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Using Electronic Data Interchange (EDI) to Improve the Efficiency of Accounting Transactions

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ABSTRACT: Electronic data interchange (EDI) is an information technology that standardizes the exchange of information between transacting parties. Using data from a major U.S. office furniture manufacturer that adopted EDI primarily to improve the efficiency of accounting transactions, we evaluate whether EDI reduces order-processing time (the time from sales order receipt to sales order scheduling) and whether this improvement is greater for more complex orders. Our measure of complexity reflects both the mix of different products the dealer orders as well as features and options the dealer selects for each product in the order. We find that EDI is associated with faster order processing, independent of complexity, and that EDI mitigates most of the negative effects of complexity on processing time. We also find that dealers learn to submit error-free orders to the manufacturer, and that previous errors provide feedback that helps dealers submit more accurate orders. However, we find only mixed evidence that order complexity impedes learning.

Keywords: *accounting information systems; complexity; learning; transaction costs.*

Data Availability: *All data are the property of the company. The authors are not permitted to redistribute the data.*

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I. INTRODUCTION

Electronic data interchange (EDI) is an information technology that standardizes the exchange of information between two parties to a transaction. Cushing and Romney (1994) classify EDI as a ''transactional'' accounting information system that reduces the cost of transactions between firms and provides timely information for decision making. Respondents to an AICPA survey judged EDI to be the most important information technology for the accounting profession, in terms of both organizational productivity and projected impact on the work of the professional accountant (Anonymous 1995).[1] However, there is little evidence that EDI improves the performance of administrative work (e.g., Borthick and Roth 1993).

This study uses data from a large, office furniture manufacturing firm to evaluate the performance effects of EDI. The firm adopted EDI primarily to improve the efficiency of accounting transactions with many of the licensed dealers who order its products (e.g., to expedite acknowledgment of customer orders and to reduce order and billing errors).[2] We evaluate whether EDI reduces order-processing time (the time from order receipt to order scheduling), and whether this improvement is greater for more complex orders. Our measure of complexity reflects both the mix of different products the dealer orders as well as features and options the dealer selects for each product in the order. Data limitations prevent us from determining whether EDI reduced the level of order errors as compared to conventional order submission methods. However, we are able to investigate whether dealers who adopt EDI submit fewer orders with errors over time and with experience (i.e., learning), whether feedback from the EDI system on the dealer's prior errors stimulates their learning, and whether order complexity impedes learning.

Research in accounting and operations management has documented that the production of complex products reduces manufacturing performance, measured as productivity, cost, and quality (Banker et al. 1990; Banker et al. 1995; Foster and Gupta 1990; Banker and Johnston 1993; Datar et al. 1993; Noreen and Soderstrom 1994; Anderson 1995, 2001; Ittner and MacDuffie 1995; MacDuffie et al. 1996; Ittner et al. 1997). Several studies also consider how technology and management practices affect the relation between product complexity and manufacturing performance. In their study of 70 automotive assembly plants, MacDuffie et al. (1996) find that differences in the sophistication of information technology and the extent to which the plants use advanced manufacturing practices account for differences in the effect of complexity on plant performance. Specifically, plants that employ ''lean'' manufacturing methods ''seem to be more capable of minimizing the complexity penalty arising from higher product variety than traditional mass production plants'' (MacDuffie et al. 1996, 364). This is consistent with Sakurai's (1990) description of Japanese manufacturers who pioneered advanced manufacturing methods to ''overcome the high cost of producing lower volumes and a wider variety of products.'' In a study of three textile-manufacturing plants, Anderson (1995) finds that the plant where complexity is the norm has a lower marginal cost of complexity than the two plants with less complex product mixes. She posits that managers may ''learn'' to accommodate complexity, with the associated costs of complexity declining as learning takes place.

[1] Tsay (1993, 20) describes the accounting applications of EDI: ''An important task of accounting information systems is to support business operations. Source data automation allows an EDI-integrated accounting system to provide timely information that supports management decision making.''

[2] We use the term ''dealer'' for the firm that orders products directly from the furniture manufacturer. The term ''customer'' refers to the end-user of the product. Typically, the customer places an order with the dealer.

In this study, we use data on more than 1.5 million orders submitted through either EDI or conventional methods to investigate whether information technology—in this case EDI—reduces the negative effects of complexity on administrative processes. We find strong support for the hypotheses that order complexity slows order processing and that, independent of order complexity, EDI is associated with faster order processing. We also find that the benefits of EDI, in terms of faster order-processing times, increase in order complexity. The benefit of EDI that increases with order complexity offsets most of the negative effect of order complexity, supporting the proposition that information technologies may render the notion of ''complexity'' obsolete. Unfortunately, when EDI orders contain errors, the time to correct the errors offsets most of the improvement associated with EDI submission. We find that dealers who adopt EDI learn to submit error-free orders over time and with experience, and that errors in prior periods provide feedback that improves current period performance. We find only mixed support for the hypothesis that order complexity impedes learning.

Our findings have several implications for accounting research and practice. First, research in the operations and the information technology literatures documents benefits of EDI in manufacturing (e.g., reduced inventory holding and spoilage, faster delivery). However, there is no evidence on how EDI affects its primary users—back office, accounting functions of the firm and its transaction partners. We provide evidence that EDI improves performance of administrative work in the adopting firm; however, evidence on how EDI affects the back office operations of transacting partners is still needed.

Second, evidence that order complexity impairs performance in an administrative setting (e.g., slower order completion by the furniture manufacturer and increased errors by dealers) is consistent with earlier evidence that product and process complexity impair manufacturing performance. Our findings suggest that research that focuses on the effect of these characteristics only on manufacturing efficiency underestimates the effects of product and process complexity on firm performance.

Third, evidence that performance improvements associated with EDI increase with order complexity has implications for investment justification. Our results indicate that in addition to making the traditional order-entry process more efficient, EDI also mitigates the negative effect of order complexity on order-entry time. The implication for accountants is that, as with advanced manufacturing technologies, information technologies that enhance flexibility and reduce economies of scale in administrative work may require different evaluation approaches than other capital investments.[3]

Finally, evidence that dealers learn, with time and experience, to submit error-free orders through EDI and that feedback about prior errors helps dealers learn, has implications for the design and implementation of new accounting information systems. Recent experimental research in accounting has explored the role of feedback on learning (e.g., Hirst et al. 1999). Our finding that experience and feedback on prior errors stimulates learning in the EDI task environment is consistent with theory.[4] An implication for accounting system designers is that feedback is an important feature that may reduce the payback period for

[3] Kaplan (1986) and Sakurai (1990) discuss how traditional capital investment analysis may cause manufacturing firms to underinvest in technologies that enhance flexibility and reduce economies of scale. Miller and O'Leary (2002) provide a detailed case study of how one firm replaced an obsolete approach to capital investment evaluation in recognition of these problems.

[4] Fine (1986) and Li and Rajagopalan (1997) discuss the theory of how quality failures influence the traditional economic model of the learning curve. Libby (1981) reviews the psychology and accounting literatures on how cues, such as those provided by EDI data entry forms, and feedback influence individual learning in a variety of task environments.

information technology investments. Moreover, although the furniture manufacturer did not train its dealers to use the EDI system, the negative performance effects associated with errors suggests that dealer training may have further enhanced returns to this investment.

The paper is organized in six sections. In Section II, we review the literatures on the performance consequences of product and process complexity and of information technology investments and develop the research hypotheses. Section III describes the field research setting. We develop our empirical models for testing the hypotheses in Section IV, and present the results of the analysis in Section V. Section VI concludes with a brief summary.

II. LITERATURE REVIEW AND RESEARCH HYPOTHESES

Literature Review

Accounting researchers have proposed that overhead costs are more related to the transactions caused by increasingly complex product mixes and varied production processes than to the volume of production (Miller and Vollmann 1985; Johnson and Kaplan 1987). In general, empirical management accounting research finds that overhead costs and operational performance (e.g., quality, productivity) vary both with the complexity of process transactions (activities) and with production volume (Banker et al. 1990; Banker et al. 1995; Banker and Johnston 1993; Datar et al. 1993; Anderson 1995, 2001; Ittner and MacDuffie 1995; and Ittner et al. 1997, all provide supporting evidence; Foster and Gupta 1990; Noreen and Soderstrom 1994; Maher and Marais 1998, all offer contradictory evidence). However, with the exception of studies of airline costs (Banker and Johnston 1993) and hospital costs (Noreen and Soderstrom 1994; Maher and Marais 1998), empirical research has focused on overhead that is incurred in the factory and allocated to products as ‘‘cost of goods sold.’’ As Johnson and Kaplan (1987, 244) confess:

> [W]e have been as guilty as conventional product cost systems in focusing narrowly on costs incurred only in the factory. Manufacturing costs may be important, but they are only a portion of the total costs of producing a product and delivering it to a customer. Many costs are incurred ‘‘below the line’’ (the gross margin line), particularly marketing, distribution, and service expenses.

In this paper, we evaluate the effect of complexity on administrative work (order processing) rather than manufacturing work.

Researchers have argued that advanced manufacturing technologies—including information technologies (IT) such as computer-integrated manufacturing and other factory automation—reduce the marginal cost of complexity in manufacturing (Sakurai 1990; MacDuffie et al. 1996). Discussing mechanisms through which IT increases productivity, King (1998, 70) argues that it is:

> not just increases in computing speeds and capacities or decreases in computing costs, but new ways of using computers....Among the important drivers are the integrated philosophies of...enterprise systems, mass customization, [and] integrated logistics.

Information technology often enhances customer value in ways that are not captured by conventional performance measures (e.g., increased product variety, improved delivery time and personalized service) (Brynjolfsson 1993, 1996). These observations echo assertions in the literature (Piore and Sabel 1984; Abernathy and Clark 1985; Pine 1993; Brynjolfsson 1996) that IT reduces the cost of complexity and negates the competitive advantage of economies of scale. However, we know of no empirical evidence on the proposition that complexity affects administrative work or that IT reduces the marginal effect of complexity on performance in administrative functions. In this paper we analyze how the introduction of one information technology, EDI, affects the relation between complexity and performance.

EDI technology allows business partners with recurring transactions to establish secure computer-to-computer exchange of data in standard formats. Although some have described EDI as the precursor to e-commerce (e.g., the use of the Internet to advertise, transact sales, and collect customer data), EDI differs from e-commerce in its closed community of pre-defined trading relationships. According to a 1995 study by the U.S. Department of Labor and the Internal Revenue Service, about 40,000 firms use EDI (cited in Socka 1996). EDI modifies traditional accounting information systems and alters the work of accountants (Tsay 1993; Clolery 1994; Cushing and Romney 1994; Bellone 1997). Perhaps more important, as an interorganizational system it is at the forefront of an important emerging area in accounting research—accounting across the boundaries of firms. As Kinney (2001) commented on the future of accounting research:

> We need to consider updating the accounting model to...measure and report on entities with ''cloudy boundaries.''...[h]ow should we account for an entity whose ''inventory'' is owned by another party and whose ''fixed assets'' are owned by a trading partner?

Hopwood (1996), Scapens and Bromwich (2001), and Anderson and Sedatole (forthcoming) extend Kinney's remarks, arguing that the need for new management accounting practices in the ''extended enterprise'' is equally compelling, and presenting evidence that firms are responding to this need.[5]

The operations management and the information systems literatures yield consistent but incomplete, evidence on the benefits of EDI investments. Weill (1992) finds that the firm that is at the hub of the EDI network enjoys increased productivity and profits. Mukhopadhyay et al. (1995) estimate the dollar value of improved information exchanges between Chrysler Company and its suppliers as approximately \$100 per vehicle, or \$220 million for Chrysler. They find that EDI is associated with higher inventory turnover and lower obsolete inventory write-offs and premium shipping costs. Turning to effects on suppliers that transact with the hub firm, Kekre and Mukhopadhyay (1992) find in a study of a steel manufacturer and 65 of its suppliers that suppliers that adopt EDI maintain less inventory and earn higher subjective quality ratings and overall performance ratings from the steel manufacturer than do suppliers that use manual processes. Similarly, Srinivasan et al. (1994) conclude that integrated EDI systems reduce Chrysler's suppliers' shipping errors.

Although these studies find that the more timely, accurate information that EDI provides yields improvements in *manufacturing* performance, they are silent on the question that arises in the IT literature: Does EDI improve the *administrative* work of document processing? Mukhopadhyay et al. (1995) add \$5 per EDI transaction to their empirical estimates of operational improvements (or \$40 of the claimed \$100 per vehicle savings associated with EDI) to reflect savings that managers at Chrysler believe they obtain with reduced document-processing work. Riggins and Mukhopadhyay (1994) find faster processing time for managers and buyers when buyers send orders to suppliers via an EDI automated vendor system vs. traditional methods. However, it is difficult to draw a general conclusion that EDI improves performance because, as Kauffman (1988) finds, selective use of technology (e.g., some suppliers use EDI and others do not) tends to generate selection bias between

[5] Accounting research that investigates accounting across firm boundaries includes Otley (1994), Gietzmann (1996), Seal et al. (1999), Anderson et al. (2000), Van der Meer-Kooistra and Vosselman (2000), Groot and Merchant (2000), Baiman et al. (2001), Tomkins (2001), Baiman and Rajan (2002), and Kulp (2002).

transactions that do and do not use the technology. For example, Kaufmann (1988) found that customers with complex transactions are more likely to use bank tellers, whereas those with simpler transactions use ATMs. Thus, it is unclear whether EDI improves performance independent of the complexity of the orders transmitted, or whether EDI-related improvements increase with order complexity, or both. This distinction is essential to understanding whether EDI can potentially render notions of complexity obsolete by mitigating the effect of complexity on the performance of order-entry work.

Order Complexity and Order-Processing Performance

We consider two aspects of order complexity. *Product* complexity refers to the detail required to describe a particular order at the time of order entry. This includes both the mix of products the dealer orders as well as the detailed specification of options and features for each product in the order. For EDI orders, it is primarily dealers who experience product complexity when they enter a detailed order into the electronic order system. For orders that arrive through conventional channels (e.g., mail or fax), both the dealer, who completes the paper order form, and the office furniture manufacturer's (hereafter, OFM) employees, who enter the detailed order into the electronic order system, experience product complexity. *Process* complexity, on the other hand, refers to alternative administrative paths that some orders must follow *after* they are received by OFM and before they are considered complete.[6] OFM experiences process complexity primarily as additional manual work that slows completion of an order. Dealers experience process complexity only to the extent that for some processes it is their responsibility to indicate that OFM must perform additional processes on the orders they submit. Thus, for a dealer, process complexity is similar to product complexity—an attribute or feature of the product that they must specify on the order. The need to process an order through additional manual workstations is unrelated to whether the order arrives through EDI or conventional channels. As a result, we hypothesize that for OFM, EDI reduces the time for order entry of all orders, and that this reduction increases in product complexity. We do not hypothesize that EDI alters the relation between performance and process complexity for OFM, because EDI does not alter an order's path to completion. Thus, we test the following hypotheses:

H1a: Both product and process complexity reduce administrative performance.

H1b: Transactions that arrive through EDI channels (without error) are completed with better performance than are orders that arrive through conventional order channels, independent of order complexity.

H1c: The performance improvements associated with the use of EDI channels (without error) are greater for transactions with greater product complexity as compared to conventional order channels.

We test H1a to confirm that order complexity impairs performance. We test H1b to determine whether EDI improves transactions processing.[7] Even if the benefits of EDI were

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[6] A completed order represents OFM's acknowledged commitment to produce and deliver on a specified date the products that a dealer orders. Completed orders are transmitted electronically to OFM's manufacturing group.

[7] One problem with estimating the effects of firm practices on performance is that firms choose to adopt a new practice endogenously. If all firms are in equilibrium, then we should observe no difference between the performance of adopters and non-adopters. However, in this paper, we define "performance" more narrowly. Because we do not have data on the cost of adoption or the financial benefits of adoption, we cannot assess whether adoption was optimal. We therefore limit our analysis to the question of operational performance improvements.

confined narrowly to eliminating order entry at OFM (because dealers enter orders directly into a common electronic order-entry system rather than submitting paper orders), we would expect the data to support this hypothesis. We test H1c to determine whether the benefits of EDI increase in proportion to the (product) complexity of the orders that OFM processes. Evidence of this relation would support claims that information technology such as EDI significantly reduces the extent to which complexity impairs performance. We refer to H1a–H1c together as H1, the ''Direct Effect Hypothesis.''

EDI and Order Errors

Another reason OFM adopted EDI was to reduce billing and order errors between itself and its dealers. If order complexity reduces the efficiency with which OFM completes orders, then it is also likely to reduce the performance of dealers submitting orders.[8] We do not have access to OFM's dealers or to information on the efficiency effects of EDI at the dealer level. We also do not have data on errors in orders submitted through conventional order channels that would permit us to compare the incidence of errors in EDI *vis-à-vis* conventional channels. However, we do have data on errors in orders that dealers submitted through EDI channels and, by relating these orders to the dealers who submitted them, we can investigate whether dealers who adopt EDI learn to submit error-free orders. Previous research has identified errors in the use of EDI as an important explanation of failures to realize anticipated benefits of the technology. Riggins and Mukhopadhyay (1994) find that suppliers are unlikely to support EDI implementation absent a subsidy or coercive threat from the EDI adopter, and once suppliers decide to adopt EDI, they have little motivation to master the technology.

The data also permit us to explore correlates of learning. Jovanovic and Nyarko (1995) argue that task complexity reduces the speed of learning. Anderson (1995) reports weak evidence that experience in producing a complex product mix is associated with lower marginal costs of complexity. Thus, we investigate whether order complexity impairs learning. The quality literature suggests prior-period errors also affect learning. Fine (1986) modifies the traditional approach to measuring learning as cumulative output by including only cumulative *good-quality* output. Kini (in an unpublished dissertation cited in Li and Rajagopalan [1997]) refines this further, suggesting that good- and bad-quality output influence learning in different ways. Li and Rajagopalan (1997) provide empirical evidence that bad-quality output increases learning, and they conclude that defective units are statistically more significant than good output in explaining learning curves. These models are particularly appropriate in an EDI context because, in contrast to conventional order submission methods, EDI generates an electronic report for the dealer on all changes required to make an EDI order comply with OFM requirements—changes that may or may not have required communication with the dealer. Thus, EDI supports more feedback and error diagnosis than is available for orders placed through conventional channels.

In our setting, dealers repeatedly use EDI to transmit information of varying complexity. There is little motivation to obtain training in the technology and learning is strictly by

[8] Typically a large firm adopts EDI and encourages smaller transacting partners (at times with the threat of lost business) to become EDI-compliant. Although EDI is associated with benefits for the adopting firm, anecdotal evidence on benefits to transacting partners is less encouraging (e.g., Zeidner 1994; Socka 1996). Riggins and Mukhopadhyay (1994) explore asymmetries in performance improvements between an EDI adopter and its transactions partners and conclude that reduced document-processing times are concentrated at the EDI adopter. A survey by Stern and Kaufmann (1985) reveals that trading partners who adopt EDI believe that the initiating firm gains more from the investment. Although OFM did not require EDI adoption, and we did not detect coercion in our field investigations, OFM also did not provide or subsidize dealer training in the technology.

''doing''; however, errors from prior periods may facilitate dealer learning. Applying the arguments above to our setting, we hypothesize:

H2a: Dealer errors in EDI order submission reduce the performance benefits of EDI to OFM.

H2b: Dealer learning and feedback on prior period errors lead to fewer dealer errors in EDI order submission.

H2c: Order complexity impairs the rate of dealer learning.

We test H2a to confirm that errors in EDI order submission reduce administrative performance at OFM. We test H2b and H2c to determine whether EDI is subject to dealer learning effects, and if so, whether order complexity impairs this learning. Together these hypotheses provide evidence on indirect effects of complexity and the EDI technology on OFM's performance. We refer to H2b and H2c collectively as H2, the ''Indirect Effect Hypothesis.''

III. THE RESEARCH SETTING

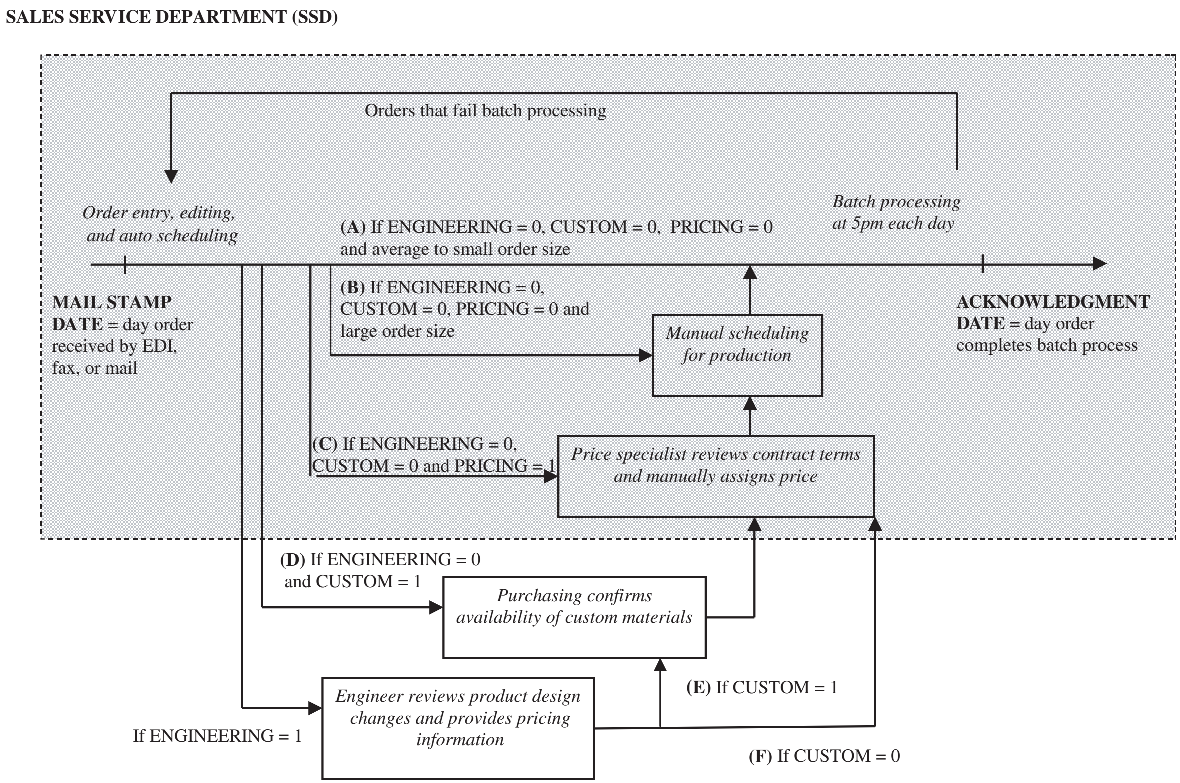
OFM provides data for the study. OFM offers more than 65,000 standard products in more than 70 paint colors, dozens of laminate surfaces, and hundreds of upholstery fabrics. Independent dealers help end-users (customers) plan office configurations, submit orders, and receive and install small orders. OFM and many of its more than 500 independent dealers have adopted EDI.

The field research setting is OFM's central Sales Service Department (SSD). SSD is the point of contact between OFM and its dealers. This group receives all orders, enters them (in a process called ''order editing'') into the information system that controls production scheduling and dealer billing, manually processes nonroutine orders, and acknowledges planned shipments to dealers. Figure 1 depicts the process flow from the date that OFM receives the order (mail stamp date) to the date that OFM commits to produce the order (acknowledgment date). The Appendix describes the paths shown in Figure 1. Processes shown in the shaded area of Figure 1 correspond to activities that are the responsibility of SSD; processes outside this area are the responsibility of other groups. The difference between the mail stamp date and the acknowledgment date is the total order completion time. OFM terms this difference ''acknowledgment delay,'' closely monitors it, and uses it to evaluate SSD's performance.[9]

Inputs to the order-entry process are labor and capital. Throughout the period, labor capacity was stable, with approximately 87 nonsupervisory salaried employees. OFM fully used capacity throughout the period; the order-entry queue was never empty. Employee head-count varied only slightly (a range of 82–90) and variation reflects short-lived, idiosyncratic circumstances rather than systematic efforts to alter the number of servers. Prior to 1993, OFM adopted EDI to transmit data (e.g., customer orders, invoices, and other dealer communications) to and from its dealers. Although it expected EDI to enhance SSD productivity by transferring key-entry tasks to dealers, the primary reason for adopting EDI was to improve the efficiency of accounting transactions (e.g., to expedite acknowledgment of customer orders, to reduce the length of the billing cycle, and to reduce order and billing

[9] Managers of SSD do not use cost information for performance measurement or control purposes, because the department's costs do not change from period to period. They limit their analysis of acknowledgment delay data to studying simple trends and to partitioning orders into priority classes (described in the Appendix) to determine whether the orders met acknowledgment delay goals.

FIGURE 1
OFM's Order-Entry Process



Definition of partitioning indicator variables when equal to 1:

CUSTOM = pseudo-orders with at least one custom material;
ENGINEERING = pseudo-orders that require engineering design changes;
PRICING = pseudo-orders that require manual pricing;
ORDERSIZE = psuedo-orders in the top quartile for all orders of net discounted value;

errors). Delayed acknowledgments undermine OFM's strategies of quick-shipping standard products and of filling other orders more rapidly than its competitors. Order errors and resulting incomplete or incorrect shipments cause misuse of production capacity and increased transportation, inventory holding, and rework costs, and also cause customer dissatisfaction. EDI implementation by OFM's dealers was gradual and voluntary, with OFM giving priority to dealers with the highest sales volume.

In theory, EDI orders are transmitted electronically to the order-processing system and require little work by an order editor (whose tasks are described in the Appendix), whereas paper orders require painstaking manual data entry. In practice, both EDI and paper orders require significant intervention by the order editor to correct dealer errors and to respond to unusual customer demands reflected in the dealer's order.[10] One form of order editor intervention is splitting orders into two or more "pseudo-orders." The order editor's objective is to minimize acknowledgment delays, subject to constraints on the sequence in which he edits the orders (i.e., queue priorities). Order splitting, described in the Appendix, helps achieve this objective by creating two or more orders that are more easily scheduled.

Our analysis includes all pseudo-orders with an acknowledgment delay of between one and 20 days and we focus on the SSD's performance in processing these pseudo-orders. Therefore, for the remainder of the paper we use the term "order" in place of "pseudo-order." We exclude orders with acknowledgment delays greater than 20 days because they represent problems that require atypical processing. During the three-year period, SSD processed 1,619,396 orders, of which 1,532,354 orders satisfy the acknowledgment delay requirement above.[11]

Table 1 provides descriptive statistics on the flow of the 1.5 million orders (of which 28 percent were from split orders) over each process path (described in detail in the Appendix) and associated acknowledgment delays for the orders included in our subsequent analyses. The average order acknowledgement delay is just under three days, although it is higher for orders that require pricing quotes, engineering quotes, or include some type of customization. The results in Table 1 show that most orders require some type of manual processing (pricing quotes, custom orders quotes, or engineering quotes). The Appendix describes the process flow and relates each path to the associated descriptive statistics. Finally, data in Table 1 show that dealers submit most orders (86 percent) through EDI and about 20 percent of these submissions have errors.

Managers of SSD have generally been satisfied with the department's performance and have no plans to alter what has been a stable complement of employees; however, they are quick to discuss two countervailing forces on performance during the period of study. First, they believe that as orders became more complex (given OFM's strategy of proliferating products and variations), service performance suffered. Order complexity led to a larger menu of products and options with which order editors must be familiar—what we term "product complexity"—as well as in manual processes that induce "process complexity" in response to custom orders. Second, although SSD's managers believe that EDI offsets some of these adverse effects on service performance, they caution that dealer errors in using the EDI technology have been costly to OFM. In sum, managers of SSD found our hypotheses plausible, although they had no evidence to support their intuition.

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[10] An order editor may detect dealer errors that include omissions, such as failure to specify a color or fabric for an upholstered chair, failure to select from a list of options, or selection of options that are inadmissible for a particular product. The order editor does not detect errors that are logically consistent with the product offering (e.g., designation of each part of a chair in a different but admissible color).

[11] We repeated the analyses reported below on the full sample with no qualitative effect on the results.

TABLE 1
Average Acknowledgment Delays and Number of Pseudo-Orders OFM Acknowledged during March 1993–February 1996

Full Sample and Partitions Corresponding to Process Flows in Figure 1	*Figure 1 Process Flow*	*Number of Pseudo-Orders*	*Acknowledgment Delay (Days)* First Quartile	*Median*	*Third Quartile*	*Mean*
Split Orders						
CUSTOM, ENGINEERING, PRICING, ORDERSIZE = 0	A	25,380	1	2	3	2.8
CUSTOM, ENGINEERING, PRICING = 0, ORDERSIZE = 1	B	9,200	1	2	3	2.9
CUSTOM, ENGINEERING = 0, PRICING = 1	C	318,585	2	3	5	3.8
ENGINEERING = 0, CUSTOM = 1	D	19,427	4	6	9	6.7
ENGINEERING = 1, CUSTOM = 1	E	2,241	7	11	15	11.1
ENGINEERING = 1, CUSTOM = 0	F	57,626	5	7	11	8.5
EDIGOOD = 1		261,820	2	3	4	3.8
EDIBAD = 1		107,360	3	5	8	7.5
All Split Orders[a]		432,459	2	3	6	4.5
Unsplit Orders						
CUSTOM, ENGINEERING, PRICING, ORDERSIZE = 0	A	310,645	1	1	2	1.6
CUSTOM, ENGINEERING, PRICING = 0, ORDERSIZE = 1	B	26,234	1	1	2	1.9
CUSTOM, ENGINEERING = 0, PRICING = 1	C	728,016	2	2	3	2.4
ENGINEERING = 0, CUSTOM = 1	D	10,631	3	4	6	5.4
ENGINEERING = 1, CUSTOM = 1	E	982	4	7	11	8.0
ENGINEERING = 1, CUSTOM = 0	F	23,387	4	6	8	6.6
EDIGOOD = 1		780,128	1	2	3	2.1
EDIBAD = 1		165,926	1	2	3	3.0
All Unsplit Orders[a]		1,099,895	1	2	3	2.3
All Orders		1,532,354	1	2	3	2.9

[a] Sample partitions with process flows labeled A–F are exclusive, together reflecting all orders. Figure 1 does not distinguish between split and unsplit orders, between EDI and non-EDI orders, or between EDI orders that contain errors and that those that do not.

Definition of variables:

Acknowledgement Delay = number of days from order receipt at OFM to the date OFM commits to produce the order.

Partitioning indicator variables (when equal to 1):

Split = a large, single order that a dealer submitted to OFM, which an order editor separated into two or more smaller pseudo-orders;
CUSTOM = pseudo-orders with at least one custom material;
ENGINEERING = pseudo-orders that require engineering design changes;
PRICING = pseudo-orders that require manual pricing;
ORDERSIZE = pseudo-orders in the top quartile for all orders of net discounted value;
EDIGOOD = pseudo-orders dealers transmitted to OFM by EDI without error; and
EDIBAD = pseudo-orders dealers transmitted to OFM by EDI that contain errors.

IV. THE EMPIRICAL SPECIFICATION

The data are daily archival records for three fiscal years of all customer orders, and include prices, quantities, product specifications, and the dates on which OFM received, acknowledged, and anticipated shipping the orders. The sales and marketing group of OFM maintains these records and uses them to analyze market trends and customer demand. The group does *not* use these records in production; consequently, the records do not include information about a product's bill of materials, manufacturing process routing, manufacturing performance, or actual shipping date.[12]

The Direct Effect Hypothesis

Our Direct Effect Hypothesis, H1, implies the following:

1. OFM acknowledges less complex orders faster than more complex orders, for a given EDI/non-EDI submission channel;
2. OFM acknowledges error-free orders that dealers submit through EDI channels faster than orders dealers submit through normal channels, for a given level of complexity;
3. For a given *increase* in the level of complexity, OFM acknowledges error-free orders dealers submit through EDI channels faster than orders dealers submit through normal channels.

We make no directional hypotheses for EDI orders that dealers submit with errors, because the net effect of error correction is unclear.

To test the Direct Effect Hypothesis, we first calculate whether OFM acknowledged the order early or late, relative to goals for its priority class. OFM assigns an incoming order one of five priority ranks. As we explain in the Appendix, order priority reflects the anticipated size of the outgoing shipment of manufactured goods as well as OFM strategies for expediting orders of certain standard products. It is not causally related to whether the order arrives by EDI.[13]

For each order, we calculate the difference between the acknowledgment date and the mail stamp date (adjusted for nonbusiness days—weekends and holidays). We label this variable DELAY. For each order, we then subtract the priority-class target completion time (two, three, five, or seven days) from DELAY to determine the extent to which OFM acknowledged an order early or late relative to its defined goal. We label this variable DEVIATION. That is:

$$\text{DELAY} = \text{Acknowledgment Date} - \text{Mail Stamp Date}$$

and

$$\text{DEVIATION} = \text{DELAY} - \text{Priority Class}.$$

Negative values of DEVIATION thus indicate early completion relative to the target, and positive values indicate orders completed late relative to the target.

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[12] A record in the database corresponds to one pseudo-order as defined in the Appendix.

[13] The database does not record the actual priority assigned to incoming orders; however, reasonable proxies exist for three of the five ranks. There is no mechanism for distinguishing the last two categories; however, interviews with sales service representatives indicate that they rarely use one of these two, and that the other category is the base case. Consequently, although two ranks are unidentifiable, after we identify the three priority classes for which proxies are available, we assume that remaining orders are the base case priority, including the few shipments in the category that is rarely used.

We evaluate the Direct Effect Hypothesis by examining the following general relation:

DEVIATION = f(ProductComplexity, ProcessComplexity, EDIGOOD, EDIBAD).

For a given order, we assign the variable EDIGOOD a value of 1 if the dealer submitted an order through EDI without error, and 0 otherwise. Similarly, we set EDIBAD equal to 1 if the dealer submitted an order through EDI with error, and 0 otherwise. ProductComplexity and ProcessComplexity represent measures of order complexity for an individual order.

Several order characteristics contribute to product and process complexity. We consider total lines in the order, finish codes, unique finish codes, price quotes, engineering quotes, custom quotes, and average item cost. Each order consists of one or more lines describing the product. The first line of an order represents the highest level of specification for a product (e.g., chair). Subsequent lines identify product options (e.g., optional chair arms) or, for modular products, the desired product configuration (e.g., one of three available chair pedestals). Each line may include up to five four-digit codes that designate finishes for the product or part to which the line refers. Finishes include paint colors, laminates, and fabrics. A special four-digit finish code indicates a custom material. Because many orders specify identical colors (finishes) for various parts, the number of *unique* finish codes is generally fewer than the number of finish codes for the order. As we discuss in the Appendix, orders that require price quotes, use custom materials, or require special engineering quotes go through processes outside the normal acknowledgment process, which contributes to the process complexity of the order. Finally, we include average item cost as a potential measure of product complexity. This variable reflects the fact that certain complex products (e.g., modular items) require fewer lines to define than does a collection of simpler items (e.g., desk and chairs), but still requires the same amount of work by the order editor.

We use principal components to identify complexity constructs. Analyzing the seven potential measures of complexity, we find two components with eigenvalues greater than 1, and this structure retains about 48 percent of the variance in the set of variables. The first component loads on order lines, finish codes, unique finish codes, and average item cost. We label this component ''product complexity.'' The second component loads on price quotes, engineering quotes, and custom quotes. We label this component ''process complexity.'' The Cronbach alpha for the four product complexity measures is 0.68, indicating a reasonable level of reliability. The Cronbach alpha for the three process complexity measures is unacceptably low; therefore, in the analysis, we use the three process complexity measures individually.[14] Rather than use the factor scores, we compute a product complexity measure by equally weighting values of the standardized measures for the four individual product complexity measures (Grice and Harris 1998).[15]

[14] We also ran the analysis using the process complexity construct in place of the individual measures, with no qualitative changes in the results.

[15] The correlation between the factor score and our computed product complexity measure is 0.96. The results in Grice and Harris (1998) suggest this approach retains many of the desirable features of regression-based factor scores while being less subject to the problems associated with using the same data to estimate the coefficients and to compute the factor scores.

To allow for idiosyncratic events on the individual days of the sample period, the regression includes indicator variables for 746 of the 747 days on which OFM acknowledged orders. The empirical specification for the regression equation we use to test the Direct Effect Hypothesis is:[16]

$$\begin{aligned} \text{DEVIATION} = \alpha &+ \gamma_1 \text{Day}_1 + \cdots + \gamma_{746}\text{Day}_{746} + \beta_1 \text{ProductComplexity} + \beta_2 \text{PriceQuotes} \\ &+ \beta_3 \text{CustomQuotes} + \beta_4 \text{EngineeringQuotes} + \beta_5 \text{EDIGOOD} \\ &+ \beta_6 \text{ProductComplexity} \times \text{EDIGOOD} + \beta_7 \text{EDIBAD} \\ &+ \beta_8 \text{ProductComplexity} \times \text{EDIBAD} + \varepsilon. \end{aligned}$$

The estimated coefficients $\beta_1 ... \beta_4$ measure the effect of complexity on performance, allowing a test of H1a. The estimated coefficient β_5 is the basis for testing H1b, the effect of EDI on performance independent of complexity. The coefficient β_6 is the basis for testing H1c, the mitigating effect of EDI on product complexity. Estimated coefficients β_5, β_6, β_7, and β_8 are the basis for testing H2a, that errors in EDI submission offset, at least in part, the benefits of EDI. Specifically, the hypothesis implies that and that $\beta_5 < \beta_7$ and that $\beta_6 < \beta_8$.

The Indirect Effect Hypothesis

We use data on the incidence of errors in orders that more than 300 dealers submitted through EDI to examine whether EDI adoption is associated with dealer learning, whether EDI-facilitated feedback on prior errors facilitates dealer learning, and whether order complexity impedes learning. Specifically, we compute the proportion, p, of EDI orders a dealer submits each month that are error-free.[17] We create this measure for each dealer who submits EDI orders in at least 10 of the 36 sample months. These monthly EDI orders must satisfy the condition $0 < p < 1$ (i.e., the dealer has submitted some, but not all, EDI orders with errors), because the dependent variable (described below) is undefined unless the condition is satisfied.[18]

We use two measures from the economics literature on learning curves to investigate factors associated with dealer errors in submitting EDI orders: elapsed time, an index reflecting the observation month (index value of 1–36 for the three years); and cumulative experience, measured as the cumulative volume of EDI orders dealers submit, where cumulative volume equals zero in the month immediately before the dealer first used EDI. Elapsed time is an appropriate measure of learning if OFM continually enhances the EDI system or if dealers become more proficient as a result of a series of activities other than order entry (e.g., training classes). Cumulative experience measures "learning-by-doing." Using cumulative errors that dealers made in the past, we examine whether feedback on their past errors reduces the incidence of errors in current orders (Li and Rajagopalan 1997).

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[16] We do not include an interaction term for process complexity and EDI submission because, given the acknowledgement process, there is nothing in the choice of submission channel that can affect the speed of the manual processes. The results we report below are not affected in terms of significance or sign if we include this interaction in the regression.

[17] We investigate the effect of dealer errors in EDI orders, but errors also arise with other submission methods. We have no data on the incidence of errors for other submission methods; consequently, we cannot determine whether errors occur with different frequency when dealers use EDI. Even if data for other order submission methods were available, it would be difficult to separate the technology-related effects from self-selection bias induced by the characteristics of dealers who adopt EDI.

[18] This condition resulted in a loss of two dealers.

We adapt methods that economists have used to detect dynamic scale economies, or what has been termed the ''learning curve,'' to estimate the rate of improvement in order-entry accuracy for EDI-equipped dealers as a function of the two measures of learning (L).[19] Specifically, for each dealer, we estimate:

$$\log(p_t/(1 - p_t)) = \gamma_0 + \gamma_1 L_t + \gamma_2 CE_t + \varepsilon, \quad (1)$$

where p is the proportion of EDI orders that are error-free, L_t is the measure of learning or experience (measured alternately as elapsed time and as cumulative volume of EDI orders submitted).[20] Consistent with H2b, CE_t is the *percentage* of cumulative EDI orders through month t – 1 that had errors. After estimating regression (1) for each dealer, we have a sample of learning rates ($\hat{\gamma}_1$) that we use in our test of the Indirect Effect Hypothesis.

To evaluate the Indirect Effect Hypothesis, we test two (related) hypotheses. The first is simply that dealer learning reduces errors in their EDI orders (which, given H2a, should improve OFM's efficiency and performance). That is, H2b predicts that both γ_1 and γ_2 will be positive. The final step is to evaluate the effect of complexity on dealer learning (H2c). We test the effect of complexity on learning by regressing the estimated learning rate, $\hat{\gamma}_{1j}$, for the jth dealer on the complexity constructs:

$$\hat{\gamma}_{1j} = f(\text{ProductComplexity, PriceQuotes, CustomQuotes, EngineeringQuotes}).$$

As with the Direct Effect Hypothesis, we measure product complexity using a construct based on an equally weighted index of order lines, finish codes, unique finish codes, and order value. We measure process complexity using the three process complexity variables—price quotes, custom quotes, and engineering quotes. Recall that process complexity reflects additional manual work that OFM must perform, regardless of whether the dealer submits the order through EDI or conventional channels. In general, process complexity is invisible to the dealer. However, these three forms of process complexity require the dealer to provide correct additional information about products. As a result, we hypothesize that the effect on learning will be similar to that of product complexity. Hypothesis 2c predicts that complexity impairs dealer learning so we expect both complexity constructs to be negatively related to the learning parameter, $\hat{\gamma}_1$.

V. RESULTS

The Direct Effect Hypothesis

Table 2 reports the correlations among the variables used in the analysis. All the correlations are significant, but they are generally less than 0.30. The positive univariate correlations between DEVIATION and the four complexity variables are consistent with H1a, the negative correlation between DEVIATION and EDIGOOD is consistent with H1b, and the positive correlation between DEVIATION and EDIBAD is consistent with H2a. We expect the interaction of product complexity and EDIGOOD to be negatively related to performance, yet it has a positive univariate correlation, contrary to H1c. In a

[19] Berndt (1991, 66–80) provides an overview of the learning curve literature and discusses econometric issues in estimating rates of learning. Ghemawat (1986) summarizes estimated rates of learning from 97 empirical studies and concludes that manufacturing activities experience greater learning effects than service or administrative activities.

[20] We estimate the learning curves separately for the two learning proxies because of the high correlation between them ($\rho = 0.99$).

TABLE 2

Correlations among the Deviation between Actual and Expected Acknowledgement Delay, EDI Orders Submitted With and Without Error, Product Complexity, Process Complexity, and the Interaction of Error-Free EDI Orders and Product Complexity

(n = 1,532,354)

Variables	*Deviation*	*EDIGOOD*	*EDIBAD*	*Product Complexity*	*Price Quotes*	*Custom Quotes*	*Engineering Quotes*
EDIGOOD	−0.197						
EDIBAD	0.217	−0.679[a]					
Product Complexity	0.059	0.043	−0.040				
Price Quotes	0.151	0.095	−0.031	0.195			
Custom Quotes	0.187	−0.197	0.254	−0.027	0.035		
Engineering Quotes	0.440	−0.256	0.308	0.029	0.045	0.026	
Product Complexity × EDIGOOD	0.025	0.017	−0.012	0.799	0.126	−0.006	0.005

[a] EDIGOOD and EDIBAD are not perfectly (negatively) correlated because some orders are submitted through non-EDI channels.

Definition of variables:

Deviation = difference between actual acknowledgment delay and expected delay based on order priority;
EDIGOOD = percentage orders dealers transmitted by EDI with no errors;
EDIBAD = percentage orders dealers transmitted by EDI with errors;
Product Complexity = an equally weighted index of standardized values of lines per order, number of finish codes, number of unique finish codes, and average item cost;
Price Quotes = percentage of orders completed that require manual pricing;
Custom Quotes = percentage of orders completed that include at least one custom material; and
Engineering Quotes = percentage of orders completed that require manual verification of engineering designs.

univariate correlation, it is not clear whether the positive effect of complexity (increasing DEVIATION) or the negative effect of EDIGOOD (decreasing DEVIATION) will dominate. However, H1c examines the interaction between EDI and complexity, or the effect of EDI on performance for a given increase in complexity.

Turning to the multiple regression analysis, we report the results of estimating the association among acknowledgment delays, order complexity, and EDI use in Table 3.

TABLE 3

Regression Results of the Deviation between Actual and Expected Acknowledgment Delay on Product and Process Complexity, Good and Bad EDI Submissions, and the Interaction between Product Complexity and Good and Bad EDI Submissions

(n = 1,532,354)

$$\begin{aligned} DEVIATION = {} & \alpha + \gamma_1 Day_1 + \cdots + \gamma_{746} Day_{746} + \beta_1 ProductComplexity + \beta_2 PriceQuotes \\ & + \beta_3 CustomQuotes + \beta_4 EngineeringQuotes + \beta_5 EDIGOOD \\ & + \beta_6 ProductComplexity \times EDIGOOD + \beta_7 EDIBAD \\ & + \beta_8 ProductComplexity \times EDIBAD + \varepsilon. \end{aligned}$$

Variables	*Hypothesis*	*Predicted Sign of the Coefficient*	*Estimated Coefficient*	*t-value*
Intercept		?	−1.2663	−1.0
Daily Indicator Variables		?	Not Reported	
Product Complexity (β_1)	H1a	+	0.2718	43.5
Price Quotes (β_2)	H1a	+	0.3175	177.7
Custom Quotes (β_3)	H1a	+	0.3876	215.5
Engineering Quotes (β_4)	H1a	+	1.0219	556.0
EDIGOOD (β_5)	H1b	−	−0.3782	−73.8
Product Complexity × EDIGOOD[a] (β_6)	H1c	−	−0.2281	−33.0
EDIBAD (β_5)	H2a	?	0.0867	11.2
Product Complexity × EDIBAD[a] (β_8)	H2a	?	−0.0650	−10.7
Adjusted R^2			0.268	

[a] The data reject the hypotheses that the coefficient on Product Complexity is equal to either the absolute value of the coefficient on Product Complexity × EDIGOOD or Product Complexity × EDIBAD at the $p < 0.001$ level.

Definition of variables:

Deviation = difference between actual acknowledgment delay and expected delay based on order priority;
Product Complexity = an equally weighted index of standardized values of lines per order, number of finish codes, number of unique finish codes, and average item cost;
Price Quotes = percentage of orders completed that require manual pricing;
Custom Quotes = percentage of orders completed that include at least one custom material;
Engineering Quotes = percentage of orders completed that require manual verification of engineering designs;
EDIGOOD = percentage orders dealers transmitted by EDI with no errors; and
EDIBAD = percentage orders dealers transmitted by EDI with errors.

Although not shown in Table 3, the daily indicator variables are generally not significant at the 10 percent level.[21] The results in Table 3 are consistent with H1a, that order complexity (both product and process complexity) is associated with significant acknowledgment delays. On average, an increase of one unit of product complexity increased acknowledgment delay by 0.27 days. A standard unit of process complexity increased delays by 0.32 to 1.02 days because process complexity often results in processing delays as the order goes through different channels.

The results indicate OFM acknowledged orders that dealers submitted without error via EDI on average about 0.38 days earlier than other orders. OFM acknowledged orders submitted using EDI, but with errors, on average about 0.09 days *later* than other orders.[22] These results suggest EDI improves acknowledgment time if dealers submit orders without error. Thus, the results are also consistent with H1b. The significantly negative coefficient on the interaction between error-free EDI submissions and product complexity (β_6) supports the hypothesis that EDI submissions without error can mitigate a portion of the delay associated with product complexity, H1c. The results in Table 3 suggest that OFM can eliminate most of the delay (0.23 of the 0.27 days) if dealers submit error-free orders via EDI. To test whether good EDI submissions completely offset the adverse effect of product complexity, we test whether the sum of the coefficients on product complexity and the interaction of complexity with good EDI submissions is equal to zero. This hypothesis (that $\beta_1 + \beta_6 = 0$) is rejected at the 0.001 level. Thus, good EDI submissions only partially offset the adverse effects of complexity.[23] Overall, the data support the Direct Effect Hypothesis.

The Indirect Effect Hypothesis

We can also use the results in Table 3 to test H2a, that EDI orders dealers submitted with error reduce the (performance) benefits OFM reaps from EDI. As noted above, submission of orders through EDI channels (with error) increases acknowledgment delay, independent of complexity. Hypothesis 2a suggests more, however. It implies that, first, orders submitted through EDI with error have longer acknowledgment delays than error-free EDI submissions, for a given level of complexity ($\beta_5 < \beta_7$) and, second, the mitigating effect of EDI for complex orders is lower for EDI orders submitted with errors ($\beta_6 < \beta_8$). The results in Table 3 support both implications; thus, the data support H2a.

Table 4, Panel A reports the results of the model designed to test H2b, namely, that dealer learning reduces EDI errors. We estimated the dealer-specific learning regression (1) for various samples of dealers, requiring different minimum numbers of EDI orders submitted in a month. To evaluate the effect of frequency of EDI ordering on the hypothesis, we separately analyzed dealers submitting a minimum of 2, 3, 5, 10, 20, or 30 orders, respectively. As shown in Table 4, Panel A, this resulted in samples of from 329 dealers

[21] We computed variance inflation factors to investigate possible estimation problems due to collinearity in the data. Although there are no formal criteria for evaluating variance inflation factors, the largest variance inflation factor for the variables other than the daily indicator variables is 6.5. This is smaller than the threshold of 10 many econometricians consider to indicate serious collinearity (Kennedy 1992, 183). The variance inflation factors were higher for the daily indicator variables. We re-ran the regression without the daily indicator variables and there was no qualitative (and virtually no quantitative) change in the other results.

[22] We do not have data on errors associated with non-EDI submissions; it is possible that EDI improves performance even for orders submitted with errors.

[23] Although we did not hypothesize any effect that EDI submissions with error would have in mitigating product complexity, the results in Table 3 show that EDI submissions do offset some of the effect of product complexity ($\beta_8 < 0$). We can also reject the hypothesis that EDI submissions with error offset completely the effect of product complexity (the hypothesis that $\beta_1 + \beta_8 = 0$ can be rejected at the $p = 0.001$ level.)

TABLE 4

Analysis of the Relation between Dealers' Experience Using EDI, the Reduction of Dealers' Errors in EDI (Learning), and the Effect of Product and Process Complexity on the Rate of Dealer Learning

Panel A: Analysis of dealer errors in EDI submissions; Z-statistics from tests of the significance of time-based and experience-based learning in EDI order entry across the population of EDI-equipped dealers (H2b)[a]

$$log(p_t/(1 - p_t)) = \gamma_0 + \gamma_1 L_t + \gamma_2 CE_t + \varepsilon$$

Minimum Orders	Number of Dealers	Time-Based Learning		Experienced-Based Learning	
		$Z(\gamma_1)$	$Z(\gamma_2)$	$Z(\gamma_1)$	$Z(\gamma_2)$
2	329	0.66	4.50*	0.23	4.20*
3	328	1.83*	4.74*	1.28	4.40*
5	327	2.87*	5.25*	2.23*	4.80*
10	311	4.39*	5.73*	3.66*	5.11*
20	284	4.19*	5.83*	3.55*	5.21*
30	255	4.05*	5.83*	3.60*	5.45*

* Significant at $p < 0.05$ (one-sided).

[a] For each dealer in the sample, we estimate Equation (1) to develop a sample of regression coefficients and their associated t-statistics. The Z-statistics test the hypothesis that the mean t-statistic is equal to 0 (Patell 1976). The number of EDI orders a dealer places in a month determines the dealer's inclusion in a particular dealer-specific sample. For example, if a dealer places four EDI orders in six months and 20 EDI orders in ten months, we include 16 months of data in the dealer-specific regression for the sample of dealers with at least three orders in a month, but only ten months of data in the dealer-specific regression for the sample of dealers with at least five EDI orders in a month.

Definition of variables:

p = the ratio of error-free EDI orders to the total number of EDI orders dealers submitted;

L = one of two measures of learning:

In the first case, L is an index that indicates the month (1–36) of the observation and β_1 is the rate of time-based learning;

In the second case, L is the cumulative number of EDI orders submitted and β_1 is the rate of experience-based learning; and

CE = CE for month t is the percentage of the dealer's orders from month 1 to t–1 that had errors.

(*Continued on next page*)

TABLE 4 (Continued)

Panel B: Regression estimates of the relation between the (1) rate of learning for dealers submitting EDI orders and (2) average product and process complexity (H2c)

$$\hat{\beta}_{1j} = f(ProductComplexity, PriceQuotes, CustomQuotes, EngineeringQuotes)$$

	Time-Based Coefficients				*Experience-Based Coefficients*			
		Process Complexity				*Process Complexity*		
Minimum Orders	*Product Complexity*	*Price Quotes*	*Custom Quotes*	*Engineering Quotes*	*Product Complexity*	*Price Quotes*	*Custom Quotes*	*Engineering Quotes*
2	−271.5	−159.6*	354.5*	109.2	−6.90	−7.81*	38.21*	1.97
3	−292.4	−142.4	333.7*	139.4	−6.77	−7.58*	38.1*	0.37
5	−245.0	−135.1*	339.1*	15.4	−7.54	−7.61*	38.85*	−4.25
10	−225.9	−133.8*	24.1	282.4*	−0.73	−3.34	2.54	1.06
20	−549.0*	57.3	−49.5	60.8	−7.77*	−1.40	−4.70	0.34
30	−510.3*	−67.2	7.9	66.6	−8.66*	0.25	−0.45	−0.44

* Significant at the $p < 0.05$ level (one-sided).
Definition of variables:
Product Complexity = an equally weighted index of standardized values of lines/order, number of finish codes, number of unique finish codes, and average item cost;
Price Quotes = percentage orders dealers submitted that require manual pricing;
Custom Quotes = percentage orders dealers submitted that include at least one custom material; and
Engineering Quotes = percentage orders dealers submitted that require manual verification of engineering designs.

with a minimum of two orders, to 255 dealers with a minimum of 30 EDI orders in each of the sample months.[24] The Z-statistics reported in Table 4, Panel A generally support the hypothesis that the learning coefficients for both time- and experience-based learning are positive and significant, indicating improved order accuracy (decreased error rates), especially for dealers submitting five or more EDI orders a month. The Z-statistic on the coefficients on the cumulative exception variable indicates that dealers learn from errors made in prior submissions, consistent with dealers learning from feedback on past errors. Thus, we find that EDI submissions are subject to learning, or more generally, to dealer adaptation, following EDI adoption. Evidence that a period of adaptation follows implementation of a new IT is consistent with Brynjolfsson's (1993) concern that a failure to find positive returns to IT investments may stem from lags due to learning and adjustment processes.

Hypothesis 2c posits that order complexity impedes dealer learning. We report the results of testing this proposition in Table 4, Panel B, where we regress the learning rates for each of the dealers (using time- or experience-based specifications of learning) on the average complexity of EDI orders the dealer submitted. Two general results are evident in Table 4, Panel B. First, for the larger sample sizes (including dealers submitting relatively few EDI orders in a month), there is a negative relation between price quotes and learning but a positive relation between custom quotes and learning. These relations appear to be due to those dealers submitting fewer than 20 EDI orders in a month. For the more restricted sample, which includes only relatively frequent EDI users, there is a consistent, though not universal, negative relation between product complexity and learning, but no evidence that process complexity impairs dealer learning. Thus, although some evidence is consistent with an adverse effect of product complexity on learning in Table 4, Panel B, we do not find strong evidence in support of H2c. Together, the results in Tables 3 and 4, Panels A and B provide partial support for the Indirect Effect Hypothesis, with strong support for H2a, generally consistent support for H2b, but only limited support for H2c.

Untabulated results reveal that task complexity explains only a small portion of the variance in the rate of learning across dealers (R^2 is less than 10 percent for all dealers and is typically less than 2 percent). Srinivasan et al. (1994) found that the supplier-specific rate of shipment errors for automotive suppliers was related to the manner of implementing EDI (e.g., level of systems integration with the customer), as well as with task complexity and heterogeneity. Unfortunately, however, we do not have dealer-specific information about EDI implementation, such as the level of training that the dealer may have sought or whether individual sales representatives or a dedicated clerk typically enters the orders.

Evidence on the relation between dealer learning and product and process complexity has implications for future advances in IT. For example, our results suggest that automatic entry of eligible price discounts may help reduce acknowledgement delays caused by manual processing of price quotes. However, evidence on how dealers gain unique mastery in the EDI task through clever process design or human resource management might have even more profound implications. Such evidence might offer simple remedies (beyond increasing the technology investment) for a problem that is costly to the firm but that is not fully internalized by the dealer. We raise this as an issue for future research and as a vivid illustration of an interorganizational approach to management control—specifically,

[24] Even though many dealers appear in more than one sample, the same data are not included in the dealer-specific regressions in the different samples. For example, if a dealer places four EDI orders in six months and 20 EDI orders in ten months, then we include 16 months of data in the dealer-specific regression for the sample of dealers with at least three orders in a month, but only ten months of data in the dealer-specific regression for the sample of dealers with at least five EDI orders in a month.

SSD could use such data to diagnose problems and suggest improvements for dealers, with an expectation that improvements will cascade throughout the value chain.

VI. SUMMARY

Electronic data interchange is an accounting information technology that reduces key entry and standardizes information exchange between firms and their customers or suppliers. Although EDI reduces total key-entry time, it places greater demands on the customer or supplier to specify orders properly. We use data on more than 1.5 million orders placed with a large, office furniture manufacturing firm by more than 500 dealers to examine two basic questions. First, does adoption of electronic data interchange (EDI) improve performance in the order-entry function? Second, do dealer errors in EDI submission decrease the productivity of firms receiving orders, and if so, do these decreases offset the productivity increases from EDI submission? We also investigate whether dealers make fewer errors in using EDI over time or with experience (i.e., learn to use the technology), whether feedback on prior errors facilitates dealer learning, and whether order complexity impedes dealer learning.

We find that EDI use is associated with better departmental performance (i.e., faster sales order processing); however, these benefits are largely offset when dealers submit EDI orders with errors. After documenting that order complexity (both product and process complexity) impairs order-entry performance, we show that the benefits of error-free orders submitted via EDI offset most of the negative effects of product complexity. For complex EDI orders that contain errors, the benefits of EDI submission partially offset the effects of product complexity, but this effect is only about 40 percent of that of error-free EDI orders.

The second research question considers how dealers have adapted to the new EDI technology. Dealers often submit incomplete or incorrect orders. We find that both the passage of time and cumulative experience in EDI order submission tend to reduce dealers' error rates. We further find that feedback on prior errors facilitates dealer learning. Specifically, current-period errors decline with cumulative errors in prior periods. Finally, we find some evidence, albeit partial and incomplete, that complexity impedes dealer learning.

A major limitation of investigating the performance effects of interorganizational systems such as EDI, when data are available on the performance of only one of the transacting parties, is that such systems may simply transfer wealth between transacting parties with no net benefits. As a result, our conclusions are limited to the operational effects of EDI on the furniture manufacturer's order-processing group and we cannot assess the effect of EDI on the entire value chain.

Anecdotal evidence suggests that EDI trading partners frequently fail to fully implement the technology (Riggins and Mukhopadhyay 1994; Srinivasan et al. 1994). In particular, they frequently neglect employee training in the use of the technology. Our results are consistent with this conjecture. Our results are also consistent with economic models suggesting that task complexity acts as a barrier to learning or improvement; however, these models explain only a modest portion of the variation in dealer-specific learning rates. Future research that considers such dealer-specific determinants of learning could advance our understanding of the learning process and could suggest methods for implementing information technology that would enhance returns to the technology.

APPENDIX
A Process Description of Order Entry, from Order Receipt to Order Acknowledgment

Orders arrive from dealers by EDI, mail, or fax (Figure 1). From 1993 to 1996, orders from EDI-equipped dealers increased steadily from 77 to 88 percent, with 86 percent of all orders on average originating from EDI-equipped dealers (Table 1). Upon receipt, the order-entry system assigns the order a mail stamp date and a rank from 0 to +7 and places the order in a single, priority (lowest rank is highest priority) queue. The incoming rank assigned equals the target acknowledgment delay for the order. Each day the order's rank decreases by 1 and it becomes a higher service priority. SSD uses five ranks that correspond to target acknowledgment classes: (1) zero delay, for small (typically original equipment manufacturer-supplied) parts; (2) two-day delay, for customer service orders and orders against the company's express shipment program (a limited set of products available in limited colors); (3) three-day delay, for ‘‘normal’’ orders of average size; (4) five-day delay, for orders of one to five full truckloads of product; and (5) seven-day delay, for orders of more than five truckloads. Order editors select from the service queue according to priority, selecting orders of the same priority in order of mail stamp date.

The order editor first determines whether splitting an order into two or more pseudo-orders is likely to reduce acknowledgment delays. Two situations prompt order splitting: nonroutine customer demands and very large orders.[25] Order editors cannot do the additional processing customized products require. If an order contains both custom and standard products, then the order editor may split it into two pseudo-orders. As a result of delays associated with manual processes, the pseudo-order with custom products will generally have a longer acknowledgment delay than the pseudo-order with standard products. This is consistent with descriptive evidence in Table 1—that split orders have a higher incidence of engineering design changes (14 percent vs. 2 percent for orders that are not split), and use of custom materials (5 percent vs. 1 percent), and are more likely to be customized in some manner (only 6 percent have *no* custom material, pricing agreements, or design changes, vs. 28 percent of orders that are not split).

A second reason for splitting an order is order size. Order editors are likely to break exceptionally large orders, defined by the number of truckloads of finished goods or the percent of capacity of any single manufacturing plant that the order represents, into smaller pseudo-orders. Splitting orders that consume a large share of any plant's capacity reduces the risk of unused manufacturing capacity or inventory build-ups in the event that the dealer withdraws the order or delays it on short notice. It also decreases the elapsed time between order acknowledgment and subsequent production and shipment of the full order. A scheduling system automatically schedules production in the earliest available period that meets customer delivery requirements. Large production lots are difficult to schedule because large blocks of empty capacity are available only in distant time periods that are likely to violate delivery deadlines. The exception to this is when the system holds blocks of capacity based on an advanced reservation for exceptionally large orders, for which negotiated cancellation penalties apply.

If, after order editing, the pseudo-order does not require manual processing, then it joins the queue of completed jobs (Process Flow A in Figure 1, denoted hereafter as the ‘‘basic’’ process). At the end of the day, a batch-processing system attempts to validate

[25] Idiosyncratic reasons for order splitting include temporary stock-outs of a raw material required for a portion of an order or major production delays (e.g., equipment failures) at a plant that produces a portion of an order. We have no data on the incidence of these sources of acknowledgment delay.

orders in the queue. Orders that do not negotiate the batch process return to a separate (from incoming orders) queue for additional editing. The system acknowledges validated orders to the dealer via the same medium (EDI or U.S. mail) by which the orders are received. The acknowledgment is OFM's commitment to deliver a product to a specified location on a particular date. Dealers are responsible for reviewing acknowledgments and identifying discrepancies.[26] The task of order checking is easier for EDI-equipped dealers because the batch process identifies any change to the original EDI order (termed an ''EDI exception flag''). EDI exceptions typically indicate dealer errors in the original order. Both split and unsplit orders arrive via EDI with approximately the same frequency (85 and 86 percent, respectively); however, the incidence of EDI exceptions for split orders is 66 percent greater than for unsplit orders.

Only 22 percent of orders follow the basic routing (Process A). Remaining orders are customized and require manual processing in at least one of four areas: scheduling, pricing, purchasing, or engineering. Order customization may reflect unique features of the business transaction or modifications to standard products. Manual production scheduling (Process B) and pricing (Process C) occur in SSD. Two other manual processes, verifying inventory of custom materials (Process D) and verifying readiness to produce specially engineered products (Processes E and F), cause orders to leave SSD for processing in engineering or purchasing. Customization creates process complexity that increases order acknowledgment delays. For example, Table 1 indicates that delays for unsplit orders that require no manual processing average 1.6 days vs. 1.9 to 8.0 days for custom orders. Order editors use order splitting to separate an order into parts, at least one of which is anticipated to have longer than average delays. The upper portion of Table 1, reports descriptive data on the average acknowledgment delay of *all* parts of split orders; for each process (A–F) the average acknowledgment delay for split orders exceeds that of the unsplit orders, shown in the lower part of Table 1. The following paragraphs describe alternative process flows (B–F).

Most production scheduling occurs automatically. The order editor submits the order to the scheduling system and, if the computer can fit the order into a production window that meets customer delivery requirements taking as given all previously scheduled orders, then it schedules the order. If the computer fails to schedule an order it goes to a scheduler, who may then override system constraints, reschedule previously scheduled orders, or work with a sales representative and the dealer to negotiate later delivery (Process B). The primary reason that an order fails automatic scheduling is size. Large orders (relative to production capacity) require manual intervention unless capacity reservations exist. Although we cannot identify orders in the database that require manual scheduling, we can obtain a conservative indication of scheduling delays by comparing the average acknowledgment delay of uncustomized orders in the top quartile of order value with all other uncustomized orders.[27] For unsplit orders, we observe an acknowledgment delay of 1.8 days—0.2 days more than for the basic process.

Approximately 68 percent of orders receive special discounting arrangements that are unrelated to product customization. Price agreements may reflect promotions on particular products for all dealers or unique arrangements with an end-user or dealer. If any item in

[26] Although the firm replaces products that are ordered in error when the error is attributable to SSD, it is not liable for late shipments of these items. Dealer representatives who handle these claims indicate that the dealer has a significant stake in detecting and reporting these errors, because end-users are very sensitive to incorrect or incomplete shipments.

[27] This estimate of scheduling delay is conservative because very large orders are likely to have reservations that allow automatic scheduling, and our field research indicates that less than 25 percent of orders are scheduled manually.

an order is covered by a special pricing agreement, then the order editor sends the entire order to pricing after order entry (Process C). Pricing specialists review the agreement and assign a price to items covered by the agreement. On average, manual pricing adds 0.9 days to the acknowledgment delay. After specialists establish the price, the order joins the queue for batch processing or, if the order requires manual scheduling, then it goes to the scheduling department.

Pricing and scheduling require manual intervention of SSD employees. The purchasing department processes orders (as shown in Process D) with custom materials (e.g., paint colors or upholstery fabrics) while the engineering department processes product design changes (Processes E and F). Because these orders leave SSD, acknowledgment delays significantly exceed those associated with pricing or scheduling. Before scheduling production of an order with custom materials, the purchasing department verifies acquisition and sufficient inventory of the material. Delays associated with custom materials add approximately five days to the acknowledgment delay of the basic process. Although submitted orders contain only design changes that OFM has accepted, an engineer reviews the order and provides cost data to the price specialists in SSD. After order editing, special orders go first to the engineering department and then to either the purchasing group (if the order requires special materials) or the pricing area of SSD. In the first case (Process E), acknowledgment delays increase 7.7 days over the base case; in the second case (Process F), acknowledgment delays increase 5.5 days.

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