Strength in Numbers:

How Does Data-Driven Decisionmaking Affect Firm Performance?

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Abstract

We examine whether performance is higher in firms that emphasize decisionmaking based on data and business analytics (which we term a data-driven decisionmaking approach or DDD). Using detailed survey data on the business practices and information technology investments of 179 large publicly traded firms, we find that firms that adopt DDD have output and productivity that is 5-6% higher than what would be expected given their other investments and information technology usage. Using instrumental variables methods, we find evidence that these effects do not appear to be due to reverse causality. Furthermore, the relationship between DDD and performance also appears in other performance measures such as asset utilization, return on equity and market value. Our results provide some of the first large scale data on the direct connection between data-driven decisionmaking and firm performance.

1. Introduction

How do firms make a better decision? Today, organizational judgment is in the midst of a fundamental change - from a reliance on a leader's "gut instinct" to increasingly data-based analytics. At the same time, we have been witnessing a data revolution; firms gather extremely detailed data and propagate knowledge from their consumers, suppliers, alliance partners, and competitors. In particular, since 1993, most large companies have invested in large enterprise resource planning (ERP), Supply Chain Management (SCM), Customer Relationship Management (CRM) and similar enterprise information technology (Aral et al., 2006; McAfee, 2002). These systems collect terabytes of detailed data on operations, suppliers, customers and other aspects of the businesses, increasing the amount of data by 10-fold to 1000-fold. Mobile phones, automobiles, factory automation systems and other devices are routinely instrumented to generate streams of data on their activities, making possible an emerging field of "reality mining" to analyze this information (Pentland and Pentland, 2008). Manufacturers and retailers use RFID tags to deliver terabits of data on inventories and supplier interactions and then feed this information into analytical models to optimize and reinvent their business processes. Similarly, clickstream data and keyword searches collected from websites generate a plethora of data, making visible interactions and patterns that previously could only be guessed at.

According to economic theory, as information becomes more fine-grained and current, decisionmakers should optimally put more weight on it and the overall quality of decision should improve on average, changing from intuitive management to more numbers-driven decision-making. As a Microsoft researcher memorably put it, objective, fine-grained data are now replacing HiPPOs (Highest Paid Person's Opinions) as the basis for decision-making at more and more companies (Kohavi et al., 2009). Managers conduct active experiments with their new business ideas and base their decisions on scientifically valid data. It is common for companies to purchase a "business intelligence" module to try to make use of the flood of data that they now have on their operations. From banks such as PNC, Toronto-Dominion, and Wells Fargo to retailers such as CKE Restaurants, Famous Footwear, Food Lion, Sears, and Subway to online firms such as Amazon, eBay, and Google, firms test many business ideas through a randomized test before launch, called as "information-based strategy" (Davenport, 2009). The innovative process in an online business is now being transformed by the information-based strategy.

While there is a great deal of anecdotal evidence of firms' using data to gain a competitive edge in the business press and popular books (See e.g. Davenport and Harris, 2007; Ayres, 2008; Loveman, 2003), there has been virtually no systematic data analysis of the productivity effects of data-driven

decisionmaking (or DDD) using statistical methods. We seek to address this gap by examining in detail business practices and the information technology investments of 179 publicly traded large firms in the US. We find that DDD can explain a 5-6% increase in their output and productivity, beyond what can be explained by traditional inputs and IT usage. DDD is also associated with significantly higher profitability and market value. While these correlations are consistent with the case evidence, as well as economic theory, econometrics alone cannot rule out the possibilities of reverse causality or omitted variables bias. However, our basic findings remain robust when we use instrumental variables and explore a number of alternative variables that might explain our results. To the best of our knowledge, this is the first study to report a large scale econometric analysis of the relationship between DDD and firm performances.

2. Theory and Literature

Information technology and productivity

Modern theories of the value of information typically begin with the seminal work of Blackwell (Blackwell, 1953). Blackwell's theorem states that decisionmakers observe signals correlated to the state of nature prior to their choice of action and hence "update" the probability distribution before the "optimal" action is chosen. In this framework the value of information (in terms of expected utility) is always positive. Since the mid 90s, many researchers have reported that IT investments indeed increase productivity (e.g. Brynjolfsson and Hitt, 1993; Oliner and Sichel, 2000; Jorgensen and Stiroh, 2000; Kohli and Devaraj, 2003; Aral, Brynjolfsson and Wu, 2006; Barua et al., 1995). While a clear positive relationship between performance and IT investments has been convincingly demonstrated, there is a great deal of individual variation in firms' success with information technology. A variety of factors including the type of IT, the usage, management practices, and organizational structure, as well as the industry environments affect the variation (e.g. Bresnahan et al., 2002; Devaraj and Kohli, 2003). Our study is aligned with the stream of this literature, showing that, after controlling for IT use as well as other traditional inputs and industry, DDD appears to differentiate high-performing firms from others.

Some case studies and a limited analysis on the relationship between DDD and firm performance have been featured in the business press and popular books. For example, Loveman (2003), the CEO of Harrah's Entertainment, states that use of database and decision-science-based analytical tools was the key to his firm's success. Davenport and Harris (2007) have listed many firms in a variety of industries that gained competitive advantage through use of data and analytical tools for decisionmaking: Procter &

Gamble in consumer products, Capital One in financial services, JCPenny in retail, to name a few. They also show a high correlation between higher levels of analytics use and robust 5-year compound annual growth rate from their survey of 32 organizations. A more recent study (Lavalle et al., 2010) has reported that organizations using business information and analytics to differentiate themselves within their industry are twice as likely to be top performers as lower performers. Our study advances the understanding about the relationship between DDD and firm performances by applying a standard econometric method to survey and financial data on publicly traded large 179 firms. In addition, using instrumental variables, we address a potential problem of reverse causality and omission variable bias and show a causal relationship between DDD and firm performance.

Information technology, profitability, and organizational learning

Our study is also related to the literature of organizational learning. Knowledge properties affect the rate of knowledge creation, accumulation, retention, and transfer. Research on the nature of knowledge characterizes knowledge with the degree to which it is codified or tacit (Polany, 1966; Nelson and Winter, 1982a). Codified knowledge refers to knowledge that is transmittable in formal, symbolic language, while tacit knowledge is hard to articulate and acquired through experience (Polany, 1966). Other researchers characterize non-transferrable information as "sticky"(Szulanski, 2000; Von Hippel, 1994). Numerous researchers have pointed out that tacit knowledge is more difficult to transfer than codified knowledge (e.g., Zander and Kogut, 1995; Nadler et al., 2003), because the transfer of tacit knowledge requires proximity, interpersonal interaction, mentorship, apprenticeship, and/or repeated practice over a period of time (Davenport and Prusak, 2000; Hansen, 1999; Szulanski, 1996; Spender, 1996).

An important research question in the aspect of knowledge transfer is whether the transfer of knowledge occurs only within an organization or across the organization and how firms keep knowledge transfer within their firm boundaries while deterring imitation by competitors. Researchers report that technology adoption in a form of codified knowledge tends to equalize organizational performances (Edmondson et al., 2003). Consistent with this research, Carr (Carr, 2003) put forth that "IT doesn't matter" because IT became a commodity that any firm can buy and use. On the other hand, other researchers report that differences in firm performances tend to increase in IT-intensive industries (Brynjolfsson et al., 2006) and firms take a strategy to balance transferring knowledge internally with keeping the knowledge in a form that it is hard for other organizations to imitate (Rivkin, 2001). Many researchers in the literature of IT and productivity also report that differences in organizational structures and human capital would deter imitation of business processes across firm boundary while replication of

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business processes within firm boundary becomes rapid in a codified platform (or IT enterprise platform) (e.g.. McAfee and Brynjolfsson, 2008). It is still unclear whether codified knowledge can be a competitive advantage for a firm or enable imitation by competitors and lose the competitive advantage.

We examine the impact of DDD on profitability as well as productivity. While the productivity measures the production of outputs for a given quantity of inputs and DDD, the business profitability indicates whether firms can gain competitive advantage and earn higher profits by employing DDD than they would have earned otherwise. Extending previous research on the impact of IT investment (e.g., Hitt and Brynjolfsson, 1996; Aral, Brynjolfsson and Wu, 2006) on profitability, we examine the impact of DDD on profitability after controlling for IT use. Similarly to the impact of DDD on productivity, the impact of DDD on profitability was also estimated by using instrumental methods in order to address a potential problem of omission variable bias and reverse causality.

Information technology and market value

The final performance metric we examined is the total market value of the firm. Accounting measures such as return on assets, return on equity, and return on sales have some weaknesses in capturing firm performance: 1) they typically only reflect past information and are not forward looking; 2) they are not adjusted for risk; 3) they are distorted by temporary disequilibrium effects, tax laws, and accounting conventions; 4) they do not capture the value of intangible assets; 5) they are insensitive to time lags necessary for realizing the potential of organizational change. Financial market-based measures can be a useful alternative to these accounting measures. In particular, variants on Tobin's q ratio, defined as the ratio of the stock market valuation of a firm to its measured book value, has been used as measure of business performance (Chen and Lee, 1995), intangible assets (Hall, 1993;Hirschey, 1982), technological assets (Griliches, 1981), brand equity (Simon and Sullivan, 1993), and other characteristics of firms.

In the context of IT-investments, market value has been used to estimate the value of intangible assets such as organizational capital, often associated with IT assets (e.g. Brynjolfsson et al., 2002;Saunders and Brynjolfsson, 2010). The underlying principle is that the total value of financial claims on the firm should be equal to the sum of the firm's assets (Baily et al., 1981;Hall et al., 2000;Hall, 2001). Therefore, the value of intangible assets can be estimated by subtracting the value of other tangible inputs from the sum of financial claims. Other researchers used Tobin's q to examine the effects of information technology on firm performance (Bharadwaj et al., 1999). Related work found that e-commerce announcements

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(Subramani and Walden, 2001) and Internet channel addition (Geyskens et al., 2002) were correlated with changes in market value.

We build in particular on the intangible assets literature and model the value of financial claims against the firm, MV, as the sum of each of its n assets, A.

$$MV = \sum_{i=1}^{n} A_i$$

What the above model formulates is that the market value of a firm is simply equal to the current stock of its capital assets when all assets can be documented and no adjustment costs are incurred in making them fully productive. For example, Google is valued at approximately \$190 billion but the company lists \$40 billion in total assets on its balance sheet. The difference, \$150 billion, can be interpreted as the sum of its intangible assets. We consider three classes of intangibles assets in this paper: those associated with IT, with advertising, and with R&D. For IT-related intangibles, we use data on the number of IT employees. The firm-specific human and organization capital of these employees, especially in knowledge-intensive firms, could be an important asset of their firm and may be reflected in the valuation of the firm. The value associated with IT-employee would thus reflect the value of IT-intangibles of the firm.

The second model is to introduce DDD in the basic model as an interaction term with the other asset as the following (Brynjolfsson, Hitt and Yang, 2002):

$$MV = \sum_{i=1}^{n} A_i + DDD \times A_i$$

Because the DDD variable is an index (with a mean of 0 and a variance of 1), it must be appropriately scaled to be comparable to the other inputs. We found that DDD is most correlated with the market value when it is scaled by a firm's IT employment.

Demand for DDD

The adoption of DDD may be driven by observable firm characteristics. By including some of these characteristics as instruments in a first stage regression, we may be able to address the potential endogeneity of DDD. In the previous research, some scholars use a set of panel data to show that productivity increases upon the usage of some information enterprise systems although productivity does

not increase upon purchase of the information systems (Aral, Brynjolfsson and Wu, 2006); others used some instrumental variables such as the age of computer capital (Brynjolfsson and Hitt, 2003). We used three instruments for DDD: adjustment cost, firm age, and consistency.

Organizations have "organizational inertia" or limited ability to make radical changes in strategy and structure in the face of environmental changes (Hannan and Freeman, 1984; Nelson and Winter, 1982b). Although organizational capabilities such as skills, routines, processes, and structures can generate positive economic returns, they are costly to create and adjust. Consequently, once firms have their routines in place, they do not find it economically optimal to engage in large adjustments to their routines. Such firms with well-established organizational structures optimal for the existing decision-making process may find it too costly to adopt DDD. A direct measure for the adjustment cost was, therefore, constructed from survey by asking the degree to which the factors such as financial resources, senior management support, and organizational culture facilitate or inhibit the ability to make organizational change in a similar fashion as in a previous study (Tambe et al., 2009) (See the section of Data for more detailed description for the construction of the measure).

The constructed measure for the adjustment cost from the survey can be itself endogenous. In order to mitigate the potential bias, we used firm age as an alternative instrumental variable. Firm age, as a proxy for firm experience, has been suggested to have two opposing effects in the literature. The first effect is the organizational inertia. Many researchers have reported that incumbents tend to fail in new radical innovations and younger firms generate innovations of higher quality (Henderson and Clark, 1990; Henderson, 1993; Bresnahan et al., 2009; Balasubramanian and Lee, 2008, Tushman and Anderson, 1986). Consistent with this argument, it has been reported that younger firms tend to show higher rates of productivity growth due to their higher innovation quality (Huergo and Jaumandreu, 2004). DDD is a new business practice that firms can be expected to adopt in the face of the new data-rich environment. Older firms, with well-established routines and business practices and thus a higher degree of organizational inertia, may find the adjustment cost to adopt DDD too high. Firm age is, therefore, likely to be negatively correlated with DDD, as shown in our sample firms. In order to control for the productivity gain caused by the higher quality of innovation, not by DDD, in younger firms, we included a measure of innovation activity in our analysis as a control variable. On the other hand, firm age may have a positive effect on productivity by learning-by-doing. Researchers report that learning-by-doing may decrease the marginal cost of production as firms accumulate production experience with age (e.g. Cohen and Levinthal, 1989;Argote et al., 2003;Levitt and March, 1988;Nass, 1994). If firm productivity increases

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with firm age through learning-by-doing rather than DDD it may jeopardize the legitimacy of firm age as an instrument for DDD. However, that the effect of firm age on productivity is positive while its correlation with DDD is negative. Therefore, any bias would be lead to an underestimate of the coefficient on DDD rather than an overestimate.

The next demand driver for DDD is the degree of consistency in business practices. In the growth literature, researchers argue for the scale effect on the demand of innovation: the scale of the market determines the demand on the innovation because the innovation or invention costs must be incurred only once and after success the discovered new idea can be used for the production of infinite units (e.g. Jones, 1999). Similar to this reasoning, we argue that the scale effect occurs in the demand for DDD as DDD has the non-rival nature as innovation: firms with more consistent business practices can scale up their new business decision, once the initial cost of making such a decision incurs, more readily and less expensively than others of the same nominal size but with inconsistent business practices. Therefore, these firms have a higher incentive to adopt a new way of making business decisions, DDD in our study, more than others with less consistent business practices.

Although all of these demand drivers pass the standard econometric tests as good instruments, they are nonetheless imperfect and we cannot exclude the possibility of omission variable bias or reverse causality. When we examine various combinations of these instruments, however, we find that that the effect of DDD on productivity is fairly robust. The result shows that the coefficient associated with DDD is still statistically significant and the magnitude is approximately the same as the results from OLS. This is consistent with the hypothesis that DDD appears to be causal in increasing productivity.

3. Data and Measures

Business Practice

Our business practice and information system measures are estimated from a survey administered to senior human resource (HR) managers and chief information officers (CIO) from large publicly traded firms in 2008. The survey was conducted in conjunction with McKinsey and Company and we received responses from 330 firms. The survey asks about business practices as well as organization and usage of information systems. The questions extend a previous wave of surveys on IT usage and workplace organization administered in 1995-1996 and 2001 (Hitt and Brynjolfsson, 1997; Tambe and Hitt, 2011), but adds additional questions on innovative activities, the usage of information for decision making, and the consistency of their business practices. To explore the effect of DDD, we used the survey response to

construct measures of firms' organizational practices. We combine these measures with publicly available financial data. This yielded 179 firms with complete data for an analysis of firm productivity. Our sample spans manufacturing, retail/wholesale trade, information, and finance/insurance industries over the period from 2005 to 2009.

1) Data-Driven Decisionmaking (DDD)

We constructed our key independent variable, data-driven decisionmaking (DDD), from three questions of the survey: 1) the usage of data for the creation of a new product or service, 2) the usage of data for business decisionmaking in the entire company, and 3) the existence of data for decisionmaking in the entire company (Table 1).

We created DDD by first standardizing each factor with mean of zero and standard deviation of 1 and then standardizing the sum of each factor:

DDD = STD(STD(use of data for creation of a new product/service) + STD(use of data for business decision in the entire company) + STD(existence of data for such a decision))

2) Adjustment Cost

A measure for the adjustment cost was constructed from 7 survey questions. The survey question was to describe the degree to which the following 7 factors facilitate organizational changes: financial resources, skill mix of existing staff, employment contracts, work rules, organizational culture, customer relationships, and senior management involvement (Table 1). Similarly to DDD, we created the composite index by first standardizing each factor with mean of zero and standard deviation of 1 and then standardizing the sum of each factor.

3) Consistency of Business Practices

Consistency of business practices is one of the instruments we used, denoted by "Consistency". The consistency measure was constructed from a composite of responses to six survey questions on consistency of business practices across operating units, within business units, across functions, and across geographies (4 questions); the effectiveness of IT for supporting consistent practices; and consistency of prioritization of projects (Table 1). Similarly to DDD, the consistency measure was created by first standardizing each factor with mean of zero and standard deviation of 1 and then standardizing the sum of each factor.

4) Exploration (EXPR)

Firm's tendency to explore a new market or technology and make a radical innovation was used as a control variable because firm age, one of our instruments, may be correlated with the firm's ability to explore and thus productivity. It was a composite index of 8 survey questions regarding the firm's tendency to explore (Table 1). This index was also standardized in the same manner as the consistency and DDD measures.

5) Human Capital

The importance of typical employee's education and the average worker's wage were used as a proxy for the firm's human capital.

Financial data

Financial measures were derived from Compustat. Measures of physical assets, employees, sales and operating income were taken directly from the Industrial annual file from 2005 to 2009. Materials were estimated by subtracting operating income before tax and labor expense from sales. In the case that labor expense was not available, the industry-average was used with the industry average based on average labor expense for all firms that report labor expense and employees in the same industry at the most detailed industry breakdown available.

Following the previous study (Brynjolfsson, Hitt and Yang, 2002), we calculated market value as the value of common stock at the end of the fiscal year plus the value of preferred stock plus total debt. The R&D ratio and the advertising expense ratio were constructed from R&D expenses and advertising expense divided by sales, respectively. The missing values were filled in two ways; 1) using the averages for the same NAICS code industry and 2) creating a dummy variable for missing values and including the dummy variable in the regression. The results were essentially the same for our variable of interest.

Firm Age

Firm age was not available in COMPUSTAT and the founding year for 128 firms in the sample was automatically collected from a semi-structured data site such as http://www.answers.com. For the rest of the firms the founding year was manually obtained either from the firm's website or from Orbis database. Firm age was the founding year subtracted from the year of the observation. In case that multiple firms

were merged, we used the founding year of the firm which kept its name. If the firm didn't adopt an existing firm's name after merger, we took the founding year of the older firm.

IT-employee data

The survey included the questions about IT budgets, outsourcing, change of IT budgets from 2008 to 2009, and full time IT employment. The number of full-time IT employees for the year 2008 was asked in the survey, but for the year 2009 it was estimated from the questions on IT budget. Using the change of IT budget from 2008 to 2009, the percentage of outsourcing, and IT FTE for 2008, we were able to estimate the IT FTE for the year 2009. The year from 2005 and 2006, we used data collected in a previous study (Tambe and Hitt, 2011). For the year 2007, a moving average from 2005, 2006, 2008 and 2009 was used. The number of non-IT employees is equal to the number of employees reported on Compustat less our computed IT employment measure.

4. Methods

Productivity Test

We use the Cobb-Douglas specification, the most commonly used model in information technology and productivity literature (e.g., Brynjolfsson and Hitt, 1993, 1996; Dewan and Min, 1997). Our primary regression model can be written as the following:

$$\ln{(sales)_{it}} = \beta_0 + \beta_1 \ln(m)_{it} + \beta_2 \ln(k)_{it} + \beta_3 \ln(IT - Employee)_{it} + \beta_4 \ln(Non - IT\ Employee)_{it}$$
$$+ \beta_4 (\text{DDD})_{it} + controls$$

where m is material, k is physical capital, IT-Employee is the number of IT employees, Non-IT Employee is the number of Non-IT employees, and DDD is our data-driven decisionmaking variable. The controls include industry, year, the firm's explorative tendency, and the firm's human capital such as importance of typical employee's education and average worker's wage, to rule out some alternative explanations for our results.

Although our data on IT and other production inputs and outputs are longitudinal, our main independent variable, DDD, is based on a single survey conducted in 2009. Because many researchers have reported that organizational practices change very slowly, especially for large firms (e.g., Milgrom and Roberts, 1990; Hannan and Freeman, 1984), we constructed a 5-year panel (2005-2009) by making

the assumption that DDD was quasi-fixed for the years from 2005 to 2009. This is consistent with the previous studies (e.g. Bresnahan, Brynjolfsson and Hitt, 2002). As a robustness check, we categorized the firms into 5 groups based on their response to one of the survey questions about the change in the consistency of their business practices. The productivity tests were conducted controlling for the group, examining the effect of DDD within the same group which is likely to have a similar degree of change in the consistency of business practices. The rationale for this test was based on the observation that the consistency of business practices was highly correlated with DDD in our sample firms and the theory that the demand for DDD would be higher for more consistent firms due to the scale effect. Therefore, the change in the consistency of business practices is likely to be correlated with the change in DDD. Estimating the effect of DDD within the same group may mitigate the bias that our assumption may cause.

Profitability Test

In the business profitability literature, there are two types of specifications and we used both to estimate the correlation of DDD with the profitability. First, a linear specification (e.g., Hitt and Brynjolfsson, 1996) implies the following general estimating equation.

$$(\text{Profitability Ratio})_{it} = \beta_0 + \beta_1(\text{IT ratio})_{it} + \beta_2(\text{DDD})_{it} + \text{controls} + \varepsilon$$

The performance numerators and denominators for the profitability ratio we tested are summarized in the following table. IT-ratio is the ratio of the number of IT-employees to the number of total employees. The controls include industry and year. IT was the number of IT employees.

Profitability Ratio	Performance Numerator	Performance Denominator
Return on Assets	Pretax Income	Assets
Return on Equity	Pretax Income	Equity
Profit Margin	Pretax Income	Sales
Asset Utilization	Sales	Assets

The second specification we used is to use log-log transformation of each variables (e.g., Aral, Brynjolfsson and Wu, 2006).

$$Log(\text{Performance Numerator})_{it} = \beta_0 + \beta_1 log(IT - \text{Employee})_{it} + \beta_2(DDD)_{it}$$
$$+ \beta_3 log(\text{Performance Denominator})_{it} + controls + \varepsilon$$

The controls here include the total number of employees as a proxy for the firm size.

Market Value Test

We extend the specification that was used in the previous studies used to estimate the market value of the firm (e.g., Brynjolfsson, Hitt and Yang, 2002; Saunders and Brynjolfsson, 2010) by including the interaction term of DDD with a various asset:

$$(MV)_{it} = \beta_0 + \beta_1 K_{it} + \beta_2(OA)_{it} + \beta_3(IT - Employee)_{it} + \beta_4(DDD)_{it} \times A_{it} + controls + \varepsilon_{it}$$

where MV is the market value of the firm, K is the capital, OA is other assets, IT is the number of IT-employees, DDD is our data-driven decisionmaking variable, A is an asset (capital, other assets, or IT-employee) and controls include industry, year, the ratio of R&D expense to sales, and the ratio of advertising expense to sales.

5. Results and Discussion

Productivity Tests

The descriptive statistics for our variables are tabulated in Table 1 and 2. The correlation of our key independent variable, DDD (data-driven decisionmaking), with the two IT measures, the employee number in IT (information technology) and IT budget, was 0.145 and 0.130, respectively (Table 3). The distributions of DDD is somewhat positively-skewed; the mode in the histogram of DDD is greater than its mean (Figure 1).

The first key result for the productivity is shown in Table 4. All results are from pooled OLS regressions, and errors are clustered by firm to provide consistent estimates of the standard errors under repeated sampling of the same firms over time. The first column (1) shows a baseline estimate of the contribution of IT to productivity during our panel from 2005 to 2009. The coefficient estimate on IT measure (the number of IT-employee) is about 0.085 (s.e.=0.022), which is broadly consistent with the results from previous studies (e.g. Tambe and Hitt, 2011). In column (2), we include our variable of interest, DDD and the coefficient estimate on DDD is 0.0475 (s.e.=0.019). This suggests that firms with one standard deviation higher score on our DDD measure are, on average, about 4.7% more productive

than their competitors, even after controlling for IT use. In column (3), we specified the productivity in a slightly different way. Instead of setting Ln(Sales) as the dependent variable, we set Ln(Value-Added) as the dependent variable. The value-added is calculated by that (sales – materials), following the previous literature for comparison (e.g. Brynjolfsson and Hitt, 1996;Tambe and Hitt, 2011). The point measure for the coefficient on DDD remains statistically the same but the range of the standard errors becomes wide in the specification. The coefficient estimate on DDD, approximately 0.05 from (2) to (3), means that one standard deviation increase in DDD is associated with a 5% increase in the revenues controlling for other traditional inputs and IT investment. It should be noted that this result is after controlling IT use; that is, the variation in productivity among the firms with the same amount of IT use can be explained by the variation in DDD.

The OLS might be biased by endogeneity: increases in productive productivity might cause firms to have higher levels of DDD rather than the other way around. In addition, there is a possibility that omitted variables may be causing both DDD and performance. To address these potential problems, we used a combination of three instruments: adjustment cost, firm age, and the consistency of business practices for DDD in the next analysis (Table 5). Furthermore, we included more control variables in addition to industry and year. The first control variable is the firm's explorative tendency (EXPR) created as described in Table 1. This control variable was included to mitigate a potential correlation between firm age and productivity through more explorative activities that younger firms or firms with lower adjustment cost may have, other than through DDD. The next control variables were 1) the importance of typical employee's education and 2) the average worker's wage to indicate the firm's general human capital. First, we run OLS regression including these additional control variables. The OLS result for the coefficient estimate on DDD with these controls, 0.045 (s.e.=0.017), was statistically the same as that without the additional control variables (0.0475 with s.e.=0.019, the column (2) in Table 4). The magnitude of this estimate is similar to that reported by other researcher that installing a bar code scanner increased the revenue by 4-5% (Basker, 2011).

The next column (model 2 in Table 5) is our next key result using IV. The weakness of the instrumental variables is not a concern as the F-statistics is 16 greater than 10 (result not shown), the cut point for weak instruments. The coefficient estimate on DDD, 0.056, is slightly higher than the result from OLS, 0.060 at $p<0.10$. This slight increase in the estimate may be due to measurement error associated with DDD that attenuates the estimates from OLS. As we have three instruments for one endogenous variable, DDD, we can employ over-identification test. The overid test statistics indicates

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that we cannot reject the null that the estimate on the coefficient for DDD using one instrument is the same as that using the other instrument at a statistically significant level. Furthermore, the value of the Hausman statistics suggests that we cannot reject the null hypothesis that DDD is exogenous and that our OLS regressions in the first column in Table 5 and Table 4 yield consistent estimates. This result suggests that DDD is may be causal associated with the increase in the productivity; one standard deviation increase in DDD increases the productivity by approximately 6%.

We assumed that DDD was the same for the tested period (2005-2009). To check the robustness of this assumption, we categorized our sample firms in 5 groups based on their answers on the change of the consistency of business practices over the last 3 years because the change of the consistency of business practices is likely to be correlated with the change of DDD. The DDD coefficient was approximately the same for both models; one controlling for the group, the other not controlling for the group (result not shown).

Business Profitability Test

We estimated the impact of DDD on various performance measures; return on assets, return on equity, profit margin, and asset utilization in two different functional forms (Table 6). In the first specification (see Method section for the exact functional form), both IT ratio and DDD are not statistically significantly correlated with the profitability ratio, consistent with the previous study which used the similar specification (Hitt and Brynjolfsson, 1996). On the other hand, using the second specification, log(IT) appears to be statistically significantly correlated with 3 profitability measures (ROA, Profit Margin, and Asset Utilization) but one (ROE). DDD appears to be correlated with ROE and Asset Utilization at $p<0.05$. The point measure on the estimates for the coefficient of DDD ranges from 4 to 8% although these differences are not statistical. In all profitability measures in this specification, log(IT), (DDD) or both can explain a portion of the profitability. This result is consistent with the previous study (Aral, Brynjolfsson and Wu, 2006) which showed the installation of ERP system was correlated with the profitability measures. We further analyzed the profitability by using IV (Table 7). The estimate on DDD coefficient in return on asset increase 3-fold from OLS to IV and is still statistically significant at $p<0.10$. In other performance metrics, however, the coefficient estimate on DDD is not statistically significant in IV estimations. The IV estimation suggests that, unlike the impact of DDD on the productivity, the relationship between DDD and profitability may not be causal.

Market Value Test

We also examined the relationship between DDD and the market value of firms (Table 8). This regression relates market value to the three types of assets; PP&E, other assets and IT. Previous studies (e.g., Brynjolfsson, Hitt and Yang, 2002;Saunders and Brynjolfsson, 2010) used the computer capital for IT asset. We used the number of IT employees as a metric for the IT asset. The result suggests that each dollar of installed PP&E is valued at about $1.8, somewhat larger than the theoretical value of $1 that would be expected if there were no adjustment costs or correlated intangible assets. A dollar of other assets, which includes accounts receivable, inventories and liquid assets, is valued at only $0.2; apparently stockholders do not believe that they will receive the full value of these assets, on average. Each one employee in IT is associated with $8,200 of the firm's market value. The number of employees may be correlated with firms' market value for two reasons. First, employees may have firm-specific human and organizational capital, a portion of which accrues to stockholders. Second, the number of IT-employee is likely correlated with the firm's computer capital and related IT assets, which are in turn correlated with market value. The correlation between IT budget and IT-employee for the sample firms from 2008 to 2009 indicated that one IT-employee is associated with $150 of the IT budget. Using the values from the previous study (Saunders and Brynjolfsson, 2010), we can convert one dollar of IT spending per year to be approximately $2 of computer capital on average. This means that each IT-employee is associated with $300 of computer capital. Our regression thus implies that each $1 of computer capital is associated with up to $27 of the firm's market value. Our estimate is higher than what previous studies reported, which was on the order of $10 of market value for $1 of computer capital. The discrepancy may be due to our approximation of computer capital from the number of IT-employee, or the additional firm-specific human capital that we pick up using this specification. The general implication from this estimate is, however, consistent with previous studies; one dollar of computer capital is associated with a much higher value for the market value than $1, suggesting that the computer capital is associated with intangible assets.

When the interaction term, IT multiplied by DDD, was included, the coefficient estimate on the interaction term was $3,000. One employee in IT itself and one employee in IT combined with one standard deviation increase in DDD increase the firm's market value by $6,000 and $3,000, respectively (the second column in Table 8). Using the same conversion factor we used earlier, this means that one dollar of IT-capital itself and IT-capital combined with one standard deviation above mean in DDD increases the firm's market value by $20 and $12, respectively. On the other hands, other assets and PP&E combined with DDD didn't increase the market value as much although the coefficient estimate for the interaction term of other assets with DDD was almost statistically significant (p<0.1). This result

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suggests that firms with a high DDD receives greater benefits from IT investment, or have lower costs of adoption, or both.

6. Conclusion

Case literature and economic theory suggest a potential connection between data driven decisionmaking and productivity. By analyzing a larger sample of firms, we find that DDD is indeed associated with higher productivity. The potential reverse causality was examined by using instrumental variable method; the result from the IV regression stayed qualitatively the same as that from OLS regression. Furthermore, profitability regressions found that DDD is associated with higher ROE and better asset utilization, but not with increases in ROA or profit margin. Last but not least, we found that DDD can account for a portion of a firm's market value. Collectively, our results suggest that DDD capabilities can be modeled as intangible assets which are valued by investors and which increase output and profitability.

Table 1. Construction of Measure of Organizational Practices

	Range	Mean	Std. Dev.	Chronbach' Alpha
Measure 1: Data-Driven Decisionmaking (DDD)				0.58
Typical basis for the decision on the creation of a new product or service (HR survey q13a)	1-5 (Experience/ expertise =1 Data = 5)	2.97	1.13	
We depend on data to support our decision making (the work practices and environment of the entire company) (HR survey q16j)	1-5	3.85	0.85	
We have the data we need to make decisions (HR survey q16p)	1-5	3.43	0.87	
Measure 2: Adjustment cost				0.69
Please rate whether the following factors at your company facilitate or inhibit the ability to make organizational changes: (1:inhibit significantly, 5:facilitate significantly)				
a) Financial resources	1-5	2.93	1.24	
b) Skill mix of existing staff	1-5	3.22	1.19	
c) Employment contracts	1-5	2.89	0.65	
d) Work rules	1-5	2.98	0.83	
e) Organizational culture	1-5	3.31	1.27	
f) Customer relationships	1-5	3.69	1.02	
g) Senior management involvement	1-5	4.11	0.98	
Measure 3: Consistency				0.77
Looking across your entire company, please rate the level of consistency in behaviors and business processes across operating units (HR survey q1)	1-5	3.02	0.75	
Regarding the first core activity of your company, the consistency within business unit (HR survey q9a)	1-5	3.79	0.93	
Regarding the first core activity of your company, the consistency across functions (e.g., sales, finance, etc) (HR survey 9b)	1-5	3.38	0.99	
Regarding the first core activity of your company, the consistency across geographies (HR survey q9c)	1-5	3.53	0.99	
Effectiveness of IT in building consistent systems and processes for each operating unit (IT survey q13b)	1-5	3.50	0.85	
Measure 4: Exploration (EXPR)				0.58
IT facilitates to create new products (IT survey 11a)	1-5	3.78	1.22	

IT facilitates to enter new markets (IT survey 11b)	1-5	3.68	1.15	
IT supports growth ambitions by delivering services or products that set us apart from competitors (IT survey 12c/HR survey 15c)	1-4	2.52; 2.56	1.08; 1.01	
IT plays a leading role in transforming our business (IT survey 12d/HR survey 15d)	1-4	2.90; 3.01	1.13; 1.12	
IT partnering with BIZ to develop new business capabilities supported by technology (IT survey 13f/HR survey 14e)	1-5	3.33; 0.96	3.01; 1.09	
Strong ability to make substantial/disruptive changes to business processes (HR survey 16l)	1-5	2.90	1.05	
Measure 5: General human capital				
EDUCATION: The importance of educational background in making hiring decisions for the "typical" job (HR survey q4)	1-5	3.34	1.00	
% of employees using PC/terminals/workstations (HR survey q7a)	%	77.0	27.1	
% of employees using e-mails (HR survey q7b)	%	73.0	29.1	

Table 2: Production Function Variables (N=111, Year 2008 cross section)

Variable	Mean	Std.Dev.
Log(Sales)	7.76	0.90
Log(Material)	7.18	1.02
Log(Capital)	6.26	1.64
Log(Non-IT Employee)	8.70	1.05
Log(IT-Employee)	5.15	1.22
Log(Avg. Workers' Wage)	11.1	0.63

Figure 1: Distribution of DDD
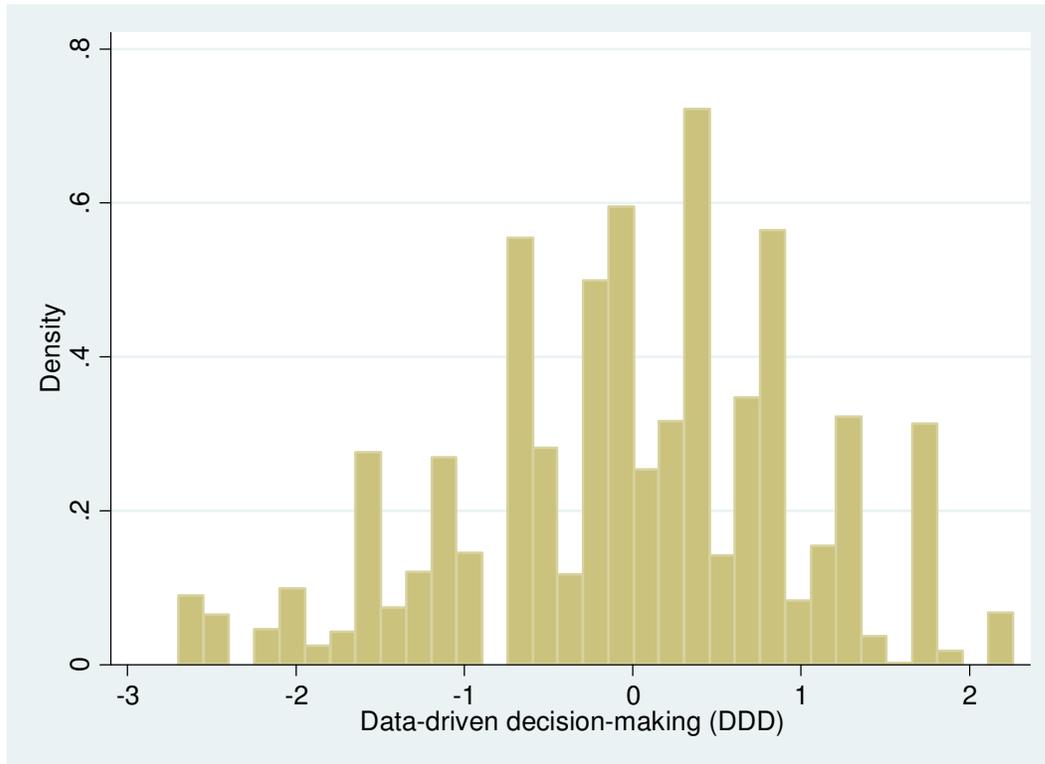
Table 3: Correlations between DDD and IT investment (Partial correlation for each pair, after controlling for size of firm (in the number of total employee for IT employee and sales for IT budget) and industry. ***$p<0.01$, **$p<0.05$, *$p<0.1$)

	IT Employee	IT Budget
DDD composite (average of the following three)	*0.145***	*0.130**
1. Use data for the creation of a new service and/or product	0.13*	0.086
2. Have the data we need to make decisions in the entire company	0.10*	0.17**
3. Depend on data to support our decision making	0.11	0.05

Table 4: OLS Regressions of DDD on Productivity Measures (Other controls include industry, year, and average workers' human capital)

DV=	Log(Sale)	Log(Sale)	Log(Value-Added)
DDD		0.0475**	0.052
		(0.02)	(0.04)
Log(Material)	0.511***	0.501***	
	(0.04)	(0.04)	
Log(Capital)	0.0984***	0.0991***	0.235***
	(0.02)	(0.02)	(0.03)
Log(IT-Employee)	0.0845***	0.0852***	0.190***
	(0.02)	(0.02)	(0.04)
Log(Non-IT Employee)	0.221***	0.224***	0.433***
	(0.03)	(0.03)	(0.05)
Constant	1.112***	1.133***	0.427
	(0.19)	(0.18)	(0.31)
Observations	682	682	674
R-squared	0.92	0.922	0.812
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Table 5: IV-Regressions of DDD on Productivity Measures (Standard errors clustered around firms are in parentheses, *p<0.10, **p <0.5, ***p < 0.01. DV means dependent variable. The overid test tests the null hypothesis that the estimates using each one instrument are the same. The Hausman Test tests the null hypothesis that OLS is inconsistent. The industry control is at 2-digit NAICS level for manufacturing industries and 1-digit NAICS level for other industries. The years are from 2005 to 2009.)

	(1)	(2)
	OLS	**IV**
Variable	**DV=Log(Sales)**	**DV = Log(Sales)**
DDD	0.045*** (0.017)	0.057* (0.031)
Log(Material)	0.53*** (0.040)	0.53***(0.040)
Log(Capital)	0.097*** (0.024)	0.096***(0.024)
Log(Non-IT Employee)	0.26*** (0.031)	0.26***(0.031)
Log(IT Employee)	0.054*** (0.020)	0.055**(0.020)
Controls	Industry, Year, Exploration, Importance of Employee education, Log(avg. workers' wage)	The same as in (1)
Observations	681	681
Number of Firms	179	179
(Adj.) R-square	0.94	0.94
Overid Test		0.75
Hausman Test		0.67

Table 6: Regressions of DDD on different performance measures in 2 different specifications.

Dependent Variable =	ROA		ROE		Profit Margin		Asset Utilization	
IT Ratio	0.00137	0.00132	0.0552	0.0518	-0.00027	-0.00014	-0.0576	-0.0742
	(0.009)	(0.009)	(0.071)	(0.070)	(0.042)	(0.041)	(0.085)	(0.083)
Data-driven decision-making (DDD)		0.000424		0.028		-0.00074		0.0967
		(0.006)		(0.023)		(0.011)		(0.084)
Constant	0.0558***	0.0557***	0.0586	0.0517	-0.0161	-0.0159	0.742***	0.720***
	(0.013)	(0.013)	(0.085)	(0.085)	(0.083)	(0.082)	(0.215)	(0.210)
Observations	582	582	579	579	682	682	682	682
R-squared	0.075	0.075	0.019	0.023	0.04	0.04	0.223	0.232
Robust standard errors in parentheses								
*** p<0.01, ** p<0.05, * p<0.1								

Dependent Variable =	Log(Pretax Income)		Log(Pretax Income)		Log(Pretax Income)		Log(Sales)	
Interpretation	ROA		ROE		Profit Margin		Asset Utilization	
Data-driven decision-making (DDD)		0.0776		0.0643**		0.0436		0.0803**
		(0.051)		(0.030)		(0.062)		(0.038)
Log(IT)	0.142**	0.141**	-0.0492	-0.0485	0.166***	0.167***	0.101***	0.103***
	(0.057)	(0.056)	(0.040)	(0.040)	(0.055)	(0.055)	(0.036)	(0.036)
Log(Asset)	0.668***	0.657***					0.378***	0.365***
	(0.055)	(0.054)					(0.036)	(0.037)
Log(Equity)			0.889***	0.881***				
			(0.034)	(0.034)				
Log(Sales)					0.999***	0.983***		
					(0.109)	(0.107)		
Log(Non-IT Employee)	0.102	0.107	0.154***	0.156***	-0.138	-0.13	0.342***	0.348***
	(0.070)	(0.069)	(0.042)	(0.042)	(0.098)	(0.097)	(0.046)	(0.042)
Constant	-1.707***	-1.678***	-2.574***	-2.554***	-2.067***	-2.031***	1.329***	1.362***
	(0.452)	(0.444)	(0.240)	(0.240)	(0.477)	(0.482)	(0.317)	(0.299)
Observations	568	568	565	565	568	568	682	682
R-squared	0.664	0.667	0.836	0.838	0.631	0.632	0.815	0.82
Robust standard errors in parentheses								
*** p<0.01, ** p<0.05, * p<0.1								

Table 7. Profitability Regressions with Extended Firm-Specific Control Variables. Control variables include log-value of R&D expense, advertising expense, capital, number of total employee, and market share. As a proxy for general human capital, the importance of employees' education was also included along with year and industry. DDD was instrumented by consistency and adjustment cost constructed from the survey variables.

Interpretation	Return on Asset		Return on Equity		Asset Utilization	
Dependent Variable=	Log(Pretax Income)		Log(Pretax Income)		Log(Sales)	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
DDD	0.068 (0.049)	0.19* (0.11)	0.059** (0.029)	0.088 (0.063)	0.066* (0.034)	0.034 (0.062)
Log(IT-Employee)	0.069 (0.054)	0.070 (0.053)	-0.041 (0.037)	-0.041 (0.036)	0.051 (0.035)	0.049 (0.035)
Log(Total Asset)	0.69*** (0.07)	0.64*** (0.08)			0.42*** (0.05)	0.43*** (0.06)
Log(Equity)			0.90*** (0.04)	0.89*** (0.04)		
Number of Firms	174	174	174	174	179	179
Number of Observations	568	568	565	565	682	682
R-square	0.76	0.76	0.85	0.85	0.84	0.84
Control variables	Industry, Year, Log(R&D expense), Log(Advertising expense), Log(Capital), Log(Total number of employees), Log(Market share), Importance of employees' education					

Table 8: Regressions of DDD on market value (1: Information Technology was the number of IT-employees, used to proxy for IT asset.)

DV = Market Value						
Property, Plant and Equipment - Total (Net)	1.772***	1.750***	1.719***	1.717***	1.748***	1.721***
(PPE)	(0.495)	(0.454)	(0.429)	(0.431)	(0.458)	(0.401)
Information Technology[1]	8,262***	6,348***	7,598***	7,983***	7,505***	6,902***
(IT)	(2,003)	(1,649)	(1,635)	(1,864)	(1,714)	(1,747)
Other assets	0.191***	0.202***	0.192***	0.192***	0.210***	0.205***
(OA)	(0.034)	(0.031)	(0.029)	(0.033)	(0.026)	(0.023)
DDD x IT		3,097**				870.8
		(1,267)				(1,230)
DDD x Employee			0.123*			0.071
			(0.073)			(0.074)
DDD x PPE				0.304		-5.03E-05
				(0.379)		(0.319)
DDD x OA					0.238*	0.138
					(0.127)	(0.089)
Constant	-5,494	-4,487	-5,060*	-5,953*	-5,332*	-4,867
	(3360.000)	(2799.000)	(2818.000)	(3396.000)	(3066.000)	(2961.000)
Observations	676	676	676	676	676	676
R-squared	0.753	0.769	0.771	0.758	0.77	0.777
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

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