Economies before Scale: Learning, Survival, and Performance of Young Plants in the Age of Cloud Computing*

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January 2019

Abstract

Young firms are central to productivity and job growth, yet they fail at high rates. This dynamic can be understood as an outcome of high uncertainty early in life combined with costly learning about the productivity of irreversible investments. Recent advances in how firms access information technology (IT) - in particular, cloud computing – have dramatically lowered the costs of learning about productivity-enhancing IT. Using detailed Census Bureau data from 2006 to 2014, we explore whether this technological change has altered young-firm dynamics in the U.S. manufacturing sector. We find that young plants enjoy a roughly 5% lower annual failure rate on average due to IT services expenditure, while traditional IT capital investment increases the chance of failure. Conditional on survival, young plants exhibit much higher productivity from recent advances in IT services than do older plants. Detailed mechanism tests support technology-driven shocks to learning: older plants benefit from new IT services only if they are in high-uncertainty industries, and new establishments of existing firms benefit only if they operate outside their parent firm's primary industry. Young, small plants benefit the most, though we find no evidence for a financial-frictions mechanism. This study provides the first large-scale evidence concerning the magnitude and mechanisms of how recent advances in IT are changing how young firms survive and thrive before they achieve significant experience and scale of their own.

Key words: cloud computing, digitization, entrepreneurship, information technology, real options

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* *This paper benefited from early feedback from Kevin Bryan, Ricard Gil, Avi Goldfarb, Jorge Guzman, Bill Kerr, Ramana Nanda, Mu-Jeung Yang, and participants in the Workshop on Information Systems and Economics, the NBER Productivity Lunch, and the Queens Economics of Entrepreneurship and Innovation Conference. Outstanding support was provided by Jim Davis at the U.S. Census Bureaus' Boston Research Data Center. This research was conducted while the authors were Special Sworn Status researchers at the U.S. Census Bureau Research Data Centers in Boston and Madison. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. All errors are our own.*

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I. INTRODUCTION

Young firms drive a significant portion of U.S. employment and output growth and innovation (Hansen 1992; Kortum and Lerner 2000; Haltiwanger et al. 2013, 2016). Yet they are more likely to die – and there is growing research and policy focus on declining startup entry and survival in many industries (Decker et al. 2014; Hathawy and Litan 2014a, 2014b and 2014c; Haltiwanger et al. 2016). Yet not all small businesses contribute equally to economic performance, and firms with particularly high growth potential have increased in recent years (Kerr and Nanda 2014; Guzman and Stern 2015, 2016). Quite recently, young establishments have actually become more prominent in the U.S. manufacturing sector (Figure 1).

We argue that a potential driver of this trend is the shock to the costs of learning brought about by the rise of cloud computing. Recently, near-ubiquitous high-speed internet infrastructure, new software tools for storage and server consolidation ("virtualization") as well as application deployment ("containers"), and rapid entry of service providers into cloud computing technologies have made it increasingly possible for firms to access frontier information technology (IT) rapidly – and on an as-needed basis. The flexibility affords firms is unprecedented, and anecdotal evidence abounds that young firms, in particular, are leveraging the cloud to experiment, pivot, and scale rapidly (e.g., Machi 2010; Manyika et al. 2011; Hardy, 2018; Ewens Nanda, and Rhodes-Kropf, forthcoming).

Much of the discussion around the impact of cloud computing focuses on finance: the shift from a fixed-cost to a variable-cost model is presumed to be disproportionately beneficial to cash-constrained young firms. However, we find evidence for a different mechanism centered on learning. Drawing on theories of investment under uncertainty (e.g., Dixit and Pindyck 1994) and recent work on the value of conducting experiments in young firms (Thomke 2003; Kerr, Nanda, and Rhodes-Kropf 2014; Davis, Muzyrya, and Yin 2014; Manso 2016), we hypothesize that the cloud will disproportionately benefit young firms because it reduces the costs of conducting experiments to learn about their IT needs. We take our predictions to a representative sample of U.S. Census micro data to provide the first large-scale empirical evidence concerning both the magnitude of and mechanisms by which recent advances in IT are affecting the survival and performance of young establishments in the U.S.

Using establishment-level data on the manufacturing sector, we observe that gains from purchased IT services – particularly during the rise of cloud computing – are disproportionately concentrated among young plants. These investments lower the risk of young plant failure and increase young plant productivity, particularly in IT-intensive and high-uncertainty industries. Older plants benefit almost not at all, and only in high-uncertainty settings. We take this as evidence that, unlike many prior IT advances, key features of the cloud are particularly useful for firms facing high uncertainty. Thus, firms in the uncertain early years of life (Knight 1957; Jovanovic 1982) are the primary – or at least the first – beneficiaries of this particular technological change.

Why is this so? Accessing IT services via the cloud fundamentally alters the economics of IT investment and the type of IT that firms rely on – thus, a variety of mechanisms are theoretically possible, and not necessarily mutually exclusive. It replaces fixed costs with variable costs, so firms that are finance-constrained might benefit from the lower up-front costs of accessing IT. It provides shared economies of scale in IT resources, thus potentially benefitting small firms that could never reach such low average costs on their own. Most importantly, we argue, cloud computing allows firms to flexibly try different types of IT solutions and scale them up or down with much shorter lead times. Thus, the costs of experimenting with different types of IT solutions is dramatically lower.

There is a tradeoff, however, that reduces the benefits of this technology for certain, predominantly older, firms. While the cloud may "democratize IT" (Bloom and Pierri 2018), the solutions it offers are relatively generic and cannot be as easily customized to particular firm needs (Schneier 2015). The strategic management literature emphasizes the importance of uniqueness and inimitability of resources for competitive advantage (e.g., Barney 1991; Ray et al. 2004), suggesting that long-term benefits for firms that know their IT needs might not rest in the cloud.

We test our hypotheses using an unusually representative panel of roughly 26,000 establishments[3] over nine years (2006-2014) from the U.S. Annual Survey and Census of Manufactures. It is worth emphasizing early on that all establishments in this data set have at least one employee, so while it covers an unusually large and representative sample of small and young operations, this is not a study of firm founding. Moreover, we do not restrict our attention exclusively to young *firms*, per se. Many of the young plants in our analysis sample belong to larger, multi-unit entities. The patterns we observe are robust to this distinction, yielding insights about how localized these learning mechanisms are and making these patterns difficult to explain in terms of access to capital.

Using heretofore unexplored fields in the Census micro data, we model survival, employment growth, and multi-factor productivity at the plant level as a function of different types of IT investment. We take advantage of a change in reporting for the manufacturing sector in 2006 that splits out IT expenditure into fine-grained categories, one of which includes expenditure on services such as the cloud just as it begins to take off in the U.S. economy. Using a variety of approaches to address endogeneity and measurement error, we find that expenditures on outsourced IT services that include the cloud are causally linked to better survival, growth, and productivity in the critical first five years of a plant's life. Interestingly, we also show that traditional IT capital, while correlated with productivity among firms that survive, is actually associated with a greater likelihood of failure among the young. The only gains for older plants associated with new IT services come when plants are very small or are in settings where uncertainty is particularly high. Importantly, the productivity gains from new IT services only appear once cloud computing diffuses and prices fall from late 2009 onwards.

We explore a number of mechanism tests to isolate the learning channel and rule out alternative hypotheses related primarily to firm size or financial frictions. While our core findings all control for plant size, we note that, among older plants of any size, owned IT capital still remains the primary driver

[3] We hypothesize that much of the relevant uncertainty and learning-by-doing may vary by industry, geography, production technology, and even plant-level "know how"; thus, we conduct our main analysis at the establishment level and then explore whether this varies for multi-establishment firms.

of IT-related productivity for older plants – even small ones. We can see the influence of size in the greater returns to young plants that are *also* small, but the learning channel remains robust.

We also find little evidence that young establishments find it difficult to finance the fixed costs of their IT investments. This may be due, in large part, to our empirical context. IT represents a relatively small cost share in manufacturing (compared to, say materials). And, when we directly test whether plants with less financial slack benefit more from the cloud, we find no evidence for this channel. Moreover, plants of existing firms (which would presumably have access to internal capital markets) follow the same patterns as young stand-alone plants, provided they are engaged in a production process that is different from that of the parent firm. Again, this points to learning, rather than to financing.

These findings are significant in a research and policy context that has expressed concern over the short lifespan of new ventures (e.g., Haltiwanger et al. 2013; Decker et al. 2014), yet has had almost no visibility into how significant technological changes have affected the youngest and smallest firms in the economy. The magnitude and timing of our results suggest that cloud computing and related IT services are rapidly providing a means for the young to achieve better performance before they achieve experience and scale of their own. It is worth emphasizing that, to the extent that the smaller young plants are also the ones with the fastest growth rates, IT services appear particularly important for mitigating uncertainty in *high-growth* manufacturing, a sector of particular interest in the literature (Guzman and Stern 2015, 2016; Haltiwanger et al. 2016). This phenomenon is recent, understudied, and has far-reaching implications for economic productivity and strategic management in the years ahead.

By providing a lifecycle perspective that emphasizes learning through experimentation, our study makes a few contributions. First, much research on innovation and learning by experimentation has taken place in the context of large, incumbent firms (e.g., Ahuja and Lampert 2001; Ahuja and Katila 2004; Henderson and Clark 1990; Henderson 1993; *inter alia*). Since Schumpeter (1934, 1942), however, there has been a robust multidisciplinary literature focused on the importance of experimentation in young firms for economic performance and innovation (Thomke 2003; Kerr et al. 2014; Davis et al. 2014; Manso 2016; Ewens et al. forthcoming). A unique dimension of our contribution to this literature is that

that we demonstrate the importance of learning about complementary investments – rather than core product market offerings– under uncertainty.

By favoring entrants in ways that traditional IT capital does not, the cloud may represent a new engine for "creative destruction" (Schumpeter 1934, 1942) in the economy as a whole. That said, the fact that these patterns hold equally for young plants of existing firms provides insight into how incumbent firms may also start to benefit – at least in a localized way - from new technologies. This is a topic of active debate in both research and practice (Henderson 1993; Christensen 1997; Bresnahan, Greenstein, and Henderson 2011; Gans 2016).

Finally, this study updates our insights on firm use of IT in the wake of rapid and fundamental technological change. The core IT productivity literature (e.g., Bresnahan and Greenstein 1996; Bresnahan et al. 1996; Hubbard 2000; Brynjolfsson and Hitt 2003; Forman et al. 2005, 2008, and 2012; Aral et al. 2006; Tambe and Hitt 2012; and studies cited therein) pre-dates, abstracts away from, or concludes with the diffusion of the commercial internet.[4] Yet "turnkey" solutions now available via the cloud have advanced the speed, scalability, and modularity of IT services dramatically over the past handful of years (Byrne and Corrado 2016). This raises important questions about how this new type of IT may or may not be productive in certain firms today– and why. Our results suggest that many pre-existing intuitions may not apply indiscriminately in the age of cloud computing. In particular, the importance of scale and intangible organizational investments may be diminishing in ways that have the potential to shift the locus and drivers of persistent productivity differences among firms in the long run.

II. PHENOMENON: THE RISE OF CLOUD COMPUTING

While "IT outsourcing" of some form has been available for decades (Dibbern et al. 2004), the mid-2000s marked a dramatic departure.[5] The "on-demand delivery of computing power, database

[4] See the useful review of this large literature in Forman and Goldfarb (2016).

[5] Some would argue for an earlier inflection point: the introduction of the commercial internet introduced a lower-cost – and, in particular, a more variable-cost – IT model beginning in the mid 1990's. Even so, there was an important distinction between "basic internet" and "advanced" applications– the former being relatively cheap but

storage, applications, and other IT resources via the internet with pay-as-you-go pricing”[6] became dramatically more available with the launch of Amazon Web Services (AWS). In 2006, Amazon started offering its beta version of Elastic Compute Cloud (EC2) services and set the price for an instance (1.7GHz Xeon processor/1.74 GB of RAM) at $0.10 per hour –a much more appealing price for startups and small- and medium-sized businesses compared to previously available products. In 2007 and 2008, Amazon introduced several larger-scale cloud computing services with much higher CPU power and more storage and RAM. From this point on, firms’ ability to access quite sophisticated IT services without incurring high fixed costs was transformed (Byrne and Corrado 2016). A wider array of offerings made it possible for cloud customers to “mix and match” their requirements for infrastructure, processing capabilities, storage, and software – and to do so very quickly (McKendrick 2011).

Price Declines Late 2009 and Onward

The price of cloud computing services experienced a sharp decline from late 2009 onward due to growth of AWS and entry of new providers (Barr 2009a, 2009b, and 2009c). In addition to growth and innovation from AWS, Microsoft fully deployed its own “Azure” cloud computing platform. NASA and Rackspace Hosting launched their joint open-source cloud software project in 2010. IBM launched its cloud computing series in 2011, and Oracle subsequently deployed its Oracle cloud in 2012 (Hauger 2010). The heated market competition among these large vendors stimulated dramatic price declines; the cost per “computing unit” per hour for Amazon compute services alone fell from to as low as a few cents by 2010 (http://www.gregarnette.com/blog/2011/11/a-brief-history-cloud-cpu-costs-over-the-past-5-years/i). Byrne, Corrado and Sichel (2017) provide compelling evidence for the decline in cloud computing costs beginning in late 2009, followed by further steep price declines in 2012 and 2014 (See Table 1).

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also less important for firm productivity, and the latter requiring greater co-invention and complementary organizational inputs (Forman, Goldfarb, and Greenstein 2005, 2008, and 2012).

[6] This definition can be viewed from Amazon website at: https://aws.amazon.com/what-is-cloud-computing/

Tradeoffs for Different Types of IT

IT has been extensively correlated with productivity in a wide range of firms (e.g., Brynjolfsson and Hitt 2003; Tambe and Hitt 2012). Why would the cloud be different from what we have seen in prior waves of computing technology?

The key benefit of this new way of accessing IT services is how it allows businesses to leverage large and powerful computing services very quickly and according to changes in their own demand. The ability to scale this activity up and down as needed – and as uncertainty about market demand and internal production was resolved – is probably most beneficial in IT-intensive services (Ewens et al. forthcoming). Yet anecdotal evidence points to benefits for manufacturing firms from cloud-based sales and marketing, enterprise resource planning, supply chain management, and payments – to name a few. Also, manufactured products increasingly rely on bundled IT services that require data collection, storage, analysis, and communication (Columbus 2013).

A couple of concrete examples are useful to motivate our study. For instance, certain types of manufacturing rely heavily on computer-aided design (CAD) and computer-aided manufacturing (CAM) technologies that allow product designers and industrial engineers to model product features and design interdependencies, experiment with different design choices, and link closely to physical production equipment. Other authors (e.g., Kerr et al. 2014) have described how manufacturers that are still developing their core products may benefit from computing resources and software applications that allow them to experiment with product details before investing in actual production resources. Additionally, it is important to consider that they need to *experiment with the types of complementary IT applications and related processes that might work for them.* Young plants may be innovating based on design approaches that are not well supported by all software vendors, but the extent of the functionality gap may be difficult to assess without using the technology. Also, a key application of CAD/CAM software is collaboration between supply chain partners. Yet young operations may also be unsure about which suppliers and customers they will want to cultivate in the long run, many of whom may have different – and incompatible – systems in place. Owning the IT required for all of those experiments up-front is prohibitively expensive; "renting" generic solutions via the cloud until specific uses and collaborations are more certain may provide better productivity and also inform later investments – i.e., creating real options that support short-term survival *and* long-term performance.

Another example comes from the increasingly prevalent practice of bundling IT functionality with physical products. Consumer electronics and cars increasingly have embedded features such as voice-activated controls, on-board diagnostics, and push notifications from manufacturers that require robust and rapidly scalable IT infrastructure. Quickly and flexibly scaling up generic capabilities until specific details are "fine-tuned" may be particularly important while firms are learning about consumer demand for these new add-ons. Again, learning from generic inputs without committing significant resources is valuable.

This list off benefits gives rise to the question of why any firm – regardless of age – would fail to take advantage of these new capabilities. Despite the many benefits, cloud-based IT services come with a number of important limitations that give rise to tradeoffs that matter differently for firms of different ages. The most important limitation is that the offerings are generally quite standardized and not necessarily well-tailored to important core business functions within a specific firm.[7] Relatedly, outsourced cloud solutions frequently do not allow the adopting firm to have tight control over its data or software upgrade schedule. Data security is an oft-cited concern, and sometimes dominates questions of cost or efficiency (Rahid 2016). In addition, unforeseen and uncontrollable downtimes do occur and have proven costly (e.g., Weise 2017). Finally, at least for large-scale operations, the unit costs of the cloud have also not tended to be competitive with owned data center investments. A prominent (albeit non-manufacturing) example is Dropbox, which stored all of its files on Amazon's servers until 2015, when it moved to its own servers to improve their unit economics. In a prominent interview about the switch, their vice president noted, "Nobody is running a cloud business as a charity. There is some margin

[7] Bruce Schneier at the Berkman Center for Internet & Society at Harvard Law School offers a useful culinary analogy: "The downside is that you will have limited customization options. Cloud computing is cheaper because of economies of scale and — like any outsourced task — you tend to get what you get. A restaurant with a limited menu is cheaper than a personal chef who can cook anything you want." (Schneier 2015)

somewhere."(Metz 2016). Thus, there are many reasons for firms to prefer their own IT capital infrastructure, conditional on knowing what they need and being able to afford it.

III. LITERATURE AND HYPOTHESES

How might the tradeoffs presented by cloud computing matter differently for firms of different ages? While the price declines in IT services over this period, and the shift from fixed to variable costs are notable, we argue that it is the flexibility of the cloud services model that mattered most for young manufacturing operations, and the lack of specificity that mattered most for older ones.

Irreversible Investments under Uncertainty

Much prior work on investment dynamics emphasizes the costs to firms of any age from making irreversible investments under uncertainty (e.g., Marschak 1949; Bernanke 1983; Pindyck 1990; Dixit and Pindyck 1994). While this has been established in the context of traditional (or simply undifferentiated) capital investment, the logic extends naturally to IT capital. Prior to the rise of the cloud, firms that required significant IT in their production process had to make bets – potentially quite large ones – on hardware and software in advance of uncertain growth and with limited ability to adjust as market and operational requirements changed. The lead-time for these bets is long: building a bespoke data center can take up to 18 months (Greenstein and Snively 2017). Exacerbating the tension in our context is the high rate of depreciation and obsolescence of IT assets due to rapid technological advances. Those bets could easily fail to pay off, leaving firms with poorly-performing IT and fewer resources for new investments.

Anticipating these risks, firms have incentives to underinvest in order to maintain flexibility, or "real options" (Dixit and Pindyck 1994). This will promote an inefficiently low level of IT investment, on average. Moreover, this distortion will be greater when firms perceive a high option value from waiting. Uncertainty exacerbates investment delays (Guiso and Parigi 1999; Bloom, Bond, and Van Reenen 2007), and uncertainty tends to be highest in the early in a firm's life (e.g., Schumpeter 1934; Knight 1957).

The canonical model in this vein, due to Jovanovic (1982), assumes that entrepreneurs lack even private information about their own future profit opportunities and require time to learn about their productivity. Foster et al. (2016) explore how firms learn about external demand, showing that this can take a long time in manufacturing. Classic learning-by-doing models (Bahk and Gort 1993; Levitt, List, and Syverson 2013 and studies cited therein) capture internal learning dynamics. Firms learn how to become more efficient as they produce their products, accumulating critical knowledge about their processes, equipment, employees, effective managerial practices, supply chain partners, and so on.

One way to learn more quickly without making costly irreversible investments is to conduct experiments (e.g., Thomke 2003). The cloud reduces the costs of experimenting with different IT products to learn about what types of IT work with the processes, customers, and partners they have – or might want to to have (Palmer 2012). As long as experiments are not too costly, they generate real options for firms to reduce uncertainty (Kerr et al. 2014). Leveraging the more-affordable learning acquired in the cloud, firms can then make better IT investment decisions later on that maximize the expected value of the firm.

Thus, all else equal, we predict that young firms would tend to benefit disproportionately – in terms of both productivity and survival – from new opportunities to access "good-enough" functionality, delay market- or relationship-specific investments, and affordably conduct experiments to learn about their IT needs. Moreover, we expect the benefits of better IT experimentation to be higher in industries where: IT knowledge is particularly valuable (i.e., IT-intensive industries), the baseline risk to survival is higher (i.e., there is less scope for failed or costly experiments, for instance when competition keeps profit margins very thin), or when learning is very difficult (i.e., when variance is very high, creating a greater noise-to-signal ratio in the experiments that are conducted and, hence, a need for more of them or more time to conduct them). Finally, if experimentation is useful, we should see higher productivity of later investment choices compared to firms that did not invest in this type of learning.

While firms are young, the value of the learning might justify the costs of undifferentiated IT services. Over time, however, older firms face less uncertainty and can optimize the expected value of the firm through their investment choices. Thus, they will benefit more from IT investments that either start out as firm-specific or become so through investments in adapting the technology to the firm's needs (Bresnahan and Greenstein 1996). We hypothesize that owned IT capital will therefore be more productive for older firms compared to younger ones and also compared to cloud-based IT inputs.

Alternative Mechanism: Economies of Scale

We have taken care, as far as is possible, to separate mechanisms related to age from mechanisms related to size. However, much prior work has emphasized that firms operating at greater scale have an advantage in being able to spread the fixed costs of IT capital across greater output (Forman and Goldfarb 2005; Tambe and Hitt 2012; McElheran 2015).

A key benefit of the cloud is its ability to pool resources across a wide range of firms to achieve *shared* economies of scale in IT services. This dramatically drives down the per-unit cost of providing IT services. However, the distinction between *cost* and *price* matters in our context. Large firms that own their own IT capital can internalize all of the cost savings achieved through scale. Smaller firms that can only access these economies through the cloud must pay a price that includes a margin for the IT service provider. While this difference may disappear, eventually (as cloud providers grow and surpass the scale achievable by all but the very largest firms), the price differential was likely still relevant for the early years in which our study takes place. This, combined with the benefits of customization and differentiation for large incumbents firms, will drive a wedge between the benefits of the cloud for young (typically smaller) versus older (typically larger firms), but for reasons unrelated to age, per se. We take advantage of variation in size for firms of all ages in our data to disentangle these effects.

Alternative Mechanism: Financial Frictions

Finally, not all young firms will choose to wait, experiment, or underinvest in IT if they have the means to finance the investment. However, the entrepreneurship literature has extensively explored the role of financial frictions in constraining firms' early investment choices (Adelino, Schoar, and Severino, 2012; Kerr and Nanda 2009). In the face of financial constraints, therefore, young firms might find it disproportionately difficult to make essential investments in owned IT capital. To the extent that the cloud allows young firms to substitute higher variable costs for fixed costs, therefore, this could conceivably alleviate financial frictions in the short term. This would particularly improve survival in industries where technology is a key input (and thus represents a large share of input costs). This is the argument that has dominated discussions of the cloud in the popular press.

However, two things are worth noting: the amount of IT that needs to be financed in the manufacturing sector is small relative to other inputs such as materials. Also, the predictions on relative productivity as firms grow are ambiguous, since the IT comes at a less-attractive per-unit price for larger volumes of output and delivers less-specific IT services to the firm..

Plants vs. Firms

Most of the existing theory of lifecycle dynamics concerns firms, rather than units of firms. However, to the extent that multi-divisional firms have distinct operations serving distinct product markets and geographies with distinct local operating conditions, individual units may be unable to leverage parent firm experience when it comes to their IT requirements. Thus, following similar work related to learning by doing in manufacturing (e.g., Bahk and Gort 1993; Levitt, List, and Syverson 2013) and the use of IT by manufacturing plants (Banker et al. 2006), we test our hypotheses at the unit-level; we then separately investigate the implications for establishments that belong to larger parents to help us disentangle the mechanisms at work.

IV. DATA AND EMPIRICAL MODEL

Our study relies on a novel data set to observe this technological shift as it unfolds in the U.S. manufacturing sector. Our core data comes from linking rich establishment-level information collected by the U.S. Census Bureau from the Annual Survey of Manufactures (ASM), the quinquennial Census of manufactures (CMF), and the Longitudinal Business Database (LBD). Important changes to the manufacturing surveys in 2002 disaggregated IT investment (on computers and data processing equipment) from other types of capital; additional changes in 2006 separated hardware, software, and IT services expenditures for the first time. The recurrence of the questions allows us to construct a large panel from 2006 through 2014 (*2015 results pending disclosure review*) at the establishment level. We accumulate and depreciate IT capital stocks using BEA deflators starting in 2002. The LBD tracks the plants from the time at which they have at least one employee to the time of their failure, regardless of ownership change[8], providing critical data on the age and survival of the plant.[9] The combined datasets allow us to observe critical inputs to the production function (labor, materials, energy) – including distinct margins of IT investment –in order to estimate revenue-based total factor productivity at the plant level.

Measuring Cloud Computing

Our measure of cloud computing comes from the IT services expenditure data, which becomes available for the first time in the Census data (and only in manufacturing) in 2006, just as the cloud is beginning to diffuse. The cloud diffuses earlier in other industries (see Ewens et al. forthcoming for a discussion), so 2006 is not a bad “pre-treatment” year. This measure is where cloud investment, once it takes off, gets captures in the manufacturing data, potentially in addition to other IT services (such as IT consulting), but excluding telecom and internet access. The presence of other costs will increase measurement error in our core measure, which will tend to be magnified in our fixed-effects models and alleviated when instrumental variables are employed. In addition, we perform a number of tests to correlate the timing of our findings to rapid changes in the availability and affordability of cloud computing and control carefully for other IT and related investments.

To increase confidence that this is a valid measure of changes in cloud computing use over time, we correlate our measure with cloud-specific uses of IT such as Software as a Service, Infrastructure as a Service, and Platform as a Service (Saas, IaaS, and PaaS, respectively) using the largest and most-used proprietary database on establishment-level IT use from Aberdeen (formerly Harte Hanks). This data set was matched up with the Census data at the establishment level for a reasonable percentage of the ASM

[8] Note that mergers and acquisitions in our data are treated as continuing operation of the plant. “Exit,” here, refers to cessation of operations.
[9] Note that “exit” in our data truly means closing down, and not acquisition by another firm.

and shows a strong correlation between the measures at the location-industry level *(results pending disclosure review).*

Sample Frame

For technical reasons, we restrict our sample to observations in the ASM and CMF from 2006 to 2014[10] with complete information on inputs (including cost of materials, energy, and employment), output (total value of shipments), value added, and the IT variables. In addition, we restrict our attention to establishments that have positive value-added, employment, and imputed non-IT capital stock. This procedure leaves us with about 460,000 establishment-years over the 9 years. We further restrict our analysis to observations with reported (as opposed to imputed) IT data, though this turns out not to matter much in our robustness checks. Our final analysis contains more than 26,000 establishments per year over 9 years. Table A1 in the Appendix shows the descriptive statistics for the ASM-based sample before dropping imputed observations.

Industry Information

We take advantage of the large sample size and fine-grained industry classifications (down to the 6-digit NAICS level) to control for industry heterogeneity in factor shares. In most specifications, in fact, we control for interacted year and industry effects; this effectively controls for industry-specific deflators in our productivity estimation.

Young Plant Coverage

While we have visibility to a large number of establishments that are within the first year of their life, we focus our analysis on plants that are five or fewer years old.[11] This subsample represents around 18.5% of the data that meet our aforementioned restrictions, totaling approximately 5,000 plant

[10] 2015 data became available recently. Extending the panel by one year does not materially change our findings (*pending disclosure review*).

[11] All results are robust to using a continuous measure of Age. Table A4 in the appendix shows that there is a statistically meaningful difference between the coefficients for plants that are five or fewer years old and for those that are older.

observations per year. Prior work (e.g., Haltiwanger 2013, 2016) finds the five-year cutoff to be meaningful; our empirical results also support this cutoff in our setting. When exploring growth models, the sample size reduces mechanically, since this requires establishments to exist for at least two consecutive years. Fixed-effects estimates also are identified only off of the plants that persist for two consecutive years and change their investment year-over year.

Figure 1 shows the birth and participation rates of young plants in the entire U.S. manufacturing sector for the years covered by our sample. Notably, the birth rate of young firms dropped precipitously during the Great Recession and recovered, with a strong up-tick in 2014. The decline of young firm participation in the sector stops by 2012 and turns around by 2014, consistent with reports of recent increases in high-growth entrepreneurship (e.g. Guzman and Stern 2015, 2016).[12]

For comparison with prior work, it is useful to note that the young plants are also small and more likely to die. The average size of a young plant is fewer than 50 employees –much smaller than is typically observed in related studies (e.g., Tambe and Hitt 2012). The average annual failure rate over our panel for young plants is 3.33% - compared to 1.35% for older plants (see Table 2).

Productivity Estimation

We take a conventional approach to modeling the plant production function (e.g., Brynjolfsson and Hitt 2003; Bartelsman and Doms 2000; Bloom et al. 2012; Tambe and Hitt 2012). Consider a production function that is Cobb-Douglas as given in equation (1):

$$Y_{it} = A_{it} K_{it}^{\alpha} IT_{it}^{\beta} L_{it}^{\lambda} M_{it}^{\gamma} X_{it}^{\mu} \tag{1}$$

Where Y_{it} is total revenue, A_{it} is technical productivity, K_{it} denotes the establishment's non-IT capital stock at the beginning of the period, IT_{it} is the establishment's IT capital stock at the beginning of the period L_{it} is labor input, M_{it} is the establishment's consumption of material and energy inputs, and

[12] All of our findings are robust to truncating the panel in 2013.

X_{it} is a vector of additional factors such as industry and age of the plant.[13] We take revenues as our main dependent variable, but also explore value-added and other measures of performance in light of concerns about capital mismeasurement in young establishments (Bartelsman and Doms 2000) and interest in other measures of firm performance (e.g., Haltiwanger, et al. 2013). Equation 1 can be considered a first-order approximation of a more general production function (such as translog), which we examine later in our robustness checks.

Taking logs provides a tractable form to take to the data:

$$Log(Y_{it}) = \alpha \log(K_{it}) + \beta \log(IT_{it}) + \lambda \log(L_{it}) + \gamma \log(M_{it}) + \mu X_{it} + p_i + \varepsilon_{it} \qquad (2)$$

where the productivity term can be decomposed into a set of plant fixed effects p_i and an added stochastic term, ε_{it}.

We innovate by separating out the different types of IT investment into traditional IT capital (ITk_{it}) and IT services ($ITpurch_{it}$), while controlling for other observed IT-related investments ($ITother_{it}$). Also, because we are primarily interested in how the coefficients on productivity vary over the lifecycle, our core specifications interact the input variables with an indicator of being *YOUNG* or split the sample according to this distinction. Equation 3 (or equivalent sample splits) represents our core estimating equation:

$$\begin{aligned} Y_{it} = {} & \alpha_0 + \beta_1 ITk_{ijt} + \beta_2 ITpurch_{ijt} + \beta_3 ITother + \beta_4 YOUNG_{ijt} + \\ & \beta_5 YOUNG_{ijt} \times ITk_{ijt} + \beta_6 YOUNG_{ijt} \times ITpurch_{ijt} + \beta_7 YOUNG_{ijt} \times ITother_{ijt} \\ & + \alpha_1 X_{ijt} + \alpha_2 YOUNG_{ijt} \times X_{ijt} + year_t \times ind_j + p_i + \varepsilon_{ijt} \end{aligned} \qquad (3)$$

Where *i* denotes the plant, *j* denotes the industry, and *t* denotes the year. X_{ijt} is a vector of plant-level time-varying controls and inputs to the production function, including capital, labor, and materials. Lower-case letters denote the log transform of the variable.

Identification

[13] We include the X_{it} controls in exponential form for the convenience of including them in levels rather than logs.

A primary concern in this literature had centered on the opportunity for unobserved demand or productivity shocks to simultaneous boost output and IT investment, creating a spurious relationship and upwardly biased estimates of the productivity impact of IT on economic output. We leverage a number of econometric techniques (Blundell and Bond 2000; Levinsohn and Petrin 2003; and Ackerberg, Caves, and Frazer 2006) that, while demanding a great deal from the data, leverage dynamic panel data estimators to identify the coefficients of interest. We also explore the timing of the effects, in order to at least rule out reverse causality

In addition, we exploit findings from prior work that technology diffusion has a local geographic component (e.g., Griliches 1956; Rogers 1995; Baptista 2000; No 2008; Forman et al. 2005; Conley and Udry 2010; Tambe 2014), to construct an additional instrumental variable. Leveraging the exhaustiveness of the LBD data on U.S. non-farming business, we calculate the percentage of establishments in a focal plant's county that are classified as being in the data hosting and processing industry (NAICS 518210). This industry contains the providers of a variety of IT services including application service providers (ASPs), automated data processing, computer data storage, computer time leasing, and computer time sharing services, to name a few. All aforementioned services constitute the main services provided by Amazon Web Services and other larger cloud-computing vendors.[14]

We take the location of these service providers as conditionally exogenous with respect to local demand based on an influential report published at UC Berkeley's Reliable Adaptive Distributed Systems Laboratory in 2009 (Armbrust et al. 2009) arguing that the location of large-scale data centers and cloud services providers is more cost-efficiency-driven than demand-driven. In particular, they provide evidence that key drivers of location choices for large cloud-computing providers centered on the cost efficiency of electricity, cooling, labor, and other operating costs. Other descriptions also cite real-estate costs as a driver of location choice (*citation pending source approval*). Among those, electricity and cooling play a dominant role as these two factors alone account for approximately one-third of the total

[14] For more details about NAICS 518210, see https://www.census.gov/econ/isp/sampler.php?naicscode=518210&naicslevel=6#

costs. We are able to control, separately for energy expenditure at the plant level (which will incorporate local energy prices) to control for this. To quote the report, "Physics tells us it's easier to ship photons than electrons; that is, it's cheaper to ship data over fiber optic cables than to ship electricity over high-voltage transmission lines." (Armbrust et al. 2009). We furthermore lag the measure by two years to reduce the likelihood of simultaneity, and use it as an instrument for cloud expenditure.

Figure 2 shows a map of the county-level intensity of data-services providers as a percentage of all local non-farm establishments from 2010 (*2006 and 2010 coming soon*). Notably, the areas of greatest concentrated are sprinkled all over the U.S., many of them in unexpected locations, such as northern Virginia and Quincy, Washington.

V. Results

Before looking at survival and performance, we first examine how investment in these different types of IT changed over the period covered by our sample, for both young and old plants. The descriptive statistics alone are informative. Looking at mean investment levels of IT capital (computers and data processing equipment, winsorized at the 1st and 99th percentiles of the distribution)[15] by age group over time in Figure 3, we observe that older establishments, on average, cut back on investment in new IT capital at the time of the financial crisis in 2008 more readily than younger ones. Young firms delayed their cutbacks and also cut less in absolute magnitudes. Over time, the combined effects of lower annual spending, having less time to accumulate IT capital (due to their age), and deferred investment show up in dramatically lower and falling accumulated IT capital stock for younger plants, as shown in Figure 4.[16] In contrast, expenditure on IT services increases (though moderately) for young plants, while initially falling for older plants as the recession hits, and then recovering and climbing over time (Figure

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[15] Winsorization is used to address outliers in the empirical distribution for investment and calculated capital stock variables from the Census survey. See Giroud (2015) for an example in the prior literature.

[16] This figure reports the winsorized IT capital stocks for young and old firms created using a conventional perpetual inventory method and using deflators provided by the US Bureau of Economic Analysis (e.g., Bloom, et al. 2013).

5). It is worth emphasizing that these are nominal expenditure levels. To the extent that prices for IT are declining – and precipitously so for cloud computing in later years – this represents a significant increase in the *quantity* of IT purchased by manufacturing firms.

To get a sense of what these trends look like controlling for size, Figure 6 shows IT capital levels and IT services expenditure on a per-employee basis for young and old plants. A central take-away from this figure is that, adjusted for size, the expenditure levels between young and old are not very different, and all are trending up over time – or, in the case of IT capital, in the years following the Great Recession. There is a noticeable increase in 2014 in IT expenditure, particularly for young plants. (We verified that none of our findings in any of tables to follow are sensitive to this late trend in our data).

To examine whether these differences between young and old are significant – and to control for potential differences between young and old in terms of industry composition – Table 3 presents results from multiple regression (OLS) with an indicator "Young" for being five or fewer years old regressed on different categories of IT expenditure. These specifications include unreported industry controls (at the 6-digit NAICS level),[17] as well as either unreported year controls (columns 1-2) or an indicator for being in the "Late" years in our sample (2008-2014 – columns 3 through 4d). The latter highlights trends during and after the financial contraction of 2008-2009.[18] As in Figure 6, this table describes expenditure on a per-employee basis to better compare firms of different sizes. Consistent with Figure 6, the differences, while statistically significant at the 1% level, are economically quite small. Column 1 indicates that the average (winsorzied) accumulated IT capital stock per employee for plants that are five or fewer years old ("Young") was 5% lower[19] on average than for their older counterparts. Annual *expenditure* (on IT of all

[17] An example of the narrowness of the North American Industry Classification (NAICS) at the 6-digit level would be the distinction between motor and generator manufacturing (NAICS 335312) and switchgear and switchboard manufacturing (NAICS 335315) within the category of Electrical Equipment Manufacturing (NAICS 3353).

[18] We report the coefficient for all of the later years combined for ease of exposition, noting that the results are similar for both the recessionary years (2008-2009) and for those immediately following (2010-2014). This is consistent with research showing the persistent effect of the Great Recession on investment (Fort et al. 2013).

[19] This percentage change is calculated by taking the coefficient of 0.063 and dividing by the mean of IT capital stock per employee for the combined sample, which is 1.27 (not reported in Table 2).

kinds) in column 2 is also lower by about 2%.[20] So, at first glance, there is little evidence that young-plant expenditure on IT was unduly constrained relative to older firms during our sample period.

Columns 3 and 4 explore how much this changes over our sample timeframe. Consistent with the descriptive statistics, we observe that even within industries, IT capital accumulates faster than it depreciates, ending up 12% higher on average in the later years (2008-2014), though it remains lower for the young plants on average by 6% percent.[21] In column 4, IT flows (all kinds combined) per employee go down, on average, about 8% in the later years. The differences between the young and old when we look at average flows are not statistically different from zero.

However, differences appear when we break the IT flows down by type in columns 4a-4d. In columns 4a and 4c we observe that, controlling for industry, young plants spend slightly more on a per-employee basis than the old on IT capital and equipment (though only the IT capital coefficient is statistically significant, at the 10% level). The young actually spend significantly less – about 9% less – on a per-employee basis on IT services than the old do; similarly for software expenditure, at 16% less (se also Table 2). The overall trend, regardless of age or industry, is towards less IT capital and equipment in later years, with more IT services and software, suggesting a substitution away from hardware towards software and services across the board. We explore this in more detail, below.

The interaction effect of being young and later in the sample is consistently negative in these models, but never statistically significant. This may be due, in part, to large reductions in young-firm employment levels during the Great Recession (Zarutskie and Young 2016) that may have exceeded the rate of IT expenditure contraction in the later years. Another interpretation is that, while all plants cut back their level of investment in the recessionary years, startups may face basic initial investments that are difficult to defer. This has implications for young firm survival, which we explore later.

[20] The sample mean for IT expenditure of all kind per employee is 1.06 (not reported in Table 2).

[21] We first examined three periods: 2006-2007, 2008-2009, and 2010-2014, but the latter two were not significantly different from each other and thus were combined for ease of interpretation.

Expenditure Shares

We explore the *shares* of observed IT spend across the different types of IT for both young and old in Table 4. Controlling for industry and year fixed-effects, column 1 of table 4 shows that both young and old plants allocated about 5.4 percentage points less of their IT spend to accumulating computer and data processing equipment in the recessionary and post-recession years.[22] Conversely, both groups also allocated higher percentages of their budgets to IT services (2.1 percentage points) and software (3.6 percentage points) in later years. These results are significant at the one-percent level and consistent to what we observed in Table 3. That said, young plants exhibit a small but statistically significant greater shift into IT services as a percentage of expenditure, and it shows up in the years associated with the diffusion and price decline of the cloud.

A key missing piece of the puzzle is how many "units of IT services" firms are able to acquire through different types of IT expenditures, and how much they may be able change them via these modest adjustments. Considering the observed reduction in prices for cloud-based IT during our sample period, and combined with anecdotal evidence concerning the rapid increases in speed, quality, and reliability of cloud computing over this time, it is likely that the expenditure levels and allocation underrepresent the actual change in use of IT services. The actual shift in IT input mix might exceed the reallocation of dollars. Unfortunately, quantities of IT inputs are beyond the reach of our data.

For completeness, it is worth recognizing that the cost of IT capital is falling over this period, as well; however, the cost savings from this channel should show up for both in-house IT and outsourced IT services. To best understand how changes in price and availability of the new technology impacted performance, we turn to measures of survival, growth, and productivity.

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[22] Again, since the results are similar for both Great Recession (2008-2009) and post-Recession (2010-2014) periods, we simplified the exposition by combing the two periods into one "Late" category. *Results available upon request.*

Survival

To test hypotheses about how different types of IT might relate to survival, we model the survival process directly using a Cox proportional hazard model, with failure as the dependent variable (other related survival models produce similar results). Table 5 presents these findings. We split the sample between young and old for ease of interpretation, so comparisons run across pairs of columns. Recall that numbers above 1 indicate an increased chance of failure; numbers below 1 indicate improved survival. We start with traditional IT capital stock to establish a baseline for comparison. Strikingly, columns 1a and 1b indicate that traditional IT capital investments are associated with an *increase* in the likelihood that a young plant will fail (decreased chance of survival); while they appear to be negatively correlated with failure in older firms. The magnitude of the coefficient is 1.046 for young, which suggests that a one-unit increase in logged IT capital stock for young (about a $23,000 increase) is associated with a roughly 4.6% *higher* risk of failure. In contrast, a one-unit increase in logged IT capital stock for old (about $77,000) is associated with a 3.2% lower risk of failure.[23] This is compared to a baseline yearly failure rate of 3.3% for the young sample and 1.3% for the older sample (Table 2).

In contrast, IT services are negatively correlated with the failure of both young and old establishments. A one-unit increase at the mean of the logged IT services distribution is associated with a 4.9% (or .16 percentage point) lower risk of exiting for young plants and a 10% (0.13 percentage point) lower risk of exiting for older plants.

Columns 2a and 2b explore the results by using "high IT" indicators, rather than continuous expenditure measures. The cutoff for the indicator is that the plant be in the top quartile for that type of expenditure within the same NAICS4 industry (this also addresses potential concerns surrounding mismeasurement of IT that could downwardly bias the other results). The results are consistent with the

[23] The dollar value of this effect for young is calculated based on the mean of the logged IT capital stock distribution for young at 2.6 (reported in table 2), which is around $13,000. A one-unit increase from the mean of the logged IT capital stock is 3.6, indicating a roughly $23,000 increase. Similarly, the dollar value of the effect for old is calculated based on the mean of the logged IT capital stock distribution for old of 3.8. A one-unit change in the logged value is 4.6, indicating a $77,000 increase in IT capital stock for this subsample.

first two columns, though the higher IT investment thresholds increase the magnitudes of the coefficients. For instance, young establishments with high IT capital stock have a roughly 26.3% higher risk of failure, while old establishments with high IT capital stock have a roughly 15.1% *lower* risk. In addition, all else equal, high investment in IT services lowers the exiting risk by 17.6% and 27.3%, respectively for young and old.

Growth

In addition to being concerned about survival, the business dynamics literature highlights the importance of young firms for aggregate employment growth (Haltiwanger et al. 2013, 2016). In columns 3a and 3b we observe that increases in IT investment of all kinds – with the notable exception of software – are associated with increases in employment. The differences between young and old, however, are primarily seen in the IT services expenditure. Table A3 shows the results when the combined sample is analyzed using a model that interacts all of the explanatory variables with an indicator for being young; the coefficient on Young interacted with IT services is 0.008 and significant at the 5% level. Thus, any output gains associated with these technologies are not coming at the expense of jobs in our sample. In short, IT services has a disproportionately greater association with both survival and growth for plants that are five are fewer years old, compared to older establishments.

IT Productivity in Young vs. Older Plants

Table 6a presents the results of an OLS estimation of the standard Cobb-Douglas production function described in equation (3) (columns 1, 2, 3, 4, & 7), as well as analogous models including plant fixed effects (columns 5 & 6). All columns focus on aggregate output (sales) as the dependent variable, controlling for a rich set of inputs including the cost of materials, the cost of energy (electricity and fuel combined), labor (both expenditure on temporary employees and the count of regular employees at the plant), accumulated non-IT capital stock, and year-industry fixed effects. We do not separately observe quantities and prices, so this represents a revenue-based measure of total factor productivity ("TFPR" as discussed in Foster et al. 2008). Note that the number of employees is included as an input, thus all results in this table are conditional on size measured in terms of employment.

We draw attention to the average coefficients for the different types of IT in column 1 to make a couple of observations. The first is that, despite concerns about slowing IT productivity in the wake of the internet boom of the late 1990s (Stiroh 2008), we find no evidence of slowing. All types of IT investments captured in the US Census data have positive coefficients, suggesting that they contribute to revenues in excess of their marginal input costs (subject to the standard concerns about causality and omitted input factors, which we address in more detail, below). This holds across all sizes and ages of plants.[24]

In column 1, the coefficient for IT capital stock is about 0.015 and significant at the one-percent level. The log-transformed production function allows us to interpret elasticities directly: a one-percent increase in IT capital stock is associated with a 0.015% increase in the total value of shipments, all else equal. This result is largely consistent with previous estimates of the productivity of traditional IT capital (e.g., Tambe and Hitt 2012; Brynjolfsson and McElheran 2016).[25]

IT services, in sharp contrast, has a smaller association with productivity on average. The coefficient is not even statistically distinguishable from zero in the overall sample.

Columns 2 and 3 of table 6a are identical to column 1, but split our sample by an indicator of being five or fewer years old. *This is the core finding of the paper:* for the subsample of firms that are five or fewer years old, IT services are significantly correlated with productivity. Specifically, a one-

[24] The IT coefficients in column 1 are robust to including or excluding plant and firm age controls and indicators of multi-unit status (*not reported*).

[25] We also tested a specification with value added as our dependent variable and estimated the production function similar to Brynjolfsson and Hitt (1995). The magnitude of our estimate on IT capital stock in the value-added specification is positive and significant but slightly smaller than the results they report. Our study differs in important ways that may explain this. First, our sample includes many more small and young establishments, which tend to have smaller returns to IT capital. In addition, we are controlling for more fine-grain industry codes at the level of 6-digit NAICS. Finally, we are measuring IT productivity for recent years while their sample is constructed from 1988 to 1992, so the technology in question is also different across studies.

percent increase in young firms' spending on IT services is associated with a roughly 0.01% increase in sales.

Column 4 shows results for the complete sample, but fully interacted with the Young indicator. This provides quick evidence that the difference between the IT Services coefficients for young versus older plants is statistically significant, at the one-percent level. The equivalent result for IT capital is quite the opposite. The effect of being young on the returns to traditional IT capital is negative, but not statistically significant. We cannot reject that the young receive, on average, the same productivity benefit as the old from their investments in traditional IT capital. Note that this is conditional on survival, however, which is likely upwardly biased by the increased likelihood of failure associated with IT capital expenditure observed in Table 5. We example a similar model with continuous age interactions in a column pending disclosure review; the results are similar.

Columns 5 & 6 include plant fixed effects, which identifies the effects of interest off of *changes* within the plant. This will differ in important ways from estimates based on levels. In particular, any benefits to plants with high initial investments who stay at that level will not contribute to the estimation. It also is based on a smaller underlying number of observations, as it only uses plants that persist for at least two consecutive years (roughly 2/3 of the young sample). Perhaps more importantly, it removes the effects of unobserved time-invariant organizational capital that may serve as an important complement to IT in the production function. In Column 5, it is interesting to find that the coefficient on IT services changes hardly at all for young plants. Among older plants (column 6), the returns to IT services are now positive and statistically significant from zero, suggesting that any long-lived organizational characteristics are actually unhelpful for IT services productivity (i.e., might generate adjustment costs). However, they are still smaller than the returns that young firms enjoy from IT services, and the difference remains statistically significant.

Selection

To the extent that young plants may be making large bets on IT, unsuccessful or unlucky plants will exit the sample without contributing to our productivity estimates. As discussed, we expect that this will exert a systematic upwards bias, contributing to high “excess returns” for owned IT capital. For IT services, the direction of the bias is harder to sign. To the extent that the cloud helps the marginal firm survive when it might otherwise fail, this will exert downward pressure on the observed average productivity of young users of the cloud. On the other hand, if other selection pressures are causing the cohort of surviving young firms to be unusually productive during and after the Great Recession (Lee and Mukoyama 2015), the relationship between IT services and productivity in young plants which weather these difficult financial times -- while also taking advantage of new cloud technology -- might be upwardly biased and our estimates need to be interpreted with this selection process in mind.

Organizational Complements

Comparing the coefficients on IT capital and IT services in the models with and without fixed effects is informative about the importance of organizational capital in IT productivity from these different types of IT. To the extent that organizational capital may be time-invariant (e.g., Tambe et al. 2012), plant fixed effects will strip these effects from the productivity estimations. Consistent with prior studies, unobserved organizational capital appears to matter a great deal for the returns to traditional IT capital. The point estimate on IT capital drops by over 75% when plant-level fixed effects are included. The coefficients remaining very precisely measured, consistent with high levels of unmeasured organizational inputs interacting positively with the accumulated IT stocks.

In sharp contrast, however, the coefficient for IT services *changes almost not at all,* on average, when plant fixed effects are included (and is not statistically lower than the estimate without fixed effects). The point estimate becomes noisier due to the demands that this specification places on the data, but the pattern suggests that accumulated plant “know-how” or other organizational capital is less of a contribution to the productivity of IT services, both on average and among younger plants. This finding is consistent with anecdotal evidence that cloud-based IT is relatively standardized and therefore not reliant on the “co-invention” of processes and technology at the plant (Bresnahan and Greenstein 1996).

How Cloud Computing Changed IT Productivity

An interesting question we can answer with these results is whether young or old plants appear to be more productive with their IT, *overall,* in the age of cloud Computing. Given the indistinguishable IT capital productivity between the two age groups and the distinct advantage for young plants in IT services, the combined returns show that the young are able to use generic IT in the cloud to close the productivity gap – and even overtake the older ones (conditional on survival). Table 6b reports on joint tests of linear combinations of the coefficients from Table 6a. Two observations are important to note. The first is that failing to account separately for IT services would misrepresent the magnitude and source of IT productivity in the U.S. economy in recent years. In table A.6, we find that omitting IT services does not inflate the IT capital coefficient to the point of accounting for this omitted variable. In short, *studies that do not measure the cloud are missing a critical part of the modern IT productivity story.*

The second observation of note is that the magnitude and age distribution of the effect we estimate for the cloud is fundamentally shifts our understanding of which types of firms are productive in the age of the cloud. The differences between the young and the old – with or without plant-fixed effects – is statistically significant and redounds disproportionately to young plants (Table 6b). Thus, the combined effect of traditional IT capital and new IT services is sufficient to make *young plants the leaders when it comes to returns on IT investments*. To the extent that this is a recent trend, young establishments may be contributing more to aggregate productivity growth in ways that have been systematically missing from prior studies.

Causal Identification

Table 7 shows how these results change when we use a range of techniques developed to account for endogenous investment decisions in productivity estimation. Column 1 shows our OLS estimates from table 6a for comparison. Column 2 uses dynamic panel structural estimation relying on 2-period lagged differences for all variable investments to instrument for current-period investment levels (Blundell and Blond 2002). We find that the coefficient on IT services is higher and significant at the one-percent level in this specification. Column 3 reports estimates developed by Levinsohn and Petrin (2003), using expenditure on intermediate inputs – in this case, cost of temporary employees, though results are consistent when we use cost of materials – to instrument for the unobserved productivity shock. This yields a coefficient much closer to our OLS estimate. Ackerberg-Caves-Frazer (2006) discuss some limitations of this approach; using their estimator, the effect in column 4 is again larger than our OLS estimate. The results of this table suggest that the results in table 6a may actually be biased downward.

Column 5 shows the second stage of our instrumental variables estimation, which again yields a higher estimate, but quite significantly so. The results pass both the weak- and under- identification tests but fail to reject the null hypothesis that IT services is exogenous. Taken at face value, all of these measures are consistent with non-trivial measurement error in the IT services variable (which is plausible, given that the survey includes a number of different expense categories in its definition). They are also consistent with stronger local average treatment effects (Angrist and Pischke 2009), whereby the instrument is picking up a stronger productivity response among plants that are also sensitive to the instrument – i.e., whose IT services expenditure is strongly affected by the presence of local suppliers and/or by industry-level factors. That said, the dramatic jump in the magnitude of the coefficients is reason to take these estimates as informative within a larger “collage” of results.

The key take-away is that all of these approaches rely on very different identifying assumptions -- and yet come to largely similar conclusions. We take this as strong evidence that endogenous adoption of IT services is not driving the results we report here.

Table 8 explores the timing of these effects to further explore whether these estimates may be interpreted as causal. Following the approach for a standard Granger Causality Test, (Granger 1969) it shows that the timing of the effects runs from IT services investment to productivity, not vice versa. In columns 1-3, we show models of lagged IT investments regressed on current sales (including the usual controls for other inputs). Column 1 shows a productivity correlation with lagged IT variables. The results here indicate that expenditure on lagged IT services is positively and significantly correlated with current sales, all else equal. In column 2, we further include lagged sales in the model as a control – and find that the effect of lagged IT services disappears. This is consistent with IT services having a contemporaneous (at least within the same year) effect on sales that disappears once we control for the productivity effect from that year. In addition, much less variation is left to explain once we control for lagged sales, as output is highly serially correlated (Foster et al. 2016). Column 3 goes on to include forward IT services in the model. For reverse causality to be a problem, we would expect a relationship between past sales and future IT investments, but we do not observe this to be the case for IT services. Interestingly, we see the potential for reverse causality with traditional IT capital, which would make sense if past performance is required to access the financial liquidity needed to make future investments or if learning is important for productivity from this type of investment.

To complete the analysis, we reverse the dependent and explanatory variables in columns 4 and 5, putting IT services on the left-hand side. Here, we see that there is serial correlation in IT investment, but that the relationship between past sales and current investment in IT services is negative and of arguable statistical significance; in fact it loses statistical significance in column 5 when we separately control for forward sales (which is positive and significant and in line with the causality in the behavioral model). In addition to the estimation procedures discussed above, we take this as reasonable evidence for a causal relationship between IT services investment and productivity in our data.

Is this Really the Cloud?

Given our concerns about measurement error, we further probe the extent to which we can attribute these effects to cloud computing, per se, as opposed to other outsourced IT services (such as IT consulting). Table 9 shows that the effects do not show up until the price declines and greater diffusion of cloud computing from roughly 2010 onward. To our knowledge, other types of outsourced IT services did not experience similar price shocks (if anything, the Great Recession should have pushed prices for consulting and related services down, earlier, but this did not have an effect we can observe in our data).

Column 1 reports on our continuous measure for IT services, column 2 uses a “High IT” indicator to capture expenditure that is in the top quartile for the plant’s industry. Both columns show that our effects are largely confined to the later years, when cloud computing had diffused further and fallen in price. For the higher levels of expenditure, the effects show up a bit earlier, during the recession years. There is no variation in the IT capital stock coefficients across these periods.

We also correlated our IT services measure with an external data set that specifically provides information on cloud computing use. We use the information available in the Harte Hanks Intelligence Infocorp data set (which is the only large-scale data set we know of that directly measures cloud use such as software as a Service (SaaS), Infrastructure as a Service (IaaS), etc. While Harte Hank coverage of these new technologies leaves much to be desired, the measures – derived in very different ways from each other – are highly correlated at the county-industry level (*results pending disclosure review*).

Mechanism Tests and Nuances: Industry Context Variation

Table 10 further explores the nuances and underlying drivers of these patterns. Again, restricting attention to the subsample of young plants, columns1 and 2 interact the IT variables with an indicator of whether the plant is in an industry that intensively relies on IT as an input. This is constructed by identifying the 3-digit NAICS[26] industries with above-sample mean IT capital in 2005 (pre-cloud). Examples of typically IT-intensive industries (Jorgenson et al. 2007) include printing, semiconductors, instruments manufacturing, aerospace, and other transportation equipment. We consider these to be industry settings where learning about IT would tend to be particularly important. This does not account for shifts over time in the IT-intensity of industries, but has the virtue of being uncontaminated by industry variation in cloud diffusion (which is likely to be more endogenous).

For the continuous measure of investment in column 1, the interaction is noisy. For indicators of top-quartile (by NAICS 4) expenditure (which applies for all of the IT variables in the table, not just IT

[26] 3-digit NAICS codes are required to keep plants in well-defined categories throughout our sample, when there were some NAICS industry classifications at finer levels of aggregation.

services) in column 2, the interaction is large at 0.062 and significant at the five-percent level. All of the correlation of IT services with plant productivity in this specification shows up where our hypotheses predict it would matter the most.

Column 3 of table 10 interacts the IT variables with an indicator of being in a "high-competition" industry.[27] This indicator includes roughly 200 6-digit NAICS industries and includes a wide range of activities from fluid milk manufacturing to boxes to fabricated metal and motor vehicle metal stamping. We would expect continuation risks to be higher in more-competitive settings were margins are thinner, and thus where the consequences of failed or costly experiences would be greater. The interaction term is again positive, but significant at only the ten-percent level. The main effect persists at a similar level of statistical significance. We interpret this as mixed evidence for our expectation that we would see that the effect of cloud-based show up disproportionately in settings where firms face lower profit margins.

Next, we explore the impact of market and production variability on these estimates. When variance is higher, learning is more difficult. Columns 4 and 5 show that the effects of IT services on productivity are dramatically increased in industries where the yearly variance in plant capacity utilization for the industry (6-digit NAICS) is higher. For the young, the coefficient on the interaction term is 0.015 and significant at the five-percent level. Interestingly, in these specific industry contexts, even older plants demonstrate productivity gains from the cloud. The coefficient is much smaller at 0.005, but also statistically significant. We interpret this as confirmatory evidence for our hypothesized importance of uncertainty in driving this overall patter in the data.

Age vs. Size

Next, we explore the extent to which these effects are due to age versus size, a distinction that has become increasingly important in the firm lifecycle literature (Keung et al. 2016). We test this distinction

[27] We calculate the Lerner Index for the plant's 4-digit NAICS industry, taking the bottom quartile as indicative of being in a more competitive industry context.

by interacting Young, size indicators, and the same set of IT variables in Table 11.[28] While the previous productivity results all control for size measured as total employment, here, we explore a sharper cutoff to further differentiate the effects. We construct an indicator for "Large" that is equal to one when the plant has a total number of employees greater than or equal to the sample median for their 4-digit NAICS industry. Unsurprisingly, large plants are much more productive in our sample, on average.

The interaction effects between the different IT measures and size are surprising in light of prior work showing that IT tends to be more productive in large firms (e.g., Tambe and Hitt 2012; McElheran 2015). These coefficients are not statistically different from zero, except for IT services, which are significantly (in both the economic and statistical meaning of the word) *less* productive in large plants compared to small ones.

To get a clearer sense of how age and size interact, we estimate linear combinations of the coefficients and test their joint statistical significance in table 11. Some meaningful patterns emerge. When it comes to traditional IT capital, the effects are primarily about age, and not about size: old plants of any size enjoy higher IT capital productivity benefits than young plants of any size. These results conform to a model of firm lifecycle dynamics based only on age effects, where learning and co-invention take time.

The results on IT services require some care to interpret. If we organize plants into size-age categories: young and small, young and large, old and small, old and large, we find that the plants that benefit the most from IT services are *both young and small (YS).* The joint coefficient, which is significant at the one percent level, shows an output elasticity of 2.2%. Plants that are *young and large (YL)* benefit, too, though not as much. Their output elasticity is 0.9% and statistically undifferentiated from the comparison group, which is *old and small (OS)* and has an output elasticity of 1.2%. Plants that are both *old and large (OL)* derive some positive benefit from their IT services expenditure, but the magnitude of the effect is considerably smaller at 0.2%.

[28] Inputs to the production function are all included, but not interacted in order to preserve degrees of freedom.

The first and last results are the easiest to interpret. *YS* plants are the ones we would expect to have the most frictions according to all of the lifecycle models. While these results provide the strongest evidence for the impact of cloud computing on young plants, they are in some respect the least informative, in that they do little to disentangle the underlying mechanisms. The *OL* plants make the most sense from an economic equilibrium perspective, because the diffusion of the technology over time and the lack of differentiation should make this sort of technology less useful for this population of firms. Adjustment costs beyond the reach of our data may also play a role.

The results in the middle provide some progress towards disentangling mechanisms. Their interpretation benefits from a lens emphasizing variation in "entrepreneurial quality" (e.g., Guzman and Stern 2015). Old small plants are plants that have had time to grow and signal their quality to the market – and yet they remain small, suggesting either that they have no aspirations to grow or limited ability to do so. For this group, some cheap (and getting cheaper) generic IT may be better than no IT, hence the association with higher productivity. To the extent that entrepreneurial quality is difficult to observe, this omitted factor would go far to explain the weaker performance of IT in smaller firms in prior studies.

The *YL* plants clearly have growth aspirations and capabilities – in fact, they had to have either entered at scale or grown very quickly to become large in five or fewer years. If size were the primary consideration, therefore, they should be more productive with all types of IT. We interpret their *weaker* performance with traditional IT capital compared to older plants and the weaker performance with IT services compared to smaller young plants as consistent with having made some big bets already (lower option value) but still being behind the older plants when it comes to co-invention (Bresnahan and Greenstein 1996) . They may also be subject to unobservable adjustment costs associated with organizational size.

Financial Frictions

Not yet cleared for disclosure is a series of tests we conducted to see if financial frictions could be driving the pattern of results we see here. Young and small businesses tend to face much tighter internal and external financial constraints. The situation became much worse during the Great Recession and has not recovered since (e.g., Chen et al. 2017; Zarutskie and Yang 2016). Therefore, the positive productivity effect of cloud on young establishments we identified could becoming through easing the financial friction of these young establishments rather than the learning channel we have emphasized thus far.

However, if the story is primarily financial, we would expect two testable patterns in the data. First, young establishments that are financially distressed (low profit margin) should have a higher return when investing in the cloud. Second, young establishments located in counties with more constrained external financial market (e.g., a weak real estate market) should have a higher return when investing in cloud. Interactions of IT services expenditure with measures of profit margins (either at the plant or industry level) or with measures of local financial conditions (following Bogin et al. 2016) are never significantly different from zero.

Multi-Unit Status

Our analysis thus far has concerned plants, but not firms. However, roughly 70% of both young and old samples are made up of plants that belong to multi-establishment firms. All of our results are robust to the inclusion of a multi-unit indicator and to models fully interacted multi-unit status with all other inputs. Table 12 presents this evidence. This mimics table 11, but substituting an indicator for belonging to a multi-unit firm (MU) with the age indicators and all of the IT variables. The joint tests of the combined coefficients show that there is no statistical difference between young single-unit plants and young multi-unit plants. This was surprising to us, as one would expect learning from the parent firm to diffuse to new extensions of the organization.

To test this intuition, we further interacted the multi-unit indicator with an indicator for being in a different industry from the parent firm.[29] Within the young firm sample (to avoid a four-way interaction),

[29] Firm industry is determined by taking the 6-digit NAICS classification of the oldest plant in the firm; ties are broken based on revenues and employment.

we learned that the higher IT services productivity is concentrated *entirely* in the subsample of plants that are doing something different from the founding establishment of the firm (*results pending disclosure review).*

This finding is consistent with our hypothesis about learning and provides a strong contradiction to mechanisms rooted in financial frictions. To the extent that multi-unit plants should be able to rely on internal capital markets to finance IT investment (Kuppuswamy and Belen 2010), there should be a sharp distinction between these types of plants where none exists.. Conversely, to the extent that learning about the operating system, its IT requirements, and how to align the two of them to each other requires very localized learning-by-doing or may be consistent with very localized uncertainty in supply of demand conditions, this lack of a distinction is precisely what our hypothesizing would predict.

IT Interactions

Table 13 explores whether these different types of IT are complements or substitutes in the production functions for both young and old plants and provides evidence (*pending disclosure review*) consistent with learning. Controlling for industry at the 6-digit NAICS level, we observe in columns 1 and 2 that there is some substitution between traditional IT capital and IT services for both young and old plants. Although the coefficients are relatively modest; they are statistically significant at the 5% level. This is useful for interpreting the investment patterns observed at the beginning, where we some reallocation of expenditure from traditional IT capital to cloud-based IT in later years. If the types of IT were good substitutes for each other and cloud was simply cheaper, we might expect this effect to be bigger. The substitution is weaker, consistent with differing willingness to tradeoff between these two types of IT for plants of different ages.

More fine-grained data would be needed to understand the details of how firms are combining these new technologies. An important concern, however, is that firms *cannot* combine them well, and that older firms with robust legacy IT systems are unable to adjust to the cloud-based platform. Column 3 lags

IT capital stock by one period, and interacts it with all of the other IT variables.[30] The coefficient is negative, but noisy, providing no strong evidence that prior IT capital stock interacts negatively with cloud-based IT.

Columns 4 and 5 (*pending disclosure review*) lag IT services by several periods to see if our hypotheses about the benefits of cloud-based experimentation lead to better IT investments, later in a plant's life. The lag required varies by the type of IT, and can only be observed for the subset of plants that a) use the cloud relatively early, b) survive a number of years. Column 4 reports that 5 or 6 years later, the early use of IT service is associated with high productivity for IT capital. The coefficient is positive and significant at the 5% level. Within 3 to 4 years, prior IT services expenditure has a positive interaction with software investments; again, this is significant at the 5% level. While there is surely selection underlying these results, the pattern is highly suggestive.

Robustness Checks

Table 14 provides evidence that our findings are robust to a range of other econometric choices. Columns 1 shows the results for a translog specification. The statistical significant on IT services disappears, potentially in part due to the tremendous demands this specification places on the data. Other results are very consistent: including interactions and squares for all of the input variables (column 2); including regional controls in addition to industry-year fixed-effects (column 3), and using a quality-adjusted measure of labor input[31] (column 4). Columns 5 and 6 test robustness to our data cleaning choices: we get similar results if we actually include observations with imputed IT values (and more than double the sample size). We conclude that our productivity findings are also robust to outliers (probably due to the log-transformed production function), as we see similar results using the non-winsorized values

[30] We accidentally disclosed only the young subsample. However, the results for the old are qualitatively similar.

[31] Calculated by multiplying the total number of production-worker hours times the ratio of total production worker wages to total salaries and wages. See Foster, Grim and Haltiwanger (2016).

(column 6). The core of the paper centers on winsorized results because the descriptive statics actually are sensitive to this decision and this keeps the underlying data consistent throughout the core analysis.

VI. Conclusion

In this paper, we provide the first large-scale empirical evidence related to the survival and performance prospects for U.S. firms in the age of cloud computing. Moreover, we provide compelling evidence for the learning channel hypothesized in theories of firm lifecycle dynamics. This emphasis on mechanisms is crucial, as relevant policy and management prescriptions depend on the underlying reasons for the patterns we observe.

Based on prior theory, we hypothesize that the key benefit of the cloud comes from a new ability to experiment with rapidly available, flexible, yet relatively generic IT early in a firm's life. Over time, as uncertainty resolves, firms benefit more from firm-specific IT capital investments. The conditional correlations are strongly consistent with our hypotheses and are robust to a range of estimation strategies geared to addressing endogenous IT adoption. Young firms show a much higher association between IT services expenditure and survival, growth, and performance. Older firms show little or no benefit, except in certain specifications and industry settings, and even so the estimates are much lower.

We find almost no support for alternative explanations such as financial frictions; we find limited evidence for mechanisms rooted in economies of scale. . Consistent with a learning-based mechanism, older plants benefit only if they are in high-uncertainty industries; new establishments of existing firms only benefit if they operate outside their parent firm's primary industry. Finally, early expenditures that include the cloud lead to better productivity of owned IT capital, later in life.

It is important to contextualize these results, as they stand in marked contrast to prior evidence indicating that IT tends to be most productive in large firms. How can we reconcile these findings? To begin, we have unusually good visibility to a representative sample of young firms, along with accurate age data. Thus, we can more precisely estimate coefficients for this tail of the distribution and can disentangle age effects from size. Also, we explore both productivity and survival. A key insight of these findings is that firm-specific IT investments are risky for young firms – they can be productivity-enhancing conditional on survival, but they tend to promote exit as well. Firms that survive to become large will be those that have won their early IT bets; luck and productivity are thus confounded.

Moreover, if we had restricted our attention only to traditional IT capital, we would have come to similar conclusions as prior studies. While our main take-away is that learning and co-invention remain central to traditional IT productivity, these mechanisms dramatically favor older, more established firms – which also tend to be large. What has fundamentally shifted is the technological landscape – and our ability to measure it.

Because our results point to core frictions for young firms rooted in uncertainty and the costs of learning, our findings provide a useful counter-perspective to the policy debate concerning how best to support entrepreneurial activity and growth (e.g., Hurst and Pugsley 2011). One take on our findings is that the cloud provides a technological – rather than a policy – solution to decreased business dynamism. Thus, at the highest level, our findings contribute a new perspective to the rich debate about the value of – and interventions required by – young firms in the U.S. economy

Like many studies of new phenomena, our findings are not free of limitations. In particular, we worry about measurement error. While the Census data is remarkably detailed, we cannot precisely disentangle cloud-specific expenditure from other IT services. The timing and profound reversal in core patterns of IT productivity advantage just as the cloud diffuses and becomes cheaper is striking. We also corroborate our measure with and external data set on cloud use, but only at the county-industry level, Ideally, we would see IT services separated by cloud and non-cloud expenditure at the plant level. This would be a useful direction for future survey development.

Also, as we discuss throughout, standard techniques for addressing endogeneity of many types are often of limited effectiveness (though the evidence against reverse causality is relatively strong). Ultimately, we lean on the very different identifying assumptions for different instrumental variables estimation techniques – and the fact that they give very similar results to the baseline OLS estimate. The addition of reverse causality tests, sharpness in the timing of the effects, and detailed mechanism tests to suggest that there was a causal link between this important technological change and meaningful firm outcomes.

Finally, another limitation of our study is that it tells us about IT performance over the lifecycle only in the short term. It becomes difficult to track the long-term effects of these investments in young firms due to their high baseline exit rates. Moreover, the changes are still quite recent. It would be useful to replicate this study as time passes and we can observe longer-term effects.

We can only sketch out the implications for what may follow in the long run. Uncertainty is a permanent feature of the economic landscape, and the association with firm age and certain industry settings is unlikely to change. Thus, we expect that these associations might be long-lived. This has important implications for market-level dynamics including entry, the basis of firm competition, and equilibrium market structure. Unpacking how this may play out for industrial organization, firm strategy, and economic outcomes over time would be an interesting area for future research.

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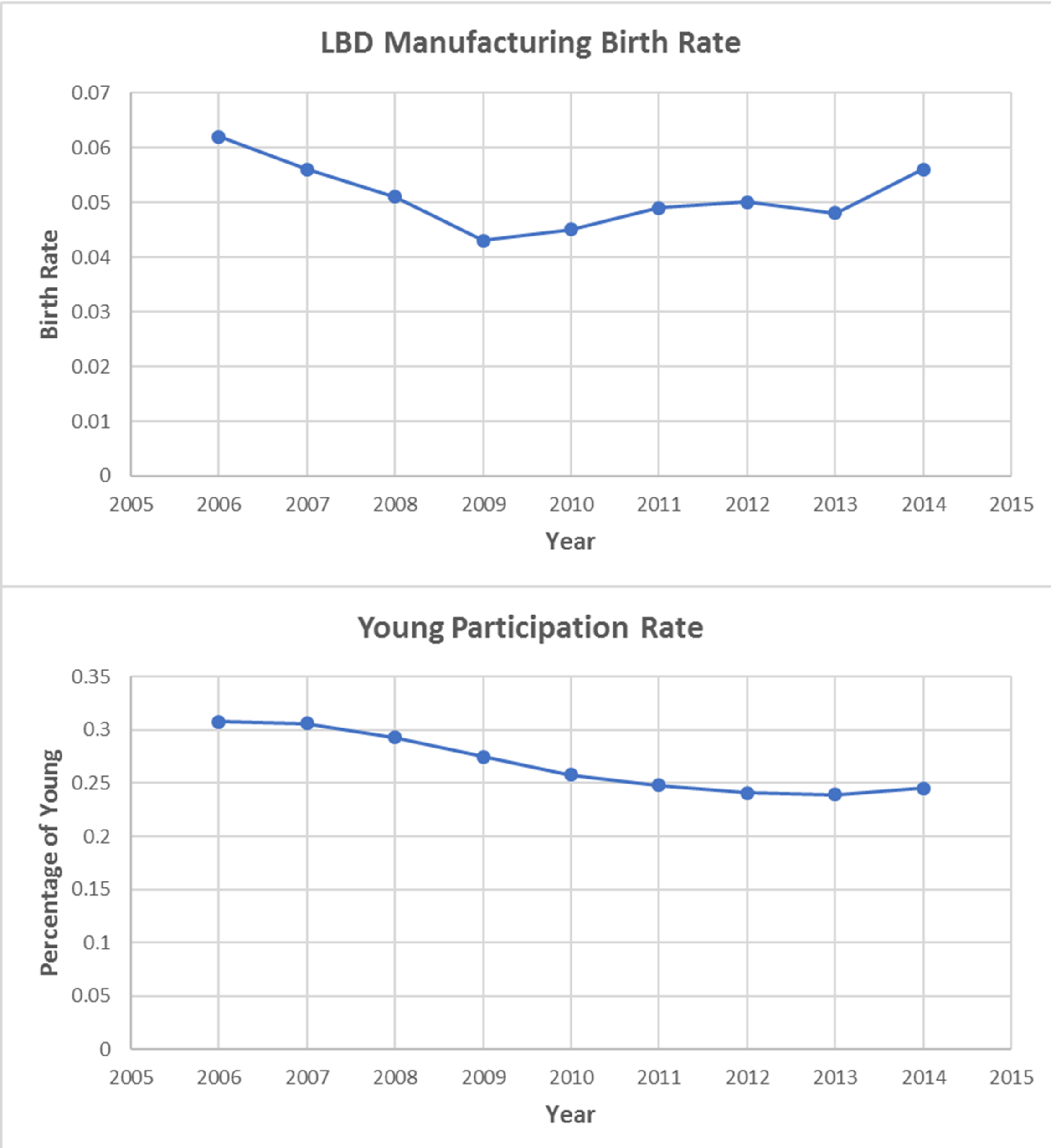
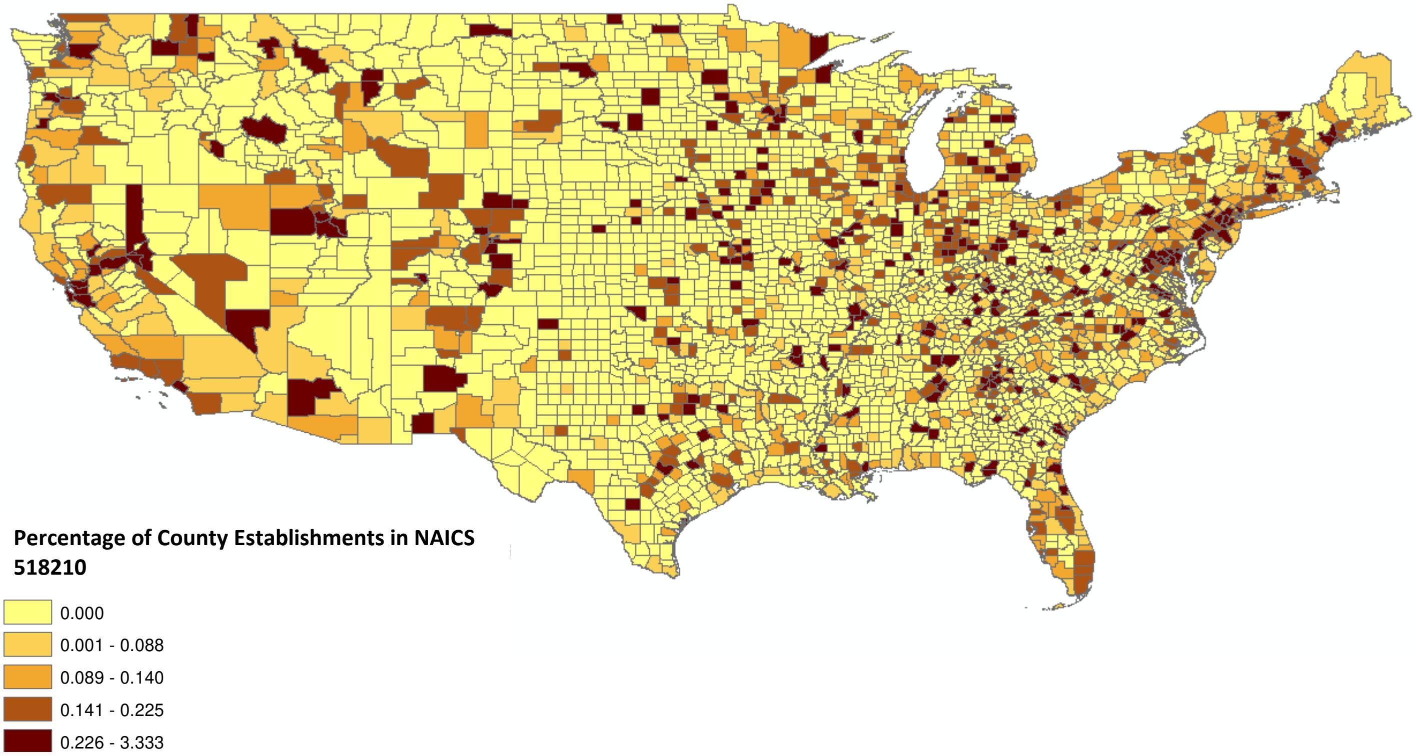
Figure 1. Population Statistics on Birth Rate and Prevalence of Young Plants in U.S. Manufacturing, 2006-2014.



Note: Based on the U.S. Census Bureau's Longitudinal Business Database for industries in the manufacturing sector, 2006 -2014.

Figure 2. Data Processing, Hosting, and Related Services Intensity by County in the U.S. 2010



Note: Values represent the ratio of establishments in Data Processing, Hosting, and Related Services (NAICS 518210) to the total number of establishments within the county. Based on public County Business Pattern 2010 data from the U.S. Census Bureau. Values reported are in percentage points – i.e., the most concentrated counties have a ratio of 0.23% to 3.33% of establishments belonging to the Data Services industry.

Figure 3. Annual Capitalized Investments in Computers and Data Processing Equipment in U.S. Manufacturing, 2006-2014 ($Thousands)
Winsorized at the 99th percentile

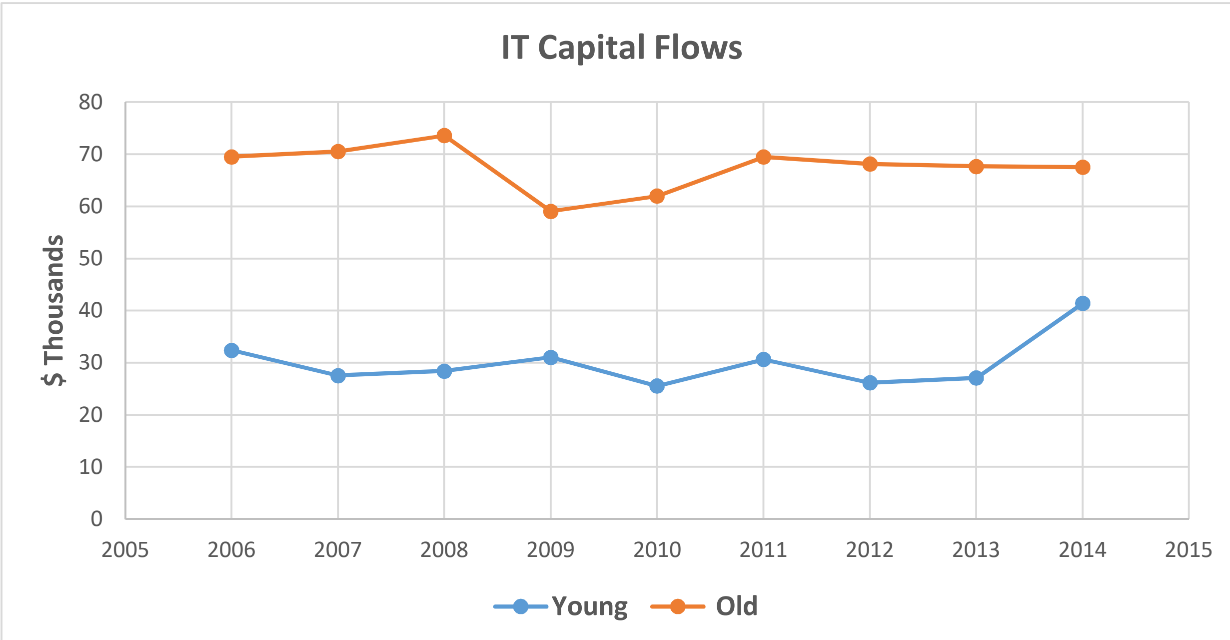


Figure 4. Accumulated and Depreciated IT Capital Stocks (Computers and Data Processing Equipment) in U.S. Manufacturing, 2006-2014 ($Thousands)
Winsorized at the 99th percentile

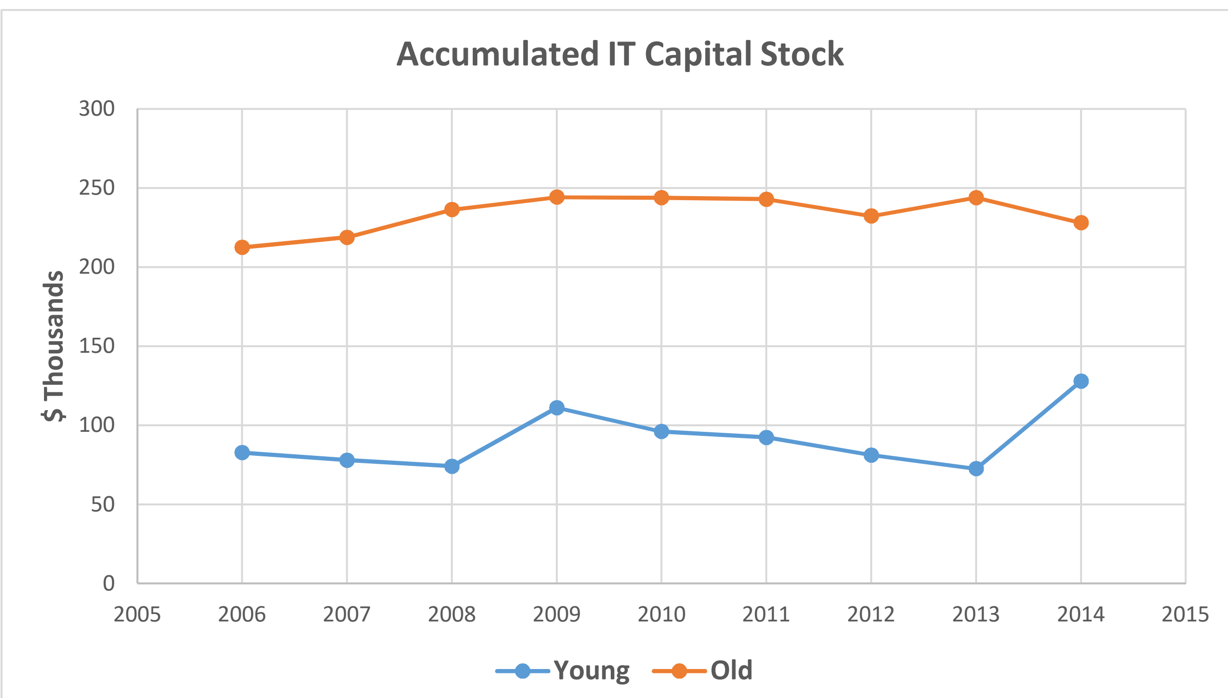


Figure 5. Annual Expenditures on IT Services in U.S. Manufacturing, 2006-2014 ($Thousands)
Winsorized at the 99th percentile

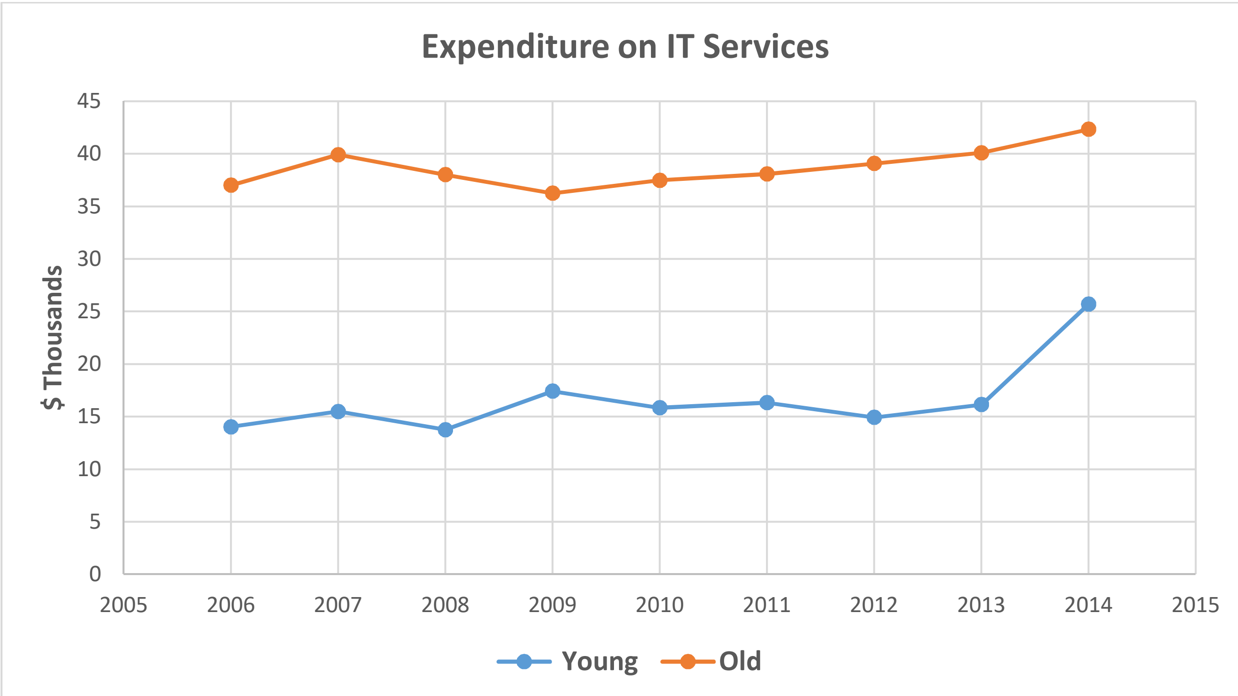


Figure 6. Per-Employee Annual Expenditures on IT Capital flows and IT Services in U.S. Manufacturing, 2006-2014 ($Thousands)
Winsorized at the 99th percentile

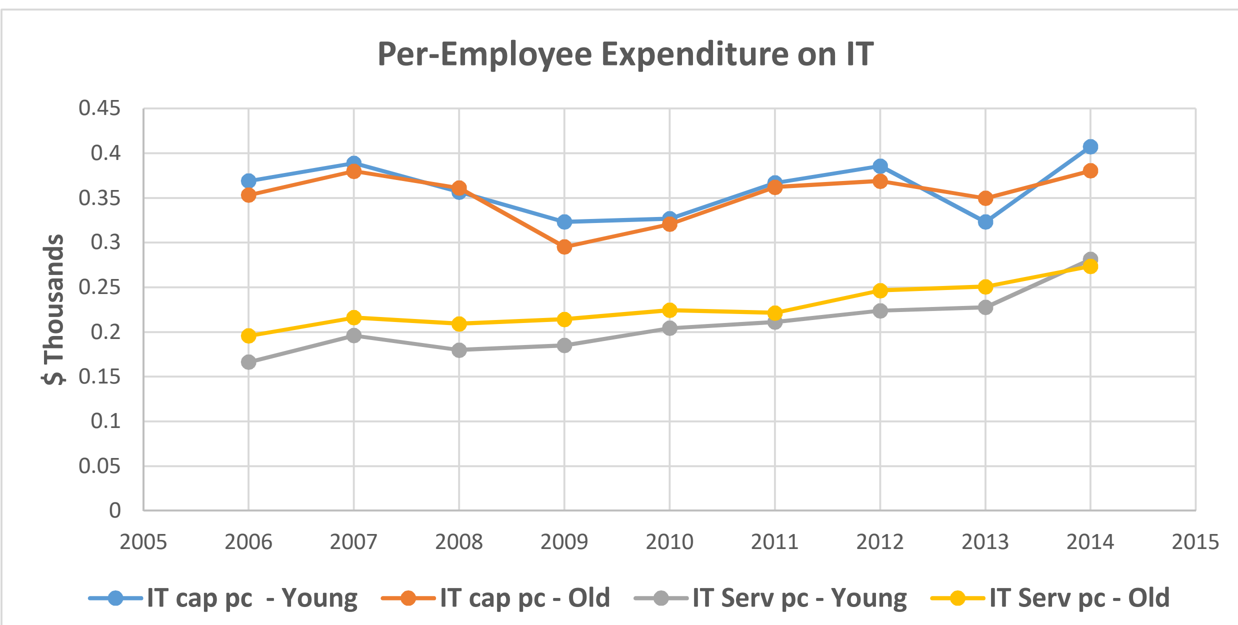
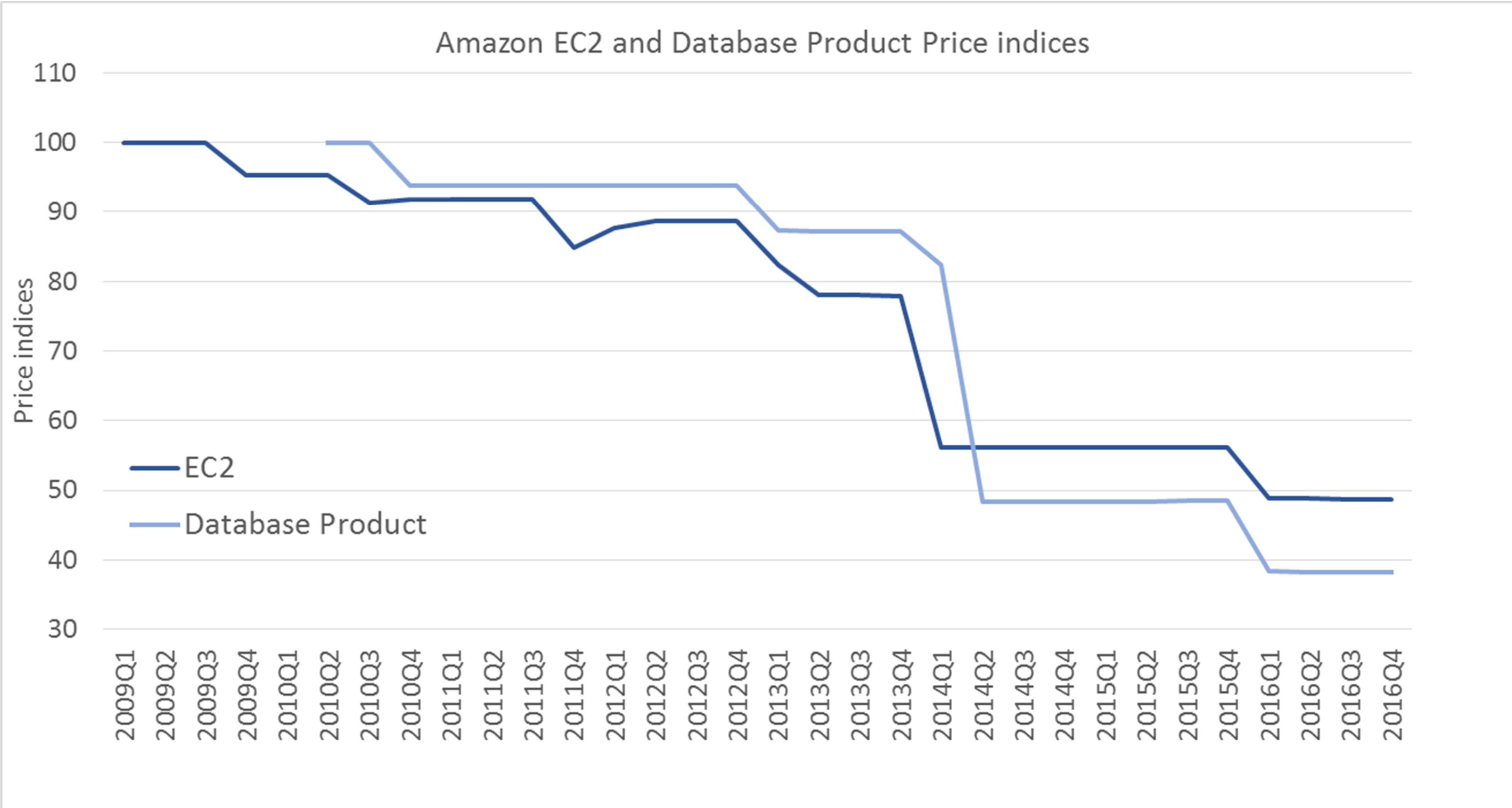


Table 1. Change of Pricing for Amazon EC2 and Database Product Price Indices



Source: Byrne, Corrado and Sichel 2017

Table 2. Descriptive Statistics

Variable	Definition	Young Less than or equal to 5 years	Older Greater than 5 years old
Age	Plant age	2.50 (1.45)	25.3 (9.98)
Exit (failure)	Average annual rate (percent) of plant exit due to failure	3.33 (17.9)	1.35 (11.5)
Number of Employees	Total number of employees	68.5 (166)	189 (421)
Sales	Total value of shipments ($Millions)	30.0 (149.7)	116 (611)
Value Added	Value added ($Millions)	12.4 (66.7)	44.4 (243)
IT Capital Stock†	Stock of IT capital such as computers and data-processing equipment ($Millions)	0.09 (0.33)	0.23 (0.58)
IT Capital annual flow†	Capital expenditure for the year on computers and data processing equipment ($Millions)	0.03 (0.13)	0.07 (0.20)
IT Services†	Operating expenses on data processing and other purchased computer services ($Millions)	0.02 (0.08)	0.04 (0.14)
Software†	Operating expenses on software ($Millions)	0.01 (0.06)	0.03 (0.10)
Equipment†	Operating expenses on equipment ($Millions)	0.02 (0.075)	0.04 (0.13)
Non-IT Capital Stock†	Traditional capital stock on non-IT equipment and structure ($Millions)	10.2 (37.6)	28.0 (65.2)
Multi-Unit Status	Indicator for whether plants belong to a multi-unit firms	0.70 (0.46)	0.69 (0.46)
Log(Sales)	Plant total sales in log terms ($Thousands)	8.88 (1.58)	10.2 (1.56)
Log (IT Capital Stock†**)**	IT capital stock in log terms ($Thousands)	2.60 (1.90)	3.80 (1.98)
Log (IT Capital flows†**)**	IT capital expenditure in log terms ($Thousands)	1.29 (1.73)	1.95 (0.21)
Log (IT Services†**)**	Operating expenses on Data processing and other purchased computer services in log terms ($Thousands)	0.87 (1.49)	1.30 (1.90)
Log (Equipment Expenditure†**)**	Operating expenses on equipment in log terms ($Thousands)	1.13 (1.51)	1.79 (1.89)
Log (Software Expenditure†**)**	Operating expenses on software in log terms ($Thousands)	0.83 (1.37)	1.39 (1.82)
Number of Observations		~41,300	~198,400

Note: Std. Deviations in parentheses; † indicates the variable is winsorized at the 1% and 99% levels.

Table 3. IT Capital and Expenditures per Employee for Young vs. Older Plants in U.S. Manufacturing 2006-2014

	(1)	(2)	(3)	(4)	(4a)	(4b)	(4c)	(4d)
Dependent Variable	**IT Capital Stock per Employee**	**Annual IT Flows (all kinds) per Employee**	**IT Capital Stock per Employee**	**Annual IT Flows (all kinds) per Employee**	**IT Capital Flows per Employee**	**IT Services Spend per Employee**	**Software Spend per Employee**	**Equipment Spend per Employee**
Young	-.063*** (0.012)	-.021*** (0.010)	-0.037* (0.022)	-0.008 (0.019)	0.017* (0.009)	-0.021*** (0.009)	-0.025*** (0.004)	0.006 (0.006)
Late (2008 – 2014)			0.150*** (0.011)	-0.081*** (0.010)	-0.029*** (0.004)	0.018*** (0.003)	0.026*** (0.002)	-0.078*** (0.003)
Young x Late			-0.041 (0.026)	-0.035 (0.022)	-0.011 (0.010)	-0.002 (0.007)	-0.002 (0.005)	-0.020 (0.007)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	N	N	N	N	N	N
N	~239,700	~239,700	~239,700	~239,700	~239,700	~239,700	~239,700	~239,700
R-Squared	0.094	0.099	0.093	0.097	0.048	0.047	0.085	0.060

Note: Results from columns 1 and 2 are from unweighted OLS regressions controlling for year- and industry- (6-digit NAICS) fixed effects. Results from columns 3 to 4d are from OLS regressions controlling for industry-fixed effects (6-digit NAICS). All columns use the entire analysis sample containing both young and old plants from 2006 to 2014. The dependent variables are the IT capital stock and annual IT expenditure variables winsorized at the 99th percentile. In addition, the rate of outliers is not correlated with age as we observe similar percentages in both young and old. **Young** is an indicator for an plant being less than or equal to 5 years old. **Late** is the indicator for the sample years 2008 through 2014. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 4. IT Expenditure Breakdown by Type for Young and Older Plants, 2006 – 2014

	(1)	(2)	(3)	(4)
Dependent Variables	**% Expenditure on IT Capital Flows**	**% Expenditure on IT Services**	**% Expenditure on Software**	**% Expenditure on Equipment**
Young	0.009** (0.004)	-0.004 (0.003)	-0.015*** (0.003)	0.010*** (0.003)
Late	-0.054*** (0.002)	0.021*** (0.002)	0.036*** (0.001)	-0.003* (0.002)
Young x Late	-0.006 (0.004)	0.011** (0.003)	0.002 (0.003)	-0.007* (0.004)
Industry Fixed Effects	Y	Y	Y	Y
N	~239,700	~239,700	~239,700	~239,700
R-Squared	0.152	0.086	0.097	0.131

Note: Results are from OLS regressions controlling for industry (6-digit NAICS) fixed effects. The dependent variables are the percentage of each type of IT spending with respect to the total expenditure reported on IT. All columns include an unreported indicator for whether the plant reported zero IT expenditure (note that these are reported, not imputed zeroes). **Late** is the indicator for the sample years 2008 through 2014. There is no statistical difference between the Great Recession years (2008-2009) and the post-Recession period (2010-2014), so they are combined for ease of exposition. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 5. IT Expenditure, Survival, and Employment Growth in Young vs. Older Plants, 2006-2014

Model Description	**(1a) Survival Young**	**(1b) Survival Older**	**(2a) Survival (High IT dummies) Young**	**(2b) Survival (High IT dummies) Older**	**(3a) Employment Growth Young**	**(3b) Employment Growth Older**
Dependent Variable	Probability of Failure	Probability of Failure	Probability of Failure	Probability of Failure	Change in Employment	Change in Employment
IT Capital stock	1.046** (0.023)	0.968** (0.014)	1.263** (0.147)	0.849*** (0.053)	0.009*** (0.003)	0.008*** (0.001)
IT Services	0.951* (0.026)	0.900*** (0.014)	0.824** (0.073)	0.727*** (0.040)	0.014*** (0.003)	0.007*** (0.001)
Software	0.923** (0.030)	0.846*** (0.016)	1.014 (0.092)	0.777*** (0.046)	-0.126*** (0.016)	-0.085*** (0.008)
Equipment	0.875*** (0.027)	0.823*** (0.014)	0.616*** (0.075)	0.523*** (0.036)	0.028*** (0.003)	0.015*** (0.001)
Non-IT Capital Stock	0.879*** (0.014)	1.007 (0.018)	0.885*** (0.012)	0.972* (0.015)	0.022*** (0.005)	0.044*** (0.005)
Industry Controls	NAICS4	NAICS4	NAICS3	NAICS3	N	N
Industry x Year Fixed Effects	N	N	N	N	Y	Y
# of Plants per Year	~4,900	~22,400	~4,900	~22,400	~2,400	~14,500
# of Years	6	6	6	6	8	8
R-Squared					0.048	0.063

Note: Results in columns 1a, 1b, 2a, and 2b are hazard rates from a Cox proportional hazard model of the likelihood of failure. Columns 3a and 3b report unweighted OLS coefficients of a regression on year-over-year change in employment at the plant controlling for year and industry fixed-effects at 4 digit NAICS (results are robust and consistent if controlling for year and 6 digit NAICS fixed-effects). The independent variables for the first two columns include levels of IT investment; the next two substitute indicators for being in the 75th percentile of that type of IT investment for that plant's NAICS4 industry. Additional controls include accumulated and depreciated non-IT capital stock in log terms and plant age (not reported but available upon request). For columns 3a and 3b, the explanatory variables are year-over-year changes in IT (calculated using log differences) and changes in non-IT capital stock in log terms. The sample for the survival models from columns 1a to 2b included data from 2006 to 2012 due to limitations in the 2013 LBD preventing identification of plant exit. The sample for the growth models requires that plants persist at least two consecutive years in the sample. Columns 1a and 1b control for 4-digit NAICS code; columns 2a and 2b control for 3-digit NAICS code because IT indicators are constructed based on 4-digit NAICS. Standard errors from specifications in columns 3a and 3b are clustered at the plant level. Statistical significance is denoted as follows: *10%, **5%, ***1%.

Table 6a. Estimates of IT Productivity for Young vs. Older Plants, 2006-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Description	**All**	**Young Only**	**Older Only**	**Sales x Young**	**Sales Young Only + F.E.**	**Sales Older Only + F.E.**	**Young Only (High IT indicators)**
IT Capital Stock	0.013*** (0.001)	0.012** (0.002)	0.012*** (0.002)	0.012*** (0.001)	0.007** (0.004)	0.003** (0.001)	0.073*** (0.011)
IT Services	0.0002 (0.001)	0.007*** (0.002)	-0.0003 (0.001)	-0.0004 (0.001)	0.009*** (0.003)	0.0014** (0.0007)	0.019** (0.010)
Software	0.002** (0.001)	0.06** (0.003)	0.002* (0.001)	0.002* (0.001)	0.009*** (0.003)	0.003** (0.001)	0.020** (0.011)
Equipment	0.012*** (0.001)	0.016*** (0.002)	0.011*** (0.001)	0.011*** (0.001)	0.012*** (0.003)	0.006*** (0.001)	0.051*** (0.010)
Young	-0.020*** (0.004)			0.270*** (0.026)			
IT Capital Stock x Young				-0.008 (0.002)			
IT Services x Young				0.007*** (0.002)			
Software x Young				0.004* (0.003)			
Equipment x Young				0.006** (0.002)			
Non-IT Capital Stock	0.049*** (0.002)	0.022*** (0.002)	0.077*** (0.003)	0.076*** (0.003)	0.011*** (0.004)	0.019*** (0.004)	0.024*** (0.003)
Non-IT Capital Stock x Young				-0.056*** (0.003)			
Inputs: Labor & Materials	Y	Y	Y	Y	Y	Y	Y
Inputs x Young	N	N	N	Y	N	N	N
Industry x Year Fixed Effects	Y	Y	Y	Y	N	N	Y
Plant & Year Fixed Effects	N	N	N	N	Y	Y	N
# of Plants per Year	~26,600	~4,600	~22,000	~26,600	~4,600	~22,000	~4,600
# of Years	9	9	9	9	9	9	9
R-Squared	0.939	0.906	0.939	0.939	0.585	0.600	0.906

Note: Results in columns 1, 2, 3, 4, and 7 are based on unweighted OLS regression controlling for year-industry (6-digit NAICS) fixed effects. Columns 5 and 6 are based on plant fixed effect models controlling for year trends. The dependent variable for all columns is total sales in log terms. Production inputs are also controlled for (but not reported) in all models in log terms, including: cost of material, cost of energy, and labor (both expenditure on temporary employees and the count of regular employees). In addition, the coefficients for interaction terms between Young and the production inputs in column 4 are not reported to save space (available upon request). Standard errors for all columns are clustered at the plant level. Results are robust to two-way clustering at county & plant and firm & plant levels, as well (*pending disclosure review*). Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 6b. Linear Combinations of IT Productivity Coefficients from Table 6a:

	(1)	(2)	(3)	(4)
Model Description	**Sales Young Only**	**Sales Older Only**	**Sales Young Only + F.E.**	**Sales Older Only + F.E.**
IT Capital Stock	0.012*** (0.002)	0.012*** (0.001)	0.007** (0.004)	0.003** (0.001)
IT Capital Stock + Equipment	0.028*** (0.003)	0.023*** (0.002)	0.019*** (0.005)	0.009*** (0.001)
IT Capital Stock + IT Services	0.019*** (0.003)	0.011*** (0.002)	0.016*** (0.005)	0.004*** (0.001)
IT Capital Stock + IT Services + Equipment	0.035*** (0.004)	0.023*** (0.002)	0.027*** (0.006)	0.010*** (0.002)
IT Capital Stock + IT Services + Equipment + Software	0.041*** (0.004)	0.024*** (0.002)	0.036*** (0.007)	0.013*** (0.002)
Industry x Year Fixed Effects	Y	Y	N	N
Plant & Year Fixed Effects	N	N	Y	Y

Note: The coefficients are calculated using the **lincom** command in Stata 13, based on coefficients from Table 6a, columns 4-7 respectively for young and old samples. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 7. IV Estimates of IT Performance Benefits for Young Plants, 2006-2014

	(1)	(2)	(3)	(4)	(5)
Model Description	**OLS**	**Blundell-Bond**	**Levinsohn-Petrin**	**Ackerberg-Caves-Frazer**	**Data Center Intensity (lagged 2 years)**
Dependent Variables	**Sales**	**Sales**	**Sales**	**Sales**	**Sales**
IT Capital Stock	0.011** (0.003)	0.005 (0.010)	0.013*** (0.002)	0.029 (0.035)	-0.004 (0.007)
IT Services	0.010*** (0.003)	0.031*** (0.012)	0.007*** (0.002)	0.022*** (0.007)	0.402** (0.146)
Software	0.005* (0.003)	-0.002 (0.013)	0.010*** (0.003)	0.026 (0.022)	-0.079* (0.032)
Equipment	0.018*** (0.003)	0.032*** (0.012)	0.023*** (0.002)	0.040*** (0.013)	-0.015 (0.014)
Non-IT Capital Stock	0.073*** (0.003)	0.008 (0.015)	0.031*** (0.011)	0.041*** (0.015)	0.023*** (0.003)
Inputs: Labor & Materials	Y	Y	Y	Y	Y
Plant & Year Fixed Effects	N	Y	Y	Y	N
Industry x Year Fixed Effects	Y	N	N	N	Y
First Stage					
Data Center Intensity	N/A	N/A	N/A	N/A	29.17*** (8.02)
F-test	N/A	N/A	N/A	N/A	13.22
# of Plants per Year	~4,600	~4,600	~4,600	~4,600	~4,600
# of Years	9	7	9	9	9

Note: **Note**: Column 1 is identical to Table 6a, column 2. Column 2 employs the system GMM estimator following Blundell and Bond (2000) to address potential endogeneity of IT adoption in the productivity estimation. It uses two-period lagged differences and levels as GMM instruments for IT services expenditure. This specification passes both over-identification and autocorrelation tests. Column 3 follows the approach in Levinsohn and Petrin (2003), using expenditure on intermediate inputs (cost of temporary employees) as proxy for unobservable productivity shocks. Column 4 employs the method developed by Ackerberg, Caves, and Frazer (2006) to further account for collinearity problems when estimating productivity using the Levinsohn-Petrin techniques. Column 5 used the lagged data center intensity (percentage of number of data centers to total establishments) in the local county as the instrument. The results in column 5 pass all tests including weak identification, under identification, and endogeneity tests. Production inputs are also controlled for (but not reported) in all models in log terms, including: cost of materials, cost of energy (both electricity and fuel), and labor (both expenditure on temporary employees and the count of regular employees). Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%. We also tested the semiparametric method developed by Olley and Pakes (1996), which uses capital investment (both structure and equipment) as a proxy for unobservable shocks that could lead to spurious correlation between IT services expenditure and productivity. The results from this method are consistent with the results presented in this table.

Table 8. Reverse Causality Tests in Young Plants

Model Description	(1) No lagged TVS	(2) Lagged TVS	(3) Forward IT	(4) Lagged TVS	(5) Forward TVS
Dependent Variables	**Sales**	**Sales**	**Sales**	**IT Services**	**IT Services**
Lagged IT Capital Stock	0.011*** (0.004)	-0.002 (0.003)	-0.016*** (0.004)	0.011 (0.007)	0.017* (0.010)
Lagged IT Services	0.008*** (0.003)	-0.002 (0.003)	0.0003 (0.004)	0.696*** (0.010)	0.704*** (0.014)
Lagged Software	0.006 (0.004)	-0.001 (0.003)	-0.001 (0.005)	0.037*** (0.010)	0.060*** (0.015)
Lagged Equipment	0.017*** (0.004)	0.002 (0.003)	-0.010** (0.006)	0.008 (0.009)	0.012 (0.013)
Lagged Sales		0.489*** (0.013)	0.527*** (0.019)	-0.045** (0.016)	-0.065** (0.031)
Forward IT Capital Stock			0.018*** (0.006)		
Forward IT Services			-0.006 (0.004)		
Forward Software			-0.004 (0.005)		
Forward Equipment			0.018*** (0.005)		
Forward Sales					0.042 (0.028)
Industry x Year Fixed Effects	Y	Y	Y	Y	Y
# of Plants per Year	~2,100	~2,100	~1,200	~2,100	~1,200
# of Years	8	8	7	8	7
R-Squared	0.918	0.949	0.956	0.594	0.617

Note: Results are from the unweighted OLS regression. All columns use young sample only and control for industry-year fixed-effects. The dependent variables for columns 1 to 3 are total value of shipment in log terms while the dependent variables for columns 4 and 5 are the IT services in log terms. The sample size is similar to those in the growth models since lagged and forward variables are needed to test for reverse causality and hence the plants in the analysis sample are required to show up two or three consecutive years. Additional controls include cost of material, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) in log terms. Standard errors are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 9. Timing of IT Productivity Effects, 2006-2014

Model Dependent Variable = Total Revenues	(1) Continuous IT	(2) High IT Indicators (Top Quartile)
IT Capital Stock	0.008** (0.004)	0.085*** (0.016)
IT Services	0.001 (0.003)	-0.010 (0.012)
Equipment	0.010*** (0.004)	0.035*** (0.013)
Software	0.006 (0.004)	-0.007 (0.013)
IT Capital Stock x Middle Period (2008-2009)	0.011** (0.006)	-0.025 (0.021)
IT Services x Middle	-0.004 (0.004)	0.012 (0.013)
Software x Middle	0.005 (0.006)	0.037** (0.019)
Equipment x Middle	0.020*** (0.005)	0.042** (0.019)
IT Capital Stock x Later Period (2010-2014)	0.006 (0.004)	-0.001 (0.022)
IT Services x Late	0.010** (0.005)	0.032* (0.016)
Software x Late	0.001 (0.005)	0.027 (0.018)
Equipment x Late	0.016*** (0.005)	0.025 (0.017)
# of Plants per Year	~4,600	~4,600
# of Years	9	9
R-Squared	0.901	0.901

Note: Results in all columns are based on the unweighted OLS regression. All columns use young sample only and control for industry fixed-effects at 3-digit NAICS since the high IT dummies are constructed at the 4-digit NAICS level. The dependent variable for all columns is total value of shipment in log terms. Additional variables including cost of material, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) in log terms are controlled but not reported to save space (available up on request). In addition, the coefficients for interaction terms between young and other inputs are not reported in the table to save space. Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 10a. Industry Variation in IT Productivity, 2006-2014

Model Description	(1) IT-Intensive in 2005	(2) IT-Intensive in 2005 (High IT Dummies)	(3) High Competition (Lerner Index)	(4) High-Uncertainty (Young)	(5) High-Uncertainty (Older)
Dependent Variables	**Sales**	**Sales**	**Sales**	**Sales**	**Sales**
IT Capital Stock	0.012*** (0.003)	0.044*** (0.013)	0.012*** (0.002)	0.019*** (0.003)	0.023*** (0.001)
IT Services	0.0002 (0.003)	-0.013 (0.010)	0.006** (0.003)	0.002 (0.003)	-0.003** (0.001)
Software	0.006 (0.004)	0.006 (0.010)	0.007*** (0.003)	0.014*** (0.003)	0.011*** (0.001)
Equipment	0.018*** (0.003)	0.043*** (0.011)	0.016*** (0.003)	0.023*** (0.003)	0.016*** (0.001)
IT Capital Stock x High IT Intensity in 2005	0.004 (0.004)	0.057*** (0.022)			
IT Services x High IT Intensity in 2005	0.009** (0.005)	0.044*** (0.015)			
Software x High IT Intensity in 2005	0.004 (0.005)	0.013 (0.016)			
Equipment x High IT Intensity in 2005	0.009** (0.005)	0.029* (0.017)			
IT Capital Stock x High Competition			0.001 (0.005)		
IT Services x High Competition			0.004 (0.006)		
Software x High Competition			-0.009 (0.006)		
Equipment x High Competition			0.002 (0.006)		
IT Capital Stock x High Uncertainty				-0.009** (0.004)	-0.004** (0.002)
IT Services x High Uncertainty				0.012*** (0.004)	0.006*** (0.001)
Software x High Uncertainty				-0.010** (0.005)	-0.006*** (0.002)
Equipment x High Uncertainty				0.003 (0.004)	0.005*** (0.002)
Industry and Year Fixed Effects	Y	Y	Y	Y	Y
# of Plants per Year	~4,600	~4,600	~4,600	~4,600	~22,000
# of Years	9	9	9	9	9

Note: Results in all columns are based on unweighted OLS regressions. All columns control for sector (2-digit NAICS) and year fixed effects using the young sample only (except column 5). The dependent variable for all columns is logged total value of shipments. **High IT Intensity in 2005** is an indicator for plants in industries (3-digit NAICS) with above-mean IT capital stock in 2005. **High Competition** is an indicator equal to 1 if the one-period lagged industry (6-digit NAICS) Lerner index is in the bottom 25th percentile for the entire ASM. **High Uncertainty** is an indicator for being in 6-digit NAICS industries with above-mean industry variance in the quarterly plant capacity utilization rate (based on data from the US Census Bureau's Plant Capacity Utilization Survey matched to our sample). Inputs including costs of material, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) in log terms are controlled for but not reported (available up on request). Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 10b Alternative Explanations, 2006-2014

Model Description	(1) Large	(2) Small	(3) Low Profit Margin	(4) Single Unit	(5) Young MU in New Market
Dependent Variables	**Sales**	**Sales**	**Sales**	**Sales**	**Sales**
IT Capital Stock	0.043*** (0.003)		0.015*** (0.002)	0.019*** (0.003)	0.017*** (0.004)
IT Services	0.018*** (0.003)		0.006** (0.002)	0.008*** (0.003)	0.001 (0.004)
Software	0.026*** (0.003)		0.010*** (0.003)	0.013*** (0.003)	0.016*** (0.005)
Equipment	0.049*** (0.003)		0.024*** (0.002)	0.024*** (0.003)	0.027*** (0.004)
Large Indicator	0.514*** (0.024)				
IT Capital Stock x Large	-0.019*** (0.005)				
IT Services x Large	-0.004 (0.005)				
Software x Large	-0.032*** (0.006)				
Equipment x Large	-0.007 (0.006)				
IT Capital Stock x Small					
IT Services x Small					
Software x Small					
Equipment x Small					
Low Profit Margin Indicator			-0.270*** (0.017)		
IT Capital Stock x Low Profit Margin			0.010* (0.006)		
IT Services x Low Profit Margin			-0.002 (0.006)		
Software x Low Profit Margin			0.007 (0.006)		
Equipment x Low Profit Margin			0.003 (0.006)		
Single-Unit Indicator				-0.096*** (0.014)	-0.078*** (0.016)
IT Capital Stock x Single-Unit				-0.004 (0.004)	-0.002 (0.005)
IT Services x Single-Unit				-0.001 (0.005)	0.007 (0.006)
Software x Single-Unit				-0.003 (0.005)	-0.005 (0.006)
Equipment x Single-Unit				-0.002 (0.005)	-0.004 (0.006)
Diff MU					0.037*** (0.014)
IT Capital Stock x Diff MU					0.004 (0.005)
IT Services x Diff MU					0.012** (0.005)

Software x Diff MU					-0.005 (0.005)
Equipment x Diff MU					-0.004 (0.006)
Industry and Year Fixed Effects	Y	Y	Y	Y	Y
# of Plants per Year	~4,600	~4,600	~4,600	~4,600	~4,600
# of Years	9	9	9	9	9

Note: Results in all columns are based on unweighted OLS regressions. All columns control for sector (2-digit NAICS) and year fixed effects using the young sample only. The dependent variable for all columns is logged total value of shipments. **Large** is an indicator for plants with less than 100 total employees. **Small** is an indicator equal to 1 if the plants have their total number employee at the bottom quartile of the analysis sample and 0 otherwise. **Low Profit Margin** is an indicator for plants having the bottom quartile of (one period) lagged markup. **Single-unit** is an indicator for single-unit firms. **Diff MU** is an indicator for plants from multi-unit firms but in an industry different from their parental firms. Inputs including costs of material, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) in log terms are controlled for but not reported (available up on request). Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 11. Size vs. Age in IT Productivity, 2006-2014

Dependent Variable	Sales
IT Capital Stock	0.015*** (0.002)
IT Services	0.002 (0.001)
Software	0.001 (0.002)
Equipment	0.012*** (0.002)
Young	0.015* (0.008)
Large	-0.015* (0.008)
Large x Young	0.009 (0.016)
IT Capital Stock x Large	0.002 (0.003)
IT Services x Large	-0.004** (0.002)
Software x Large	0.0001 (0.002)
Equipment x Large	-0.001 (0.002)
IT Capital Stock x Young	-0.021*** (0.003)
IT Services x Young	0.004 (0.003)
Software x Young	0.007** (0.004)
Equipment x Young	0.006** (0.003)
IT Capital Stock x Young x Large	0.009** (0.004)
IT Services x Young x Large	0.004 (0.005)
Software x Young x Large	-0.002 (0.005)
Equipment x Young x Large	-0.004 (0.005)
Industry x Year Fixed Effects	Y
# of Plants per Year	~26,000
# of Years	9
R-Squared	0.939

Comparison Group: IT Capital Stock + older + small	0.015*** (0.002)
Linear Combination: IT Capital Stock + young + small	-0.006** (0.002)
Linear Combination: IT Capital Stock + young + large	0.005 (0.003)
Linear Combination: IT Capital Stock + older + large	0.017*** (0.001)
Comparison Group: IT services + older + small	0.002 (0.001)
Linear Combination: IT services + young + small	0.006** (0.003)
Linear Combination: IT services + young + large	0.005 (0.003)
Linear Combination: IT services + older + large	-0.002* (0.001)

Note: Results of unweighted OLS regression. **Young** indicates 5 or fewer years old. **Large** indicates above-median employment compared to the plant's 4-digit NAICS industry in a given year. Additional controls include logged cost of materials, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees); these are not interacted with **Young** or **Large** in this specification. Joint tests of significant for the linear combinations are conducted using the STATA 13 *lincom* command. Standard errors are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 12. Age and Multi-Unit Status in Multi-Factor IT Productivity 2006-2014

Dependent Variable	**Sales**
IT Capital Stock	0.015*** (0.002)
IT Services	0.005*** (0.002)
Software	0.003** (0.001)
Equipment	0.009*** (0.001)
Young	-0.001 (0.012)
MU	0.074*** (0.008)
MU x Young	-0.007 (0.015)
IT Capital Stock x MU	0.003* (0.002)
IT Services x MU	-0.006*** (0.002)
Software x MU	-0.001 (0.002)
Equipment x MU	0.002 (0.002)
IT Capital Stock x Young	-0.019*** (0.004)
IT Services x Young	0.001 (0.004)
Software x Young	0.008* (0.004)
Equipment x Young	0.011*** (0.004)
IT Capital Stock x Young x MU	0.004 (0.004)
IT Services x Young x MU	0.009* (0.005)
Software x Young x MU	-0.001 (0.005)
Equipment x Young x MU	-0.005 (0.005)
Industry x Year Fixed Effects	Y
# of Plants per Year	~26,000
# of Years	9
R-Squared	0.939

Comparison Group: IT Capital Stock + older + single-unit	0.015*** (0.002)
Linear Combination: IT Capital Stock + young + single-unit	-0.004 (0.004)
Linear Combination: IT Capital Stock + young + MU	0.004 (0.002)
Linear Combination: IT Capital Stock + older + MU	0.018*** (0.001)
Comparison Group: IT services + older + single-unit	0.005*** (0.002)
Linear Combination: IT services + young + single-unit	0.007 (0.004)
Linear Combination: IT services + young + MU	0.009*** (0.003)
Linear Combination: IT services + old + MU	-0.001 (0.001)

Note: Results of unweighted OLS regression. **Young** indicates 5 or fewer years old. **MU** indicates whether the plants belong to multi-unit firms. Additional controls include logged cost of materials, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees); these are not interacted with **Young** or **MU** in this specification. Joint tests of significant for the linear combinations are conducted using the STATA 13 *lincom* command. Standard errors are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 13. IT Complementarities for both Young and Older Plants

Model Description	(1) Same-Year Interaction	(2) Same-Year Interaction	(3) Lagged IT Capital	(4) Lagged IT Services	(5) Lagged IT Services
Sample	**Young**	**Older**	**Young**	**All**	**All**
Dependent Variables	**Sales**	**Sales**	**Sales**	**Sales**	**Sales**
IT Capital Stock	0.015*** (0.003)	0.011*** (0.001)	0.012** (0.005)		
IT Services	0.009** (0.005)	-0.001 (0.002)	0.002 (0.007)		
Software	-0.012** (0.005)	-0.005* (0.003)	-0.023** (0.009)		
Equipment	0.022*** (0.005)	0.006*** (0.002)	0.023*** (0.008)		
IT Capital Stock x IT Services	-0.003** (0.001)	-0.001** (0.0005)	-0.002 (0.002)		
IT Capital Stock x Lagged† IT Services				+**	
Software x IT Services	0.003** (0.002)	0.002*** (0.0004)			
Software x Lagged†† IT Services					+**
Equipment x IT Services	0.001 (0.001)	0.001*** (0.0005)			
IT Capital Stock x Software	0.003** (0.001)	0.001 (0.001)	0.005** (0.002)		
IT Capital Stock x Equipment	-0.002* (0.001)	0.001 (0.001)	-0.003 (0.002)		
Non-IT Capital Stock	0.021*** (0.002)	0.077*** (0.003)	0.029*** (0.004)		
Other inputs	Y	Y	Y		
Industry x Year Fixed Effects	Y	Y	Y		
# of Plants per Year	~4,600	~22,000	~2,000		
# of Years	9	9	8		
R-Squared	0.906	0.939	0.919		

†Lagged 5-6 years; other lags are noisy.
††Lagged 3-4 years; other lags are noisy.

Note: Results in all columns are based on the unweighted OLS regression. Column 1 uses young sample only and column 2 uses the older sample. Column 3 uses young sample and interacts other IT variables with one period lagged IT capital stock. All specifications control for industry-year fixed-effects. Additional controls include cost of material, cost of energy (both electricity and fuel), and labor (both expenditure on temporary employees and the count of regular employees) – all in log terms. The coefficients for these variables are not reported to save space (available up on request). Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 14. Robustness Tests

Models	(1) Propensity-Score Weights	(2) Regional Controls	(3) Different Labor calculation	(4) Including Imputed Data	(5) Non-Winsorized
Dependent Variables	**Sales**	**Sales**	**Sales**	**Sales**	**Sales**
IT Capital Stock	0.016*** (0.004)	0.013*** (0.003)	0.026*** (0.002)	0.014*** (0.002)	0.013*** (0.002)
IT Services	0.020*** (0.004)	0.007*** (0.003)	0.015*** (0.002)	0.016*** (0.002)	0.007*** (0.002)
Software	0.013*** (0.005)	0.006** (0.003)	0.020*** (0.003)	0.012*** (0.002)	0.006** (0.003)
Equipment	0.028*** (0.005)	0.016*** (0.003)	0.027*** (0.003)	0.022*** (0.002)	0.016*** (0.002)
Industry x Year Fixed Effects	Y	Y	Y	Y	Y
# of Plants per Year	~4,600	~4,600	~4,600	~11,300	~4,600
# of Years	9	9	9	9	9
R-Squared	0.904	0.907	0.899	0.919	0.906

Note: Column 1 estimates the specification in table 6a, column 2 with the weighted OLS regression using estimated weights from the LBD. The calculation of weights follows the approach described in Appendix section C in Foster, Grim, and Haltiwanger 2016. To account for geographical differences, column 2 further controls for reginal, industry and year fixed effects. Column 3 addresses the concern of omitted variable bias on the quality of the labor input by using the quality adjusted labor measure (calculated by multiplying the total production hours with the ratio of the production worker wage to the total salary in log term following Foster, Grim, and Haltiwanger 2016). In column 4, the specification utilizes the observations with the Census imputed values for IT variables to test the sensitivity of our results to the Census imputation. Finally, column 5 re-estimates the production function using the non-winsorized variables from the ASM and CMF. Results for columns 2 to 5 are based on the unweighted OLS regression controlling for industry-year fixed-effects. Additional variables including cost of material, cost of energy, imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) – all in log terms are controlled for all columns. Young sample is used for all columns in the table. Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Appendix Table A.1 Descriptive Statistics for ASM-based Sample (Young vs. Older)

Variable	Definition	ASM-based Sample Young	ASM-based Sample Older
Missing no IT data	All four IT variables are reported	0.41 (0.49)	0.56 (0.50)
Missing only IT Services data	Only the IT services expenditure is missing	0.01 (0.09)	0.02 (0.13)
Missing all Expensed IT	Missing all IT operating expenses	0.50 (0.50)	0.31 (0.46)
Missing all IT data	Missing all IT variables	0.47 (0.50)	0.28 (0.45)
Age	Plant age (truncated due to the start of the LBD in 1967).	2.13 (1.58)	24.9 (10.1)
Number of Employees	Total number of employees	56.1 (184)	178 (419)
Sales	Total value of shipment (in $millions)	23.9 (164)	102 (532)
Sales per employee	Total value of shipment per employee	0.41 (1.35)	0.50 (1.52)
Value Added	Value added (in $millions)	10.4 (89.8)	41.1 (234)
Value-Added per employee	Value added per employee (in $thousands)	176 (518)	201 (624)
IT Capital Stock†	Traditional IT capital stock (accumulated and depreciated using a perpetual inventory method) (in $thousands)	70.9 (285)	220 (543)
IT Capital Stock per employee†	Accumulated and depreciated IT capital stock per employee (in $thousands)	1.25 (2.25)	1.33 (2.22)
IT Capital flows†	Capital expenditure on computers and peripheral data processing equipment (in $thousands)	24.0 (103)	62.0 (181)
IT Capital flows per year per employee†	Capital expenditure on computers and peripheral data processing equipment per employee (in $thousands)	0.39 (0.85)	0.36 (0.79)
IT Services†	Operating expenditure on data processing and other purchased computer services (in $thousands)	11.5 (57.7)	32.9 (111)
IT Services per employee†	Operating expenditure on data processing and other purchased computer services per employee (in $thousands)	0.19 (0.48)	0.21 (0.53)
Software†	Operating expenditure on purchased software, including prepacked, custom coded or vendor customized software (in $thousands)	8.63 (42.20)	26.8 (80.64)

Software per employee†	Operating expenditure on software per employee (in $thousands)	0.13 (0.31)	0.16 (0.35)
Equipment†	Operating expenditure on equipment (expensed computer hardware and other equipment such as copiers, fax machines, telephones, shop and lab equipment, CPUs, monitors) (in $thousands)	12.4 (56.4)	36.2 (107)
Equipment per employee†	Operating expenditure on equipment per employee (in $thousands)	0.20 (0.47)	0.22 (0.48)
Non-IT Capital Stock†	Traditional (non-IT equipment and structure) capital stock. Accumulated and depreciated using a perpetual inventory method) (in $millions)	9.60 (38.4)	24.6 (55.7)
Non-IT Capital Stock per employee†	Traditional (non-IT equipment and structure) capital stock per employee (in $thousands)	151 (275)	160 (249)
Multi-Unit Status	Indicator for whether plants belong to a multi-unit firms	0.62 (0.49)	0.67 (0.47)
Log (IT Capital Stock†)	Traditional IT capital stock in log terms	2.41 (1.85)	3.76 (1.95)
Log (IT Capital flows†)	IT capital expenditure in log terms	1.32 (1.63)	1.93 (2.08)
Log (IT Services†)	Operating expenditure on data processing and other purchased computer services in log terms	0.92 (1.34)	1.36 (1.83)
Log (Equipment Expenditure†)	Operating expenditure on equipment in log terms	1.08 (1.36)	1.76 (1.83)
Log (Software Expenditure†)	Operating expenditure on purchased software in log terms	0.84 (1.24)	1.39 (1.75)

Note: Std. Deviations in parentheses; † indicates the variable is winsorized at the 1% and 99% levels.

Appendix Table A.2. Testing Age Cutoffs

Model	(1) Age Cutoff	(2) With Age Square
Sample	All	
Dependent Variables	Sales	
IT Capital Stock	0.011*** (0.003)	
IT Services	0.010*** (0.002)	
Software	0.006* (0.003)	
Equipment	0.018*** (0.003)	
Age quintiles (2, 3, 4, and 5)	Y	
IT Services x Age 6-15	-0.006* (0.003)	
IT Services x Age 16-25	-0.008** (0.003)	
IT Services x Age 26-35	-0.010*** (0.003)	
IT Services x Age 36+	-0.011*** (0.003)	
Industry x Year Fixed Effects	Y	
Other IT x Age Indicators	Y	
# of Plants per Year	~26,000	
# of Years	9	
R-Squared	0.943	

Note: Results are based on the weighted OLS regression using ASM sampling weights. The dependent variable is total sales log terms. Additional controls include cost of material, cost of energy (both electricity and fuel), imputed non-IT capital stock, and labor (both expenditure on temporary employees and the count of regular employees) in log terms. The coefficients for these variables are not reported to save space (available up on request). Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%. Age groups one is defined for the plants from new entries to less than 6 years old; age group two contains the plants from 7 to 15 years old; age group three contains the plants from 16 to 25 years old; age group four contains the plants from 25 to 34 years old; the rest of older plants are considered age group five. These cutoffs are selected to make sure there are roughly equal number of plants in each group. Results are generally consistent and robust across various age cutoffs and grouping methods.

Add the plot chart using the calculated marginal effect of IT as services by age here (based on the table 9 in list)

Appendix Table A3. Employment and Output Growth (Young vs. Older Plants)

Models	(1) Employment Growth	(2) Output Growth
Dependent Variables	**Change in Employment**	**Change in Sales**
IT Capital Stock	0.008*** (0.002)	0.001 (0.002)
IT Services	0.008*** (0.001)	0.003*** (0.001)
Software	-0.092*** (0.012)	0.039*** (0.008)
Equipment	0.017*** (0.001)	0.008*** (0.001)
Young	0.013*** (0.004)	0.008* (0.004)
IT Capital Stock x Young	0.004 (0.004)	0.007* (0.004)
IT Services x Young	0.008** (0.004)	0.001 (0.003)
Software x Young	-0.034 (0.021)	0.062*** (0.022)
Equipment x Young	0.007* (0.004)	0.001 (0.003)
Non-IT Capital Stock	0.034*** (0.008)	-0.015 (0.013)
Industry x Year Fixed Effects	Y	Y
# of Plants per Year	~16,900	~16,900
# of Years	8	8
R-Squared	0.076	0.525

Note: Results in both columns reported the coefficients from the employment and output growth models. The common independent variables for columns 1 and 2 are the changes in IT variables (calculated using log differences) and changes in non-IT capital stock in log term. Note that all the changes in IT except those for IT services are likely to be a bit lumpy. Column 2 contains additional controls for input changes including changes in cost of material, cost of energy, and changes in the cost of temporary employees and total number of employment. The coefficients for these controls are omitted to save space but available upon request. The sample for the growth models requires the plants to show up at least two consecutive years in the analysis sample. Standard errors from specifications in both columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Appendix Table A.4. Pairwise Correlation

	E-AGE	Log EMP	Log TVS	Log VA	Log nonIT-KST	Log ITK	Log IT Serv	Log ITK Flow	Log Exp SW	Log Equip	Log Ctemp	MU	IT-Using	High Comp
Plant Age	1													
Log Total Employment	0.350	1												
Log Total Value of Shipment	0.324	0.826	1											
Log Value Added	0.321	0.822	0.916	1										
Log non-IT K stock	0.364	0.689	0.760	0.706	1									
Log IT K stock	0.239	0.598	0.551	0.558	0.555	1								
Log IT Services	0.109	0.279	0.247	0.255	0.201	0.280	1							
Log IT Capital Flow	0.137	0.436	0.388	0.408	0.318	0.557	0.259	1						
Log Expenditure on Software	0.150	0.392	0.349	0.370	0.292	0.404	0.319	0.375	1					
Log Expenditure Equipment	0.152	0.452	0.420	0.435	0.346	0.398	0.280	0.352	0.505	1				
Log Cost of Temporary Emp	0.109	0.442	0.467	0.460	0.380	0.349	0.218	0.273	0.293	0.331	1			
Multi-Unit Status	0.005	0.168	0.316	0.258	0.278	0.065	-0.024	-0.007	-0.001	0.082	0.182	1		
IT-Using Industries	-0.009	0.057	-0.034	0.016	-0.062	0.119	0.0799	0.111	0.125	0.108	0.055	-0.080	1	
High-competitive Industries	0.006	0.063	0.167	0.043	0.085	-0.036	-0.030	-0.046	-0.052	-0.036	-0.013	0.100	-0.138	1

Note: All correlations are significant at least the 5% level except the correlations between MU status and plant age, and between MU status and log expenditure on software. The correlations are based on non-imputed sample.

Appendix Table A.5. Correlation between IT Services and Other Inputs

Models	(1) Cost of Temp Employee	(2) Cost of Material	(3) Cost of Energy	(4) Total number of Employee	(5) IT software	(6) Equipment	(7) All
Dependent Variables	**IT Services**	**IT Services**	**IT Services**	**IT Services**	**IT Services**	**IT Services**	**IT Services**
Cost of Temporary Employee	0.061*** (0.011)						0.043*** (0.011)
Cost of Material		0.085*** (0.018)					0.033* (0.019)
Cost of Energy			0.036* (0.019)				-0.003 (0.019)
Number of Total Employee				0.189*** (0.037)			0.080** (0.038)
Expenditure on IT software					0.147*** (0.022)		0.117*** (0.022)
Expenditure on Equipment						0.105*** (0.018)	0.069*** (0.017)
Non-IT Capital Stock							-0.006 (0.017)
IT Capital Stock							0.026 (0.017)
Plant & Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y
# of Plants per Year	~4,600	~4,600	~4,600	~4,600	~4,600	~4,600	~4,600
# of Years	9	9	9	9	9	9	9
R-Squared	0.654	0.653	0.651	0.653	0.657	0.655	0.663

Note: Results in columns 1 to 6 reported the correlations between IT services and other key inputs from the basic OLS model controlling for plant and year fixed-effects respectively. Column 7 also controls for plant and year fixed-effects but include all key inputs in the same specification. Standard errors for all specifications are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Appendix Table A.6. Estimates of IT Productivity – I.T. CAPITAL ONLY -- for Young vs. Older, 2006-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Description	**Sales All**	**Sales Young Only**	**Sales Older Only**	**Sales x Young**	**Sales Young Only + F.E.**	**Sales Older Only + F.E.**	**Sales x Young + F.E.**
IT Capital Stock	0.017*** (0.001)	0.013** (0.003)	0.016*** (0.001)	0.016*** (0.001)	0.007** (0.004)	0.003** (0.001)	0.002** (0.001)
Young	0.013*** (0.005)			0.206*** (0.039)			0.084** (0.039)
IT Capital Stock x Young				-0.002 (0.003)			0.005 (0.003)
Non-IT Capital Stock	0.055*** (0.002)	0.027*** (0.003)	0.073*** (0.003)	0.073*** (0.003)	0.011*** (0.004)	0.019*** (0.004)	0.021*** (0.004)
Non-IT Capital Stock x Young				-0.047*** (0.004)			-0.010*** (0.004)
Inputs: Labor & Materials	Y	Y	Y	Y	Y	Y	Y
Inputs x Young	N	N	N	Y	Y	Y	Y
Plant and Year Fixed-Effects	N	N	N	N	Y	Y	Y
Industry x Year Fixed-Effects	Y	Y	Y	Y	N	N	N
# of Plants per Year	~26,600	~4,600	~22,000	~26,600	~4,600	~22,000	~26,600
# of Years	9	9	9	9	9	9	9

Note: Results in columns 1, 2, 4, and 5 are based on weighted OLS regression using ASM sampling weights controlling for year-industry fixed effects. Columns 3, 6 and 7 are based on plant-fixed effect models controlling for year trends. The dependent variable for all columns is total sales in log terms. Production inputs are also controlled for (but not reported) in all models in log terms, including: cost of material, cost of energy, and labor (both expenditure on temporary employees and the count of regular employees). In addition, the coefficients for interaction terms between Young and the production inputs in columns 2, 3, 6 & 7 are not reported to save space (available upon request). Results are also robust to inclusion of an indicator for and/or restriction of the sample to single-unit status (not shown). Standard errors for all columns are clustered at the plant level. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%