Strength in Numbers: How does data-driven decision-making affect firm performance?

Completed Research Paper

Introduction

How do firms make better decisions? In more and more companies, managerial decisions rely less on a leader's "gut instinct" and instead on data-based analytics. At the same time, we have been witnessing a data revolution; firms gather extremely detailed data from and propagate knowledge to their consumers, suppliers, alliance partners, and competitors. Part of this trend is due to the widespread diffusion of enterprise information technology such as Enterprise Resource Planning (ERP), Supply Chain Management (SCM), and Customer Relationship Management (CRM) systems (Aral et al. 2006; McAfee 2002), which capture and process vast quantities of data as part of their regular operations. Increasingly these systems are imbued with analytical capabilities, and these capabilities are further extended by Business Intelligence (BI) systems that enable a broader array of data analytic tools to be applied to operational data. Moreover, the opportunities for data collection outside of operational systems have increased substantially. Mobile phones, vehicles, 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" (Pentland and Pentland 2008). Manufacturers and retailers use RFID tags to track individual items as they pass through the supply chain, and they use the data they provide optimize and reinvent their business processes. Similarly, clickstream data and keyword searches collected from websites generate a plethora of data, making customer behavior and customer-firm interactions visible without having to resort to costly or ad-hoc focus groups or customer behavior studies.

Leading-edge firms have moved from passively collecting data to actively conducting customer experiments to develop and test new products. For instance, Capital One Financial pioneered a strategy of "test and learn" in the credit card industry where large number of potential card offers were field-tested using randomized trials to determine customer acceptance and customer profitability (Clemons and Thatcher 1998). While these trials were quite expensive, they were driven by the insight that existing data can have limited relevance for understanding customer behavior in products that do not yet exist; some of the successful trials created led to products such as "balance transfer cards," which revolutionized the credit card industry. Online firms such as Amazon, eBay, and Google also rely heavily on field experiments as part of a system of rapid innovation, utilizing the high visibility and high volume of online customer interaction to validate and improve new product or pricing strategies. Increasingly, the culture of experimentation has diffused to other information-intensive industries such as retail financial services (Toronto-Dominion Bank, Wells Fargo, PNC), retail (Food Lion, Sears, Famous Footwear), and services (CKE Restaurants, Subway) (see Davenport 2009).

Information theory (e.g., Blackwell 1953) and the information-processing view of organizations (e.g. Galbraith 1974) suggest that more precise and accurate information should facilitate greater use of information in decision making and therefore lead to higher firm performance. There is a growing volume of case evidence that this relationship is indeed true, at least in specific situations (e.g., Davenport and Harris 2007; Ayres 2008; Loveman 2003). However, there is little independent, large sample empirical evidence on the value or performance implications of adopting these technologies.

In this paper, we develop a measure of the use of "data-driven decision making" (DDD) that captures business practices surrounding the collection and analysis of external and internal data. Combining measures of this construct captured in a survey of 179 publicly traded firms in the US with public financial information and private data on overall information technology investments, we examine the relationships between DDD and productivity, financial performance and market value. We find that DDD is associated with a 5-6% increase in their output and productivity, beyond what can be explained by traditional inputs and IT usage. Supplemental analysis of these data using instrumental variables methods and alternative models suggest that this is a causal effect, and not driven by the possibility that productive firms may have a greater propensity to invest in DDD practices even in the absence of real benefits.

Theory, Literature, and Model

Value of Information

Modern theories of the value of information typically begin with the seminal work of Blackwell (1953). In this approach, a decision maker is attempting to determine what "state of nature" prevails so that they can choose the action that yields the highest value when that state is realized. If the state of nature can be determined with certainty, the decision maker has perfect information and the decision process reduces to a simple optimization problem. However, decisionmakers rarely know what state will prevail with certainty. Blackwell's contribution was to create an approach for describing when one set of imperfect information set was better ("more informative") than another in the sense that a rational decision maker acting on better information should achieve a higher expected payoff. In this perspective, improved information always (weakly) improves performance.[1] One operationalization of "more informative" is that it enables the decisionmaker to identify a finer subset of possible outcomes from the set of all possible outcomes. This description has a natural interpretations of either finer-grained information (narrower and narrower sets of states can be described) or reduced statistical noise in information (since noise makes it impossible to distinguish among closely related states). Theoretically, improvements in technologies that collect or analyze data can reduce error in information by decreasing the level of aggregation that makes it difficult to distinguish among possible states or eliminating noise.

A different but complementary perspective on information and decision making within organizations was put forth by Galbraith (1974) who argued that performing complex tasks require a greater amount of information to be processed, and therefore organizations should be designed to facilitate information processing. Technologies that enable greater collection of information, or facilitate more efficient distribution of information within an organization (in Galbraith's language, "vertical information systems") should lower costs and improve performance. Galbraith's approach has been widely used as a foundation for understating the organizational effects of information technology and has led to a number of other theoretical developments broadly described as the "information processing view of the firm" (see e.g. Attewell and Rule 1984; Radner 1993).

Business Value of Information Technology

Since the mid-1990s, it has been recognized that information technology is a significant driver of productivity at the business unit (Barua et al. 1995), firm (e.g., Brynjolfsson and Hitt 1996; Bresnahan et al. 2002), industry (e.g., Jorgenson and Stiroh 2000) and economy level (Oliner and Sichel 2000; Jorgenson and Stiroh 1999). While there are a number of possible explanations for this relationship (see e.g., Melville et al. 2004), the role of information technology in driving organizational performance is at least due in part the increased ability of IT intensive firms to collect and process information. Organizational factors that would tend to make organizations more effective users of information such as decentralized decision rights or worker composition have been demonstrated to significant influence the returns to IT investments (Bresnahan et al. 2002; Francalanci and Galal 1998). More recently, studies have suggested that the ability of a firm to access and utilize external information is also an important complement to organizational restructuring and IT investment (Tambe et al. 2009).

---

[1] Theoretically, Blackwell's arguments apply to one-agent decision problems. These insights also extend to many types of multi-agent games – for example, improved information about performance will generally increase total welfare in moral hazard problems (see e. g., Holmstrom, B., and Milgrom, P. 1991. "Multitask Principal–Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, and Organization* (7:special issue), p. 24.). In some cases, it is possible for improved information to reduce welfare because parties may refuse to trade in the presence of adverse selection when one party is known to be better informed than the other (e.g., the Akerlof "Lemons" problem). However, this is not an issue if the presence of improved information is not known (firms keep their information advantage hidden and thus will benefit from their position), or information is shared reducing information asymmetries.

Closely related to these studies is the emerging literature on the value of enterprise systems, that have shown that investments in ERP (Hitt et al. 2002; Anderson et al. 2003) and combinations of ERP systems with other complementary enterprise technologies such as SCM or CRM is associated with significantly greater firm value (Aral et al. 2006). It has long been recognized that a key source of value of ERP systems is the ability to facilitate organizational decision making (see e.g. McAfee 2002), and this view has begun to receive large sample empirical support (see e.g. Aral et al. 2009). In addition, McAfee and Brynjolfsson (2008) argue that it is enterprise systems and related technologies that allow firms to leverage know-how developed in one part of the organization to improve performance across the firm as a whole.

There have been some analyses that directly relate DDD to economic performance, although these tend to be case studies or illustrations in the popular business press. For example, Loveman (2003), the CEO of Caesar's Entertainment, states that use of databases 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 decision making such as Proctor and Gamble and JC Penney. They also show a correlation between higher levels of analytics use and 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 performance by applying a standard econometric method to survey and financial data on publicly traded large 179 firms.

Measuring the Impact of Information Technology Investments

Productivity

The literature on IT value has used a number of different approaches for measuring the marginal contribution of IT investment accounting for the use of other firm inputs and controlling for other firm, industry or temporal factors that affect performance (see a summary of these in Hitt and Brynjolfsson 1996). Our focus will be on determining the marginal contribution of DDD on firm performance. As we will describe later, DDD will be captured by an index variable (standardized to mean zero and variance one) that captures a firm's position on this construct relative to other firms we observed, and can be incorporated directly into various performance measurement regressions.

The most commonly used measure of performance in this literature is multifactor productivity, which is computed by relating a measure of firm output such as Sales or Value-Added, to firm inputs such as capital (K), labor (L), and information technology capital or labor (IT). Different production relationships can be modeled with different functional forms, but the most common functional form assumption is the Cobb-Douglas production function which provides the simplest relationship between inputs and outputs that is consistent with economic production theory. The model is typically estimated in firm-level panel data using controls for industry and year, and inputs are usually measured in natural logarithms. The residuals of this equation can be interpreted as firm productivity after accounting for the contributions of all inputs (sometimes called "multifactor productivity" or the "Solow residual"). Including additional firm factors additively into this equation can then be interpreted as factors that "explain" multifactor productivity and have a direct interpretation as the marginal effect of the factor on firm productivity. This results in the following estimating equation:

$$\ln(\boldsymbol{sales})_{it} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\ln(\boldsymbol{m})_{\mathrm{it}} + \boldsymbol{\beta_2}\ln(\boldsymbol{k})_{\mathrm{it}} + \boldsymbol{\beta_3}\ln(\boldsymbol{ITE})_{\mathrm{it}} + \boldsymbol{\beta_4}\ln(\boldsymbol{NonIT\ Employee})_{\mathrm{it}} + \boldsymbol{\beta_4}(\mathbf{DDD})_{\mathrm{it}} + \boldsymbol{controls} + \boldsymbol{\varepsilon} \quad \text{-- (1)}$$

where m is materials, k is physical capital, ITE is the number of IT employees, Non-IT Employee is the number of Non-IT employees, and DDD is our data-driven decision-making variable. The controls include industry, year. To help rule out some alternative explanations for our results we also include the firm's explorative tendency and the firm's human capital such as importance of typical employee's education and average worker's wage. Our performance analysis is based on a five year panel (2005-2009) including a single cross-section of DDD data observed in 2008 match to all years in our panel.[2]

Profitability

An alternative method of measuring firm performance is to relate an accounting measure of profitability to the construct of interest and other control variables. This approach is particularly popular in the management literature, and has been employed in many studies that have examined the performance impact of ERP (e.g., Hitt et al. 2002; Aral et al. 2006). However, it has the disadvantage that it is less theoretically grounded than other performance measurement methods, but has a significant advantage that it allows a diversity of interpretations of performance, and is closely related to how managers and securities analysts actually compare the performance of firms. The general form of this estimating equation is:

$$\boldsymbol{Log(Perform.Numerator)_{it} = \beta_0 + \beta_1 log(IT)_{it} + \beta_2 (DDD)_{it} + \beta_3 log(Perform.Denominator)_{it} + control + \varepsilon} \quad \text{---(2)}$$

The performance numerators and denominators for the profitability ratio we tested are summarized in Table 1.

Table 1. Performance numerator and denominator in the profitability analysis

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

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), and brand equity (Simon and Sullivan, 1993).

In the context of IT-investments, market value has been used to estimate the value of intangible assets such as organizational capital associated with IT assets (e.g. Brynjolfsson et al., 2002; Saunders and Brynjolfsson, 2010; and Brynjolfsson et al. 2011). 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 (Subramani and Walden, 2001) and Internet channel addition (Geyskens et al., 2002) were correlated with changes in market value.

We build 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.

---

[2] This assumes that our measure of DDD in 2008 is correlated with the true value of DDD in other years. We test whether our results are sensitive to this assumption and find no evidence that the relationship between measured DDD and productivity varied over the sample period.

$$MV = \sum_{i=1}^{n} A_i \qquad \text{---------------- (3)}$$

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. However, in practice firm value can deviate significantly from tangible book value. For instance, at the time of writing 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.

Following the emerging literature on IT and intangible assets, we consider three classes of intangibles – those related to information technology and its associated organizational complements (captured as IT employees), brands (captured as advertising), and technology (captured as R&D investment). We also consider the possibility that the value of some types of assets increase with the presence of DDD (similar to the treatment of organizational assets in Brynjolfsson et al. 2002). This yields the following equation:

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

$$(MV)_{it} = \beta_0 + \beta_1 K_{it} + \beta_2 (OA)_{it} + \beta_3 (IT)_{it} + \beta_4 (DDD)_{it} \times A_{it} + controls + \varepsilon_{it} \qquad \text{---------------- (4)}$$

where MV is the market value of the firm, K is the capital, OA is other assets, IT is either IT capital or the number of IT-employees, DDD is our data-driven decision-making 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. This also provides a more natural relationship since one would generally expect that firms of different sizes would have a different marginal effect of market value as DDD (measured as a standardized index) varies.

Endogeneity of DDD

All of the performance methods above must either be interpreted as conditional correlations rather than causal relationships or rely on an assumption that DDD is exogenous with respect to firm performance. For the purposes of this study, neither is an attractive approach since the former limits the managerial relevance of this analysis, and the latter is unlikely to be true (although a number of recent studies have suggested that the bias on at least IT investment due to endogeneity is not large – see Tambe and Hitt 2011).

The literature on IT value has generally used three types of approaches for directly addressing endogeneity concerns. First, researchers can make arguments of temporal precedence either by including lagged values of other input variables (e.g. Brynjolfsson and Hitt 1996;Dewan and Kraemer 2000), or by looking at differences in performance before and after a system becomes live rather than when the investment is made (Aral et al. 2006; Hitt and Frei 2002). Second, econometric methods that rely on internal instruments in panel data (such as the Arellano and Bond, or Levinsohn and Petrin estimators) can be used to control for endogeneity under the assumption that changes in past investment levels are uncorrelated with current performance. However, both of these approaches rely on significant temporal variation in the variables of interest, and cannot be readily applied to our context since we have a single cross-sectional observation of DDD. However, we are able to pursue the more traditional instrumental variables approaches, where researchers specify a set of factors (instruments) that drive the demand for the endogenous factor but are not correlated with the unobserved component of performance.

In prior work, researchers have used measures of the composition of IT (relative proportion of mainframes versus PCs) and the overall age of capital within an organization (Brynjolfsson and Hitt, 2003) under the assumption that these factors determine the ability of a firm to adapt their IT infrastructure to changing business needs. Recent work by Brynjolfsson, Tambe and Hitt (2011) attempts to more directly measure the IT-related adjustment costs or organizational inertia (see e.g. Hannan and Freeman, 1984; Nelson and Winter, 1982b) by developing a scale capturing the factors that facilitate or inhibit IT investment such as senior management support or organizational culture, and used this scale as an additional instrument.

To these existing instruments, we add additional instruments that may be especially useful in explaining cross-sectional variation in DDD. Prior work has specifically linked organization experience, operationalized as *firm age*, to organizational inertia (Henderson and Clark 1990; Henderson 1993;

Bresnahan et al. 2009; Balasubramanian and Lee 2008; Tushman and Anderson 1986). By this argument, younger firms are more likely able to adopt new innovations such as business analytics or other technologies underlying DDD, thus leading to a negative correlation between DDD and firm age (which is observed in our data). To reduce the possibility that our instrument would be invalidated by a correlation between innovation-driven productivity and firm age (see Huergo and Jaumandreu 2004), we include controls for innovation activity when this instrument is used. It is also possible that firm age has a correlation with productivity due to learning by doing (e.g. Cohen and Levinthal 1989;Argote et al. 2003;Levitt and March 1988;Nass 1994) but since this would yield positive correlation between firm age and productivity, any bias from using this instrument would likely reduce our observed effect of DDD, making the results more conservative.

Another potential demand driver for DDD is the degree of consistency in business practices. Brynjolfsson and McAfee (2008) argue that one way in which firms are able to capture the value of IT-related innovation, including discoveries facilitated by DDD, is that they can replicate good ideas across the organization. This is motivated by the observation that information (e.g. Shapiro and Varian 1999) or specific information about innovative practices (e.g., Jones 1999) is non-rival and therefore more valuable with scale. Thus, firms that have demonstrated the ability to deploy common business practices across large numbers of organization units are likely to be more effective users of DDD, and therefore more likely to have invested in developing DDD capabilities than firms that have disparate business practices.

Thus, our set of instruments includes constructs employed in prior literature for capital age (Brynjolfsson and Hitt 2003) barriers to IT adoption (Brynjolfsson et al. 2011) as well as new measures of firm age, and consistence of business practices. As we will show later, these constructs pass the normal empirical instrument validity tests, and when utilized, demonstrate that our observation relationships between DDD and performance are robust to concerns about reverse causality.

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 of the information systems function 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; Brynjolfsson et al. 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 covering all major industry segments over the period from 2005 to 2009. The exact wording of the survey questions appears in Table 2.

Data-Driven Decision Making (DDD). We constructed our key independent variable, data-driven decision making (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 decision making in the entire company, and 3) the existence of data for decision making in the entire company (Table 2).

We created DDD by first standardizing (STD) 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 or service) + STD(use of data for business decisions in the entire company) + STD(existence of data for such a decision))

Adjustment Cost. A measure for the adjustment cost was constructed from 6 survey questions. Respondents were asked to describe the degree to which the following 6 factors facilitate organizational changes: financial resources, skill mix of existing staff, employment contracts, work rules, organizational culture, customer relationships, and senior management involvement (Table 2). Similarly to DDD, we created the composite index by first standardizing each factor with mean of zero and standard deviation of 1 and then and then standardizing the sum of the scale components.

Consistency of Business Practices. Consistency of business practices ("Consistency") is constructed as 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 2). 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 the scale components.

Exploration (EXPR). Firm's tendency to explore a new market or technology and to engage in radical innovation was used as a control variable because firm age, one of our instruments, may be correlated with a firm's innovative activity which, in turn, can affect productivity and other performance measures. It was a composite index of 8 survey questions regarding the firm's tendency to explore new markets or technologies (see Table 2). This index was also standardized in the same manner as the consistency and DDD measures.

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.

Table 2. Construction of Measure of Organizational Practices

	Range of scale	Mean	Std. Dev.	Cronbach's Alpha
Measure 1: Data-Driven Decision-making (DDD)				0.58
Typical basis for the decision on the creation of a new product or service (HR survey q13a)	1-5[3]	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) (HR survey q11)				
a) Skill mix of existing staff	1-5	3.22	1.19	
b) Employment contracts	1-5	2.89	0.65	
c) Work rules	1-5	2.98	0.83	
d) Organizational culture	1-5	3.31	1.27	
e) Customer relationships	1-5	3.69	1.02	
f) 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	

[3] Scale ranges from 1 to 5, with 5=greatest reliance on data

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 the business 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	

Other Data

Production Inputs and Performance. Measures of physical assets, employees, sales and operating income were taken directly from the Compustat 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, it was estimated from number of employees and the industry average wage for the most disaggregated industry data available that matched the primary industry of the firm.

Following prior work (Brynjolfsson et al. 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 variables of interest.

Firm Age. Firm age was collected from a semi-structured data site (http://www.answers.com) where available, and supplemented with additional data from firm websites and the 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. For mergers where the new entity did not retain either prior firm name, we used the founding year of the oldest firm engaged in the merger.

Information Technology Staff. 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 value interpolated 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.

While the construction of the IT input series is less than ideal, we do not believe that this introduces any biases in the analysis, and enables us to extend existing IT input datasets almost through the current period. Tambe and Hitt (2011) showed that IT employees appear to be a good proxy of overall IT input, at least for conducting productivity analyses (results using IT capital and IT employees are essentially the same, with the IT employee data showing less error variance). To reduce the impact of using different sources over time, we include year dummy variables that will control for any scaling differences. The remaining variance in these measures is likely noise which may tend to bias our results toward zero, making them more conservative.

Results and Discussion

Productivity Tests

The descriptive statistics for our variables are tabulated in Table 2 and Table 3. Most of the business practice measures were captured on 5-point Likert scales with a mean on the order of 3-4 and a standard deviation of approximately 1. When formed into scales, the control variables for adjustment costs and consistency of business practices appear to be fairly internally consistent with Cronbach's alpha of .69 and .77 respectively. The DDD measure shows a Cronbach's alpha of 0.58, which is consistent with the fact that firms can pursue some aspects of DDD (such as using data to develop new products) independently of the others. The same appears true for the exploration measure. The distributions of DDD is somewhat positively-skewed; the mode in the histogram of DDD is greater than its mean (Figure 1). The average firm in our sample is large, with a geometric mean of approximately $2.3 billion in sales, 6000 non-IT employees and 172 IT employees.

Table 3. 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

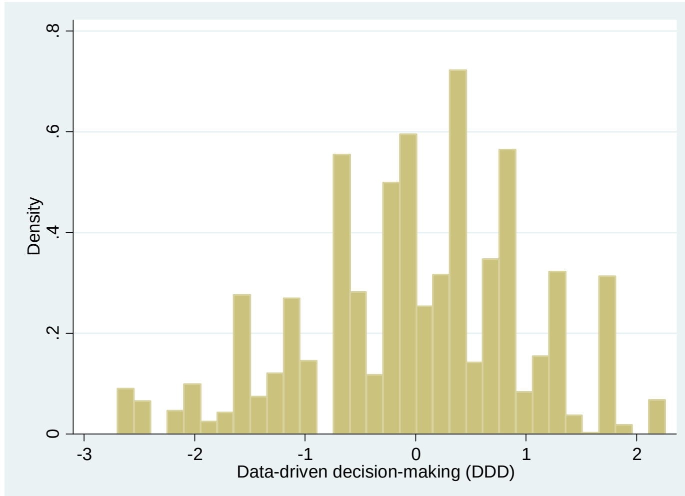

Figure 1. Distribution of DDD

Table 4 reports the conditional correlation of our key construct, data-driven decision-making (DDD), with the two IT principal IT measures. The correlation is 0.145 between IT staff and DDD, and .130 between IT budget and DDD (Table 4). Interestingly, this correlation is slightly lower than correlations between IT and other organizational complements which tend to be on the order of 20%. This may be because, as a new practice, DDD may be in the process of diffusing across firms. Firms that were historically high in IT may or may not have made investments in DDD. This will tend to lower estimates of correlations, but strengthen the power of tests for performance. In fact, if the correlation between DDD and IT investment were perfect, it would be impossible to distinguish the performance effects of the two.

Table 4. Correlations between DDD and IT investment

	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

(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. ***$p<0.01$, **$p<0.05$, *$p<0.1$)

The primary results regarding the relationship between DDD and productivity are shown in Table 5. All results are from pooled OLS regressions, and errors are robust and clustered by firm to provide consistent estimates of the standard errors under repeated sampling of the same firms over time. To rule out an alternative explanation, we included average worker's wage as a measure of human capital in all models. 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-employees) is about 0.056 ($t=2.8$, $p<0.01$), 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 0.046 (s.e.=0.02) while the coefficient estimate on IT remains the same. This suggests that firms with one standard deviation higher score on our DDD measure are, on average, about 4.6% more productive than their competitors. It should be noted that this result is *after* controlling IT use; that is, the additional variation in productivity can be explained by the variation in DDD among the firms with the same amount of IT use.

Table 5. OLS Regressions of DDD on Productivity Measures

DV=Log(Sales)	(1) 2005-2009	(2) 2005-2009	(3) 2008-2009
DDD		0.046***(0.02)	0.043**(0.02)
Log(Material)	0.54***(0.04)	0.53***(0.04)	0.51***(0.04)
Log(Capital)	0.095***(0.02)	0.096***(0.02)	0.10***(0.03)
Log(IT-Employee)	0.056***(0.02)	0.057***(0.02)	0.12***(0.03)
Log(Non-IT Employee)	0.25***(0.03)	0.25***(0.03)	0.24***(0.04)
Constant	-1.48***(0.40)	-1.44***(0.37)	-1.10**(0.46)
Number of firms	179	179	113
Observations	681	681	211
R-squared	0.94	0.94	0.94
Other Controls	Industry; Year; Log(average worker's wage)		

(Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, *p<0.1)

To check the robustness of our assumption that the effects of DDD did not vary over the test period (2005-2009), we subdivide our sample into smaller periods and repeat our main productivity analysis. We find that when the sample is restricted to periods around our survey (2008-2009) the results are similar to the full sample (see Table 5) suggesting that we are not biasing our results by extending the data to prior periods. We can also compare the results of different subsamples over time in fully balanced panel of 72 firms. While the precision of the estimates is significanly reduced, the coefficients on DDD are virtually identical whether we consider the full sample, the pre-survey subsample (2005-2007) or the survey period (2008-2009) (see Table 6). We confirmed this observation with a Chow test which showed no significant variation in the DDD coefficient between subperiods. This suggests that our results are not biased by extending the panel in the time dimension.

Table 6. Regression analysis of balanced panel when the sample period was divided into two periods.

DV=Log(Sales)	(1)2005-2009	(2) 2005-2007	(3) 2008-2009
DDD	0.058**(0.02)	0.054**(0.03)	0.052*(0.03)
Log(Material)	0.50***(0.05)	0.52***(0.08)	0.48***(0.04)
Log(Capital)	0.14***(0.03)	0.15***(0.03)	0.13***(0.04)
Log(IT-Employee)	0.039(0.03)	0.005(0.03)	0.11***(0.04)
Log(Non-IT Employee)	0.24***(0.05)	0.22***(0.03)	0.26***(0.05)
Constant	-1.43***(0.44)	-1.44***(0.45)	-1.43***(0.55)
Number of firms	72	72	72

Observations	360	216	144
R-squared	0.95	0.95	0.96
Other Controls	Industry; Year; Log(Average Worker's Wage)		

(Robust standard errors in parenthesis. *** $p<0.01$, ** $p<0.05$, *$p<0.1$)

While our preferred interpretation of the OLS results is that DDD is causing higher performance, there are at least two plausible endogeneity problems that could lead to this estimate having a positive bias. First, it is possible that high performing firms have slack resources enabling them to invest in a number of innovative activities including DDD, which would lead to a reverse causal relationship between performance and DDD. Second, there may be omitted variables such as management quality or greater firm-specific human capital that could be associated with both higher performance and the use of DDD, also creating upward bias. To address these problems, we treat DDD as endogenous and use three instruments: adjustment costs, firm age, and consistency of business practices. In addition, we extend the base specification to include a measure of innovation (EXPR) to remove any potential omitted variables bias related to the innovative activity in our sample firms, as well as measures of firm human capital.

First, we run OLS regression including these additional control variables. The OLS result for the coefficient estimate on DDD with these controls (column (1) in Table 7), 0.045 ($t=2.7$, $p<0.01$), was statistically the same as that without the additional control variables (0.046 with s.e.=0.02, the column (2) in Table 5). We then conduct an instrumental variables regression using 2SLS and find that the coefficient on DDD is slightly higher than the prior OLS estimates (0.059, $p<0.10$) but is less precisely estimated due to the use of IV (see column 2 in Table 7). Nonetheless, our instrument set does pass the usual tests for weak instruments (the F-statistic on the excluded instruments in the 1st stage is 20 – see Staiger and Stock 1997 for a justification of this test). In addition, Hausman test fails to reject the null hypothesis that the OLS and IV coefficients are the same, thus suggesting that any biases due to endogeneity are small. Finally, because we have three instruments but only a single endogenous variable, we can conduct tests of over identification restrictions (the Sargan Test) and find that the coefficient on DDD is unaffected by the choice of instruments within our instrument set. Overall, these tests suggest that our original tests are unbiased, and firms that are one standard deviation above the means of our DDD scale have received a 5-6% productivity increase over the average firm.

Table 7. IV-Regressions of DDD on Productivity Measures

	(1) OLS	**(2) IV**
Variable	**DV=Log(Sales)**	**DV = Log(Sales)**
DDD	0.045*** (0.017)	0.059* (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)
Importance of Employee Education	0.018(0.02)	0.016(0.02)
Log(Avg. Workers' Wage)	0.20***(0.031)	0.20***(0.029)
Exploration	-0.009(0.02)	-0.012(0.023)
Controls	Industry, Year	The same as in (1)

Observations	681	681
Number of Firms	179	179
(Adj.) R-square	0.94	0.94
Overid Test (Sargan Test)		0.75
Hausman Test		0.67

(Standard errors clustered around firms are in parentheses, *p<0.10, **p <0.05, ***p < 0.01. DV means dependent variable. The overide 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 consistent. The numbers for the Sargan and Hausman test indicate p-value. 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.)

Business Profitability Test

We estimated the impact of DDD on three performance measures; return on assets (ROA), return on equity (ROE), and asset utilization (sales/assets) (see the equation 2). Because the data for some firms lacked values necessary to these regressions, we used 174 firms, a subset of the 179 firms used in the productivity estimation. IT appears to be significantly correlated with two profit measures in the expected direction (ROA and Asset Utilization) but not ROE (Table 8). 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 6 to 8% although these differences are not statistically significant across regressions. It should also be noted that the coefficients on the denominators are all significantly less than one, which would be the value expected if a pure ratio best fit the data.

Table 8. Regressions of DDD on different performance measures

Interpretation	Return on Asset		Return on Equity		Asset Utilization	
Dependent Variable=	Log(Pretax Income)		Log(Pretax Income)		Log(Sales)	
DDD		0.063 (0.05)		0.067** (0.03)		0.076** (0.04)
Log(IT-Employee)	0.10* (0.06)	0.11* (0.06)	-0.045 (0.04)	-0.043 (0.04)	0.065* (0.04)	0.067* (0.04)
Log(Asset)	0.65*** (0.06)	0.64*** (0.06)			0.39*** (0.04)	0.37*** (0.04)
Log(Equity)			0.90*** (0.04)	0.89*** (0.04)		
Log(Non-IT Employee)	0.16** (0.07)	0.16** (0.07)	0.14*** (0.05)	0.14*** (0.04)	0.36*** (0.05)	0.36*** (0.05)
Constant	-1.77* (0.10)	-1.79* (1.01)	-2.26*** (0.6)	-2.29*** (0.57)	1.52** (0.62)	1.50** (0.61)
Number of firms	174	174	174	174	174	174
Number of observations	564	564	564	564	564	564
R-squared	0.67	0.78	0.84	0.84	0.82	0.83
Other controls	Industry; Year; Log(avg. worker's wage); Importance of education of typical employees					

(Standard errors clustered around firms are in parentheses, *p<0.10, **p <0.05, ***p < 0.01.)

Overall, these results are consistent in direction and magnitude with prior work using similar methods (Hitt, Wu and Zhou, 2002; Aral et al. 2006) which showed the installation of ERP systems was correlated increases in some profitability measures. When this analysis is repeated with extended controls using instrumental variables regressions (see Table 9), we find that the results are reinforced for return on assets, but are too imprecisely estimated for the other factors to make any conclusions. For the most part, the results are neither statistically different from the OLS results or from zero. Furthermore, the Sargan test statistic for the asset utilization regression is borderline significant, raising questions as to whether our instrument set can be used for this analysis. Thus, we are unable to make any inferences on whether the profit relationship is causal, most likely due to the reduced power (relative to productivity models) of this profit ratio analysis.

Table 9. Profitability Regressions with Extended Firm-Specific Control Variables

Interpretation	Return on Asset		Return on Equity		Asset Utilization	
DV=	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)	0.092 (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
Overid Test		0.77		0.27		0.04
Hausman Test		0.23		0.54		0.54
Other 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					

(Standard errors clustered around firms are in parentheses, *p<0.10, **p <0.05, ***p < 0.01.)

Market Value Test

We also examined the relationship between DDD and the market value of firms (**Error! Reference source not found.** and 11). This regression relates market value to the three types of assets; PP&E, other assets, and IT. We repeat this analysis using two proxies for IT assets. First, we estimate IT budgets over time using the actual observation in 2008 and the ratio of IT employees to budgets to estimate the values in all other years. Second, we used the IT employees estimate directly (the same measure as in the productivity analysis)

The results measuring IT using budgets is presented in Table 10. Examining the control variables we find that the coefficient for property, plants and equipment (PP&E) is larger than the theoretical value of $1 (closer to $2 per dollar of PP&E) while the coefficient on other assets is substantially less (close to $0.20). The high value on PP&E may indicate short-run adjustment costs, or correlations with omitted assets; the low value on other assets perhaps suggests that stockholders do not believe that they will receive the full value of these assets, on average. Each dollar of IT budget is associated with $26 of market value, which after converting from a flow to a stock measure (see Saunders and Brynjolfsson 2010 – they find approximately a 2:1 ratio between IT spending and IT capital stock), yields a marginal value of IT capital of about $13. This is slightly higher than estimates reported in prior work (which are on the order of $10), but the differences are not statistically significant. We also find that the marginal value of IT is higher when combined with DDD – the interaction term implies, after a stock to flow adjustment, that IT capital is worth about $6.5 more in firms that have one standard deviation higher in DDD. The fact that the IT budget coefficient drops slightly when the interaction is included is consistent with DDD being related to IT. These interactions are not significant (economically or significantly) for PP&E or other assets.

Table 10. Regressions of DDD on market value, using IT budget as a proxy for IT capital

DV=Market Value	(1)	(2)	(3)	(4)
Property, Plant and Equipment (PPE)	2.00*** (0.71)	1.95*** (0.64)	1.91*** (0.59)	1.98*** (0.64)
IT Budget (ITB)	25.7*** (8.55)	19.1*** (5.34)	24.4*** (7.3)	21.5*** (6.3)
Other Assets (OA)	0.18*** (0.04)	0.19*** (0.03)	0.18*** (0.04)	0.21*** (0.035)
DDDxITB		13.6* (8.1)		
DDDxPPE			0.44 (0.52)	
DDDxOA				0.32 (0.18)
Constant		-747.5 (3,329)	-2,747 (4,238)	-992.3 (2,007)
Number of observations	481	481	481	481
Number of firms or observations	110	110	108	
R-squared	0.69	0.714	0.70	0.71

(Robust standard errors in parentheses, *p<0.10, **p <0.05, ***p < 0.01.)

Results are similar when proxy IT capital with IT employees. The results suggest that each employee is associated with $8.2K of IT capital stock, and that firms that invest in DDD have an addition $3.1K of value per employee for each standard deviation of DDD above the mean. The results are otherwise similar to the prior analysis except there appears to be a small positive interaction between DDD and other assets (we are reluctant to interpret this because of the heterogeneity of other assets, and the low direct coefficient). Altogether, these analysis suggest that firms that adopt DDD have a higher market value, and that this value is most closely related to their level of IT capital.

Table 11. Regressions of DDD on market value

DV=Market Value	(1)	(2)	(3)	(4)
Property, Plant and Equipment (PPE)	1.77*** (0.50)	1.75*** (0.45)	1.72*** (0.43)	1.75*** (0.46)
IT-Employee (ITE)	8262*** (2003)	6348*** (1649)	7983*** (1864)	7505*** (1714)
Other Assets (OA)	0.19*** (0.03)	0.20*** (0.03)	0.19*** (0.03)	0.21*** (0.03)
DDDxITE		3097** (1267)		

DDDxPPE			0.30 (0.38)	
DDDxOA				0.24* (0.13)
Constant	-5494 (3360)	-4487 (2799)	-5953 (3396)	-5332 (3066)
Number of firms	179	179	179	179
Number of observations	676	676	676	676
R-squared	0.75	0.77	0.76	0.77
Other Controls	Industry, Year, R&D per sales, Advertising expense per sales			

(1: Information Technology was the number of IT-employees, used to proxy for IT asset. Standard errors clustered around firms are in parentheses, *p<0.10, **p <0.05, ***p < 0.01.)

Conclusion

Case literature and economic theory suggest a potential connection between data driven decision making and productivity. By analyzing a large sample of firms, we find that DDD is indeed associated with higher productivity and market value, and that there some evidence that DDD is associated with certain measures of profitability (ROE, asset utilization). Our results are consistent with different measures of our IT variable and changes in the time period of the panel. In the productivity estimation, it appears to be robust to the use of instrumental variables methods to control for reverse causality or other forms of endogeneity. Collectively, our results suggest that DDD capabilities can be modeled as intangible assets which are valued by investors and which increase output and profitability.

References

Anderson, M.C., Banker, R.D., and Ravindran, S. 2003. "The New Productivity Paradox," *Communications of the ACM* (46:3), pp. 91-94.

Aral, Brynjolfsson, and Wu. 2009. "Testing Three Way Complementarities: Performance Pay, Monitoring and Information Technology," *ICIS*.

Aral, S., Brynjolfsson, E., and Wu, D. 2006. "Which Came First, It or Productivity? The Virtuous Cycle of Investment and Use in Enterprise Systems," *International Conference on Information Systems*, pp. 1-22.

Argote, L., McEvily, B., and Reagans, R. 2003. "Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes," *Management Science* (49:4), pp. 571-582.

Attewell, P., and Rule, J. 1984. "Computing and Organizations: What We Know and What We Don't Know," *Communications of the ACM* (27:12), pp. 1184-1192.

Ayres, I. 2008. *Super Crunchers: Why Thinking-by-Numbers Is the New Way to Be Smart*. Bantam.

Balasubramanian, N., and Lee, J. 2008. "Firm Age and Innovation," *Industrial and Corporate Change* (17:5), p. 1019.

Barua, A., Kriebel, C.H., and Mukhopadhyay, T. 1995. "Information Technologies and Business Value: An Analytic and Empirical Investigation," *Information Systems Research* (6:1), p. 3.

Blackwell, D. 1953. "Equivalent Comparison of Experiments," *Ann. Math. Statist.* (24), pp. 265-272.

Bresnahan, T., Brynjolfsson, E., and Hitt, L. 2002. "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence*," *Quarterly Journal of Economics* (117:1), pp. 339-376.

Bresnahan, T., Greenstein, S., and Henderson, R. 2009. "Schumpeterian Competition and Diseconomies of Scope: Illustrations from Leading Historical Firms in Computing."

Brynjolfsson, E., Hitt, L., and Yang, S. 2002. "Intangible Assets: How the Interaction of Computers and Organizational Structure Affects Stock Market Valuations," *Brookings Papers on Economic Activity: Macroeconomics* (1), pp. 137-199.

Brynjolfsson, E., and Hitt, L.M. 1996. "Paradox Lost? Firm-Level Evidence of High Returns to the Information Systems Spending," *Management Science* (42:4).

Brynjolfsson, E., and Hitt, L.M. 2003. "Computing Productivity: Firm-Level Evidence," *Review of economics and statistics* (85:4), pp. 793-808.

Brynjolfsson, E., Tambe, P., and Hitt, L. 2011. "The Extroverted Firm: How External Information Practices Affect Productivity," *Management Science* (Forthcoming).

Clemons, E.K., and Thatcher, M.E. 1998. "Capital One: Exploiting an Information-Based Strategy," IEEE, pp. 311-320 vol. 316.

Cohen, W.M., and Levinthal, D.A. 1989. "Innovation and Learning: The Two Faces of R & D," *The Economic Journal* (99:397), pp. 569-596.

Davenport, T. 2009. "How to Design Smart Business Experiments," *Harvard Business Review*), February.

Davenport, T.H., and Harris, J.G. 2007. *Competing on Analytics: The New Science of Winning*. Harvard Business Press.

Dewan, S., and Kraemer, K.L. 2000. "Information Technology and Productivity: Evidence from Country-Level Data," *Management Science*), pp. 548-562.

Francalanci, C., and Galal, H. 1998. "Information Technology and Worker Composition: Determinants of Productivity in the Life Insurance Industry," *MIS Quarterly*), pp. 227-241.

Galbraith, J.R. 1974. "Organization Design: An Information Processing View," *Interfaces* (4:3), pp. 28-36.

Henderson, R. 1993. "Underinvestment and Incompetence as Responses to Radical Innovation: Evidence from the Photolithographic Alignment Equipment Industry," *The RAND Journal of Economics* (24:2), pp. 248-270.

Henderson, R.M., and Clark, K.B. 1990. "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms," *Administrative Science Quarterly* (35:1), pp. 9-30.

Hitt, L., and Brynjolfsson, E. 1997. "Information Technology and Internal Firm Organization: An Exploratory Analysis," *Journal of Management Information Systems* (14:2), p. 101.

Hitt, L.M., and Brynjolfsson, E. 1996. "Productivity, Business Profitability, and Consumer Surplus: Three Different Measures of Information Technology Value," *Management Information Systems Quarterly* (20:2).

Hitt, L.M., and Frei, F.X. 2002. "Do Better Customers Utilize Electronic Distribution Channels? The Case of Pc Banking," *Management Science*), pp. 732-748.

Hitt, L.M., Wu, D., and Zhou, X. 2002. "Investment in Enterprise Resource Planning: Business Impact and Productivity Measures," *Journal of Management Information Systems* (19:1), pp. 71-98.

Holmstrom, B., and Milgrom, P. 1991. "Multitask Principal–Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, and Organization* (7:special issue), p. 24.

Huergo, E., and Jaumandreu, J. 2004. "Firms' Age, Process Innovation and Productivity Growth," *International Journal of Industrial Organization* (22:4), pp. 541-559.

Jones, C.I. 1999. "Growth: With or without Scale Effects?," *The American Economic Review* (89:2), pp. 139-144.

Jorgenson, D.W., and Stiroh, K.J. 1999. "Information Technology and Growth," *American Economic Review, Papers and Precedings* (86:2).

Jorgenson, D.W., and Stiroh, K.J. 2000. "U.S. Economic Growth at the Industry Level," *American Economic Review Papers and Proceedings* (90:2).

Lavalle, S., Hopkins, M.S., Lesser, E., Shockley, R., and Kruschwitz, N. 2010. "Analytics: The New Path to Value," *MIT Sloan Management Review* (Fall).

Levitt, B., and March, J.G. 1988. "Organizational Learning," *Annual Review of Sociology* (14), pp. 319-340.

Loveman, G. 2003. "Diamonds in the Data Mine," *Harvard Business Review* (81:5), pp. 109-113.

McAfee, A. 2002. "The Impact of Enterprise Information Technology Adoption on Operational Performance: An Empirical Investigation," *Production and Operations Management* (11:1), pp. 33-53.

McAfee, A., and Brynjolfsson, E. 2008. "Investing in the It That Makes a Competitive Difference," *Harvard Business Review* (86:7/8), p. 98.

Melville, N., Kraemer, K., and Gurbaxani, V. 2004. "Review: Information Technology and Organizational Performance: An Integrative Model of It Business Value," *MIS Quarterly* (28:2), pp. 283-322.

Nass, C. 1994. "Knowledge or Skills: Which Do Administrators Learn from Experience?," *Organization Science* (5:1), pp. 38-50.

Oliner, S.D., and Sichel, D.E. 2000. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?," *Federal Reserve Board Working Paper*).

Pentland, A., and Pentland, S. 2008. *Honest Signals: How They Shape Our World*. The MIT Press.

Radner, R. 1993. "The Organization of Decentralized Information Processing," *Econometrica: Journal of the Econometric Society*), pp. 1109-1146.

Saunders, A., and Brynjolfsson, E. 2010. "Valuing It-Related Intangible Capital," Working Paper, MIT.

Shapiro, C., and Varian, H.R. 1999. *Information Rules: A Strategic Guide to the Network Economy*. Harvard Business Press.

Staiger, D., and Stock, J.H. 1997. "Instrumental Variables Regression with Weak Instruments," *Econometrica* (65:3), pp. 557-586.

Tambe, P., Hitt, L., and Brynjolfsson, E. 2009. "The Extroverted Firm: How External Information Practices Affect Productivity," *working paper*).

Tambe, P., and Hitt, L.M. 2011. "The Productivity of Information Technology Investments: New Evidence from It Labor Data," *SSRN eLibrary*).

Tushman, M.L., and Anderson, P. 1986. "Technological Discontinuities and Organizational Environments," *Administrative Science Quarterly* (31:3), pp. 439-465.