Information Systems Research

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

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Information Systems Research
Vol. 27, No. 1, March 2016, pp. 6–26
ISSN 1047-7047 (print) | ISSN 1526-5536 (online)
http://dx.doi.org/10.1287/isre.2015.0618

On the Longitudinal Effects of IT Use on Firm-Level Employment

Hilal Atasoy, Rajiv D. Banker, Paul A. Pavlou
Fox School of Business, Temple University, Philadelphia, Pennsylvania 19122
{hilal.atasoy@temple.edu, banker@temple.edu, pavlou@temple.edu}

The effect of information technology (IT) on employment is a crucial question in today's economy given the increased digitization of work. To analyze the relationship between IT use and firm-level employment, we examine the longitudinal role of IT use in the firm's total number of employees. Our data set comes from the emerging economy of Turkey, and it represents firms of different sizes and industries. The data capture the firm's use of enterprise applications, such as enterprise resource planning and customer relationship management, and the use of Web applications, such as e-banking and e-government. Our empirical specifications exploit both within-firm and between-firm variations to show the positive effect of IT use on firm-level employment, which varies across IT applications over time. Interestingly, we find that the effects of the use of enterprise applications materialize after two years, whereas the effects of the use of Web applications are realized in the current year. We also examine whether the role of IT use in firm-level employment are moderated by firm size, average wage rate, and industry technology intensity. The long-term effects of the use of enterprise applications on firm-level employment are more pronounced in larger firms, with higher average wages, and in high-technology industries. The results are robust to alternative specifications and tests that address causality and endogeneity concerns. Implications for research, practice, and public policy are discussed.

Keywords: IT use; firm-level employment; longitudinal effects of IT; causality tests
History: Chris Forman, Senior Editor; Prasanna Tambe, Associate Editor. This paper was received on June 10, 2013, and was with the authors 13 months for 4 revisions. Published online in *Articles in Advance* February 23, 2016.

1. Introduction

Concerns of the effects of technology on employment date back to industrialization, and they continue with rapid digitization (*Economist, The* 2014). Such concerns are supported by the view that if technology accomplishes more work through automation, there would be fewer jobs left for people (e.g., Brynjolfsson and McAfee 2011). On the other hand, information technology (IT) facilitates job creation and growth in firm productivity (e.g., Lichtenberg 1995; Brynjolfsson and Hitt 1996, 2003; Mittal and Nault 2009), and the literature has suggested that increases in firm productivity due to IT may also increase labor demand in the firm. For instance, enterprise applications can affect the firm's productivity by enhancing its business processes. They can also improve the firm's supply chain, and they can help to reach out to new suppliers and customers. The empirical evidence on the effect of IT on the firm's labor demand is mixed (e.g., Brynjolfsson et al. 1994, Hitt 1999, Ray et al. 2013), implying that IT can either lead to smaller firms with fewer employees or larger firms with more employees. Thus, the relationship between IT and labor demand within a firm, and whether this relation has changed with recent advances in IT, is still an open research question (*MIT Technology Review* 2015). In this study, we focus on the longitudinal role of IT use on *firm-level employment*, specifically, whether firms employ more or less labor as they increasingly use IT. We examine how the effect of IT use on the firm's employment is shaped by the use of different types of IT applications and several moderating variables (i.e., firm size, average wages, industry technology intensity). Our research question is, How does IT use affect firm-level employment? We employ a recent data set (2007–2011) from Turkey to examine the moderated relationship between IT use and firm-level employment.

Since IT applications differ in their purpose and scale and can have different effects on economic outcomes (Weill 1992), we examine how the *type* of IT application, specifically, *enterprise applications* (e.g., enterprise resource planning (ERP), customer relationship management (CRM), supply chain management (SCM)) versus *Web applications* (e.g., e-banking, e-government, corporate website) moderates the effect of IT use on firm-level employment. Given the recent increased emphasis on Web applications relative to enterprise applications, we seek to explore how Web and enterprise applications differentially play a role in the firm's employment. Although our firm fixed-effects results show that higher IT use is linked to higher firm employment, this relationship depends on the type of IT application over time; interestingly, enterprise applications have a long-term positive role in the firm's employment that only materializes after two years, whereas Web applications have an immediate role that is observed in the current year.

We also examine the role of IT use in firm-level employment as moderated by *firm size*. There is a positive link between firm size and IT investment (e.g., Harris and Katz 1991), and firm size may be an important factor in explaining variations in the magnitude and timing of IT effects on economic outcomes (e.g., Brynjolfsson and Hitt 2003, Tambe and Hitt 2012). The labor economics literature also shows that the productivity and job creation capabilities of firms differ by their size (e.g., Hall 1987; Acs and Audretsch 1988; Idson and Oi 1999). We find that the lagged coefficient of the use of enterprise applications on firm employment is significant in large and medium firms, whereas the current coefficient of the use of Web applications is significant in small firms.

Additionally, labor substitution and labor complementarity are among the mechanisms through which IT use can affect firm-level employment. IT alters the firm's labor skill requirements and shapes the relative demand for skilled versus unskilled labor, as shown by the skill-biased technological change (SBTC) literature (e.g., Autor et al. 1998, 2003; Acemoglu 2002; Bresnahan et al. 2002; Autor and Dorn 2013). Although we do not directly observe the skill level of each employee in the data, we test the premise of SBTC theory by using the *average wage rate* as a proxy for the firm's average skill level of its employees (Acemoglu 1998, 2002; Autor and Dorn 2013). We find a stronger lagged positive relationship between the use of enterprise applications and labor demand in firms with a higher average wage rate, supporting the notion that enterprise IT use is more likely to complement skilled versus unskilled labor.

Finally, we examine whether the relationship between IT use and firm-level employment differs by *industry technology intensity* because high-tech industry firms can have higher productivity increases associated with IT use, and they have different skill requirements than low-tech industry firms. We find that both the lagged coefficient of use of enterprise applications and the current coefficient of the use of Web applications on firm employment are more pronounced in high-tech firms than in low-tech firms.

We utilize firm-level IT use data collected by the Turkish Statistical Institute (TurkStat) in 2007–2011 to test our research questions. The TurkStat data include variables that are not usually observed in common IT databases such as the Computer Intelligence Technology Database (Ray et al. 2013), *InformationWeek* (Lichtenberg 1995), and *Computerworld* (Brynjolfsson and Hitt 1996) and offer incremental value to the literature in three ways: *First*, the TurkStat IT use survey, administered by the Turkish government, is designed to be nationally representative of firms of different sizes and several industries. Selected firms are required to complete the comprehensive survey by law, which ensures a high response rate (90%) and avoids the inherent problem of response bias in voluntary surveys. This makes it feasible to draw inferences about the entire population of the Turkish firms, leading to a more representative sample of firms compared to the common IT databases that primarily consist of large publicly traded companies. *Second*, our data set provides a refined measure of IT by capturing the actual use of specific IT applications (e.g., ERP, CRM, and SCM). Going beyond aggregate IT variables, such as IT capital, IT investment, or IT spending enables us to identify the different effects of the actual use of specific IT applications on firm-level employment, thus observing relationships that cannot be determined using aggregate IT measures. Although these aggregate IT measures are valuable (e.g., Brynjolfsson et al. 1994, Hitt 1999, Bresnahan et al. 2002, Ray et al. 2013), and indeed we use them in this paper for validation, different types of IT systems, and whether they are in active use, may have differential effects. Given that the value creation potential of IT requires implementation and use after the initial purchase, and firms often fail to assimilate new IT systems, it is important to go beyond aggregate IT variables and examine actual IT use (e.g., Devaraj and Kohli 2003, Barua et al. 2004, Barki et al. 2007, Mishra and Agarwal 2010), helping us understand the microfoundations of the role of IT systems in economic outcomes (e.g., Aral et al. 2006, Forman and McElheran 2013). *Third*, having data on small/medium firms enables us to test the relationship between IT and labor demand by firms of different sizes. Most firm-level studies in the information systems (IS) literature rely on large public firms from the United States, such as Fortune 500 or Fortune 1000 companies. Lack of data on small and medium firms raises the question of whether empirical evidence from larger firms extends to smaller firms. This is because firms of different sizes may have different complementary resources to IT applications, or they may vary in their ability to acquire, implement, and assimilate new IT systems (e.g., Dedrick et al. 2003, Tambe and Hitt 2012).

2. Background and Theoretical Development

2.1. Review of Relevant Empirical IS Literature and Data Sources

There is a substantial body of empirical literature on the effects of IT on various firm-level outcomes, such

Table 1 **Related Empirical Studies in IS Literature and Data Properties**

Paper	Unit of analysis	Representativeness (size and industry)	How IT is measured	Time frame
Osterman (1986) (*Industrial Labor Relations Review*)	Industry	Several sizes Several industries	Number and size of CPUs	1972–1978
Brynjolfsson et al. (1994) (*Management Science*)	Industry	Several sizes Several industries	IT investment	1976–1989
Brynjolfsson and Hitt (1996) (*Management Science*)	Firm	Fortune 500 firms Manufacturing and services	IT spending	1987–1991
Hitt (1999) (*Information Systems Research*)	Firm	Fortune 1000 firms Several industries	IT cost share, IT capital	1987–1994
Bresnahan et al. (2002) (*Quarterly Journal of Economics*)	Firm	Fortune 1000 firms Several industries	IT capital, total PCs, processing power	1987–1994
Aral et al. (2006) (*27th ICIS Proceedings*)	Firm	Large public firms Several industries	ERP, CRM, SCM use, purchase, and go-live	1998–2005
Mittal and Nault (2009) (*Information Systems Research*)	Industry	Several sizes Manufacturing sector	IT capital	1948–2000
Tambe and Hitt (2012) (*Information Systems Research*)	Firm	Several industries Public medium-large firms	IT employment	1987–2006
Ray et al. (2013) (*Academy of Management Journal*)	Firm	Fortune 1000 firms Several industries	IT capital, ERP, SCM	2002–2009
Forman and McElheran (2013) (Working paper)	Plant	Large firms Manufacturing sector	External IT, supplier IT, and customer IT use	1992–1999
This paper	*Firm*	*Several sizes and industries*	*Seven IT systems use*	*2007–2011*

as productivity, output, and labor demand. Each one of these studies has a different time frame, unit of analysis, and measurement of IT. Table 1 presents some of the relevant empirical IS studies and summarizes their data properties to establish the incremental value of our data source.

Most of the data sources quantify IT with IT capital, IT investment, or IT spending, and these aggregate IT measures are commonly used in the IS literature (e.g., Brynjolfsson et al. 1994, Brynjolfsson and Hitt 1996, Hitt 1999, Bresnahan et al. 2002, Ray et al. 2013). There is evidence that although firms purchase IT systems, they often fail to assimilate and use them (e.g., Chatterjee et al. 2002, Liang et al. 2007, Pavlou and El Sawy 2006). Notably, Devaraj and Kohli (2003) found that "actual" IT use may be a mediating variable in explaining IT effects, and omission of IT use may be the missing link in studies of the business value of IT. The few studies that do include details on the use of IT systems offer interesting results. In particular, Aral et al. (2006) found that although ERP purchase events were not correlated with increased firm productivity, ERP use (go-live) led to higher firm productivity, thereby supporting the notion that the essence of the impact of IT can be attributed to the actual use rather than mere IT investment or IT spending. Besides, Forman and McElheran (2013) found that customer-focused IT applications, supplier-focused IT applications, and the simultaneous use of these two types of IT have different effects on the firm's vertical integration, emphasizing the complementarities in the use of different IT applications.

The common firm-level IT databases rely on large public firms, usually Fortune 500 and Fortune 1000 firms (e.g., Computer Intelligence Technology Database, *InformationWeek*, *Computerworld*). We have little understanding on whether the evidence on the economic effects of IT based on large firms generalizes to smaller firms. One exception to this is Tambe and Hitt's (2012) study that used a unique comprehensive data set to identify interesting differences between patterns of IT returns across large Fortune 500 and medium-sized firms. The authors found that large firms realize higher productivity gains from IT investments that materialize more slowly than medium-sized firms. Other studies utilized industry-level data to overcome representation issues (e.g., Osterman 1986, Brynjolfsson et al. 1994, Mittal and Nault 2009). Industry-level analyses are important and more generalizable; however, they may miss some firm-level dynamics because firm trends and interfirm competition within an industry may not be captured by aggregate industry statistics. In sum, we are not aware of firm-level data in the IS literature that are representative of multiple firm sizes and industries, and our data set aims to offer a representative view across these two dimensions.

Our data seek to improve on the above gaps in the literature: First, the representative design and the administrative collection of the TurkStat survey helps us to achieve a representative sample and seek to alleviate response bias. Second, the granular usage data at the IT application level helps us to observe important variations and relationships that cannot be identified using aggregate IT measures because the use of various IT applications may differ in how they influence labor demand within a firm. Third, having data on smaller firms enables us to test the relationship between IT use and firm labor demand by firm size.[1]

2.2. Theoretical Foundations on the Role of IT Use in Firm-Level Employment

The mechanisms through which IT use may affect firm-level employment can be attributed to (1) *productivity gains*, (2) *make versus buy decisions*, and (3) *labor complementarity versus substitution*.

There is extensive literature on the effects of IT on firm productivity, performance, and profitability (please see Dedrick et al. 2003 for a detailed review). The majority of these studies focused on the effects of IT investments on productivity (e.g., Lichtenberg 1995; Brynjolfsson and Hitt 1996, 2003; Mittal and Nault 2009) and found significant effects, especially for firms in which IT investments coexist with complementary resources in the firm. Technological progress explains the rapid increase in a firm's productivity, and this positive relationship between IT and productivity is well documented at the firm level. Productivity growth can lead to firm expansion and an increase in the firm's demand for labor. On the other hand, if the firm's production level remains the same, labor demand can decrease since fewer employees would be needed to produce the same amount of output. Similarly, the overall effect can be zero, in theory, if these two competing forces perfectly cancel each other out.

IT use can also influence the make versus buy decisions, and thus alter a firm's labor requirements. The transaction cost economics (TCE) literature explains that IT affects the allocation of the production activities through changes in the frictional costs of transactions, such as search and communication costs. The literature discusses two major types of costs: internal coordination and external coordination costs (Malone 1987, Brynjolfsson et al. 1994, Zenger and Hesterly 1997, Hitt 1999, Forman and McElheran 2013, Ray et al. 2013). Internal coordination costs include communication, data transfer, and managing employee incentives such as agency costs. External coordination costs consist of locating, communicating, maintaining external business partners, contracting, and transaction costs (e.g., Hitt 1999). The impact of IT on production depends on its relative effects on these two types of costs. If internal coordination costs decrease more than external coordination costs, we expect firms to grow internally and firm size to increase. If the decrease in external costs is greater than the decrease in internal coordination costs, we expect firm size to decrease because firms will shift a portion of their production to external sources. The change in production levels along with internal and external coordination costs can in turn affect firm-level employment. Thus, there are predictions that go in both directions following the TCE logic. Therefore, the net effect of IT use on firm-level employment can be positive, negative, or even zero, depending on whether the decrease in internal or external coordination costs dominate each other, or whether they cancel each other out.

Regardless of the level of internal production, IT can change labor requirements by changing the firm's business processes and needs of various labor skills. Brynjolfsson et al. (1994) argued that labor substitution could be the simplest explanation of why firm-level employment may be linked to IT, despite coordination costs. The SBTC literature analyzes the complementary or substitutive relationship between technology and different types of labor, arguing that the increase in the relative demand for skilled versus unskilled labor could be attributed to new technology developments (e.g., Acemoglu 1998, 2002; Bresnahan et al. 2002; Autor et al. 2003; Autor and Dorn 2013). IT substitutes for unskilled labor and routine labor tasks, and complements skilled labor and nonroutine tasks. Routine tasks can be completed by following clearly predefined rules, and can therefore be replaced by IT. Some examples of routine tasks are manual assembly line jobs (e.g., packaging gadgets into containers) and cognitive clerical, administrative, or formulaic tasks (e.g., evaluating mortgage applications). By contrast, nonroutine tasks are not defined by explicit rules but require human judgment, creativity, and problem solving skills. For example, a manager's job involves analyzing complex situations and using subjective decision making, and therefore cannot be entirely performed by predetermined rules. Moreover, the high-volume and low-cost information flow enabled by IT favors skilled employees who can analyze data and managers who can utilize additional insights gained from information to improve their decision making (Bresnahan et al. 2002). Accordingly, the net effect of IT use on firm-level employment can be positive, negative, or even zero, depending on whether the substitution or complementary effects of IT use dominate or cancel each other out within a given firm.

2.3. Proposed Categories of IT Applications

IT applications differ in their purpose and scale, and can have varying effects on economic outcomes (Weill 1992). In this study, we make a distinction between enterprise applications and Web applications. *Enterprise applications* are typically large-scale systems used across the entire firm that are central to the firm's strategy. They restructure internal and external interactions, define the firm's business processes, and may have a

[1] The average firm size in our sample is smaller compared to previous studies. For example, the average number of employees in Tambe and Hitt's (2012) comprehensive sample is 13,831 employees, whereas the average number of employees in our sample is 1,044. The industry distribution is similar in our sample and in Tambe and Hitt's (2012) sample.

Table 2 Proposed Categories of IT Applications

IT category	Definition	Characteristics	Examples
Enterprise applications	IT systems that define and restructure business processes	—Used widely in the organization —Define processes and workflows —Require several complements and substantial customization	—Enterprise resource planning —Customer relationship management —Supply chain management —Procurement
Web applications	Specialized IT systems deliver content over the Internet through a Web browser interface	—Used narrowly in the organization —Affect specific business processes —Require modest complements and moderate or small customization	—e-banking —e-government —Corporate website

transformative nature (McAfee 2006). Enterprise applications require several complementary investments, changes in workplace organization, and substantial customization for their benefits to be realized. ERP systems are a prime example of enterprise applications. Also, CRM and SCM systems fall in the enterprise applications category, although their role in the business processes can depend on the firm's strategy and industry. Similarly for procurement applications, the extent of their use in the firm, their significance and role in the firm's business processes, and requirements for complementary organizational changes can vary across firms. *Web applications* are systems that deliver content and functionalities over the Internet through a Web browser and are relatively narrow-scale systems that affect the firm's business processes and workplace organization only within specific functions in the firm. Their role in business processes is usually smaller, and they require fewer complementary changes and less customization compared to enterprise applications. Table 2 provides a brief summary of the definitions, characteristics, and examples of the proposed IT categories.

The three mechanisms through which IT use can affect firm-level employment, (1) productivity gains, (2) TCE, and (3) SBTC, relate to both enterprise applications and Web applications, and we generally expect both to affect firm-level employment. Since enterprise applications typically lead to larger productivity gains and more changes in business processes and workplace organization than Web applications, one may expect their role in firm-level employment to be more pronounced.[2] However, since for each of the three theoretical mechanisms our predictions can go in either direction, as discussed in §2.2, we are unable to unequivocally predict their net effects on the firm's labor demand and their relative magnitudes compared to each other.

2.4. Longitudinal Role of IT Use in Firm-Level Employment

We expect the effects of enterprise applications to materialize over a longer period of time compared to Web applications. An extensive body of IS literature provides compelling evidence that the returns of IT are generally more pronounced over the long term (e.g., Peffers and Dos Santos 1996, Devaraj and Kohli 2003, Brynjolfsson and Hitt 2003, Tambe and Hitt 2012). This is because firms do not simply plug in IT and enjoy its effects immediately; they have to undertake a challenging transition from their existing business processes and have to make complementary investments (e.g., Bresnahan and Greenstein 1996, Brynjolfsson et al. 2002, Brynjolfsson and Hitt 2003). Restructured business processes and changes in workplace organization are achieved through time-consuming experimentation, innovation, and redesign (e.g., Bresnahan et al. 2002). Brynjolfsson et al. (1994) showed the effects of IT investments on firm size to be most pronounced after two to three years. Besides, it takes time for employees to learn new IT systems as they follow a learning curve (e.g., Reis 1991, Peffers and Dos Santos 1996, Armstrong and Sambamurthy 1999, Singh et al. 2011). In sum, the consensus in the literature is that the long-term effects of IT are stronger than the short-term effects.

The arguments and evidence in the IS literature on the lagged effects of IT are proposed to apply to enterprise applications more than Web applications. This is because enterprise applications shape the firm's business processes, and they require more complementary investments, customization, experimentation,

[2] Enterprise applications can reshape business processes significantly and thus affect the firm's productivity. They can also lead to a higher demand for products and services and a higher need for labor to address the increased demand via enhancing the firm's supply chain and helping to reach new suppliers and customers. Web applications, however, usually affect a narrower set of operations, and their potential for productivity gains and firm growth is relatively small. Enterprise applications can typically change coordination costs more than Web applications because they affect the communication and monitoring of internal and external processes to a large extent. Moreover, enterprise applications generally increase data availability by enabling systematic records of business events (e.g., ERP) and interactions with customers (e.g., CRM) and suppliers (e.g., SCM), thus increasing skilled labor requirements for data analysis and data interpretation (Bresnahan et al. 2002). Finally, enterprise applications could lead to the automation of routine tasks, such as inventory tracking and sales ordering, thus decreasing demand for unskilled labor, usually more than the typically narrower Web applications. Therefore, the role of enterprise applications in the firm may be more extensive.

and learning compared to Web applications. Thus, the implementation and assimilation of enterprise applications are likely to take longer than that of Web applications. Integration of Web applications requires less time because they are generally out-of-the box solutions with minimal required customization and changes in business processes. This implies that when firms start using enterprise applications, they may not experience productivity gains, changes in their coordination costs, or changes in their skill composition right away. These changes in the proposed mechanisms through which IT use influence the firm's labor demand would occur more slowly when using enterprise applications compared to Web applications. Therefore, the effect of enterprise applications on firm-level employment is likely to materialize slower than that of Web applications. Similarly, the effect of Web applications on firm-level employment is expected to materialize faster due to their easier assimilation, thus leading to higher current effects on labor demand within the firm compared to enterprise applications, although we cannot unequivocally predict the direction of these proposed effects.

2.5. Moderated Role of IT Use in Firm-Level Employment

2.5.1. Firm Size. A firm's size can play a role in how the relationship between IT use and its labor demand materializes over time, although there is scarce evidence across firms of different sizes. For the effects of IT investments to be realized in practice, they must be accompanied by changes in business processes and the organizational structure. These accompanying changes often take a longer time to occur in large firms given the bigger organization. In fact, the effects of IT investments on firm productivity were shown to materialize more slowly in larger firms (Tambe and Hitt 2012). Similarly, economic effects can be realized more quickly in smaller firms because the implementation, assimilation, and use of IT applications are generally easier compared to larger firms. Therefore, we expect larger firms to experience stronger lagged effects from their use of IT applications compared to small firms, although we cannot predict the magnitudes of these effects.

2.5.2. Average Wage Rate. IT can substitute for low-skilled labor and routine tasks, but it can also complement high-skilled labor and nonroutine tasks, as documented by the SBTC literature. Wage rate is the most common empirical measure of skill level in the economics literature (e.g., Acemoglu 1998, 2002; Autor and Dorn 2013). Thus, we use the average wage rate as a proxy for the firm's average skill level since we cannot measure the exact distribution of skilled and unskilled labor within the firm. We explore the effect of IT use on firm-level employment using the average wage rate per employee in a firm as a moderator. If the SBTC logic holds, we would expect IT use to have a stronger role in employment for firms that have more skilled labor, and thus a higher average wage rate. Although we cannot observe the exact composition of the skills or occupations within each firm, testing the direction of the moderating effect would shed light on how the firm's average skill level may play a role in IT use in the firm's employment, at least across firms.

2.5.3. Industry Technology Intensity (High-Tech vs. Low-Tech Industry). IT use may lead to higher productivity for high-tech firms (e.g., consulting, software development) since IT is a more important component of their production function. Also, for high-tech firms, business processes often require more nonroutine labor tasks that have higher complementarities with IT. These factors can lead to a stronger positive effect of IT use on firm-level employment in high-tech industries than firms in low-tech industries with similar levels of IT use. On the other hand, high-tech firms can achieve a higher automation of routine tasks, which can reduce their demand for labor. Because we cannot unequivocally predict the direction of the role of IT use in firm-level employment when moderated by the industry's technology intensity, this is delegated to empirical testing.

3. Data

We use firm-level IT use surveys between 2007 and 2011 from the TurkStat, which are consistent with the European Commission's Eurostat methodology.[3] The main purpose of the survey is to obtain information on the firms' use of computers, the Internet, various IT applications, and their technological integration. The surveys are conducted for firms that have 10 or more employees, including both public and private firms, in the following industry categories: manufacturing, energy, construction, wholesale/retail trade, transportation, accommodation and food service activities, information and communication, real estate, professional, scientific/technical activities, and administrative and support activities (please see Online

[3] The European Commission, Eurostat, and the National Statistical Offices have developed a methodological manual for the surveys on IT usage in enterprises and households. The main objectives of this manual are to provide guidelines for developing the national surveys, to help harmonize the national surveys, to help share experiences of the countries, and to gather best practices. Please see Eurostat's Information Society page for more details: http://ec.europa.eu/eurostat/web/information-society/methodology.

The IT use data can be accessed at TurkStat's data research centers in Turkey. Currently, data between 2007 and 2011 are available. The collection of data is still ongoing; however, there is a time lag between the collection of surveys and preparation of the data for researchers. Subsequent years of data are expected to become available in the near future.

Appendix 2 (available as supplemental material at http://dx.doi.org/10.1287/isre.2015.0618) for detailed industry representation). The industry categories are based on Eurostat's Statistical Classification of Economic Activities in the European Community, referred to as NACE, which is the European equivalent of the North American Industry Classification System (NAICS) in the United States. Stratified random sampling was used by taking into account TurkStat's firm size classes and industries (NACE Rev.2). Therefore, the TurkStat survey is representative of the industries and size categories according to the shares of the population for each given year.[4]

The data are administratively collected by the Turkish government, and firms that are selected for the survey are required to provide information by law. The IT use survey is required to be filled out by a manager in the IT department, or, for smaller firms without an IT department, by someone who works with computers and software. If firms do not respond, they pay a monetary fine that is added to their tax debts automatically, and they are still required to respond immediately. Also, TurkStat keeps contacting these firms several times. These steps help to increase the response rates and representation of the survey. Around 90% of the firms responded to the survey each year (see Online Appendix 2, Table A5). Accordingly, the data are representative *nationally* and across the size categories and industries noted above. However, they may not be representative *regionally* (e.g., cities, provinces, etc.) since this is not pursued by TurkStat by design.

The IT use survey is an unbalanced panel where the number of observations ranged from 3,363 in 2007 to over 8,000 in 2011. We matched the firm-level IT use data set with the firm-level Annual Industry and Service Statistics data set of TurkStat, which is the most comprehensive firm-level survey in Turkey, representative of the population of firms with 10 or more employees.[5] This survey contains financial information and firm characteristics, such as sales, wages, and assets. For our main specification, we used firm fixed effects models to utilize within-firm variation for identification because firms with different levels of IT use significantly differ across observable dimensions, implying that there can be several other unobservable differences not captured by the data. Among the 13,231 unique firms in the matched full sample, 9,115 firms exist for only one year during the panel, and thus they cannot be used for any firm fixed effects model. Additionally, we wanted to identify two-year lagged coefficients, which require at least four years of observations per firm in the firm fixed effects model. There are 1,103 firms that exist for at least four years in the panel (620 firms exist for four years and 483 firms exist for five years), resulting in a total of 4,895 observations (please see Online Appendix 2 for more details). Accordingly, for our main empirical analysis, we maintained this particular sample across all specifications.

Firms included in the final sample tend to be larger and have higher levels of IT use than the entire set of firms. TurkStat employs stratified random sampling to select firms within the size categories in each industry. In the entire population of Turkish firms, the total number of small and medium firms (fewer than 250 employees) is greater than the total number of large firms (250 or more employees). Since there is a smaller pool of large firms compared with the pool of small and medium firms, a given large firm has a higher probability of being selected for the survey in consecutive years and appearing longitudinally in the data. Besides, larger firms typically have a higher probability of survival over time than small firms. Thus, our final sample, where we retain firms that have at least four years of observations, is biased toward larger firms. We discuss the implications of this sampling issue for our findings in §4.

We used TurkStat's firm IT use data set because of its advantages over the common IT databases in the United States in terms of information on different types of IT application use and representation. However, we note that several market and country characteristics of Turkey might affect the relationship between IT use and the firm's labor demand differently compared to other countries. For example, market frictions and labor regulations are generally high in Turkey, which is similar to other European countries, such as France and Germany. Business transactions have higher value added tax rates in Turkey compared to the United States. These differences can render market-based transactions costly for Turkish firms. All factors that create high market frictions may encourage firms to expand more internally as a result of IT use rather than through market-based transactions. Additionally, the Turkish economy has been experiencing high growth rates since the mid-2000s (for example, in our sample, the average sales growth rate is 8.2%). We discuss these country characteristics and how they relate to our findings in detail in §5.

3.1. Measuring the Firm's Type of IT Use

A novel feature of the data is the information on the use of specific IT applications. The IT use survey consists of

[4] Small firms have 10–49 employees, medium-sized firms have 50–249 employees, and large firms have 250 employees or more.

The representation parameters include design weights, adjustments for nonresponse, external distribution checks, and an ultimate multiplying factor. For more details, please see the home page of TurkStat's IT use survey, where press releases, statistical tables, and metadata information are provided. The metadata section provides extensive details about the scope, characteristics, and compilation of the IT survey: http://www.turkstat.gov.tr/PreTablo.do?alt_id=1048.

[5] For details on the Annual Industry and Service Statistics Survey, see http://www.turkstat.gov.tr/PreTablo.do?alt_id=1035.

Table 3 Examples of IT Applications

IT application	Examples and functionalities
ERP	Integrated systems that enable efficient use of resources, such as labor, capital, and materials
SCM	Systems that enable coordination with suppliers provide demand and inventory forecasts
CRM	Systems that collect, integrate, and analyze customer information (operational or analytical CRM)
Procurement	Systems for acquisitions and purchasing, inventory replenishment, billing, and payment
e-banking	Systems that facilitate payments and transactions with financial institutions over a Web browser
e-government	Web systems for e-auctions, tax filings, sending forms and requests to the government offices
Website	Web systems for customer/employee support, marketing, providing product and price information

several indicator variables that denote whether a certain IT application is in active use at the firm. We focus on seven IT applications that were measured over the five-year panel: ERP, CRM, SCM, procurement, e-banking, e-government, and corporate website.[6] Table 3 presents the descriptions and examples of each IT application (as indicated in the TurkStat survey).

These seven IT use variables are highly correlated with each other, and using them all together in a single specification leads to multicollinearity. We first ran the analysis using each IT application one at a time. The challenge in this case is that we could not identify the incremental effect of each IT application, controlling for the presence of the others, leading to potential omitted variable bias. Hence, we conducted a principal components analysis (PCA) to investigate whether these variables of interest are linearly related to a smaller number of factors that explain the same amount of variation. PCA can enable grouping of the IT use indicators into more meaningful categories by exploring which IT applications are used together and thus share a common variance. Additionally, having multiple measures of a latent firm variable, such as "enterprise application use," decreases measurement error and introduces another benefit of reducing the number of variables and summarizing them into different categories. Two factors were retained from PCA, resulting in two categories: the first group consists of ERP, CRM, SCM, and procurement, whereas the second group is e-banking, e-government, and corporate website (see Online Appendix 1). This grouping implies that the IT applications in each category are frequently used together. In other words, firms that use ERP also tend to use CRM, SCM, and procurement (or the other way around), and therefore it is hard to identify their individual effects because they share a common variation. The PCA approach allows us to utilize the same amount of variation among all seven IT use indicators with two factors, thus avoiding multicollinearity. Moreover, this grouping is meaningful because the first group includes large, firmwide enterprise applications that affect several business processes, and the second group includes small, narrow-scale electronic applications with a specific use. We term the IT applications in the first category as *enterprise applications* and the ones in the second category as *Web applications.* We summarize the indicator variables within each of these two groups into a single index by using the normalized PCA loadings as weights. This leads to two IT-use indices between 0 and 1 for each firm: (a) enterprise application use index and (b) Web application use index. We checked the robustness of the results by using different weights for the indices (such as equal) as well as different groupings of these IT applications and the results were similar (please see Online Appendix 3).

3.2. Summary Statistics

Table 4 presents the summary statistics of the main variables for the final sample of firms that have at least four years of observations and for the full sample of firms, which includes all observations. The averages of the individual IT applications represent the proportions of firm-years that have the system in use. The percentage of firm-years that use ERP systems is 59%, the percentage that use CRM is 34%, and the percentage that use SCM is 30%. On average, firms use 47% of the enterprise applications and 87% of the Web applications. The enterprise application use and the Web application use indices used in our analyses vary from 0 to 1, representing a weighted scheme of the IT applications included in each index. The means for the enterprise application use index and the Web application use index are 0.411 and 0.866, respectively, slightly differing from the averages reported above since the indices do not weigh the IT applications evenly. Overall, the use of enterprise applications is less prevalent than the use of Web applications because enterprise applications are typically more costly and challenging to implement. Comparing the summary statistics across the final sample and the full sample, firms that are retained in the final sample for the longitudinal analysis tend to be larger with higher levels of IT use than the firms in the full sample because of the nature of the sampling, as described in detail above.

[6] There was a change in the definition of the CRM variable in the 2011 study that asked about open source CRM use rather than overall CRM use. We conducted a sensitivity test by removing the CRM variable, and the results are similar.

Table 4 Summary Statistics and Variable Definitions

	Final sample		Full sample	
	Mean	STD	Mean	STD
Enterprise application use index (between 0 and 1)	0.411	0.340	0.353	0.345
Web application use index (between 0 and 1)	0.866	0.177	0.772	0.229
Enterprise resource planning (binary variable 0/1)	0.592	0.491	0.384	0.486
Customer relationship management (binary variable 0/1)	0.344	0.475	0.241	0.428
Supply chain management (binary variable 0/1)	0.297	0.457	0.208	0.406
Procurement (binary variable 0/1)	0.641	0.480	0.461	0.498
e-banking (binary variable 0/1)	0.902	0.214	0.721	0.449
e-government (binary variable 0/1)	0.832	0.251	0.869	0.337
Corporate website (binary variable 0/1)	0.887	0.242	0.797	0.402
Employment	1,044	1,884	399.6	1,162
Log(*Employment*)	6.430	0.988	4.911	1.395
Sales (in million TL)	301.0	1,040	90.92	508.1
Log(*Sales*)	18.18	1.577	16.27	1.986
Sales growth	0.082	0.468	0.044	0.247
Log(*Assets*)	13.23	4.849	10.4	5.563
Log(*Costs*)	18.20	1.576	16.31	1.943
Termination costs/total cost	0.006	0.014	0.006	0.017
Log(*Average wage rate*)	9.759	0.737	9.433	1.012
	4,895 observations		20,913 observations	

Notes. $Employment_{i,t}$ is the total number of employees of firm i in year t; Log($Sales_{i,t}$) is the log of total deflated (adjusted for inflation) sales (in million Turkish Lira (TL)) of firm i in year t; Log($Assets_{i,t}$) is the log of total deflated fixed assets (in million TL) of firm i in year t; Log($Costs_{i,t}$) is the log of total deflated costs (in million TL) of firm i in year t; $Termination\ costs/total\ cost_{i,t}$ is the total deflated labor termination costs divided by total deflated costs (in million TL) of firm i in year t; Log($Average\ wage\ rate_{i,t}$) is the log of deflated average annual wage per employee (in thousand TL) in firm i in year t.

4. Empirical Specification and Results

4.1. A Firm Fixed Effects Model of IT Use and Firm-Level Employment

We used the following firm fixed effects model for the main empirical specification:

$$\begin{aligned}\log(Employment)_{i,t} &= \beta_0 + \beta_1 Enterprise\ Application\ Use\ Index_{i,t}\\ &\quad + \beta_2 Web\ Application\ Use\ Index_{i,t}\\ &\quad + \delta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t},\end{aligned}$$

where $\log(Employment)_{i,t}$ is the log of number of employees in firm i at time t, $Enterprise\ Application\ Use\ Index_{i,t}$ is the level of enterprise application use index of firm i at time t, and $Web\ Application\ Use\ Index_{i,t}$ is the level of Web application use index of firm i at time t. We introduce the lagged values of the IT application use indices in further specifications. We control for firm-level characteristics such as lagged sales, assets, total costs, and sales growth rate ($X_{i,t}$). The firm fixed effects (α_i) absorb any permanent heterogeneity at the firm level. Time fixed effects (λ_t) absorb time-specific shocks shared by all firms. All nominal variables are adjusted for inflation.

4.2. Identification Strategy and Endogeneity

Analyzing the relationship between IT use and firm-level employment is subject to several potential sources of endogeneity. First, firms that have different IT use levels may be systematically different from each other (*unobserved heterogeneity*). We may be able to observe some of these different characteristics; still, unobserved differences may remain. Indeed, we find firms with different levels of IT application use to differ across observable dimensions, suggesting that there can be other differences that we may fail to observe. We used firm fixed effects to account for unobserved time-invariant heterogeneity across firms. Hence, our identification is driven by within-firm changes in IT use and firm-level employment over time, and not by permanent unobserved differences across firms.

Another potential source of endogeneity could be *omitted variable bias*, such as a positive shock to the firm's cash flows, that will affect both IT use and employment levels. Also, growing firms may have a greater demand for communication tools and enterprise systems, such as ERP. High growth firms that invest both in IT and labor can lead to a spurious positive correlation between the two variables. Some of these confounding firm-level trends can be due to macroeconomic conditions and business cycles. First, we included time fixed effects to control for time specific shocks to the economy experienced by all firms. Time fixed effects also control for national factors that can affect employment, such as changes in population, labor force, and unemployment rates. Also, we controlled for past sales and sales growth rates to account for some of the shocks to the firm's cash flows and growth trend. These controls specifically take into account how each firm is affected by economic conditions. We also used additional control variables to account for firm growth and performance, and how firms may be affected by economic conditions. Since current values of control variables might be directly driven by current employment levels and thus could be highly enodogenous, we used lagged values. Control variables included *lagged sales*, *sales growth rate* between the past and current year, *lagged assets*, and *lagged costs* capturing shocks that might affect a firm's cash flows and performance. Related to the shocks in the firm's labor strategy, we controlled for the lagged *ratio of termination fees to total costs* since termination fees may reflect labor downsizing policies in a firm. In the specifications where the control variables were removed, we found that failing to control for sales growth and other variables that account for firm performance results in an upward bias in the estimated coefficients (please see Table A10 in Online Appendix 3 for details).

We also exploited the panel structure of the data and analyzed the timing of changes in IT use and employment to test for *reverse causality*. This is similar to the Granger (1969) causality test, which is a common test between two variables in a time series context. We found that past levels of IT use predict current employment levels, whereas past employment levels do not predict current IT use. This finding indicates that changes in IT precede changes in employment, and hence the evidence does not support reverse causality and suggests that the causal direction is from IT use to firm-level employment only.

We addressed some potential remaining endogeneity bias using generalized propensity score (GPS) matching by taking advantage of the rich data set. GPS estimates rely on a different identifying assumption where only *observed heterogeneity* is accounted for, and they confirm a similar positive relationship. Nonetheless, despite using several methods to address potential endogeneity, the results could still be subject to unobserved time-varying factors that cannot be captured in the data, such as an unobserved positive shock that manifests its effect over time, affecting both the firm's IT use and employment levels.

4.3. Results: Effects of IT Use on Firm-Level Employment by IT Application Type

We first present the results where individual IT applications are disaggregated and are included in specifications individually. Table 5 presents firm fixed effects regressions where log employment is regressed on ERP, CRM, SCM, procurement, e-banking, e-government, and website use indicators and their lagged values, *one IT application at a time*. Each column is a separate regression. ERP, CRM, and SCM have significant two-year lagged coefficients, and their current and one-year lagged coefficients are statistically insignificant and small in magnitude. On the other hand, e-banking, e-government, and website applications have significant current coefficients, where all their lagged coefficients are insignificant with small magnitudes. In column (4), the procurement application has significant one-year and two-year lagged coefficients, differing slightly from the enterprise applications that only have effects after two years, and also differing from the Web applications that have current year effects. Although the procurement clusters with the other enterprise applications (ERP, CRM, SCM) in the PCA, its effects materialize relatively faster. These results may imply that the timing of the effects of the procurement application lies in between that of the enterprise applications and Web applications. Therefore, for robustness checks, we used various alternative categorizations where the procurement application was included in the Web application use index versus the enterprise application use index, the procurement application was not included in either index, and the procurement application was totally omitted from the analysis (please see Online Appendix 3 for more details).

Omitted variables are potential problems in Table 5. For example, ERP and CRM variables are highly correlated. In columns (1) and (2), we included ERP and CRM one at a time in different regressions, and it is uncertain whether the significant effect of CRM use is due to its correlation to the ERP use (or vice versa). To estimate the incremental effects of each IT application, we needed to control for the presence of other IT applications in each specification. However, IT use indicators have high correlations with each other, and including all IT use indicators in one specification leads to multicollinearity problems because this requires estimation of 21 highly correlated coefficients (i.e., three coefficients for each IT application, current use, one-year lagged use, and two-year lagged use). Thus, we employed the enterprise use and Web application use categories obtained with PCA, which groups the IT applications based on their common variance.

Table 6 presents the estimates of the effects of enterprise application and Web application use levels on log firm-level employment over time. In column (1), we include only the current IT use indices, and introduced one-year lagged and two-year lagged IT use measures in columns (2) and (3), respectively.[7] The results indicate that enterprise applications do not

[7] Our sample includes 1,103 firms that exist at least four years in the data. Out of the 1,103 firms, 483 of them have observations for five years and 620 of them have observations for four years. The specification in column (1) does not include any lagged coefficients of IT use variables; however, we have one-year lagged control variables, which leads to losing one year of observation per firm and 3,792 observations ($4{,}985 - 1{,}103 = 3{,}792$, or $483 \times 4 + 620 \times 3 = 3{,}792$).

Table 5 The Role of Individual IT Applications in Firm-Level Employment

DV: Log *Employment*	(1) ERP	(2) CRM	(3) SCM	(4) Procurement	(5) e-banking	(6) e-government	(7) Website
Independent variables							
IT application use at time$_t$	0.031	−0.003	0.008	0.008	0.126**	0.110**	0.078*
	(0.027)	(0.025)	(0.025)	(0.027)	(0.057)	(0.054)	(0.046)
IT application use at time$_{t-1}$	0.005	0.026	−0.017	0.073***	0.049	0.018	0.015
	(0.035)	(0.028)	(0.029)	(0.028)	(0.064)	(0.066)	(0.069)
IT application use at time$_{t-2}$	0.159***	0.111***	0.090***	0.056**	0.001	0.004	−0.029
	(0.034)	(0.034)	(0.029)	(0.025)	(0.065)	(0.037)	(0.101)
Control variables							
Log(*Sales$_{t-1}$*)	0.633***	0.649***	0.645***	0.647***	0.645***	0.646***	0.641***
	(0.071)	(0.050)	(0.071)	(0.071)	(0.050)	(0.071)	(0.072)
Sales growth$_t$	0.097***	0.099***	0.099***	0.100***	0.098***	0.103***	0.097***
	(0.031)	(0.030)	(0.032)	(0.031)	(0.030)	(0.032)	(0.032)
Log(*Assets$_{t-1}$*)	−0.003	−0.002	−0.003	−0.003	−0.002	−0.003	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(*Total cost$_{t-1}$*)	0.005	0.027	0.002	0.005	0.029	−0.029	0.001
	(0.016)	(0.022)	(0.016)	(0.015)	(0.021)	(0.030)	(0.015)
Termination cost ratio$_{t-1}$	−1.394	−1.418*	−1.393	−1.299	−1.254	−1.156	−1.355
	(1.123)	(0.809)	(1.098)	(1.113)	(0.810)	(1.014)	(1.134)
Log(*Average wage rate$_{t-1}$*)	−0.126***	−0.138***	−0.138***	−0.136***	−0.136***	−0.133***	−0.134***
	(0.033)	(0.036)	(0.033)	(0.033)	(0.036)	(0.032)	(0.032)
Observations	2,689	2,689	2,689	2,689	2,689	2,689	2,689
Number of firms	1,103	1,103	1,103	1,103	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

instantly affect firm labor demand. The coefficients of the current and one-year lagged enterprise application use are insignificant with small magnitudes.

However, the two-year lagged enterprise application use coefficient is positive and significant; notably, the use of all four enterprise applications is associated with a 22% higher labor demand after two years.[8] The difference in the coefficients of the enterprise application use over two years is statistically significant ($p < 0.01$). For Web applications, we observe a significant current effect, whereas the coefficients of the lagged use of Web applications are insignificant with small magnitudes. This can be interpreted as an immediate effect that persists as long as the applications are in use in the following years. The use of all three Web applications is associated with a 12.5% higher firm-level employment in the current year. Overall, the results imply that the effects of the use of enterprise applications take time to manifest themselves, whereas the use of Web applications has immediate effects that are realized in the current year.

In our final sample, we retain firms that have at least four years of observations to be able to identify longitudinal effects. The sampling issues outlined in §3 might lead to an underestimation of the marginal effects of IT use on firm employment for two reasons. First, the firms in the final sample tend to be larger with higher levels of IT use, and thus realize a lower rate of change in their IT use during the sample period. Our identifying variation comes from within-firm changes, and thus we may not be able to identify marginal effects for some of the large firms that already have very high levels of IT use. These firms that can be viewed as early adopters may be the ones that received the largest returns from IT, which we may not be able to capture in our estimates. Second, there is a lower probability for smaller firms to be present in the final panel, and this can lead to the omission of important identifying variations from these firms that

Similarly, in column (2), we include one-year lagged IT use variables and control variables, and lose one year of observation per firm. In column (3), we include two-year lagged IT use variables, and this leads to losing two years of observations per firm and a total of 2,689 observations ($4{,}985 - 2 \times 1{,}103 = 2{,}689$, or $483 \times 3 + 620 \times 2 = 2{,}689$).

[8] This interpretation is for cases when firms start using all associated IT applications in one year; however, this change may not be reasonable empirically. Hence, we also interpret the coefficients based on a one-application increase. Enterprise and Web application use indices are weighted averages of the corresponding applications based on PCA weights; therefore, the change in the indices based on a one-application increase would depend on which specific IT application is added. Here, we interpret the changes in equally weighted IT use indices as averages. The effect of one additional enterprise application use on log (*employment*), on average, would be $0.219 \times 0.25 = 0.547$, which suggests about a 5.5% increase in the employment level within the firm. The estimated effect of one additional Web application use on log (*employment*) is $0.125 \times 0.33 = 0.04125$, or about a 4.1% increase in the level of firm-level employment.

Table 6 Role of Enterprise Application and Web Application Use in Firm-Level Employment

DV: Log *Employment*	(1)	(2)	(3)
Independent variables			
Enterprise application use index	0.001	0.004	0.020
	(0.031)	(0.032)	(0.043)
Enterprise application use index$_{t-1}$		0.010	0.017
		(0.036)	(0.047)
Enterprise application use index$_{t-2}$			0.219***
			(0.050)
Web application use index	0.121**	0.123**	0.125**
	(0.050)	(0.054)	(0.063)
Web application use index$_{t-1}$		0.034	0.023
		(0.060)	(0.086)
Web application use index$_{t-2}$			0.019
			(0.093)
Control variables			
Log(*Sales$_{t-1}$*)	0.581***	0.586***	0.629***
	(0.036)	(0.036)	(0.073)
Sales growth$_t$	0.058***	0.059***	0.094***
	(0.020)	(0.020)	(0.032)
Log(*Assets$_{t-1}$*)	0.001	0.001	−0.003
	(0.002)	(0.002)	(0.003)
Log(*Total cost$_{t-1}$*)	0.029	0.036	0.032
	(0.035)	(0.035)	(0.035)
Termination cost ratio$_{t-1}$	−1.393*	−1.448**	−1.428
	(0.715)	(0.717)	(1.104)
Log(*Average wage rate$_{t-1}$*)	−0.197***	−0.195***	−0.129***
	(0.029)	(0.029)	(0.033)
Observations	3,792	3,792	2,689
Number of firms	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Note. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

may experience a larger change in their IT use levels over time. We would expect the results to be similar, or even stronger, if all firms could be incorporated into the analysis because there may be a higher marginal impact of IT use for less IT-oriented firms. This is especially true for Web application use that has a high mean and a low standard deviation, and may possibly have low marginal returns on the firm's labor demand, simply because the diffusion of Web applications is significantly higher than the diffusion of enterprise applications across all firms, making it harder for us to detect their effects. This is an inevitable sampling bias inherent in the survey, and we conducted two robustness checks that expand the representation to make sure our results are not driven by the bias toward larger firms that have higher IT use levels. First, we employed weighted regressions to generate a sample that represents the entire population of firms annually. The weights were calculated for each year of the survey; thus, they are appropriate for cross-sectional analysis and only useful as a robustness check for the longitudinal analysis. We found similar coefficients with weighted regressions (see Online Appendix 3, Table A9). Second, we did not restrict the analysis to the final sample across specifications to include more firms from the full sample where possible and found similar results (see Online Appendix 3, Table A10).

4.4. Effects of IT Use on Firm-Level Employment by Firm Size

To analyze whether the relationship between IT use and firm-level employment varies by firm size, we divided the sample into terciles to create size groups. The firms in the bottom one-third of the size distribution were placed in the *small* category, firms in the middle were placed in the *medium* category, and those in the top one-third were placed in the *large* category. To estimate the coefficients of lagged IT use, we conditioned the analysis on the initial size category to identify the effects over time. Table 7 shows the results where the IT use variables are interacted with the firm's size category. The baseline category is small firms; the interaction terms between IT use and medium-sized (or large) firms show the differences between small and medium-sized (or large) firms. The enterprise application use coefficients are not significant for small firms. The two-year lagged coefficient of enterprise application use is significantly higher in large versus small firms; however, the difference between large and medium firms is not statistically significant. Also, the current Web application use coefficient is significant for small firms, but insignificant for medium and large firms. In sum, enterprise application use is associated with a higher labor demand over time for medium and large firms; by contrast, Web application use is associated with a higher labor demand for small firms.

4.5. Effects of IT Use on Firm-Level Employment by Average Wage Rate

We used the *average wage rate* per employee as a proxy for the average skill level of the firm's employees. Table 8 presents the results of the interactions between the average wage rate and the IT use indices. The two-year lagged coefficient of enterprise application use on firm-level employment is stronger for firms with higher average wages. On the other hand, the interaction term between the current Web application use and the average wage rate is not statistically significant, implying that the relationship between Web application use and firm labor demand does not vary with the firm's wage levels. It should be noted that average wages could also vary due to several other factors besides skills, such as location and industry, and thus there can be several alternative explanations to the findings. Nonetheless, we may interpret the stronger positive longitudinal relationship between the enterprise application use and the firm's labor demand

Table 7 Role of IT Use on Firm-Level Employment by *Firm Size*

DV: Log *Employment*	(1)	(2)	(3)
Enterprise application use index	0.019 (0.054)	0.011 (0.055)	0.011 (0.063)
Enterprise application use index × *Medium*	−0.011 (0.074)	−0.004 (0.075)	0.000 (0.076)
Enterprise application use index × *Large*	0.039 (0.072)	0.041 (0.072)	0.04 (0.096)
Enterprise application use index$_{t-1}$		0.020 (0.062)	0.005 (0.065)
Enterprise application use index$_{t-1}$ × *Medium*		0.008 (0.078)	−0.031 (0.081)
Enterprise application use index$_{t-1}$ × *Large*		0.053 (0.080)	0.046 (0.085)
Enterprise application use index$_{t-2}$			0.035 (0.066)
Enterprise application use index$_{t-2}$ × *Medium*			0.197** (0.088)
Enterprise application use index$_{t-2}$ × *Large*			0.324*** (0.099)
Web application use index	0.201* (0.121)	0.218* (0.125)	0.214* (0.124)
Web application use index × *Medium*	−0.001 (0.132)	−0.027 (0.148)	−0.039 (0.156)
Web application use index × *Large*	−0.026 (0.130)	−0.017 (0.145)	−0.022 (0.153)
Web application use index$_{t-1}$		0.002 (0.102)	0.004 (0.143)
Web application use index$_{t-1}$ × *Medium*		0.012 (0.156)	0.014 (0.154)
Web application use index$_{t-1}$ × *Large*		0.041 (0.156)	0.042 (0.156)
Web application use index$_{t-2}$			−0.051 (0.139)
Web application use index$_{t-2}$ × *Medium*			0.051 (0.170)
Web application use index$_{t-2}$ × *Large*			0.084 (0.173)
Observations	3,792	3,792	2,689
Number of firms	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Notes. Control variables include Log(*Sales$_{t-1}$*), *Sales growth rate$_t$*, Log(*Assets$_{t-1}$*), Log(*Total cost$_{t-1}$*), Log(*Average wage rate$_{t-1}$*), and *ratio of termination costs to total costs$_{t-1}$*. Robust standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8 Role of IT Use on Firm-Level Employment by *Average Wage Rate*

DV: Log *Employment*	(1)	(2)	(3)
Enterprise application use index	−0.003 (0.039)	−0.003 (0.038)	0.009 (0.053)
Enterprise application use index × Log(*Average wage rate*)	−0.005 (0.040)	−0.003 (0.039)	0.030 (0.049)
Enterprise application use index$_{t-1}$		−0.011 (0.045)	−0.007 (0.072)
Enterprise application use index$_{t-1}$ × Log(*Average wage rate*)		0.057 (0.047)	0.046 (0.047)
Enterprise application use index$_{t-2}$			0.133** (0.063)
Enterprise application use index$_{t-2}$ × Log(*Average wage rate*)			0.222*** (0.067)
Web application use index	0.139* (0.072)	0.163** (0.073)	0.147** (0.074)
Web application use index × Log(*Average wage rate*)	−0.016 (0.032)	−0.002 (0.077)	−0.014 (0.115)
Web application use index$_{t-1}$		0.045 (0.068)	−0.017 (0.102)
Web application use index$_{t-1}$ × Log(*Average wage rate*)		0.015 (0.051)	0.029 (0.093)
Web application use index$_{t-2}$			0.017 (0.120)
Web application use index$_{t-2}$ × Log(*Average wage rate*)			−0.011 (0.122)
Log(*Average wage rate*)	−0.208*** (0.047)	−0.212*** (0.046)	−0.145*** (0.035)
Observations	3,792	3,792	2,689
Number of firms	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Notes. Control variables include Log(*Sales$_{t-1}$*), *Sales growth rate$_t$*, Log(*Assets$_{t-1}$*), Log(*Total cost$_{t-1}$*), Log(*Average wage rate$_{t-1}$*), and *ratio of termination costs to total costs$_{t-1}$*. Robust standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

as a piece of evidence that is consistent with the notion of SBTC, where IT complements skilled labor relatively more than unskilled labor.

4.6. Effects of IT Use on Firm-Level Employment by Industry Technology Intensity

We examined whether the relationship between IT use and firm-level employment differs across firms of different industry technology intensity. We used Eurostat's classifications of industry technology intensity and used three categories for our analysis: (a) high-tech, (b) medium-tech, and (c) low-tech.[9] *High-tech* industries include computers, electronics, scientific instrument production, pharmaceuticals, telecommunications, research and development, and financial intermediation. Some examples of *medium-tech* industries are petroleum refining, metal products, plastics, and shipbuilding, and examples of *low-tech* manufacturing industries are paper printing, textiles, wholesale trade, and accommodation services.

[9] The classification scheme categorizes each three-digit manufacturing/services industry code to an industry technology intensity group: high-tech, medium-high-tech, medium-low-tech, and low-tech. We combined the high-tech and medium-high-tech categories (termed *high-tech*) because there are very few observations in the high-tech category. The full classification list of Eurostat's technology intensity groups is available at http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech.

Table 9 Role of IT Use on Firm-Level Employment by *Industry Technology Intensity*

DV: Log *Employment*	(1)	(2)	(3)
Enterprise application use index	0.001 (0.056)	0.006 (0.057)	0.127 (0.078)
Enterprise application use index × *Medium-tech*	0.003 (0.083)	−0.011 (0.083)	−0.169 (0.108)
Enterprise application use index × *High-tech*	−0.030 (0.074)	−0.014 (0.075)	−0.131 (0.101)
Enterprise application use index$_{t-1}$		0.038 (0.063)	0.151* (0.088)
Enterprise application use index$_{t-1}$ × *Medium-tech*		−0.068 (0.093)	−0.170* (0.093)
Enterprise application use index$_{t-1}$ × *High-tech*		0.019 (0.081)	−0.127 (0.081)
Enterprise application use index$_{t-2}$			0.087 (0.086)
Enterprise application use index$_{t-2}$ × *Medium-tech*			0.302*** (0.095)
Enterprise application use index$_{t-2}$ × *High-tech*			0.483** (0.138)
Web application use index	0.002 (0.071)	0.009 (0.074)	0.003 (0.076)
Web application use index × *Medium-tech*	0.120* (0.066)	0.130** (0.065)	0.134** (0.066)
Web application use index × *High-tech*	0.197** (0.091)	0.200** (0.090)	0.214** (0.092)
Web application use index$_{t-1}$		0.005 (0.107)	−0.012 (0.110)
Web application use index$_{t-1}$ × *Medium-tech*		−0.014 (0.153)	−0.004 (0.153)
Web application use index$_{t-1}$ × *High-tech*		0.142 (0.153)	0.136 (0.153)
Web application use index$_{t-2}$			−0.194 (0.135)
Web application use index$_{t-2}$ × *Medium-tech*			0.083 (0.186)
Web application use index$_{t-2}$ × *High-tech*			0.119 (0.185)
Observations	2,979	2,979	2,118
Number of firms	861	861	861
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Notes. Control variables include Log(*Sales$_{t-1}$*), *Sales growth rate$_t$*, Log(*Assets$_{t-1}$*), Log(*Total cost$_{t-1}$*), Log(*Average wage rate$_{t-1}$*), and *ratio of termination costs to total costs$_{t-1}$*. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9 shows the results where current and lagged IT use indices are interacted with the high-, medium-, and low-tech categories. The omitted category is low-tech, and therefore the baseline coefficients represent the effects of IT use for low-tech firms. The interaction terms between current and lagged IT use and the medium-tech (high-tech) category provide the differences in coefficients between the low-tech and medium-tech (high-tech) categories. We find the one-year lagged enterprise application use coefficient to be marginally significant and positive for low-tech firms. On the other hand, the two-year lagged coefficients are significant for medium-tech and high-tech firms and insignificant for low-tech firms. Similarly, current Web application use coefficients are significant for high-tech and medium-tech firms, but not for low-tech firms. We found that both enterprise and Web application use coefficients are stronger in medium- and high-tech firms compared to low-tech firms, but they are not statistically different between medium- and high-tech firms.

4.7. Generalized Propensity Score Matching of Firms

We further addressed the endogeneity issue by conducting analyses based on a different assumption and providing evidence that our results are not driven by a particular identification. Specifically, we used the GPS matching method that accounts for the observable heterogeneity across firms by estimating the effects of IT use on firm-level employment comparing only firms that are similar across observables. Hirano and Imbens (2004) and Imai and Van Dyke (2004) developed the GPS method to be an extension of the binary treatment propensity scores (Rosenbaum and Rubin 1983) with continuous treatment variables (for GPS application examples, please see Bia and Mattei 2008, Kluve et al. 2012). The idea is to match the firms that are most similar along several characteristics that determine IT use and firm employment levels simultaneously to eliminate the bias associated with differences in observables. This method first predicts the IT use based on observable characteristics, such as industry, sales, sales growth, investment, loss, and other financial and business statistics. This is one of the main differences of the GPS matching method compared to regression based methods, as GPS estimates the level of the independent variable rather than using the actual realized levels, which are potentially endogenous.

The first step is to estimate the conditional density of the treatment given the covariates by using the equation $r(t, x) = f_{T\mid X}(t \mid x)$, where T is the treatment level (IT use index in this case) and X represents the observable covariates. The generalized propensity score is $R = r(T \mid X)$. Next, we estimate the conditional expectation of the outcome (firm-level employment) as a function of the treatment level T (IT use index) and GPS level R (estimated IT use index), $\beta(t, r) = E[Y \mid T = t, R = r]$. To estimate the dose-response function at a particular level of treatment, we averaged this conditional expectation over the GPS at a particular level of IT use (which is denoted by t): $\mu(t) = E[\beta(t, r(t, x))]$.

To evaluate whether this specification of the propensity score is adequate, we examined how it affects the balancing of covariates. We divided the IT use indices into three levels and examined whether the adjusted

Figure 1 (Color online) Generalized Propensity Score Matching Results

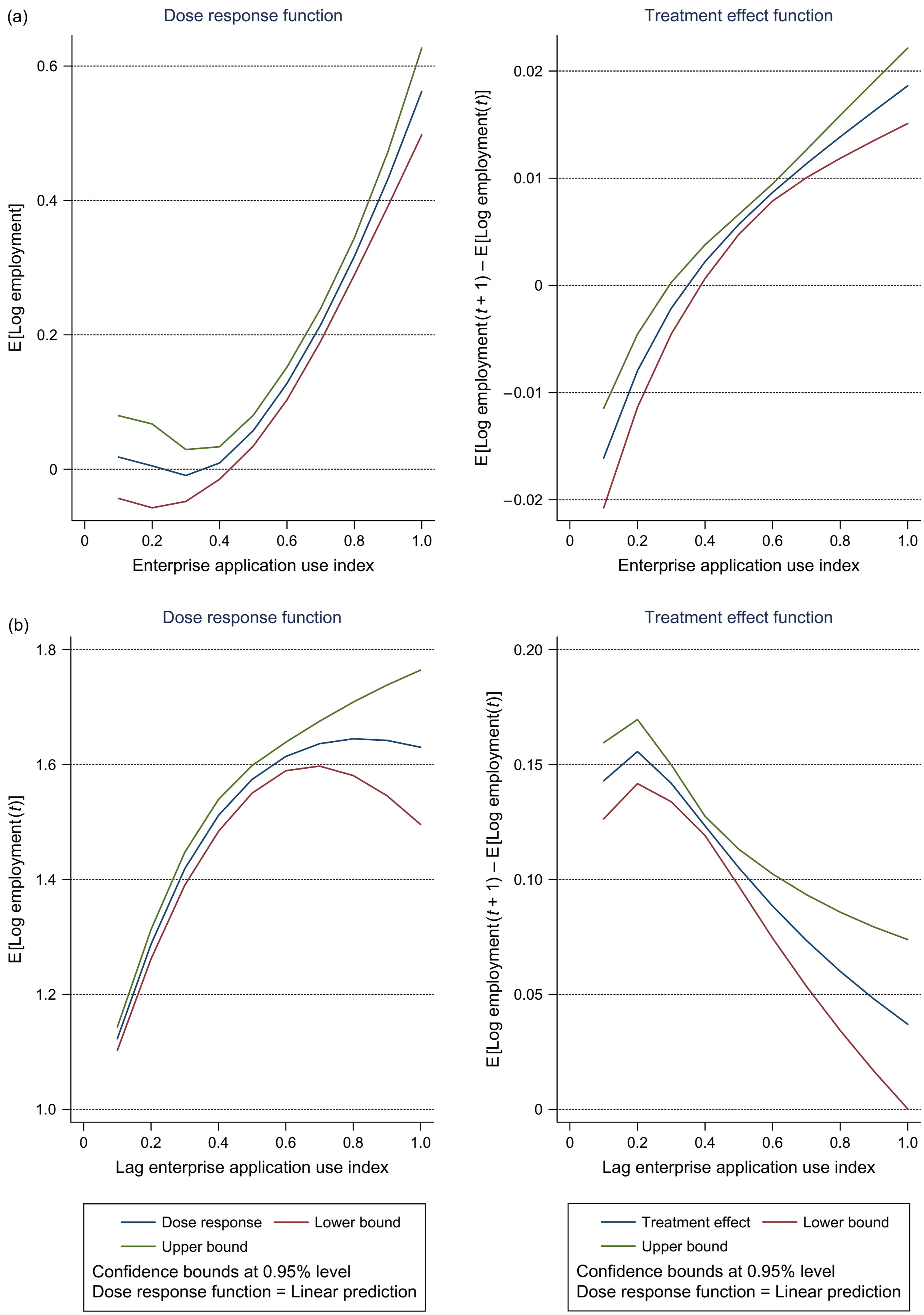

Table 10 **Relationship Between Current IT Use and Past Firm-Level Employment**

	DV: *Enterprise application use*			DV: *Web application use*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(*Employment*)	−0.000	0.001	0.000	0.017*	0.017*	0.017*
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Log($Employment_{t-1}$)		−0.001	0.007		0.000	−0.000
		(0.008)	(0.006)		(0.008)	(0.008)
Log($Employment_{t-2}$)			0.006			−0.002
			(0.008)			(0.008)
Observations	3,792	3,792	2,689	3,792	3,792	2,689
Number of firms	1,103	1,103	1,103	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

mean in each level is different from the adjusted means in the other two levels. Covariates are not balanced when unadjusted, meaning that firms with different levels of IT use significantly differ across their observable dimensions. These observable covariates are balanced when adjusted for GPS. The means of the covariates are not statistically different from each other across the three levels of estimated IT use. This indicates that the GPS method was able to correct for any observable heterogeneity among firms.

Figures 1(a) and 1(b) present the dose-response functions and corresponding treatment effect functions estimated by GPS. The first part of each graph presents the *dose-response function*, which shows the distribution of outcome for the corresponding levels of IT use. The second part of each graph presents the *treatment effect function*, which is the derivative of the dose-response function. In economic terminology, these are the marginal effects: $(\mu(t+\Delta t)-\mu(t))$. In Figures 1(a) and 1(b), we report the dose-response differences (marginal effects) distribution, for an increase of 0.1 in the IT use indices $(\mu(t+0.1)-\mu(t))$ from each IT use level and the corresponding 95% confidence bands calculated by bootstrapping. For instance, in Figure 1(a), if the current enterprise application use index increases from 0.6 to 0.7 $(\mu(t+0.1)=\mu(0.6+0.1)=\mu(0.7))$, the number of employees would increase by 0.75%. The marginal effects are increasing, indicating a convex relationship for current enterprise use and firm-level employment. Figure 1(b) shows that the marginal lagged effect of the use of enterprise applications is increasing at a decreasing rate, implying a concave relationship between lagged use and firm-level employment. The total effect was still larger for higher levels of lagged enterprise application use. However, the marginal positive effects are diminishing over time as firms use more enterprise applications (the cumulative effect still increases). The current marginal effects of Web application use are not statistically significant (see Online Appendix 3). The lagged effects of Web application use are more precisely estimated than current effects, where an increase in Web application use by 0.1 corresponds to about a 2% increase in employment (for Web application use index levels above 0.4). These magnitudes are not directly comparable to regression coefficients that report average effects because GPS provides effects for different levels of IT use, and the average would depend on the actual distribution. We also found different results using GPS, and one potential reason for this is the difference in the identifying assumption and the possibility of remaining unobserved heterogeneity in the GPS analysis. This can imply that there are unobservable variables that play a significant role in the relationship between IT use and the firm's labor demand. However, the GPS results indicate positive effects of both enterprise application use and Web application use on firm-level employment, consistent with the fixed effects results. Although GPS is informative on causal effects in rich data sets with many observables, it suffers from unobserved variable bias, which can be addressed by fixed-effects. In summary, these results complement each other, since they confirm a similar pattern with two different identifying assumptions.

4.8. Robustness Checks

4.8.1. Relationship Between IT Use and Past Firm-Level Employment. Our main results indicate that past levels of enterprise application use predict current levels of employment, proposing a causal direction from IT use to firm employment. We tested the opposite by analyzing the relationship between the past levels of firm employment and current levels of IT use, in the spirit of Granger's (1969) causality test. If past levels of firm employment can predict current IT use levels, this would raise endogeneity concerns, implying that changes in firm-level employment lead to the changes in IT use. In Table 10, we regressed the current IT use

Table 11 Role of IT Use on Average Wage Rate

DV: Log *Average wage rate*	(1)	(2)	(3)
Enterprise application use index	0.043	0.046	0.059
	(0.039)	(0.039)	(0.051)
Enterprise application use index$_{t-1}$		0.103**	0.166**
		(0.042)	(0.073)
Enterprise application use index$_{t-2}$			0.043
			(0.086)
Web application use index	0.022	0.106	0.081
	(0.067)	(0.078)	(0.095)
Web application use index$_{t-1}$		0.080	0.102
		(0.075)	(0.091)
Web application use index$_{t-2}$			0.125
			(0.106)
Observations	3,792	3,792	2,689
Number of firms	1,103	1,103	1,103
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Notes. Control variables include Log(*Sales*$_{t-1}$), *Sales growth rate t*, Log(*Assets*$_{t-1}$), Log(*Total cost*$_{t-1}$), Log(*Employment*$_{t-1}$), Log(*Average wage rate*$_{t-1}$), and the *ratio of termination costs to total costs*$_{t-1}$. Robust standard errors are in parentheses.

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

levels on current and past firm-level employment (using the same set of controls as used in the main analysis). The dependent variables (DVs) in columns (1)–(3) are the levels of enterprise application use, and the dependent variables in columns (4)–(6) are the levels of Web application use. Current and lagged firm-level employment levels are *not* correlated with enterprise application use. Also, past levels of firm employment do not predict Web application use, but there is a positive correlation between Web application use and current employment levels (as in the main analysis). These results, combined with the finding that changes in firm employment follow changes in enterprise application use from our main analysis, support a causal direction from IT use to firm-level employment.

4.8.2. Effects of IT Use on Average Wage Rates. We also analyzed the relationship between IT use and average wage rates to examine whether the increase in the number of employees in the firm is accompanied by a change in average wage. In Table 11, the dependent variable is log average wages, and the independent variables are current and lagged IT use levels. We also controlled for the number of employees. There are significant one-year lagged coefficients of enterprise application use. Although the use of Web applications also shows large positive coefficients, they are not statistically significant due to large standard errors. Overall, these results imply that the increase in the number of employees is not at the expense of lower average wages at the firm, and there can be positive effects of the use of IT applications on both workers' average wages and employment.

4.8.3. Alternative Specifications and Categorizations of IT Use Applications. We checked the robustness of our main results with different specifications and IT use calculations. Also, we checked the results using an ordinary least squares specification, where changes in log employment were regressed on changes in IT use indices. Additionally, we used several alternative measures of IT use. We used different weights for calculating the IT use indices (ranging from equal weights to PCA weights, and different linear combinations). Finally, we conducted robustness checks with different categorizations of the procurement application. These robustness checks were performed to ensure that our results were not driven by certain idiosyncratic loadings in the PCA or how IT use indices were calculated. In summary, our results are qualitatively similar with these alternative specifications (please see Online Appendix 3 for the tests in this section).

5. Discussion

5.1. Key Findings

This paper analyzes the longitudinal effects of IT use on firm-level employment and how they differ by *IT application types* and are moderated by (1) *firm size*, (2) *average wage rate*, and (3) *industry technology intensity*. We found a positive relationship between IT use and firm-level employment on average, and the relationship varies by the category of IT applications. The results show that the use of enterprise applications affects firm-level employment over time, whereas the effects of the use of Web applications materialize in the current year. We found that the use of all four enterprise IT applications is associated with about a 22% higher firm labor demand, and this effect materializes after two years in medium and large firms. The use of all Web applications is linked to about a 12.5% higher firm labor demand, and this effect is observed in the current year in small firms.[10] We also showed that the longitudinal relationship between the use of enterprise applications and firm-level employment is more pronounced in larger firms with higher average wages in high-tech industries, whereas the current effects of the use of Web

[10] We found that the use of one more enterprise application is associated with a 5.5% increase in firm-level employment after two years, whereas the use of one more Web application is linked to a 4.1% increase in the firm-level employment in the current year. Although we cannot directly compare our main findings to previous studies on IT and firm labor demand, since we do not have measures of aggregate IT spending or IT capital at the firm, we observe sizeable effects in terms of the magnitudes. For example, Brynjolfsson et al. (1994) found that a 1% increase in IT investment leads to a 0.13% decrease in employees per establishment. Similar 1% increases in enterprise and Web application use at their sample averages are associated with about 0.09% and 0.10% increases in firm-level employment, respectively. However, this calculation does not take into account the empirical distributions of the IT use variables.

applications are more pronounced in small firms. The results are robust to GPS matching and several tests that address endogeneity concerns. However, it should be noted that there can be alternative explanations to the findings, especially for the moderated relationships, since firm size, average wage rate, and industry can be correlated with unobserved factors.

5.2. Contributions and Implications for Research

We used recent nationally representative firm-level data provided by the TurkStat that include information on the use of different types of IT applications. The findings supplement our understanding derived from the other data sources (Table 1) in three main aspects. The first advantage of our data is that the selected firms are required to complete the TurkStat survey by law, and this led to a high response rate and a sample of a comprehensive set of firms, thus enabling us to draw inferences that are more applicable to the entire population of Turkish firms. Second, there is detailed information on the use of specific IT applications, such as ERP, SCM, and CRM. This allowed us to test the effects of the use of specific IT applications and gain an understanding of how enterprise versus Web applications might influence the firm's employment, which may not be readily identified with aggregate IT measures, such as IT capital, IT investments, or IT spending. Going beyond an aggregate measure of IT enables us to provide insights on the role of specific IT applications in firm outcomes, similar to Aral et al. (2006) and Forman and McElheran (2013). Third, our data include smaller firms across industries, whereas the majority of IT studies are primarily based on large, publicly traded firms (one exception is Tambe and Hitt 2012). This allows us to test the relationship between IT use and firm labor demand for firms of different sizes.

Most of the IS literature has relied on data from the United States to show that IT investments can lead to either smaller or larger firms (Brynjolfsson et al. 1994, Hitt 1999, Forman and McElheran 2013, Ray et al. 2013). In our data from Turkey, IT use is associated with higher firm-level employment, on average. The differences between our results and the IS literature may arise from IT measurement and country characteristics. In terms of context-specific distinctions, country and time frame differences can play an important role. Our data are from a developing country, Turkey, which is considered to be a high-growth emerging economy. There are market characteristics of Turkey that may affect the relationship between IT use and firm-level employment. First, the role of IT in the firm's internal and external coordination costs can be different in Turkey. One possible explanation is the high business-to-business transaction taxes (18% value-added tax) in Turkey, which may limit the ability of IT to reduce external transaction costs. Furthermore, even though IT use may decrease external communication costs, other market frictions due to the country's regulatory environment can limit the scope of external business transactions, thus affecting the relationship between IT use and firm-level employment.[11] Labor market regulations can play a role as well. Compared to the United States, the labor market in Turkey is more regulated, which is a common characteristic among European countries, such as France and Germany. Moreover, the high growth rates observed in developing and emerging economies release the sales constraints on the firm's cash flows that enable further firm expansion. Combining all these factors, firms may find it optimal to grow internally rather than externally in a market with high external frictions and potential for internal growth, and IT use can thus lead to higher firm-level employment. The distinctions in these market characteristics can explain some of the differences between our results and previous studies that found a negative relationship between IT investments and firm size (e.g., Brynjolfsson et al. 1994, Hitt 1999). Since there is not much evidence on the economic effects of IT in developing countries and emerging economies, this study can have direct implications for developing countries with high growth rates, and further research can shed more light on our findings. Finally, this study is likely to have indirect implications for developed countries that are similar to Turkey in terms of market characteristics, such as many European countries.

5.3. Implications for Practice and Public Policy

The effect of IT on employment has been an important practical and public policy question because there are concerns that innovation and growth due to IT can also have potential job-destroying effects. The relationship between IT use and aggregate employment includes different components, such as workers, firms, and local and national labor markets. Several studies analyzed the role of IT in regional employment, and empirical evidence indicates that greater IT infrastructure and IT use in local areas are associated with higher regional employment and average wages (e.g., Crandall et al. 2007, Kolko 2010, Forman et al. 2012, Atasoy 2013). One of the key questions in this literature is whether the

[11] The Index of Economic Freedom accounts for market-based business, labor, tax, regulatory, legal, and other frictions and provides a summary of the overall economy's freedom. Turkey and France are similar to each other in market frictions and barriers, whereas the United States has lower economic frictions. Turkey ranks 69th among 177 countries in the 2013 Index of Economic Freedom, France ranks 61st, whereas the United States ranks 10th (low ranking numbers represent higher economic freedom). Also, the relative tax burden in the 2013 Index of Economic Freedom ranks Turkey 109th out of 185 countries, whereas the United States ranks 148th (low ranking numbers suggest a higher tax burden). Further details about the Index of Economic Freedom can be found at http://www.heritage.org/index/about.

positive relationship between IT and regional employment is due to increasing the number of firms in the region, or caused by each firm in the region hiring more employees. Our study explicitly focuses on the relationship between IT use and *firm-level* employment, and our data cannot directly infer about the broader effects of IT use on aggregate employment levels at regional or national labor markets. Nonetheless, the effect of IT use on firm-level employment remains an important question to fully understand the interplay between IT, labor markets, and aggregate-level employment.

A main practical and policy implication at the firm level is that IT is not necessarily replacing all types of jobs in the firm, and can create a positive net impact on the firm's total number of employees. The effects can be larger for labor in sectors that employ skills complementary to IT. The positive relationship between IT use and the firm's labor demand is more pronounced in firms with higher average wages and high-tech firms, supporting this logic. However, similar to many economic effects realized through IT, the effects on firm employment can materialize gradually over time, particularly for enterprise applications, and this should be taken into account in managerial and public policies that seek to stimulate jobs through IT investments.

Turkey has been experiencing fast growth rates over the last decade, except during the global financial crisis of 2008 and 2009. This was reflected in the national unemployment rate, which reached as high as 14% during the financial crisis. The unemployment rate recovered back to its precrisis levels of 9%–10% in 2010 and thereafter. We controlled for the macroeconomic time trends in our analysis, and the signs of time dummies in the firm-level employment regressions reflected this trend, although they are not statistically significant. We found a positive relationship between IT use and firm-level employment, on average, after taking into account these shocks to national employment. Since our final panel sample tends to be larger firms that survived the economic downturns, some of the positive effects of IT use may be offset in the aggregate employment levels by firms that did not survive, or non-IT savvy firms, which may have lost employment. In other words, IT-oriented firms can grow at the expense of other firms. Thus, firm-level employment effects might not directly translate into aggregate-level employment effects. However, our results could be cautiously generalized to imply that the use of IT may also contribute to the national employment growth, and policies aiming to expand the use of IT can be important tools for stimulating employment growth and job creation beyond the firm level.

5.4. Limitations and Suggestions for Future Research

There are certain limitations to this study that create interesting opportunities for future research. First, we used five-year panel data, and although we could identify up to two-year lagged coefficients, this is still a relatively short time frame to analyze longer-term effects. Compared with research in developed countries, IT investment and IT use are relatively recent topics of interest in developing countries, such as Turkey. Detailed census panel data on IT use that is consistent over a longer period of time would be useful for further longitudinal analysis. We provided empirical evidence from the specific context of Turkey, and we discussed several market characteristics that are likely to play a role in the relationship between IT use and firm-level employment. Market frictions and regulations can vary significantly across countries leading to differential impacts of IT on firm employment. Empirical research from other developing countries is needed to demonstrate the generalizability of our results.

The positive effects of IT use on firm-level employment can be attributed to at least three mechanisms, which are not directly testable with our data: (a) productivity gains, (b) decrease in internal coordination costs relatively more than external coordination costs, and (c) increase in complementary (skilled) labor due to IT relatively more than a decrease in substitutable (unskilled) labor due to automation due to IT (following SBTC theory). We related to the final mechanism using average wages as a proxy for the average labor skill in the firm; however, direct data on skills, education, or occupations of all workers would provide a better test for SBTC theory, because wages may vary for many other reasons besides skills. This type of information can also provide evidence on who benefits from the use of IT at the firm the most because the benefits from IT are not likely to be equally distributed among different occupations and skills. Future research could explore the change in composition of skills and tasks within firms and question which occupations benefit or suffer as IT use increases. This has implications for workers as to which skills they should invest in to stay competitive in the labor market by matching the fast pace of IT growth.

Endogeneity is a key empirical challenge when studying the economic effects of IT, and the relationship between IT use and firm employment is not an exception. We used many approaches to address endogeneity, and each has its own underlying assumption. We address time-invariant, unobserved heterogeneity across firms with firm fixed effects models. Controlling for past sales and sales growth rates accounts for some of the confounding firm trends. Timing indicates that changes in firm employment follow changes in IT use over time, providing evidence against reverse causality.

GPS accounts for observed heterogeneity, and it shows that there is a positive relationship between IT use and the firm's labor demand under this different identifying assumption. However, we cannot completely rule out all alternative explanations, such as unobserved time-varying factors that may simultaneously increase IT use and firm employment over time.

Finally, although our study provides insights by offering empirical evidence on the effects of IT use on firm-level employment, understanding the broader effects of IT use on employment is essential. Still, the TurkStat data are not representative at a regional level, which prevents us from deriving direct implications for local, regional, or national labor markets, implications that would be of great interest from a public policy perspective. We hope that our study on the role of IT use in firm-level employment is a modest step toward stimulating future research on the broader effects of IT use on labor demand.

5.5. Concluding Remarks

The alleged job-destroying effect of technology has been a concern since industrialization, and it remains an important question for IS research today given the rapid digitization of the economy. For example, the "lump of labor" fallacy assumes that the amount of work is fixed, and there are fewer jobs available as IT can automate tasks and substitute for unskilled labor (e.g., Autor et al. 2003, Brynjolfsson and McAfee 2011, Autor and Dorn 2013). This seems to be a misbelief because IT can also increase labor demand by increasing productivity levels. Productivity increases were shown to increase labor demand by previous research; however, whether this relationship has continued in recent years remains an unanswered question (*MIT Technology Review* 2015). Moreover, how IT affects labor demand depends on the unit of analysis since the effects of IT can be different at the firm, regional, and national levels. In this study, we focused on the role of IT applications in labor demand at the firm level using a unique data set from Turkey. Our results imply that, at least in our context, the use of IT applications can increase firm-level employment. This study is a modest step toward fully understanding the role of IT in labor demand at the firm level and ultimately in aggregate employment by offering microlevel evidence on the role of IT use in firm-level employment.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/isre.2015.0618.

Acknowledgments

The authors are grateful to the senior editor, the associate editor, and the three anonymous reviewers for their excellent comments and suggestions. The authors would also like to thank the participants at the 2012 Workshop on Information Systems and Economics, the 2012 International Symposium of Information Systems and the 2013 ICT Munich Conference. This research uses data provided by the Turkish Statistical Institute and the results presented in this paper do not reflect the opinions of the aforementioned organization. Financial support from the University of Illinois Graduate College Dissertation Travel Grant and from the NET Institute are gratefully acknowledged.

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