THE IMPACT OF IT-ENABLED MANUFACTURING CAPABILITIES ON PLANT PROFITABILITY: NEW MODELS AND EVIDENCE

Completed Research Paper

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Abstract

We propose and conceptualize a new measure of information technology-enabled manufacturing capability, based on a plant’s ability to use its mix of inputs to maximize its process outputs, and study the impact of these capabilities on manufacturing plant profitability. Our study extends the literature on IT-enablement of process capabilities using Data Envelopment Analysis, a non-parametric approach to estimate relative efficiency. We empirically test our models using data from U.S. plants in 2006 and 2007. Our results suggest that manufacturing capabilities and IT spending are positively associated with plant profitability. In addition, we observe that manufacturing process capabilities partially mediate the effect of IT spending on profitability. Our study makes two salient contributions. First, we conceptualize and test a new measure of organizational capability based on the relative efficiency of converting plant resource inputs into process outputs. Second, our findings reveal new pathways through which IT spending can impact plant profitability.

Keywords: Information Technology, Manufacturing Process, Capability, Efficiency, Data Envelopment Analysis
Introduction

The manufacturing sector, one of many industries that has reaped benefits from widespread adoption and use of IT, has consistently outpaced the pace of economic growth in U.S. According to the Bureau of Labor Statistics, the annual productivity growth rate of the manufacturing sector averaged 4.1% between 1990-1999, 3.6% between 2000-2006, and 2.2% in the last five years between 2007 and 2011 (U.S. Bureau of Labor Statistics 2012). The U.S. GDP growth rate was significantly lower though for the same periods, with an average annual growth of 3.22%, 2.7% and 0.62%, respectively, for the same periods (World Bank 2012). Jorgenson et al. (2011) attribute the difference in growth rates across different sectors of the U.S. economy to the role that IT plays in each industry. They conclude that more than 25% of the productivity growth in the last decade can be attributed to IT, with IT-intensive industries such as manufacturing enjoying a substantially higher growth rate than non-IT intensive industries such as agriculture. IT has become a major component of firm-level investments, accounting for 41% of total equipment and software investments by the end of 2004 (Dewan and Ren 2011; Doms 2005).

It is no accident that the past decade has witnessed a significant amount of research in the domain of IT-enabled capabilities and their impact on firm-level performance. Advances in IT-enabled capabilities have had a significant impact on inter- and intra-firm coordination processes (Cotteeleer and Bendoly 2006; Lee et al. 1997). Manufacturing plants are increasingly reliant on integrated information systems, such as plant operations management systems and enterprise resource planning systems, to manage plant schedules and coordinate complex information processing requirements of their customers and suppliers (Banker et al. 2006; Bharadwaj et al. 2007; Gattiker and Goodhue 2005). Recent research has shown that IT is a critical enabler of the coordination required between manufacturing, marketing, and supply chain processes in order for firm managers to manage their supply chains efficiently (Pavlou and El Sawy 2010; Rai et al. 2006). However, most of these studies focus on firm-level analysis, whereas there is less evidence at the plant level. Peng et al. (2008) argue that, "while management scholars recognize the importance of manufacturing capabilities in achieving competitive advantage (Hayes and Pisano 1996), they rarely investigate capabilities at the plant level, where manufacturing capabilities are actually realized." Hence, a primary research objective of our study is to develop a better estimate of the relationship between manufacturing capabilities, IT spending, and plant profitability of manufacturing plants, while developing an improved methodology for such estimation.

In spite of a large body of work on capabilities and their relationship with firm performance in the IS literature, a critical gap in the prior research on IT-enabled capabilities lies in the conceptualization and definition of capabilities. Capabilities represent the ability of a firm to efficiently combine several resources to engage in productive activities and attain its objectives (Amit and Schoemaker 1993). Dutta et al. (2005) argue that capabilities can be measured as the relative efficiency with which a firm converts the input resources that are available to it into outputs to attain its objectives. They characterize firm capability as the intermediate transformation ability between resource inputs and outputs. In other words, if capabilities are hard to observe, they would be hard to imitate or buy, as the tenets of RBV theory suggest.

A limitation of prior studies on IT-enabled capabilities lies in their usage of latent variables to measure firm- or process-level capabilities. Typically, these approaches involve survey questions that are designed to elicit responses based on perceptions about competencies and capabilities associated with different functional areas (Banker et al. 2006; Bharadwaj et al. 2007; Pavlou and El Sawy 2010). It is important, however, to develop more objective approaches to measure such capabilities which involve representing the production function as a set of process inputs and outputs that are manifested in the form of process-level capabilities.

Hence, our second research objective in this study is to conceptualize and operationalize a measure of plant manufacturing capabilities using a multi-input, multi-output framework. We address these limitations in the prior literature by modeling a manufacturing plant's activities as a production frontier (or transformation) function that relates the use of plant resource inputs into outputs as an intermediate step toward attainment of its financial objectives. Our study differs from earlier research on IT-enabled capabilities along several dimensions. First, unlike earlier approaches, we define plant manufacturing capability as a relative efficiency measure based on the usage of multiple resource inputs to produce
multiple outputs. Second, our input and output measures represent objective, process-level metrics of production processes based on the extant operations literature (compared to perceptual measures that have been used in the past to define firm capabilities). Third, we estimate the effect of changes in plant-level IT spending on plant profitability, and reveal the pathways and mechanisms through which plant capabilities mediate such impacts.

We empirically test our models using data from U.S. plants in 2006 and 2007. Our results suggest that manufacturing capabilities and IT spending are positively associated with plant profitability. In addition, we observe that manufacturing process capabilities partially mediate the effect of IT spending on profitability. Our study makes two salient contributions. First, we conceptualize and test a new measure of organizational capability based on the relative efficiency of converting plant resource inputs into process outputs. Second, our findings reveal new mechanisms through which IT spending can impact plant profitability.

The rest of this paper is organized as follows. We develop the theoretical foundation for measurement of plant capabilities in the next section. Then, we propose our conceptual research framework and related hypotheses. We then describe the data and estimation methods, followed by a discussion of the results. We conclude with a summary of the key findings and implications for research and practice.

**Theory Foundation**

We draw on the resource-based view (RBV) of the firm to frame our measurement of manufacturing capabilities, and their central role in determining plant performance. Specifically, we measure plant capabilities using a non-parametric measure of efficiency, based on their conceptualization as an ability to transform plant resource inputs into intermediate process-level outputs, which are determinants of the overall plant financial performance.

**Conceptualizing Manufacturing Capabilities**

Capabilities are dynamic to the extent that 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 (Eisenhardt and Martin 2000; Pavlou and El Sawy 2010). Teece et al. (1997) define dynamic capabilities as the “ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments.” In new product development, dynamic capabilities are measured as a composite construct consisting of firms’ market sensing capabilities, learning (or absorptive capacity) capabilities, coordination capabilities, as well as integration capabilities (Pavlou and El Sawy 2006).

Consistent with this theory, the ability of firms in leveraging their manufacturing capabilities to develop closer relationships with partners and create agile and flexible manufacturing competencies can lead to improved customer value (Sambamurthy et al. 2003; Sambamurthy and Zmud 2000; Wheeler 2002). For example, (Schroeder et al. 2002) show that plants’ ability to incorporate external and internal learning, through interactions with customers and suppliers, translates into proprietary capabilities, an important enabler of plant performance. Prior research has shown that firm capabilities are determinants of firm-level financial performance (Bharadwaj 2000; Day 1994; Dutta et al. 1999; Irwin and Klenow 1994).

Our study focuses on the measurement of manufacturing capability at the plant level. Building on prior research in the strategy literature, we measure plant manufacturing capability along multiple dimensions that include intermediate, process-level measures such as plant quality, time to market, and inventory turnover (Ferdows and De Meyer 1990). It is important to measure plant capabilities along different dimensions since there exist tradeoffs between improvements across these dimensions. For example, improvements in capabilities in terms of product time-to-market may co-occur with the complication of having lower quality or higher defect rates. Hence, we collect metrics that represent multiple dimensions to develop a holistic view of plant performance.

Resource-based theory links superior firm performance to the resources and capabilities possessed by firms with respect to their peers (Barney 1991). While it has offered a solid theoretical foundation to
explain a number of phenomena in the management literature, it has often been criticized due to its conceptualization and measurement of firm 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 against low performing firms, and then those performance-based capabilities that are significantly different between the two groups of firms are deemed as critical. Dutta et al. (2005) argue that what is needed is a “… conceptualization and measurement approach for capabilities that is independent of a firm’s rent generation ability ….”

In a manufacturing context, we posit that manufacturing capability may be defined as the efficiency with which a plant uses the resource inputs that are available and converts them into outputs that are aligned with its manufacturing strategy. Dutta et al. (2005) and Li, Shang and Slaughter (2010) formalize the measurement of firm capabilities by modeling a firm’s activities as a transformation function that relates the usage of resource inputs to optimal attainment of its objectives/outputs.

A firm’s competitive capabilities are measured based on attaining or maintaining competitive advantage along various dimensions related to process quality, delivery, flexibility and cost, relative to its competitors (Banker et al. 2006; Pavlou and El Sawy 2006; Rai et al. 2006). Operations researchers have proposed the concept of a “performance frontier” as a way to understand the tradeoffs between these different dimensions of capability and study whether implementation of certain types of manufacturing process initiatives can lead to changes in competitive capabilities that are mutually reinforcing. In other words, a performance frontier represents plants’ capabilities along several dimensions, based on its usage of a given set of input resources.

Research shows that firms that are at or very close to their performance frontier may have to make tradeoffs in terms of improvement on one or more capabilities, while those firms that experience slack in their usage of resource inputs or resulting outputs are more likely to exhibit cumulative capabilities as they implement new types of initiatives over time (Clark 1996; Hayes and Pisano 1996). However, measurement of their performance frontier remains an open question. Swink et al. (2006) use Data Envelopment Analysis (DEA) as one approach to develop an efficiency metric that captures the relative performance of organizations involved in new product development. The relative efficiency metric derived from DEA provides a proxy of the firm’s distance from the performance frontier relative to its industry peers. While DEA provides one approach to derive the performance frontier, other papers address position relative to a performance frontier by proposing metrics that are reasonable proxies for slack (Lapré and Scudder 2004; Schmenner and Swink 1998)

Estimating Plant Manufacturing Capabilities using DEA

We define a plant’s manufacturing capability as its relative efficiency in converting its manufacturing inputs into outputs following the framework proposed by Dutta et al. (2005) and adopted by Li et al. (2010). In other words, capability is not an absolute measure of plant performance but represents the relative efficiency of the process through which inputs are transformed into outputs. For example, Li et al. (2010) measure a firm’s R&D capability as the efficiency with which a firm translates its R&D spending into new patents, relative to its peers. Hence, larger firms with more resources and correspondingly high levels of outputs are not necessarily more capable than smaller peers with lower levels of outputs. Rather, a key distinction is the manner in which a firm is rated as more capable if it generates greater output compared to its peers with respect to its level of input. In contrast, the conventional view of firm capability (e.g. those built on RBV) overlooks the expenses that a firm has to incur to attain certain level of capabilities.

We deploy DEA to estimate the manufacturing capability of each plant. DEA is a nonparametric approach that constructs an efficient frontier (envelopment) over the data, and calculates each data point’s efficiency relative to this frontier. Each data point corresponds to a plant or decision-making unit (DMU) whose objective is to convert plant inputs into outputs as efficiently as possible. DEA uses mathematical programming to identify the efficient frontier which consists of DMUs that are 100% efficient (relative to other DMUs) and the efficiency of other DMUs are computed with respect to the efficient frontier. Note that, the main challenge of applying the stochastic frontier approach to our study is that we have multiple outputs while extant stochastic frontier estimation methods only deal with a single output variable (Li et al. 2010; Narasimhan et al. 2006), with the exception of the Cobb-Douglas cost function formation in SF
(Greene 2005). However, this formulation requires that an overall cost measure be observed such that the overall goal is to minimize this overall cost, a condition that is not met for this study. DEA, on the other hand, can deal with multiple inputs and outputs. From a managerial point of view, DEA can be used to benchmark organizations or business units and allow managers to evaluate the relative performance of their organizations (or business units) against their peers within an industry sector or across multiple sectors (Sarkis and Talluri 2004).

We adopt the classic BCC model (Banker et al. 1984) that deals with the variable returns to scale (VRS) case. We briefly discuss the formulation of the output oriented BCC model. Suppose N data points (i.e. DMUs) are to be evaluated. Each data point consists of M inputs and S outputs. The MxN input matrix, X, and the SxN output matrix, Y, represent the data consisting of N DMUs. Note that in this formulation, the columns represent the data points and the rows are the variables. Hence for the jth DMU the inputs are represented by the Mx1 vector \( x_j \) and the outputs by the Sx1 vector \( y_j \) respectively. The output-oriented BCC model to be solved for a specific DMU, call it DMU 0, is presented in (1) as follows:

\[
\text{Max}_{\theta, \lambda} \{ \theta + \epsilon (1' s^- + 1' s^+) \mid X\lambda + s^- = x_0; \quad Y\lambda - s^+ = \theta y_0; \quad 1' \lambda = 1; \quad \lambda \geq 0 \} \tag{1}
\]

In the above equation, \( 1 \) is a vector of all ones, \( \epsilon \) is a scalar, \( \lambda \) is an Nx1 vector of constants, \( s^- \) and \( s^+ \) are Mx1 and Sx1 slack variable vectors for inputs and outputs respectively, \( \epsilon > 0 \) is a non-Archimedean element smaller than any positive real number. In the model, \( \theta \) and \( \lambda \) are the two variables to be optimized. All other values (X, Y) are observed in the data. For DMU 0, its efficiency \( \theta \) is simply the ratio of weighted outputs to weighted inputs or the maximum distance to the surface of the convex hull, which is identified by the mathematical model in (1) by obtaining appropriate weights for inputs and outputs. The value of \( \theta \) is bounded between 0 and 1. A DMU is rated as 100% efficient if its radial efficiency score \( \theta = 1 \), and all input and output slacks in the optimization model are equal to zero.

**Research Hypotheses**

We measure the efficiency of plant manufacturing processes using the manufacturing capability construct as conceptualized in the previous section. We develop our research hypotheses with a focus on how IT-enabled manufacturing capabilities impact manufacturing plant performance.

**Information Technology and Manufacturing Capability**

Plant capability refers to a plant’s ability to use its resources in a cost-effective manner. A plant’s IT infrastructure provides greater visibility to the manufacturing processes of its value chain, including that of its partners and suppliers, which in turn enables plants to monitor real-time changes in customer requirements and product specifications. By helping to aggregate project information across the supply chain, IT solutions (such as supplier portals) enable plants to update information about forecasting, scheduling and pricing in one central location, which allows their suppliers to make adjustments and react more efficiently to customer-driven changes. For example, Cisco Systems’ Manufacturing Connection Online (MCO) includes a supplier portal and access to the underlying source data used by Cisco and its contract manufacturers (Bardhan et al. 2006). MCO enables Cisco to increase the efficiency of its order fulfillment processes and effectiveness in monitoring performance goals related to cost, quality and delivery. In addition, supply chain management software, warehouse management systems, and transportation management systems serve as critical enablers of customer and supplier integration capabilities in manufacturing plants (Barbosa and Musetti 2010; Helo and Szekely 2005; Marchet et al. 2009; Rai et al. 2006). For the valve manufacturing industry, adoption of new IT-enhanced equipment was found to improve the efficiency of production processes with observed reductions in setup times, run times and inspection times (Bartel et al. 2007).

Information technology enables operational and supply chain capabilities related to production and distribution planning & scheduling; demand planning and forecasting; sourcing planning (e.g. planning current inventory and future demand in collaboration with suppliers); inbound, production and outbound operations (including all fulfillment activities, warehousing and transportation to customers); and accounting for all constraints in the supply chain (including all suppliers, manufacturing facilities,
distribution centers, and other customers). In sum, a plant’s IT investment can benefit the entire value chain of its manufacturing processes. Hence, we hypothesize that:

**H1:** Higher levels of plant IT spending are associated with greater manufacturing capabilities compared to plants with lower levels of IT spending.

**Manufacturing Capability and Plant Profitability**

Firms gain a competitive advantage over their peers by effectively leveraging their resources to create greater margins based on the productive efficiency of their operations processes (Roth and Jackson III 1995). Factors that affect manufacturing capability include labor costs as well as costs associated with worker training and materials, since well-trained workers are vital for retooling of manufacturing processes to develop world-class capabilities that allow plants to adjust to changing customer requirements. Such costs can be substantial especially considering that implementation of capabilities, such as just-in-time and lean manufacturing initiatives, involve significant investments in worker training, process reengineering, and equipment.

We operationalize manufacturing capability as a plant’s ability to convert a set of operational inputs (e.g. labor, materials and training cost) into outputs from its plant operations (e.g. cycle time, inventory turnover, product acceptance rate). Measures such as product cycle time and lead time represent effective indicators of manufacturing capability since they measure effective adherence to manufacturing completion time and order management practices. Other measures such as inventory turnover and on-time delivery rate measure the effectiveness with which inventory is managed and on-time delivery schedules are maintained, respectively. Hence, the manufacturing capability construct takes into account multiple plant input and output measures and is measured as the relative efficiency with which these inputs are converted into outputs relative to the competitors.

Greater manufacturing capability helps a plant execute its current operations more efficiently (Li et al. 2010) and gain competitive advantage in the long run because capabilities are often difficult to copy (Day 1994; Ray et al. 2004; Wade and Hulland 2004; Wu et al. 2010). Plant-specific operational processes may not be easily imitated especially if they require substantial organizational process change and workflows/routines that are domain-specific (Banker et al. 2006). Hence, we posit that,

**H2:** Plants with greater levels of manufacturing capability are more likely to realize higher profitability compared to plants with lower manufacturing capability.

**Information Technology and Plant Profitability**

IT may have a direct effect on plant costs and quality. A plant can leverage its IT infrastructure to integrate processes and resources within and across firms. Investment in appropriate IT solutions can enable plants to participate in electronic exchanges and online procurement auctions, providing a channel to identify low cost suppliers and partners for outsourced production of primary products (Banker et al. 2006). These solutions provide an avenue for plants to lower their costs of material procurement, and reduce their labor and overhead costs. In other words, IT can lower the procurement costs of raw material and related services by providing manufacturing plants with alternative procurement channels to identify low-cost suppliers.

IT can also impact the direct costs of production by providing greater automation capabilities, e.g., self-service technologies, that help plants to reduce labor costs (Mithas et al. 2012). Deployment of IT systems has improved the efficiency of operational and supply chain processes within and across firms by supporting lean transformational efforts (Ilebrand et al. 2010). Wal-Mart’s RetailLink system allows it to improve manufacturing-marketing coordination with its vendors, providing them with frequent, timely, and store-specific sales information, and has led to reduced labor and inventory costs in their supply chain processes (Manyika and Nevens 2002). Hence, we argue that IT systems can have a direct impact on plant profitability by reducing production, transaction, and supply chain coordination costs and providing the infrastructure required to enable revenue growth opportunities such as participation in electronic exchanges.
**H3:** Plants with greater levels of IT spending are more likely to exhibit higher levels of profitability compared to plants with lower levels of IT spending.

**Mediating Role of Manufacturing Capability**

Early research by Cooper and Zmud (1990) suggest that plants’ information processing requirements are closely aligned to their manufacturing capabilities. Schroeder et al. (2002) find that plants’ ability to incorporate external and internal learning, through interactions with customers and suppliers, translates into proprietary capabilities, an important enabler of plant performance. Based on their prior work on manufacturing plant capabilities, Banker et al. (2006) find that implementation of different types of plant information systems are associated with just-in-time and customer-supplier participation capabilities which are, in turn, associated with improvements in plant operational performance. Recent research on new product development suggests that operational capabilities mediate the impact of IT usage on competitive advantage in product development (Pavlou and El Sawy 2010). A recent example from the valve manufacturing industry suggests that investments in new CNC machines, flexible manufacturing systems and 3D-CAD reduces setup times, which in turn eases the shift from production of one product to another and supports a business strategy of customized production (Bartel et al. 2007).

In this research, our focus is not restricted to specific types of information systems and their association with plant operational performance measures. Rather, our locus of interest lies in studying the relationship between overall plant-level IT spending, manifestation of operational, process-level capabilities, and their impact on plant financial performance measured in terms of profitability. We argue that the impact of IT on plant profitability will be mediated through the enablement of manufacturing capabilities which allow plants to develop competencies related to just-in-time manufacturing, collaborate with supply chain partners, and facilitate integration between product development and manufacturing processes (Banker et al. 2006; Bharadwaj et al. 2007). Hence, we hypothesize that,

**H4:** The impact of IT spending on plant profitability is mediated through their enablement of manufacturing process capabilities.

**Research Methodology**

**Data and Variables**

We obtained the data for this research from the Manufacturing Performance Institute (MPI) census survey on U.S. manufacturing plants for the years 2006 and 2007. The manufacturing plants are classified based on the North American Industry Classification System (NAICS) codes. The web-based online survey collects factual information about plant manufacturing practices, marketing strategies, and various plant performance measures based on responses provided by plant managers. Financial data related to plant costs, revenue and profitability are based on responses by plant controllers. The MPI survey does not reveal the identities of the plants. Therefore, we cannot track the performance trends of the plants in our sample across multiple years and the data is not panel data per se. This led us to test our hypotheses separately for both years. The 2006 and 2007 data consist of 412 and 263 manufacturing plants, respectively, for which we have complete data on all variables.

The plants in our study are drawn from seven industry sectors that belong to NAICS codes 31, 32 or 33, as shown in Table 1. For each year, we chose the industry sectors for which a sample of at least 15 plants are available (per sector) in order to conduct meaningful statistical analysis.

**Manufacturing Capability**

We employ three inputs and five outputs to estimate a relative efficiency measure of plant manufacturing capability via DEA. The three inputs are labor costs (LaborCost), material costs (MaterialCost) and training cost (TrainCost). Labor and material costs represent two key cost components for a manufacturing plant, accounting for 72.3% percentage of total manufacturing costs in our sample. Our data also captures the training costs incurred at each plant which varies significantly among
manufacturing plants. These variables are critical inputs into the manufacturing process since expenditures on labor, material, and worker training are determinants of manufacturing process capabilities.

<table>
<thead>
<tr>
<th>Industry Sector</th>
<th>NAICS</th>
<th>2006 (N)</th>
<th>2007 (N)</th>
<th>Overall US *(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NONDURABLES</td>
<td>31</td>
<td>21</td>
<td>16</td>
<td>20.54</td>
</tr>
<tr>
<td>CHEMICALS</td>
<td>32</td>
<td>91</td>
<td>70</td>
<td>25.90</td>
</tr>
<tr>
<td>METALS</td>
<td>331, 332</td>
<td>86</td>
<td>55</td>
<td>19.59</td>
</tr>
<tr>
<td>MACHINERY</td>
<td>333</td>
<td>84</td>
<td>42</td>
<td>7.91</td>
</tr>
<tr>
<td>ELECTRICAL &amp; ELECTRONICS</td>
<td>334, 335</td>
<td>58</td>
<td>42</td>
<td>6.22</td>
</tr>
<tr>
<td>TRANSPORTATION</td>
<td>336</td>
<td>31</td>
<td>20</td>
<td>3.88</td>
</tr>
<tr>
<td>MISCELLANEOUS</td>
<td>337, 339</td>
<td>41</td>
<td>18</td>
<td>15.96</td>
</tr>
<tr>
<td>Total Number of Manufacturing Plants</td>
<td>412</td>
<td>263</td>
<td>NA</td>
<td></td>
</tr>
</tbody>
</table>

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

Unlike prior firm-level studies which used COGS as a DEA input variable, we did not use COGS because it represents non-material costs that typically occur at the firm level (instead of the plant level). Furthermore, since COGS is used to calculate a firm’s profitability (i.e. gross margin = revenue minus COGS), its use as an input variable in the DEA model would create a tautological problem in our computation of efficiency, i.e. everything else being equal, higher level of COGS would be associated with lower profits, leading to higher inefficiency by construction.

The five manufacturing outputs consist of cycle time (CycleTime), inventory turnover rate (TurnRate), on-time delivery rate (OnTime), lead time (LeadTime) and product acceptance rate (AcceptRate). These variables represent a comprehensive set of objective measures of manufacturing process-level competence. These outputs represented well-accepted and objective measures of plant manufacturing prowess, yet they measure different dimensions of manufacturing capability, as evident from the relatively low correlation among them (the highest correlation is 0.29 between CycleTime and LeadTime). Our plant outputs represent direct measures of manufacturing process capability compared to other measures such as plant return on invested capital (ROIC) which depend on external factors such as market competition, economic environment, and product promotion that should not be factored into the calculation of a manufacturing capabilities.

**Capital Expenditures**

Our data captures the two components of plant expenditures: IT expenditure and non-IT capital expenditure. Plant IT spending (ITSpending) is measured as the plant-level IT spending as a percentage of plant sales. Non-IT capital expenditure (Capex) is defined as plant-level spending on capital expenditures as a percentage of plant sales. We do not use Capex as an input variable in our DEA model because decisions on such expenditures are usually made at the firm level (Brynjolfsson and Hitt 1996; Chwelos et al. 2010; Gurbaxani et al. 2000). However, we account for these expenditures by controlling for their impact in our econometric models.

**Plant Characteristics**

Other plant-level characteristics that are included in our model are (a) Size (number of plant employees); (b) Age (number of years the plant has been operating); (c) plant industry affiliation based on 3-digit NAICS code; and (d) type of plant ownership (PlantType) which indicates if the plant is public or privately owned. Table 2 presents the definition and descriptive statistics of all model variables. The average gross margin of all plants in our sample is about 35%, while the average annual plant sales in 2007 is $41.35 million. The average capital expenditures and IT spending as a percentage of plant sales are 4.8% and 2.3%, respectively.
Summary Statistics

Table 3 provides summary descriptive statistics of the data envelopment analysis conducted on plant manufacturing process data. We report the estimated DEA efficiency ratings for the entire sample and by industry sector. The left panel in Table 3 reports the plant manufacturing capabilities based on binary ratings of their efficiency, i.e. a plant is rated as being fully efficient if its raw DEA efficiency score is 1 and slacks on all input and output variables are equal to zero. The raw DEA efficiency scores are not directly comparable across different industry sectors since plants rated as fully efficient may still have non-zero slacks based on the DEA estimation. In 2007, 24% of plants in our sample were rated as being fully efficient, i.e. high manufacturing capability. However, there exists high variation in plant efficiency rankings across industries. For example, only 14% of plants in the Electrical and Electronics industry were rated as efficient, while about 60% of plants in the Transportation industry are efficient. The right panel of Table 3 provides the average raw (radial) DEA efficiency scores for each industry which does not account for the presence of slacks.

Table 2. Variable Definitions and Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measurement</th>
<th>Unit</th>
<th>2006</th>
<th>2007</th>
<th>2006</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Margin</td>
<td>Plant sales less COGS divided by sales</td>
<td>%</td>
<td>35.7 (19.2)</td>
<td>35.31 (18.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPEX</td>
<td>Plant capital-equipment spending as a percentage of sales</td>
<td>%</td>
<td>5.33 (5.4)</td>
<td>4.8 (4.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>Annual plant sales</td>
<td>$M</td>
<td>35.54 (38.0)</td>
<td>41.35 (57.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Cost</td>
<td>Total direct labor cost divided by total sales</td>
<td>%</td>
<td>13.29 (9.4)</td>
<td>13.14 (8.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Material Cost</td>
<td>Total direct material cost divided by total sales</td>
<td>%</td>
<td>30.5 (14.2)</td>
<td>33.97 (15.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TrainCost</td>
<td>Annual employee training cost at plant divided by sales</td>
<td>%</td>
<td>0.16 (0.3)</td>
<td>0.17 (0.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CycleTime</td>
<td>Time elapsed from start of production to completion of primary product</td>
<td>Hrs</td>
<td>82.03 (177.7)</td>
<td>71.63 (146.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AcceptRate</td>
<td>Customer acceptance rate (in decile format)</td>
<td>0-7</td>
<td>5.35 (1.4)</td>
<td>5.38 (1.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inventory Turnover</td>
<td>Annual COGS divided by average value of total inventory on hand</td>
<td>Turns / year</td>
<td>9.58 (6.7)</td>
<td>22.22 (48.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OnTime</td>
<td>Percentage of goods delivered on time</td>
<td>%</td>
<td>91.53 (9.4)</td>
<td>92.92 (8.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LeadTime</td>
<td>Days elapsed from order-entry through production to shipment for specific product</td>
<td>0-7</td>
<td>5.53 (1.6)</td>
<td>5.41 (1.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IT Spending</td>
<td>Level of IT spending divided by total sales</td>
<td>%</td>
<td>1.81 (1.9)</td>
<td>2.31 (2.8)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

Table 3. DEA Evaluations of Manufacturing Capability

<table>
<thead>
<tr>
<th>INDUSTRY</th>
<th>MNF Cap (Binary Efficiency)</th>
<th>MNF Score (Raw Efficiency)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2006</td>
<td>2007</td>
</tr>
<tr>
<td>ALL</td>
<td>0.15</td>
<td>(0.36)</td>
</tr>
<tr>
<td>NONDURABLES</td>
<td>0.33</td>
<td>(0.48)</td>
</tr>
<tr>
<td>CHEMICALS</td>
<td>0.12</td>
<td>(0.33)</td>
</tr>
<tr>
<td>METALS</td>
<td>0.1</td>
<td>(0.31)</td>
</tr>
<tr>
<td>MACHINERY</td>
<td>0.1</td>
<td>(0.3)</td>
</tr>
<tr>
<td>ELECTRICAL</td>
<td>0.19</td>
<td>(0.4)</td>
</tr>
<tr>
<td>TRANSPORTATION</td>
<td>0.29</td>
<td>(0.46)</td>
</tr>
<tr>
<td>MISCELLANEOUS</td>
<td>0.2</td>
<td>(0.4)</td>
</tr>
</tbody>
</table>

*Values on left in each cell represent the mean while numbers in the parentheses represent standard deviations
We present a pairwise correlation matrix of our model variables in Table 4. The correlation matrix indicates that all correlations are relatively low (the highest value is -0.302 between Size and PlantType). We further compute the variance inflation factor (VIF) for all variables, and observe that all VIF values are far below the threshold of 10 (the highest VIF is 1.54), which indicates that multi-collinearity is not a concern in our data.

Table 4. Correlation Matrix

<table>
<thead>
<tr>
<th>Gross Margin</th>
<th>MNF Cap</th>
<th>IT Spending</th>
<th>CAPEX</th>
<th>Size</th>
<th>Age</th>
<th>Plant Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEAN</td>
<td>35.306</td>
<td>0.243</td>
<td>2.312</td>
<td>4.800</td>
<td>4.673</td>
<td>18.075</td>
</tr>
<tr>
<td>STD</td>
<td>18.487</td>
<td>0.430</td>
<td>2.807</td>
<td>4.442</td>
<td>1.059</td>
<td>3.915</td>
</tr>
<tr>
<td>N</td>
<td>263</td>
<td>263</td>
<td>263</td>
<td>263</td>
<td>263</td>
<td>263</td>
</tr>
</tbody>
</table>

*Bold values are statistically significant at p = 0.05 and size is log-tranformed.

Model Specification

We test our research hypotheses by estimating the conceptual research model (shown in Figure 1) using a hybrid modeling approach consisting of DEA followed by econometric estimation. First, we estimate plant manufacturing capabilities using DEA as described in section 3.2. We conduct a separate DEA analysis for each industry sector (as shown in Table 3), which allows us to estimate a relative efficiency frontier based on plant comparisons against best performing plants in the same industry sector. This relative efficiency analysis provides a more accurate measure of plant capability rather than a cross-industry comparison.

Next, we use the estimated plant capability scores as explanatory variables in the econometric model. The hypothesized relationships in our conceptual model are represented by four distinct paths represented as follows: 1) IT Spend $\rightarrow$ MNF Cap, 2) MNF Cap $\rightarrow$ Margin, 3) IT Spend $\rightarrow$ Margin, 4) MNF Cap and IT Spend $\rightarrow$ Margin. To test our hypotheses, we develop three systems of equations to estimate these distinct paths. We now describe the econometric representation of these models.

Model 1 (IT and Manufacturing Capability)

\[
\text{MNF Cap}_{ij} = \frac{1}{1 + \exp(-\alpha_0 - \alpha_2 \cdot \text{IT Spend}_{ij} - \alpha_3 \cdot \text{Capex}_{ij} - \sum_{k=1}^9 \alpha_{3+k} \cdot \text{Controls}_{ijk} + \varepsilon_{ij})} \tag{2}
\]

where i denotes an individual plant and j indexes the industry sector it belongs to. MNF Cap is measured as a binary variable where MNF Cap = 1 if a plant is fully efficient (based on DEA) and zero otherwise. This binary variable approach enables us to focus on comparing high-capability (fully efficient) plants with low-capability (inefficient) ones. The Controls vector represents the control variables in our estimation model, and includes plant size, age, type of plant ownership, and the six dummy variables that represent the industry sectors. Since our dependent variable is binary, we estimate Model 1 using a logistic regression where $\alpha_0 - \alpha_{12}$ represent the logistic regression coefficients.

Model 2 (Manufacturing Capability and Plant Profitability)

\[
\text{Margin}_{ij} = \beta_0 + \beta_1 \cdot \text{MNF Cap}_{ij} + \beta_3 \cdot \text{Capex}_{ij} + \sum_{k=1}^9 \beta_{3+k} \cdot \text{Controls}_{ijk} + \varepsilon_{ij} \tag{3}
\]

where the dependent variable Margin denotes plant gross margin. This model estimates the direct impact of manufacturing capability on plant profitability, and represents the case where the impact of IT on profitability is fully mediated through MNF Cap.
Model 3 (IT and Plant Profitability)

\[ \text{Margin}_{ij} = \gamma_0 + \gamma_2 \cdot \text{ITSpends}_{ij} + \gamma_3 \cdot \text{Capex}_{ij} + \sum_{(k=1)}^{9} \gamma_{3+k} \cdot \text{Controls}_{ijk} + \varepsilon_{ij} \]  

(4)

where we estimate the direct impact of IT Spending on plant profitability. Note that Model 3 does not capture the impact of MNFCap on plant margins.

Model 4 (Manufacturing Capability, IT and Plant Profitability)

\[ \text{Margin}_{ij} = \delta_0 + \delta_1 \cdot \text{MNFCap}_{ij} + \delta_2 \cdot \text{ITSpends}_{ij} + \delta_3 \cdot \text{Capex}_{ij} + \sum_{(k=1)}^{9} \delta_{3+k} \cdot \text{Controls}_{ijk} + \varepsilon_{ij} \]  

(5)

where we estimate the impact of manufacturing capability, IT and capital expenditures on plant profitability in a single model.

Figure 1. Conceptual Research Model

**Estimating the System of Equations**

We estimate these models by using a “system of equations” estimation approach where different combinations of these four models are estimated simultaneously. Our systems of equations are defined as follows: **System 1** represents a simultaneous estimation of Models 1 and 2; **System 2** represents a simultaneous estimation of Models 1 and 3; and **System 3** represents a simultaneous estimation of Models 1 and 4.

Under each system, the error terms between the individual models are assumed to be correlated since Margin and MNFCap are determined simultaneously for each plant. Therefore, we employ non-linear system equation techniques to estimate the above three systems because Model 1, the common component of these three systems is a non-linear model - a logistic form. The estimation procedure we use is the nonlinear system of equations method.
Econometric Estimation: Robustness Checks

We address several econometric issues to ensure unbiased and consistent estimation of our models. Since the plants in our sample are quite diverse in terms of plant size (ranging from 20 to 1000 employees), we address heterogeneity in two ways. First, we group the plants into seven industry sectors based on their NAICS codes (see Table 1) and conduct DEA efficiency estimation for each industry sector separately. This ensures that plant capabilities are based on evaluations against their peers in the same industry. Second, we control for several sources of heterogeneity by including plant size, age, and plant ownership in our regression models.

A concomitant phenomenon of having a heterogeneous sample of plants is heteroscedasticity. In order to address this issue, we first compute the Breush-Pagan statistics for all models. In Model 1, we observe the presence of heteroscedasticity with a test statistic of 25.34 ($p < 0.05$). Accordingly, for the systems of equations results, heteroscedasticity-adjusted standard errors are reported in Table 5. Another possible source of heteroscedasticity is the cluster structure present in our data, i.e., the seven industries that represent our sample plants. Intuitively, plants in the same industry will exhibit similar characteristics, resulting in heteroscedasticity of their error terms. Hence, we further adjust the standard errors with cluster-robust standard errors (Wooldridge 2010) using the clustered regression on our models and report separate clustered regression results for Models 1 through 4 in Table 6.

One may argue that our main variable of interest, MNFCap, may be subject to potential endogeneity, as plants with higher profitability are likely to invest greater resources to improve their manufacturing capability. We maintain that endogeneity is unlikely to be a significant concern here because MNFCap is not an observable decision variable in our model. Recall that we define capability as a plant’s relative efficiency in converting its inputs into outputs. Since MNFCap is a relative and unobservable measure, this suggests that plants may not be able to directly manipulate or endogenously determine their capability levels to yield an optimal level of performance.

Nevertheless, we follow the approach described in Bharadwaj et al. (2007) and Mani et al. (2010) to account for other potential sources of endogeneity. This is achieved by applying the two-step Heckman procedure. Wooldridge (2010) differentiate four types of causes of endogeneity: measurement error, omitted variable, simultaneity and self selection bias. The Heckit approach is most appropriate to address the endogeneity resulting from the self-selection bias (Heckman 1976; Heckman 1979). In the first step, we obtain the inverse Mill’s ratio ($\lambda$) based on a first-stage logit model with an estimation equation $P(y_2=1 | X_2) = \Phi(X_2\beta_2)$. Then the inverse Mill’s ratio is estimated as $\lambda^* = \lambda(X_2\beta_2^*) = (\Phi(X_2\beta_2^*)/(\Phi(X_2\beta_2^*))$. $\Phi(.)$ and $\Phi(.)$ denote the probability density and cumulative distribution functions of a standard normal distribution, respectively. $X_1$, $X_2$ are observed vectors of explanatory variables. In addition, whenever $y_1$ is observed $y_2$ takes the value of 1 and 0 otherwise. In the second step, we obtain $\beta^*$ and $\gamma^*$, from the clustered regression model of $E(y_1 | X_1, y_2=1) = X_1\beta_1 + \gamma_1\lambda(X_2\beta_2^*)$. Incorporating $\lambda$ the inverse Mills ratio, into the second stage model accounts for endogeneity (Wooldridge 2010).

However, we note that the inverse Mill’s ratio is prone to collinearity, leading to incorrect standard errors in the second stage (Dow and Norton 2003; Leung and Yu 1996). To overcome this problem, we impose an exclusion restriction in the second stage equation in order to increase the variation in $\lambda$. This can be achieved by adding at least one exogenous explanatory variable to the selection model (Leung and Yu 1996; Little and Rubin 1987). Hence, we add four exogenous variables available in our data. These variables include the degree to which a plant outsourced its production functions (ProdOut), degree to which a plant outsourced its supply chain functions (SuppOut), a binary indicator variable if a plant’s primary strategy is to focus on cost reduction (LowCost), or high quality (HighQual). We describe the results of the Heckman correction approach in the next section.

Results

In this section, we report the estimation results for the 2007 plant data. Table 5 shows the estimation results of the three systems of equations and these results are used to test our research hypotheses. As a robustness check, we also report separate clustered regression results using Heckman approach for Models 1, 2, 3 and 4 in Table 6.
System 1 consists of Models 1 and 2. Note that Model 1 estimates the impact of ITSpendspend on MNFCap, while Model 2 estimates the impact of MNFCap on Margin. It represents a full mediation model where the impact of IT on plant margin is mediated through MNFCap. We observe that the estimation results of System 1 are significant, with an F-value of 2.322 and $R^2 = 0.197$, whereas System 2 is not significant, with an overall F-value of 1.202. These results suggest that MNFCap is a significant determinant of plant profitability and indicates that ITSpendspend alone does not explain a significant portion of the variance in plant profitability.

System 3 consists of Models 1 and 4, where all variables are included. Our estimation results suggest that System 3 is significant with a system F-value of 2.525 and $R^2 = 0.218$. We will mainly refer to the System 3 results with respect to our hypothesis testing below. The estimation results of System 3 show that ITSpendspend has a positive impact on MNFCap ($\delta_2 = 0.103$, $p<0.05$), supporting our hypothesis H1. The robustness of this result is ensured in a separate Logit regression using the Heckman approach where the estimated coefficient is 0.095, significant with a $p$-value = 0.05 as shown in Table 6. This shows that a 1% increase in ITSpendspend increases the odds ratio of being “manufacturing capable” by 10.3%. In other words, a 1% increase in ITSpendspend is associated with a 10% increase in the likelihood of a plant being fully efficient.

### Table 5. System of Equations Estimation Results for 2007

<table>
<thead>
<tr>
<th>Model Number</th>
<th>System 1 with NonLinear OLS</th>
<th>System 2 with NonLinear OLS</th>
<th>System 3 with NonLinear OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.02</td>
<td>36.287***</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(1.27)</td>
<td>(8.84)</td>
<td>(1.27)</td>
</tr>
<tr>
<td>MnfCap</td>
<td>-</td>
<td>15.711***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.582)</td>
<td></td>
</tr>
<tr>
<td>IT Spending</td>
<td>0.103**</td>
<td>-</td>
<td>0.103**</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td></td>
<td>(0.051)</td>
</tr>
<tr>
<td>Capex</td>
<td>0.017</td>
<td>0.529**</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.252)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.218*</td>
<td>-1.021</td>
<td>-0.218*</td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(1.085)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.02</td>
<td>0.061</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.278)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Plant Type</td>
<td>-0.433</td>
<td>-0.914</td>
<td>-0.433</td>
</tr>
<tr>
<td></td>
<td>(0.377)</td>
<td>(2.594)</td>
<td>(0.377)</td>
</tr>
<tr>
<td>System F-Val</td>
<td>2.322</td>
<td>1.202</td>
<td>2.525</td>
</tr>
<tr>
<td>System $R^2$</td>
<td>0.197</td>
<td>0.113</td>
<td>0.218</td>
</tr>
<tr>
<td>System Adj $R^2$</td>
<td>0.112</td>
<td>0.019</td>
<td>0.131</td>
</tr>
<tr>
<td>Objective</td>
<td>274.43</td>
<td>303.10</td>
<td>267.31</td>
</tr>
<tr>
<td>N</td>
<td>263</td>
<td>263</td>
<td>263</td>
</tr>
</tbody>
</table>

Industry dummies are included in all estimation models.

* Significant at $p < 0.10$; ** at $p < 0.05$; and *** at $p < 0.10$. Standard errors are shown in parentheses.

Next, MNFCap is positively associated with Margin and significant ($\delta_1 = 14.912$, $p<0.01$), supporting our Hypothesis H2. This result suggests that efficient (capable) plants exhibit a 14.9% higher gross margin, compared to plants with inefficient manufacturing processes. This positive relationship remains consistent when Model 4 is separately estimated with a clustered regression using the Heckman approach. Hypothesis H3 posits that ITSpendspend is positively correlated with plant profitability. Our results suggest that the coefficient of ITSpendspend ($\delta_2 = 1.004$, $p<0.01$) is significant, and indicate that a 1% increase in ITSpendspend increases gross margin by 1.004%.
**Mediation Effect**

To examine the indirect effect of IT spending on profitability, we estimate the linkages between the independent variable (ITSpends), the mediator (MNFCap) and the dependent variable (Margin) simultaneously. This is achieved by estimating System 3 where Models 1 and 4 are estimated simultaneously. The estimated regression coefficients of System 3 are reported in the right-hand panel in Table 5. We observe that the path MNFCap -> Margin is statistically significant at p < 0.01, while ITSpends -> Margin is also significant at p < 0.01.

<table>
<thead>
<tr>
<th>Model Number</th>
<th>Dependent Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MNFCap</td>
<td>Margin</td>
<td>Margin</td>
<td>Margin</td>
<td>Margin</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.051</td>
<td>47.15***</td>
<td>41.465***</td>
<td>34.244***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(8.085)</td>
<td>(6.704)</td>
<td>(11.978)</td>
<td></td>
</tr>
<tr>
<td>MnfCap</td>
<td>-</td>
<td>15.016***</td>
<td>-</td>
<td>14.962***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.884)</td>
<td></td>
<td></td>
<td>(2.043)</td>
<td></td>
</tr>
<tr>
<td>IT Spending</td>
<td>0.095**</td>
<td>-</td>
<td>1.275***</td>
<td>1.041***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td></td>
<td>(0.193)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Capex</td>
<td>0.008</td>
<td>0.457***</td>
<td>0.45***</td>
<td>0.423***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.115)</td>
<td>(0.186)</td>
<td>(0.137)</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>-0.243*</td>
<td>-0.482</td>
<td>-1.907*</td>
<td>-1.436*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(1.2)</td>
<td>(1.16)</td>
<td>(0.94)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.011</td>
<td>0.107</td>
<td>0.055</td>
<td>-0.082</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.197)</td>
<td>(0.257)</td>
<td>(0.2)</td>
<td></td>
</tr>
<tr>
<td>Plant Type</td>
<td>-0.292</td>
<td>-0.01</td>
<td>-2.077</td>
<td>-1.347</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.389)</td>
<td>(1.984)</td>
<td>(2.134)</td>
<td>(1.88)</td>
<td></td>
</tr>
<tr>
<td>Inverse Mill’s Ratio</td>
<td>-</td>
<td>-18.187**</td>
<td>-</td>
<td>2.087</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(9.345)</td>
<td></td>
<td>(9.997)</td>
<td></td>
</tr>
<tr>
<td>ProdOut</td>
<td>0.116</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.212)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SuppOut</td>
<td>0.318**</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.173)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LowCost</td>
<td>0.504*</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.361)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HighQual</td>
<td>0.357</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.398)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-Val (LR for Model 1)</td>
<td>37.012</td>
<td>5.397</td>
<td>2.894</td>
<td>5.332</td>
<td></td>
</tr>
<tr>
<td>R² (AIC for Model 1)</td>
<td>0.286.869</td>
<td>0.203</td>
<td>0.113</td>
<td>0.218</td>
<td></td>
</tr>
<tr>
<td>Adj R² (-2 Log L for Model 1)</td>
<td>254.869</td>
<td>0.165</td>
<td>0.074</td>
<td>0.177</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>263</td>
<td>263</td>
<td>263</td>
<td>263</td>
<td></td>
</tr>
</tbody>
</table>

Industry dummies are included in all estimation models.

* Significant at p < 0.10; ** at p < 0.05; and *** at p < 0.10. Standard errors are shown in parentheses.

Selection model (Model 1) is estimated with a function MNFCap = f(ITSpendingPerSales, CAPEX, ProdOut, SuppOut, LowCost, HighQual, Size, Age, CompType, IndustryDummies) where ProdOut and SuppOut are the summative indexes of the production outsourcing and support outsourcing activities carried out in the plant respectively (Bardhan et al. 2007). Each activity indicator is a binary variable which takes a value of one if the process is outsourced, and zero otherwise. ProdOut includes fabrication, assembly and staging packaging activities. Similarly, SuppOut is measured as a six-item summative index that includes outsourcing of six types of plant support processes: warehousing and distribution, IT, maintenance, transportation, purchasing and customer service. In addition, LowCost is a binary variable that indicates whether a plant’s strategy is to reduce costs (0=no, 1=yes). Similarly, HighQual measures whether a plant’s manufacturing strategy is focused on high quality. Our measurement of these variables is consistent with Bardhan et al. (2007). These four additional variables are introduced to the selection model in order to reduce the collinearity between the Inverse Mill’s Ratio and other explanatory variables in the second model.
To test for the presence of a mediation effect, we perform a Sobel test for a dichotomous mediator (Herr 2006; Kenny 2012; MacKinnon and Dwyer 1993). The Sobel test statistic is equal to 1.93 with a p-value < 0.06. This result suggests that there exists a marginal mediation effect (Baron and Kenny 1986; Sobel 1982). In addition to detecting the presence of mediation, we differentiate whether the effect of IT spending is fully or partially mediated through manufacturing capability. As suggested by Kenny (2012) and Tallon and Pinsonneault (2011), these two types of mediation effects can be tested by comparing the coefficients of IT Spend when the mediator (MNFCap) is included and removed as in Systems 2 and 3, respectively. When MNFCap is included in System 3, we observe a considerable decrease in the impact of IT Spend on the plant profitability, from 1.275 down to 1.004 (t-test for the difference is 7.79). This significant drop in the impact of IT Spend suggests a partial mediation of IT spending through MNFCap on plant profitability, consistent with Baron and Kenny (1986). In other words, IT spending has both direct and indirect effects on plant profitability.

The indirect (mediation) effect is realized by the positive impact of IT spending on manufacturing capability which, in turn, is partially subsumed in the plant capability’s positive association with profitability. Our result provides new evidence on the importance of IT on plant performance by suggesting that IT spending is mediated through the manufacturing capability of a plant leading to greater plant profitability (Banker et al. 2006; Mithas et al. 2005).

The Heckman estimation results in Table 6 are qualitatively consistent with our earlier “system of equations” estimation results and support our main estimation results presented in Table 5.

**IT versus non-IT Capital Expenditures**

In order to study the differential effect of IT versus non-IT capital expenditures on plant profitability, we also include Capex as a regressor in our systems of equation estimation models. In Model 1 of System 1, Capex is not significantly associated with plant MNFCap ($\alpha_3 = 0.017$). Based on this result, we cannot infer a mediation effect of non-IT capital expenditures on plant profitability. On the other hand, in System 3, Capex is significantly associated with an increase in plant profitability ($\alpha_3 = 0.419$, p-value<0.05), Hence, a 1% increase in Capex is associated with a 0.42% increase in plant Margin. We observe that the magnitude of Capex is much lower than the magnitude of IT Spend. In other words, the impact of IT spending on plant profitability (increase of 2.62% in Margin) is five times more than that of Capex when the mediation effect for IT spending is taken into account.

Our estimation results for the 2006 plant data are not shown due to space limitations. These results are qualitatively consistent with our main results presented earlier and support our hypotheses and findings related to the mediation impact of manufacturing capability on the relationship between IT spending and plant profitability.

**Conclusions**

There are few empirical studies in the literature that are based on actual plant-level data to study manufacturing capabilities. The contributions of this study are two-fold: First, we develop a measure of plant manufacturing capabilities using a multi-input, multi-output framework, based on observed plant data. Our methodology is an improvement over earlier studies that measure plant capabilities using perceptual, qualitative measures of plant performance which focus primarily on plant outputs without considering the input resources that are expended to obtain these outcomes. Second, we estimate the relationship between IT spending and manufacturing capabilities on the profitability of plants, and provide empirical validation of the mediation role of manufacturing capabilities.

We observe that manufacturing capabilities are key drivers of plant performance. Our results suggest that it pays off for plants to improve their manufacturing capabilities relative to their peers. Our findings indicate that the effect of IT on plant performance is partially mediated through their enablement of plants’ manufacturing capabilities.

Our study is not without limitations and our results should be interpreted within the scope of this study. Due to the cross-sectional nature of our data, our findings entail only associational patterns. It is important to extend this work in future studies using panel data to evaluate causal relationships across a
multi-year time period. Although we do not have access to panel data, the associational patterns in this
study provide a starting point for future longitudinal studies. In addition, our results reported here for
2007 were validated with a second year of cross-sectional plant data from 2006. These results were
consistent with our main findings and provide yet another piece of evidence of the robustness of our
analyses.

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