

INTER-INDUSTRY IT SPILLOVERS AFTER THE DOT-COM BUST

Completed Research Paper

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Abstract

This paper uses a novel source of fine-grained data on IT labor mobility to test the hypothesis that patterns of productivity growth observed after the dot-com bust can be partially explained by spillovers of e-commerce know-how from IT industries to other industries. The analysis treats the timing and geographic concentration of dot-com layoffs as a source of exogenous variation in the effects of the bust on different IT labor markets. IT-enabled productivity growth from 2001 onwards was faster for IT-using firms that experienced large changes in the skill content of the IT labor pool as a result of the dot-com bust. The evidence suggests that some of the social returns from dot-com IT investments were captured by IT-using industries in the same regions after the bust. Implications for the current wave of investment in data analytics and future productivity growth patterns are discussed.

Keywords: IT spillovers, IT productivity, IT labor, IT workforce, e-commerce, cities

Introduction

Most existing research on IT productivity has focused on private returns to information technology (IT) investments through the mid 1990's (e.g. Brynjolfsson and Hitt 1996, 2003; Dewan and Min 1997), but economists have recently begun to examine why some groups of firms, such as firms in specific regions or industries, experience faster productivity growth during periods of rapid technical change (Bloom, Sadun, and Van Reenen 2012; Forman, Goldfarb, and Greenstein 2012). For example, researchers have noted that growth shifted from IT-producing to IT-using industries immediately after the dot-com bust¹, but the reasons remain mysterious (Stiroh 2006; Oliner, Sichel, and Stiroh 2007). This paper examines “spillovers” of new technical know-how, transmitted through the IT labor market, as a source of differences in productivity growth rates. Specifically, it tests the hypothesis that a reallocation of e-commerce skills from IT industries to other industries after the dot-com bust can explain changes in productivity growth rates for firms in different industries and regions (see Bresnahan 2002 for a similar hypothesis).

Moving beyond the study of private returns to IT investment, towards spillovers created by IT investments, is important for several reasons. The strategy and economics literature has long recognized the importance of social returns to R&D for explaining productivity growth and economic geography (e.g. see Griliches 1992 for a survey). During the information age, spillovers related to new IT innovations are likely to be similarly important—for example, an understanding of private returns to IT investment is inadequate for explaining the agglomeration of firms in high-tech clusters. Furthermore, spillovers from IT investment are distinct from R&D spillovers in at least two important ways that merit further analysis. As a “general-purpose” technology with application to all sectors of the US economy, spillovers of IT innovations are likely to have broad reach. Therefore, spillovers from large waves of IT investment such as dot-com investment have implications for the productivity of firms in all industries. On the other hand, know-how related to new IT innovations is primarily transmitted through the movements of IT labor, and is therefore bounded by the geography of the labor market. Together, these two notable attributes of spillovers of IT know-how suggest an especially important role for inter-industry IT spillovers that are circumscribed by economic regions, which has implications for managerial decision-making and urban policy.

This analysis is also of interest because there has been relatively little research on how the skill content of IT labor markets contributes to productivity growth. This is surprising because a) qualitative work suggests that know-how related to new technologies within the IT labor pool has an important effect on innovation patterns (Saxenian 1996; Bresnahan and Gambardella 2000) and b) labor market differences are a potentially important explanation for the regional differences in IT-enabled growth that have been observed in the academic literature (Dewan and Kraemer 2000; Bloom, Sadun, and Van Reenen 2012; Forman, Goldfarb, and Greenstein 2012). Developing an understanding of how effectively the supply of new technical skills adjusts to meet demand is also important for evaluating the effectiveness of a number of labor policies, such as those related to H-1B visas, offshoring, and non-compete restrictions. Furthermore, mismatches between the supply and demand for IT skills are the source of mainstream media attention on skill “gaps” that tend to accompany rising demand for new information technologies, such as e-commerce skills in the late 1990's or data analytics in the current era (Rooney 2012).

Progress in this area of research, however, has been slow because spillovers of new technical know-how are generally transmitted through the labor market, and analysis therefore requires human capital data at levels of granularity that have been prohibitively difficult to obtain. Prior work in IT economics studies how IT human capital impacts wages (Ang, Slaughter, and Ng 2002; Levina and Xin 2007; Mithas and Krishnan 2008), but does not connect employers and employees or examine the cross-firm flow of technical skills, both of which are critical for understanding how the emergence and diffusion of new technical skills can explain productivity growth patterns. The Internet-enabled explosion in data

¹This paper classifies “IT-producing” industries as those defined in Jorgenson, Ho, and Stiroh (2005). The same classification has been used in some prior work (Forman, Goldfarb, and Greenstein 2012). “IT-using” industries are industries that are not IT-producing. The latter classification is slightly different than some prior work that defines IT-using industries to be an IT-intensive subset of non IT-producing industries.

collection, however, offers new channels through which to collect human capital data at unprecedented levels of detail. To test the hypothesis that a reallocation of IT skills explains productivity growth patterns, this study analyzes self-reported employment histories from hundreds of thousands of IT workers, collected in partnership with one of the leading Internet job sites. This is the first data source that enables the analysis of the flow of technical skills across employers.² Comparable data on the cross-firm mobility of workers by occupation are not available from administrative sources, employers, or from any other source. These data have been used in prior work connecting IT labor flows to aggregate productivity growth patterns³, but never for testing whether frictions in the market for new technical know-how can explain why growth rates differ across industries and regions.

The main analysis uses Cobb-Douglas production functions to estimate if productivity growth patterns after the bust can be explained by spill-outs of new technical know-how from firms in IT industries. The principal endogeneity concern is that employers anticipating higher demand would have tended to absorb more newly displaced workers (i.e. output growth in these industries reflects a shift in the demand curve, rather than a shift in the supply of technical know-how). To address this issue, the analysis treats the dot-com bust as a “natural experiment” that due to the highly geographically concentrated nature of dot-com layoffs had stronger short-run effects on firms in labor markets with a higher density of firms in IT industries. For example, the business press reported that firms in Seattle were flooded with job applications after the dot-com crash, while firms in Philadelphia continued to face IT skill shortages (Vaas 2001; Cook 2002). Therefore, the outward shift in the supply of IT labor would have been significantly sharper in some regions than in others.

The paper argues that dot-com investment in IT industries produced new technical know-how, and that workers who moved from IT to non-IT firms after the dot-com bust transmitted this new technical know-how to their new employers. To provide additional evidence for this hypothesis, two supplementary analyses are conducted that stratify the data according to skill and by category of IT innovation. First, I use new data on the adoption of individual IT innovations from a panel data set constructed by text mining firms’ financial reports (Saunders and Tambe 2012). This adoption variable is used to demonstrate that the flow of IT skills across sectors after the crash not only explains productivity growth patterns, but was systematically associated with the adoption of e-commerce technologies, but not other types of information technologies. Second, detailed data on the technical skills reported by individual workers are used to test the hypothesis that the flow of e-commerce skills, rather than IT skills in general, drove productivity growth patterns during the years shortly after the bust. The evidence produced by these analyses is inconsistent with alternative explanations, such as those related to outsourcing or changes in the market for Y2K skills.

The analysis generates a number of key findings. First, the data on IT labor flows indicate that the dot-com bust resulted in a reallocation of technical skills, and especially e-commerce skills, from firms in IT industries to other industries. In the short-run, the largest beneficiaries were firms in non-IT industries located in high-tech labor markets. In fact, the evidence suggests that during the dot-com boom, these firms were systematically *underperforming* competitors located in other labor markets. Therefore, the post-bust acceleration in productivity growth rates experienced by these firms reversed a downward trend that these firms had been experiencing during the boom. The acquisition of e-commerce skills by IT-using firms after the crash was associated with higher e-commerce adoption rates, and the results support the hypothesis that faster productivity growth in non-IT firms after the bust can be explained by this labor reallocation across firms—these effects are robust to the application of fixed-effects estimators, differences estimators, and instrumental variable regressions based on the geographic proximity to firms in IT industries.

² Although there are other sources of matched employer-employee data in the US (such as the LEHD), few identify employers, and none provide information on skills and occupations, all of which are critical for this analysis.

³ Tambe and Hitt (2012) use these IT labor flow data to measure the contribution of IT-related spillovers to productivity growth from 1987-2006.

This paper contributes to two academic literatures. First, it offers a human capital based explanation for some of the productivity growth patterns observed between 2000 and 2005, which appear to have been driven by firms in a broader set of industries than the relatively narrow set of IT industries that drove productivity growth from 1995 to 2000. Some competing explanations for this shift include spill-outs of technical and managerial innovations from IT sectors to other sectors or lag effects associated with the installation of organizational complements in large firms (Bresnahan 2002, Stiroh 2008). This paper provides evidence for the spill-outs hypothesis, and contributes to a rapidly emerging literature on how IT spillovers affect productivity (Cheng and Nault 2007; Chang and Gurbaxani, forthcoming; Cheng and Nault, forthcoming; Tambe and Hitt, 2012a; Tambe and Hitt, 2012b). Second, this is the first study to demonstrate how the market for technical know-how can contribute to short-run productivity growth differences across regions and industries, and connects the literature on IT labor markets (e.g. Ang, Slaughter, and Ng 2002; Levina and Xin 2007; Mithas and Krishnan 2008) with the literature on IT productivity growth (e.g. Brynjolfsson and Hitt 2000). The analysis should also be of interest to managers and policy makers because it has implications for policy issues related to how IT labor supply constrains growth in some regions and countries (Bapna et al 2010) and because policy decisions can create persistent cross-regional differences in IT labor supply (e.g. by raising the costs of cross-firm mobility).

Theory and Hypotheses

The paper focuses on the dot-com boom, a period of economic growth viewed by scholars as qualitatively different from prior waves of computerization because of the public attention it attracted and because of its focus on e-commerce and the Internet, new information technologies which required the development of new skills (see Forman, Goldfarb, and Greenstein 2012 for a similar claim). Theoretically, higher IT investment levels within a labor market change the skill content of the IT labor pool through two mechanisms: a) learning-by-doing and b) specialization. Learning-by-doing is 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 & Thompson 2001), and chemical processes (Lieberman 1984). For earlier waves of general-purpose technologies, the development of a cohort of engineers with experience redesigning materials workflow was a key mechanism for the diffusion of new production methods (David 1990). During the dot-com boom, IT labor played a similar role in redesigning the information workflow of modern organizations, and recent studies have provided evidence of learning-by-doing specific to IT implementation (e.g. Boh, Slaughter, and Espinosa 2007). Higher IT investment levels within a labor market also enable employees to specialize in rare combinations of skills, leading to higher labor productivity.

The analysis posits a two-sector model of IT employment where e-commerce workers during the boom were concentrated in IT industries. The dot-com bust lowered the demand for these workers within the IT-producing sector. If these changes brought wages close to or lower than the market wage in other sectors, some of the IT labor from these firms would have spread to “old economy” companies, such as banks and retailers developing e-commerce products and services, as well as to consulting firms that developed web sites and e-commerce infrastructures for other firms. Anecdotal evidence suggests that this is an accurate reflection of post-bust labor mobility patterns, and moreover, that from the firm’s perspective, the most important labor market adjustments at the time corresponded to changes in the availability of specific e-commerce skills, rather than technical skills more generally. This paper argues that this change in the market for e-commerce skills drove e-commerce adoption and subsequent productivity growth in other industries. The two hypotheses tested are:

- H1: Spillovers of technical skills from IT-producing firms after the bust were associated with higher e-commerce adoption rates.*
- H2: Spillovers of technical skills from IT-producing firms after the bust were associated with faster productivity growth.*

The analysis uses regional variation in the concentration of dot-com layoffs and the timing of the bust to identify the effects of these labor market shifts on firms. The displacement of IT labor after the dot-com

bust was concentrated in a few cities. Anecdotal evidence suggests that HR managers in these cities hired only the most productive of these displaced technical workers.

“While the economic slowdown and dot-com demise have increased the overall supply of IT workers somewhat, shortages of key skills- particularly those most sought by enterprises- remain as pronounced as ever. There are several reasons for that: One, experts say, is that many dot-com refugees simply don’t have the skills for which enterprise IT hungers; another is that many enterprises have become more picky about the people- and skill sets- they’ll bring on board; and a third is that dot-com layoffs have been concentrated in a few geographic areas. ... More and more, those hiring managers are after specific skills- not just anything that fits underneath the umbrella term “IT.” According to hiring managers, the skills they still hunger for include networking, customer relationship management, ERP (enterprise resource planning), security and e-commerce/Internet skills such as database management and server administration.” (Vaas, 2001)

Although this rapid change in labor supply would have equalized across markets as workers moved across regions, there is significant support in the labor economics literature for the assertion that shocks to labor markets tend to take years to equalize because workers face significant costs when moving across regions (e.g. see Borjas, Freeman, and Katz 1996). Therefore, in the short-run, changes to the skill content of the IT labor pool in cities where dot-com layoffs were concentrated would have disproportionately affected firms in those cities for several years after the bust.

Data

The key measures and data sources used in this study are summarized in Table 1.

IT Labor Data

IT labor mobility patterns after the bust are computed from fielded employment history information for over ten million users collected from a leading online jobs board in 2007. These jobs board users also provided occupation (e.g. IT, sales, management, accounting, etc.), education, and other demographic and human capital variables including skills and certifications. This study focuses specifically on IT workers, who self-identify by choosing the IT occupation from a drop-down box. These IT labor data have been described, benchmarked, and used in other published work (for greater detail on these data, see Tambe and Hitt, forthcoming). When compared with IT workers sampled in the 2006 Current Population Survey (CPS), a nationally representative Census administered survey⁴, these data are not particularly skewed towards higher or lower education. The average job tenure of IT workers in the sample is approximately two years lower than the average job tenure of IT workers in the CPS survey because the sample is skewed towards job-hoppers. However, this may not be a significant limitation for this analysis because the key population of interest is IT workers who move across firms, so the job-hopping sample may be a better representation of this population than the CPS sample, which includes workers who never or infrequently switch jobs. Nevertheless, selection concerns with using these data to capture the flow of technical skills across firms are addressed further later in this section.

Table 1: Key Measures and Data Sources

Variable	Data Source	Description
Value Added	Compustat	Compustat sales minus materials. Deflated to base year.
Capital	Compustat	Computed from Compustat PPE. Deflated to base year.
Non-IT Employment	Compustat	Non-IT employees at firm
IT Employment	IT Labor	IT employees at firm
IT Producer Pool	IT Labor	IT intensity of IT-producing firms in labor pool
IT Using Pool	IT Labor	IT intensity of other IT-using firms in labor pool

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/>.

Post-Crash		Dummy variable indicating if year is 2000 or after
E-commerce Skills	IT Labor	Self-reported e-commerce skills and certifications
Industry	Compustat	2 digit SIC classification
Proximity	IT Labor	% of firm's IT labor employed near IT-producing firms
E-commerce adoption	Adoption Data	Extracted from 10-K documents (binary)
ERP adoption	Adoption Data	Extracted from 10-K documents (binary)
Data mining adoption	Adoption Data	Extracted from 10-K documents (binary)

In addition to cross-firm mobility data, this study introduces new data on technical skills, self-reported by IT workers in the sample. E-commerce workers are identified as those who have acquired Internet related skills such as HTML, Web programming, or SQL programming. Because to the best of my knowledge, there are no standardized, independent taxonomies of skills according to different technical innovations, the list of skills associated with e-commerce was chosen using an external source, Foote Consulting's list of "hot" IT e-commerce skills published in 2000. To the best of my knowledge, these labor and skills mobility data represent the first large-scale measurement of the cross-firm mobility of workers with individual technical skills, and therefore represent a unique opportunity to track the flow of new technical know-how within the US economy across sectors. However, one important limitation of the skills data is that they are reported in 2006. Therefore, assigning these skills to particular employer-employee pairs in earlier years produces measurement error if workers acquired the skill after the year of assignment. This measurement error will be larger in earlier years than in later years, and one-sided—it misclassifies IT workers in some years as having an e-commerce skill who have not (yet) acquired that skill but will not omit IT workers who do have the skill. If these misclassification errors are uncorrelated with the error term, measurement error of this type imposes a downward bias on the key estimates, making it more difficult to find a meaningful result when using these skills data.

Geographic Location

Geographic locations were self-reported in 2006, and in combination with the employer data, are used to characterize the firm's market for IT labor. For each firm in the sample (i), a measure of the density of firms in IT industries in the firm's labor pool is computed as:

$$ITLM_i = \sum_{j=1}^J w_{ij} (\%ITPROD_j)$$

w is the percentage of a firm i 's total IT employment in metropolitan area j , and $\%ITPROD_j$ is the percentage of IT employment in metropolitan area j employed in IT industries. Regions with the highest concentration of the IT workforce in IT industries include San Jose, Seattle, and San Francisco. The $ITLM$ measure, therefore, is highest for firms that employ greater fractions of IT workers in establishments in cities such as Seattle and San Jose. IT-using firms with a high $ITLM$ index experienced the greatest change in the IT labor pool after the bust. Like the skills data, the location data are reported in 2006, but the magnitude of the measurement error produced by this limitation is bounded by the rate of entry and exit for establishments in different cities, which should be relatively small.

IT Investment, IT Adoption, and Supplementary Economic Data

The IT investment data are created from the IT labor series and are constructed, benchmarked, and described in prior published work (Tambe and Hitt forthcoming). The IT investment data are based on IT employment and IT employment intensity (IT employment divided by total employment) within the firm and have been shown to perform comparably to other IT datasets such as the CITDB capital stock data in productivity regressions. For this analysis, they have the significant advantage that they are collected in a consistent manner in the years leading up to and after the dot-com bust. The CITDB IT capital stock data, by comparison, are unavailable in a consistent manner after the late 1990's, precluding this type of analysis.

E-commerce, ERP, and data-mining adoption data were created by text-mining firms' financial documents (10-K reports) for keywords related to each of these individual technological innovations. These data span the time period 1995 and 2010 and the data and their error characteristics are described in other work (Saunders and Tambe 2012). Other economic data used in productivity regressions, such as

value added (sales minus materials), capital, employment, and industry are collected from the Compustat database and deflated to a common base year. The variables were created using methods common in the micro-productivity literature, and were chosen to maintain consistency with prior work on IT productivity.

Selection and Measurement Error

The human capital data described above enable several new types of measurement. In addition to the cross-firm flow of technical skills, that there are no alternative data sources describing the distribution of a firm's IT employment across US cities⁵, so using the firm-city distribution of IT employment improves the accuracy of the analysis over one in which the locations of IT employees are approximated using the location of firms' corporate headquarters. However, the use of such data sets is accompanied by several sources of measurement error. For example, a selection problem arises if IT workers who use job boards are systematically different than other IT workers who switch employers (note that for this study, the population of interest is the job-hopping IT worker, rather than the average IT worker). If the historical movements of job board candidates accurately represent the employers that comprise a firm's IT labor pool (weights between firms), then there is no measurement error. However, systematic differences between workers who post employment histories on the jobs board and the underlying population of job-switchers introduces error into the measurement of a firm's labor pool. It is noteworthy, however, that this error term will impose a downward bias on the estimates of interest if IT job board candidates are less likely than other candidates to transfer skills and human capital, which is the concern about job board candidates is one of adverse selection. In other words, the contributions of industry leading IT innovators to productivity spillovers will be underweighted if employees from these firms are less likely to use job boards. Moreover, because the estimates reported in the analysis are based on differences, the bias occurs when the flow of labor from IT producing firms disproportionately rises as a result of the dot-com bust, which would only over-estimate the true parameter of interest if the jobs board over samples IT labor in IT-producing sectors, which is also inconsistent with adverse selection, because prior work has shown that IT producing firms tend to attract higher quality IT human capital.

Note that systematic differences in the quality of workers who obtained jobs after the dot-com bust does not introduce biases into the estimates produced by this analysis. Indeed, an important part of the argument in this paper is that employers benefited from the new human capital generated in IT-producing firms during the dot-com boom. Unbiased estimates are produced when changes to the IT labor pool are "randomized" across firms. Although this type of experiment is difficult in practice, the within firm and cross-regional comparisons used in this study approximate this type of experiment.

Methods and Measures

Productivity Regressions

The main analysis tests if IT investment by IT industries benefited other industries after the bust through spill-outs of technical know-how embodied in the IT labor force. The Cobb-Douglas functional form is used because it is the most common specification in the IT productivity literature and forms the basis for US productivity growth measurement (Brynjolfsson and Hitt 1996; Dewan and Min 1997). The starting point for the econometric analysis is a widely used framework that connects firms' productivity to the R&D investments of other firms and forms the basis for a very large literature on R&D "spillovers". Similar specifications have been adapted for the study of returns to the IT investments of other firms (e.g. see Chang and Gurbaxani forthcoming). In logs, the most basic model testing how a firm's own productivity is affected by the IT investments of other firms is:

$$(1) \quad va = \alpha_K k + \alpha_E e + \alpha_{IT} it + \alpha_S s + controls + \epsilon_{ijt}$$

⁵ The closest alternative are the CITBD data published by Harte Hanks which only have information on the number of programmers in establishments with at least 100 people.

All lowercase variables are in logs, k is capital stock, e is employment, it is a firm's own IT investment levels, and s is the spillover pool, comprised of the IT investments of other firms. IT investment and IT intensity have been used in prior research to measure the firm's technical capabilities (Bharadwaj et al 1999; Brynjolfsson et al 2002; Saunders 2010)—these studies argue that firms with greater IT investment tend to have superior IT capabilities and superior performance. The use of IT investment as a measure of the skill content of the firm's technical labor is supported by a literature demonstrating that investment in R&D is a superior measure of human capital accumulation than calendar time or other measures (Lieberman 1984).

In this paper, the key mechanism for the transmission of productivity spillovers is the transfer of know-how through the flow IT labor. Firms derive productivity benefits from the rising IT investment levels of other firms in the IT labor pool. The measure is constructed by summing the IT intensity of firms from which the focal firm hires new technical workers, weighted by incoming IT labor share hired from all other firms. The availability of micro-data on cross-firm labor flows is what makes it possible to trace out the firm's labor pool and construct these measures. To explicitly test whether IT-using firms benefited from a reallocation of technical skills from IT-producing firms as opposed to firms from all sectors, the analysis examines how the firm's IT labor pool changed before and after the bust by treating the skills acquired from IT-producing and IT-using firms as two separate factors of production. Measures from the two sectors are computed as follows:

$$(2) \quad S_{it}^p = \sum_{j \neq i}^{IT\text{-prod}} \Phi_{ijt} IT_{jt}$$

$$(3) \quad S_{it}^u = \sum_{j \neq i}^{IT\text{-using}} \Phi_{ijt} IT_{jt}$$

S_{it} is the IT pool of firm i in year t , the p and u superscripts signify investments made by firms in either IT producing or IT using industries, IT is the IT intensity of firm j in year t , the weighting term (Φ_{ijt}) is the fraction of firm i 's incoming technical workers (where the denominator is summed across both IT producing and IT using firms) that come from firm j in year t and the superscript signifies that the summation is restricted to IT producing or IT using firms. The employee weights across both measures add to one. A shift in hiring towards IT-producing firms increases the value of (2) relative to (3). The final productivity model interacts these IT labor pool measures with a time-based dummy variable to test the hypothesis that these factors contributed to productivity differently after the bust:

$$(4) \quad \ln va = \alpha_K k + \alpha_E e + \alpha_{IT} it + \alpha_{S-p} s^p + \alpha_{S-u} s^u + \alpha_S (s^p * \rho) + \alpha_S (s^u * \rho) + \alpha_\rho \rho + controls + \epsilon_{ijt}$$

In this model, lowercase variables are in logs, k is capital stock, e is employment, it is a firm's own IT investment levels, s^u is the skill content of the IT-using portion of the firm's labor pool and s^p is the skill content of the IT-producing portion of the labor pool, and ρ is a dummy variable that assumes the value one in the years after the dot-com crash and zero for all other years. The model in (4) is estimated in fixed-effects and differences. Fixed-effects models remove most sources of unobserved heterogeneity, but differences estimates provide more suitable controls for idiosyncratic firm characteristics that evolve over time, so results are reported from both. The hypothesis that the reallocation of technical skills from IT-producing to IT-using industries contributed to productivity growth in IT-using firms after the bust is supported if the coefficient estimate α_{S-p} is significantly greater than zero, implying that the sharp shifts in the availability of technical workers from IT-producing firms were systematically associated with productivity growth. Where appropriate, standard errors are clustered on firm.

Endogeneity

The regression approach described in (4) filters out most omitted variable concerns. It primarily relies on differences, and omitted variables that bias the value of α_{S-p} must share the idiosyncratic timing of the dot-com bust—in other words, they must be correlated not only with the changes in investments of other IT producing firms in a firm's IT labor pool, but also correspond to the timing of the dot-com crash. Two different approaches are taken to address remaining sources of omitted variable bias.

Matching Estimator and Instrumental Variables

Testing the causal direction of the relationship in (4) requires exogenously shifting the structure of the firm's labor pool (i.e. random reassignment of sp). This paper considers differences in dot-com layoffs across IT labor markets as a short-run, quasi-experimental source of variation in the change in the labor pool of some firms. These geographic differences are used in two ways. First, an "experimental" comparison is conducted using a difference-in-differences matching estimator. Matching estimators have the advantage of being non-parametric, and have been widely used in the empirical economics literature on program evaluation. For this analysis, IT-using firms are placed in the treatment group when they are located very close to IT-producing firms, and the treatment effect is estimated by comparing differences in productivity growth after the bust for a treated firm with that of another, otherwise similar firm that differs only in its exposure to IT labor markets dominated by IT-producing firms. The analysis matches firms on total employment, the location of corporate headquarters, IT employment levels, industry, and productivity levels at the beginning of the time period. For example, it compares the productivity growth rates of two similar-sized manufacturing companies with headquarters in the same state that had equivalent productivity levels immediately before the bust, but differences in the location of IT hiring.

Second, the productivity analysis uses instrumental variables based on the geographic location of IT using firms: a) proximity to firms in IT-producing industries and b) the total layoffs from IT-producing firms in the county of the firm's corporate headquarters. These variables measure the extent to which the dot-com bust affected a firm's local IT labor market. The validity of this research design requires a) that location provides an adequate "treatment" effect for firms located in IT-producer intensive regions and b) that these geographic differences are exogenous to changes in demand among IT-using firms. Evidence for both of these conditions is provided in later sections.

Fine-grained data on e-commerce adoption and e-commerce skills

I use two additional data sources to establish that the observed productivity growth patterns specifically reflect spill-outs of e-commerce know-how from IT-producing firms. First, I test statistical associations between changes in the technical labor pool and e-commerce adoption, rather than productivity growth. The analysis uses a probit regression where e-commerce adoption is a binary dependent variable and the independent variables are the labor pool variables interacted with the post-bust dummy variable.

The second approach stratifies the flow of IT labor from the different industries according to skill group. Alternative measures of the pool of external IT investment are computed using only the mobility of IT workers who report having e-commerce skills, rather than all IT workers. When embedded in a production function like (4) along with the broader measures of the technical labor pool, this measure connects productivity growth in IT-using firms with IT industry investment specifically through the flow of e-commerce workers, rather than all IT workers. This analysis is intended to provide support for the argument that the observed productivity patterns reflect returns to e-commerce spillovers, and that the observed effects are not due to the transfer of other skills, like Y2K skills, the market for which may also have been changing at that time.

Descriptive Statistics

Productivity Growth Patterns

Figure 1 plots the productivity growth of non-IT firms against labor market proximity to firms in IT industries from 1995 to 1999 and from 2001 to 2005. The plot suggests no correlation between proximity to IT firms and productivity growth during the dot-com boom, but a positive correlation appears between these variables from 2001 to 2005. Being embedded in labor markets with a high density of IT firms appears to be associated with faster productivity growth for non-IT firms, but only after the bust. Figure 2 plots productivity growth from 2001 to 2005 for firms in IT and non-IT sectors against proximity to firms in IT industries. Non-IT firms embedded in high-tech labor markets appear to have experienced faster IT productivity growth during these years, while IT firms in high-tech labor markets underperformed their competitors located in other labor markets. Although not conclusive, these two graphs suggest a reallocation of resources from IT industries to firms in other industries after the bust.

Labor Reallocation

Figure 3 uses Bureau of Labor Statistics (BLS) data to illustrate the employment collapse that occurred in IT industries after the dot-com crash. The job separation rate rose from 40,000-50,000 annual separations in IT industries during the late 1990's to a rate of about 200,000 in 2000, and remained at higher than normal rates through 2003. These changes indicate a qualitative shift in the quantity of IT labor displaced from IT sector firms during the dot-com bust and for a few years afterwards.

The advantage of collecting micro-data on labor movements is that they enable detailed analysis of the migration paths of IT labor displaced from IT firms. Figure 2 suggests a reallocation of resources from IT-producing to IT-using industries in IT-producer intensive regions after the bust. For firms in IT-using sectors, Figure 4 illustrates changes in the fraction of total incoming IT labor acquired from IT industries, separating firms by geographic proximity to IT producing firms. The flow of IT skills from IT-producing to IT-using firms jumps significantly immediately after the dot-com bust, but this is concentrated in firms that are nearby IT producers. There is no effect for firms located further away. This figure resembles a short-run “treatment” effect, in which firms in some regions experienced sharp changes in the pool for IT labor, while firms in other regions experienced almost no change.

Figure 1: IT-Using Industries Productivity Growth by Time Period

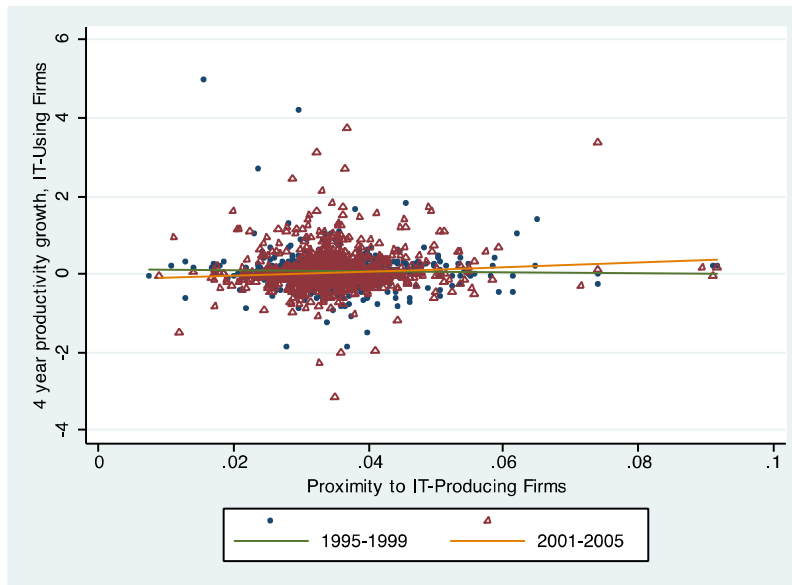
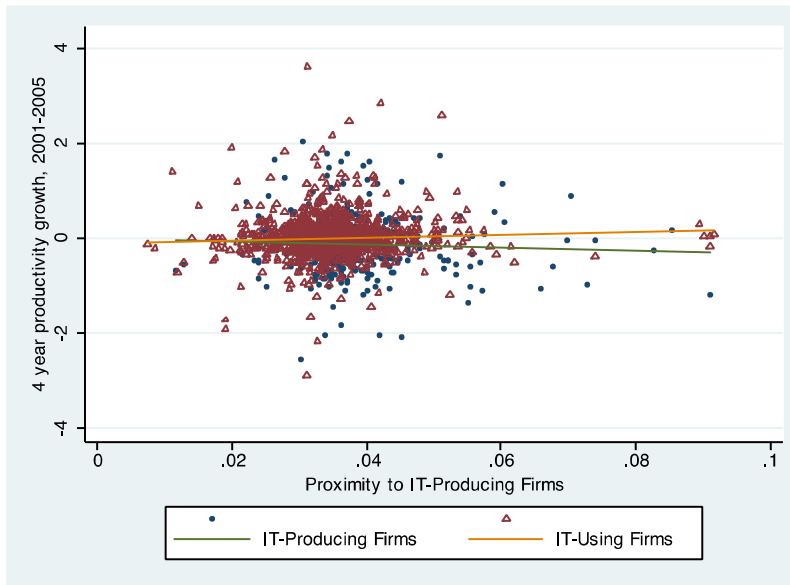


Figure 2: 2001-2005 Productivity Growth by Sector



The magnitude of the jump in Figure 4 is not large as a fraction of the total incoming IT labor force. However, this effect becomes much larger in Figure 5 after restricting the sample to IT labor with e-commerce skills. For IT-using firms located close to IT-producing firms, the percentage of IT workers with e-commerce skills spilling out from IT-producing firms jumped significantly, from about 20% before the crash to 80% after the crash. By contrast, there is very little change in the industry composition of IT labor for non e-commerce related skills, indicating that the jump in Figure 4 was primarily driven by spill outs of e-commerce skills from IT sectors into IT-using firms. Collectively, these figures suggest that the dot-com bust was associated with a flow of workers with e-commerce skills from IT industries to non-IT firms, and that firms located closest to IT-producing firms disproportionately benefited.

Figure 3: IT Sector Job Displacement After the Bust

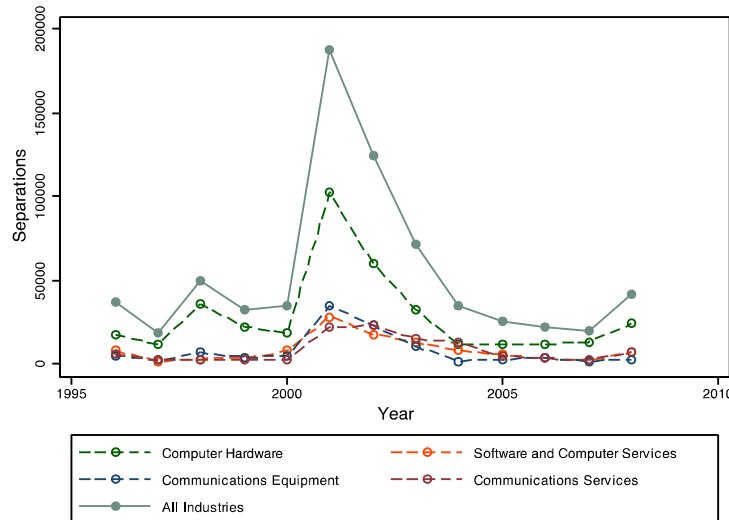


Figure 4: Differences in IT Labor Reallocation by Region

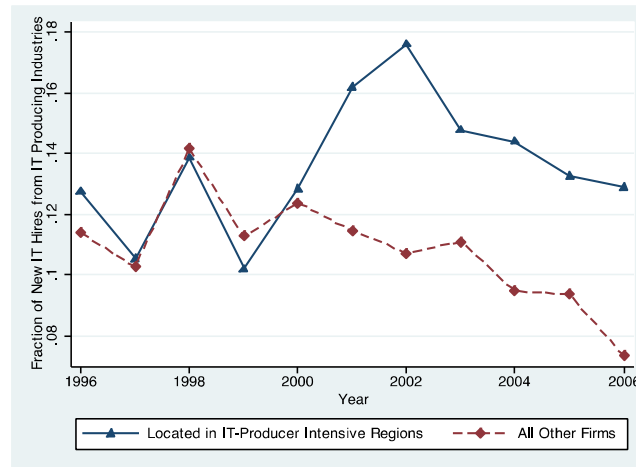
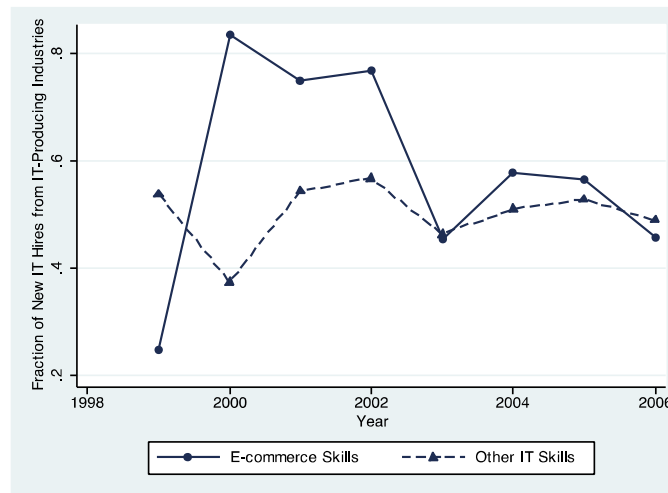


Figure 5: Differences in E-Commerce Labor Reallocation by Region



Results

Matching Estimator Output

Figures 1 and 2 above suggest a systematic shift in productivity growth rates related to proximity to IT producing firms. Before examining whether correlations in the IT labor pool and productivity data are consistent with these observations, I more formally test whether differences in firms’ growth patterns by region are consistent with the timing of the dot-com bust. The results from a matching estimator are reported in Table 2. In the set of results at the top of Table 2, the dependent variable is four-year productivity growth from 2001 to 2005 where “exact” matches are enforced where possible. The percentage of exact matches is high—over 90%—and the results are consistent with faster growth levels for non-IT firms located closest to IT-producing firms. Columns (2) through (4) use different levels of industry classification for matching, from 1 digit industry through 4 digit industry, where increasing the precision of the classification reduces the percentage of exact matches but the estimates change little across the different match criteria.

In general, the estimates indicate that firms hiring IT labor in regions with a high density of firms in IT industries experienced significantly faster productivity growth after the bust than firms in other regions, conditional on size, industry, location of corporate headquarters, and 2001 productivity levels. Column (5)

further narrows the location match for firms' corporate headquarters to state and county. This reduces the percentage of exact matches but the results are not substantially different.

Table 2: Matching Estimator Output

	(1)	(2)	(3)	(4)	(5)
DV: Productivity Growth	State	State 1 digit	State 2 digit	State 4 digit	State/County 1 digit
	2001-2005	2001-2005	2001-2005	2001-2005	2001-2005
Top Region	361.3*	425.9**	293.4*	345.8**	372.4**
	(186.8)	(193.2)	(173.2)	(170.6)	(181.9)
Exact matches	90.5%	68.4%	38.7%	9.0%	18.3%
Observations	431	431	431	431	431
	1995-1999	1995-1999	1995-1999	1995-1999	1995-1999
Top Region	-313.8**	-316.7**	-311.3**	-312.7**	-284.4*
	(155.6)	(160.8)	(152.4)	(154.1)	(159.5)
Exact matches	91.5%	69.8%	34.1%	8.2%	22.4%
Observations	352	352	352	352	352
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Estimates are from a matching estimator that matches firms in most proximate regions to the closest firm match in next most proximate regions. Firms are matched on total employment, IT employment, value added levels at beginning of duration, location, and industry (level of location and industry variables described in column headers).					

In the second set of results, at the bottom of Table 2, the four-year period considered is 1995 through 1999, which predates the bust. Notably, the productivity effects of being close to firms in IT industries reverses suggesting significantly slower productivity growth than competitors in other locations. The magnitude of the estimate is similar to the estimates from 2001 to 2005, suggesting that IT-using firms may have fallen behind during the boom, and may have been catching up from 2001 to 2005. This reversal provides circumstantial but compelling evidence that the dot-com bust changed the fortunes of non IT firms located near IT producers. The next section provides evidence for a labor market explanation.

Productivity Regressions

Table 3 presents estimates from equation (4) which directly associates changes in the firm's labor pool with productivity growth. The estimates in columns (1) and (2) are based on fixed-effects estimators that remove the effects of time-invariant omitted variables, including most persistent differences that could influence a firm's access to labor (e.g. reputation, management). The estimates in column (1) are from IT-using firms only and indicate associations between faster productivity growth and IT investment growth in both IT-using (t=2.56) and IT-producing industries (t=3.30) after the bust. The results in column (2) suggest that for firms in IT-producing industries, there is no statistical association between productivity growth and growth in IT investment in either sector.

Fixed effects estimates may not provide suitable controls for idiosyncratic firm characteristics that evolve over time. Columns (3)-(6) present differences results for IT-using firms with varying difference lengths. In addition to providing the same control for firm-specific effects as a fixed-effects analysis, the coefficient estimates at varying difference lengths can be interpreted as a comparison of the short run (1st differences) versus long run (3 year or more differences) (Bartelsman, Caballero and Lyons 1994). Point estimates from the differences regressions suggest associations between the acquisition of IT skills from IT-producing firms and productivity growth after the bust, but the point estimates do not become significantly different from zero until the differences window is extended to four years (t=2.22). By comparison, the results from a four-year differences regression on IT-producing firms (Column 7) indicate that the acquisition of skills from other IT-producing firms has a significant association with productivity in general but there is no change after the dot-com bust. These results are consistent with the interpretation of IT-producing firms as incubators for skills that drive productivity spillovers within the IT producing sector during the boom and which are spread to other sectors after the bust.

Table 3: Main productivity regressions

DV: Log(VA)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	1 Yr Diff	2 Yr Diff	3 Yr Diff	4 Yr Diff	4 Yr Diff	4 Yr Diff, IV
Sample	IT Using	IT Using	IT Using	IT Using	IT Using	IT Produce	IT Using
Log(Capital)	.173*** (.006)	.100*** (.023)	.114*** (.020)	.112*** (.021)	.121*** (.022)	-.002 (.032)	.118*** (.042)
Log(Non IT Emp)	.727*** (.008)	.693*** (.034)	.742*** (.029)	.769*** (.030)	.765*** (.031)	1.03*** (.044)	.801*** (.049)
Log(IT Emp)	.030*** (.004)	.035*** (.006)	.035*** (.006)	.031*** (.007)	.032*** (.007)	.055** (.023)	-.010 (.024)
Log(IT-Using)	.002 (.003)	-.001 (.002)	.001 (.002)	.001 (.002)	.004 (.003)	-.004 (.010)	
Log(IT-Prod)	-.002 (.003)	-.001 (.002)	-.002 (.002)	-.001 (.003)	-.001 (.003)	.013* (.007)	
Log(IT-Using) · Post	.009** (.003)	.001 (.003)	.004 (.003)	.006 (.003)	.004 (.004)	.014 (.013)	.017 (.036)
Log(IT-Prod) · Post	.012*** (.003)	.001 (.002)	.005 (.003)	.006 (.004)	.009** (.004)	-.013 (.010)	.086** (.030)
Observations	29,324	24,951	21,653	18,945	16,649	3,081	2,355
First-stage R ²							.05
R ²	0.688	0.304	0.453	0.536	0.595	0.615	0.466

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Estimates are from a Cobb-Douglas production function shown in (4) using value added as the dependent variable. All regressions include controls for year and one-digit industry.

The results from regressions using instrumental variables are shown in Column (7) of Table 3. The model is a four-year differences regression, restricted to the years after the dot-com bust and the instruments are a vector of variables related to proximity to IT producers and layoffs in the region. The estimates from this model are significant ($t=2.87$), although the poor explanatory power in the first-stage produces inflated estimates of the effect of IT-producing investment on IT-using productivity in the second stage. In general, however, the results over the fixed-effects, differences, and instrumental variable regressions are consistent with the hypothesis that a shift in labor pool structure towards IT producers after the bust was associated with faster productivity growth for IT-using firms.

Robustness Tests Using E-commerce Data

The regression results in this provide further support for the argument that the productivity effects observed earlier were due to the diffusion of e-commerce know-how. Table 4 presents results from IT adoption probit regressions that span the years 1995 to 2006. The dependent variable in (1) takes the value 1 if the firm indicates using e-commerce practices in its 10-K financial reports in any prior year and 0 otherwise. The results in (1) suggest that the acquisition of IT labor from IT-producing firms after the bust was associated with a higher probability of adoption for e-commerce technologies, but these effects are only weakly significant ($t=1.93$). In (2), the sample is limited to firms in the regions closest to IT producers. The effects are larger and more precisely estimated ($t=2.81$), indicating that the statistical correlations between the post-bust IT labor pool changes and e-commerce adoption are stronger for firms in high-tech labor markets.

As a falsification test, the adoption of two other classes of IT innovations, data mining and ERP, are used instead of e-commerce as dependent variables. If the correlations in (1) and (2) primarily reflect returns to the growing e-commerce skill content of a firm's IT workforce, these correlations should disappear when substituting on the left hand side technologies for which e-commerce skills do not facilitate adoption. The estimates in (3) indicate that data mining is associated with the flow of skills from other IT-using firms ($t=3.73$) with no significant differences before or after the bust—there is no evidence that skills required to install these technologies were being produced in the IT sector during this time period. The use of ERP technologies in (4), rather than e-commerce technologies, produces no significant correlations between adoption and any of the measures of IT investment during this time period. These analyses are suggestive of a special relationship between the acquisition of IT labor from IT firms after the dot-com bust and e-commerce adoption rates. The probit analysis in (5) is restricted to years after the dot-com bust, and uses

the location-based variables described above as instruments for the reallocation of IT labor across sectors. The association between IT sector skills and subsequent e-commerce adoption persists in the IV regression (t=3.05).

Table 4: IT adoption probit regressions

	(1)	(2)	(3)	(4)	(5)
DV: Adoption	E-commerce	E-commerce	Data mining	ERP	E-commerce
	probit	probit	probit	probit	probit, IV
Location	all	closest 20%	closest 20%	closest 20%	all
Log(IT-Using)	.054 (.033)	.060 (.060)	.196*** (.053)	.031 (.053)	-.088 (.054)
Log(IT-Producing)	-.011 (.028)	-.093* (.056)	.035 (.050)	.001 (.038)	.452*** (.148)
Log(IT-Using) · Post	-.008 (.033)	.009 (.047)	-.048 (.058)	-.002 (.053)	
Log(IT-Producing) · Post	.059* (.030)	.164*** (.058)	.069 (.049)	.057 (.042)	
Observations	8,346	2,597	2,597	2,597	4,170

Estimates are from probit regressions using technology adoption as the binary dependent variable. IT adoption variables are based on text-mining 10-K reports and described in Saunders and Tambe (2012). Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Estimates in (2)-(4) are from the 20% of IT-using firms that are closest to IT-producing firms. Instruments in (5) are based on geographic proximity to IT-producing firms. IV Regression in column (5) only uses observations after 2000.

Table 5: Productivity regressions using IT skill data

DV: Log(Value Added)	(1)	(2)
	OLS	OLS
Log(IT-Prod)		.036*** (.011)
Log(IT-Prod) · Post		-.024* (.013)
Log(IT-Using)		.036*** (.012)
Log(IT-Using) · Post		.001 (.013)
Log(IT-Prod E-Commerce)	-.009 (.026)	-.031 (.027)
Log(IT-Prod E-Commerce) · Post	.052* (.028)	.066** (.030)
Log(IT-Using E-Commerce)	.041* (.024)	.015 (.024)
Log(IT-Using E-Commerce) · Post	-.006 (.027)	.006 (.027)
Observations	5,577	5,577
R-squared	.93	.93

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimates are from the Cobb-Douglas production function shown in (4) using value added as the dependent variable. Each regression includes controls for year and one-digit industry. All regressions also include IT employment, capital, and non IT-employment (not shown).

Table 5 reports estimates from labor pool measures that use the e-commerce skills data. OLS estimates are reported due to cross-sectional limitations with the skills data—they are most accurate in recent years, so the distribution of these skills across firms is more representative than within-firm changes in this distribution over time—furthermore, the number of samples of movements for workers with these skills is relatively small compared to the number of samples of workers in firms, so the signal to noise ratio will be higher across firms than within firms. The estimates in columns (1) and (2) suggest that the productivity effects of the broader measure of labor-weighted IT investment disappear when jointly estimated with a measure based on the flow of e-commerce skills. There are significant associations with the IT-using pool

($t=1.75$), although these do not appear to be significantly different before or after the dot-com bust. Nevertheless, the fact that the productivity effects of the technical labor pool measure after the bust disappear when directly including e-commerce measures provides some support for the argument that the earlier results specifically reflect the transfer of e-commerce skills from IT-producing to IT-using firms.

Conclusion

The main finding of this study is that dot-com investment in IT industries during the boom contributed to productivity growth in other industries after the crash through spill-outs of e-commerce know-how. These results are robust to multiple specifications, as well as regressions using proximity to IT producing firms along with the timing of the dot-com bust as a source of exogenous variation in the change in the IT labor pool experienced by non-IT firms.

For policy makers, these results provide insight into the important role that early IT investment plays in incubating technical skills when other institutions for creating this type of human capital are not yet in place. The results indicate that during periods of rapid technical change, frictions in the market for new technical skills can be important for understanding productivity growth patterns. These findings are also relevant to urban policy. Most of the cross-industry productivity spillovers from dot-com investment appear to have been captured by firms located in IT-intensive regions, suggesting “multiplier” effects from local IT investment. Policy makers analyzing the effectiveness of subsidies for regional high-tech investments should consider the full “social” returns to local high-tech investments on the region.

For policy makers and managers, these findings have implications for the current boom—one perspective on the current “social media bubble” was voiced by an early Facebook employee, who was quoted as saying “The best minds of my generation are thinking about how to make people click ads. That sucks.” (Vance, 2011). An implication of the findings in this study is that the data and analytic skills being acquired at social media companies are likely to support productivity growth in other industries as these industries begin to exploit large data sets using techniques pioneered by social media companies. Consequently, the supply of technical skills related to managing large data sets (e.g. Hadoop and MapReduce) that is currently concentrated in a few IT firms will eventually be reallocated to firms in other industries if a shakeout occurs in the social media sector—with firms that are located in the same metropolitan areas as these social media companies being the first to benefit.

Finally, these findings suggest several directions for future research. Research on the strategic role of compensation, location, and other firm-level factors for attracting, retaining, and motivating skilled IT workers to complement a firm’s technical initiatives would provide important guidance about how firms can attract the skills needed for productivity. Furthermore, this study does not discuss how the dot-com crash affected labor outcomes for IT workers. A question for future research is how the collapse of this bubble affected long-term labor outcomes for IT workers with e-commerce skills, especially in conjunction with outsourcing, offshoring, and other changes to IT labor supply that became increasingly important after the bust.

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