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Economies Before Scale: I.T. Strategy and Performance Dynamics of Young U.S. Businesses

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Abstract. We examine how dimensions of information technology (IT) strategy affect the performance of young businesses, as well as dynamics as they age. Drawing from lifecycle theory and firm boundary research, we derive the relationship between age-based performance differences and IT sourcing decisions. We highlight the dynamic tension between outsourcing's support for accessing frontier inputs in the short term and ownership's advantages for developing organization-specific resources and capabilities over time. Leveraging a large panel of Census Bureau microdata from 2006 to 2014, we provide the first systematic evidence that young manufacturing establishments (both startups and new units of existing firms) disproportionately benefit from modern IT outsourcing (ITO). The young also enjoy productivity benefits from owned IT capital (ITK), despite high uncertainty, smaller operational scale, and less complementary organizational capital. Although these returns appear commensurate with those of older producers, they are conditional on survival, which is improved by ITO but harmed by ITK accumulation. Combining flexibility-related gains from ITK with vintage-related advantages in early ITK investment, the young are revealed to have significantly greater IT productivity than older incumbents. A large battery of tests supports a causal interpretation, as well as mechanisms rooted in mitigating the effects of uncertainty (as opposed to size- or cost-related reasons). These findings illuminate an often-overlooked pattern of young-business dynamism relevant to economic trends and management practices in an increasingly digital age.

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1. Introduction

Concerns are growing about declining economic dynamism (e.g., Decker et al. 2014, 2017; Calvino et al. 2020) and the rise of "superstar" firms in the digital age (Autor et al. 2020, Camuffo et al. 2022). Yet, although incumbency and scale do confer advantages with respect to information technology (IT) use (Tambe et al. 2020, Lashkari et al. 2024), this narrative overlooks the most-dynamic participants in the economy: young businesses. The young are elusive—roughly half fail within five years—yet also central to economic growth and innovation (e.g., Haltiwanger et al. 2013, Acemoglu et al. 2018). Against a backdrop of rising digitization, understanding the connection between early lifecycle dynamics and IT-related performance is thus crucial.

It has received scant attention, however, because the young have been systematically missing from IT productivity research, while entrepreneurship and business dynamics studies have largely overlooked the role of IT. We address this gap by examining how dimensions of IT strategy, including modern IT outsourcing (ITO) and IT capital investment (ITK), affect performance across the producer lifecycle.

Addressing this gap is important because the challenges and advantages of young businesses are distinct from those of older ones (Kerr et al. 2014, Gans et al. 2019), with strategic imperatives to access and leverage resources in distinct ways (Anthony and Ramesh 1992, Dickinson 2011, Arikan and Stulz 2016). In the context of IT use, prior work hints at disadvantages for the young. The organizational complements vital for IT productivity (Bresnahan et al. 2002, Dedrick et al. 2003, Tambe and Hitt 2012, Brynjolfsson 2021a) often take time to accumulate. Early in life, uncertainty is often profound and scale-based economies are lacking just when investment in learning and growth is critical (Foster et al. 2016). Effective digital strategies for the young are therefore likely differ from what works for older incumbents. Yet how and why they differ, including how IT should be sourced and whether similar considerations apply to new units of existing firms as well as to startups, remain open questions.

This study makes progress both empirically and theoretically. Empirically, we leverage a detailed panel of U.S. Census Bureau microdata from 2006 to 2014 to estimate IT-related productivity and survival among manufacturing establishments. Contrasting returns to ITO versus ITK, we shed light on digital strategy and performance for both young firms and new units of existing firms. We also form novel comparisons against a representative sample of older plants to examine dynamics. The nonpublic data is unusual in its coverage of both the age distribution and range of IT inputs, as well as its recency. We thus add a new perspective on the apparently mixed returns to ITO (Bapna et al. 2023) while also re-examining IT productivity, overall, in an updated and important setting.[1]

Conceptually, we first appeal to firm lifecycle theory to ground our focus on young businesses and develop an understanding of their distinct needs. Originating in theories of the product lifecycle, industry-level patterns (Gort and Klepper 1982) have been translated into firm- or establishment-level ones through age-related regularities in investment strategy (e.g., Spence 1977, 1979) and learning-by-doing (e.g., Spence 1981, Agarwal and Gort 1996). Distinct strategic imperatives linked to changing internal and external circumstances thus arise at different lifecycle stages (e.g., Porter 1980). Viewed through this lens, optimal resource allocations are understood to be contingent and dynamic.

We connect the dynamic tensions central to lifecycle theory to dynamic tensions in IT strategy through an examination of sourcing choices. Our approach is motivated by the insight that sourcing decisions may affect different dimensions of performance across different time horizons (Novak and Stern 2008). To our knowledge, this insight has yet to be applied to IT strategy, where outsourcing increasingly plays a role in how firms seek to gain and sustain competitive advantage (e.g., Mithas et al. 2013).

ITO has been studied predominantly through the lens of transaction cost economics (TCE) (Williamson 1989, Bapna et al. 2023). We complement this approach with insights from the resource-based view (RBV) (Wernerfelt 1984, Barney 1991, Helfat and Peteraf 2003) and knowledge-based view (KBV) (Kogut and Zander 1992, Grant 1996, Nickerson and Zenger 2004) of the firm to predict returns to differently sourced IT at different lifecycle stages. Synthesizing and extending these frameworks, we derive the dynamic tradeoff between outsourcing's support for flexibly accessing frontier (yet widely available) IT, in the short term, and ownership's advantages for developing organization-specific IT inputs, over time.

To first examine the early lifecycle implications of this tradeoff, we build on prior ITO research (e.g., Levina and Ross 2003, Chang and Gurbaxani 2012) to hypothesize that outsourcing's advantages will be especially valuable in the face of early uncertainty and resource constraints, making ITO expenditure performance-enhancing for young businesses. In contrast, the benefits of resources and capabilities developed via owned and accumulated ITK will be greater at maturity, consistent with prior work (Tambe and Hitt 2012).

What does this mean for young-business returns to ITK? Anticipating later benefits, forward-looking young producers may make early—and even risky—investments to jump-start valuable capacity and/or learning. Following this logic, early ITK investment might make strategic sense, while nevertheless harming dimensions of performance (e.g., likelihood of survival) or failing to yield returns in the short run. Yet, the young also enjoy certain advantages. Lifecycle theory emphasizes the role of obsolescence in shaping resource allocation and performance as producers age (e.g., Agarwal and Gort 1996). With respect to rapidly depreciating ITK, the young will tend to enjoy vintage-related advantages compared with older plants (Jensen et al. 2001), as well as lower organizational adjustment costs (Bresnahan and Greenstein 1996, McElheran 2015). This will boost returns from investing in ITK early on. How such competing mechanisms net out in observed returns to ITK among the young is thus ultimately an empirical question.

We next turn attention to the later lifecycle to shed light on dynamics and probe the mechanisms at work. Within our framework, the value of specificity increases relative to flexibility as producers grow and mature. All else equal, returns to ITO should thus decline with age. Returns to ITK, while increasing with age by the same logic, will additionally be shaped by declining proximity to the technological frontier and rising adjustment costs. We thus anticipate a curvilinear relationship between age and ITK, overall.

Our approach appeals to mechanisms that vary at the level of a production unit operating within a narrowly defined industry or product market, as opposed to applying uniformly across larger, multidivisional firms (e.g., Dickinson 2011, Syverson 2011). Thus, core predictions are formulated at the level of a "business" or production unit. We argue, however, that early-lifecycle pressures will also be present for new units of established firms if they operate in an industry that is new to the corporate parent. This particular (and not-unusual) context should drive a wedge between ideal plant- and firm-level IT strategies, presenting an opportunity to further probe our theorized mechanisms and extend managerial insights.

We take these predictions to a detailed dataset of more than 26,000 U.S. manufacturing plants per year from 2006 to 2014 with unusually good coverage of young producers: Among the roughly 240,000 producer-year observations, more than 41,000 have been in business five or fewer years. Picking up where most prior studies leave off, we leverage the data to paint an updated portrait of IT expenditure that has shifted moderately but clearly toward ITO (both in levels and shares), particularly among young plants. Yet size-adjusted ITK investment has remained robust among the young, even as its share of overall spend declined. This mixing of sourcing modes, both within and across the lifecycle, notably defies simple characterization of digital strategies as "make-versus-buy" (Williamson 1991), underscoring the need for a holistic assessment.

Over the same period, we see an upswing in the entry and survival of young establishments, both within the sector and across the United States, consistent with reports of resurging entrepreneurship (Guzman and Stern 2020). A key contribution of our analysis is shedding light on the extent to which these trends are connected.

For our core results, we triangulate on dimensions of IT strategy performance using fine-grained controls for variable production inputs and industry-time trends, plant- and firm-fixed effects, and a range of instrumental variables. Our main finding is that IT-related productivity over this period differs significantly by both sourcing mode and producer age. With respect to ITO, both young firms and young units of existing firms benefit disproportionately compared with older plants. This is most apparent in the first five years of life—those most crucial for learning, survival, and growth (Decker et al. 2014, Foster et al. 2016)—and declines quickly across the age distribution. In contrast, ITK-related productivity is always positive, even among the young. This is, however, conditional on survival, which is improved by early ITO expenditure yet actually harmed by early ITK investment. Among older plants, ITK contributes most to performance, although we find diminishing returns starting around 18–20 years old.

When we combine returns across sourcing modes, we find the previously unexamined first five years of life to be the most "IT productive" overall. This finding is novel and suggests one channel connecting trends in IT expenditure to rising young business participation in the economy.

We explore, in depth, the extent to which these results may be interpreted as causal. System Generalized Method of Moments (GMM) and Instrumental Variables (IV) estimation, "Granger-style" tests for reverse causality (Granger 1969), and other robustness—all of which rely on different assumptions about the data-generating process—lend support to our interpretation.

Our hypothesized mechanisms further receive empirical support. Leveraging additional Census Bureau data, we find robust evidence for uncertainty as a key driver of the patterns we observe versus alternative drivers linked to producer size or financial constraints (for which we also test). For instance, uncertainty augments the returns associated with ITO, even among older plants. Notably, young units of multi-unit incumbents also show significant returns to ITO–but only when operating in new-to-the-firm industries.

Finally, we explore the extent to which we are picking up innovation due to the rise of cloud computing. Our ITO measure effectively captures cloud-based IT expenditure, even as the new service and cost model first diffused. Exploiting variation over time, we find returns to ITO among the young to be insignificant until after 2009, consistent with more-developed "enterprise-ready" cloud-based services around that time (Staten 2008). In contrast, young-producer gains from ITK do not vary by period, suggesting an outsourcing-specific shift. Although we cannot partial out cloud-only spend in the data, we take this as supportive of claims concerning the rise of the, both within and across the lifecycle, (Cusumano 2010, Willcocks and Lacity 2016, Sunyaev 2020, DeStefano et al. 2023), and particularly among young firms (Bloom and Pierri 2018, Ewens et al. 2018).

Our findings contribute to a few streams of work. To our knowledge, this is the largest and most-recent study of how IT productivity varies by sourcing mode. On the outsourcing side, it builds on a small, largely older literature on the link between ITO and firm performance (Knittel and Stango 2007, Chang and Gurbaxani 2012, Han and Mithas 2013), which oversamples large firms and large contracts (Bapna et al. 2023). On the ownership side, it builds on a larger IT productivity literature (e.g., Melville et al. 2004) that has worked to establish a causal link between IT investment and firm performance (e.g., Brynjolfsson and Hitt 2000, 2003; Tambe and Hitt 2012, Aral et al. 2024), again primarily in samples of larger incumbents (Dedrick et al. 2003). This predominance of large-firm data has led to an emphasis on adjustment costs (Bresnahan and Greenstein 1996, Tambe and Hitt 2012) and organizational complements (Bresnahan et al. 2002, Bloom et al. 2012, Saunders and Brynjolfsson 2016), even in more-representative studies (Bloom et al. 2012, McElheran 2015, Brynjolfsson et al. 2021a). Age is unexamined. Moreover, little evidence concerning overall IT expenditure exists beyond 2006 (Tambe et al. 2020). We contribute updated insights and new understanding of age-based heterogeneity to this important digitization literature.

Conversely, this study brings digitization insights to entrepreneurship and economic dynamics questions. Although entrepreneurship has recognized distinct early-life considerations (Kerr and Nanda 2009, Kerr et al. 2014, Gans et al. 2019), the role of modern IT has been under-appreciated until recently (Ewens et al. 2018). Research into the lifecycles of establishments (Foster et al. 2016), firms (Agarwal and Gort 1996), and products (Wernerfelt 1985, Novak and Stern 2008) has both overlooked IT and struggled to disentangle age-based mechanisms from those owing to size (Haltiwanger et al. 2013, Kueng et al. 2014). We contribute on both fronts, as well as to lifecycle research into financial strategy and performance (e.g., Anthony and Ramesh 1992, Dickinson 2011, Arikan and Stulz 2016, Hasan and Cheung 2018).

Our findings have key implications for practice and policy. To begin, if distinct aspects of firm performance are in tension and manifest along different timelines, managers and policymakers must anticipate dynamics both within and across performance metrics over the producer lifecycle. Distinct time trends in our results also point to underlying innovation in how firms access and leverage IT—a topic of keen interest in the age of cloud computing. Further, insights into the link between uncertainty and returns to differently sourced IT yield guidance for young businesses in need of economies *before* scale, not to mention certain older producers and new units of existing firms seeking greater productivity. Ultimately, despite flagging aggregate productivity (Brynjolfsson et al. 2021b) and rising industry concentration (Bessen 2020), our study offers grounds for optimism, as well as new avenues for inquiry and exploration.

2. Conceptual Background and Hypothesis Development

2.1. IT Productivity and Economic Dynamism in the Digital Age: Missing Young Businesses

IT use has been robustly linked to firm performance (Bharadwaj 2000, Brynjolfsson and Hitt 2003, Tambe and Hitt 2012, Aral et al. 2024), although primarily among large incumbents with key organizational complements (Brynjolfsson and Hitt 2000, Bresnahan et al. 2002, Bloom et al. 2012, Saunders and Brynjolfsson 2016). IT productivity in young businesses is poorly understood, as size has received far more attention than age, and younger (often smaller) businesses have been underrepresented (Dedrick et al. 2003, Tambe and Hitt 2012). Yet roughly 35% of U.S. firms are five years old or younger[2]: a nontrivial omission.

This could be innocuous if the young depend less on IT or are able to participate in an increasingly digital economy without traditional IT investment. In fact, recent statistics reveal lower rates of both digitization and advanced technology use among younger firms, yet a greater reliance on purchased IT services (Zolas et al. 2020). This preference for ITO (especially via the cloud) is well known among high-tech startups (Impink 2022). However, the extent to which different types of young businesses (including "bricks-and-mortar" entities) are able to leverage advancing digital technologies is incompletely understood (Galdon-Sanchez et al. 2022, Keyhani 2022). This includes not knowing whether they are participating in a growing ITO trend (Chang et al. 2017), nor what this means for their productivity and survival.

ITO has been on the rise for decades, with annual U.S. revenues exceeding $167 billion by 2021.[3] This has led to a vast literature on whether, when, and how firms should outsource their IT.[4] Yet little direct evidence on performance outcomes exists. Exceptions include a few firm-level productivity studies (Knittel and Stango 2007, Chang and Gurbaxani 2012, Han and Mithas 2013), along with project-level (Mayer and Nickerson 2005, Mayer and Salomon 2006, Bapna et al. 2023), industry-level (Han et al. 2011), and case-study evidence (Levina and Ross 2003). Almost none extend beyond the early 2000s. Further, large incumbents remain overrepresented, and variation based on age is largely absorbed or ignored—but never explored.

This inattention to young businesses in both IT productivity and ITO research is problematic due to the vital role that young producers, both startups and new extensions of existing firms, play in the economy. Research on economic dynamism has established that young businesses disproportionately contribute to job creation and innovation (e.g., Decker et al. 2014, Acemoglu et al. 2018) and that this is a function of age rather than size (Haltiwanger et al. 2013). Missing the young could mean missing an essential pathway to productivity and economic growth in an increasingly digital era.

In particular, insights based on large incumbents are likely to fall short in explaining how the young leverage IT. Larger-firm studies have emphasized adjustment costs (Bresnahan and Greenstein 1996, Tambe and Hitt 2012, McElheran 2015) and organizational complements (Tambe et al. 2020, Brynjolfsson et al. 2021a)—both of which will differ in magnitude and/or kind for the young (Kueng et al. 2014). Well-known scale advantages will be in short supply. Instead, option value, which has received limited attention in IT productivity research, will be in high demand (Kerr et al. 2014). Lacking an existing framework for understanding the implications of these differences, we synthesize and extend insights from lifecycle theory and related economics and management research to form predictions about how producers access and leverage IT at different stages of their development.

2.2. Producer Lifecycle Theory

Originating in theories of the product lifecycle, industry-level patterns (Gort and Klepper 1982) have been translated into firm- and establishment-level ones based on investment strategy (e.g., Spence 1977, 1979) and learning-by-doing (e.g., Spence 1981, Jovanovic 1982, Wernerfelt 1985, Agarwal and Gort 1996). Close linkages between these mechanisms and age have led to typologies evocative of the human lifecycle: *birth, growth, maturity,* and *decline.*[5] Yet, although used extensively to understand age-based differences in financial strategy and performance (Anthony and Ramesh 1992, Dickinson 2011, Arikan and Stulz 2016, Hasan and Cheung 2018), lifecycle-based implications for IT strategy and performance remain unexplored.

2.2.1. "Early" vs. "Later." Given our interest in young businesses, we emphasize contrasts between stages that are prevalent earlier in life and those that tend to occur later. Note that progression through the stages tends to be monotonic and most correlated with age, empirically, for *birth*, *growth*, and *maturity* (Anthony and Ramesh 1992, Dickinson 2011). Death is an exception, as firms can decline from any stage, particularly in the first five years of life (Decker et al. 2014). Thus, we include survival in our analysis. With that caveat, a simplified early-versus-later lifecycle comparison yields a tractable and meaningful way to unpack whether and why youth matters for IT strategy and performance.

2.2.2. "Producer"-Level Analysis. We follow the business dynamics literature by developing and testing our predictions at the establishment, or "producer," level. Although in many economics and management theories, makers-of-things are referred to as "firms," in practice, key lifecycle mechanics tend to operate at the level of a production unit. Moving down the experience curve, updating production technology, and learning about product-market demand (Argote and Epple 1990, Jensen et al. 2001, Foster et al. 2016) have all been theoretically and empirically situated within narrow industry contexts, requiring additional assumptions to apply readily across multi-industry firms (Dickinson 2011). This is particularly true in U.S. manufacturing, where economic performance has predominantly been modeled at the plant level to capture variation in factor shares, technology inputs, and management practices (e.g., Jensen et al. 2001, Syverson 2011, Bloom et al. 2019), as well as entry and exit dynamics (e.g., Dunne et al. 1989).

Central to our research question, decisions over IT investment and use have also been found to vary within multi-unit firms (McElheran 2014, Forman and McElheran 2024). This may be, in part, because of variation in decision rights over IT purchasing. Again, industry context matters, with plant-level authority more likely if the industry context differs from the focus of the corporate parent (McElheran 2014).

Taken together, a firm-level analysis could thus obscure important heterogeneity in the mechanisms shaping both IT strategy and performance, yielding aggregation bias (e.g., Syverson 2011) and/or "one-size-fits-all" managerial guidance based on parent-firm characteristics. At the same time, an establishment-only approach could limit visibility into within-firm spillovers (McElheran et al. 2024) or knowledge transfer across units (Argote et al. 2020). Therefore, although we focus primarily on production units in our theory development and empirical tests, we also incorporate key firm-level considerations—including the special case of new additions multi-unit firms—to extend insights.

2.2.3. Early Lifecycle Stages and Dynamics. *Birth* takes place at the founding of a new venture or opening of a new establishment. This earliest stage is the riskiest,[6] which often limits the magnitude of initial investments. Entrants thus tend to be small and face tight resource constraints (Kerr and Nanda 2009, Kerr et al. 2014). Performance depends heavily on initial "endowments" of productive assets (Agarwal and Gort 1996), which may include organizational as well as physical capital, per the RBV (Hasan and Cheung 2018). The value of initial endowments may be unknown, even to founders (Jovanovic 1982).

This profound uncertainty, combined with resource scarcity, increases the returns to option value and learning-by-experimentation (Kerr et al. 2014). Yet the "paradox of entrepreneurial decision making" is that certain opportunity costs must be incurred in order to learn (Gans et al. 2019). As a result, strategic imperatives at this stage tend to focus on surviving and resolving uncertainty (Camuffo et al. 2020) while pursuing means (traditionally, through financing) to augment endowments quickly in anticipation of growth.

Progress through the lifecycle depends on learning-by-doing and investment (e.g., Spence 1977, 1979, 1981; Agarwal and Gort 1996). Thus, while experimentation may be critical early on, producers also acquire "skill" such as supply-side cost reductions and demand-side product or marketing improvements as a function of experience (Foster et al. 2016). Endowments may be augmented in a more stepwise fashion through investment, although they likewise tend to accumulate with time. Such mechanics drive a close, if imperfect, relationship between lifecycle stage and producer age (e.g., Dickinson 2011, Kueng et al. 2014).

Conditional on survival, the *growth* stage follows. Characterized by significant increases in output, this progression is not guaranteed: roughly 75% of U.S. firms six years and older have fewer than 10 employees

(U.S. Census Bureau Business Dynamics Statistics 2021). Lifetime profit maximization may come from prioritizing capacity and market share expansion over profitability in this stage (Wernerfelt 1985). Pre-emptive investment in scaling may deter competitors (Spence 1977, 1979), as may demand- and supply-side learning in this stage (Spence 1981). In practice, younger businesses often trade off early revenue in order to learn about demand (Foster et al. 2016). Strategic imperatives during this stage thus favor creating barriers to competition over profit maximization or efficiency (Porter 1980, Anthony and Ramesh 1992).

We argue that developing organization-specific inimitable resources and capabilities (e.g., Barney 1991) is another strategically important early-life objective in need of inclusion. Essential for exploiting IT inputs that may be readily available to competitors (Bharadwaj 2000), examples include IT-specific skills, aligned processes and management practices, and software customization (Mata et al. 1995, Bresnahan et al. 2002, Bloom et al. 2012, McElheran 2015, Tambe et al. 2020, Brynjolfsson 2021a). Learning and organizational capital increase at their highest rate in this stage, although with diminishing returns (Agarwal and Gort 1996), and are typically drawn down in pursuit of growth (Hasan and Cheung 2018). Thus, net levels of accumulated endowments, broadly speaking, tend to be lower compared with later in life.

2.2.4. Later Lifecycle Stages and Dynamics. *Maturity* comes as growth levels off. Uncertainty tends to be lowest in this stage, allowing producers to leverage prior learning and accumulated endowments to improve efficiency and support market positioning. Prior growth, along with selection pressures, means that mature producers tend to be larger (Kueng et al. 2014). Risks come increasingly from external shocks that may be difficult to meet due to the specificity of both productive assets and capabilities. Obsolescence of earlier endowments becomes a concern over time (Agarwal and Gort 1996).

On net, lifecycle dynamics up to this point mean that more-mature producers will have a substantial resource and capability advantage over the young, having had more time to learn and invest. Economies of scale further provide advantages in both making and benefitting from high-fixed-cost investments in this stage. However, depreciation of earlier investments and learnings will draw down the stock of productive endowments. Absent other mechanisms, this tension will promote a curvilinear ("inverted-U shape") relationship, with increases in endowments up to an optimal level of "senility" (Agarwal and Gort 1996)—after which endowment stocks tend to level off and even diminish.

Failure to sustain in the face of external and internal challenges leads next to *decline*. Producers can enter this stage from any of the others, yet death is not inevitable. Instead, producers that replace or revitalize endowments may transition into *renewal* and even back into *growth* (e.g., Lester et al. 2003). This nontrivial heterogeneity later in life warrants care. Yet, the high-level view of older producers is one of lower uncertainty and larger scale, along with a greater stock of more-specific productive assets and organizational capital compared with early in life. Strategically, whereas survival and growth take precedence early on, later imperatives tend to center on efficiency (Anthony and Ramesh 1992) and maintaining the productivity of endowments (Dickinson 2011).

2.3. IT Strategy over the Producer Lifecycle

We connect these dynamic tensions central to lifecycle theory to dynamic tensions in IT strategy through an examination of sourcing choices. Outsourcing is well understood to be an integral dimension of IT strategy (e.g., Mithas et al. 2013). Less-understood is how different sourcing modes affect dimensions of performance across the lifecycle—especially among the young.

2.3.1. IT Outsourcing Tradeoffs. In the short term, ITO is argued to facilitate rapid and cost-effective access to frontier technology and knowledge via external economies of scale and specialization (Levina and Ross 2003, Chang and Gurbaxani 2012). Yet, outsourcing tends to incur higher monitoring and coordination costs compared with internal development of IT, per the widely used transaction cost economics (TCE) framework (Williamson 1989, Poppo and Zenger 1998, Mayer and Nickerson 2005). Also, the inputs accessed in this fashion are readily available to competitors. Early research into ITO performance found positive returns, on net, although primarily among larger incumbents that selected into ITO[7] and developed outsourcing-related capabilities such as expertise in defining requirements and performance measures (Mayer and Nickerson 2005, Chang and Gurbaxani 2012). Follow-on work emphasizes that contract misalignment often leads to poor performance (Susarla and Barua 2011, Bapna et al. 2023), and such misalignment tends to be firm-specific (Handley 2017). This, combined with heterogeneity in later lifecycle progression, suggests that expected returns to ITO among older producers are best viewed as contingent and, on average, theoretically ambiguous.

With respect to young producers, however, we can formulate sharper predictions by homing in on a dynamic benefit of ITO that is particularly salient for them: option value. Outsourcing promotes flexibility by allowing producers to forego sunk investments in rapidly depreciating assets and/or peak capacity while leveraging the "autonomous adaptation" of the marketplace (Williamson 1991). It is therefore particularly valuable in contexts of high technological and demand uncertainty (Balakrishnan and Wernerfelt 1986, Abraham and Taylor 1996). Extending this logic to IT, producers can access frontier IT while pushing obsolescence risks onto IT services providers. Given the high uncertainty and resource constraints characterizing the early lifecycle, the young will tend to benefit (perhaps disproportionately) from this aspect of ITO.

We expect that they will further benefit from another source of flexibility: leveraging external economies of scale and specialization unavailable to them internally. Young producers building out from a core founding team often lack IT-specific expertise (Street and Meister 2004), as well as the scale to support skilled IT-focused labor (Palmer 2012). Accessing cost-effective IT services may therefore only be *possible* for young producers through ITO. In addition, it may also be *preferable*, as many of the resources and capabilities in question, although new to the firm, are unlikely to be completely new to the world. In such cases of knowledge exchange (versus knowledge generation), the KBV (Kogut and Zander 1992, Grant 1996, Nickerson and Zenger 2004) argues that outsourcing will be optimal.

Core TCE arguments also point to a youth-based advantage in ITO. Outsourcing is argued to be a better fit for activities that are not highly specific to a particular producer or exchange relationship (Williamson 1989, Handley 2017). For younger producers without well-developed market positions or well-understood customers (both associated with later lifecycle stages), less-specific IT assets may suffice and even be easier to adjust to new information or market conditions. Thus, although the average expected returns to ITO for older producers may be ambiguous, taking into account option value, external economics of scale and specialization, and the need for less-specific IT, we predict the following:

Hypothesis 1. *Young producers will demonstrate positive short-term performance benefits from ITO expenditure.*

2.3.2. IT Ownership Tradeoffs. This does not imply, however, that the young should outsource *all* of their IT. A key downside of outsourcing is that the resources thus accessed may be readily available to competitors as well (e.g., Quinn and Hilmer 1994), making ownership of strategically important inputs appealing. Further, as we examine overall digital strategy—not just the optimal choice for a particular type of transaction or long-lived contract—we need to assess the lifecycle implications of IT ownership, as well.

In IT productivity research, the standard null hypothesis is one of no effect, with the modal empirical study predicting and then exploring evidence for positive returns, particularly among older incumbents (see Section 2.1). Yet there are sound theoretical reasons to expect that young producers might instead exhibit *negative* near-term returns to ITK investments.

According to TCE, for instance, ownership provides superior incentives for noncontractible dimensions of performance and internalizes spillovers across activities and over time within the firm (Williamson 1989, Mayer and Nickerson 2005). Appealing to a complementary set of mechanisms, the KBV further argues that internally governed activities will be superior for complex, often tacit, organization-specific knowledge acquisition and retention (Kogut and Zander 1992, Grant 1996, Nickerson and Zenger 2004). Anticipating the need to learn and develop the business-specific IT required later in life, forward-looking young producers should invest in some amount of ITK, even if they expect returns to manifest later.[8]

Limits on short-run returns will be further exacerbated if complementary organizational capital is required and takes time to accumulate (Brynjolfsson and Hitt 2003, Tambe and Hitt 2012). Taken together, we might expect to observe young-firm investment in ITK, while also seeing no—or even negative—returns (Brynjolfsson et al. 2021b) in the short run. If we take the case of no observable returns as our null, the relevant negative-returns hypothesis may be formulated as follows:

Hypothesis 2a. *Young producers will demonstrate negative short-term performance effects from ITK investment.*

Two clarifying points are essential here. First, although producer performance is typically operationalized in terms of output or productivity, our theoretical framework emphasizes the importance of different dimensions of performance at different lifecycle stages. Thus, we expect this to vary by how "returns" are defined. Our approach examines both productivity and survival for this reason.

Second, implicit in this logic is the assumption that the productivity of ITK will, conditional on survival, increase with age. However, unlike generic production technology or materials, the rate of obsolescence of IT is high and rising. The depreciation rate for personal computers, for instance, is 35% per year, with proposed increases up to 52%, whereas depreciation for physical capital is often under 20% (e.g., 14% for medical equipment and 6% for ships). At any given point in time, younger producers investing in developing their own IT resources and capabilities will be able to leverage a newer vintage of technology (Jensen et al. 2001) and related human capital (Chari and Hopenhayn 1991, Barth et al. 2023). Their adjustment costs will also be lower without extant infrastructure and processes (Bresnahan and Greenstein 1996, Tambe and Hitt 2012, McElheran 2015), which could shorten the time required for returns to manifest (Tambe and Hitt 2012). If such vintage effects dominate, we would expect higher returns to ITK investments among younger producers. This leads to a converse hypothesis with respect to ITK (Giandrea et al. 2021):

Hypothesis 2b. *Young producers will demonstrate positive short-term performance effects from ITK investment.*

Without these vintage-related mechanisms, short- versus long-term tradeoffs in ownership would be in sharper tension (Novak and Stern 2008). In the context of ITK, however, determining which mechanism dominates (and according to which performance measure) is ultimately a nuanced empirical question.

2.3.3. Dynamics. As producers mature, the option value so important early in life will be eroded as uncertainty declines. At the same time, the costs of foregone specificity will increase as competitive positioning is established and efficiency takes on more importance relative to growth. Also, in cases where ITO represents a long-lived strategic decision, for instance, in high-value contracts, misalignment is more likely as time passes (Handley 2017, Bapna et al. 2023). Thus, we predict the following:

Hypothesis 3. *Returns to ITO will decrease with age.*

Some care is required here, as the ITO we study is not restricted to large, long-lived contracts, and we only observe annual expenditures, which could include new or renewed contracts. That said, contracting costs are a key friction in ITO (e.g., Willcocks and Lacity 2016) and may prevent renegotiation as often as shifting circumstances would ideally require, leading to misalignments that can accumulate over the lifecycle.[9] In addition, later life admits more heterogeneity with respect to a producer's specific lifecycle stage that may, in turn, affect the flexibility-specificity tradeoff at the heart of our framework. We therefore directly examine key mechanisms (e.g., uncertainty) across the age distribution in our empirical analyses.

With respect to ITK, although returns should tend to increase with age due to rising IT stocks and organizational capital accumulation (Tambe and Hitt 2012), dynamics remain nuanced. Diminishing returns to additional investment may set in (Agarwal and Gort 1996), whereas vintage effects and adjustment costs exert downward pressure on returns to existing ITK stocks, even in the face of continued investment. Thus, we anticipate that ITK productivity will increase up to a point and then decline:

Hypothesis 4. *Returns to ITK will be curvilinear in age.*

Despite synthesizing a range of distinct views on lifecycle dynamics and sourcing decisions, our approach necessarily abstracts away from a number of theoretically and managerially relevant considerations. One that nonetheless merits special attention is the potential difference between standalone startups and new units of existing firms. This margin of variation provides an opportunity to probe the importance of uncertainty—versus other lifecycle mechanisms such as financial constraints—that covary over the lifecycle. Specifically, we anticipate that all new units of existing firms will face lower financial constraints than standalone startups (Kuppuswamy and Villalonga 2016). Uncertainty, on the other hand, may be similarly high across both types of entrants whenever extensions of incumbent firms open in new-to-the-firm industries. This is because knowledge transfer and productivity gains of various kinds translate poorly across industry boundaries (e.g., Syverson 2011), even within firms (e.g., Argote et al. 2020). Discretion for IT purchasing, in particular, has been found to devolve to establishments operating in idiosyncratic industries within multiunit firms (McElheran 2014). Thus, we anticipate a wedge between patterns for incumbents and those for new units of existing firms when the industry context is also novel to the firm.

3. Data and Empirical Context

Our empirical analysis leverages nonpublic microdata from the U.S. Census Bureau, starting with the Annual Survey of Manufactures (ASM). This establishment-level sample—stratified by industry and size, with response required by law—covers roughly 70% of activity in the sector. We link to the population-level Census of Manufactures (CMF) and Longitudinal Business Database (LBD) to construct an annual panel. The LBD tracks all private-sector establishments from the time they have at least one employee, yielding reliable data on age and survival (beginning in 1975). These data have been used extensively to study U.S. productivity and dynamism (e.g., Dunne et al. 1989, Haltiwanger et al. 2013, Decker et al. 2017).

Our analysis sample covers more than 26,000 establishments per year from 2006 to 2014, or just under 240,000 plant-year observations. To our knowledge, this is the largest, most detailed, and most recent study of IT strategy—particularly with visibility to both ITK and ITO—to date. Coverage of young businesses is robust, with 41,300 plant-years of data for plants that have been in business for five or fewer years. See Online Appendix B for details of the sample construction and pairwise correlations among key variables.

3.1. Outsourced IT

Our measure of ITO is collected annually by Census from 2006 on. Labeled "data processing and other purchased computer services," it includes a range of IT services, from more-traditional management of computer facilities and "computer-related advice and services" to data preparation, storage, and processing. It notably does not restrict attention to large, long-term contracts (Chang and Gurbaxani 2012, Handley 2017, Bapna et al. 2023) that may be inaccessible to younger, smaller firms. It further allows ITO spend to vary independently and continuously from investment in ITK stocks versus relying on the share of overall budget that is outsourced (Mithas et al. 2013) or on binary indicators (Knittel and Stango 2007) and is thus well suited to estimating marginal productivity contributions using standard approaches.

It further reflects the managerial challenge of allocating IT budgets across types of resources (all of which should ideally be accounted for in the productivity estimation) while incorporating the rising recognition that firms often both "make *and* buy" similar inputs.[10] Indeed, empirically imposing substitution across sourcing modes could be misleading. Thus, visibility to plants' overall IT strategy via this comprehensive and flexible characterization of both sourcing modes and expenditure levels is vital.[11]

A final detail is worth noting. The complete survey wording also allows for the inclusion of IT services, such as training, that are usefully thought of as augmenting complementary organizational capital (Tambe et al. 2020). Although this would ideally be observed separately to assess their distinct contribution, having them in the measure ameliorates omitted-variable bias.[12] In our sample, mean ITO expenditure is $0.02M for younger plants versus $0.04M for older ones.

3.2. Owned IT

Following prior work (Van Reenen et al. 2014), we calculate owned ITK based on capital investment in "computers and data processing equipment," available on an annual basis in the ASM from 2002 on. Leveraging this longer panel, we implement a perpetual inventory approach using an industry-level deflator for hardware from the Bureau of Economic Analysis (BEA) of 35% per year. Mean ITK for young and older plants is $0.09M and $0.23M, respectively, with high variance.[13]

Another notable feature of our IT measures is the significant within-firm variation for both types of IT (Online Appendix, Table B.1). This further justifies taking an establishment-level approach in our analysis.

3.3. Flexibility vs. Specificity

These measures exhibit empirical patterns consistent with the flexibility-specificity tradeoff from Section 2. Mean ITK in Table 1 is 50%–75% larger than expenditure on ITO. It is further quite "lumpy": A single period of ITK investment ("flows" into the stock) accounts for more than 50% of the total across nine years (Online Appendix, Figure B.2). This is consistent with a larger sunk commitment that is difficult to adjust. In contrast, per-year ITO expenditure is flatter and highly correlated with variable inputs (e.g., temporary labor, materials, and energy) while showing little co-movement with fixed outlays such as ITK and non-IT capital stock (Online Appendix, Table B.2), consistent with higher flexibility.

3.4. Software and Hardware

The ASM also collects software expenditure data, but it combines customized vendor-provided software with internally developed resources, thus confounding sourcing modes. Noncapitalized CPUs and IT peripherals are collected in yet another category but are lumped in with "equipment" such as copy and fax machines that are unlikely to be strategic. We thus focus on the cleaner distinction between the ITO and ITK measures above and include these other IT inputs as controls.

Table 1. Sample Descriptive Statistics

Variables	Definition	Young (standard deviation)	Older (standard deviation)
Age	Establishment age	2.51 (1.45)	25.3 (9.98)
Size	Total number of employees	68.5 (166)	189 (421)
Sales	Total value of shipments ($Millions)	30.0 (150)	116 (611)
Outsourced IT (ITO)[a]	Operating expenses on data processing and other purchased computer services, including computer facilities management, data storage, computer time rental, and other computer-related advice and services, including training ($Millions)	0.02 (0.08)	0.04 (0.14)
IT Capital Flows[a]	Capitalized investment for the year on computers and data processing equipment ($Millions)	0.03 (0.13)	0.07 (0.20)
IT Capital (ITK) Stock[a]	Accumulated and depreciated stock of investment in computers and data-processing equipment ($Millions)	0.09 (0.33)	0.23 (0.58)
IT Cost Share	Total IT investment as a percentage of total operating costs	0.55% (1.5%)	0.47% (1.2%)
Multi-Unit Status (MU)	Indicator for whether the establishment belongs to a multi-unit firm	0.70 (0.46)	0.69 (0.46)
N		~41,300	~198,400

Note. Standard deviations in parentheses.
[a]Variable is winsorized at the 1% and 99% levels.

3.5. Producer Age and Exit

Despite visibility to an unusually large number of plants within their first year of operation, we focus most of our analysis on those that are five or fewer years old.[14] This "Young" group represents around 18.5% of the sample, or roughly 5,000 plants per year. Exit in our context represents "death," determined by extended periods of unreversed exit in the LBD (see Online Appendix B for details) and is only flagged in our data through 2012 (limiting the survival analysis sample somewhat).

3.6. Size and Industry

Young plants in our sample, quite characteristically, tend to be small. The average young plant in our sample has fewer than 70 employees, with $30M in revenues (Table 1). The average older business is larger, although still more representative of the overall size distribution compared with prior IT studies at 190 employees and $116M in revenues. Industry is assigned at the six-digit North American Industry Classification System (NAICS) level, allowing us to address heterogeneity in factor shares and market context in an unusually fine-grained way.[15]

3.7. Trends over Time

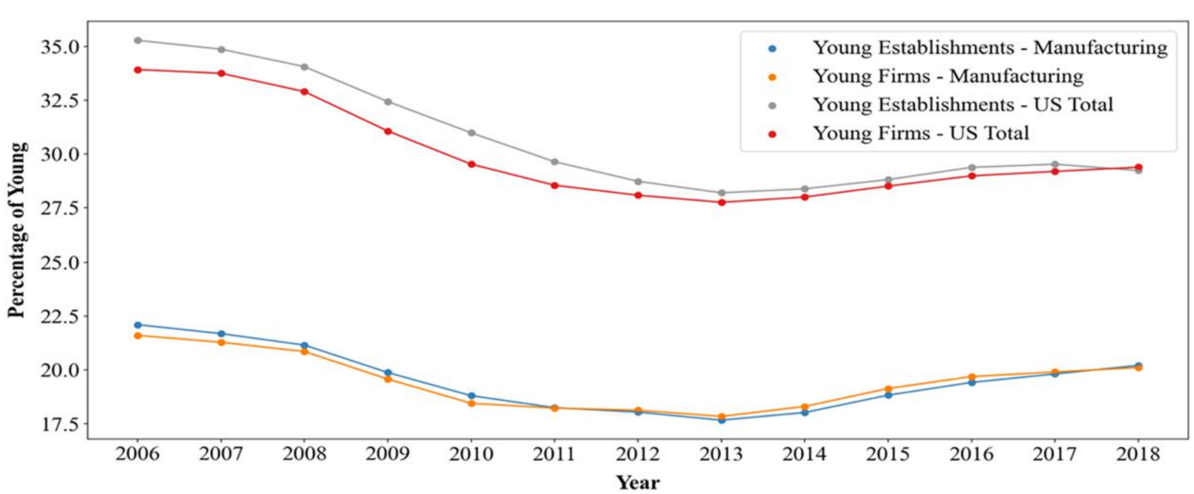
The usefulness of a representative sample is apparent in Figure 1, which shows participation rates of young establishments in the entire U.S. manufacturing sector from 2006 to 2014. The birth rate dropped precipitously during the Great Recession, recovering around 2013–2014, consistent with reports of rebounding high-quality entrepreneurship in the United States (Guzman and Stern 2020). Exit rates similarly rose during the Great Recession but declined below prerecession levels by 2012 (see Figure B.3 in the Online Appendix).

To view these trends against trends in IT investment, Figure 2 depicts unweighted per-employee IT expenditures from the ASM.[16] Throughout this period, ITO represents a smaller share of overall expenditure than flows into ITK at $161 to $281 per employee versus $300 or more for ITK investment. Flows into ITK dip notably during the Great Recession and do not exceed 2006 levels until 2014. Combined with normal depreciation rates, this represents a significant draw-down of ITK stocks over this period. In contrast, the share of spending on ITO rises steadily throughout.

Comparing across age groups, we see only small size-adjusted differences. Dynamics are important to keep in mind, however, as the young do not remain young indefinitely, and entrants continually renew the under-five category. Thus, these trends could also reflect compositional shifts by age and industry over time.

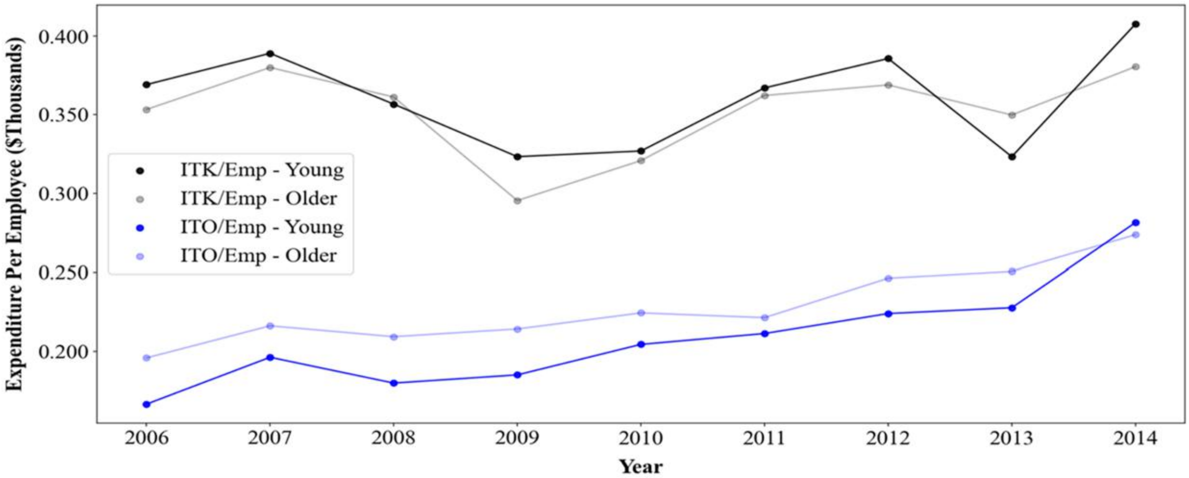
To address this, we estimate changes in expenditure shares by age group and time period within six-digit NAICS categories in Table 2. Interacting *YOUNG* with indicators for different time periods, we observe a statistically significant shift as early as 2008–2009 away from ITK (column (1)) and equipment (column (2)) toward more-flexible ITO (column (3)), and software (column (4)). The coefficients for 2008–2009 and 2010–2014 indicate that, on average, ITK and equipment expenditures declined—roughly five and two percentage points, respectively—whereas ITO and software gained around three and four percentage points each. Against an average allocation of 16.6% to ITO and 28.4% to ITK flows, these magnitudes represent a reallocation of roughly 18% from owned IT capital stocks to outsourced IT services. These patterns are slightly different for younger plants, which devote a larger *share* to ITK accumulation in the earlier period but also shift into outsourced IT from 2008 on (column (3)). We turn next to unpacking the performance implications of these high-level digital strategy trends for business performance at the microlevel.

Figure 1. (Color online) Young Establishment and Young Firm Prevalence in the U.S. Economy (2006–2018)



Note. Derived from the U.S. Census Bureau Business Dynamics Statistics (2019), https://www.census.gov/newsroom/press-releases/2021/2019-business-dynamics-statistics.html.

Figure 2. (Color online) Per-Employee IT Expenditures in ASM-Based Sample by Sourcing Mode (2006–2014)



Note. Aggregate per-employee expenditure on IT capital (ITK) flows and outsourced IT (ITO) by age group.

4. Empirical Approach

The richness of our empirical setting is ideal for estimating total-factor productivity (TFP) as a central—although not only—dimension of producer performance. We take a conventional approach to modeling the plant production function (Brynjolfsson and Hitt 1995, Bloom et al. 2012, Tambe and Hitt 2012) by considering a production function that is Cobb-Douglas, as in

$$Y_{it} = A_{it}K_{it}{}^{\alpha_1}L_{it}{}^{\alpha_2}M_{it}{}^{\alpha_3}\ IT_{it}{}^{\alpha_4}$$

where Y_{it} is total revenue (sales) of plant i at time t, A_{it} is technical productivity, K_{it} denotes non-IT capital stock at the beginning of the period, L_{it} is labor input, M_{it} is material and energy inputs, and IT_{it} is the establishment's IT input.

The Cobb-Douglas function is a useful first-order approximation of an arbitrary production function and particularly appropriate for estimating the output return to inputs calculated at the mean. Taking logs provides a tractable form to take to the data:

$$\ln Y_{it} = \alpha_1 \ln K_{it} + \alpha_2 \ln L_{it} + \alpha_3 \ln M_{it} + \alpha_4 \ln IT_{it} + \gamma X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (2)$$

where X_{it} is a vector of time-varying plant characteristics, λ_t is a year fixed effect, and the productivity term is decomposed into a set of plant fixed effects, μ_i, and an added stochastic term, ε_{it}.

We build on this standard approach by dividing IT inputs into IT capital stock (ITK_{it}) and outsourced IT (ITO_{it}), to distinguish sourcing modes, while controlling for other IT-related expenditures. This accommodates

Table 2. IT Expenditure by Type and Age Group (2006–2014)

Model description / Dependent variables	(1) *% Expenditure on Flows into ITK*	(2) *% Expenditure on Equipment*	(3) *% Expenditure on ITO*	(4) *% Expenditure on Software*
Young	0.009**	0.010***	−0.004	−0.015***
	(0.004)	(0.003)	(0.003)	(0.003)
2008–2009	−0.045***	−0.026***	0.029***	0.041***
	(0.003)	(0.003)	(0.002)	(0.002)
Young × 2008–2009	−0.004	−0.009*	0.011**	0.002
	(0.005)	(0.005)	(0.004)	(0.004)
2010–2014	−0.052***	−0.016***	0.024***	0.044***
	(0.004)	(0.004)	(0.004)	(0.003)
Young × 2010–2014	−0.007	−0.009**	0.012***	0.004
	(0.004)	(0.004)	(0.004)	(0.003)
Industry fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.155	0.134	0.086	0.098

Notes. Results of OLS estimation in the full sample, controlling for industry (NAICS6) fixed effects. Dependent variables are the percentage of each type of IT expenditure out of total IT-related spending at the plant level. All columns include an unreported indicator for whether the establishment reported zero IT expenditure (these are reported, not imputed, zeroes). There is no statistically significant difference between ITO share in the Great Recession years (2008–2009) and in the post-Recession period (2010–2014).

*, **, and ***Statistical significance is denoted as follows: 10%, 5%, and 1%, respectively.

the entire portfolio of IT investments (thereby reducing omitted-variable bias), while disentangling the sourcing dimensions of IT strategy laid out in Section 2. Also, because we are primarily interested in how the coefficients on IT productivity vary across the early (versus later) stages of the lifecycle, our core specifications interact all input variables with an indicator of a plant being *YOUNG*, defined as five or fewer years old (see Section 3). If we relegate all of the plant-varying controls and production inputs to production (non-IT capital, labor, and materials, all logged) to X_{ijt} and allow the annual time trend (λ_t) to further vary by industry j, we get our core estimating equation:

$$Y_{it} = \alpha_0 + \beta_1 \ln ITO_{it} + \beta_2 \ln ITK_{it} + \beta_3 YOUNG_{it} + \beta_4 (YOUNG_{it} \times \ln ITO_{it})] + \beta_5 (YOUNG_{it} \times \ln ITK_{it}) + \alpha_1 X_{it} + \alpha_2 (YOUNG_{it} \times X_{it}) + \lambda_t \times ind_j + \mu_i + \varepsilon_{it} \tag{3}$$

4.1. Pooled Linear Estimation

We first estimate Equation (3) using pooled Ordinary Least Squares (OLS). Despite the popularity of within estimators (i.e., including unit-level fixed effects) for absorbing unobserved time-invariant heterogeneity, they have shortcomings for our phenomenon of interest. Put simply, diffusion curves (the rates at which technologies spread through populations) matter for both estimation and interpretation. In particular, estimates of technology-related performance in the presence of unit fixed effects are only identified by *changes* over time in technology use. If this changes little, as is commonly the case once IT has been adopted at sufficient scale or intensity, then sustained use over time will be differenced out from the estimate. Problematically, early and sustained "frontier" adopters will be dropped from the estimation in favor of "laggards." In the case of beneficial technologies, this will tend to bias downward the estimated relationship between IT adoption and performance (Brynjolfsson et al. 2021a).

This problematic outcome may be avoided in two cases. The first is when technology use is highly variable. For this reason, intensity measures are often preferable to binary indicators. Given the variation in our data, estimates of ITO performance will be less affected than will the "lumpier" ITK estimates (Figure B2 in the Online Appendix). The second case is if the data panel begins before any adoption is possible (Forman and McElheran 2024). Traditional IT outsourcing long predates our sample and was rising steadily over the period covered by our data (Han and Mithas 2013). In contrast, innovation in outsourced IT services provision related to the introduction of cloud computing in the mid-2000s will be quite minimal at the start of our sample, yet well captured midway through. Thus, although our measure does not disentangle cloud from other forms of IT outsourcing, changes over time in what it captures will pick up this much-discussed paradigm shift in ITO (Willcocks and Lacity 2016, Sunyaev 2020). We explore the potential role of the cloud paradigm in a post hoc fashion after presenting our main findings (see Section 5).

We exploit the richness of our data to address a number of potential plant-level confounds. First, we control for a large number of time-varying production inputs (costs of materials and parts, electricity and fuel, operating expenses on software and hardware, cost of temporary workers, and total number of employees) and use industry-year indicators to absorb transitory shocks at a very fine-grained level (typically six-digit NAICS). We also account for both accumulated and depreciated IT and non-IT capital stock, the lack of which constitutes a common barrier to TFP estimation (DeStefano et al. 2023).

4.2. Survival

Next, we address another time-varying empirical challenge: plant survival. Young businesses are disproportionately prone to exit in the first years of life (Decker et al. 2014). Therefore, productivity estimates will only capture one dimension of performance. An extensive treatment is beyond the scope of this study. However, the data allow us to directly explore the relationship between IT strategy and survival with a Cox proportional hazard model, controlling for industry at the four-digit NAICS level.[17] We also address survival bias by instrumenting for IT using approaches that account for exit (Olley and Pakes 1996).

4.3. Within-Producer Estimates

We add to our "collage of evidence" by controlling for plant and firm fixed effects. Whereas this addresses time-invariant unobserved heterogeneity, it may also bias our estimates by stripping out organizational complements that may be central to IT productivity (Brynjolfsson and Hitt 1995, Tambe and Hitt 2012, Tambe et al. 2020, Brynjolfsson et al. 2021a), as well as increasing measurement error (and attenuation bias) in the panel (Griliches and Hausman 1986).

4.4. Instrumental Variables

A primary concern in the productivity literature centers on unobserved time-varying shocks that may simultaneously boost output and variable inputs (such as IT investment), upwardly biasing estimates of the productivity impact of IT. We assess this concern using a number of dynamic panel data estimators to identify the coefficients of interest (Arellano and Bond 1991, Blundell and Bond 2000, Levinsohn and Petrin 2003, Ackerberg et al. 2015). These have the benefit of relying on very different identifying assumptions and performing well in

Table 3. IT Performance (Productivity and Survival) by Sourcing Mode and Age Group (2006–2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Full	Full	Young	Older	Young	Older	Full
Model description	Pooled OLS		Cox proportional hazard		Establishment fixed effects		Firm fixed effects
Dependent variable	*ln Sales*		*Exit*		*ln Sales*		*ln Sales*
ln ITO	0.0002	−0.0004	0.951*	0.968**	0.009***	0.001**	0.002*
	(0.001)	(0.001)	(0.026)	(0.014)	(0.003)	(0.0007)	(0.001)
ln ITK	0.013***	0.012***	1.046**	0.900***	0.007**	0.003**	0.009***
	(0.001)	(0.001)	(0.023)	(0.014)	(0.004)	(0.001)	(0.001)
Young	−0.020***	0.270***					0.163***
	(0.004)	(0.026)					(0.036)
ln ITO × *Young*		0.007***					0.007***
		(0.002)					(0.003)
ln ITK × *Young*		−0.001					−0.001
		(0.002)					(0.003)
Controls for production inputs and size	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year controls	Yes	Yes	Yes	Yes	No	No	Yes
Establishment and year fixed effects	No	No	No	No	Yes	Yes	No
No. of establishments per year	~26,600	~26,600	~4,900	~22,400	~4,600	~22,000	~26,600
No. of years	9	9	6	6	9	9	9
Adjusted R^2	0.939	0.939			0.585	0.600	0.961

Notes. Results in columns (1) and (2) are OLS estimates of plant-level productivity based on the full sample, controlling for year-NAICS6 fixed effects. Columns (3) and (4) report hazard ratios from Cox proportional hazard model estimates of survival for the young and older samples, respectively. The survival-model samples are based on data from 2006 to 2012 because of LBD limitations on identifying exit at the time of the analysis. Columns (5) and (6) report within-plant productivity estimates for the young and older samples, respectively, controlling for year trends. Column (7) reports productivity estimates based on the full analysis sample, replacing plant-level fixed effects with firm-level ones while controlling for year trends. The dependent variable for columns (1), (2), (5), (6), and (7) is total sales in log terms, whereas the dependent variable for columns (3) and (4) is probability of exit (i.e., death). Unreported production inputs are also controlled for in all columns in log terms: cost of materials, cost of energy, labor (both expenditure on temporary employees and the count of regular employees), non-IT capital stock, as well as all other IT expenditures on software and equipment. The models in columns (2) and (7) fully interact Young with all production inputs (coefficients available upon request). Standard errors for columns (1), (2), (5), and (6) are clustered at the establishment level; column (7) is clustered at the firm level. Results are robust to two-way clustering at county and establishment and firm and establishment levels as well.

*, **, and ***Statistical significance is denoted as follows: 10%, 5%, and 1%, respectively.

prior panel-methods studies of IT productivity (Tambe and Hitt 2012). We also explore the timing of the effects in order to rule out reverse causality (Granger 1969).

Finally, we build on prior findings that IT diffusion often has a local geographic component (Forman et al. 2005, Tambe 2014) to construct an additional instrumental variable. Leveraging the LBD, we calculate the percentage of establishments in a focal plant's county that are in the data hosting and processing industry (NAICS 518210). This includes 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. We further lag this by two years to reduce any remaining simultaneity.

5. Results

Table 3 presents our main findings on the relationship between IT strategy and producer performance by sourcing mode and age group. Setting aside the age group interaction for a moment to highlight what its omission would yield, Column (1) estimates Equation (3) using pooled OLS. Here, we observe no productivity benefit from ITO expenditure, on average, whereas the coefficient on ITK is positive and both economically and statistically significant (at the 1% level). A 1% higher ITK is associated with 0.013% higher sales, controlling for inputs (including other IT) and size. This magnitude is similar to or slightly lower than results in prior work.[18]

This pattern shifts, however, once we account for whether the plant is in the early stages of its lifecycle in column (2). Interacting all covariates with an indicator for being five or fewer years old (*YOUNG*), a 1% higher ITO expenditure is significantly associated with 0.007% higher productivity (consistent with Hypothesis 1). In contrast, the interaction between *YOUNG* and ITK in the next row is both small and imprecisely estimated.[19] From this, we cannot reject that the young enjoy the same ITK-based productivity as older plants, on average. In other words, when "returns" are defined in terms of multifactor, revenue-based productivity, the empirical evidence is more in line with Hypothesis 2b than Hypothesis 2a.

Next, we examine survival as a distinct dimension of performance. In columns (3) and (4) of Table 3, estimation of a Cox proportional hazard model indicates that

ITO expenditure promotes survival among both the young and the old. Among the young, a one-unit increase from mean logged ITO is associated (at the 10% significance level[20]) with being 4.9% less likely to exit, ameliorating the 14.7% average exit rate for young plants during this period.[21]

In contrast, the next row in column (3) indicates an *increasing* likelihood of death among young plants with greater ITK: A one-unit increase in ITK is associated with being 4.6% more likely to die (significant at the 5% level). This contrasts with the survival *advantages* of ITK among older plants in column (4) (10% less likely to exit), which significantly exceed their survival gains from ITO (3.2% lower hazard).

One implication of this is potential survival bias in the ITK estimates for young plants in columns (1) and (2), to which we turn in Table 4. At face value, however, these findings support both the benefits of option value from ITO early in life (Hypothesis 1) and reveal a novel dimension of well-known performance gains for incumbents from traditional ITK investment (Tambe and Hitt 2012). This pattern further supports our hypothesis concerning the dynamic tradeoff faced by young producers with respect to ITK investment (Hypothesis 2a). On net, it highlights the importance of considering different ways to assess performance across the producer lifecycle.

Columns (5) and (6) explore within-plant changes in IT use, splitting the sample by *YOUNG* to identify age-based differences. Relying on fixed effects shrinks the effective sample and introduces additional survival-based selection (plants must persist for at least two consecutive years to remain in the sample, which eliminates one third of the young). Also, this approach identifies the relationship between *changes* in productivity and changes in IT expenditure, which has advantages and disadvantages (see Section 4).

Despite these sample differences and reliance on different sources of variation in the data, our estimate of ITO productivity among the young (row 1, column (5)) does not change significantly. This is striking compared with prior IT productivity studies, which typically report lower estimates once fixed effects are stripped out (Brynjolfsson and Hitt 1995). This is consistent with a limited role for time-invariant organizational complements with regard to this type of IT among the young (Hypothesis 1).

We compare with older plants, next, to examine dynamics. In column (6), average returns to ITO are both positive and significant, although small (coefficient of 0.001). One interpretation is that long-lived organizational complements may actually be *counterproductive* for ITO in our setting. This is consistent with recent

Table 4. IV Estimates of IT Productivity for Young Producers (2006–2014)

Model description	(1) OLS	(2) Arellano-Bond System GMM	(3) Olley-Pakes (accounting for exit)	(4) Levinsohn-Petrin	(5) Ackerberg-Caves-Frazer (ITO and ITK endogenous)	(6) Data center intensity (lagged two years)
Dependent variable				*ln Sales*		
ln ITO	0.007***	0.031***	0.007***	0.007***	0.019***	0.402**
	(0.002)	(0.012)	(0.003)	(0.002)	(0.006)	(0.146)
ln ITK	0.012**	0.005	0.019***	0.013***	0.030***	−0.004
	(0.002)	(0.010)	(0.001)	(0.002)	(0.009)	(0.007)
Establishment and year fixed effects	No	Yes	No	No	No	No
Industry × year fixed effects	Yes	No	Yes	Yes	Yes	Yes
First stage						
Data center intensity	N/A	N/A	N/A	N/A	N/A	29.2***
						(8.02)
F-test	N/A	N/A	N/A	N/A	N/A	13.22
No. of establishments per year				~4,600		
No. of years	9	7	9	9	9	9

Notes. Based on the Young sample (five or fewer years old). Column (1) reports pooled OLS estimates including year-NAICS6 fixed effects. Column (2) reports system-GMM estimates following Arellano and Bond (1991) and Blundell and Bond (2000), using two-period lagged differences and levels as GMM instruments for ITO expenditure. This specification passes both the overidentification and autocorrelation tests. Column (3) estimates rely on the semiparametric method developed by Olley and Pakes (1996), which uses capital investment (both structure and equipment) as a proxy for unobservable shocks. It also addresses selection arising from establishment exit. Column (4) follows the approach in Levinsohn and Petrin (2003), using expenditure on intermediate inputs (i.e., cost of temporary employees) as a proxy for unobservable productivity shocks. Column (5) employs the method developed by Ackerberg et al. (2015) to address collinearity in the Levinsohn-Petrin approach. This approach notably treats both ITO and ITK as endogenous variables. Column (6) instruments for ITO using lagged data center intensity (percentage of number of data centers to total establishments) in the local county in a standard IV framework and passes all tests for weak identification, under-identification, and endogeneity. Unreported controls in all models include, in log terms: cost of materials, cost of energy (both electricity and fuel), software and equipment operating costs, and labor (both expenditure on temporary employees and count of regular employees); columns (3)–(6) also include year-NAICS6 fixed effects.

*, **, and ***Statistical significance is denoted as follows: 10%, 5%, and 1%, respectively.

emphasis on misalignment in IT outsourcing (Handley 2017, Bapna et al. 2023), although using a very different measure of ITO. In addition, the magnitude of within-plant returns to ITO is a fraction of that for the young, consistent with diminishing returns to ITO over the lifecycle (Hypothesis 3).

For ITK, reported in the next row across both columns (5) and (6), stripping out time-invariant organizational complements reduces ITK returns relative to column (2)—although only significantly so for older plants.[22] This is consistent with vintage-related advantages for young producers (Hypothesis 2b). Also, the reduced sensitivity to including fixed effects among the young is consistent with lower organizational complements early in life that, presumably, will accumulate over time. Yet, in column (6), the lower point estimate (even though confidence intervals overlap) among older producers might indicate diminishing or even declining returns to ITK at some point in the lifecycle (consistent with Hypothesis 4).

A key takeaway from Table 3 is that overall IT productivity (i.e., combining returns across both sourcing modes) is markedly higher for the young. This observation holds true, particularly when we strip out organizational complements in the plant fixed-effects model (Figure A.1 in the Online Appendix). This finding diverges significantly from the existing IT productivity literature focused on larger firms, indicating a unique channel linking trends in IT expenditure to the increasing participation of young producers in the broader economy.

Column (7) explores robustness with regard to our level of analysis. Although most establishments in the U.S. economy are single-unit firms (U.S. Census Bureau Business Dynamics Statistics 2021), roughly 70% of plants in our sample belong to multi-unit parents (Table 1). In column (7), replacing plant-level fixed effects with firm-level ones yields coefficients between the OLS and plant fixed-effects estimates. On the one hand, this is consistent with a role for both establishment and firm unobservables and replicates prior findings that IT-related capabilities spill over across establishments within firms (Forman et al. 2008, McElheran et al. 2024). On the other hand, the mechanism at work appears quite distinct from those related to age and lifecycle stage because interactions of *YOUNG* with both types of IT are nearly identical to those in column (2). We thus infer that the link between producer age and IT strategy performance is quite localized, even within multiestablishment firms, supporting arguments in Section 2 concerning our level of analysis.

5.1. Identification

Table 4 explores a number of approaches for addressing endogeneity and survival bias in OLS (reprised in column (1)). Column (2) uses the system GMM estimator, relying on two-period lagged differences for all variable expenditures to instrument for current-period ITO expenditure (Arellano and Bond 1991, Blundell and Bond 2000). The ITO coefficient becomes much larger at 0.031. Column (3) follows the semiparametric method developed by Olley and Pakes (1996), which uses capital investment as a proxy for unobservable shocks and addresses survival bias, yielding an ITO estimate identical to that in column (1). The instrument in column (4) relies on intermediate inputs (Levinsohn and Petrin 2003); leveraging detailed data on temporary-employee expenditures,[23] the ITO estimate remains the same, despite very different identifying assumptions. Following the alternative approach of Ackerberg et al. (2015), in column (5), we again obtain a higher estimate of 0.019. All estimates remain statistically significant at the 1% level and point to downward bias, if any, in the OLS estimates.

In column (6), we leverage geographic variation in the supply-side of IT services as a conditionally exogenous shifter of ITO expenditure. Figure A.2. in the Online Appendix maps the county-level intensity of data services providers as a percentage of all local nonfarm establishments (as of 2010). Areas of high concentration are observed to be distributed across the United States, including in places, such as northern Virginia and Quincy, Washington, that are distant from known technology clusters in California and Massachusetts.[24]

Instrumenting for ITO using lagged intensity of IT services suppliers in the local county, we find a very strong first stage. The results pass both the weak and underidentification tests but fail to reject the null that ITO is exogenous. The second stage yields a positive and statistically significant coefficient, though with a point estimate that is an order of magnitude larger.[25] One interpretation could be a strong local average treatment effect (LATE), whereby the instrument captures a disproportionate productivity response among plants that are sensitive to the instrument (Angrist and Pischke 2009). Concretely, if local plant managers are susceptible to high real (or perceived) risks related to observability and monitoring (Mayer and Salomon 2006), they may be constrained from beneficial use of ITO if far from a local services provider. Another, more convoluted explanation could be access to unmeasured local inputs that increase with presence of IT services providers (and persist at least two years), contributing to ITO productivity in ways not addressed by our other detailed controls (which notably include energy expenditure and wages).[26]

Overall, despite common concerns about upward bias due to selection into IT strategies, results for ITO in Table 4 suggest otherwise. Regarding ITK, the point estimate in the Olley-Pakes model (column (3)), which accounts for plant exit, is quite close to the OLS estimate, mitigating concerns about survival bias. An IV estimate for ITK is also reported in column (5), where both ITO and ITK are treated as endogenous variables. The ITK coefficient is significantly larger than the OLS estimate, again consistent with downward bias and in line with prior findings with respect to IT investment (Tambe and Hitt 2012).

As part of our "collage of evidence," we also exploit the panel structure of our data to rule out reverse causality via a Granger (1969)-style test. Reported in Table A.3 in the Online Appendix, we find that the timing runs from ITO to productivity gains (not vice versa), although ITK appears to be more vulnerable to this set of concerns.

5.2. Performance Dynamics

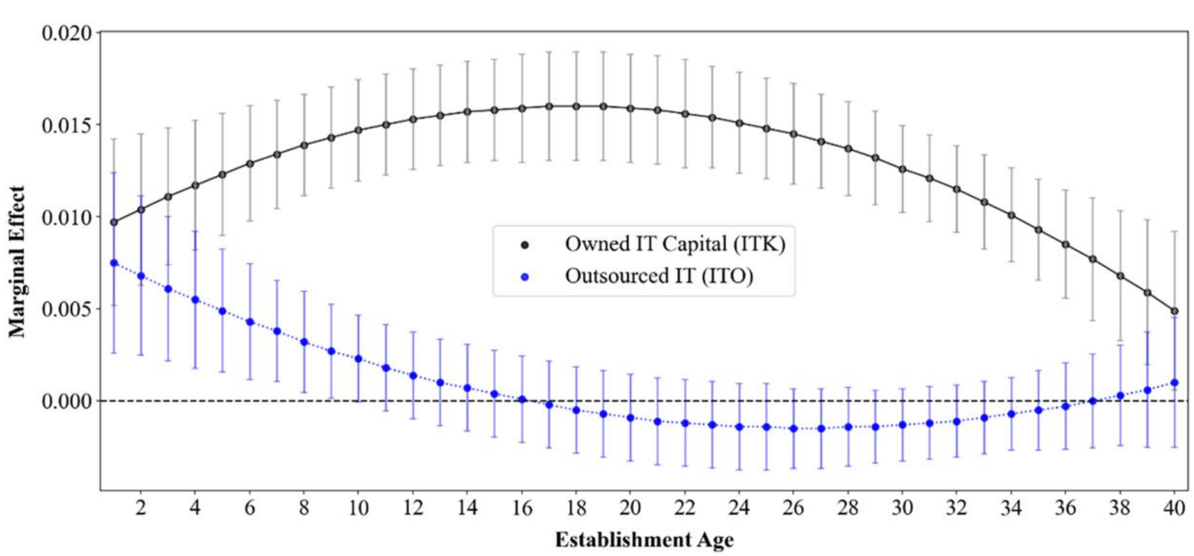
For completeness, we replicate the above tests for the older subsample in Table A.4 in the Online Appendix. We find that instrumenting for ITO yields consistently small and noisy coefficients, with the exception of using the intensity of local IT services providers (column (6)). Here, the coefficient for ITO is both large and statistically significant (again, possibly due to a large LATE). However, the point estimate is smaller than that for younger producers, in line with declining returns to ITO with age (Hypothesis 3).

What about ITK? As in Table 4, columns (3) and (5) in Table A.4 in the Online Appendix employ different approaches for addressing survival bias and endogeneity in ITK. Accounting for exit, the Olley-Pakes coefficient on ITK in column (3) remains positive and highly significant, although slightly larger than the OLS estimate in column (1). When both ITO and ITK are treated as endogenous in the Ackerberg-Caves-Frazer model in column (5), the ITK coefficient more than doubles. Similar to our findings among the young, the overall pattern is one of downward bias in OLS, particularly with respect to ITK. Comparing across age groups (Table 4 versus Table A.4), the ITK estimates overlap, consistent with the compensating effects of vintage-related advantages for the young (Hypothesis 2b) and experience-related advantages for older incumbents (Tambe and Hitt 2012).

To better observe how IT strategy performance varies more-granularly with age, we deviate from the standard TFP framework, estimating a specification similar to column (2) in Table 3, but using a continuous age measure in the interaction term and including a quadratic in age and its interactions with all inputs. Figure 3 plots the marginal returns to both ITO and ITK against plant age, along with 95% confidence intervals. Despite gains early in life from ITO, we observe its productivity declining sharply as plants age, although at a decreasing rate. By 11 years of age, productivity returns from ITO are statistically indistinguishable from zero (again consistent with Hypothesis 3).

In contrast, the marginal contribution of ITK displays an "inverted U" shape. Returns are positive and significant regardless of age, increasing until roughly 18–20. The upward-sloping part of the curve is consistent with vintage-specific advantages for the young with respect to ITK (Hypothesis 2b). Yet, consistent with challenges of maintaining endowments and rising obsolescence later in life, returns to ITK flatten out and then diminish over the observed age distribution (top-coded at 40 in our data). This curvilinear pattern, although apparent in the graph, is actually muted by overlapping confidence intervals. Thus, although we interpret these results as

Figure 3. (Color online) IT Productivity by Sourcing Mode and Producer Age (2006–2014)



Notes. Based on OLS estimation of models with industry-year fixed effects, interacting establishment age and age squared with the IT measures and controlling for other production inputs. Vertical bars indicate 95% confidence intervals.

supportive of Hypothesis 4, they underscore the difficulty inherent in empirically disentangling age-specific heterogeneity from other effects, such as size (Kueng et al. 2014).

5.3. Mechanism Tests

With that in mind, we probe the mechanisms underlying our results. Table 5 seeks to pin down the role of uncertainty as a driver of dynamic tradeoffs in IT strategy. Leveraging other Census data on plant capacity utilization (PCU)—variation in which has been used to identify contexts where uncertainty in market demand, supply of inputs, or other aspects of production is higher[27]—column (1) shows that young-producer gains from ITO are dramatically increased in industries where uncertainty is higher: the interaction term is 0.012 and significant at the 1% level. In column (2), we find that, in these specific contexts, even older plants show productivity gains from ITO. The coefficient is much smaller at 0.006 but statistically significant at the 1% level. ITO has a negative and significant association with productivity for older plants outside of these industry settings, suggesting that losses from outsourcing are nontrivial when not balanced by gains from flexibility. Consistent with the survival results (Table 3), greater ITK harms the performance of both younger and older producers in high-uncertainty contexts.

Columns (3) and (4) use a different measure of uncertainty based on the cross-sectional dispersion of industry-level sales growth (Bloom et al. 2018), lagged by two years, yielding near-identical results. Industry-level measures are arguably more exogenous to plant-level performance and data constraints for the young subsample are less binding (younger plants lack the historical data required to construct plant-specific measures). Nevertheless, we also explore plant-level uncertainty (following Bloom et al. 2020) in the older subsample in column (5).[28] Returns to ITO are positive and

Table 5. Uncertainty Mechanism Tests (Industry-, Plant-, and Firm-Level Measures)

Model description	(1) High uncertainty	(2) High uncertainty	(3) High uncertainty	(4) High uncertainty	(5) High uncertainty	(6) Young MU in new market
Uncertainty measure	Industry-level PCU based		Industry-level sales based		Plant level	Firm level
Sample	Young	Older	Young	Older	Older	Young
Dependent variable	*ln Sales*					
ln ITO	0.002	−0.003**	0.004	−0.002	−0.002*	0.001
	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)
ln ITK	0.019***	0.023***	0.017***	0.018***	0.012***	0.013***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
High Uncertainty	0.007	−0.021***	0.013	−0.073***	0.001	
	(0.011)	(0.006)	(0.013)	(0.009)	(0.007)	
ln ITO × High Uncertainty	0.012***	0.006***	0.011**	0.006***	0.005***	
	(0.004)	(0.001)	(0.005)	(0.002)	(0.002)	
ln ITK × High Uncertainty	−0.009**	−0.004**	−0.002	0.014***	−0.001	
	(0.004)	(0.002)	(0.005)	(0.002)	(0.002)	
ln ITO × Single-Unit						0.007
						(0.006)
ln ITO × Multi-Unit + New Market						0.012**
						(0.005)
No. of establishments per year	~4,600	~22,000	~4,600	~22,000	~22,000	~4,600
No. of years	9					
Adjusted R^2	0.897	0.928	0.898	0.928	0.939	0.899

Notes. Columns (1), (3), and (6) are based on the Young sample, columns (2), (4), and (5) are based on the remaining sample of older plants. All columns report OLS estimates of productivity at the plant level, with logged sales as the dependent variable (controlling for production inputs). The first four columns include sector (two-digit NAICS) and year fixed effects, whereas the last two columns include year-NAICS6 fixed effects. All columns control for software and related equipment and interactions of these investments with the uncertainty measure indicated for that column. High uncertainty in columns (1) and (2) denotes being in a six-digit NAICS industry with above-mean variance in the quarterly plant capacity utilization rate. In columns (3) and (4), it denotes being in a three-digit NAICS industry with a top-quartile standard deviation in average sales growth (lagged one year). In column (5), it indicates being in the top quartile for standard deviation in plant-level sales growth. Note that this establishment-level measure can only be constructed for older plants due to the requirement of having four prior years of data to calculate standard deviations in sales growth. Uncertainty in column (6) is captured by differentiating between single-unit firms and plants belonging to multi-unit parent firms, with *Multi-Unit* + New Market indicating plants operating in an industry different from their corporate parent. Interaction terms for ITK are included in column (6) but are all noisy (and hence omitted to save space). Also controlled for but not reported: costs 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) in log terms (available upon request). Standard errors for all columns are clustered at the establishment level.

*, **, and ***Statistical significance is denoted as follows: 10%, 5%, and 1%, respectively.

significant among older plants facing greater idiosyncratic uncertainty while having a negative (albeit noisy) direct effect within this age group.

Finally, we exploit the data's nested structure to understand the extent to which these findings apply to new units of existing firms as well as to new standalone startups. Specifically, we distinguish new single-unit firms from new units of larger, multi-unit parents. In column (6) of Table 5, interacting ITO with an indicator for being a young single-unit firm (versus a young multi-unit plant) yields a small and statistically insignificant estimate. This indicates that new firms and new units of existing firms show very similar (positive, although noisy) returns to ITO (see also Figure A.3 in the Online Appendix). However, interacting ITO with an indicator for being a young multi-unit plant that operates in an industry different from the industrial focus of its corporate parent, we find a much larger and statistically significant return to ITO early in life.

Overall, this supports our arguments that superior flexibility in outsourced versus owned IT is disproportionately valuable for mitigating uncertainty. Although this does not rule out other early lifecycle considerations, it is quite telling that this pattern holds not only early in the life of standalone startups, but also among older producers and new units of existing firms in high-uncertainty contexts.

5.4. Alternative Explanations

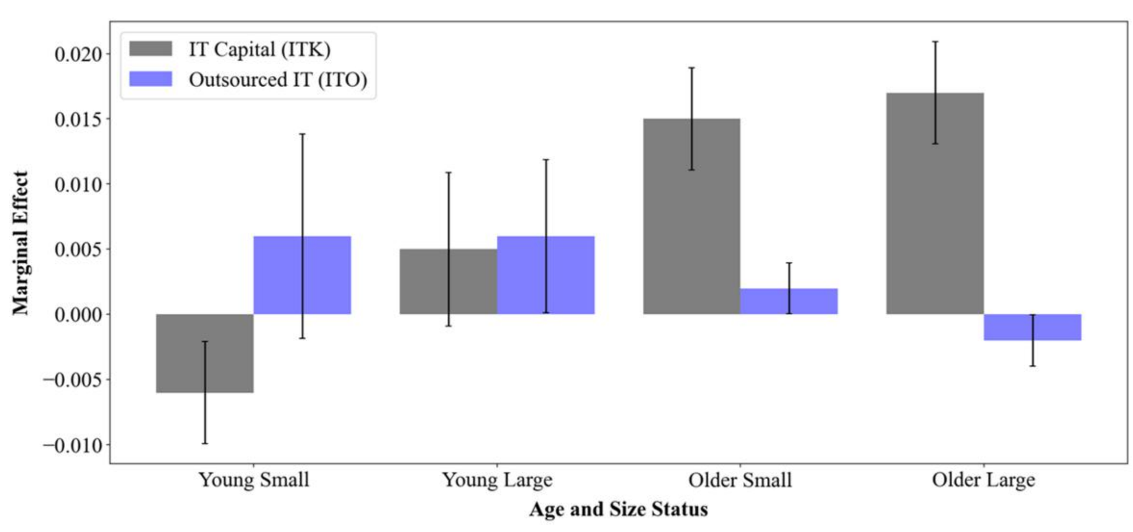
Alternative mechanisms have been proposed for the lifecycle patterns we observe. Size, in particular, is both widely observable and often confounded with age (Kueng et al. 2014), despite distinct managerial and policy implications (Haltiwanger et al. 2013). Although our core findings control for size measured by total employment, we employ a sharper cutoff and interaction effects to further disentangle mechanisms. Presented in Figure 4, we find that young plants below the median size for their industry are more productive with ITO compared with ITK, which actually shows negative returns. However, older plants, regardless of size, benefit disproportionately from ITK, contradicting size as the main driver.[29]

We further examine common claims that a chief benefit of ITO comes via cost efficiency. The lack of difference between single-unit and multi-unit plants with respect to ITO productivity in column (6) of Table 5 casts doubt on this argument (otherwise startups should show larger returns to ITO). We probe further, however. A well-established finance literature argues that businesses with low markups, in counties with lower growth in their collateral values, and those that operate in high-competition (low profit-margin) industries are more likely to face higher external financial constraints (Cvijanović 2014). As this would make cost savings on IT particularly valuable, we interact our IT measures with indicators for having lower markups, being located in counties with low growth of real estate values,[30] and operating in low profit-margin industries. Yet we find no support for this cost-based mechanism (see Table A.5 in the Online Appendix). Direct effects are as expected, yet interactions between these indicators and ITO are small and noisy across specifications.[31]

5.5. Robustness and Heterogeneity

Table 6 provides evidence that our young-producer findings are robust to a range of other econometric

Figure 4. (Color online) IT Productivity by Sourcing Mode by Age and Size Group (2006–2014)



Notes. Young indicates establishments that are five or fewer years old. Small indicates establishments with below-median employment within their four-digit NAICS industry in a given year. The *y* axis indicates the marginal effect on plant productivity of owned IT capital stock (ITK) and outsourced IT (ITO) by age and size group. Joint significance tests for the linear combinations of the indicators (e.g., Young and Large) are conducted using the STATA 13 **lincom** command. Vertical bars indicate 95% confidence intervals. Detailed results are available upon request.

Table 6. Robustness and Heterogeneity for Young Producers (2006–2014)

Model description	(1) Regional controls	(2) Alternative labor measure	(3) Include imputed data	(4) Nonwinsorized	(5) Translog production function	(6) LBD P-Score weights	(7) ASM weights	(8) IT-intensive industry interaction
Dependent variable				*ln Sales*				
ln ITO	0.007***	0.015***	0.016***	0.007***	0.008***	0.020***	0.010***	0.0002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
ln ITK	0.013***	0.026***	0.014***	0.013***	0.009***	0.016***	0.011***	0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
ln ITO × IT-Intensive Industry								0.009**
								(0.004)
ln ITK × IT-Intensive Industry								0.004
								(0.004)
Controls for production inputs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
No. of establishments per year	~4,600	~4,600	~11,300	~4,600	~4,600	~4,600	~4,600	~4,600
No. of years				9				
Adjusted R^2	0.907	0.899	0.919	0.906	0.909	0.909	0.911	0.898

Notes. Based on the Young sample. All columns report OLS estimates of productivity at the plant level, with logged sales as the dependent variable controlling for production inputs. Columns (1)–(7) also control for industry-year fixed effects. Columns (1)–(5) are based on unweighted OLS. Column (1) adds regional fixed effects. Column (2) employs a quality-adjusted measure of labor inputs calculated by multiplying total production hours by the ratio of production-worker wages to total wages (in log terms). Column (3) includes observations with Census Bureau–imputed values for the IT measures. Column (4) re-estimates the production function using nonwinsorized variables. Column (5) estimates a translog production function instead of a Cobb-Douglas model. Columns (6) and (7) report weighted-OLS estimates based on propensity-score weights from the LBD and on the ASM sampling weights, respectively. Column (8) interacts the IT variables with an indicator for being in an IT-intensive industry (three-digit NAICS), defined as having above-mean IT capital stock in 2005, and controlling for sector (two-digit NAICS) and year fixed effects. Also controlled for in all columns but not reported: cost of material, cost of energy, software and equipment operating costs, and labor (both expenditure on temporary employees and the count of regular employees), all in log terms.
*, **, and ***Statistical significance is denoted as follows: 10%, 5%, and 1%, respectively.

choices such as adding regional controls (column (1)) and quality-adjusted labor inputs (column (2)). Column 3 uses Census Bureau–imputed IT values, which we excluded due to lack of visibility to the imputation method(s). Column (4) relies on nonwinsorized values.[32] We estimate a translog production function in column (5). To rule out any remaining sample selection concerns, we report propensity score weighted estimates based on the population-wide LBD and ASM survey sample weights (columns (6) and (7), respectively).[33] Overall, results are similar to or less conservative than those in Table 3.

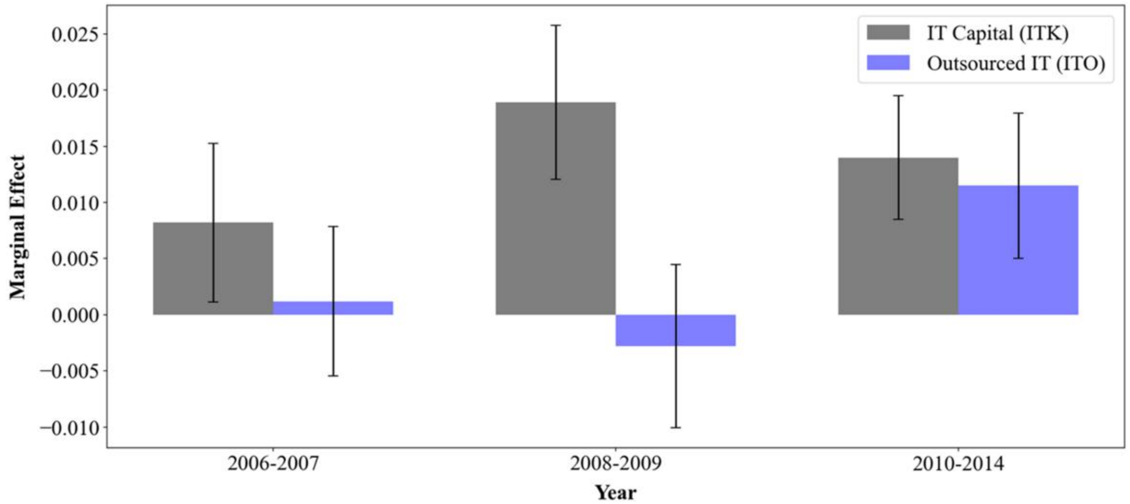
We explore heterogeneity in column (8), interacting the IT variables with an indicator of whether the plant is in an industry that relies intensively on IT as an input. Controlling for sector (NAICS-2) and an annual time trend, the interaction in column (8) is positive and significant at the 5% level and commensurate with the magnitudes from Table 3. The direct effects of ITO become insignificant, suggesting that the productivity benefits of ITO are relatively concentrated in IT-intensive industries.

5.6. Timing and the Rise of Cloud Computing

We next investigate the extent to which the young-producer advantage with ITO may be attributed to changes ushered in by cloud computing. By the mid- to late 2000s, near-ubiquitous high-speed Internet and entry of cloud services providers granted firms new access to highly scalable IT resources on an as-needed basis (Brynjolfsson et al. 2010, Cusumano 2010). Public cloud computing quickly became a prominent form of ITO (Willcocks and Lacity 2016, Sunyaev 2020) and arguably the dominant platform for startups (Ewens et al. 2018, Impink 2022). Compelling claims about the cloud's ability to "democratize IT" (Bloom and Pierri 2018) are widespread, yet they are also short on systematic evidence (DeStefano et al. 2023). The specific term "cloud computing" was not captured in administrative data collections in the United States until 2017 (Zolas et al. 2020), despite being increasingly available in the market.

Ultimately, we cannot directly disentangle various models of ITO with the data to hand. Yet, we can exploit the timing of these effects across our sample, which captures the initial rise of the cloud. By most reasonable accounts, the cloud platform was not widely available to enterprises until 2009 or later (Staten 2008). Figure 5 reports how our core estimates vary across the earliest years (2006–2007), middle years (2008–2009, which includes the Great Recession), as well as later ones (2010–2014). Here, returns to our measure of ITO do not show up until *after* 2009. Further robustness tests using IV estimation similar to column (6) of Tables 4 and 5 display similar patterns (see Table A.8 in the Online Appendix). Although the included industry-year controls will dampen the effect of a large number of secular trends,

Figure 5. (Color online) Young-Producer IT Productivity over Time (2006–2014)



Notes. Based on column 1 of Table 3. The *y* axis indicates the marginal effect on plant productivity of owned IT capital stock (ITK) and outsourced IT (ITO) by time period. Vertical bars indicate 95% confidence intervals. Detailed results are available upon request.

this timing is consistent with the diffusion and price declines widely associated with the rise of the cloud. This is in line with discussions emphasizing the substantial advantages for startups stemming from declining costs of founding and scaling in the cloud (Ewens et al. 2018), as well as more-recent evidence suggesting that cloud technologies favor digitalization and growth of smaller firms (Caldarola and Fontanelli 2024). In contrast, incumbent productivity across periods remains rooted in ITK, with noisy returns to ITO, regardless of timing (see Figure A.5 in the Online Appendix).

6. Discussion and Conclusion

This study theoretically and empirically examines how dimensions of IT strategy, including modern ITO expenditure and ITK investment, affect young businesses and their performance across the lifecycle. Synthesizing and extending core ideas from diverse work in lifecycle theory and the theory of the firm, we highlight the dynamic tension between outsourcing's support for flexibly accessing frontier (yet widely available) inputs in the short term, and ownership's advantages for developing organization-specific resources and capabilities over time. We further account for obsolescence—a salient characteristic of modern IT—in establishing core intuitions. To our knowledge, this is the first study to leverage lifecycle theory to examine dimensions of IT strategy performance and dynamics, particularly among the young. In particular, the organizational complements and economies of scale known to affect IT productivity among larger incumbents tend to be systematically lacking among the young, while market and technological uncertainty are systematically higher—just when investments in future growth may be most pressing.

Empirically, we test our predictions in a large and detailed panel of U.S. Census Bureau microdata, finding that returns to IT vary both by age and by sourcing mode, with the highest returns to ITO in the earliest years of the producer lifecycle. ITO supports both early survival and productivity, yet quickly gives way to superior—though eventually diminishing—gains from owned ITK. We observe in the rich administrative data that young establishments—both young firms and new units of existing firms—invest early in both ITO and ITK. However, large bets on ITK may not always pay off, and sunk IT capital is implicated in an increased likelihood of exit during the vulnerable early years of life.

Stepping back from the detailed findings, we conclude that how "performance" is defined and measured matters: survival and productivity are in tension, early in life. Whereas ITO helps along both dimensions, ITK investment is more likely to promote exit in the first five years of life. On net, however, the combination of option value and vintage-related advantages help the young leverage *both* ITO and ITK to demonstrate, overall, greater IT productivity than older and larger producers. This finding is novel in the context of IT productivity research that has oversampled large incumbents and an entrepreneurship literature that has overlooked IT.

These findings have profound implications for economic dynamism and productivity in the broader economy. In particular, if young firms are more able to survive, thrive, and scale by leveraging modern IT inputs than previously recognized, this suggests an underappreciated channel by which innovation and job creation may increase, potentially uncovering the productivity gains that have been elusive in recent years (despite significant and growing IT investment). Indeed, our findings with respect to ITO echo a puzzle receiving attention in recent IT productivity research, whereby significant IT outlays fail to yield measured productivity gains (Brynjolfsson et al. 2021b). Whereas prior work focuses on computer hardware and software investment, we also observe this pattern with respect to ITO over this time period.

Yet, unlike these previously observed patterns, organizational intangibles appear unhelpful in realizing returns to our measure of ITO. This runs counter to a literature that has focused overwhelmingly on incumbents and taken their accumulated organizational capital as given—and almost universally productivity-enhancing. This may be due, in part, to our more fine-grained measure, which does not rely only on large IT outsourcing contracts. It may also reflect innovations due to the rise of the cloud that were surely present in the latter part of our sample period. Ultimately, the patterns we observe are informative of the role that learning and accumulated knowledge play in realizing returns to modern IT strategy, more broadly. In particular, it suggests that this stock of expertise not only takes time to build but is disproportionately valuable for specific IT resources and capabilities like ITK. Visibility to the broader IT portfolio (i.e., both ITO and ITK together) and comparison across types of IT is critical to this understanding.

It is worth noting, further, that a reliance on popular fixed-effects models would have both imposed significant selection on our core analysis sample and also worked to obscure the sensitivity of these estimates to unobserved organizational capital. Thus, triangulating using a range of models and data is essential.

We cannot rule out every mechanism that could contribute to the patterns we observe. However, we find robust evidence for mechanisms rooted primarily in managing uncertainty, rather than financial or size-based constraints. This manifests not only in plants, but also among older establishments that face particularly high levels of uncertainty. It also appears among new units of incumbents when the industry context is also novel.

The managerial implications of these patterns are nuanced. One key takeaway is not to over-prioritize ITO early in life. Early investment and gains from owned ITK among the young point to a need for a balanced digital strategy that considers both short-term survival and productivity and longer-term learning and resource accumulation in IT sourcing. That said, the risks of large sunk ITK investments, particularly at a time of high and rising obsolescence, require more consideration than they typically receive. Finally, a recognition of how localized core mechanisms are (particularly drivers of uncertainty such as novel or high-variance industry contexts) is important in matching IT resources to production contexts. This applies not only among, but also within firms.

Here, it is worth underscoring that a large number of our robustness tests point to the advantage of studying this phenomenon at the subfirm level. Both managerial practice and follow-on research would benefit from disentangling firm-level dynamics from these more micro-level relationships.

Our ability to exploit unusually rich, granular, and nested panel data are foundational to these new insights. That said, these data are not without limitations. In particular, the theoretically and empirically important question of how much of what we observe is due to the rise of cloud computing can only be incompletely addressed. In addition to timing tests, our IV estimation highlights important links between innovations in ITO and the patterns we observe. Yet, these results are more suggestive than dispositive, and this remains an area of study in need of further data collection and inquiry.

Our manufacturing context is an important one in which to examine this phenomenon. It is a leading user of modern IT (Zolas et al. 2020) and a well-established setting for studying productivity and related dynamics at the plant level (Syverson 2011, Foster et al. 2016). However, it is also widely assumed to be less impacted by innovations such as the cloud (Ewens et al. 2018). Again, this points to a need for more detailed measurement and exploration across sectors.

This study draws new attention to the most dynamic contributors to economic dynamism, growth, and innovation: young businesses. Research that extends beyond convenience samples of large, surviving incumbents and that takes both lifecycle and technological dynamics seriously is urgently needed to keep academic insights up to speed with a rapidly shifting technological and economic landscape. Our holistic view on IT strategy across sourcing profiles and over the lifecycle yields insights that contribute to a number of pressing managerial and policy considerations. Yet much more remains to be done to understand how producers may achieve—and sustain—economies *before* scale in an increasingly digital age.

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Endnotes

[1] The U.S. manufacturing sector is a leading user of modern IT (Zolas et al. 2020) and a well-established context for both productivity and business dynamism research (Syverson 2011, Foster et al. 2016).

[2] Authors' calculation based on the U.S. Census Bureau Business Dynamics Database (2021) from the U.S. Census Bureau.

[3] See https://www.statista.com/forecasts/963909/it-outsourcing-services-revenue-in-united-states.

[4] See Kotlarsky et al. (2018) and Bapna et al. (2023) for reviews.

[5] Although a strict linear progression through them is not required, these stages convey the understanding that businesses evolve in ways that have some degree of predictability—and thus should predictably shift their strategies in response to changing internal and external circumstances (Porter 1980, p. 248).

[6] A total of 24.2% of U.S. firms fail at age 1, whereas the death rate for firms under six is 14.7% (authors' calculations based on the U.S. Census Bureau Business Dynamics Database 2021). Employment-weighted cumulative exit within the first five years is ~47% (Haltiwanger et al. 2013).

[7] However, this can be nuanced (Knittel and Stango 2007); we address selection into treatment in Section 5.

[8] Novak and Stern (2008) develop a related set of arguments with respect to vertical integration across the *product* lifecycle, which shares certain characteristics with the producer lifecycle, particularly for new businesses.

[9] An alternative prediction is that self-selection will result in a lack of observed difference, not only across governance modes (Hamilton and Nickerson 2003) but also across lifecycle stages. In fact, much of the firm boundary literature explicitly or implicitly assumes that managers can and will appropriately weigh time-varying cost-benefit profiles in sourcing (Novak and Stern 2008). Yet achieving such "discriminating alignment" turns out to be difficult in practice, leading to identifiable differences in returns across sourcing modes in a range of settings (Handley 2017).

[10] For more on why this is important, see discussion in Forman and McElheran (2024) and citations therein.

[11] Our approach aggregates expenditures at the producer level, departing from prior work studying the "make-versus-buy" decision at the level of a transaction, problem, or project (Williamson 1991, Nickerson and Zenger 2004, Mayer and Salomon 2006) and is closer in approach to a "digital strategic posture" as described in Mithas et al. (2013).

[12] Brynjolfsson and Hitt (1995) find returns to IT capital fall about 50% in within-firm estimates, suggesting that unmeasured and slowly changing organizational features contribute significantly to estimated IT gains.

[13] These are lower than means reported in comparable studies due to the plant-level measure and a thicker tail of the young and small in our sample. Also, IT cost shares (Table 1) tend to be smaller than in nonmanufacturing sectors.

[14] The five-year threshold has proven meaningful in prior work (Haltiwanger et al. 2013, Decker et al. 2014). Robustness to different age cutoffs is reported in Table A.1 in the Online Appendix and supports this choice in our empirical strategy.

[15] Two-digit or three-digit NAICS controls are common in the IT productivity literature. Yet NAICS 31-33 represents the entire manufacturing sector, whereas NAICS 311 is Food Manufacturing and 322 is Paper Manufacturing. In contrast, we can distinguish, for example, Chocolate and Confectionery Manufacturing from Cacao Beans (311351) from Chocolate and Confectionary Manufacturing from Purchased Chocolate (311352).

[16] Core patterns are unchanged when ASM sampling weights are used to represent the overall population.

[17] Several five- and six-digit NAICS industries have no variation in survival outcomes in some years; four-digit NAICS controls stabilize the sample for disclosure avoidance and yield statistically indistinguishable results.

[18] For example, Brynjolfsson and Hitt (1995), Bloom et al. (2012), and Tambe and Hitt (2012). Adjusted R^2 values, as well as a specification focused on value added, are also commensurate with prior findings.

[19] The negative coefficient on *YOUNG* in column (1) is consistent with young establishments suffering from lower initial demand (Foster et al. 2016). The contrasting positive coefficient in column (2) is an artifact of interacting *YOUNG* with all of the other (unreported) production inputs, which is necessary to reveal the vintage-based technical productivity advantages of younger plants that are often obscured in standard approaches (Jensen et al. 2001).

[20] The column (3) coefficient loses precision in the smaller sample imposed by needing to observe exit in the LBD.

[21] Based on authors' calculations using the U.S. Census Bureau Business Dynamic Database (2021); reported in Figure B.3 in the Online Appendix. To contextualize this magnitude further, note that a "one-unit" increase in natural logs is roughly equivalent to a 2.718 increase in ITO (i.e., *exp*(1)).

[22] The coefficient in column (5) of 0.007 falls within the 95% confidence interval of the estimated return to ITK in column (2), based on the linear combination of the ITK coefficient and the *YOUNG* interaction term (roughly 0.011).

[23] Results are consistent when using cost of materials as the instrument (available upon request).

[24] Results are not driven by any particular state or geographic regions; however, additional splits of the data by geography are not reported in accordance with Census' disclosure avoidance policies.

[25] Prior IT productivity studies relying on instrumental variables have generated similarly high magnitudes in the second-stage estimation (Forman et al. 2012, Tambe and Hitt 2012).

[26] Results are robust to using the wage bill to control for labor inputs, which alleviates the concern that higher-quality labor colocates with high data-center intensity areas. We address other threats to identification concerning local unobservable demand shocks or financial support in three ways (thanks to an anonymous reviewer). First, we construct a measure of the employment growth for each county (excluding IT services industries) as a control; Second, we add time-varying state fixed effects. Lastly, we re-estimate our IV regressions at the MSA level (see Table A.2 in the Online Appendix).

[27] A useful discussion of how capacity and capacity utilization are linked to different sources of uncertainty can be found in Paraskevopoulos et al. (1991). We use quarterly variation in plant capacity utilization as our measure.

[28] Roughly one-fifth of the old establishments have missing values for this establishment-level uncertainty measure; we flag and absorb the average effect of the missing observations.

[29] Organizational structure, on its own, also appears uncompelling as a main driver. Although new units of existing firms that are also in distinct industries show different returns to ITO (column (6) of Table 5), splitting the sample by multi-unit status (Figure A.4 in the Online Appendix) indicates that returns are quite similar between young firms and new units of existing firms.

[30] We use county-level house price index database from the Federal Housing Finance Agency. See Bogin et al. (2019) for more details. We constructed an indicator for counties with the bottom quartile house price growth in a given year.

[31] We also split the sample by the plant's percentage of overall firm employment. The effects of ITO above and below the median are

indistinguishable, again contradicting cost-based mechanisms in our setting (available upon request).

[32] The paper centers on winsorized results because the descriptive statics are sensitive to this decision, and this choice keeps the underlying data consistent throughout the core analysis, per Census disclosure avoidance policies.

[33] We conducted two additional sets of robustness tests. The first explores aggregation up to the firm level. Despite incomplete coverage in the ASM of all plants reporting to the same parent firm, we aggregate observed units up to the firm level and rerun the analysis with firm-level fixed effects and time-varying firm-level controls. Results are consistent to those reported in Table 2, column (7), and are presented in Table A.6 in the Online Appendix. The second shows robustness to using alternative IT measures, plant-year fixed effects, alternative performance measures (labor productivity and markups), and a matched-sample approach. Again, results are largely consistent (see Table A.7 in the Online Appendix).

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