Casalin F, Pang G, Maioli S, Cao T.

[Inventories and the concentration of suppliers and customers: Evidence from the Chinese manufacturing sector.](#)

International Journal of Production Economics 2017, 193, 148-159.

Copyright:

© 2017. This manuscript version is made available under the [CC-BY-NC-ND 4.0 license](#)

DOI link to article:

<https://doi.org/10.1016/j.ijpe.2017.07.010>

Date deposited:

10/07/2017

Embargo release date:

12 January 2019

This work is licensed under a [Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International licence](#)

Inventories and the concentration of suppliers and customers: Evidence from the Chinese manufacturing sector

Fabrizio Casalin*, Gu Pang, Sara Maioli, Ting Cao

Newcastle University Business School, 5 Barrack Road, Newcastle upon Tyne, UK, NE1 4SE

Abstract

This study investigates the links between supplier- and customer-base concentrations, and inventory holdings in the Chinese manufacturing sector. Using financial data from a cohort of 516 companies, we find that firms that face higher supplier density - benefiting from better co-ordination with suppliers - hold fewer inventories, whereas firms with higher customer density retain larger inventories, as a result of the bargaining power exercised by customers. We then extend the analysis by investigating the impact of account payables, receivables and bad debt reserves, finding that inventory holdings are positively associated with the two forms of financing, and negatively associated with bad debts. This last relationship, however, becomes less severe when firms have access to large volumes of payables. Finally, we show that the above results hold – with varying degrees of similarity - also when we partition the dataset into six homogenous industrial segments. Overall, this study contributes to the growing literature on inventories and the structure of the supply chain by shedding new light on the importance of both supplier and customer densities, as well as the volume of payables and receivables, for inventory management.

Key words: Supplier-base concentration; Customer-base concentration; Inventory holdings

*Corresponding author. E-mail fabrizio.casalin@ncl.ac.uk.

1. Introduction

Inventories are essential, unavoidable components of the business activity of firms as they serve as a strategic tool to achieve customer satisfaction and profit maximization (Ho et al, 2015). For instance, given the widespread adoption of Just-In-Time (JIT) practices, managers often view inventories as an indicator of process capability and efficiency (see, e.g., Lieberman and Demeester, 1999, and Lieberman and Asaba, 1997). Moreover, some recent studies have shown that firms with volatile inventories underperform in the stock markets (Allen et al., 2013).

The literature has traditionally focussed on the linkage between inventory levels of manufacturing firms and micro-level indicators.¹ Many scholars have documented a positive relationship with non-financial indicators such as the uncertainty in demand, production lead times, variety in the specification of products sold and number of dealerships, as well as a negative linkage with firms' size. The relationship between inventory levels and financial indicators is instead less clear-cut. For instance, a number of studies finds that the linkage with various specifications of gross income margins varies from positive to negative depending on the type of industry analyzed. Focussing instead on the financial strength of firms, Caglayan et al. (2012) show that firms with more liquid assets are associated with lower levels of inventory.

A more recent strand of research has focused on the cooperation among firms in the upper- and lower-stream of the supply chain as a tool to achieve efficiency in working capital management. The underlying idea is that inventories can be efficiently managed only by developing partnerships with both suppliers and customers. These last, in fact, can help firms secure timely deliveries of raw materials, work-in-process, and final goods, with the agreed standard of quality. For instance, a well-known supply-chain practice is the Vendor Managed Inventory (VMI), where the manufacturer firms hand over the inventory replenishment decisions onto their suppliers. The advantage of VMI agreements is that they improve coordination and information sharing which help mitigate demand uncertainty, thereby allowing for leaner inventories.

¹ A companion strand of studies investigates the linkage between inventories and macroeconomic indicators. For example, Chen *et al.* (2005) find that when the interest rate rises the levels of inventory drop - as they become more expensive relative to holding bonds - whereas when managers hold optimistic views on future economic outlook then inventories increase.

A specific form of cooperation among firms hinges on the issuance of receivables and payables. These last are financial tools used to extend credit to customers and to finance the purchasing of supplies. Recently, scholars have focussed their interest on the linkage between inventories and the volume of payables and receivables, as they can affect the purchasing of raw materials as well as sales of finished goods and, ultimately, the elasticity of inventories. While the literature on payables and inventory holdings is still relatively scarce, the link between receivables and inventories have been extensively scrutinized, with empirical results which are however inconclusive and dependant on the type of countries and industries. Early studies, in fact, have highlighted that firms, by increasing accounts receivables, can sell more and hold fewer inventories, whereas more recently scholars have shown that the opposite link holds.

A different form of cooperation consists of shaping the size and composition of the supplier and customer bases, so that firms can better liaise with their counterparties in the upper- and lower-stream of the supply chain. The links between supplier and customer density, and inventory holdings are ex-ante unclear and still largely unexplored. Focussing on the lower end of the supply chain, scholars have identified two competing views on how customer density affects inventory holdings, namely the Bargaining Power and OM views (see Ak and Patatoukas, 2016). According to the former, firms facing a concentrated customer-base are held captive by their counterparties and forced to retain excess inventories. Less concentrated bases, instead, would generate diversification benefits that make firms less exposed to peaks and troughs in sales. The latter puts forward the idea that a limited number of major customers would facilitate closer partnerships, enabling firms to minimize inventory holdings, whereas less concentrated bases would make the cooperation more difficult. An alternative explanation to the OM view is the so-called Demand Fragmentation Hypothesis according to which lower concentration of customers would cause a fragmentation of the demand, leading to increased volatility of sales and larger inventories (see Cachon and Olivares, 2010). The strand of research on the upper end of the supply chain is even scarcer, with virtually no studies investigating the relationship between supplier density and inventories. Thus, in order to postulate the type of relationship linking the concentration of suppliers with inventories, we draw on two close strands of studies that implicitly acknowledge the existence of such a link. The first one is based on the idea that the consolidation in the volume of supplies enables a closer and more profitable relationship between the firm and its suppliers. This is the so-called Volume Consolidation argument proposed by Cai et al. (2010).

The second one consists of the aforementioned studies on the link between customer density and inventories. In fact, the two alternative views proposed by these last – i.e. the Bargaining Power and OM views – can easily be adapted to model the relationship between the upper end of the supply chain and inventory holdings. Overall, this literature is in the early stages of development, with only a handful of studies that focus on the links between customer-base and inventory holdings, and virtually no evidence available for non-US firms. In fact, an important limitation to the development of this strand of research is that data on customer- and supply-bases are not readily available, and they must be manually collected from financial statements.²

This study contributes toward the above literature in a number of different aspects. Firstly, we investigate the link between the concentration of customers (CC) and inventory holdings for a large sample of 516 listed Chinese firms. Secondly, we extend our analysis to the upper end of the supply chain by shedding light on the link between the concentration of suppliers (SC) and levels of inventory. By doing so we are able to study the impact of the two types of densities on inventories within a unifying setting. Finally, we contribute to the literature on inventories and trade finance by investigating how payables and receivables affect inventory holdings. To examine the above relationships we hand-collect data on the volume of transactions with the 5 largest suppliers and customers for each firm. Since such data are not readily available from the usual academic sources, we retrieve them from the annual financial statements using a text-sourcing algorithm. To the best of our knowledge, this study is the first attempt to unravel the relationships among supply- and customer-bases, payables and receivables, and inventory holdings for the Chinese manufacturing sector.

Our empirical results suggest that firms facing more concentrated bases of suppliers hold significantly fewer absolute and relative inventories, whereas more concentrated customer-bases are associated with larger inventory holdings. This last relationship, however, is weaker and only occurs for relative inventories. These results provide strong support to the OM view that concentrated supply-bases are associated with lower inventory levels, whereas for the lower end of the supply chain we find evidence in favor of the Bargaining Power view. We then expand our

² For instance, Ak and Patatoukas (2016) study US manufacturing firms by hand-collecting data on customer densities, whereas Cachon and Olivares (2010) focus their analysis only on the four largest US car manufactures.

analysis by investigating three additional hypotheses that link with the literature on financial flows (account payables and receivables), financial performances (levels of bad debts) and inventory holdings. Our results suggest that these last are positively associated with both payables and receivables, whereas the level of bad debts negatively affects inventories. We also find that firms less financially constrained - i.e. firms with large access to account payables - are less sensitive to the level of bad debts than firms with limited access to payables.

The above results hold after controlling for a large array of firm-specific characteristics such as size, margins, effects of economies of scale, as well as industry fixed effects. More specifically, in line with the predictions of classical inventory models (like the Newsvendor and EOQ models), we find that absolute inventories are positively associated with higher margins and economies of scale, whereas we obtain weak evidence that relative inventory levels are negatively associated with the size of firms. We then supplement our analysis by carrying out the same hypothesis testing for six homogenous industrial segments – i.e. Machinery, Electronics, Chemicals, Pharmaceutical, Food & Beverages and Metal Manufacturing - finding that most of the hypotheses hold when tested on disaggregated data, although there are some significant differences across segments.

The paper is organized follows. Section 2 discusses the relevant literature. Section 3 specifies the research hypotheses. Section 4 describes the dataset, sets out the empirical models as well as the econometric methodologies. Section 5 discusses the empirical results. Finally, section 6 concludes.

2. Literature Review

What is the link between supplier density, customer density, and inventory holdings? Does the volume of payables and receivables affect the level of inventories? In this section, we discuss the strands of literature on which we build our empirical analysis. We start by discussing the large body of research in the Operations Management literature which investigates the determinants of inventory holdings. We then focus on the more recent studies on the link between trade finance – in the form of account payables and receivables – and inventories. Finally, we discuss the latest developments in the literature that explore the costs and benefits for firms arising from specific structures of the supply chain.

2.1 Financial/Non-financial Indicators and Inventory holdings

A large strand of studies investigates the relationship between firms' balance sheet indicators and inventory holdings of manufacturing firms. Focussing on non-financial indicators, Fisher and Ittner (1999), and Lieberman et al. (1999) show that, for firms in the car assembly sectors, the levels of inventory are affected by set-up and holding costs, production lead times, level of coordination with customers, as well as the variety of products offered. Cachon and Olivares (2010) focus on the four largest US automobile manufacturers and find that a higher number of dealerships makes the demand of final products more volatile, thus leading to larger inventory, whereas a wider range of variants in final products reduces demand volatility and inventory holdings. Rumyantsev and Netessine (2007) consider a larger cohort of US firms and show that demand uncertainty, longer lead times and higher gross margins are associated with higher levels of inventories, whereas larger firms retain relatively fewer inventories than smaller firms (see also Gaur et al. (2005)). The literature on the links between inventories and financial indicators is also rather vast. A number of studies documents a negative link between the profitability of firms and inventory levels which holds for different inventory specifications, industries and time periods (see, e.g., Deloof (2003), Capkun et al. (2009), and Kroes and Manikas (2014)). Eroglu and Hofer (2011) show that such link is concave, so that there is an optimal level of inventory leanness beyond which firms' profits deteriorate.

2.2 Trade Finance and Inventory Holdings

The more recent literature on inventory holdings and trade finance (in the form of payables and receivables) builds on the idea that cooperation in the upper- and lower-stream of the supply chain is a key tool for effective working capital management. For instance, Chikán (2009, 2011) argues that - given the growing complexity of inventory management - firms can efficiently manage inventories only as parts of their supply chain. This strand of research is substantial and focusses mainly on the lower end of the supply chain. Payables are normally treated as a financial resource, as payments to suppliers are postponed and the cash spared used by the company in operations, whereas receivables can be seen as an investment with the goals of boosting sales, beating the competition, and improve relationships with customers. Fabbri and Klapper (2009) study the influence of trade credit on supply chain participants and find that firms are more likely to extend trade loans to customers if they receive higher credit levels from suppliers. Focussing on the lower end of the supply chain, Mittal (2010) emphasizes that receivable policies could affect the profitability as well as the financial risks taken by firms. On the one hand, lenient credit

policies could help firms boost sales, but also increase the risk of bad debts. On the other hand, by adopting tighter credit policies, firms increase their liquidity and reduce the probability of bad debts, but the profitability could also decrease. Thus, striking a balance between profitability and risks of bad debt is the main goal of receivables management. Bougheas et al. (2009) argue that accounts receivables are important for the performance of inventory management, whereas the impact of payables is negligible. For a given aggregate demand, these authors show that firms can minimize the inventory costs by increasing receivables in order to sell more, and thus hold less inventory. Caglayan et al. (2012) investigate the empirical linkages between company's inventory decisions and their financial strength, showing that inventories decline as firms hold more liquid assets or extend more net trade credit to customers. A competing strand of studies has instead shown that inventory holding is positively correlated with both the volumes of trade credit and debit (see, among others, Fabbri and Klapper, 2009; Brigham and Houston, 2009; Mittal, 2010). As emphasized by Ferrando and Mulier (2013), what matters is not the separate role of payables or receivables, but the combination of the two working as a credit channel. All in all, both customer receivables and supplier payables are two crucial working capital measures.

2.3 Performance Indicators and Supply Chain Structure

The linkage between performance indicators and the supply chain structure is the object of a recent strand of research. For instance, Hofmann and Kotzab (2010) show that the lack of coordination with suppliers can result in higher costs of goods sold in comparison with competitors that establish more collaborative practices. Scholars have modeled the upper and lower end of the supply chain mainly through the concepts of supplier and customer density, i.e. on the idea that firms can rely on many rather than few suppliers, and they can sell to many rather than few customers. Cai et al (2010) emphasize how heightened competition to reduce costs, improve quality and increase efficiency can lead firms to reduce the number of suppliers in the attempt of achieving better coordination with these last (see also Fisher, 1997). Ogden (2006) finds that there are several critical success factors behind the practice of supply base reduction, such as effective information sharing, managing relationships, and choosing the right suppliers. Lorentz et al (2016) collect data on about 550 Finnish manufacturers and show that there is an optimal level of supply-base complexity – as measured by the geographic dispersion of suppliers - that minimizes supply chain risks. Demeeter and Golini (2014) is the only study that investigates the link between features of the upper-stream supply chain and inventory holdings. By gathering

survey data for as many as 500 firms internationally, the authors show that vertical integration, information sharing, and local sourcing are drivers of inventory configurations.

Also the linkage between performance indicators and the structure of the lower-stream supply chain remains largely unexplored. For instance, Patatoukas (2012) shows that more concentrated customer bases are positively associated with financial performances (see also Irvine et al, 2016). Dhaliwal et al (2016) document a positive link between customer concentration and firms' cost of capital, suggesting that more concentrated customer bases increase the risk of losing market shares, resulting in higher financing costs (see also Campello and Gao (2017)). On the contrary, Cen et al (2016) find that firms facing more concentrated customer bases benefit from an implicit certification provided by large customers that have incentives to monitor suppliers. Such certification, in turn, enables firms to reap lower interest rates on loans. Finally, Ak and Patatoukas (2016), and Cachon and Olivares (2010), are the only two studies that examine the link between customer bases and inventories. The former, using hand-collected data of about 600 US manufacturer firms, document a negative association between customers' concentration and inventory holdings, whereas the latter find similar results for the four largest US car manufacturers. However, as Ak and Patatoukas (2016) emphasize, the above link remains ex-ante unclear. On the one hand, large customers have bargaining power and can exercise pressure on their suppliers to maintain larger inventory holdings (Bargaining Power view).³ On the other hand, firms dealing with a limited number of customers can better implement supply-chain practices that mitigate demand uncertainty and reduces inventory holdings (OM view).⁴ As already emphasized, this last strand of research is still in the early stages of development, with a handful of studies based on US data for customer density only, and extremely limited evidence available on non-US firms.⁵

3. Research Hypotheses

³ For example, under the practice of consignment inventory, large customers compel the manufacturer to retain ownership of the items delivered until the customer re-sell these last.

⁴ An example of such practices is the so-called Collaborative Planning, Forecasting, and Replenishment (CPFR) where the manufacturer and its customers set up a common platform to exchange demand forecast updates, so that demand uncertainty can be mitigated (see, e.g., Ren et al. 2010, Terwiesch et al. 2005).

⁵ For instance, Patatoukas (2012), Ak and Patatoukas (2016), and Dhaliwal et al (2016) extract information on costumers from the Compustat Segment Files. However, this type of data is not available in electronic format for non-US firms, and as such they must be hand-collected from financial statements.

Inventory, unlike sales, is one of the few variables that are largely determined by internal decisions made by firms. As discussed above, a large body of literature has shown that firms hold inventories because of a mismatch between the timing of production and sale of products, because the demand for final products is characterised by seasonality and volatility and production capacity adapts to changes in demand with a time lag, and because there are economies of scale in handling inventories. Moreover, a parallel strand of research has highlighted the role of firm-level financial indicators - such as liquidity as well as volumes of receivables and payables - as determinants of inventories. Recently, a handful of scholars has put forward the idea that the structure of upper and lower end supply chain might have an impact on inventory holdings (see Ak and Patatoukas, 2016, and Cachon and Olivares, 2010). We now introduce eight testable hypotheses that draw on the above strands of literature.

The literature on volume consolidation argues that firms dealing with fewer suppliers have more scope for coordination and exchange of information (see, among others, Cai et al., 2010). If there existed a mutual exchange of information, then the trading partners could potentially coordinate delivery time and quantities to maximize their respective profits. In such a scenario, the optimal quantity to stock would be monotonically decreasing with the number of suppliers. We can postulate the occurrence of a similar link between supplier density and inventories by applying the OM view to the upper end of the supply chain. On the contrary, if the suppliers held more bargaining power, then firms might be forced to stock up more for precautionary reasons. Thus, we formulate the hypothesis that higher supplier density, implying better cooperation with suppliers, leads to lower inventory holdings:

HYPOTHESIS 1: Aggregate inventory level is negatively related to the density of suppliers.

Ak and Patatoukas (2016) argue that higher customer density, by enabling better cooperation, leads to lower inventory holdings. This is the so-called OM view applied to the lower end of the supply chain. Taken from a different angle, scholars have also put forward the idea that fragmenting demand across different products, variety of a given product, or different geographic locations leads to a more volatile demand and higher inventories (see, e.g., Cachon and Olivares, 2010). In line with these studies, we test the following hypothesis:

HYPOTHESIS 2: Aggregate inventory level is negatively related to the density of costumers.

The literature on the relationship among inventories, account payables and receivables has provided two competing views. On the one hand, Bougheas *et al.* (2009) found that inventory holdings decline as firms extend more credit to customers (see also Caglayan *et al.*, 2012). This result can be explained by the behavior of firms decreasing the stock of inventories when they sell on credit, and increasing inventories when they buy on credit from suppliers. On the other hand, Fabbri and Klapper (2009) have shown that firms' inventory investment is positively correlated with the volume of both trade credit and trade debt (see also Brigham and Houston, 2009; Mittal, 2010). This strand of the studies highlights the importance for a firm of receiving trade credit from its suppliers in order to finance the production and to extend trade credit, so that goods can be sold to financially constrained customers (see Ferrando and Mulier, 2013). Thus, we formulate the following hypothesis:

HYPOTHESIS 3: Aggregate inventory level is positively associated with both trade credit and trade payments.

A substantial strand of literature has investigated the relationship between inventories and financial flows (see, among others, Gaur and Bhattacharya, 2011; Kroes and Manikas 2014). Rather than focussing on these last, we tackle the issue from a different angle and we look into the link between stocks of bad debts held by firms and inventory holdings. We argue that firms might be negatively affected by trade debtors going into financial distress and hence delaying or defaulting on payments. In fact, firms with large accumulated bad debts might suffer from denied access to trade credit as they become more financially vulnerable, and the more severe are such financial constraints the higher will be the sensitivity of inventories to bad debts. By taking the volume of payables as indicator of the level of financial constraints of firms, we investigate the link between bad debts and inventories by formulating the following two hypotheses:

HYPOTHESIS 4: Aggregate inventory levels are negatively related with the level of bad debts.

HYPOTHESIS 5: The sensitivity of aggregate inventory levels to changes in bad debts decreases with the volume of payables.

We then test for three additional hypotheses extensively explored for developed economies, yet relatively unexplored for emerging economies such as China (see, e.g., Rumyantsev and Netessine, 2007). The first hypothesis focusses on absolute inventory and mean

demand. Its theoretical foundation can be found in the EOQ model which derives a square-root relationship between inventories and demand. Such relationship holds even when the demand is stochastic (Johnson and Montgomery, 1974). If, however, inventory ordering costs are minimal like in the Newsvendor or the Order-up-to model, the relationship between inventory and demand becomes linear (Cachon and Terwiesch, 2013). By aggregating over products with or without ordering costs, we should observe a concave relationship between expected demand and average inventory levels. Hence:

HYPOTHESIS 6: Aggregate inventory level is positively associated with aggregate mean demand through a concave function.

This hypothesis can be extended by the consideration that there exist economies of scale in inventory management because manufacturing and distribution require high fixed costs. The EOQ model considers fixed inventory ordering costs and shows that inventories increase more slowly than demand. Consequently, a firm facing larger mean demand, i.e. a larger firm, should exhibit economies of scale in inventory management. This can also be explained by risk pooling since a larger firm can afford to hold relatively fewer inventories because it pools together demand from various products, locations, stores or warehouses (see Eppen, 1979). Thus, we formulate the following hypothesis:

HYPOTHESIS 7: Aggregate relative inventory level (i.e. the ratio of inventory to sales) is negatively associated with the size of firms.

A typical trade-off studied by classical stochastic inventory models is the one between underage costs and overage costs - i.e. the costs of having too little or too much inventory. Larger underage costs lead to higher inventories in these models (see Silver *et al.* 1998). The underage cost is typically assumed to be the product's gross margin. This seems reasonable in the case of lost sales. But even in the case of full back ordering, Cachon and Terwiesch (2013) show that the penalty for stocking out is likely to be correlated with the product's margin. Assuming that higher margins correspond to higher costs of underage, we formulate the following hypothesis:

HYPOTHESIS 8: Aggregate inventory level is positively associated with aggregate product margins.

4. Data

We gather a representative sample of 516 Chinese listed manufacturing companies. Such companies are required to provide operational and financial information following the standard accounting principles defined by the China Securities Regulatory Commission. We access corporate reports for the year 2012 via the Shanghai and Shenzhen Stocks Exchange website (www.cninfo.com.cn). We collect data for firms listed on the A-share markets, whereas we exclude firms listed on the B- and H-share segments.⁶ We exclude the service, construction, and transportation industries and focus only on manufacturing firms, which are traditionally the most inventory-rich segments of the economy. Within the manufacturing industry we focus on six segments: Machinery, Electronics, Chemicals, Pharmaceutical, Food & Beverages and Metal Manufacturing.⁷ From these segments, we excluded companies that have merged or been acquired, as well as companies that had zero sales and inventory. This filtering process ensures that the final sample contains only companies that have been actively operating in inventory-related business activities. For each firm, we hand-collect data on the volume of transactions with the 5 largest suppliers and customers.⁸ Since such data are not readily available from any data provider, we retrieve them from the annual financial statements by using a text-sourcing algorithm, and manually check that the identified matches correspond to the data we actually need. Such dataset is then matched with an array of balance sheet indicators containing inventories, assets, sales, payables, receivables, as well as other firm-level indicators.

We denote absolute inventory for firm i by Inv_i , which is expressed in monetary terms at the end of 2012 as reported in the annual financial statements. Relative inventory is measured by the ratio of inventory to cost of goods sold ($CoGS_i$), and it is denoted by $RelInv_i = Inv_i/CoGS_i$.

⁶ A-shares are traded on the Shanghai and Shenzhen stock exchanges whereas B-shares are owned by foreign investors. H-shares refer to shares of companies incorporated in mainland China that are traded on the Hong-Kong Stock Exchange. Both B- and H-shares must comply with different account standards, which make the corporate reports not comparable with those of companies listed on the A-share market.

⁷ Our dataset includes also a small number of companies which operate in segments different from the six reported above. More specifically, there are 14 companies in the petroleum, coking and nuclear fuel processing, 10 in the rubber and plastic products, 9 in the paper products, 6 in the furniture manufacturing and 3 in other manufacturing.

⁸ The disclosure of the five major suppliers and customers is mandatory according to the Standards for the Contents and Formats of Information Disclosure by Companies offering Securities to the Public No. 2 (Chapter II, art. 21).

The cost of goods sold represents the cost of products sold over the financial year, and it includes all costs of purchase and conversion, and other costs allocated to goods sold.

Following Banerjee et al. (2008), we adopt a measure of customer concentration that consists of the ratio between the volume of sales obtained from the 5 largest customers and the total volume of sales (see also Campello and Gao, 2017).⁹ We then construct an equivalent measure for the supply-base concentration. The two measures are therefore specified as follows:

$$CC_i = \frac{\sum_{j=1}^5 Sales_{ij}}{Sales_i} \quad (1)$$

$$SC_i = \frac{\sum_{j=1}^5 Pur_{ij}}{Pur_i} \quad (2)$$

where $Sales_{ij}$ and Pur_{ij} represent the firm i 's sales to the major customer j , and the purchasing from the major supplier j , and $Sales_i$ and Pur_i represent the total sales and purchasing. The two ratios range from 0 to 1 - where lower (higher) values correspond to less (more) concentrated bases - and capture the relative importance of major customers and suppliers in the firm's annual revenues and costs.

Account Receivables ($AcRec_i$) and Account Payables ($AcPay_i$) are respectively the volume of trade credit that firms extend to customers and the volume of trade borrowing that firms obtain from suppliers. Also these two variables are expressed in monetary terms at the end of 2012, as reported in the annual financial statements.

Bad debt reserves represent the amount of cash set aside for possible reductions in the book value of account receivables. High levels of bad debt reserves indicate poor quality of account receivables, and it negatively affects the firm's working capital position. The Bad Debt Ratio is calculated as $BadDebt_i = Accumulated\ Bad\ debt\ Reserve_i / Book\ Value\ Account\ Receivables_i$.

Fixed Assets ($FAssets_i$) refers to all non-current assets, and includes tangible, intangible and other fixed assets. Fixed assets are used as proxy for the size of companies, and the relative figures can be extracted from the annual statement.

⁹ Both these studies use a measure of concentration based on the sum of the percentage sales generating from a set of major customers defined as those with a share of total sales of at least 10%.

Gross Margin Ratio (GMG_i) represents the generated margin between sales and the costs of goods sold, which provides the most fundamental and important source of profits. This ratio measures how well the firm manages the selling of products and reduces costs allocated to products sold, and it is calculated as $GMG_i = (SALES_i - CoGS_i)/SALES_i$.

Table 1 reports some preliminary statistics for the above industrial segments. Figures suggest that companies in the sample hold on average ¥1,954 million of inventory and produce on average \$8,865 million of annual sales for the year 2012. Companies vary in size across segments, with those in the machinery and metal manufacturing segments showing larger size. Also relative inventory levels vary by segment: electronics and pharmaceutical segments have the largest relative inventory levels (0.724 and 0.622 respectively), whereas the food & beverages segment is the smallest with a relative inventory ratio of 0.149. Differences in terms of supplier and customer densities across segments are less evident, with the only exception being the pharmaceutical sector where both are significantly below the average values. Figures 1 and 2 plot the kernel probability distributions for both the absolute and relative inventory ratios. Both the diagrams suggest that the above variables for the six segments are characterised by different empirical distributions. We carry out statistical tests for equality in mean, median, variance and distributions. The above statistics soundly reject the null of equality in mean, median, variance and distributions at standard significance levels, suggesting that both absolute inventories and relative inventory ratios for the six segments are statistically different.¹⁰

TABLES 1 AND 2 HERE

FIGURES 1 AND 2 HERE

5. Methodology

In line with previous studies, we use two multiplicative regression models to capture the dynamics of inventories and to test the hypotheses previously set out. Similar specifications have

¹⁰ More specifically, this analysis is conducted by carrying out 2-sample t-statistics for the null of equality in mean, Mann-Whitney Test for the null of equality in median, Levene test for the null of equality in variance, and Barnett and Eisen (1982) and Kolmogorov-Smirnov tests for the null of equality in distribution. Results are not reported to save space but are available from the authors upon request.

been extensively used in previous studies such as Gaur et al. (2005), and Rumyantsev and Netessine (2007). The first model considers absolute inventory levels as dependent variable whereas the second focuses on relative inventory levels. The specification of the model for absolute inventory levels is:

$$\begin{aligned} \log(\text{Inv}_i) = & \alpha_1 + \alpha_2 \log(\text{CoGS}_i) + \alpha_3 \log(\text{GMG}_i) + \alpha_4 \log(\text{SC}_i) + \alpha_5 \log(\text{CC}_i) + \\ & + \alpha_6 \log(\text{AcPay}_i) + \alpha_7 \log(\text{AcRec}_i) + \alpha_8 \log(\text{BadDebt}_i) + \\ & + \alpha_9 \log(\text{BadDebt}_i) \times \log(\text{AcPay}_i) + \varepsilon_i \end{aligned} \quad (3)$$

The model for relative inventory levels is similarly defined with the only exception being that we control for firm size by excluding *CoGS* and by including *FAssets* to avoid any possible problem of collinearity:

$$\begin{aligned} \log(\text{Inv}_i / \text{CoGS}_i) = & \beta_1 + \beta_2 \log(\text{FAssets}_i) + \beta_3 \log(\text{GMG}_i) + \beta_4 \log(\text{SC}_i) + \beta_5 \log(\text{CC}_i) + \\ & + \beta_6 \log(\text{AcPay}_i) + \beta_7 \log(\text{AcRec}_i) + \beta_8 \log(\text{BadDebt}_i) + \\ & + \beta_9 \log(\text{BadDebt}_i) \times \log(\text{AcPay}_i) + \varepsilon_i \end{aligned} \quad (4)$$

where for both the specifications i spans from 1 to 516. We use log-log models because it helps deal with heteroscedasticity and with the distribution of inventory data that is not normal but skewed to the right. Moreover, such models have been shown to be the most appropriate specifications in previous studies.¹¹ Given that we find significant differences in inventory data across different industries, we control for this by supplementing both Eqs. (3) and (4) with industry dummies in the intercept.

Table 2 reports some preliminary statistics for all the above variables. The lower panel sets out the correlation indices together with the relative eigenvalues. Figures suggest that the above variables are actually correlated. The first seven eigenvalues account for approximately 98 percent of the total, which implies that the variation in the 8th independent variables can be represented in 7 dimensions, suggesting that collinearity in the explanatory variables could be an issue. More specifically, the presence of collinearity is generated by the high correlation between the variables $\log(\text{BadDebt}_i)$ and $\log(\text{BadDebt}_i) \times \log(\text{AcPay}_i)$. Collinearity, by inflating the standard errors of parameter estimates, might reduce their statistical and economic significance. As such,

¹¹ Moreover, by using the log-log specification the slope coefficients of both Eqs.(3) and (4) can be interpreted as elasticities.

in the next section we will make use of econometric methods that correct for such undesirable effects.

We initially carry out empirical estimations of Eqs. (3) and (4) by using standard heteroscedasticity consistent (Eicher-White) OLS estimators. While OLS provides consistent and asymptotically normal estimates under a broad range of assumptions, it is well known that the same estimates are sensitive to outliers or fat-tailed distributions of the disturbance term (see Greene, 2003, p. 448). When there are reasons to believe that the above conditions occur, it makes sense to use alternative estimators that are less sensitive than standard OLS to tail values. One such estimator is the Least Absolute Deviations (LAD). LAD estimators are consistent and asymptotically normal under broader assumptions than those required for OLS. Their drawback relative to OLS estimators is that they will be less efficient if disturbance terms are well-behaved (see, e.g., Koenker and Bassett, 1978).

To account for the undesirable effects of collinearity, we carry out empirical estimates of Eqs. (3) and (4) by using both Mixed Regression (MR) and Ridge Regression (RR) methods. The MR technique combines sample data with prior linear stochastic constraints on the parameters of the model. Its principal advantages over standard OLS are that, under appropriate circumstances, MR estimators are superior in mean squared error and can mitigate the effects of collinearity (see Belsey et al, 1980). We feed MR estimators with priors taken from LAD estimates. In contrast to standard OLS estimators, RR methods add a constant k to each diagonal element of the cross-product matrix of the explanatory variables before it is inverted (see Hoerl *et al.*, 1975). While this introduces bias into the coefficient estimates, the inflated variances are simultaneously reduced. Extensive Monte Carlo simulation experiments support the use of RR when the independent variables are highly correlated, and several successful applications of ridge analysis have been reported.

We carry out OLS, LAD, MR and RR estimates of Eqs. (3) and (4) for the pooled dataset. We then re-estimate the same relationships when the dataset is partitioned into the 6 industrial segments previously set out. For this last exercise, we report only OLS and LAD empirical results to save space.¹² To check the robustness of our results we carry out Breusch-Pagan, Harvey and

¹² Empirical results for MR and RR are very similar to those based on OLS and LAD regressions, and are available from the authors upon request.

White tests for the null of homoscedastic versus the alternative of heteroscedasticity of different forms. We then compute RESET tests for the null of correct functional form, as well as MacKinnon *et al.* (1983) statistics to test whether standard additional or log-log specifications are the most appropriate functional form.¹³ Finally, we re-estimate the two equations in slightly different specifications, on a reduced dataset, and with a set of explanatory variables slightly modified by using alternative methods such as cluster-robust regressions.

6. Results

Empirical estimates of Eqs. (3) and (4) are reported in Table 3. In order to isolate the empirical results from the effects of possible outliers, we estimate the two specifications on a restricted dataset of 511 firms constructed by dropping observations for which the standardized residuals, obtained from a previous OLS regression estimated on the full sample, are in absolute value greater than 3.5. Both specifications explain a sizeable share of absolute and relative inventory total variability, as the adjusted R-squared statistics are respectively 0.82 and 0.33. Similar goodness of fit is obtained for LAD, MR and RR estimates, as well as for the segment-specific regressions reported in Tables 4 and 5.¹⁴

When we focus on the role played by the upper- and lower-stream of the supply chain, we find strong evidence in support of Hypothesis 1 - as higher supplier density has negative and statistically significant impact at the 1% level on both absolute and relative inventories. For instance, an increase of 1% in supplier density is associated with a decrease in absolute and relative inventories of 0.12 and 0.18% respectively. Thus, in line with the OM view, we find that higher supplier concentration - enabling better co-ordination between firms and suppliers - leads to lower inventory levels. From Tables 4 and 5 we can see that such negative and significant relationship is particularly strong for the Electronics and Chemicals segments, whereas the same link weakens for the remaining industries.

Focusing now on the customer density, we find strong evidence that higher concentration is associated with larger relative inventory. The same link becomes somehow weaker for absolute

¹³ The MacKinnon *et al.* (1983) test is constructed under the null that the log-log is the correct specification.

¹⁴ We carry out empirical estimates of Eqs (3) and (4) by using LAD estimators which are consistent and asymptotically normal under broader assumptions than are required for OLS. This feature of LAD estimators is important for the analysis of the segments where data availability, at least for some specific industries, is limited to about 50 companies.

inventories. For instance, our results suggest that a 1% increase in customer concentration is associated with a 0.08% and a 0.18% increase in absolute and relative inventories respectively. We also find that a similar link holds for the Chemicals, Metal Manufacturing, Electronics and Food & Beverages segments, where higher customer concentrations are associated with an increase in both absolute and relative inventory. All in all, the above results do not provide support to Hypothesis 2 that higher customer density would lead to lower inventory levels, and are at odds with two recent studies which document a negative link between customer concentration and inventory holdings for US firms (see Ak and Patatoukas (2016), and Cachon and Olivares (2010)).¹⁵ We posit that Chinese firms might act in a precautionary way to minimize the likelihood of stock-outs. The stock out-avoidance motive is fostered by the argument that the frictions involved in international transactions are more severe than those for domestic transactions, leading therefore firms which engage in international trade to hold larger inventories (Alessandria et al. (2011)). We can only observe that given the predominant role of Chinese firms in international trade, the latter explanation could fit well our results, meaning that firms that rely on fewer customers might fear over-exposure to the risk of stock-outs that would lose them precious customers. Such risk becomes more severe for firms engaging in international trade, as their deliveries tend to be lumpier due to the higher costs of serving foreign markets.

Our results provide strong support for Hypothesis 3 that account receivables and payables are positively associated with inventory holdings. This finding is particularly strong for absolute inventories, as both are significant at the 1% level, and it is in line with the strand of studies documenting that inventory holdings are positively correlated with both the volume of trade credit and trade debit (see Fabbri and Klapper, 2009; Brigham and Houston, 2009; Mittal, 2010; Ferrando and Mulier, 2013). The same hypothesis holds only partially for relative inventories which are strongly associated with receivables only. For instance, a 1% increase in account receivables is, on average, associated with increases which range from 0.08 to 0.09% for absolute, and from 0.09 to 0.13% for relative inventories. When we run segment-specific regressions, we find that account payables and receivables are positively associated with inventory holdings in the Machinery, Pharmaceutical, Electronics, Food & Beverages segments, and the Machinery, Metal Manufacturing and Food & Beverage industries respectively. With regard to the Chemicals

¹⁵ Similarly, we do not find any evidence in support of the demand fragmentation hypothesis.

and Pharmaceutical segments, we obtain instead evidence that account receivables are negatively associated with inventory holdings. This last result is consistent with the strand of literature showing that inventory holdings decline as firms extend more credit to customers (see, e.g., Bougheas et al., 2009).

We then shed light on the relationship between inventories and bad debts finding strong support for Hypothesis 4, as absolute and relative inventory holdings are negatively associated with levels of bad debts. For instance, a 1% increase in the bad debt ratio is associated with a decrease in absolute and relative inventory holdings of 0.68 and 0.50% respectively. Similarly, we find support for Hypothesis 5 that the sensitivity of absolute and relative inventories to changes in bad debt ratio decreases with the volume of payables held by firms. For instance, our results suggest that a 1% increase in account payables from their average value decreases in absolute terms the elasticity of inventories to bad debts from -0.018 to -0.012. We find relationships of the same sign and similar magnitude for relative inventories. When we run segment-specific regressions we find strong support for both these hypotheses in the Machinery and Food & Beverage segments, whereas the tested relationships are not significant for the Pharmaceutical, Metal Manufacturing, and Electronics segments.

We then focus on Hypotheses 6, 7 and 8, a set of predictions which has been only partially explored for the Chinese economy. We obtain strong support for the hypothesis that inventory level is positively associated with mean demand through a concave function. In fact, the elasticity of absolute inventory to *CoGS* takes values between 0.54 and 0.63, and inventories are therefore a sub-linear function of sales - implying a concave relationship with presence of economies of scale. For instance, we find that a 1% increase in *CoGS* is, on average, associated with an increase in absolute inventories within the range 0.54-0.63 percent. The same hypothesis holds across all segments with the elasticity coefficients spanning from 0.98 for Metal Manufacturing to 0.31 for Machinery. On the contrary, we find weak support for Hypothesis 7 that relative inventory level is negatively associated with the size of firms. In fact, for the entire sample relative inventories are negatively associated to fixed assets, with the estimated coefficient being not statistically significant. Similar results hold also for the different segments under scrutiny. Finally, our results are consistent with Hypothesis 8 as both absolute and relative inventory are positively related with product margins, with elasticity coefficients statistically significant at the 1% level. Moreover,

such relationship holds also when tested across all industries with the exception of the Machinery segment.

The bottom panels of Tables from 3 to 5 report a battery of diagnostic tests to check whether Eqs. (3) and (4) are correctly specified. When the two models are estimated on pooled data, F-tests soundly reject the null that all the explanatory variables are jointly not statistically significant. While the Breusch-Pagan and Harvey tests suggest the presence of moderate heteroscedasticity, the White test soundly rejects the null of homoscedasticity for both the specifications. The RESET tests consistently fail to reject the null of no specification errors at the 10 and 1% level for the two specifications. The MWD tests fail to reject the null that the log-log specification of Eqs. (3) and (4) are preferable to standard additive models at the 1% level. We obtain a similar pattern of results when we run the segment-specific regressions. All in all, the above statistics suggest that both Eqs. (3) and (4) are reasonably well specified.

We then check for the robustness of our empirical results by carrying out the following empirical exercises. Firstly, as fixed asset encompasses intangible assets that might not be necessarily associated with the size of firms, we re-estimate Eq. (4) by replacing these last with total sales. Secondly, as our dataset can be partitioned into different industrial segments, the level and type of heteroscedasticity might be dependent on such industries. We therefore re-estimate Eqs. (3) and (4) by using cluster-robust OLS methods (Cameron and Miller, 2015). Thirdly, we re-estimate the two specifications on a restricted dataset constructed by dropping observations for which the standardised regression residuals in absolute value are greater than 2.5. Finally, we carry out MR estimates by using as priors a set of results previously obtained by Rummyantsev and Netessine (2007). Taken together, the empirical results obtained suggest that the sign, magnitude and statistical significance of the estimated parameters are consistent with the estimates set out in Tables 3, 4 and 5.

TABLES 3, 4 AND 5 HERE

7. Conclusions

This study sheds light on the linkages between specific features of the supply chain and inventory holdings for a large dataset of Chinese manufacturing companies. We begin our study by exploring the linkage between supplier and customer density, and inventory holdings. We then extend the analysis to investigate the role of financial indicators – such as account payables and receivables - on inventory management. We do so by gauging the marginal impact of the above factors within one setting. These are the novel contributions of this study to the emerging literature on inventory management and supply chain structure.

In line with the OM view, we find that more concentrated supply-bases - enabling a better co-ordination between firms and suppliers – are associated with lower inventory levels. When we look at the individual industries, such relationship is particularly strong for the Chemicals and Electronics segments. We then focus on the lower end of the supply chain by looking into the relationship between inventory levels and customer density. Our results suggest a positive link between the concentration of customers and inventory holdings, so that we obtain evidence consistent with the so-called Bargaining Power view. Such relationship is particularly strong for relative inventories across the full sample, as well as for absolute inventories in the Chemicals, Metal Manufacturing and Food & Beverages segments. This last result is at odds with some previous findings that document a negative link between customer concentration and inventory holdings for US firms. We make sense of this result by noting that Chinese firms operate in international markets with a large variety of products and high substitutability, with customers prone to switch supplier in case of stock-out. In this scenario, firms might become highly sensitive to the risk of losing customers and therefore willing to stock up higher inventories for precautionary reasons.¹⁶ The importance of stocking up inventories strengthen when firms sell to fewer international customers.

When we extend our analysis to the role of financial factors, we document how payables and receivables are positively associated with inventory holdings, lending support to the idea that both credit received and extended are positively linked - so that firms can finance the production

¹⁶ A similar argument was proposed by Netessine *et al.* (2005).

and sustain sales. Only for the Chemicals and Pharmaceutical segments we find evidence in line with the conventional view that inventory holdings decline as firms extend more trade credit.

We then show that both absolute and relative inventory holdings are negatively associated with the level of bad debts, suggesting that firms that are more financially constrained - i.e. those more exposed to potential losses generated by the default of customers - have to reduce their levels of inventories. The use of bad debts is novel in the inventory management literature and our findings supplement the empirical evidence already reported that other financial flows, such as various types of margins and cash flows, are associated with inventory holdings. However, we also find that as the volume of payables increases, the sensitivity of absolute and relative inventories to changes in the bad debt ratio decreases. This is because the amount of payables acts in the opposite way to bad debts - i.e. the higher the trade credit received and the less financially constrained is likely to be the firm - making the impact of bad debts less severe. When looking at the segment analysis, the relationships involving bad debts hold for the Machinery, Chemicals and Food & Beverages segments.

Finally, we test for a number of hypotheses on inventory holdings already largely investigated for developed economies, but only partially explored on Chinese data. In line with the existing literature, we find that the elasticity of absolute inventory to demand is lower than one, suggesting the presence of economies of scale in inventory management. Such elasticity varies across segments, with Metal manufacturing showing nearly constant returns to scale and Machinery displaying the strongest economies of scale. We also find that higher gross margins are associated with larger inventories.

These results offer several implications for managers. Firstly, the structure of the upper- and lower-stream supply chain has sizeable impact on inventory holdings, as managers can create value by increasing the concentration of suppliers and decreasing that of customers. However, the positive impact arising from the management of supply- and customer-bases varies across the different segments under scrutiny. Secondly, the finding that higher levels of bad credits have a negative effect on inventories suggests that managers should extend receivables to customers with particular care. The trade-off between the issuance of receivables and the likelihood of facing non-performing loans requires skilful judgment, constant monitoring, and gathering of information on the lower stream of the supply chain. Finally, the finding that firms less financially

constrained - i.e. firms with full access to payables - are less sensitive to the level of bad debts than firms more financially constrained, provides support to the view that managers should take particular care in removing or mitigating the financial constraints faced by firms. More specifically, firms with full access to trade payments can benefit from a more flexible management of inventories, something that managers should take into consideration when shaping the upstream supply chain. Taken together with the previous point, this highlights a dependency that requires firms to integrate activities across the whole supply chain.

We conclude by briefly discussing the main limitations of our study and some avenues for future research. Unfortunately, the lack of available data on supplier and customer density has limited our study to a cross-section analysis. While the use of cross-section data has provided us with a neat picture of the link between the supply chain structure and inventory holdings, such data prevent us from shedding light on their time dynamics. Another limitation is that our analysis neglects a number of important firms' features - such as the type of business (B2B or B2C) and production (make-to-order vs make-to-stock), the position within the supply chain and the degree of internationalization in the market of sourcing and distribution - that could be important determinants of inventory holdings. While this is a promising development, the gathering of such data is compounded by the fact that they are not readably available from financial statements. We leave the above tasks in our agenda for future research.

Table 1 - Mean, median and standard deviation of Inventories, Cost of goods sold (CoGS), Inventories/CoGS, Density of suppliers (SC) and Density of customers (CC) for six homogeneous segments.

Segment	Obs	Mean Inventory, ¥M (median, std dev)	Mean COGS, ¥M (median, std dev)	Mean Inv/COGS (median, std dev)	Mean SC (median, std dev)	Mean CC (median, std dev)
Machinery	122	2,591 (503; 5,701)	10,09 (1,911; 37,73)	0.389 (0.321; 0.326)	0.274 (0.231; 0.163)	0.337 (0.270; 0.222)
Electronics	95	1,518 (512; 3,015)	7,200 (1,843; 15,03)	0.724 (0.264; 3.987)	0.354 (0.304; 0.197)	0.350 (0.290; 0.230)
Chemicals	86	715 (404; 828)	3,793 (2,393; 4,616)	0.275 (0.170; 6.895)	0.421 (0.383; 0.207)	0.250 (0.200; 0.175)
Pharmaceuticals	48	631 (397; 806)	1,916 (1,068; 2,240)	0.622 (0.333; 0.964)	0.232 (0.186; 0.137)	0.190 (0.155; 0.117)
Food & Beverage	40	1,256 (681; 1,535)	5,493 (1,345; 12,43)	0.149 (0.398; 0.603)	0.292 (0.275; 0.179)	0.211 (0.161; 0.185)
Metal Manufacturing	52	5,060 (1,790; 6,369)	26,424 (9,861; 36,90)	0.258 (0.169; 0.232)	0.400 (0.364; 0.223)	0.280 (0.238; 0.190)
Total	443	1,954 (641; 3,351)	8,865 (2,780; 20,21)	0.427 (0.270; 2.469)	0.332 (0.291; 0.185)	0.289 (0.235; 0.196)

Notes: Inventories (Inv) and Cost of goods sold (CoGS) expressed in millions of Chinese Yuan at the end of 2012.

Supplier (SC) and Costumer Concentration (CC) computed according to Eqs. (1) and (2).

Table 2 - Descriptive statistics for dependent and explanatory variables of Eqs. (3) and (4).

	log(Invt)	log(Invt/CoGS)	log(CoGS)	log(Fasset)	log(GMG)	log(SC)	log(CC)	log(AcPay)	log(AcRec)	log(BadDebt)	log(BadDebt) x log(AcPay)
Mean	20.21	-1.319	21.53	21.33	0.260	-1.268	-1.499	19.66	19.56	-2.447	-48.80
Std Dev	1.452	0.861	1.517	1.415	0.296	0.649	0.752	1.580	1.612	1.161	23.91
Min	16.12	-4.215	15.89	16.82	-0.221	-4.034	-4.063	14.67	13.10	-9.784	-89.65
Max	24.20	3.666	26.72	25.58	3.801	0.000	-0.005	24.59	23.94	-0.006	-0.107
Obs	516	516	516	516	516	516	516	516	516	516	516
log(Invt)	1.000										
log(Invt/CoGS)	0.213	1.000									
log(CoGS)	0.834	-0.362	1.000								
log(Fasset)	0.768	-0.143	0.813	1.000							
log(GMG)	-0.045	0.416	-0.278	-0.067	1.000						
log(SC)	-0.323	-0.141	-0.228	-0.248	-0.143	1.000					
log(CC)	-0.300	0.059	-0.320	-0.368	-0.111	0.368	1.000				
log(AcPay)	0.828	-0.089	0.841	0.782	-0.108	-0.343	-0.265	1.000			
log(AcRec)	0.607	0.079	0.535	0.453	-0.029	-0.295	-0.128	0.698	1.000		
log(BD)	-0.240	0.074	-0.271	-0.173	0.018	0.041	-0.069	-0.243	-0.269	1.000	
log(BadDebt) x log(AcPay)	-0.354	0.084	-0.385	-0.286	0.029	0.094	-0.028	-0.384	-0.364	0.985	1.000
Eigenvalues ¹			3.177	-	1.684	1.228	0.779	0.637	0.379	0.111	0.004
Eigenvalues ¹			-	3.056	1.739	1.144	0.774	0.659	0.441	0.144	0.003

Notes: Inventories (Invt), Cost of goods sold (CoGS), Fixed Assets (Fasset), Account Payables (AcPay) and Receivables (AcRec) expressed in millions of Chinese Yuan at the end of 2012. Gross Margin Ratio (GMG) computed using the formula $GMG = (SALES - CoGS) / SALES$. BadDebt computed as ratio between reserves for bad debt and book value of Account Receivables. Supplier (SC) and Costumer Concentration (CC) computed according to Eqs. (1) and (2).

¹ Eigenvalues obtained for the matrix XX' where X is the design matrix of Eqs. (3) and (4) with dimension (516 x 8).

Table 3 - Ordinary Least Squares (OLS), Least Absolute Deviations (LAD), Mixed (MIXED) and Ridge (RIDGE) regression estimates of Eqs. (3) and (4).

Explanatory Variables	Eq.(3)				Eq.(4)			
	OLS	LAD	MIXED	RIDGE	OLS	LAD	MIXED	RIDGE
Const	0.398 (0.845)	-0.974 (0.897)	0.580 (0.519)	0.421 (0.697)	-3.032*** (0.929)	-2.936*** (0.992)	-2.561*** (0.478)	-2.139*** (0.729)
log(CoGS)	0.544*** (0.044)	0.626*** (0.043)	0.596*** (0.055)	0.607*** (0.052)	- (-)	- (-)	- (-)	- (-)
log(Fasset)	- (-)	- (-)	- (-)	- (-)	-0.017 (0.039)	-0.019 (0.040)	-0.036 (0.035)	-0.038 (0.037)
log(GMG)	0.719*** (0.106)	0.618*** (0.116)	0.752*** (0.156)	0.741*** (0.153)	1.115*** (0.109)	1.190*** (0.115)	1.139*** (0.142)	1.139*** (0.146)
log(SC)	-0.093* (0.051)	-0.116** (0.055)	-0.133*** (0.060)	-0.146** (0.058)	-0.142*** (0.055)	-0.175*** (0.058)	-0.220*** (0.060)	-0.218*** (0.061)
log(CC)	0.028 (0.045)	0.082* (0.047)	0.044 (0.051)	0.024 (0.049)	0.175*** (0.048)	0.184*** (0.051)	0.138*** (0.050)	0.136*** (0.051)
log(AcPay)	0.325*** (0.054)	0.291*** (0.057)	0.251*** (0.068)	0.241*** (0.063)	0.020 (0.054)	-0.037 (0.057)	-0.015 (0.052)	-0.034 (0.050)
log(AcRec)	0.077*** (0.026)	0.091*** (0.027)	0.082*** (0.032)	0.084*** (0.031)	0.087*** (0.029)	0.135*** (0.030)	0.106*** (0.032)	0.106*** (0.033)
log(BadDebt)	-0.196 (0.291)	-0.667** (0.309)	-0.349 (0.239)	-0.195 (0.199)	-0.507* (0.313)	-0.329 (0.335)	-0.392** (0.202)	-0.206 (0.166)
log(BadDebt) × log(AcPay)	0.011 (0.015)	0.035*** (0.016)	0.018 (0.012)	0.010 (0.010)	0.029* (0.016)	0.021 (0.017)	0.023*** (0.010)	0.013* (0.008)
F-test ¹	256.1 (0.000)	224.3 (0.000)	319.0 (0.000)	230.7 (0.000)	18.27 (0.000)	21.51 (0.000)	17.64 (0.000)	16.31 (0.000)
RESET ²	2.240 (0.083)	2.262 (0.106)	1.395 (0.248)	1.925 (0.147)	2.787 (0.041)	3.405 (0.034)	3.041 (0.029)	3.903 (0.021)
B-P ³	46.29 (0.000)	35.38 (0.008)	76.23 (0.000)	32.33 (0.029)	36.27 (0.004)	21.27 (0.266)	20.13 (0.325)	20.54 (0.197)
MWD ⁴	0.001 (0.039)	-0.001 (0.375)	0.000 (0.005)	0.001 (0.001)	0.024 (0.734)	0.171 (0.013)	0.163 (0.029)	0.161 (0.020)
HARV ⁵	228 (0.000)	19.51 (0.361)	35.78 (0.007)	264 (0.000)	294 (0.000)	17.88 (0.463)	15.20 (0.648)	296 (0.000)
WHITE ⁶	139.7 (0.000)	64.48 (0.002)	115.1 (0.000)	73.72 (0.008)	117.8 (0.000)	64.43 (0.002)	62.26 (0.004)	67.79 (0.016)
R ²	0.819	0.781	0.754	0.793	0.325	0.224	0.281	0.254
N	511	511	511	511	511	511	511	511

Notes:

OLS, LAD, Mixed and Ridge regression estimates of Eqs.(3) and (4) with dependent variables $\ln(\text{Inv}_i)$ and $\ln(\text{Inv}_i/\text{CoGS}_i)$. MR estimates obtained by using priors taken from LAD estimates. * (**) [***] significant at 10, (5) and [1] percent level.

¹ F-test for the null that all the regressors are jointly not statistically significant. P-value in parentheses.

² RESET test for the null of no specification errors. P-values in parentheses.

³ Breusch-Pagan test for the null of homoscedasticity. P-values in parentheses.

⁴ MacKinnon-White-Davidson (1983) test for the null of correct specification. P-values in parentheses.

⁵ Harvey test for the null of homoscedasticity. P-values in parentheses.

⁶ White test for the null of homoscedasticity. P-values in parentheses.

Adjusted R squared calculated as $1 - (\text{RSS}/\text{TSS}) \times (N-1)/(N-k)$.

Table 4 - Ordinary Least Squares (OLS) and Least Absolute Deviations (LAD) estimates of Eqs.(3) and (4) for six homogeneous segments.

Explanatory Variables	Eq.(3)		Machinery Eq.(4)		Eq.(3)		Chemicals Eq.(4)		Eq.(3)		Pharmaceuticals Eq.(4)	
	OLS	LAD	OLS	LAD	OLS	LAD	OLS	LAD	OLS	LAD	OLS	LAD
Const	-4.507*** (1.796)	-4.765** (2.105)	-6.492*** (2.165)	-5.064** (2.437)	-3.333* (1.785)	-4.523* (2.376)	-5.119* (2.589)	-6.849** (2.814)	3.007 (2.212)	4.353 (3.235)	1.604 (2.419)	0.860 (2.663)
log(CoGS)	0.314*** (0.103)	0.360*** (0.113)	- (-)	- (-)	0.330*** (0.101)	0.528*** (0.117)	- (-)	- (-)	0.387* (0.221)	0.442* (0.253)	- (-)	- (-)
log(Fasset)	- (-)	- (-)	0.005 (0.099)	0.064 (0.094)	- (-)	- (-)	-0.186 (0.115)	-0.160 (0.125)	- (-)	- (-)	0.041 (0.105)	0.047 (0.116)
log(GMG)	0.450 (0.511)	0.644 (0.560)	0.861 (0.697)	1.229* (0.642)	0.118 (0.121)	0.340* (0.204)	0.902*** (0.170)	0.888*** (0.185)	0.635** (0.239)	0.729** (0.309)	0.829*** (0.210)	0.826*** (0.232)
log(SC)	-0.045 (0.115)	-0.011 (0.105)	-0.168 (0.131)	-0.153 (0.120)	-0.199* (0.108)	-0.043 (0.107)	-0.040 (0.117)	0.022 (0.125)	0.134 (0.177)	0.078 (0.232)	0.103 (0.155)	0.078 (0.171)
log(CC)	-0.098 (0.089)	-0.100 (0.094)	0.110 (0.093)	0.119 (0.105)	0.660*** (0.115)	0.514*** (0.154)	0.275 (0.169)	0.316* (0.184)	-0.159 (0.204)	-0.095 (0.195)	0.051 (0.154)	0.014 (0.169)
log(AcPay)	0.507*** (0.141)	0.440*** (0.149)	-0.113 (0.141)	-0.263* (0.149)	-0.110 (0.143)	-0.178 (0.135)	-0.264* (0.145)	-0.252* (0.157)	0.488** (0.228)	0.565** (0.278)	0.071 (0.152)	0.232 (0.167)
log(AcRec)	0.366*** (0.051)	0.399*** (0.065)	0.363*** (0.057)	0.378*** (0.075)	-2.486*** (0.590)	-2.411*** (0.814)	-2.242** (0.901)	-2.397** (0.982)	-0.040 (0.134)	-0.249 (0.151)	-0.249** (0.112)	-0.385*** (0.124)
log(BadDebt)	-1.572** (0.725)	-1.962*** (0.720)	-1.319* (0.766)	-0.806 (0.831)	0.122*** (0.039)	0.120** (0.049)	0.068 (0.053)	0.088 (0.057)	0.104 (1.194)	1.646 (1.597)	0.602 (1.162)	0.950 (1.279)
log(BadDebt) log(AcPay)	0.075** (0.034)	0.095*** (0.035)	0.068* (0.037)	0.044 (0.041)	0.117*** (0.028)	0.114*** (0.040)	0.108** (0.045)	0.116** (0.049)	0.000 (0.063)	-0.079 (0.084)	-0.025 (0.062)	-0.043 x (0.068)
F-test ¹	170.1 (0.000)	79.71 (0.000)	9.298 (0.000)	4.638 (0.000)	78.61 (0.000)	31.77 (0.000)	30.37 (0.000)	5.339 (0.000)	33.26 (0.000)	17.97 (0.000)	6.627 (0.000)	2.967 (0.011)
RESET ²	0.011 (0.988)	0.389 (0.678)	0.135 (0.873)	2.105 (0.127)	0.081 (0.922)	2.047 (0.140)	0.619 (0.541)	0.568 (0.569)	1.249 (0.298)	1.393 (0.261)	1.604 (0.214)	1.391 (0.262)
B-P ³	17.32 (0.027)	22.81 (0.004)	29.89 (0.000)	31.91 (0.000)	6.743 (0.564)	4.511 (0.810)	4.185 (0.840)	3.557 (0.894)	11.48 (0.175)	11.09 (0.196)	10.78 (0.148)	11.79 (0.161)
MWD ⁴	0.001 (0.018)	0.001 (0.037)	2.005 (0.006)	2.927 (0.011)	0.001 (0.011)	0.001 (0.388)	-0.050 (0.273)	0.075 (0.265)	0.001 (0.004)	0.001 (0.452)	1.221 (0.004)	1.921 (0.036)
HARV ⁵	5.762 (0.763)	11.83 (0.106)	14.55 (0.068)	16.16 (0.040)	17.53 (0.025)	10.74 (0.220)	26.56 (0.000)	8.552 (0.384)	9.265 (0.320)	9.023 (0.341)	14.77 (0.064)	5.129 (0.744)
WHITE ⁶	62.76 (0.004)	62.48 (0.004)	68.77 (0.000)	75.24 (0.000)	48.55 (0.079)	23.75 (0.941)	35.52 (0.491)	38.86 (0.474)	38.26 (0.367)	39.94 (0.299)	42.02 (0.226)	38.14 (0.372)
R ²	0.867	0.806	0.223	0.161	0.770	0.752	0.360	0.301	0.778	0.695	0.476	0.613
N	122	122	122	122	84	84	84	84	48	48	48	48

Notes: OLS and LAD empirical estimates of Eqs.(3) and (4) with dependent variables $\ln(\text{Inv}_i)$ and $\ln(\text{Inv}_i/\text{CoGS}_i)$.

* (**) [***] significant at 10, (5) and [1] percent level.

¹ F-test for the null that all the regressors are jointly not statistically significant. P-value in parentheses.

² RESET test for the null of no specification errors. P-values in parentheses.

³ Breush-Pagan test for the null of homoscedasticity. P-values in parentheses.

⁴ MacKinnon-White-Davidson (1983) test for the null of correct specification. P-values in parentheses.

⁵ Harvey test for the null of homoscedasticity. P-values in parentheses.

⁶ White test for the null of homoscedasticity. P-values in parentheses.

Adjusted R squared calculated as $1 - (\text{RSS}/\text{TSS}) \times (N-1)/(N-k)$.

Table 5 - Ordinary Least Squares (OLS) and Least Absolute Deviations (LAD) estimates of Eqs.(3) and (4) for six homogeneous segments.

Explanatory Variables	Metal Manufacturing				Electricals				Food & Beverage			
	Eq.(3) OLS	Eq.(3) LAD	Eq.(4) OLS	Eq.(4) LAD	Eq.(3) OLS	Eq.(3) LAD	Eq.(4) OLS	Eq.(4) LAD	Eq.(3) OLS	Eq.(3) LAD	Eq.(4) OLS	Eq.(4) LAD
Const	-2.302 (1.933)	-5.917** (2.609)	-3.608* (1.852)	-5.497** (2.263)	0.755 (1.741)	1.686 (1.945)	-4.050* (2.056)	-4.112* (2.107)	-4.589 (3.431)	-5.610 (4.064)	-5.188 (3.746)	-8.204** (3.858)
log(CoGS)	0.901*** (0.097)	0.987*** (0.118)	- (-)	- (-)	0.371*** (0.085)	0.413*** (0.090)	- (-)	- (-)	0.511** (0.198)	0.416* (0.244)	- (-)	- (-)
log(Fasset)	- (-)	- (-)	-0.083 (0.113)	-0.057 (0.136)	- (-)	- (-)	0.132* (0.078)	0.045 (0.080)	- (-)	- (-)	-0.111 (0.196)	-0.133 (0.202)
log(GMG)	2.187* (1.163)	3.766*** (0.946)	3.716*** (0.709)	3.807*** (0.792)	0.524 (0.418)	0.786 (0.506)	1.555*** (0.473)	1.540*** (0.485)	1.278*** (0.299)	1.498*** (0.369)	1.553*** (0.282)	1.418*** (0.291)
log(SC)	0.040 (0.098)	-0.018 (0.152)	0.068 (0.125)	-0.005 (0.152)	-0.088 (0.105)	-0.074 (0.121)	-0.411*** (0.115)	-0.321*** (0.118)	-0.231 (0.226)	-0.350 (0.276)	-0.080 (0.226)	-0.172 (0.233)
log(CC)	0.153 (0.117)	0.325** (0.151)	0.220* (0.132)	0.254 (0.160)	-0.023 (0.071)	0.010 (0.086)	0.152* (0.082)	0.044 (0.084)	0.363** (0.171)	0.437** (0.209)	0.429** (0.183)	0.478** (0.188)
log(AcPay)	0.034 (0.090)	0.075 (0.121)	0.073 (0.118)	0.120 (0.143)	0.499*** (0.109)	0.404*** (0.133)	-0.048 (0.120)	0.058 (0.123)	0.568* (0.280)	0.654* (0.341)	0.085 (0.234)	0.260 (0.241)
log(AcRec)	0.119* (0.068)	0.172* (0.103)	0.132 (0.085)	0.150 (0.104)	0.066 (0.072)	0.070 (0.086)	0.018 (0.086)	0.010 (0.088)	0.138* (0.083)	0.196* (0.102)	0.241*** (0.085)	0.245*** (0.085)
log(BadDebt)	0.225 (0.543)	-0.581 (0.793)	-0.088 (0.638)	-0.549 (0.778)	-0.320 (0.585)	0.075 (0.660)	-0.609 (0.687)	-0.799 (0.704)	-3.024* (1.576)	-4.359** (1.933)	-4.099** (1.673)	-5.504*** (1.723)
log(BadDebt) x log(AcPay)	-0.010 (0.028)	0.034 (0.040)	0.007 (0.032)	0.032 (0.039)	0.020 (0.029)	0.000 (0.033)	0.034 (0.034)	0.045 (0.035)	0.148* (0.081)	0.208** (0.099)	0.194** (0.084)	0.266*** (0.087)
F-test¹	72.81 (0.000)	39.50 (0.000)	2.289 (0.019)	5.096 (0.000)	86.61 (0.000)	60.14 (0.000)	5.938 (0.000)	4.259 (0.000)	29.42 (0.000)	12.91 (0.000)	23.42 (0.000)	7.368 (0.000)
RESET²	1.045 (0.361)	5.747 (0.006)	0.961 (0.391)	0.004 (0.996)	3.092 (0.051)	2.309 (0.106)	12.84 (0.000)	0.234 (0.792)	0.662 (0.523)	0.948 (0.399)	0.209 (0.812)	0.455 (0.639)
B-P³	12.37 (0.135)	11.79 (0.161)	9.697 (0.287)	11.68 (0.166)	21.16 (0.005)	34.07 (0.000)	35.09 (0.000)	16.63 (0.024)	6.388 (0.604)	7.720 (0.461)	7.230 (0.405)	5.231 (0.732)
MWD⁴	0.001 (0.068)	0.001 (0.397)	1.744 (0.282)	-0.079 (0.927)	0.001 (0.065)	0.001 (0.293)	0.002 (0.946)	1.232 (0.000)	0.001 (0.562)	0.001 (0.878)	0.261 (0.520)	0.887 (0.107)
HARV⁵	7.593 (0.474)	4.505 (0.809)	3.076 (0.929)	6.581 (0.582)	9.924 (0.270)	9.947 (0.268)	16.24 (0.039)	12.81 (0.118)	6.754 (0.563)	13.35 (0.100)	9.869 (0.274)	12.80 (0.118)
WHITE⁶	36.40 (0.449)	42.83 (0.201)	41.00 (0.260)	46.53 (0.112)	47.15 (0.101)	74.29 (0.000)	76.74 (0.000)	44.18 (0.164)	37.59 (0.396)	37.76 (0.388)	38.81 (0.344)	37.00 (0.422)
R²	0.893	0.860	0.520	0.161	0.853	0.733	0.256	0.482	0.819	0.662	0.967	0.667
N	51	51	51	51	93	93	93	93	38	38	38	38

Notes: OLS and LAD empirical estimates of Eqs.(3) and (4) with dependent variables $\ln(\text{Inv}_i)$ and $\ln(\text{Inv}_i/\text{CoGS}_i)$.

* (**) [***] significant at 10, (5) and [1] percent level.

¹ F-test for the null that all the regressors are jointly not statistically significant. P-value in parentheses.

² RESET test for the null of no specification errors. P-values in parentheses.

³ Breush-Pagan test for the null of homoscedasticity. P-values in parentheses.

⁴ MacKinnon-White-Davidson (1983) test for the null of correct specification. P-values in parentheses.

⁵ Harvey test for the null of homoscedasticity. P-values in parentheses.

⁶ White test for the null of homoscedasticity. P-values in parentheses.

Adjusted R squared calculated as $1 - (\text{RSS}/\text{TSS}) \times (N-1)/(N-k)$.

Figure 1 – Kernel probability distributions of logarithm of Absolute Inventories ($\log(\text{Inv})$) for Food & Beverages, Metal Manufacture, Chemicals, Pharmaceutical, Machinery and Electronics segments.

Figure 2 – Kernel probability distributions of logarithm of Relative Inventories ($\log(\text{Inv}/\text{CoGS})$) for Food & Beverages, Metal Manufacture, Chemicals, Pharmaceutical, Machinery and Electronics segments.

References

- Ak, B. K., Patatoukas, P. N., 2016. Customer-Base concentration and inventory efficiencies: Evidence from the manufacturing sector. *Production and Operation Management*. 25(2), 258-27.
- Alessandria, G., Kaboski, J., and Midrigan, V., 2011. US trade and inventory dynamics. *American Economic Review*. 101(3), 303-307.
- Allen, E., Larson, C., Sloan, R. G., 2013. Accrual reversals, earnings, and stock returns. *Journal of Accounting and Economics*. 56(1), 113–129.
- Banerjee, S., Dasgupta, S., Kim. Y., 2008. Buyer-supplier relationships and the stakeholder theory of capital structure. *Journal of Finance*. 63(5): 2507-2552.
- Barnett, A., Eisen, E., 1982. A quartile test for differences in distribution. *Journal of American Statistical Association*. 77 (377), 47-51.
- Belsey, D. A., Kuh, E., Welsch, R. E., 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: John Wiley & Sons.
- Bougheas, S., Mateut, S., Mizen, P., 2009. Corporate trade credit and inventories: New evidence of a trade-off from accounts payable and receivable. *Journal of Banking & Finance*. 33(2), 300-307.
- Brigham, E. F., Houston, J. F., 2009. *Fundamentals of Financial Management*. 12th edition. Mason: South Western Cengage Learning, 68.
- Cachon, G. P., Olivares, M., 2010. Drivers of finished-goods inventory in the U.S. automobile industry. *Management Science*. 56(1), 202-216.
- Cachon, G. P., Terwiesch, C., 2013. Matching supply with demand: An introduction to operations management. McGraw – Hill, New York, United States.
- Caglayan, M., Maioli, S., Mateut, S., 2012. Inventories, sales uncertainty, and financial strength. *Journal of Banking & Finance*. 36(9), 2512-2521.
- Cai, S., Yang, Z., Hu, Z., 2010. The effects of volume consolidation on buyer–supplier relationships: A study of Chinese firms. *Journal of Purchasing, Supply Management*. 16(3), 152-162.
- Cameron, A. C., Miller, D. L., 2015. A practitioner’s guide to cluster-robust inference. *Journal of Human Resources*. 50(2), 317–372.

- Campello, M., Gao, J., 2017, Customer concentration and loan contract terms, *Journal of Financial Economics*. 123(1), 108-136.
- Capkun, V., Hameri, A. P., Weiss, L. A., 2009. On the relationship between inventory and financial performance in manufacturing companies. *International Journal of Operations & Production Management*. 29(8), 789-806.
- Cen, L., Dasgupta, S., Elkamhi, R., Pungaliya, R., 2016. Reputation and loan contract terms: The role of principal customers. *Review of Finance*. 20 (2), 501-533.
- Chen, H., Frank, M.Z., Wu, O.Q., 2005. What actually happened to the inventories of American companies between 1981 and 2000? *Management Science*. 51(7), 1015-1031.
- Chikán, A., 2009. An empirical analysis of managerial approaches to the role of inventories. *International Journal of Production Economics*. 118(2), 131-135.
- Chikán, A., 2011. Managers' view of a new inventory paradigm. *International Journal of Production Economics*. 133(1), 54-59.
- Dhaliwal, D., Judd, S., Serfling, M., Shaikh, S., 2016. Customer concentration risk and the cost of equity capital, *Journal of Accounting & Economics*. 61(1), 23-48.
- Deloof, M., 2003. Does working capital management affect profitability of Belgian firms? *Journal of Business, Finance & Accounting*. 30(3), 573-587.
- Demeeter, K., Golini, R., 2014. Inventory configurations and drivers: An international study of assembling industries. *International Journal of Production Economics*. 157, 62-73.
- Eppen, G. D., 1979. Effects of centralization on expected costs in a multi-location newsboy problem, *Management Science*. 25(5), 498–501.
- Eroglu, C., Hofer, C., 2011. Lean, leaner, too lean? The inventory-performance link revisited. *Journal of Operations Management*. 29, 356-369.
- Fabbri, D., Klapper, L.F., 2009. Trade credit and the supply chain. FEB: Amsterdam Business School Research Institute, The Netherlands. Retrieved from <<http://dare.uva.nl/search?arno.record.id=394831>>.
- Ferrando, A., Mulier, K., 2013. Do firms use the trade credit channel to manage growth? *Journal of Banking & Finance*. 37 (8), 3035-3046.
- Fisher, M. L., 1997. What is the right supply chain for your product? *Harvard Business Review*. 75(2), 105-116.

- Fisher, M. L., Ittner, C. D., 1999. The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis. *Management Science*. 45(6), 771-786.
- Gaur, J., Bhattacharya, S., 2011. The relationship of financial and inventory performance of manufacturing firms in Indian context. *California Journal of Operations Management*. 9(2), 70-77.
- Gaur, V., Fisher, M., Raman. A., 2005. An econometric analysis of inventory turnover performance in retail services. *Management Science*. 51(2), 181-194.
- Greene, W., 2003. *Econometric Analysis*, Prentice Hall, 5th edition.
- Hoerl, A. E., Kennard R. W., Baldwin K. F., 1975. Ridge Regression: Some simulations. *Communication in Statistics*. 4 (2), 105-123.
- Ho, W., Zheng, T., Yildiz, H., Talluri, S., 2015. Supply chain risk management: a literature review, *International Journal of Production Research*. 53(16), 5031-5069.
- Hofmann, E., Kotzab, H., 2010. A supply chain-oriented approach of working capital management. *Journal of Business Logistics*. 31(2), 305-330.
- Irvine J., Park, S., Yildizhan, C., 2016, Customer-base concentration, profitability and distress across the corporate life cycle, Working paper, Texas Christian University, Fort Worth, TX.
- Johnson, L. A., Montgomery, D. C., 1974. Operations Research in Production, Planning, Scheduling, and Inventory Control. John Wiley & Sons, New York, United States.
- Koenker, R., Basset, G., 1978. Regression Quantiles. *Econometrica*. 46 (1), 107-112.
- Kroes, J. R., Manikas, A. S., 2014. Cash flow management and manufacturing firm financial performance: A longitudinal perspective. *International Journal of Production Economics*. 148, 37-50.
- Lieberman, M. B., Asaba, S., 1997. Inventory reduction and productivity growth: A comparison of Japanese and US automotive sectors. *Managerial and Decision Economics*. 18, 73-85.
- Lieberman, M. B., Demeester, L., 1999. Inventory reduction and productivity growth linkages in the Japanese automotive industry. *Management Science*. 45(4), 466-485.
- Lieberman, M.B., Helper, S., Demeester, L., 1999. The Empirical Determinants of Inventory Levels in High-Volume Manufacturing. *Production and Operations Management*. 8(1), 44-55.

- Lorentz, H., Töyli, J., Solakivi, T., Ojala, L., 2016. The effect of a geographically dispersed supply base on downside risk: Developing and testing the N-shaped theory. *International Business Review*. 25(4), 872-882.
- MacKinnon, J., White, H., Davidson, R. 1983. Tests for model specification in the presence of alternative hypotheses: Some further results. *Journal of Econometrics*. 21 (1), 53-70.
- Mittal, R.K., 2010. *Management Accounting*. 11th edition. New Delhi: V.K. Enterprises, 490-492.
- Ogden, J. A., 2006. Supply Base Reduction: An empirical study of critical success factors. *The Journal of Supply Chain Management*. 42(4), 29-39.
- Patatoukas, P. N. 2012. Customer-base concentration: Implications for firm performance and capital markets. *The Accounting Review*. 87(2), 363-392.
- Ren, Z. J., Cohen, M. A., Ho, T. H., Terwiesch. C., 2010. Information sharing in a long-term supply chain relationship: The role of customer review strategy. *Operations. Research*. 58(1), 81-93.
- Rumyantsev, S., Netessine, S., 2007. What can be learned from classical inventory models? A cross-industry empirical investigation. *Manufacturing & Service Operations Management*. 9(4), 409-429.
- Silver, E., Pyke, D., Paterson, R., 1998. Inventory management and production planning and scheduling, 3rd ed. John Wiley & Sons, New York, United States.
- Terwiesch, C., Ren, Z. J., Ho, T. H., Cohen, M. A., 2005. An empirical analysis of forecast sharing in the semiconductor equipment supply chain. *Management Science*. 51(2), 208-220.