Data in Action: Data-Driven Decision Making and Predictive Analytics in U.S. Manufacturing

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Abstract

Management in America has become significantly more data-intensive, yet the economic, organizational, and strategic implications of this shift are poorly understood. Working with the U.S. Census Bureau, we developed measures of how manufacturing firms have used data to guide decision making over the past decade. In our large and representative sample, data-driven decision making (DDD) is strongly associated with increased productivity. The benefits attributable to DDD are distinct from those associated with other structured management practices or investment in IT, though the latter is an important complement. Moreover, instrumental variables estimates and timing falsification tests suggest a causal relationship. Implications for firm strategy, however, are nuanced; we find evidence of significant advantages for early adopters of DDD, particularly in the 2005-2010 window, when adoption rates in the sector were lower. Yet we also observe timing-dependent complementarities. The frontier of data-centric practices shifts during our study period, with increased use of predictive analytics becoming the key driver of productivity gains from 2010 to 2015.

Keywords: data, analytics, productivity, management practices, information technology, data-driven decision making

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1. Introduction

Dramatic improvements in data collection, storage, and processing capabilities have created new opportunities for firms in recent years (e.g., Brynjolfsson and McAfee 2014, Deloitte 2018). In particular, the collection of and reliance on data for managerial activities—i.e., data-driven decision making (DDD)—has grown rapidly in the United States (Brynjolfsson and McElheran 2016) and promises a "data-driven revolution in management" (McAfee and Brynjolfsson 2012, Tambe 2014). There is suggestive evidence that DDD is associated with better performance in a modest sample of large public firms (Brynjolfsson et al. 2011). Yet important questions remain about the magnitude of this relationship in the broader economy, whether complementary investments may be necessary to exploit these new opportunities, and whether DDD can be a source of competitive advantage. This study addresses these questions, highlighting how persistent performance differences from readily-available technology depend on how it is deployed in practice across organizational contexts and activities (Powell and Dent-Micallef 1997, Bharadwaj 2000, Brynjolfsson and Hitt 2000, Aral and Weill 2007, Bloom et al. 2012).

The rise of the internet and other digital technologies spurred a rapid, exponential growth in the availability of digital data. This created demand for new tools and techniques collectively referred to as "big data analytics" (Chen et al. 2012, Tambe 2014). Data was upgraded from the "sludge of the information age" to "the new oil" (Acito and Khatri 2014). Cautious optimists emphasized the need for certain firm competencies to derive competitive advantage from big data (e.g., Lambrecht and Tucker 2015). Yet aside from compelling anecdotes, little systematic evidence exists to inform managerial choices concerning these novel and potentially powerful digital resources.

Ironically, large-scale data on the use of data by firms has been lacking. To address this gap, we worked with the U.S. Census Bureau to design and field two waves of a survey to examine this phenomenon in detail over the past decade. The survey went to a representative sample of over 30,000 manufacturing establishments, providing unusual visibility into data-related practices and IT investments within firms. Work based on the first wave of the survey shows how DDD diffused quickly among establishments of different types in the early years, highlighting the importance of size, IT investments, and worker education for DDD adoption (Brynjolfsson and McElheran 2016). Here, we offer some of the first (and almost certainly the largest) systematic evidence that data-related management practices are causally linked to better performance in a wide range of operational settings.

We estimate that being at the frontier of DDD is conditionally correlated with improvements in revenue-based productivity of 4-8%, depending on the specification and time period. To contextualize the magnitude, this increase is, on average, comparable to that associated with moving into the top quartile of IT capital stock—which has its own, separate relationship with productivity. Rich time-varying controls, establishment fixed effects, timing falsification, and IV estimation suggest that this relationship is causal.

Timing, however, is essential. We observe a pattern resembling the classic "S-curve" diffusion model, with leading adopters receiving the biggest gains, some effective following in the middle period, and a tail of laggards that reach the frontier later with lower net benefits or not at all.[3] Consistent with tests of complementarities as described by Athey and Stern (1998) and Brynjolfsson and Milgrom (2013), DDD has a stronger relationship with performance in earlier years and a stronger correlation with investments that support DDD—in particular, IT infrastructure—in later years, as diffusion increases.

Notably, while the relative gains from our initial DDD measure fade during the 10-year period we study, more-recent practices centered on the use of predictive analytics become observable and are strongly associated with higher productivity in the second wave of the survey. Predictive analytics are distinct from general DDD, consistent with anecdotal evidence that the frontier of data usage moved beyond early DDD practices. The stand-alone importance of IT increases in this later period, as well. This pattern is consistent with a *shifting* S-curve of practice, whereby early gains are time-delimited and leaders maintain their advantage by transitioning to the next frontier in a timely fashion (Foster 1985).

We find that having robust IT capital in place makes it more likely that firms will implement and benefit from frontier DDD. This is consistent with recent work emphasizing the role of IT in competition

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[3] See Stoneman (2002) for an overview of this large literature.

over the past decade (Bennett and Gartenberg 2016, Bessen 2017). However, again, timing matters. Having high IT capital stocks *prior* to adopting DDD satisfies the formal tests for complementarity. When pursued in this order, DDD and IT reinforce each other to ease adoption and improve performance. However, adding high levels of IT capital *after* early DDD has been adopted does not confer the same benefits. Among possible explanations is path-dependence in DDD, making DDD leading up to 2005 more "low-tech" and rooted in earlier lean manufacturing practices that prioritized information over IT (Womack et al. 1990). This contrasts with later "high-tech" DDD that relies on advances in IT. Progressing in sophistication, predictive analytics distinguishes the most productive firms in later years. Taken together, this pattern points to an advancing technological and managerial frontier that boosts firm performance while conferring transient competitive advantage: firms that keep up with the leading edge achieve and sustain gains relative to less data-centric establishments.

Our findings contribute to a number of areas of existing work. To begin, they provide evidence to support common, yet heretofore speculative, claims concerning the returns from increased use of data and related practices such as predictive analytics (e.g., Manyika et al. 2011, Ernst and Young 2014, Deloitte 2018) in a large representative sample of manufacturing firms. The productivity benefits we find from DDD are not only empirically significant and robust but they also appear to be causal.

The importance of timing and complementary IT investment contribute to a management literature that is increasingly interested in digitization. Prior work has addressed the role of IT in organizational design (Brynjolfsson et al. 1994; Brews and Tucci 2004; Ray et al. 2009; Bloom, Garicano et al. 2014; Rawley and Simcoe 2013; Forman and McElheran 2019), business model strategy (Gambardella and McGahan 2010, Casadesus-Masanell and Zhu 2013), innovation (Dougherty and Dunne 2012, Yin et al. 2014, Furman and Teodoridis 2017) and competitive advantage (Bharadwaj 2000, Ray et al. 2009). An increasingly important question is how much prior intuitions need to adjust to newer digital technologies (Adner et al. 2018). Our focus on overlapping advances in both IT and related practices within the organization adds to this growing conversation.

Our study not only emphasizes the practices required to take advantage of new digital resources but also distinguishes them from more general "structured" management. As such, it contributes to a growing stream of research on management practices, quite generally (Bloom, Eifert et al. 2013; Bloom et al. 2019, Yang et al. 2015, Blader et al. 2015 & forthcoming, Hong et al. 2019), and data- or IT-intensive practices, more specifically (Pierce et al. 2015, Hoffman et al. 2017, Kleinberg et al. 2017, Cowgill 2018).

Finally, while ours is one of a few studies that treat data and/or analytics as separate production inputs,[4] we build on a rich IT productivity literature.[5] In particular, we extend prior findings that the organizational context in which IT is deployed may matter as much as investment (Bresnahan et al. 2002, Brynjolfsson et al. 2002, Devaraj and Kohli 2003, Melville et al. 2004, Aral and Weill 2007, Bloom et al. 2012), and that organizational complementarities influence returns to IT (Milgrom and Roberts 1990, Bartel et al. 2007, Bharadwaj et al. 2007, Aral et al. 2012, Tambe et al. 2012).

2. Motivation and Literature

Because organizations may be thought of as "information processors" (Galbraith 1974), large decreases in the costs of data collection, storage, and analysis have the potential to change many processes in organizations (e.g., Manyika et al. 2011, McAfee and Brynjolfsson 2012). However, changing organizational systems to adapt to new technologies is costly, time-consuming, and risky (Bresnahan and Greenstein 1996, Brynjolfsson and Hitt 2003, Tambe and Hitt 2012) and dependent on other systems within firms (Milgrom and Roberts 1990, Rivkin 2000). Thus, declines in data-related costs could have uneven effects as learning unfolds and complementary changes are invented and executed over time. We lean on a rich diversity of prior research to motivate our empirical exploration of this phenomenon.

2.1 Performance Gains from Data

Information in Individual Decision Making. At the individual level, decision theory points to the benefits of using objective information in a rational-choice setting (e.g., Raiffa 1968). Blackwell (1953)

[4] Notable exceptions are Aral et al. (2012), Saunders and Tambe (2013), Tambe (2014), Wu et al. (forthcoming) and the related smaller-scale study by Brynjolfsson et al. (2011).
[5] See Cardona et al. (2013) for a review.

established that, in terms of expected payoff, imperfect yet "more informative" sets of inputs weakly improve performance. Finer-grained information or lowered statistical noise reduce the level of aggregation that decision-makers face in distinguishing different states of the world. Reducing uncertainty in this fashion is valuable in most settings, conditional on the cost required to do so (Raiffa 1968).

Connecting this to digitization, reductions in the cost of sensors and other automation for collecting data in recent years have led to more and more-precise information through higher-fidelity measurement as well as more-frequent sampling in both internal production environments and external markets. The tools and techniques for data collection, management, and analysis have become less expensive and more sophisticated, making it easier for firms to digest greater volumes of more diverse data inputs. Greater use of digital platforms by consumers and other sources of "digital exhaust" allow firms to run online experiments and leverage increasingly powerful empirical techniques to uncover new relationships (McAfee and Brynjolfsson 2012, Chen et al. 2012, Tambe 2014).

Note that rationality need not be assumed: data and data-driven models can also be useful in counteracting psychological biases in decision making (e.g., Milkman, et al. 2009). Empirical evidence confirms the benefits of using data and automation in decision making by individuals in a wide range of settings (e.g., Pierce et al. 2015, Hoffman et al. 2017, Kleinberg et al. 2017, Cowgill 2018).

The Information-Processing View of the Firm. Individual decisions are strategically important because they allocate scarce resources (March 1994) within firms. Prior work confirms that, at the organization level, when a firm allocates inputs under limited information about its specific production and market context, misallocations reduce productivity (David et al. 2016). Managers can learn about these firm-specific features in a variety of ways (more on that below), but technologies or practices that enable greater collection of information or facilitate its dissemination should lower production and coordination costs and improve performance, all else equal. This line of argument has been used extensively to explore the value of IT in firms (e.g., Brynjolfsson and Hitt 2003, Bloom et al. 2012). Yet IT is not required: a recent study points to the productivity benefits of better-quality financial data achieved though accounting audits (Barrios et al. 2019). An open question raised by these findings is how much data use and IT use substitute for or reinforce each other, and under what conditions.

Clarity and Coordination within Firms. To the extent that firms can also be conceptualized as coordinating mechanisms (Kogut and Zander 1996), objective information can play a different but crucial role in aligning the work, expectations, and incentives of workers and managers within firms. Objective data can improve clarity on firm, worker, and process performance, promoting coordination around shared objectives and scaffolding "relational contracts" (Gibbons and Henderson 2012). The latter may be critical for boosting worker engagement and more effective managerial guidance in firms (Gibbons and Henderson 2012, Helper and Henderson 2014, Blader et al. 2015 & forthcoming). This channel is distinct from, but not necessarily mutually exclusive of, the information processing arguments laid out above.

Legitimizing Decisions. Theodore Porter (1996) argues forcefully that the modern drive for quantification derives from powerful social and political forces—aside from any direct relationship to performance—and much data may be more accurately described as *impersonal* as opposed to objective *truth*. Quantitative measures have a history of legitimizing decisions that appeal to data, particularly in the absence of other sources of authority. Thus, while data may vary considerably in quality concerning the "state of the world," relying on objective measures for decisions may still improve performance if it promotes adherence to decisions taken by managers (DiMaggio and Powell 1983, Zuckerman 1999).

Process of Moving from Tacit to Objective Information. Finally, choosing to become more data-driven can alter important processes within firms, separately from changing the inputs on which they rely. In particular, in firms with relatively new or highly variable production processes, management must progress from being an "art" to a "science" (Bohn 2005) in order to replace managerial intuition with objective information. Employee effort is invested in greater standardization and instrumentation of processes. Key performance indicators are chosen and tracked. For this, managers work to determine what data to collect, how often, and how to evaluate it. Firms often go through a lengthy process of "learning what they know," consulting with employees and discovering what knowledge resides in scattered locations throughout the organization. Importantly, this process is useful for capturing tacit knowledge that employees have acquired through less-formalized channels, and codifies and centralizes it in accessible formats. If firms, like people, "can know more than they can tell" (Polanyi 1969), the steps necessary to implement DDD both increase access to more objective information and adjust how processes are designed and governed. To be clear, this channel emphasizes a range of benefits to the firm that are not inherent in features of data inputs *per se*, but in the process required to *become* "data-driven."

Understanding this process-level adjustment is useful for thinking about the costs of DDD. Much of the data we explore here is captured by the firm itself, not purchased from outside.[6] Thus, costs typically involve managerial time and attention, as well as the opportunity cost of worker effort devoted to these discovery, formalization, and socialization processes instead of producing more measurable outputs. Thus, any performance gains observed will be net of these costs. Moreover, they are likely to be quite heterogeneous among firms of different types, in different industries, with different operating systems.

2.2 Persistent Performance Gains from Data

Given this diversity of channels though which firms may benefit from data— and the heterogeneous costs required to become data-driven—our first tests focus on whether we can identify these proposed benefits of data-driven decision making in a large, heterogeneous sample of firms. However, even if the average productivity of a set of practices can be established, the core management concern is whether relative gains from these new practices can be sustained by some firms over time, and under what circumstances.

To begin, adopting new technologies and related processes typically involve significant investments across many margins. Complementary organizational features may be affected, such as decision rights (McElheran 2014), organizational design (Brynjolfsson et al. 1994; Brews and Tucci 2004; Ray et al. 2009; Bloom, Garicano et al. 2014; Rawley and Simcoe 2013; Forman and McElheran 2019), and other processes and practices (performance pay, promotion, hiring, etc.) that interact with each other and with

[6] Prior work suggests this is the norm (David 2016).

the firm's culture and strategy.[7] The returns on these investments will vary by firm, along dimensions that are often difficult to observe. Similar to Brynjolfsson and McElheran (2016), we report on potential drivers and complements of adoption in Table 3 (see below), paying particular attention to IT, and then control as much as possible for these other confounds in our performance regressions.

These multi-faceted changes are costly, time-consuming, and often subject to mistakes and inertia (Bresnahan and Greenstein 1996, Leonard-Barton 1992, Henderson 1993). On the other hand, once implemented, they can be difficult for competitors to imitate (Porter and Siggelkow 2008). The more complex, embedded, and causally ambiguous the cluster of complementary investments are, the more likely they are to contribute to competitive advantage (Barney 1991, Rivkin 2000, Ray et al. 2004). This will promote significant differences in performance—at least in the short term.

As awareness of new technologies and complementary investments diffuses through the economy, however, two patterns are predicted by theory. The first is that later adopters of the technology are likely to enjoy lower relative returns compared to earlier-adopting competitors (Karshenas and Stoneman 1993, Stoneman 2002). Any early-mover advantage would go to firms that adopt first and leverage the technology for strategic benefits (Powell and Dent-Micallef 1997).[8] Later adopters are likely to be those with lower benefits and/or higher costs of adopting (David 1969). However, this may be difficult to detect empirically, as those with no firm-specific net benefits from adopting should never adopt, leading to a sample of laggards that is optimally not employing DDD. Also, competitive pressure will tend to drive out firms that do not adopt when it would be productivity-enhancing (Nelson and Winter 1982), compressing the differential between late adopters and non-adopters from the low end of the productivity distribution. Thus, comparisons among firms as diffusion unfolds requires care and attention to timing.

[7] Brynjolfsson et al. (2019) find evidence of complementarities between data-driven decision making and certain clusters of human resources management (HRM) practices. Westerman et al. (2014) detail at least nine organizational dimensions of "digitization" identified via interviews with leaders of large global companies. Porter and Siggelkow (2008) emphasize the importance of considering contextual features for understanding the benefits of certain practices.

[8] Note that first-mover advantage due to technology adoption is not a foregone conclusion, given adjustment costs and the challenges of implementing IT before local complements (such as IT consulting) are well-developed. See, e.g., Porter (1985) and Forman et al. (2005).

The other predicted pattern is that certain complementary bundles of practices and investments will become understood across more firms over time. Joint adoption of these clusters should become more observable. In fact, these two mechanisms work in opposition. The less-widely understood are the complementary relationships, the greater the relative gains for firms with the right combinations (which will show up as interaction effects in a standard performance model). As understanding diffuses, relative performance gains should decrease while correlated adoption rises (Brynjolfsson and Milgrom 2013).

The importance of complementary investments and organizational adjustment are long-established with respect to "embodied" technological advances such as computers, software applications, and network infrastructure (e.g., Bresnahan and Greenstein 1996, Brynjolfsson and Hitt 2000, Bresnahan et al. 2002, Forman 2005, Bharadwaj et al. 2007, Tambe et al. 2012, McElheran 2015, among others). However, less extant work has tested for these patterns in IT-centered managerial practices such as DDD and data analytics (exceptions include Aral et al. 2012, Saunders and Tambe 2013, and Wu et al. forthcoming). Leveraging our long panel of data, we can explicitly explore the timing of benefits and perform productivity and correlation tests for certain complementarities, particularly with IT.

2.3 Advancing Frontiers of Practice

Innovations in technology as well as in related practices continually arise and diffuse, creating new frontiers over time. Firms that stay with one technology-practice cluster will not only see competitors catch up, but they will see adopters of improved technologies and practices overtake them (e.g., Stoneman 2002). Thus, relative performance gains over time will be associated with firms' positions on more recent "S-curves" of technology and their ability to shift across different technology clusters (Foster 1985, Christensen 1997, McElheran 2015, Gans 2016). We focus on three distinct approaches to gaining the advantages of reduced uncertainty, improved coordination, and broader process improvement described in section 2.1 that may substitute for each other over time, generating strategic tradeoffs for adopters.

Lean Manufacturing. Collecting vast quantities of digital data is not the only way for firms to learn about the state of their particular firm or market. Computer printouts or electronic displays are relatively recent approaches to disseminating time-sensitive information within a firm or coordinating among employees and supply chain partners. Before a growing reliance on digital data collection, analysis, visualization, and prediction, the "state of the art" for managing many firms—particularly in the manufacturing context we explore here—was lean manufacturing.

Popularized by the success of Toyota Motors in the 1980s and influential books and case studies (e.g., Womack et al. 1990), manufacturing firms across the sector worked to develop more-responsive operations that carried less on-hand inventory, emphasized short lead- and cycle times, promoted high visibility to real-time operating conditions, and a "pull" versus "push" approach to everything from raw materials to information gathering (Womack et al. 1990, Hines et al. 2004, Holweg 2007).

Understanding this set of practices prior to our sample period is useful for knowing what the alternative to modern DDD might be. Given the ability to be advanced in lean practices using "low-tech" approaches such as physical *Kanban* cards to initiate raw materials replenishment orders, there is a subset of firms in our data with strong practices in place that may substitute effectively for high-tech methods (Helper and Henderson 2014). Moreover, given the emphasis devoted within the lean system to tracking real-time performance and relying on objective information rather than managerial intuition, we expect that a number of firms will appear to be quite data-driven according to our survey, but in a way that does not resemble the push towards "big data analytics" observed later on. In particular, the older set of practices should lead to weaker complementarities with IT, which we explore.

IT-Intensive DDD. An open question is the extent to which data-centric practices are separable from the well-documented gains from IT use, particularly in the manufacturing sector (e.g., Dunne et al. 2004, Atrostic and Nguyen 2005). If distinguishable, we expect there to be increasing returns to having both the infrastructure and the practices in place. In our setting, we can further explore if the order of investment matters, and what this tells us about how firms maintain the frontier of practice (or not). This dynamic approach to testing complementarities is a refinement on existing studies, which have historically identified cross-sectional relationships (e.g., Bharadwaj et al. 2007, Tambe et al. 2012)

Predictive Analytics. As the availability of digital information continues to increase unabated, tools to harness it have arisen in tandem. In particular, firms have increasingly turned to predictive analytics, the practice of applying statistical analysis to rich historical data in order to predict a wide range of firm, market, and supply chain outcomes. Anecdotal evidence abounds on the desirability of using these new tools to reduce uncertainty and improve efficiency in firms (Lambrecht and Tucker 2015, Dilda et al. 2017, Agrawal et al. 2018), along with a few early single-firm studies (e.g., Akturk et al. 2018). Open questions remain, however, about the extent to which this practice is distinct from being generally more data-driven, and whether it is applicable across diverse firm contexts.

3. Data

Disentangling different strands of this fast-emerging phenomenon poses a substantial data challenge. We therefore worked with the U.S. Census Bureau to design questions specifically targeted to understanding the adoption and performance implications of DDD. They are embedded in a new survey on management practices collected by the U.S. Census Bureau for 2010 and 2015 (for more details, see Bloom, Brynjolfsson et al. 2013 and Buffington et al. 2017). This Management and Organizational Practices Survey (MOPS) was included as a supplement to the Annual Survey of Manufactures (ASM), which targets roughly 10% of the over 300,000 establishments in the U.S. manufacturing sector. Response is required by law, minimizing response bias, and the sample is stratified to produce a representative annual snapshot of the manufacturing sector.

The first section of the survey, labeled "management practices," is based on work by Bloom and Van Reenen (2007) and focuses primarily on "structured management practices," some of which figure prominently in lean manufacturing. These primarily focus on monitoring, communication, and incentives at the plant. Examples include the collection, review, and communication of key performance indicators (KPIs) and targets (e.g., production targets, costs, quality, inventory, absenteeism, and on-time deliveries), as well as human resources practices such as promotion and bonus pay.

The second section, labeled "organization," focuses on decision making within the firm. Based on prior work by Brynjolfsson et al. (2011), two questions in this section of the 2010 survey query the availability and use of data to support decision making at the plant. For the second wave of data collection, the authors worked with Census to develop an entire section on "Data and Decision Making," including a range of new questions on data-related practices. In particular, one question explores who has authority for choosing what data to collect. An option for "government regulations or agencies" was included in order to tease out data collection that was exogenously imposed on the plant. We use this in an instrumental variables estimation of the causal impact of DDD (see below). This expanded section also contains the first large-scale data collection of the use of predictive analytics by U.S. firms. [9]

Sample Construction. Our analysis requires restricting attention to establishments that have positive value added, positive employment, and positive imputed capital in the ASM.[10] We further restrict attention to records with complete responses to the data-driven decision making questions and a critical mass of the management questions.[11]

Although the MOPS only took place twice in conjunction with the 2010 and 2015 ASM, all of the questions also asked about the state of practice five years earlier. Thus, we also have information about practices in 2005 from the 2010 survey and about 2010 from the 2015 survey. Wherever possible, we use reported data for 2010. If we are missing some 2010 MOPS information, we take the recall values from the 2015 wave of the survey. Based on extensive validation of the survey,[12] we further restrict recall data

[9] The full questionnaire is available at http://bhs.econ.census.gov/bhs/mops/form.html.

[10] This makes the standard productivity calculations possible and excludes low-quality records that may introduce systematic biases to the estimation. To meet these requirements requires a match between the MOPS and the ASM, that the establishment be flagged for tabulation in the national statistics, and that it have a valid linkage to the Longitudinal Business Database (LBD), which ensures accurate panel data linkages and age controls.

[11] Specifically, we further require that firms answer at least five of questions 1,5,7,8,9,11,13,14,15, and16. We explore but do not require responses to questions 3 and 4 on the frequency with which KPIs are reviewed. We exclude these questions from our core analysis because they are highly correlated with our other measures, have a relatively higher percentage of missing data, and offer no additional insights while restricting the sample size.

[12] Before being released to the Research Data Center network for access by outside researchers, all new Census surveys are subject to extensive internal validation (see Bloom, et al. 2013 and Buffington et al. 2017). As in Bloom, Brynjolfsson, et al. (2013), we explored similarities between the 2005 recall questions regarding plant-level employment and actual IRS records for that year and find the differences to be negligible. In cross-sectional explorations, we included a measure of the discrepancy between these numbers in 2005 as a "noise" control in many specifications. The impact of these measures is trivial and not reported due to space constraints.

to records provided by respondents (usually the plant manager, but sometimes other members of management) who had been at the firm at least five years, and who therefore likely had first-hand knowledge about the state of practice five years preceding. We employ a fixed-effects research design in certain analyses to control for time-invariant unobserved heterogeneity at the plant.

These restrictions yield two waves of roughly 22,900 and 26,500 establishments, respectively.[13] In certain analyses, we use each wave of the survey and recall separately to maximize the size of the data set. We also rely on two types of balanced panels: one with complete information across 2010 and 2015 (18,500 observations) and one with complete information that also includes the 2005 recall data (7,100).

The ASM linkage and survival requirement implied by these restrictions yield samples that are somewhat biased towards larger and more productive plants compared to the entire ASM mail-out sample (Buffington et al. 2017).[14] We use the ASM sampling weights where possible to generate estimates that are more representative of the entire population. While we interpret our results as being principally informative about the larger manufacturing units that dominate the sector, our sample does include a greater proportion of young and small plants than other data sets such as Compustat.

Subject to these limitations, examining these practices in a panel setting is a significant advance, as it expands the scope for addressing unobserved heterogeneity that could bias estimates of the return to adopting DDD.[15] Finally, our sample is representative of the diversity of activities comprising U.S. manufacturing, covering all industries from food to automobile to furniture manufacturing and everything in between (86 industries at the 4-digit NAICS level of aggregation).

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[13] Exact records counts are suppressed in the interest of disclosure avoidance. More details on cleaning the MOPS data and implications for sample size are discussed in Bloom, Brynjolfsson, et al. (2013).

[14] Due to the stratified sampling, the survey somewhat over-samples large plants. Establishments with over 1,000 employees are sampled with certainty; the likelihood of sampling is lower but increasing with size for all plants below this threshold. See https://www.census.gov/programs-surveys/asm/technical-documentation/methodology.html for more details.

[15] In principle, the bias could go either way. While unobserved factors could simultaneously promote both productivity and DDD adoption, we also have a sampling approach that could bias the effect towards zero, as we discuss in detail later on. Note that measurement error, which can attenuate coefficient estimates, will also be worse in a fixed-effects model (e.g., Griliches and Hausman 1986).

Data-Driven Decision Making (DDD). To evaluate how firms use data to support managerial decision making, respondents were asked to choose a value on a 5-point Likert scale according to "what best describes the availability of data to support decision making at this establishment," and "what best describes the use of data to support decision making at this establishment." Empirically, they are highly correlated and we combine information from both to reduce measurement error.

The perceived availability and use of data in U.S. manufacturing was moderately widespread by 2005. About 50% of our sample report being in the top two categories for the availability of data by 2005; 39% report being relatively intensive both in collection and use of data by 2005 (see Table 1). To help identify firms closer to the frontier, we leverage an earlier question on the survey which asks about the number of key performance indicators (KPIs) tracked at the establishment. Our expectation, which has been corroborated by qualitative interviews with plant managers[16] and Census's own field testing of the survey instrument, was that the number of identified and tracked performance measures is an essential measure of the breadth and/or intensity of data collection and analysis at the establishment. Thus, we combine the aforementioned DDD questions with an indicator of whether plants collect data on 10 or more KPIs (the highest category). These measures are strongly correlated in our data.

Next, having appropriate targets against which to compare real-time or historical data plays an important role in decision making. Targets help inform managers about whether the production system is performing appropriately (i.e., is the data conveying "good news" or "bad news"), identifying the locus and magnitude of the problem, and formulating appropriate actions. Again, this interpretation of the role of targets in DDD was qualitatively corroborated in independent interviews with plant managers. We use another survey item that asks about the presence and time-frame of production targets (short-term, long-term, or combined). We take the combined approach as a measure of more advanced engagement with the dimensions of performance that must be monitored and controlled.

Combining these four items, we create an indicator for being at the frontier of data availability and

[16] These were conducted independently of the Census Bureau data collection and survey validation process and do not represent responses from actual firms in the ASM sample frame.

use of data in decision making, extensive use of key performance indicators, and employing a combined approach to target-setting. We call this frontier cluster of practices “data-driven decision making” (DDD) throughout this paper. Our decision to rely on this combination of practices to identify DDD is empirically supported by a formal polychoric principal factor analysis (see Appendix table A1).[17]

Finally, while our main focus is on frontier use of data-related practices, we also investigate less-discrete shifts in DDD by normalizing the responses to the four questions (which are on different scales) and summing the scores. We scale this “DDD Index” to lie on the [0, 10] interval to make it easier to interpret alongside the binary measure. Note that a one-standard-deviation increase in this index in 2010 entails moving to the next-higher category for two to three questions or making a greater shift for one to two questions. For example, this difference would capture the distance between plants that report being “moderate” for both data availability and use versus those that have both a “great deal of data” available for decision making (question 27) and “rely heavily on data” in decision making (question 28). The challenge with interpreting this measure is that there is no meaningful “distance” between categories within or between questions, hence our preference for the categorical indicator in most specifications.

Table 1 shows how adoption of DDD changed over time in the 3-year balanced panel. Rapid growth in the early years is apparent. Only 13% of plants reported intensive DDD according to our definition in 2005. By 2010, 30% of plants in our sample achieve the DDD threshold. This rapid uptake slows significantly, however, by 2015. DDD adoption by 2015 is only slightly higher at 32%. Our interpretation of this differing rate of change is that the early wave captures the steep part of the “S-curve” of adoption (e.g., Foster 1985, Rogers 2010), whereas the later wave captures the flatter part where additional adoption comes from laggard firms that have much higher costs or much lower benefits of adopting (David 1969); a non-trivial fraction never adopt at all. As is typical with new technologies—and their associated management practices—there was also an important diffusion of more-sophisticated

[17] Applying this technique—appropriate for factor analysis of discrete variables—to these four dimensions of practice reports a single factor with an eigenvalue of 2.28 accounting for 57% of the variance in the balanced sample in 2010. An oblique promax rotation confirms a single factor; similar results also obtain for principal-component factor analysis (available upon request).

techniques for collecting and using data during this time. We hypothesize that the frontier of being "data-driven" moved in response to these innovations such that even relatively well-managed firms were reluctant to claim being at the frontier, and that measures of more-advanced practices became necessary to tease out frontier practices. We anticipated this in the second wave of the MOPS by adding several more questions on data-related practices. In particular, the second wave of the MOPS includes a question about the use of predictive analytics at the plant.

Predictive Analytics. This question asks "How often does this establishment typically rely on predictive analytics (statistical models that provide forecasts in areas such as demand, production, or human resources)?" We found that 69% of respondents to the 2015 survey recall having predictive analytics of some sort in place by 2010 (see Table 1). The rate rises to 76% by 2015.

Information Technology. IT capital stock is calculated using the ASM questions on computer and data processing equipment expenditure dating back to 2002 and software expenditure questions dating back to 2006. We use the Bureau of Economic Analysis (BEA) deflators and a perpetual inventory approach, combining hardware and software investment, imputing values for years in which they are missing,[18] and depreciating at the rate of 35% per year.[19]

Management Practices. A key concern for identifying the relationship between DDD and productivity is the possibility that DDD may proxy for other useful practices at the firm. Bloom, Brynjolfsson et al. (2013) show robust positive correlations between the use of structured management practices and performance measures similar to the ones we study here. To address this concern, we construct an index of structured management that is similar to theirs but omit the data-related measures discussed above.[20]

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[18] For plant-years where IT expenditure information is missing, we impute the missing values using the average of the IT investment from the closest before and after years that have non-missing values. For instance, if IT investment in 2008 is missing, we impute it using the average IT investment for the plant in 2007 and 2009 or using the 2007 and 2010 values if 2009 is missing. Similar logic is applied to missing values from other years. Our core results are robust to excluding observations with missing IT data, but imputation is useful for stabilizing the sample.
[19] Based on the BEA Consumer Price Index (All Urban Consumers): Personal computers and peripheral equipment.
[20] This consists of normalizing the response of all of the following questions to the [0,1] interval and summing them to create the composite management score: 1, 5, 7, 8, 9, 11, 13, 14, 15 and 16. These questions cover how the firm

Performance Measures and Controls. We rely on value added as the dependent variable, controlling for expenditure on non-materials inputs including depreciated capital stock,[21] labor measured in terms of the number of employees, and energy inputs.[22] This approach is useful for measuring a plant's productivity, because it estimates how much output the plant creates while controlling for how much it spends on primary inputs. Note that this is a revenue-based measure, not a quantity-based one, so competitive effects (such as being able to charge higher prices) may be confounded with "pure" technical productivity. We view this as beneficial for our research question emphasizing strategic outcomes, but this has been subject to some debate in the productivity literature (Foster et al. 2008 and 2016).

In all cross-sectional analyses we rely on very detailed industry (6-digit NAICS) and time controls; panel analyses rely on plant-level fixed effects to control for time-invariant unobserved heterogeneity. We include other controls collected from the ASM files, such as multi-unit status and the presence of e-commerce activity. Means and standard deviations for all of these variables are reported for the balanced sample in Table 2; pairwise correlations can be found in the appendix (Table A2).

4. Empirical Approach

In order to investigate the relationship between DDD and performance, we take a conventional approach to modeling the plant production function (e.g., Bartelsman and Doms 2000, Brynjolfsson and Hitt 1996, Tambe and Hitt 2012, Bloom, Brynjolfsson et al. 2013). Assume that the establishment production function is as given in equation (1):

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} E_{it}^{\gamma} IT_{it}^{\lambda} e^{\mu SM_{it}} e^{\eta X_{it}} e^{\delta DDD_{it}} \tag{1}$$

where Y_{it} is value added (output - materials), A_{it} is productivity, K_{it} denotes the establishment's capital

reacted to an exception in its production process, whether and where display boards showed output and other key performance indicators, who was aware of production targets at the plant, what the basis (if any) was for performance bonuses for managers and non-managers, the basis for promotion of managers and non-managers (performance and ability versus other factors such as tenure or family connections), and how quickly an underperforming manager or non-manager was dismissed or re-assigned.

[21] Calculated using the perpetual inventory method used for IT and following Bloom, Brynjolfsson et al. (2013).

[22] The energy consumption measure combines expenditures on electricity and fuels, logs the value, and then winsorizes it at the 99th percentile to reduce the impact of outliers and help with disclosure avoidance. We log the capital and labor measures, as well, to address the highly-skewed nature of their distributions.

stock at the beginning of the period, L_{it} is the labor force, E_{it} is the establishments consumption of energy inputs, IT_{it} is the establishment's IT capital stock (hardware and software) at the beginning of the period, SM_{it} is a measure of structured management at the establishment, X_{it} is a vector of additional factors such as industry and education, and DDD_{it} is our measure of data-driven decision making.

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

$$Log(Y_{it}) = a\log(K_{it}) + \beta\log(L_{it}) + \gamma\log(E_{it}) + \lambda\log(IT_{it}) + \mu SM_{it} + \eta X_{it} + \delta(DDD_{it}) + p_i + \varepsilon_{it} \quad (2)$$

where the productivity term has been decomposed into plant fixed effects, p_i and a stochastic term, ε_{it} .

5. Results

Adoption. While the performance implications of DDD are our primary focus, we briefly investigate potential drivers of adoption in the first survey in order to verify some of the mechanisms hypothesized in Section 2 and to explore potential complementarities between DDD and other practices or investments. We take the subsample of plants that report not clearing our threshold for frontier DDD by 2005 so that we may cleanly observe the transition into DDD. It is worth noting that the earliest adopters, i.e., those that report already being quite data-driven by 2005, cleared that threshold at some unspecified point prior to 2005, precluding our ability to conduct a similar experiment for the earlier period. We return to the importance of considering the timing of adoption in estimating the returns to DDD, below.

Table 3 reports the average marginal effects of a probit model of adoption (e.g., David 1969, Forman 2005, Forman et al. 2005), using 2005 covariates and industry controls.[23] Columns 1 - 3 show that both IT adoption and structured management strongly predict adoption of DDD in the 2005-2010 window ("middle adoption"), as does establishment size. However, these effects are significantly attenuated once we account for multi-unit status (belonging to a firm with more than one unit) and having a relatively high level of non-IT capital investment in column 4. These findings are strongly consistent with prior findings that large, professionally-managed plants tend to be found in large, capital-intensive, and relatively more-

[23] Indicators for top-quartile IT or non-IT capital stock are computed at the 4-digt NAICS level in 2005.

productive firms, with more structured approaches to management, instrumentation, data collection, and other activities associated with a shift from tacit to objective information and other mechanisms hypothesized in section 2.1 (e.g., Bloom, Brynjolfsson et al. 2013, Atalay et al. 2014, Hong et al. 2019).

Column 5 reports that having more employees with college degrees in the prior period is also correlated with middle-period adoption of DDD. Older establishments are, all else equal, less likely to clear the threshold in this middle period, consistent with path dependence in these practices. Column 6 includes measures specifically related to the diffusion of these practices and their relationship to new digital technologies (see Section 2). Having a greater number of sources from which the plant managers learn about new management practices is strongly correlated with middle DDD. Having engaged in e-commerce, which boosts the amount of digital information available to the establishment, is also strongly associated with DDD in this period, all else equal.

One challenge with this type of analysis is that all else is not likely to be equal. As mentioned, size, multi-unit status, and capital intensity are historically correlated with each other (Atalay et al. 2014) and with IT and structured management (Bloom, Brynjolfsson et al. 2013 & 2014). This points to underlying clusters of complementary plant characteristics, practices, and investments that reinforce each other and are therefore typically adopted together (Brynjolfsson and Milgrom 2013). For this study, we are particularly interested in understanding the relationship between IT and DDD. Depending on the specification, IT capital stocks in 2005 predict DDD in 2010, but the relationship is clearly nuanced. Our approach, therefore, is to explore the performance implications of DDD while controlling for and interacting it with IT, and then to delve into the details of potential complementarities between IT investment and the timing of those investments in the analyses to follow.

Conditional Productivity Correlations. We first estimate versions of equation (2) using the three pooled cross-sections of data with sufficiently complete information for 2005, 2010 and 2015.[24] Column 1 of

[24] The cross-section sample represents all MOPS observations with: complete answers to the data questions, at least 5 non-missing responses to the non-data management questions for 2010 or 2015, a successful match to the relevant

Table 4 shows the coefficient for our index of DDD-related practices, controlling for IT capital stock, inputs to the production function, worker education, fine-grained year-industry fixed effects (6-digit NAICS). Multiplying the coefficient of 0.027, which is significant at the 1% level, by the standard deviation of the index in 2010 (which is equivalent to moving to a higher category for 2 to 3 questions or making a substantial leap in intensity for 1 to 2 questions) yields an estimate of roughly 23% higher value added. IT capital stock has a significant positive association with output on its own: a 1% increase in IT capital stock is associated with a 0.04% increase in value added. In column 2, controlling for levels of structured management practices and employee education has a large impact on the point estimate for DDD, roughly halving the magnitude. This is largely due to the structured management index, supporting concerns about confounding different types of management practices within the plant.

Columns 3 and 4 focus on an indicator for clearing our "frontier DDD" threshold in any period. Firms that are intensive in DDD practices are roughly 7-8% more productive than those that are not. To contextualize this effect, column 5 reports indicators for being in the top quartile of the plant's industry distribution for IT capital stock and structured management for that year. Comparing the coefficient on DDD to these indicators suggests that the superior performance associated with frontier DDD is roughly the same as being high (top quartile) on the structured management index (8% increase), and lower than being an industry leader in IT investment (which contributes 13.5% more value added).

Columns 5 and 6 of Table 4 present conditional correlations between DDD and firm performance for the balanced subsample for 2005-2015, to facilitate comparison to the table to follow. Column 6 indicates that plants that remained relatively data-intensive from 2005-2015 ("early DDD") are associated with sustained higher performance of roughly 7.6%. Those that adopted after 2005 but by 2010— the middle adopters examined in Table 3—also have a similar productivity advantage. Interpreting this causally, these plants are able to adopt late but nevertheless catch up in terms of productivity. However, plants that

tabulated ASM sample (i.e., either 2005, 2010, or 2015), and that have positive value added, positive employment and positive imputed capital. Recall data from the 2010 wave is used for 2005. See Section 3 for more details.

adopted late in our sample—reporting frontier DDD for the first time in 2015— show a noisy and small correlation between DDD and productivity.

Figure 1 provides more insight into how these effects vary over time. Here, we achieve greater power and representativeness by analyzing the two waves of the MOPS separately, rather than requiring the 3-year balanced sample (as in columns 6 and 7 of Table 3). This shifts the number of observations from roughly 7,100 per year to 26,500 plants (106,000 plant-year observations) for the first wave and roughly 22,900 plants (91,500 plant-year observations) in the second wave. This also eliminates the survival condition in our sample, increasing the proportion of small and young establishments.

Although we only observe reported DDD, management practices, and employee education for 2005, 2010, and 2015, we exploit the rich Census data to observe performance and non-MOPS-based controls for every year. We analyze a specification identical to the one in column 5, Table 4, except that all coefficients (including controls) are interacted with year indicators. To do this, we impute the MOPS-only information from the nearest MOPS year[25] for the two waves of the MOPS. The first half of Figure 1 shows the 2010 survey with 2005 recall data. The second half shows the 2015 MOPS with reported data from MOPS 2010, where recall data (subject to the aforementioned tenure restrictions concerning the respondent being present at the plant in the prior wave) is used to fill out the balanced panel. The top line shows the coefficient on "early" (pre-2005) adoption, the bottom line shows "middle" (in the 2005–2010 window) adoption. By the last year of data, there is no statistical difference between the two, consistent with our hypotheses about the challenges of maintaining persistent performance gains over time compared to follow-on adopters. Note that both sets of adopters outperform non-adopters.

The second half of the figure reinforces the finding that middle adopters enjoy productivity benefits from DDD despite moving later. Those that wait to adopt sometime after 2010 (but get to the frontier by 2015) eventually achieve some benefits, but the gap between middle and late adoption is significant in

[25] Specifically, in the first wave, we use 2005 values for 2004–2005 and 2010 values for 2006–2010. Similarly, we use 2010 values for 2009 and 2015 values for 2011–2015 in the second wave. Results are robust to splitting the sample in different years for different imputations (e.g., using 2005 MOPS values up through 2007).

2012 and 2013. Finally, in 2015, the “late adopter” coefficient climbs to 0.035 (significant at the 5% level) and becomes statistically indistinguishable from the middle adopters. This contrasts with the finding in Table 4, where the effect is a bit lower and not statistically different from zero. Despite noise in this last coefficient, both sets of results are consistent with early returns to early adopters, reasonable catching up for middle adopters, and potentially some benefits to the very latest adopters compared to those that never adopt DDD, though at lower levels.

This figure is informative about whether the relationship between DDD and performance can be interpreted as a causal one. The pattern in Figure 1 shows that the positive correlation between DDD and performance only shows up *after* adoption for the relevant population of plants. We never observe the precise year when they adopt, but it is reasonable to assume that practices were improving over the few years prior to reaching our threshold for DDD by 2010. Similarly, we observe whether plants that did not have DDD in 2010 did so by 2015. But if they do not actually reach the frontier until 2013 or 2014, that would go far to explaining the significantly lower productivity in this cohort in 2012 and 2013. Consistent with needing time to get to the frontier, we observe relatively incremental changes in DDD-related practices over time (see Table 1), suggesting that to go from very low availability and use of data to frontier DDD is not a rapid adjustment. This pattern is consistent with frontier DDD causing higher performance. We discuss the causal relationship in more detail below.

Our hypothesizing in section 2.3 suggests there might be advances in practices that would supplant DDD as a key driver of performance differences between firms over time. Column 7 of Table 4 explores whether predictive analytics might play such a role over the time period we study. When included together in the same regression, both DDD and predictive analytics have a positive and significant coefficient. This result changes when we include plant-specific fixed effects in the next table (see below).

Pooled cross-section analyses can be informative about the productivity of plants that are early adopters of the practice. Difference models *by construction* eliminate plants that adopt DDD early and stay at the frontier in our sample. If diffusion is progressing over time and the returns to adoption depend on the level of adoption by competitors, focusing on middle and late adopters (as the difference models require) may significantly underestimate the benefits of a technology or practice.

Difference-in-Differences. The advantage of difference models, of course, lies in understanding how unobserved time-invariant plant characteristics might influence these estimates, and controlling for these potentially confounding factors. Table 5 shows fixed-effects estimates for DDD. In column 1, the coefficient on the DDD index falls by a very small amount compared to Table 4, but it is noisier: here it is only significant at the 10% level. For the indicator of frontier DDD, reported in column 2, the magnitude of the effect is roughly half that reported in Table 4 and significant at the 5% level. However, much of this is coming from the first wave of the sample: when analyzed separately in column 3, the coefficient of 0.07 is comparable to that reported in Table 4. This approach shows a consistently strong relationship between middle adoption and productivity, even controlling for plant fixed effects. Notably, the returns to moving to the top quartile for IT capital between 2005 and 2010 are not significant here.

Column 6, in contrast, reports no statistically significant positive benefit associated with moving to the frontier of DDD in the later 2010-2015 period, but a significant (at the 1% level) return to moving into the top quartile for IT capital investment. Consistent with an advancing—and increasingly IT-intensive—frontier of practice, a significant productivity impact appears for plants reporting some use of predictive analytics. Column 5 shows, in fact, that all of the significant productivity benefits of using data shift onto the predictive analytics indicator, which has a coefficient of 0.062 and is significant at the 5% level.

Figure 2 repeats the exercise of Figure 1, but looks at how the combined use of predictive analytics and DDD performs over time in the cross section. Here, the adoption of predictive analytics and DDD by 2010, combined, shows significant benefits – both compared to non-adopters and compared to plants that only adopted DDD (the grey line repeats the "DDD by 2010" line from Figure 1 for comparison). Later adopters of these practices are thus able to catch up and enjoy productivity that is indistinguishable from early adopters as long as they reach the frontier. Distinguishing the effects of "DDD only" by year suggests that later adopters still enjoy benefits compared to "never-adopters" later in the sample, but this specification fails to control for the plant-level fixed effects that absorb much of the late-DDD benefit.

Column 6 of Table 5 provides some insights into where variation in these effects are taking place. Almost all of the middle-DDD benefit shows up for plants that were in the top quartile for IT capital stock accumulation in 2005. The direct effect is differenced out and the interaction term has a coefficient of 0.091 and is significant at the 5% level. This is consistent with a move to "high-tech DDD", which we explore in more detail below. In contrast, column 7 shows that the insignificant effect of late DDD by itself in the second wave does not vary by the intensity of IT. Column 8 shows that predictive analytics is most productive at the highest levels of IT investment.

This pattern is consistent with complementarities between data-driven management practices and IT, as well as an advancing frontier of practice. Tables 6a and 6b more formally tests for complementarity and reports on important nuances of the phenomenon. While standard tests of complementarities (e.g., Brynjolfsson and Milgrom 2013, Tambe et al. 2012) often rely on cross-sectional variation, we are able to explore time-series variation in both DDD and IT investments. We create 16 cells for combinations of no adoption, adopting only one option (either top IT or DDD), or adopting both DDD and being in the top quartile of IT capital stock for that year. We compare adding DDD alone from 2005–2010 (row 1, column 3) to layering DDD on top of pre-existing (by 2005) high IT investment (row 2, column 4). The prior has a coefficient of 0.012 and is not significant at conventional levels, the latter has a coefficient of 0.121 and is significant at the 1% level. The difference is significant at the 5% level and clearly passes the performance test of complementarity in this direction.

In contrast, we find no evidence of increasing productivity effects when IT is added to organizations that already had a form of DDD in 2005. Adding high IT alone in the 2005–2010 window (row 1, column 2) has a coefficient of 0.054 and is significant at the 10% level. Adding high IT to existing DDD practices (i.e., early adoption of DDD by 2005), shown in row 3, column 4, has a very small coefficient of 0.005 that is not statistically different from zero. This fails the formal complementarities test.

One interpretation is that early adopters who were not IT-intensive implemented a "low-tech" approach to DDD that did not benefit from nor easily absorb significant investment in digital infrastructure. Descriptions of lean manufacturing practices with low-tech white boards or blackboards to track KPIs, physical *Kanban* tokens, or duct-tape delineated production areas to control excess work-in-progress come to mind. Our data our limited with regards to lean-specific practices, making it difficult to pin down various "vintages" of DDD, but the stark order of the complementary investments is telling.

Finally, the coefficient for going from having neither top-quartile IT investment nor DDD in 2005 to having both by 2010 (row 4, column 4) suggests that simultaneous adoption, while possibly incurring higher adjustment costs, pays off. The coefficient of 0.119 is significant at the 5% level and is on par with the IT-plus-DDD combination, as well as with early and sustained adoption of DDD. This is consistent with complementary practices and infrastructure being adopted at the same time, allowing later adopters to reach the productivity enjoyed by earlier movers by maintaining alignment between these activities.

Table 6b confirms that DDD and IT pass the correlation test for complementarities (Brynjolfsson and Milgrom 2013) as well. The correlation is strongest in 2010, consistent with increasing awareness of the gains to "high-tech" DDD. A slight increase in DDD without the highest level of IT in 2015 weakens this correlation a bit, but not materially so. We do not test for dynamic complementarities between DDD and IT in the second wave of data, due to the weaker stand-alone benefits of DDD.

Timing Falsification. We next explore the extent to which these results may be interpreted as causal. As discussed, Figures 1 and 2 are inconsistent with reverse causality. In Table 7, we test this more formally. If better performance were preceding DDD adoption, a regression of DDD adoption on value added in our pre-period should show a positive relationship. However, a probit analysis of DDD adoption in 2005 shows that value-added growth from 2002 to 2005 does not predict the presence of DDD in 2005. A similar regression for those plants that did not have DDD in 2005, using growth in the 2005 to 2010 period as the key explanatory variable, again shows that growth in value added does not predict adoption of DDD in the window between 2005 and 2010. In light of the complementarities test above, it is notable that IT in the pre-period does not predict DDD until the later wave of data.

Despite this pattern of evidence, the classic problem with ascribing positive performance results to any type of technology or management practice is that adoption is typically voluntary, and those adopting are more likely to be those who expect to benefit most (David 1969). Our study thus far is subject to this critique as well, with one important caveat: DDD is an intangible practice that requires investments in managerial attention and time, in contrast to traditional investment such as various types of capital that often require free cash flow. Hence it is less likely that only firms with prior good performance, and the associated financial slack, will be able to invest in DDD.

IV Estimation. We explored the potential to find exogenous adoption of DDD in the second wave of the MOPS by adding a question on government-mandated data collection. A sizeable fraction of our sample—34%—report that "government regulations or agencies" choose what type of data to collect at the plant. Being required to collect data for regulatory purposes may improve the availability of data for reasons unrelated to firm preferences for data. Prior work on the "Porter Hypothesis" has proposed that forcing firms to comply with regulations, government-mandated investments—presumably including data collection and reporting—may trigger firms to take steps that have the collateral effect of improving productivity.[26] Note that plants may both collect data for their own purposes and collect data to conform to government mandates, so firms that already are data-centric may not be very sensitive to this instrument. We explore the effect of using government mandates as an instrument for DDD in Table 8.

For comparison, column 1 of Table 8 reports the conditional OLS estimation of the relationship between this index of DDD-related practices and value added, controlling for inputs, predictive analytics, employee education, IT investment, and structured management.[27] Significant at the 1% level, this

[26] The most famous version of this hypothesis was advanced by Michael Porter (Porter 1991, Porter and Van der Linde 1995), though many subsequent studies have explored the impact of regulation on firm performance. See Ambec et al. 2013 for a detailed review of this literature.
[27] We revert to the DDD index for this analysis to avoid potential complications with our non-linear DDD indicator in the IV specification.

coefficient is 0.019. The first stage of our IV test is reported in column 2, Table 8, where the conditional correlation between government-mandated data collection and the use of data to manage the plant is both economically and statistically significant. Critically, this measure has no significant direct relationship to productivity on its own (available upon request), satisfying the exclusion restriction.

The second stage, reported in column 3, shows a likewise positive and statistically significant relationship between instrumented DDD practices and firm performance. The magnitude of the coefficient is 0.125, consistent with a positive causal relationship and either a downward bias on our OLS coefficient (e.g., due to measurement error) or a higher local average treatment effect. The latter could occur if there is a sizeable subsample of plants whose data collection efforts are shifted by government requirements that then show a greater productivity response. This could be interpreted as consistent with the "Porter Hypothesis" if plants had not previously been profit-maximizing for a variety of reasons (see Ambec et al. 2013). Recalling Table 3, larger plants with more structured management belonging to multi-unit firms are more likely to voluntarily adopt DDD, leading to less variance in DDD adoption—and possibly lower relative benefits—among this larger, higher-performing (Atalay et al. 2014) cohort. Alternatively, if the costs of these data collection efforts are not accounted for in the other controls for costs of labor, capital, energy, and IT, the IV estimate could be upwardly biased by this omission. Taken together, this combination of the IV results, fixed effects, and timing supports a causal relationship between adoption of DDD and improved productivity across a wide range of establishments.

6. Conclusion

Theory, case evidence, and no small amount of speculation have predicted that firms will become more productive by becoming more data-driven. However, large-scale evidence on this phenomenon has been limited up to now, reflecting a lack of relevant data. Working with the U.S. Census Bureau, we collected the relevant measures of DDD and found systematic evidence that putting data "into action" through analysis and use by decision makers causes significantly higher productivity in a wide range of manufacturing settings. We observe that, while tracking and monitoring operations has always been beneficial, the rise of new digital technologies has fueled a rapidly advancing frontier of practice. IT alone cannot account for these gains. Distinct data-driven management practices that are complementary to IT arise, diffuse, and give way to more sophisticated tools— in this case, predictive analytics. Fixed effects, timing falsification, and instrumental variables estimations suggest this relationship is causal. Timing matters, however, exactly as theory would predict for the diffusion of a valuable innovation. While early adopters enjoy the largest relative gains, followers are able to catch up to some extent, increasing the correlation among the key practices but decreasing the performance differences. Firms that track the moving frontiers of both IT and uses of data are better able to maintain a competitive advantage.

Being able to observe this phenomenon in a large and representative panel of firms, using questions purpose-built to disentangle features of the phenomenon, constitutes a significant advance. Nevertheless, certain limitations are worth noting. For instance, we cannot objectively measure variation in the quality of data inputs beyond our questions on availability, number of KPIs, and intensity of IT investment. We have no data on specific human capital beyond the education of employees at the plant (which we control for). This is often cited as a key determinant of whether firms can achieve competitive advantage from data (Tambe 2014, Lambrecht and Tucker 2015). Finally, we lack visibility to other key contingencies that have been shown to matter for management practices such as culture (Blader et al.forthcoming) and competitive strategy (Yang et al. 2015). To the extent that many of these contingencies tend to work against a positive relationship between objective data and performance, the effects we estimate will tend to be attenuated by this underlying heterogeneity.

We hope to spur further research into the relationship between data-driven decision making and firm performance in manufacturing and other sectors of the economy—particularly retail and services. Given the large increases we are certain to see in both IT capabilities and the availability of digital data, the effects we identify and the role of complementary technology investments will undoubtedly evolve further in the coming years.

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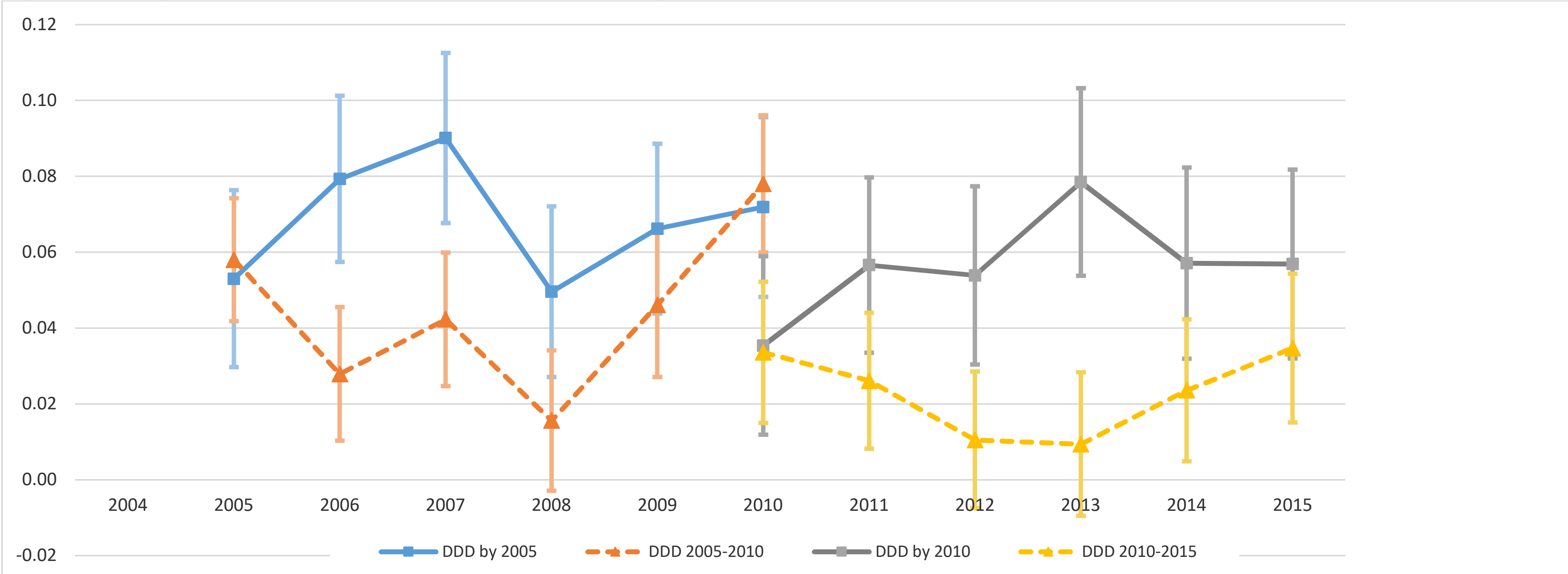
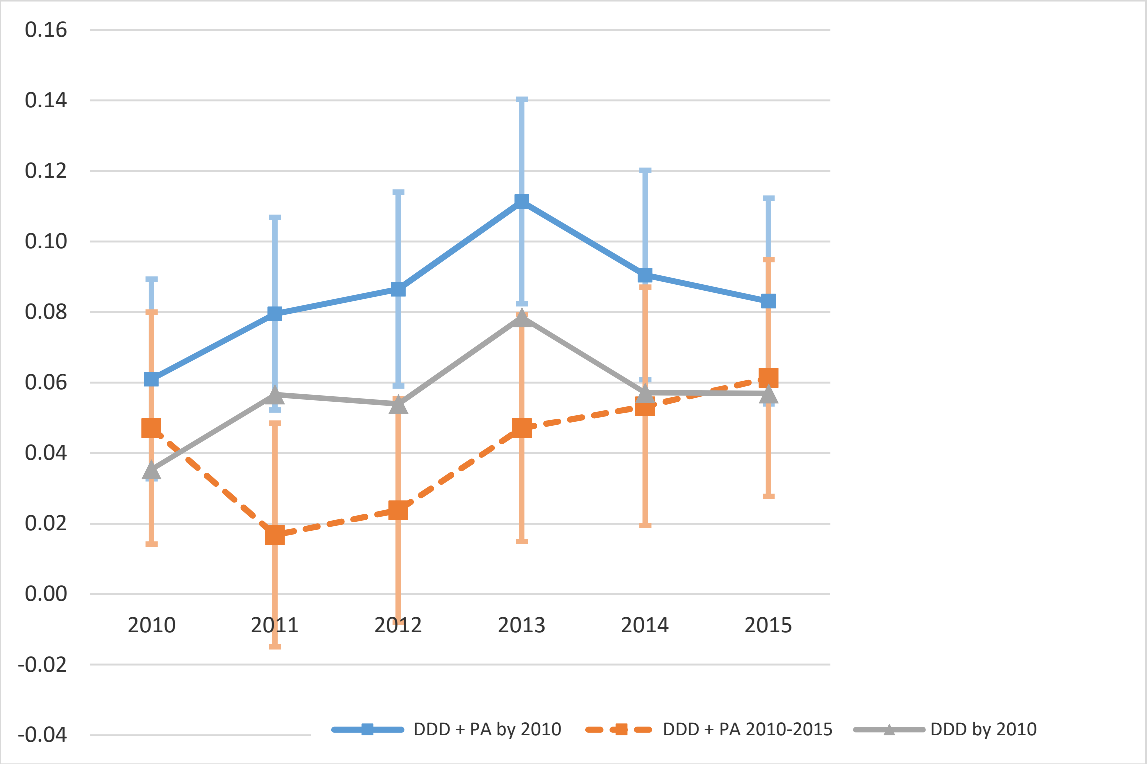
Figure 1. Marginal Effects of Data-Driven Decision Making on Productivity for Different Cohorts of Adopters over Time



Notes: Plotting the pooled OLS coefficient on DDD interacted with year, controlling for industry (6-digit NAICS) based on both 2010 and 2015 waves of the MOPS. Dependent variable is value-added. Controls (all interacted with year indicators) include: logged non-IT capital stock, logged IT capital stock, logged employment, and logged energy expenditures. An index of structured management practices and a measure of employee (manager and non-manager) education from nearby MOPS years are also included and interacted with year indicators. Two samples are used for this figure: on the left are establishments that in the 2005 and 2010 MOPS sample matched to other years of the ASM and CMF from 2004 to 2009. On the right are establishments from the 2010 and 2015 MOPS sample matched to other years of the ASM and CMF from 2009 to 2014. Both samples restrict on the respondent being at the plant for at least five years prior to the survey year. Robust standard errors are clustered at both the plant and firm levels and represented as confidence intervals around the point estimates in the graph.

Figure 2. Marginal Effects of Data-Driven Decision Making + Predictive Analytics by Year, 2009-2015



Notes: Plotting the combined pooled OLS coefficients for DDD and an indicator for having some predictive analytics by 2010 interacted with year, controlling for industry (6-digit NAICS) based on the most recent wave of the MOPS survey (2015). Combined coefficients and standard errors are calculated using the **lincom** command in Stata 15. The grey line reports the coefficient on having DDD by 2010 in the recall data from 2015 (Figure 1) for comparison. As above, to provide an estimate of productivity, the dependent variable is value-added and controls (all interacted with year indicators) include: logged non-IT capital stock, logged IT capital stock, logged employment, and logged energy expenditures. An index of structured management practices and a measure of employee (manager and non-manager) education from nearby MOPS years are also included and interacted with year indicators The sample used for this figure consists of establishments from the 2010 and 2015 MOPS sample matched to the ASM and CMF from 2009 to 2014, where the respondent had been at the plant for at least five years prior to the survey. Robust standard errors are clustered at both the plant and firm levels and represented as confidence intervals around the point estimates in the graph.

Table 1. Data-Driven Decision Making and Predictive Analytics Practices 2005 - 2015

Data-Related Management Practice	2005	2010	2015
Top 2 categories for "availability of data"	0.50	0.76	0.77
Top 2 categories for "use of data"	0.48	0.73	0.74
Tracking 10 or more KPIs	0.35	0.56	0.56
Having both short- and long-term targets	0.44	0.62	0.64
Top 2 categories for both availability and use of data	0.39	0.65	0.66
Top 2 categories for both availability and use of data, plus tracking 10 or more KPIs	0.19	0.41	0.43
DDD Indicator: top 2 categories for availability and use of data, tracking 10 or more KPIs, & use of both short-term and long-term targets	0.13	0.30	0.32
DDD Index: sum of the normalized responses to all four DDD-related questions (2, 6, 27, & 28), scaled to lie on the [0, 10] interval	6.7 (1.72)	7.7 (1.46)	7.5 (1.47)
Predictive Analytics Use	NA	0.70	0.76
N	21,500	21,500	21,500
Number of Establishments	7,100	7,100	7,100

Notes: Based on the three-year balanced subsample, comprised of plants in both the 2010 and 2015 waves, with complete data for 2005, 2010 (supplemented with 2010 recall), and 2015, as well as matches to the relevant ASM and CMF years, and respondent had been at the plant for at least five years prior to the survey year. Reporting unweighted statistics. Questions on predictive analytics were not on the 2010 survey. Observation counts rounded according to Census disclosure avoidance policy.

Table 2. Descriptive Statistics by Year

Variable	Description	2010 Balanced Sample (S.D.)	2015 Balanced Sample (S.D.)
Log Value Added	Log of value added at the plant (total value shipped minus total cost of goods sold) in $Thousands	9.95 (1.34)	10.1 (1.35)
Log IT Capital Stock	Log of the value of computers and data processing equipment and software in $Thousands at the plant, calculated using the perpetual inventory method and BEA deflators	4.33 (1.92)	4.17 (1.97)
Log Employment	Log of the total number of employees at the plant	4.92 (1.06)	4.98 (1.08)
Log Capital stock	Log of the value of non-IT capital stock at the plant in $Thousands, calculated using the perpetual inventory method and BEA capital deflators	9.73 (1.45)	9.59 (1.45)
Log Energy Costs	Winsorized and logged total cost of both fuel and electricity in $Thousands	6.47 (1.56)	6.42 (1.67)
Structured Management Z-Score	Index created by summing up the normalized values from non-DDD questions in the first 16 MOPS questions	0.66 (0.15)	0.63 (0.17)
Employee Education	Percent of managers and non-managerial employees at the plant with Bachelor's degrees	13% (12%)	16% (13%)
Age	Establishment age	26.9 (9.41)	31.9 (9.46)
Multi-Unit Status	=1 if the plant belongs to a multi-unit firm	0.79 (0.41)	0.81 (0.40)
Government-Mandated Data Collection	=1 if Question 26 of the MOPS 2015 indicates that government regulations or agencies chose what data to collect at the establishment		0.341 (0.474)
Number of Establishments		7,100	7,100

Notes: Based on the three-year balanced subsample, comprised of plants in both the 2010 and 2015 waves, with complete data for 2005, 2010 (supplemented with 2010 recall), and 2015 as well as matches to the relevant ASM and CMF years, and respondent that had been at the plant for at least five years prior to the survey year. Reporting unweighted means with standard deviations in parentheses. Energy expenditure winsorized at 1% and 99% to address extreme outliers (all other variables produce the same results whether winsorized or not). Time-series variation in government-mandated data collection was extremely low and disclosure avoidance policies preferenced a reliance on 2015 cross-sectional variation only, as well as rounded observation counts.

Table 3. Adoption of Data-Driven Decision Making between 2005 and 2010

Dependent Variable	Indicator of Frontier Data-Driven Decision Making (DDD)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log IT capital stock in 2005	0.016*** (0.002)					
Top-quartile IT in 2005		0.090*** (0.007)	0.020** (0.008)	0.013* (0.008)	0.012 (0.008)	0.012* (0.008)
Structured management in 2005	0.146*** (0.021)	0.147*** (0.020)	0.089*** (0.020)	0.061*** (0.020)	0.052*** (0.020)	0.007 (0.020)
Log employment in 2005			0.056*** (0.004)	0.045*** (0.005)	0.048*** (0.004)	0.042*** (0.004)
Multi-unit status				0.098*** (0.010)	0.096*** (0.010)	0.090*** (0.010)
Top-quartile capital stock in 2005				0.028*** (0.008)	0.028*** (0.008)	0.026*** (0.008)
Percent workers with college education in 2005					0.061** (0.029)	0.041 (0.029)
Establishment age					-0.001*** (0.0004)	-0.001*** (0.0004)
Number of learning sources						0.016*** (0.002)
E-commerce activity						0.026*** (0.007)
Sample	Subsample of 2010 wave with no adoption of DDD by 2005					
# Establishments	~16,300					

Note: Weighted Maximum likelihood probit estimation. Reporting marginal effects calculated at sample means of the covariates. Sample is all MOPS observations with complete answers to the data questions and at least 5 non-missing responses to the non-data management questions in 2010, as well as successful matches to tabulated ASM observations in 2005 and 2010, with positive value added, employment, and imputed capital in the ASM for the relevant years. In addition, this sample is restricted to plants that report not clearing the frontier for DDD in 2005. All columns include controls for industry at the 3-digit NAICS level and rely on 2005 recall data or 2005 ASM values for the covariates; multi-unit status and worker education do not vary much by year. Top-quartile capital stock is an indicator of being in the top quartile for non-IT capital stock for the plant's 4-digit NAICS industry code in 2005. Number of learning sources is a count of responses to question 29 in 2010. E-commerce activity is an indicator of whether the plant used any electronic network to control or coordinate the flow of outbound shipments or received orders over an electronic network; captured on the 2005 ASM. Robust standard errors are reported in parentheses. Exact record counts suppressed per Census disclosure avoidance policies. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 4. Conditional Correlations between Data-Driven Decision Making (DDD), Predictive Analytics, and Plant Performance 2005 – 2015

Dependent Variable	Log Value Added						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	DDD Index with IT	Add Controls	DDD Indicator	Compare to Top IT & Top Mgmt	3-year Balanced Panel	Timing of Adoption	Predictive Analytics
Index of DDD Practices	0.027*** (0.003)	0.014*** (0.003)					
DDD Indicator			0.071*** (0.010)	0.084*** (0.010)	0.068*** (0.015)		0.069*** (0.012)
Predictive Analytics Indicator							0.074*** (0.016)
Log IT Capital Stock	0.037*** (0.003)	0.034*** (0.003)	0.034*** (0.003)				
Structured Mgmt.		0.250*** (0.030)	0.283*** (0.029)				
% Employees with Bachelor's degrees		0.451*** (0.038)	0.453*** (0.038)	0.492*** (0.038)	0.509*** (0.057)	0.513*** (0.057)	0.488*** (0.048)
Top-quartile IT Capital				0.135*** (0.013)	0.091*** (0.015)	0.091*** (0.015)	0.082*** (0.018)
Top-quartile Structured Management				0.082*** (0.012)	0.089*** (0.013)	0.093*** (0.013)	0.076*** (0.015)
Early DDD (by 2005)						0.076*** (0.030)	
Middle DDD Adoption (2005-2010)						0.084*** (0.025)	
Late DDD adoption (2010-2015)						0.022 (0.018)	
Capital, Labor, and Energy inputs (logged)	Y	Y	Y	Y	Y	Y	Y
Industry x Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y
N	83,500	83,500	83,500	83,500	21,500	21,500	36,500
# of Establishments		Varies by year			7,100	7,100	18,500
Adjusted R-Squared	0.810	0.811	0.811	0.810	0.759	0.759	0.771

Notes: Weighted pooled OLS regressions using ASM sampling weights and industry-year fixed effects (6-digit NAICS). Dependent variable is logged nominal value added at the plant. Unreported controls in all columns include: indicator of belonging to a multi-unit firm, logged non-IT capital stock, logged employment, and logged energy expenditures. The sample in columns 1-4 is all MOPS observations with complete answers to the data questions, and at least 5 non-missing responses to the non-data management questions for 2010, a successful match to the relevant tabulated ASM sample, that have positive value added, employment and imputed capital. Columns 6 and 7 are restricted to establishments observed in all three years and also where the respondent was at the plant at least five years prior. Column 7 is restricted to the balanced sample in MOPS 2015 and complete data onpredictive analytics adoption for both years. Robust standard errors are clustered at both the plant and firm level and reported in parentheses. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 5. Plant Fixed-Effects Estimation of Data-Driven Decision Making, Predictive Analytics, and Firm Performance, 2005-2015

Dependent Variable	Log Value Added						
Model	(1) DDD Index	(2) DDD Indicator	(3) 2005-2010	(4) 2010-2015	(5) Analytics	(6) 2005-2010 IT Interaction	(7) 2010-2015 IT Interaction
Index of DDD-related practices	0.011* (0.006)						
DDD Indicator		0.042** (0.019)	0.072** (0.023)	0.018 (0.013)	0.018 (0.013)	0.045 (0.028)	0.009 (0.014)
Analytics Indicator					0.062** (0.026)		0.074*** (0.016)
IT capital stock	0.007 (0.005)						
Structured Management index	0.195*** (0.082)						
% Employees with Bachelor's degrees	-0.003 (0.099)	0.012 (0.097)	-0.097 (0.176)	0.036 (0.068)	0.034 (0.068)	-0.111 (0.176)	0.036 (0.068)
Top IT Capital		0.041** (0.018)	0.018 (0.024)	0.062*** (0.022)	0.062*** (0.022)		
Top Structured Management		0.037*** (0.014)	0.044** (0.022)	0.024 (0.017)	0.023 (0.017)	0.045*** (0.022)	0.025 (0.017)
DDD x Top IT in 2005						0.091** (0.037)	
DDD x Top IT in 2010							0.025 (0.017)
Capital, Labor, and Energy inputs	Y	Y	Y	Y	Y	Y	Y
Plant Fixed Effects	Y	Y	Y	Y	Y	Y	Y
N	21,500	21,500	24,000	36,500	36,500	24,000	36,500
# of Establishments	7,100	7,100	12,000	18,500	18,500	12,000	18,500
Within Adjusted R-Squared	0.226	0.225	0.248	0.203	0.203	0.248	0.189

Notes: Two-period weighted linear regression with establishment-fixed effects using 2005 ASM sampling weights in columns 1–3 and 6 and 2010 ASM sampling weights in columns 4, 5, and 7. Unreported controls in all columns include: logged non-IT capital stock, logged employment, and logged energy expenditures. The sample is all MOPS observations with complete answers to the data questions, at least 5 non-missing responses to the non-data management questions for the relevant wave of the survey, as well as successful matches to tabulated ASM observations, positive value added, employment, and imputed capital in the ASM for the relevant years. The recall data is restricted to observations where the respondent to the survey was at the firm five years prior to the year of the survey. "Top" indicators represent the top quartile of that variable for the relevant industry (4-digit NAICS) in the prior period. Robust standard errors are reported in parentheses. Significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 6a. Tests of Dynamic Complementarity between DDD & Top-Quartile IT (2005 – 2010)

		2010 Adoption			
		(1) Neither	(2) Top IT Capital	(3) DDD	(4) Both
2005 Adoption	(1)Neither	Base group	**0.108*** (0.041)**	**0.012 (0.034)**	-0.023 (0.053)
	(2)Top IT Capital	0.054* (0.032)	0.066** (0.026)	0.102** (0.052)	**0.121*** (0.037)**
	(3)DDD			0.098*** (0.031)	0.005 (0.089)
	(4)Both			0.012 (0.076)	0.119** (0.051)

Performance Test 1: compare adding DDD alone from 2005 - 2010 (row 1 column 3) to adding DDD by 2010 to existing top-quartile IT in 2005 (row 2 column 4). **Passes at the 5% level.** Coefficient = 0.110** SE = 0.043

Performance Test 2: compare adding top-quartile IT alone from 2005 - 2010 (row 1 column 2) to adding top-quartile IT by 2010 to existing DDD in 2005 (row 3 column 4) is better (i.e., adding IT to existing DDD is better than adding it by itself). **Fails.** Coefficient = -0.103 SE= 0.096

NOTE: Few establishments "de-adopt" DDD in 2010 if they report having it in 2005, and thus are not analyzed for disclosure avoidance reasons.

N	24,000
# of Establishments	12,000
Sample	2005-2010 Balanced Sample

Note: Results are based on weighted regression with establishment-fixed effects using 2005 ASM sampling weights. Each cell represents an element in the transition matrix for DDD and Top-quartile IT capital stock adoption between 2005 and 2010. For example cell 1 (row 1 column 1) indicates that the establishment has NOT adopted either DDD4 nor reached the top quartile for IT capital investment in both 2005 and 2010; cell 2 (row 1, column 2) indicates that the plants have not reached top IT in 2005 but did so by 2010; cell 3 indicates the group of plants have not adopted DDD in 2005 but did so by 2010; cell 4 (row 1, column 4) indications plants that have not adopt top IT nor DDD in 2005 but have both by 2010, and so on. Coefficients on some indicators are suppressed because the count of plants in these cells is low and pose problems for disclosure avoidance. Unreported controls include: logged non-IT capital stock, logged employment, structured management index and winsorized logged energy expenditures. Joint tests are conducted using the **lincom** command in Stata 15. Robust standard errors are reported in parentheses and statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Table 6b. Correlation Tests of Dynamic Complementarity between DDD and Top-Quartile IT (2005-2010 and 2010-2015)

2005 -2010

Year = 2005	Top-Quartile IT		
		0	1
DDD	0	67%	21%
	1	8%	4%

Pearson Chi2(1) = 77.48 Pr < 0.001; N = 12,000

Year = 2010	Top-Quartile IT		
		0	1
DDD	0	57%	16%
	1	18%	9%

Pearson Chi2(1) = 235.2 Pr < 0.001; N = 12,000

2010 - 2015

Year = 2010	Top-Quartile IT		
		0	1
DDD	0	57%	15%
	1	18%	10%

Pearson Chi2(1) = 318 Pr < 0.001; N = 18,500

Year = 2015	Top-Quartile IT		
		0	1
DDD	0	54%	15%
	1	21%	10%

Pearson Chi2(1) = 246.2 Pr < 0.001; N = 18,500

Table 7. Timing of DDD Adoption is Inconsistent with Reverse Causality: Marginal Effects from Probit Estimation

Dependent Variable:	DDD adoption		
	(1)	(2)	(3)
Models	DDD in 2005	Adopted DDD in 2005-2010 period	Adopted DDD in the 2010-2015 period
Value-added growth 2002 – 2005	-0.0001 (0.0001)		
Value-added growth 2005 – 2010		-0.0007 (0.0001)	
Value-added growth 2010-2015			0.0018 (0.0012)
IT capital stock in pre-period	-0.0002 (0.0012)	0.001 (0.003)	0.011** (0.005)
Log Employment in pre-period	0.024*** (0.003)	0.045*** (0.006)	0.040*** (0.012)
Structured management index in pre-period	NA	0.059* (0.034)	0.298*** (0.044)
% Bachelor's Degree in pre-period	NA	0.148*** (0.047)	0.235*** (0.058)
MU Status	0.056*** (0.011)	0.106*** (0.016)	0.124*** (0.018)
Age	-0.002*** (0.0004)	0.0001 (0.0006)	0.0003 (0.0007)
# Establishments	7,100	6,200	5,000
Sample	2005 Balanced	2010 Balanced & not-DDD in 2005	2015 Balanced & not DDD in 2010

Notes: Maximum likelihood probit estimation of DDD adoption with industry-fixed effects (3-digit NAICS) and ASM sampling weights from the appropriate year. Results are robust to finer-grained industry controls but shift the sample counts. Reporting marginal effects calculated at mean values of the covariates using the **margins** command in Stata 15. The sample for column 1 is plants in the balanced panel for 2005. The sample for column 2 is plants in the same sample, but that reported not clearing the threshold for the DDD indicator (see Table 2) in 2005. The sample for column 3 adds the condition that the DDD threshold not have been cleared by 2010. Robust standard errors are clustered at firm level and reported in parentheses. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%

Table 8. IV Regression

Dependent Variable:	Log Value Added	DDD Index	Log Value Added
Model	(1) OLS (DDD Index)	(2) IV first stage	(3) IV second stage
Index of DDD-related practices	0.019*** (0.003)		0.125*** (0.060)
Indicator for Government-Mandated data collection		0.196*** (0.018)	
Analytics	0.034*** (0.012)	0.6812*** (0.028)	-0.039 (0.043)
% Employees with Bachelor's degrees	0.456*** (0.039)	0.763*** (0.069)	0.373*** (0.059)
Top-quartile IT Capital	0.105*** (0.013)	0.002 (0.019)	0.105*** (0.013)
Top-quartile Structured Management	0.063*** (0.012)	0.492*** (0.017)	0.009 (0.033)
Capital, Labor, and Energy inputs	Y	Y	Y
Industry x Year Fixed Effects	Y	Y	Y
N	36,500	36,500	36,500
# of Establishments	18,500	18,500	18,500
Weak identification test	NA	NA	142.3
Under-identification test	NA	NA	113.6
Adjusted R-Squared	0.733	0.224	0.723

Note: Weighted pooled OLS regressions using ASM sampling weights and industry-year fixed effects (6-digit NAICS level). The dependent variable is logged nominal value added at the plant for columns 1 and 3. Column 2 uses the DDD index as the dependent variable in the first-stage regression; this was chosen to avoid potential non-linearities with the binary indicator. As above, unreported controls in all columns include: indicator of belonging to a multi-unit firm, logged non-IT capital stock, logged employment, and winsorized logged energy expenditures. The sample for all columns is restricted to the MOPS 2015 observations for which we can observe the government-mandated data collection measure and predictive analytics adoption, as well as the relevant ASM and CMF matches and respondent tenure restrictions as described above. Robust standard errors are clustered at both the plant and firm level and reported in parentheses. Statistical significance is denoted as follows: * 10%, ** 5%, *** 1%.

Appendix

Table A1. Principal Factor Analysis of Data-Related Management Practices

Principal Factor Analysis of Balanced Sample		
	Eigenvalue	Proportion of Variance
Factor 1	2.64	0.440
Factor 2	2.38	0.3

Polychoric Correlation Matrix and Factor Loadings							
	Top 2 categories for "availability" of data	Top 2 categories for "use" of data	Track 10 or more KPIs	Use of short-term and long-term targets	Review of KPIs by Managers	Review by Non-Managers	Factor 1 Loadings
Top 2 categories for "availability" of data	1						0.936
Top 2 categories for "use" of data	0.803	1					0.931
Track 10 or more KPIs	0.412	0.421	1				0.508
Use of short-term and long-term targets	0.349	0.367	0.355	1			0.554
Review of KPIs by Managers	0.299	0.316	0.378	0.271	1		-0.044
Review by Non-Managers	0.275	0.297	0.362	0.253	0.825	1	-0.078

Note: Calculated using the **polychoric** command in Stata 13.

Table A2. Pairwise Correlations

Variables	Log VA	DDD	IT Stock	Mgmt	% BA	Log Emp	Log K stock	Energy	MU	Age
Log Value-Added	1									
DDD	0.225	1								
IT capital stock	0.471	0.129	1							
Structured Management	0.311	0.303	0.185	1						
% Bachelors Degrees	0.275	0.153	0.250	0.198	1					
Log Total Employment	0.756	0.163	0.499	0.261	0.169	1				
Log Capital stock	0.719	0.221	0.441	0.300	0.224	0.644	1			
Energy Expenditure	0.645	0.214	0.276	0.274	0.127	0.562	0.751	1		
Multi-Unit Status	0.256	0.144	0.050	0.240	0.083	0.167	0.294	0.289	1	
Establishment Age	0.154	0.087	0.119	0.039	0.067	0.161	0.122	0.146	-0.011	1
N					21500					
# of Establishments					7100					
Sample					Balanced 2005-2015					

Note: Detailed variable definition are provided in Table 2. All correlations are significant at 1% level except the correlations between multi-unit status and establishment age.