasks</i>	OLS	OLS	OLS	OLS
<i>Captive center in India (Y/N)</i>	−0.080*** (0.024)	−0.063* (0.033)	−0.086*** (0.022)	−0.060*** (0.026)
<i>N</i>	1,583	162	2,090	1,318
R ²	0.20	0.73	0.15	0.13

Notes. Standard errors are robust, clustered on firm. All regressions include controls for year and two-digit SIC industry.

* $p < 0.10$; *** $p < 0.01$.

indicates that although Indian captive centers are popular in both industries, offshore outsourcing as the sole method of Indian offshoring is more common in the financial sector (Rajeevan et al. 2007). In the high-tech sector, 10% of their sample chose offshore outsourcing as the sole method of offshoring, whereas the comparable figure for financial services was about 30%. If omitting firms that use offshore outsourcing as the sole method of offshoring exerts a downward bias on the estimates, the coefficient estimates in the high-tech sector should be higher than in financial sectors, and this is consistent with what we find in (3) and (4), although we cannot rule out the hypothesis that these differences are caused by cross-industry differences. Nevertheless, the estimates in Table 12 suggest that omitting firms that only use offshore outsourcing from our sample will affect our estimates in predictable and relatively minor ways.

7. Discussion

We use new microeconomic data to test how IT offshoring affects IT occupation composition in the United States. 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 offshore activity to employment shifts. Our results, using fine-grained IT offshoring and IT workforce data, provide support for the argument that offshoring shifts labor composition toward tasks that are not easily tradable across computer networks. Our estimates indicate that although the percentage of domestic IT workers in “offshorable” occupations has risen about three points in nonoffshoring firms over the last decade, it has dropped by about eight points in offshoring firms in the same time period. We also find implications for IT workers paid on an hourly basis, who, in our sample, were more likely to perform tradable IT tasks. Accordingly, our estimates indicate that in offshoring firms, hourly workers comprise about 2%–3% less of the total IT workforce than in other firms, which is about one-sixth of the total hourly workforce in those firms.

We contribute primarily to a literature on IT workers and IT skills. In particular, we look at how IT offshoring, an important form of globalization, affects the skill distribution within the U.S.-based IT workforce, which contributes to a literature that has focused primarily on how human capital and institutional factors affect IT worker demand. Earlier studies have found that interpersonal skills will play an increasingly important role for IT workers. Our study indicates that offshoring will further accelerate this shift in the U.S.-based IT workforce toward interpersonal skills.

Our results, however, also have important implications for managers. They indicate that IT jobs that

remain in the United States will have a greater component of tacit work and may also require more hands-on or interactive work. This has implications for IT retention, which has historically been an important issue faced by IT managers (Agarwal and Ferratt 2001). The workforce reorganization implied by our findings suggests that IT managers may be able to divert some of their domestic personnel resources from hiring and retention to job redesign and internal development. These findings also describe how managers are distributing human resources in the new global economy.

Our findings also have policy implications. Any proposed policy interventions intended to address the labor market effects of IT offshoring, such as worker retraining, could productively be focused on workers with specific skill sets. These results are also a useful lens through which to examine IT educational policies. Our findings suggest that U.S.-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 therefore are consistent with recommendations from education scholars who advocate shifting some emphasis in the U.S. educational system to “softer” skills such as creativity and complex communication, both for the workforce at large (Levy and Murnane 1996) and for the IT workforce more specifically. They also suggest that U.S.-based IT workers may find it productive 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 offshoring measures omit third-party offshore outsourcing, which suggests a potential avenue for future research. However, this may be more of a limitation toward the end of our panel, when offshore outsourcing was becoming increasingly common. The basic assertion that jobs are easier to offshore if the job output can easily be delivered over computer networks should be true regardless of organizational form, and the available data suggest that offshore captive centers and third-party offshoring are positively correlated, so to some extent our estimates are probably capturing the combined effect of these sourcing practices in firms that have enough scale to establish offshore centers. We have examined this possibility with the available data and find no evidence that this omission significantly biases our results.

A second limitation of this work is that 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 be shifting substantially 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, could 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.

Acknowledgments

The authors are grateful for valuable feedback from Yannis Bakos, Natalia Levina, and seminar participants at INFORMS, New York University, the Workshop for Information Systems and Economics, the International Conference on Information Systems, and the Industry Studies Conference.

References

Abowd, J., J. Haltiwanger, J. Lane. 2004. Integrated longitudinal employer-employee data for the United States. *Amer. Econom. Rev.* 94(2) 224–229.

Abraham, K., S. Taylor. 1996. Firms’ use of outside contractors: Theory and evidence. *J. Labor Econom.* 14(3) 394–424.

Agarwal, R., T. Ferratt. 2001. Crafting an HR strategy to meet the need for it workers. *Comm. ACM* 44(7) 58–64.

Anderton, B., P. Brenton. 1999. Outsourcing and low-skilled workers in the UK. *Bull. Econom. Res.* 51(4) 267–286.

Ang, S., S. Slaughter. 2001. Work outcomes and job design for contract versus permanent information systems professionals on software development teams. *MIS Quart.* 25(3) 321–350.

Ang, S., S. Slaughter, K. Ng. 2002. Human capital and institutional determinants of information technology compensation: Modeling multilevel and cross-level interactions. *Management Sci.* 48(11) 1427–1445.

Apte, U., R. Mason. 1995. Global disaggregation of information-intensive services. *Management Sci.* 41(7) 1250–1262.

Aspray, W., F. Mayadas, M. Vardi. 2006. Globalization and offshoring of software: A report of the ACM Job Migration Task Force. Association for Computing Machinery, New York.

Autor, D., F. Levy, R. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *Quart. J. Econom.* 118(4) 1279–1333.

Bapna, R., N. Langer, A. Mehra, R. Gopal, A. Gupta. 2010. Examining return on human capital investments in the context of offshore it workers. Working paper, University of Minnesota, Minneapolis.

Bardhan, A., C. Kroll. 2003. The new wave of outsourcing. Research Report 1103, Fisher Center, University of California, Berkeley, Berkeley.

Barley, S., G. Kunda. 2004. *Gurus, Hired Guns, and Warm Bodies: Itinerant Experts in a Knowledge Economy*. Princeton University Press, Princeton, NJ.

Becker, S., K. Ekholm, M. Muendler. 2009. Offshoring and the onshore composition of occupations, tasks, and skills. Working paper, University of Warwick, Coventry, UK.

Berman, E., J. Bound, Z. Griliches. 1994. Changes in the demand for skilled labor within U.S. manufacturing: Evidence from the annual survey of manufactures. *Quart. J. Econom.* 109(2) 367–397.

Bidwell, M. 2009. Do peripheral workers do peripheral work? *Indust. Labor Relations Rev.* 62(2) 200–225.

Blinder, A. 2009. How many U.S. jobs might be offshorable? *World Econom.* 10(2) 41–78.

Brainard, L., D. Riker. 1997. Are U.S. multinationals exporting U.S. jobs? NBER Working Paper 5958. National Bureau of Economic Research, Cambridge, UK.

Crino, R. 2010. Service offshoring and white collar employment. *Rev. Econom. Stud.* 77(2) 595–632.

Desai, M., C. Foley, J. Hines. 2009. Domestic effects of the foreign activities of US multinationals. *Amer. Econom. J.* 1(1) 181–203.

Dossani, R. 2004. Origins and growth of the software industry in India. Working paper, Stanford University, Stanford, CA.

Feenstra, R., G. Hanson. 1996. Globalization, outsourcing, and wage inequality. *Amer. Econom. Rev.* 86(2) 240–245.

Gokarn, S., D. Joshi, V. Mahambare, P. Mirchandani, M. Mohta, K. Subramaniam. 2007. The rising tide—Employment and output linkages of IT-ITES. White paper, NASSCOM, India.

Gopal, A., T. Mukhopadhyay, M. S. Krishnan. 2002. The role of software processes and communication in offshore software development. *Comm. ACM* 45(4) 193–200.

Government Accountability Office. 2004. Current government data provide limited insight into offshoring of services. GAO-04-932, Government Accountability Office, Washington, DC.

Grossman, G., E. Rossi-Hansberg. 2008. Trading tasks: A simple theory of offshoring. *Amer. Econom. Rev.* 98(5) 1978–1997.

Gurbaxani, V. 1996. The new world of information technology outsourcing. *Comm. ACM* 39(7) 45–46.

Hakkala, K., K. Huttunen. 2010. Offshored job tasks and displaced workers. Working paper, VATT Government Institute for Economic Research, Helsinki, Finland.

Harrison, A., M. McMillan, C. Null. 2007. U.S. multinational activity abroad and U.S. jobs: Substitutes or complements? *Indust. Relations* 46(2) 347–365.

Head, K., J. Ries. 2002. Offshore production and skill upgrading by Japanese manufacturing firm. *J. Internat. Econom.* 58(1) 81–105.

Hijzen, A., H. Gorg, R. Hine. 2005. International outsourcing and the skill structure of labour demand in the United Kingdom. *Econom. J.* 115(506) 860–878.

International Data Corporation (IDC). 2007. The economic impact of IT, software, and the microsoft ecosystem of the global economy. White paper, IDC, Framingham, MA.

Jensen, J., L. Kletzer. 2005. Tradable services: Understanding the scope and impact of services offshoring. *Brookings Trade Forum* 75–116.

Lee, D., E. Trauth, D. Farwell. 1995. Critical skills and knowledge requirements of is professionals: A joint academic/industry investigation. *MIS Quart.* 19(3) 313–340.

Leitheiser, R. 1992. MIS skills for the 1990’s: A survey of mis managers’ perceptions. *J. Management Inform. Systems* 9(1) 69–91.

Levina, N., M. Xin. 2007. Research note—Comparing IT workers’ compensation across country contexts: Demographic, human capital, and institutional factors. *Inform. Systems Res.* 18(2) 193–210.

Levy, F., R. Murnane. 1996. *Teaching the New Basic Skills*. The Free Press, New York.

Lewin, A., V. Couto. 2007. Next generation offshoring: The globalization of innovation. Accessed November 27, 2011, https://offshoring.fuqua.duke.edu/or_n_report.pdf.

- Lohr, S. 2009. Adding layers of skills to a science background. *New York Times* (August 19), <http://www.nytimes.com/2009/08/20/education/20INNOV.html>.
- Machin, S., J. Van Reenen. 1998. Technology and changes in skill structure: Evidence from seven OECD countries. *Quart. J. Econom.* **113**(4) 1215–1244.
- Matusik, S., C. Hill. 1998. The utilization of contingent work, knowledge creation, and competitive advantage. *Acad. Management Rev.* **23**(4) 680–697.
- Mithas, S., M. Krishnan. 2008. Human capital and institutional effects in the compensation of information technology professionals in the United States. *Management Sci.* **54**(3) 415–428.
- Mithas, S., J. Whitaker. 2007. Is the world flat or spiky? Information intensity, skills, and global service disaggregation. *Inform. Systems Res.* **18**(3) 237–259.
- Overby, S. 2009. Outsourcing: The demise of the offshore captive center. Accessed November 27, 2011, http://www.cio.com/article/496322/Outsourcing_The_Demise_of_the_Offshore_Captive_Center.
- Rajeevan, M., M. Subramanian, P. Beligre, R. Williams. 2007. Research study of captives in india and china: A majority of parent organizations also rely on third-party relationships! White paper, Infosys, Bangalore, India.
- Shea, K. 2008. Correctly classifying IT employees as exempt or non-exempt. HRhero.com (October 17), <http://hrhero.com/hl/articles/2008/10/17/correctly-classifying-it-employees-as-exempt-or-non-exempt/?TOPIC>.
- Slaughter, M. 2000. Production transfer within multinational enterprises and American wages. *J. Internat. Econom.* **50**(2) 449–472.
- Slaughter, S., S. Ang. 1996. Employment outsourcing in information systems. *Comm. ACM* **39**(7) 47–54.
- Strauss-Kahn, V. 2004. The role of globalization in the within-industry shift away from unskilled workers in france. Working paper, National Bureau of Economic Research, Cambridge, MA.
- Tambe, P., L. M. Hitt. 2010. How offshoring affects IT workers. *Comm. ACM* **53**(10) 62–70.
- Tambe, P., L. M. Hitt. 2012. The productivity of information technology investments: New evidence from IT labor data. *Inform. Systems Res.*, ePub ahead of print March 7, <http://isrjournal.informs.org/content/early/2012/03/07/isre.1110.0398.abstract>.