1. Introduction

Important benefits for firm performance have been linked to digital information technologies (IT) (Brynjolfsson and Hitt 1996, Tambe and Hitt 2012, Cardona, et al. 2013, Tambe 2014). Cloud computing, in particular, is being hailed as the new platform for enterprise computing (Cusumano 2010) and has been linked to important shifts in firm survival, productivity, and organizational design (Jin and McElheran 2017, DeStefano, et al. 2018). The public cloud is widely viewed as a critical enabler of digital transformation (Forrester 2017) and is a springboard for the adoption of other technologies such as machine learning and “artificial intelligence” (AI) (Zolas et al. 2020), that have gain significant attention, of late (e.g., Agrawal et al. 2018). Yet, as with many emerging technologies, advances have both arrived quickly and unevenly (Gibson, 1999), with profound implications for how different types of organizations may adapt and thrive at a time of fast-moving change.

While data on cloud computing use remains quite sparse, a striking puzzle characterizes the early years of this emerging technology. There is growing evidence that the public cloud favors entrepreneurial ventures (Ewens, et al. 2018) and young firms (Jin and McElheran 2017) rather than the large incumbents that have benefited disproportionately from prior IT advances (e.g., Tambe and Hitt 2012). While it is tempting to chalk this up to “disruption” of incumbents (Christensen 1997) in the face of competence-destroying technological change (Tushman and Anderson 1986, Henderson 1993, Henderson 2006), this popular interpretation is challenged by another, less-known, empirical fact: incumbent adoption of and investment in the public cloud is on par with or even exceeds that of younger, smaller, firms (Jin and McElheran 2017, Zolas et al. 2020).1 Typically, we expect leading adopters of new technologies to be those most likely to benefit from their use (e.g., David 1969), thus raising important questions about the apparent disconnect between investment and returns among incumbents. We address this puzzle by

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1 Looking within U.S. manufacturing (the context for this study), Jin and McElheran (2017) report a statistically significant difference between older and younger plants in their purchased IT services investment during the rise of cloud computing. However, when adjusted for plant size as measured by total employees, expenditure flows are strikingly similar (Figure 6, p. 50). In addition, a recent report based on data from over 500,000 firms conducted by the U.S. Census Bureau—with highly-targeted questions on cloud computing— the adoption patterns are very clearly skewed, with greater adoption among both older and larger firms across the U.S. economy (Zolas et al. 2020).
developing a contingency view of the effect that strategic commitments and environmental uncertainty have on the performance of this new type of IT resource. Combining traditionally disparate theoretical perspectives with new purpose-built empirical measures, we argue that IT innovation is taking place along multiple trajectories and that performance benefits for incumbents are contingent on the alignment of different types of IT with the organizational context. We focus, in particular, on the congruence in how both the IT and the organizational contexts trades off flexibility for efficiency. We further argue that approaches to achieving strategic IT alignment are also context-dependent and may unfold over time. Our findings yield new insights for theory as well as practice that extend beyond our empirical context.

While tradeoffs between flexibility and efficiency are well-understood in organizations research (e.g., Thompson 1976, Galbraith 1973, Tushman and Nadler 1978, Govindarajan 1986, Ghemawat and Costa 1993), we highlight that certain dimensions of the organizational context may be beyond a firm’s control. Firms that have committed to a distinct market position (Porter 1980, Porter 1996), pursuing for example a differentiation or high-variety product market strategy, will enjoy better returns from IT resources that are optimized for flexibility at the expense of cost-efficiency and firm-specificity. A cost leadership strategy is better aligned with IT that can be optimized for efficiency within a particular firm context.

This positioning can be fixed or quasi-fixed for a given organization (particularly in the manufacturing sector) to the extent that the supporting production strategy is driven by production technology that is embodied in physical capital and facility layouts (Hayes and Wheelright 1979). These strategic choices will determine, in part, the amount of task uncertainty faced by a given organization (Tushman and Nadler 1978, Govindararajan 1986). External uncertainty may also play a role, and likewise constrain managers choices. We consider both dimensions of external and internal alignment between IT resources and the organizational context.

If production strategy is fixed in the short term, this establishes a fixed point around which other organizational choices must be brought into alignment and contrains organizational choice at the time of a new innovation’s introduction. This typically means that dimensions beyond the production strategy need to be adjusted to achieve alignment. How to go about achieving this may not be readily apparent to
managers in the face of a discontinuous change. Moreover, in the early years of a new IT innovation, the locus of know-how and “co-invention” (Bresnahan and Greenstein 1996) capability that can facilitate alignment is typically found outside of the firm. Over time, as expertise diffuses and IT departments within large firms gain the ability to combine technical know-how with firm-specific tacit knowledge, the locus of complementary capabilities for matching IT to the organizational context moves within the firm (Attewell 1992). Prior work has emphasized the importance of highly tailored, firm-specific IT (Powell and Dent-Micaleff 1997, Bharadwaj 2000, Bresnahan et al. 2002, Brynjolfsson et al. 2002, Ray et al. 2004, Aral and Weill 2007). This will not be possible for the most novel technologies, yielding sharp predictions for what types of complementary expertise should augment the productivity of different types of IT in the early years of cloud computing diffusion.

Finally, the degree of fit that exists—or that can be achieved by investing in co-invention—may not be known to firms at the early years of a new technology (Brynjolfsson and Milgrom 2013), and it may take time for understanding of and costs due to misalignment to lead firms to shift investment towards better fit (Zajac et al. 2000). If so, it may take time for the organizational and impact of new technologies to manifest, a pattern that has characterized important technological innovations in the past (e.g., Bresnahan and Trajtenberg 1995, Rosenberg and Trajtenberg 2004, Jovanovic and Rousseau 2005).

We make progress in testing these propositions by investing in the creation of novel empirical measures and combining them with heretofore underexplored administrative data. To measure organizational commitments to different production strategies, we worked with the U.S. Census Bureau to develop a new survey question specifically designed to distinguish different operational contexts along this dimension. This question was included on the 2015 Managerial and Organizational Practices Survey, or MOPS (Buffington, et al. 2017, Bloom, et al. 2013), which went to a large representative sample of manufacturing establishments in the U.S. We thus have unprecedented visibility into the production strategy of ~32,500 establishments for both 2010 and 2015.

Linking the MOPS survey data with underexplored Census data on detailed categories of IT investment from the Annual Survey of Manufactures from 2006 to 2015 allows us to not only estimate
how the productivity of public cloud expenditure varies by production strategy, but also to explore the performance of a key substitute to public cloud computing: owned IT capital. Innovation in software and hardware owned by firms has continued apace (Brynjolfsson and McAfee 2014), offering a divergent but potentially equally effective path to IT-driven competitive advantage. We lean on another under-explored Census data set to capture external uncertainty by using a measure of variation in plant-capacity utilization in a plant’s industry (Paraskevopoulos et al. 1991).

Consistent with our hypotheses, we find that plant expenditure on cloud-based IT is only productive in settings characterized by high-flexibility production and high external uncertainty. Firm-specific IT capital is the primary source of IT productivity among inumbents with a low-variance, high-efficiency production strategy; likewise for those in low-uncertainty settings. Examining both types of IT concurrently allows us to rule out the facile narrative of incumbent incompetence in favor of more nuanced variation among incumbents in the strategic fit of different types of IT resources.

Because strategic alignment IT has been argued to be a “journey, not an event,” (Henderson and Venkatraman 1999, p. 481), we empirically test predictions about how adaptation of IT resources varies by organizational context and unfolds over time. Consistent with our hypotheses, the more-novel cloud technology performs better when organizations also invest in outsourced IT capabilities in the form of management consulting services. The adjustment path for owned IT capital is sharply different, benefitting primarily from skilled labor employed by the plant.

We further observe learning among firms that appear more misaligned in the early years of our sample. We exploit timing in the meaningful rise of cloud computing to validate our measure of cloud computing and show a significant shift in the share of IT expenditure going to outsourced IT versus owned IT capital as the cloud becomes a leading paradigm for outsourced IT—and as firms have more experience deploying it in practice. As predicted, organizations in low-flexibility settings begin to scale back their investment in the cloud relative to high-flexibility establishments and increase their share of investment in owned IT capital bewteen 2009 and 2016.
Taken together, these results provide an unusually comprehensive picture of how incumbent firms are responding to an important, fast-moving technology at a time when digitization is only becoming more salient. While a key contribution is to provide new empirical facts at time when the ratio of “hype” to evidence is high (Gartner 2019), this study also leans on diverse theoretical perspectives, thereby contributing to a number of literatures. By combining the positioning and strategic commitment insights of strategy with contingency theory (Thompson 1967, Galbraith 1973, Govindarajan 1986, inter alia), it provides insight into what types of choices are subject to adjustment and contributes to a frontier of research providing practical guidance for managers struggling to adapt new practices and technologies to their particular contexts (e.g., Blader et al. 2019).

The “disruption” (Christensen 1997) narrative is a popular one for predicting the outcomes of cloud computing diffusion. We add nuance to the literature on predicting when innovation will disrupt incumbent firms (e.g., Tushman and Anderson 1986, Henderson 1993, Tripsas 1997, Adner 2002, Henderson 2006, McElheran 2015, Adner and Kapoor 2016), by showing how our interpretations change when there is a reasonable, competence-enhancing substitute available to incumbent firms at the same time – one that shows no sign of obsolescence for reasons we document here.

Finally, our focus on the approaches and timeline required for adjustment contributes to a large literature concerned with how firms adopt and adapt “general purpose technologies” or GPTs (e.g. Bresnahan and Trajtenberg 1995, Rosenberg and Trajtenberg 2004, Jovanovic and Rousseau 2005, Cardona et al. 2013, Furman and Teodoridis 2017). Adjustment to novel IT is generally assumed to be possible, but potentially costly in terms of time, money, and risk (Brynjolfsson and Hitt 1996, Bresnahan and Greenstein 1996, Black and Lynch 2001, Bresnahan et al. 2002, McElheran 2015). We capture only the first 10 years of this potentially transformative innovation, while it took decades for the full impact of electrification to become apparent in the U.S. economy. The meaningful shifts we document here indicate that the full organizational and economic impact of cloud computing – and of the technologies it enables – have yet to be fully realized.
2. Phenomenon: Emerging IT Innovation in the Cloud – and Elsewhere

Innovative possibilities for how firms access IT arose with the introduction of cloud computing in 2006. While distributed computing and IT outsourcing of some form have been available for decades (Byrne et al. 2018), the mid-to-late 2000s witnessed a paradigm shift towards the long-held notion of “computing as a utility” (e.g., Armbrust et al. 2009, Bayrak et al. 2011). Amazon Web Services (AWS) capitalized on this shift, introducing Elastic Compute Cloud in 2006. The economics of the public cloud became more attractive after 2009 due to growth of AWS and entry of new service providers such as Microsoft (in 2010), the joint open-source cloud software project between NASA and Rackspace (in 2010), IBM (in 2011) and Oracle (in 2012). Key to our study, while public cloud-based IT was technically available as early as 2006, its widespread applicability was not until 2009 or later (Ewens et al. 2018), in part due to a lack of “enterprise ready” solutions (Staten 2008). Since then, expenditures on cloud services have been growing at a rate 4.5 times faster than traditional IT investment expenditure, representing over 37% of global IT infrastructure investment by 2016 (Columbus 2017).

Compared to hardware and software owned and maintained by firms, IT services accessed through the public cloud are more flexible and require less lead-time and lower managerial effort to initiate (Mell and Grance 2011, Ewens et al. 2018). They can be scaled up or down on demand and the cost structure substitutes variable costs for fixed costs (e.g., Candel-Haug et al. 2016). This flexibility has proven important for the productivity and survival of young firms (Jin and McElheran 2017).

Yet, cloud computing entails important tradeoffs, particularly for the incumbent firms we study here. Key among these is lack of firm-specificity. Unlike traditional IT outsourcing, which may be highly tailored to a firm or even to a project within a firm, solutions available in the public cloud are, by design, relatively generic and cannot be customized to a particular organization’s needs (Armbrust et al. 2009, Schneier 2015, Schneider and Sunyaev 2016). For example, sharing a single instance of a software program across many firms is central to the value proposition of many software-as-a-service (SaaS) offerings (Xin and Levina 2008, Susarla et al. 2009). While it may be possible for firms to cultivate unique IT capabilities that build and expand on generic, widely available inputs (e.g., Bharadwaj 2000),
consensus is emerging that cloud-based solutions are imperfect substitutes for firm-specific IT, particularly for business-critical applications (e.g., Brynjolfsson et al. 2010, Retana et al. 2018).

Another key consideration –glossed over in the cloud computing “hype” (Gartner 2019) – is that the variable costs of IT in the cloud are typically higher than what a large firm can achieve on its own. While cost savings features prominently in popular accounts, vendor marketing copy, and analyst reports (e.g., Staten 2008), objective evidence for an absolute cost advantage is limited. Brumec and Vrček (2013), for instance, find that cloud computing is cost efficient for less-demanding applications, but that complex tasks are most cost-effectively executed via owned IT. The organizational costs of the cloud are often underplayed (Golden 2018), and evidence of significant adjustment costs are beginning to emerge in our limited empirical evidence (e.g., Retana et al. 2015).

Importantly for our study, any technical cost advantage for cloud-based IT is less likely to hold for large incumbents. Large firms can balance loads internally within their organization (Armbrust et al. 2009, Bayrak et al. 2011), spread fixed costs widely, and avoid paying markups by investing in their own IT. A well-known example of a firm that switched from the public cloud to their own IT is Dropbox. Storing all of its files on Amazon’s servers until 2015, the firm moved to its own servers to improve the unit economics. In an interview about the switch, one vice president noted, “Nobody is running a cloud business as a charity. There is some margin somewhere.” (Metz 2016).

Incumbents might willingly and effectively absorb these higher costs if cloud computing were the best or only way to access rapidly-evolving innovations in hardware and software. However, innovation in software and hardware has continued to advance apace across a range of platforms (Brynjolfsson and McAfee 2014). Moreover, owned IT has important advantages derived from firm-specificity. In prior work, the economic and strategic value of IT has been theoretically and empirically linked to technologies that are built or configured to be highly tailored to the organizational context (Brynjolfsson and Hitt 1995, 2000, Bresnahan and Greenstein 1996, Ray et al. 2004), aligning with key features of the internal organization (Aral and Weill 2007, Ray et al. 2013) or the external value chain (McElheran 2015).

Finally, upgrading owned IT resources may entail lower adjustment costs by allowing firms to
improve the automation or information-richness of existing processes while maintaining existing systems and organizational architectures. While the popular National Institute of Standards and Technology (NIST) definition adds “minimal managerial effort” to the list of cloud computing features (Mell and Grance 2011), recent work by Retana et al. (2018) emphasizes that key features of enterprise-grade servers, such as redundant components and physical access, are not present in the cloud. The cloud requires firms to design for failure (Reese 2009) and consider how to keep an application running if a server disappears for reasons beyond the firm’s control. Applications not already designed for parallel processing (Thompson 2017) need to be re-architected to take advantage of the cloud model. This will be more competence-destroying for established incumbents (Henderson and Clark 1990).

In summary, while emerging cloud computing technologies offer unprecedented flexibility in access to IT, owned IT resources remain an important alternative source of IT capabilities with appealing advantages in terms of unit cost efficiency, firm-specificity and lower adjustment costs. These tradeoffs are unlikely to play out evenly across organizational contexts. Thus, we require a framework for understanding which contingencies will lead firms to benefit from these disparate approaches to IT.

3. Theory and Hypotheses

It is well-accepted that organizations face a fundamental trade-off between flexibility and efficiency, or the “paradox of administration,” (Thompson 1967). Organizations that pursue efficiency via rules, routinization, and structured practices often end up stifling a flexible response to unforeseen contingencies. On the other hand, flexibility can come at the cost of excess capacity, low resource utilization, and inefficient “slack”, harming productivity (e.g., Burns and Stalker, 1961).

A large body of research has explored how to achieve the best fit between these organizational tradeoffs and diverse internal and external contexts (e.g., Thompson 1967, Galbraith 1973, Tushman and Nadler 1978). Key contingencies that appear throughout this work are the choice of production technology, task uncertainty, and environmental uncertainty (Tushman and Nadler 1978, Govindarajan 1986). We lean on this framework not to study the contingent performance of decision-making structures.
(i.e., centralization vs. decentralization) within the firm, but to use similar machinery to understand the fit of different IT resources as described in Section 2.

Much contingency theory research has explicitly or implicitly assumed that multiple margins of adjustment are available to managers to bring these dimensions into alignment. In contrast, the foundational strategic management literature emphasizes the importance of choosing and committing to a unique position in the market (Porter 1980, 1996) and the significant benefits to be achieved by making costly commitments to a given position (Ghemawat 1991) or, conversely, the high costs of repositioning (Menon and Yao 2017). New insights emerge when we combine these perspectives to take into account that repositioning may either not be feasible or will take considerable time and investment to execute.

3.1 Production Technology, Irreversible Strategic Commitments, and Internal Fit

Production technology has been an active subject of exploration since at least Hage and Aiken (1969). Govindarajan (1986) provides a useful overview of this research, articulating the importance of distinguishing between mass production technologies and job shop operations for understanding task uncertainty. Mass production typically demand high levels of standardization, sequenced integration of tasks, and a high level of routinization, which all lead to a relatively high task predictability (p. 846). In contrast, the job shop form of operation entails the use of highly skilled labor, multi-purpose machinery, and a sequence of task that varies by product; the mix of products is high and leans on “craftsmanship” and adaptiveness to customer requirements. Task uncertainty in these environments is therefore quite high (p. 846). Taken together, efficiency is therefore much easier to maintain in mass production environments, while flexibility is much more important in job shop environments.

The link between these considerations and product market positioning was articulated in the operations management literature first by Hayes and Wheelright (1979) and empirically validated by follow on work by Safizedeh et al. (1996). While this work has not diffused far outside its disciplinary silo, it usefully argues that product market positioning choices (e.g., low-cost versus differentiation in Porter 1980) require well-aligned production or operations strategy choices. Firms that pursue low-cost
product market strategies require high-efficiency, “continuous flow” production, while differentiation and high-variety product market strategies require job shop production. Critically for our theory and empirical approach, these production strategy decisions – at least in the manufacturing sector – are typically embodied in physical capital and facility layouts. This makes them both difficult to reverse and easier to measure.

If product strategy decisions both determine internal task uncertainty and are difficult to reverse in this way, then they may be considered fixed or quasi-fixed among incumbent firms at the time a new IT innovation is introduced. As such, the order of operations for firms seeking alignment can be established. And, based on the differences between cloud-based IT and firm-specific IT capital, we can formulate the following predictions to take to the data:

*Hypothesis 1a*: Cloud computing will be more productive in high-flexibility production settings

*Hypothesis 1b*: Owned IT capital will be more productive in high-efficiency production settings

### 3.2. Environmental Uncertainty and External Fit

While firm strategic choices are also argued to impact external uncertainty ((Chandler 1962), Gupta 1987) additional external factors may be beyond the immediate control of managers. Thus, we can also explore the performance implications of achieving good external fit of IT resources by examining the degree of uncertainty in the organization’s external market.

*Hypothesis 2a*: Cloud computing will be more productive in high-uncertainty market settings

*Hypothesis 2b*: Owned IT capital will be more productive in low-uncertainty market settings

### 3.3 Locus of Co-Invention Capabilities

If production strategy is fixed in the short term, this establishes a fixed point around which other organizational choices must be brought into alignment and constrains organizational choice at the time of a new innovation’s introduction. This typically means that dimensions beyond the production strategy need to be adjusted to achieve alignment. How to achieve this may not be readily apparent to managers in the face of a discontinuous change (Brynjolfsson and Milgrom 2013). Moreover, in the early years of a new
IT innovation, the locus of know-how and “co-invention” (Bresnahan and Greenstein 1996) capability that can facilitate alignment is typically found outside of the focal firm. Over time, as expertise diffuses and IT departments within large firms gain the ability to combine technical know-how with firm-specific tacit knowledge, the locus of complementary capabilities for matching IT to the organizational context moves within the firm (Atewell 1992). This yields sharp predictions for what types of complementary expertise should augment the productivity of different types of IT in the early years of cloud computing diffusion:

Hypothesis 3a: Capabilities for achieving alignment of cloud resources will be found outside the firm

Hypothesis 3b: Capabilities for achieving alignment of owned IT capital will be found inside the firm

3.4 Adjustment of Investment over Time

Also, understanding what strategies and IT fit together may be difficult for firms to know prior to trying them out, particularly while the technology is relatively new (Brynjolfsson and Milgrom 2013). An absence of alignment will likely be both difficult to correct and will erode the performance that firms might otherwise expect from their IT investments. The experience of misalignment (and its costs) should induce firms to make changes in favor of better fit over time (Zajac et al. 2000).

Hypothesis 4: Firms with a poor alignment will adjust investment over time.

4. Data and Sample Descriptives

To test our hypotheses, we worked with the U.S. Census Bureau to develop novel measures of plant-level production strategy in the U.S. Manufacturing sector. A question based on the Hayes and Wheelright (1979) “Product-Process Matrix” was included in the 2015 Management and Organizational Practices (MOPS) survey, which was included as a supplement to the Annual Survey of Manufactures (ASM).\(^2\) Developed and fielded with support from the Census Bureau, the National Science Foundation, the MIT Initiative on the Digital Economy, the Kauffman Foundation, and the Sloan Foundation, this

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\(^2\) See Buffington et al. (2017) and Bloom et al. (2013) for additional details of the MOPS methodology.
survey targets roughly 10% of the roughly 500,000 establishments in the U.S. manufacturing sector, sampling all large manufacturing plants and a random sample of medium and smaller plants. Response is required by law, which results in high response rates of about 75% with more than 30,000 respondents per wave and minimal response bias. The sample is stratified to produce a representative annual snapshot of the manufacturing sector. To illustrate the sample selection, average plant size in the MOPS in 2015 is around 80 employees (see Table 1), thus establishments are large compared to the underlying population.

We combine this data with the Longitudinal Business Database (LBD), which provides a complete census of all establishments in the U.S. economy since 1976, to estimate age (Jarmin and Miranda 2002). Based on this information, the establishments in our sample are also found to be older, averaging 25 years old (Table 1). We exploit the novel organizational measures included in the MOPS and also bring in rich plant-level IT investment data from the ASM, as described below.

**Cloud Computing.** To gauge the average productivity of different types of IT resources, we first construct a representative panel of roughly 27,000 establishments over ten years (2006-2015) from the ASM. This contains little-explored but rich measures of different types of IT expenditures. In particular, it tracks operating expenditures on “IT services,” which contain cloud-related expenses including data processing, computer input preparation, data storage, and computer time rental from 2006 onwards (the latest available year is currently 2016) and meaningfully captures the rise of the public cloud in this sector of the economy (Jin and McElheran 2017). We use the data on software and hardware/equipment expenditure as key controls but focus on the sharp contrast between outsourced IT resources available in the cloud and owned IT capital stock for our core analyses.³

**IT Capital Stock.** We calculate establishments’ owned IT capital stock using data on capital expenditure on computer and peripheral data processing equipment dating back to 2002 from the ASM and the quinquennial Census of Manufactures (CMF), which covers the entire population of manufacturing establishments. We use a perpetual inventory approach and industry level deflator for

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³ This measure has also been found to be significantly correlated with advanced uses of cloud computing in the manufacturing subsample of the 2017 Annual Business Survey. (*Results pending disclosure avoidance review.*).
hardware from the Bureau of Economic Analysis (BEA). We impute values for years in which they are missing, and depreciate at the rate of 35% per year following Bloom et al. (2014) and Brynjolfsson and McElheran (2019).

**Production Strategy.** The content of the MOPS survey is a collaborative undertaking between the U.S. Census Bureau and a team of academics who have worked to develop, test, and field novel questions aimed at measuring the management practices, organizational design, use of data and predictive analytics, and other difficult-to-measure features of the organizational context. One question added to the 2015 wave of the survey, including a recall question asking about 2010, was specifically designed to capture the production strategy of different manufacturing establishments along the dimensions introduced by Hayes and Wheelwright (1979) and validated by later empirical research in operations management (e.g., Safizadeh et al. 1996). Specifically, it asks respondents, who are typically plant managers or other senior managers at the establishment to best categorize the production at the plant as 1) job shop, 2) batch production, 3) cellular manufacturing, 4) continuous flow (other than cellular manufacturing, or 5) research and development or prototyping.

Linking this to the IT investment data yields a sample of roughly 32,500 establishments across 2010 and 2015. Plants reporting “continuous flow” or “cellular” processes will be organized around low-variability, high-efficiency production and constitute roughly 27 percent of our pooled sample (Table 1).

Notably, the survey asks about this measure for both 2010 and 2015, so we can observe changes in this variable. Empirically, there is no significant change over time in this measure, validating our assumption that this feature of the organizational context is fixed over reasonably long time horizons and, in particular, did not change in our particular sample during the rise of cloud computing in manufacturing.

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4 We impute the missing values using the average of the IT investment from the closest before and after years that have non-missing values for the plant-years where the capital expenditure on computer and data processing equipment is missing. For instance, if IT investment in 2008 is missing, we impute it using the average IT investment for the plant in 2007 and 2009 or using the 2007 and 2010 values if 2009 is missing. Similar logic is applied to missing values from other years. Our core results are robust to excluding observations with missing IT data, but imputation is useful for stabilizing the sample. Similar method has been used in Bloom et al. (2014), see appendix for more detail.

5 Based on the BEA Consumer Price Index for All Urban Consumers: Personal computers and peripheral equipment.
**Environmental Uncertainty.** We follow Paraskevopoulos et al. (1991) to construct a measure of uncertainty in the external environment based on plant capacity utilization published by the U.S. Census Bureau’s Quarterly Survey of Plant Capacity Utilization (QSPCU) from 2010 to 2016. It contains the industry average plant capacity utilization (PCU) by 3 to 5-digit NAICS category. Production capacity has been studied as one of the key factors used to hedge against demand uncertainty in the manufacturing sector (Praskevopoulos et al. 1991; also see Mula et al. 2006 for a helpful review). Plants endogenously choose their capacities *ex ante* and then utilization rates are the realization of demand (i.e. capacity utilization rate increases as demand increase and vice versa) (Sheshinski and Dreze 1976; Mills 1984; Calvo and Thoumi 1984). Thus, plant capacity utilization will fluctuate more as demand becomes more volatile. Following this line of research, we calculate the variance of plant capacity utilization rate across quarters within a given year as a proxy for demand uncertainty.

We first calculate the variance of the PCU across four quarters for a given year based on the most-granular industry definition possible. Then, take the mean value of these variances at the 3-digit NAICS level and identify industries with above-median variance in PCU. Examples of high-uncertainty industries include Textile Product Mills (314), Apparel Manufacturing (315), Petroleum and Coal Products Manufacturing (324), Chemical Manufacturing (325), Nonmetallic mineral product manufacturing (327), Computer and Electronic Product Manufacturing (334), and Electrical Equipment, Appliance, Component Manufacturing (335), and Transportation Equipment Manufacturing (336). These industries are largely consistent with the high-uncertainty industries discussed in Dyer et al. (2014).

**IT Co-Invention Capabilities.** From 2006 onwards, the U.S. Census Bureau also collected information on purchased professional and technical services including management consulting in the ASM. We use reported expenditure on professional management consulting as a measure of external investment in “co-invention” to bring IT resources into alignment. To measure internal capabilities for aligning IT, we follow Bresnahan et al. (2002) and Brynjolfsson et al. (2002), using data on skilled workers at the establishment. Specifically, we calculate the percentage of workers (both managers and non-managers) with bachelor’s degree as reported in the MOPS. In our baseline sample, the average
establishment has about 14% of their employees with bachelor’s degree (Table 1). Also noteworthy is that this organizational characteristic is also quasi-fixed– changes in the percentage of skilled workers from 2010 to 2015 is trivial.

5. Results

Table 2 relies on our large panel of ASM data from 2006 to 2015 to introduce the puzzle at the heart of our study. Prior work has shown similar investment in public cloud by both young establishments and older incumbents in the manufacturing sector (Jin and McElheran 2017, p. 50) as well as higher reported adoption of the cloud by older and larger firms across the U.S. Economy (Zolas et al. 2020, p. 32). Yet, when we estimate the productivity associated with different types of IT investment in this large and representative sample, we find no significant return, on average, to cloud investment. A 1% increase in IT services expenditure during the rise of the cloud paradigm is associated with a 0.001% rise in sales, controlling for other production inputs, age, and industry-year fixed effects at the 6-digit NAICS level (column 1). We find a somewhat larger but still small – 0.003% -- and marginally significant return once we add in plant-level fixed-effects (column 2).

In sharp contrast, we see that owned IT capital is associated with significant productivity gains of roughly 0.008% in the pooled OLS estimation (column 1). However, this disappears once plant-specific time-invariant characteristics are absorbed (column 2). This pattern suggests an important role for typically-unobserved features of the organizational context in determining returns to these different types of IT (more on that, below).

Higher levels of investment are associated with better returns from the cloud (columns 3 and 4), with 0.013% to 0.017% higher sales (significant at the 1% level) if plant investment is in the top quartile for its industry. Higher levels of owned IT capital are also associated with a much higher productivity effect. Again, however, the magnitude of the coefficient on IT capital in column 4 is sharply reduced by the

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6 Statistics on percentage change of educated worker in between 2010 and 2015 are pending disclosure review and will be available upon request.
inclusion of plant fixed effects. This pattern is consistent with findings in the IT productivity literature (Brynjolfsson and Milgrom 2013, Aral et al. 2012, Tambe et al. 2012, and Tambe 2014) that owned IT capital appears less productive once slow-moving organizational complements (e.g. organizational practices and percentage of highly educated workers) are separately controlled for.

This typical pattern is reversed, however, for cloud computing, suggesting that organizational characteristics might actually *impede* returns to cloud computing on average. Also of note is the similarity of the coefficients in column 4. Controlling for plant-specific characteristics, the returns to both types of IT are commensurate, indicating that there is more than one path to achieving IT productivity during the time of our sample.

As we argue in Sections 2 and 3, we expect the returns to these different types of IT to be highly contingent on the organizational context, and the patterns we observe in Table 2 are likely driven in large part by underlying – and poorly understood – heterogeneity. We turn to our matched MOPS-based sample to gain critical insights into the organizational context.

Table 3 reports the first of these tests. In column 1, we explore whether plants with a “continuous flow” manufacturing process can benefit from new cloud-based IT. The omitted category is higher-flexibility production settings such as batch production and job shops. Looking at top-quartile investment in IT services during the rise of the cloud, the direct effect shows a strong productivity association among plants with a flexibility-focused production strategy. Controlling for a wide range of plant characteristics including plant age, percentage of workers with bachelor’s degrees, other production inputs, as well as industry-year fixed effects at the 6-digit NAICS level, the coefficient on top-quartile cloud investment is positive and significant at the 5% level. The magnitude indicates 0.012% higher output associated with these new IT investments. In contrast, we find that high-efficiency production eliminates all returns from the cloud. The coefficient on the interaction term between high cloud expenditure and efficiency-focused continuous flow production is negative, highly significant, and of even greater magnitude. This implies that efficiency-focused plants are actually losing money on their IT services investments in the early years of cloud computing.
In contrast, high levels of owned IT capital are productive in both types of settings, but with a much higher return in continuous-flow operations. The magnitude of the interaction term, which is significant at the 5% level suggests that the productivity of owned IT capital is almost doubled in efficiency-focused contexts. Overall, our findings in column 1 support both Hypotheses 1a and 1b.

In column 2, we explore contingencies with the external context. Following Jin and McElheran (2017), we interact the indicator for high uncertainty industries with both types of IT. Detailed results are still pending disclosure review but the sign and significance of the results are consistent with our hypotheses. The interaction between IT services and the high uncertainty indicator is positive and highly significant while the interaction between owned IT capital and this indicator is negative and significant. These findings support Hypotheses 2a and 2b arguing that cloud computing is more productive in high-uncertainty settings while owned IT capital is more productive in low-uncertainty environments.

In columns 3 and 4, we explore variance in how firms pursue alignment of their IT with their organizational context. Results from column 3 show that IT services investment performs better in the presence of external non-IT consulting services (i.e. positive interaction terms between IT services and log operation expense on professional consulting that are significant at 1% level), which may suggest investments by firms in tailoring the business process to fit the technology. In addition, we find that the performance of IT services does not depend on internal expertise measured in terms of educated managers (see interactions between IT services with percentage of workers with bachelors’ degree in column 4). This is consistent with descriptions of cloud computing as an IT resource that is novel, difficult to customize (i.e., off the shelf), and demanding less internal managerial skill to deploy.

These patterns are again reversed for traditional, owned IT capital. The results in column 4 of Table 3 show a positive and significant interaction between traditional IT capital and the percentage of workers with bachelor’s degrees – a proxy for an internal capability. For this type of IT, internally-sourced skill is more valuable. This is what one would expect for more-customizable but irreversible investments whose value depends on being matched to particular firm needs that are best understood (or strategically guarded) within the firm. Conversely, results from column 4 show that the interaction between traditional
IT capital and expenditure on professional management consulting – a proxy for an external capability - is small and noisy. Overall, hypotheses 3a and 3b are supported.

As we argue in Section 3, certain dimensions of alignment for cloud investment may be either beyond a firm’s control or take significant time to adjust. That said, we expect to see a better alignment of IT resources over time through learning. Figures 1 and 2 document heterogeneity in establishments’ strategy for IT spending allocation between IT services and traditional IT capital flow, splitting the sample by production strategy types from 2006 to 2016. Results for figures 1 and 2 are based on the pooled OLS regressions controlling for industry fixed-effects and the regression results are available upon request.

Figure 1 provides supporting evidence that low-mix type of plants with continuous flow operations allocated lower percentages of their IT spending towards IT services over time compared to their counterparts. Moreover, the gap between the two types of plants becomes larger and highly significant as diffusion of cloud computing picks up.

Critically, this divergence between the two plot lines appears in 2009. This is exactly when the price of cloud computing drops significantly and diffusion becomes more widespread in manufacturing (Jin and McElheran 2017). Again, this trend is reversed in figure 2 for IT capital flow. These results support Hypothesis 4 and demonstrate that firms appear capable of learning about these differences and adjust their IT investment to achieve better alignment over time (Zajac et al. 2000).

Robustness

Our results thus far have taken IT investment as exogenous. One of the major concerns for our baseline estimation is that the endogenous choice of inputs (i.e. more capable and productive plants choose to invest more on cloud) might bias our estimates. We employ recent advances in dynamic panel structural estimation, particularly system GMM methods developed by Arellano and Bond (1991) and Blundell and Bond (2000). These results, pending Census disclosure avoidance review, reveal coefficient on IT services that are very similar to those in the pooled OLS models. This suggests that the effect reported in our main tables is unlikely to subject to endogeneity bias, similar to findings in similar work on IT productivity (Tambe and Hitt 2012).
6. Conclusion and Discussion

Cloud computing is rapidly emerging as an important platform IT innovation, however evidence is very sparse on its performance implications in the economy. In this paper, we provide novel evidence on the productivity implications of both cloud computing and traditional owned IT capital, which remains an appeal substitute due to innovation in software and hardware accessed via traditional methods. By developing a contingency view of the effect that strategic commitments and environmental uncertainty have on the performance of this new type of IT resource, we provide evidence that the returns to the cloud are highly context-dependent and vary on the degree of congruence between the firms internal and external environment and the type of technology. Because public-cloud based IT emphasizes flexibility over firm-specificity, its productivity benefits are largely confined to organizational contexts with high internal and external uncertainty. Owned IT capital remain critical for productivity in stable organizational contexts where it can better enhance efficiency though higher firm-specificity and lower variable costs.

We further shed light on how firms achieve alignment in different settings and over time. Consistent with prior theorizing, the complementary know-how needed to achieve strategic IT alignment varies by the type of IT. Cloud based computing benefits from outsourced know-how, while owned IT capital benefits from firm-specific skilled labor. Alignment may not be possible in every case, nor its potential well-understood by managers during the early years of cloud computing’s diffusion. Consistent with dynamic adjustments towards better strategic alignment, plants shift their IT investments over time. Firms in low-flexibility, high-efficiency settings – which are a poor fit for the cloud – shift their investment away from this type of IT and towards firm-specific IT capital.

Our study relies heavily on significant investments in novel data collection to make typically hard-to-observe features of organizational context measurable in a large, representative sample over a reasonably significant period of time. That said, it is not without limitations. Our data are highly suited to measuring productivity, as we have detailed information on both production outputs and inputs from administrative data collected by the Census Bureau. However, we are only measuring one dimension of performance. It
is possible that the incumbents leveraging the cloud in other settings may enjoy different benefits, such as product innovation, that are beyond the reach of our data. Also, the manufacturing setting in which we have conducted the study allows us to use a very sharp and well-validated measure of strategic commitment by studying production strategies that are embodied in physical capital and facilities layouts. It may be much easier to adjust such positioning in other settings, such as services, where the costs of repositioning are much lower. Finally, we can only observe organizational contingences through the MOPS survey linkage, which limits us to studying incumbent firms – and not the entrepreneurial and younger firms that have proven responsive to the cloud in prior works.

Despite these constraints, we believe our findings have considerable application outside our empirical context. Understanding what organizational choices are fixed versus those that are malleable – and how to bring them into alignment -- is both theoretically and practically useful for understanding how firms may adapt and thrive at a time of unprecedented technological change. Ultimately, despite spanning nearly a decade of organizational response to this new IT, growth and innovation in this technology continues at a staggering pace, and it is still early days in terms of understanding its ultimate impact. Our hope is that future research will extend these insights across industry contexts and over time to illuminate the impact of cloud computing on diverse organizations and the overall economy.
<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Definition</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Sales</td>
<td>Logged total value of shipments ($T)</td>
<td>10.1</td>
<td>1.60</td>
</tr>
<tr>
<td>Log IT K</td>
<td>Logged accumulated IT capital stock ($T)</td>
<td>5.09</td>
<td>2.28</td>
</tr>
<tr>
<td>Log IT Services</td>
<td>Logged IT services operating expenditure ($T)</td>
<td>1.38</td>
<td>1.89</td>
</tr>
<tr>
<td>Log SW</td>
<td>Logged software operating expenditure ($T)</td>
<td>1.49</td>
<td>1.83</td>
</tr>
<tr>
<td>Log HW/Equip</td>
<td>Logged computer hardware and other equipment operating expenditure ($T)</td>
<td>1.81</td>
<td>1.85</td>
</tr>
<tr>
<td>Degrees</td>
<td>Percentage of employees with bachelor's degrees</td>
<td>14.0%</td>
<td>13.7%</td>
</tr>
<tr>
<td>Log non-IT K</td>
<td>Logged non-IT capital stock ($T)</td>
<td>8.72</td>
<td>1.67</td>
</tr>
<tr>
<td>Log M</td>
<td>Logged cost of materials ($T)</td>
<td>9.23</td>
<td>1.88</td>
</tr>
<tr>
<td>Log Energy</td>
<td>Logged cost of energy ($T) in log (includes costs of both fuel and electricity)</td>
<td>5.64</td>
<td>1.89</td>
</tr>
<tr>
<td>Log L</td>
<td>Logged employment (total number of employees)</td>
<td>4.41</td>
<td>1.20</td>
</tr>
<tr>
<td>Age</td>
<td>Plant age (based on LBD database)</td>
<td>24.5</td>
<td>12.3</td>
</tr>
<tr>
<td>Log Consulting</td>
<td>Logged expenditures on purchased professional and technical services ($T) (includes management consulting, accounting, auditing, etc.)</td>
<td>3.84</td>
<td>2.28</td>
</tr>
<tr>
<td>Low Mix</td>
<td>Indicator for plants reporting operating systems that are continuous flow, cellular</td>
<td>0.268</td>
<td>0.443</td>
</tr>
<tr>
<td>% IT Services</td>
<td>Percentage of IT spending on IT services</td>
<td>18.0%</td>
<td>28.5%</td>
</tr>
<tr>
<td>% IT K</td>
<td>Percentage of IT spending on IT capital</td>
<td>27.1%</td>
<td>34.5%</td>
</tr>
<tr>
<td>Number of Observations</td>
<td></td>
<td>65,000</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>Baseline sample in MOPS 2010 and 2015</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Average Productivity by IT Resource Type

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
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<tbody>
<tr>
<td>Log Cloud Expenditure</td>
<td>0.001</td>
<td>0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log IT Capital</td>
<td>0.008***</td>
<td>0.0026</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top-Quartile Cloud Expenditure</td>
<td></td>
<td></td>
<td>0.013***</td>
<td>0.017***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Top-Quartile IT Capital</td>
<td></td>
<td></td>
<td>0.040***</td>
<td>0.011**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Log Software</td>
<td>0.005***</td>
<td>0.005***</td>
<td>0.005***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Log HW/Equip</td>
<td>0.012***</td>
<td>0.009***</td>
<td>0.012***</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Management Index</td>
<td>0.194***</td>
<td>0.092***</td>
<td>0.193***</td>
<td>0.093***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Bachelor Degrees</td>
<td>0.215***</td>
<td>0.004</td>
<td>0.214***</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.022)</td>
<td>(0.016)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Log non-IT Capital</td>
<td>0.078***</td>
<td>0.018***</td>
<td>0.079***</td>
<td>0.018***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0005***</td>
<td>N/A</td>
<td>-0.0005***</td>
<td>N/A</td>
</tr>
<tr>
<td>Logged L, M, Energy Inputs</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry (NAICS6) * Year fixed effects</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Plant and Year fixed effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>65,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared (adjusted)</td>
<td>0.941</td>
<td>0.608</td>
<td>0.941</td>
<td>0.608</td>
</tr>
</tbody>
</table>

Notes: Results for all columns are based on baseline sample from MOPS 2010 and 2015. Columns 1 and 3 report OLS coefficients controlling for year-industry (6-digit NAICS) fixed effects. Columns 2 and 4 are based on plant fixed effects models controlling for year trends. The dependent variable for all columns is total sales in log terms. Production inputs also controlled for (but not reported) in all models include (in log terms) total employment, cost of materials, and cost of energy. 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. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.
Table 3. Contingent IT Productivity

<table>
<thead>
<tr>
<th>Models</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tr>
<td></td>
<td>Product Strategy</td>
<td>Uncertainty (pending disclosure review)</td>
<td>External Capabilities</td>
<td>Internal Capabilities</td>
</tr>
<tr>
<td>LHS Variables</td>
<td>Log Sales</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>High Cloud Expenditure</td>
<td>0.012**</td>
<td>-0.037***</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High IT Capital</td>
<td>0.024***</td>
<td>0.053***</td>
<td>0.021***</td>
<td></td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.015)</td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low-Mix Production</td>
<td>0.029***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.006)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Cloud × Low-Mix.</td>
<td>-0.020**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High IT K × Low-Mix</td>
<td>0.023**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Uncertainty Indicator</td>
<td>-***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Cloud × High Uncertainty Indicator</td>
<td>+***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High IT K × High Uncertainty Indicator</td>
<td>-***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Consulting</td>
<td>0.003*</td>
<td>0.004**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Cloud × Log Consulting</td>
<td>0.010***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High IT K × Log Consulting</td>
<td>-0.003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>0.211***</td>
<td>0.172***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.016)</td>
<td>(0.020)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>High Cloud × Degree</td>
<td>0.026</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.030)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High IT K × Degree</td>
<td>0.010***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.031)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Other controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry (NAICS6) * Year fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>65,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R2</td>
<td>0.941</td>
<td>0.941</td>
<td>0.941</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>Baseline MOPS</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Results for all columns are based on baseline sample from MOPS 2010 and 2015. All columns report results from pooled OLS regression controlling for year-industry (6-digit NAICS) fixed effects. The dependent variable for all columns is total sales in log terms. Production inputs also controlled for (but not reported) in all models include (in log terms) total employment, non-IT capital stock, cost of materials, and cost of energy, and the Management practice index. Standard errors for all columns are clustered at the firm level. Low-Mix indicates the plants with “continuous flow” production process. “High” dummies are constructed based on top-quartile of the sample-year for a given variable. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.
Figure 1. Percentage of IT flow for IT Services over time by plant type (Continuous Flow VS. Other)

Notes: results are based on pooled OLS regression controlling for industry fixed-effects using a sample of plants that exist in the MOPS 2010 and 2015 and are also observable in the 2006-2016 ASM and CMF panel in order to have information on both IT spending allocation over time and the plant type. In addition, we require the values of both IT services and IT capital expenditure variables are reported by the respondents (not imputed by the U.S. Census Bureau). Regression results are available upon request.
Figure 2. Percentage of Expenditure Flow for Traditional IT Capital over time by plant type (Continuous Flow VS. Other)

Notes: results are based on pooled OLS regression controlling for industry fixed-effects using a sample of plants that exist in the MOPS 2010 and 2015 and are also observable in the 2006-2016 ASM and CMF panel in order to have information on both IT spending allocation over time and the plant type. In addition, we require the values of both IT services and IT capital expenditure variables are reported by the respondents (not imputed by the U.S. Census Bureau). Regression results are available upon request.
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