The Rise of Industrial AI in America: Microfoundations of the Productivity J-curve(s)*

Kristina McElheran† Mu-Jeung Yang‡ Zachary Kroff§

Erik Brynjolfsson¶

March 20, 2025

Abstract

We examine the prevalence and productivity dynamics of artificial intelligence (AI) in American manufacturing. Working with the Census Bureau to collect detailed large-scale data for 2017 and 2021, we focus on AI-related technologies with industrial applications. We find causal evidence of *J-curve*-shaped returns, where short-term performance losses precede longer-term gains. Consistent with costly adjustment taking place within core production processes, industrial AI use increases work-in-progress inventory, investment in industrial robots, and labor shedding, while harming productivity and profitability in the short run. These losses are unevenly distributed, concentrating among older businesses while being mitigated by growth-oriented business strategies and within-firm spillovers. Timing also matters: earlier (pre-2017) adopters exhibit stronger growth, conditional on survival. Notably, among older establishments, abandonment of structured production-management practices accounts for roughly one-third of these losses, revealing a specific channel through which intangible factors shape AI's impact. Taken together, these results provide novel evidence on the microfoundations of key dynamics in technology adoption and impacts, identifying mechanisms and illuminating how and why *J-curves* differ across firm types. These findings extend our understanding of General Purpose Technologies, explaining why their economic impact—exemplified here by AI—may initially disappoint, particularly in contexts dominated by older, established firms.

JEL Classification: D24, O33, M11, L60,

Keywords: Artificial Intelligence, General Purpose Technology, Manufacturing, Organizational Change, Productivity, Management Practices

*We thank Tobias Kretschmer, Cristina Tello-Trillo, Martha Stinson, and Cheryl Grim for helpful comments, as well as to participants in the Rotman Strategy brownbag seminar, Wharton's AI and the Future of Work conference, the Columbia/Wharton Management of Analytics and Data conference, and the NBER Productivity Lunch. We are grateful to the Stanford Digital Economy Lab for partial funding. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7512395: CBDRB-FY24-CED006-0016, CBDRB-FY25-CED006-001).

†University of Toronto, Email: k.mcelheran@utoronto.ca

‡University of Oklahoma, Email: mjyang@ou.edu

§U.S. Census Bureau, Email: zachary.kroff@census.gov

¶Stanford University, Email: erikb@stanford.edu

1 Introduction

Advances in artificial intelligence (AI) are poised to reshape corporations, industries, and economies. Productivity gains from AI have been established in favorable contexts such as software development (Peng et al., 2023), drug and materials discovery (Lou and Wu, 2021; Toner-Rodgers, 2024), and business services (Brynjolfsson et al., 2023). However, broad-based causal evidence remains scarce. To date, AI adoption among firms has lagged expectations (Bonney et al., 2024) and varies widely (Calvino and Fontanelli, 2023; McElheran et al., 2024), echoing historical cases where transformative technologies required significant organizational adaptation before yielding measurable and often-uneven gains (David, 1990; Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Forman et al., 2012; Feigenbaum and Gross, 2024). Understanding how technology adoption and performance are unfolding in the context of AI is crucial, yet also empirically challenging.

To meet this challenge, we worked with the U.S. Census Bureau to collect new data on AI use in the manufacturing sector at different points in time. In addition to providing granular statistics on firms' AI use and barriers to adoption, we leverage a novel instrumental variable (IV) strategy and within-firm changes to estimate the causal impact of AI on business performance. We find a *J-curve* pattern at the micro-level: the average effects of AI deployment are quite negative in the short run, followed by growth along multiple dimensions over our four-year panel (2017-2021). Averages, however, mask key contingencies that ultimately shape how the *J-curve* pattern plays out across diverse organizational settings.

Our findings contribute to longstanding questions, dating back to Schmpeter (1934; 1942), about what types of firms lead the adoption and application of important innovations. Larger incumbents tend to benefit from economies of scale, as well as from more-developed organizational complements (Bresnahan et al., 2002; Brynjolfsson et al., 2021a; Jin and McElheran, 2024). Yet they also face higher adjustment costs compared to smaller entrants (Henderson, 1993; Bresnahan and Greenstein, 1996; McElheran, 2015; Gans, 2016). This tension is evident in the early AI diffusion data, where larger firms have emerged as leading adopters, but high-growth startups also show a marked propensity to rely on AI in production (McElheran et al., 2024). Our approach addresses this puzzle by disentangling size from correlated orga-

nizational characteristics such as age (Kueng et al., 2014), digital infrastructure (Brynjolfsson et al., 2021a; Zolas et al., 2021), structured management practices (Bloom et al., 2012; Scur et al., 2021), and multi-unit organizational structure (Atalay et al., 2014). We further isolate the role of in-house AI-related human capital (Fontanelli et al., 2024), which we leverage to address self-selection when estimating the returns to AI use.

Even when voluntary, technology adoption does not guarantee productivity gains, especially in the short term (e.g., Tambe and Hitt, 2012). This paper's main contribution, therefore, is providing new micro-level evidence on *J-curve* patterns previously observed at the macro level (Brynjolfsson et al., 2021b), offering novel insights into their shape and duration—and specifically in the context of AI use.

Our empirical context of manufacturing is a particularly interesting one for understanding AI's nuanced impacts. It encompasses a highly innovative set of industries, accounting for 60 percent of all patents (National Science Foundation, 2021) and 70 percent of all corporate patents (Autor et al., 2020a). At the same time, it demonstrates large opportunities and risks from AI adoption. On one hand, some estimates (e.g. Deloitte, 2020) suggest that manufacturing generates twice as much digital information as other data-intensive industries such as media and finance/banking, much of it firm-specific and therefore potentially more-valuable from a competitive strategy perspective (Lambrecht and Tucker, 2016). High levels of physical automation also provide natural inputs and potential complements to AI-related technologies (McElheran et al., 2024). On the other hand, manufacturing production processes are often not modular (Bresnahan, 2024), but instead depend on complex interactions of physical and virtual environments, requiring coordination of machinery, material flows, management practices, human capital, business strategy, information, and technology (e.g., Hayes and Jaikumar, 1991; Parthasarthy and Sethi, 1993; Ichniowski et al., 1995; Milgrom and Roberts, 1990, 1995). Heterogeneity in how to accomplish this abounds. For instance, task interdependence, which has been found to mediate technological change (Combemale et al., 2021), ranges from tightly-coupled continuous-flow production to batch manufacturing and modular "job shops," with accompanying and distinct complementary systems (Hayes and Wheelwright, 1979; McElheran et al., 2019). Understanding how these features shape returns to AI use is critical to gauging its economic and managerial implications.

The theoretical motivation for our study derives from the rich literature on general purpose technologies, or GPTs (Bresnahan and Trajtenberg, 1995) and related work focused on both the challenges and gains associated with technological and organizational "co-invention" (Bresnahan and Greenstein, 1996). Recent macroeconomic studies have highlighted the lag between investment in AI-related technologies and observed economic gains (Furman and Seamans, 2019), highlighting the need for significant investments in intangibles such as process redesign, worker retraining, and complementary software development (Brynjolfsson et al., 2021b). We build on this prior work by examining the phenomenon causally and at the micro-level, leveraging direct measures of otherwise-intangible activities such as management practices (Bloom et al., 2019; Scur et al., 2021), business strategy (Yang et al., 2024), availability of digital inputs (Brynjolfsson and McElheran, 2016), and production process design (Hayes and Wheelwright, 1979; McElheran et al., 2019). We seek to understand not just whether or not *J-curve* patterns characterize early Industrial AI use, but also the organizational channels affecting which firms benefit most or soonest—and why.

Our empirical analysis relies on two separate datasets with tens of thousands of observations and rich information on AI use, use of other digital technologies, and a range of management practices. The data collection was designed for-purpose, in partnership with the U.S. Census Bureau, and has been combined with detailed balance-sheet and performance data from both Census and Internal Revenue Service (IRS) tax records. In addition, we apply three distinct identification strategies to triangulate on the causal impact of AI on performance: selection on observables (with unusually rich time-varying controls), IV, and firm fixed effects.

We find robust evidence of a micro-level productivity *J-curve*, where short-term losses precede longer-term gains. Controlling for many potential confounds (size, age, capital stock, IT infrastructure, and more), the conditional correlation between a standard-deviation higher AI index and productivity is -1.33 percentage points. This loss jumps to -60 percentage points when we address selection into treatment. For this, we instrument for AI use based on the plant not reporting an AI skills gap when asked about barriers to AI adoption, conducting a number of additional analyses to establish the validity of our approach. We further see similar patterns for both productivity and profits.

We link these losses to organizational and production-process adjustment in three ways that are of rising managerial and policy interest. First, we observe increased WIP in response to AI use, consistent with problems maintaining the tight coordination required of modern, often Lean, manufacturing processes (e.g., Milgrom and Roberts, 1988; Womack et al., 2007; Holweg, 2007). Next, AI-induced increases in industrial robots points to tangible production-process adjustments and likely complementarity (Brynjolfsson and Milgrom, 2013) between these different types of automation. Finally, adjustments in factor shares manifest as labor shedding among AI users, consistent with labor substitution (Acemoglu and Restrepo, 2018) in the short run.

Exploiting the panel dimension of our data yields essential nuance. We find that the short-term negative relationship between AI use and performance is robust to including plant-level fixed effects in the 2012-2017 period, which represents the early years of AI deployment in production in the U.S. (McElheran et al., 2024). Allowing more time for adjustment to unfold, however, is beneficial (as predicted by the *J-curve* model). From 2017-2021, which is the earliest we can cleanly separate firms using AI from those that do not, firms that had adopted AI by 2017 enjoyed greater growth in revenue, labor productivity, and employment.

That said, not all firms travel along the same *J-curve*. Adjustment is more challenging for older businesses, whereas young firms—especially those with growth-oriented strategies—show stronger AI-related performance improvements. Digging further, we find that older firms, in particular, struggle to maintain key production management practices. This fall-back in "structured" management (Bloom et al., 2019; Cornwell et al., 2021; Scur et al., 2021) accounts for about one-third of their productivity loss. Conversely, significant within-firm spillovers amplify returns, as productivity gains in one establishment positively affect others. This diversity of challenges and advantages attributable to age, strategic positioning, management practices, and organizational structure underscores the necessity of accounting for heterogeneity in assessing the "impact" of AI in diverse firm populations.

Our findings contribute to several strands of literature. First, we advance the growing body of work on the productivity impacts of general-purpose technologies, or GPTs (Bresnahan and Trajtenberg, 1995), which AI-related technologies are increasingly argued to be (Brynjolfsson et al., 2021b; Goldfarb et al., 2023). Previous research highlights the implemen-

tation lags and complementary investments necessary for GPTs to yield measurable gains (e.g., David, 1990; Milgrom and Roberts, 1990; Brynjolfsson and Hitt, 2000; Brynjolfsson et al., 2021b; Feigenbaum and Gross, 2024). We extend this literature by providing micro-level insights into timing and key sources of heterogeneity across a large and diverse panel of firms.

Second, we contribute to the literature on organizational complements to technology adoption and use. Prior studies have explored how IT interacts with firm characteristics such as worker skills and management practices (e.g., Bresnahan et al., 2002; Tambe et al., 2012; Aral et al., 2012; Brynjolfsson et al., 2021a). Our analysis introduces novel insights by quantifying the contribution of specific management practices associated with Lean Manufacturing (Womack et al., 2007; Holweg, 2007) to the productivity of AI. Furthermore, we document significant within-firm spillovers, adding to the understanding of how local productivity gains propagate across organizational boundaries, amplifying the overall returns to technology investments (which has been relatively underexplored due to data limitations). This may help explain variation in AI returns across countries due not only to different size distributions but also systematic differences in organizational structure (e.g., prevalence of single-unit versus multi-unit firms).

Finally, we add to the literature on strategic positioning and heterogeneity in firm performance over time (e.g., Rumelt et al., 1991; McGahan and Porter, 1997; Teece et al., 1997; Bennett, 2020). By distinguishing between growth-oriented firms and older, established firms, we highlight how strategic differences influence AI's impact on firm outcomes. Our findings on startups demonstrate the outsized gains from early adoption, aligning with recent research on the dynamism of young firms in driving innovation and growth (e.g.Haltiwanger et al., 2013, 2016; Chava et al., 2013; Guzman and Stern, 2020). Our evidence in the context of AI supports a more-nuanced understanding of how firm age, strategy, and adaptability interact with emerging technologies, enriching both theoretical and empirical discussions in strategic management and industrial organization.

Taken together, our findings highlight industrial AI's dual role as a transformative technology and source of organizational disruption, tracing out patterns familiar to scholars of technological change. They further underscore the importance of complementary practices,

structures, and strategies that mitigate adjustment costs and enhance longer-term returns to AI, providing practical guidance to managers and policy-makers interested in "flattening" AI *J-curves* in their firms and economies.

2 Literature and Hypothesis Development

Rising digitization and the diffusion of advanced tools to extract value from data have transformed economic activity along various dimensions, with profound implications for firm performance, competition, and strategy (e.g., Goldfarb and Tucker, 2019; Adner et al., 2019; Tambe et al., 2020). In this section, we extend insights from digitization research in economics and management to formulate testable predictions concerning the adoption and impact of AI use in industrial (i.e., physical goods) production.

2.1 AI as a Digital Resource

2.1.1 Scale Free

Recent theoretical developments in strategic management analyze the organizational and strategic implications of "digital resources, such as data, software and AI that are essentially scale free" (Giustiziero et al., 2023).[1] This work aligns with and extends fundamental economic insights about information and knowledge as non-rival goods (Arrow, 1962a; Romer, 1990), where consumption does not reduce availability to others and reproduction occurs at near-zero marginal cost (Levinthal and Wu, 2010; Adner et al. 2019; Goldfarb and Tucker 2019). AI-related technologies, once trained, share these features. As a result, they are prone to strong economies of scale, creating more value at larger production volumes. These scale economies will be further reinforced by often-significant up-front training costs (Svanberg et al. 2024).[2]

[1] See Helfat et al. (2023) for a review of related work focused on AI and digitization.

[2] Consider the benefits of machine vision technology to analyze digital pictures of finished products to diagnose any quality defects that might often be too subtle to quickly notice for human quality control employees. The initial training of this technology with training data will be expensive but once a sufficient number of training instances is used, the supervised learning algorithm will eventually outperform human vision. In terms of the unit cost economics, training the machine vision algorithm is a large fixed cost, which will be spread out across many units, leading to a decline in marginal cost. Additionally, ongoing training of the machine vision technology will increase

These characteristics work in favor one of the few robust "stylized AI facts" across countries and industries: early AI adoption rates are systematically higher among larger firms (e.g., Calvino and Fontanelli 2023; McElheran et al. 2024; Bonney et al. 2024; Hoffreumon et al. 2024). We anticipate similar size-based adoption patterns in our setting. It is worth noting that properly identifying size-related effects, however, is challenging due to the high correlation between size and other potential shapers of digital technology adoption and performance such as age (Kueng et al., 2014), organizational structure (e.g., multi-unit status, per Atalay et al., 2014), and production process design (McElheran et al., 2019). We control for size in all of our specifications and lean on the richness of our plant- and firm-level data to tease apart these relationships.

2.1.2 One of Many "Waves" of Digital Transformation

The reliance of AI-related technologies on data and digital infrastructure is both taken for granted and widely overlooked as a driver of both adoption and outcomes. Yet it is non-trivial for firms to evolve from physical, manually-managed systems to collecting data and leveraging it in decision making (Brynjolfsson and McElheran, 2016), to building out and updating digital infrastructure (e.g., deploying sensors and moving to flexible cloud computing systems), to ultimately being able to leverage AI-related technologies. Relatively few firms skip the middle steps on the way to AI use (McElheran et al., 2024), suggesting that varying levels of digital capabilities are important both for adopting and effectively leveraging AI.

In particular, we hypothesize that firms that have organized their production processes and management practices to leverage prediction (Brynjolfsson et al., 2021a)—improvements in which are the hallmark of the latest AI technologies (Agrawal et al., 2018)—will be better-positioned to incorporate AI than firms that lack digital infrastructure or that rely on relatively "analog" capabilities to manage their processes.

Hypothesis 1: Reliance on pre-AI predictive analytics will increase the likelihood of AI adoption.

Yet digitization has not been required for significant advances in production and supply chain management in the Lean Manufacturing tradition (Womack et al., 2007; Holweg, 2007).

accuracy, thereby increasing value created from the technology by continued quality improvements of products

These approaches, emphasizing just-in-time (JIT) production, rely on "pull" and "make-to-order" processes that emphasize responsiveness to realized demand, in sharp contrast to sophisticated *ex ante* prediction in service of "make-to-stock" activities. Production systems tend to be organized for one or the other approach, but not both (Milgrom and Roberts, 1988). Thus, it is an open question whether less-sophisticated uses of data, such as descriptive analytics (Berman and Israeli, 2022; Galdon-Sanchez et al., 2022), will represent some level of digital capability enabling AI adoption or, instead, proxy for organizational misalignment with AI-based prediction. The competing hypotheses are thus:

Hypothesis 2A: Reliance on descriptive analytics will ***increase*** *the likelihood of AI adoption.*

Hypothesis 2B: Reliance on descriptive analytics will ***decrease*** *the likelihood of AI adoption.*

2.2 Industrial Production, Adjustment, & the J-Curve

As our study takes place in the manufacturing sector, meaningful hypothesis development demands that we bridge insights from the study of "digital firms" (Giustiziero et al., 2023) with longstanding intuitions about industrial production. The strategic implications of economies of scale in physical-goods production have been understood since at least the early 1960s (Arrow, 1962; Henderson, 1968).[3] One is early-mover advantage. Economies of scale can be an important isolating mechanism, protecting early movers (Rumelt, 2005). First-movers are by definition able to accumulate production experience earlier. Under economies of scale, this increases value creation (by reducing unit costs, increasing quality, or both), and feeds back into yet more demand and higher production volumes (Cabral and Riordan, 1994). Early exploitation of supply-side scale economies can also help early movers shape customers' cost structure (Lieberman and Montgomery, 1998), lead to costly-to-imitate historical path-dependencies (Barney, 1991), or even promote technological lock-in (David, 1985). While industrial firms do not have the same demand-side economies as firms whose products and

[3]Indeed, Kiechel (2010) documents that the first popular tool sold by the Boston Consulting Group (BCG) in the 1960s was the "experience curve" or the empirical claim of a "consistent" decline of 20-30 percent of costs for each doubling of output (Henderson, 1968). In turn, this tool was used in turn by companies such as Black & Decker to undercut its competitors in terms of price, anticipating lower future unit costs.

services are also digital (Giustiziero et al., 2023), we anticipate that "traditional" economies of scale combined with scale-free AI technologies will mutually reinforce early-mover benefits from AI adoption.

A key limiting factor, however, arises from the general-purpose nature of the technologies in question. General-purpose technologies (GPTs), such as the steam engine, electricity or digital computers, are a class of economically and socially transformative technologies that share characteristics of being widely used, constantly improving, and innovation-spawning (Bresnahan and Trajtenberg, 1995). When we look at the family of technologies increasingly referred to as "AI" (e.g., machine learning, machine vision, speech recognition, etc.) they are already observedin every sector of the economy, in far-ranging use cases, advancing at unprecedented rates, and closely linked to innovation (Cockburn et al., 2018; Iansiti and Lakhani, 2020; Felten et al., 2021; Miric et al., 2023; McElheran et al., 2024). While there is some debate at the moment as to whether AI-related technologies will definitively emerge as the next influential GPT (Goldfarb et al., 2023; Eloundou et al., 2023; Bresnahan, 2024) or remain an important "enabling technology" (Teece, 2018; Rathje and Katila, 2021; Gambardella et al., 2021), the GPT lens is nevertheless useful for focusing attention on early deployment challenges.

According to work in this vein, technologies with such broad potential, ongoing improvement, and often-uncertain trajectories typically require significant investments in co-invention (Bresnahan and Greenstein, 1996) or co-specialization (Teece, 1986) to align technological capabilities with core business activities, processes, products, and resources—and vice versa. The pervasiveness and magnitude of this adjustment challenge is credited with widespread and lengthy delays in the early diffusion and productivity impacts of important technologies (e.g. David, 1990; Brynjolfsson and Hitt, 1996). Recent GPT research examines this process among public U.S. firms, predicting and finding evidence for a "productivity J-curve" of initially declining measured productivity followed by a sharp rise in returns for investments such as software and R&D that arguably require significant—often intangible—complementary investment (Brynjolfsson et al., 2021b).

The implications of costly co-invention for scale-free AI-related technologies is that short-term returns from deploying AI may be minimal (or even negative) on average, and any early-

mover advantages will emerge with a delay. Yet firms that can weather initial performance losses stand to enjoy significant returns to AI use, as observed in early narrow applications among digital giants like Amazon, Netflix, Google, and Facebook (Bresnahan, 2024).

How might this play out in our manufacturing context? Consider that a new AI-enabled production line might use a reinforcement-learning algorithm to optimally adapt production parameters, starting with a set of initial parameter values that are locally but not globally optimal.[4] As is well known from strategic management theory (e.g., Levinthal, 1997), finding a global optimum requires exploration and radical experimentation with parameter values to avoid being trapped in local optima (March, 1991). However, this exploration might prove costly in the short run, if trial parameter values lead to foregone output that would otherwise have been produced if the AI system had stayed at the initial, locally optimal parameter values. At the same time, however, exploration of new parameter values as production volume increases enables reinforcement learning algorithms to try out new parameter values for each newly produced unit, ultimately leading to rapidly improving performance at higher volumes of production.

This example describes a *J-curve* at the level of a given algorithm. However, similar mechanisms will arguably be at work beyond any individual AI deployment. Increasingly, the system-wide challenges of deploying AI beyond a "point solution" are receiving attention (Agrawal et al., 2024). Reconfiguring production processes can lead to short term coordination failures and operational efficiencies that require additional buffers in the system (e.g., WIP). If responsiveness is improved at one point in the production process, increased automation (e.g., robots or additional AI technologies) may be required elsewhere. Factor inputs may shift, particularly if this increased automation substitutes for human labor (Acemoglu and Restrepo, 2018). Working through these adjustments will require additional time and investment, with associated short-term losses before returns fully materialize.

As this plays out at the producer level, we anticipate that:

Hypothesis 3: Returns to AI use will exhibit a "J-curve" pattern, with performance declining upon initial adoption and eventually improving over time.

[4] An example for a similar technology from practice can be found here: https://www.pwc.de/en/digitale-transformation/the-perfect-match-digital-twins-and-reinforcement-learning.html.

Furthermore, we should be able to observe organizational adjusmtents along other dimensions (WIP, physical automation, and labor demand). We will test these additional implications, empirically, recognizing that many margins of adjustment will remain intangible (Brynjolfsson et al., 2021b).

2.3 Strategic Responses

Thus, far, our predictions have concerned average tendencies and are of intense interest in economics, management, and public policy. Yet the managerially-relevant question quickly becomes how strategic decisions might help "flatten" the adjustment dip for a given producer.

Traditional learning-by-doing in manufacturing is well known to eventually run into diminishing returns, based in physical or cognitive limits of workers (e.g., Thompson, 2012; Levitt et al., 2013). In contrast, scale economies of digital resources such as AI are unlikely to face similar limits.[5] As a result, acceleration of benefits (the upward part of the "J-curve) from AI will tend to be supported by business strategies that emphasize growth. That said, we argue that the nature of a given growth-oriented strategy will matter.

To understand this, consider the BCG consultants that sold insights from the experience curve to manufacturing firms in the 1960s. This typical "cost-leadership" strategy (Porter, 1980) was designed to increase sales volume. Yet cost-leadership strategies quickly run into decreasing returns to scale on the demand side (Giustiziero et al., 2023). In contrast, growth through market expansion—via novel offerings and tapping new customer segments, including new domestic and international markets (Yang et al., 2015, 2021)—avoids these demand-side diseconomies (Babina et al., 2024). Indeed, co-occurrence of growth-oriented strategies and AI use has recently been documented among U.S. startups (McElheran et al., 2024); however, the performance implications in a broader population remain unknown. We anticipate that:

Hypothesis 4: Business strategies focused on adding scale via market expansion or innovation will attenuate any initial performance declines due to AI use, while cost-leadership strategies will worsen initial performance declines.

[5]This does, of course, not mean that we believe that AI resources are literally scale-free. Indeed Bajari et al. (2019) argue that dataset size runs into diminishing returns at a "square-root N" rate for forecasting tasks.

2.4 AI vs. the Experience Curve

Our examination of *J-curve* effects at the micro level further has important implications for how mature, more-experienced firms compete with young startups. This "creative destruction" debate about whether larger incumbents or smaller startups are best equipped and/or incentivized to undertake this adjustment dates back at least to Schumpeter (1934, 1950),[6] and is too large to summarize, here. Our contribution to this long-standing conversation, however, is to highlight that, if *J-curve* effects are both strong and uniform across incumbents and entrants, incumbents will naturally benefit from scale economies earlier, leading to entry barriers for startups (Cabral and Riordan, 1994) and eventually higher industry concentration, as incumbents continue to benefit disproportionately from AI use. This dynamic seems to be emerging with regard to "superstar" firms in settings where intangible capital is very important (Autor et al., 2020b; Tambe et al., 2020). Yet, if short-run performance losses are instead worse for mature incumbents, then AI adoption might conversely lead to less industry concentration, in the long run.

Anchoring again in our industrial production settings, we argue that old firms or establishments are more likely to derive productivity from accumulated experience (Thompson, 2012; Levitt et al., 2013), the accumulation of firm-specific resources such as customized IT capital (Jin and McElheran, 2024), and an established set of operational capabilities (Helfat and Peteraf, 2003). Corresponding management practices (Bloom et al., 2019), vintage-specific human capital (Chari and Hopenhayn, 1991; Barth et al., 2023), and other core competencies (Henderson, 1993) will also tend to sustain incumbent performance dervied from a familiar set of technologies. When old firms intensively adopt a novel, AI-based technology, experience with prior technologies may not be transferable to the new system, leading to relatively larger productivity losses for more-established firms (see Christensen et al., 2018 for a review of the large "disruption" literature). In contrast, young startups by definition have none of this accumulation and will thus have lower opportunity costs of innovating (Arrow, 1962 *inter alia*). Thus, we anticipate:

[6]Schumpeter (1934) initially suggested that technological change and innovation would be led by small entrepreneurial firms yet subsequently (Schumpeter 1950) argued that large incumbents possessed superior incentives and resources to innovate and appropriate the returns to innovation.

Hypothesis 5: Old producers will experience greater performance losses from AI adoption than younger ones.

2.5 AI as a Knowledge-Based Resource

To better understand the specific channels by which older manufacturing firms might exhibit larger initial performance losses in response to AI adoption, we build on insights from the Knowledge-Based View of the firm (Grant, 1996; Kogut and Zander, 1993; Nickerson and Zenger, 2004). A key question posed by this work is how firms solve the problem of generating and integrating knowledge that is distributed across different employees within the same firm.[7] Grant (1996) discussed structured operational practices, such as Total Quality Management (TQM) "nonhierarchical, team-based organizing technology that permits an organization to access and utilize individuals' knowledge located at low levels of the organization." However, other structured practices (Scur et al., 2021; Scur and Wolfolds, 2024) beyond TQM can likewise utilize the knowledge and experience of front-line employees.

For example, Levitt et al. (2012) analyze a single car manufacturing plant in the U.S. and show the critical role of structured management practices in realizing learning-by-doing gains from production. Specifically, they document the use of real-time reports and quality audits by engineers, combined with whiteboard system that allowed frontline workers to report individually-experienced production problems on an ongoing basis, thereby leading to generation and sharing of valuable knowledge,[8] which Levitt et al (2012) argue can be understood as a form of "organizational capital." Structured management practices as measured by Bloom et al. (2013; 2019) similarly scaffold the generation and aggregation of frontline employee knowledge by defining standard operating practices, promoting proactive

[7] Grant(1996) poses this problem as: "The dilemma is this: if production (and decisions about production) require many types of knowledge, if that knowledge is resident in many individuals, and if integration mechanisms can involve only relatively small numbers of individuals-what organizational structures are possible?"

[8] Levitt et al. (2012) describe the interaction of one structured practices, namely the use of whiteboard for problem tracking and frontline employees in knowledge creation as follows: "(...) large amounts of information about production still originated from the workers on the line. (...) Aggregation and diffusion of this knowledge were the purposes of the whiteboard system. Workers were encouraged to note problems on the boards, (...) The system therefore quickly pulled information from individual line workers and allowed management to manipulate the production process in ways that benefited any worker at a similar position (...). The system therefore acted as a conduit that gathered worker knowledge and, through the complementary efforts of management, transformed it into plant knowledge that became embodied in the plant's physical and organizational capital."

investigation of root causes of problems, routinizing the review of key performance indicators (KPIs) by managers and frontline employees, and enabling widespread awareness of production targets among all factory workers (including frontline employees) to make production exceptions quickly salient and less costly to address (Womack et al., 2007; Holweg, 2007). But such structured practices are fundamentally still 'analog' in that they do not rely on digitalized information or much technology at all, but rather on the interaction of standardized operating procedures and employee training and practices. Older factories will tend have more accumulated organizational capital of this type.

The implication, then, is that AI adoption could interfere with reliance on the old knowledge generation system, yielding observable declines in structured management practices and, potentially, the human employees in which they are embodied. And, this will be exacerbated among older producers.

Hypothesis 6: Early adjustment to AI use leads to de-adoption of structured management practices, reduced employee counts, and reduced wages—especially at old establishments.

2.6 Spillovers within Multi-Unit Firms

The non-rival or scale-free nature of AI as a digital resource opens up additional considerations for large multi-unit manufacturing firms. Specifically, Pratt (2015) has argued that robotics or AI systems that are remotely connected via cloud computing could lead to increased knowledge spillovers across these systems, as newly valuable information of each system is immediately accessible and valuable to all connected systems. A similar argument should apply to establishments or factories as unit of analysis: AI systems in one factory will generate productivity spillovers in other connected factors, even enabling "parallelization" of learning if production problems are modular across factories.

Hypothesis 7: AI adoption at other establishments within the same firm will increase productivity at the focal manufacturing establishment.

3 Data and Measurement

3.1 Two Datasets and Samples

To provide robust estimates, we use two datasets on AI use by manufacturing businesses in the U.S. at different time periods. Our main dataset is the 2021 Management and Organizational Practices Survey (MOPS), supplement to the 2021 Annual Survey of Manufacturing (ASM). The ASM is one of the oldest large-scale Census Bureau data collections, targeting 10% of the roughly 300,000 manufacturing establishments across the entire country. Stratified by size and industry, the ASM nevertheless oversamples large establishments, covering over 70% of the sector's total value added in the certainty sample. Response to the ASM and the MOPS is required by law, yielding a response rate of 68% in 2021.[9]

[Table 1, Panel A]

Panel A of Table 1 shows that the average establishment in our main sample has roughly 170 employees, is 29 years old, ships more than 60% of its products via e-commerce, and has approximately $11 million in profits.

Linking the MOPS to the broader ASM yields a striking breadth of organizational characteristics. In addition to fine-grained data on the use of AI-related technologies, it provides rich information on the use of other digital technologies (predictive analytics, descriptive analytics, cloud computing, digitalization of information, IT capital) and structured management practices (Bloom et al., 2013, 2019). Additionally, the data structure identifies establishments that are part of large multi-unit manufacturing corporations, allowing us to analyze spillovers from AI adoption across different establishments within the same firm.

Our second main dataset is a panel of approximately 55,000 manufacturing firms combining data from the 2018 Annual Business Survey (ABS)[10] with the Economic Census of Manufacturing (CMF) from 2012 to 2017. This panel dataset allows us to estimate the effects of AI adoption on performance while controlling for firm fixed effects. The ABS-CMF

[9]We also link to the Longitudinal Business Database (LBD), a dataset of tax records covering the entire nonfarm employer economy of the United States, to merge in data on establishment and firm age. Establishment age is measured as the number of years since the establishment first reported having March 12 employment on their tax records. Firm age is determined by the age of the oldest establishment.

[10]Note that 2017 is the reference year for the 2018 ABS. See Zolas et al. (2020) for details.

data are more representative of the large population of single-unit firms in the U.S. economy (Zolas et al., 2020; McElheran et al., 2024). This different size coverage adds robustness to our findings, while also supporting an identification strategy focused on within-firm changes over time.

[Table 1, Panel B]

Panel B of Table 1 characterizes manufacturing firms in the ABS–CMF sample. The firms in this sample are by no means small or young, on average, with mean employment of 344 workers and age of 25. However, when comparing the ABS–CMF and MOPS–ASM data it is useful to keep in mind that the majority of establishments in MOPS–ASM measure individual locations of multi-unit firms, and such multi-unit firms will consist of many establishments.

3.2 Measurement

3.2.1 New Measures of Technology Use by Establishments in the MOPS

Working with the U.S. Census Bureau, members of the author team created new, designed-for-purpose measures of AI-related technologies and their applications for the Management and Organizational Practices Survey (MOPS).

AI-Related Technologies. Measuring fast-emerging technologies systematically and at scale is a perennial challenge. Given the recency and lack of consensus about what "AI" encompasses, our measurement approach is multifaceted. First, we clearly define what we mean by "AI" in the survey, as well as "predictive analytics," we which separately measure, to avoid confusion (and to distinguish from prior work, e.g., Brynjolfsson et al., 2021a). These definitions underwent systematic cognitive testing involving members of the research team and dedicated Census experts, as well as respondents pulled from the official ASM sampling frame, to ensure validity and reliability of responses. MOPS respondents are typically plant managers (Bloom et al., 2013). The specific definition given to respondents is "Artificial Intelligence is a machine-based system that can perceive and learn about its environment and then make relevant predictions, recommendations or decisions for an objective that is determined by humans." This definition is close to the legal definition of AI in the recent

EU AI Act.[11] Two points are worth emphasizing about this definition of AI. First, it shares with the EU AI Act the emphasis on systems that learn from their environment and adapt. Second, the last part was added because respondents were resistant to the idea that adaptive technologies might actually be choosing the objectives (more in line with "artificial general intelligence"). Including this caveat increased respondent confidence and lowered cognitive burden, as required by the U.S. Office of Management and Budget to greenlight this mandatory survey.

We rely on two question "blocks" to triangulate AI use. In one, we ask about AI use in business functions such as production scheduling/monitoring, quality control, environmental and safety compliance, equipment maintenance, logistics, and sales forecasting. In the other, we ask about specific AI technologies, such as machine vision, speech recognition, automated guided vehicles, and AI-enabled industrial robots. This combined measurement allows us to capture two related but distinct ways in which respondents tend to be aware of AI use in their establishments. This helps to mitigate potential concern that respondents might be unaware of AI technology "under the hood" of factory equipment. At the same time, we believe that lack of awareness of AI technologies is unlikely for our respondents, who are plant managers in manufacturing industries, due to two reasons. First, plant managers typically have a strong understanding of the technical aspects of the manufacturing process, due to the importance of this technical knowledge in diagnosing potential "root causes" of production or logistics problems. Second, unlike in consumer technology adoption, in B2B contexts, AI vendors need to clearly explain the underlying technologies to make a successful sale—and AI has been marketed as a productivity-enhancing technology for years by large consulting and software companies.

[Table 1, Panel C]

Contrary to a number of recent unofficial accounts, baseline average AI adoption rates in the U.S. economy have been low for some time, including in manufacturing (see McElheran

[11] Specifically, the EU definition is: "a machine-based system that is designed to operate with varying levels of autonomy that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations or decisions that can influence physical or virtual environments."

et al. 2024; Bonney et al. 2024). Combining all of our AI-related questions to capture a measure of *at least some* use of AI, we estimate only about 23 percent of plants used any form of AI by 2021. Intensity of use is even lower, at around 8 percent (Panel C of Table 1).

For our regression analysis, we construct a continuous measure of AI use based on the two question blocks. We first construct dummy indicators of whether the establishment reports using AI in specific business functions [12] or in terms of adopting specific AI technologies.[13] We normalize these, i.e. subtract the sample mean and divide by the sample standard deviation, and then sum them into an overall index, which in turn is normalized again. This facilitates interpretation in terms of a standard-deviation change and is a longstanding practice in the related literature (e.g., Bloom and Van Reenen, 2007).

3.2.2 AI Measurement in the ABS

Our AI measure in the MOPS is even more expansive than that captured in the ABS, which focuses on a range of AI-related technologies such as machine vision, voice recognition etc. (McElheran et al., 2024), but not applications. Replicating this narrower measure in the MOPS data, we estimate AI use in 2021 at only 13% with intensity even lower at 2.3% as shown in Panel C of Table 1. Since our assessment of AI use between 2012 and 2017 relies on the ABS, we follow the narrower McElheran et al. (2024) definition for that analysis.

3.2.3 Other Variables in the MOPS

A critical set of variables for our identification strategy includes questions on what respondents report to be the main barriers to AI use. Additionally, AI adoption barriers help us understand why AI adoption is low despite rising interest and attention.

[Table 1, Panel D]

As Panel D of Table 1 shows, the leading factor associated with preventing or delaying AI use was (financial) cost, which approximately 43% of plant managers consider prohibitive.

[12] Each dummy for business functions is one if AI is relied upon "Up to 50%", "More than 50% but not all" and "All or nearly all" the time. The dummies are otherwise zero.

[13] Each dummy for AI technologies is one if AI is reported to cover "Up to 50% of direct production", "More than 50% of direct production but not all" and "All direct production". It is otherwise zero, including if the AI technology is reported to be used in "Testing or piloting only".

In descending order of prevalence, other barriers include difficulty of identifying business use cases for AI (28%), the level of AI expertise at the establishment (12%), and employee attitudes towards AI (9%). Only about 1% of respondents see uncertainty about government regulations or industry standards as a barrier, while nearly 6% of plant managers reported no barriers to AI use and stated that AI is widely used in the establishment.

[Table 1, Panel E]

We carefully measure other digital technologies in order to empirically separate them from AI. The closest of these digital technologies is predictive analytics (PA), defined as "statistical or algorithm-based models that analyze historical and current data to make predictions about future or unknown events." Our question on PA ask respondents to report use of PA across the same six business functions discussed in the previous section for AI usage. In contrast to AI, PA use is high at nearly 65% of respondents reporting any use, with 30% reliance on this technology. Another potentially related technology is the use of descriptive analytics and statistics (DS) which is defined as "descriptive analyses of data ... typically used to support making key decisions", such as summary statistics, time trends, real-time dashboards etc. Panel E of Table 1 shows that DS adoption is also very high, as 73% of respondents reporting using any DS technologies. Underlying these data-intensive technologies is the background digitalization of information, defined on the survey as "information stored in digital format" and measured across the previously-described six business functions. The vast majority of plants report some level of data availability, as 91% of respondents report at least some information being digitized, along with high intensities at 64%. The MOPS and ASM also allow us to measure IT infrastructure, either measured by IT capital—cumulative computer equipment expenses over the last 3 years—or cloud computing expenses.

In addition to digital technologies, the MOPS also includes a comprehensive list of variables to measure structured management practices. These measures have been extensively discussed by Bloom et al. (2013; 2019) in the Census data and more-generally by Scur et al. (2021; 2024), so we refer the interested reader to this work.

3.2.4 Other Variables in the ABS

A particularly useful set of variables from the 2018 ABS are questions about the business strategies that firms pursue. Prior work has shown systematic relationships between business strategies and AI adoption (McElheran et al., 2024), technology use (Wu et al., 2020) firm organization and innovation outcomes (Yang et al., 2015), and firm performance responses to competitive shocks (Yang et al., 2021). The ABS asks respondents about the importance of 14 different business strategies, from a focus on "introducing new products or services" and "expand into new markets" (domestic and international) to "low price" and "reduction costs." We use principal component analysis to extract three factors. The first factor captures the intensity of pursuing growth through new markets, including expansions into new (domestic or international) existing markets or creation of new markets through innovation, and we call it "new markets strategy." The second factor is about pursuit of growth via cost leadership, close in spirit to Porter's cost leadership strategy (Porter, 1980). The third factor captures the intensity of pursuing satisfaction of current main customers via excellent product and service quality. We call this factor "quality strategy," and it is close in spirit to Porter's "differentiation strategy." These three generic business strategies are similar to ones found by Yang et al. (2015) in the Workplace and Employee Survey (WES) in Canada.

4 Endogeneity and Identification Strategy

We are interested in regressions of the form

$$y_i = \beta \cdot AI_i + C_i\gamma + \epsilon_i \tag{1}$$

where i typically indexes different establishments, and the dependent variable y_i is typically (log) value added or profits, defined as value of shipments minus salaries/wages, employee benefits, cost of work-in-progress, raw materials, intermediate inputs, fuels, purchased energy, services, and resales. Establishment productivity is our measure of value creation, while profits are our measure of value captured—a distinction particularly important in strategic management. C_i denotes a matrix of control variables typical in productivity re-

gressions, including input controls such as number of employees and non-IT capital capital stock, as well as other rich controls described below. The key endogeneity problem for regressions such as (1) is selection bias (e.g., Hamilton and Nickerson, 2003), whereby better-performaing or better-managed businesses will tend to more-intensively use AI. This will bias upwards any effects estimated via ordinary least squares (OLS). We pursue three idenification strategies to address this selection bias. The fourth captures key organizational design features such as the establishment being part of a multi-unit firm (MU), being co-located with the firm headquarters (HQ), or being one of three different plant types that differ by the production process design (job shops or R&D, batch production, continuous flow or cellular).

Our first identification strategy is the use of an unusually rich set of proxy variables to control for typically-unobservable organizational factors (e.g., managerial skill or digital capabilities) and can therefore be understood as a matching, or "selection-on-observables," identification strategy. As mentioned, the particular strength of the MOPS–ASM data is the availability of four sets of variables that are rarely available at scale. The first set includes controls for data-intensive technologies that are not AI. Similar to the AI index, the MOPS–ASM data allows us to construct continuous indexes for DS and PA, which we use as controls throughout. The second set captures IT infrastructure, either by measuring on-premises IT capital or cloud computing expenses, both of which have been closely linked to the use of prediction technologies and AI (Brynjolfsson et al., 2021a; McElheran et al., 2024). Our third set includes indices for structured management as in Bloom et al. (2019), as well as controls for the percent of college-educated employees and union membership. These measures directly proxy for the quality of management as well as for employee skill and organization. The fourth set includes indicators for the establishment being part of a multi-unit firm (MU), being co-located with the firm headquarters (HQ), or being one of three different plant types that differ by the production process design (job shops or R&D, batch production, continuous flow or cellular), which may capture systematic differences in AI adoption and its effects associated with quasi-fixed organizational design characteristics that have previously been linked to business performance (e.g., Atalay et al., 2014; Bloom et al., 2013; McElheran et al., 2019).

A key concern with selection-on-observables estimators is that they can only control for

unobserved factors that are correlated with observables. We therefore leverage a natural experiment available in the MOPS–ASM data to address unobservable confounders. Specifically, we use the reported perception of "no lack of AI expertise" as an instrument for more intensive AI use. This IV is relevant for AI adoption (as we document below) and plausibly exogenous: lack of AI expertise does not necessarily imply lack in manufacturing operations expertise. Importantly, we follow Angrist and Pischke (2009) and evaluate the plausibility of the exclusion restriction by showing for a subset of establishments with zero first-stage effects that reduced-form estimates exhibit zero effects as well.

Since exclusion restrictions in IV estimation can never be directly tested, we offer a third identification strategy based on the ABS–CMF data. Specifically, as documented by McElheran et al. (2024), AI adoption by U.S. firms by 2017 was very low. Maintaining the assumption that AI adoption as of 2012 (the closest year for the full Census of Manufactures, which maximizes our balanced panel sample) was essentially nonexistant[14] allows us to estimate regressions of the form

$$y_f = \beta \cdot AI_f + C_f\gamma + D_f + \epsilon_f \tag{2}$$

where f is a manufacturing firm, t indicates different years (2012 and 2017), and D_f denotes a full set of firm fixed effects. In other words, we use within-firm changes to control for permanent or slowly changing unobservable confounders. As before we use firm productivity (labor productivity and TFP) to measure value creation and profits to measure value captured.

It is useful to remember that first difference approaches as (2) will exacerbate any attenuation bias of coefficients towards zero as a result of "over-differencing" (Angrist and Pischke, 2009), so, setting aside potential upward bias due to selection (which is unaddressed in this approach), we expect the estimates for this specification to be smaller in magnitude compared to the IV estimates, as IV automatically corrects for classical measurement error.

[14]This identifying assumption is similar in spirit to that used by Forman et al. (2012) and Forman and McElheran (2025) to study the impact of the commercial internet in the 1990s.

5 Results

5.1 Correlates of AI Use

In this section we examine the variables that help predict AI adoption in our MOPS-ASM sample. Controlling for size, there remains a great deal of heterogeneity in AI uptake.

[Table 2]

The first two rows in Table 2 demonstrate that AI is distinct from other digital technologies such as descriptive analytics, measured by the DS index, and predictive analytics, measured by the PA index. Among these two digital technologies, AI is positively and significantly related to predictive analytics. This is in line with Hypothesis 1. However, the overlap between AI and PA is far from perfect. Quantitatively a one standard deviation increase in the PA index is only associated with a 0.39 standard deviation increase in the AI index. In contrast to PA, DS is negatively correlated with AI adoption, consistent with Hypothesis 2b. This finding underscores the importance of examining different digital technologies separately from each other and taking a nuanced approach to potential complementarity among technologies and organizational characteristics.

Table 2 also documents the correlation between IT infrastructure and AI. IT infrastructure includes on-premise IT equipment such as computers and servers as well as cloud computing. The results in Table 2 indicate that AI adoption is systematically correlated with cloud computing but not with on-premise IT capital. This evidence is consistent with potential benefits of cloud-connected AI systems hypothesized by Pratt (2015) and the technological interdependencies documented in McElheran et al. (2024).

5.2 IV Relevance

A key question of this analysis is the relevance of our instrumental variable. Based on the importance of "lack AI expertise" as a reported barrier to AI adoption, we reverse-coded our instrument to be one if "lack of AI expertise" is not reported to be an issue. As Table 2 shows, our instrument significantly and robustly predicts more intensive AI adoption. Plant managers who report no lack of AI expertise on average have 8% higher AI usage.

5.3 Organizational Complements

A key test for complementarity between technology and organizational characteristics (Milgrom and Roberts, 1990) is the "correlation test" examining co-adoption of the technology and key organizational features (Brynjolfsson and Milgrom, 2013; Brynjolfsson et al., 2021a). The next rows in Table 2 indicate the importance of structured management practices in predicting AI adoption. Strikingly, the effects are concentrated in *process*-focused managerial activities. Highlhy-structured human resources management is negatively associated with AI adoption. Age is, perhaps unsurprisingly, negatively correlated with AI use (though the coefficient is only statistically significant in column 3, alongside the other covariates).

It is perhaps worth noting the positive correlation between non-IT capital and AI use documented here, as capital stocks are often missing from standard data sets. This will promote upward bias in estimates of the contribution of AI to productivity in the absence of capital stock controls (more on this, below).

Prior growth and productivity are either insignificantly or negatively correlated with AI use (columns 4 and 5). This works against standard concerns that reverse causality would drive a positive relationship between AI use and performance.

5.4 *J-Curve* Patterns

Panel A of Table 3 provides a cumulative regression build of OLS regressions of value added on AI and other control variables to test Hypothesis 3.

[Table 3, Panel A]

The first column indicates that in the cross section, AI adoption is significantly correlated with (log) value added, even controlling for the presence of other data-intensive analytics tools (DS and PA). This continues to be true when we control for IT infrastructure in column (2). However, as column (3) of Panel A in Table 1 shows, AI is not systematically correlated with labor productivity. This result is not merely driven by the noisiness of the AI measure, but instead is a result of substantially lower coefficient magnitudes after controlling for (log) number of employees. In fact, the standard errors across columns (2) and (3) indicate that,

if anything, the labor productivity OLS regression in column (3) is more precisely estimated. The next two columns add structured management practices and plant age and show that adjusting for the quality of management leads to AI adoption being negatively correlated with labor productivity. Finally, adding capital stock controls in column (5) allows us to analyze whether more AI-intensive plants tend to have higher or lower total factor productivity (TFP). This column shows that plants with a one standard deviation more intensive AI adoption tend to be 1.33 percentage points *less* productive. The remainder of this paper seeks to establish the robustness and causal direction of this finding, including insights into the dynamics, heterogeneity, and specific channels underpinning this result.

5.5 IV Results

We start by investigating causality in Panel B of Table 3.

[Table 3, Panel B]

The first column of Panel B in Table 3 reprises findings in Table 2 that the instrument of "no lack of AI expertise" is indeed relevant. Columns (2) and (3) report second-stage IV results with column (2) estimating the impact of a one standard deviation higher AI index on labor productivity while column (3) estimates the impact on TFP. The esimtated effects are quantitatively very large. Focusing on TFP, column (3) indicates that a one standard deviation increase in AI reduces TFP by 0.59 log points or over 60 percentage points. Although these effects are substantially larger than the OLS coefficient reported in column (5) of Panel A, these effect sizes are still plausible for a couple of reasons. First, OLS is well known to suffer from attenuation bias when classical measurement error is sizable, which is both likely in the context of fast-changing AI technologies and addressed by IV estimation. Second, the quantitative implications of our IV results on TFP are not implausibly large compared to prior research. One reference for well-estimated causal effects on productdivity are those for structured management on establishment TFP from a field experiment in Indian manufacturing from Bloom et al. (2013). The estimates in Bloom et al. (2013) suggest that a one standard deviation higher structured management score increases plant TFP by 0.47 log points (over 50 percentage points). These productivity effects are of the same order of

magnitude as our estimated negative TFP effects of AI adoption.

While productivity measures capture the idea of value creation, value capture is more appropriately measured by profits. Column (7) of Panel A and column (4) of Panel B in Table 1 report the relationship of AI adoption and profits. Although positive and quantitatively small in OLS, our IV estimates suggest that a one standard deviation more AI use causes a loss of about $11 million for the average manufacturing establishment in our sample. Given very similar average profits in the estimation sample (see Table 1, Panel A), this is a quantitatively important magnitude and underscores the short-term risks of industrial AI adoption.

The central concern of any IV analysis is whether failure of the exclusion restriction might bias the results. For example, one could worry that lack of AI expertise at the plant might be indicative of a broader lack of operational capabilitiy (despite our direct controls for management practices and employee skills), which might directly reduce establishment productivity. In this case, one would expect establishments with no lack of AI expertise to have higher productivity than establishments reporting a lack of AI expertise. However, as the first column of Panel A in Table 4 shows, the opposite appears (and is statistically significant) when we regress labor productivity directly on our "no lack of AI expertise" instrument.

[Table 4, Panel A]

A related selection-based bias could arise if the response of "no lack of AI expertise" were indicative of plant managers who expect disproportionate gains from AI. If true, this would imply that respondents reporting "AI is widely used" should exhibit systematically higher AI-related productivity. We therefore use the response "AI is widely used" as a placebo instrument, for which we report the first stage in the second column of Panel A in Table 4. As expected, this response is strongly positively correlated with AI use. However, as column (3) shows, the second stage effect is statistically indistinguishable from zero. This is consistent with plants led by managers who expect higher returns to AI being more likely to adopt. However, we cannot rule out that the realized costs exceed these anticipated gains. Note, further, that the sign and significance of the placebo effects differ from our main IV results, ruling out a mechanical relationship driven by this "barriers" question.

More broadly, we are interested in the plausibility of the exclusion restriction identifying the causal effect. We thus follow Angrist and Pischke (2009) in using a "zero first stage" approach. For this, we require a subsample of plants for which no lack of AI expertise nevertheless fails to lead to more AI adoption. In other words, in such a subsample, the instrument is irrelevant to being treated. If the exclusion restriction holds, one should then observe no correlation between the eventual performance outcome and the instrument, since the exclusion restriction requires that the instrument only impact performance via the treatment (in our case, AI use). There are good theoretical reasons to believe that the IV is irrelevant for at least two particular subsamples of manufacturing establishments.

The first is "job shops," which flexibly make a variety of made-to-order products in small batches or even one-off prototypes. Products and production parameters will typically vary widely from order to order. In this high-mix, low-volume context (Hayes and Wheelwright, 1979), uncertainty is high by design. An AI technology such as machine vision will typically not have enough data or repeated use cases to train and leverage prediction algorithms. Prior work on predictive analytics use found a similar constraint on returns to prediction (Brynjolfsson et al., 2021a).

The second subsample is single-unit (SU) establishments. Systmatically smaller than multi-unit plants, SU factories will be less likely to adopt AI systems due to lack of scale (Svanberg et al., 2024).

[Table 4, Panel B]

For both of these subsamples, we find that the instrument fails as predicted in the first stage, as documented in columns (1) and (3) of panel B of Table 4. Importantly, not only are the IV first stages for the subsamples statistically insignificant, they exhibit opposite signs compared to the first stage in column (1) of Panel B in Table 3.Further, in each of these cases, the reduced-form labor productivity regressions (columns (2) and (4) of panel B) show a quantitatively small, statistically insignificant, and negative relationship between AI use and. This is exactly the result one would expect if the IV exclusion restriction holds.

5.6 Within-Business Changes

Despite the plausibility of our IV exclusion restriction, exclusion restrictions can never be conclusively tested unless the instrument is generated by an actual randomized controlled trial (RCT). We therefore pursue yet another identification strategy to triangulate on the causal effects of AI use on business performance. Leveraging the panel structure of the ABS-CMF data, we estimate equation (2) with firm fixed effects to control for time-invariant firm-level confounders.

[Table 5, Panel A]

The first three columns of Panel A in Table 5 show that more-intensive AI adoption between 2012 and 2017 is associated with declining sales, lower TFP, and lower profits. The magnitudes of these effects are all an order of magnitude smaller than effects estimated via IV. This is unsurprising since any type of classical measurement error (discussed above) will be magnified in simple first-difference estimators. At the same time, the sign of the effects is consistent with both the OLS estimates and the IV estimates from the MOPS–ASM data. AI adoption is associated, again, with short-term within-firm productivity declines. In these analyses, the magnitude of a one standard deviation higher AI use comes with a performance loss of around .02 log points.

The panel data also allow us to investigate the dynamic patterns predicted by the *J-curve* theory, expressed in Hypothesis 3. Specifically, we can analyze the longer-term growth and performance outcomes of manufacturing firms as a function of their AI use in 2017. For this, we track growth in terms of employment, sales, and labor productivity in the Longitudinal Business Database (LBD) from 2017 to 2021.

[Table 5, Panel B]

Columns (1) to (3) in Panel B of Table 5 show growth in employment, sales, and labor productivity to be significantly higher for manufacturing firms that deployed AI in production (the ABS definition of adoption) by 2017. These positive growth effects are consistent with Hypothesis 3 (and *J-curve* arguments more generally), that initial performance losses should be considered investments in co-investemt and intangible capital accumulation that yield

returns in the longer run.

Columns (5)–(7) of Panel B in Table 3 report additional IV estimates that reinforce this adjustment explanation and deepen our understanding of the causal effect. Motivating the specification in column (5) is recognition of how important "Lean" production has become in U.S. manufacturing (e.g., Womack at al. 2007). Key characteristics of Lean include purposefully driving down inventory in the production process so as to make problems and defects more visible, to force responsiveness to process exceptions, and to improve (shorten) the lead times and inventory carrying costs of the entire system (e.g., Holweg 2007). It also tends to be a very "pull-based" and often low-tech approach to operating a production process, focused more on responsiveness to demand and preventing defects than buffering for them (Milgrom and Roberts, 1988). As such it is arguably not a straightforward fit for more-digitized methods associated with sophisticated prediction, make-to-forecast, and ultimately AI. Disrupting established "analog" processes rooted in the Lean tradition should therefore become visible in other metrics such as inventory levels and carrying costs. We find empirical evidence consistent with this in column (5) of Panel B in Table 3, which shows that WIP systematically increases in response to AI adoption.

Another consideration is that AI systems might be replacing manual, human-led activities with physical automation. If this is the case then early adjustment should also manifest as increased investment in production capital—especially industrial robots. Robot use and reliance on AI in production have been correlated in prior work McElheran et al., 2024), but the timing of adoption and causality remain poorly understood. Column (6) of Panel B in Table 3 shows that the number of active and purchased industrial robots increases as a result of AI adoption. Again, this is consistent with significant co-invention in production processes due to moving to reliance on AI.

Finally, AI use causes the number of workers to decline, as shown in column (7) of Panel B in Table 3. While this is, at first glance, consistent with substitution of human labor with automation (Autor and Salomons, 2018), this is a short-term result that must be interpreted in the context of employment growth over time. We do not observe which workers are shed, nor which ones contribute to employment growth over time. We note, however, that this pattern is consistent with a need to shuffle labour inputs as businesses shed prior practices

and reconfigure their operating systems.

5.7 The Role of Business Strategy

In this section we investigate what firm characteristics might impact how AI shapes competition. We first begin with generic business strategies. Following Hypothesis 4, we expect that the strategic decisions of how firms pursue growth matter for the initial performance decline of their *J-curve*.

[Table 5, Panel A]

Column (4) of Panel A in Table 5 yields results consistent with this hypothesis. Specifically, firms with more strategic emphasis on growth through market expansion and innovation ("new markets strategy") tend to exhibit significantly lower initial productivity losses as seen in the positive and significant interaction term. This result is consistent with early benefits from scale economies helping to reduce initial foregone output from adopting AI. At the same time, pursuing scale through cost leadership does not work as well, as shown by corresponding interaction term in column (4) of Panel A in Table 5. Although we do not find statistically significant results, the negative sign of this effect is consistent with the view that growth through cost leadership still implies demand-side dis-economies of scale, which limit how much firms can avoid initial *J-curve* losses from foregone output.

We now move to the tests of Hypothesis 5, which predicts that old firms will exhibit greater performance losses from AI adoption because they disproportionatelylose productivity benefits from prior accumulated experience.

[Table 5, Panels A and B]

Results in Panel A of Table 5 confirm this intuition. Column (5) of Panel A shows that after controlling for the interaction of firm age and AI adoption, the main effect of AI adoption on productivity is actually positive and statistically significant.

The last two columns of Panel B in Table 5 build on this analysis and estimate growth outcomes from 2017 to 2021 in the LBD as a function of AI adoption and firm age. These estimates show that older firms systematically benefit less in the wake of AI adoption and

that once the interaction of AI adoption and firm age is controlled for, other firms also gain substantially more in terms of sales growth and labor productivity.

5.8 Mechanisms

In this section we dig into the specific channels underlying the age effects documented in the last section as well as the implications of AI as a scale-free resource within large multi-unit firms.

5.8.1 What is Driving Age Effects of AI Adoption?

We begin by documenting that age effects documented for the ASM–CMF data are indeed also present in the MOPS–ASM data. For purposes of this analysis, we define old establishments as establishments that are at least 25 years old, with the average plant age being almost 29 as shown in Table 1.

[Table 6, Panel A]

The first two columns of Panel A in Table 6 show that the negative effects of AI adoption on labor productivity (in column 1) and TFP (in column 2) are either substantially larger in old establishments, or even completely driven by old establishments.

[Table 6, Panel B]

We then move to exploit a key strength of the MOPS data to investigate whether AI adoption causes a change of structured management practices. Column (1) of Panel B in Table 6 shows that more intensive AI adoption causes a de-adoption of structured management practices, concentrated in old establishments. Quantitative magnitudes of the de-adoption of structured management are large: estimates from column (1) of Panel B in Table 6 imply that a one standard deviation in AI intensity reduces structured management by 0.83 log points. This result is meaningful in at least two ways. First, de-adoption of structured management practices is likely to have a direct effect by reducing the quality of management. Second, de-adoption of structured management practices is indicative of a broader loss of

production experience/know-how and "organizational capital" (Levitt et al. 2012) as argued in Hypothesis 6.

To quantify the direct productivity effect of the de-adoption of structured management, we can combine the estimate of column (3) with estimates of the causal effect of structured management on TFP from Bloom et al. 2013. Doing so results in an estimated TFP loss of $0.39 (= 0.83 \times 0.477)$ log points at old establishments. Alternatively, one can use the OLS regression estimates of TFP on structured management by Bloom et al. (2019) of 0.209 in combination with the finding in that paper that classical measurement error attenuates the OLS coefficient by 1/2 to obtain a measurement error corrected coefficient of $0.418 (= 0.209 \times 2)$, which then implies a productivity loss of $0.346 = (0.83 \times 0.418)$. In both cases, this mechanism alone can explain roughly one third (0.39/1.133) of the TFP loss from AI adoption in column (2) of Panel A in Table 6 for old establishments. Another way to restate the result is that the indirect loss of experience/organizational capital could potentially explain up to 2/3 of the measured TFP loss due to AI adoption.

Additionally, the MOPS data allows us to more fully understand which of the structured management practices are affected in particular. Indeed, columns (2) –(4) of Panel B in Table 6 show that the de-adoption is driven by production monitoring and targeting practices and especially by de-adoption of "KPI reviews by non-managerial employees" and the degree of "Target awareness across employees," which is higher the more non-managerial employees are typically aware of production targets. These results are consistent with old establishments removing operations practices that previously helped them to utilize frontline employee knowledge (Hypothesis 6). This is also consistent with the results from the last two columns of Panel A in Table 6, which show that more intensive AI adoption causes reduction in employee wages and overall workforce, consistent with the replacement of frontline employees with industrial AI systems such as predictive maintenance and AI-enabled industrial robots.

5.8.2 Within-Firm Spillover Benefits of AI Adoption

Hypothesis 7 suggests large multi-unit establishments might mitigate some of the direct losses from AI adoption by indirectly benefiting from positive spillovers across establishments within the same firm. We investigate this mechanism by deriving a second instrument from our first for multi-unit firms. Specifically, we construct an AI measure for AI adopted at other establishments of the same firm and call it "elsewhere AI index" (EAI). This EAI index increases with the average AI index for other establishments within the same firm, excluding the focal one. In other words, it is a "leave out mean" AI index with the mean being calculated across all establishments belonging to the same firm as the focal establishment but excluding the focal establishment. We then use the number of plants outside the focal plant but inside the same firm which reported no lack of AI expertise as instrument for EAI.

[Table 6, Panel C]

Columns (1) and (2) of Panel C in Table 6 shows that the system of equations of two IV first stages confirm that both instruments are relevant. Column (3) of Panel C in Table 6 shows that the causal effect of AI adoption at the focal plant is still negative, but that AI adoption at other plants within the same firm has a positive and sizable causal effect.

6 Conclusion

This paper examined the performance impact of AI on U.S. manufacturing over different time horizons and across diverse organizaitonal settings. Using two distinct but related datasets on tens of thousands of establishments and firms, we document three key findings. First, early industrial AI adoption in U.S. manufacturing robustly causes statistically and economically significant productivity losses in the short run. Second, however, we find evidence for recovery and growth in the longer run. Together these findings are consistent with *J-curve* mechanisms that have not heretofore been established at the micro-level.

Last but not least, we unpack heterogeneity in these effects and their implications for competitive dynamics. Productivity losses are driven by old establishments and old firms. This suggests that industrial AI adoption does not necessarily favor incumbents over entrants,

at least not in our context of industrial AI in U.S. manufacturing. In addition, we find that growth-oriented startups benefit disproportionately, suggesting that Industrial AI use may tend to promote "creative destruction" in the sector, as AI diffuses. Further, we provide direct evidence on the quantitative importance of a particular causal mechanism leading to the AI-related decline in establishment productivity: the displacement of structured management practices (Bloom et al. 2012; Bloom et al. 2019) and obliteration of knowledge management systems combining worker feedback and structured practices (Grant, 1996; Levitt et al. 2012). The labor shedding we observe is likely linked to this adjustment process, which also manifests in WIP and increased robot investment

Our empirical analysis has several limitations that constitute opportunities for future research. The first is that industrial AI diffusion remains in its early stages. As AI matures as a technology or co-invention know-how also diffuses, productivity losses from initial adoption might be better balanced by productivity gains. Further, our estimates of dynamic effects are not as well-identified as the baseline short-term losses and probably suffer from some remaining (upward) selection bias. So, the long-term effects could be less rosy than portrayed in these estimates. It will be useful to continue gathering empirical evidence on this question as AI-related technologies continue to evolve and diffuse.

A second limitation of this study is the focus on (U.S.) manufacturing. This focus on a given industry context allows us to better understand and interpret the results. But if AI is really a GPT, then it will be widely adopted across many different industries and sectors of the economy. Future work should therefore continue to explore other business contexts to better understand and evaluate the effects of AI on productivity and workers across the economy.

Finally, more work is needed on the specific uses to which AI-related technologies are being put by firms. The low baseline adoption, combined with Census' disclosure avoidance rules prevents us from providing more-granular breakdowns of AI use and potentially differing performance implications. Yet a hallmark of GPTs is their broad applicability. Better understanding specific applications of AI in specific contexts is needed to understand other dimensions of heterogeneity, trace dynamics, and "flatten" the curve for more organizations and industries.

Table 1: Summary Statistics

	(1) Mean	(2) Std. Dev.
Panel A: Establishment Characteristics (MOPS–ASM)		
Number of employees	171.5	263.4
Age of establishment	28.54	14.23
Percentage of shipments through e-commerce	62%	42%
Number of active and purchased industrial robots	1.73	6.96
Establishment-level profits (in thousands)	11,000	16,000
Change in work-in-progress inventory (in thousands)	445	6370
Panel B: Firm Characteristics (ABS–CMF)		
Number of employees	344.3	7,678
Age of firm	24.85	12.59
Percentage of shipments through e-commerce	23.5%	37.7%
Establishment-level profits (in thousands)	19,500	42,000
Early adopters	7.5%	9.1%
Panel C: AI Adoption (MOPS–ASM)		
Any AI	22.8%	41.9%
Any technical AI application	12.6%	33.2%
Production using AI	8.0%	20.4%
Production using technical AI applications	2.3%	9.1%
Panel D: Barriers to AI Adoption (MOPS–ASM)		
No applications or business use cases	28.4%	45.1%
Regulation uncertainty	1.0%	10.1%
No expertise	12.3%	32.8%
Cost	43.2%	49.5%
Employee attitudes	9.4%	29.2%
No barriers	5.5%	22.9%
Panel E: Other Digital Technologies (MOPS–ASM)		
Any predictive analytics	64.6%	47.8%
Any descriptive statistics	72.8%	44.5%
Any digitalized data	91.0%	28.6%
Expenditures on cloud computing (in thousands)	7.63	33.21

Notes: Panel A is using the MOPS–ASM sample and is comprised of roughly 28,500 manufacturing establishments. Panel B is using the ABS–CMF data and consists of roughly 55,000 manufacturing firms. Panels C, D, and E report weighted summary statistics based on data from the MOPS–ASM, combined with sample weights that make estimates representative for roughly 300,000 manufacturing establishments in the U.S. The AI, descriptive statistics, and predictive analytics indices are normalized, with zero mean and unit standard deviation.

Table 2: Correlates of AI Use by U.S. Manufacturers

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DS Index	-0.0504***	-0.0506***	-0.0526***	-0.0506*****	-0.0502***
	(0.0177)	(0.0177)	(0.0177)	(0.0177)	(0.0176)
PA Index	0.386***	0.385***	0.385***	0.385***	0.385***
	(0.0119)	(0.0119)	(0.0118)	(0.0119)	(0.0119)
Log IT Capital	-0.0007	-0.0006	-0.0047	-0.0006	-0.0002
	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0032)
Log Cloud Expense	0.0116**	0.0117**	0.0117**	0.0117**	0.0119**
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
No lack of AI expertise	0.0827***	0.0824***	0.0840***	0.0824***	0.0818***
	(0.0174)	(0.0174)	(0.0175)	(0.0174)	(0.0174)
Structured Mgmt - Process	0.0433***	0.0434***	0.0407***	0.0434***	0.0440***
	(0.0092)	(0.0092)	(0.0091)	(0.0092)	(0.0093)
Structured Mgmt - HR	-0.0283***	-0.0287***	-0.0281***	-0.0288***	-0.0294***
	(0.0072)	(0.0072)	(0.0072)	(0.0072)	(0.0071)
Union	0.0771**	0.0813**	0.0755**	0.0812**	0.0826**
	(0.0363)	(0.0363)	(0.0361)	(0.0363)	(0.0362)
Plant Age		(-)	(-)**	(-)	(-)
Log Capital			(+)***		
VA Growth 2019–2021				-0.0013	-0.0060
				(0.0077)	(0.0085)
Log Labor Prod. 2019					-1.521*
					(0.894)
Additional Controls:	Size, Industry, Skill, Plant Type, MU, Energy, HQ				

Notes: AI Index (the dependent variable) measures adoption of applications of AI in business functions or adoption of specific AI technologies, with the index being normalized to have zero mean and unit standard deviation. DS index measures use of descriptive statistics in decision making with the index being normalized to have zero mean and unit standard deviation. PA index measures use to prediction algorithms across six business functions with index being normalized to have zero mean and unit standard deviation. Other variables include "log IT capital": accumulated IT equipment expenses in the past 3 years; "log cloud expense": expenses on cloud computing, "size": log number of employees; "energy": energy expenses; "MU": dummy that is one if establishment is part of multi-unit firm; "skill" percentage of employee with BA degree; "structured management – process": Bloom et al (2019) structured management index for monitoring and target setting of production; "structured management – HR": Bloom et al (2019) index for incentives and promotion practices; "plant type": index with 0 for R&D plants or job shops, 1 for batch production and 2 for continuous flow or cellular manufacturing plants; "union": ; "HQ": ; "plant age": log of establishment age; "log capital": log of capital stock calculated using perpetual inventory method. "No lack of AI expertise" is a dummy, reverse-coded from respondents reporting lack of AI expertise as reason not to adopt or to delay AI use. "Industry" refers to 3-digit NAICS fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Note that we do not report first stage F-Stats, since according to Angrist and Pischke (2007), a significant first stage and significant second stage are sufficient if the endogenous variable is just-identified (as many endogenous variables as instruments).

Table 3: Performance Regressions of AI Adoption

Panel A: OLS

	Log Value Added (VA)						Profits
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
AI Index	0.097***	0.078***	0.006	-0.004	-0.003	-0.013**	81.63
	(0.014)	(0.013)	(0.007)	(0.007)	(0.007)	(0.007)	(130.3)
DS Index	0.559***	0.451***	0.077***	0.031***	0.032***	0.015*	7.42
	(0.014)	(0.014)	(0.008)	(0.009)	(0.009)	(0.009)	(113.8)
PA Index	0.063***	0.054***	0.008	-0.002	-0.0009	-0.002	-39.46
	(0.013)	(0.012)	(0.007)	(0.007)	(0.007)	(0.007)	(107.2)
Controls:							
IT Capital and Cloud	No	Yes	Yes	Yes	Yes	Yes	Yes
Size & MU Status	No	No	Yes	Yes	Yes	Yes	Yes
Skill, Structured Mgmt, Plant Type, HQ, & Unionization	No	No	No	Yes	Yes	Yes	Yes
Plant Age	No	No	No	No	Yes	Yes	Yes
Capital Stock	No	No	No	No	No	Yes	No
Industry	No	No	Yes	Yes	Yes	Yes	Yes

Panel B: IV

	AI Index	Log Value Added		Profits	Change in WIP Inventory	Log # of Robots	Log Employment
	(1)	**(2) LP**	**(3) TFP**	**(4)**	**(5)**	**(6)**	**(7)**
No lack of AI expertise	0.0827***						
	(0.0174)						
AI Index		-0.775***	-0.587**	-11,300***	2,900**	0.412**	-0.555**
		(0.271)	(0.230)	(4,110)	(1,408)	(0.184)	(0.243)
DS Index	-0.050***	-0.007	-0.015	-565**	111	0.039***	0.087***
	(0.018)	(0.020)	(0.017)	(271)	(103)	(0.0125)	(0.0166)
PA Index	0.386***	0.297***	0.219**	4339***	-1202**	-0.155**	0.238**
	(0.0119)	(0.104)	(0.0888)	(1585)	(545.8)	(0.0710)	(0.0943)
Additional Controls	See table notes						

Notes: AI Index (the dependent variable) measures adoption of applications of AI in business functions or adoption of specific AI technologies, with the index being normalized to have zero mean and unit standard deviation. DS index measures use of descriptive statistics in decision making with the index being normalized to have zero mean and unit standard deviation. PA index measures use to prediction algorithms across six business functions with index being normalized to have zero mean and unit standard deviation. **Panel A**: As indicated by column, control variables may include: accumulated capitalized IT equipment expenditures over the prior 3 years; expenditures on Cloud computing; size in terms of logged employment; indicator of multi-unit status; worker skill in terms of the percentage of employee with a BA degree; the Bloom et al (2019) index of structured management practices; a plant type indicator capturing production strategy (0 for R&D plants or job shops, 1 for batch production and 2 for continuous flow or cellular manufacturing); percentage of unionized employees; logged plant age from the LBD; logged capital stock; industry at the 3-digit NAICS level. Columns 3-7 also control for logged energy expenditures; column 6 includes an indicator for missing data on non-IT capital to stablize the sample size.
Panel B: All columns include all control variables from column 5 of Panel A. "No lack of AI expertise" is a dummy, reverse-coded from respondents reporting lack of AI expertise as reason not to adopt or to delay AI use (see Table 1, Panel D). "WIP" denotes the value of work-in-progress inventory reported on the ASM. Number of robots includes active and purchased industrial robots from the ASM.
Standard errors for both panels are clustered at the firm level and reported in parentheses. Note that we do not report first stage F-Stats, since according to Angrist and Pischke (2007), a significant first stage and significant second stage are sufficient if the endogenous variable is just-identified (as many endogenous variables as instruments).

Table 4: IV Robustness

Panel A: Ruling out sample-selected IV

	log VA	AI Index	log VA
	(1)	**(2)**	**(3)**
No lack of AI expertise	-0.0639***		
	(0.0176)		
AI is widely used		0.603***	
		(0.041)	
AI Index		0.065	
		(0.044)	
DS Index	0.0320***	-0.043**	0.035***
	(0.00866)	(0.018)	(0.009)
PA Index	-0.00175	0.373***	-0.027
	(0.00673)	(0.012)	(0.019)
Log IT Capital	(+)***	(-)	(+)***
Log Cloud Expense	(+)***	(+)***	(+)***
Additional Controls	See table notes		

Panel B: Plausibility of Exclusion Restriction

	Job Shops		SU Firms	
	AI Index	Log VA	AI Index	Log VA
	(1)	**(2)**	**(3)**	**(4)**
No lack of AI expertise	-0.0204	-0.0213	-0.0149	-0.011
	(0.034)	(0.0308)	(0.0272)	(0.0284)
Additional Controls	See table notes			

Panel A Notes: Placebo instrument is the affirmative response that "Artificial intelligence is widely or increasingly used at this establishment." Unreported controls include accumulated capitalized IT equipment expenditures over the prior 3 years, expenditures on Cloud computing, size in terms of logged employment, worker skill in terms of the percentage of employees with a BA degree, the Bloom et al (2019) index of structured management practices, percentage of unionized employees, plant age, energy expenditures, and industry at the 3-digit NAICS level. Where appropriate, also included are indicators of plant production strategy, multi-unit status, and headquarters status.

Panel B Notes: Instrumenting "no lack of AI expertise" for the AI Index. First stage is reported in columns 1 and 3. Reduced forms are reported in columns 2 and 4. Job Shops are plants reporting high mix, low volume production in a job shop or prototyping production strategy. SU firms are single-unit firms. Controls match the unreported controls of Panel A.

Standard errors for both panels are clustered at the firm level and reported in parentheses. Note that we do not report first stage F-Stats, since according to Angrist and Pischke (2009), a significant first stage and significant second stage are sufficient if the endogenous variable is just-identified (the same number of endogenous variables as instruments).

Table 5: Performance of Early AI Adopters

Panel A: First Difference 2012–2017

	Log Sales	Log Value Added	Profits	Log Value Added	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
AI Index	-0.0262***	-0.0187***	-4073.1*	-0.0247***	0.0790**
	(0.00467)	(0.00473)	(2241.5)	(0.00561)	(0.0352)
AI Index X Strategy: Quality				-0.00189	
				(0.00667)	
AI Index X Strategy: New Markets				0.0144***	
				(0.00491)	
AI Index X Strategy: Cost Leadership				-0.0014	
				(0.00547)	
AI Index X log firm age					-0.0307***
					(0.0103)
Additional Controls			See table notes		

Panel B: Growth during 2017–2021

	Growth: Employment	Growth: Revenue	Growth: Labor Productivity	Growth: Revenue	Growth: Labor Productivity
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
AI Index	0.00843***	0.00473***	0.00336**	0.0330***	0.0197**
	(0.00225)	(0.00178)	(0.00160)	(0.0108)	(0.00910)
AI Index X Log Firm Age				-0.00895***	-0.00514*
				(0.00324)	(0.00274)
Additional Controls			See table notes		

Notes: AI Index measures adoption of applications of AI in business functions or adoption of specific AI technologies, with the index being normalized to have zero mean and unit standard deviation. Strategy measures from the 2018 Annual Business Survey. Firm age per the LBD. **Panel A Notes**: Unreported controls include logged employment, logged capital stock, logged capitalized IT equipment expenses, logged IT outsourcing expenses, logged energy expenses, logged software expenses. Standard errors are clustered at the firm level. Years included are 2012 and 2017 with year fixed effects. Number of firm observations is roughly 55,500. **Panel B Notes**: Growth rates are calculated using Davis, Haltiwanger and Schuh (1996) symmetric growth rates between 2017 and 2021. Additional controls include initial year (2017) logged employment (column 1), initial year logged sales (columns 2 & 4), initial year logged sales per worker (columns 3 & 5). Robust standard errors are reported in parentheses. Panels A and B also include a full set of 3-digit NAICS fixed effects.

Table 6: Investigating the Causal Mechanism

Panel A: Causal Effects of AI at Old Establishments

	Log Value Added (LP)	Log Value Added (TFP)	Log Wages	Log Employment
	(1)	**(2)**	**(3)**	**(4)**
AI Index	-0.1497	0.0835	-0.0534	-0.0952
	(0.2643)	(0.2456)	(0.166)	(0.2584)
AI Index X Old	-1.224**	-1.133**	-0.6961**	-0.9205*
	(0.5766)	(0.4678)	(0.3265)	(0.5199)
Additional Controls	See table notes			

Panel B: Causal Effects of AI on Structured Management at Old Establishments

	Structured Management	Structured Management: Process	KPI Review by Non-Managers	Production Target Awareness
	(1)	**(2)**	**(3)**	**(4)**
AI Index	0.1189	0.1795	0.1734	0.2534
	(0.2051)	(0.2088)	(0.0865)	(0.1109)
AI Index X Old	-0.8322**	-0.8602**	-0.286***	-0.2941**
	(0.3991)	(0.397)	(0.1363)	(0.1486)
Additional Controls	See table notes			

Panel C: Within-Firm Spillover Effects of AI

	AI Index	EAI Index	Log Value Added (LP)
	(1)	**(2)**	**(3)**
No lack of AI expertise	0.0810***	-0.000746	-0.822***
	(0.0174)	(0.0172)	(0.278)
No lack of AI expertise elsewhere	0.0922***	0.790***	0.343***
	(0.0348)	(0.0847)	(0.0632)
Additional Controls	See table notes		

Notes: Panel A: "Old" is any plant older than 25 years. Additional control variables include: DS index, PA index, accumulated IT equipment expenses in the past 3 years, expenses on cloud computing, size in terms of logged employment, energy expenditures, multi-unit indicator, skill in terms of number of employees with bachelors degrees, a plant type indicatory capturing production strategy, and percentage of unionized employees. Columns (1), (2) and (7) and (8) also include an index of structured management practicess (Bloom et al., 2019). Column (2) includes logged capital stock, calculated via perpetual inventory method. **Panel B** includes controls from column 1 of Panel A. Both Panels A and B include 3 digit NAICS industry fixed effects. Number of establishment observations is roughly 28,500. Standard errors are clustered at the firm level and reported in parentheses.

Table 7: Heterogeneity in Treatment Effects

	Full Sample	Cont. Flow Prod.	Old (25+ years)
	(1)	**(2)**	**(3)**
First Stage	0.083***	0.136***	0.068
	(0.017)	(0.031)	(0.022)
Second Stage	-0.775***	-0.394	-1.424
	(0.271)	(0.257)	(0.556)

Notes:

References

Acemoglu, D. and P. Restrepo (2018): "The race between man and machine: Implications of technology for growth, factor shares, and employment," *American economic review*, 108, 1488–1542.

Adner, R., P. Puranam, and F. Zhu (2019): "What is different about digital strategy? From quantitative to qualitative change," *Strategy Science*, 4, 253–261.

Agrawal, A., J. Gans, and A. Goldfarb (2018): *Prediction Machines: The Simple Economics of Artificial Intelligence*, Harvard Business Press.

Agrawal, A., J. S. Gans, and A. Goldfarb (2024): "Artificial intelligence adoption and system-wide change," *Journal of Economics & Management Strategy*, 33, 327–337.

Angrist, J. D. and J.-S. Pischke (2009): *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Aral, S., E. Brynjolfsson, and L. Wu (2012): "Three-way complementarities: Performance pay, human resource analytics, and information technology," *Management Science*, 58, 913–931.

Arrow, K. J. (1962): "The economic implications of learning by doing," *The Review of Economic Studies*, 29, 155–173.

Atalay, E., A. Hortaçsu, and C. Syverson (2014): "Vertical integration and input flows," *American Economic Review*, 104, 1120–1148.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu (2020a): "Foreign competition and domestic innovation: Evidence from US patents," *American Economic Review: Insights*, 2, 357–374.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. V. Reenen (2020b): "The Fall of the Labor Share and the Rise of Superstar Firms ["Automation and New Tasks: How Technology Displaces and Reinstates Labor"]," *The Quarterly Journal of Economics*, 135, 645–709.

Autor, D. and A. Salomons (2018): "Is Automation Labor Share–Displacing? Productivity Growth, Employment, and the Labor Share," *Brookings Papers on Economic Activity*, 49, 1–87.

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

Barney, J. (1991): "Firm resources and sustained competitive advantage," *Journal of Management*, 17, 99–120.

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

Bennett, V. M. (2020): "Changes in persistence of performance over time," *Strategic Management Journal*, 41, 1745–1769.

Berman, R. and A. Israeli (2022): "The value of descriptive analytics: Evidence from online retailers," *Marketing Science*, 41, 1074–1096.

Bloom, N., E. Brynjolfsson, L. Foster, R. Jarmin, M. Patnaik, I. Saporta-Eksten, and J. Van Reenen (2019): "What drives differences in management practices?" *American Economic Review*, 109, 1648–1683.

Bloom, N., E. Brynjolfsson, L. Foster, R. Jarmin, I. Saporta-Eksten, and J. Van Reenen (2013): "Management in America," CES Working Paper 13-01, US Census Bureau Center for Economic Studies.

Bloom, N., R. Sadun, and J. Van Reenen (2012): "Americans do IT better: US multinationals and the productivity miracle," *American Economic Review*, 102, 167–201.

Bloom, N. and J. Van Reenen (2007): "Measuring and explaining management practices across firms and countries," *The quarterly journal of Economics*, 122, 1351–1408.

Bonney, K., C. Breaux, C. Buffington, E. Dinlersoz, L. S. Foster, N. Goldschlag, J. C. Haltiwanger, Z. Kroff, and K. Savage (2024): "Tracking firm use of AI in real time: A snapshot from the Business Trends and Outlook Survey," NBER Working Paper w32319, National Bureau of Economic Research.

Bresnahan, T. (2024): "What innovation paths for AI to become a GPT?" *Journal of Economics & Management Strategy*, 33, 305–316.

Bresnahan, T. and S. Greenstein (1996): "Technical progress and co-invention in computing and in the uses of computers," *Brookings Papers on Economic Activity. Microeconomics*, 1996, 1–83.

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

Bresnahan, T. F. and M. Trajtenberg (1995): "General purpose technologies 'Engines of growth'?" *Journal of Econometrics*, 65, 83–108.

Brynjolfsson, E. and L. Hitt (1996): "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," *Management Science*, 42, 541–558.

Brynjolfsson, E. and L. M. Hitt (2000): "Beyond computation: Information technology, organizational transformation and business performance," *Journal of Economic perspectives*, 14, 23–48.

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

Brynjolfsson, E., D. Li, and L. R. Raymond (2023): "Generative AI at work," NBER Working Paper w31161, National Bureau of Economic Research.

Brynjolfsson, E. and K. McElheran (2016): "The rapid adoption of data-driven decision-making," *American Economic Review*, 106, 133–39.

Brynjolfsson, E. and P. Milgrom (2013): "Complementarity in organizations," *The handbook of organizational economics*, 11–55.

Brynjolfsson, E., D. Rock, and C. Syverson (2021b): "The productivity J-curve: How intangibles complement general purpose technologies," *American Economic Journal: Macroeconomics*, 13, 333–372.

Cabral, L. M. B. and M. H. Riordan (1994): "The learning curve, market dominance, and predatory pricing," *Econometrica*, 62, 1115–1140.

Calvino, F. and L. Fontanelli (2023): "A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity," OECD Working Paper 2023/02, OECD.

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

Chava, S., A. Oettl, A. Subramanian, and K. V. Subramanian (2013): "Banking deregulation and innovation," *Journal of Financial economics*, 109, 759–774.

Christensen, C. M., R. McDonald, E. J. Altman, and J. E. Palmer (2018): "Disruptive innovation: An intellectual history and directions for future research," *Journal of management studies*, 55, 1043–1078.

Cockburn, I. M., R. Henderson, and S. Stern (2018): "The impact of artificial intelligence on innovation," NBER Working Paper 24449, National Bureau of Economic Research.

Combemale, C., K. S. Whitefoot, L. Ales, and E. R. Fuchs (2021): "Not all technological change is equal: how the separability of tasks mediates the effect of technology change on skill demand," *Industrial and Corporate Change*, 30, 1361–1387.

Cornwell, C., I. M. Schmutte, and D. Scur (2021): "Building a productive workforce: The role of structured management practices," *Management Science*, 67, 7308–7321.

David, P. A. (1985): "Clio and the Economics of QWERTY," *American Economic Review*, 75, 332–337.

——— (1990): "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox," *American Economic Review*, 80, 355–361.

Deloitte (2020): "AI Manufacturing Application Survey," `https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/cip/deloitte-cn-cip-ai-manufacturing-application-survey-en-200116.pdf`, accessed: 2024-03-23.

Eloundou, T., S. Manning, P. Mishkin, and D. Rock (2023): "GPTs are GPTs: An early look at the labor market impact potential of large language models," *arXiv preprint arXiv:2303.10130*.

Feigenbaum, J. and D. P. Gross (2024): "Organizational and economic obstacles to automation: A cautionary tale from AT&T in the twentieth century," *Management Science*, forthcoming.

Felten, E., M. Raj, and R. Seamans (2021): "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses," *Strategic Management Journal*, 42, 2195–2217.

Fontanelli, L., F. Calvino, C. Criscuolo, L. Nesta, and E. Verdolini (2024): "The role of human capital for AI adoption: evidence from French firms," .

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

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

Furman, J. and R. Seamans (2019): "AI and the Economy," *Innovation Policy and the Economy*, 19, 161–191.

Galdon-Sanchez, J. E., R. Gil, and G. Uriz Uharte (2022): "The value of information in competitive markets: The impact of big data on small and medium enterprises," *Available at SSRN 4022675*.

Gambardella, A., S. Heaton, E. Novelli, and D. J. Teece (2021): "Profiting from enabling technologies?" *Strategy Science*, 6, 75–90.

Gans, J. (2016): *The disruption dilemma*, MIT press.

Giustiziero, G., T. Kretschmer, D. Somaya, and B. Wu (2023): "Hyperspecialization and hyperscaling: A resource-based theory of the digital firm," *Strategic Management Journal*, 44, 1391–1424.

Goldfarb, A., B. Taska, and F. Teodoridis (2023): "Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings," *Research Policy*, 52, 104653.

Goldfarb, A. and C. Tucker (2019): "Digital Economics," *Journal of Economic Literature*, 57, 3–43.

Grant, R. M. (1996): "Toward a knowledge-based theory of the firm," *Strategic Management Journal*, 17, 109–122.

Guzman, J. and S. Stern (2020): "The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 32 US States, 1988–2014," *American Economic Journal: Economic Policy*, 12, 212–243.

Haltiwanger, J., R. S. Jarmin, R. Kulick, and J. Miranda (2016): "High growth young firms: contribution to job, output, and productivity growth," in *Measuring entrepreneurial businesses: Current knowledge and challenges*, University of Chicago Press, 11–62.

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

Hamilton, B. H. and J. A. Nickerson (2003): "Correcting for endogeneity in strategic management research," *Strategic organization*, 1, 51–78.

Hayes, R. H. and R. Jaikumar (1991): "Requirements for successful implementation of new manufacturing technologies," *Journal of Engineering and Technology Management*, 7, 169–175.

Hayes, R. H. and S. C. Wheelwright (1979): "Link manufacturing process and product life cycles," *June*, 2, 1999.

Helfat, C. E., A. Kaul, D. J. Ketchen Jr, J. B. Barney, O. Chatain, and H. Singh (2023): "Renewing the resource-based view: New contexts, new concepts, and new methods," *Strategic Management Journal*, 44, 1357–1390.

Helfat, C. E. and M. A. Peteraf (2003): "The dynamic resource-based view: Capability lifecycles," *Strategic Management Journal*, 24, 997–1010.

Henderson, R. (1993): "Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry," *The RAND Journal of Economics*, 248–270.

Holweg, M. (2007): "The genealogy of lean production," *Journal of Operations Management*, 25, 420–437.

Iansiti, M. and K. R. Lakhani (2020): *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World*, Harvard Business Press.

Ichniowski, C., K. L. Shaw, and G. Prennushi (1995): "The effects of human resource management practices on productivity," .

Jin, W. and K. McElheran (2024): "Economies before Scale: IT Strategy and Performance Dynamics of Young U.S. Businesses," *Management Science*, forthcoming.

Kogut, B. and U. Zander (1993): "Knowledge of the firm and the evolutionary theory of the multinational corporation," *Journal of international business studies*, 24, 625–645.

Kueng, L., M.-J. Yang, and B. Hong (2014): "Sources of firm life-cycle dynamics: Differentiating size vs. age effects," NBER Working Paper w20621, National Bureau of Economic Research.

Lambrecht, A. and C. E. Tucker (2016): "The Limits of Big Data's Competitive Edge," *MIT IDE Research Brief*.

Levinthal, D. A. (1997): "Adaptation on rugged landscapes," *Management Science*, 43, 934–950.

Levitt, S. D., J. A. List, and C. Syverson (2013): "Toward an understanding of learning by doing: Evidence from an automobile assembly plant," *Journal of political Economy*, 121, 643–681.

Lieberman, M. B. and D. B. Montgomery (1998): "First-mover (dis) advantages: retrospective and link with the resource-based view," *Strategic Management Journal*, 19, 1111–1125.

Lou, B. and L. Wu (2021): "AI on drugs: Can artificial intelligence accelerate drug development? Evidence from a large-scale examination of bio-pharma firms," *Evidence from a Large-scale Examination of Bio-pharma Firms,(March 15, 2021). MISQ Forthcoming*.

March, J. G. (1991): "How decisions happen in organizations," *Human-Computer Interaction*, 6, 95–117.

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

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. Foster, and N. Zolas (2024): "AI Adoption in America: Who, What, and Where," *Journal of Economics & Management Strategy*, 33, 375–415.

McElheran, K., S. Ohlmacher, and M. J. Yang (2019): "Strategy and Structured Management," *Available at SSRN 4660979*.

McGahan, A. M. and M. E. Porter (1997): "How much does industry matter, really?" *Strategic management journal*, 18, 15–30.

Milgrom, P. and J. Roberts (1988): "Communication and inventory as substitutes in organizing production," *The Scandinavian Journal of Economics*, 275–289.

——— (1990): "The Economics of Modern Manufacturing: Technology, Strategy, and Organization," *American Economic Review*, 80, 511–528.

——— (1995): "Complementarities and fit strategy, structure, and organizational change in manufacturing," *Journal of accounting and economics*, 19, 179–208.

Miric, M., N. Jia, and K. G. Huang (2023): "Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents," *Strategic Management Journal*, 44, 491–519.

National Science Foundation (2021): "Data Tables," `https://ncses.nsf.gov/pubs/nsf23314/assets/data-tables/tables/nsf23314-tab066.pdf`, accessed: 2024-03-23.

Nickerson, J. and T. Zenger (2004): "A knowledge-based theory of governance choice–A problem-solving approach," *Organization science*, 15, 617–632.

Parthasarthy, R. and S. P. Sethi (1993): "Relating strategy and structure to flexible automation: a test of fit and performance implications," *Strategic Management Journal*, 14, 529–549.

Peng, S., E. Kalliamvakou, P. Cihon, and M. Demirer (2023): "The impact of AI on developer productivity: Evidence from GitHub Copilot," *arXiv preprint arXiv:2302.06590*.

Porter, M. E. (1980): *Competitive Strategy*, New York: Free Press.

Pratt, G. A. (2015): "Is a Cambrian Explosion Coming for Robotics?" *Journal of Economic Perspectives*, 29, 51–60.

Rathje, J. M. and R. Katila (2021): "Enabling technologies and the role of private firms: A machine learning matching analysis," *Strategy Science*, 6, 5–21.

Rumelt, R. P. (2005): "Theory, strategy, and entrepreneurship," in *Handbook of Entrepreneurship Research: Interdisciplinary Perspectives*, Boston, MA: Springer US, 11–32.

Rumelt, R. P., D. Schendel, and D. J. Teece (1991): "Strategic management and economics," *Strategic management journal*, 12, 5–29.

Schumpeter, J. A. (1934): *The Theory of Economic Development*, Cambridge, Mass.: Harvard University Press.

——— (1942): *Capitalism, Socialism and Democracy*, New York: Harper & Brothers.

Scur, D., R. Sadun, J. Van Reenen, R. Lemos, and N. Bloom (2021): "The World Management Survey at 18: lessons and the way forward," *Oxford Review of Economic Policy*, 37, 231–258.

Scur, D. and S. Wolfolds (2024): "Revisiting the world management survey in strategy: Applications to theory and replication," *Strategy Science*, 9, 58–78.

Svanberg, M., W. Li, M. Fleming, B. Goehring, and N. Thompson (2024): "Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision?" Working Paper 4700751, SSRN.

Tambe, P., L. Hitt, D. Rock, and E. Brynjolfsson (2020): "Digital capital and superstar firms," NBER Working Paper w28285, National Bureau of Economic Research.

Tambe, P. and L. M. Hitt (2012): "The productivity of information technology investments: New evidence from IT labor data," *Information Systems Research*, 23, 599–617.

Tambe, P., L. M. Hitt, and E. Brynjolfsson (2012): "The extroverted firm: How external information practices affect innovation and productivity," *Management Science*, 58, 843–859.

Teece, D. J. (1986): "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy," *Research Policy*, 15, 285–305.

——— (2018): "Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world," *Research Policy*, 47, 1367–1387.

Teece, D. J., G. Pisano, and A. Shuen (1997): "Dynamic capabilities and strategic management," *Strategic management journal*, 18, 509–533.

Thompson, P. (2012): "The relationship between unit cost and cumulative quantity and the evidence for organizational learning-by-doing," *Journal of Economic Perspectives*, 26, 203–224.

Toner-Rodgers, A. (2024): "Artificial intelligence, scientific discovery, and product innovation," *arXiv preprint arXiv:2412.17866*.

Womack, J. P., D. T. Jones, and D. Roos (2007): *The machine that changed the world: The story of lean production–Toyota's secret weapon in the global car wars that is now revolutionizing world industry*, Simon and Schuster.

Wu, L., L. Hitt, and B. Lou (2020): "Data analytics, innovation, and firm productivity," *Management Science*, 66, 2017–2039.

Yang, M.-J., M. Christensen, N. Bloom, R. Sadun, and J. Rivkin (2024): "A Scientific Approach to Business Strategy," Tech. rep., Working Paper: https://tinyurl.com/kyw5kdkp.

Yang, M.-J., L. Kueng, and B. Hong (2015): "Business Strategy and the Management of Firms," NBER Working Paper 20846, National Bureau of Economic Research.

Yang, M.-J., N. Li, and L. Kueng (2021): "The Impact of Emerging Market Competition on Innovation and Business Strategy: Evidence from Canada," *Journal of Economic Behavior and Organization*, 181, 117–134.

Zolas, N., Z. Kroff, E. Brynjolfsson, K. McElheran, D. N. Beede, C. Buffington, N. Goldschlag, L. Foster, and E. Dinlersoz (2020): "Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey," NBER Working Papers 28290, National Bureau of Economic Research, Inc.

——— (2021): "Advanced technologies adoption and use by US firms: Evidence from the annual business survey," NBER Working Paper w28290, National Bureau of Economic Research.