

Supply Chain Learning and Spillovers in Vendor Managed Inventory

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ABSTRACT

Despite extensive literature on the value of supply chain collaboration programs, little research has examined the issue from the perspective of organizational learning. Using a unique, operational level dataset, we empirically examine the learning process through which performance improvements are realized under Vendor Managed Inventory (VMI). Performance is measured at the downstream distributor locations by examining inventory levels after controlling for customer service performance (stockouts). We identify and assess three sources of learning – a supply chain dyad’s self-learning, learning spillovers from Electronic Data Interchange (EDI), and learning spillovers from other supply chain dyads. We find that self-learning, learning spillovers from EDI, and learning spillovers from other supply chain dyads, all have positive and significant impacts on a supply chain dyad’s inventory performance. Self-learning and learning spillovers from EDI exhibit a U-shaped learning curve (i.e., performance first improves and then plateaus or declines), whereas learning spillovers from other supply chain dyads follow an inverted U-shaped learning curve (i.e., “worse-then-better”). These findings suggest that the various learning experiences with VMI and EDI can lead to improved performance over time, but the path to improvement may be complex and nonlinear.

Key Words: Vendor-Managed Inventory; Supply Chain Learning; Spillovers; Empirical Analysis; Organizational Learning

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1. Introduction

Vendor Managed Inventory (VMI) is a supply chain collaboration program that allows an upstream firm (for the purposes of this paper, a manufacturer) to manage inventories for its downstream supply chain partner (for the purposes of this paper, a distributor). Vendor Managed Inventory (VMI) was first implemented by Wal-Mart and Procter & Gamble as part of the Efficient Consumer Response initiative (Kurt Salmon Associates Report 1993), and has since been adopted by many firms, such as Johnson & Johnson, Black & Decker, and Ace Hardware. As outlined by Fry et al. (2001), VMI programs have met with mixed success. For example, Kimberly Clark reportedly saved \$200 million in costs through managing its Huggies diapers at Costco and 43 other retailers over the first two years of a VMI program. Oshawa Foods, a Canadian retailer, tripled its inventory turns and increased its service level to 99% after teaming with food manufacturers, such as H. J. Heinz, in VMI relationships (KPMG Report 1996). On the other hand, after experimenting with VMI for twelve months, Spartan Stores, a Michigan co-op, terminated its VMI program, citing planning inefficiencies by the vendors and increased costs at its stores (KPMG Report 1996).

The uncertain outcomes from the implementation of VMI and similar supply chain initiatives may be attributed, in part, to the nature of the programs. The implementation of VMI usually occurs over a long period of time, and involves not only coordination among multiple departments within an organization (e.g., purchasing, manufacturing, and logistics) but also coordination between firms in the supply chain. The long implementation process and the resulting complexities imply that there may be a learning process of different sources associated with implementation. Previous empirical work on VMI and similar programs (e.g., Lee et al.

1999; Clark and Hammond 1997; Kulp 2004) has focused on the comparison of performance levels pre- and post-implementation. Their results provide a snapshot of performance at two points of time, leaving the learning process unexplored. As a result, our understanding of VMI effectiveness is limited since firms may improve their performance through a complex learning process and from different sources of learning (Yelle 1979; Thornton and Thompson 2001). Prior studies on technology adoption, across a range of operations and new technologies, have documented a “performance dip” at the beginning of the implementation of a new technology (e.g., McAfee 2002). Similarly, in the case of VMI, firm performance could first decline for a certain period of time as the firms adapt to VMI procedures, before eventually improving.

In this research, we use a dataset from an electronic components manufacturer and its distributors to examine, empirically, the learning processes of VMI implementation. We study the supply chain learning that emanates from three distinct sources: (1) from the supply chain dyad’s (manufacturer and distributor’s) own experience with VMI implementation (self-learning); (2) from the supply chain dyad’s experience with the implementation and use of a prerequisite supply chain initiative, namely EDI, (i.e., learning spillovers from EDI); and (3) from the manufacturer’s prior experience from undertaking VMI with other distributors (i.e., learning spillovers from other supply chain dyads). Supply chain learning performance is measured at the distributor locations by examining inventory levels while controlling for customer service levels; that is, number of stockouts.

Our primary finding is that VMI reduces inventory levels and therefore improves supply chain inventory performance. However, the learning process through which performance improvements are realized may be nonlinear. This nonlinear learning process may, in part, explain the mixed success from the anecdotal evidence for VMI implementation. In particular,

self-learning, learning spillovers from EDI, and learning spillovers from other supply chain dyads, all may have positive and significant impacts on a distributor's performance. However, self-learning and learning spillovers from EDI exhibit a U-shaped learning curve (i.e., performance first improves and then plateaus or declines), possibly due to the tradeoff between exploitation and exploration of learned procedures; whereas learning spillovers from other supply chain dyads follow an inverted U-shaped learning curve (i.e., "worse-then-better"), perhaps due to the knowledge internalization process.

Our paper makes several contributions. First, this paper is the first to investigate organizational learning in a supply chain collaboration program. Supply chain collaboration programs are not simple arm's-length relationships, but relationships with much inter-organizational embeddedness (Baker and Faulkner 2005), such as shared business models and processes. Hence, the learning that must be undertaken to improve the efficiency of a supply chain program, such as VMI, may be different from the learning that takes place exclusively within an organization. Second, through the theoretical lens of organizational learning, we provide a more complete picture of how VMI implementation improves a supply chain dyad's operational performance over time. Supply chain collaboration programs are settings where learning plays an important role in determining program effectiveness. By examining the learning processes surrounding VMI implementation, we are able to answer not only "if" VMI contributes to improved performance, but "how" the performance benefits from VMI are attained. Third, we identify three distinct learning sources important for the implementation of VMI. Our findings reveal a rather complex learning process that combines nonlinear self-learning and learning spillovers from a precursor program and from other supply chain dyads. These findings expand the breadth and depth of the understanding of the sources that drive the performance

improvements for supply chain programs, such as VMI. In the supply chain literature, prior research has not considered multiple sources that may drive these performance improvements, although studies in the organizational learning literature have shown significant impacts from multiple sources of learning (e.g., Argote et al. 1990, Baum and Ingram 1998).

The rest of the paper is organized as follows. Section 2 reviews theory and relevant literature on VMI and organizational learning; Section 3 presents the research methodology, including the empirical context, data, and econometric models; Section 4 provides the estimation results; Section 5 presents a discussion of our findings; and finally, Section 6 draws conclusions and implications from the research.

2. Theory and Literature Review

2.1 Organizational Learning and VMI

Organizational learning has been addressed in a number of research areas, including economics, operations management, management, and information systems.¹ There is general agreement among researchers that organizations are capable of creating, retaining, and transferring knowledge and that this knowledge contributes to performance improvements.

Literature on learning has found that a product's unit cost tends to fall by a constant percentage with each doubling of cumulative output, or time in production (Dutton and Thomas 1984). The theoretical rationale for this reduction in production cost is that a firm is able to learn from "trial and error" (i.e., from its experience), leading to an improvement in the effectiveness and efficiency of task performance (Pisano et. al. 2001). While performance improvements through learning have been documented in diverse industries (e.g., Thornton and Thompson 2001 and Argote 1990 in the shipbuilding industry), understanding how these improvements

¹ For a comprehensive review, please see Argote (1999).

occur in the collaborative context of supply chains is still limited (Macher and Mowery 2003; Im and Rai 2008).

Although much of the research has focused on learning in the manufacturing environment, performance improvements may also apply to services (Boone et al. 2008; Lapré and Tsikriktsis 2006) and collaborative process development and re-engineering (Pisano 1994; Pisano et al. 2001; Hatch and Mowery 1998), such as the implementation and use of VMI. As discussed in Edmondson et al. (2001), a collaborative learning process involves learning about the collaborator's role, improvising, and making numerous small adjustments. In the VMI implementation stage, when procedures, codes, and routines are being created and tested, learning may result primarily from the search for superior procedures, codes, and routines. For example, a supplier may recalibrate its forecasting and replenishment parameters to achieve better forecasting accuracy. In a later stage of VMI, when proper procedures, codes, and routines are already in place, learning may result from increased worker efficiency and effectiveness due to multiple task repetitions.

In addition to self-learning from the implementation of a particular program (i.e., learning-by-doing), learning may result from spillovers from experience with similar processes (i.e., "learning-before-doing") (e.g., Pisano 1996; Levin 2000) and from other organizations or from other processes (e.g., Thornton and Thompson 2001; Ittner et al. 2001; Argote et al. 1990; Lapré and van Wassenhove 2001; Irwin and Kelnow 1994). For example, knowledge from an EDI implementation between a manufacturer and distributor may result in learning spillovers to a later VMI implementation for the same manufacturer-distributor dyad. As well, a manufacturer's knowledge from past VMI experiences may spill over to subsequent VMI implementations with different distributors.

For learning spillovers from EDI, the learning may take place before VMI is actually implemented, given that supply chain dyads that adopt VMI likely already communicate through EDI.² Since EDI and VMI share certain routines and processes, such as those required to implement electronic purchase orders, the knowledge and experience accumulated in understanding and implementing EDI may be directly applicable to the implementation of VMI. This knowledge and experience can be recorded in documents, accounts, files, standard operating procedures, and rule books, and will be a component of organizational memory (Levitt and March 1988; Huber 1991). A VMI program may, therefore, be able to capture the experiences learned from an existing EDI program through the transfer of knowledge in the forms of technologies, codes, procedures, or similar routines (Levitt and March 1988; Huber 1991), and the transfer of tacit knowledge through personal experience (Arrow 1962; Song et al. 2003; Boone et al. 2008).

As noted above, learning spillovers from a manufacturer's previous VMI implementations with other distributors may lead to improved outcomes with subsequent VMI implementations. When a distributor establishes a strategic relationship, such as VMI, with a manufacturer with prior VMI experience, the dyadic relationship may benefit from the manufacturer's previous VMI knowledge. Such knowledge spillovers have been documented in research; such as Agote et al. (1990) who found that organizations beginning production at a later date are more productive than those with early start dates; Levin (2000) who found that car models with the latest debuts have the best quality; and Dyer and Hatch (2006) who found that greater knowledge-sharing on the part of Toyota resulted in a faster rate of learning for suppliers. The knowledge transfer can be accomplished through the exchange of technologies, codes,

² We acknowledge that there may be other prerequisite technology enablers for VMI, such as the Internet. Without loss of generalizability, we use EDI as the technology enabler throughout the paper.

procedures, or personnel (Levitt and March 1988; Song et al. 2003). In other words, the supply chain dyad may “jump-start” the learning curve by bypassing or minimizing the need for trial-and-error experimentation and for the search for best routines from a pool of alternatives (Levitt and March 1988).

Learning processes may be complex or nonlinear. Organizations often face trade-offs in learning between exploitation and exploration (i.e., the competency trap), resulting in a U-shaped learning curve (March 1991). While exploitation requires investments in refinement and efficiency to improve execution of a given set of routines, exploration requires investment in discovery, innovation, and experimentation to address new demands or opportunities (Holmqvist 2004). As elaborated in Baum and Ingram (1998, p. 998), “organizations may reduce their exploratory activity prematurely and, in the case of a changing environment, not renew exploratory search and learning activities despite the fact that new opportunities and threats are present.” Emphasizing exploitive learning may lead an organization to employ established routines beyond their point of usefulness, even though there has been environmental change. Baum and Ingram (1998), for example, find that the operating experience of Manhattan hotels is consistent with a U-shaped function, with decreasing failure rates initially, but with increasing failure rates in the longer term as firms fall into competency traps. With VMI, the competency traps may happen as well. Experience may become less relevant over time as procedures and routines first produced (or emulated from others) becoming obsolete and irrelevant. Unless firms engage in sufficient explorative learning for new procedures and routines, performance improvements can be slowed or disappear altogether. In addition, the law of diminishing returns in economic theory suggests that the marginal contribution of a factor of production may decrease as more of the factor is used (Johns et al. 1999). Thus, the returns to learning may

diminish while experience increases. In addition, there may also be decreasing opportunities for improvement once an organization has harvested all “low hanging fruit”, making gains in performance more difficult and costly to achieve.³

2.2 Empirical Literature on VMI

A number of empirical studies have examined the impact of VMI and related programs on performance improvements. Cachon and Fisher (1997) researched the benefits from VMI to the Campbell Soup Company (e.g., inventory reductions), and concluded that these benefits could have been achieved through information sharing alone, without the addition of a VMI program. Clark and Hammond (1997) and Lee et al. (1999) examined the use of continuous replenishment programs (CRP, which encompass VMI) in the grocery products supply chain. In a series of case studies, the authors found that the use of CRP allows for performance improvements while controlling for information sharing from EDI. Lee et al. (1999), also using data from the grocery industry, showed that inventory turns and stockouts improved after the implementation of CRP. Finally, Kulp et al. (2004), through an extensive survey in the food and consumer packaged goods industry, found VMI to be directly and positively related to manufacturer margins.

A common theme of these empirical studies on VMI is their focus on addressing “if” VMI adds value to companies. The studies do not explore “how” the value might be realized through a learning process. No papers have empirically examined VMI, or supply chain collaboration programs in general, through the theoretical lens of organizational learning. In this paper, we study the various learning processes through which benefits from VMI are realized in an effort to fill this gap in the literature.

³ We thank an anonymous reviewer for this helpful point.

3. Research Methodology

3.1 Research Context and Data

The setting for this research is a manufacturer supplying electronic components to a number of independent distributors. The manufacturer is a multi-billion dollar global provider of a broad range of products and services, with electronic components comprising the firm's largest product line. The components are sold to distributors that service a range of industry segments, including consumer products, transportation, petrochemical and mining, metals, and forest products. The majority of the manufacturer's electronic component sales are in the U.S., where such products are sold primarily through these independent distributors.

Data were collected from a third party information services provider that facilitates EDI and VMI operations between the manufacturer and its distributors. The information services provider helps the manufacturer integrate its operations with distributor-customers by facilitating the exchange of information through EDI, and by supporting VMI arrangements. It is important to note that the information services provider is only a facilitator of information exchange; that is, it is the manufacturer and its distributors that make decisions on VMI implementation. As outlined to us through interviews with various parties, the manufacturer encourages all distributors to implement VMI as well as EDI, although not all distributors enter into VMI arrangements with the manufacturer.

All distributors have EDI arrangements with the manufacturer and share point-of-sales (POS) and inventory information via the standard EDI form, UCS 852. UCS 852 is sent from the distributor to the manufacturer on a prearranged schedule. Under VMI arrangements, the manufacturer uses these data to undertake inventory replenishment decisions. Ownership of inventory at the distributor's location resides with the distributor. Consignment is not used.

Inventory, stockout, and related information were collected on a weekly basis from twenty distributors supplied by the manufacturer and chosen through a stratified random sample, stratified on the basis of VMI experience. Collecting data from distributors supplied by the same manufacturer strictly controls for supplier influences on VMI performance. Ten of the distributors had been using VMI for more than a year at the time the data were collected (2003), while ten of the distributors began using VMI during the period of data collection. Selecting a stratified sample of distributors that have a variety of experience levels with VMI allows for a robust test of the learning effects from VMI.

Both item- and firm-level data were collected. Twenty items that were carried by all twenty distributors were randomly selected and were used for our analysis. Data for the most recent 52 week period (at the time of the data collection) were used, including data on inventory levels, stockouts, and weekly sales. Inventory levels and stockouts were measured at the distributor premises. Firm level data, included start (implementation) dates for both EDI and VMI arrangements between each distributor and the manufacturer, were collected as well.

3.2 Econometric Models

We construct two econometric models to assess the learning processes through which inventory reductions may be realized through VMI. Each model consists of a single equation with inventory levels as the dependent variable. Model 1, as specified in (1), examines the linear learning effects from VMI through the inclusion of three experience variables. Model 2, as specified in (2), adds squared terms for the experience variables to allow for potential nonlinear effects on performance from self-learning and learning spillovers (Argote et al. 1990; Thornton and Thomson 2001).

A number of control variables are included in the models. Stockouts (STOCKOUT) is included to control for service levels. All other things being equal, higher service levels (i.e., fewer stockouts) should be associated with greater inventory levels. Weekly Sales (SALES) is an item-level control variable included to account for environmental, seasonal, and demand effects on inventory levels. All other things being equal, higher weekly sales should be associated with higher inventory levels. Item Price (PRICE) is also an item-level control variable included to account for possible differences in levels of inventory for high versus low priced items. Leadtime (LEADTIME) is included to control for the difference in replenishment leadtimes among the manufacturer-distributor dyads. Longer leadtimes are expected to be associated with higher inventory levels at the distributors. Annual transaction volume (VOL) is included to control for the size of the relationship between a distributor and the manufacturer. Finally, we control for the fixed time effects that account for technological advancement, productivity improvement, or any other time-varying factors during our 52 week sample time.

For both models, an exponential functional form is used.⁴ The exponential functional form, first introduced by Levy (1965), has been used widely in estimating learning curves in the organizational learning literature (e.g., Lapré and Tsikriktsis 2006; Lapré et al. 2000). The exponential form is appropriate when learning exhibits initial downward concavity and then plateaus (Lapré et al. 2000). In addition, the exponential functional form is appropriate when estimating a learning curve that is based on experience prior to the period for which data are gathered. For our sample, ten distributors used VMI prior to our data collection period.

Let subscript i denote firm, subscript j denote item, and subscript t denote week. Our two-equation models can be specified as follows:

Model 1:

⁴ When the inventory value is zero, we add 1 to avoid taking the log of 0 (Ba and Pavlou 2002).

$$\begin{aligned} \ln(INV_{ijt}) = & \beta_0 + \beta_1 \ln(STOCKOUT_{ijt}) + \beta_2 E_{1it} + \beta_3 E_{2i} + \beta_4 E_{3it} \\ & + \beta_5 SALES_{ijt} + \beta_6 PRICE_j + \beta_7 LEADTIME_i + \beta_8 VOL_i + \varepsilon_{ijt} \end{aligned} \quad (1)$$

Model 2:

$$\begin{aligned} \ln(INV_{ijt}) = & \beta_0 + \beta_1 \ln(STOCKOUT_{ijt}) + \beta_2 E_{1it} + \beta'_2 (E_{1it})^2 + \beta_3 E_{2i} \\ & + \beta'_3 (E_{2i})^2 + \beta_4 E_{3it} + \beta'_4 (E_{3it})^2 + \beta_5 SALES_{ijt} + \beta_6 PRICE_j + \beta_7 LEADTIME_i \\ & + \beta_8 VOL_i + \varepsilon_{ijt} \end{aligned} \quad (2)$$

where:

- Inventory Level (*INV*) is the average on-hand quantity at the distributor's premises for an item during a week.
- Stockouts (*STOCKOUT*) is the counted days of stockouts for an item managed during a week and can range from 0 (no stockouts) to 7 (stockout each day of the week).⁵

Stockouts occur when quantities requested by customers are greater than on-hand inventory at the distributor.

- A supply chain dyad's *self-learning* from VMI (E_1) is measured by the number of days that VMI has been in place; i.e., $E_1^{it} = t - t_{VMI}^i$, where i and t denote supply chain dyad and time, respectively, and t_{VMI}^i denotes the time when supply chain dyad i started VMI.⁶

In the organizational learning literature, learning has been operationalized as either a function of cumulative output (e.g., Argote et al. 1990) or cumulative time (e.g., years or days) of operating experience (e.g., Ingram and Baum 1997; Levin 2000; Dyer and Hatch 2006). For this research, we operationalize learning (this variable and the others discussed below) in terms of cumulative time. As a service program, experience with

⁵ Data availability restricted us from using stockout quantities.

⁶ For example, if a manufacturer and a distributor (supply chain dyad) started VMI on 1/1/2003 (i.e., t_{VMI}^i) and the current date is 1/31/2003 (i.e., t), the firm's cumulative experience from self-learning (E_1) is 30 days.

VMI tends to be gained through each order placement and concurrent process management activities. Experience accumulates from day-to-day or week-to-week, depending on the frequency of order placement, as firms involved in VMI become familiar with the ordering process and demand requirements. Learning from experience is less likely to vary as closely with order quantities or purchase volumes.

- Learning *spillovers* from EDI to VMI (E_2) are measured by the length of time the distributor has communicated with the manufacturer via EDI, less the length of time it has implemented VMI; i.e., $E_2^{it} = t - t_{EDI}^i - (t - t_{VMI}^i) = t_{VMI}^i - t_{EDI}^i$. Therefore, E_2 measures a dyad's experience with EDI before the adoption of VMI.⁷
- Learning *spillovers* from other supply chain dyads (E_3) are measured by the manufacturer's cumulative VMI experience with all distributors,⁸ excluding the focal supply chain dyad's distributor; i.e., $E_3^{it} = \sum_j E_1^{jt}$ where $i \neq j \in \{Distributors\}$. E_3 captures the amount of experience a manufacturer in a supply chain dyad has had with distributors other than the focal distributor at a given time.
- Weekly Sales (*SALES*) is the total quantity of an item sold by a distributor for the given week.
- Item Price (*PRICE*) is the list price for an item.
- Leadtime (*LEADTIME*) is the estimated number of days between placing an order and receiving the shipment from the manufacturer for a distributor.
- Annual Transaction Volume (*VOL*) is the annual transaction volume in dollars between a distributor and the manufacturer.

⁷ It should be noted that E_2 is a firm-level variable that does not vary over time for a given distributor.

⁸ We use information from all distributors (not just 20 distributors in our sample) to calculate E_3 . We thank an anonymous reviewer for this suggestion.

- β 's are parameters to be estimated, and ε is a random disturbance term.

Table 1 presents means, standard deviations, and the correlation matrix for the variables in our dataset. To check for potential multicollinearity, we computed variance inflation factor (VIF) scores for all independent variables. The VIF scores for variables in Model 1 are between 1.01 and 3.25, lower than the commonly accepted cutoff of 10, indicating that multicollinearity may not be a problem. For Model 2, as might be expected, we find collinearity between the linear and squared learning terms (e.g., $E1$ and $E1^2$ are collinear). However, further tests show that this collinearity does not significantly affect our results.⁹

<<Insert Table 1 about here>>

4. Estimation Results

We use the Wooldridge test to check for first order autocorrelation in our panel dataset (Wooldridge 2002) and find that autocorrelation is present ($F=939$, $p<0.001$). Therefore, we estimate our models using the Feasible Generalized Least Squares (FGLS) method (Greene 1997). FGLS allows for an autocorrelated structure between observations. Since inventory levels and stockouts may be endogenous (e.g., Lee et al. 1999), a two stage estimation approach is used for each of the models.¹⁰ In the first stage, stockouts are estimated from the instrumental variable and other exogenous variables, and the fitted values of the dependent variable are saved. In the second stage, the fitted values for stockouts are used in the estimation of inventory. We use lagged inventory (i.e., inventory at time $t-1$) as the instrumental variable for the Stockouts equation. As discussed in Greene (page 295, 1997), for time series data, a lagged variable is a

⁹ In order to test for the effects of potential collinearity, first we dropped the squared terms one at a time and noted that the VIF for the corresponding linear terms fell to below “normal” (i.e., under 10). During the process, we observed the changes in the estimated coefficients and standard errors for all other variables. These changes were small in magnitude. Furthermore, we estimated our models on random sub-samples of the data (Greene 1999) and observed that the parameter estimates were not substantially changed. These techniques used are similar to those in Ingram and Simons (2002). Therefore, we conclude that multicollinearity is not an issue and our results are valid.

¹⁰ The first stage regression results are shown in Table A1 in the Appendix.

natural choice as an instrumental variable (e.g., Berry 1994) since the lagged variable is correlated with the dependent variables but uncorrelated with the disturbance terms; therefore, a valid instrument.

Table 2 presents the results from the second stage estimations of Models 1 and 2. For Model 1, the coefficients for all learning variables, E_1 (self-learning), E_2 (learning spillovers from EDI to VMI), and E_3 (learning spillovers from other supply chain dyads) are all negative and significant, indicating all three types of learning improve a distributor's inventory performance; that is, reduce inventory levels. These results suggest that organizational learning plays an important role in realizing the value of VMI.

For Model 2, the coefficient for E_1 is negative and significant, while the coefficient for $(E_1)^2$ is positive and significant. These results suggest that self-learning improves performance but at a decreasing rate; that is, the performance follows a U-shaped learning curve as presented in Figure 1. A further analysis shows that the "bottom" of the U-shaped learning curve corresponds to 1,284 days; that is, the number of days of VMI experience that results in the minimum inventory level.¹¹

In addition, as indicated in Model 2, the coefficient for E_2 is negative and significant, while the coefficient for $(E_2)^2$ is positive and significant. These results suggest that the learning spillovers from EDI to VMI improve distributor performance, but at a decreasing rate; that is, the performance follows a U-shaped learning curve as presented in Figure 2. A further analysis shows that the "bottom" of the U-shaped learning curve is 3,955 days for inventory reductions.¹²

Finally, the coefficient for E_3 is positive and significant in Model 2, while the coefficient for $(E_3)^2$ is negative and significant. These results indicate that the learning spillovers from other

¹¹ In our data sample, 5 of the supply chain dyads had surpassed 1,284 days of VMI experience by the end of the data collection period.

¹² None of the supply chain dyads surpassed 3,955 days of EDI experience by the end of the data collection period.

supply chain dyads lead to increased inventory levels at first before performance begins to improve, as presented in Figure 3 (i.e., a “worse-then-better” sequence). Further examination finds that the turning point is at 747,126 days of cumulative experience.¹³

<< Insert Table 2, Figures 1, 2 and 3 about here >>

For all model estimations, control variables generally produce consistent and predictable results. For example, higher weekly sales are associated with higher inventory levels; higher prices are associated with lower inventory levels; longer leadtimes are associated with higher inventory levels; and greater annual transaction volumes are associated with higher inventory levels. Finally, the Wald Chi-squared statistics are significant, rejecting the null hypothesis that the coefficients are jointly zero.

5. Discussion

Despite the extensive literature on VMI, previous research has not considered VMI implementation and operations as a learning process. As shown in our results, the failure to account for the learning process may lead to a biased or limited assessment of the program’s benefits, given the nonlinear nature of the learning process. The nonlinear results may also provide a possible explanation as to why some industry studies do not report benefits (or report negative benefits) from VMI implementation (e.g., KPMG 1996). It may be that the studies did not give firms sufficient time to implement VMI before assessing the results.

We show how various learning processes influence the success of VMI programs. An especially interesting finding is that, in addition to self-learning, two types of learning spillovers; that is, learning spillovers from EDI and spillovers from other supply chain dyads, contribute significantly to performance improvement at the distributors. These results suggest that a supply

¹³ All of our dyads reached 747,126 days of cumulative VMI experience by the end of the data collection period.

chain dyad can learn to implement and operate an efficient and effective VMI program from its self-learning experience, as well as from past EDI experience and prior VMI experience from other supply chain dyads. For example, EDI knowledge, recorded through documents, in files, written in standard operating procedures, and set down in rulebooks, may be saved and used at a later time by the VMI implementation team. The manufacturer and distributor may emulate existing operating procedures already established through EDI programs when exchanging order information for VMI. The firms may not have to go through trial-and-error experimentation to arrive at new procedures under VMI. In addition, if the manufacturer has already implemented VMI with other distributors, it can simply transfer relevant knowledge in the forms of technologies, codes, procedures, or similar routines to a new implementation, creating cross-supply chain spillovers.

Furthermore, the results show that performance improvements resulting from VMI are nonlinear. Self-learning and the learning spillovers from EDI to VMI demonstrate U-shaped curves (i.e., performance first improves and then plateaus or declines), whereas learning spillovers from other supply chain dyads demonstrate an inverted U-shaped learning curve (i.e., “worse-then-better”).

The finding of U-shaped learning curves is consistent with previous findings in the learning literature (e.g., Baum and Ingram 1998; Lapre and Tsiriktsis 2006). A possible explanation for the U-shaped curve for self-learning may be the “competency trap” (Levitt and March 1998), a tradeoff between exploratory and exploitive learning (Baum and Ingram 1998; Ingram and Baum 1997). Organizations may focus on exploitative learning and reduce their

exploratory activity prematurely in a changing environment,¹⁴ despite the fact that new opportunities and threats are present (Baum and Ingram 1998). Emphasizing exploitive learning may lead an organization to employ established routines beyond their point of usefulness, even though there has been environmental change. Once process changes are completed and efficient routines and procedures established, both partners may focus on the existing VMI procedures, rather than on engaging in additional explorations for new procedures and routines; for example, better forecasting algorithms and replenishment plans. In addition, our U-shaped results are consistent with the law of diminishing returns in economic theory which suggests that the marginal contribution of a factor of production may decrease as more of the factor is used. There may also be decreasing opportunities for improvement once an organization has harvested all “low hanging fruit”, making gains in performance more difficult and costly to achieve. Thus, performance improvements can be slowed before disappearing altogether. Similarly, the U-shaped learning curve for learning spillovers from EDI to VMI indicates that experience transfers from EDI to VMI may become less relevant over time as procedures and routines first produced during EDI implementation becoming obsolete and irrelevant when implementing VMI. Thus, there is an optimal time window following the introduction of EDI when the spillovers to VMI are most important. If firms introduce VMI during this time window, then they are most likely to benefit from the learning that took place when EDI was first introduced.

The “worse-then-better” curve for learning spillovers from other supply chain dyads may imply that knowledge learned cannot always be directly applied from one VMI implementation to another since organizations are unique. Knowledge acquired from the outside may have to be first absorbed and digested before it can be used successfully in a new implementation

¹⁴ Note that there were significant environmental changes during the year in which the data were collected. Over the twelve month period, sales and inventory in the electronic components sector (U.S. Census sector M3 Code: 35S) declined significantly.

(Holmqvist 2004). Literature has stressed that outside-in learning capabilities are critical in knowledge absorption (Cohen and Levinthal 1990). For example, Dyer and Hatch (2006), studying the supply chain network of Toyota and its suppliers, found that some relation-specific knowledge from other parts of the supply chain are not easily transferable, although general knowledge from other parts of the supply chain can have a positive influence on the focal firms's performance. Hence, when a new routine or technology is introduced to an organization, it may disrupt the existing work routines, creating reduced performance (Pisano et al. 2001). Empirical work on technology adoption has found a "performance dip" at the beginning of an implementation process. The focal organization may have to go through a learning procedure, making cognitive, interpersonal and organizational adjustments, a process called "internalization" (Holmqvist 2004). As elaborated in Bierly and Hamalainen (1995, p.218): "Often, the external knowledge needs to be translated into a new language so that organizational members can understand and interpret its meaning." This additional learning process, of translating external to internal knowledge, may, at least temporarily, lead to deterioration in performance. Once the process is finished, the external knowledge may be able to help improve performance at an increasing rate. Another possible explanation for the worse-then-better learning process is that the manufacturer exhausted its internal resources quickly during early implementations. Later, as further distributors implemented VMI, the manufacturer may be able to find new resources to improve implementations.¹⁵

Finally, it should be noted that there are a number of mechanisms that have been implemented by the manufacturer to facilitate the spillover of learning from the VMI processes. First, the manufacturer has a centralized functional unit, "VMI Services", that manages all of the implementation and operational issues concerning VMI. Through this centralized functional unit,

¹⁵ We thank an anonymous reviewer for this helpful point.

experience can be easily preserved by the manufacturer and shared among colleagues in the unit. Second, the manufacturer developed a repository system of business process templates and data conversion tools from early implementations that can readily be used for later implementations, thereby, facilitating the knowledge spillovers. Third, periodic seminars, with participation by the manufacturer, distributors, the third-party information services provider, and consulting firms, are held to discuss issues associated with implementing and operating VMI, hence facilitating knowledge sharing across participants.

6. Concluding Remarks

Using an empirical approach, we examine the learning processes by which performance improvements are realized under VMI. A unique, operational-level dataset is used that allows us to identify and examine three different types of learning processes that may enhance VMI performance. Although there is extensive literature documenting the positive relationship between a firm's learning and performance (e.g., Argote 1999), our paper is the first (to our best knowledge) to investigate learning in the supply chain context. In addition, our paper is the first to examine performance improvement from the implementation of a supply chain program from a learning perspective. Thus, our study fills an important gap in the supply chain management literature.

Although our use of data from a single manufacturer has significant advantages in the control of exogenous factors that may influence performance, it also leads to a limitation of this study; that is, the generalizability of the results to other firms and to other industries. Therefore, results from this research, as with other studies (e.g., Clark and Hammond 1997), should be generalized with caution. Another limitation of this study is the measure of stockouts. Due to data limitations, we use number of days when stockouts occurred during a week to measure

stockouts. This measure does not differentiate stockouts in terms of number of units stocked out, and therefore does not provide the highest degree of granularity in assessing stockout performance. Although we show how various learning curves impact the performance results from VMI programs, we do not explore how these learning curves may vary across firms and products. Future research can examine the conditions under which certain firms (e.g., large vs. small) or certain products (e.g., fast vs. slow moving) may experience slower or faster learning curves in performance improvements.

Performance improvements in our study, in terms of inventory reductions, are found to be driven by all three types of learning processes. However, the benefit realization process from VMI is nonlinear. Learning from self experience and learning spillovers from EDI follow U-shaped learning curves, while learning spillovers from other supply chain dyads follow a “worse-then-better” sequence. The nonlinear nature of the learning processes provides a reasonable explanation to the anecdotal evidence that VMI does not always appear to improve performance (e.g., KPMG 1996).

Our finding of complex learning processes that combine nonlinear self-learning and learning spillovers from other sources expands the current understanding of how supply chain performance is actually realized. Our research results have a number of potential implications for managers: First, our finding that VMI produces performance benefits for downstream firms under certain conditions could provide guidance to managers when choosing to implement VMI. For example, managers may wish to implement VMI shortly after introducing EDI in order to realize maximum benefits from cross-program spillovers. Second, our results suggest that firms may need to be patient to fully realize the benefits from VMI due to the learning process involved in implementing VMI. Third, firms may benefit from using the same personnel to

implement multiple supply chain programs due to knowledge retention and cross-program spillovers. Finally, inexperienced firms planning to implement a supply chain program may wish to choose a partner with considerable experience in the implementation and use of the program in order to exploit the knowledge gained from previous VMI implementations.

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Table 1: Descriptive Statistics and Correlation Matrix (N=14,290)

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1. Inventory (INV)	131.75	255.55	0	3534.57	1							
2. Stockouts (STOCKOUT)	0.17	0.88	0	7	-0.08***	1						
3. Self-learning (E1)	796.60	653.74	1	2119	-0.09**	0.02**	1					
4. Learning Spillovers from EDI to VMI (E2)	452.12	290.22	112	1078	0.02*	-0.02*	-0.76***	1				
5. Learning Spillovers from Other SC Dyads (E3)	750096	7212.94	736068	761124	0.02**	-0.02*	-0.17***	0.37***	1			
6. Weekly Sales (SALES)	25.80	74.09	0	1643	0.61***	0.01	-0.07***	-0.02*	-0.002	1		
7. Annual Transaction Volume	5157803	4.88e+6	539253	1.43e+7	0.31***	-0.04***	-0.20***	0.03***	0.02***	0.31***	1	
8. Price (PRICE)	90.98	171.61	0.40	746.35	-0.22***	0.02*	0.0002	0.005	-0.002	-0.15***	-0.01	1
9. Lead Time (LEADTIME)	5.61	1.44	4	8	-0.17***	0.06***	-0.04***	0.28***	0.11***	-0.19***	-0.60***	0.009

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 2: Estimation Results
(Standard Errors in Parentheses)

	Model 1 Inventory	Model 2 Inventory
Intercept	5.58*** (0.25)	-480.04*** (25.56)
Stockouts - Fitted Value (STOCKOUTHAT)	-6.88*** (0.02)	-6.88*** (0.02)
E_1 ($\times 10^{-3}$)	-0.15*** (0.01)	-1.13*** (0.02)
$(E_1)^2$ ($\times 10^{-6}$)		0.44*** (0.01)
E_2 ($\times 10^{-3}$)	-0.26*** (0.01)	-0.87*** (0.05)
$(E_2)^2$ ($\times 10^{-6}$)		0.11** (0.04)
E_3 ($\times 10^{-3}$)	-0.003*** (0.0003)	1.30*** (0.07)
$(E_3)^2$ ($\times 10^{-9}$)		-0.87*** (0.05)
Weekly Sales (SALES) ($\times 10^{-3}$)	4.82*** (0.04)	4.83*** (0.04)
Lead Time (LEADTIME)	0.13*** (0.002)	0.12*** (0.002)
Price (PRICE) ($\times 10^{-3}$)	-3.72*** (0.01)	-3.71*** (0.01)
Annual Transaction Volume (VOL) ($\times 10^{-6}$)	0.11*** (0.001)	0.11*** (0.001)
Time Dummy Variables	Included	Included
Model Statistics		
N	14,290	14,290
Log Likelihood	-3,170	-3,168
Wald Chi2	382,517***	382,778***

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Note: STOCKOUTHAT is the fitted values of stockouts in the first stage estimations.

Figure 1: Impact of Self-learning (E_1)

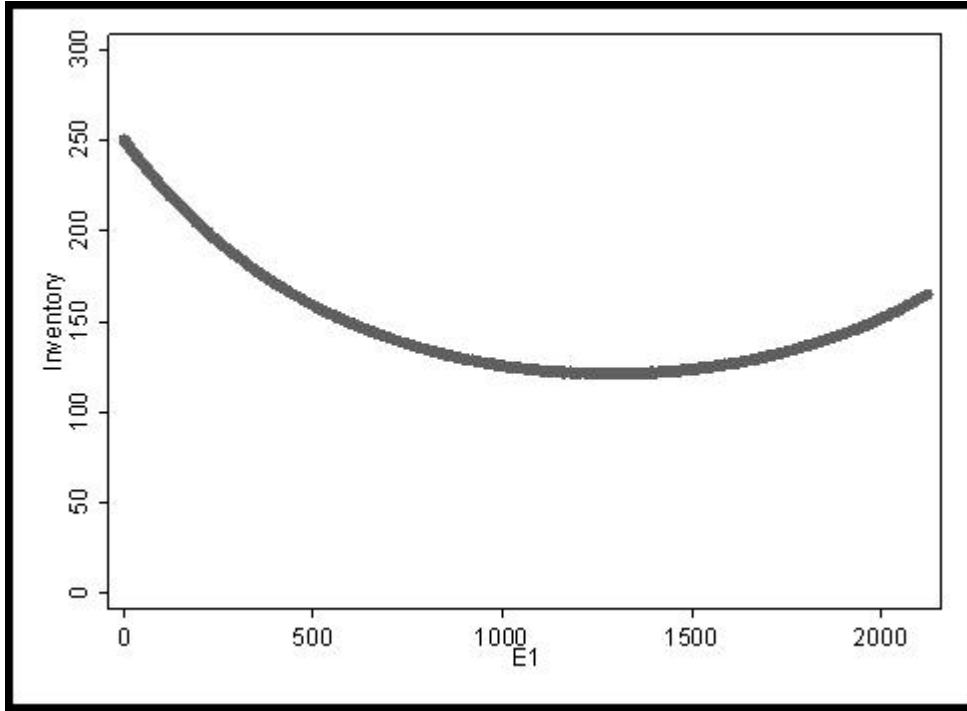


Figure 2: Impact of Learning Spillovers from EDI to VMI (E_2)

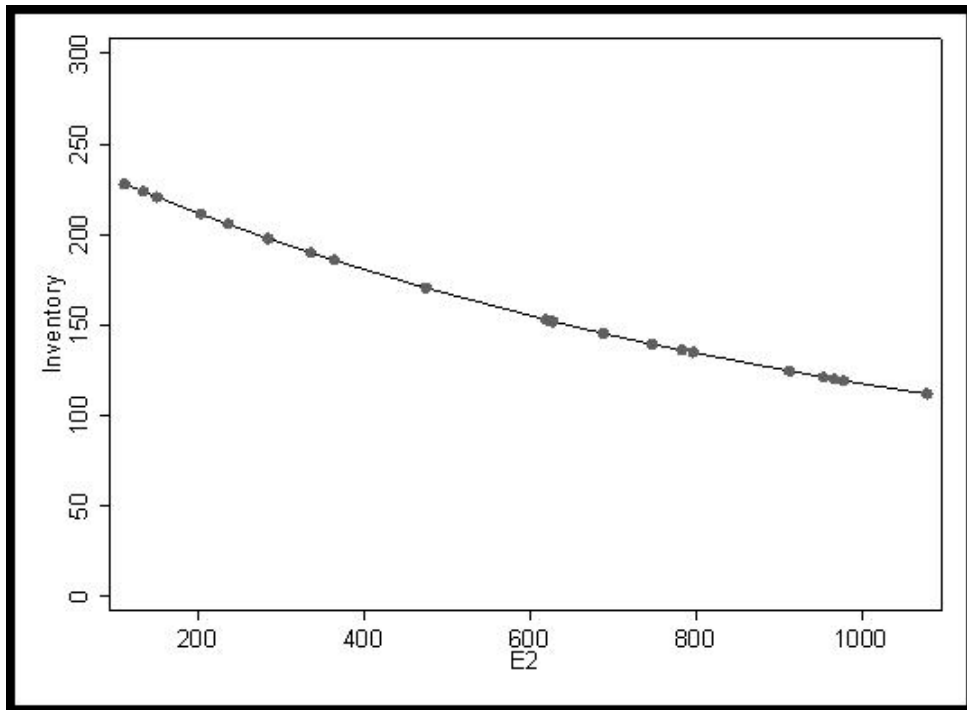
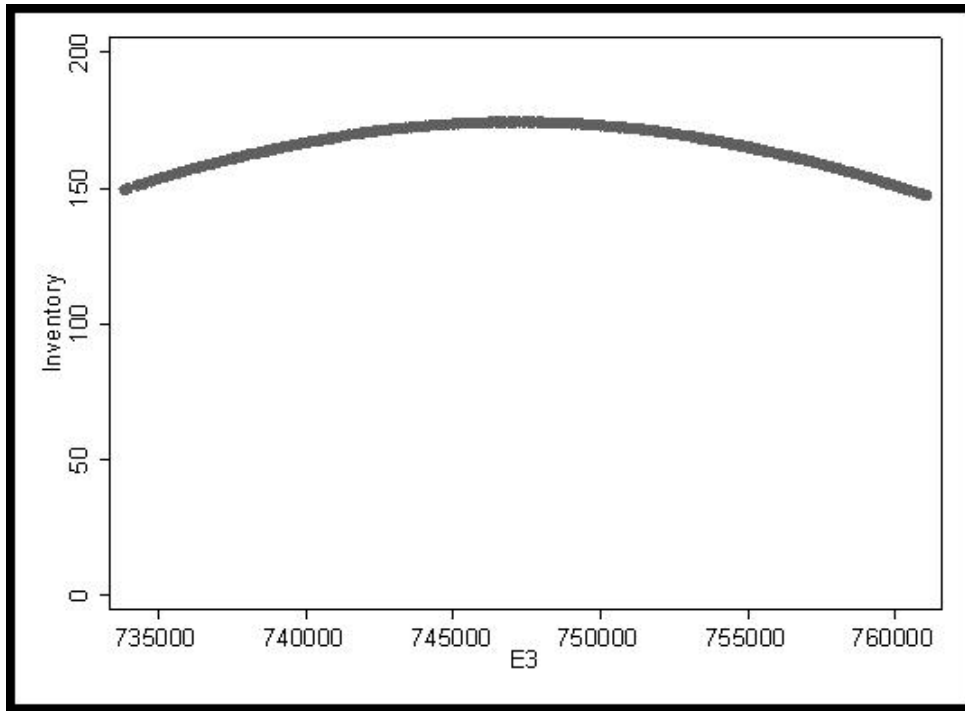


Figure 3: Impact of Learning Spillovers from Other Supply Chain Dyads (E_3)



Note: The figures are graphed based on the regression estimates from Model 2 in Table 2 within the range of sample minimums and maximums of E_1 , E_2 , and E_3 , respectively.

Appendix

Table A1: Results for the First Stage Estimation
(Standard Errors in Parentheses)

	Model 1 Stockouts	Model 2 Stockouts
Intercept	0.74* (0.30)	-73.73*** (28.62)
Lag Inventory	-0.14*** (0.003)	-0.14*** (0.003)
E_1 ($\times 10^{-3}$)	-0.02 (0.01)	-0.16*** (0.04)
$(E_1)^2$ ($\times 10^{-6}$)		0.06*** (0.02)
E_2 ($\times 10^{-3}$)	-0.04 (0.03)	-0.12 (0.09)
$(E_2)^2$ ($\times 10^{-6}$)		0.01 (0.07)
E_3 ($\times 10^{-3}$)	-0.0003 (0.0004)	0.20** (0.08)
$(E_3)^2$ ($\times 10^{-9}$)		-0.13** (0.05)
Weekly Sales (SALES) ($\times 10^{-3}$)	0.73*** (0.05)	0.73*** (0.05)
Lead Time (LEADTIME)	0.02*** (0.004)	0.02*** (0.004)
Price (PRICE) ($\times 10^{-3}$)	-0.52*** (0.03)	-0.52*** (0.03)
Annual Transaction Volume (VOL) ($\times 10^{-6}$)	0.02*** (0.001)	0.02*** (0.004)
Time Dummy Variables	Included	Included
Model Statistics		
N	14,290	14,290
Wald Chi2	1781***	1796***

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$