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RESEARCH NOTE

A DATA ENVELOPMENT ANALYSIS APPROACH TO ESTIMATE IT-ENABLED PRODUCTION CAPABILITY[1]

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Information systems researchers have drawn on the resource-based view (RBV) and dynamic capabilities theory to offer a sharper theoretical lens to study the impact of information technology (IT) enabled capabilities on organizational performance. In this study, we propose a new conceptualization of IT-enabled production capability, based on the ability of a manufacturing plant to use its mix of resource inputs to maximize its process outputs. Our approach extends the literature on firm capability using data envelopment analysis (DEA), a nonparametric approach for estimating relative efficiencies of decision-making units. We tested our models using plant-level data collected from a sample of U.S. plants. Our study makes a key contribution by developing a new methodology to measure IT business value with respect to the role of IT-enabled production capability. We operationalize a new DEA-based measure of capability using the relative efficiency of converting plant inputs into process outputs, a significant departure from extant research that has primarily focused on subjective and absolute measures to conceptualize capability.

Keywords: Production capability, data envelopment analysis, efficiency, resource-based view, information technology

Introduction

In spite of a large body of literature on capabilities and their relationship with firm performance, a critical incongruence in prior information systems research on information technology enabled capabilities lies in the conceptualization and definition of capabilities. Capabilities represent the ability of a firm or business unit to efficiently combine several resources to engage in productive activities and attain its objectives (Amit and Schoemaker 1993). Dutta et al. (2005) characterize *capability* as the intermediate transformation ability between resource inputs and outputs. The central term, capability, is still elusive. There does not exist a consistent and well-accepted approach to defining and measuring capabilities. A dominant approach in IS research involves the use of survey instruments designed to elicit user responses on their perceptions about competencies and capabilities associated with different functional areas (Banker et al. 2006; Bharadwaj et al. 2007; Pavlou and El Sawy 2010). Typically, multiple responses are elicited and capability is assumed to be the underlying latent variable governing these responses. A limitation of such perception-based approaches is that they represent a subjective measure of firm/organizational capabilities (Armstrong and Shimizu 2007; Collis and Montgomery 1995). Given the prevalence of objective, archival data on firm activities and performance, it is important to

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leverage such data to develop objective methods to measure capabilities.

The literature on firm capability has largely drawn on resource-based theory and conceptualized "capability" as a latent construct with multiple measurement items (Barney et al. 2001; Bollen and Long 1993; Godfrey and Hill 1995). While RBV has offered a solid theoretical foundation to explain a number of phenomena in the IT management literature, it has often been criticized due to its lack of clarity for conceptualization and measurement of capabilities (Porter 1994; Williamson 1999). A major criticism against the manner in which the tenets of RBV have been tested is that high performance firms have been compared to low performing ones, followed by a test of whether the identified capabilities are critical, thus creating a tautological approach. Dutta et al. (2005, p. 278) argue that what is needed is a "conceptualization and measurement approach for capabilities that is independent of a firm's rent generation ability."

We aim to develop a new method of measuring process capability, in the context of measuring the production capability of manufacturing plants, which can be extended to other types of business processes that can be conceptualized using a production function. Our primary research objective is to conceptualize and operationalize a measure of relative production capability (compared to competitors) using a multi-input, multi-output framework. We address limitations in the prior literature by modeling a plant's activities as a production frontier (or transformation function) that converts its production inputs into outputs, as an intermediate process toward attainment of its financial objectives. Our research model and methodology, using data envelopment analysis (DEA), can be extended to develop other capability measures such as supply chain capability, marketing capability, and IT capability.

Our work differs from earlier research on IT-enabled capabilities and makes several contributions to the extant literature on measurement of capability. First, we operationalize production capability as a process-centric measure of the *relative* efficiency of converting multiple inputs into multiple outputs. Specifically, we propose a DEA-based methodology to measure relative production capability across multiple manufacturing plants. Second, our proposed production capability measure is derived from objective, process-level metrics of production, as compared to subjective, perceptual measures that have typically been used in the past. Third, our study provides a new measurement of the *IT-enablement effect* by explicitly accounting for the effect of IT spending as part of the process of estimating production capability; this approach offers a new lens to understand the mechanisms through which IT can impact organizational performance. In contrast, prior studies typically conceptualize IT-enablement as a single separate construct (Bharadwaj 2000; Lu and Ramamurthy 2011; Rai et al. 2012; Santhanam and Hartono 2003). Our proposed research framework and methodology addresses the call for an interdisciplinary examination to assess new ways to build IT-enabled operational capabilities (Setia and Patel 2013).

Theoretical Foundation

Dutta et al. (2005, p. 278) define firm capabilities as "the efficiency with which a firm employs a given set of resources (inputs) at its disposal to achieve certain objectives (outputs)." Capabilities represent the extent to which firms must continually reorganize internal and external resources to adapt to business conditions, especially in fast-paced technological environments where speed to market is critical (Pavlou and El Sawy 2010; Teece et al. 1997). In a manufacturing context, Schroeder et al. (2002) argue that plants' ability to incorporate organizational learning, through interactions with customers and suppliers, translates into proprietary capabilities, an important enabler of plant performance.

Our measure of *capability* addresses two key concerns: (1) capturing the multidimensional nature of capability where considering the tradeoffs among multidimensions is critical, and (2) measuring relative capability instead of using absolute measures commonly used in the past.

Multidimensional Conceptualization of Relative Capability

One stream of work has conceptualized capability in a unidimensional setting, where output measures related to organizational performance are combined into a single construct (Ray et al. 2005; Rosenzweig et al. 2003). It is important to note that there often exist tradeoffs among multiple dimensions that comprise the capability construct. For example, improvements in product time-to-market may occur at the cost of reducing quality. These dimensions often do not converge into a single construct (Combs et al. 2005). However, commonly used latent variable methods to conceptualize capability (formative or reflective) start with the assumption that these multiple measurement items converge to a single latent construct (Bollen 1998), as is evident in the convergent validity requirement of the measurement model in structural equation models.

An extensive literature review reveals that prior studies measure capability using either an input- or output-oriented framework, exclusively (Barua et al. 2004; Bhatt and Grover

2005; Pavlou and El Sawy 2010). For example, Barua et al. (2004) proposed output-oriented, supplier- and customer-specific online informational capabilities which measure firm capabilities to exchange strategic and tactical on-demand information with customers and suppliers, respectively. Pavlou and El Sawy (2010) conceptualized the dynamic capability of new product development processes in terms of firms' ability to sense, coordinate, and integrate the outputs of their product development and innovation processes. Although these output-oriented measures are useful to gauge a firm's capability, they overlook the input resources expended by the firm to attain its capabilities. Hence, we argue that using inputs or outputs alone does not shed light on the "black box" of firm capabilities. Rather, it is necessary to deploy a *multiple input, multiple output* framework that captures the intermediate transformation ability of firm processes.

A firm's capability should be measured *relative* to its competitors in terms of its relative ability to transform a similar set of input resources into outputs (Santhanam and Hartono 2003). The literature has commonly used two approaches to measuring the relative capability of a firm: (1) benchmarking against the industry leader (or group of leaders) and (2) benchmarking against industry averages (Rouse and Daellenbach 2002). For example, managers are asked to rate their firms' innovation capabilities with respect to the industry leaders (Pavlou and El Sawy 2010). Armstrong and Shimizu (2007) observe that the use of survey methodology to measure relative capability may lead to inaccurate constructs because managers completing these surveys are prone to overconfidence and hubris about their own capabilities. Collis and Montgomery (1995) also call for *objective* benchmarking techniques to evaluate relative firm capabilities.

Hence, there is a need to develop an objective measure that considers input–output tradeoffs to assess relative capabilities. Toward this end, we proposed a new DEA-based approach to capturing the input–output tradeoffs involved in the measurement of relative capabilities.

DEA Operationalization

DEA is a nonparametric approach which uses a mathematical programming model to construct an efficient frontier over the data, and calculates each data point's efficiency relative to the frontier. Each data point corresponds to a decision-making unit (DMU) whose objective is to convert inputs into outputs as efficiently as possible. The DEA efficiency score provides a proxy of a DMU's distance from the efficient frontier, relative to its peers, and represents its transformational ability to convert multiple inputs into multiple outputs (Mehra et al. 2014).

We adopt the classic BCC model (Banker et al. 1984) that accounts for variable returns to scale (VRS) in the data. The output-oriented BCC model for a specific DMU, say DMU*o*, is represented in equation (1) as follows:

$$\begin{aligned} & Max_{\theta,\lambda}\Big\{\theta+\varepsilon\big(1's^{-}+1's^{+}\big)\big| X\lambda+s^{-}=x_o; \\ & Y\lambda-s^{+}=\theta y_o; 1'\lambda=1; \lambda\geq 0\Big\} \end{aligned} \tag{1}$$

where each DMU consists of X and Y representing the vector of inputs and outputs, respectively. This linear programming formulation is used to identify a Pareto efficient frontier across all data points and compute a radial efficiency score θ for each DMU. The value of θ is bounded between 0 and 1. A DMU is rated as 100% efficient if its radial efficiency score θ = 1, and all input and output slacks in the optimization model shown in equation (1) are equal to zero.

IT and Production Capability

The operations management (OM) literature has recognized IT as a backbone of operational activities (Alavi and Leidner 2001), and has called for interdisciplinary research to examine and assess new ways to measure IT-enabled operations capabilities (Peng et al. 2008). Our research contributes to this interdisciplinary field to explore the impact of IT on operational capabilities in the context of production processes. We summarize the extant literature on the role of IT in driving business unit (BU) performance (i.e., plant production, in our context) into three scenarios:

- *CASE A (Direct)*: IT and non-IT resources as direct drivers of BU production performance.
- *CASE B (Moderation)*: IT as a moderator of the impact of non-IT resources on BU production performance.
- *CASE C (Mediation)*: The IT impact on BU performance is mediated through non-IT resources.

Both Cases A and B have been widely studied in the IS literature (for a comprehensive review, see Melville et al. 2004). A few studies have also explored the *mediation* model (Case C) as an alternate pathway to explain the mechanism through which IT impacts performance, via its enablement of organizational capabilities (Banker et al. 2006; Melville et al. 2004).

We propose a new scenario, Case D, which highlights the role of IT as an input resource in the measurement of production capability. Specifically, we propose a new DEA-based methodology that measures the relative production capability of manufacturing plants in transforming their IT and other non-IT resource inputs into plant production outputs. We propose that our process capability measure has a significant impact on BU performance as

- *CASE D (Capability as combination of IT and non-IT resources)*: IT as an essential input to the transformative (production) capability that impacts BU production performance.

IT as an Input Resource of Production Capability

Manufacturing plants are increasingly becoming reliant on integrated information systems to manage plant schedules and coordinate complex information processing requirements of their customers and suppliers (Bharadwaj et al. 2007; Gattiker and Goodhue 2005). IT is a critical enabler of the coordination required between manufacturing, marketing, and supply chain processes in order for managers to manage their supply chains efficiently (Pavlou and El Sawy 2010; Rai et al. 2006). Banker et al. (2006) showed that manufacturing capabilities mediate the impact of information systems on plant performance. In addition, high quality, real-time information flow is a crucial element in managing efficient inventory levels (Mishra et al. 2013). For instance, the integration of end-customer information into inventory management processes can be achieved by augmenting electronic data interchange and point-of-sale systems into the IT infrastructure, in order to support firms' operational strategy and capabilities (Lee et al. 1997). These examples describe the enabling role of IT where the impact of IT on firm/BU performance is realized through an intermediate operations capability.

Our proposed research framework, as depicted in Figure 1, explores the role of IT as an input resource into the measurement of production capability, estimated using DEA. We note that the conceptual framework in Figure 1 is consistent with the RBV theory in understanding the linkage between IT and non-IT resources, their enablement of production (process) capability, and organizational performance. According to RBV, IT resources alone are not considered to be a strategic asset if they can be imitated and substituted by competitors (Wade and Hulland 2004). However, superior firm performance can be realized through leveraging IT resources to develop firm-specific processes (Mishra et al. 2013). For example, advanced manufacturing information technologies, such as enterprise resource planning (ERP) systems, flexible manufacturing systems, or computer-aided manufacturing, help firms develop operations capabilities in conjunction with other types of firm-specific processes and resources (Chung and Swink 2009; Kotha and Swamidass 2000). Similarly, Lai et al. (2008) argue that it is the combination of IT infrastructure with other non-IT resources that determines firms' logistics performance.

These findings imply that IT needs to be combined with other resources to create firm-specific, sustained, strategic advantage. Hence, we conceptualized a new alternative framework (scenario D) in which IT resources are treated as an integral input into the measurement of production capability. Note that Scenarios C and D may differ in terms of how IT impacts process capability, that is, whether IT is integral to process capability as in Scenario D (Melville et al. 2004), or whether IT is a distinct but required resource that enables a process capability as in Scenario C (Setia and Patel 2013).

A unique aspect of this study is our unit of analysis which is at a more granular plant-level, as opposed to the typical firm-level analysis (Melville et al. 2004). Unlike Banker et al. (2006), our focus is not on specific types of information systems or their association with plant performance. Rather, our interest lies in studying the relationship between IT resources, their enablement of production capabilities, and plant profitability. Hence, our study focuses on a new methodology for operationalization of DEA to measure production capability.

DEA-Based Production Capability: A Comparison

Studies in the OM literature have conceptualized manufacturing or production capabilities as realized competitive performance or strength of operational processes of business units (Peng et al. 2008). These operational performance measures include a multidimensional view of cost, quality, flexibility, and delivery measures (Boyer and Lewis 2002), and operational capabilities are conceptualized as bundles of interrelated routines (Peng et al. 2008). Hence, based on this stream of research, we conceptualized production capability in terms of a multi-input, multi-output framework, in which the outputs represent a multidimensional view of routines and outcomes in a production environment.

In Table 1, we contrast our operationalization of DEA-based capability against prior studies in the literature, with respect to methodological differences in the implementation of DEA. First, we classified the studies based on the size (the number of DMUs) of the observation data set (the rows in Table 1).[2] We then classified these studies into two groups based on the

[2]The DEA literature suggests a small sample when the number of DMUs is less than 30; medium size between 30 and 100; and large samples when the number of DMUs is greater than 100 (e.g., Banker et al. 2010).

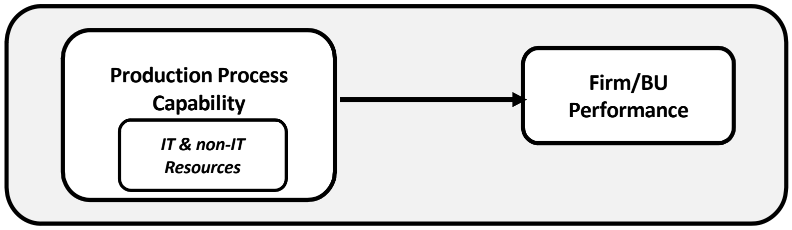

Figure 1. Research Framework: IT-Enabled Capability and Organizational Performance

Table 1. Comparative Analyses of Prior DEA Applications in the Literature

	One Stage		Two Stage	
	Multi-input – Single-output	**Multi-input – Multi-output**	**Multi-input – Single-output**	**Multi-input – Multi-output**
# DMUs < 30		Athanassopulos (1998)[γ] Chang et al. (2013)[γ] Duzakin and Duzakin (2007)[γ] Korhonen and Syrjänen (2004)[γ] Reiner et al. (2013)[γ]	Narayanan et al. (2014)[π]	Our study[γ]
30 ≤ DMUs < 100	Bendheim et al. (1998)[γ]	Duzakin and Duzakin (2007)[γ] Koster and Balk (2008)[γ,π] Reiner et al. (2013)[γ] Sueyoshi (1997)[γ]	Fung (2008)[π] Iyer et al. (2013)[π] Mehra et al. (2014)[π]	Bendoly et al. (2009)[γ] Our study[γ]
# DMUs ≥ 100		Ayanso and Mokaya (2013)[γ] Bessent et al. (1982)[γ] Chen and Delmas (2011)[γ] Grosskopf et al. (1999)[γ] Reiner et al. (2013)[γ]		Ray (1991)[γ] Swink et al. (2006)[γ] Worthington (2000)[γ]

Note: [γ] represents cross section and [π] represents panel data.

number of stages involved in their implementation of DEA (see the columns in Table 1). For instance, some studies used the mathematical programming formulation, as shown in equation (1), to compute the relative efficiency scores of DMUs in a single stage. Other studies used a two-stage formulation that involves computation of DEA-based efficiency scores in the first stage, followed by estimation of an econometric regression model in the second stage using the DEA efficiency scores as an independent variable. Finally, we classified these studies based on the number of inputs and outputs included in the DEA model.

From Table 1, we observed that a majority of the studies were based on a single-stage DEA model while we used a two-stage, multi-input, multi-output model specification. Our study was consistent with the prior studies in terms of size (i.e., number of DMUs between 30 and 100). Although prior work by Bendoly et al. (2009) is close to our research, they did not conceptualize a capability construct; rather, they analyzed differences with respect to input and output variables between the efficient DMUs (on the efficient frontier) and inefficient DMUs in the second stage.

Empirical Analysis

Data and Variable Construction

We obtained secondary plant data from the Manufacturing Performance Institute (MPI) census survey of U.S. manufacturing plants for the year 2007. The plants were classified based on the North American Industry Classification System (NAICS) codes. The survey was mailed electronically to plant managers and controllers. The web-based survey collected factual information about plant manufacturing practices, go-to-market strategy, outsourcing, and various performance measures as well as financial data related to plant costs, revenue, and profitability. The MPI survey did

Table 2. Distribution of Manufacturing Plants by Industry

Industry Sector	NAICS	Industry Sector	Sample 2007 (N)	Overall US Manufacturers* (%)
Nondurables	31	Nondurable items	16	20.54
Chemicals	32	Raw materials (petroleum, chemicals)	70	25.90
Metals	331, 332	Metals	55	19.59
Machinery	333	Machinery	42	7.91
Electrical & Electronics	334, 335	Electronics	42	6.22
Transportation	336	Transportation equipment	20	3.88
Miscellaneous	337, 339	Furniture and misc.	18	15.96
Total Number of Manufacturing Plants			263	NA

*Source: U.S. Census Bureau, Statistical Abstract of the United States, 2007.

not reveal the identities of the plants or names of parent firms, which precluded us from tracking performance trends across multiple years. Our data consisted of 263 plants drawn from 7 industry sectors that belong to NAICS codes 31, 32, or 33, as shown in Table 2. We chose only industries with at least 15 plants available in order to conduct meaningful DEA analysis.

Plant Performance

Plant performance, *Margin*, was measured as a ratio of the difference between plant sales and costs of goods sold (*COGS*), and is expressed as a percentage of plant sales. *Margin* measured plant profitability, an indicator of overall plant performance.

Production Capability

Our choice of operational performance measures was based on the prior operations literature and drew on earlier work on a multidimensional view of operations performance in terms of cost, quality, flexibility, and delivery performance (Boyer and Lewis 2002; Schmenner and Swink 1998). Specifically, the four output measures that we considered in developing our capability construct include (1) product cycle time, (2) inventory turnover rate, (3) on time delivery rate, and (4) product acceptance rate. Both cycle time and on-time delivery rate represent different dimensions of plant delivery performance (Boyer and Lewis 2002); while inventory turnover rate represents plant flexibility with respect to its operations, and product acceptance rate is a common measure of plant quality (Schmenner and Swink 1998). These output measures represented well-accepted and objective measures of production capability.

Similarly, we considered multiple inputs that capture various dimensions of input resources that are expended in the plant production processes. These costs include labor, material, and IT spending (Adler and Clark, 1991; Aigner and Chu, 1968). Because our data span seven diverse industries, our choice of these generic input measures allowed us to estimate a generic production capability that is applicable across multiple industry sectors.

Hence, we employed these three input and four output variables to compute a relative efficiency measure of production capability using DEA. The three inputs were labor costs (*LaborCost*), material costs (*MaterialCost*) and IT Spending (*ITSpend*). Labor and material costs represent two key cost components for a manufacturing plant, accounting for 72.3% of total manufacturing costs in our sample. Our data also captured IT spending that represents a significant investment in plant-level automation. *ITSpend* is measured as the dollar value of IT spending as a percentage of plant sales, the average of which is 2.3%. We observed that *ITSpend* varies significantly across plants and prior research has shown that IT investments provide a source of competitive differentiation between plants (Banker et al. 2006; Bartel et al. 2007).

The four production outputs consist of cycle time (*CycleTime*), inventory turnover rate (*TurnRate*), on-time delivery rate (*OnTime*), and product acceptance rate (*AcceptRate*). *CycleTime* measures the time elapsed (in hours) from the start of production to completion of primary product. *TurnRate* measures the plant inventory turnover rate; *OnTime* measures the percentage of goods delivered on time; while *AcceptRate* is an indicator of product quality. These outputs represent different dimensions of plant performance, as evident from low correlations among the individual indicators. Furthermore, they represent *direct* measures of production capability compared to other measures, such as return on invested capital or dollar value of goods sold, which depend on external market factors, such as market competition and economic environment that have little direct bearing on production capabilities.

IT Application Usage

Next, we considered the usage of four types of plant-level IT applications to construct *ITUsage*: (1) ERP I or II, (2) material requirements planning I or II (MRP), (3) product life cycle management (PLM), and (4) electronic data interchange (EDI). ERP software systems integrate various functional areas within an organization: supply chain management, inventory control, manufacturing scheduling, production, sales support, customer relationship management, and other managerial processes (Hitt et al. 2002). It has been reported that ERP implementation results in increased information availability to customers, reduced cycle times, increased completion, on-time delivery, and production rates (Bardhan et al. 2007; Hitt et al. 2002; McAffee and Upton 1996). MRP supports production planning, shop floor control, and order tracking (Banker et al. 2006). MRP systems increase plant flexibility in terms of production process, product variability, and customizability (Plenert 1999). PLM systems help organizations manage their product lifecycle from the product ideation stage to the product launch phase (Banker et al. 2006). RFID enables product information visibility, increases response capability and flexibility in high volatile market conditions (Bardhan et al. 2007), facilitates data standards, and increases return on investment (Whitaker et al. 2007). We applied principal component analysis (PCA), using the proc factor procedure in SAS 9.3, with these four variables (ERP, MRP, PLM, and RFID) to obtain one single factor, *ITUsage*.[3]

Capital Expenditures and other Controls

Non-IT capital expenditure (*Capex*) is defined as the dollar value of capital expenditures as a percentage of plant sales. We did not use *Capex* as an input in our DEA model because decisions on such expenditures are usually made at the firm level, whereas the DEA model was calibrated based on the production process at the plant level as the decision making units (Brynjolfsson and Hitt 1996; Gurbaxani et al. 2000). Hence, we account for these expenditures as control variables in our econometric estimation.

[3]Note that *ITSpend* and *ITUsage* capture different IT activities in a plant. *ITUsage* gauges the extent of usage of the four IT applications considered, while *ITSpend* measures the dollar amount of IT spending. The distinction can also be seen from their low correlation (0.198).

Our data capture the plant training costs (*TrainCost*) which represents an investment in human capital at each plant and varies significantly across plants. Other plant-level characteristics included in our model are (1) *Size* (number of plant employees); (2) *Age* (number of years the plant has been operating); (3) *Type* (type of plant ownership takes the value of 1 if private and 0 if public), (4) plant industry affiliation based on three-digit NAICS codes.

Table 3 presents the definitions and descriptive statistics of all model variables. The average gross margin of all plants in our sample was about 35%, while the average annual plant sales in 2007 was $41.35 million. The average *Capex* as a percentage of plant sales was 4.8%.

Conceptual Research Model

We first tested our conceptual research model as described in Case D. Specifically, we operationalized an IT-integrated measure of production capability (*PRODCap*), which was derived from three inputs (*LaborCost*, *MaterialCost,* and *ITSpend*) and four outputs (*CycleTime*, *InvTurn*, *OnTime*, and *AcceptRate*), using DEA. In other words, *PRODCap* represents the capability of plant production processes in transforming IT and non-IT resources into production outputs. Consistent with the tenets of the RBV theory (Devaraj and Kohli 2003), we examined whether the impact of IT application usage (*ITUsage*) on plant profitability was mediated through our IT-integrated measure of production capability. Our research model, as shown in Figure 2, depicts the mediation role of our IT-integrated measure of *PRODCap*.

Summary DEA Statistics

Table 4 reports the DEA evaluations of plant production capabilities based on binary ratings of plant efficiency (i.e., whether a plant was rated as fully efficient if its DEA efficiency score was 1 and slacks on all input and output variables were equal to zero). Approximately 51.3% of plants in our sample were rated as being fully efficient as rated by DEA. We observed significant variations in plant efficiency across industries, as only 34.6% of plants in the *Metals* industry were efficient, while about 80% of plants in the *Transportation* industry were rated as efficient.

Model Specification

We deployed a two-stage method to estimate the research model shown in Figure 2. In the first stage, we estimated plant production capability using DEA as described in the "IT and Production Capability" section. We conducted separate

Table 3. Variable Definitions and Descriptive Statistics

Variable	IT Spending ($) Divided by Total Sales	Unit	Mean (St. Dev.)
Margin	Plant sales less COGS divided by sales	%	35.31 (18.5)
Capex	Plant capital-equipment spending as a percentage of sales	%	4.8 (4.4)
Sales	Annual plant sales	$M	41.35 (57.4)
LaborCost	Total direct labor cost divided by total sales	%	13.14 (8.8)
MaterialCost	Total direct material cost divided by total sales	%	33.97 (15.8)
TrainCost	Annual employee training cost at plant divided by sales	%	0.17 (0.2)
CycleTime	Time elapsed from start of production to completion of primary product	Hrs	71.63 (146.4)
AcceptRate	Customer acceptance rate (in decile format)	0-7	5.38 (1.6)
Inventory Turnover	Annual COGS divided by average value of total inventory on hand	Turns/year	22.22 (48.2)
OnTime	Percentage of goods delivered on time	%	92.92 (8.1)
ITSpend	$ value of IT spend divided by total sales	%	2.31 (2.8)
ITUsage	PCA Factor obtained from ERP, MRP, RFID, and PLS application usage information	Cont.	1.02 (1.00)
Size	Log of number of employees	Cont	4.67 (1.06)
Age	Years in operation	Cont	18.08 (3.92)
PlantType	Type of plant ownership; private = 1 and public = 0	Binary	0.76 (0.43)

*Values on left in each cell represent the mean while numbers in the parentheses represent standard deviations.

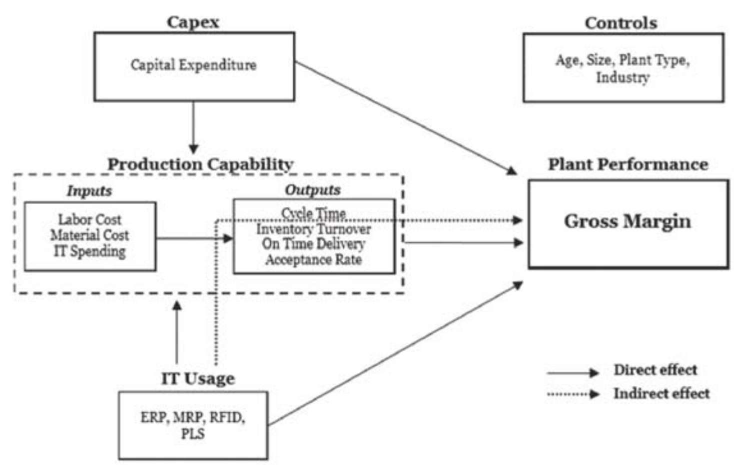

Figure 2. Research Model

Table 4. DEA Evaluations of Production Capability

Industry	N	IT-Integrated ProdCap (Binary Efficiency)	
All	*263*	*0.513*	*(0.501)*
Nondurables	16	0.688	(0.479)
Chemicals	70	0.443	(0.500)
Metals	55	0.346	(0.480)
Machinery	42	0.429	(0.501)
Electrical	42	0.595	(0.497)
Transportation	20	0.800	(0.410)
Miscellaneous	16	0.833	(0.383)

Note: Numbers in parentheses represent standard deviations.

EA analysis for each industry that allowed us to estimate a relative efficiency frontier based on comparisons against best performers in the *same* industry sector. This ensures an accurate measurement of production capability based on industry-specific comparisons of manufacturing plants. In the second stage, we used the DEA-based capability (*PRODCap*) ratings as explanatory variables in an econometric model. We specified and estimated several models to estimate the relationships between *ITUsage, PRODCAP,* and *Margin*.

Model 1 (IT Usage and Production Capability)

First, we estimated a logistic regression model specified in equation (2), as

$$\text{logit}\left(PRODCap_{ij}\right) = \alpha_0 + \alpha_2 \cdot ITUsage_{ij} + \alpha_3 \cdot Capex_{ij} + \sum_{k=1}^{10} \alpha_{3+k} \cdot Controls_{ij}^{k} \tag{2}$$

where i denotes an individual plant and j indexes its NAICS industry. *PRODCap* is equal to one if a plant is efficient based on DEA evaluation, and zero otherwise. This approach enabled us to differentiate between high-capability and low-capability plants.

Model 2 (Production Capability and Plant Profitability)

Next, we estimated the direct impact of *PRODCap* on plant profitability, specified as

$$Margin_{ij} = \beta_0 + \beta_1 \cdot PRODCap_{ij} + \beta_3 \cdot Capex_{ij} + \sum_{k=1}^{10} \beta_{3+k} \cdot Controls_{ij}^{k} + \varepsilon_{ij} \tag{3}$$

where the dependent variable *Margin* denotes plant gross margin. This model represents the case where the impact of *ITUsage* on profitability is fully mediated through *PRODCap*.

Model 3 (IT Usage and Profitability)

We then estimated the direct impact of *ITUsage* on *Margin*, specified as

$$Margin_{ij} = \gamma_0 + \gamma_2 \cdot ITUsage_{ij} + \gamma_3 \cdot Capex_{ij} + \sum_{k=1}^{10} \gamma_{3+k} \cdot Controls_{ij}^{k} + \varepsilon_{ij} \tag{4}$$

Note that Model 3 did not capture the impact of *PRODCap* on plant margins.

Model 4 (Production Capability, IT Usage and Profitability)

Finally, we estimated the full model, specified in equation (5) as

$$Margin_{ij} = \delta_0 + \delta_1 \cdot PRODCap_{ij} + \delta_2 \cdot ITUsage_{ij} + \delta_3 \cdot Capex_{ij} + \sum_{k=1}^{10} \delta_{3+k} \cdot Controls_{ij}^{k} + \varepsilon_{ij} \tag{5}$$

where we estimated the impact of *PRODCap,* and *ITUsage* on profitability.

We estimate Models 1 through 4 using a "system of equations" estimation approach, as follows:

- System 1 represents a *full mediation* model, where we estimate Models 1 and 2 simultaneously.
- System 2 represents the direct IT impact, where we estimate Models 1 and 3 simultaneously.
- System 3 represents a *partial mediation* model, where 1 and 4 are estimated simultaneously, and the impact of *ITUsage* on *Margin* is partially mediated through *PRODCap*.

Because the error terms may be correlated and Model 1 represents a nonlinear model, we employed a "nonlinear system of equations" technique to estimate the three systems.

Econometric Considerations

We addressed several econometric issues to ensure unbiased and consistent estimation of our models. Because the plants in our sample were quite diverse, we addressed heterogeneity in two ways. First, we grouped the plants into seven industry sectors and conducted DEA efficiency estimation for each industry sector separately. This ensured that plant capabilities were based on evaluations relative to their peers in the same industry. Second, we accounted for other sources of heterogeneity by including industry dummies and other plant characteristics such as size, age, and plant type in our models.

In order to address the potential heteroscedasticity, we first computed the Breush-Pagan statistics. In Model 2 and Model 4, we observed the presence of heteroscedasticity with a test statistic of 22.38 ($p < 0.05$) and 21.38 ($p < 0.05$) respectively. We corrected for heteroscedasticity in these models by weighing each observation by the inverse of the standard deviation of the error. Another possible source of heteroscedasticity was the cluster structure present in our data, wherein plants in the same industry may exhibit similar characteristics, resulting in clustered heteroscedasticity of their error terms. Hence, we further adjusted the standard errors with cluster-robust standard errors using clustered regression on our models (Wooldridge 2010).

One may argue that our main variable of interest, *PRODCap*, may be subject to potential endogeneity, as plants with higher profitability were likely to invest greater resources to improve their production capability. We followed Bharadwaj et al. (2007) and Mani et al. (2010) to account for other potential sources of endogeneity in the presence of cross-sectional data, and applied a two-step Heckman (aka Heckit) procedure (Heckman 1979; Wooldridge 2010). Because the inverse Mill's ratio is prone to collinearity (Dow and Norton 2003), we imposed an exclusion criteria by adding at least one exogenous explanatory variable to the selection model (Little and Rubin 1987). We included the degree to which a plant outsourced its production functions (*ProdOut*), supply chain outsourcing (*SuppOut*),[4] and a binary indicator if a plant's primary strategy focused on cost reduction (*LowCost*), or high quality (*HighQual*) (Bardhan et al. 2007).[5]

We also checked for possible evidence of multicollinearity among our model variables. We presented a correlation matrix of our model variables of interest in Table A1 in Appendix A and observed that the highest pairwise correlation coefficient was 0.41 between *Size* and *ITUsage*. The VIFs (variance inflation factor) of all variables were less than 10, suggesting that multicollinearity was not of serious concern in our data.

Results

Table 5 reports the estimation results for the systems of equations specified in equations (2) through (5). We observed that the estimation results for all models were significant. System 1 indicated that *ITUsage* had a positive association with *PRODCap* (α_2 = 0.237, $p < 0.10$), and that *PRODCap* was also a significant determinant of plant *Margin* (β_1 = 10.593; $p < 0.01$). Our results in System 2 suggested that the direct associations between *ITUsage* ➔ *PRODCap* (α_2 = 0.274, $p < 0.01$) and *ITUsage* ➔ *Margin* (γ_2 = 3.895; $p < 0.01$) were positive and statistically significant. The estimation results of System 3 indicated that the IT-integrated measure of *PRODCap* had a strong association with *Margin* (δ_1 = 9.913, $p < 0.01$); efficient plants exhibited a 9.913% higher margin compared to inefficient plants.

Mediation Effect

To examine the indirect effect of IT usage on profitability, we simultaneously estimated the linkages between the independent variable (*ITUsage*), the mediator (*PRODCap*), and the dependent variable (*Margin*). To test the presence of a mediation effect, we performed a modified Sobel test for a dichotomous mediator (MacKinnon and Dwyer 1993). The test statistic was equal to 1.423, with a p-value < 0.077 (Goodman test = 1.488, p-value < 0.068). This result suggested that there existed a marginal mediation effect (Kenny 2012; Sobel 1982).[6] In order to test whether the effect of *ITUsage* was fully or partially mediated through *PRODCap*, we compared the coefficients of *ITUsage* when the mediator was included and removed, in Systems 2 and 3, respectively (Kenny 2012, Tallon and Pinsonneault 2011). When *PRODCap* was included in System 3, we observed a significant decrease in the impact of *ITUsage* on plant profitability, from 3.895 to 3.146. This drop in the magnitude of the impact of *ITUsage* suggested a partial mediation of *ITUsage* through *PRODCap* on plant profitability, consistent with Baron and Kenny (1986).

Our result indicated that the impact of *ITUsage* was partially mediated through enablement of production capabilities leading to greater plant profitability. We further reported the clustered regression results, using the Heckman correction approach, in Table 6. The Heckman results were qualitatively consistent with our earlier results presented in Table 5. Our Heckit results showed that the impact of *ITUsage* was partially mediated through production capability (Sobel test = 1.405, p-value < 0.080; Goodman test = 1.527, p-value < 0.063).

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[4]We adopted the approach described in Bardhan et al. (2007) that used a summative index to represent the extent of production outsourcing (*ProdOut*) and supporting process outsourcing (*SuppOut*).

[5]*LowCost* is a binary variable that indicates whether a plant's strategy focuses on cost reduction (0 = no, 1 = yes). *HighQual* measures whether a plant's manufacturing strategy is focused on high quality (Bardhan et al. 2007).

[6]A common approach to testing mediation is the Sobel test. We used a modified version of the test known as the Goodman test, for a model with dichotomous mediator. This tests

$$\frac{a \times b}{\sqrt{stderr_a^2 b^2 + stderr_b^2 a^2 - stderr_a^2 stderr_b^2}}$$

against a standard normal distribution, where *a* and *b* are the coefficients of the mediation paths respectively. With a dichotomous mediator, the correction approach standardizes the coefficients by multiplying each coefficient with the standard deviation of the predictor variable, divided by the standard deviation of the outcome variable.

Table 5. System of Equations Estimation Results: IT-integrated Production Capability

System	System 1		System 2		System 3	
Model	Model 1	Model 2	Model 1	Model 3	Model 1	Model 4
Dependent Variable	ProdCap	Margin	ProdCap	Margin	ProdCap	Margin
Intercept	0.866 (1.134)	36.272*** (8.996)	1.242 (1.168)	48.31*** (9.468)	0.866 (1.134)	41.564*** (9.112)
ProdCap	–	10.593*** (2.229)	–	–	–	9.913*** (2.218)
ITUsage	0.237* (0.154)	–	0.274** (0.159)	3.895*** (1.241)	0.237* (0.154)	3.146*** (1.188)
Capex	-0.013 (0.032)	0.553** (0.26)	-0.018 (0.033)	0.464** (0.269)	-0.013 (0.032)	0.472** (0.259)
TrainCost	0.711 (0.698)	1.464 (5.595)	0.711 (0.703)	3.31 (5.641)	0.711 (0.698)	1.088 (5.531)
Size	-0.209* (0.151)	-1.349 (1.107)	-0.262** (0.156)	-2.966*** (1.234)	-0.209* (0.151)	-2.601** (1.192)
Age	-0.038 (0.035)	0.152 (0.274)	-0.047* (0.037)	0.019 (0.293)	-0.038 (0.035)	0.168 (0.271)
PlantType	0.278 (0.33)	-2.482 (2.605)	0.299 (0.339)	-0.947 (2.736)	0.278 (0.33)	-1.973 (2.581)
F-Val	2.8623	3.5596	2.9196	2.4878	2.8623	3.9199
R^2	0.1300	0.1567	0.1323	0.1150	0.1300	0.1812
Adj R^2	0.0883	0.1162	0.0906	0.0725	0.0883	0.1384
Heteroscedasticity Adjustment	No	Yes	No	No	No	Yes

Industry dummies are included in all estimation models. Significant one-sided * at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.01$. Standard errors are shown in parentheses. Sobel Mediation test p = 0.077 and Goodman Mediation test p = 0.068 (one-sided p-values).

Comparison of DEA with other Methods

Next, we compared our DEA-based methodology to several other alternative approaches for conceptualizing and measuring capabilities. These included structural equation modeling (SEM), stochastic frontier analysis (SFE), and principal component analysis (PCA). We provide a detailed discussion on these methodologies and their application to our problem domain in Appendix B. Table 7 provides a summary of the model explanatory power of these three methods against our DEA-based approach, in terms of R^2 and adjusted R^2 values for each method. Overall, we observed that IT-integrated operationalization of plant production capability, using DEA, exhibits greater explanatory power to explain variations in plant performance compared to the other methods that have been used in prior literature. These results demonstrated the superiority of our approach, which was based on a relative measure of process capability that considered both IT and non-IT resources.

Robustness Checks

We conducted several robustness checks with respect to our model specification, as well as variable specification and data inclusion criteria, in order to ensure the robustness of our results.

First, we developed an alternate DEA-based approach that did **not** include IT resources (i.e., *ITSpend*) in the measurement of production capability. In this alternate model, we excluded *ITSpend* as an input into the DEA model. Hence, the DEA measure of *PRODCap* was based on two inputs and four outputs in the alternate model, while other variables in our system of equations estimation remained the same. We estimated this model using a similar two-stage approach (as deployed in our previous section), and reported these results in Table A2 of Appendix A. We observed that the estimation results in Table A2 were qualitatively similar to our earlier results reported in Table 5, in terms of the sign

Table 6. Heckman Estimation Results

Model	Model 1^y	Model 2	Model 3	Model 4
Dependent Variable	ProdCap	Margin	Margin	Margin
Intercept	1.252 (1.197)	45.92*** (13.257)	48.31*** (6.884)	31.666* (17.558)
ProdCap	–	10.411*** (3.266)	–	10.462** (3.451)
ITUsage	0.262** (0.157)	–	3.895*** (0.886)	5.185** (2.402)
Capex	-0.016 (0.032)	0.632** (0.228)	0.464** (0.175)	0.393* (0.21)
TrainCost	0.815 (0.702)	-3.088 (6.668)	3.31 (4.723)	7.185 (11.119)
MillsRatio	–	-27.067* (15.456)	–	32.265 (40.92)
ProdOut	-0.006 (0.191)	–	–	–
SuppOut	-0.133 (0.15)	–	–	–
LowCost	0.034 (0.326)	–	–	–
HighQual	-0.202 (0.31)	–	–	–
Size	-0.221* (0.154)	-0.37 (1.349)	-2.966** (1.126)	-4.103* (2.272)
Age	-0.047* (0.036)	0.374* (0.2)	0.019 (0.265)	-0.19 (0.359)
PlantType	0.325 (0.341)	-3.856* (2.085)	-0.947 (2.32)	0.569 (2.583)
F-Val (*LR* for Logistic)	37.853	3.809	2. 01	4.044
Adj R^2 (*-2 Log L* for Logistic)	326.557	0.122	0.073	0.139
N	263	263	263	263

Industry dummies are included in all estimation models. Clustered Standard errors are shown in parentheses. Significant one-sided * at p < 0.10; ** at p < 0.05; and *** at p < 0.10. ^y represents Heckit selection model.

Table 7. Comparison of DEA Models with other Methods

Approach	Characteristics	Model 1 R^2	Model 1 Adj R^2	Model 4 R^2	Model 4 Adj R^2
DEA: IT-integrated	Multi-output multi-input framework with relative efficiency scores	**0.130**	**0.088**	**0.181**	**0.138**
DEA: without IT resources	Multi-output multi-input framework with relative efficiency scores	0.134	0.092	0.176	0.133
SEM	Relies on survey questions on perceptions about competencies / capabilities	0.118	0.072	0.115	0.069
SFE	Restricted to a single output variable	0.113	0.070	0.119	0.073
PCA	Merges outputs into a single construct, ignores possible tradeoffs among outputs	0.124	0.071	0.115	0.069

and significance of the coefficients of the variables of interest as well as the role of *PRODCap* in mediating the impact of IT on plant *Margin*. The overall R^2 decreased from 0.181 to 0.176 when *ITSpend* was excluded.[7]

In order to test the sensitivity of our results with respect to any idiosyncratic characteristics of our sample plants, we further analyzed data from another random sample of plants from the preceding year (i.e., 2006). These results were qualitatively consistent with our 2007 results, lending further support to our application of the DEA methodology to (1) measure and operationalize process capability, and (2) test the integrated IT measure of process capability in terms of its usefulness as a predictor of plant profitability.

Finally, we tested our model by excluding industries with a low number of DMUs (plants), since it was possible that the DEA efficiency evaluations in these industries may not be very stable. Cooper et al. (2011) suggest calculating the minimum number of DMUs as the product of the number of inputs and outputs, which was equal to 12 in our model, or three times the sum of inputs and outputs (i.e., 21 in our model). We followed a more conservative approach and excluded industries, such as *Nondurables, Transportation,* and *Miscellaneous*, which had less than 30 DMUs. Enforcing this criterion resulted in a reduction in the total number of observations in our sample down to 209 plants. We reported the regression estimation results, corresponding to the two-stage DEA and system of equations approach, in Table C1 of Appendix C. These results were qualitatively consistent with our main results in Table 5, and supported the explanatory power of our DEA-based measure of production capability.

Conclusions

The contributions of our study are four-fold. From a methodological perspective, we developed an objective measure of plant production capability using a multi-input, multi-output framework based on DEA. Our methodology represented a significant improvement over earlier studies that measured plant capabilities using perceptual, qualitative measures of plant performance that focused primarily on plant outputs, without considering input resources that were expended to achieve these outputs. Second, our approach provided a *relative* measure of process capability, a key difference when compared to the extant literature which has primarily focused on absolute measures of capabilities. Third, we conducted extensive comparative analyses to demonstrate the advantage of our DEA approach with other common alternatives such as PCA, the latent variable approach (in SEM), and stochastic frontier estimation. Fourth, we showed that our DEA approach, which included both IT and non-IT resources, provided greater explanatory power compared to an alternative DEA models where IT was not considered as an input in the operationalization of production capability

Our findings indicated that the effect of IT usage on plant performance was partially mediated through their enablement of production capabilities. Furthermore, our results indicated that the impact of IT was significantly greater than other types of capital expenditures, and the IT-enablement effect was a significant determinant of variations in plant profitability. Our results not only demonstrated the viability of our DEA-based measure in estimating relative capability, but also shed new light on the pathways through which IT can impact organizational and business unit performance. Our proposed approach can be potentially extended to construct other capability measures such as supply chain management and marketing capabilities, provided that researchers can identify the inputs and outputs of these capabilities.

Our study was not without limitations and our results should be interpreted within the scope of this study. Due to the cross-sectional data, our findings represented associational patterns. It is important to extend this work in future studies using panel data to evaluate longitudinal relationships across a multiyear time period. Although we did not have access to panel data, the relationships observed in this study provide a starting point for future longitudinal studies.

Our operationalization of the DEA-based approach was based on the classic BCC model and inherits its limitations. These limitations include the lack of statistical properties associated with the DEA-based measure of process capability. A common criticism of DEA is its nonstatistical and nonparametric efficiency score estimation (Banker et al. 2010). Unlike a linear regression model, DEA does not estimate the coefficients of the model variables and, hence, lacks interpretability. Although a few studies have tried to provide statistical properties to DEA estimates (Kuosmanen and Johnson 2010; Liu et al. 2010; Simar and Wilson 2002; Wilson 2003), an interesting avenue for future extension would be to develop a parametric interpretation on the importance of inputs and outputs for a DEA-based capability construct.

While DEA was originally developed for cross-sectional data, a fully longitudinal panel version of DEA awaits future research. The dynamic DEA model developed by Färe and

[7]Testing the significance of this decrease (with versus without *ITSpend*) requires a new statistic since the DEA component is a nonparametric model. If we treat the case of *without-ITSpend* as the reduced model nested within the case of the full model *with-ITSpend*, the usual F-statistic is 7.44, indicating a significant decrease.

Grosskopf (2012), and the across-group DEA comparison by Banker et al. (2010) are some early attempts in this regard. Finally, due to its nonstatistical properties, DEA does not impose any restrictions on the selection of the inputs and outputs. The general guidance is that inputs represent resources that should be minimized, while outputs are outcomes that should be maximized (Morita and Avkiran 2009). An excellent review by Cook et al. (2014) addresses the issues of choosing inputs and outputs, determining the appropriate number of DMUs, and selecting different DEA specifications. There are also some notable recent advancements in DEA that include a factorial design approach to optimize the selection of DEA inputs and outputs (Morita and Avkiran 2009); heterogeneity DEA to deal with heterogeneous DMUs (Cook et al. 2013); two-stage DEA where the outputs of the first stage become the inputs of the second stage (Lim and Zhu 2016); outlier detection using DEA (Yang et al. 2014); missing-data robust DEA (Cook et al. 2013); and DEA with contextual variables (Cook and Zhu 2008). Our paper can stimulate future work to incorporate these new advancements toward a new and improved operationalization of DEA-based capability.

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RESEARCH NOTE

A DATA ENVELOPMENT ANALYSIS APPROACH TO ESTIMATE IT-ENABLED PRODUCTION CAPABILITY

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Appendix A

Correlation Matrix and Estimation Results

Table A1. Correlation Matrix

	Variables	v1	v2	v3	v4	v5	v6	v7	v8
v1	Margin	1							
v2	ProdCAP	0.25*	1						
v3	ITUsage	0.16*	0.06	1					
v4	Capex	0.11	0.01	0.06	1				
v5	TrainCost	0.07	0.05	0.04	0.13*	1			
v6	Size	-0.08	-0.08	0.41*	-0.12*	-0.03	1		
v7	Age	-0.01	-0.12*	0.07	-0.01	0.05	0.20*	1	
v8	PlantType	-0.01	0.05	-0.20*	0.01	-0.02	-0.30*	-0.02	1

*Statistically significant at p = 0.05

Table A2. Estimation Results for Production Capability Model (Without ITSpend)

System	System 1		System 2		System 3	
Model	Model 1	Model 2	Model 1	Model 3	Model 1	Model 4
Dependent Variable	ProdCap	Margin	ProdCap	Margin	ProdCap	Margin
Intercept	1.095 (1.123)	36.024*** (9.014)	1.296 (1.152)	48.31*** (9.468)	1.095 (1.123)	41.07*** (9.137)
ProdCap	–	10.617*** (2.283)	–	–	–	9.813*** (2.281)
ITUsage	0.278** (0.15)	–	0.323** (0.155)	3.895*** (1.241)	0.278** (0.15)	3.03*** (1.194)
Capex	-0.02 (0.032)	0.57** (0.26)	-0.022 (0.032)	0.464** (0.269)	-0.02 (0.032)	0.49** (0.259)
TrainCost	1.208* (0.743)	0.245 (5.604)	1.381** (0.779)	3.31 (5.641)	1.208* (0.743)	0.026 (5.545)
Size	-0.119 (0.149)	-1.6* (1.101)	-0.163 (0.153)	-2.966*** (1.234)	-0.119 (0.149)	-2.771*** (1.183)
Age	-0.069** (0.035)	0.214 (0.277)	-0.076** (0.035)	0.019 (0.293)	-0.069** (0.035)	0.222 (0.274)
PlantType	0.069 (0.329)	-1.864 (2.608)	0.107 (0.339)	-0.947 (2.736)	0.069 (0.329)	-1.357 (2.588)
F-Val	2.9515	3.4579	3.0056	2.4878	2.9514	3.7841
R^2	0.1335	0.1529	0.1356	0.1150	0.1335	0.1760
Adj R^2	0.0919	0.1123	0.0941	0.0725	0.0919	0.1330
Heteroscdasticity Adjustment	No	Yes	No	No	No	Yes

Industry dummies are included in all estimation models. Significant one-sided * at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.01$. Standard errors are shown in parentheses. Sobel Mediation test p = 0.03 and Goodman Mediation test p = 0.025 (one-sided p-values).

Appendix B

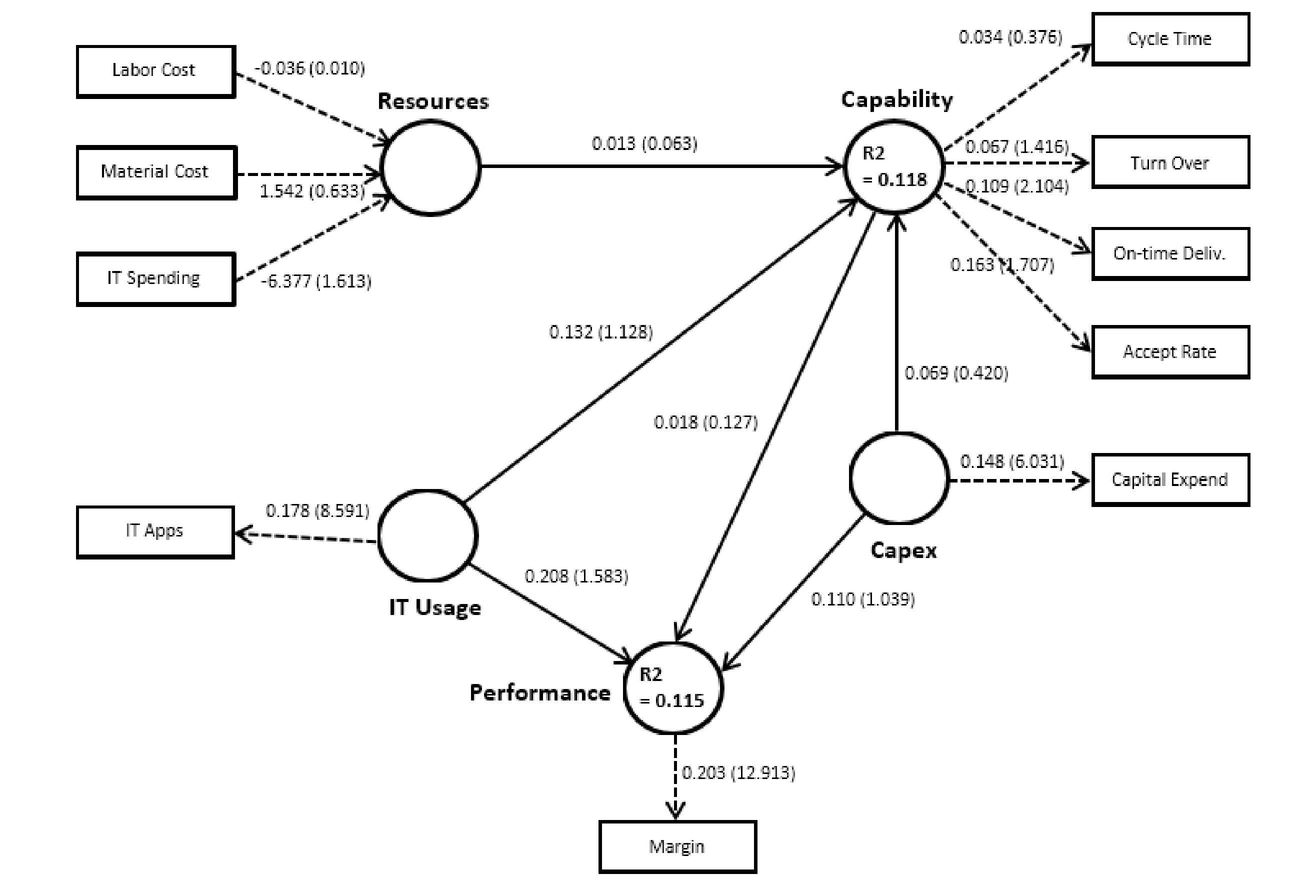
Comparison of DEA-Based Methods with Other Approaches

We compared our DEA-based approach for conceptualizing production capability with three other approaches commonly used in the RBV literature: (1) structural equation modeling (SEM); (2) stochastic frontier estimation (SFE); and (3) principal component analysis (PCA). We compared the R^2 and Adj R^2 values of these estimation methods with those obtained from the DEA approach, as reported in Table 7. Based on the greater R^2 and Adj R^2 values of the DEA-based methods, we concluded that our DEA approach exhibited greater explanatory power in explaining variations in plant performance.

Next, we provide further details of our estimation for each of these alternative methods.

Structural Equation Modeling

One stream of the literature on capabilities conceptualizes and operationalizes capabilities as a latent variable governing manifested measurement items using the SEM techniques (Schroder et al. 2002). Typically these studies involve survey questions that are designed to elicit responses (measurement items) based on perceptions about competencies and capabilities associated with different functional areas (Bharadwaj et al. 2007; Pavlou and El Sawy 2010).



** PLS model controls for Training Cost, Age, Size, Plant Type and Industry Dummies

Figure B1. PLS Estimation Results

In order to make a direct comparison between DEA- and SEM-based methods, we created two constructs, each representing a latent variable that governs inputs and outputs to our DEA model respectively. The construct "Resources" captures *Labor*, *Material Costs*, and *IT Spending* in a formative manner; and the construct "Capability" incorporates *CycleTime*, *TurnRate*, *OnTime*, and *AcceptRate* in a reflective manner.

We then used partial least squares (PLS) techniques to estimate the SEM model specified in Figure B1. PLS was preferred here to LISREL because of the presence of the "Heywood cases," in which some of the loadings can be negative (Fornell and Bookstein 1982). We used SmartPLS 2.0 to estimate the path coefficients as well as error variances. Figure B1 depicts the estimated path coefficients, as well as the t-values obtained from bootstrapping.

According to Chin (1998), existing goodness of fit measures assume that all measures in the assumed model are reflective and are related to how strongly the model accommodates sample covariances. However, some SEM procedures, such as PLS, have different objective functions and allow for formative measures. It is suggested that more attention should be paid to the fit of the SEM model when both reflective and formative constructs are present. In addition, Bollen and Long (1993) also suggest that fit of the components of a model, specifically R^2, can provide insight into the choice of a goodness-of-fit index. For this reason, we focused on R^2 to evaluate the fit of the SEM model. We observed that the R^2 of Model 1 in the DEA-based approach was 0.130, whereas in SEM it was 0.118. Similarly, the R^2 of Model 4 using our approach was 0.181, whereas it dropped to 0.115 using SEM. Of greater importance, none of the path coefficients in the SEM model were significant except *ITUsage* → *Margin* (one-sided p-value = 0.058), rendering an overall, insignificant model. We also noted that the latent variable conceptualization of capability did not capture the relative capability across plants.

Stochastic Frontier Estimation (SFE)

The key limitation of SFE compared with DEA is that the former only accommodates a single output, while it is common for firms to make tradeoffs between multiple outputs. Nevertheless, for the purpose of comparing SFE with the DEA approach in our case, we factorized the multiple outputs into a single factor, *Fact_Out*, using principal component analysis (PCA), while maintaining the same input set. We followed the same procedure specified in Li et al. (2010) in developing the production function. We estimated the technical efficiency scores using a half-normal distribution for the inefficiency variable in the SFE model (Battese and Coelli 1988). We then applied "systems of equations" estimation using the SFE-based efficiency scores. These results are presented in Table B1. We observed that the R^2 of Model 1 of the SFE approach was lower than the corresponding values in the DEA approach (i.e., 0.113 versus 0.130). Likewise, the R^2 of Model 4 decreased from 0.181 to 0.119 when SFE was applied.

Table B1. Estimation Results with Stochastic Frontier Estimation

System	System 1		System 2		System 3	
Model	Model 1	Model 2	Model 1	Model 3	Model 1	Model 4
Dependent Variable	Fact_Out	Margin	Fact_Out	Margin	Fact_Out	Margin
Intercept	0.616*** (0.082)	36.238*** (10.349)	0.616*** (0.082)	48.31*** (9.468)	0.616*** (0.082)	43.67*** (10.49)
Fact_Out	–	10.341* (7.382)	–	–	–	7.527 (7.33)
ITUsage	0.022** (0.011)	–	0.022** (0.011)	3.895*** (1.241)	0.022** (0.011)	3.73*** (1.251)
Capex	0.001 (0.002)	0.556** (0.271)	0.001 (0.002)	0.464** (0.269)	0.001 (0.002)	0.457** (0.269)
TrainCost	0.04 (0.049)	3.478 (5.734)	0.04 (0.049)	3.31 (5.641)	0.04 (0.049)	3.012 (5.648)
Size	0 (0.011)	-1.563* (1.158)	0 (0.011)	-2.966*** (1.234)	0 (0.011)	-2.967*** (1.234)
Age	-0.004* (0.003)	0.05 (0.299)	-0.004* (0.003)	0.019 (0.293)	-0.004* (0.003)	0.049 (0.294)
PlantType	0.057*** (0.024)	-2.198 (2.797)	0.057*** (0.024)	-0.947 (2.736)	0.057*** (0.024)	-1.373 (2.767)
F-Value	2.43	1.83	2.43	2.488	2.43	2.386
R^2	0.113	0.087	0.113	0.115	0.113	0.119
Adj R^2	0.070	0.043	0.070	0.073	0.070	0.073
N	263		263		263	

Industry dummies are included in all estimation models. Significant one-sided at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.01$. Standard errors are shown in parentheses.

Principal Component Analysis (PCA)

PCA has been used to conceptualize capability as a driver of performance. This is typically done by combining multiple process output measures into a single construct using the loadings derived from PCA as the weights (e.g., Ray et al. 2005; Rosenzweig et al. 2003). However, there may be various dimensions of outcomes in analyzing the operational and financial performance of organizations (Venkatraman and Ramanujam 1986). For example, indicators for operational performance may include innovation and productivity, while financial performance indicators may include earnings growth and stock price. Often, these disparate dimensions of outcomes do not converge (Combs et al. 2005). Therefore, one of the challenges of merging multiple outputs into a single construct lies in the possible tradeoffs among these various performance measures.

We applied PCA to our output variables and transformed them into one factor, in order to check if a single construct of output performance can satisfactorily represent plant production capability. We used PCA to merge *CycleTime*, *TurnRate*, *OnTime*, and *AcceptRate* into one factor, *Factor_Out*. We present the results obtained from the system of equations estimation using this derived factor in Table B2. We observed that *Factor_Out* failed to explain the variations in *Margin* in Model 2 as well as Model 4. In Model 1, none of the input variables appeared to be significant determinants of *Factor_Out* and most of the control variables were insignificant. In terms of R^2, our DEA-based approach exhibited better fit across all models.

Table B2. Estimation Results with Principal Component Analysis

System	System 1		System 2		System 3	
Model	**Model 1**	**Model 2**	**Model 1**	**Model 3**	**Model 1**	**Model 4**
Dependent Variable	**Factor_Out**	**Margin**	**Factor_Out**	**Margin**	**Factor_Out**	**Margin**
Intercept	0.173 (0.533)	42.341*** (9.428)	0.173 (0.533)	47.933*** (9.404)	0.173 (0.533)	47.896*** (9.421)
Factor_Out	–	0.75 (1.182)	–	–	–	0.348 (1.171)
ITUsage	0.141** (0.07)	–	0.141** (0.07)	3.755*** (1.257)	0.141** (0.07)	3.717*** (1.268)
Capex	0.016 (0.015)	0.528** (0.273)	0.016 (0.015)	0.439* (0.269)	0.016 (0.015)	0.436* (0.27)
TrainCost	0.244 (0.309)	3.277 (5.892)	0.244 (0.309)	2.963 (5.758)	0.244 (0.309)	2.873 (5.777)
LaborCost	0.004 (0.007)	–	0.004 (0.007)	–	0.004 (0.007)	–
MaterialCost	-0.002 (0.004)	–	-0.002 (0.004)	–	-0.002 (0.004)	–
ITSpend	-0.014 (0.023)	–	-0.014 (0.023)	–	-0.014 (0.023)	–
Size	-0.022 (0.067)	-1.568* (1.167)	-0.022 (0.067)	-2.975*** (1.231)	-0.022 (0.067)	-2.971*** (1.234)
Age	-0.023* (0.016)	0.053 (0.296)	-0.023* (0.016)	0.058 (0.29)	-0.023* (0.016)	0.064 (0.291)
PlantType	0.317** (0.149)	-1.826 (2.781)	0.317** (0.149)	-0.929 (2.716)	0.317** (0.149)	-1.025 (2.743)
F-Val	2.192	1.705	2.192	2.492	2.192	2.311
R^2	0.124	0.081	0.124	0.114	0.124	0.115
Adj R^2	0.071	0.037	0.071	0.072	0.071	0.069
Heteroscedasticity	No	Yes	No	Yes	No	Yes

Industry dummies are included in all estimation models. Standard errors are shown in parentheses. Significant one-sided * at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.01$.

Appendix C

Robustness Check on DEA Sample Size

The DEA literature suggests using large samples for DEA calculation in order to obtain statistical validity in two-stage estimations, where DEA estimation is followed by a regression analysis (Banker 1993; Iyer et al. 2013). For this reason, as a robustness check of the sensitivity of our results to sample size, we excluded industries with less than 30 observations. Hence, we only kept the industries of *Chemicals*, *Metals*, *Machinery*, and *Electrical*. The total number of observations in our sample decreased to 209, with the exclusion of *Nondurables*, *Transportation*, and *Miscellaneous* industries. Our regression results of system of equations estimation are reported in the Table C1. Accordingly, our results were consistent with this additional analysis.

Table C1. System of Equations Estimation Results

System	System 1		System 2		System 3	
Model	**Model 1**	**Model 2**	**Model 1**	**Model 3**	**Model 1**	**Model 4**
Dependent Variable	**ProdCap**	**Margin**	**ProdCap**	**Margin**	**ProdCap**	**Margin**
Intercept	1.67* (1.295)	32.032*** (10.068)	1.67* (1.295)	49.865*** (10.762)	1.67* (1.295)	38.123*** (10.244)
ProdCap	–	13.609*** (2.411)	–	–	–	12.951*** (2.396)
ITUsage	0.233* (0.168)	–	0.233* (0.168)	3.99*** (1.395)	0.233* (0.168)	3.166*** (1.326)
Capex	-0.035 (0.038)	0.783*** (0.301)	-0.035 (0.038)	0.538** (0.32)	-0.035 (0.038)	0.647** (0.303)
TrainCost	0.573 (0.713)	3.36 (5.689)	0.573 (0.713)	4.887 (5.917)	0.573 (0.713)	3.041 (5.607)
Size	-0.314** (0.176)	-0.745 (1.248)	-0.314** (0.176)	-3.061** (1.421)	-0.314** (0.176)	-2.052* (1.337)
Age	-0.042 (0.039)	0.159 (0.312)	-0.042 (0.039)	0.047 (0.336)	-0.042 (0.039)	0.161 (0.309)
PlantType	0.218 (0.369)	-3.442 (2.885)	0.218 (0.369)	-2.335 (3.073)	0.218 (0.369)	-2.955 (2.86)
F-Val	1.613	4.421	1.613	1.907	1.613	4.67
R^2	0.075	0.182	0.075	0.087	0.075	0.206
Adj R^2	0.033	0.145	0.033	0.046	0.033	0.166
Heteroscedasticity Adjustment	No	Yes	No	No	No	Yes

Industry dummies are included in all estimation models. Standard errors are shown in parentheses. Significant one-sided * at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.01$. Sobel Mediation test p = 0.09 and Goodman Mediation test p = 0.08 (one-sided p-values).

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