Management Science

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

Job Hopping, Information Technology Spillovers, and Productivity Growth

Prasanna Tambe, Lorin M. Hitt

To cite this article:
Prasanna Tambe, Lorin M. Hitt (2014) Job Hopping, Information Technology Spillovers, and Productivity Growth. Management Science 60(2):338-355. https://doi.org/10.1287/mnsc.2013.1764

MANAGEMENT SCIENCE
Vol. 60, No. 2, February 2014, pp. 338–355
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2013.1764

Job Hopping, Information Technology Spillovers, and Productivity Growth

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

The movement of information technology (IT) workers among firms is believed to be an important mechanism by which IT-related innovations diffuse throughout the economy. We use a newly developed source of employee microdata—an online resume database—to model IT workers' mobility patterns. We find that firms derive significant productivity benefits from the IT investments of other firms from which they hire IT labor. Our estimates indicate that over the last two decades, productivity spillovers from the IT investments of other firms transmitted through this channel have contributed 20%–30% as much to productivity growth as firms' own IT investments. Moreover, we find that the productivity benefits of locating near other IT-intensive firms can primarily be explained by the mobility of technical workers within the region. Our results are unique to the flow of IT workers among firms, not other occupations, which rules out some alternative explanations related to the similarity of firms that participate in the same labor flow network.

Keywords: IT spillovers; labor mobility; general-purpose technologies; high-tech clusters; regional growth; productivity; IT labor; IT value
History: Received November 4, 2011; accepted February 23, 2013, by Yu (Jeffrey) Hu, guest department editor, information systems. Published online in *Articles in Advance* October 24, 2013.

Introduction

Researchers have argued that like earlier general-purpose technologies such as electricity or the steam engine, information technology (IT) investments generate productivity "spillovers" as the know-how required to implement new IT innovations diffuses among firms (David 1990, Dedrick et al. 2003). Superior access to the specialized know-how required for implementing new information technologies should lead to higher IT returns and higher productivity levels. Identification and measurement of the economic impact of these spillovers of technical know-how has implications for understanding productivity differences and heterogeneity in IT returns, as well as for understanding how benefits from IT investments are allocated among firms. To the extent that IT has been responsible for a significant portion of multifactor productivity growth in the last two decades (Jorgenson and Stiroh 2000), IT spillovers are also a potentially important source of long-run economic growth in advanced economies and may partly explain the divergence of IT-related returns across different countries.

However, the implementation of new IT-related innovations is a complex process. As with some scientific knowledge (Almeida and Kogut 1999, Franco and Filson 2006), the technical know-how required to implement new IT innovations is primarily embodied within the IT workforce, acquired through hands-on experience at firms, and transmitted to other firms through the flow of IT labor, such as the movements of employees, contractors, and consultants (Dedrick et al. 2003, Draca et al. 2006, Oettl and Agrawal 2008). This is consistent with patterns observed for the spread of other general-purpose technologies; for example, economists have hypothesized that skilled engineers were important for the diffusion of know-how required for the installation of the electric dynamo in U.S. factories (David 1990).[1]

[1] The economic importance of this type of employee mobility in the IT sector is suggested by recent press covering the Department of Justice investigation of collusive nonpoaching agreements in several prominent technology firms (Catan and Kendall 2010), as well as in coverage of the difficulties faced by large tech firms in slowing the defection of employees to competitors (Efrati and Morrison 2010).

Because the mobility of these skilled technical workers tends to be rapid and local (Fallick et al. 2006, Dahl and Sorenson 2010), geographic location may play a particularly important role in determining access to the specialized skills and know-how required for the installation of these new technologies. It also may partly explain why firms locate in high-tech clusters despite facing higher factor costs for other inputs, such as land and labor (Saxenian 1996). The primary goal of this study is to test the hypothesis that firms benefit from the IT investments of other firms because the flow of specialized technical know-how among organizations facilitates the implementation of new IT innovations.

Although a substantial literature has focused on estimating the impact of spillovers from research and development (R&D) investment, there has been little empirical work on IT spillovers, and no work on IT spillovers generated through the IT labor pool. This study makes a contribution to this domain through the analysis of a new data set describing IT labor flow patterns. These data are derived from the employment histories of several hundred thousand U.S.-based IT workers matched to information on employers; they represent the career movements of as much as one-sixth of the IT workforce over the last 20 years. These data also include detailed experience and education information about these workers, as well as flows of other types of workers, so we can control for the flow of IT-related and other human capital among firms and, in particular, distinguish the contribution of IT worker flows from the contribution of labor mobility generally. No other existing administrative data sets enable measurement of the firm-to-firm flow of workers by occupation.

Compared to prior research, the availability of these data enables uniquely precise measurement of the channels through which spillovers of IT-related know-how are likely to occur. The prevailing statistical approach for testing the effects of spillovers on firms' productivity has been to create measures of the external pool of investment in the knowledge-generating asset, where variation in the size of this pool is generated through assumptions about how firms differ in their access to this know-how (see, e.g., Griliches 1992). For example, when productivity spillovers are hypothesized to occur among firms within the same region or industry, measures of extramural investment are constructed from the investments of other firms in the same region or industry. However, the use of measures based on such broad classifications has been subject to criticism because these measures can confound productivity spillovers with other unobserved factors (Breschi and Lissoni 2001, Bloom et al. 2013). For instance, regional growth or labor migration, industry demand shocks, local policy factors such as taxes, and labor market conditions can affect all firms in an industry or geographic region without having any linkages among firms. These effects can work in concert, as a demand shock to an industry that is overrepresented in one region (e.g., computer firms in Silicon Valley) can confound both industry and geographic spillover measures. Emphasis has, therefore, shifted toward explicit modeling of the underlying mechanisms that generate spillovers though the collection of fine-grained data on social or economic activity that enables identification of the "network" that provides the basis for the flow of knowledge.

Through the analysis of these types of fine-grained data, this paper contributes to the literature on IT productivity (e.g., see Brynjolfsson and Hitt 1996, Dewan and Min 1997). Although this literature has primarily focused on private returns to IT investment, some recent attention in this literature has been focused on estimating the economic importance of IT spillovers, which has implications for optimal investment strategy and growth policy (Cheng and Nault 2007, 2012; Chang and Gurbaxani 2012). Our study is the first to analyze how IT labor flows drive IT spillovers and, to the best of our knowledge, is the first study to investigate this issue using microdata on labor mobility. Because of the geographically constrained nature of the labor pool, it is also closely related to a recent stream of literature emphasizing geographic region as a basis of comparison for returns to IT investment (Dewan and Kraemer 2000, Bloom et al. 2012, Forman et al. 2012). Finally, this paper contributes to the literature on IT human capital. Although significant attention has been paid to IT labor markets (Ang et al. 2002, Levina and Xin 2007, Mithas and Krishnan 2008), the research has not been tied to the larger IT productivity literature; therefore, how IT human capital explains variation in IT returns is not yet well understood (see Bapna et al. 2013 for a recent exception).

Our findings suggest that a substantial amount of variation in IT returns can be explained by productivity spillovers generated by IT labor flows. The elasticity of the external pool of IT investment is about 20% of the elasticity on own IT investment; given the growth rate in these factors, this implies that the growth contribution of the IT pool is about 20%–30% that of own IT investment. One motivation for "job hopping" among IT workers is higher salaries (Freedman 2008). Consequently, it is important to distinguish between spillovers, which are benefits that accrue to firms net of the additional compensation paid to incoming workers, and gains received by workers in the form of higher wages. To distinguish true externalities from private benefits captured by job hopping IT workers, we use cross-sectional

IT wage data from 2006 to test whether IT workers are compensated for the technical know-how they bring to new employers. The results from this analysis suggest that the productivity benefits from IT labor mobility are divided between firms and IT workers. The magnitudes of the spillover estimates are diminished but remain significant, after controlling directly for the wages paid to incoming IT workers. Therefore, our findings are consistent with recent evidence that firms pay for some, but not all, of the knowledge transferred by incoming workers (Balsvik 2011, Stoyanov and Zubanov 2012).

There are two types of identification problems that arise in our analysis. First, our analysis is subject to endogeneity problems associated with the productivity measurement framework, especially unobserved demand or productivity shocks that increase the demand for labor. To address these concerns, we employ modern panel data methods specifically developed to address these concerns in productivity analysis, such as the Arellano–Bond and Levinsohn–Petrin estimators. Our results using these methods suggest that there is limited bias in our spillover estimates from these issues (consistent with recent work in IT-productivity measurement, such as Tambe and Hitt 2012). Second, there are identification problems that are known to arise in network analysis, such as similarity among firms that participate in the same labor flow network. To address these problems, we perform a number of supplemental analyses using alternative externalities measures that suggest our results only appear for the flow of IT labor from IT-intensive firms. We do not find evidence of externalities for labor flows generally, from geographically proximate firms generally, or from IT labor flows from R&D intensive or highly productive firms. Although this does not rule out all potential sources of endogeneity, it rules out reverse causal paths that are not coincident with the flow of IT workers among firms with significant IT investments. We also demonstrate that our spillover estimates are robust to limiting the sample to firms that hire workers from less-productive, less IT-intensive, or lower human capital firms, which is inconsistent with the hypothesis that the spillover estimates reflect unobserved effects associated with hiring workers from high-productivity firms. Finally, we report results from additional robustness tests that show our results are not driven by model choices or other technical assumptions.

Background

Differences in the adoption of new IT-related production innovations have been associated with substantial IT-related performance differentials, raising the question of why some firms are faster to adopt the most effective combinations of new IT innovations (e.g., McElheran 2011 analyzes the case of e-business adoption). One explanation for these differences is that IT-related business transformation requires costly technical "co-invention" (Bresnahan 2003), which requires specialized skills and know-how related to technologies, programming languages, protocols, standards, and information architectures. In prior research, scholars have argued that these costs can be a substantial impediment to adoption (Levy and Murnane 1996). Therefore, the pace at which new information technologies lead to productivity growth is partly regulated by the accumulation of a body of technical know-how, embodied in technical workers, that helps lower technological barriers in adopting firms (Attewell 1992, Bresnahan 2003). Researchers have suggested that the primary conduit for the transmission of this expertise among firms is the movement of technical labor, especially job switchers but also consultants and system integrators (Dedrick et al. 2003, Draca et al. 2006).

IT investment can be linked to productivity spillovers created by the movement of IT workers through several mechanisms. Firms capture spillovers when the acquisition of IT labor leads to the introduction of new technical know-how into the firm, gained through on-the-job learning at other employers. This type of on-the-job skill acquisition has long been theorized as an important mechanism for rising labor productivity with new tools and technologies (Arrow 1962), and robust empirical evidence linking labor productivity to learning-by-doing has been provided in contexts as varied as aircraft building (Benkard 2000), naval ship construction (Thornton and Thompson 2001), and chemical processes (Lieberman 1984). For other general-purpose technologies, such as the electric dynamo, the development of a workforce of engineers with experience redesigning workflow was important for the diffusion of new production methods (David 1990). IT workers play a similarly important role in spreading the expertise required for redesigning technology practices in modern organizations. Especially when technologies are new, hands-on implementation experience is an important mechanism through which engineers learn about working with new technologies—for example, in the early days of the Internet boom, the expertise required to design and build a professional e-commerce site was acquired by working at one of a few prominent Web companies. As IT workers move between firms, some of this technical know-how is transferred to new employers. The literature on IT workers has established the importance of external labor markets for employers needing to acquire technical skills (Barley and Kunda 2004).

IT spillovers are also produced by thicker labor markets. Higher IT investment levels within a labor market enable employees to specialize in rarer combinations of technical skills, leading to higher labor productivity (Rosen 1983, Kim 1989, Becker and Murphy 1992, Duranton and Puglia 2004). Prior empirical work has demonstrated that the adoption of new technology requiring highly specialized skills is faster in thicker labor markets for technical skills (Forman et al. 2005). As with the acquisition of know-how obtained through hands-on experience, the productivity benefits of thicker labor markets are realized by employers as they acquire IT labor. Therefore, the central thesis of this paper is that rising IT investment levels for firms in the same IT labor market generate productivity spillovers through the development of technical skills related to new and emerging technologies and standards. The primary hypothesis tested in this paper is as follows:

Hypothesis 1. *The IT investments of other firms generate productivity spillovers through IT labor flows among firms.*

Labor as a primary conduit for IT spillovers has implications for their geographic scope. Labor mobility tends to be local, so the economic effects of IT spillovers are likely to be stronger over smaller distances. This assertion is consistent with an extensive and influential literature on the role of geography for R&D spillovers (Jaffe et al. 1993, Audretsch and Feldman 1996). Higher R&D spillovers in some regions are due in part to the importance of employee mobility for facilitating knowledge transfer (Audretsch and Stephan 1996, Almeida and Kogut 1999). The importance of labor mobility for the transmission of IT skills suggests that geography will also be important for understanding IT spillovers, and this argument is supported by the literature on the importance of labor mobility within high-tech clusters for economic growth (Saxenian 1996, Bresnahan et al. 2001), which emphasizes the importance of location for high-tech innovation and argues that the flow of technical skills among firms is a principal driver of the rapid innovation rates observed for firms in these cities.

Empirical Framework

Our empirical approach is closely related to the literature on the impact of R&D spillovers on productivity, as well as the literature on the productivity of IT investments. An approach common in both literatures is to use methods from production economics that enable researchers to estimate the contributions of various inputs, such as capital, labor, R&D, and IT, to firm productivity. To estimate how R&D spillovers affect productivity, productivity models are augmented with measures of the external R&D pool available to a firm (Griliches 1992). A similar approach has been proposed for studying IT spillovers, with IT substituted for R&D as the knowledge-generating asset (e.g., Draca et al. 2006).

To implement this approach, a standard production function relating capital (K) and labor (L) to output is augmented with measures of computer investment (C) and computer investment by other firms within the network defined by the spillover transmission mechanism (S). Taking logarithms of both sides of an augmented Cobb–Douglas production function produces

$$va_{ijt} = \alpha_k k_{ijt} + \alpha_L l_{ijt} + \alpha_c c_{ijt} + \alpha_s s_{ijt} + \varepsilon_{ijt}. \qquad (1)$$

A positive and significant coefficient on the spillover term (α_s) is interpreted as evidence that spillovers generate substantial productivity benefits. Value added (sales minus materials) was chosen as a dependent variable for consistency with much of the prior research on IT productivity (Brynjolfsson and Hitt 2003). Using value added as a measure of output also has the advantage of being less subject to reverse causality problems generated by demand shocks because most of these are also reflected in materials and are therefore removed from the final measure.

Because data on investments in capital, labor, and value added are widely available, the most significant challenge in using this approach is the development of reliable measures of the relevant internal and external IT investments for each firm. A great deal of attention has been paid in the literature on knowledge spillovers to how best to measure external pools of know-how (Griliches 1992). Historically, most research on R&D spillovers has relied on the assumption that firms benefit from the knowledge of other firms when they are "close," in a technological or geographical sense (Griliches 1992, Jaffe 1986). Under these assumptions, the knowledge available to the focal firm i (T_i), is modeled as the weighted sum of the knowledge of other firms in the sample (T_j), where the weights (Φ_{ij}) between firms i and j reflect the amount of knowledge leakage between the two firms, proxied by a measure of proximity:

$$S_{it} = \sum_{j \neq i} \phi_{ijt} T_{jt}. \qquad (2)$$

In the R&D spillovers context, T would be measured as R&D capital stock or a measure of R&D intensity. A similar approach is possible for the measurement of IT spillovers. As with the R&D literature, it is important to capture the actual transmission path of knowledge to avoid the known criticisms of this approach, which is why the R&D spillovers literature has migrated from the use of industry-based measures to measures of technological position (using patent citations) or direct measurement of flows of R&D workers (as disclosed on patent applications). In our context, since we hypothesize that the transfer of IT-related knowledge occurs through the mobility of workers, the appropriate measure of proximity is the actual flow of IT labor. This approach is similar to work that has tracked the paths of inventors but has the advantage that we are able to observe many more employees because of the unique characteristics of our data. For comparison, we also model the potential IT spillover pool available to firms based on industry and geographic proximity. The spillover-augmented production function in (1) can be estimated using standard regression techniques such as ordinary least squares (OLS) (with suitable standard error corrections for panel data) or panel methods such as fixed effects, as well as other approaches from the microproductivity literature for addressing endogeneity in the production function framework.

Data

Our IT labor mobility data were obtained from a leading website through which participants post employment histories (resumes) online. These data include employment information for about 10 million users who posted or modified their career histories through this service in 2007. Users provide information about occupation (e.g., information technology, sales, management, etc.), education, and other demographic and human capital variables. In this study, we primarily focus on IT workers, although we use data from other occupations to test the robustness of our results. Our data set includes career information about full-time employees as well as hourly workers. We include both worker types in our analysis because our primary interest is in knowledge transfer, and contractors and part-time workers also play an important role in knowledge transfer.

We use the interfirm mobility patterns of workers in the data to model the flow of IT labor among U.S. firms. The educational distribution of the workers in our sample is similar to that of IT workers in the Current Population Survey (CPS) data published by the Census Bureau. Our data are not particularly skewed toward either higher or lower education levels, although workers with vocational training appear to be slightly overrepresented. We also compared job tenure statistics against the job tenure of IT workers who appeared in the CPS Job Tenure supplement, last published in 2000. Unsurprisingly, the average job tenure of workers in our sample is about two years lower than the average job tenure of workers in the CPS survey ($p < 0.01$). One reason for this difference is that our sample is disproportionately weighted toward younger workers and job hoppers. However, because the population of interest in this study is the job-switching IT worker, our sample may actually be a better representation of this population than the CPS sample, which includes workers who never or infrequently switch jobs.

To construct the IT labor flow network using these employee data, we associate employer names with unique identifiers by matching them against external databases of publicly listed companies and subsidiaries, including Compustat, the Compact Disclosure Database, and the National Bureau of Economic Research Patents Database; we then aggregate the data by firm-year. The analysis is restricted to the movements of employees among public firms because of the availability of supplementary economic data on these firms through Compustat. Aggregating these data to the level of the firm provides information on (1) how many IT workers were employed at a particular firm in a particular year and (2) how many workers a firm hired from each other firm in our data set. In the next section, we explain how we use these data to develop measures of internal and external IT investment levels.

Measures

IT Investments

We utilize two measures of IT investment. First, for comparability with prior work, we use IT capital stock measures from the Computer Intelligence Technology Database (CITDB). The CITDB has been used extensively in prior IT productivity and adoption research (Brynjolfsson and Hitt 2003, Forman et al. 2005), as well as in recent work on measuring the productivity of IT spillovers (Chang and Gurbaxani 2012). Using these measures has a number of advantages. These capital stock data have been consistently collected from 1987 through 1994, and their measurement properties have been well documented in prior work. However, for our purposes, these data are also subject to some limitations. The main panel of these data is restricted to Fortune 1,000 firms, the definitions of variables changed significantly after 1994, and—most importantly—the CITDB no longer includes direct IT capital stock measures, so it is unclear if the measurement advantages of these data over the 1987–1994 time period extend to more recent years.[2]

[2] Chwelos et al. (2010) provide a method for extending CITDB 1994 valuation data through 1998 by imputing the values of equipment in the earlier part of the data set and adjusting for aggregate price changes. However, this differs from the method employed by Computer Intelligence, which determined equipment market values by looking at actual prices in the new, rental, and resale computer markets.

These limitations are important for several reasons. First, because of the large wave of investment in new Internet technologies that occurred after 1994, the economic impact of IT spillovers may have grown significantly after 1994. Second, our IT labor flow data offer much greater coverage in the years after 1995, so the effect sizes can be estimated with greater precision with more recent data. Third, when dealing with network data such as that used to compute the spillover pool measures, missing network points can unduly influence estimates on network measures (Kossinets 2006). It is therefore important to cover as much of the network as possible to minimize measurement error.

To expand this sample and study a more recent time period, we supplement our IT capital stock-based analysis with alternative IT measures that are based on IT employment measures generated from the IT labor database. IT staff is complementary to physical IT assets and is the primary means for creating or maintaining other types of IT-related assets such as software- or IT-enabled business processes. IT labor measures have been used in prior published work as a measure of IT investment (Lichtenberg 1995, Brynjolfsson and Hitt 1996, Tambe and Hitt 2012). In addition, recent work has suggested that computer hardware is only 10%–20% of the relevant capital stock of IT, broadly defined, which also includes investments in packaged software, packaged software configuration and customization, in-house developed software, training, and process engineering (see, e.g., Saunders 2010). Since most of these other components are associated with IT labor, our IT labor-based measures may be an interesting alternative measure for total IT investment, especially in recent years. The construction of the IT labor-based measures, their sampling properties, correlations with other external IT data sets, and applications to productivity measurement are described in detail in our other work (see Tambe and Hitt 2012). In general, the labor-based measures track the capital stock data quite well over overlapping time periods and can be consistently measured for more than a decade beyond the preferred time period of the CITDB data.

Measuring the External IT Pool

Our external IT investment measure is computed as the IT intensity of other firms (IT per employee using either the CITDB IT measure or our IT labor measure), weighted by the share of incoming IT labor hired from that firm in a given year. The use of IT investments to measure the IT know-how of other firms closely follows an approach from the literature on R&D spillovers, where R&D expenses are used to measure firms' R&D knowledge stock. We choose to use the IT intensity of other firms rather than levels for several reasons. The use of IT intensity removes the effects of firm size, which is important because the spillover mechanism advanced in this paper is the acquisition of human capital and subsequent transfer across firm boundaries, and the rate of acquisition of human capital is likely to be more closely related to average levels of IT investment at the firm rather than its total levels because employees are likely to interact with a fixed set of other employees and practices within a firm. Empirically, correlations reported in survey-based studies have demonstrated that the IT intensity of firms rather than IT levels is most closely associated with complementary investments in IT know-how and capabilities (Bresnahan et al. 2002, Tambe et al. 2012). Therefore, firms are more likely to benefit from hiring technical workers from IT-intensive workplaces rather than from employers with the largest overall IT investments. However, in the appendix, we conduct sensitivity tests that indicate that our results are not substantially changed when IT stock or investment levels are substituted for IT intensity levels.

Weighting the IT intensity of other firms by incoming IT labor share is similar to approaches commonly used in R&D spillover studies, where the R&D pool is constructed as the aggregate R&D stock of other firms within a certain radius or within a particular industry or weighted by technological similarity (see, e.g., Jaffe 1986, Orlando 2004). This weighted measure essentially captures the IT investment levels of firms in the focal firm's IT labor pool, and the assumption is that a firm receives "spill-ins" from organizations from which it hires IT labor.[3] A key distinction of our study is the acquisition of data on a specific pathway by which the externality is transmitted. Positive returns to our spillover measure imply that firms that have access to employees from other IT-intensive firms, regardless of their location or industry positions, will capture IT spillovers.

To behave under the log transformation, spillover pools with zero values are seeded with a minimum nonzero value.[4] For some analyses, we also create external IT investment measures based on industrial proximity. Industry measures are constructed as the IT intensity of other firms within the same four-digit Standard Industrial Classification (SIC) industry. Within-industry IT spillovers have been identified in prior research as having an important effect on productivity (Chang and Gurbaxani 2012).

[3] Our primary results are not significantly affected when considering firms from which the focal firm draws 1%, 2%, 5%, or 10% of its IT labor as a threshold. Robustness results using these thresholds are reported in the appendix.

[4] In the appendix, we test the sensitivity of our results to this seeding by altering the seeding assumptions, excluding firms with a zero spillover pool and estimating a Heckman-style selection model. None of these adjustments substantially affects our results.

For some analyses, we separate firms by geography and IT labor flow patterns. Sets of geographically proximate firms are identified in two different ways. First, we construct broad regional measures by grouping firms that have headquarters within the same state and county, where county and state of a firm's corporate headquarters are from the Compustat data set. These data are available for most firms and years in our sample, making it possible to match these data to almost the entire panel. The use of corporate headquarters to identify regional influences on a firm, however, is an imperfect measure because IT workers are generally geographically scattered across multi-establishment firms. To test how our results are affected by this type of measurement error, we use workers' self-reported metro-area locations in 2006 in the IT labor data set to construct finer-grained establishment-level measures for each firm at the metro-area level. Using these metro-area data, we consider two firms to be geographically proximate if they have establishments within the same metropolitan area. Across establishments, the aggregate pool for each firm is computed as the pool for each of its establishments, weighted by IT intensity at that establishment. This measure is more precise than our earlier measure based on the location of corporate headquarters, but the drawback to using these measures is that these employment dispersion data are only available in the final year of our sample, so only cross-sectional comparisons are possible.

Using these location measures, we specifically test if spillovers generated through IT labor flows explain localized spillovers. To separate the contributions of IT labor flows from other potential localized IT spillover channels, we estimate the contributions of four separate pools that vary along two dimensions, labor flows and geographic distance, using the approach described in Orlando (2004). Following Orlando (2004), rather than using IT investment weighted by incoming labor share to create the spillover pool measure, we divide the IT investments of firms into four quadrants, depending on labor proximity and geographic proximity, where a firm is said to be proximate in the labor network if it is the source of at least 5% of a firm's incoming IT workers. Specifically, the IT intensity of other firms is broken into one of four pools: firms that are (1) proximate in terms of employee flows and geography, (2) proximate in terms of employee flows but geographically distant, (3) distant in terms of employee flows but geographically proximate, and (4) distant in terms of both employee flows and geography. The division of firms into these four groups separates the estimates of the effects of employee flows from other localized spillover channels.

Non-IT Inputs, Human Capital, Wages, and Value Added

Compustat data were used to compute employment, capital,[5] sales, value added, and materials in constant 2000 dollars, using standard methods from the microproductivity literature. Non-IT employment was computed by subtracting IT employment from total employment, and non-IT capital measures were constructed by subtracting IT capital from total capital.

In some regressions, we also included measures of the human capital and wages of incoming IT workers and of the firms' IT workforce. We constructed these measures using data on the education and experience of the workers employed at firms and the workers moving between firms. Education, experience levels, and 2006 wages were self-reported by individual IT workers. Education was selected from one of a number of different education levels, including doctorate, graduate school, four-year degree, vocational degree, some college experience, high school degree, and some high school experience. To compute experience in a particular year, we adjusted 2006 experience levels backward, assuming full employment in the interim periods. In addition to experience, we separately estimated worker age based on the years workers report attaining various education levels, as reported in the full text portion of their resume.[6] Measures of firm-level IT wages were constructed by averaging the wages of IT workers within a particular firm and year.

We also included several control variables in our model. We used Compustat data to assign firms to an SIC industry. Depending on the specification, we included industry dummies at either the one- or two-digit SIC level. We also include year dummies to account for time trends and unobserved sources of productivity that vary over time.

Descriptive Statistics

The industry composition of the firms in our sample, as well as the means, standard deviations, and correlations for all variables including the spillover pools are shown in Tables 1 and 2. In Table 3, we show correlations between the IT measures and spillover pools

[5] Capital measures are computed using property, plant, and equipment reported in Compustat.

[6] For every worker we have both fielded data, which forms the bulk of our measures, as well as the full text of their resume. Using a text-mining application, we are able to identify the years that a particular employee completed different levels of education (high school, vocational school, community college, or four-year college). We assume that high school is completed at age 18, vocational or community college is completed at age 20, and undergraduate degrees are completed at age 23. We compute a separate age estimate for each school attended and then take the minimum of these estimates to accommodate the possibility of a delay between entry into higher education and the completion of high school.

Table 1 Industry Composition of Sample Across All Firm-Years

	IT capital sample (1987–1994)		IT employment sample (1987–2006)	
Industry	*N*	Percent	*N*	Percent
Mining	0	0.0	37	0.10
Durable manufacturing	737	34.6	11,142	30.7
Nondurable manufacturing	731	34.3	6,383	17.6
Transportation and utilities	247	11.6	3,458	9.5
Wholesale trade	90	4.2	1,506	4.2
Retail trade	167	7.8	3,670	10.1
Financial services	51	2.4	2,345	6.5
Nonfinancial services	110	5.2	7,764	21.4
Total	2,133	100	36,300	100

Table 2 Means and Standard Deviations for Variables

	Levels		Log levels	
	Mean	Std. dev.	Mean	Std. dev
1. *Value added* (mm)	1,046.7	3,262.4	5.23	1.99
2. *Non-IT employment* (m)	13.7	42.9	7.84	1.93
3. *Capital* (mm)	2,071.8	8,053.8	5.19	2.39
4. *IT capital*	24.6	41.7	2.31	1.36
5. *IT employment*	271.3	1,006.7	3.99	1.82
6. *IT pool* (*capital*)[a]	0.524	2.78	0[c]	4.46
7. *IT pool* (*employment*)[b]	0.013	0.022	0[c]	2.77
8. *Industry IT pool*	0.034	0.025	0[c]	1.89

Note. Nominal variables are in 2000 dollars.
[a]IT pool measure constructed using IT capital stock to measure the IT investment levels of other firms.
[b]IT pool measure constructed using IT employment levels to measure the IT investment levels of other firms.
[c]Means have been removed from logged spillover pools.

for the sample in which the CITDB capital stock data are available, spanning the years 1987–1994. There are several notable correlations in Table 3. The first is a high correlation (0.67) between the IT capital stock and IT employment measures, which indicates that the two IT measures capture similar IT input variation. (Additional correlations for the IT input variables are reported in Tambe and Hitt 2012.) The IT spillover pools computed using the two different IT measures are even more highly correlated (0.86). It is likely, therefore, that the use of IT capital and IT employment data to measure IT inputs will produce similar estimates in our production context, although we explicitly test this in head-to-head productivity regressions. Third, it is notable that the IT spillover pools computed from labor and industry proximity have a low correlation, indicating that these two constructs are measuring nonoverlapping channels for spillovers.

Table 3 Correlations Between Key Measures and IT Spillover Pools

	1	2	3	4	5	6	7
1. *Value added*	1						
2. *Capital*	0.79	1					
3. *Non-IT employment*	0.89	0.61	1				
4. *IT capital*	0.75	0.60	0.65	1			
5. *IT employment*	0.81	0.58	0.80	0.67	1		
6. *IT pool* (*capital*)[a]	0.38	0.21	0.34	0.38	0.40	1	
7. *IT pool* (*employment*)[b]	0.41	0.24	0.37	0.40	0.43	0.86	1
8. *Industry IT pool*	−0.08	0.04	−0.23	0.03	−0.08	−0.05	−0.05

Note. Correlations are within sample for which all measures exist from 1987 to 1994. $N = 1{,}944$.
[a]IT pool measure constructed using IT capital stock to measure the IT investment levels of other firms.
[b]IT pool measure constructed using IT employment levels to measure the IT investment levels of other firms.

Results

Labor Mobility and IT Spillovers

We begin in Table 4 by testing the effects of IT-related labor market spillovers on productivity using the CITDB IT capital stock database to construct measures of both own and external IT investment. Baseline IT productivity estimates with no spillover pool measures in column (1) indicate an output elasticity of slightly over 0.04 ($t = 12.3$) for IT capital, which is consistent with estimates from other studies using the CITDB IT capital database (Brynjolfsson and Hitt 2003). In columns (2) and (3), we report results from OLS specifications that include the IT pool measure as well as industry controls at the one-digit and two-digit levels, respectively. The IT pool measure has a positive and significant association with productivity when including one-digit controls ($t = 2.63$). Adding in two-digit controls in column (3) reduces the estimated returns from own IT investment to about 0.026, but the magnitude of the estimate on the IT pool changes little and is still significant ($t = 2.74$). In column (4), we add in measures of the industry IT pool. The coefficient estimate on the industry IT pool is close to that of prior work using similar data (Chang and Gurbaxani 2012), but consistent with the low correlation between the two spillover measures: including the industry pool into the regression only slightly alters the magnitude of the labor pool. The labor pool estimate is not as precisely estimated as in columns (2) and (3), most likely because of the smaller sample size, but it is still significant ($t = 1.78$). In column (5), we report estimates from a fixed-effects estimator. Including fixed effects wipes out the effects of the industry pool and the own IT coefficient. The effect of the fixed-effect estimator on the industry pool estimate is likely caused by limited data variation (firms do not rapidly change industry participation), whereas the own-IT coefficient is likely a combination of time invariant complementary factors and measurement error (see Brynjolfsson and Hitt 2003 for a discussion of these issues using the CITDB data). Finally, columns (6) and (7) test how the addition of R&D capital stock measures affects the productivity

Table 4 Productivity Effects of IT Spillover Pool (IT Capital Measures)

DV: Log(*Value added*) Time: Variables	(1) 1987–1994 OLS	(2) 1987–1994 OLS	(3) 1987–1994 OLS	(4) 1987–1994 OLS	(5) 1987–1994 FE	(6) 1987–1994 OLS	(7) 1987–1994 OLS
Log(*Labor*)	0.714***	0.709***	0.723***	0.717***	0.776***	0.788***	0.785***
	(0.0205)	(0.0210)	(0.0218)	(0.0198)	(0.0233)	(0.0312)	(0.0313)
Log(*Non-IT capital*)	0.213***	0.213***	0.217***	0.219***	0.116***	0.199***	0.179***
	(0.0144)	(0.0143)	(0.0162)	(0.0155)	(0.0187)	(0.0207)	(0.0250)
Log(*IT capital*)	0.0438***	0.0403***	0.0261***	0.0343***	−0.00110	−0.00383	−0.0200
	(0.0109)	(0.0108)	(0.00880)	(0.00983)	(0.00771)	(0.0148)	(0.0141)
Log(*IT pool*)		0.00641***	0.00609***	0.00558*	0.00176*	0.00527**	0.00420**
		(0.00244)	(0.00220)	(0.00313)	(0.00107)	(0.00215)	(0.00190)
Log(*IT industry pool*)				0.0259***	0.00614		
				(0.00921)	(0.00613)		
Log(*R&D*)							0.0405*
							(0.0235)
Controls	one-digit industry year	one-digit industry year	two-digit industry year	one-digit industry year	year year	one-digit industry year	one-digit industry year
Observations	2,133	2,133	2,133	1,429	1,429	974	974
R-squared	0.961	0.961	0.971	0.968	0.710	0.981	0.981
Number of firms					261		

Notes. Robust standard errors are in parentheses. All IT pool measures constructed using IT capital stock to measure the IT investment levels of other firms.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

estimates. For comparison, we report estimates in column (6) without including R&D but using only the smaller sample of firms for which both the IT capital stock and R&D capital stock data are available. Column (7) then adds the R&D capital stock measures into the regression. The point estimate on the IT pool measure is only slightly lower after adding R&D, but the coefficient estimates on the IT pool are statistically significant in both columns (6) and (7).

In all of these regressions, the coefficients on other factors are consistent with theoretical values (factor share) and with prior estimates in the IT productivity literature. The slight drop in the direct IT coefficient when the spillover pools are included is consistent with the idea that some of the apparent returns to IT investment are caused by spillovers.[7] The magnitudes of the estimates suggest an IT pool elasticity that is about 15%–20% the elasticity of own IT investment. Combined with the growth rates in these factors during the years in our sample, these estimates imply that the growth contribution of the IT pool is about 20%–30% as large as the growth contribution of own IT investment.

In Table 5, we introduce own and external measures of IT investment based on IT employment alongside the IT capital measures into the baseline specifications. In column (1), we include measures of own IT capital and IT employment into the regression model, but no spillover measures. Both the IT capital and IT labor measures are positive and significant. In column (2), we include the IT pool constructed from the IT capital data to measure the IT inputs of other firms in the labor pool. The ratio of the estimates of social to private returns from IT investments is consistent with the results in Table 4. The coefficient estimates in column (3), in which we substitute the IT employment pool for the IT capital pool, imply a very similar impact on output for a pool that is one standard deviation above the mean.[8] The rise in the magnitude of the IT capital and IT spillover coefficients when compared to Table 4 are caused by the substitution of non-IT employment for labor expenses as a production input, because these measures are likely to be correlated with unobserved workforce heterogeneity (e.g., higher wages paid to a more educated workforce), which normally would be captured in the labor coefficient.

[7] For both the estimates in Table 4, we tested the effects of also including industry-level customer and supplier-driven IT investment pools constructed from the Bureau of Economic Analysis input-output tables (see a full discussion of these spillover pathways in Cheng and Nault 2007, 2012). Including these customer and supplier IT investment measures did not significantly affect the coefficient estimates on our primary measure of interest, IT investment in the IT pool; in all cases the estimate remained significant and very similar in magnitude.

[8] In other regressions (not shown), we jointly included two separate IT spillover pool measures, constructed using IT capital and IT employment. Only the IT pool using IT employment as the input measure is significant when both pools are included into the regression, although the estimate is only significant at the 10% level, perhaps due to the high level of collinearity between the two measures since an F-test easily rejects the hypothesis that there is no joint effect ($F(2,370) = 8.40$, $p = 0.0003$).

Table 5 Spillover Estimates Using IT Capital and IT Employment Measures

DV: Log(*Value added*) Time: Variables	(1) 1987–1994 OLS	(2) 1987–1994 OLS	(3) 1987–1994 OLS	(4) 1987–1994 FE	(5) 1987–1994 LP	(6) 1987–1994 AB
Log(*Non-IT employ*)	0.527***	0.527***	0.526***	0.647***	0.558***	0.630***
	(0.0321)	(0.0319)	(0.0320)	(0.0246)	(0.0384)	(0.0356)
Log(*Non-IT capital*)	0.266***	0.266***	0.266***	0.236***	0.406***	0.250***
	(0.0232)	(0.0232)	(0.0232)	(0.0194)	(0.122)	(0.0269)
Log(*IT capital*)	0.122***	0.115***	0.115***	0.000519	0.115***	0.0100
	(0.0170)	(0.0167)	(0.0165)	(0.00755)	(0.0180)	(0.00944)
Log(*IT employ*)	0.0459**	0.0380**	0.0373**	0.00533	0.0435*	0.0240*
	(0.0191)	(0.0186)	(0.0187)	(0.00978)	(0.0250)	(0.0130)
Log(*IT pool*) *capital*[a]		0.0121***				
		(0.00318)				
Log(*IT pool*) *employ*[b]			0.0188***	0.00194	0.0179***	0.00163
			(0.00464)	(0.00158)	(0.00428)	(0.00152)
Log(*Value added*) − 1 lag						0.127
						(0.0952)
Observations	2,133	2,133	2,133	2,133	2,133	1,476
R-squared	0.914	0.916	0.916	0.666		
Number of firms				371		309

Notes. Robust standard errors are in parentheses. All regressions include controls for one-digit industry and year. Columns (5) and (6) are Levinsohn–Petrin and Arellano–Bond estimates, respectively.

[a]IT pool measure constructed using IT capital stock to measure the IT investment levels of other firms.

[b]IT pool measure constructed using IT employment levels to measure the IT investment levels of other firms.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In columns (4)–(6), we report results from additional robustness tests. Column (4) presents fixed-effects estimates from a specification including IT capital, IT employment, and an IT spillover pool constructed using the IT employment of other firms. The point estimate on the IT pool is similar to the FE estimate in Table 4, but it is not significant. In columns (5) and (6), we report estimates from the Levinsohn–Petrin and Arellano–Bond estimators, which address cases in which the regressors may be correlated with the error term (Arellano and Bond 1991, Levinsohn and Petrin 2003). The Levinsohn–Petrin estimator utilizes changes in materials inputs to measure the effect of short-run productivity shocks; it uses this information to correct the estimates of other input terms—in practice, it tends to return results similar to levels regressions (rather than differences or fixed effects), and the coefficient estimates on the terms of interest on the Levinsohn–Petrin estimator in column (5) are very similar to the corresponding estimates produced by the pooled OLS estimate.

The Arellano–Bond estimator uses an optimal weighting of two regressions: a regression using input levels as instruments for changes in inputs as well as a regression using differences as an instrument for levels. Empirically, the Arellano–Bond estimator tends to perform closer to an instrumental variables regression in first differences. The point estimate on the spillover term from the Arellano–Bond estimator is positive, but, like the fixed-effects estimate in column (4), is not significant. Since the Arellano–Bond estimator is an instrumental variable estimator in first differences, there can be a considerable amount of variance in the coefficient estimates because of low instrument power from using levels to instrument differences and exacerbating measurement error from the differencing, especially for capital or other slow-changing terms that do not have a large amount of time series variation over short periods. We primarily provide these for completeness to demonstrate that the coefficients are not markedly different than the fixed-effects estimates in order to rule out endogeneity bias as an explanation. The differences in the output of the Levinsohn–Petrin and Arellano–Bond estimators are caused by substantive economic issues rather than simply reflecting misspecification. As discussed in prior work, fixed-effects estimators remove the portion of IT returns that are caused by complementary organizational factors and focus on short-term rather than long-run returns of IT investments (see Brynjolfsson and Hitt 2003 for a discussion of OLS versus fixed effects in the IT-productivity context). As such they have a different interpretation than the Levinsohn–Petrin and levels regressions. Most of the IT value literature and the R&D productivity literature focuses on levels estimates.

In Table 6, we report estimates from the expanded sample for which IT employment measures are available. This sample provides a longer time period and

Table 6 Estimates from Expanded Sample Using IT Employment Measures

DV: Log(*Value added*) Time: Variables	(1) 1987–1994 OLS	(2) 1987–2006 OLS	(3) 1987–2006 OLS	(4) 1987–2006 FE	(5) 1987–2006 LP	(6) 1987–2006 AB
Log(*Non-IT employ*)	0.563***	0.629***	0.629***	0.799***	0.605***	0.781***
	(0.0336)	(0.0113)	(0.0123)	(0.00792)	(0.00974)	(0.0113)
Log(*Capital*)	0.301***	0.273***	0.274***	0.126***	0.446***	0.0435***
	(0.0228)	(0.00874)	(0.00946)	(0.00621)	(0.0249)	(0.0105)
Log(*IT employ*)	0.0701***	0.0719***	0.0791***	0.0296***	0.0654***	0.0384***
	(0.0225)	(0.00711)	(0.00783)	(0.00421)	(0.00723)	(0.00532)
Log(*IT pool*)	0.0242***	0.0304***	0.0247***	0.00418***	0.0276***	0.00124
	(0.00530)	(0.00204)	(0.00233)	(0.000979)	(0.00226)	(0.000840)
Log(*IT pool*) $*$ 1995–2000			0.0151***			
			(0.00300)			
Log(*Value added*) −1 lag						−0.0368**
						(0.0180)
Observations	2,176	36,300	36,300	36,300	36,300	25,611
R-squared	0.911	0.917	0.917	0.642		
Number of firms				4,731		3,620

Notes. Robust standard errors are in parentheses. All regressions include controls for one-digit industry and year. All own and external IT measures constructed using IT employment data. Column (2) also includes interaction variables with (1995–2000) and IT employment, capital, and non-IT employment. Columns (5) and (6) are Levinsohn–Petrin and Arellano–Bond estimates, respectively.
$^{**}p < 0.05$; $^{***}p < 0.01$.

more observations, so we can conduct subsample comparisons over time and there is greater support for statistical tests that are more demanding of the time-series dimension in the data. In column (1), we report estimates from the sample limited to the years 1987–1994 for direct comparability with the estimates from Table 5 that cover the same period but include IT capital in the specification. The estimate on the IT pool is slightly higher when IT capital is not directly included, which is consistent with some prior work that suggests that measurement error in own IT investment can lead to an upward bias on the IT spillover measure (Tambe and Hitt 2013). Nonetheless, the relatively small gap between the IT pool estimates when using IT employment alone or using both IT employment and IT capital suggests that measurement error–related biases are not likely to be especially large. In column (2) of the table, we report estimates using the extended sample ranging from 1987 to 2006. The magnitude of the estimate using the extended panel is slightly larger than that of the 1987–1994 sample from column (1). The regression in column (3) uses the same sample but tests whether the magnitude of the spillover coefficient is significantly larger from 1995 to 2000, a period in which firms made larger investments in emerging IT. The coefficient estimate on the interaction term is positive and significant ($t = 6.0$) and suggests two things: the magnitude of the spillover estimate grew in size during this period and the higher coefficient in column (2) is caused by a significant change in the magnitude of the spillover estimate after 1994. In column (4), we report firm fixed-effect estimates from the expanded sample, which removes the effects of time-invariant factors that could bias the spillover pool estimates. The baseline IT effect sizes implied by the fixed-effects model in column (4) are consistent with prior research on IT productivity and suggest an own IT elasticity of about 0.03 ($t = 7.5$). The estimates of the IT and capital contribution are somewhat lower in these regressions, reflecting measurement error in capital and the fact that IT returns are in part driven by unobserved (in these regressions) firm-specific differences in organizational practices. In fixed-effects, rising levels of IT investment in the IT pool are still positively associated with productivity growth ($t = 5.0$).

In columns (5) and (6), we report results from Levinsohn–Petrin and Arellano–Bond estimators. The coefficients on the terms of interest from the Levinsohn–Petrin estimator are again similar to that of the corresponding OLS regression. As expected, the Arellano–Bond regression produces estimates that are more similar to the fixed-effects estimators. The point estimate on the spillover term from the Arellano–Bond estimator is again positive, but not significant. Nevertheless, the estimates produced by the regressions in Table 6 provide evidence that the statistical associations between our spillover measure and firm performance persist over longer periods, using larger samples. Thus, although endogeneity may play a role in the precise estimates of the elasticities of various inputs, unobserved differences in firm productivity do not appear to substantially bias our spillover results. To some extent this is not surprising, because our estimates should only be biased in the presence of endogeneity that is coincidentally transmitted through a path similar to IT labor mobility patterns.

Table 7 **Comparisons of Labor Flow and Geographic Proximity Measures**

DV: Log(*Value added*) Grouping of firms into pools	OLS All firms (1)	FE All firms (2)	OLS Within metro 2006 (3)	Pooled OLS Software publishing (4)	FE Software publishing (5)
Hire many workers and geographically near (S_{NN})	0.023**	0.007**	0.013**	0.019**	0.011*
	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
Hire many workers and geographically distant (S_{NF})	0.024**	0.004**	0.008**	0.003	−0.004
	(0.002)	(0.001)	(0.003)	(0.005)	(0.004)
Hire few workers and geographically near (S_{FN})	0.005	−0.003	−0.003	0.012	0.004
	(0.004)	(0.002)	(0.005)	(0.015)	(0.012)
Hire few workers and geographically distant (S_{FF})	−0.022**	−0.002	−0.026**	0.041	−0.022
	(0.008)	(0.005)	(0.013)	(0.032)	(0.043)
Controls	Industry year	Year	Industry	Industry year	Year
Observations	36,300	36,300	6,110	2,447	2,447
R-squared	0.92	0.89	0.92	0.88	0.87

Notes. Standard errors are clustered on firm. All regressions are based on the baseline model estimated in column (1) of Table 6 and include logged measures of capital, labor, IT investment, industry IT spillovers, as well as the variables that are shown. The sample of software firms for regressions in columns (4) and (5) are those in SIC code 7372, an industry that is highly agglomerated (Freedman 2008). All variables are in logs. All own and external IT measures constructed using IT employment data.
$^{*}p < 0.1$; $^{**}p < 0.05$.

Comparisons with Regional Measures

In this section, we compare how the benefits of IT investment transmitted through IT labor flows compare with benefits derived through the IT investments of geographically proximate firms. If labor flows are the primary mechanism through which regional IT investment produces spillovers, then we should observe productivity effects from the investments of firms within the same IT labor flow network, regardless of distance. We also should observe no productivity effects from the investments of firms outside the labor flow network, even if they are geographically proximate. We report estimates from models in which the external IT investment pool is broken into four different pools that vary along two dimensions: geographic proximity and IT labor flows. The aggregate IT intensity of other firms falls into one of the four pools based on their location and whether they are an important source of IT labor. In Table 7, we report estimates from this decomposition. In our OLS and fixed-effect estimates in columns (1) and (2), the coefficient estimates on the spillover pools are only positive and significant for the pool of firms that contribute IT labor to the focal firm. Otherwise, the IT intensity of other firms, even when located in the same region, does not significantly influence output. These estimates indicate that for spillovers generated by IT investments, (1) regional spillovers appear to be driven by IT labor flows, and (2) IT labor flows appear to be an important source of spillovers even outside a fixed region. Broadly, these results suggest that it is employee flows rather than proximity per se that drive these measured spillovers.

A potentially important source of error in columns (1) and (2) is that we use corporate headquarters to fix firm location, although in larger firms, IT workers are likely to be distributed across different states. This type of measurement error should create a downward bias on the estimated effect of the "near-near" spillover pool and an upward bias on the "near-far" pool. In column (3), we test a model in which our proximity measures are constructed at the establishment-city level; we consider two firms to be geographically proximate when they have establishments in the same cities. The estimates produced from this characterization provide further validation for the hypothesis that IT labor mobility is an important channel for knowledge spillovers; as with our earlier estimates, only the coefficient estimates on the near-near and near-far pool are significant, indicating that spillovers are generated through labor mobility and that these effects are stronger over smaller distances. Furthermore, the higher coefficient estimate on the near-near pool is consistent with the reduction of measurement error in our construction of the near-near and near-far pools, as would be expected if the use of corporate headquarters as the location of a firm's IT workers is a noisy measure. The coefficient estimate on the "far-far" pool is negative and significant in columns (1) and (3), but this is likely to be caused by high correlations between the constructed pool variables, and it is no longer significant when using fixed-effects estimators in column (2).

In columns (4) and (5), we report estimates from the subsample of firms in the software publishing industry (SIC 7372), an industry that is highly agglomerated (Freedman 2008) and in which most cross-firm moves will therefore occur within the same region. Estimates from this sample of firms indicate that in these industries, within-region job hopping has the

Table 8 Robustness Tests—Sample Restrictions

DV: Log(*Value added*) Variables	(1) Educ OLS	(2) Exp OLS	(3) R&D OLS	(4) VA OLS	(5) VA FE	(6) VA FE
Log(*Non-IT employment*)	0.534***	0.542***	0.311***	0.538***	0.597***	0.596***
	(0.0174)	(0.0163)	(0.0680)	(0.0381)	(0.0249)	(0.0249)
Log(*Capital*)	0.289***	0.286***	0.359***	0.271***	0.220***	0.220***
	(0.0128)	(0.0120)	(0.0388)	(0.0252)	(0.0168)	(0.0168)
Log(*IT employment*)	0.152***	0.146***	0.265***	0.153***	0.049***	0.049***
	(0.0127)	(0.0111)	(0.0656)	(0.0160)	(0.0166)	(0.0166)
Log(*IT pool*)	0.0199***	0.0200***	0.0202*	0.0973***	0.0259***	0.0259***
	(0.00288)	(0.00222)	(0.0118)	(0.0102)	(0.0075)	(0.0075)
Log(*Non-IT pool*)						0.0007
						(0.0103)
Observations	6,721	15,619	533	5,067	4,723	4,723
R-squared	0.931	0.927	0.914	0.942	0.901	0.901

Notes. Robust standard errors are in parentheses. Variation in sample size is because of limitations in the availability of the gap variable for some fields. Columns (1)–(4) limit the baseline regression in column (1) of Table 6 to employers that tend to hire IT labor from other firms with lower (1) mean IT education, (2) mean IT experience, (3) R&D intensity, and (4) value added per employee. Column (5) limits the sample in the same way as (4), but is in FE, and matches the sample to (6). Column (6) also includes a labor network measure constructed from the flow of non-IT labor. All own and external IT measures constructed using IT employment data.

$^{*}p < 0.1$; $^{***}p < 0.01$.

most significant impact on productivity. After including measures based on within-region job hopping, regional IT investment measures no longer appear to have an important effect on productivity.

Beyond demonstrating that IT labor flows explain much of the regional "spillover" effect in technology clusters, the estimates in columns (1)–(5) suggest that it is unlikely that the estimates in Table 7 are being caused by regional or technological heterogeneity. Any biases associated with unobserved firm status or reputation should not be constrained to firms within the same geographic region. Similarly, regional heterogeneity, such as that related to demand shocks or changes in statewide policies, should not be limited to firms from which employees are being hired. It is unlikely, therefore, that our estimates are being driven by these types of influences.

Robustness Tests

This section presents evidence from additional tests that address some of the endogeneity concerns related to the baseline estimates presented above. One concern is that the coefficient estimates on the IT pool are biased upward by unobserved attributes of higher productivity firms; for example, if IT intensive firms tend to be better firms and performance is a good signal of worker quality, firms may disproportionately hire from these firms and receive employees that are "better" than an average employee on unobserved dimensions.[9] This mechanism would not be present when hiring from low-productivity and low human capital firms, so one way to test this alternative is to restrict our sample to firms that hire from lower-productivity or lower human capital firms.[10] If our spillover estimates persist in these subsamples, this would be inconsistent with the alternative that our results are driven by productivity benefits associated with poaching high-quality workers from better firms.

The results from this analysis are presented in Table 8. Estimates are presented from a number of subsample analyses, where the samples are restricted to firms that tend to hire workers away from firms with lower levels of IT worker education, IT worker experience, R&D intensity, and a measure of productivity (value added per employee). The magnitude of the estimate on the IT spillover pool changes little through all these subsample analyses and is only slightly lower in magnitude than the baseline estimates using the full sample of the IT employment data. This indicates that this potential alternative mechanism is likely to have a relatively small effect on these estimates. The exception to this is when limiting the sample to firms that hire IT labor from firms with lower value added per employee, but this restriction is likely to exert a downward bias on the spillover term because it reflects negative firm attributes. Nonetheless, the spillover estimate is still significant. In general, however, the

[9] It is possible that receiving firms hire these workers because they anticipate using a new technological innovation and that firms derive benefits from using this new technology. In this sense, the use of new IT innovations is complementary to demand for workers with the necessary skills. From a conceptual standpoint, this should not impact the interpretation of causality in the model, because productivity gains from the new IT innovations cannot be realized until firms acquire these workers. We thank an anonymous reviewer for making this point.

[10] We thank an anonymous editor and an anonymous reviewer for suggesting these tests.

estimates in columns (1)–(4) of Table 8 are inconsistent with the hypothesis that the spillover results reflect firms acquiring better human capital by hiring from "good" firms.

We can further restrict this analysis by testing whether spillovers captured from the lower-productivity firms in column (4) are uniquely generated by the mobility of IT workers rather than other occupations, as would be expected if our estimates reflect productivity benefits from the transfer of IT know-how. We construct an IT spillover pool identical to the one using the mobility of IT workers, but instead using the mobility patterns of workers in all other major occupations in our data set, including management, sales, production, and finance. IT workers represent a *smaller* number of observations than other types of employees, so to the extent that statistical power is limited by sample size, our test is conservative. Our estimates using these variables are shown in columns (5) and (6) of Table 8. Column (5) presents fixed-effects results using the IT worker pool, limited to the subsample of observations for which both the IT worker and non-IT worker pools are available. Column (6) adds the non-IT worker pool. After including this measure, the estimate on the IT worker pool is similar to that in column (5), and the estimate on the non-IT worker spillover pool is not significantly different from zero. The test in column (6) indicates that these productivity benefits are captured even from lower-productivity firms, but only through lower-productivity firms in the IT labor flow network.

We can also directly test for the effects of human capital differences in incoming employees, such as greater education or experience or higher status levels in the hiring firm, which are associated with higher productivity. Proximity in the IT labor flow network may also reflect heterogeneity in the underlying production function, so the human capital data allow us to test the robustness of our results to some of these alternative explanations. Because we have data on the human capital of individual employees moving between firms, we can control for differences in other types of human capital by embedding them directly in the production function. We include the education and experience levels of the firm's existing IT workforce, using data for each of the workers in our data set. The point estimates on IT education and IT experience in column (1) of Table 9 are positive and significant, but including these measures does not substantially change the estimate on the spillover term.

In column (2), we include measures of the education and experience of incoming IT workers. The estimates in column (2) indicate that higher education levels in the incoming IT pool are associated with higher productivity, but that the effect of higher experience levels in the incoming IT worker pool is not significantly different than zero. The coefficient estimate on the spillover term falls slightly in magnitude but is still significant, so our spillover results are unlikely to reflect differences in other types of human capital among firms, either in a firm's existing stock of IT human capital or in the pool of incoming IT workers. The spillover estimate remains unchanged in column (3), after including human capital measures for both the incoming IT pool and firm's IT workforce in a single regression.

Table 9 Robustness—Direct IT Human Capital and Wage Measures

DV: Log(*Value added*) Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Log(*Non-IT employment*)	0.625***	0.549***	0.553***	
	(0.0126)	(0.0182)	(0.0186)	
Log(*Capital*)	0.273***	0.279***	0.277***	0.306***
	(0.00960)	(0.0133)	(0.0133)	(0.0218)
Log(*IT employment*)	0.0769***	0.161***	0.157***	
	(0.00831)	(0.0112)	(0.0116)	
Log(*IT pool*)	0.0290***	0.0174***	0.0174***	0.0162***
	(0.00214)	(0.00293)	(0.00293)	(0.00486)
Log(*IT education*)	0.0585***		0.102***	
	(0.0185)		(0.0310)	
Log(*IT experience*)	0.0402**		0.00760	
	(0.0162)		(0.0310)	
Log(*Incoming IT education*)		0.0887**	0.0693*	
		(0.0374)	(0.0375)	
Log(*Incoming IT experience*)		0.0301	0.0278	
		(0.0255)	(0.0253)	
Log(*Non-IT labor wages*)				0.667***
				(0.0274)
Log(*IT labor wages*)				0.0385***
				(0.0136)
Observations	30,401	13,731	13,731	1,978
R-squared	0.919	0.921	0.922	0.929

Notes. Robust standard errors are in parentheses. Column (1) includes mean levels of IT education and experience at the firm. Column (2) includes the education and experience of incoming IT workers only. Column (3) includes all of the human capital variables. Column (4) includes IT wages. All own and external IT measures constructed using IT employment data.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

A related question is to what extent spillovers are fully internalized in the labor market through higher wages for more productive IT workers. In column (4), we use cross-sectional 2006 IT wage data to create measures of IT and non-IT labor expenses, which we substitute for employment-based measures. Including data on wages in our regressions reduces the spillover estimate further, suggesting that employees are partially compensated for the IT expertise they bring from other firms. However, after including wages, the IT spillover pool is still significant ($t = 3.33$). Overall, these results are consistent with the hypothesis that firms pay for some, but not all, of the IT know-how transferred by IT labor from other firms. In the appendix, we report additional results testing the sensitivity of our findings to (1) seeding the zero-value spillover pools, (2) using alternative measures of the external IT pool, and (3) setting capital and labor to factor share to address production function heterogeneity.

The results from all of these tests provide stronger support for the spillovers story than for the alternative explanations. If our estimates reflected unobserved factors related to hiring IT labor from other high-performing firms, we should not have observed evidence for spillovers when firms hire from less-productive firms. Furthermore, we would have expected that the effect sizes on the potential spillover pool constructed using the mobility of workers in other occupations would be significant, because these workers are as likely as IT workers to be sensitive to firm reputation. If our estimates reflected returns to the transfer of other types of human capital or network similarity, evidence for spillovers should not have been stronger for IT workers. If our estimates primarily reflected geographic effects or the effects of spillover mechanisms correlated with general employee mobility, the mobility of workers in other occupations—who are more likely to be geographically bounded in their job search than high-skill IT workers—would have provided a superior measure than measures based on the mobility of IT workers. Instead, our results indicate that (1) firms receive productivity benefits proportional to the IT intensity of other firms from which they hire, and (2) these benefits are transmitted through incoming IT labor, not through workers in other occupations. The story most consistent with this set of results is that IT-related skills and know-how are transferred through IT labor mobility.

Discussion

Our results suggest that IT labor flows are an important mechanism for the transmission of productivity spillovers related to IT-enabled production methods. In our most robust estimates, the elasticity of the pool of external IT investment is about 20% that of internal IT investment. Therefore, firms located in high-tech regions, where IT investment is likely to be much higher, may receive substantial economic benefits (although it is likely that they also face higher costs). Our results suggest that these benefits are directly due to IT labor flows among firms. Our measured IT labor flows appear to be the driving mechanism behind positive regional IT spillovers. The labor flow spillovers appear to be distinct from industry-related spillovers.

These findings have implications for both managers and policy makers. From a managerial perspective, our findings imply that because firms appear to benefit from the IT investments of other firms through labor mobility, managers should pay close attention to "opening" their firms to "spill-ins" of knowledge. Our results are consistent with other work that suggests that labor market flexibility may play an important role in explaining cross-country IT-related productivity differentials (Bloom et al. 2012). To the extent that access to skilled technical labor is governed in part by location, our results at least partially explain why many firms find it advantageous to locate in places like the Silicon Valley.

Given the potential competitive benefits of attracting workers from IT-intensive firms, these firms have naturally responded by implementing strategies to retain their employees. Google gave a 10% pay raise to all its employees in an effort to slow the defection of staff to competitors (Efrati and Morrison 2010). Furthermore, the U.S. Department of Justice launched an investigation into the hiring practices of several prominent technology companies in Silicon Valley to determine whether they colluded to prevent cross-firm employee poaching (Catan and Kendall 2010). This investigation was closed several months later, after firms agreed to abandon the practices in question. The attention paid to this type of employee mobility by managers and policy makers suggests its economic importance, especially in areas characterized by competitive labor markets. Our study is among the first to attempt to quantify the economic impact of this type of employee mobility in IT occupations.

From a policy perspective, our emphasis on a particular mechanism for the transfer of IT spillovers—labor mobility—has several implications. For example, our findings may partially explain why countries with more rigid labor markets and lower levels of labor mobility appear not to have experienced the same productivity growth from IT investments as the United States, as well as why regions within the United States may have disproportionately benefited from the IT boom. Similarly, our results are consistent with a high degree of high-tech agglomeration in states where mobility is high (such as California).[11] Policies that facilitate employee mobility, such as noncompete agreements (Marx et al. 2009), might ultimately affect growth levels through the channels studies in this paper (Samila and Sorenson 2011).

There are a number of questions that would be interesting to pursue in future work. Developing a deeper understanding of how IT spillovers are distributed across firms in different industries and regions will be important for understanding how

[11] When we repeated our analysis of geographic spillovers (as per Table 3), focusing specifically on whether a firm was located in California, firms showed even more substantial geographic IT spillovers. However, controlling for IT labor flow measures substantially reduced this effect, consistent with our analysis (results available from the authors).

economic geography and industrial organization are affected by computerization. Furthermore, although employee mobility is an important mechanism for the diffusion of IT know-how among firms, there are others. Best practices can also be transferred among firms through consulting firms; through purchases of software packages, which encode large amounts of business logic into standardized software; or through managerial social networks. The collection and analysis of data on these transmission mechanisms will prove useful for further understanding the dynamics of returns to computerization.

Acknowledgments
The authors are grateful for valuable feedback from David Autor, Matthew Bidwell, Nicholas Bloom, Erik Brynjolfsson, Peter Cappelli, Eric Clemons, Avi Goldfarb, Lori Rosenkopf, and AnnaLee Saxenian; anonymous reviewers from the International Conference on Information Systems; and seminar participants at the Workshop for Information Systems and Economics, International Conference on Information Systems, Wharton People and Organizations Conference, the National Bureau of Economic Research Economics of Information Technology and Digitization Summer Institute, Massachusetts Institute of Technoloy, Purdue University, the Industry Studies Association Conference, Cornell University, the University of California at Irvine, New York University, the University of Pennsylvania, the University of Maryland, and the University of Minnesota.

Appendix. Additional Robustness Tests
In Table A.1, we test the sensitivity of our estimates to sample selection. In columns (1) and (2), we present results from models where we include only firms with nonzero spillover pools. The estimate on IT investment rises, which is consistent with higher IT returns in larger firms, and the estimates on the spillover pools remain significant and positive. In column (3), we include all firms in the sample, but we include a dummy variable for firms that have a seeded spillover pool. The estimates from this model indicate that our estimates are not sensitive to the value we choose to seed the spillover pool. Finally, in column (4), we show that our estimates are substantively similar when using location, industry, year, sales growth, employment growth, size, and IT employment to predict selection in a Heckman regression model.

Table A.1 **Pool Seeding and Selection**

Variables	Nonzero pool (1)	Nonzero pool (2)	Dummy for zero pool (3)	Heckman (4)
Log(*Non-IT employment*)	0.538*** (0.0195)	0.545*** (0.0194)	0.631*** (0.0113)	0.518*** (0.00793)
Log(*Capital*)	0.284*** (0.0141)	0.284*** (0.0140)	0.273*** (0.00874)	0.293*** (0.00514)
IT employment	0.170*** (0.0119)	0.163*** (0.0118)	0.0711*** (0.00709)	0.174*** (0.00772)
IT pool		0.0415*** (0.00867)	0.0651*** (0.00893)	0.0435*** (0.00767)
Observations	13,076	13,076	36,300	30,433
R-squared	0.923	0.923	0.917	

Notes. Robust standard errors are in parentheses. All variables are in logs. Each regression includes controls for industry and year. Industry controls are included at the one-digit SIC level. All include logged measures of capital, labor, and IT investments as well as the variables shown. Columns (1) and (2) report the results when regressions are performed only on firms with nonzero spillover pools. In column (3), all firms are included, but the firms with no spillover pools receive a value of zero, and the specification includes a dummy variable indicating a zero spillover pool. Column (4) uses the Heckman selection model.
***$p < 0.01$.

Table A.2 **Sensitivity to Alternative Spillover Measures**

Threshold	IT levels (1)	Mean values (2)	1% threshold (3)	2% threshold (4)	5% threshold (5)	10% threshold (6)
IT	0.073** (0.007)	0.055** (0.007)	0.066** (0.007)	0.066** (0.007)	0.069** (0.007)	0.074** (0.007)
IT pool	0.011** (0.001)	0.026** (0.002)	0.030** (0.002)	0.030** (0.002)	0.028** (0.002)	0.024** (0.002)
Average network size		28.14	10.05	6.44	6.05	2.34
N	36,300	36,300	36,300	36,300	36,300	36,300

Notes. Robust standard errors are in parentheses. All variables are in logs.
**$p < 0.05$.

In Table A.2, we test the sensitivity of our estimates to the construction of our spillover pool. In column (1), we present results using a spillover measure computed as the IT investments (levels) of all other firms rather than IT intensity, weighted by the fraction of incoming employees coming from that firm. In column (2), we report results using a spillover measure based on mean IT intensity values, rather than the sum of IT intensity at other firms. In both regressions, the estimates on the IT and spillover term are lower but similar to the estimates from our extended IT employment based regressions in Table 6. We also test regressions constructing our spillover measure from all other firms which a firm hires at least 1%, 2%, 5%, and 10% of its IT employees, and we report in the table how the average number of firms in the IT pool changes from over 28 firms with no threshold to 2 firms at a threshold of 10%. The estimate on the spillover pool falls slightly as we shift the threshold from 1% to 10%, and the estimate on internal IT investment rises, consistent with measurement error in the spillover pool. As we introduce larger amounts of error into the spillover pool, it introduces a downward bias on the spillover coefficient estimate, some of which may be transferred to a firm's internal IT investment because of correlation between the two measures.

We also address the concern that our results may reflect production function heterogeneity that is not removed by our industry dummies and that our IT spillovers are correlated with firm-level variation in production function parameters. Our results from Table A.3, in which we set capital and labor to their theoretical values, are inconsistent with the interpretation that our estimates reflect heterogeneity in the production function. The spillover estimates are

Table A.3 Capital and Labor Set to Factor Share

Variables	(1) OLS	(2) OLS
IT employment	−0.0422	
	(0.0505)	
IT pool	0.122***	0.0441
	(0.0269)	(0.0548)
Observations	36,300	1,978
R-squared	0.287	0.311

Notes. Robust standard errors are in parentheses. In column (1), coefficients on capital and labor are set to their theoretical values. In column (2), we use 2006 IT wages and also set IT to its theoretical value.

$^{***}p < 0.01$.

still positive and significant in column (1) after setting capital and labor to their respective factor shares. In column (2), we use cross-sectional IT wage data reported by the IT employees in our sample to set IT to its theoretical value. The spillover term is no longer significant in this regression, but the magnitude and direction of the estimate are similar to our prior estimates.

References

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers in regional networks. *Management Sci.* 45(7):905–917.

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

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econom. Stud.* 58(2):277–297.

Arrow KJ (1962) The economic implications of learning by doing. *Rev. Econom. Stud.* 29(3):155–173.

Attewell P (1992) Technology diffusion and organizational learning: The case of business computing. *Organization Sci.* 3(1):1–19.

Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. *Amer. Econom. Rev.* 86(3):630–640.

Audretsch DB, Stephan PE (1996) Company-scientist locational links: The case of biotechnology. *Amer. Econom. Rev.* 86(3): 641–652.

Balsvik R (2011) Is labor mobility a channel for spillovers from multinationals? Evidence from Norwegian manufacturing. *Rev. Econom. Statist.* 93(1):285–297.

Bapna R, Langer N, Mehra A, Gopal R, Gupta A (2013) Human capital investments and employee performance: An analysis of IT services industry. *Management Sci.* 59(3):641–658.

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

Becker GS, Murphy KM (1992) The division of labor, coordination costs, and knowledge. *Quart. J. Econom.* 107(4):1137–1160.

Benkard CL (2000) Learning and forgetting: The dynamics of aircraft production. *Amer. Econom. Rev.* 90(4):1034–1054.

Bloom N, Sadun R, Van Reenen J (2012) Americans do I.T. better: US multinationals and the productivity miracle. *Amer. Econom. Rev.* 102(1):167–201.

Bloom N, Schankerman M, Van Reenen J (2013) Identifying technological spillovers and product market rivalry. *Econometrica* 81(4):1347–1393.

Breschi S, Lissoni F (2001) Knowledge spillovers and local innovation systems: A critical survey. *Indust. Corporate Change* 10(4):975–1005.

Bresnahan TF (2003) The mechanisms of information technology's contribution to economic growth. Touffut J-P, ed. *Institutions, Innovation and Growth: Selected Economic Papers*, Chap. 5 (Edward Elgar Publishing, Cheltenham, UK).

Bresnahan TF, Brynjolfsson E, Hitt LM (2002) Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quart. J. Econom.* 117(1):339–376.

Bresnahan TF, Gambardella A, Saxenian A (2001) "Old economy" inputs for "new economy" outcomes: Cluster formation in the new Silicon Valleys. *Indust. Corporate Change* 10(4):835–860.

Brynjolfsson E, Hitt L (1996) Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Sci.* 42(4):541–558.

Brynjolfsson E, Hitt LM (2003) Computing productivity: Firm-level evidence. *Rev. Econom. Statist.* 85(4):793–808.

Catan T, Kendall B (2010) U.S. tech probe nears end. *Wall Street Journal* (September 17), http://online.wsj.com/article/SB10001424052748703440604575496182527552678.html.

Chang YB, Gurbaxani V (2012) The impact of IT-related spillovers on long-run productivity: An empirical analysis. *Inform. Systems Res.* 23(3, part 2):868–886.

Cheng Z, Nault BR (2007) Industry-level supplier-driven IT spillovers. *Management Sci.* 53(8):1199–1216.

Cheng Z, Nault BR (2012) Relative industry concentration and customer-driven IT spillovers. *Inform. Systems Res.* 23(2): 340–355.

Chwelos P, Ramirez R, Kraemer K, Melville N (2010) Does technological progress alter the nature of information technology as a production input? New evidence and new results. *Inform. Systems Res.* 21(2):392–408.

Dahl M, Sorenson O (2010) The migration of technical workers. *J. Urban Econom.* 67(1):33–45.

David P (1990) The dynamo and the computer: An historical perspective on the modern productivity paradox. *Amer. Econom. Rev.* 80(2):355–361.

Dedrick J, Gurbaxani V, Kraemer K (2003) Information technology and economic performance: A critical review of the empirical evidence. *ACM Comput. Surveys* 35(1):1–28.

Dewan S, Kraemer K (2000) Information technology and productivity: Evidence from country-level data. *Management Sci.* 46(4):548–562.

Dewan S, Minn C-K (1997) The substitution of information technology for other factors of production: A firm level analysis. *Management Sci.* 43(12):1660–1675.

Draca M, Sadun R, Van Reenen J (2006) Productivity and ICT: A review of the evidence. CEP Discussion Paper 749, Centre for Economic Performance, London School of Economics and Political Science, London. http://eprints.lse.ac.uk/4561/.

Duranton G, Puga D (2004) Micro-foundations of urban agglomeration economies. Henderson JV, Thisse J-F, eds. *Handbook of Regional and Urban Economics*, Vol. 4 (Elsevier, Amsterdam), 2063–2117.

Efrati A, Morrison S (2010) Google to give staff 10% raise. *Wall Street Journal* (November 10), http://online.wsj.com/article/SB10001424052748703523604575605273596157634.html.

Fallick B, Fleischman C, Rebitzer J (2006) Job-hopping in Silicon Valley: Some evidence concerning the microfoundations of a high-technology cluster. *Rev. Econom. Statist.* 88(3):472–481.

Forman C, Golfarb A, Greenstein S (2005) How did location affect adoption of the commercial Internet? Global village vs. urban leadership. *J. Urban Econom.* 58(3):389–420.

Forman C, Goldfarb A, Greenstein SM (2012) The Internet and local wages: A puzzle. *Amer. Econom. Rev.* 102(1):556–575.

Franco A, Filson D (2006) Spin-outs: Knowledge diffusion through employee mobility. *RAND J. Econom.* 37(4):841–860.

Freedman M (2008) Job hopping, earnings dynamics, and industrial agglomeration in the software publishing industry. *J. Urban Econom.* 64(3):590–600.

Griliches Z (1992) The search for R&D spillovers. *Scandanavian J. Econom.* 94:29–47.

Jaffe A (1986) Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *Amer. Econom. Rev.* 76(5):984–1001.

Jaffe A, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *Quart. J. Econom.* 108(3):577–598.

Jorgenson DW, Stiroh KJ, Gordon RJ, Sichel DE (2000) Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers Econom. Activity* 1(2000):125–235.

Kim S (1989) Labor specialization and the extent of the market. *J. Political Econom.* 97(3):692–705.

Kossinets G (2006) Effects of missing data in social networks. *Soc. Networks* 28(3):247–268.

Levinsohn J, Petrin A (2003) Estimating production functions using inputs to control for unobservables. *Rev. Econom. Stud.* 70(2):317–341.

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

Levy F, Murnane R (1996) With what skills are computers a complement? *Amer. Econom. Rev.* 86(2):258–262.

Lichtenberg F (1995) The output contributions of computer equipment and personnel. A firm-level analysis. *Econom. Innovation New Tech.* 3(3–4):201–218.

Lieberman MB (1984) The learning curve and pricing in the chemical processing industries. *RAND J. Econom.* 15(2):213–228.

Marx M, Strumsky D, Fleming L (2009) Mobility, skills, and the Michigan non-compete experiment. *Management Sci.* 55(6): 875–889.

McElheran K (2011) Do market leaders lead in business process innovation? The case(s) of e-business adoption. HBS TOM Unit Working Paper 10-104, Harvard Business School, Boston.

Mithas S, Krishnan M (2008) Human capital and institutional effects in the compensation of information technology professionals in the United States. *Management Sci.* 54(3):415–428.

Oettl A, Agrawal A (2008) International labor mobility and knowledge flow externalities. *J. Internat. Bus. Stud.* 39(8):1242–1260.

Orlando MJ (2004) Measuring R&D spillovers: On the importance of geographic and technological proximity. *RAND J. Econom.* 35(4):777–786.

Rosen S (1983) Specialization and human capital. *J. Labor Econom.* 1(1):43–49.

Samila S, Sorenson O (2011) Non-compete covenants: Incentives to innovate or impediments to growth. *Management Sci.* 57(3): 425–438.

Saunders A (2010) Valuing IT-related intangible capital. *ICIS 2010 Proc.*, Paper 243. http://aisel.aisnet.org/icis2010_submissions/243.

Saxenian A (1996) *Regional Advantage*: *Culture and Competition in Silicon Valley and Route* 128 (Harvard University Press, Cambridge, MA).

Stoyanov A, Zubanov N (2012) Productivity spillovers across firms through worker mobility. *Amer. Econom. J.: Appl. Econom.* 4(2):168–198.

Tambe P, Hitt LM (2012) The productivity of information technology investments: New evidence from IT labor data. *Inform. Systems Res.* 23(3, part 1):599–617.

Tambe P, Hitt LM (2013) Measuring information technology spillovers. *Inform. Systems Res.*, ePub ahead of print October 31, http://dx.doi.org/10.1287/isre.2013.0498.

Tambe P, Hitt LM, Brynjolfsson E (2012) The extroverted firm: How external information practices affect innovation and productivity. *Management Sci.* 58(5):843–859.

Thornton RA, Thompson P (2001) Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding. *Amer. Econom. Rev.* 91(5):1350–1368.