Information Technology Adoption and Human Capital Flows: The Case of Electronic Networks

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Abstract:

This paper investigates how technology adoption, specifically electronic networks, alters human capital flows and wages within firms. While prior studies have linked information technology investments to firm growth and evolving workforce composition, direct evidence on worker inflows, outflows, and wage effects remains limited. We develop a model where technology adoption raises firm productivity but also increases the costs of replacing workers due to greater specialization, incentivizing firms to reduce turnover by offering higher wages. Using a novel linkage of non-public U.S. Census Bureau microdata at the firm-state-CBSA-year level, we show that electronic network adoption increases net worker flows by 1.7% and boosts average wages by 2.2% while decreasing both worker inflows and outflows, with stronger effects among younger and high-wage workers. Contrary to expectations, our results reveal that firm expansion is achieved mainly through improved employee retention rather than increased hiring. We further document heterogeneity in adoption effects by local labor market conditions and firm size. Our findings imply an important role for replacement costs and wage incentives in shaping human capital dynamics following information technology adoption.

Keywords: Worker Turnover, Retention, Replacement Costs, Training.

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1. Introduction

The implications of information technology (IT) investments for the size of firms have been of increasing interest, with recent work suggesting that such investments have led to larger and, in some cases, more dominant (larger market share) firms (Aghion et al 2019; Autor et al 2020; Bessen 2020; Basker and Simcoe 2021; Brynjolfsson, Jin, and Wang 2023; Dixon, Wang, and Wu 2021; Fort et al 2018), reflecting productivity improvements and accompanying changes in vertical relationships and firm scope (e.g., Babina et. al., 2024; Basker and Simcoe 2021; Balsmeier & Woerter, 2019; Brynjolfsson, Jin, & Wang, 2023; Forman & McElheran, 2024; Fort et al 2018; Alekseeva et. al., 2024).

Often accompanying such growth are complementary changes to firm processes and systems (e.g., Bresnahan, Brynjolfsson, & Hitt 2002; Brynjolfsson, Jin, & McElheran, 2021; Brynjolfsson, Rock, & Syverson, 2019; Tambe, 2014), as well as to human capital (e.g., Brynjolfsson, Jin, & McElheran, 2021; Choudhury, Starr, & Agarwal, 2020; Allen & Choudhury, 2022; McElheran et al. 2023), which can significantly change occupational structure and wage profiles (e.g., Barth et al 2023; Bresnahan, Brynjolfsson, and Hitt 2002; Feigenbaum and Gross 2024; Dixon, Wang, and Wu 2021; Bennett, Black, and Hall 2024).

Overall, these studies suggest that firms grow by reshaping the composition of employee human capital towards skills that complement new technology investments. However, we know little about the human capital flows that underlie these changes. For example, does the inflow of workers increase? What happens to outflows? Do evolving skill requirements lead to increased employee retention, or does worker turnover rise? Some early work indicated that technology investments may reduce employee retention (Bidwell 2013). However, beyond evidence related to robotic investments (Dixon, Wang, and Wu 2021), there is little direct empirical work related

to these dynamics. Understanding these dynamics is important because the managerial and policy implications critically depend on the extent and direction of individual flows, not just their net impact. For example, achieving 2% growth by increasing inflows by 2% requires a focus on attracting human capital and reducing hiring barriers (Barron, Bishop & Dunkelberg, 1985; Davis, Faberman & Haltiwanger, 2013), which is fundamentally different from achieving the same growth through a 2% reduction in outflows, where the emphasis is on turnover and retention (Jovanovic, 1979). In this paper, we seek to advance our understanding by taking a direct and granular look at human capital flows after new technology adoption. To guide our empirical analysis, we develop a parsimonious model of worker flows. Firms in the model face costs of replacing departing workers such as search and training expenses. While technology adoption increases firm productivity, worker replacement costs also increase, as working with new technologies requires more specialized skills and additional training. A central implication is that firms adopting new technologies seek to lower the rate of worker outflows and do so by paying higher wages. Implications for worker inflows are ambiguous and depend upon the joint effects of technology adoption: increased productivity drives firm growth and necessitates greater inflows, while reduced turnover diminishes the need for replacements, thereby decreasing inflows.

We evaluate the empirical salience of our model results by examining the adoption of a specific, but important technology, electronic networks, which refer to use of the Internet, electronic data interchange (EDI), e-mail, extranet, or other online systems to control or coordinate shipments (Fort, 2017). Prior work has argued that this technology may involve process change, co-invention, and changes to organizational structure (McElheran 2015, Forman and McElheran 2025; Fort 2017). Further, it shares characteristics with other business software

technologies, like enterprise resource planning, supply chain management, and customer relationship management that involve extensive training and firm-specific human capital investments (Aral et al, 2024; Hendricks et al, 2006) in the adopting unit.

Our empirical analysis uses non-public U.S. Census Bureau microdata. Worker-level employment history, earnings, and individual worker characteristics come from the Longitudinal Employer-Household Dynamics (LEHD) database, a linked employer-employee data covering 30 U.S. states. Establishment-level inputs and outputs come from economic datasets including the Census of Manufactures (CMF), Annual Survey of Manufactures (ASM), and the Longitudinal Business Database (LBD). We examine the implications of technology adoption – measured in the CMF and ASM between 2002-2012 – on worker inflows and outflows as measured in the LEHD and average wages measured in the economic datasets.

Research documents considerable variation in adoption of networking technology across units within the same firm over this period (e.g., Forman and van Zeebroeck 2012; Forman and McElheran 2025), suggesting that the effects of electronic networks adoption are best examined at the sub-firm unit level. However, there is no unique establishment- or sub-firm-level concordance between the LEHD and the economic datasets (LBD, ASM and CMF). To address this challenge, we employ a novel approach that leverages Core-Based Statistical Area (CBSA) information available in both datasets, to link the two datasets at a more granular firm-CBSA-state level. Consequently, our unit of observation is the firm-state-CBSA-year.

In line with the predictions from our model, our baseline analysis shows an increase in average wage of 2.2% following adoption of electronic networks. This is accompanied by a decline in inflows and outflows of 5.5% and 8.3% relative to their respective sample means, resulting in a net growth. While the reduction in inflows is unexpected given documented firm

growth following adoption, it aligns with our model: growth is achieved by curbing outflows more than inflows, reflecting a focus on reducing turnover.

We confirm that our baseline findings (of reduced worker flows and increased wages) are largely robust across alternative metrics for dependent variables and to using alternative model specifications. To address concerns that could weaken a causal interpretation of our results, we check and confirm robustness to potential bias from pre-adoption trends, and to using instrumental variable approaches from the literature.

Next, we explore heterogeneity of our core findings across worker, firm and location characteristics. Our model provides a framework for predicting how such heterogeneity influences outcomes, utilizing comparative statics derived from the model. Consistent with the notion that replacement costs increase more for workers with skills complementary to electronic networks, we find that the effects of technology adoption (both the increase in wages and the decline of inflows and outflows) are stronger for high-wage and younger workers. Additionally, these effects are stronger for firm subunits located in urban areas, while the effect on wages is attenuated for subunits located in states with stronger NCA enforcement. These results align with our model, under the assumption that urban areas and locations with weaker NCA enforcement experience greater labor market competition (i.e., higher probability of workers receiving attractive outside wage offers).

Finally, motivated by prior work that has argued that the benefits of IT investments may vary with organization size (Bessen 2022; Tambe and Hitt 2012; Tambe et al 2020; Lashkari et al 2024), we examine how our results vary by size of the subunit. Because it is unclear (both theoretically and from empirical studies) how the impact of adoption on productivity and replacements costs varies by firm size, our model does not yield clear predictions. Our findings

indicate that smaller firms experience a greater increase in wages following adoption, although the effect on worker flows appears to depend on the measurement approach.

Together, our results show that extending analysis to human capital flows yields richer insights into the underlying drivers of changes documented in studies of IT adoption and firm growth. Broadly, our results imply an important role for replacement costs in determining human capital flows associated with IT adoption. Although here we have studied only one specific technology, electronic networks, we believe these findings are likely to generalize to other instances where adopting firms also need to make costly complementary investments in human capital and influence worker replacement costs.

Our research contributes to existing literature, particularly the small literature that has examined the implications of technology adoption for labor flows. This literature has largely examined technologies that substitute for labor, particularly routine or non-skilled work. For example, Dixon et al. (2021) show that robot adoption reduces managerial hiring and increases managerial departures while increasing churn among non-managerial employees. Similarly, Feigenbaum and Gross (2024a) document large-scale operator layoffs during AT&T's mechanization of call switching, alongside selective inflows for middle skill clerical and lower-skill service jobs. In contrast, our study focuses on a labor-augmenting technology, more akin to the complementary effects observed in the Greenwood et al. (2019) study of the implications of basic electronic health records technology, which reduce outflows of physicians. (They find that adoption of more advanced systems increases physician departures.) Thus, our findings of reduced outflows and churn is largely different from much of the prior work, and consistent with that of an enterprise system that reorganizes production and fulfillment but is not directly labor-

substituting. Moreover, unlike most prior studies, which do not measure wage effects, we offer direct evidence on wage changes and thus provide a more complete picture of the phenomenon.

Our paper also speaks to the broader literature exploring the drivers of worker mobility and turnover. Campbell et al (2011) document that employees with higher earnings are less likely to leave (and more likely to create new ventures than join another firm). Carnahan et al (2012) find that high performing individuals are less likely to leave firms that have higher compensation dispersion (but more likely to create new ventures if they leave). Our results echo these findings, as firms raise wages to reduce turnover, more so for high wage workers, after IT adoption. Kryscynski (2021) documents a role for firm-specific incentives in reducing both turnover and cash compensation, while Friebel et al (2022) find that middle management effort reduced turnover and increased profits despite null effects on revenue (due to reduced turnover costs). Our results suggest that firms use higher wage compensation as a tool to reduce turnover, consistent with greater firm specificity of investments driving higher replacement costs after adoption of electronic networks.

2. Theoretical Motivation

2.1 Model Summary

In this section we describe an overview of the model that motivates our empirical tests. A complete discussion of the model is available in the Appendix, here we provide a non-technical overview of the key assumptions and results.

In our model, profit-maximizing, wage-setting, firms choose the optimal number of workers to employ and the optimal wage to pay, balancing production revenue against labor and turnover costs. The impact of IT adoption works through its impact on productivity. Following a large literature on the productivity implications of general IT investments (e.g., Brynjolfsson and

Hitt 2003; Brynjolfsson, Rock, and Syverson 2021; Bloom, Sadun, and Van Reenen 2012; Tambe and Hitt 2012) and electronic networks specifically (Fort, Pierce, and Schott 2018), we assume that IT adoption increases firm productivity. In turn, productivity increases make it more optimal for firms to employ more workers, consistent with empirical evidence that more productive firms tend to be larger (Syverson, 2011) and with the corresponding assumption adopted in many theoretical models (e.g., Hopenhayn, 1992; Melitz & Ottaviano, 2008).

Consequently, IT adoption increases firm size, by increasing inflows and/or decreasing outflows. Critically, however, the magnitude and direction of these worker flows are also shaped by replacement and turnover costs, which determine firms' incentives to retain workers as productivity rises. In our model, following earlier work on wage setting in monopsony models, workers quit if they receive an offer that is higher than their current wage.[1] If workers quit, the firm must spend money to replace them. These replacement costs include costs associated with search (e.g., advertising, interviewing, and search agency fees), training (e.g., including on-the-job training and certification), as well as indirect costs (e.g., lost productivity of others who worked with the focal employees and now need to re-learn those relationships).[2] We assume that these replacement costs are increasing in firm productivity. This assumption is consistent both with studies that find search and replacement costs to be positively associated with firm size and wage (e.g., Blatter, 2012; Dube, Freeman and Reich, 2010), and with what is known about

[1] This is closely related to the standard assumption in basic wage setting monopsony models. E.g., in Section 2 of Kline's (2025) handbook chapter, a firm is able to hire a F(w) workers if it offers a wage w, where F(w) is the CDF of outside offers available to the workers.

[2] Bushey and Glynn (2012) document replacement costs in the range of 10% to 30% of employees' annual salary, and find some evidence for higher replacement cost (as percentage of salary) for higher wage workers.

process and human capital changes (we elaborate on these changes in the next section) following technology adoption (e.g., Bartel, Ichniowski, and Shaw 2007).[3]

Taken together with the assumption that IT adoption enhances productivity, the positive relationship between productivity and replacement costs implies that IT-adopting firms will have stronger incentives to retain workers to avoid higher turnover and replacement costs. This leads to two key predictions.

Prediction 1: IT adoption leads to higher wages.

Prediction 2: IT adoption leads to lower outflow rate and lower outflow conditional on employment.

While the model yields unambiguous predictions for wages and outflows, the consequences for inflows are less clear. On the one hand, as noted above, IT adoption will yield higher productivity growth, which will translate into a positive effect on hiring and inflows. On the other hand, per prediction 2, IT adoption will also decrease outflows, which will reduce the need for the firm to hire new workers to replace departing ones.

These are the baseline predictions from the model. In the results section, we will discuss some additional empirical tests that can be motivated using our framework, in particular how worker- and firm-specific factors create heterogeneity in conditions that influence how IT adoption influences wages, inflows, and outflows.

[3] Using Swiss administrative data, Blatter et al (2012) document that average interview time, as well as median hourly wage of interviewer per applicant is higher, and consequently recruitment costs are substantially greater, for larger firms, across all skill categories. They document that hiring costs per vacancy is strongly increasing in firm size: firms with 100 or more employees face recruitment costs that are on average four times higher than those for the smallest firms. Based on a panel survey of California businesses, Dube, Freeman and Reich (2010) find evidence that replacement costs are positively associated with establishment size and wage.

2.2 Technology Adoption, Systems Change, and Worker Human Capital

In this section we provide background information on one of the key assumptions that IT adoption will increase worker replacement costs. Broadly, this occurs because IT adoption is typically accompanied by complementary firm specific organizational changes, so that any replacement workers must be retrained to operate effectively within the adopting firm's new systems. We start by briefly reviewing earlier results on the complementary changes the accompany the adoption of business IT. We describe how adoption in one part of the organization can involve systems changes that appear elsewhere, and how these changes often require on-the-job worker training that is borne by the adopting firm and thus increase its cost of replacing such trained workers. We then provide specifics about the types of changes that co-occur with the adoption of electronic networks.

2.2.1 General Results on Technology Adoption, Systems Change, and Worker Human Capital

The existing literature on effective implementation of IT within businesses has emphasized the view of IT as a business process innovation.[4] Productivity gains often depend on whether the employees of the adopting organization invent new processes or changes to adapt new IT systems to the idiosyncratic needs of specific enterprises, also known as co-invention (Bresnahan and Greenstein 1996). Importantly, because the implications of the changes described above extend beyond the direct application of technology and often involve changes to other systems and processes, adoption of technology can involve changes for workers across the organization. Here, we provide two well-known examples from the literature, in the next section we provide further details within the specific context of electronic networks.

[4] See, for example, Bresnahan and Greenstein (1996), Bresnahan, Brynjolfsson, and Hitt (2002), Bartel, Ichniowski, and Shaw (2007), Bloom, Sadun, and Van Reenen (2012), Brynjolfsson, Rock, and Syverson (2021), Dranove et al (2014), and Jin and McElheran (2025).

Bartel, Ichniowski, and Shaw (2007) describe the implications of the adoption of computer numerically controlled machines (CNC). They show that adoption of CNC machines affects setup times, run times, and inspection times during the production stage. Importantly, however, “plants that introduce technical training programs realize an additional reduction in setup times and run times" (Bartel, Ichniowski, and Shaw 2007, p. 1745) beyond the effects of the IT itself. As they note, “HRM policies designed to improve the specific skills needed to operate new technologies in the plant are in fact the initiatives that are associated with improvements in the speed of machining operations during a given product run” (Bartel, Ichniowski, and Shaw 2007, p. 1745).

However, these changes not only involve modifications to manufacturing processes but also to business strategy: reduction in setup times make it easier for plants to shift from one product to another, enabling a strategic shift towards customization. Further, these changes are also accompanied by changes to human resource practices: skill demand shifts, new human resource management practices are adopted, and workforce composition changes. As the authors conclude: "the falling price of an input—the price of computerized capital—not only changes the quantity of that input and related inputs, but also changes a business's competitive strategy, as well as the skill requirements and work practices needed to implement the new strategy" (Bartel, Ichniowski, and Shaw 2007, p. 1756-1757).

Feigenbaum and Gross (2024b) examine the adoption and implications of mechanical call switching within AT&T, providing an example of how technology adoption can influence processes and systems across an organization. At local telephone exchanges, adoption of mechanical call switching required equipment replacement and rewiring, as well as changes to information services, emergency services, and call monitoring. However, it also required broader

changes at the corporate level, including the need for further R&D investment to improve call switching technology, the development of new manufacturing capabilities, and education of company managers. The authors note, “call switching's centrality in this web of activities makes it our canonical example of an 'integral task.' Its embeddedness meant that significant changes in call switching technology (like automation) were not a straightforward proposition, as they would have ripple effects across the business" (Feigenbaum and Gross 2024, p. 8527).

These examples illustrate how the adoption of new technology can generate idiosyncratic changes in skills for workers across the organization. If such workers leave, firms have to incur the costs of recruiting and retraining replacements to attain comparable firm-specific skills and familiarity with newly implemented systems. These costs are likely to be pronounced in the early stages of a technology’s life cycle, when relatively few workers in the external labor market possess experience with the new processes and associated organizational changes. In the next section we discuss how similar changes may appear in our setting when firms adopt electronic networks, specifically electronic selling.

2.2.2 Process and Human Capital Change in Electronic Networks

Electronic networks can be used to coordinate buying and selling activities with external organizations. The margin of investment that we examine is electronic selling (e-selling). Previous work has argued that the size of adjustment costs for e-selling will exceed those of electronic buying (e-buying) (McElheran 2015). Electronic selling was costly and involved internal adaptation to the new technology as well as changes to relationships with downstream partners (McElheran 2015). There was no “one size fits all” technology to support the new sales approach within companies. According to one analyst report at the time “What the [e-selling] projects lack in simplicity they make up for with diversity” (Parker 1999, p. 4).

Further, leading vendors did not provide complete solutions during the early years of the diffusion of e-selling (Teach 1999). For example, at metalworking products company Milacron, one executive noted that "The intricacies of buying, ordering, shipping and invoicing, or working with pricing, quantities, special shipment handling, back orders, acknowledgements, cancellations – this is not a simple process. Business systems and enterprise resource planning systems have been at it for years and years and have the process down pretty well. You don't see that level of sophistication in e-commerce systems."

These costs could be significantly higher for (often larger) companies who sought to integrate their e-selling investments with backend databases and systems such as accounting and order fulfillment, ERP, and customer relationship management (Teach 1999). However, leading vendors did not provide complete end-to-end solutions to support these initiatives (Teach 1999). In the case of Milacron, they co-developed with an external vendor a front end to their e-selling system that could be used to determine which Milacron products best fit customer needs (Schultz 1999). More broadly, companies adopting e-selling would often employ a "platform and toolkit" approach to their e-selling adoption that had the flexibility to be tailored to company needs, but with the additional cost of extensive development work (Teach 1999).

Importantly, however, these projects not only involved significant development work, but also process reengineering and co-invention (Parker 1999, McElheran 2015). As one executive at Milacron notes, "This is not an IT project. This is a market channel." (Schultz 1999, p. 58) While another notes, "E-commerce touches every part of the company. It has forced us to take a good hard look at everything we do and ask how and why" (Schultz, 1999, p. 58).

Dell Computer was another example of an early company to adopt electronic selling and implement a system of changes to support it. Premier Pages was a web-based marketing effort

that gave customers access to information about Dell's products and services (Payne and Allen 1999). This involved changes to the sales process. Dell customers would use the web page for simple transactions, but work with the sales force for more complex transactions (Payne and Allen 1999). Dell also offered complementary services over the Internet, including an on-line service manual, the ability to check in on orders, and PC management (Payne and Allen 1999). In short, the adoption of electronic selling was the start of a series of changes that changed the way Dell interacted with its customers.

Recent empirical research using Census data has demonstrated the organizational implications of adopting electronic networks technology like electronic selling. Forman and McElheran (2025) show that adoption of electronic networks that involve supply chain coordination can change firm boundaries, showing that they can lead to a decline in the share of the value of shipments that are sold internally. In short, adoption of electronic networks can increase the share of output sold to external customers. Fort (2017), also examining the implications of adopting electronic selling using Census data, shows that adoption of electronic selling gives rise to an increase in production fragmentation in manufacturing firms. These changes led to an increase in labor productivity and employment growth in adopting establishments (Fort, Pierce, and Schott 2018).

To summarize, prior research on technology adoption highlights that implementing IT systems often entails organizational changes and substantial retraining. Similarly, the adoption of electronic selling has required adjustments that extend beyond the technology itself, necessitating broader idiosyncratic organizational changes. Together, these insights drive the key assumption in our model: IT adoption induced productivity increases are associated with increased cost of replacing workers.

3. Data

Our empirical analysis utilizes non-public U.S. Census Bureau microdata. Worker-level employment history, earnings, and individual characteristics come from the Longitudinal Employer-Household Dynamics (LEHD) database. The LEHD is a linked employer-employee data constructed using administrative records collected from the state unemployment insurance (UI) system. It covers over 95% of total wage and salary civilian jobs in the United States (Tate and Yang, 2015). Availability of restricted access microdata for researchers is dependent on each state's participation in the LED Partnership through a Memorandum of Understanding (MOU), and we have access to data from 30 states.[5] Individual job-level information is obtained from the Job History File (JHF) in the LEHD, while Individual characteristics are from the Individual Characteristics Files – Demographics and – Residential Geography databases in the LEHD. These datasets are linked via individual-level identifiers. We further obtain firm identifiers from the Employer Characteristics File in the LEHD to link to economic datasets.

Establishment-level inputs and outputs come from the Census of Manufactures (CMF), Annual Survey of Manufactures (ASM), and the Longitudinal Business Database (LBD). These datasets are linked by establishment-level identifiers and have been used extensively to study economic activity in the US economy (Haltiwanger et al., 2013; Decker et al., 2014, 2017; Jin and McElheran, Forthcoming). The LBD tracks all establishments in the U.S. private sector from the time they have at least one employee, providing data on birth and age of establishments. The CMF provides population-level data for establishments in the manufacturing sector for

[5] These include data from Alabama, Arizona, Colorado, Connecticut, District of Columbia, Delaware, Hawaii, Idaho, Illinois, Kansas, Louisiana, Maine, Maryland, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, Wyoming. The first available year for JHF data is 2004 for Arizona, and 2006 for the District of Columbia. For the other 28 states, we have data covering our entire 2002-2012 sample period.

Economic Census years ending in "2" and "7." Data for other years is from the ASM, which contains a representative sample of activity in the manufacturing sector, stratified by industry and size, covering roughly 70% of economic activity (Jin and McElheran 2025). Responses to the CMF and ASM are required by law.

The LEHD data contains firm-level identifiers for each state, but does not have establishment-level identifiers, and thus, the lowest level at which we can map LEHD to the economic databases (CMF/ASM/LBD) using LEHD identifiers is at the firm-state level (Juhn et al., 2018).[6] As a result most prior work linking the LEHD data to the Census economic data match at the firm or firm-state level (e.g., Bloom et al., 2021; Juhn et al., 2018; Kim, 2025; Patki, 2025; Tate and Yang, 2015). However, the variation in our measure of IT adoption occurs at the establishment level, and in our analysis, we seek to maximize the local-level variation that will influence the replacement costs of workers in our analysis. As a result, we focus our analysis on the sub-firm unit level.

While we are unable to aggregate our data to the establishment level, we employ a novel method to combine the two datasets at the most granular level possible by leveraging CBSA information available in both datasets. We obtain the CBSA where each worker lives from the individual's residence location in the Individual Characteristic File in the LEHD, and is available for all workers in the U.S. We make the assumption that individuals work and live in the same CBSA, and assign pseudo-CBSAs for employees located outside CBSAs within each state (recall that CBSAs do not completely cover a state). We then aggregate these worker data to the firm-state-CBSA level for each year. For the economic data, we aggregate establishment-level

[6] The LEHD does contain sub-firm state-firm reporting units (SEINUNIT), which are available for firms in Minnesota and a subset of firms in other states, however there is no link between these identifiers and the establishment-level identifiers in the economic databases.

variables to the firm-state-CBSA level using the share of employment in each establishment as weights. We validate this approach by comparing the total employment at the firm-state-CBSA level in the LEHD and LBD and find that the totals are broadly comparable.

3.1 Sample Description

The sample period is from 2002 to 2012. This is a period starting shortly after the earliest years of the diffusion of electronic networking technology that automates business processes (Forman, Goldfarb, and Greenstein 2005, McElheran 2015).[7] We begin our sample in 2002 because it is the first year for which we have annual data on electronic networks. We do not have a balanced panel of firm-state-CBSAs due to two data limitations. First, data outside of Census years are from the ASM, which is an establishment-level survey that includes a set of establishments that are included with certainty (i.e., the probability of selection in the survey is 1.0) with remaining units assigned a probability of sample inclusion that is dependent on size and industry.[8] Thus, in our baseline sample data from ASM years will be influenced by the composition of the ASM sample. Second, in the economic census years (i.e., 2002, 2007, 2012), not all establishments received questions about electronic networks. As a result of these limitations, establishments may enter and exit our data, which affects the composition of our firm-state-CBSA sample.

Because the construction of some variables requires two years of data, we exclude from our sample the first year of an employer's entry and the last year of an employer's exit. The main

[7] E-Commerce as a share of shipments was 51.9% in 2012 (https://www.census.gov/content/dam/Census/library/publications/2014/econ/2012_report.pdf). Of course, the share of shipments will be much lower than the share of establishments adopting electronic networks because of the long tail of small manufacturers.
[8] More details are available at https://www.census.gov/programs-surveys/asm/technical-documentation/methodology.html.

sample contains approximately 179,000 firm-state-CBSAs belonging to [] firms.[9] Given limitations in our baseline sample, we construct an alternative "stacked" sample that we use as a robustness check. We describe this later.

3.2 Key Variables

Labor Flows. The key dependent variables in our analysis are labor flows and wages. We define an individual's inflow and outflow based on job spell records in the JHF in the LEHD. For each individual *j* and job spell *s*, the JHF provides the first and last quarter of employment. We identify an inflow for individual *j* as occurring for firm-state-CBSA *i* in year *t* if her first quarter of employment for job-spell *s* for firm-state-CBSA *i* is within year *t*. Similarly, we identify an outflow for individual *j* as happening for firm-state-CBSA *i* in year *t* if her last quarter of employment at job-spell *s* for firm-state-CBSA *i* occurs between the last quarter in year *t-1* to the third quarter in year *t*. We then calculate the total labor inflow and labor outflow for firm-state-CBSA *i* in each year *t* by summing all the individuals classified as inflow and outflow in year *t* at firm-state-CBSA *i*, respectively. We check that total inflow minus total outflow equals the change in total employment (*net flow change*) for each firm-state-CBSA *i* in year *t*. We also compute average wage for *i and t* and use the log of that variable in our analyses.

Table 1 shows that the standard deviation of inflows and outflows are large. Moreover, firm-state-CBSA-years with no change in employment will yield a mass of zero in our data. As a result, in our results, we examine the robustness of our results to several alternative measures. First, we winsorize the top 1%, 2.5%, and 5% levels for total inflow/outflow/net flow change. Second, we calculate the fraction of inflow/outflow/net flow change $\frac{inflow_{it}}{0.5 \times (E_{t-1}+E_t)}$, $\frac{outflow_{it}}{0.5 \times (E_{t-1}+E_t)}$,

[9] The number is approximate according the Census disclosure requirement.

and $\frac{netflow_{it}}{0.5 \times (E_{t-1}+E_t)}$. This fraction measure has become standard in analysis of establishment or firm dynamics because it shares some useful properties of log differences but also accommodates entry and exit (Davis et al., 1996; Haltiwanger et al., 2013; Törnqvist et al., 1985). We further construct measures for all dependent variables using the inverse hyperbolic sine transformation and a binary variable indicating whether the flow is above median as robustness checks.

Electronic Networks. The key independent variable is the adoption of electronic networks by firm-state-CBSA *i* in year *t*. Specifically, we use a question from a section of the CMF and ASM on "E-commerce Sales, Shipments, Receipts, or Revenue" that asks "Did any of the amount reported in 4, line A [which asks about total value of products shipped and other receipts] include e-commerce sales, shipments, or receipts? (E-commerce sales, shipments, or receipts are online orders for products from customers where price and/or terms of the sale are accepted or negotiated over an Internet, Extranet, Electronic Data Interchange (EDI) network, electronic mail, or other online system. Payment may or may not be made online.)" (Form MC31000, 2002 Economics Census and Form MA-10000, 2002 Annual Survey of Manufacturers) (from the 2002 CMF and 2003 ASM; wordings slightly differ across years but substantively remain unchanged).[10] In this measure, the usage of electronic network to manage shipments involves beyond simply using the internet or other networks but integrating electronic communication in the production process (Fort, 2017; Fort et al., 2018). We first define the adoption of electronic networks as a binary variable (equal to 1 if the percentage of electronic

[10] Although the general question has been the same over time, the wording was slightly changed in later years. The specific question was changed to "Did this plant use any electronic network to control or coordinate the flow of any of the shipments of goods reported in 4, line A [which asks about total value of products shipped and other receipts]? Or, were the orders for any of the shipments reported in 5, line A, received over an electronic network? Electronic networks include: Internet, Extranet, Electronic Data Interchange (EDI) network, electronic mail, or other online system."

networks at an establishment is positive in year *t*) and then aggregate the variable to firm-state-CBSA weighted by the share of employment. In the baseline analysis, we allow employers to "unadopt" after adoption (i.e., respond as not using e-selling). We explore the robustness of our results to assuming an absorbing state for the adoption of electronic networks.

Following previous literature on IT adoption, we control for other variables related to production inputs, including the age of the employer, IT capital, total capital expenditure, cost of electricity, cost of materials, cost of fuels, inventory, number of establishments within each unit, and total employment (Jin and McElheran, 2025), as these variables could impact or be correlated with both our dependent variable of interest as well as the electronic networks adoption decision. Like our other variables, the firm-state-CBSA level control variables are weighted by the share of employment in each establishment within the firm-state-CBSA unit. The IT capital stock control variable is measured as follows. We first obtain IT flow data in the CMF and ASM from 1992 to 2012 and merge the IT flow information with LBD data. We use linear interpolation to estimate missing IT flow values for the middle years. For the earliest and latest years with missing data, we assign the value observed in the first or last available year, respectively. Leveraging this longer panel, we implement a perpetual inventory approach using an industry-level deflator for hardware from the Bureau of Economic Analysis (BEA) of 35% per year to calculate IT capital stock.

Table 1 shows the summary statistics.

Table 1 Summary Statistics

Variable Type	Variable	Description	Mean	Std. Dev
Inflow	Total inflow	Total number of hires	14.72	90.56
	Fraction inflow	Hires as fraction of employment	0.195	0.244
	IHS inflow	Inverse Hyperbolic Sine of total number of hires	1.977	1.561
	Inflow above median	Dummy if total inflow is above median	0.483	0.5
Outflow	Total outflow	Total number of exiting workers	13.76	72.79
	Fraction outflow	Exiters as fraction of employment	0.2	0.312
	IHS outflow	Inverse Hyperbolic Sine of total number of exiters	2.001	1.515
	Dummy outflow above median	Dummy if total outflow is above median	0.489	0.500
Net flow	Total net flow	Difference between total hires and total exiters	0.955	44.85
	Fraction net flow	Net flow as a fraction of employment	-0.005	0.331
	IHS net flow	Inverse Hyperbolic Sine of net flow	0.205	2.096
	Net flow above median	Dummy if net flow is above median	0.431	0.495
Wage	Log avg. wage	Log (average wage+1)	3.632	0.508
	IHS avg. wage	Inverse Hyperbolic Sine of average wage	4.294	0.527
	Dummy avg. wage above median	Dummy if average wage is above median	0.501	0.500
E_adoption	E-network	Weighted average of dummy for reported e-network adoption among units in CBSA in that year	0.270	0.441
	E-network (absorbing)	1since the first adoption year and 0 otherwise	0.316	0.465
Heterogeneity Characteristics	Dummy Urban	Indicator for firm-CBSAs located in Metropolitan Statistical Areas	0.825	0.380
	NCA	Hausman and Lavetti (2021) enforceability measure	0.752	0.170

Variable Type	Variable	Description	Mean	Std. Dev
	Dummy small	Indicator for initial employment less than sample median value of the firm-state-CBSA employment	0.481	0.500
Control Variables	Age	Weighted average of the age of individual establishments	18.02	11.190
	# establishments	Number of establishments within firm-CBSA	1.016	0.138
	Log IT capital stock	Log (weighted IT capital stock+1)	2.415	1.900
	Log IT capital flow	Log (weighted IT investments+1)	1.448	1.704
	Log total employment	Log (total employment+1)	3.452	1.518
	Log total expenditure	Log (weighted total of all input costs+1)	3.96	2.580
	Log cost of electricity	Log (weighted expenditure on electricity+1)	3.504	2.160
	Log cost of material	Log (weighted expenditure on materials+1)	7.42	2.262
	Log cost of fuel	Log (weighted expenditure on fuels+1)	2.316	2.278
	Log total inventory	Log (weighted total inventory+1)	5.723	2.407
Number of observations		Firm-state-CBSA-year observations	474000	
Number of firm units		Firm-state-CBSA observations	179000	

4. Empirical Approach

Our empirical analysis is at the subfirm unit level, rather than the firm level. Prior work has demonstrated that there is considerable within-firm variation in the adoption of electronic networking technology that coordinates economic activity within and between firms (Forman and van Zeebroeck 2012; Forman and McElheran 2025). For these reasons, recent work using Census data examining the adoption and implications of electronic networking technology, both similar and identical to the margin we examine, have been conducted at the establishment level (McElheran 2015; Forman and McElheran 2025; Fort 2017). As noted above, while it is

infeasible to match the Census economic data to the LEHD at the establishment level, we are able to link the datasets at firm-state-CBSA level. Further, while some data in the LEHD are collected at the quarterly level, we aggregate to the yearly level to match the Census economic data. Thus, we conduct our analysis at the firm-state-CBSA-year level.

Our primary specification examines how the adoption of electronic networks is associated with changes in labor inflow, outflow, net flow, and average wages from 2002 to 2012. Our baseline empirical model takes the following form:

$$Y_{it} = \alpha + \beta Networks_{it} + \gamma Z_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

where Y_{it} represents, depending on the specification, labor inflow, labor outflow, net flow change, and (log) average wages at firm-state-CBSA *i* in year *t*, $Networks_{it}$ reflects the adoption of electronic networks in that firm-state-CBSA-year, Z_{it} is a set of control variables, while μ_i and τ_t are firm-state-CBSA and year fixed effects, respectively. Standard errors are robust and clustered by firm. The unit of analysis is at the firm-state-CBSA-year level.

Our main coefficient of interest is β, which denotes the change in labor flow and average wages in firm-state-CBSAs associated with the adoption of electronic networks, after controlling for other factors. Specifically, if β is negative (positive), it indicates that the adoption of electronic networks is associated with a decrease (increase) in the labor flow or average wages.

Our approach shares similarities with other work that has examined the implications of the adoption of information technology on firm and sub-firm unit outcomes.[11] A common theme throughout this work is that it requires strong assumptions for estimates to be viewed causally. In particular, an issue raised in prior work (e.g., Forman, Goldfarb and Greenstein, 2012; Forman

[11] This literature is too large to be summarized here, but for examples of work that has specifically examined the implications of IT on labor outcomes, see Im, Grover and Teng (2013) and Brynjolfsson, Jin and Wang (2023).

and McElheran, 2025) is that IT adoption is often part of a system of complementary changes that are co-determined. Ascertaining causality amid this system of changes is difficult. We address these concerns through a combination of instrumental variables estimation and a timing falsification. Perhaps most significantly, we use our model to motivate a series of predictions and additional heterogeneity analyses that allow us to examine how our baseline effects vary based on employee, employer, and local labor market characteristics. In addition to deepening our understanding of factors that moderate the baseline estimates, these additional tests provide further confidence in a causal interpretation of our results if they are consistent with our theory-based predictions. Nonetheless, given the absence of strictly exogenous variation, we interpret our estimates cautiously.

5. Results

5.1 Baseline Results

In Table 2, we present the baseline results, including the full set of control variables as specified in the data section. In the Appendix Table D1, we present results from a specification with no controls except for firm-state-CBSA employment size, and one with the complete set of controls while also adding industry-year fixed effects. The results in Table 2 show that the adoption of electronic networks is negatively associated with both labor inflow and labor outflow, and has a significant positive association with average wages. Based on our baseline results using levels of inflows and outflows, the adoption of electronic networks is associated with about a 0.81 decline in inflows of workers (5.5% of the mean inflows of 14.72) and a decline of 1.14 in worker outflows (8.3% of the mean outflows of 13.76). The adoption of electronic networks is further associated with an increase in net flow of 0.33, though the estimated coefficient is insignificant in this specification. These declines in inflows and outflows

are accompanied by about a 2.15% increase in the average wage. Therefore, the results are largely consistent with the predictions of our model.

Table 2 Baseline effects of electronic network adoption on labor flows and wages

	(1)	(2)	(3)	(4)
	Inflow	Outflow	Net Flow	Avg. Wage
E-network	-0.8076***	-1.1420***	0.3344	0.0215***
	(0.1888)	(0.1830)	(0.2295)	(0.0018)
Log (employment)	17.43***	16.09***	1.338***	-0.0109***
	(0.9463)	(0.7583)	(0.4590)	(0.0024)
Age	0.0077	-0.0548	0.0625	-0.0042***
	(0.0593)	(0.0724)	(0.0793)	(0.0004)
Log (IT capital stock)	-0.2176	0.3589**	-0.5765***	0.0051***
	(0.1666)	(0.1648)	(0.2138)	(0.0009)
Log (IT capital flow)	0.0869	-0.1026	0.1895	-0.0005
	(0.1316)	(0.1494)	(0.1947)	(0.0005)
Log (electricity cost)	-0.2641***	-0.3257***	0.0617	0.0069***
	(0.0921)	(0.1181)	(0.1553)	(0.0009)
Log (total capex)	0.3490***	-0.3661***	0.7151***	0.0080***
	(0.0531)	(0.0738)	(0.0876)	(0.0004)
Log (material cost)	0.0071	-1.411***	1.418***	0.0382***
	(0.1881)	(0.1674)	(0.2716)	(0.0013)
Log (fuel cost)	-0.1751*	-0.1776	0.0025	0.0014**
	(0.1057)	(0.1138)	(0.1160)	(0.0006)
Log (inventory)	-0.7437***	0.0185	-0.7622***	0.0009
	(0.0992)	(0.1160)	(0.1232)	(0.0007)
# establishments	7.336*	12.23***	-4.890	-0.0158**
	(4.370)	(2.454)	(3.587)	(0.0068)
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). All logged control variables are adjusted

by 1 to avoid zeros (i.e., measured as log (control variable+1). All variables are firm-state-CBSA-year aggregates. Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

As noted above, our baseline measures of labor flows have large standard deviations and substantial mass at zero. As a result, we evaluate the robustness of our results to alternative measures of labor flows. Table 3 presents the results using the labor flow as fraction of employment as dependent variables with the same control variables as in the baseline specification. The results in Table 3 are broadly consistent with the estimation in Table 2. The estimates imply that adoption of electronic networks is associated with a 0.3 percentage point decline in worker inflows (1.4% of mean, column 1), and a 2.0 percentage point decline in worker outflows (10.2% of mean, column 2). These declines in inflows and outflows are accompanied by a 1.75percentage point increase in net flows.

Table 3 Effects on labor flows as fraction of unit employment

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
E-network	-0.0028***	-0.0203***	0.0175***
	(0.0011)	(0.0013)	(0.0016)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

5.2 Robustness checks

We first examine the robustness of our results to key assumptions regarding variable measurement and sample construction. We then assess our identification assumptions by providing estimates from a timing falsification and instrumental variable analysis.

Alternative metrics for dependent variables:

In addition to levels and fraction of labor flows presented above, we assess robustness to several alternative metrics for our dependent variables. First, we winsorize the top 1%, 2.5%, 5% levels for levels of inflows, outflows, and net flows. The model estimates using these alternative measures are shown in Appendix Table C1, and the results remain consistent, although the magnitudes are generally attenuated.

We explore the robustness of our results to different transformations of our dependent variable, given the high standard deviation.[12] For each of our dependent variables in the baseline model, we calculate the inverse hyperbolic sine transformation and also construct a binary measure for whether the dependent variable exceeds the in-sample median. The results, shown in Appendix Table C2, are qualitatively consistent with our baseline findings.

Alternative model specifications:

In Appendix Table D1, we present specifications that probe the robustness of our results to different sets of model controls. First, in a more restricted specification, we show the results of excluding all controls except firm-state-CBSA employment and rerun our baseline regressions. Second, we include industry (3-digit NAICS)-year fixed effects to account for industry-specific time trends. All results are qualitatively consistent with the baseline findings.

[12] For a detailed discussion of these issues, see Chen and Roth (2024). Because of the large standard deviation of inflows and outflows relative to the mean other approaches, such as Poisson regression are inappropriate.

Prior work has argued that in large organizations older systems continue to be used even when new and better alternatives appear, leading to lock-in (e.g., Bresnahan et al. 1996). This is true for enterprise software systems like enterprise resource planning (Cho et al 2013), and may also apply to electronic networks. As a result, changes from adoption to unadoption in our data may reflect response error. In Appendix Table D2 we show the results of model estimates where we assume that electronic network adoption variable is an absorbing state, i.e. the state of adoption is assumed to remain "on" throughout the entire sample period. Again, the results are qualitatively robust to this change.

Pre-trend analysis:

One approach to understanding if observed effects are truly related to technology adoption is a timing falsification test. That is, observed effects should manifest after adoption and should not simply reflect differential trends prior to the adoption. To undertake this relative time model analysis (similar to event study approaches used in difference-in-differences studies), we construct a "stacked" data sample. We first linearly interpolate missing values for all variables as long as a firm-state-CBSA has at least two observations within our sample period and extract a five-year window for each firm-state-CBSA centered around the adoption date. We require a firm-state-CBSA to have at least one pre-treatment observation and one post-treatment observation to be in this five-year interpolated sample. We then calculate the propensity score of adopting the electronic networks for each firm-state-CBSA in this sample and match each treated unit with one nearest (in the adoption year) control unit without replacement.[13] The propensity score is estimated using a probit model based on covariates including firm-state-CBSA variables for average wage, age, IT capital expenditure, ratio of inventory to total value of shipments, and

[13] A firm-CBSA-state in the control group can be matched to different adopting firms in non-overlapping five-year windows.

total employment, and firm-level variables for total firm employment, an indicator for multi-establishment firm, and year fixed effects. This final matched sample contains about 45,000 firm-state-CBSAs and 218,000 firm-state-CBSA-years. The sample extends from 2004-2010, so that we could have a five year window for each "stack" of the data. Appendix Table E1 provides a comparison of covariates for treated and control units in this sample.

In Table E2 we provide estimates for worker flows (levels and fraction) and wages using this alternative stacked sample. The results are qualitatively similar, though sometimes weaker economically, for outflows and wages. For inflows and, by consequence, net flows, results differ somewhat from baseline estimates depending upon whether the dependent variable is based upon levels or fraction. However, given the lack of clear directional predictions for inflows from our model, the results are not inconsistent with our predictions.

With this matched stacked sample, we estimate a relative time model as specified below:

$$Y_{it} = \delta + \sum_{\tau=-2}^{+2} \rho_\tau \, Networks_{it,\tau} + \pi Z_{it} + \eta_i + \zeta_t + \epsilon_{it}$$

where $Networks_{it,\tau}$ is a dummy variable indicating whether year t is the τth before or after the adoption of electronic networks (so, $\tau = 0$ in the year of adoption). The set of coefficients ρ_τ show how the impact of electronic network adoption evolves and help understand if the observed effects happen after adoption or are continuation of trends that existed prior to adoption.

Appendix Table E3 exhibits the relative time results on labor flow and average wages. None of the coefficients before adoption are significantly different from zero. After the adoption of electronic networks, the labor inflow and labor outflow significantly decrease, while the average wages significantly increase. All these results suggest it is unlikely that pre-adoption trends confound our estimates of electronic network adoption.

Using instrumental variables for e-network adoption:

To address potential endogeneity concerns, we construct several instrumental variables motivated by approaches used in similar contexts in the literature. Our first instrument is an industry-level proxy of the adoption of electronic networks outside the focal state-CBSA, which is sometimes called a Bartik index (Bartik, 1991; Blanchard and Katz, 1992). For each location, we compute the mean propensity to adopt electronic networks adoption by industry using 3-digit NAICS, excluding the establishments in the focal location. We then sum these industry propensities up, using the percentage of establishments in each industry in the local county as weights. Formally, the instrument is equal to $\hat{\rho}_i = \sum_j \gamma_{ij}\ \hat{\theta}_{ij}$, where γ_{ij} is the share of establishments in industry *j* in location *i*, and $\hat{\theta}_{ij}$ is the average adoption rate for industry *j* excluding the establishments in location *i*. This Bartik index satisfies the correlation assumption of a valid IV because it reflects industry-level propensities to adopt electronic networks and variance in industry composition across locations. However, because it excludes any local information, it is expected to be uncorrelated with local labor demand or supply shocks that could simultaneously influence labor flows and technology adoption.

Our second instrument contains a set of zip-code- or state-level variables reflecting the cost of Internet access in the focal location, including terrain information, hybrid cost proxy model (HCPM), the number of connections ARPANET, and the year when a state adopted a price cap (Forman et al., 2012; Xu et al., 2019). These variables are highly correlated with the propensity of electronic networks adoption in the corresponding location but unlikely to be correlated with unobservables influencing labor flow and wage of the focal firm-state-CBSA.

5.3 Heterogeneous effects of electronic networks adoption

In this section we explore heterogeneity in our core results based on differences in worker and firm characteristics. Natural assumptions about how heterogeneity in these characteristics affect the replacement costs for workers and local labor market competition yield empirical predictions about how they affect average wage rates and worker flows. These predictions can also be motivated by our model, as discussed in Appendix F. Assessing the extent to which these predictions are consistent with our empirical results adds nuance to our core results, and provides additional confidence in the extent to which our baseline results can be characterized by the assumptions and mechanisms set forth in our model.

Worker characteristics:

Prior work has argued that IT investments may be complementary with skilled labor (Bresnahan, Brynjolfsson, and Hitt 2002; Autor, Levy, and Murnane 2003). If that is the case, then the retraining that we describe above that leads to higher replacement costs may be particularly relevant to skilled workers. In our model, this leads to a natural assumption that the impact of IT replacement costs for workers is higher for skilled workers. As an immediate consequence, the impact of electronic networks adoption on wages and worker outflows will be stronger (more positive on wages and more negative on outflows) for skilled workers than for unskilled workers. Intuitively, the work for skilled workers will be more directly affected, and so the mechanisms that we describe in Section 2 will be stronger for this group of workers.

We are not able to directly observe reliable information on individual employee's education or occupation, and thus we use high-wage and young employees as a proxy for those who are likely to be most affected by the adoption of electronic networks.[14] We use high wages

[14] Although there is education information in the LEHD data, it has been documented that the variable is imputed and will raise measurement error problems in previous literature (e.g., Barth et al., 2023).

because skilled workers have been shown to earn more, on average (Krussell et al 2000). Further, prior work has demonstrated that earnings for younger workers are affected more by capitalized software investment (Barth et al 2023).

We estimate the regressions analogous to those in the baseline specification in Table 2 but in a chow-test regression framework. For instance, to examine old workers, we define a dummy variable for workers who are at least 45 (age >= 45), duplicate the dataset and assign a dummy variable *old = 1* to the first copy and *old = 0* to the second. We create a new dependent variable

$$\text{inflow age} = \begin{cases} \text{total old worker inflow, if old} = 1 \\ \text{total young worker inflow, if old} = 0 \end{cases}$$

and interact all the independent variables with the dummy variable, *old*. We construct similar variables for outflow, net flow, and average wages, respectively. We repeat this process for workers in high vs low wage groups.

Table 4 presents the analysis of heterogeneity across young and old employees.[15] Column (1) to Column (3) show that the negative effects of electronic network adoption on outflows and inflows is exclusive to young employees. Among older employees, electronic networks adoption has no statistically significant effect on outflows and a positive one on inflows. Similarly, Column (4) shows that the increase in average wage following the adoption of electronic networks is much stronger for young employees, in line with expectations.

[15] Age 45 has been used in previous literature as a threshold for old workers (e.g., Bersin and Chamorro-Premuzic, 2019; McGee and Wegman, 2004).

Table 4 Heterogeneity by employee age

	(1)	(2)	(3)	(4)
	Inflow	Outflow	Net Flow	Avg. Wage
Old Dummy* E-network	1.712***	0.6576*	1.054***	-0.0970***
	(0.4870)	(0.3811)	(0.3189)	(0.0078)
E-network	-1.260***	-0.8998***	-0.3597*	0.1036***
	(0.2570)	(0.2232)	(0.1996)	(0.0062)
Implied net effect of E-networks for old workers	0.4520*	-0.2422	0.6942***	0.0066
	(0.2652)	(0.1989)	(0.1933)	(0.0056)
Control for firm-location size	Y	Y	Y	Y
All other controls	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	948000	948000	948000	948000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

In Table 5 we examine heterogeneity in adoption effects based on employee wages. We classify an individual employee as high-wage employee if her wage was above the median value of wage in our full sample. Consistent with expectations and model predictions, the negative effects of electronic networks on outflows and positive effects on average wages are exclusive to high wage workers. Low wage workers experience no statistically significant change in outflows and no change in average wages.

Table 5 Heterogeneity by employee wage levels

	(1)	(2)	(3)	(4)
	Inflow	Outflow	Net Flow	Avg. Wage
High wage Dummy * E-network	-2.051***	-1.780***	-0.2712	0.0317*
	(0.4578)	(0.3457)	(0.3670)	(0.0166)
E-network	0.6216**	0.3188	0.3028	-0.0069
	(0.2278)	(0.1965)	(0.2036)	(0.0129)
Implied net effect of E-networks for high-wage workers	-1.429***	-1.461***	0.0316	0.0248***
	(0.2659)	(0.1947)	(0.2285)	(0.0093)
Control for firm-location size	Y	Y	Y	Y
All other controls	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	948000	948000	948000	948000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Employer and location characteristics:

Next, we examine the heterogeneous effects of electronic network adoption by employer characteristics. In Table 6 we explore the heterogeneity in our baseline effects between employers located in urban and in rural areas. In urban locations, competition for outside workers is likely to be stronger. As a result, firms adopting a new technology that increases replacement costs may pay even higher wages in urban areas, relative to adopters in rural areas. As shown in the Appendix F, in our model the impact of IT adoption on wages and labor outflow depends on two key parameters: (1) the fraction of workers that receive an outside offer, and (2) the lower bound of the wage offer distribution. In urban areas, we expect both these parameters to be higher, leading to a larger decline in outflows and greater wage increase after the adoption of electronic networks.

We define an urban indicator variable for employers located in a Metropolitan Statistical Areas, and interact this variable with the adoption of electronic networks. The estimated results in Table 6 show that the effects of electronic networks on worker retention and wages are stronger in urban areas than in rural areas. In rural areas, electronic networks adoption has no statistically significant effect, though it does have a (smaller) positive effect on wages. Thus, the results are consistent with our predictions.

Table 6 Heterogeneity across urban and rural areas

	(1)	(2)	(3)	(4)
	Inflow	Outflow	Net Flow	Avg. Wage
Urban Dummy * E-network	-0.8434**	-0.7354**	-0.108	0.0120***
	(0.4272)	(0.3713)	(0.4194)	(0.0046)
E-network	-0.1239	-0.5542	0.4303	0.0116***
	(0.3665)	(0.3413)	(0.3561)	(0.0043)
Implied net effect of E-networks	-0.9674***	-1.290***	0.3223	0.0235***
for urban firm-state-CBSA	(0.2175)	(0.2014)	(0.2606)	(0.0019)
Control for firm-location size	Y	Y	Y	Y
All other controls	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

In Table 7, we explore differences in local labor market competition through a different approach, using state-level variance in the strength of enforceability of non-compete agreements (NCA). Employers in states with stronger NCA enforcement may face a lower risk of employee departures. As a result, the increase in wages offered by adopters in high enforcement states is likely to be lower, relative that offered by adopters in states with weaker NCA enforcement. This

In our model (see Appendix F), this intuition is captured by the assumption that a lower fraction of workers receive outside offers in states with stronger NCA enforcement. Then, the positive impact of adoption on wages (which is mediated by this fraction) will be lower in states with stronger NCA enforcement. This will lead to a weaker (less negative) effect on worker outflows.

We use the state-level NCA enforceability measure developed by Hausman and Lavetti (2021), which calculates the weighted sum of scores for seven components of enforceability based on case law and normalize the measures by each component's maximum value.[16] Higher values of the NCA variable indicate stronger enforceability. Consistent with expectations, the estimated results in Table 7 show that employers in states with stronger NCA enforceability experience smaller wage increases following the adoption of electronic networks than those in states with weaker enforceability. However, we do not find significant differences regarding the effects of electronic network adoption on labor flows.

Table 7 Heterogeneity by NCA enforceability

	(1)	(2)	(3)	(4)
	Inflow	Outflow	Net Flow	Avg. Wage
NCA * E-network	1.06	-1.35	2.41	-0.0179*
	(1.501)	(1.353)	(1.835)	(0.0104)
E-network	-1.606	-0.1256	-1.48	0.0349***
	(1.161)	(1.011)	(1.405)	(0.0081)
Implied net effect of E-networks	-0.5456	-1.476***	0.9298*	0.0170***
allowing for NCA differences	(0.4026)	(0.4010)	(0.5045)	(0.0031)
Control for firm-location size	Y	Y	Y	Y
All other controls	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are

[16] Details in Hausman and Lavetti (2021) online Appendix Table A2.

approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Prior work has argued that the benefits of firm IT investments may vary with firm size (Bessen 2022; Tambe and Hitt 2012; Tambe et al 2020; Lashkari et al 2024). Therefore, a natural question is whether and how we expect the impact of electronic networks adoption to vary with firm size. However, the relationship between IT, firm size, and performance is complex, and attempts to unpack the source of size differences and isolate their effects from other factors that covary with size are challenging.[17] The richness of the implications of firm size also appears in our model, in which firm size and technology adoption can influence outcomes both through their effects on productivity as well as their implications for replacement costs.[18]

Given this ambiguity, we explore heterogeneity in our core results based on the size of the firm-state-CBSA but without clear ex ante predictions. We define a firm-state-CBSA as "small" if its first observed employment value in our data is below the median value of the firm-state-CBSA employment. The results in Table 8 show that the effects of electronic networks adoption on worker inflows and outflows are weaker in small firm units, but the effect on average wages is stronger. This mixed pattern appears to be a consequence of naturally lower levels of labor flows in smaller firms. Notably, when we re-estimate the regression models using labor flows expressed as fractions of employment (see Appendix Table B3), the effects on labor flows become stronger for small firm units. This suggests that, while absolute changes in labor

[17] These issues are discussed at length in Jin and McElheran (2025), who note that size may influence the effects of IT investment through economies of scale (e.g., Bresnahan, Brynjolfsson, and Hitt 2002) and adjustment costs (e.g., Bresnahan and Greenstein 1996), among other factors, but also that size differences could reflect the effects of alternative firm features that may covary with size, such as firm age.

[18] In particular, the predictions from the model would depend on whether (i) smaller or larger firms experience greater productivity gains, and (ii) smaller or larger firms experience greater increase in replacement costs following e-networks adoption. The empirical literature is unclear about this for information technology investments in general (Jin and McElheran 2025).

flows are smaller in small firm units compared to larger ones, these shifts represent a larger proportional change relative to their total employment.[19]

Table 8 Heterogeneity by firm subunit size

	(1)	(3)	(5)	(7)
	Inflow	Outflow	Net Flow	Avg. Wage
Small Dummy* E-network	0.8336***	0.8129***	0.0207	0.0224***
	(0.2839)	(0.2610)	(0.3432)	(0.0038)
E-network	-0.8954***	-1.157***	0.2611	0.0133***
	(0.2789)	(0.2656)	(0.3408)	(0.0022)
Implied net effect of E-networks	-0.0619	-0.3437***	0.2818***	0.0356***
for small firm-state-CBSA	(0.0832)	(0.0549)	(0.0758)	(0.0031)
Control for firm-location size	Y	Y	Y	Y
All other controls	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N of obs	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

6. Discussion and Conclusion

Electronic networks represent a transformative IT technology with substantial documented impacts on firm performance and growth (e.g., Fort 2017, Fort et al. 2018). Importantly, electronic networks share critical features with other major IT systems, such as enterprise resource planning, notably the need for extensive complementary investments in

[19] In addition to the heterogeneity by firm-location size, we also reran the regression models using labor flows as fractions of employment for all the other heterogeneity analyses, with results reported in Appendices A and B. The estimated results are broadly consistent with the ones using levels in most cases. However, one exception is that the high-wage worker inflow expressed as a fraction of employment is positively associated with the adoption of electronic networking technologies. Note that in our model there are contrasting effects of technology adoption on inflows: increased productivity has a positive impact, while higher replacement costs exert a negative influence. As a result, the net effect on inflows remains ambiguous

organizational processes and considerable firm-specific tailoring during adoption. These characteristics entail significant idiosyncratic employee training and reskilling, which in turn elevate worker replacement costs for adopting firms.

To understand the implications of how such technology adoption should affect worker inflows, outflows, and wages, we develop a parsimonious model that extends the standard monopsony wage setting framework by explicitly accounting for replacement costs. Consistent with the predictions of our model, we find that firms respond to higher worker replacement costs associated with the adoption of electronic networks by increasing wages and curbing both employee inflows and outflows, thereby reducing turnover and fostering retention. Notably, these effects are more pronounced among younger, high-wage workers and in urban areas, suggesting that local labor market dynamics and skill requirements mediate outcomes.

Taken together, our findings extend prior work along two lines. First, we provide a more granular look at how firm size changes occur around IT adoption by moving beyond net employment growth and examining the underlying worker flows. While a growing literature links IT investments to larger firms (Aghion et al., 2019; Autor et al., 2020; Bessen, 2020; Basker and Simcoe, 2021; Dixon, Wang, and Wu, 2021; Fort et al., 2018), it has largely focused on changes in firm size rather than the inflows and outflows through which those changes occur. Our results point to a more nuanced and counterintuitive pattern: employment growth following IT adoption appears to operate primarily through worker retention (lower outflows), rather than through increased hiring. This suggests that a fuller understanding of technology-driven firm expansion may require accounting for turnover and retention mechanisms employed by firms. These findings also bring to the fore the role of these mechanisms in firm growth more generally

(e.g., Sivasadan et al., 2025) and raise the question of how much growth occurs through improved retention rather than expanded hiring, and under what conditions.

Second, our work also extends prior work by linking IT adoption to broader organizational changes beyond productivity, specifically through adjustments in human capital management. In this regard, our results imply an important role for replacement costs in determining human capital flows associated with IT adoption. To our knowledge, prior studies have not explicitly highlighted this aspect. Thus, our findings connect the literature on worker mobility and retention incentives to the organizational changes triggered by IT adoption. Specifically, the results suggest that IT adoption represents a juncture at which firm-specific human capital becomes especially important (Bartel, Ichniowski, and Shaw, 2007) and the costs of worker replacement rise, strengthening firms' incentives to use compensation, and potentially mechanisms such as retention strategies, training investments, and other HR practices, to reduce turnover (Campbell et al., 2011; Kryscynski, 2021; Friebel et al., 2022).

Turning to the implications of our study, the findings further underscore the complementarities between IT and human resource practices emphasized in prior studies such as Bartel, Ichniowski, and Shaw (2007). By highlighting the role of replacement and turnover costs, we show that IT adoption does not operate solely through productivity and output expansion, but also through adjustments in wages. While prior work has documented complementarities between IT and organizational change, our contribution is to identify worker retention and replacement costs as a mechanism shaping firm behavior following adoption.

From a broader perspective, these dynamics also have implications for technology diffusion. If IT adoption raises the value of firm-specific human capital, as we find, firms may respond by retaining workers more aggressively. This will potentially slow labor reallocation

across firms, and consequently slow technology diffusion. Thus, training systems that expand the supply of workers with relevant skills in reducing replacement frictions and facilitating diffusion of new technologies may become more policy-relevant.

Although our findings provide valuable insights, they must be interpreted cautiously. Our findings may generalize to a broader class of technologies that share key elements with electronic network adoption—namely, those involving "systems change": technologies that reconfigure processes and foster interdependence among organizational units, such as ERP and major business software systems. However, emerging AI technologies, particularly generative AI, may differ fundamentally. For example, tools that automate discrete tasks, like copyediting, represent more straightforward task substitution rather than deep, organization-wide systems change. In our study, retention effects were strongest among skilled workers, likely because their expertise complemented the newly adopted technology. In contrast, early evidence suggests generative AI may substitute for skilled labor. Given the ongoing evolution in technology, there is considerable uncertainty about whether such technologies will require the same complementary investments in processes, human capital, and training as e-network adoption did. Further, as AI technologies approach general intelligence, they may require less initial employee training and could even directly facilitate on-the-job learning and mentoring, potentially reducing worker replacement costs. AI also has the potential to generate demand for entirely new skill sets and job categories, further complicating the impact of adoption on human capital flows.

In addition to the focus on a specific technology as discussed above, our study has some important limitations, which suggest avenues for further research. First, while our framework emphasizes changes in worker human capital following IT adoption, we do not directly observe worker-level skill content or task reallocation for workers within firms. Hence, we cannot

disentangle whether the observed lower outflows pertain only to some kinds of workers or more broadly. Analyses using such direct measures of skill and task evolution can complement our study and yield new insights. Second, given the scope of our work, we do not track mobility or long-run wage trajectories of individual workers. Nor have we examined within-firm differences in wages of workers. Future work linking firm IT adoption decisions to such worker-level paths and outcomes could provide a richer understanding of these dynamics.

In conclusion, this study advances our understanding of how IT adoption affects worker flows by highlighting the role of retention incentives created by higher replacement and turnover costs as separate from productivity-driven size changes studied thus far. By doing so, we hope it encourages further research into the organizational and labor-market mechanisms through which technological change reshapes dynamics of human capital.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial Intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1), S293-S340.

Alekseeva, L., Azar, J., Gine, M., & Samila, S. (2024). The demand for AI skills in the labor market. *Labour Economics*, 71, 102002.

Allen, R., & Choudhury, P. (2022). Algorithm-augmented work and domain experience: The countervailing forces of ability and aversion. *Organization Science*, 33(1), 149-169.

Aral, S., Brynjolfsson, E., Gu, C., Wang, H., & Wu, D. J. (2024). Understanding the returns from integrated enterprise systems: The impacts of agile and phased implementation strategies. *MIS Quarterly*, 48(2).

Atalay, E., Hortaçsu, A., & Syverson, C. (2014). Vertical integration and input flows. *American Economic Review*, 104(4), 1120-1148.

Athey, Susan and Scott Stern. 2002. The Impact of Information Technology on Emergency Health Care Outcomes. *RAND Journal of Economics,* 33(3): 399-432.

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

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5), 1553–1597.

Autor, D.H., Levy, F., & Murnane, R.J. (2003) The Skill Content of Recent Technological Change: An Empirical Exploration, *Quarterly Journal of Economics*, 118(4), 1279-1333

Babina, T., Fedyk, A., & He, A. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. *Research Policy*, 48(8), 103765.

Bartel, Ann, Ichniowski, C, and Shaw, Kathryn (2007) How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *Quarterly Journal of Economics*, 1721-1758.

Barth, E., Davis, J. C., Freeman, R. B., & McElheran, K. (2023). Twisting the demand curve: Digitalization and the older workforce. *Journal of Econometrics*, 233(2), 443-467.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?.

Bersin, J., & Chamorro-Premuzic, T. (2019, September 26). The case for hiring older workers. Harvard Business Review. https://hbr.org/2019/09/the-case-for-hiring-older-workers

Bessen, James. 2019. *Learning By Doing: The Real Connection between Innovation, Wages, and Wealth*. Yale University Press.

Bessen, J. (2022) *The new goliaths: How corporations use software to dominate industries, kill innovation, and undermine regulation*. Yale University Press.

Bjelland, M., Fallick, B., Haltiwanger, J., & McEntarfer, E. (2011). Employer-to-employer flows in the United States: estimates using linked employer-employee data. *Journal of Business & Economic Statistics*, 29(4), 493-505.

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings papers on economic activity*, 1992(1), 1-75.

Blatter, M., Muehlemann, S., & Schenker, S. (2012). The costs of hiring skilled workers. *European Economic Review*, 56(1), 20-35.

Blatter, M., Muehlemann, S., Schenker, S., & Wolter, S. C. (2016). Hiring costs for skilled workers and the supply of firm-provided training. *Oxford Economic Papers*, 68(1), 238-257.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2012. Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review* 102(1): 167-201.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen (2012) Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review* 102(1): 167-201.

Bloom, N., Ohlmacher, S. W., Tello-Trillo, C. J., & Wallskog, M. (2021). Pay, productivity and management (No. w29377). *National Bureau of Economic Research*.

Boushey, Heather and Sarah Jane Glynn. (2012). There are Significant Business Cost to Replacing Employees. Available at https://www.americanprogress.org/wp-content/uploads/sites/2/2015/08/CostofTurnover0815.pdf.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics*, 117(1), 339–376.

Bresnahan, Timothy F. (2019) Technological change in ICT in light of ideas first learned about in the machine tool industry. *Industrial and Corporate Change* 28(2): 331-349.

Bresnahan, Timothy F and Greenstein, Shane. (1996) Technical progress and co-invention in computing and in the uses of computers. *Brookings Papers in Economic Activity*, 1-83.

Bresnahan, Timothy F, Brynjolfsson, Erik, and Hitt, Lorin. 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Quarterly Journal of Economics* 117(1): 339-376.

Bresnahan, T., Greenstein, S., Brownstone, D., & Flamm, K. (1996). Technical progress and co-invention in computing and in the uses of computers. *Brookings Papers on Economic Activity. Microeconomics*, 1996, 1-83.

Bresnahan, T.F., Brynjolfsson, E., & Hitt, L.M. (2002) Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence, *Quarterly Journal of Economics*, 117(1), 339-376.

Brynjofsson, Erik and Lorin M. Hitt. 2003. Computing Productivity: Firm-Level Evidence. *Review of Economics and Statistics* 85(4): 793-808.

Brynjolfsson, E., Jin, W., & McElheran, K. (2021). The power of prediction: Predictive analytics, workplace complements, and business performance. *Business Economics*, 56, 217–239.

Brynjolfsson, E., Jin, W., & Wang, L. (2023). Information technology, firm size, and industrial concentration. No. w31065. National Bureau of Economic Research.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda* (pp. 23–57). University of Chicago Press.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2021. The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics* 13(1): 333-372.

Brynjolfsson, Erik, Rock, Daniel, and Syverson, Chad (2021) The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics* 13(1): 333-372.

Brynjolfsson, E., Jin, W., & Wang, X. (2023). Information technology, firm size, and industrial concentration (No. w31065). National Bureau of Economic Research.

Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, *33*(1), 65-87.

Carnahan, S., Agarwal, R., & Campbell, B. A. (2012). Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal*, *33*(12), 1411-1430.

Chari, VV and Hopenhayn, H (1991) Vintage human capital, growth, and the diffusion of new technology. *Journal of Political Economy* 99(6): 1142-1165.

Chen, R., Balasubramanian, N., & Forman, C. (2024). How does worker mobility affect business adoption of a new technology? The case of machine learning. *Strategic Management Journal*, 45, 1510-1538.

Chen, J., & Roth, J. (2024). Logs with zeros? Some problems and solutions. *Quarterly Journal of Economics*, 139(2), 891-936.

Cho W, Subramanyam R, Xia M (2013) Vendors' incentives to invest in software quality in enterprise systems. *Decision Support Systems* 56: 27–36. https://doi.org/10.1016/j.dss.2013.04.005

Choudhury, P., Starr, E., & Agarwal, R. (2020). Machine learning and human capital complementarities: Experimental evidence on bias mitigation. *Strategic Management Journal*, 41(8), 1381–1411.

Criscuolo, Chiara, Peter Gal, Time Leidecker, and Giuseppe Nicoletti. 2021. The Human Side of Productivity: Uncovering the Role of Skills and Diversity for Firm Performance. OECD Productivity Working Papers No. 29.

Davis, S.J., Haltiwanger, J.C., & Schuh, S. (1998) Job creation and destruction. MIT Press Books.

Decker R, Haltiwanger J, Jarmin R, Miranda J (2014) The role of entrepreneurship in U.S. job creation and economic dynamism. *Journal of Economic Perspectives*, 28(3): 3-24.

Decker R, Haltiwanger J, Jarmin R, Miranda J (2017) Declining dynamism, allocative efficiency, and the productivity slowdown. *American Economic Review*, 107(5): 322-326.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in US job creation and economic dynamism. *Journal of Economic Perspectives*, 28(3), 3–24.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2017). Declining dynamism, allocative efficiency, and the productivity slowdown. *American Economic Review*, 107(5), 322–326.

Dixon, J., Hong, B., & Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science*, 67(9), 5586-5605.

Doms, M., Jarmin, R. S., & Klimek, S. D. (2004). Information technology investment and firm performance in US retail trade. *Economics of Innovation and New Technology*, 13(7), 595–613.

Dranove, David, Forman, Chris, Goldfarb, Avi, and Greenstein, Shane (2014) The Trillion Dollar Conundrum: Complementarities and Health Information Technology. *American Economic Journal: Economic Policy* 6(4): 239-270.

Dube, Arindrajit, Eric Freeman, and Michael Reich. 2010. Employee Replacement Costs. IRLE Working Paper 201-10. Available at https://irle.berkeley.edu/wp-content/uploads/2010/03/Employee-Replacement-Costs.pdf .

Feigenbaum, James and Gross, Daniel. P. (2024a). Answering the call of automation: How the labor market adjusted to mechanizing telephone operation. *Quarterly Journal of Economics*, 139(3), 1879-1939.

Feigenbaum, James and Gross, Daniel. P. (2024b) Organizational and Economic Obstacles to Automation: A Cautionary Tale from AT&T in the Twentieth Century. *Management Science* 70(12): 8520-8540.

Forman, C., & McElheran, K. (2024). Product chain organization in the digital age: Information technology use and vertical integration in US manufacturing. *Management Science*, 71(2):1027-1049.

Forman, Chris and McElheran, Kristina. 2025. Production Chain Organization in the Digital Age: Information Technology Use and Vertical Integration in U.S. Manufacturing. *Management Science* 71(2): 1027-1049.

Forman, C., Goldfarb, A., & Greenstein, S. (2012). The Internet and local wages: A puzzle. *American Economic Review*, 102(1), 556-575.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2005. How did location affect adoption of the commercial Internet? Global village vs. urban leadership. *Journal of Urban Economics* 58: 389-420.

Forman, C., & McElheran, K. (2025). Production chain organization in the digital age: information technology use and vertical integration in US manufacturing. *Management Science*, 71(2), 1027-1049.

Forman, Chris and van Zeebroeck, Nicolas. 2012. From Wires to Partners: How the Internet Has Fostered R&D Collaborations within Firms. *Management Science* 58(8): 1549-1568.

Fort, T. C., Pierce, J. R., & Schott, P. K. (2018). New perspectives on the decline of US manufacturing employment. *Journal of Economic Perspectives*, 32(2), 47-72.

Fort, T. C. (2017). Technology and production fragmentation: Domestic versus foreign sourcing. *Review of Economic Studies*, 84(2), 650-687.

Friebel, G., Heinz, M., & Zubanov, N. (2022). Middle managers, personnel turnover, and performance: A long-term field experiment in a retail chain. *Management Science*, *68*(1), 211-229.

Greenwood, Brad N, Kartik K Ganju, and Corey M. Angst. (2019) How Does the Implementation of Enterprise Information Systems Affect a Professional's Mobility? An Empirical Study. *Information Systems Research* 30(2): 563-594.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, 95(2), 347–361.

Hausman, N., & Lavetti, K. (2021). Physician practice organization and negotiated prices: evidence from state law changes. *American Economic Journal: Applied Economics*, 13(2), 258-296.

Hendricks, K. B., Singhal, V. R., & Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *Journal of Operations Management*, 25(1), 65-82.

Hitt, L. M. (1999). Information technology and firm boundaries: Evidence from panel data. *Information Systems Research*, 10(2), 134–149.

Hyatt, H. R., McEntarfer, E., McKinney, K. L., Tibbets, S., & Walton, D. (2014). Job-to-job (J2J) flows: New labor market statistics from linked employer-employee data. US Census Bureau Center for Economic Studies Paper No. CES-WP-14-34.

Ilmakunnas, Pekka, Mika Maliranta, and Jari Vainiomäki. 2004. The Roles of Employer and Employee Characteristics for Plant Productivity. *Journal of Productivity Analysis* 21(3): 249-276.

Im, K.S., Grover, V., & Teng, J.T. (2013). Research note - Do large firms become smaller by using information technology? *Information Systems Research*, 24(2), 470–491.

Jin, W & McElheran K. (2025) Economies Before Scale: I.T. Strategy and Performance Dynamics of Young U.S. Businesses. *Management Science* 71(9): 7449-7473.

Juhn, C., McCue, K., Monti, H., & Pierce, B. (2018). Firm performance and the volatility of worker earnings. *Journal of Labor Economics*, 36(S1), S99-S131.

Kim, S. (2025). Workers' Job Prospects and Young Firm Dynamics. US Census Bureau, Center for Economic Studies.

Kline, Patrick M. (2025). Labor Market Monopsony: Fundamentals and Frontiers. NBER Working Paper 33467.

Kryscynski, D. (2021). Firm-specific worker incentives, employee retention, and wage–tenure slopes. *Organization Science*, *32*(2), 352-375.

Krusell, P., Ohanian, L.E., Ríos-Rull, J.V., & Violante, G.L. (2000). Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68(5), 1029-1053.

Lashkari D, Bauer A, Boussard J (2024) Information technology and returns to scale. *American Economic Review* 224(6): 1769-1815.

McElheran, K. (2014). Delegation in multi-establishment firms: Evidence from I.T. purchasing. *Journal of Economics & Management Strategy*, 23(2), 225–258.

McElheran, K. (2015). Do market leaders lead in business process innovation? The case(s) of e-business adoption. *Management Science*, 61(6), 1197–1216.

McElheran, K. S., Bai, J., Jin, W., & Williams, R. (2023). The Effects of Technology Adoption on Firms, Supply Chains, and Rivals. In *Academy of Management Proceedings* (Vol. 2023, No. 1, p. 19351). Briarcliff Manor, NY 10510: Academy of Management.

McElheran, Kristina. 2015. Do Market Leaders Lead in Business Process Innovation? The Case(s) of E-business Adoption. *Management Science* 61(6): 1197-1216.

McGee, J. P., & Wegman, D. H. (Eds.). (2004). Health and safety needs of older workers.

Parker, B (1999) An overview of the sell-side e-commerce market. Report, AMR Research, Boston.

Patki, D. (2025). Breaking the Implicit Contract: Using Pension Freezes to Study Lifetime Labor Supply. *Journal of Political Economy Macroeconomics*, 3(3), 305-342.

Payne, Graham and Allen, Brandt R. 1999. Dell Computer: Business to Business Over the Web. Darden Business Publishing, University of Virginia.

Rosenberg, Nathan (1963) Technological change in the machine tool industry, 1840-1910. *Journal of Economic History* 23(4): 414-443.

Schultz, B (1999) Tooling along online: Metalworking products maker Milacron wins our debut E-Comm Innovator Award. Network World (February 22), 55,56, 58.Syverson, Chad. 2011. What Determines Productivity? *Journal of Economic Literature* 49(2): 326-365.

Tambe, P. (2014). Big data investment, skills, and firm value. *Management Science*, 60(6), 1452–1469.

Tambe, P., & Hitt, L. M. (2014). Job hopping, information technology spillovers, and productivity growth. *Management Science*, 60(2), 338–355.

Tambe, Prasanna and Lorin M. Hitt. 2012. The Productivity of Information Technology Investments: New Evidence from IT Labor Data. *Information Systems Research* 23(3-1): 599-617.

Tambe, Prasanna and Hitt, Lorin M. (2012) The productivity of information technology investments: New evidence from IT labor data. *Information Systems Research* 23(3-part 1): 599-617.

Tambe, Prasanna, Hitt Lorin, Rock Daniel, and Brynjolfsson Erik (2020) Digital capital and superstar firms. NBER Working Paper 28285. National Bureau of Economic Research, Cambridge, MA.

Tate, G., & Yang, L. (2015). The bright side of corporate diversification: Evidence from internal labor markets. *Review of Financial Studies*, 28(8), 2203-2249.

Teach, E (1999) Setting up cybershop. CFO. (October 1), 101, 102, 105.

Törnqvist, L., Vartia, P., & Vartia, Y.O. (1985) How should relative changes be measured?. The American Statistician, 39(1), 43-6.

Xu, J., Forman, C., & Hu, Y. J. (2019). Battle of the internet channels: How do mobile and fixed-line quality drive internet use?. *Information Systems Research*, 30(1), 65-80.

Appendix A Heterogeneous effects on fraction of labor flows by employee characteristics

Table A1 Effects on fraction of labor flows by employee age

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
Old Dummy * E-network	0.0027***	0.0033***	-0.0006
	(0.0007)	(0.0007)	(0.0006)
E-network	-0.0028***	-0.0118***	0.0090***
	(0.0007)	(0.0007)	(0.0009)
Implied net effect of E-networks	-0.0000	-0.0085***	0.0084***
for old workers	(0.0006)	(0.0007)	(0.0008)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	948000	948000	948000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate
per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A2 Effects on fraction of labor flows by employee wage

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
High wage Dummy * E-network	0.0076***	-0.0039***	0.0116***
	(0.0008)	(0.0008)	(0.0009)
E-network	-0.0052***	-0.0082***	0.0029***
	(0.0006)	(0.0007)	(0.0008)
Implied net effect of E-networks	0.0024***	-0.0121***	0.0145***
for high-wage workers	(0.0007)	(0.0008)	(0.0010)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	948000	948000	948000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix B Heterogeneous effects on fraction of labor flows by employer characteristics

Table B1 Effects on fraction of labor flows between urban and rural areas

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
Urban Dummy * E-network	-0.0009	-0.0066**	0.0058
	(0.0027)	(0.0033)	(0.0039)
E-network	-0.0022	-0.0149***	0.0127***
	(0.0026)	(0.0030)	(0.0037)
Implied net effect of E-networks	-0.0030***	-0.0215***	0.0185***
for urban firm-state-CBSA	(0.0011)	(0.0014)	(0.0017)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table B2 Effects on fraction of labor flows by NCA enforceability

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
NCA * E-network	0.0081	-0.0146**	0.0227***
	(0.0061)	(0.0070)	(0.0087)
E-network	-0.0089*	-0.0093*	0.0004
	(0.0048)	(0.0054)	(0.0068)
Implied net effect of E-networks	-0.0008	-0.0239***	0.0230***
allowing for NCA differences	(0.0018)	(0.0021)	(0.0026)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table B3 Effects on fraction of labor flows by firm-location size

	(1)	(2)	(3)
	Inflow	Outflow	Net Flow
Small Dummy * E-network	-0.0108***	-0.0135***	0.0028
	(0.0024)	(0.0028)	(0.0034)
E-network	-0.0011	-0.0157***	0.0146***
	(0.0011)	(0.0014)	(0.0018)
Implied net effect of E-networks	-0.0119***	-0.0293***	0.0174***
for small firm-state-CBSA	(0.0021)	(0.0025)	(0.0030)
Control for firm-location size	Y	Y	Y
All other controls	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y
Year FE	Y	Y	Y
N of obs	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix C Alternative metrics for dependent variables

Table C1 Effects on winsorized labor flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Inflow			Outflow			Net Flow		
	1%	2.5%	5%	1%	2.5%	5%	1%	2.5%	5%
E-network	-0.5847***	-0.4912***	-0.3613***	-0.8112***	-0.6796***	-0.5308***	0.2265**	0.1884**	0.1695***
	(0.1005)	(0.0752)	(0.0545)	(0.0818)	(0.0590)	(0.0425)	(0.1132)	(0.0862)	(0.0625)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y	Y	Y
All other controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N of obs	474000	474000	474000	474000	474000	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000	179000	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit.
The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy).
Robust standard errors in parentheses, clustered at firm level.
* p<0.1, ** p<0.05, *** p<0.01.

Table C2 Effects on labor flows and wages (alternative DV metrics)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inflow		Outflow		Net Flow		Avg. Wage	
	IHS	Above median	IHS	Above median	IHS	Above median	IHS	Above median
E-network	-0.0090*	-0.0015	-0.0401***	-0.0099***	0.0520***	0.0111***	0.0223***	0.0249***
	(0.0049)	(0.0021)	(0.0039)	(0.0019)	(0.0142)	(0.0030)	(0.0019)	(0.0024)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y	Y
All other controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N of obs	474000	474000	474000	474000	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix D Alternative model specifications

Table D1 Effects on labor flows and wages (alternative model specifications)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Inflow				Outflow				Net Flow				Avg. Wage	
	Level	Fraction	Level	Fraction	Level	Fraction	Level	Fraction	Level	Fraction	Level	Fraction	log	log
E-network	-1.092***	-0.0067***	-0.8726***	-0.0037***	-1.507***	-0.0230***	-1.128***	-0.0203***	0.4146	0.0164***	0.2553	0.0166***	0.0271***	0.0206***
	(0.2067)	(0.0011)	(0.1866)	(0.0011)	(0.2186)	(0.0013)	(0.1831)	(0.0013)	(0.2619)	(0.0016)	(0.2276)	(0.0016)	(0.0018)	(0.0018)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
All other controls	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y			Y	Y			Y	Y			Y	
INDUSTRY*YEAR FE			Y	Y			Y	Y			Y	Y		Y
N of obs	474000	474000	474000	474000	474000	474000	474000	474000	474000	474000	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000	179000	179000	179000	179000	179000	179000	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table D2 Effects on labor flows and wages (absorbing state)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inflow		Outflow		Net Flow		Avg. Wage
	Level	Growth	Level	Growth	Level	Growth	Logarithm
E-network (absorbing)	-0.9199***	-0.0046***	-0.6126***	-0.0108***	-0.3073	0.0062***	0.0148***
	(0.3185)	(0.0013)	(0.2165)	(0.0013)	(0.2932)	(0.0017)	(0.0022)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y
All other controls	Y	Y	Y	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y	Y	Y	Y
N of obs	474000	474000	474000	474000	474000	474000	474000
N of firm-state-CBSAs	179000	179000	179000	179000	179000	179000	179000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix E Alternative "stacked" sample

Table E1 Covariates Balance Check

	Mean		
Variable	Control	Treated	T-statistic
log avg. wage	7.234	7.237	-0.1886
age	18.42	18.42	-0.0517
log IT capital flow	1.684	1.684	0.0272
inventory to tvs ratio	0.116	0.119	-1.056
log total firm employment	4.211	4.227	-0.8952
log total firm-location employment	3.653	3.679	-2.195**
multi-unit	0.361	0.361	-0.0196
N of obs	218000		
N of firm-state-CBSAs	45000		

Table E2 Effects on labor flows and wages (alternative "stacked" sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inflow		Outflow		Net Flow		Avg. Wage
	Level	Fraction	Level	Fraction	Level	Fraction	Logarithm
E-network (absorbing)	0.1188	-0.0050***	-0.6468***	-0.0064***	0.7656**	0.0014	0.0039*
	(0.3112)	(0.0014)	(0.2316)	(0.0014)	(0.3871)	(0.0018)	(0.0022)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y
All other controls	Y	Y	Y	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N of obs	218000	218000	218000	218000	218000	218000	218000
N of firm-state-CBSAs	45000	45000	45000	45000	45000	45000	45000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit.
The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy).
Robust standard errors in parentheses, clustered at firm level.
* p<0.1, ** p<0.05, *** p<0.01.

Table E3 Event study for the effects of electronic network adoption on labor flows and wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inflow		Outflow		Net Flow		Avg. Wage
	Level	Fraction	Level	Fraction	Level	Fraction	Logarithm
t=-1 * E-network (absorbing)	0.066	-0.0005	0.2058	-0.0037**	-0.1398	0.0032	0.0042
	(0.3822)	(0.0021)	(0.2799)	(0.0017)	(0.3575)	(0.0025)	(0.0028)
t=0 * E-network (absorbing)	-0.0917	-0.0033	-0.8609	-0.0069***	0.7692	0.0036	0.0012
	(0.4569)	(0.0022)	(0.5591)	(0.0018)	(0.6522)	(0.0026)	(0.0030)
t=1 * E-network (absorbing)	-0.0969	-0.0016	-0.6632*	-0.0108***	0.5663	0.0093***	0.0084**
	(0.4923)	(0.0022)	(0.3722)	(0.0024)	(0.4682)	(0.0030)	(0.0033)
t=2 * E-network (absorbing)	0.8639	-0.0042*	-0.3182	-0.0044	1.182**	0.0002	0.0034
	(0.5460)	(0.0022)	(0.3790)	(0.0027)	(0.5711)	(0.0032)	(0.0036)
Control for firm-location size	Y	Y	Y	Y	Y	Y	Y
All other controls	Y	Y	Y	Y	Y	Y	Y
Firm-state-CBSA FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N of obs	218000	218000	218000	218000	218000	218000	218000
N of firm-state-CBSAs	45000	45000	45000	45000	45000	45000	45000

Note: Control variables: age, total employment, IT capital flow, IT capital stock, total expenditure, cost of electricity, cost of material, cost of fuel, inventory, number of establishments within each unit. The unit of observation is a firm-state-CBSA-year (numbers of observations are approximate per Census disclosure avoidance policy). Robust standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix F: A Model of IT Adoption and Worker Turnover

Setup

The firm's production function is univariate in labor:

$$q = \theta l^{\phi}$$

where q is output per period, l is the number of workers employed for period, and $\phi < 1$.

Firm demand is CES:

$$p = Dq^{-\frac{1}{\epsilon}} = D\, q^{-\sigma}$$

where $\epsilon > 1$, and so $\sigma < 1$. (With $\sigma > 0$, firms have monopoly power and price is at a markup over marginal cost; we get a perfect competition model with $\sigma = 0$.)

Firm sets wage w, influenced by possibility of outside offers and the need to minimize turnover costs. Suppose an (exogenous) fraction $\rho < 1$ of workers receive an outside offer at the beginning of the year.[20] Wage offers are drawn from a Pareto distribution with shape parameter α and scale parameter (minimum wage) $\bar{w}$, so the pdf of outside wage offers is given by:

$$F(w) = 1 - \left(\frac{\bar{w}}{w}\right)^{\alpha}$$

where $w \in [\bar{w}, \infty)$, $\bar{w} > 0, \alpha > 0$.[21]

The worker quits if outside wage offer is greater than her current wage, so probability of quit for a worker receiving an outside offer is:[22]

$$\mathrm{P}[\mathrm{w_o} > w] \equiv \mu = 1 - F(w) = \left(\frac{\bar{w}}{w}\right)^{\alpha}$$

For a firm with l workers and wage w, the "Outflow rate" (i.e., fraction of workforce that quits) $= \rho \left(\frac{\bar{w}}{w}\right)^{\alpha}$, and the expected number of quits= $l\rho \left(\frac{\bar{w}}{w}\right)^{\alpha}$.

Suppose that there is a replacement cost r associated with each worker that quits. As discussed in the literature (e.g., Bushey and Glynn, 2012), worker replacement costs include direct costs associated with search (advertising, interviewing, search agency fees), temporary help/overtime (to cover duties of lost employee), and training (including on the job-training and certifications), as well as indirect costs (lower productivity in period before quit and lost firm-specific human

[20] This assumption allows for some workers to be retained even by firms that pay low wages, potentially due to non-wage job characteristics that are relevant to the workers. Also, local labor market factor competition or regulations such as non-compete enforceability could be considered as impacting this fraction ρ.

[21] Assume $\alpha > 1$ to ensure finite mean for the wage distribution.

[22] This is closely related to the standard assumption in basic wage setting monopsony models. E.g., in Section 2 of Kline's (2025) handbook chapter, a firm is able to hire a F(w) workers if it offers a wage w, where F(w) is the CDF of outside offers available to the workers.

capital). The replacement cost may be heterogenous across firms due to differences in search and training costs.[23] We posit that this replacement cost is a function of firm productivity to allow for replacement cost to potentially be higher for more productive and hence larger firms (Blatter et. al, 2012; Dube, Freeman, Reich, 2010)[24], i.e., $r = r(\theta)$.

Then total expected replacement cost for a firm with l workers is: $l\rho\mu r(\theta)$. Expected profit for year is given by:

$$\Pi\,(\mathrm{q},\mathrm{w}) = pq - wl - l\rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha} = Dq^{1-\sigma} - w\left(\frac{q}{\theta}\right)^{\frac{1}{\phi}} - \left(\frac{q}{\theta}\right)^{\frac{1}{\phi}}\rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha}$$

Rewriting the choice variables as labor and wage yields a simpler setup:

$$\Pi(l,w) = D(\theta l^{\phi})^{1-\sigma} - wl - l\rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha}$$

FOC 1: wrt l yields: $\frac{\partial\pi}{\partial l} = (1-\sigma)\phi D\theta^{1-\sigma}l^{\phi(1-\sigma)-1} - w - \rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha} = 0$

FOC 2: wrt w yields: $\frac{\partial\pi}{\partial w} = -l + \alpha\rho l r(\theta)\overline{w}^{\alpha}(w)^{-\alpha-1} = 0$

Then FOC 2: implies:

$$\alpha\rho l r(\theta)\overline{w}^{\alpha}(w)^{-\alpha-1} = l$$

$$\rightarrow w^{1+\alpha} = \alpha\rho r(\theta)\overline{w}^{\alpha}$$

$$\rightarrow w^{*} = [\alpha\rho r(\theta)]^{\frac{1}{1+\alpha}}\overline{w}^{\frac{\alpha}{1+\alpha}} \qquad (1)$$

Note that since we need w to be within the region of support $[\overline{w},\infty)$, we need $[\alpha\rho r(\theta)]^{1/(1+\alpha)}\ \overline{w}^{\frac{\alpha}{1+\alpha}} > \overline{w}$, which implies $\alpha\rho r(\theta) >\ \overline{w}$.

FOC 1 combined with equation 1 above yields:

$$(1-\sigma)\phi D\theta^{1-\sigma}l^{\phi(1-\sigma)-1} = w + \rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha}$$

From (1), we get $\rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha} = \frac{w}{\alpha}$ which implies:

$$\rightarrow\ l^{1-\phi(1-\sigma)} = \left((1-\sigma)\phi D\theta^{1-\sigma}\right)\left[\frac{1}{w+\frac{w}{\alpha}}\right] = \frac{\left((1-\sigma)\phi D\theta^{1-\sigma}\right)}{w}\left[\frac{\alpha}{1+\alpha}\right]$$

[23] Based on a review of 31 case studies, Bushey and Glynn (2012) document replacement costs in the range of 10% to 30% of employees' annual salary, and find some evidence for higher replacement cost (as percentage of salary) for higher wage workers.

[24] More productive firms will be larger so long as the increase in replacement costs with size is not too steep. Based on a panel survey of California businesses, Dube, Freeman and Reich (2010) find evidence that replacement costs are positively associated with establishment size and wage.

$$\rightarrow l^* = \left\{\left[\frac{(1-\sigma)\phi D}{1+\alpha}\right]\left[\frac{\theta^{1-\sigma}}{(\rho r(\theta))^{\frac{1}{1+\alpha}}}\right]\left(\frac{\alpha}{\overline{w}}\right)^{\frac{\alpha}{1+\alpha}}\right\}^{\frac{1}{\eta}} \tag{2}$$

Where $\eta = 1 - \phi(1-\sigma)$. Optimum profit is:

$$\Pi(l^*, w^*) = D(\theta l^{*\phi})^{1-\sigma} - w^* l^* - l^* \rho r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha}$$

From (1), we get: $w^* = \alpha\rho r(\theta)\left(\frac{\overline{w}}{w^*}\right)^{\alpha}$. Then from intermediate step for FOC1 we can write:

$$(1-\sigma)\phi D\theta^{1-\sigma} l^{*\phi(1-\sigma)-1} = w^* + \rho r(\theta)\left(\frac{\overline{w}}{w^*}\right)^{\alpha} = w^*\left(1 + \frac{1}{\alpha}\right)$$

$$\rightarrow w^* l^* = (1-\sigma)\phi D\theta^{1-\sigma} l^{*\phi(1-\sigma)}\frac{\alpha}{1+\alpha}$$

This implies:

$$\Pi(l^*, w^*) = D\left(\theta l^{*\phi}\right)^{1-\sigma} - w^* l^* - \frac{l^* w^*}{\alpha} = D\left(\theta l^{*\phi}\right)^{1-\sigma} - w^* l^* \frac{(\alpha+1)}{\alpha}$$

$$= D\left(\theta l^{*\phi}\right)^{1-\sigma} - (1-\sigma)\phi D\theta^{1-\sigma} l^{*\phi(1-\sigma)} = D\theta^{1-\sigma} l^{*\phi(1-\sigma)}\left(1 - \phi(1-\sigma)\right)$$

$$\Pi(l^*, w^*) = Dq^{*1-\sigma}\left(1 - \phi(1-\sigma)\right) = Revenue\ (1 - \phi(1-\sigma)) \tag{3}$$

Also, above derivation shows that:

$$\text{Wage bill} = \mathrm{w}^* l^* = (1-\sigma)\phi D\theta^{1-\sigma} l^{*\phi(1-\sigma)}\frac{\alpha}{1+\alpha} = \text{Revenue}\left[\phi(1-\sigma)\frac{\alpha}{1+\alpha}\right]$$

$$\text{Turnover costs} = l^* r(\theta)\left(\frac{\overline{w}}{w}\right)^{\alpha} = \frac{w^* l^*}{\alpha} = \text{Revenue}\left[\phi(1-\sigma)\frac{1}{1+\alpha}\right]$$

So this model yields tractable predictions for profits, and different components of the cost, with each of these proportional to revenue. Substituting back the expression for optimal labor we get:

$$\Pi(l^*, w^*) = D\theta^{1-\sigma}\left(1 - \phi(1-\sigma)\right)\left[\left\{\left[\frac{(1-\sigma)\phi D}{1+\alpha}\right]\left[\frac{\theta^{1-\sigma}}{\left(\rho r(\theta)\right)^{\frac{1}{1+\alpha}}}\right]\left(\frac{\alpha}{\overline{w}}\right)^{\frac{\alpha}{1+\alpha}}\right\}^{\frac{1}{1-\phi(1-\sigma)}}\right]^{\phi(1-\sigma)}$$

$$= (D\theta^{1-\sigma})^{\frac{1}{\eta}}\left\{\left[\frac{(1-\sigma)\phi}{1+\alpha}\right]\left[\frac{1}{\left(\rho r(\theta)\right)^{\frac{1}{1+\alpha}}}\right]\left(\frac{\alpha}{\overline{w}}\right)^{\frac{\alpha}{1+\alpha}}\right\}^{\frac{\phi(1-\sigma)}{1-\phi(1-\sigma)}}\left(1 - \phi(1-\sigma)\right)$$

$$\Pi^* = (D\theta^{1-\sigma})^{\frac{1}{1-\phi(1-\sigma)}}\left\{\left[\frac{\alpha}{1+\alpha}\right]\left[\frac{\phi(1-\sigma)}{(\alpha\rho r(\theta))^{\frac{1}{1+\alpha}}(\overline{w})^{\frac{\alpha}{1+\alpha}}}\right]\right\}^{\frac{\phi(1-\sigma)}{1-\phi(1-\sigma)}}\left(1 - \phi(1-\sigma)\right) \tag{4}$$

A reasonable and natural assumption is that the effect of productivity on labor choice (in equation 1) is net positive. That is, productivity's positive effect on firm size (through increased output) is not fully offset by the higher replacement cost for more productive firms. This is ensured by the following assumption about the parameters of the model.

Assumption 1: $\frac{\theta^{1-\sigma}}{r(\theta)^{\frac{1}{1+\alpha}}}$ is increasing in θ. For parametrization of $r(\theta) = r\theta^{\gamma}$, a sufficient condition is that $(1+\alpha)(1-\sigma) > \gamma$. This implies that more productive firms employ more workers. Since $\sigma < 1$, this assumption implies that $(1+\alpha) > \gamma \rightarrow (1+\alpha) > \phi\gamma$, which then implies that profits are increasing in productivity (in expression 4 above).

Assumption 2: Adjustment costs per worker are larger for more productive firms, i.e., $\frac{dr(\theta)}{d\theta} > 0$. This is because their workers need to be more skilled, and are therefore harder to find (require larger search costs) and train (require larger training costs).

The model implies the following.

Prediction 1: More productive and larger firms will choose to pay higher wages.

Proof: Follows directly Assumptions (1) and (2), and from equation (1) above (i.e. $w^* = [\alpha\rho r(\theta)]^{\frac{1}{1+\alpha}}\bar{w}^{\frac{\alpha}{1+\alpha}}$), which implies that optimal wages increase with productivity.

Prediction 2: Outflow rate is lower for more productive (and hence larger) firms.

Proof: Follows directly from prediction 1 and fact that outflow rate (fraction of workers that quit)= $\rho\left(\frac{\bar{w}}{w}\right)^{\alpha}$.

Interestingly, if adjustment costs r is independent of firm size/productivity, this model implies that wage (and hence outflow rate) would be independent of firm size/productivity.[25]

IT Adoption Decision and Baseline Effects

Using parametrization of $r(\theta) = r.\theta^{\gamma}, \gamma > 0$, we can write expected profits from (4) as:

$$\Pi^*(\theta) = A(r)\theta^{\psi}$$

Where $A(r) = (D)^{\frac{1}{1-\phi(1-\sigma)}}\left(1-\phi(1-\sigma)\right)\left\{\left[\frac{\alpha}{1+\alpha}\right]\left[\frac{\phi(1-\sigma)}{(\alpha\rho r)^{\frac{1}{1+\alpha}}(\bar{w})^{\frac{\alpha}{1+\alpha}}}\right]\right\}^{\frac{\phi(1-\sigma)}{1-\phi(1-\sigma)}}$,

[25] Thus, it is plausible that in sectors where turnover cost is the same or lower for large firms, we may observe lower wages and higher outflow rates for large firms. This is consistent with anecdotal evidence suggesting high turnover rates and low (effort-adjusted) wages at Amazon warehouses (e.g., National Employment Law Project Report, June 23, 2022 which suggests "*Annual worker turnover at Amazon warehouses in New Jersey is approximately 124 percent, almost double the rate of turnover at non-Amazon warehouses in the state*").

and $\psi = \left[\frac{1-\sigma}{1-\phi(1-\sigma)}\right]\left[\frac{1+\alpha-\gamma\phi}{1+\alpha}\right]$

Assumption 3: IT adoption enhances productivity (e.g., Fort 2017[26]), say by a factor $\tau > 1$, so that adoption increases productivity to $\theta' = \theta\tau$. However, adoption entails a fixed cost F, and raises the replacement cost parameter r to r', where $\frac{r'}{r} = \omega > 1$. The productivity enhancement effect is stronger than the impact on the replacement cost, so that variable profit (excluding the fixed costs) increases with adoption of IT, i.e., $\tau^{\psi} > \omega^{\left[\left(\frac{1}{1+\alpha}\right)\left(\frac{\phi(1-\sigma)}{1-\phi(1-\sigma)}\right)\right]}$.

Prediction 3: Larger firms (specifically firms above a cutoff productivity $\bar{\theta}$) will adopt IT.

Proof: Given assumption 3, a firm adopts IT iff:

$$\mathrm{A(r')}(\tau\theta)^{\Psi} - F > \mathrm{A}(r)(\theta)^{\Psi}$$

$$\leftrightarrow \theta^{\psi} > \frac{F}{(A(r')\tau^{\psi} - A(r))}$$

$$\leftrightarrow \theta > \left[\frac{F}{(A(r')\tau^{\psi} - A(r))}\right]^{\frac{1}{\psi}} = \bar{\theta}.$$

Prediction 4: IT adoption leads to higher wages.

Proof: The impact of IT (E-commerce) adoption on wages is summarized below:

$$\frac{dw}{dT} = \left([\alpha\rho]^{\frac{1}{1+\alpha}}\overline{w}^{\frac{\alpha}{1+\alpha}}\right)\left(\frac{1}{1+\alpha}r(\theta)^{\frac{-\alpha}{1+\alpha}}\right)\left(\frac{dr(\theta)}{dT}\right)$$

$$= \left([\alpha\rho]^{\frac{1}{1+\alpha}}\overline{w}^{\frac{\alpha}{1+\alpha}}\right)\left(\frac{1}{1+\alpha}r(\theta)^{\frac{-\alpha}{1+\alpha}}\right)\left(\theta^{\gamma}\frac{dr}{dT} + r\gamma\theta^{\gamma-1}\left(\frac{d\theta}{dT}\right)\right) \quad (5)$$

Then the result follows directly from Assumption 3.

Prediction 5: IT adoption would lead to lower outflow rate, or lower outflow conditional on employment.

Proof: The impact of IT (E-commerce) adoption on outflow rate is summarized below:

$$\frac{d(\text{Outflow rate})}{dT} = \frac{d\left(\rho\left(\frac{\overline{w}}{w}\right)^{\alpha}\right)}{dT} = -\rho(\overline{w})^{\alpha}\frac{\alpha}{w^{\alpha+1}}\frac{dw}{dT}$$

$$\frac{d(\text{Outflow rate})}{dT} = \rho(\overline{w})^{\alpha}\frac{-\alpha}{w^{\alpha+1}}\left([\alpha\rho]^{\frac{1}{1+\alpha}}\overline{w}^{\frac{\alpha}{1+\alpha}}\right)\left(\frac{1}{1+\alpha}r(\theta)^{\frac{-\alpha}{1+\alpha}}\right)\left(\theta^{\gamma}\frac{dr}{dT} + r\gamma\theta^{\gamma-1}\left(\frac{d\theta}{dT}\right)\right) \quad (6)$$

[26] Fort, T.C., 2017. Technology and production fragmentation: Domestic versus foreign sourcing. *The Review of Economic Studies*, 84(2), pp.650-687.

Then the result follows directly from Assumption 3.

Inflow vs Outflow rate

Replacement cost $r(\theta)$arises from need to the identify, hire and train new workers to replace that quit. In steady state (i.e., when firm growth is zero), inflow rate would equal outflow rate. In the model, firm growth is zero if productivity growth is zero. When examining outcomes around IT adoption (or increase in intensity of IT use), the firm experiences positive productivity growth. In the presence of productivity growth, we can write:

$$\begin{aligned}\text{Inflow rate } &= \text{Inflow rate due to productivity growth} \\ &\quad + \text{Inflow rate to replace workers lost to outflow} \\ &= \frac{dlnl^*}{dt} + \rho\left(\frac{\bar{w}}{w^*}\right)^{\alpha} = \frac{dlnl^*}{d\theta}\frac{d\theta}{dt} + \rho\left(\frac{\bar{w}}{w^*}\right)^{\alpha}\end{aligned} \tag{7}$$

This yields the following prediction:

Prediction 6: The impact of IT adoption on inflow rates is ambiguous.

Proof: Assumption 2 implies that IT adoption enhances productivity, which translates to a positive effect on $\frac{d\theta}{dt}$ for at least a few periods after IT adoption. So, IT adoption has a positive effect on the first term in (7). However, the effect is negative for the second term (see Prediction 5 above), as IT adoption leads to higher wages and hence lower outflows. Thus, the net effect of IT adoption on inflows is ambiguous.

Heterogeneous Effects by Worker, Firm and Location Characteristics

Various factors can be expected to impact the replacement/hiring cost. E.g., it is plausible that the replacement cost is higher for more skilled workers. The production function in the case with two types of workers can be assumed for simplicity as linear in the two types of workers, so $q = \theta(l_1^{\phi_1} + l_2^{\phi_2})$. Then in the simpler case of perfect competition ($\sigma = 0$) we get profit as a function of labor and wage choices for both types of workers:

$$\Pi(l_1, l_2, w_1, w_2) = D\theta(l_1^{\phi_1} + l_2^{\phi_2}) - w_1 l_1 - w_2 l_2 - l_1 r_1(\theta)\left(\frac{\bar{w}_1}{w_1}\right)^{\alpha_1} - l_2 r_2(\theta)\left(\frac{\bar{w}_2}{w_2}\right)^{\alpha_2}$$

This yields optimal wages and labor choice expressions similar to (1) and (2) above for each type of worker.[27]

(a) Heterogeneity by worker skill (wages) and age

[27] The relative wage and turnover rates for high skilled and low skilled workers would depend also on the shape and scale parameters of the distributions of outside wage offers for the two types. If the shape parameter (lowest wage) is higher for more skilled workers and the scale parameter is similar, then we would get higher wages and lower turnover rates for more skilled workers.

Assumption 4: The impact of IT on replacement cost is higher for skilled workers than for less skilled.

Since the predictions for wage and outflow rate depend directly on $\frac{dr(\theta)}{dT}$, the results for these variables follow directly from Assumption 4. As discussed above, in a steady state equilibrium, heterogeneity of impact on inflows will mirror that for outflows. However, around IT adoption, the implications for inflow rates can be different, as the additional positive effect on labor demand through the impact of IT on productivity $\left(\frac{dlnl}{d\theta}\left(\frac{d\theta}{dT}\right)\right)$ could be stronger for more skilled and younger workers. In particular, if the output elasticity with respect skilled labor $(\phi_s)$is greater than that for unskilled workers (ϕ_u), then the $\frac{dlnl}{d\theta}$ is larger for skilled workers. Thus, there may be offsetting effects for inflows leading to ambiguous prediction for whether the change in inflow rates due to IT adoption are higher or lower skilled workers.

Prediction 7: IT adoption would increase wages and reduce outflow rate for higher skilled employees relative to lower skilled employees. The heterogeneity of impact of IT adoption on inflows by skill level is ambiguous.

Prediction 7a: Heterogeneity by worker skill (wage) level: If higher wage workers are more skilled, we would expect increased wages and lower outflows for higher wage workers following IT adoption. The heterogeneity of impact of IT adoption on inflows by worker wage is ambiguous.

Prediction 7b: *Heterogeneity by worker age*: If younger workers have the types of skills needed for adopters of IT technology, and the replacement cost for these younger workers is higher after adoption of IT, we would expect increased wages and lower outflows for younger workers. The heterogeneity of impact of IT adoption on inflows by worker age is ambiguous.

(b) Heterogeneity by firm size and location

Equations (5) and (6) show that the effects of IT adoption on wages and outflows depend in a nuanced way on firm productivity level (and hence on firm size). From equation 5, we get:

$$\frac{dw}{dT} = \left([\alpha\rho]^{\frac{1}{1+\alpha}}\overline{w}^{\frac{\alpha}{1+\alpha}}\right)\left(\frac{1}{1+\alpha}r(\theta)^{\frac{-\alpha}{1+\alpha}}\right)\left(\theta^{\gamma}\frac{dr}{dT} + r\gamma\theta^{\gamma-1}\left(\frac{d\theta}{dT}\right)\right)$$

The effect of size on $\frac{dw}{dT}$ depends on Sign $\left(\frac{dH}{d\theta}\right)$, where

$$H = \left[\left(\frac{1}{1+\alpha}r(\theta)^{\frac{-\alpha}{1+\alpha}}\right)\left(\theta^{\gamma}\frac{dr}{dT} + r\gamma\theta^{\gamma-1}\left(\frac{d\theta}{dT}\right)\right)\right] = \left[\left(\frac{1}{1+\alpha}r^{\frac{-\alpha}{1+\alpha}}\right)\left(\theta^{\left(\frac{\gamma}{1+\alpha}\right)}\frac{dr}{dT} + r\gamma\theta^{\left(\frac{\gamma}{1+\alpha}-1\right)}\left(\frac{d\theta}{dT}\right)\right)\right] \quad (8)$$

This expression clarifies that the effect is likely to be ambiguous for the following reasons:

- The first term $\theta^{\left(\frac{\gamma}{1+\alpha}\right)}\frac{dr}{dT}$ is clearly increasing in θ.

- Assumption 1 implies that $\gamma < 1 + \alpha$, so the second term $\left(r\gamma\theta^{\left(\frac{\gamma}{1+\alpha}-1\right)} \left(\frac{d\theta}{dT}\right)\right)$ on the RHS of (8) is decreasing in θ.

Thus, the net effect depends on the relative sizes of the two opposing effects, which is ex ante unclear. For example, if the impact of IT adoption on the parameter r is modest relative to the impact on productivity, H would be decreasing in productivity and hence we could expect larger positive wage effects from IT adoption for smaller firms. But even this prediction could be reversed, if it is the case that the impact of IT adoption on productivity $\left(\frac{d\theta}{dT}\right)$is increasing in productivity. [28] Consequently, since the effect for outflows is the reverse of the effect for wages, how size moderates the effect of IT adoption on outflows is also ambiguous.

To understand heterogeneity in inflow effects (equation 7), note that given our functional form assumptions, $\frac{dlnl}{d\theta}$ is independent of θ. Then, the heterogeneity by firm size of the impact of IT on inflows is the same as that on outflows, and hence is also ambiguous.

Prediction 8: *Heterogeneity by firm size*: How the impact of IT adoption on wages, outflows and inflows varies by firm size is ambiguous.

Results (5) and (6) above suggest that the impact of IT adoption on wages and outflow rates depend on two key parameters: ρ which is the fraction of workers that receive an outside offer, and $\overline{w}$ which is the lower bound of the wage offer distribution.

Both these parameters could vary with local characteristics. Specifically, for urban areas with thicker local labor markets, we expect ρ as well as $\overline{w}$ to be higher than in rural labor markets. This then would imply larger increase in wage, and larger reduction in outflows for urban locations. Supposing other model parameters and the impact of IT adoption on productivity $(\frac{d\theta}{dT})$ is similar between rural and urban regions, we would expect similar relation of urban status to the impact of IT adoption on inflows, i.e., we expect relatively lower inflows from IT adoption in urban markets.

Prediction 9: *Heterogeneity by urban vs rural regions*: The positive impact of IT adoption on wages is expected to be larger for workers in urban regions. Similarly, reduction in worker outflows following IT adoption is expected to be bigger in urban areas. Worker inflow effect from IT adoption is expected to be more negative in urban areas.

Enforceability of non-compete covenants would likely imply a lower ρ, as competitors are less likely to make offers to workers at rival firms. This would then imply lower impact of IT adoption on wages and outflows in places with stronger non-compete enforceability. Again, if

[28] The literature suggests that in fact the impact of IT/technology adoption could be larger for bigger or more productive firms. One reason is that smaller firms make more incremental changes (e.g., use email for purchasing/selling products) while larger firms make more substantial investments (e.g., use of a new integrated ordering software). Another reason is that successful IT adoption requires complementary investments in training and other systems, which smaller firms are not able to do.

other model parameters are independent of local non-compete enforceability, the effects for inflows should mirror those for outflows.

Prediction 10: *Heterogeneity by non-compete enforceability*: The positive impact of IT adoption on wages is expected to be lower for workers in regions with non-compete enforceability. Similarly, reduction in worker outflows following IT adoption is expected to be smaller in places with stronger non-compete enforceability. Worker inflow effect from IT adoption is expected to be more positive in locations with stronger non-compete enforceability.