Supply Chain Relational Capital and the Bullwhip Effect: An Empirical Analysis Using Financial Disclosures

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ABSTRACT

Purpose: The primary objective of this study is to conduct a large-sample empirical investigation of how relational capital impacts bullwhip at the supplier.

Design/methodology/approach: The study uses mandatory disclosures in regulatory filings of US firms to identify a supplier's major customers and constructs empirical proxies of supply chain relational capital i.e., length of the relationship between suppliers and customers, and partner interdependence. Multivariate regression analyses are performed to examine the effects of relational capital on bullwhip at the supplier.

Findings: The findings show that bullwhip at the supplier is greater when customers are more dependent on their suppliers, but is reduced when suppliers share longer relationships with their customers. The results also provide additional insights on several firm characteristics that impact supplier bullwhip, including shocks in order backlog, selling intensity, and variations in profit margins. Further, we document that the effect of supply chain relationships on bullwhip tends to vary across industries and over time.

Originality/value: The study employs a novel dataset that is constructed using firms' financial disclosures. This large panel dataset consisting of 13,993 observations over 36 years enables thorough and robust analyses to characterize supply chain relationships and gain a deeper understanding of their impact on bullwhip.

Keywords: Bullwhip effect, relational capital, supply chain, regression analysis, financial statements.

1. Introduction

The bullwhip effect (BWE) is considered to be a key phenomenon in supply chain management. The principal notion of BWE is that demand variability increases as one moves upstream in a supply chain. This can cause several inefficiencies for the upstream supplier including poor forecasting, stockouts, high inventory, lower service levels, capacity planning issues, higher costs, and increased supply chain risk (Metters, 1997; Billington, 2010). The importance of this problem has prompted extensive research since the early works of Simon (1952) and Forrester (1958) using theoretical frameworks as well as experimental settings (Kahn, 1987; Sterman, 1989; Metters, 1997; Lee et al., 1997a, 1997b; and more recently Cao et al., 2017, to name a few).[1] There had not been, however, much large-sample empirical evidence until recent studies started to use archival data to document the prevalence and the magnitude of the BWE at the industry and the firm level (e.g., Cachon et al., 2007; Bray and Mendelson, 2012; Shan et al., 2014; Mackelprang and Malhotra, 2015; and Isaksson and Seifert, 2016). The costs and inefficiencies linked to BWE underscore the importance of understanding influential factors that might help mitigate the BWE, an effect that previous studies have shown to exist globally.

In this study, we build on prior research by identifying linkages between supply chain management research on inter-organizational relationships and research on the BWE. The 'relational view' of the firm suggests that close relationships between supply chain partners engender relational capital, promote mutual trust, and facilitate accurate information flows (Dyer and Singh, 1998; Cousins et al., 2006). Since the sharing of more accurate information has the potential to mitigate the BWE (Lee et al., 1997a; Haines et al., 2017), higher relational capital between supply chain partners should help mitigate the BWE. However, recent research

[1] For detailed reviews of the current literature on the bullwhip effect see Miragliotta (2006), Geary et al. (2006), Towill et al. (2007), Giard and Sali (2013), and Wang and Disney (2016).

documents the ‘dark side’ of relational capital and suggests that stronger ties between supply chain partners may lead to opportunistic or gaming behavior, which has the potential to increase BWE (Villena et al., 2011; Zhou et al., 2014). The above contrasting views present an interesting empirical question about the net effect of relational capital on BWE that we investigate in this study. Accordingly, the principal research question in our study is stated as follows: *Does relational capital between supply chain partners mitigate or exacerbate the bullwhip effect?*

The availability of large-scale panel data on customer-supplier relationships offers a unique opportunity to examine BWE using variation in firm and supply chain characteristics across different industries and time periods. This can help researchers understand not only the underlying causes of BWE but also potential mitigating factors that have been theorized to impact BWE. Consistent with a recent article encouraging the use of archival data (Simpson et al., 2015), we exploit firms’ financial disclosures of their business relationships to create a dataset that identifies suppliers and their customers for the period 1978-2013. We measure bullwhip for the supplier firms in our data using a methodology commonly used in previous studies (e.g., Chen et al., 2000; Cachon et al., 2007; Shan et al., 2014). Following Krause et al. (2007), we consider three aspects of relational capital – namely, the length of relationship, customers’ dependence on suppliers, and suppliers’ dependence on customers – and examine their individual impact on BWE from the perspective of the supplier.

In our empirical model, we use information obtained from the firms’ financial statements to measure and control for several supplier characteristics that may potentially impact the BWE. For example, we include changes in backlogged orders to control for demand shocks that can cause BWE due to demand signal processing. Variations in suppliers’ gross margins are included to capture price fluctuations that have been known to cause BWE. We include selling intensity since we argue that suppliers with high degree of sales-intensive activities are likely to experience higher

BWE as salespeople concurrently book larger orders to meet sales targets (Lee et al., 1997a). We note that large-sample data that is aggregated at the firm level makes it challenging to construct distinct and unambiguous empirical proxies for specific causes and influential factors for BWE. Consequently, prior literature does not provide much guidance for measuring such factors using large-sample data. We use theories embedded in prior literature to guide our choice and measurement of supplier characteristics while being mindful of the inherent limitations of the data. Our empirical measures therefore constitute a first attempt and contribute to the literature by providing a useful starting point for future research that can validate and improve on these measures.

We find that longer relationships lead to lower BWE at the supplier. While suppliers' dependence on customers has no significant effect on bullwhip, customers' dependence on suppliers results in greater bullwhip at the supplier. The latter result is suggestive of an increase in gaming behavior such as duplicate or "phantom" ordering when customers are dependent on a specific supplier (Sterman and Dogan, 2015; Armony and Plambeck, 2005; Mitchell, 1924). These results are not only new to the literature, but also provide direction to practitioners in terms of being able to manage their supply chains more effectively.

Our multivariate regression analysis of the drivers of BWE also shows that higher selling intensity, higher variations in gross margin, and greater shocks to order backlogs are associated with greater bullwhip at the supplier. Similar to Shan et al. (2014) we use additional controls including serial correlation in demand, days in inventory, supplier size, supplier profit margin, days payable outstanding, and seasonality. We confirm Shan et al.'s (2014) findings for Chinese firms in our sample of US firms. For example, we find that higher serial correlation in demand and longer inventory days are associated with larger BWE in US firms.

In the next section we present a brief overview of the related literature and our research hypotheses. This is followed by a description of our data, sample, and our empirical results. In the subsequent section we discuss the managerial implications of our results. Finally, we present our concluding remarks.

2. Literature review

2.1. Evidence of the BWE

The BWE has been extensively studied in a variety of theoretical and experimental settings. The formal evidence on BWE has been corroborated by several instances of real-world evidence. For instance, Procter and Gamble (P&G) observed the BWE phenomenon with its suppliers and wholesalers (Schisgall, 1981). Lee et al. (1997a) document the experience of Hewlett-Packard (HP) which found that orders received from a major printer distributor had much bigger swings than fluctuations in the sales of the distributor. Dooley et al. (2010) found that during 2007-2009, demand variation due to the economic recession was larger for manufacturers than for retailers, which is indicative of the BWE. Evidence of BWE has been found in other countries as well. For example, Bu et al. (2011) report the existence of BWE in the Chinese manufacturing sector, providing evidence of significant cross-sectional differences in the extent of BWE across industries. Amplification of demand variance has been observed in several studies focusing on specific firms or product categories, including apparel (Stalk and Hout, 1990), groceries (Hammond, 1994; Panda and Mohanty, 2012), automotive (Taylor, 1999), perishable foods (Fransoo and Wouters, 2000), mechanical parts (McCullen and Towill, 2001b), toys (El-Beheiry et al., 2004), printers (Disney et al., 2013), retail (Lai, 2005), and spare parts (Pastore et al., 2017).

In one of the first large-sample investigations of BWE, Cachon et al. (2007) document BWE using industry-level data from the US Census Bureau. They compare the amplification of production variance relative to demand variance for retail, wholesale and manufacturing industry groups. Cachon et al. (2007) find some evidence that BWE exists for wholesale industries but not for manufacturing and retail industries. As they note, "[H]owever, it is not possible to conclude from industry-level volatility whether amplification occurs at the firm, division, category or product-level (p. 477)". Firms within an industry could belong to different tiers of the supply chain. For instance, within the pharmaceuticals industry firms could exist at different tiers such as large, diversified manufacturers and marketers (e.g., Merck), which are served by upstream biotechnology firms developing new drugs (e.g., Micromet), which in turn buy technical knowhow or materials from suppliers even further upstream (e.g., Curis). When information for firms belonging to different supply chain tiers is aggregated at the industry level, information regarding the firm's placement in the supply chain is lost. Hence, the analysis using aggregate industry-level data could mask the underlying supply chain relationships. Also, industry-level analysis leads to a smaller set of data points, which reduces the statistical power of empirical tests.

More recently, Bray and Mendelson (2012) investigate the BWE at the firm rather than the industry level by developing a firm-level measure of amplification of demand signals. Using a sample of US companies, they find significant demand amplification for 65 percent of the firms in their sample, while for the remaining firms there is no BWE. This shows that there are significant cross-sectional differences in the BWE across the sample. In another study focusing on Chinese firms, Shan et al. (2014) document similar results – two-thirds of the firms in their sample exhibit demand amplification. Isaksson and Seifert (2016) replicate these findings in US firms, providing strong evidence of the magnitude and prevalence of BWE across industries. However, none of the above studies exploit characteristics of specific supplier-customer relationships to examine their impact on BWE. Our study helps fill this gap in the literature.

2.2. Relational Capital and BWE

The BWE literature has also focused on identifying causes and factors that influence BWE with the intent of providing insights that may be useful to managers in reducing the impact of BWE. Lee et al. (1997a; 1997b) adopt the view that BWE results from managers acting rationally in responding to demand signals. They identify four distinct causes of the BWE, namely, demand signal processing, order batching, supplier rationing, and price variations. These causes have since been accepted as the standard explanation for the existence of BWE in empirical settings (e.g., Miragliotta, 2006). In addition to the direct causes of the BWE, Lee et al. (1997a) speculate about the counter measures that would help reduce the BWE. For example, greater demand information sharing between supplier and customer is likely to mitigate the BWE. Lee et al. (1997a, 1997b) provide an example of the grocery industry where electronic data interchange (EDI) systems facilitate greater information sharing between the retailer and the supplier, and provide the supplier with greater visibility of the end consumer demand, thus reducing BWE. Other studies add support to the view that information sharing and cooperation between the supplier and customer reduce BWE (e.g., Gavirneni et al., 1999; Zhao and Xie, 2002).

Much of the supply chain literature over the past two decades has examined customer-supplier relationships through the lens of relational theory. The theory describes how information sharing is impacted by close relationships between supply chain partners. Relational capital is developed through a history of interactions between partner firms, enabling the partners to earn various benefits or 'relational rents' that may not otherwise be available to them (Nahapiet and Ghoshal, 1998; Krause et al., 2007; Yim and Leem, 2013). Closer relations between suppliers and customers lead to improved communications (Hoetker, 2005), development of relationship-specific information-sharing routines (Dyer and Singh, 1998), and greater trust between partners (Helper, 1991; Sako and Helper, 1998). Thus, as relational capital grows, greater trust and better communication between partners will help facilitate the flow of potentially useful and important information quickly and accurately through the network (Cousins et al., 2006). With greater trust, such information flows would be transmitted upstream in a more timely fashion, potentially reducing the propagation of BWE (Lee et al. 1997a). Thus, in the context of BWE, relational capital, as represented by the length of the supplier-customer relationship and the interdependency of the customer and supplier (Krause et al., 2007), can be expected to be negatively related to the BWE.

However, recent research also documents the potential negative consequences of relational capital, which can include opportunistic behavior (Granovetter, 1985) and restricted information flows (Villena et al., 2011). When the customer has a high level of trust in the supplier, the customer may reduce its monitoring of the supplier (Villena et al., 2011). Responding to lower customer monitoring, the supplier may reduce sharing of critical information with the customer (Zhou et al., 2014). Additionally, if a customer becomes reliant on a limited number of suppliers, then in times of short supply the customer might resort to placing phantom orders to ensure supply. When the customer gets adequate delivery, it cancels outstanding orders, causing BWE to propagate through the supply chain. This type of phantom or duplicate ordering has been well-documented in the literature (Sterman and Dogan 2015; Lee et al. 1997b; Armony and Plambeck 2005; Mitchell 1924), and has been seen in many industries such as electronic components, consumer electronics, and personal computers (Lee et al., 1997a); and semiconductors (Terwiesch et al., 2005). Hence, such opportunistic behaviors combined with restricted information flows could lead to an increase, rather than a reduction, in BWE with higher relational capital. Therefore, given that relational capital can have a mixed impact on BWE, the net effect of relational capital on BWE remains an empirical question, which forms the basis of our research hypotheses.

3. Hypothesis development

In this section we develop specific hypotheses regarding the impact of three distinct aspects of relational capital – namely the length of the relationship between suppliers and customers, customers' dependence on suppliers, and suppliers' dependence on customers (Krause et al., 2007) – on BWE.

3.1. Length of relationship between customers and suppliers

In the traditional model of supplier-customer relationships, customers frequently changed suppliers in search of lower prices (Lamming, 1993). The lack of sustained relationships likely led to poor information flows between customers and suppliers (Langfield-Smith and Greenwood, 1998). However, starting in the mid-1980s, there was a growing recognition in the US and other developed economies of the importance of building collaborative long-term relationships with suppliers. Automotive companies, largely emulating their Japanese counterparts, adopted aspects of 'just-in-time' (JIT) or 'lean' supply chain practices that preferred longer-term contracts. Describing this move towards Lean Management, Schonberger (1982, p157) states, "the Japanese tend to buy from the same few suppliers year after year, so that the suppliers develop a competency that is particularly attuned to the delivery and quality needs of the buying firm. Confidence in the supplier reduces buffer inventories carried in the buying plans to quantities that are used up in only a few hours."

The practice of lean management led to greater information sharing and stronger relationships between customers and suppliers (Langfield-Smith and Greenwood, 1998), which in turn, helped suppliers improve their performance.[2] In a study of both Japanese and U.S. automotive manufacturers and suppliers, Kotabe et al. (2003) find that both knowledge transfer and supplier

[2] See Bhamu and Sangwan, (2014) for a review of studies on lean manufacturing and how customer-supplier relationship strength promotes lean implementation success.

performance improve with longer relationships. Examining first-tier US suppliers to both US-based Japanese as well as US automakers, Liker and Yen-Chun (2000) show that closer and longer-term relationships that existed with Japanese automakers led to more stable production. MacDuffie and Helper (1997) document the case of Honda USA and its supplier Progressive Industries. Progressive had experienced cyclical demand traditionally, but after building up its relationship with Honda over time it was able to move to a more stable production schedule. McCullen and Towill (2001a) discuss the case of a British manufactured products supplier (primarily to USA and Japan) that implemented agile systems (including lean, and closer relationships with customers) and experienced significant attenuation in BWE. Similarly, Pozzi et al. (2018) consider the benefits of lean management in the case of a beer game supply chain and find that lean thinking helps in reducing BWE.

Following this trend towards longer customer-supplier relationships engendered by lean management, more recent studies in the supply chain management literature use the relational view to examine the costs and benefits of collaborative relationships between suppliers and their customers. Long-term relationships result in investment in relationship specific assets (De Toni and Nassembini, 1999; Prajogo and Olhager, 2012), more information sharing, logistics integration, and better performance (Prajogo and Olhager, 2012). The literature on relational capital suggests that repeated interactions between supply chain partners influence their respective behaviors. These interactions are a prerequisite for the creation of trust (Li et al., 2014). The increased trust tends to improve communication and information sharing (Hoetker, 2005). For instance, Toyota encourages frequent interactions between its employees and those of its suppliers to encourage information transfer (Adler et al., 2009; Liker and Choi, 2004). Through these interactions the customer and the supplier are able to develop relational ties, building trust in one another, that are instrumental in promoting two-way information flows and improving operational efficiency such as lead time (Cousins and Menguc, 2006). The supply chain partners could share information about market demand, production planning, and inventory (Li and Lin, 2006). Relational capital encourages not just higher quantity, but also the quality, of the shared information such as accuracy and timeliness (Li et al., 2014). Further, this increased communication results in enhanced relational assets (Kotabe et. al., 2003).

The bullwhip effect is created when an upstream supplier processes demand input from their immediate downstream customer in producing their own forecasts. However, as Lee et al. (1997a) suggest, if the customer shares accurate data on end-demand with the supplier on a frequent basis, this is likely to reduce the impact of BWE at the supplier. For instance, supply chain partners can use electronic data interchange (EDI) or other information integration methods (as was the case with the British supplier in McCullen and Towill, 2001a) to share raw demand data on a timely basis. The reduction of operational lead times is also likely to reduce BWE at the supplier (Lee et al., 1997b). Hence, we posit that the improved information sharing (both quality and quantity), and the reduction of lead times due to the longer relationships between suppliers and customers, will serve to reduce the impact of BWE at the supplier.

Nonetheless, researchers have cautioned against the potential risks and negative consequences associated with longer relationships between suppliers and customers. Longer relationships could lead to relational inertia (Villena et al., 2011) by locking both parties into relationships with restricted information flows and increasing the risk of opportunistic exploitation (Yan and Kull, 2015). Agency theory and transaction cost theory indicate that monitoring acts as a safeguard against opportunism and is useful in reducing information asymmetry (Bergen et al., 1992; Wathne and Heide, 2000). However, high levels of trust in long-term relationships can reduce the monitoring efforts of partner firms. This may potentially slow the sharing of critical information amongst supply chain partners, and also lead to more opportunistic behavior (Zhou et al., 2014). These negative consequences may counteract the positive effects of longer relationships on supplier BWE. We examine this issue in our first set of two-sided research hypotheses which we state as follows:

Hypothesis (H1a): *The longer the relationship between the supplier and its customers, the lesser will be the supplier bullwhip.*

Hypothesis (H1b): *The longer the relationship between the supplier and its customers, the greater will be the supplier bullwhip.*

3.2. Dependence on Suppliers

Customers' dependence on suppliers can influence the BWE in two distinct ways. The relational view of the firm (Dyer, 1996; Madhok and Tallman, 1998) suggests that the customer accrues tangible benefits from investing in and sharing knowledge with suppliers via reduced costs, greater quality and flexibility (Yao and Zhu, 2012). If a customer is dependent on a given supplier for a bulk of its purchases, then the customer will be more willing to invest in relationship-specific assets and supplier development through information sharing (Krause et al., 1998). For example, collaborative planning, forecasting, and replenishment (CPFR) is a technique for coordinating the supply chain (Panahifar et al., 2015). These benefits to the customer are likely to be the greater, the more dependent a customer is on a given supplier. Since these relationship-specific investments by the customer that promote greater information sharing require an outlay of fixed costs, the customer is more likely to share information with only its major suppliers. This provides suppliers with greater visibility of end-demand conditions, leading to a reduction in bullwhip at the supplier.

However, when customers are dependent on a limited set of suppliers, this leads to small number bargaining problem (Clemons et al., 1993). Such negative effects of a dependency relationship are seen while implementing JIT. Frazier et al. (1988, p.60) noted that the "coercive use of power in interfirm relationships seriously weakens their collaborative nature." When there are only few potential suppliers for a product, this also increases the potential for gaming behavior such as phantom ordering (Armony and Plambeck, 2005; Zarley and Damore, 1996) and rationing (Lee et al., 1997a,b) which can increase BWE at the supplier. When a customer is dependent on a supplier, and the supplier is unable to fill all orders, customers may respond by ordering more than their needs (Sterman and Dogan, 2015). This phenomenon is well-documented in the literature and is often referred to as phantom ordering (Mitchell, 1924). After a lag, once the customers get all the products they need, customers will cancel their phantom orders. Such phantom ordering followed by cancellation of duplicate orders distorts the demand pattern of the supplier leading to bullwhip. Anecdotal evidence of this phenomenon is found in de Kok et al. (2005) where they describe the BWE reduction efforts undertaken by Philips Semiconductors, one of the largest suppliers of semiconductors in the world. Presumably, the customers of Phillips depended heavily on it as a supplier. de Kok et al. (2005) indicate that customers had been shortage gaming Philips before the latter undertook deliberate efforts to reduce such behavior by its customers.

Thus, there are two countervailing forces at work when customers are dependent on suppliers. While information sharing and cooperation can serve to reduce bullwhip at the supplier, the increased potential for gaming behavior can lead to greater bullwhip. The net effect of these two forces remains an empirical question which we address in our next hypothesis. To accommodate a two-sided hypothesis, we present it as follows:

> Hypothesis (H2a): *The dependence of customers on a given supplier has a negative impact on supplier bullwhip.*
>
> Hypothesis (H2b): *The dependence of customers on a given supplier has a positive impact on supplier bullwhip.*

3.3. Dependence on Customers

Suppliers' dependence on customers (i.e., customer concentration) can also affect bullwhip at the supplier. We illustrate this impact using a simple example. Let us consider two supplier-customer pairs S1-C1 (i.e., S1 supplies to C1) and S2-C2 (S2 supplies to C2). Suppose, firm S1 supplies to only one customer while firm S2 supplies to multiple customers, with customer C2 constituting only a small percentage of S2's customer base. Both customers will transmit bullwhip upwards, reflected in increased production variance for their respective suppliers. However, the effect of C2's bullwhip on S2's *total* production will be relatively muted since demand from customer C2 only accounts for a small percentage of S2's total production. To the extent individual bullwhips transmitted by firm S2's multiple customers are not perfectly positively correlated, S2 should experience a lower degree of bullwhip compared with S1 who is fully exposed to the bullwhip from a single customer C1. In sum, when suppliers are more dependent for their sales on a few customers, this creates greater uncertainty for the supplier. In a study of over 450 grocery suppliers, Panda and Mohanty (2012) found that a number of suppliers depended on a limited number of supermarket chains for a significant portion of their revenues, which led to an increase in BWE at the supplier.

The above argument is not without tension. If a supplier is highly dependent on a customer then they are more likely to cooperate closely with customers, as discussed in the relational view above. For example, Carr et al. (2008) find in a multi-industry survey that such dependence tends to increase suppliers' participation in training and involvement during product development. Such collaborative behavior allows supply chain participants to jointly gain a clear understanding of future demand and to coordinate their activities accordingly (Wu et al., 2014). Suppliers are also more likely to make investments in information technology (e.g., EDI) that promote information sharing (Disney and Towill, 2003) and reduce the impact of bullwhip (Zhang and Chen, 2013). Asanuma (1989) provides an example from the Japanese auto industry where parts manufacturers depend on large customers such as Toyota. Despite the size differences, information regarding demand is shared by the customer with the supplier, due to close relationships that exist in the Japanese auto industry.

Hence, similar to the case of customers' dependence on their suppliers, the net effect of customer concentration for reducing supplier bullwhip is an empirical issue due to the presence of some factors that alleviate the BWE but other factors that exacerbate it. Consistent with hypothesis H2, we present our next set of two-sided hypotheses as follows:

> Hypothesis (H3a): *The dependence of a supplier on its customers has a negative impact on supplier bullwhip.*

> Hypothesis (H3b): *The dependence of a supplier on its customers has a positive impact on supplier bullwhip.*

4. Sample selection and empirical results

4.1. Sample selection

We identify supplier-customer relationships at the supplier-fiscal year level during 1978-2013 using the Segment Customer File in Standard & Poor's COMPUSTAT database. Under *Statement of Financial Accounting Standards* (SFAS) No. 14 and No. 131, a supplier is required to disclose the identity and the amount of revenue from a single external customer when revenue from this customer amounts to 10 percent or more of the supplier's total revenue. Suppliers also often disclose information about customers that account for less than 10 percent of suppliers' total revenues if they consider them to be major customers (Patatoukas, 2012). The Segment Customer File contains the names of major customers along with the amount of revenue from each major customer.

We match each customer's name to a firm listed on the COMPUSTAT Industrial files. Following Bray and Mendelson (2012), we focus on retail, wholesale, manufacturing and resource extracting sectors (SIC 5200-5999, 5000-5199, 2000-3999, and 1000-1400). Our preliminary sample includes 30,279 supplier-customer pairs at the fiscal year level comprising 3,934 (1,594) unique suppliers (customers). Table 1 presents the data requirements we impose on this preliminary sample to arrive at the regression sample. We eliminate 5,377 observations where we do not have sufficient data to measure the BWE for suppliers and 1,610 observations where we do not have sufficient data on supplier-customer relationship. These steps result in 23,292 supplier-customer pairs which we aggregate (across multiple customers) to arrive at a sample of 16,746 supplier-year observations. Requiring sufficient data to construct other influential factors and control variables further eliminates 2,753 observations. Our final sample includes 13,993 supplier-year observations for 2,786 unique suppliers.

------------------------ Insert Table 1 Approximately Here ------------------------

4.2. Measurement of bullwhip effect

Cachon et al. (2007) measure BWE at the industry level using U.S. Census Bureau data. They interpret "production" as the inflow of material from upstream suppliers to an industry (or the demand an industry imposes on its upstream suppliers), and margin-adjusted aggregate industry sales as the "demand" imposed on an industry by its downstream customers. Cachon et al. (2007) construct amplification ratio as the variance of monthly production divided by the variance of monthly margin-adjusted sales to customers. Measuring BWE at the firm level using quarterly financial statement data from COMPUSTAT, Bray and Mendelson (2012) and Shan et al. (2014) define BWE as the variation of production relative to the variation of demand. Similar to prior studies, we measure the bullwhip for a given supplier in a given year as follows:

$$BWE = \frac{\sigma(PRODUCTION)}{\sigma(DEMAND)} \tag{1}$$

$\sigma(PRODUCTION)$ is the standard deviation of quarterly *PRODUCTION* in a fiscal year and $\sigma(DEMAND)$ is the standard deviation of quarterly *DEMAND* in a fiscal year. Following Bray and Mendelson (2012) and Shan et al. (2014), we use cost of goods sold (*COGS*) as the proxy for customer orders or demand, and *COGS* plus changes in inventory (*INVT*) as the proxy for production. Similar to Cachon et al. (2007) and Shan et al. (2014), we log and first difference production and demand. That is, for every firm-quarter, production or demand is transformed into $\{ln(X_t) - ln(X_{t-1})\}$, which we label as *PRODUCTION* and *DEMAND* in equation (1). The BWE measured in (1) indicates the variation of production upstream as a ratio of the downstream demand variation. Hence, values greater than one indicate amplification of demand information.

The use of firm level, rather than product-level, demand and production data poses some challenges. Ideally, researchers would like to link the variance in demand for an individual product at a downstream customer with the variance of production of the same product by an upstream supplier. However, product-level data is not readily available, leading to the use of industry-level or firm-level data in prior research (see, e.g., Cachon et al., 2007; Bray and Mendelsohn, 2012; and Mackelprang and Malhotra, 2015). At the customer firm level, demand and production data aggregates different product lines supplied by a number of suppliers which are likely to exhibit varying degrees of variance amplification. Empirically, however, such comingling of multiple demand and production streams is expected to increase the noise (alternatively, diminish the signal to noise ratio), thus biasing against finding results.

4.3 Measuring supply chain relational capital

4.3.1 Length of relationship between customers and suppliers

The mandatory disclosures required in a supplier firm's annual regulatory filings allow us to measure the number of years that the supply chain relationship existed using the following equation:

$$CS\_LENGTH_{it} = \frac{\sum_{j=1}^{J}(w_{ijt} \times YEAR_{ijt})}{\sum_{j=1}^{J} w_{ijt}} \qquad (2)$$

$$w_{ijt} = \frac{CSALE_{ijt}}{SSALE_{it}} \qquad (3)$$

CS_LENGTH is the length of the relationship between the supplier i and its customers in year t, measured as the number of years that the supplier-customer relationship has existed, scaled by the number of years since the customer first appeared in the sample (denoted *YEAR*).[3,4] For any supplier that reports multiple major customers in a given year, we use the weighted-average length of the relationship where the weight (w_{ijt}) is the relative importance of each major customer to the supplier based on sales to customer j ($CSALE_{ijt}$) divided by the supplier i's total sales in year t ($SSALE_{it}$).

4.3.2. Customers' dependence on suppliers

CSALE_CCOGS, captures the degree of customers' exposure to the supplier (Pandit et al., 2011) and it is calculated as follows:

$$CSALE\_CCOGS_{it} = \frac{\sum_{j=1}^{J}\left(w_{ijt}\times\frac{CSALE_{ijt}}{CCOGS_{jt}}\right)}{\sum_{j=1}^{J} w_{ijt}} \quad (4)$$

$CSALE_{ijt}$ is defined as before and $CCOGS_{jt}$ is cost of goods sold reported by customer j in year t.[5] Similar to how we construct *CS_LENGTH*, for any supplier that reports multiple major customers in a given year, we average across the customer using the relative importance of each major customer to the supplier as the weight.

[3] Consistent with the approach in Hertzel et al. (2008), we assume that the supplier-customer relationship continues if the gap between two identified relationship years is less than five.

[4] For some observations in our sample (less than 8% of the data) the first year that the relationship between a supplier and customer is identified is the same as the first year that the customer exists in the database. For these observations, $YEAR_{ijt}$ is equal to one for the supplier-customer pair throughout the sample period, thus implying that the customer and supplier maintain a relationship for the entire period of the customer's existence. As a robustness check, we eliminate observations where $YEAR_{ijt}$ remains one and rerun our regressions. Our results (untabulated) remain robust.

[5] Since customers and suppliers are linked based on fiscal year our measurement could be affected by a mismatch resulting from customers and suppliers reporting in different months of the fiscal year. However, in our sample of 23,292 dyads, the median difference in the fiscal year end of suppliers and their customers is 31 days, which suggests that for the majority of suppliers and customers their fiscal year ends are not far apart even if they do not report on the same month. As a robustness check, we construct an alternative *CSALE_CCOGS* as follows. First, we match the supplier's fiscal year end with the customer's closest fiscal *quarter* end (quarter t). We then replace the customer's annual cost of goods sold with the sum of past 4 quarters of cost of goods sold (quarters t, t-1, t-2 and t-3) and recalculate *CSALE_CCOGS*. The correlation between this alternative measure and our original measure is 0.986. Our results are robust to using this alternative measure (untabulated).

4.3.3. Suppliers' dependence on customers

We measure supplier's dependence on the customer using a variable developed by Patatoukas (2012) to measure customer-base concentration (*CCONC*) which is calculated as follows:

$$CCONC_{it} = \sum_{j=1}^{J} \left(\frac{CSALE_{ijt}}{SSALE_{it}}\right)^2 \quad (5)$$

where $CSALE_{ijt}$ is sales from supplier i to customer j in year t and $SSALE_{it}$ is total sales reported by supplier i in year t. *CCONC* is determined by the number of major customers and the relative importance of each major customer to the supplier. Similar in spirit to the Herfindahl-Hirschman index, higher values of *CCONC* indicate a more concentrated customer base, and thus greater dependence of the supplier on its customers.

4.4. Controlling for Supplier Characteristics

In our empirical models, we include controls for other supplier characteristics that could influence BWE. We develop measures for these characteristics based on financial disclosures. While some of these are new to the literature, we also include other characteristics that have been used as control variables in prior studies. We describe these control variables below.

Order Backlog

One of the known and documented causes of BWE is demand signal processing by the supplier (Lee et al., 1998b). If a supplier experiences a demand shock in one period, it will interpret this as a signal of high future demand, and order more than the observed sales leading to BWE. We use order backlogs disclosed by the supplier to control for such demand shocks. Order backlog reflects customer orders that have been received by the supplier but have not been completed as of the reporting date. Firms are required to disclose the dollar amount of order backlog based on SEC regulations on an annual basis (Rajgopal et al., 2003)[6]. The level of order backlog for a firm in a given year is likely to be driven by industry factors or firm characteristics such as the firm's business model (Chang et al., 2018). However, any demand shock will result in a change in the order backlog (from the prior period) assuming that the operating capacity of the supplier remains fixed in the short run. Hence, we capture order fluctuations using the changes in order backlog (*BACKLOG*). Since we are interested in controlling for the variation in order backlog, we do not distinguish between positive shocks and negative shocks, and measure *BACKLOG* using the absolute difference between supplier's current year backlog and prior year backlog, scaled by total assets.

Variation in Gross Margin

We use variation in gross margins (*CV_GM*) to control for price variations that can cause bullwhip. *CV_GM* is the coefficient of variation in a supplier's deseasonalized gross margin (gross profit divided by net sales) measured using four quarters of data in any given year. A lowering of the selling price is likely to reduce the supplier's gross margins, while an increase will result in an increase in the gross margins. To the extent such discounts or price increases are temporary, they will introduce a greater degree of variation in the supplier's gross margin compared with suppliers who offer steady prices. The variation in gross margin can also be driven by changes in the costs of goods sold (COGS). However, changes in COGS alone are not likely to contribute to the BWE. It is the variation in customer demand driven by price variation that is a primary cause of the BWE. If margin variations are driven not by price variation but by changes in COGS, we would not expect to find a relation between the variation in gross margin and the BWE.

Selling Intensity

[6] Since order backlog is reported only in annual financial statements, this measure may not capture all demand shocks that occur during the year.

Incentive contracts of salespersons and executives typically involve a nonlinear relationship between compensation and sales and/or profits with bonuses received when the employee reaches a minimum threshold at the end of the fiscal period (Oyer, 1998). This creates incentives to manipulate the timing of purchases by customers to reach the required thresholds before the fiscal period ends (Oyer, 1998). Consistent with this observation, Lee et al. (1997b) state that providing such sales incentives pushes salespeople to close deals towards the end of a period to reach their sales targets. This results in a positive correlation of sales orders from different salespeople. The variance of orders received by the supplier from multiple customers is highest when the orders are correlated, thus giving rise to BWE (Lee et al., 1997b). Prior literature finds that firms that have high selling intensity are more likely to offer incentive plans to salespersons (John and Weitz, 1989). Thus, we include a control for selling intensity in our empirical models to capture the extent of sales incentives provided to salespersons.[7] We define selling intensity (*SGA_INTENSITY*) as the amount of annual selling and general administrative expenses (*SG&A*) divided by annual net sales.

Other Control Variables

In addition to these three variables that capture the operational characteristics of suppliers, we also include additional controls that are included in Shan et al. (2014): serial correlation in demand, inventory lead times, seasonality, supplier size, supplier profit margin, and account payable days. As discussed in Lee et al. (1997a,b), demand signal processing is a primary cause of the BWE. A firm creates an order to its supplier by forecasting future demand (often using demand smoothing techniques) and incorporating safety stock considerations. This distorts the

[7] Selling intensity may be a noisy proxy for incentives offered to salespersons that might cause BWE, since it is also related to the efficiency/slack of a firm's marketing resources. While we use this measure as a control in our main analysis, we also check the robustness of our results in a model that excludes this control variable. In untabulated results, we find that our inferences are not altered by the exclusion of this control variable from our analysis.

original market demand information and amplifies the variance of the firm's order to its supplier. The variance amplification increases upstream as the supplier aggregates orders from customers and adds its own safety stock. In the Lee et al. (1997a,b) framework, this amplification is further exacerbated if: (1) demand is serially correlated, because then temporary surges in demand are interpreted by suppliers as signals of high future demand,[8] and (2) lead times are longer, because of the necessity for additional safety stock inventory. Consistent with the above logic, Shan et al. (2014) report a significantly positive relation between serial correlation in demand and the BWE. Similar results are found in Cachon et al. (2007). Hence, we include serial correlation in demand shocks (*AR1RHO*) in our empirical investigation. *AR1RHO* is the autoregressive coefficient estimated with deseasonalized *DEMAND* series using eight quarters of data.

The other empirical proxy related to demand signal processing is inventory lead time. Prior studies such as Shan et al. (2014) argue that high inventory days can indicate a firm's inability to forecast demand, which leads to higher BWE. Hence, we include inventory days (*DAYSINVT*) in our empirical investigation to confirm this well-established result. *DAYSINVT* measures how many days a supplier holds its inventory before selling. We expect to find that the BWE is greater when there is greater serial correlation in demand shocks, and when inventory days are higher.

Shan et al. (2014) also find that the BWE is negatively associated with the seasonality of demand, thus we control for *SEASONALITY* which is calculated as the difference between the variance of *DEMAND* and the variance of deseasonalized *DEMAND*, divided by the variance of *DEMAND*. The remaining control variables are *SIZE* which is the supplier's total assets, *GM*

[8] Alternatively, high serial correlation could make it easier to anticipate future demand, resulting in more accurate demand forecasts. In the extreme case of perfect correlation, the firm can make a naïve yet accurate forecast.

which is the supplier's gross margin, and *DAYSAP* which is the number of days a supplier takes to pay its accounts payable.[9]

4.5 Regression specifications

To investigate the influential factors for the BWE, we estimate the following ordinary least squares (OLS) regression with industry sector fixed effects and cluster the standard errors on two dimensions (firm and year) following Petersen (2009):

$$BWE_{it} = \beta_0 + \beta_1 ln(CS\_LENGTH_{it}) + \beta_2 ln(CCONC)_{it} + \beta_3 ln(CSALE\_CCOGS)_{it} + \sum_{k=1}^{K} \gamma_k Control_k + \sum_{m=1}^{M} \alpha_m Industry_m + e_{i,t} \qquad (6)$$

Subscripts *i* and *t* indicate supplier firm *i* and fiscal year *t*, respectively. *BWE* is the bullwhip effect experienced by the supplier as previously defined. *ln(CS_LENGTH)*, *ln(CCONC)* and *ln(CSALE_CCOGS)* are empirical measures for the length of the supplier-customer relationship, dependence on customers, and dependence on suppliers, respectively. We control for other influential factors that may affect BWE including *ln(SGA_INTENSITY)*, *ln(BACKLOG)*, and *ln(CV_GM)*. We use natural log transformation of these influential factors to mitigate the skewness of these variables.[10] We also control for variables that Shan et al. (2014) have shown to be associated with the BWE - *AR1RHO*, *ln(DAYSINVT)*, *ln(SIZE)*, *ln(GM)*, *ln(DAYSAP)* and *SEASONALITY*. Following Shan et al. (2014), all control variables except *AR1RHO* and *SEASONALITY* are also log-transformed to mitigate the skewness. Finally, we include indicator variables for industry sectors to account for unobservable industry heterogeneity and to control for shocks common to all firms in an industry that can produce a cross-correlation of residuals across firms in the same industry.

[9] Shan et al. (2014) measure firm size using sales in their tabulated results and disclose in an endnote that their results are robust to using fixed assets or the number of employees as alternative proxies. Since sales are highly correlated with cost of goods sold that is used in the construction of the BWE, we use assets to proxy for size.

[10] We add one to *BACKLOG* before log-transformation to accommodate observations with zero *BACKLOG*.

Research designs relying on panel data sets, i.e., those containing observations on multiple firms over multiple years, can be subject to two forms of correlation across observations. The residuals of a given firm may be correlated across years for that firm (time-series dependence), or the residuals of different firms may be correlated in a given year (cross-sectional dependence). In the case of correlated residuals, the true variability of the coefficient estimates is likely to be misestimated by OLS standard errors. An option considered in the literature is to use firm and year fixed effects to correct for this issue. However, our panel is rather sparse with approximately five observations per unique supplier firm, on average. Using firm fixed effects would severely limit the statistical power of our tests. Moreover, our interest is in capturing both within-firm variation *and* across-firm (cross-sectional) variation. Therefore, in our analysis we implement "two-way clustering" of standard errors along two dimensions (firm and year) to obtain unbiased standard errors. This approach is increasingly adopted in empirical studies that employ financial data in panel data estimation to account for residual dependence due to year and firm fixed effects. Petersen (2009) finds that two-way clustering of standard errors by firm and time is the most effective approach to mitigate biases in standard errors due to the prevalence of time and firm effects. Two-way clustered standard errors are unbiased, produce confidence intervals that are correctly sized, and are robust to heteroscedasticity as well. We also present the results of estimating a model with year fixed effects with standard errors clustered by firm to confirm our findings. Both models include controls for sector fixed effects.[11]

4.6 Empirical results

Table 2 presents descriptive statistics on the BWE at the individual supplier-fiscal year level across different industry sectors as well as the influential factors hypothesized to affect the BWE.

[11] Additionally, we examine variance inflation factors (VIF) for multicollinearity. We find no VIF that are greater than the recommended threshold of 10, suggesting that multicollinearity was not a problem (Hair et al., 2006).

As reported in Panel A of Table 2, BWE has an overall mean of 1.346, which is significantly different from one (p-value < 0.01), indicating that, on average, production variance of suppliers is higher than the market demand variance. Results show that 57.4% of our overall sample observations exhibit amplifying BWE (i.e., greater than one), slightly lower than the percentage documented in Shan et al. (2014) for a sample of Chinese public companies. The average BWE is significantly different from one in each industry ranging from 1.124 in the consumer nondurables industry to 1.548 in the business equipment industry. The percentage of supplier firms that exhibit amplifying BWE ranges from 45.9% in the consumer nondurables industry to 65.9% in the business equipment industry. Our results suggest that the BWE is pervasive across all industry sectors in our sample.

Panel B of Table 2 presents the descriptive statistics for supplier-customer relationship variables as well as control variables used in regression analysis of BWE.[12] The median *Length of Relationship* between the supplier and its customers is 0.250, which indicates the supplier has maintained a significant relationship with its customers in about a quarter of the time since the customers first appear in our sample. Median *Dependence on Customers* is 0.033, which reflects the proportion of a supplier's total revenue accounted for by its major customers (akin to the Herfindahl–Hirschman Index), and is in line with the median value of 0.04 reported in Patatoukas (2012). The median value of 0.003 for *Dependence on Suppliers* indicates that purchases from suppliers is about 0.3% of customers' total costs, consistent with descriptive statistics in Pandit et al. (2011) that suppliers are typically smaller in size compared to their customers. More than half of our suppliers experience no shocks in order backlog. Median coefficient of variation in deseasonalized quarterly gross margins (*Variation in Gross Margin*) is 0.154, indicating that

[12] We present descriptive statistics for the original untransformed values of these variables in Panel B of Table 2. In the subsequent regression analysis we use log-transformation of the original values (except for *AR1RHO* and *SEASONALITY* following Shan et al. 2014).

standard deviation in deseasonalized quarterly gross margins is about 15.4% of its mean. Median *Selling Intensity* is 0.22 which implies selling, general, and administrative expense is about 22% of sales.

Regarding other control variables, *Correlation in Demand* ranges from -0.477 at the first quartile to -0.038 at the third quartile, consistent with mean reversion in demand shocks. *Days in Inventory* has a median of 80.7, implying that the half of the supplier base holds its inventory for about 81 days or less. Median *Firm Size* of the suppliers is about $145 Million in total assets. Median supplier's *Gross Margin* is 32.1%. *Days Payable Outstanding* has a median of 42.5, implying that half of the supplier base takes around 43 days or less to pay off its accounts payable. Median *Seasonality in Demand* is negative, which means for half of the sample, variance in *DEMAND* is smaller than variance in deseasonalized *DEMAND*.

Finally, Panel C of Table 2 reports univariate Pearson correlations among *BWE* and our empirical proxies. *Dependence on Suppliers*, *Selling Intensity*, *Correlation in Demand*, *Days in Inventory*, *Gross Margin*, and *Days Payable Outstanding* are positively associated with *BWE* while *Length of Relationship* and *Seasonality in Demand* are negatively associated with *BWE* (significant at the 5% level).

------------------------ Insert Table 2 Approximately Here ------------------------

Next, we use multivariate regression analysis to investigate the factors that determine the cross-sectional variations in the bullwhip measured at the supplier level (Table 3). The dependent variable is the supplier's bullwhip effect (*BWE*). In Column 1, we present the results of estimating the model with two-way clustered errors (i.e., by firm and year) along with sector fixed effects. Column 2 documents the results of estimating the model with standard errors clustered by firm along with sector and year fixed effects. Column 1 shows a negative association between *Length* *of Relationship* and *BWE* that is significant at the 1% level (coefficient -0.047, t-statistics -3.71) and a positive association between *Dependence on Suppliers* and *BWE* that is significant at the 5% level (coefficient 0.012, t-statistics 1.99). These results show that when a supplier shares a longer relationship with its customers, it experiences lower BWE. However, greater dependence of customers on a supplier leads to greater BWE at the supplier, possibly a result of gaming behavior such as phantom ordering by the customers. We do not find a significant association between *BWE* and *Dependence on Customers*, suggesting that the negative effect of phantom ordering is being offset by the positive effect of information sharing, on average.

Table 3 also shows that *Order Backlog*, *Variation in Gross Margin,* and *Selling Intensity* all have positive and significant (at least 10% level) associations with *BWE*. Suppliers with high selling intensity or bigger shocks in order backlog experience greater BWE, consistent with price promotions driven by sales incentive problems and large demand fluctuations leading to higher BWE. The positive association between the variation in profit margins and *BWE* indicates that price variation results in greater bullwhip at the supplier.

Among the other control variables, we find that *BWE* is positively associated with *Correlation in Demand*, *Days in Inventory*, *Gross Margin*, and *Days Payable Outstanding,* and negatively associated with *Firm Size* and *Seasonality in Demand*. Thus, we extend the empirical evidence regarding the influence of supplier characteristics on BWE from a sample of Chinese firms in Shan et al. (2014) to a large sample of US firms. Demand signal processing, as proxied by demand correlation and inventory days, is one of the primary causes of BWE. Seasonality has a negative association with the BWE. Further, suppliers with greater gross margins, suppliers that take longer to pay their accounts payable, and smaller suppliers, experience greater BWE.

As can be seen in Column 2 of Table 3, our inferences are similar when using the alternative specification of the regression model that includes year and sector fixed effects with standard errors clustered by firm.

------------------------ Insert Table 3 Approximately Here ------------------------

4.7 Additional analyses

4.7.1 Alternative model specification

In our main analysis we employ clustered standard errors as well as year and sector fixed effects to control for any time-series and cross-sectional dependence of residuals across observations in the panel dataset. As a robustness check, we use an alternative specification based on a mixed-effects model that incorporates both firm effects and year effects (similar to Shan et al., 2014). The detailed specification of the model along with the estimation results are described in Appendix B. Our inferences are similar using this alternative model specification.

4.7.2 Industry sector and time-period subsamples

We also conduct additional analyses to compare and contrast the effects of our key variables on BWE across industry sectors and different time-periods. To do so, we estimate the regression model for subsamples based on suppliers' industry sectors, and based on two distinct time periods in our sample (1978-1995 and 1996-2013). The results using industry subsamples are presented in Panel A of Table 4.[13] As can be seen from the table, the *Length of Relationship* between suppliers and customers appears to have the strongest effect in the consumer nondurables industry, followed by the business equipment and machinery industries. Customers' *Dependence on Suppliers* has a significant impact only in the consumer durables industry. We do not see a significant impact of customers' dependence on suppliers on BWE in other industries. Higher

[13] For brevity, we present the results using two-way clustered standard errors.

supplier *Dependence on Customers* is associated with greater BWE for suppliers in the business equipment and resource extraction industries. The results of subsamples based on time periods are presented in Panel B of Table 4. While the mitigating impact of *Length of Relationship* on BWE is greater in the latter period (i.e., 1996-2013), the impact of *Dependence on Customers* is greater in the earlier period (i.e., 1978-1995). The bullwhip-enhancing impact of *Dependence on Suppliers* is present in both periods. We assess the implications of these subsample analyses along with our key results in the discussion section.

------------------------ Insert Table 4 Approximately Here ------------------------

4.7.3 Potential nonlinearity in relationships

Since we propose competing hypotheses for our key variables in the theoretical development, it creates the potential for non-linear effects in the relationships that are examined in our tests. In additional analysis, we explore the possibility of non-linearity in the effects for our key independent variables (i.e., *Length of Relationship*, *Dependence on Customers*, and *Dependence on Suppliers*) by including quadratic terms for each of them in our empirical model. The results from this estimation are presented in Table 5. As can be seen from the table, we do not find evidence of nonlinearity in the impact of *Length of Relationship* on BWE. However, for the effect of *Dependence on Suppliers*, the quadratic term is significant and negative, suggesting that BWE increases with greater dependence on suppliers, but at a decreasing rate. The linear term capturing the effects of *Dependence on Customers* remains insignificant.

------------------------ Insert Table 5 Approximately Here ------------------------

5. Discussion

Our study provides important empirical evidence on the impact of relational capital on the BWE at the supplier. There are several important implications for different aspects of relational capital as well as for BWE. The first is that longer relationships between customers and suppliers are associated with less BWE. The impact of relationship length seems to have become more salient in recent decades in comparison to the earlier half of our sample period (Table 4, panel B). This is consistent with the growth in the adoption of new technologies in the 1990s that enable greater information sharing between suppliers and customers. It also underscores the growing importance of information sharing in supply chains that increasingly span the globe (Sahin and Topal, 2018). Managers who are tempted to go with transactional supplier/customer relationships would be advised to invest the effort and resources to build long term close relationships with supply chain partners. All partners in the supply chain will benefit from doing so since the BWE has many deleterious effects across the supply chain. We find that the impact of the length of the relationship is most significant in the consumer nondurables, machinery, and business equipment sectors (Table 4, panel A). The consumer sector has experienced widespread use of vendor-managed inventory (VMI), EDI, and continuous replenishment programs (CRP) which can mitigate bullwhip due to better sharing of demand information (Lee et al., 1997a). Greater trust and commitment driven by long-term relationships make it more likely that both suppliers and customers in this sector make these relationship-specific investments (Ganesan, 1994). Such relationship-specific investments are also more likely in the machinery and business equipment sectors that often rely on customized parts and services. In other industries, the motivation for information sharing and collaboration may be independent of the length of the relationship once the relationships become stable (Lee et al., 2010). It is also possible that the smaller sample size of some industries in our sample may mask the impact of relationship length. While we speculate on possible reasons for the differences in impact across industries, we believe future research can investigate this issue further to establish the precise reasons for such differences.

Given that lower BWE leads to better performance (Metters, 1997), these results are consistent with previous research that has shown a positive link between the length of relationship between the supplier and customer, and supplier performance, such as Kotabe et al. (2003), MacDuffie and Helper (1997) and McCullen and Towill (2001a). Our results are also consistent with studies on the JIT (lean) type long term relationships, as seen in the meta-study by Bhamu and Sangwan (2014) that found a link between customer-supplier relationship strength and lean implementation success, which would imply performance improvement.

Our results provide evidence that greater dependence on suppliers, i.e., customers having to rely on fewer suppliers, leads to increased bullwhip at the supplier. This is consistent with Lee et al. (1997a) who suggest that opportunistic behavior can lead to bullwhip. It also implies that even with supplier concentration, there exists insufficient information sharing to offset BWE enhancing behavior like gaming. The impact of customers' dependence on suppliers is seen to be particularly strong in the consumer durables industry, but not in other industries. These results are not entirely surprising given that different industries could be at different stages of supply chain maturity (Dellana and Kros, 2014; Broft et al., 2016) which has an impact on the willingness of supply chain partners to collaborate (Lockamy and McCormack, 2004). Consumer durable manufacturers, such as automotive producers, have become increasingly dependent on suppliers due to significant reduction in the number of suppliers in the last few decades (Helper, 1991). This greater dependence on suppliers may increase bullwhip since a customer's reliance on a supplier can lead to opportunistic behavior (Joshi and Arnold, 1998).

The implication here is that suppliers who know that their customers depend heavily on them should also understand that a real risk of the BWE exists and they should take steps to avoid it. The Philips Semiconductor example (de Kok et al., 2005) is illustrative here. In order to reduce their BWE, in 2000 Philips Semiconductors initiated a project with a customer which involved agreeing that (1) strong collaboration was needed for a winning supply chain, (2) key supply chain information must be shared, (3) high volatile capacities and material flows should be synchronized, and (4) decisions had to be made in a timely manner. This effort was supported by innovative software. The project which resulted in a better coordinated supply chain, brought BWE reduction for Philips Semiconductors, and performance benefits for both the customer and supplier.

Overall, we do not find that customer concentration has a significant effect on bullwhip in the combined sample. This leads us to conclude that, on average, the positive effect of information sharing offsets any tendency of the customer to distort demand information up the supply chain. However, in the business equipment and resource extraction sectors, higher customer concentration is associated with greater bullwhip. The business equipment sector consists of manufacturers of computers and electronics. This industry experiences a high level of demand uncertainty due to continuous updating of technology and products (Sodhi, 2005). Suppliers with heterogenous customers may be able to diversify and reduce their exposure to demand uncertainty emanating from a single customer (Bartezzaghi et al., 1999). However, those dependent on a fewer customers will be more prone to demand swings that lead to greater bullwhip. The output of the resource extraction sector mainly consists of commodities such as oil and gas, minerals, etc. These resources have multiple uses with potentially uncorrelated demand patterns. For instance, a commodity such as aluminum is used by customers in a wide range of industries such as transportation, construction, consumer durables and consumer non-durables. For an aluminum extractor, having heterogeneous customers that cover different end-uses is likely to shield it from the risk associated with demand shock in a particular end-use. In other sectors this is less likely to be true, since products may be designed for a limited use only. In this case, any demand shock in the end-use will be more likely to be correlated across customers, causing bullwhip at the supplier. Thus, having multiple customers in such a scenario will not reduce the risk of customer base concentration.

While we document the differences in the impact of suppliers' dependence on customers across industry sectors, we also find that a dependence on customers helps mitigate BWE in the early half of our sample period (i.e., 1978-1995) but there is no association between the two in the latter half (1996-2013). As our industry results show, the business equipment sector experiences greater BWE with higher customer concentration. The growth in this sector (particularly, computers and electronics) in the latter half of our sample period may have offset the mitigating impact of customer concentration in this period from other industries, leading to an overall lack of association during the 1996-2013 period.

The other variables that capture operational characteristics of suppliers also provide some useful insights into the causes and drivers of BWE that has important implications for researchers and practitioners. With regard to these variables, we find that order backlog and variation in gross margin are positively associated with BWE. What does this imply for the management of the BWE, which as Metters (1997) and Billington (2010) have discussed, can be detrimental to companies? Order backlog may be a symptom of order batching which is often caused by higher machine setup costs or larger costs of placing orders with suppliers. This results in longer lead times and greater BWE. Lean Management has focused on reducing this setup or ordering cost, which makes smaller batches more economical. Thus, our results are consistent with McCullen and Towill (2001a) who found that implementing lean and agile operations reduced the BWE.

We also find that price fluctuations influence the BWE as conjectured in Lee et al. (1997a). This suggests that managers should avoid unnecessary changes in pricing that cause variations in gross margin. As Lee et al. (1997a) point out, pricing variations result in 'forward buying' which leads to bullwhip. Further, Lee at al. (1997a) point out that trade promotions can cause forward buying resulting in the BWE. Thus, managers may consider options such as ‘everyday low prices’ (as practiced by retailer Walmart) which can be attractive purely from a BWE avoidance perspective, since it reduces the incentive to forward buy. However, trade promotions are at times required due to reasons such as the competitive environment. In these situations, planning trade promotions in concert with suppliers could result in superior end demand visibility and better coordination, thus reducing bullwhip for suppliers.

Finally, we find that firms with high selling intensity experience greater BWE. When companies set sales targets for salespersons based on monthly, quarterly, or annual targets, this is likely to lead to a bunching of orders during the end of the period. Order batching that results from such incentives leads to greater BWE, which would be more severe for firms with higher selling intensity. As an antidote, the company may want to manage sales targets on a rolling basis, which gives fewer incentives for the ‘end of year’ booking phenomenon.

6. Conclusions

In this paper, we investigated linkages between relational capital and the bullwhip effect (BWE) using a large sample of firm-level data. Following Krause et al. (2007) we examined three distinct aspects of relational capital – relationship length, customers’ dependence on suppliers, and suppliers’ dependence on customers. Using firms’ financial statements to develop empirical proxies for capturing the aspects of relational capital, we found that the length of the relationship between suppliers and customers serves to reduce the bullwhip at the supplier. However, customers’ dependence on suppliers acts to increase supplier bullwhip. We did not find that supplier exposure to customers has an influence on bullwhip, on average. Further, we found that different aspects of relational capital may be more or less important depending on the industry. We also documented how these influences on BWE vary over time.

Our findings have several implications for different aspects of relational capital as well as for BWE. We find that longer relationships between customers and suppliers are associated with less BWE. Therefore, consistent with the relational view, firms should invest the effort and resources to build stable relationships across the supply chain, rather than engage in merely transactional relationships with their customers and suppliers. As evidenced by the experience of sectors such as consumer nondurables, machinery, and business equipment, greater trust and commitment driven by long-term relationships make it more likely that both suppliers and customers make relationship-specific investments and build relational capital.

Our results also speak to the effect on BWE of the mutual dependence of customers and suppliers on each other. In particular, we find that customers' reliance on fewer suppliers leads to increased bullwhip at the supplier, suggesting that even with supplier concentration, there may be insufficient information sharing to offset opportunistic behavior that exacerbates BWE. This implies that suppliers with dependent customers should anticipate risks of potential BWE, and take preventive steps to avoid it. On the other hand, we do not find that customer concentration has a significant effect on bullwhip on average, implying that the positive effect of information sharing may offset the customers' incentives to distort demand information up the supply chain. We should note that exceptions exist in our sample, for example, in the business equipment and resource extraction sectors.

In our empirical analysis, we also include operational characteristics of suppliers that could be manifestations of several theorized causes of BWE. Our examination of these characteristics reveals evidence consistent with roles played by order batching and price variations in causing the BWE. We found evidence that the BWE is greater when there is higher intensity of selling costs, greater shocks in order backlog, and more variations in gross margins. These results have implications for managers. Our results also support the propositions of Lee et al. (1997a) regarding the causes of the BWE that could potentially be tested, which has not been done previously using large samples.

Our inferences come with important caveats. We limit our choice of empirical proxies to those that can be constructed using publicly available data included in firms' reported financial statements. These proxies may be noisy measures of the theorized constructs, in part because bullwhip and its drivers are likely to be captured most accurately at the individual product line level; the effects are likely to be muted when aggregated across multiple product lines at the firm level. We believe that a more comprehensive understanding of the role of supplier-customer relationships on the BWE will require the efforts of multiple researchers that have access to more detailed data. Additionally, our measures of interdependence are based on a sample consisting of mostly small suppliers and large customers due to the nature of financial disclosure requirement. While the results of our estimation would apply to relationships that are similar to those in our sample, they may not be generalizable to relationships that are substantially different. Finally, our study documents variation in the impact of supplier-customer relationships on BWE across different industries and over time. While we speculated on probable causes for these differences, further empirical studies are needed to investigate and establish the reasons for these observed differences.

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APPENDIX A
Variable Definitions

Variable Label	***Variable Name*/Unit of Measurement**	**Definition**	**Supporting Literature**
Dependent Variable:			
Bullwhip Effect	*BWE* ratios	Bullwhip effect for each supplier in a given year, calculated as standard deviation of quarterly PRODUCTION divided by standard deviation of quarterly DEMAND during a fiscal year. PRODUCTION is the adjusted production, calculated as the first difference in the natural log of quarterly production, where quarterly production is quarterly cost of goods sold plus changes in inventory level quarter-over-quarter. DEMAND is the adjusted demand, calculated as the first difference in the natural log of quarterly cost of goods sold, where cost of goods sold captures the margin-adjusted sales.	Bray and Mendelson (2012), Cachon et al., (2007), Shan et al. (2014)
Independent Variables – Supplier-customer Relationship:			
Length of Relationship	*ln(CS_LENGTH)* log-transformation of weighted average percentages	Natural log of weighted average of the length of supplier-customer relationship, where the length is the number of years that the supplier-customer relationship has existed, divided by the number of years since the customer first appears in our sample. The weight for each major customer is the sales to the major customer divided by the supplier's total sales.	Krause et al. (2007)
Dependence on Customers	*ln(CCONC)* log-transformation of sum of squared percentages	Natural log of a given supplier's customer base concentration, where concentration is calculated as the sum of the squares of the sales to any major customer divided by the supplier's total sales.	Krause et al. (2007), Pandit et al. (2011)
Dependence on Suppliers	*ln(CSALE_CCOGS)* log-transformation of weighted average percentages	Natural log of weighted average of sales to a major customer divided by the customer's cost of goods sold, averaged across all major customers for a given supplier. The weight for each major customer is the sales to the major customer divided by the supplier's total sales.	Krause et al. (2007), Patatoukas (2012)

Independent Variables – Supplier Characteristics:			
Order Backlog	*ln(BACKLOG)* log-transformation of percentages	Natural log of supplier's backlog shock, where backlog shock is the absolute difference between current year order backlog and prior year order backlog scaled by total assets. We add one to all observations before the log transformation to keep the observations with zero shocks.	Rajgopal et al. (2003), Chang et al. (2018)
Variation in Gross Margin	*ln(CV_GM)* log-transformation of ratios	Natural log of coefficient of variation in deseasonalized quarterly gross profit margin, where gross profit margin is net sales minus cost of goods sold divided by net sales	Lee et al. (1997a,b)
Selling Intensity	*ln(SGA_INTENSITY)* log-transformation of percentages	Natural log of selling and general administrative expenses divided by net sales	Lee et al. (1997a,b)
Correlation in Demand	*AR1RHO* autoregressive coefficient	Autoregressive coefficient estimated with the deseasonalized DEMAND in the past eight quarters. We estimate the AR(1) model on a rolling basis for every firm every year using eight quarters of quarterly data and require a minimum of 3 quarters for each regression.	Shan et al. (2014)
Days in Inventory	*ln(DAYSINVT)* log-transformation of number of days	Natural log of number of days in inventory, where number of days in inventory is calculated as 365 divided by inventory turnover ratio. Inventory turnover is cost of goods sold divided by average inventory.	Shan et al. (2014)
Firm Size	*ln(SIZE)* log-transformation of dollars in millions	Natural log of supplier's total assets	Shan et al. (2014)
Gross Margin	*ln(GM)* log-transformation of percentages	Natural log of annual gross profit margin, where gross profit margin is net sales minus cost of goods sold divided by net sales.	Shan et al. (2014)

Days Payable Outstanding	*ln(DAYSAP)* log-transformation of number of days	Natural log of days payable outstanding, where days payable outstanding is calculated as 365 divided by accounts payable turnover ratio. Accounts payable turnover is cost of goods sold divided by average accounts payable.	Shan et al. (2014)
Seasonality in Demand	*SEASONALITY* ratios	The difference between variance of DEMAND and variance of deseasonalized DEMAND, divided by variance of DEMAND. Variances are calculated using eight quarters of data on a rolling basis.	Shan et al. (2014)

Appendix B: Mixed-effects Model

We estimate a mixed-effects model that incorporates both year effects (u_t) and firm effects (v_i) as below:

$$BWE_{it} = \beta_0 + \beta_1 \ln(CS\_LENGTH)_{it} + \beta_2 \ln(CCONC)_{it} + \beta_3 \ln(CSALE\_CCOGS)_{it}$$

$$+(\beta_4 + u_t)(Year - 1978) + v_i + \sum_{k=1}^{K} \gamma_k Control_k + e_{it}$$

where *ln(CS_LENGTH)* represents the length of relationship, *ln(CCONC)* represents suppliers' dependence on customers, and *ln(CSALE_CCOGS)* represents customers' dependence on suppliers.

We model the between-firm variability as a random effect (i.e., as a random-intercept term v_i at the firm level) and allow the effect due to *Year* to be systematic to that year and common to all firms (i.e., as a random slope u_t). Both v_i and u_t are assumed to be normally distributed with mean zero and uncorrelated with explanatory variables. This type of mixed-effects model takes into account both time-variant and time-invariant effects associated with an individual firm (Shan et al. 2014). Results below show that our inferences remain unchanged using this alternative model specification.

Dependent Variable = BWE	
Supplier-Customer Relationship:	
Length of Relationship	-0.016*
	[-1.71]
Dependence on Customers	-0.000
	[-0.02]
Dependence on Suppliers	0.013***
	[2.65]
Supplier Characteristics:	
Order Backlog	0.152*
	[1.86]
Variation in Gross Margin	0.092***
	[3.50]
Selling Intensity	-0.001
	[-0.06]
Correlation in Demand	0.258***
	[11.36]
Days in Inventory	0.141***
	[10.50]
Firm Size	-0.023***
	[-3.56]
Gross Margin	0.081***
	[4.78]

Days Payable Outstanding	0.035***
	[2.59]
Seasonality in Demand	-0.203***
	[-24.66]
Year	0.006***
	[4.53]
Constant	0.938***
	[8.08]
Observations	13,993
Firm and Year Effects	Yes
Log Likelihood	-16,445.2

***, **, and * indicate significance level of 1%, 5%, 10%, respectively, based on two-sided tests.

TABLE 1
Sample Selection

This table presents our sample selection procedure. Retail sector includes SIC 5200-5999. Wholesale sector include SIC 5000-5199. Manufacturing sector includes SIC 2000-3999. Resource extracting sector includes SIC 1000-1400.

Sample Selection	Number of Observations
Annual supplier-customer pairs where both customer and supplier are from one of the four sectors (retail, wholesale, manufacturing or resource extracting) and both customer and supplier names can be matched to corporate names on Compustat	30,279
Less observations where:	
Data unavailable to construct the bull whip effect for the supplier	5,377
Data unavailable to construct supplier-customer relationship variables at the supplier-customer pair level	1,610
Subtotal: Supplier-customer pairs	23,292
Supplier-customer pairs aggregated at the supplier-year level	16,746
Less observations where:	
Data unavailable to construct other influential factors including the control variables	2,753
Total: Supplier-Years	13,993
Number of unique suppliers	2,786

TABLE 2
Descriptive Statistics

This table presents descriptive statistics for our sample. Panel A present the descriptive statistics for the bullwhip effect (*BWE*) measures. Significance at the 1%, 5%, 10% level are denoted ***, **, and *, respectively, based on two-sided t-tests. Panel B presents the descriptive statistics for supplier-customer relationship variables and control variables (before log-transformation). Panel C presents Pearson correlations. Correlations significant at the 5% level are in **bold.** See Appendix A for complete variable definitions.

Panel A: Descriptive Statistics for the Bullwhip Effect (BWE)

	N	Mean	Std Dev	1st Quartile	Median	3rd Quartile	% Great Than one
Retail & Wholesale	648	1.359***	0.804	0.880	1.106	1.514	63.3%
Consumer Nondurables	2,213	1.124***	0.736	0.604	0.946	1.360	45.9%
Consumer Durables	1,383	1.230***	0.726	0.762	1.037	1.462	53.8%
Machinery	3,887	1.277***	0.800	0.738	1.063	1.531	54.8%
Business Equipment	3,965	1.548***	0.938	0.854	1.268	1.997	65.9%
Healthcare	1,282	1.468***	0.948	0.794	1.132	1.894	60.2%
Resource Extraction	615	1.268***	0.731	0.922	1.023	1.345	57.2%
All	13,993	1.346***	0.851	0.769	1.093	1.642	57.4%

Panel B: Descriptive Statistics for Supplier-Customer Relationship Variables and Control Variables

Variable Label	N	Mean	Std Dev	1st Quartile	Median	3rd Quartile
Supplier-Customer Relationship:						
Length of Relationship	13,993	0.337	0.276	0.129	0.250	0.458
Dependence on Customers	13,993	0.076	0.116	0.014	0.033	0.082
Dependence on Suppliers	13,993	0.017	0.041	0.001	0.003	0.011
Supplier Characteristics:						
Order Backlog	13,993	0.054	0.115	0.000	0.000	0.050
Variation in Gross Margin	13,993	0.156	0.043	0.141	0.154	0.165
Selling Intensity	13,993	0.294	0.292	0.129	0.220	0.358
Correlation in Demand	13,993	-0.254	0.319	-0.477	-0.245	-0.038
Days in Inventory	13,993	94.007	65.325	50.011	80.734	119.663
Firm Size	13,993	1256.845	3362.216	34.965	145.485	754.332
Gross Margin	13,993	0.354	0.184	0.220	0.321	0.465
Days Payable Outstanding	13,993	55.968	51.040	29.159	42.526	62.707
Seasonality in Demand	13,993	-0.331	0.966	-0.502	-0.040	0.200

Panel C: Pearson Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*Bullwhip Effect*	1												
(2)	*Length of Relationship*	**-0.057**	1											
(3)	*Dependence on Customers*	0.001	**0.078**	1										
(4)	*Dependence on Suppliers*	**0.018**	**0.101**	**0.105**										
(5)	*Order Backlog*	0.013	**0.030**	0.001	**-0.056**	1								
(6)	*Variation in Gross Margin*	0.001	**0.058**	-0.005	**0.053**	**0.018**	1							
(7)	*Selling Intensity*	**0.096**	**-0.151**	**0.028**	**-0.266**	**-0.040**	**-0.231**							
(8)	*Correlation in Demand*	**0.046**	**-0.017**	0.013	**0.040**	**0.019**	**0.022**	**-0.037**	1					
(9)	*Days in Inventory*	**0.116**	0.010	**-0.033**	**-0.111**	**0.085**	**-0.130**	**0.499**	**-0.051**	1				
(10)	*Firm Size*	-0.006	**-0.043**	**-0.146**	**0.515**	**-0.224**	**0.019**	**-0.315**	**0.043**	**-0.170**	1			
(11)	*Gross Margin*	**0.103**	**-0.127**	**-0.021**	**-0.090**	**-0.091**	**-0.219**	**0.630**	**-0.030**	**0.342**	0.014	1		
(12)	*Days Payable Outstanding*	**0.081**	**-0.158**	**0.067**	**-0.034**	**-0.050**	**-0.143**	**0.365**	0.006	**0.137**	**0.039**	**0.331**	1	
(13)	*Seasonality in Demand*	**-0.194**	**-0.029**	**0.036**	**-0.157**	**0.067**	**-0.059**	**0.178**	**0.221**	**0.120**	**-0.186**	**0.086**	**0.082**	1

TABLE 3
Regression Results

This table presents results of regressing the BWE on supplier-customer relationship variables and control variables. Two-way clustered standard errors are standard errors are clustered on two dimensions (firm and year). Significance at the 1%, 5%, 10% level are denoted ***, **, and *, respectively, based on two-sided t-tests. See Appendix A for complete variable definitions.

Dependent Variable = BWE	(1)	(2)
Supplier-Customer Relationship:		
Length of Relationship	-0.047***	-0.033***
	[-3.71]	[-2.88]
Dependence on Customers	0.002	-0.005
	[0.29]	[-0.77]
Dependence on Suppliers	0.012**	0.015***
	[1.99]	[2.64]
Supplier Characteristics:		
Order Backlog	0.206*	0.246**
	[1.92]	[2.57]
Variation in Gross Margin	0.089***	0.089***
	[3.46]	[3.32]
Selling Intensity	0.034*	0.014
	[1.76]	[0.73]
Correlation in Demand	0.294***	0.285***
	[11.55]	[10.94]
Days in Inventory	0.138***	0.143***
	[8.15]	[9.05]
Firm Size	-0.017**	-0.032***
	[-2.55]	[-4.50]
Gross Margin	0.083***	0.086***
	[4.63]	[4.38]
Days Payable Outstanding	0.063***	0.067***
	[3.79]	[4.02]
Seasonality in Demand	-0.221***	-0.220***
	[-18.68]	[-19.55]
Constant	1.028***	1.069***
	[6.96]	[7.77]
Observations	13,993	13,993
Adjusted R-squared	8.40%	8.79%
Sector fixed effects	Yes	Yes
Two-way clustered standard errors	Yes	
Year fixed effects		Yes
Standard errors clustered by firm		Yes

TABLE 4
Subsample Regression Results

This table presents results of regressing the BWE on supplier-customer relationship variables and control variables by industry (Panel A) or by sub-period (Panel B). Two-way clustered standard errors are standard errors are clustered on two dimensions (firm and year). Significance at the 1%, 5%, 10% level are denoted ***, **, and * respectively, based on two-sided t-tests. See Appendix A for complete variable definitions.

Panel A: By Industry

Industries	Retail & Wholesale	Consumer Nondurables	Consumer Durables	Machinery	Business Equipment	Healthcare	Resource Extraction
Supplier-Customer Relationship:							
Length of Relationship	0.032	-0.093***	-0.048	-0.038**	-0.040*	0.018	-0.040
	[0.71]	[-2.94]	[-1.28]	[-2.32]	[-1.87]	[0.58]	[-1.18]
Dependence on Customers	-0.025	-0.031	-0.008	-0.011	0.026**	0.006	0.054**
	[-1.00]	[-0.96]	[-0.44]	[-1.14]	[2.08]	[0.37]	[2.13]
Dependence on Suppliers	-0.005	0.007	0.037**	0.002	0.007	-0.013	-0.018
	[-0.24]	[0.41]	[2.22]	[0.19]	[0.61]	[-0.88]	[-0.95]
Supplier Characteristics:							
Order Backlog	0.521	-0.293	0.176	0.440***	-0.105	0.493	-0.369
	[0.83]	[-1.29]	[0.56]	[2.80]	[-0.56]	[0.86]	[-1.56]
Variation in Gross Margin	0.149	0.238**	0.050	0.153***	0.040	0.028	-0.003
	[1.09]	[2.19]	[0.68]	[2.94]	[0.72]	[0.42]	[-0.07]
Selling Intensity	-0.083	-0.021	0.045	0.004	0.085**	-0.076	-0.076
	[-0.74]	[-0.36]	[0.53]	[0.14]	[2.38]	[-1.06]	[-1.31]
Correlation in Demand	0.247**	0.169**	0.177**	0.215***	0.375***	0.390***	0.084
	[2.04]	[2.57]	[1.99]	[4.01]	[9.61]	[3.78]	[1.02]
Days in Inventory	0.181***	0.011	0.011	0.160***	0.139***	0.157***	0.185***
	[3.52]	[0.27]	[0.19]	[5.53]	[4.91]	[3.09]	[4.72]
Firm Size	-0.009	-0.023	-0.061***	-0.031***	0.002	0.057***	-0.011
	[-0.33]	[-1.11]	[-4.63]	[-2.85]	[0.16]	[3.24]	[-0.55]
Gross Margin	0.019	-0.070	0.018	0.017	0.120***	0.016	0.062
	[0.18]	[-1.29]	[0.26]	[0.47]	[3.29]	[0.17]	[1.08]

Days Payable Outstanding	0.049	0.093*	0.039	0.083***	-0.012	0.010	0.086**
	[0.73]	[1.70]	[0.94]	[3.03]	[-0.40]	[0.22]	[2.24]
Seasonality in Demand	-0.213***	-0.164***	-0.165***	-0.193***	-0.279***	-0.276***	-0.200***
	[-5.82]	[-5.16]	[-7.12]	[-9.87]	[-12.46]	[-5.55]	[-4.02]
Constant	0.541	1.034***	1.695***	0.630***	1.351***	0.398	0.254
	[0.85]	[2.46]	[2.97]	[2.71]	[6.07]	[1.06]	[0.88]
Observations	648	2,213	1,383	3,887	3,965	1,282	615
Adjusted R-squared	15.5%	5.3%	5.7%	8.3%	8.5%	9.9%	12.5%
Two-way clustered standard errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 4 CONTINUED

Panel B: By Sub-period

Years	1978-1995	1996-2013
Supplier-Customer Relationship:		
Length of Relationship	-0.016	-0.050***
	[-0.89]	[-3.15]
Dependence on Customers	-0.025**	0.008
	[-2.47]	[0.97]
Dependence on Suppliers	0.018**	0.012*
	[2.11]	[1.67]
Supplier Characteristics:		
Order Backlog	0.311**	0.216
	[2.04]	[1.55]
Variation in Gross Margin	0.095***	0.076**
	[2.71]	[2.03]
Selling Intensity	0.005	0.016
	[0.16]	[0.69]
Correlation in Demand	0.256***	0.308***
	[8.26]	[9.31]
Days in Inventory	0.101***	0.165***
	[4.42]	[8.02]
Firm Size	-0.038***	-0.025***
	[-3.92]	[-3.02]
Gross Margin	0.047**	0.101***
	[2.56]	[4.29]
Days Payable Outstanding	0.061**	0.068***
	[2.27]	[3.32]
Seasonality in Demand	-0.249***	-0.210***
	[-13.42]	[-16.08]
Constant	1.164***	0.935***
	[5.53]	[4.90]
Observations	4,868	9,125
Adjusted R-squared	7.61%	8.97%
Sector fixed effects	Yes	Yes
Two-way clustered standard errors	Yes	Yes

TABLE 5
Regression Results – Nonlinearity

This table presents results of regressing the BWE on linear and squared terms of variables measuring supplier-customer relationship and control variables. Two-way clustered standard errors are standard errors clustered on two dimensions (firm and year). Significance at the 1%, 5%, 10% level are denoted ***, **, and * respectively, based on two-sided t-tests. See Appendix A for complete variable definitions.

Dependent Variable = BWE	(1)	(2)
Supplier-Customer Relationship:		
Length of Relationship	-0.052***	-0.036***
	[-3.96]	[-2.89]
(Length of Relationship)^2	-0.017	-0.009
	[-1.45]	[-0.88]
Dependence on Customers	0.005	-0.003
	[0.65]	[-0.43]
(Dependence on Customers)^2	0.006**	0.006**
	[2.21]	[1.97]
Dependence on Suppliers	0.013**	0.017***
	[2.19]	[2.86]
(Dependence on Suppliers)^2	-0.004**	-0.005***
	[-2.52]	[-2.77]
Supplier Characteristics:		
Order Backlog	0.202*	0.241**
	[1.87]	[2.52]
Variation in Gross Margin	0.087***	0.087***
	[3.46]	[3.24]
Selling Intensity	0.036*	0.017
	[1.87]	[0.90]
Correlation in Demand	0.292***	0.283***
	[11.39]	[10.88]
Days in Inventory	0.140***	0.144***
	[8.15]	[9.20]
Firm Size	-0.019***	-0.034***
	[-2.79]	[-4.74]
Gross Margin	0.078***	0.081***
	[4.41]	[4.13]
Days Payable Outstanding	0.062***	0.066***
	[3.65]	[3.98]
Seasonality in Demand	-0.223***	-0.222***
	[-18.85]	[-19.64]
Constant	1.048***	1.073***
	[8.13]	[8.54]
Observations	13,993	13,993

Adjusted R-squared	8.55%	8.94%
Sector fixed effects	Yes	Yes
Two-way clustered standard errors	Yes	
Year fixed effects		Yes
Standard errors clustered by firm		Yes