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Prasanna Tambe
New York University, ptambe@stern.nyu.edu

Lorin M. Hitt
University of Pennsylvania, lhitt@wharton.upenn.edu

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Prasanna Tambe
New York University
New York, NY 10012
ptambe@stern.nyu.edu

Lorin M. Hitt
University of Pennsylvania
Philadelphia, PA 19013
lhitt@wharton.upenn.edu

Abstract

We show that substantial regional differences in returns to information technology (IT) investments by US firms are attributable in part to knowledge spillovers generated by the movements of IT workers among firms. We use a newly developed source of employee micro-data with employer identifiers and location information to model IT workers' mobility patterns. Access to an external IT pool one standard deviation larger than the mean is associated with a 20% increase in the output elasticity of own IT investment. We discuss implications for managers and for policy makers.

Keywords: IT spillovers, IT productivity, IT labor, knowledge spillovers, high-tech clusters

Introduction

Researchers have argued that like earlier general-purpose technologies, such as electricity or the steam engine, IT investments may generate substantial knowledge "spillovers" as new, improved methods of IT-enabled production diffuse among firms (David, 1990).[1] From an economic perspective, superior access to spillovers of new production methods and work practices should lead to higher IT returns and higher productivity levels. Therefore, identification and measurement of the economic impact of IT spillovers has implications for understanding heterogeneity in IT returns as well as for measuring social returns to IT investment, two topics of interest in the modern literature on IT business value (Melville, Gurbaxani, and Kraemer, 2004).

The transfer of new IT-related production innovations, however, is a complex process that requires adapting new practices to fit a specific organizational context. More so than spillovers of patent-based scientific knowledge, the diffusion of IT-related production methods may be governed by knowledge transfer mechanisms that promote face-to-face interaction, such as the movements of contractors, consultants, and employees among firms (Attewell, 1992; Dedrick, Kraemer, & Gurbaxani, 2003; Draca, Sadun, & Van Reenen, 2006). This is consistent with earlier generations of production technologies—economic historians have argued that skilled factory architects and electrical engineers were instrumental in diffusing work practices related to installation of the electric dynamo in US factories (David, 1990). Moreover, because most labor market activity is local, location may play a particularly important role in the diffusion of new production methods, and may partially explain why some firms choose to locate in high-tech, urban areas despite facing higher costs for other factors such as land and labor. Indeed,

[1] It is worth clarifying at the outset is that our focus is on "knowledge spillovers", rather than the pecuniary externalities that have been discussed in some prior research and that are also often referred to as "spillovers" (Mun & Nadiri, 2002; Cheng & Nault, 2007). Knowledge spillovers of the type that we are interested in arise when knowledge is transferred among firms.

researchers have recently connected geographic clustering in service industries with access new IT-related production methods (Desmet & Rossi-Hanbserg, 2009).

The primary goal of this study is to test the hypothesis that firms benefit from the IT investments of other firms because IT labor flows generate spillovers related to IT production methods. The primary contribution of the study is collection of a new data set describing the mobility of IT workers. These data are derived from the employment histories of several hundred thousand US-based IT workers over the last twenty years and include information on employers and skills. Access to this unusually large and unique sample allows us to map the mobility patterns of IT workers among firms and the likely diffusion paths of IT practices, and therefore to test one important mechanism through which firms may benefit from the IT investments of other firms.

Our paper, therefore, contributes to a large literature on IT productivity, where there is currently interest in understanding the heterogeneity in IT returns that has been observed across firms and countries (Dewan & Kraemer, 2000; Van Reenen, Sadun, & Bloom, 2008). Our study is among the first to attempt to identify how IT knowledge spillovers might drive regional IT productivity differentials, and to the best of our knowledge, is the first study to investigate this issue using micro-data on inter-firm labor flows, which scholars have hypothesized is an important transmission path for this type of production knowledge. We also contribute to an emerging literature on the allocation of value from IT investments. Although most of the attention in the IT literature has been focused on private IT returns, there has been recent interest in the allocation of IT business value among groups of firms (Saraf, Langdon, & Gosain, 2007). If IT knowledge spillovers are economically significant, this has implications for understanding how firms benefit from the IT investments of other firms, which in turn has implications for optimal investment strategy and growth policy.

Our findings suggest that IT labor flows generate IT productivity spillovers that in turn, explain a significant amount of regional variation in IT returns. Our spillover estimates indicate a rate of return to external IT investment that is about 20% the rate of return to internal investment, suggesting that firms receive substantial benefits from the investments of other firms. In other words, assuming that firms tend to hire most of their workers locally, firms located in regions with a one standard deviation higher average IT investment level experience a rate of return to own IT investment that is higher by about 20%.

Theory and Hypotheses

The IT productivity literature has heavily emphasized the role of organizational complements in explaining IT returns (Bresnahan, Brynjolfsson, & Hitt, 2002; Caroli & Van Reenen, 2002). This stream of research has shown that higher productivity levels are generated not simply from investing in IT capital, but also from investing in new, complementary production methods. Much of the empirical research has focused on the decentralization of work practices, but some scholars have also considered the role of other information practices, such as external information gathering and workflow digitization (Mendelson, 2000; Aral & Weill, 2007; Tambe, Hitt, & Brynjolfsson, 2008). Differences in the adoption of these practices across firms have been connected to substantial IT-related performance differentials, raising the question of why the most effective combinations of IT and these new practices are not simply adopted by all firms.

One explanation for these differences is that organizational transformation is a difficult and costly process. Indeed, organizational adjustment costs (i.e. the costs of making changes within the organization to best use the new technology) have been shown to be substantial in prior research (Applegate, Cash, & Mills, 1988; Murnane, Levy, & Autor, 1999; Milgrom & Roberts, 1990). Attewell argues that integrating information technologies is a complex, iterative process because of the difficult nature of technical knowledge transfer and because new practices have to be adapted to a specific organizational context before becoming useful (Attewell, 1992). Therefore, rather than being re-invented within each firm, new IT-related production methods are likely to be transferred to firms by technical experts with relevant experience, suggesting that these combinations of information practices, once "discovered", will be transferred among firms.

These spillovers are likely to be stronger over small geographic distances because most knowledge transmission mechanisms that are rich enough to facilitate this type of knowledge transfer, such as employee mobility or shared membership in technical user groups, are more densely concentrated over small distances. Therefore, the diffusion of new technology and information practices, and the associated IT returns, should be localized. The central thesis of this paper is that some of the geographic variation in IT returns may therefore be due to regional spillovers of new IT production methods generated by IT labor flows. A common method for testing for the presence of spillovers is to treat the pool of know-how available to firms as an input into a production function. For example, if knowledge spillovers are hypothesized to occur only among firms within the same industry as might be expected for specialized knowledge pertaining to scientific advances, a spillover pool could be constructed from the R&D knowledge of other firms in the same industry. If spillovers are regional, then spillover pools can be constructed from the investment levels of geographic neighbors. Spillovers are economically important if firms with access to larger pools of external knowledge are more productive, all else equal. Therefore, because firms will have greater access to IT spillover in more IT-intensive regions, we hypothesize:

H1: Returns to IT investment are higher in regions with higher IT investment levels.

Although associating productivity differences with differences in aggregate levels of regional or industry IT investment has been common in the knowledge spillovers literature, the measurement of spillover pools based solely on industry or region has recently come under criticism (Breschi & Lissoni, 2001; Van Reenen, Schankerman, & Bloom, 2007). In addition to confounding the effects of individual spillover mechanisms that operate within regions or industries, broad measures may produce spurious results in models that confound industrial or technological proximity to other firms with economic shocks. For instance, a positive association between performance and regional IT investment may simply reflect an unexpected increase in demand for certain high technology products that happened to be produced in a localized area such as Silicon Valley.

Emphasis has therefore turned towards explicitly modeling the individual mechanisms of knowledge transfer though the collection of fine-grained data on social or economic activity. For example, in the case of R&D spillovers, researchers have correlated patent citations and technology alliances with knowledge spillovers. For IT spillovers, scholars have argued that an important mechanism for knowledge transfer is IT labor mobility (Dedrick, Gurbaxani, & Kraemer, 2003) because it allows for the repeated face-to-face interaction required for adapting technical knowledge to a new organizational context. Therefore, rather than relying on broad and potentially problematic regional or industry measures, we explicitly model this transmission path using detailed data on IT employment paths. The second hypothesis that we test, therefore, is that:

H2: Returns to IT investment are higher at firms that hire IT workers from other IT-intensive firms.

In the next section, we describe the data, methods and measures we use to test these hypotheses.

Empirical Framework

Our empirical approach is closely related to an established literature on the impact of R&D knowledge spillovers on productivity, and to a literature on the productivity of information technology investments. A common approach in both literatures is to use methods from production economics that estimate of the contribution of various inputs, such as capital, labor, R&D, and IT, to firm productivity. To estimate the contribution of R&D to productivity, scholars embed R&D measures, along with other inputs, into a "production function", an econometric model of how firms convert inputs to outputs[2], and to estimate the contribution of R&D knowledge spillovers to productivity, researchers augment this function with measures of the external knowledge pool available to a firm (Griliches, 1992). For estimating the contribution of IT investment, researchers have included IT instead of R&D measures (Brynjolfsson & Hitt, 2003). Although there has so far been less research on knowledge spillovers generated by IT investments, scholars have suggested a similar framework for studying IT externalities where IT is substituted for R&D as the knowledge producing asset (Draca, Sadun, & Van Reenen, 2006).

Economic theory places some constraints on the functional form used to relate these inputs to outputs, but a number of different functional forms have been widely used depending on the firm's economic circumstances. The most common is the Cobb-Douglas specification. Aside from being among the simplest functional forms, this specification has also been the most commonly used model in research relating inputs such as information technology or R&D knowledge to output growth and forms the basis for productivity measurement of the US economy as a whole. Moreover, since the Cobb-Douglas function can be considered a first order approximation of

[2] Mairesse and Sassenou (1991) survey this work.

an arbitrary production function, it is well suited to estimating the contribution of inputs to outputs which are typically quoted at the sample mean, the region where the first order approximation is especially accurate.[3]

To test how knowledge spillovers affect productivity, researchers augment the existing production framework by adding a term representing the knowledge pool available to the firm. Therefore, in addition to traditional inputs such as capital (K) and labor (L), this framework includes measures of the firm's stocks of the knowledge producing asset (C), and the knowledge stocks of all of the firm's neighbors (S). Taking logs of both sides of the Cobb-Douglas production function described in (1) produces a model that can be estimated using standard OLS regression techniques.

$$(1) \quad va_{ijt} = \alpha_k k_{ijt} + \alpha_l l_{ijt} + \alpha_c c_{ijt} + \alpha_s s_{ijt} + controls + \varepsilon_{ijt}$$

Researchers look for evidence of knowledge spillovers by testing whether larger external spillover pools are associated with higher productivity levels. The null hypothesis, which is that spillovers do not contribute significantly to productivity, is rejected when α_s is significantly greater than zero.

Because data on investments in capital, labor, and output are widely available, the most significant challenge in using this approach is the development of reliable measures of firm's internal and external knowledge sets. In the R&D literature, firms' internal stocks of R&D knowledge are modeled using R&D investment data. Modeling the potential external pool of knowledge available to a firm, however, is more difficult because it requires assumptions about how knowledge is transferred among firms. A great deal of attention has been paid in the literature on knowledge spillovers to how best to measure external knowledge pools (Griliches, 1992). Historically, R&D researchers have made 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 (K_i), is modeled as the weighted sum of the knowledge of other firms in the sample (K_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.

$$(2) \quad S_{it} = \sum\nolimits_{j \neq i} \phi_{ijt} K_{jt}$$

This measure, inserted into a production function such as the one described in (1), enables researchers to test the economic contribution of knowledge spillovers.

Although a similar approach is also possible for the measurement of IT externalities, the use of broad proximity measures based on technological position or location to measure spillovers has come under much criticism for the reasons described above, such as confounding industry or regional growth with spillovers. Therefore, accurate modeling of transmission paths may be especially important for estimating IT spillovers. The primary contribution of this study is that we compile data capturing an important transmission path for IT externalities. Access to fine-grained data on the transmission path for IT externalities provides a foundation on which to connect IT employee mobility to knowledge spillovers based on the model in (2). Rather than basing our spillover measure on geographic or industrial proximity, we create our measures based on the flow of employees among firms, where firms have access to the knowledge of firms from which they hire. In some of our analyses, we also model IT spillover pools based on industry and geographic proximity for comparison. Then the spillover augmented production function (1) can be estimated using standard regression techniques such as ordinary least squares (with suitable standard error corrections for panel data) or panel methods such as fixed effects.

Data

Our employee mobility data were obtained from a leading jobs board that requires participants to post their employment histories online. We have access to fielded employment history information from about ten million users who posted or modified their career histories through this service in 2007. Users also provide information about occupation (e.g. information technology, sales, management, etc.), education level, and other demographic

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[3] Estimates of transcendental logarithmic or constant elasticity of substitution production functions using these data (functions used in prior work such as Dewan and Min, 1997), yield nearly identical estimates of the output elasticities of all inputs as our Cobb-Douglas estimates, as expected.

and human capital variables. In this study, we focus on IT workers, although we also use data from other occupations to test the robustness of our results. Our data set includes both full-time employees as well as hourly workers, such as contractors and part-time workers. We include all of these types of workers in our analysis because our primary interest is in knowledge transfer, and researchers have argued that contractors and consultants play an important role in the transfer of IT knowledge (Barley & Kunda, 2004).

We use the inter-firm mobility patterns of the IT workers in our data to model the flow of IT workers among US firms. The educational and occupational characteristics of the IT workers in the data set are shown in Table 1. We compare their educational attainment to that of the IT workers sampled in the 2006 Current Population Survey (CPS), a Census administered survey that is designed to be nationally representative.[4] The educational distribution of the workers in our sample is very similar to the educational distribution of the IT workers in the CPS. Although there are differences within categories, our data do not appear to be particularly skewed towards either higher or lower education levels. We also compared job tenure statistics against the job tenure of information technology workers who appeared in the CPS Job tenure supplement, last published in 2000. Not surprisingly, 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 ($p<.01$). One reason for this difference is that our sample is likely to contain a higher fraction of younger workers and job-hoppers. However, because the population of interest in this study is the job-hopping IT worker, our sample may actually be a better representation of this population than the CPS sample, which includes workers who never switch jobs.

Table 1: Educational Characteristics of IT Worker Sample

	IT Worker Sample	**CPS, 2006**
Education		
High School Degree or Less	24.7	25.1
Vocational Degree	2.8	.81
Two Year Degree	14.3	10.8
Four Year Degree	38.8	42.8
Graduate Degree	18.6	18.9
Doctorate	0.7	1.7
Table shows comparison between data sample and administrative sample.		

To develop inter-firm measures of IT worker flows from these employee micro-data, we associate employer names in the data with unique identifiers by matching them against external databases of publicly listed companies and subsidiaries, including Compustat, the Compact Disclosure Database, and the NBER Patents database, and then aggregating the data by firm-year. Although knowledge spillovers are not limited to public firms, we focus on the movements of employees between public firms because of the availability of supplementary economic data on these firms that is available through Compustat. Aggregating these data to the firm-level provides information on 1) how many IT workers were employed at a particular firm in a particular year[5], and 2) how many workers switched from one firm to another in a particular year. In the next section, we explain how we use these data to develop our IT-intensity and IT spillover measures.

Measures

We combine data from a variety of sources to test our empirical models. The key measures used in our analysis, their data sources, and their construction, are summarized in Table 2.

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[4]The survey is administered monthly to 50,000 households and is conducted by the Bureau of Labor Statistics (BLS). The sample is selected to represent the civilian non-institutional population. More information is available at http://www.census.gov/cps/.

[5] In Tambe & Hitt (2010a), we show that these firm-level IT worker measures compare favorably to external data sets on firm-level IT employment.

IT Expenditures

Our IT intensity measure, intended to represent IT investment (including hardware, software, human capital, and IT-enabled business processes), is constructed by dividing a firm's IT employment by its total employment. The IT employment data are constructed using the employment history data describe above. Construction of the IT employment data set, its sampling properties, comparison with other external IT data sets, and its behavior in productivity regressions is described in detail elsewhere (Tambe & Hitt, 2010a). The data set includes information on firm-level IT employment over the last two decades, which we use as a proxy for firms aggregate IT expenditures. Although actual firm-level IT expenditure data has been used in some recent studies, it is generally based on limited surveys, available only for a small sample of firms, and difficult to combine with external data sets. By contrast, broader archival datasets such as our IT employment data, although a somewhat noisier measure of total IT expenditure, are generally available for much longer timer periods, and for a much larger sample of firms. For this reason, archival data on IT capital and IT employment have been used by researchers to measure the IT intensity of firms in a number of other contexts (Lichtenberg, 1995; Brynjolfsson & Hitt, 1996; Dewan & Min, 1997). Furthermore, a number of studies have directly demonstrated that the IT intensity of firms, measured using IT employment or IT capital data, is highly correlated with investment in accompanying organizational and information practices (Bresnahan, Brynjolfsson, & Hitt, 2002; Aral & Weill, 2007; Tambe, Hitt, & Brynjolfsson, 2010). The use of these IT investment proxies to measure IT intensity closely follows an approach used in the literature on R&D spillovers, where R&D expenses are used to represent the stock of R&D capital within firms.

Among archival data sets, our employment based data set is preferred over alternative data sets, such as the CITDB capital stock data, for several reasons. Although recent research on IT productivity has relied heavily on the Computer Intelligence Technology Database (CITDB), the main panel of these data is restricted to Fortune 1000 firms, the definitions of variables changed significantly after 1994 and most importantly, the CITDB no longer includes direct measures of IT capital stock.[6] Our employment based data set has been shown to be highly correlated with other available IT capital, employment, and labor expense data, suggesting that it is a reasonable proxy for aggregate IT expenditure.[7] In this study, therefore, we use IT employment as our primary IT measure. In a longer version of this paper, however, we also report results from regressions using the CITDB IT capital stock measures to demonstrate robustness to our choice of IT measure (Tambe & Hitt, 2010b).

Measuring the IT Spillover Pool

Our primary spillover measure (S_E) is computed as the pool of IT know-how available through IT labor flows. One approach is to compute the spillover pool as the equally weighted summed IT intensity of all other firms from which a firm hires workers—so for our primary measure, we sum the IT intensity of firms from which a firm hires at least 5% of its new IT workers. This approach is similar to that used in several R&D knowledge spillover studies, where the R&D spillover pool is defined as the summed R&D intensity of other firms within a certain radius or within a particular industry (e.g., see Orlando, 2004). In the robustness section of our analysis, we show that our results are very similar when using 1%, 2%, or 10% thresholds rather than 5%. An alternative way to construct this measure that does not rely on a threshold value would be to simply weight the IT investments of other firms based on the fraction of employees that come from each firm. In our analysis, we also show that our results are robust to using this type of construction of the spillover pool.

These types of spillover measures are invariant to the number of employees hired, but increase with the average IT investments of other firms. From a network perspective, if the mobility of IT workers is important for the transfer of IT-related knowledge, our spillover measure is larger for firms that are central to other IT-intensive firms in the IT labor flow network. Firms embedded in high-tech industry clusters, for example, are more likely to exchange employees with other high-tech firms, and should benefit from the flow of skills and knowledge from the employees

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[6] Chwelos, Ramirez, Kraemer and Melville (2007) provide a method for extending CITDB 1994 valuation data through 1998 by imputing the values of equipment in the earlier part of the dataset 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.

[7] Correlations between our employment data set and other well known data sets, such as the CITDB, ComputerWorld, and InformationWeek data sets are generally above .5 (Tambe & Hitt, 2010a).

coming from these firms. However, a key distinction of our measure is the focus on a specific micro-mechanism that facilitates knowledge transfer within and across regions. Therefore, positive returns to our spillover measure imply that firms that hire from other IT-intensive firms, regardless of location, should capture spill-ins.

Table 2: Key Variables Used in Study

Variable Description	Variable Name	Data Source and Construction
Value Added	*VA*	Computed as output minus materials (from Compustat).
IT Employment	*IT*	Computed using IT labor data described in Tambe and Hitt (2010).
Capital	*K*	Compustat variable.
Non IT-Employment	*NITE*	Total firm employment from Compustat minus IT employment.
IT Intensity	*ITINT*	IT employment divided by total firm employment.
IT Labor Flow Pool	S_E	IT Intensity of firms from which an employer hires at least 5% of incoming IT employees.
Industry Pool	S_I	IT Intensity of firms within the same 4 digit SIC classification.
Local Pool	S_L	IT Intensity of firms within the same county and state.
Near-Near Pool	S_{NN}	IT Intensity of firms that are geographically close and from which an employer hires at least 5% of incoming IT employees.
Near-Far Pool	S_{NF}	IT Intensity of firms that are geographically far and from which an employer hires at least 5% of incoming IT employees.
Far-Near Pool	S_{FN}	IT Intensity of firms that are geographically close but from which an employer does not hire at least 5% of incoming IT employees.
Far-Far Pool	S_{FF}	IT Intensity of firms that are geographically far and from which an employer does not hire at least 5% of incoming IT employees.
Industry	*INDUSTRY*	1 and 2 digit SIC codes.
Corporate HQ	*HQ*	Compustat variable.

For some of our analyses, we also create spillover measures based on industrial and geographic proximity. Our broadest spillover measures based on geographic proximity (S_L)are constructed as the IT intensity of other firms that have corporate headquarters within the same state and county, where county and state of a firm's corporate headquarters are from Compustat. However, because our IT labor flow data measure the flow of employees into and out of all of a firm's establishments, the use of corporate headquarters as the basis of a geographic spillover measure is imperfect. Therefore, we test the robustness of our location-based findings using data that measures spillovers at the establishment-city level, but is limited to a single-year cross-section. Industry spillover measures (S_I) are constructed as the IT intensity of other firms within the same four-digit SIC industry. Adding industry based spillover measures to our regressions is important to account for the competitive effects of IT investment, which Bloom and colleagues have argued are necessary to identify technological spillovers because the positive effects of technological spillovers in productivity regressions are confounded with the negative effects of competitive investment (Bloom, Schankerman, & Van Reenen, 2007).

We also test whether IT labor flow patterns can explain associations between productivity and local IT investment levels. To separate the contributions of job-hoppers from other local spillover channels, we use frameworks developed in earlier research to jointly estimate the contributions of knowledge spillover pools that vary along two dimensions, hiring proximity and distance (Orlando, 2005). Therefore, the IT Intensity of other firms is broken into one of four pools: firms that are 1) proximate in terms of IT labor flows and geography (S_{NN}), 2) proximate in terms of IT labor flows but geographically distant (S_{NF}), 3) distant in terms of employee flows but geographically proximate (S_{FN}), and 4) distant in terms of both employee flows and geography (S_{FF}). We consider a firm to be proximate in terms of IT labor flows using the same metrics above—we include into the pool firms from which an employer has hired at least 5% of its incoming IT workers. Geographic proximity is measured in the two ways described above. We create proximity measures based on whether or not two firms have corporate headquarters in the same county and state location and then use the more detailed data on the geographic locations of individual establishments – firms are geographically proximate if they have establishments in the same city, which is a more detailed measure than one based solely on the location of corporate headquarters. The division of firms into these four groups separates the effects of IT labor flows from other localized productivity effects.

Other Inputs and Sales

Compustat firm data were used to compute employment, capital, sales, value added, and materials in constant 2000 dollars, using standard methods from the micro-productivity literature. Non-IT employment was computed by subtracting IT employment from total employment. Means, standard deviations, and correlations for these variables are shown in Table 3. We also include several control variables in our model. We used Compustat data to assign firms to a SIC industry. Depending on the specification, we included industry dummies at either the one or two digit SIC level. We also included year dummies to account for time trends and temporary productivity shocks.

Table 3: Means, Standard Deviations, and Correlations for Key Compustat Variables

Variable	Mean	Std. Dev.	1	2	3	4
1. Value Added (mm)	1046.7	3262.4	1			
2. Non IT Employment (m)	13.7	42.9	.93	1		
3. Capital (mm)	2071.8	8053.8	.88	.86	1	
4. IT Employment	271.3	1006.7	.83	.85	.75	1
N=33,918. Correlations in all cases are shown for logged variables.						

Results

Location, Regional IT Investment, and IT Productivity

First, we benchmark IT returns over the last two decades. In column (1) of Table 4, we report estimates from a model that includes capital, labor, and employment-based IT measures in a Cobb-Douglas function. Our estimates indicate an output elasticity of slightly less than .09 (t=12.3) for IT investment, which is consistent with IT productivity estimates from other studies that use IT employment data in cross-sectional regressions (Lichtenberg, 1995; Brynjolfsson & Hitt, 1996). In Columns (2)-(4), we look for regional differences by testing whether IT investments are associated with higher productivity in the state of California. We focus on California because it has been the focus of much of the literature on high-tech clusters, job hopping, and IT innovation (Saxenian, 1994; Fallick et al. 2006; Freedman, 2008). We include a dummy variable into our main regression indicating whether a firm's corporate headquarters are located in California, and we include an interaction term between this variable and the IT investments of firms. The interaction term in Column (2) is positive and significant (t=2.30), suggesting that the measured output elasticity of IT investment for firms in California is higher than for firms in other states. In Column (3), we include 2-digit industry controls to test if the interaction term may be reflecting differences in industry composition across states, but the estimate on the interaction term remains significant (t=3.0). In Column (4), we include interactions between the California dummy and other production inputs, but the estimates on the new interaction terms are not significant, indicating that the higher output elasticity documented in (2) and (3) is unique to IT investment.

In Columns (5) through (8), we add measures of regional IT investment into our regression. We construct a pool of regional IT intensity as the IT intensity of other firms with corporate headquarters in the same county. Column (5) shows the regression results using the model in (2) for the subsample of firms for which the headquarter location data are available. The results in (6) after including the location investment levels and interactions with own IT investment indicate that adding these variables removes some of the estimated IT productivity benefits associated with being located in California. This is more pronounced in the fixed-effect regressions shown in (7) and (8), which indicate that the California IT productivity effect largely disappears after including regional IT investment levels. The main effect estimates on the industry and location spillover pools are negative, which is consistent with the negative competitive effects of increased IT investment.

There are at least two reasons why higher returns to IT investments might be associated with being located in IT-intensive areas within the US. The first, consistent with the argument being in this paper, is that returns to IT investments are higher in regions where complementary factors are more readily available. For instance, if some regions are characterized by spillovers of ideas related to how best to use the new technology, then firms in these regions may experience higher returns to computerization. Alternatively, regional productivity shocks may simultaneously drive increases in computer investment and output. In this case, a larger spillover "pool" might indicate that regional productivity growth led to higher levels of IT investment. To separate these stories, it is useful to model differences in a firm's access to spillovers in a way that "holds constant" other industry or location specific factors that could affect IT returns. One way to do this is to explicitly model a knowledge transmission path, such as IT labor flows, which produces variation in access to knowledge spillovers within firms located within the same region or industry. In the next two sections, we test if spillovers generated by IT labor flows are associated with productivity, and whether these IT labor flows can explain the productivity effects of being located in IT-intensive regions.

Table 4: Location and IT Returns

DV: Value Added	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Baseline	CA	CA	CA	CA	+Local IT Investment	CA	+Local IT Investment
Employees	**.631** (.011)**	**.634** (.012)**	**.708** (.014)**	**.640** (.012)**	**.663** (.013)**	**.662** (.013)**	**.793** (.009)**	**.794** (.009)**
Capital	**.274** (.009)**	**.274** (.009)**	**.254** (.011)**	**.272** (.009)**	**.267** (.010)**	**.268** (.010)**	**.131** (.007)**	**.131** (.007)**
IT	**.086** (.007)**	**.081** (.007)**	**.047** (.007)**	**.078** (.008)**	**.065** (.008)**	**.066** (.007)**	**.029** (.005)**	**.030** (.005)**
CA		**.120** (.024)**	**.047** (.007)**	**.156** (.064)***	**.082** (.023)**	**.057** (.024)**		
CA x IT		**.030** (.013)**	**.045** (.015)**	**.050** (.018)**	**.026** (.013)**	**.019** (.014)	**.015** (.008)*	**.007** (.008)
CA x Capital				**.015** (.022)				
CA x Employment				**-.040** (.032)				
S_L (Local IT Pool)						**.020** (.005)**		**-.011** (.005)**
S_L (Local IT Pool) x IT						**.006** (.003)*		**.007** (.002)**
S_I (Industry IT Pool)					**.049** (.004)**	**.048** (.004)**		**-.008** (.003)**
Controls	Industry Year	Industry Year	2-digit Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	36,300	36,300	36,300	36,300	32,856	32,856	32,856	32,856
R-squared	.92	.92	.93	.92	.92	.92	.89	.89

** p<.05. Standard errors are robust and are clustered on firm. All estimates are from Pooled OLS regressions. S_L is county IT investment. S_I is industry level investment (4 digit SIC level). All variables are in logs.

IT Labor Mobility and Spillovers

We first look directly at IT labor flows, without considering location. In Table 5 we report results from models where IT labor flows are used to model the potential spillover pool. For ease of comparison, in Column (1) we report the benchmarked results from Column (1) in Table 4. Column (2) shows our estimates after including the spillover pool. The coefficient estimate on the spillover pool is positive and significant (t=12.5), indicating that hiring IT workers from IT-intensive firms is associated with higher productivity levels, in support of Hypothesis 2. After including the spillover term, the size of the coefficient estimate on private IT investment becomes smaller, suggesting that some of the returns to private IT investment may reflect the fact that IT intensive firms tend to have superior access to extramural sources of IT knowledge. The coefficient estimate on the industry spillover term is also positive and significant, perhaps because competitive effects caused by the IT investments of competitors are confounded with industry effects at the 1 digit industry level. The magnitude of the spillover estimate indicates that IT spillovers generated from employee mobility are associated with a rate of return to external IT investment that is about 20-30% of the internal rate of IT investment, large enough to influence firm's strategic location or human resource decisions.

In columns (3) and (4), we report fixed-effect estimates which hold constant unobserved, time-invariant factors that could influence the spillover pool and output levels. The effect sizes implied by the fixed effect IT estimates in Column (3), without the spillover term, are consistent with prior research on IT productivity, and suggest an output elasticity of about .03-.04 after accounting for firm effects (t=8.25). The coefficient estimate on the spillover term, shown in Column (4), continues to be positive and significant after including firm effects (t=5.0). The negative and significant coefficient on the industry spillover term indicates that after controlling for firm-level effects, IT investment by industry competitors has negative effects on firm productivity. The magnitude of the spillover estimate from the fixed effects model, while smaller than the OLS estimate, supports the interpretation that the external rate of return to IT investment for firms produced by knowledge spillovers is about 20% that of internal IT investment.

In the next two columns, we report results from a variety of other estimators, including the Levinsohn-Petrin (LP) and Arellano-Bond (AB) estimators, which account for various cases in which the regressors may be correlated with the error term (Arellano and Bond, 1991; Levinsohn and Petrin, 2003). The LP estimator utilizes changes in firm materials inputs to measure the effect of short run productivity shocks and uses this information to correct the estimates of other input terms. The Arellano and 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 and Bond estimator tends to perform closer to an instrumental variables regression in first differences. Interestingly, the coefficients on the terms of interest in the LP and AB estimators are very similar to those in the corresponding OLS/Fixed-effects regression. Thus, while it suggests that endogeneity may play a role in the precise estimates of the elasticities of various inputs, unobserved firm-specific productivity shocks do not appear to substantially bias our spillover results. To some extent this is not surprising, as our estimates would only be biased if there were common shocks across firms that are coincidentally transmitted through a path that is similar to IT labor mobility patterns.

Finally, in Columns (7) and (8), we test whether firms can "free-ride" on the IT investments of other firms, or whether investments in internal IT infrastructure are required to successfully capture IT externalities. Our estimates from Columns (7) and (8) are from OLS/Fixed-Effect regressions that include an interaction term between own IT investment and the external IT pool. The estimates from both models suggest that IT externalities transmitted through labor flows are increasing in a firm's own IT investment. Access to an external IT pool that is one standard deviation higher than the mean increases the output elasticity of a firm's own IT investment by about 7%. At mean levels of IT investment, this increase in mean productivity is consistent in magnitude with estimates from our earlier models with no interaction terms. In the next section, we investigate whether spillovers due to IT labor flows can explain associations between productivity and regional IT investment levels.

Comparing Spillovers from IT Labor Mobility with Regional Measures

In Table 6, we report estimates from models in which the spillover pool is broken into four different pools that vary along two dimensions, geographic proximity and IT labor flows. The aggregate IT investments of other firms fall into one of the four pools based on whether they are geographically proximate, and whether they are an important source for IT labor. In our OLS and fixed effect estimates in Columns (1) and (2), the coefficient estimates on the spillover pools are only positive and significant when a firm is proximate in terms of labor flows. Otherwise, the IT investments of other firms, even when they are located in the same region, are not significant. These estimates indicate that for spillovers generated by IT investments, 1) regional spillovers appear to be driven primarily by IT labor flows, and 2) IT labor flows appear to be an important source of knowledge spillovers even outside of a fixed region.

Table 5: Spillover Estimates from Labor Mobility

DV: Value Added	**OLS**	**OLS**	**FE**	**FE**	**Lev-Pet**	**A-B**	**OLS**	**FE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Employees	**.631** (.011)**	**.658** (.012)**	**.797** (.008)**	**.800** (.008)**	**.605** (.014)**	**.780** (.011)**	**.656** (.012)**	**.798** (.008)**
Capital	**.274** (.009)**	**.268** (.009)**	**.126** (.006)**	**.126** (.006)**	**.445** (.025)**	**.037** (.010)**	**.268** (.009)**	**.126** (.006)**
IT	**.086** (.007)**	**.053** (.007)**	**.033** (.004)**	**.029** (.004)**	**.064** (.008)**	**.039** (.005)**	**.055** (.007)**	**.030** (.004)**
IT * S_E							**.005** (.001)**	**.002** (.000)**
S_E **(Labor Flow Pool)**		**.025** (.002)**		**.005** (.001)**	**.026** (.002)**	**.0014** (.0007)*	**.003** (.005)	**-.003** (.002)
S_I **(Industry IT Pool)**		**.047** (.004)**		**-.007** (.002)**	**.004** (.005)	**-.003** (.004)	**.047** (.004)	**-.007** (.002)**
Controls	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	36300	36300	36300	36300	36300	25616	36300	36300
R-squared	0.92	0.92	0.89	0.89			.92	.89

**p<.05. Standard errors are clustered on firm. All regressions include dummy variables for industry and year. All variables are in logs. The Levinsohn-Petrin estimator uses material inputs as the proxy variable.

A potentially important source of error in (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 establishments in 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 where our geographic proximity measures are constructed at the establishment-city level – firms are geographically proximate when they have establishments in the same cities. The estimates that are produced from this model provide further validation for the hypothesis that IT labor mobility is an important channel for knowledge spillovers—only the coefficient estimates on the near-near and near-far pool are significant, indicating that knowledge spillovers are generated from 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 location for a firm's IT workers is noisy.

In Columns (4) and (5) we report estimates from the subsample of firms in the software publishing industry (SIC 7372), an industry which is known to be highly agglomerated (Freedman, 2008), and in which most cross-firm moves will therefore occur within the same region. Estimates from this sample of firms indicates that in these industries, within-region job-hopping has the most significant impact on productivity.[8] 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 the estimates in Table 5 are not being caused by regional or technological productivity shocks. For instance, biases associated with unobserved firm status or reputation should not be constrained to firms within the same geographic region. Similarly, regional productivity shocks should not be constrained only to firms from which employees are being hired. It is unlikely, therefore, that our estimates are being driven by these types of influences. In the next section, we address some remaining endogeneity concerns.

[8]The effects may also influence strategic location decisions to maximize appropriability. See, for instance, Alcacer and Zhao (2008).

Table 6: Comparison of Labor Mobility And Geographic Proximity Measures

DV: Value Added	**Pooled OLS**	**FE**	**OLS**	**Pooled OLS**	**FE**
	All Firms	**All Firms**	**Within Metro 2006**	**Software Publishing**	**Software Publishing**
Grouping of Firms into Pools	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Hire Many Workers and Geographically Near (S_{NN})	**.023** (.003)**	**.007** (.002)**	**.022** (.006)**	**.019** (.005)**	**.011** (.005)*
Hire Many Workers and Geographically Distant (S_{NF})	**.024** (.002)**	**.004** (.001)**	**.010** (.004)**	**.003** (.005)	**-.004** (.004)
Hire Few Workers and Geographically Near (S_{FN})	**.005** (.004)	**-.003** (.002)	**.003** (.004)	**.012** (.015)	**.004** (.012)
Hire Few Workers and Geographically Distant (S_{FF})	**-.022** (.008)**	**-.002** (.005)	**-.035** (.012)**	**.041** (.032)	**-.022** (.043)
Controls	Industry Year	Industry Year	Industry	Industry Year	Industry Year
Observations	36300	36300	2107	2447	2447
R-squared	.92	.89	.91	.88	.87

**p<.05. Standard errors are clustered on firm. All regressions are based on the baseline model estimated in Column (2) of Table 4 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. All variables are in logs.

Endogeneity Tests

Several of our earlier estimates provided evidence against the criticism that our results might reflect endogeneity in the spillover pool. The Arellano-Bond estimates in Table 5, for instance, are robust to cases in which the error term is correlated with the regressors, and the estimates from the interaction terms in the last two columns of Table 5, which indicate that spillovers are only captured by specific firms that are simultaneously investing in IT transformation, suggest that the estimates do not simply reflect productivity shocks transmitted through the labor network. Additionally, the Table 6 estimates suggest that our estimates are probably not being driven by regional productivity effects.

There are additional strategies we can use to eliminate some remaining alternative explanations, such as the possibility that productive firms tend to attract workers from other IT-intensive, highly productive firms. We can explicitly test if the IT investments of other firms reflect other attributes of a firm's neighbors, such as productivity or management quality, by constructing an alternative network measure where value-added per employee is substituted for IT-intensity, using the same weighting structure as the IT spillover pool. We jointly estimate these in a productivity framework along with the original IT spillover pool. The results from this regression are shown in Column (1) of Table 7. The coefficient estimate on the IT spillover pool of other firms is .011 (t=2.75), and the coefficient estimate on the value-added measure is not significantly different from zero, suggesting that firms uniquely benefit from the IT investment levels of IT management practices of other firms from which they hire new IT workers, not their overall performance levels.

We also test whether our estimates are uniquely generated by the mobility of IT workers rather than other types of workers, as would be expected if our estimates reflect productivity benefits from IT-related knowledge transfer. We construct spillover pools identical to the one using the mobility of IT workers, but 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 much *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 are shown in Column (2) of Table 7. The estimate of .012 (t=3.0) on the spillover pool generated by IT workers is similar to earlier estimates, but the estimate on the non-IT worker spillover pool is not significantly different from zero.

Table 7: Additional Robustness Tests

DV: Value Added	**Asset Type**	**Occupation Type**
	(1)	**(2)**
IT	**.019** (.010)*	**.033** (.011)**
$S_{E\text{-}IT}$ ***(IT Worker Flows)***		**.012** (.004)**
S_E ***(All Other Worker Flows)***		**.000** (.004)
S_E ***(IT Intensity)***	**.011** (.004)**	
S_E ***(Value-Added)***	**.001** (.001)	
Observations	13,079	10,791
R-squared	0.89	0.88

Robust standard errors are in parentheses. All variables are in logs. ** p<.05. Each regression includes controls for industry and year. Industry controls are included at the 1 digit SIC level. All regressions are based on the baseline model estimated in Column (2) of Table 5 and include logged measures of capital, labor, IT investment, industry IT spillovers, as well as the variables that are shown. Column (1) includes spillover measures computed using the IT investment per employee levels of other firms as well as the value-added per employee levels of other firms. Column (2) includes spillover measures computed using the mobility of IT workers as well as the mobility of all other types of workers.

These results provide evidence against several alternative explanations. If our spillover estimates reflected factors related to the performance or management of other firms, value-added would have been a superior measure. Furthermore, we might have expected that the effect sizes on the potential spillover pool constructed by using the mobility of other workers to be significant because these workers are just as likely as IT workers to be sensitive to firm reputation. If our estimates reflected the returns to overall human capital available in IT-intensive firms, it is unlikely that its transfer would be restricted to IT workers. If our estimates primarily reflected geographic effects, or the effects of other spillover mechanisms correlated with employee mobility, than the mobility of other workers, some of whom are more likely to be geographically bounded in their job search than high-skill IT workers, would have provided a better proxy than IT workers. Instead, our results indicate that 1) firms benefit from the IT investments of other firms, not from performance, and 2) that these benefits are accessed through incoming IT workers, not other types of workers. The story most consistent with this set of results is that IT-related know-how is transferred through the mobility of IT workers among firms.

Another potential source of endogeneity is that hiring workers from IT-intensive firms may reflect unobserved differences in human capital levels in incoming IT employees. Because we have data on the human capital of the individual employees moving between firms, we can control for these factors, as well as for the human capital of the firm's IT workforce. In Table 8, we control for the education and experience levels in the firm's existing IT workforce, using human capital data for each of the workers in our data set. The point estimates on IT education ($t=3.05$) and IT experience ($t=2.5$) in Column (1) are positive and significant, but including these measures does not substantially change the spillover estimate. In Columns (2) and (3), we include measures for the human capital of incoming IT workers. The estimates in (2) indicate that higher education levels in the incoming IT labor pool are associated with higher productivity ($t=3.33$), but that higher experience levels in the incoming IT worker pool are associated with lower productivity. However, after adding the average age of incoming IT workers in (3), the point estimate on experience is no longer significantly different than zero, which indicates that the estimates on experience and age reflect a selection effect in which younger workers choose higher productivity, higher growth firms. Nonetheless, the coefficient estimate on the spillover term does not change significantly in any of these models, so our spillover results are unlikely to reflect differences in IT human capital among firms, either in a firm's existing stock of IT human capital, or in the pool of incoming IT workers. Finally, the spillover estimate remains unchanged in (4), after including human capital measures for both the incoming IT labor pool and firm's IT workforce in a single regression.

Table 8: Testing for IT Human Capital

DV: Value Added	(1)	(2)	(3)	(4)
	OLS	**OLS**	**OLS**	**OLS**
IT	**.075** (.008)***	**.171** (.013)***	**.171** (.013)***	**.168** (.013)***
IT Workforce Education	**.058** (.019)***			**.143** (.044)***
IT Workforce Experience	**.040** (.016)**			**.020** (.039)
$S_{LF\text{-}IT}$ (*IT Workers*)	**.027** (.002)***	**.022** (.002)***	**.022** (.003)***	**.022** (.003)***
Education of Incoming IT Workers		**.060** (.018)***	**.061** (.018)***	**.022** (.018)
Experience of Incoming IT Workers		**-.011** (.008)	**-.009** (.009)	**-.012** (.008)
Age of Incoming IT Workers			**-.019** (.021)	**-.022** (.022)
Observations	30,401	10,691	10,691	10,691
R-squared	0.92	.93	0.93	0.93

Robust standard errors are in parentheses. All variables are in logs. ** p<.05. Each regression includes controls for industry and year. Industry controls are included at the 1 digit SIC level. All regressions are based on the baseline model estimated in Column (2) of Table 5 and include logged measures of capital, labor, IT investment, as well as the variables shown.

In Table 9, we test the sensitivity of the assumptions underlying the construction of our spillover pool. In (1) we remove the 5% threshold, and present results using a spillover measure computed as the IT investments of all other firms, weighted by the fraction of incoming employees coming from that firm. In (2), we report results using a spillover measure based on the mean value, rather than the sum of other firms from which a firm hires at least 5% of its IT workers, which distinguishes firms that hire employees from a few, IT-intensive firms from those that hire workers from many firms. In both regressions, the estimates on the IT and spillover term are somewhat lower but similar to the estimates from our earlier regressions. We also run baseline regressions constructing our spillover measure from all firms which a firm hires at least 1, 2, 5, and 10% of its employees (5% is the baseline used in our earlier analyses). 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 firms' internal IT investment because of correlation between the two measures.

Table 9: Sensitivity to Alternative Spillover Measures

Threshold	Emp Flow Weighted	Mean IT Levels	1% Threshold	2% Threshold	5% Threshold	10% Threshold
	(1)	(2)	(3)	(4)	(5)	(6)
IT	**.055** (.007)**	**.056** (.007)**	**.066** (.007)**	**.066** (.007)**	**.069** (.007)**	**.074** (.007)**
S_E	**.026** (.002)**	**.026** (.002)**	**.030** (.002)**	**.030** (.002)**	**.028** (.002)**	**.024** (.002)**
N	36,300	36,300	36,300	36,300	36,300	36,300

Robust standard errors are in parentheses. All variables are in logs. ** p<.05. All regressions are from the specification used in Table 5, Column (2).

Discussion

Our results suggest that regional differences in IT returns can be explained in part by localized knowledge spillovers generated by the mobility of IT workers. How large an economic effect is indicated by the estimates? In our most robust estimates, the external rate of return to IT investment is about 20% that of internal IT investment. Therefore, firms located in high-tech regions, where average IT investment levels are likely to be much higher, may receive substantial economic benefits from locating in these regions.

These findings have implications for managers and public policy makers. From a managerial perspective, our findings imply that because firms appear to benefit from the IT investments of other firms, managers should pay close attention to "opening" their firms to "spill-ins" of knowledge to maximize IT productivity (Tambe, Hitt, & Brynjolfsson, 2010). Our results are also consistent with work which finds that human capital management practices may play an important role in explaining cross-country IT-related productivity differentials (Bloom, Sadun, & Van Reenen, 2007). To the extent that access to skilled labor is governed in part by location, our results suggest the importance of regions like the Silicon Valley. However, managers should combine these location decisions with a focus on hiring workers who have hands-on experience at other firms. Recruiting IT workers from firms that have already developed sophisticated digital infrastructures may produce significant "spill-ins" to the hiring firms.

From a policy perspective, our findings indicate that computerization will occur at a slower than optimal rate because managers will be unable to appropriate the full value of their IT investments. Therefore, firms may invest less than the socially optimal amount in new technologies. Policy makers should therefore consider if subsidies are appropriate in order to encourage higher IT investment levels. Our emphasis on the mechanism of knowledge transfer, IT labor mobility, has additional implications for policy makers. 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 (Dewan & Kraemer, 2000; Bloom, Sadun, & Van Reenen, 2007), as well as why some regions within the US may have disproportionately benefitted from the IT boom. Although managers are often incentivized to retain employees, this may not be socially optimal, so policy makers should carefully consider how practices and policies that affect mobility rates, such as non-compete agreements or health insurance portability might ultimately affect regional growth levels.

There are a number of questions that would be interesting to pursue in future work. Although employee mobility is an important mechanism for the diffusion of this type of knowledge 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, or through managerial social networks. The collection and analysis of data on these transmission mechanisms will prove useful for understanding the dynamics of regional computerization.

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