Do Electronic Linkages Reduce the Bullwhip Effect? An Empirical Analysis of the U.S. Manufacturing Supply Chains

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The bullwhip effect is a major source of supply chain inefficiency. Whereas prior literature has identified a number of potential contributing factors and recommended such remedies as information sharing enabled by information technology (IT) or electronic linkage (EL), few studies have provided empirical support. We use industry-level data to examine whether EL use with buyer and supplier industries helps reduce the bullwhip effect as measured by inventory–demand variance ratio. Our major findings are that (1) EL use with supplier industries reduces the bullwhip effect, whereas (2), surprisingly, EL use with buyer industries increases it, but (3) this adverse effect tends to be mitigated by IT use. These findings point to the possible asymmetric effects of EL use in supply chains and provide a different perspective to the existing conclusions in the literature that EL use improves performance. Combining the above results, we have learned that the use of EL tends to behave differently depending on whether it is used upstream or downstream in the supply chain. This also sheds light on the conditions under which such investment may be more (or less) beneficial.

Key words: supply chain management; bullwhip effect; information technology; electronic markets; empirical operations; econometrics

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1. Introduction

According to the U.S. Bureau of Economic Analysis, investment in information technology (IT) accounted for more than 50% of capital expenditures in the United States, and amounted to more than $400 billion. This is, in part, driven by the increasing trend of conducting business transactions through electronic linkages (ELs). Data from the U.S. Census Bureau show that transactions through ELs reached $2.94 trillion (or 14% of total transactions) in 2006 as measured by the value of sales in manufacturing, wholesale, and retail industries. One would expect that such an increase in the use of ELs would have brought about significant benefits, yet research quantifying the benefits of ELs is still limited (e.g., Zhu and Kraemer 2002, Mitkas and Jones 2007), whereas extensive research examines the business value of IT in general (e.g., Brynjolfsson and Hitt 1996, Srinivasan et al. 1994, Mukhopadhyay et al. 1995, Barua et al. 1995).

Among the limited research, the focus has been on operational benefits at the firm level. For example, Zhu (2004b), using data from 114 retail firms, found that electronic market use, a form of EL, is positively related to firm performance in terms of sales per employee, inventory turnover, and cost reduction. Choudhury et al. (1998) studied the aircraft parts industry and found that inventory levels were unaffected by the use of electronic markets, although there are some improvements in identifying parts and reducing aircraft downtime. Whereas these studies examine firm-level operational benefits from EL use, our research sets out to examine the issue from a supply chain perspective, where interfirm use of EL is more important.1 That is, we look at whether such EL use has helped improve supply chain efficiency (as opposed to individual firms), as manifested by the inventory–demand variance ratio (a proxy for the bullwhip effect).

Consistent with studies in the literature, an electronic linkage refers to an interfirm linkage enabled by an electronic medium (Bakos 1991), including both

1 The bullwhip effect is a supply chain phenomenon because it involves both buyers and suppliers in a supply chain. The demand variance results from buyer’s orders, whereas inventory variance results from suppliers’ inventory levels (Cachon et al. 2007).
electronic hierarchies (EHs) and electronic markets (EM).\(^2\) ELs, including both EHs (e.g., EDI linkages) and EMs, are forms of interorganizational systems (IOSs). An IOS is defined as “an automated information system shared by two or more companies” (Cash and Konsynski 1985) and “is built around information technology that facilitates the creation, storage, transformation and transmission of information” (Johnston and Vitale 1988). Typically, an EDI-based EL facilitates \textit{bilateral} linkages enabled by industry-standard protocols, whereas an EM-based EL features \textit{multilateral} relationships enabled by the Internet open protocol and standards (i.e., TCP/IP) (Zhu et al. 2006). These definitions are consistent with those used in the previous research, such as Bakos (1997), Choudhury et al. (1998), Dong et al. (2009), and Zhou and Zhu (2010).

The \textit{bullwhip effect} refers to “the amplification of demand variability from a downstream site to an upstream site” (Lee et al. 2004, p. 1887). The phenomenon has been documented in several industries (e.g., Holt et al. 1968, Anderson et al. 2000, Terwiesch et al. 2005). For example, Cachon et al. (2007) found that wholesale industries exhibit a bullwhip effect, whereas retail industries do not. The bullwhip effect is shown to lead to tremendous inefficiencies in supply chains such as “excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules” (Lee et al. 1997a, p. 93). As a result, mitigating the bullwhip effect becomes a major task for supply chain managers across manufacturing industries.

Among the possible solutions, using IT-based electronic linkages for greater information sharing or for better order management has been proposed as a solution to mitigate the bullwhip effect (e.g., Lee et al. 1997b, Zhu 2004a, Dong et al. 2009). To the best of our knowledge, however, most of the studies in the literature are analytical in nature, and empirical evidence that links EL use to reduced bullwhip effect is still limited, as reviewed by Cachon et al. (2007).

Our study seeks to fill this gap. We use an industry-level data set from the U.S. Census Bureau and the U.S. Bureau of Economic Analysis (BEA) to examine our research question of whether EL use with buyer and supplier industries has resulted in any reduction in the bullwhip effect in manufacturing supply chains.

The amplified bullwhip effect has been manifested at the industry level.\(^3\) For example, in the automobile industry, anecdotes and empirical evidence documented the bullwhip effect at suppliers (Aeppel 2010) and buyers (Cachon et al. 2007). In particular, Cachon et al. (2007), using industry-level data, found that “motor vehicles and parts dealers” see amplified inventory–demand variance. Blanchard (1983) found that “in the automobile industry, inventory behavior is destabilizing: the variance of production is larger than the variance of sales,” providing evidence of the bullwhip effect at the industry level.

We distinguish the effect of EL use with buyer industries versus EL use with supplier industries, as they may have different implications for the bullwhip effect in upstream versus downstream supply chains. We develop several hypotheses and test them by constructing an econometric model based on a data set of the U.S. manufacturing supply chains. We obtain the following results: (1) EL use with \textit{supplier} industries tends to reduce the inventory–demand variance ratio, whereas (2) surprisingly, EL use with \textit{buyer} industries tends to increase it; hence the effects seem rather asymmetric. But (3) this adverse effect seems to be mitigated by IT. These effects are not only statistically significant but also economically significant.

Our findings on EL use provide a different perspective to the existing views in the literature that EL use improves performance and shed light on the conditions under which such investment may or may not be beneficial. When EL is used with buyer industries for \textit{selling}, it may unexpectedly hurt seller industries with an increased inventory–demand variance ratio; when EL is used with supplier industries for \textit{procurements}, it increases supply chain efficiency by reducing the inventory–demand variance ratio. These findings underscore the importance of better understanding of EL’s asymmetric effects on the upstream and downstream supply chains. Overall, the counter-intuitive findings on EL use with buyer industries, together with the paucity of empirical research on EL

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\(^2\) There are different forms of electronic linkages (Malone et al. 1987, Bakos 1991). We do not have more granular data to further differentiate among various forms of electronic linkages. Meanwhile, the focus of this research is not to study the differential effect of EM versus EH, but both EM and EH as a whole. Thus, although we do not have granular data to differentiate various forms of EL, our data can still capture their effect as a whole.

\(^3\) Prior studies have shown that the firm-level bullwhip effect can be manifested at the industry level (Cachon et al. 2007) as the aggregation does not necessarily bias the estimation of the bullwhip effect. For example, Caplin (1985) showed that if the bullwhip effect is due to \((S, s)\) policies, it is preserved under aggregation for any demand correlation structure. Allen (1997) found that aggregation tends to preserve whether the amplification ratio falls above or below 1. Literature in economics studied similar phenomena (termed production smoothing) using industry-level data. Studies such as Ghali (1987), Krane and Braun (1991), and Miron and Zeldes (1989) further demonstrated that the bullwhip effect can be studied at the industry level. As Cachon et al. (2007) put it, “...an industry exhibits the bullwhip effect when the variability of the inflow to the industry (production) is greater than the variability of the outflow from the industry (demand).”
use on the inventory–demand variance ratio in particular, point to the major contributions of this research to the literature.

The rest of this paper is organized as follows. Section 2 discusses the theory and relevant literature, §3 develops a number of hypotheses, §4 describes the research methodology and empirical model, §5 presents our estimation and results, §6 interprets the findings, and §7 closes the paper.

2. Theory and Literature

2.1. Theoretical Considerations Based on Transaction Cost Economics

Transaction cost economics (TCE) addresses behavioral implications of firms in transactions and provides a theoretical view about how market structures are chosen (Coase 1937; Williamson 1975, 1979). The choice of market structure depends on the costs associated with buyer–seller transactions. Transaction costs exist because of the presence of coordination and search costs, governance, opportunism, asset specificity, and incomplete contracting (Demsetz 1968, Williamson 1979). When the market structure is chosen, these cost components may be impacted by the use of IT, thereby leading to different performance outcomes. Therefore, TCE is an appropriate theory to analyze the effect of IT-enabled EL on performance in a supply chain setting (Grover and Malhotra 2003, Saeed et al. 2005).

Along this line, Malone et al. (1987) identified three effects that IT can bring about:

- the electronic communication effect: IT may allow more information to be communicated in the same amount of time, and it thus may decrease the cost of communications;
- the electronic brokerage effect: by electronically connecting many buyers and suppliers and matching them through online markets, EMs can fulfill a similar function to a traditional brokerage, possibly with greater efficiency; and
- the electronic integration effect: a supplier and a buyer use IT to create joint processes at the interface between value-added stages, thereby leading to tighter coupling of business processes.

Based on this three-effect framework, Clemons et al. (1993) introduced the “move to the middle” hypothesis, which was subsequently tested by Dedrick et al. (2008), arguing that IT has the ability to lower coordination cost without increasing the associated transaction risk. In particular, they argued that IT is (1) able to reduce the cost of exchanging and processing information, thus reducing the coordination costs; (2) able to increase information availability and processing capacity, thus reducing the monitoring costs; and (3) increasingly standardized and interconnective, thus reducing the relationship-specific investment as articulated in TCE.

Similar arguments have also been made specifically with respect to EL use. Lucking-Reiley and Spulber (2001) summarized the productivity gains from EL use into four areas: efficiencies from automation of transactions, economic advantage of new market intermediaries, consolidation of demand and supply through organized exchanges, and changes in the extent of vertical integration companies. These are consistent with those argued above. Bakos (1997) studied economics of ELs in particular and concluded that ELs would reduce a buyer’s search costs, promote price competition, weaken the market power of sellers, and lower coordination costs by reducing inventory and monitoring costs. Zhou and Zhu (2010), using a game-theoretic model, studied the effects of e-markets on upstream suppliers and downstream manufacturers.

To put these in the three-effect framework, with regard to the impacts of IT-enabled EL on transaction costs, the electronic communication effect and electronic integration effect may reduce coordination costs and monitoring costs, thus reducing operations risk, whereas the electronic brokerage effect may reduce search costs and switching costs.

Such reductions in TCE costs (i.e., coordination, monitoring, search, and switching) have important implications on supply chain performance. First, the use of EL may yield better supply chain performance (e.g., faster inventory turnover) because of the electronic communication and electronic integration effects. Malone et al. (1987) had an example for the electronic integration effect: “Systems linking the supplier’s and procurer’s inventory management processes so that the supplier can ship the products ‘just in time’ for use in the procurer’s manufacturing process enable the latter to eliminate inventory holding costs, thus reducing total inventory costs for the linked companies.”

Second, the implication of the electronic brokerage effect is not as clear because it provides greater choices of alternatives and lower costs of the selection process, which reduces opportunism risk for buyers. Opportunism risk is determined by small number bargaining, relationship specific investment, and loss of control (Clemons et al. 1993). Because of increasingly standardized technology (i.e., reduced relationship-specific investment) and reduced buyer search costs, EL can mitigate the opportunism risk for buyers (Dedrick et al. 2008). In addition, it expands the market reach for the buyers (Barua et al. 1997); thus it may lead to greater demand volatility for suppliers. In the meantime, because of reduced search cost for buyers, suppliers face heightened competition and weakened bargaining power, whereas buyers...
enjoy reduced search and switching costs. That is, the impact of EL may be different when it is used with buyers and when it is used with sellers.

Table 1 summarizes these theoretical arguments from the TCE perspectives discussed so far.

2.2. Review of Empirical Literature

In addition to the above theoretical literature, two streams of empirical research are relevant to our study. One stream examines the performance impacts of EL use, whereas the other stream analyzes the causes and consequences of the bullwhip effect. The first stream includes research in both operations management and information systems. Their foci are quite distinct though. The latter focuses on evaluating the payoffs from EL use by assessing the mechanisms through which business values are created. The former, on the other hand, examines the operational impacts of EL use on supply chains. We highlight the relevant studies in both streams.

Mukhopadhyay and Kekre (2002) showed that business-to-business (B2B) procurement processes bring not only strategic but also operational benefits to suppliers and buyers in the auto manufacturing industry. Choudhury et al. (1998) studied the aircraft parts industry and found that aggregate inventory levels are unaffected by the use of EL, although there are some more specific improvements as a result of EL use in identifying parts and reducing aircraft downtime. Barua et al. (1995) studied the business value of IT by developing a two-stage analysis of intermediate- and higher-level output variables and found significant, positive impacts of IT at the intermediate level. In a more recent study, Barua et al. (2004) examined the business value from Internet-enabled value chain activities using data from over 1,000 firms in manufacturing, retail, and wholesale sectors, and they found that supplier-side digitization has a strong positive impact on customer-side digitization. Zhu and Kraemer (2002) found that the use of Internet technology is associated with lower costs of goods sold and higher inventory turns in the manufacturing industry. In a follow-up study, Zhu (2004b) found that EL capabilities and IT infrastructure reinforce each other (i.e., the “complementarity effect”) and are both positively related to firm performance in the retail industry. Yao et al. (2009), using data from the U.S. government, compared the performance between EDI and EM and found that EM tends to outperform EDI in terms of order cycle time and order fill rate. As found in most of these studies, EL use improves firms’ operational performance.

Specifically about EMs, Mithas and Jones (2007) studied the use of a particular form of EM, reverse auctions, in B2B procurement, using field data on more than 700 online procurement auctions, and they found bidding competition, reserve price, and information sharing affect buyer surplus. Mithas et al. (2008) studied EM of reverse auctions and found that noncontractible elements of interorganizational relationships have greater explanatory power for reverse auction use than asset specificity. Dedrick et al. (2008) showed how the use of IT (and EL in particular) shapes supply chain structure, particularly in terms of the number of suppliers.

The bullwhip effect is studied to a lesser extent, but the literature is growing. Lee et al. (1997b) identified four sources of the bullwhip effect: demand signal processing, rationing game, order batching, and price variation. Several possible solutions have been proposed to mitigate the bullwhip effect, including the use of IT-based electronic markets (e.g., Zhu 2004a, Dong et al. 2009). Chen et al. (2000) further analyzed the bullwhip effect in a two-stage supply chain through modeling demand forecasting and order lead time, and they showed that the bullwhip effect can be reduced, but not completely eliminated, by information sharing.

Building on such theoretical work, several studies have attempted to empirically test the existence (or
lack) of the bullwhip effect. Anderson et al. (2000) found substantial volatility in the machine tool industry and attributed it to the bullwhip effect. Terwiesch et al. (2005) showed that the semiconductor equipment (upstream) industry is more volatile than the personal computer (downstream) industry. Cachon et al. (2007) found that wholesale industries exhibit a bullwhip effect, whereas retail industries do not, and manufacturing industries do not have substantially greater demand volatility than retail industries. These analyses seem to point out that different industries demonstrate considerable heterogeneity in terms of the bullwhip effect.4

2.3. Distinctions from the Literature

Our paper is grounded on the above theoretical and empirical literature, but it is also distinct from the literature in several ways. First, the major focus in the literature so far has been on identifying the bullwhip effect. As far as we are aware, none has used hard data to test whether the bullwhip effect (or inventory–demand variance ratio) can be mitigated if one or more of the four causes are allayed or eliminated. Second, none of the studies on EL has used the inventory–demand variance ratio as the dependent variable, although the literature has used other metrics such as order cycle time or shipment errors to examine supply chain performance. Third, unlike most of the prior studies that evaluated EL use in general, we examine the impact of EL use with buyer and supplier industries simultaneously on a focal industry (as shown in Figure 1), thereby providing a finer-grained picture of the effect of EL use in a supply chain dyad. By separating EL use with buyers and EL use with suppliers, we hope this paper may discover some hidden patterns of EL effects on buyers and suppliers and may help narrow the gap through providing empirical evidence on whether EL use with different supply chain partners can mitigate the inventory–demand variance ratio.

3. Hypothesis Development

Building on the theoretical foundation of TCE and the relevant literature discussed above, we develop four hypotheses that link EL use with the inventory–demand variance ratio, as well as the interaction effect between EL use and IT. Figure 2 summarizes the research model and the hypotheses.

As discussed in §2.2, prior research has documented the relationship between EL use and operational performance. The main theoretical underpinning is that ELs have brought about the electronic communication, the electronic integration, and the electronic brokerage effects through which coordination costs can be reduced and operations risk and opportunism behaviors can be mitigated. As discussed in the theoretical section, when EL is used, suppliers and buyers are able to process transactions with greater efficiency or at lower transaction costs. In particular, firms can automate their online sales process with their supply chain partners through online search and order tracking. For example, Tatsiopoulos et al. (2002) described such EL use in a clothing supply chain, in which EL helps automate customer order management and production order release. The cost savings can be substantial. As stated in Lucking-Reiley and Spulber (2001, p. 57), “Processing a purchase order manually, including paperwork, data entry, phone calls, faxes and approval requests, can be quite expensive, so online transactions might easily reduce costs by a factor of five or ten or more.” Such reduction in transaction costs may lead to more frequent order placements with smaller quantities—that is, less order batching, which is a major cause of the bullwhip effect (Lee et al. 1997b). Furthermore, improved capability in data transmission, capture, process, and analysis resulting from EL use (e.g., open standards and protocol) may help companies better interpret demand signals and more accurately plan inventory and replenishment (Terwiesch et al. 2005), thereby resulting in smaller inventory variations, and thus smaller inventory–demand variance ratio.

On the other hand, the electronic brokerage effect may take place where search costs are reduced through “consolidating markets, providing market

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4In addition, a few experimental studies have also examined the behavioral causes of the bullwhip effect, such as decision bias in the form of underweighting the supply line (Croson and Donohue 2006).
information, and offering an assortment of goods and services, so that buyers obtain the cost efficiency of one-stop shopping, rather than spending time contacting multiple suppliers” (Lucking-Reiley and Spulber 2001, p. 58). By participating in electronic markets, buyers have a greater number of alternative products and supplier options (i.e., electronic brokerage effect) and greater bargaining power because of reduced search/switching costs (Zhou and Zhu 2010), thereby attaining a greater possibility and frequency of switching among suppliers. In other words, everything else being equal (buyer–supplier relationships, supplier quality, etc.), EL use will expand a buyer’s market reach, thus enabling the buyer to find an additional supplier easier (Barua et al. 1997). The increased possibility of switching creates greater demand uncertainty for the suppliers (e.g., demand spikes). According to Lee et al. (1997b), because of information lag (e.g., lead-time), the increased demand uncertainty from buyers will be amplified for suppliers. Thus, dependent on the magnitude of the amplification, it is possible that the inventory–demand variance ratio may actually be increased for upstream suppliers.

Although both scenarios are theoretically possible, we propose the relationship in a positive way (i.e., EL use improves performance) as a hypothesis to be tested, under the conjecture that the positive effect of EL use will outweigh the negative effect, recognizing that the competing hypothesis exists.

**Hypothesis 1 (H1).** EL use with buyer industries is negatively associated with the inventory–demand variance ratio.

In a supply chain setting, firms sometimes place inflated orders to suppliers to guard against supply uncertainty. Inflated orders often result from rationing and shorting gaming. As argued in Lee et al. (1997a), “When product demand exceeds supply, a manufacturer often rations its product to customers….Knowing that the manufacturer will ration when the product is in short supply, customers exaggerate their real needs when they order. Later, when demand cools, orders will suddenly disappear and cancellations pour in.” Such order inflation is one of the major contributing factors that cause the bullwhip effect (Chen et al. 2000, Lee et al. 1997b).

Because of the electronic brokerage effect and expanded market reach discussed above, EL use with suppliers provides access to a greater number of potential suppliers (Dedrick et al. 2008). The buyer can easily compare and shop for a product in terms of prices and product availability from these suppliers, because the search cost is lower. These effects provide the buyer with some level of comfort on the availability of the products; thus they do not need to play the rationing game as much as they did before (Zhou and Zhu 2010). As a result, the buyer may not feel the need to place inflated orders anymore, thus leading to a reduced inventory–demand variance ratio. Therefore, we propose the following hypothesis.

**Hypothesis 2 (H2).** EL use with supplier industries is negatively associated with the inventory–demand variance ratio.

In this paper, consistent with studies in the literature, IT refers to IT infrastructure that encompasses computers and peripheral equipment, software, and communication equipment (Zhu 2004b). EL, as defined earlier, refers to a transaction linkage interacting with trading partners and enabled by an electronic medium (e.g., the Internet) (Bakos 1997). IT and EL use measures different functionalities. IT use is associated with back-end operations (e.g., production planning, warehouse management), whereas EL use is associated with the front-end operations, either with buyer industries or with supplier industries (e.g., sales or procurements) (Zhu 2004b). Thus, an interesting question arises: Is IT use complementary to EL use? In other words, can EL use with buyer industries generate greater performance benefits when IT use is higher? Or are the benefits of EL use dampened by the lack of IT systems?

Prior literature has discussed that performance benefits may come from how supply chain partners leverage their investments to create unique IT-based processes that streamline the supply chain (e.g., Dong et al. 2009). Alignment between IT and supply chain processes can help firms improve their operations. Such alignment generates transactional efficiencies, which may further create operational and strategic benefits (Barua et al. 1995, 2004). For example, in examining the business value of EDI using an empirical approach, Lee et al. (1999) found that EDI and business process change in terms of continuous replenishment processes that when implemented together may generate a compounding effect to performance improvement. At the industry level, when IT use is high for an industry, the industry may be able to gain more benefits and efficiencies from EL use because of the compounding effect (Zhu 2004b). Therefore, we have our final pair of hypotheses.
Hypothesis 3 (H3). EL use with buyer industries is more negatively associated with the inventory–demand variance ratio when IT use is higher.

Hypothesis 4 (H4). EL use with supplier industries is more negatively associated with the inventory–demand variance ratio when IT use is higher.

4. Research Methodology

4.1. Data

Data used for this research were gathered from the U.S. Census Bureau (referred to as the “Census” hereafter) and the Bureau of Economic Analysis (BEA). The Census and BEA classify the U.S. manufacturing industries using the North American Industry Classification System (NAICS) of coding. As a result, 21 industries are classified to represent the manufacturing sector of the U.S. economy. We collected data on all 21 industries for our research. Table 2 shows the sample characteristics, including the names of the 21 industries in column 1.

The Census began publishing annual e-commerce data (called “E-Stats”) for manufacturing industries in 1998. The Census conducts a survey for e-commerce use every year and publishes it as E-Stats. The e-commerce use is defined by the Census as the value of goods and services sold online, including the Internet, extranet, and EDI. The most recent year of data collected for the present study was 2005. Because the data for the first year (1998) were incomplete, we excluded that year and collected E-Stats data for the period 1999–2005 (seven years). From 1958 to the current month, the Census has also reported monthly sales and inventories for manufacturing, wholesale, and retail industries. We collected the monthly inventory and sales data for the same period during which E-Stats data are available. The monthly sales and inventory data were aggregated to an annual level to match the annual E-Stats data. In addition, we collected data on investment in IT infrastructure from BEA. This includes total annual dollars (adjusted to current dollars) invested in computers and peripheral equipment, software, and communication equipment.

Because both sales and inventory are reported in dollar value, sales data need to be adjusted by a gross margin so that data can be comparable with inventory. Both sales and inventory values also need to be adjusted by price index to account for price variation over time. We collected gross margin information for each manufacturing industry from the Census. The monthly gross margin is not readily available, but the Census conducted a benchmark study for manufacturing industries every five years, which we used to calculate gross margins. Price deflator information was collected from the BEA, which reports annual implicit price deflators for manufacturing and trade sales with the price for the year 2000 designated as 100.

Because reported data on EL use are for buyer industries, we need to know who the supplier industries are for each manufacturing industry to calculate EL use with supplier industries. We collected the input–output accounts table, which shows how much a manufacturing industry output was used as an input of another industry. Specifically, the table shows how the manufacturing industries provide input to and receive output from each other to produce the gross domestic product. Using this table, we were able to determine the supplying industries to a focal industry and their contributing shares.7 The fifth column

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6 Following Cachon et al. (2007), we calculated the gross margin as (value added – production wages)/(value of shipments).

7 See Cheng and Nault (2007) for the methodological details on how to use the input–output account table to calculate the supply shares for any given industry.
of Table 5 shows, for each manufacturing industry, the total percentage of supplies that come from industries within our sample.\(^6\) For example, for the food products industry (NAICS 311), 40.65\% of its supplies come from the industries within our sample (including from own industry). For most industries, a great percentage of supplies comes from the manufacturing industries within our sample (in the range of 40\% to 80\%, except for two industries), suggesting that our sample is sufficiently significant in terms of supplying volume to construct a manufacturing supply chain dyad (i.e., a supplier industry and buyer industry dyad).

### 4.2. Variables

Given our research questions defined earlier, the inventory–demand variance ratio (IDVR) is naturally the dependent variable. Following the approach used in Cachon et al. (2007), we use IDVR to measure the bullwhip effect. That is, our theoretical variable is the bullwhip effect, and its operationalized variable is IDVR. Mathematically, IDVR is computed as follows:\(^9\)

$$IDVR = \frac{\text{inventory variance}}{\text{demand variance}}.$$  

This measure is slightly different from the conventional definition of the bullwhip effect: the ratio of order variance to demand variance. As noted in Cachon et al. (2007), because industry order data are generally not available, this alternative measure is a reasonable proxy. The lower the IDVR, the lower the bullwhip effect. The lower the bullwhip effect, the greater the operational efficiency and supply chain performance.

Electronic linkage use with buyer industries (ELB) is measured as the cost of goods sold (COGS) in an EL as a percentage of total COGS. Because sales are a potential driving force for the inventory–demand variance ratio, the extent to which sales are conducted in an EL is a reasonable measure for the use. This measure is adopted from the literature (Zhu and Kraemer 2002). The third column of Table 2 presents the statistics of EL use with buyers for each individual industry. It ranges from as low as 6.62\% for wood products to as high as 47.12\% for transportation equipment.

Electronic Linkage Use with Supplier Industries (ELS) is defined as follows:

$$ELS_i = \sum_j \left( \frac{s_{ij}}{\sum_j s_{ij}} \cdot ELB_j \right), \quad i \neq j,$$

where \(i\) denotes the focal industry, \(j\) denotes the supplier industries, \(s_{ij}\) denotes the total value of supplies from industry \(j\) to industry \(i\), and \(ELB_j\) is the EL use with buyer industry \(j\). Based on the input–output accounts table, we identified all of the supplier industries and their shares of input for a focal industry (\(s_{ij}\)). We then calculated the weighted average of EL use, based on the above formula, for all of the industries in our sample to generate the ELS variable. This methodology is consistent with Cheng and Nault (2007). The fourth column of Table 2 shows the ELS for each industry.

IT is measured by the total stocks of investment in computers and peripheral equipment, software, and communication equipment by a manufacturing industry per year. Because it is measured in dollars, and to account for price variation over time, the variable is deflated by using the annual implicit price deflators for manufacturing and trade sales collected from the BEA. This is consistent with the literature (e.g., Shah and Shin 2007).

#### 4.3. Econometric Models

To test our hypotheses, we develop two model specifications: a main effect model and an interaction effect model. For both models, the key issue is whether there is a significant effect of those independent variables on the dependent variable IDVR after controlling for industry- and time-specific effects. To do so, we include a number of control variables that are believed to be relevant to our dependent variable based on prior literature (e.g., Gaur et al. 2005, Rumyantsev and Netessine 2007).

First, we add COGS to control for the size effect in an industry. Larger industries may have levels of IDVR different from smaller industries. Second, we add a dummy variable for the durable goods industry to control for the difference between durable and nondurable goods. Third, we add price index variation to control for price variation over time for each industry. Fourth, we add gross margin to control for the heterogeneity between industries with different gross margins. Finally, we control for the fixed time effect that accounts for technological advances and productivity improvement during our sample time.

For industry \(i\) in year \(t\), the econometric models are specified as follows. Main effect model:

$$IDVR_{it} = \beta_0 + \beta_1 IT_{it} + \beta_2 ELB_{it} + \beta_3 ELS_{it} + \beta_4 COGS_{it} + \beta_5 DURABLE_i + \beta_6 \text{VPRICE}_{it} + \beta_7 GM_i + \epsilon_{it}. \tag{1}$$

Interaction effect model:

$$IDVR_{it} = \beta_0 + \beta_1 IT_{it} + \beta_2 ELB_{it} + \beta_3 ELS_{it} + \beta_4 XITELB_{it} + \beta_5 XITES_{it} + \beta_6 COGS_{it} + \beta_7 DURABLE_i + \beta_8 \text{VPRICE}_{it} + \beta_9 GM_i + \epsilon_{it}. \tag{2}$$

\(^6\)The input–output tables aggregate NAICS 311 and 312, 313 and 314, and 315 and 316, respectively. We assume each individual industry follows the aggregated input–output shares.

\(^9\)The ratio is widely used in the economics literature to measure production smoothing (e.g., Kahn 1992).
In these models, 
- IDVR, ELB, ELS, and IT are defined as in the previous section. 
- The interaction term between IT and ELB (XITELB) is the interaction term of mean-centered IT and ELB. 
- Similarly, the interaction term between IT and ELS (XITELS) is the interaction term of mean-centered IT and ELS. 
- Cost of goods sold (COGS) is the total sales in dollars adjusted for gross margin for an industry. 
- Durable goods industry (DURABLE) is a dummy variable, where 1 is for the durable goods industry (e.g., machinery), and 0 is for the nondurable goods industry (e.g., food products). 
- Price variance (VPRICE) is defined as the variance of the monthly price over the period of a year and is calculated using a standard variance formula. 
- Gross margin (GM) is calculated as \((\text{value added} - \text{production wages})/\text{value of shipments})\).

Table 3 presents the descriptive statistics and correlation matrix. To check for potential multicollinearity, we computed variance inflation factor (VIF) scores for all independent variables. The VIF scores are between 1.09 and 1.98, lower than the commonly accepted level of 10 (Kennedy 2003), indicating that multicollinearity is not a concern for our data.

### 5. Estimation and Results

Because our data are panel data, we used standard panel data techniques to estimate our models. Given that inventory and demand, two key components of the dependent variable, are often affected by the previous status, we performed the Wooldridge test for autocorrelation in the panel data (Wooldridge 2002). We found that first-order autocorrelation (AR1) does exist \((F = 7.49, p < 0.001)\). Furthermore, the AR1 process is likely to be different across industries, resulting in panel-specific AR1s. We performed a likelihood ratio test to check whether the AR1 coefficients are common across panels. We found that the test statistics were significant, suggesting that a panel-specific AR1 was more appropriate.

Another issue related to the panel data analysis is the variance of the error term structure between panels (i.e., industries). Given that industries differ from each other (e.g., in size), it is likely that the variances of the error terms are different across panels (i.e., heteroskedasticity). We performed a modified Wald test (Greene 1997) and found significant test statistics \((\chi^2 = 1.3 \times 10^6, p < 0.001)\), confirming that heteroskedasticity does exist. Therefore, we use the feasible generalized least squares (FGLS) procedure with the specification of panel-specific AR1 and heteroskedasticity to estimate our models.

The results are summarized in Table 4. For the main effect model, the coefficient for ELB is positive and significant \((\beta = 3.44, p < 0.05)\), indicating that EL use with buyer industries tends to increase the inventory–demand variance ratio. This finding is counter to H1. As discussed in the §2.1, the net impact of EL is to be determined by two conflicting forces: the IDVR-enlarging effect from the increased market reach and demand uncertainty versus the IDVR-reducing effect from the reduced coordination cost and operations risk. Our result indicates that EL use leads to a greater IDVR likely because the former outweighs the latter.\(^\text{10}\)

The coefficient for ELS is negative and significant \((\beta = -6.51, p < 0.05)\), indicating that EL use with suppliers reduces the inventory–demand variance ratio.\(^\text{10}\)

\(^\text{10}\)To clarify, our analysis shows that ELB tends to increase IDVR, but this does not necessarily conclude the total effect of ELB to be negative. IDVR, after all, is only a partial reflection of the total costs incurred and benefits received from the use of EL. For example, ELB can reduce transaction costs. The net benefit of using ELB may still be positive. Hence, this study only shows that the bullwhip effect could possibly be enlarged by ELB, but it does not show that the net effect of ELB is negative.
Thus, H2 is supported, confirming our theoretical conjectures in §3.

The coefficient for IT is insignificant, indicating that the direct relationship between IT and IDVR is inconclusive.

For the interaction effect model, the coefficients for the independent variables (i.e., ELB and ELS) and IT are consistent with those in the main effect model, indicating the robustness of the model. The coefficient for the interaction term of ELB and IT is negative and significant ($\beta = -0.81 \times 10^{-9}, p < 0.05$). Because the sign of the coefficient is opposite to that of ELB, this result indicates that greater IT helps to mitigate the adverse effect of ELB on IDVR. The total effect of ELB on IDVR can be calculated as $(2.67 - 0.81 \times 10^{-9} \times IT) \times ELB$. Clearly, the direction of the total effect is dependent on the level of IT. That is, when IT is small, ELB tends to increase IDVR; when IT is large, ELB tends to reduce IDVR. Thus, because IT results in more negative effects of ELB on IDVR, H3 is supported. However, the coefficient for the interaction term of ELS and IT is positive but insignificant, indicating that H4 is unsupported.

The coefficients for the control variables are significant and generally expected. The coefficient for COGS is negative and significant, suggesting that large firms tend to have smaller IDVR, possibly because large firms are often more diversified than small firms, which helps to smooth IDVR. The coefficient for DURABLE is negative and significant, suggesting that the durable goods industries have smaller IDVR, likely because of more stable demands in these industries. Wald statistics are 23.67 and 25.10 ($p < 0.001$) for the main and interaction effect models, respectively, indicating significance of the estimates.\footnote{Because the FGLS procedure does not compute $R^2$ statistics, we ran ordinary least squares variants of the equations to obtain the $R^2$ statistics. The adjusted $R^2$ is 0.16 for the main effect model and 0.16 for the interaction effect model, respectively, indicating a reasonable fit.}

To alleviate the concern about potential endogeneity between EL use and IT, we performed an instrumental variable (IV) estimation as a robustness check. We used the number of employees and the number of establishments for an industry as the instrumental variables to estimate IT. The number of employees correlates with IT (e.g., the more employees, the higher IT investment), but it does not necessarily correlate with EL use (i.e., sales online). The number of establishments also correlates with IT (e.g., the more factories, the higher IT investment), but it does not necessarily correlate with EL use (i.e., sales online). Hence, both of the variables are valid instrumental variables. The results from the IV estimation are consistent with our main results, demonstrating the robustness of our estimation.

### Table 4  Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>Main effect</th>
<th>Interaction effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.95*</td>
<td>2.24*</td>
</tr>
<tr>
<td>(0.76)</td>
<td>(0.64)</td>
<td></td>
</tr>
<tr>
<td>EL use with buyer industries (ELB)</td>
<td>3.44*</td>
<td>2.67*</td>
</tr>
<tr>
<td>(1.47)</td>
<td>(1.11)</td>
<td></td>
</tr>
<tr>
<td>EL use with supplier industries (ELS)</td>
<td>-6.51*</td>
<td>-4.99*</td>
</tr>
<tr>
<td>(2.96)</td>
<td>(2.01)</td>
<td></td>
</tr>
<tr>
<td>IT ($\times 10^{-12}$)</td>
<td>14.30</td>
<td>13.10</td>
</tr>
<tr>
<td>(15.80)</td>
<td>(16.90)</td>
<td></td>
</tr>
<tr>
<td>Interaction term between ELB and IT (XITELB) ($\times 10^{-3}$)</td>
<td>-0.81*</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Interaction term between ELS and IT (XITELS) ($\times 10^{-3}$)</td>
<td>0.52</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Cost of goods sold (COGS) ($\times 10^{-12}$)</td>
<td>-4.30*</td>
<td>-3.56*</td>
</tr>
<tr>
<td>(1.85)</td>
<td>(1.22)</td>
<td></td>
</tr>
<tr>
<td>Durable goods industry (DURABLE)</td>
<td>-0.76*</td>
<td>-0.71*</td>
</tr>
<tr>
<td>(0.25)</td>
<td>(0.24)</td>
<td></td>
</tr>
<tr>
<td>Price index variation (VPRICE) ($\times 10^{-3}$)</td>
<td>-0.03</td>
<td>-0.10</td>
</tr>
<tr>
<td>(0.15)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Gross margin (GM) ($\times 10^{-3}$)</td>
<td>15.02</td>
<td>5.22</td>
</tr>
<tr>
<td>(13.98)</td>
<td>(12.49)</td>
<td></td>
</tr>
<tr>
<td>Model statistics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$</td>
<td>146</td>
<td>146</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-241.94</td>
<td>-234.30</td>
</tr>
<tr>
<td>Wald $\chi^2$</td>
<td>23.67***</td>
<td>25.10***</td>
</tr>
</tbody>
</table>

Notes. For industry NAICS 316 in 2003, its IDVR is 95.34, much higher than the average IDVR. As an outlier, we excluded it from our analysis. A further look at the raw data showed that the industry experienced a significant reduction in inventory during 2003. Standard errors are in parentheses.

\* $p < 0.10$; \*\* $p < 0.05$; \*\*\* $p < 0.01$; \*\*\*\* $p < 0.001$.

6. Discussion and Interpretations

In a supply chain setting, our analysis distinguishes EL use with buyers and EL use with suppliers, and it shows that the effects of EL on IDVR are asymmetric: EL use with buyer industries (ELB) tends to have an effect different from EL use with supplier industries (ELS).

Surprisingly, ELB does not always reduce IDVR; instead, it tends to increase IDVR, especially when IT is low. Theoretically, both directions are possible, depending on the relative strength of the conflicting forces. ELB may increase buyer industries’ purchase uncertainty with a supplier industry, because it expands its market reach and provides a greater number of products and supplier offerings and reduces search/switching costs. If this effect dominates, ELB would lead to increased demand uncertainty for the supplier industries, resulting in higher inventory variation for the suppliers as they have to guard against greater demand uncertainty from the buyer industries. Our result confirms that this is indeed the case.

Meanwhile, our results do not necessarily contradict those in prior studies. First, consistent with the...
argument in Barua et al. (2004), ELs may not be used symmetrically between buyers and suppliers, and ELS may be an enabler for ELB; that is, to realize the potential benefits from ELB, firms need to tackle the difficult task of interacting with suppliers through ELS. Second, although IDVR could be worse for suppliers after using EL with buyer industries, other performance metrics such as sales per employee, inventory turnover, and cost reduction can still be improved (Zhu 2004b); thus the net benefits from using EL with buyer industries can still be positive.

In contrast, EL use with supplier industries helps reduce the inventory–demand variance ratio. The reduction may come from reduced transaction costs, including coordinating costs and monitoring costs with their supplier industries. In particular, EL use will expand a buyer’s market reach, which helps the buyer find additional suppliers easier and with smaller search cost. As a result, the buyer does not need to play the rationing game (i.e., placing inflated orders) as much as before. Our findings, complementary to earlier literature on EDI (Barua et al. 1995) or Internet-based EM (Zhu 2004a), provide further evidence that EL use with supplier industries can be significant and positive on performance improvement.

In addition, to better understand these direct effects, we also examine the interaction effect between IT and EL. Our results show that the adverse effect of ELB on IDVR is smaller for industries with greater IT. In other words, given that when a supplier industry may be facing increased uncertainty by using an electronic linkage such as an electronic market, the increased uncertainty can be mitigated if the suppliers have stronger information systems to smooth the industry’s operations. For example, the supplier industry may be able to use IT to achieve better forecasting and planning so that the effect of increased uncertainty is mitigated. This finding is consistent with Zhu (2004b), who found a strong complementarity between IT and e-commerce capability, which improves firm performance in terms of inventory turnover, cost reduction, and sales per employee at the firm level. This finding is also consistent with the findings in Barua et al. (2004); as discussed in their paper, “…processes and IT have to be aligned with each other to create certain capabilities for better communication and coordination across value change members.” Because ELs can be viewed as processes (e.g., sales, procurement), more IT investment can be complementary to bring about greater value of these processes. Our study extends this insight to the supply chain setting where cross-firm usage of electronic linkages is considered.

Although most of our results are statistically significant, the question as to whether these results are economically significant is equally important. We examine the economic significance by computing the potential effect using the regression estimates in Table 4. The potential effects are computed as the change to the dependent variable when an independent variable changes from its sample minimum to sample maximum, while maintaining the rest of the variables at their means. We also computed a case when IT use is 0 to compare the value of IT as a moderating variable. Table 5 presents the results. When IT is 0, the potential effects can change the dependent variable by 1.34 for ELB and −0.80 for ELS, respectively, when ELB (or ELS) is changed from its respective sample minimum to sample maximum. When IT is at the mean value, the potential effects can change the dependent variable by −0.61 for ELB and −0.40 for ELS, respectively. Note that the mean value of IT has surpassed the breakeven point, so that the total effect of ELB is negative, suggesting that ELB reduces the inventory–demand variance ratio with help from IT. In particular, when IT is at the mean value, the reductions of IDVR from ELB and ELS are about 61% and 40%, respectively, suggesting that they are not only statistically significant but also economically significant.

In addition, the average IDVR for all independent variables at their means is 1.17. When we increased IT by a standard deviation, while all other variables remain unchanged, the IDVR dropped to 0.74—a 37% decrease—further demonstrating that the moderating role of IT to ELB is indeed substantial.

### Table 5. Potential Impacts

<table>
<thead>
<tr>
<th>IT = 0</th>
<th>ELB</th>
<th>At sample minimum</th>
<th>At sample maximum</th>
<th>Potential impacts</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Predicted IDVR = 1.46)</td>
<td>ELS</td>
<td>1.71</td>
<td>0.91</td>
<td>−0.80</td>
</tr>
<tr>
<td>(Predicted IDVR = 1.17)</td>
<td>ELS</td>
<td>1.34</td>
<td>0.73</td>
<td>−0.61</td>
</tr>
</tbody>
</table>

Note. Calculated based on regression estimates of interaction effect model in Table 4.

7. Conclusions

The objective of this study is to examine whether the use of electronic linkages (ELs) (decomposed into EL use with buyer industries and EL use with supplier industries) has resulted in supply chain improvement in terms of reducing the bullwhip effect (as measured by the inventory–demand variance ratio or IDVR). We develop several hypotheses and test them by constructing an econometric model based on a data set of the U.S. manufacturing supply chains.

By doing so, this paper makes several contributions to the literature. First, most of the prior literature has shown that the use of electronic linkages
would improve supply chain performance. We empirically test this hypothesis. Surprisingly, we found that EL use with buyer industries may actually hurt the supply chain performance in terms of the bullwhip effect. In particular, when an industry uses ELs with its buyer industry for sales, the bullwhip effect is increased. Based on the transaction cost economics, such counterintuitive findings may be partly attributed to the electronic brokerage effect and market reach expansion; that is, the use of ELs provides greater product and supplier offerings for buyers such that their search-switching costs are reduced. This makes it easier for buyers to switch among different suppliers, leading to increased demand uncertainty for the supplier industry. Fortunately, we find that there is a way to mitigate this adverse effect. That is, our interaction model shows that when IT is sufficiently large, EL use with buyer industries may become beneficial in reducing the bullwhip effect.

Second, we find that EL use with supplier industries has a significant effect on reducing the bullwhip effect, as theoretically expected. The focal industry, as a buyer now, is able to take advantage of increased offerings and lowered search-switching costs for better inventory management, materials, and production planning, in addition to reduced coordination cost and operational risk. Combining the above two results, we have learned that the use of EL tends to behave differently, depending on whether it is used upstream or downstream in the supply chain. That is, ELs benefit buyers more than sellers. As far as we are aware, this has not yet been empirically established in the supply chain literature.

Third, we show that these effects are not only statistically significant but also economically significant. Although it has been argued that IT and IT-enabled ELs have been commoditized, investment in information systems and proper use of ELs are still valuable in improving supply chain performance. Therefore, given our surprising results on EL use with buyer industries and the paucity of research on the empirical evaluation of the bullwhip effect, our research adds useful insights to the literature in these dimensions.

Meanwhile, our study has several limitations. First, although industry-level data analysis has been proved useful by prior studies, such aggregate data fall short of providing the granularity needed to investigate what exactly happens between firms in a supply chain. In particular, it may be helpful to also examine the bullwhip effect using firm-level data. Although we were constrained by data availability, future research can extend our analysis to the firm level and examine under what conditions our results, especially the surprising results with ELB, hold at the firm level as well. Second, our measure of EL use is the volume of sales conducted in ELs. We use this measure because of data limitation. EL use includes many other activities as well, such as marketing, customer services, and collaboration. Future research may include these broader measures. Finally, future research can decompose EL use into electronic markets and electronic hierarchies to further explore the possible different effects among these various forms of EL.

Withholding these limitations, our research findings bring several managerial implications. First, managers need to understand that participating in electronic linkages may not always improve performance. Internet-enabled EL, in particular, tends to be more interconnected and standardized than EDI such that, by using it, firms may lose their bargaining power to buyers. This needs to be carefully studied before implementing any EL solutions. Second, managers should realize that, although investing in IT may or may not create direct benefits, it may bring indirect benefits, for example, through mitigating the adverse effect resulting from EL use with buyers. While moving sales online, firms may want to consider investing more in IT to improve their back-end operations. Finally, the upstream integration through electronic linkages (e.g., electronic procurement with suppliers) can help reduce bullwhip effects. It gives the firm a greater choice of procurement sources in terms of products and suppliers, thereby mitigating their procurement risk.

In conclusion, this study provides new evidence at the supply chain level about the effect of the use of EL on the bullwhip effect. Our findings show that the downstream and upstream uses of EL tend to have asymmetric effects. These results provide a different theoretical perspective to the existing conclusions in the literature of the business value of information systems, and shed light on the conditions under which electronic linkages may be more (or less) beneficial. We also show that inventory-demand variance ratio is a good metric for measuring business value of IT in the supply chain setting. These findings help extend the literature on IT value to the supply chain setting and help uncover the role of electronic linkages in buyer-supplier relationships under the lens of transaction cost economics. We hope these results will stimulate more research in this important area.

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