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# Managing Global Sourcing: Inventory Performance

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The use of global suppliers has increased considerably over the last three decades. Operations management theory establishes that global sourcing requires more units of inventory, but since these units are often procured at a lower cost from global suppliers the capital invested in inventory and the consequent financial burden may increase or decrease with global sourcing. This study provides rigorous firm-level empirical evidence that links the global sourcing practices of public U.S. firms and their inventory investments. We process bill of lading manifests (customs forms) to extract information on over half a million sea shipments from global suppliers to U.S. public firms and link this information with quarterly financial data from the Compustat database. We provide stylized facts on the participation of different firms and sectors in global trade. Using a simultaneous equation model, we find that an increase in global sourcing results in an increase in inventory investment. A 10% shift in sourcing from domestic to global suppliers increases the inventory investment by 8.8% for an average firm in our sample. We also find that increasing the number of suppliers can mitigate this increase in inventory investment: for example, going from single to dual sourcing reduces inventory investment by about 11%. We illustrate the use of our estimates to identify the impact of changing global sourcing strategy on inventory investment and operational performance metrics.

**Keywords:** global sourcing; inventory performance; imports; supply diversification; sourcing strategy; empirical analysis; panel data

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## 1. Introduction

Over the last three decades, several factors have led firms to source globally, including increasing differences in input costs among countries, improved communication technologies, and geographical skill specialization (Hausman et al. 2005). In fact, imports of goods to the U.S. economy accounted for 17.8% of the gross domestic product in 2008 (Imports of goods and services, World Bank 2011). The centrality of global sourcing to modern business has made evaluating the impact of global sourcing on different aspects of firm performance a key management challenge. In this paper, we focus on one such aspect: inventory investment, i.e., the dollar investment in inventory, a key driver of firm survival and performance (Chen and Shimerda 1981, Hendricks and Singhal 2009).

The operational impacts of global sourcing are at the center of considerable debate (see Goel et al. 2008). With respect to inventory investment, on one hand operations management theory and practice both recognize that global sourcing necessitates larger inventory levels due to longer lead times as well as a higher likelihood of supply chain disruptions (Cachon and

Terwiesch 2005). On the other hand, since inventory is sourced at significantly lower unit costs (see Paterson 2006), it is not clear if these increased inventory levels translate into higher inventory investments and thus a financial burden for the firm. The net impact of global sourcing on inventory investments depends on the relative magnitudes of the cost advantage of global sourcing as well as the inventory level disadvantage. This study is the first to provide firm-level empirical evidence on this trade-off and estimate the net impact of global sourcing on a firm's inventory investments.

Additionally, we study the role of different global supplier portfolio management strategies. Operations management theory provides competing recommendations. On one hand, theory recognizes the advantages of sourcing from a small group of suppliers such as reduced unit and fixed costs on account of economies of scale (Cachon and Harker 2002) and cooperative behavior (see Belavina and Girotra 2012). These lead to lower inventory investments. On the other hand, theory also demonstrates advantages of splitting orders among a large group of diversified suppliers, including reduced lead times (Ramasesh

et al. 1991) and increased resilience (see Tomlin 2006), that may necessitate lower inventory levels and, as a result, decrease in inventory investments. In this study, we empirically identify if a smaller or larger supplier base is associated with lower inventory investments.

The key impediment to empirically resolving the competing arguments around the impact of global sourcing on inventory investment and in identifying preferred supplier portfolio management strategies has been the unavailability of firm-level data. We overcome this impediment by constructing a novel firm-level data set on imports by public U.S. firms using information from bill of lading manifests. Through a combination of data mining techniques, free-text search, and manual efforts, we parse over 25 million import transactions between global suppliers and U.S. firms from 2007 to 2010 to build our data of imports by public U.S. retail and wholesale firms. We link this data with financial information from the Compustat database and with data on customs delays by the World Bank. We use this combined data set to analyze the effect of global sourcing and supplier diversification on inventory investment. We estimate a system of simultaneous equations that allows us to identify the concurrent effects of the extent of global sourcing and supplier diversification on product margins, cost of goods sold, and inventory investment, while controlling for other relevant variables identified in previous research. We obtain estimates that are robust to a very wide variety of alternate specifications, measures, samples, and estimation techniques.

We find that firms that employ more global sourcing also have higher dollar investments in inventory. This suggests that, on average, the effect of higher inventory levels dominates the effect of lower global procurement costs. Our estimates indicate that a 10% shift in sourcing from domestic to global suppliers leads to a \$104 M increase in inventory investment for an average firm in our sample, an increase of about 8.8%. We also find that in terms of inventory investment, the benefits of supplier diversification, on average, dominate the benefits of limiting sourcing to few suppliers. Supplier diversification can be used effectively to decrease the inventory investment required for global sourcing. Specifically, we find that an average firm that goes from single to dual sourcing can decrease inventory investment by \$134 M. Finally, these effects vary considerably by sector. Although inventory investments increase on average for most sectors as a result of global sourcing, notable exceptions include motor vehicles and parts, and toys.

This study makes two important contributions. First, we conduct a firm-level empirical examination of the net impact of the extent and diversification of global sourcing on inventory investment.

Thus, we complement the vast body of theoretical research that has analyzed global sourcing, and we identify the dominant of the competing hypotheses that comes from the theoretical literature. In particular, we establish that with increasing levels of global sourcing the impact of an increase in inventory levels dominates the impact of a decrease in procurement costs, leading to higher inventory investments accompanying higher levels of global sourcing. We also find that there are benefits to supplier diversification leading to a decrease in inventory investment. Second, we describe the process of developing a new data set that records import transactions made by public U.S. wholesale and retail firms. The data set offers a glimpse into the adoption and practice of global sourcing by public firms in different industries. We provide a number of stylized facts about firm-level global sourcing policies that can be used to validate assumptions and calibrate numerical experiments based on theoretical operations models. Further, many research questions beyond those addressed in the paper may be answered with these data and our study paves the way to collect, clean, and analyze such data, while documenting various difficulties involved in this process.

## 2. Literature Review

Operations management textbooks (e.g., Cachon and Terwiesch 2005) extensively discuss global sourcing and its importance to supply chain management, and this discussion forms the basis of our theory. Further, two streams of empirical literature are most immediately relevant for our study: the growing literature in operations management that uses publicly available data to study the inventory investments of individual firms and the vast literature in economics studying global trade at the country and/or industry level.

In the first stream, the pioneering work of Rajagopalan and Malhotra (2001) shows that between 1961 and 1994 firms significantly reduced their raw material, work in progress, and finished goods inventory. Chen et al. (2005) find a similar decline in inventory for U.S. manufacturing and wholesale firms from 1981 to 2000; however, retail firms observed the decline only after 1995 (Chen et al. 2007). Although the decline observed in these studies is contemporaneous with the increase in global sourcing, the multiple advances in logistics, operations management, and information technology are all legitimate candidates to explain this reduction. Chen et al. (2007) relate the amount of inventory that a firm holds to long-term stock performance, whereas Hendricks and Singhal (2009) relate “demand–supply” mismatches to short-term market performance. Similarly, in a recent study, Alan et al. (2011) find inventory productivity to be a

strong predictor of future stock returns. These studies highlight the central role that inventory management plays in firms' financial performance. Finally, publicly available inventory data has also been employed to identify and understand the bullwhip effect (see Cachon et al. 2007b, Osadchiy et al. 2010, Bray and Mendelson 2012).

The literature most closely related to our work includes studies that explain inventory investments using firm-level variables. Gaur et al. (2005) find that a firm's gross margins and investments in effective supply chain management practices significantly influence both the absolute and relative inventory level of a firm. Rumyantsev and Netessine (2007) use classical inventory theories to identify additional influential factors: demand uncertainty, lead time for procuring goods, and holding costs. In line with this work, our study identifies elements of global sourcing strategy that influence inventory levels. Kesavan et al. (2010) offer a more advanced empirical model that accounts for simultaneous dependence between product margins, demand, and inventory level and they use this model to build better sales forecasts. We employ this state-of-the-art model to explain inventories, and we extend it by incorporating sourcing information. Taken together, this literature provides the relevant variables that explain inventory performance as well as an appropriate methodology for unraveling the drivers of inventory investment, but it does not study global sourcing strategies. Although there is general agreement among both academics and practitioners that sourcing strategy is a key determinant of inventory investment, these studies do not possess the relevant data to examine these effects.

The second set of relevant literature studies global sourcing and global trade at a macroeconomic level. This vast body of economics literature typically employs gravitational models to identify the factors explaining bilateral trade (see Eaton and Kortum 2002), the impact of trade agreements, the characteristics of firms that participate in imports (Bernard et al. 2009), and the impact of imports on macroeconomic performance (Foster et al. 2006). Perhaps the most closely related study from this stream is Hausman et al. (2005), where the authors link global trade with the logistical challenges within certain countries. Basker and Van (2010) study the relationship between firm size and firm propensity to import. Although analysis of global trade in this stream provides important aggregate insights, it does not study the link between firm-level global sourcing decisions and firm-level inventory investment; hence, it cannot help individual managers make better decisions. The only study that we are aware of that attempts to link global sourcing and inventory investment is Han et al. (2008), but it does not possess firm-level data

and instead focuses on the 19 manufacturing sectors. To summarize, our study utilizes firm-level data on global sourcing to analyze the link of global sourcing strategies with firm-level inventory performance, thus providing actionable insights for company managers, financial analysts, and private investors.

### 3. Theory and Hypotheses

Inventory investment (i.e., the unit cost of inventory times the number of units inventoried) is the capital that is deployed as inventory. It is a key asset for firms in many industries (e.g., consumer retail, wholesale, etc.). Inventory investment decisions are of paramount importance to the field of operations management, with a rich research history going back more than 50 years. This theoretical literature makes a variety of predictions regarding the impact on inventory investment of lead times, the number of suppliers, fixed ordering costs, demand uncertainty, and variable procurement costs. All of these variables are strongly affected by a firm's global sourcing strategy, and thus we expect a deep relationship between the extent and dispersion of global sourcing and inventory investment.

#### 3.1. The Extent of Global Sourcing and Inventory Investment

We conceptualize the extent of global sourcing as the percentage of a firm's demand that is sourced from *foreign* sources via *sea shipments*, which make up about 90% of all global trade, with cross-border air and road shipments constituting the rest (International Maritime Organization 2012). Sea shipments are more likely to significantly affect inventory investment, since cross-border air and road shipments are not sufficiently different from domestic procurement with respect to associated costs and lead times (see Cachon et al. 2007a). Based on accounts from case studies, the popular press, and supply chain textbooks, we identify four mechanisms by which the extent of global sourcing might affect inventory investment.

*Unit Procurement Cost.* The key driver of the move toward global sourcing is the cost advantage of global producers due to lower labor costs and, possibly, scale, favorable regulations, superior infrastructure, and export incentives. The cost advantage translates into a lower unit cost of the inventory procured, and, all else being equal, a lower inventory investment. However, this lower cost also changes a firm's choice of inventory level. In particular, the consequences of having too much inventory are now likely to be smaller, which incentivizes the firm to target a higher inventory level (see the order-up-to model, in Cachon and Terwiesch 2005, pp. 242–275).

*Lead Times.* One of the key disadvantages of sourcing globally is the increase in lead time, which



includes cross-border transit time, and customs clearance time. Sourcing globally typically adds between 20 and 50 days to the lead time.<sup>1</sup> This longer replenishment time requires that firms maintain higher inventory levels for two reasons. First, the on-hand inventory at the destination must be increased to cover demand during the replenishment time (see Cachon and Terwiesch 2005, Boute and Van Mieghem 2013). Second, there is a possible increase in the pipeline inventory, which is linear in lead time but may depend on who owns inventory in transit (Figure 13.11 in Cachon and Terwiesch 2005).

*Fixed Order Costs, Large Container Shipping.* Sourcing from global suppliers typically entails additional per-order costs due to import procedures that include extra documentation, customs charges, broker fees, terminal handling charges, etc. Typically, such additional per-order costs range from US\$450 (Malaysia) to US\$3,865 (Afghanistan) (Doing Business 2010). Classical inventory models such as the economic order quantity model predict that higher ordering costs would lead to fewer orders but a larger amount of inventory per order, thus leading to a higher average inventory level (Cachon and Terwiesch 2005, p. 88). Moreover, sea-based global sourcing typically requires the use of large indivisible containers, leading to a further increase in cycle stocks and, consequently, a higher average inventory level.

*Delivery Reliability.* Firms have increasingly come to the realization that global sourcing exposes them to supply chain disruption risks that arise because of political and economic unrest, labor strikes, acts of terrorism, and natural disasters in the exporting or transit countries. In addition to these low-probability but high-impact supply chain disruptions (see Sheffi 2007), the frequent occurrence of congestion at different ports of call, the knock-on effects of delays suffered in previous ports, and bad weather at sea adds significantly to unreliability in delivery time. For example, the schedule reliability attained by the shipping industry was just 56%, on average, during quarter 2, 2011 (Raper 2011). Numerous theoretical models suggest that this additional variability due to global sourcing must be compensated by holding additional inventories (see Tomlin and Wang 2005).

To summarize, the above mechanisms suggest two competing impacts of the extent of global sourcing on inventory investment. First, because of longer lead times, higher fixed order costs, and lower delivery reliability associated with global sourcing, firms that

employ higher levels of global sourcing must increase their inventory levels. On the other hand, on account of lower unit procurement costs, these firms may pay less per unit of inventory. Since inventory investment is the product of these two effects, the direction of the combined effect is ambiguous, and we thus provide two competing hypotheses.

**HYPOTHESIS 1A.** *Firms that employ more global sourcing have lower inventory investments.*

**HYPOTHESIS 1B.** *Firms that employ more global sourcing have higher inventory investments.*

### 3.2. The Dispersion of Global Sourcing and Inventory Investment

We conceptualize the dispersion of global sourcing as the degree to which a firm's orders are split among different global suppliers. The operations literature relates the degree of supplier dispersion to costs, lead times, and reliability. Based on this literature, we identify four mechanisms by which the extent of dispersion in global sourcing might affect inventory investment.

*Unit Procurement Cost.* All else being equal, when a firm sources from a more dispersed supplier base it creates an option to dynamically allocate order quantities between suppliers on the basis of prices and terms offered by different suppliers. This lowers the effective unit procurement cost. At the same time, a less dispersed supplier base implies allocating a larger volume to each supplier, which may result in volume discounts (see Cachon and Harker 2002), and cooperative behavior (Belavina and Girotra 2012), which reduce effective procurement cost. Taken together, although both the competitive dynamics with more dispersion and the relational dynamics with less dispersion can lead to lower procurement costs, the superior strategy from a cost and, consequently, inventory investment point of view depends on the relative magnitude of the two effects.

*Fixed Order Costs.* A less dispersed supplier base allows a firm to source a larger volume from each supplier. This, in turn, facilitates lower transactional frictions (such as low per-order transportation costs), which leads to lower fixed ordering costs. As the classic economic order quantity model predicts, lower order costs lead to ordering in frequent but smaller batches, which lowers average inventory levels and, consequently, lowers inventory investments for the firm.

*Lead Times.* A large body of literature has studied the statistical properties of lead times under multisourcing (see Ramasesh et al. 1991 and references therein). This literature finds that, under a wide range of distributional assumptions, a firm with a more dispersed supplier base can split orders across suppliers and decrease the mean effective lead time, which,

<sup>1</sup> The transit time from Ningbo Port, China, is, on average, 18 days to the Long Beach, California, port, and 32 days to the New York, New York, port (<http://www.searates.com>). In addition, in China customs clearance of an export takes, on average, 21 days (Doing Business 2010).

in turn, implies a decrease in the safety-stock levels. Similarly, a firm with a more dispersed supplier base may be able to provoke supplier delivery competition that would also lead to shorter lead times and lower inventory investment (see Cachon and Zhang 2007).

**Delivery Reliability.** Global sourcing exposes a supply chain to new sources of political and natural phenomenon-related risks, thus lowering delivery reliability (Sheffi 2007). A substantial literature demonstrates that delivery reliability problems can be mitigated by multisourcing, or having a more dispersed supplier base. For example, Pan et al. (1991) demonstrate that “order splitting” leads to a reduction in the variation of effective lead times, which, in turn, implies a decrease in the safety-stock levels. Furthermore, when a firm disperses its sourcing it can dynamically shift orders from a disrupted source to another source, mitigating the consequences of unreliable delivery (see Tomlin 2006) and reducing the required inventory investments.

From a delivery reliability and lead time basis, a more dispersed supplier base leads to lower inventory investments; from the fixed order costs point of view, a less dispersed supplier base lowers inventory investments and the effects via procurement costs are ambiguous. Taken together, plausible arguments can be made to suggest that more dispersion can lead to higher or lower inventory investments. We thus provide two competing hypotheses:

**HYPOTHESIS 2A.** *Firms with a more dispersed supplier base have lower inventory investments.*

**HYPOTHESIS 2B.** *Firms with a more dispersed supplier base have higher inventory investments.*

The above discussion illustrates that the theoretical findings of the existing analytical work lead to competing hypotheses regarding the relationship between a firm’s global sourcing strategy and its inventory investment. Thus, the two questions we pose are best answered empirically.

## 4. Data Sources

We construct our data set by linking three distinct data sources: (i) a novel, proprietary transaction-level data set on *all* U.S. sea Imports; (ii) a publicly available country-year-level data set on business regulations compiled by the World Bank; and (iii) publicly available firm-quarter-level accounting data. This allows us to empirically analyze the above hypotheses while controlling for the firm-level financial characteristics that are known to influence inventory investments (Gaur et al. 2005, Rumyantsev and Netessine 2007).

### 4.1. Sample Description

We restrict our attention to firms with publicly available data on inventory investment, covered by the Standard & Poor’s Compustat Industrial Quarterly database. We consider all firms that are classified as retail or wholesale firms—North American Industry Classification System (NAICS) sectors 42, 44, and 45. There are more than 300 such firms. Unlike manufacturing firms, retail and wholesale firms typically do not transform their imports, nor do they assemble components sourced from different suppliers, providing a clearer picture of inventory, imports, and suppliers. Further, past empirical research on inventory investments has often focused on these sectors (Chen et al. 2007, Gaur et al. 2005, Rajagopalan and Malhotra 2001), and we can convincingly isolate our effects by using the controls identified in past research. We exclude online retailers (NAICS 454111, 454112), jewelry stores (NAICS 448310), and energy sector firms (NAICS 4247, 4543) from our sample. Online stores often employ drop shipping and thus carry no physical inventory and the value of inventory in the jewelry and energy sectors varies with commodity prices, thus confounding the supply chain and speculative roles of inventory.

### 4.2. U.S. Sea Imports Data

We construct a novel transaction-level data set on *all* sea imports into the United States by compiling multiple unstructured data sources through data structuring, natural language processing, and manual cleaning. U.S. firms are mandated to report all physical imports to the Federal Customs and Border Protection Agency of the Department of Homeland Security. Sea-import transactions are reported to the agency using information available on the *bill of lading* (Figure 1). This is a document issued by a carrier to a shipper (supplier) certifying that goods have been received on board as cargo for transport to a named place and for delivery to an identified consignee (buyer). The document typically includes the supplier’s name and address, the buyer’s name and address, a description of the goods, the quantity imported, and additional transaction-specific information.

In recent years, the U.S. Customs and Border Protection Agency has agreed to share these data with commercial “supplier intelligence services.” These services typically sell analysis of aggregate import trends and make available small, processed subsets of the original bill of lading data. The recent availability of this processed data has attracted the attention of practitioners (Green 2009) and is now being used extensively by scholars of maritime economics and transportation science (Meneses and Villalobos 2010). Our paper brings this data to the study of firm operations.

**Figure 1** Sample Bill of Lading

<b>Bill of Lading:</b> CMDUNCHN265928 <b>Vessel:</b> CSCL Ninbgo (Code: 9227015)	<b>House/Master:</b> House <b>Carrier:</b> CMDU	<b>Estimated Arrival:</b> 08/04/2008 <b>Actual Arrival:</b> 12/04/2008	<b>Mode of Transport:</b> 10 <b>Voyage:</b> px432
<b>Shipper</b>	<b>Consignee</b>	<b>Notify</b>	<b>Notify 2</b>
Fine Furniture (shanghai) limited, Donghai farm, Nanhui district Shanghai China 201303 tel:86-21-58292929	Hellmann Worldwide Logistics, 635 airport south parkway suite 200 Atlanta, GA 30349 tel:770-909-0888	Havertys Furntiure (edc), 1090 Broadway Ave Braselton, GA 30517 attn:chrissa danzis email:cdanzis havertys com	order
<b>Port:</b> 57035—Shanghai, China <b>Place Receipt:</b> Shanghai, China <b>InBond:</b>	<b>Port:</b> 1703—Savannah, GA <b>U.S. Dist Port:</b> <b>Foreign Port:</b>	<b>Weight:</b> 5,086 (KG) <b>Quantity:</b> 68 (CTN) <b>Measurement:</b>	TEU: 1.74
<b>Container Number (Info)</b>	<b>Product Description</b>	<b>Marks &amp; Numbers</b>	
	wooden furniture hs code:94016190	no marks	

Through one such data service, we obtained direct access to raw, unprocessed bill of lading forms for each import transaction into the United States during the period of July 2007 to July 2010. We Web crawled this database to obtain over 25.8 million import transactions executed during this three-year window. To ensure complete coverage of our data set, we compared the total tonnage (weight) of imports of our 25.8 million transactions and aggregate data on imports provided by the Center for Economic Studies of the U.S. Census Bureau (see Bernard et al. 2009). For the entire period the discrepancy between the weight of imports in our data set and the weight reported by the U.S. census is 0.87% and the average discrepancy, across 12 quarters, is just 0.76%. Direct access to the complete set of raw data allows us to ensure sample accuracy and full transparency in constructing our imports data set. On the other hand, the raw bill of lading data pose a number of challenges with respect to identifying the buyers and suppliers, which we detail below.<sup>2</sup>

#### 4.2.1. Identification of the Importing Firm.

A firm invests in inventory when it imports goods directly or through a logistics firm such as DHL, FedEx, etc.<sup>3</sup> For direct imports, the importer's (inventory owner's) name is entered in the consignee field of the bill of lading. For imports through logistics firms, typically the consignee field records the logistics company name and the importer's name is entered in

the notifier field. Many variants of a firm's name are used, which necessitates significant cleaning (see Figure 1 for an example). For the public firms that constitute our sample, we obtained all their registered corporate names and those of associated entities. We then searched for these registered names in both relevant fields of the bill of lading. This search process helped identify transactions conducted by the firm in question, but it also included a number of spurious entries. For instance, searching for the apparel retailer Gap also returns transactions for Gap Promotions, a completely different corporate entity. To clean such spurious transactions, we utilized additional information contained in the consignee's and notifier's addresses. We standardized these addresses to the U.S. postal service's standardized address format using an application programming interface provided by Google Maps and compared them to all known corporate addresses for the firms of interest. The corporate addresses were obtained from the union of three different commercial business directory services: Cortera, Manta, and 411.com. As a result of this process, we obtained 741,949 import transactions for 211 Compustat firms in our sample.<sup>4</sup>

**4.2.2. Identification of Suppliers.** The shipper information in the bill of lading typically contains the supplier's name and address (see Figure 1 for an example). For about 56% of the above transactions this supplier name was an indexed corporate name with a verifiable address. For a little over half of the remaining transactions, the supplier information was entered in a wrong field, or was entered to include the name of the logistics company (e.g., "Maersk Logistics on behalf of Chairworks Manufacturing Group, Shenzhen, China"). We extracted the supplier information from such transactions using text-pattern recognition algorithms and manual inspection. Taken together, we were able to identify detailed supplier

<sup>2</sup> Transaction-level import data are also available through a direct partnership with the Center for Economic Studies of the U.S. Census Bureau (see Bernard et al. 2009). However, the Census Bureau anonymizes the importing firm when sharing these data. Although this data set fits the requirement of sector or economy-wide (see Han et al. 2008) studies, the absence of firm names is a fatal impediment for firm-level studies that require linking import data to other firm-specific attributes such as accounting data.

<sup>3</sup> Increasingly, some firms have started completely outsourcing the sourcing function to supply chain orchestration firms. In such cases, often the buyer firm is not directly liable for inventory and supply chain costs on account of imports, and as such the theory at the center of this study does not apply to them.

<sup>4</sup> In line with previous studies (see Bernard et al. 2009), only 211 of our 300 Compustat retail and wholesale firms import.



**Table 1** Sample Transactions

Panel A: Transaction-level imports data								Panel B: Firm-quarter level data			
Bill of lading no.	Shipper name	Consignee name	Arrival	Value (\$)	HS code	Sea distance (nmiles)	Custom time (days)	Firm gvkey	Fiscal qtr.	Global sourcing share (%)	Supplier dispersion
Polnhcmatl00629	Sanlim Furniture, Vietnam	Haverty Furniture	Sep 8, 2007	36,339	940350	10,779	24	5523	Q3, 07	2.03	0.91
Nlusnl420809518	Creative Kids Far East, Hong Kong	Big Lots Stores	Oct 12, 2008	14,006	950341	6,370	6	12123	Q3, 08	0.77	0.67
Exdo6731026702	Ebelco Industries, Malaysia	Universal Power Group	Jan 17, 2008	6,057	830120	7,543	17	176325	Q1, 09	25.2	0.13

information including the establishment name and country for 589,459 of the original 741,949 transactions. The supplier may be an independent company, a company affiliated with the importer, or a wholly owned subsidiary of the importer.

**4.2.3. Dollar Value and Product Category of Goods Imported.** The bill of lading contains some self-reported information about the value of imported goods but the corresponding fields are not disclosed to supplier intelligence services. Thus, following Leachman (2008), we use the *Journal of Commerce's* Port Import Export Reporting Service (PIERS) to supplement our data with proprietary data on the dollar value of imported goods. In the past, scholars have used PIERS data to study different trade-related questions such as the export market structure and pricing behavior of U.S. firms (Patterson and Abbott 1994). Furthermore, these PIERS data also provide product category classification of goods imported based on the six-digit Harmonized Commodity Description and Coding System (HS).<sup>5</sup> We merged the import values and the HS code classification provided by PIERS into our transaction-level bill of lading data using the unique identification numbers for each bill of lading, which allowed us to obtain dollar value and product category estimates for 94.88% of transactions in our data set.

**4.2.4. Sourcing Lead Time for an Import Transaction.** We compute sourcing lead time for an import transaction as a sum of the travel time based on the sea distance between the supplier country and the United States and the average time taken to obtain customs clearance in the supplier country. We obtain the customs clearance time from World Bank's *"Doing Business"* data, which covers 152 countries, accounting for 98.67% of the transactions in

our sample.<sup>6</sup> Travel time is computed from the sea distance between the supplier countries and U.S. ports. We obtain sea distances from <http://www.sea-distances.com>, and compute time using an average continuous-travel ship speed of 14 nautical mph. As a result of these steps to identify the buyer, the supplier, the dollar value, the product classification, and the sourcing lead time for each transaction, we are left with 558,177 import transactions by 211 public firms.

Panel A of Table 1 illustrates three sample transactions from this data set. We aggregate this transaction-level information to the (buyer) firm-quarter level and obtain the aggregated global sourcing share and the supplier dispersion for each sample buyer firm in each quarter. We include an aggregated firm quarter in our sample if and only if the supplier information is available for more than 80% of the import transactions executed by the firm in that quarter but, as we detail later, our analysis is robust to alternate inclusion criteria.<sup>7</sup> We further merge the compiled firm-quarter level imports data with firm-quarter level accounting data available from the Compustat database. We include a firm in our analysis only if we have more than two quarters of data available for it, which leaves us with 177 firms and 1,661 firm-quarter observations.<sup>8</sup> Panel B of Table 1 illustrates the three

<sup>6</sup> Doing Business, World Bank at <http://http://www.doingbusiness.org>, accessed August 20, 2011. These data are compiled through annual surveys that measure the impact of various business regulations, including the time and cost associated with import/export transactions by sea transport. The time measure for exports records the average time spent in various procedural activities such as the processing of documents, customs clearance, and port and terminal handling.

<sup>7</sup> Note that different U.S. retail and wholesale firms may follow different fiscal-year cycles (see Chen et al. 2007).

<sup>8</sup> In our 12 quarters of data, our sample is, on average, 0.76% of total sea shipments into the United States. The remaining sea shipments into the United States arise from private firms that we exclude and from sectors such as manufacturing (NAICS 31–33), mining (NAICS 21), and energy. Oil imports alone account for 40% of all sea shipments in our data.

<sup>5</sup> The Harmonized Commodity Description and Coding System is an internationally standardized system of names and numbers for classifying traded products. It is developed and maintained by the World Customs Organization (WCO), which is an independent intergovernmental organization with over 170 member countries.

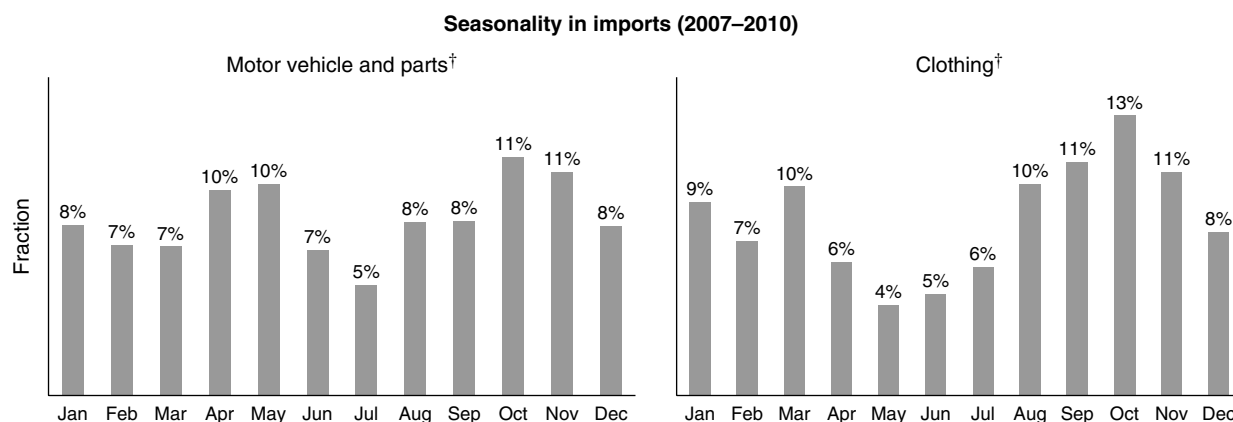


Figure 2 Imports: How, What, and When?

U.S. ports		Sourcing ports		Products		
Name	\$ %	Name	\$ %	HS code	\$ %	Typical products in category
Los Angeles	26.26	Yantian	20.63	61-62 <sup>a</sup>	24.13	Garment infant girls/boys, ladies woven pants, knitted pullover cardigan
Long Beach	12.35	Shanghai	17.51	85 <sup>b</sup>	10.27	Stereo RF wireless headphones, color video monitor, 9" slim line portable DVD
Tacoma	11.31	Hong Kong	14.22	94 <sup>c</sup>	8.29	Plywood round table, gas grill, patio furniture, high back executive chair
New York	10.46	Kaohsiung	6.49	95 <sup>d</sup>	7.14	Paddle boom ball, toilet golf, quad elite helicopter
Norfolk	7.12	Ningbo	5.89	64 <sup>e</sup>	4.85	Ladies leather sandals, sporting shoes, men's work boot

<sup>a</sup>Articles of apparel and clothing accessories. <sup>b</sup>Electrical machinery and parts, telecommunications equipment, sound and television recorders.

<sup>c</sup>Furniture and the like, prefabricated buildings. <sup>d</sup>Toys, games, and sports equipment, parts and accessories. <sup>e</sup>Footwear, gaiters, and the like.



† Motor vehicle and parts: NAICS 4231, 4411. Apparel: NAICS 4243, 4481.

rows of our panel that correspond to the importing firms in the transactions shown in panel A.

In our sample of public U.S. retailers and wholesalers, we find that the busiest U.S. port for imports is Los Angeles, handling almost 26% of imported goods by value. Likewise, the top sourcing port is Yantian, China, from which approximately 21% of imported goods are sourced; it is closely trailed by Shanghai at 18%. Apparel and clothing is the top imported product category, accounting for over 24% of the value of total imports, followed by electronics and footwear (Figure 2, top). We also find that the seasonal pattern of imports varies widely across product categories: whereas clothing imports are highly seasonal and peak in anticipation of the holiday season to an average of 13% in the month of October; motor vehicles and parts have a much more muted seasonal pattern that peaks in anticipation of the summer driving season to an average of 10% in the month of May (Figure 2, bottom).

## 5. Variable Operationalization

Inventory investment, our main dependent variable, is operationalized as the average inventory

investment by firm  $i$  in quarter  $t$ ,  $AINV_{it}$ . We compute the average investment as

$$AINV_{it} \equiv \frac{1}{2} \times (INV_{it-1} + INV_{it}), \quad (1)$$

where  $INV_{it}$  denotes the end-of-period inventory value for firm  $i$  in quarter  $t$ , i.e., the Compustat data field INVTQ.

We operationalize the extent of global sourcing employed by firm  $i$  in quarter  $t$  as the weighted global sourcing share,  $WGSS_{it}$ , defined as the weighted measure of the global sourcing share from different supplier countries wherein the respective weights are set to equal the sourcing lead time from the supplier country to the United States. The lead time, which includes customs and other delays, captures the effective “delivery lead time.” Weighting the sourcing share by the delivery lead time allows us to calibrate the degree to which the lead time and reliability effects influence each sourcing transaction. In particular, Asian countries have a higher delivery lead time than do Central American countries, and therefore in our analysis a firm importing from Asia is considered to have higher extent of global sourcing than a firm importing the same fraction from Central America.

At the same time, firms importing higher fractions have a higher global sourcing share than firms sourcing from U.S. suppliers. Specifically, we compute the  $WGSS_{it}$  as

$$WGSS_{it} \equiv 100 \times \frac{\sum_{j=1}^M TT_j \times IMP_{itj}}{\sum_{j=1}^M TT_j} \times \frac{1}{COGS_{it}}, \quad (2)$$

where  $M$  is the total number of distinct sea routes<sup>9</sup> over which firm  $i$  has imported goods in quarter  $t$ ,  $TT_j$  is the lead time associated with the  $j$ th sea route,  $IMP_{itj}$  is the total value of imports shipped via the  $j$ th sea route by firm  $i$  in period  $t$ , and  $COGS_{it}$  is the corresponding cost of goods sold, Compustat field  $COGSQ$ .

Note that this weighted average definition deflates the actual extent of a firm's global sourcing that is better captured by an unweighted definition of the global sourcing share  $GSS_{it} \equiv 100 \times \sum_{j=1}^M IMP_{itj} / COGS_{it}$ . For example, the average global sourcing share for Haverty Furniture, a leading retailer of home decor furniture, is 16.3%, but the weighted measure for the retailer is only 1.2%. Similarly, the unweighted share for the Weyco Group, a leading wholesaler of men's footwear, is 60.3% whereas the weighted measure is only 10.4%.

We operationalize the extent of dispersion in global sourcing as a weighted measure of dispersion in firm  $i$ 's supplier base in quarter  $t$ ,  $WSD_{it}$ . Weighted supplier dispersion is measured as one minus the weighted average of the Herfindahl index at the product-category level wherein the respective weights are set equal to the import value of the product category. Measuring dispersion at the product-category level allows us to capture the diversity of the supplier base while controlling for the product variety offered by a firm (or for intertemporal differences in product variety). Further, to a buyer, each supplier-country pair provides distinct sourcing characteristics such as exchange rates, expected lead times, or geopolitical risk, so we treat a supplier's establishments in two different countries as two distinct suppliers. Specifically we compute the supplier dispersion as

$$\text{Herfindahl Index}_k = \sum_{j=1}^{N_{itk}} (IMP_{itkj} / IMPV_{itk})^2, \quad (3)$$

$$WSD_{it} \equiv 1 - \frac{\sum_{k=1}^{PV_{it}} IMPV_{itk} \times \text{Herfindahl Index}_k}{\sum_{k=1}^{PV_{it}} IMPV_{itk}}, \quad (4)$$

where  $N_{itk}$  is the total number of suppliers from whom product category  $k$  is sourced by firm  $i$  in quarter  $t$ ,  $IMP_{itkj}$  are the imports by firm  $i$  from supplier  $j$ ,  $IMPV_{itk}$  is the total value of imports under

product category  $k$ , and  $PV_{it}$  is the total number of product categories imported in quarter  $t$ . We define the product category using the four-digit HS codes.<sup>10</sup> Hereafter, for brevity, we use global sourcing share and supplier dispersion when referring to our global sourcing variables. We add the prefix "weighted" only when necessary for clarity.

Figure 3 shows variation in the extent and dispersion of global sourcing and related stylized facts. Panels (a) and (c) show the distribution of average extent of global sourcing and supplier dispersion employed by the final 177 firms of our panel data during the study period (2007–2010). Likewise, in panels (b) and (d), we show the distribution of effective lead time  $WLT_{it} \equiv \sum_{j=1}^M IMP_{itj} \times TT_j / \sum_{j=1}^M IMP_{itj}$  and the number of suppliers per product category  $NPS \equiv \sum_{k=1}^{PV_{it}} N_{itk} / PV_{it}$ . Note that firms follow a wide variety of different strategies. Panels (e)–(h) show the difference in average value of these variables across 14 subsectors of retail and wholesale sector (based on three-digit NAICS codes). Panels (i) and (j) show a small positive correlation between the extent and dispersion of global sourcing; firms that rely more on global sourcing typically employ multiple suppliers. Finally, panels (k) and (l) show that imports are considerably concentrated among large size firms, a fact that has been observed previously in samples of public and private firms (Bernard et al. 2010).

In addition to these key variables of interest, we use a number of control variables motivated by previous studies. Gaur et al. (2005) find that gross margins, capital intensity, and sales surprise significantly explain both the absolute and relative inventory level of a firm. Rummyantsev and Netessine (2007) identify demand uncertainty as an important additional variable. In this study, we measure gross margins over costs  $GM_{it} \equiv (REV_{it} - COGS_{it}) / COGS_{it}$ , where  $REV_{it}$  are the sales (Compustat field,  $REVTQ$ ); capital intensity  $CAPINT_{it} \equiv PPE_{it} / (TA_{it} - INV_{it})$ , where  $PPE_{it}$  is the net investments in property, plant, and equipment (PPENTQ); and  $TA_{it}$  are the gross total assets (Compustat field,  $ATQ$ ). Following Rummyantsev and Netessine (2007), we compute the sales forecast,  $SF_{it}$ , using a linear trend model with seasonal dummies  $SF_{it} = a_1 + a_2t + b_1q_1 + b_2q_2 + b_3q_3$ . We use this sales forecast to compute the sales surprise measure,  $SS_{it} \equiv REV_{it} / SF_{it}$ , and a measure of demand uncertainty,  $DU_{it}$ :

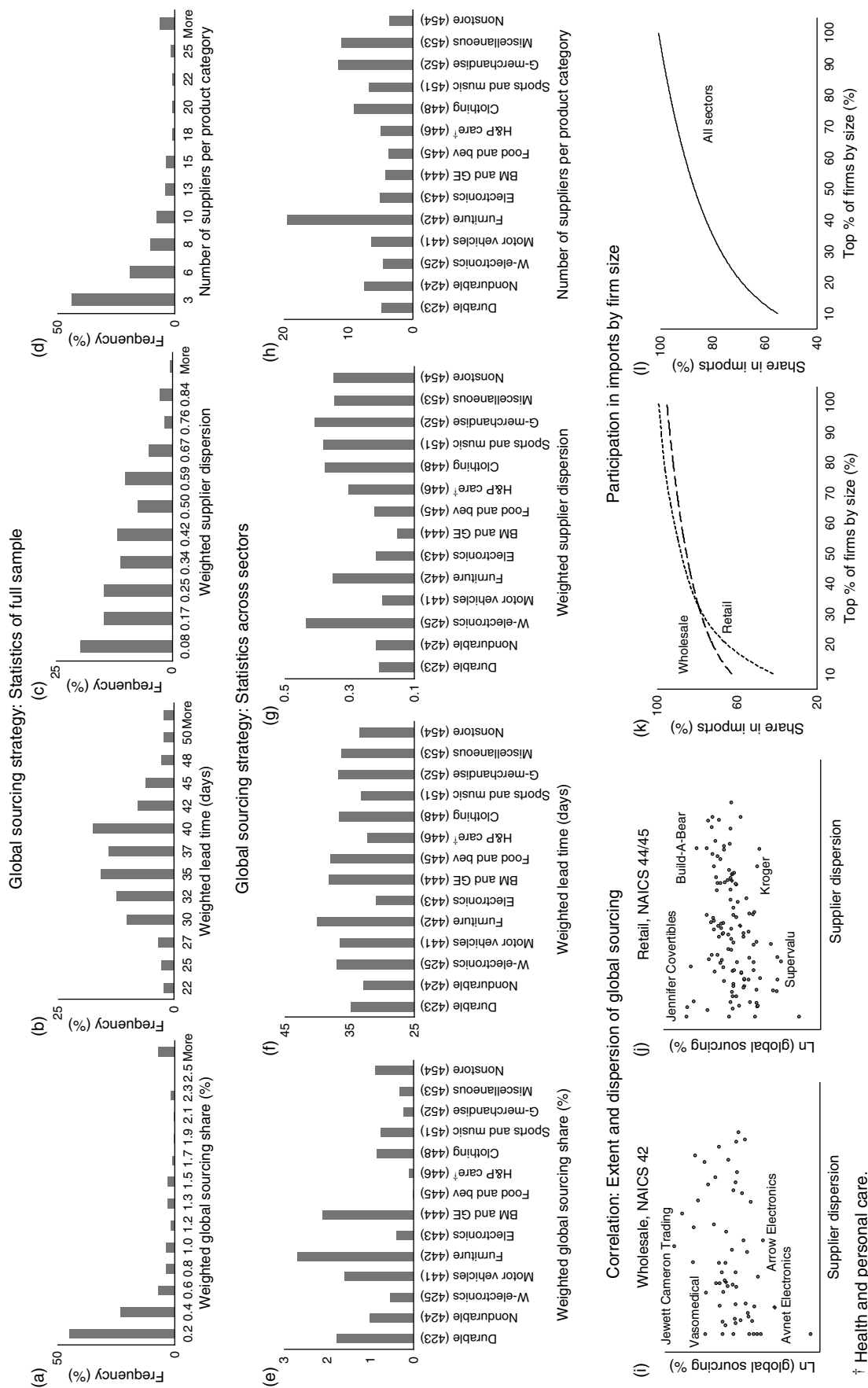
$$DU_{it} \equiv \left( \frac{1}{3} \sum_k (REV_{ik} - SF_{ik})^2 \right)^{0.5}, \quad (5)$$

where  $k$  is the set of observations for firm  $i$  in the same quarter as quarter  $t$ . Table 2 provides the

<sup>9</sup> A sea route is defined as a pair of supplier country and the U.S. East/West Coast.

<sup>10</sup> The four-digit HS codes are relatively fine product categorizations. For instance, HS code 5208 denotes "woven cotton fabrics, nu 85% cot, wt not over 200 g/m2," whereas HS code 5209 denotes "woven cotton fabrics, nu 85% cot, wt ov 200 g/m2."

Figure 3 Global Sourcing Strategy: Sample and Sector Statistics



† Health and personal care.

**Table 2** Summary Statistics

Variables		Mean	Standard deviation			N	
			Overall	Between	Within	No. of firms	No. of obs.
Global Sourcing Share (GSS)	%	6.17	13.00	10.77	6.57	177	1,688
W-Global Sourcing Share (WGSS)	%	1.15	4.30	3.61	2.19	177	1,688
W-Lead Time (WLT)	Days	35.74	7.60	6.40	4.61	177	1,688
W-Supplier Diversification (WSD)	Ratio	0.32	0.25	0.22	0.14	177	1,688
No. of Suppliers (NSP)	Count	7.86	13.09	9.36	8.97	177	1,688
Average Inventory (AINV)	\$ M	1,173.59	3,339.21	3,239.88	179.20	177	1,696
Cost of Goods Sold (COGS)	\$ M	1,967.14	6,748.51	6,516.86	557.39	177	1,705
Gross Margin Over Costs (GM)	%	0.54	0.53	0.49	0.09	177	1,705
Capital Intensity (CapInt)	Ratio	0.39	0.25	0.25	0.05	177	1,702
Sales Surprise (SS)	Ratio	1.01	0.10	0.03	0.09	177	1,706
Demand Uncertainty (DU)	\$ M	152.84	361.66	332.05	118.45	177	1,694
Sales, General & Admin (SGA)	\$ M	479.47	1,680.58	1,594.74	101.66	177	1,705
Product Variety (PRODVAR)	Count	24.22	38.06	32.45	17.70	177	1,706

summary statistics of the variables in our panel. Note that these summary statistics are constructed using firm-quarter level observations, our unit for empirical analysis. Thus these are not directly comparable to financial statistics that are typically reported at the firm-annual level. Likewise, the global sourcing share should not be directly compared with the equivalent sector or country-level statistics: Bernard et al. (2010) show that firms exhibit a vast differential in the propensity to import, with large-sized firms accounting for a disproportionate share of imports. For instance, in the retail sector, the top 1% of firms with respect to size account for 54% of total imports! We find similar evidence in our data set (see panels (k) and (l) in Figure 3). With this skewed propensity to import, a sector or country-level measure will, by definition, be much larger than any averaged firm-level measure.

## 6. Model Specification

There are two empirical challenges in estimating the impact of the global sourcing strategy on inventory investment. First, theory and recent empirical models (see Kesavan et al. 2010) suggest that inventory, gross-margin, procurement cost, and demand influence each other and thus must be simultaneously determined as an equilibrium outcome. In particular, although the choice of inventory is influenced by margins, procurement costs, and demand level, the inventory investment itself may also influence the demand level and margins. Higher inventory is known to stimulate demand (Balakrishnan et al. 2004) and a higher (lower) demand level may allow firms to earn higher (lower) margins, which again influences demand and inventory. This simultaneous dependence between the *dependent* variable (inventory) and several *independent* variables (demand, costs, gross-margin) creates a contemporaneous correlation between the regressors and the error term in

the estimation model of inventory investment, which, if not controlled for, leads to inconsistent estimates.

Second, global sourcing changes a firm's procurement costs and demand. Global procurement is often at a lower cost. Further, the firm may partially share the procurement cost savings with customers by reducing selling prices and thus increasing demand. Alternatively, customer preferences may depend on product origin. These changes in demand and costs in turn influence inventory level. Thus, in addition to the direct impact of global sourcing on inventory investment, there is an indirect effect of global sourcing that we must account for in estimating the impact of sourcing on inventory investment.

We employ the simultaneous equation model introduced by Kesavan et al. (2010) to address these challenges. We supplement the original model with our new variables on the global sourcing strategy. In particular, following Kesavan et al. (2010), our model includes three simultaneous equations. The first, Equation (6), models inventory investment (measured as average inventory, *AINV*), the second, Equation (7), models the cost of goods sold (*COGS*), which is a composite measure of the unit procurement cost and sales (a proxy for demand), and the third, Equation (8), models gross margins:

$$\begin{aligned} \log AINV_{it} &= \alpha_{11} \log COGS_{it} + \alpha_{12} \log GM_{it} + \alpha_{13} \log AINV_{it-1} \\ &\quad + \alpha_{14} \log SS_{it} + \alpha_{15} \log DU_{it} + \alpha_{16} \log CAPINT_{it-1} \\ &\quad + \alpha_{17} \log WGSS_{it} + \alpha_{18} WSD_{it} + \alpha_{19} \log PV_{it} \\ &\quad + F_{1i} + \beta_{1s} q_s + \tau_{1r} y_r + \epsilon_{it}, \end{aligned} \quad (6)$$

$$\begin{aligned} \log COGS_{it} &= \alpha_{21} \log GM_{it} + \alpha_{22} \log AINV_{it} + \alpha_{23} \log COGS_{it-1} \\ &\quad + \alpha_{24} \log SGA_{it} + \alpha_{25} \log WGSS_{it} + \alpha_{26} WSD_{it} + \\ &\quad + F_{2i} + \beta_{2s} q_s + \tau_{2r} y_r + \eta_{it}, \end{aligned} \quad (7)$$



$$\log GM_{it} = \alpha_{31} \log COGS_{it} + \alpha_{32} \log AINV_{it} \\ + \alpha_{33} \log GM_{it-1} + F_{3i} + \beta_{3s} q_s + \tau_{3r} y_r + \delta_{it}, \quad (8)$$

where  $i$  and  $t$  are the firm and quarter indices, and  $F_{3i}$ ,  $q_s$ ,  $s \in \{1, 2, 3\}$ , and  $y_r$ ,  $r \in \{1, 2\}$  are the firm, quarter, and year dummies, respectively.

The three equations are in a log-multiplicative form that previous research has found to best fit the relationship between multiple inventory measures and a wide range of explanatory variables (Gaur et al. 2005, Rumyantsev and Netessine 2007). Some variables in this model exhibit significant firm-size-related variance: larger firms have larger demand (COGS), carry larger inventories (AINV), carry larger product assortment (PV), and have larger overheads (SGA). This scale-dependent variance could lead to spurious econometric inferences. Following the guidelines in Barth and Clinch (2009), we control for scale effects in our model by deflating all scale-dependent variables—COGS<sub>it</sub>, AINV<sub>it</sub>, SGA<sub>it</sub>, DU<sub>it</sub>, and PV<sub>it</sub>—by the market value of equity for firm  $i$  at the end of quarter  $t$  (measure for firm size, Compustat variable MKVLTQ).<sup>11</sup>

Further, macroeconomic studies have found that the global sourcing strategy of firms depends on a number of firm-specific factors (see Bernard et al. 2009) and moreover, a firm's interdependent choice of inventory investment, demand, and margin may also depend on unobserved firm characteristics. To account for such unobserved firm-specific characteristics, we include firm-level dummies in each of our simultaneous equations. Quarterly inventory and financial data exhibit strong seasonality, so we include quarter dummies. To control for annual trends, we include year dummies.

In the inventory equation (Equation (6)), past research (Gaur et al. 2005, Rumyantsev and Netessine 2007) suggests the control variables sales surprise (SS), demand uncertainty (DU), and lagged capital intensity (CAPINT). In addition, we control for product variety (PV) because it can influence inventory levels (see Zipkin 1998, Rajagopalan 2013). We control for inventory investment from the last quarter (AINV<sub>it-1</sub>) to ensure that we are capturing only the impact of a sourcing decision and a contemporaneous growth in inventory. We supplement the above control variables with our two focal global sourcing strategy variables, the extent of global sourcing, WGSS, and the supplier dispersion, WSD.

In the cogs equation (Equation (7)), following Kesavan et al. (2010), we include the sales and general and administrative expenses, SGA, allowing firm demand to depend on marketing expenditures. Further, to control for other firm-specific time-variant

factors such as marketing mix, brand strength, etc. that can impact demand but for which we do not have direct measures, we use lagged cost of goods sold (COGS<sub>it-1</sub>). Finally, as discussed above, the average unit cost of goods procured and the demand for them depends on the global sourcing strategy, so we also include the WGSS and WSD variables. Finally, in the gross margin equation (Equation (8)), we add lag of gross margin GM<sub>it-1</sub> to control for firm-specific time-variant factors such as brand strength.

Each of the above three equations in our simultaneous model satisfies the sufficient rank condition that ensures our model is identified (Greene 2008, p. 365). The direct effect of the global sourcing strategy variables (WGSS and WSD) on inventory investment is captured by coefficients  $\alpha_{17}$  and  $\alpha_{18}$  in the inventory Equation (6) and the direct effect on the demand-cost composite measure, COGS, by coefficients  $\alpha_{25}$  and  $\alpha_{26}$  in the cogs Equation (7). The indirect effects of the sourcing strategy on inventory investment that operate via the cogs equation are  $\alpha_{11} * \alpha_{25}$  for the sourcing extent, and  $\alpha_{11} * \alpha_{26}$  for the sourcing dispersion, where  $\alpha_{11}$  is the direct effect of COGS on inventory investment (from Equation (6)). From a managerial insights point of view, firms are most interested in the holistic impact of the global sourcing strategy. The total effect is computed as the sum of direct and indirect effects.

In our data, we find strong support for the presence of endogeneity among the three simultaneous variables. The two-step endogeneity test (see Wooldridge 2006, pp. 532–533) suggests the presence of endogeneity in the inventory equation ( $p < 0.001$ ), the demand equation ( $p < 0.001$ ), and the gross-margin equation ( $p < 0.07$ ). This supports the use of our simultaneous equation modeling approach.

## 7. Results

We estimate the three-equation system one by one using the two-stage least squares (2SLS) single-equation method (see Greene 2008, pp. 371–375). We use the error component two-stage least square (EC2SLS; Baltagi and Liu 2009) estimator to estimate the coefficients ( $\alpha_{11}, \dots, \alpha_{33}$ ). This is a matrix-weighted estimator of the fixed-effect estimator and the between estimator, i.e., the estimator uses both the within-firm variation (using the fixed-effect estimator) and the cross-sectional variation (using the between estimator) of explanatory variables. This estimator is particularly suited to “smaller” panels and it outperforms the generalized two-stage least square estimator (Baltagi and Liu 2009).<sup>12</sup>

<sup>11</sup> Our results are robust to using an alternate measure of firm size, the number of employees.

<sup>12</sup> Baltagi and Liu (2009) show that the variance of the two estimators differs by a positive-semi definite matrix. Although this difference reduces as the sample size tends to infinity, the difference can

**Table 3** Model Estimates

No.	Variables	Panel A: Base model			Panel B: + Global sourcing share			Panel C: + Supplier diversification		
		Inventory equation	COGS equation <sup>a</sup>	Margin equation	Inventory equation	COGS equation <sup>a</sup>	Margin equation	Inventory equation	COGS equation <sup>a</sup>	Margin equation
1	<i>W-Global Sourcing Share (WGSS)</i>				0.019***	−0.026***		0.026***	−0.036***	
2	<i>W-Supplier Diversification (WSD)</i>							−0.129***	0.216***	
3	<i>Cost of Goods Sold (COGS)</i>	0.300***		−0.049***	0.319***		−0.049***	0.342***		−0.048***
4	<i>Gross Margin (GM)</i>	0.135***	−0.748***		0.111***	−0.737***		0.116***	−0.754***	
5	<i>Average Inventory (AINV)</i>		0.103***	0.029***		0.130***	0.029***		0.135***	0.029***
6	<i>Lag Avg Inventory (AINV')</i>	0.721***			0.693***			0.681***		
7	<i>Capital Intensity (CapInt)</i>	0.014*			0.014*			0.018**		
8	<i>Demand Uncertainty (DU)</i>	0.029***			0.017*			0.009		
9	<i>Sales Surprise (SS)</i>	0.091			0.087			0.064		
10	<i>Product Variety (PV)</i>				0.017***			0.017***		
11	<i>Lag Cost of Goods Sold (COGS')</i>		0.200***			0.172***			0.151***	
12	<i>Sales, General &amp; Admin (SGA)</i>		0.624***			0.625***			0.634***	
13	<i>Lag Gross Margin (GM')</i>			0.938***			0.938***			0.938***
14	<i>N_observations</i>	1,661	1,661	1,661	1,661	1,661	1,661	1,661	1,661	1,661
15	<i>N_firm</i>	177	177	177	177	177	177	177	177	177
16	<i>Within R<sup>2</sup> (%)</i>	68	86	2	70	87	2	71	87	2
17	<i>B/w R<sup>2</sup> (%)</i>	98	96	99	98	96	99	98	96	99
18	<i>Overall R<sup>2</sup> (%)</i>	94	95	93	94	95	93	94	95	93

<sup>a</sup>The dependent variable is *COGS*, which proxies for demand.

\*10% level; \*\*5% level; \*\*\*1% level.

Table 3 provides the estimated values for the coefficients in the three equations that constitute our model. Panel A shows the estimation results for the three constituent equations in a base model. This model is provided for comparison with past studies and as such excludes our two focal global sourcing strategy variables (*WGSS* and *WSD*) and the product variety control variable (*PV*). It is reassuring to note that our three-equation model supports the simultaneous dependence that required using it—all the endogenous dependencies turn out to be significant (rows 3–5 of Table 3). Specifically, as predicted by inventory theory and supported by empirical research on inventory investment, we find that inventory investment increases with an increase in demand/costs (*COGS*) and in margins (*GM*). The cost of goods sold decreases with margins but increases with inventory, indicating a demand stimulation effect of inventory. Lastly, our estimated system shows that gross margins decrease with the increasing cost of goods sold, but increase with inventory. This suggests that firms may be partially leveraging the demand stimulation effect of higher inventory levels by increasing the margins charged to buyers.

Panel B adds the extent of global sourcing (*WGSS*) and the product variety control variable (*PV*) to the

model, and panel C shows our full model, which includes both the extent of global sourcing and the degree of supplier dispersion (*WGSS* and *WSD*). In the full model, we find that the estimation results of various control variables, in each of three equations, are largely in line with the past studies. We find positive and significant impact of product variety on inventory investment (Rajagopalan 2013) and of marketing expenditures (*SGA*) on demand (Kesavan et al. 2010). Also, as expected, we find that the lagged variables significantly explain the variance in the respective dependent variables. Interestingly, we find a positive and significant effect of capital intensity that is in contrast to previous work (Gaur et al. 2005). Although previous work had conceptualized capital intensity as a proxy for supply chain and information technology investments that might reduce inventory, we suspect that it also includes other investments (such as additional warehouses) that may increase inventory while increasing supply chain responsiveness. Among the remaining control variables, we do not find significant support for impact of demand uncertainty and sales surprise.<sup>13</sup> From here on, we focus on the estimation results of our main global sourcing variables in panel C.

With respect to our main results, we find a positive and significant direct effect of global sourcing share

still be very substantial in small samples such as our panel data. Thus, in our case, the EC2SLS estimator is more efficient. The Stata command *xtivreg, ec2sls* is used for estimating each of the three equations in our model.

<sup>13</sup> When we use the conventional single equation relative inventory model specification, in line with past research, these variables also turn out to be significant (see §8 for more details).

on inventory investment ( $\alpha_{17} = 0.026$ ); all else being equal, a firm that sources more globally invests more in inventory. However, there are also indirect effects that we discuss shortly. We find a negative and significant direct effect of supplier dispersion on inventory investment ( $\alpha_{18} = -0.129$ ); all else being equal, a firm with a more dispersed sourcing strategy invests less in inventory.

The effects of the global sourcing strategy on demand/costs are opposite. In particular, the extent of global sourcing has a negative effect on COGS ( $\alpha_{25} = -0.036$ ), which suggests that increased global sourcing does indeed reduce the cost of goods sold. At the same time, the extent of supplier dispersion has a positive effect on COGS ( $\alpha_{26} = 0.216$ ), which suggests that a more concentrated supplier base leads to a lower cost of goods sold.

The coefficients shown in Table 3 capture the direct effect of the extent and dispersion of global sourcing on inventory investment and on the cost of goods sold. In addition to these direct effects, we must consider the indirect effects that arise out of concomitant changes in the cost of goods sold due to changes in the extent and dispersion of global sourcing. We follow Baron and Kenny (1986) in computing the size and significance of these indirect effects. To test our main hypotheses, we need to compute the aggregated impact of the direct and indirect effects, the “total effect,” and we developed a bootstrap procedure to compute the significance of this total effect that is based on the sample distribution of the total effect statistic.<sup>14</sup> For each total effect, we run 1,000 repetitions of our estimation, embedded in the bootstrap. We ensure that our bootstrapped sample has the same relative share of observations from wholesalers and retailers in each simulation run.<sup>15</sup> We provide the computed indirect and total effects in Table 4.

The indirect effect of the extent of global sourcing on inventory ( $\alpha_{11} * \alpha_{25} = -0.012$ ) is negative and significant; however, the total effect of increased global sourcing on inventory investment is positive and significant (0.014). This suggests that the effect of higher inventory levels associated with global sourcing, dominates the competing effect of decrease in per-unit procurement costs. Therefore, our results support Hypothesis 1B (§3.1): *firms that employ more global sourcing have higher inventory investments*, despite lower costs of inventory.

<sup>14</sup> This definition of total effect allows us to capture first-order indirect effects. An alternative approach would be to also capture higher-order indirect effects. Our analysis reveals that the cumulative sum of all higher-order indirect effects is 2.56% and 1.18% of the first-order indirect effect for WGSS and WSD, respectively.

<sup>15</sup> The following Stata command is used: bootstrap, reps(1000) strata (NAICS\_2\_DIGIT\_CODE).

**Table 4** Direct, Indirect, and Total Effects on Inventory Investment

Variables	Direct effect	Indirect effect <sup>a</sup>	Total effect <sup>b</sup>
<i>W-Global Sourcing Share (WGSS)</i>	0.026***	−0.012***	0.014***
<i>W-Supplier Diversification (WSD)</i>	−0.129***	0.074***	−0.055***

<sup>a</sup>Computed as per Baron and Kenny (1986).

<sup>b</sup>Bootstrapped errors; see text for details.

\*\*\*1% level.

The indirect effect of the supplier dispersion variable on inventory investment is positive and significant ( $\alpha_{11} * \alpha_{26} = 0.074$ ); however, the total effect of increased dispersion on inventory investment is negative (−0.055). This demonstrates that the benefits of supplier diversification, such as lower expected lead time and more reliable supply chain, etc. dominate the disadvantages, which include loss of economies of scale and bargaining power. Therefore, our results support Hypothesis 2A (§3.2): *firms with more dispersed supplier base have lower inventory investments*.

## 8. Robustness Tests

We test the robustness of our results at two key levels. First, we estimate multiple alternative versions of our three simultaneous equations model by examining alternative ways to construct variables, alternative equation specifications, as well as alternative estimators, plus we use only subsamples of our data. Second, to compare our results with past research, we estimate the traditionally used single-equation relative inventory model and its many variants. In our extensive robustness analysis, we continue to find very strong results that support the above conclusions.

### 8.1. Alternative Formulations of the Simultaneous Equations Model

In Table 5, we show the results of alternative estimates. Columns 1, 2, and 3 show, respectively, the estimated direct, indirect, and total effects of the extent of global sourcing on inventory investment. Columns 4, 5, and 6 show the same effect for the supplier dispersion variable. For benchmarking purposes, we place the original estimates (Tables 3 and 4) in row 1. Each subsequent row provides estimates for a different robustness check.

*Alternative Variable Constructions.* The accuracy of demand forecasts is a key driving variable for inventory investment. As empiricists, we have no way of knowing the true demand forecasts of the firms, and therefore we begin robustness checks by constructing alternative measures for sales surprise (SS) and demand uncertainty (DU) variables. First, we compile analysts’ forecast data from the

**Table 5** Alternative Formulations for the Three Simultaneous Equations Model

No.	W-Global Sourcing Share			W-Supplier Diversification			No. of obs. (firms)	Robustness test description
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect		
Original assumptions								
1	0.026***	−0.012***	0.014***	−0.129***	0.074***	−0.055***	1,661 (177)	EC2SLS matrix-weighted estimator of between- and fixed-effects estimators
Alternate variable construction								
2	0.021***	−0.010***	0.011***	−0.139***	0.052***	−0.087***	1,276 (141)	Sales forecast measure constructed using I/B/E/S analyst forecast data
3	0.023***	−0.013***	0.010***	−0.119***	0.071***	−0.048***	1,711 (185)	Noncyclical demand uncertainty measure
4	0.023***	−0.010***	0.013***	−0.094***	0.050***	−0.044***	1,589 (171)	30-day lag for measuring <i>WGSS</i> and <i>WSD</i>
5	0.023***	−0.010***	0.012***	−0.118***	0.062***	−0.056***	1,601 (177)	Supplier dispersion measure constructed using annual level supplier ties
6	0.023***	−0.010***	0.012***	−0.117***	0.074***	−0.043**	1,661 (177)	Supplier dispersion in sourcing measured at country level
7	0.026***	−0.014***	0.012*	−0.131***	0.084***	−0.047**	1,661 (177)	Gross margins over sales
Alternate specification for inventory equation								
8	0.025***	−0.012***	0.013***	−0.131***	0.071***	−0.060***	1,661 (177)	Without sales surprise covariate
9	0.028***	−0.014***	0.014***	−0.141***	0.080***	−0.061***	1,661 (177)	Without demand uncertainty covariate
10	0.022***	−0.010***	0.012***	−0.115***	0.065***	−0.050***	1,661 (177)	With sales growth covariate
Sub samples								
11	0.027***	−0.002***	0.025***	0.004	0.036***	0.040***	586 (61)	Wholesalers (NAICS two-digit code 42)
12	0.029***	−0.037***	−0.008***	−0.241***	0.202***	−0.039***	1,075 (116)	Retailers (NAICS two-digit code 44-45)
13	0.022***	−0.011***	0.011***	−0.105***	0.070***	−0.035***	1,766 (180)	Reconstruction of panel data with supplier information threshold < 20%
14	0.033***	−0.015***	0.018**	−0.136***	0.088***	−0.048***	1,429 (168)	Subsample with number of routes <i>M</i> > 1
Alternate estimators								
15	0.058***	−0.019***	0.039***	−0.358***	0.022	−0.336***	1,661 (177)	Three-stage least square (3SLS) estimator
16	0.038***	−0.023***	0.015***	−0.220***	0.042***	−0.178***	1,661 (177)	Fixed-effects estimator
17	0.009	−0.006***	0.003***	−0.065***	0.042***	−0.023***	1,661 (177)	Generalized two-stage least square (G2SLS) random effects estimator

\*10% level; \*\*5% level; \*\*\*1% level.

Thomson Reuters Institutional Brokers Estimate System (I/B/E/S) database (along the same lines as Gaur et al. 2007). The I/B/E/S database covers 151 of the 177 firms in our panel. Typically, more than one analyst tracks a firm's performance, so we have multiple forecasts for each firm quarter. Suppose  $ASF_{ik}$  is the  $k$ th analyst forecast of  $i$ th firm's sales for quarter  $t$ . We construct the sales forecast measure as the mean of the multiple forecasts available for firm  $i$  in quarter  $t$ ,  $SF_{it} = (\sum_{k=1}^{M_{it}} ASF_{ik})/M_{it}$ , where  $M_{it}$  is the number of analysts tracking the firm. We use the difference in opinions of analysts to construct a demand uncertainty measure,  $DU_{it} = (\sum_{k=1}^{M_{it}} (ASF_{ik} - (1/M_{it}) \sum_{k=1}^{M_{it}} ASF_{ik})^2 / M_{it})^{0.5}$ , that is the standard deviation of the multiple forecasts for firm  $i$ 's sales in quarter  $t$ . Finally, we calculate the sales

surprise as  $SS_{it} = REV_{it}/SF_{it}$ . Estimation results using these new proxies are shown in row 2. For a quarter, the difference between the sales forecast and the realized sales for a firm is also a proxy for the demand uncertainty for the firm in that quarter. In row 3, we show the results in which the demand uncertainty variable is computed as the difference between sales forecast and realized sales, i.e.,  $DU_{it} = |SF_{it} - REV_{it}|$ . We apply the linear trend sales forecast method to compute  $SF_{it}$ .

In row 4, we show the results of estimation using alternative measures for the global sourcing share (*WGSS*) and supplier dispersion (*WSD*). It is conceivable that imports in a quarter may not get sold in the same quarter, which may induce measurement error in the *WGSS* and/or *WSD*. To test whether our



results are sensitive to this, we perform a robustness test in which we counted a firm's imports over the period that preceded the firm's fiscal quarter period by 30 days (approximately half of the average inventory holding period). The WGSS and WSD measures are recomputed using imports in this preceding window. Further to control for edge effects, we include a control variable  $LAGIMPORT_{it}$  that measures imports that are done during this 30 day gap. We normalize this variable for scale and include it in the inventory equation.

As described in §5, we construct the supplier dispersion measure by counting import allocation across suppliers at the quarter level and by assuming the supplier's establishments in two different countries as two distinct suppliers. We test the robustness of our findings by relaxing these assumptions. Row 5 shows the estimation results using an annual level measure of supplier dispersion constructed by counting import allocations across suppliers over a year (i.e., four quarters). In row 6, we show estimation results using a supplier dispersion measure constructed by assuming all suppliers in a country as a single supplier. This provides a measure of dispersion in sourcing at the country level that provides an alternative measure for sourcing characteristics such as exchange rates, expected lead times, and geopolitical risk. Finally, in row 7, we show results of estimation using an alternative definition of gross margins constructed as the ratio of gross profits over sales (Gaur et al. 2005).

*Alternative Specifications.* We test alternative specifications for the inventory equation by excluding variables from it. Rows 8 and 9 show the results of models in which sales surprise (SS) and demand uncertainty (DU) are removed. Furthermore, Rumyantsev and Netessine (2007) proposed that using the sales growth rate variable (measured as  $SALGRW_{it} = COGS_{it}/COGS_{it-1}$ ) that impacts investment in inventory indirectly, i.e.,  $SALGRW$  has a second-order effect on inventory investment because of the deterministic trend in sales (see Rumyantsev and Netessine 2007, p. 422). Row 10 shows the results when  $SALGRW$  is included as an additional control variable in the inventory equation.

*Different Subsamples.* Rows 11 and 12 show the estimation results based on subsamples of wholesalers and retailers. Further, as we describe in §4.2, when aggregating transaction-level data to the firm-quarter level, we only included those firm quarters in which the supplier information was known for more than 80% of the import transactions. In row 13, we show the estimation results obtained when a threshold of 20% is used (other thresholds yield qualitatively similar results). We note that our measure of WGSS ignores the impact of lead times when the number of distinct routes  $M$  employed by a firm in a quarter equals one. In our sample, we find that  $M = 1$  for

about 14% observations (232 of 1,661). To test whether our results are sensitive to these observations, we estimate our model using a subsample that excludes these observations in row 14.

*Alternative Estimators.* Row 15 shows the results obtained by applying the three-stage least square (3SLS) system estimator to our model in (Equations (6)–(8)).<sup>16</sup> The 3SLS estimator captures the full information structure available within the data set to estimate the coefficients. We also estimate our model with the fixed-effects estimator (row 16), and a generalized 2SLS random-effects estimator (row 17).

To summarize, across the 16 robustness tests described above, we confirm the positive and significant direct impact of the extent of sourcing on inventory investment for 15 of 16 alternative robustness tests. The indirect effect is confirmed to be negative and significant across all 16 tests. The total effect is positive and significant across 13 tests. The direct effect of supplier dispersion is negative and significant across 15 tests. The indirect and total effects are significant across 14 tests. In some cases, we note an expected decrease in significance, especially when smaller samples are involved. Further, our coefficient signs are always consistent, with just two exceptions of insignificant estimates in 96 tests. Taken together, these robustness tests strongly reinforce and confirm our main findings.

In addition to the robustness tests reported in Table 5, we also performed numerous other alternative estimations to test our findings. A few notable ones are estimation using unweighted measures of global sourcing share and supplier dispersion, an alternative construction of the WGSS measure using purchases instead of COGS to scale imports, where  $Purchase_{it} = COGS_{it} + INV_{it} - INV_{it-1}$ , an alternative specification of inventory and cogs equation wherein a separate lead times measure  $WLT$  is included along with the unweighted measure of global sourcing share  $GSS$  in place of  $WGSS$ , an alternative specification of the cogs equation wherein product variety  $PV$  is included to control for its impact on demand (Kadiyali et al. 1998), and an alternative sector-specific definition of quarter-level dummies to control for sector-specific seasonality in imports as observed in Figure 2. Across all these tests we continue to find strong support for our main findings.

## 8.2. The Traditional Relative Inventory Investment Model

In existing work on inventory level, a single-equation model is often estimated with the relative inventory

<sup>16</sup> In Stata, we run the estimation using the `reg3` command after transforming our data set for fixed-effect (within) estimation using the Stata command `xtdata, fe`.

**Table 6** Estimates from the Relative Inventory Investment Model

	Original assumptions			Alternate variable construction		Alternate specification		Subsamples		Alternate estimators	
	Base 1	+ WGSS 2	+ WSD 3	I/B/E/S 4	30-day lag 5	Without sales surprise 6	With sales growth 7	WS (42) 8	RS (44–45) 9	GLS 10	Swamy– Arora 11
<i>InvToCOGS</i>											
WGSS		0.025***	0.031***	0.022***	0.026***	0.034***	0.027***	0.018	0.039***	0.031***	0.031***
WSD			−0.157***	−0.124***	−0.136***	−0.168***	−0.141***	−0.112***	−0.190***	−0.169***	−0.170***
GM	0.197***	0.156***	0.164***	0.098*	0.198***	0.175***	0.148***	0.147	0.145***	0.191***	0.192***
CAPINT	0.040	0.041	0.041	0.075***	0.024	0.094*	0.095*	−0.046	0.075*	0.058	0.058
SS	−0.747***	−0.591***	−0.584***	−0.900***	−0.706***		−0.494***	−0.629***	−0.457***	−0.574***	−0.574***
DU	−0.070***	−0.070***	−0.071***	−0.015***	−0.066***	−0.059***	−0.036***	−0.011	−0.068***	−0.071***	−0.071***
PV		0.006	0.014	0.002	0.01	0.014	0.007	−0.005	0.008	0.020**	0.020**
SG							−0.326***				
No. of obs.	1,682	1,675	1,675	1,281	1,604	1,675	1,675	589	1,086	1,675	1,675
No. of firms	178	178	178	141	173	178	178	61	117	178	178
Within $R^2$ (%)	29	25	26	32	34	17	43	32	31	26	26
B/w $R^2$ (%)	17	24	26	37	23	28	28	28	8	27	28
Overall $R^2$ (%)	19	23	27	37	26	28	30	28	12	29	29

Note. WS, wholesalers; RS, retailers; GLS, generalized least squares.

\*10% level; \*\*5% level; \*\*\*1% level.

level as a dependent variable. Following Rumyantsev and Netessine (2007), we measure the relative inventory level of firm  $i$  for quarter  $t$  as  $RINV_{it} = AINV_{it}/COGS_{it}$ . Conceptually, the relative inventory measure embeds the indirect effect of the global sourcing strategy on inventory investment because of its impact on the demand and unit procurement cost and, consequently, it captures the total effect. Although such a formulation makes it hard to accurately distill the impact of global sourcing on inventory investment ( $AINV$ ) from its impact on demand and cost ( $COGS$ ), we nevertheless expect the directional impact of our global sourcing variables on the relative inventory level to be the same as that of the total effect obtained for these variables from the three-equation model: firms that employ more global sourcing should have a *higher* relative inventory level, and firms with a more distributed supplier base should have a *lower* relative inventory level.

To verify these effects, we control for previously identified salient variables and our additional control variable for product variety ( $PV$ ), and we estimate the impact of the extent and dispersion of global sourcing ( $WGSS$  and  $WSD$ ) on the relative inventory ( $RINV$ ) using the following multiplicative model:

$$\begin{aligned} \log RINV_{it} = & \alpha_1 \log GM_{it} + \alpha_2 \log CAPINT_{it-1} + \alpha_3 \log SS_{it} \\ & + \alpha_4 \log DU_{it} + \alpha_5 \log WGSS_{it} + \alpha_6 \log WSD_{it} + \alpha_7 \log PV_{it} \\ & + F_i + \beta_{1s} q_s + \tau_{1r} y_r + \epsilon_{it}, \end{aligned} \quad (9)$$

where  $F$ ,  $q$ , and  $y$  are dummy variables to control for firm, quarter, and year-level effects, respectively. We test the specification using firm-level fixed-effects estimation and we assume a cluster-correlated error

structure that allows for a firm's global sourcing strategy to depend on other unobservable firm-specific characteristics.<sup>17</sup>

Table 6 shows estimation and robustness results for the relative inventory model. The first three columns provide the single-equation model results with stepwise addition of our variables of interest. Columns 4–11 demonstrate the results of eight different robustness tests of the single-equation relative inventory model as follows:

*Models with Alternative Variable Construction.* Column 4 of Table 6 shows the estimation results when the sales surprise ( $SS$ ) and demand uncertainty ( $DU$ ) measures are constructed using the I/B/E/S data set. Column 5 shows the estimation results when the  $WGSS$  and  $WSD$  are computed using firm imports over a window that precedes the firm's fiscal quarter by 30 days (see §8.1 for details).

*Alternative Variables.* In column 6, we show the results obtained after dropping the sales surprise ( $SS$ ) variable from the main specification. In column 7, we show the results obtained after including sales growth ( $SALGRW$ ) as an additional control.

*Subsamples.* Columns 8 and 9 show the results for estimation performed using the subsample data of wholesalers and retailers separately.

*Alternative Estimators.* We supplement our main results using two firm-level random-effects estimators. Column 10 shows the results with the consistent generalized least square random-effects estimator. Column 11 shows the results obtained with the Swamy–Arora estimator for small samples (Swamy and Arora 1972).

<sup>17</sup> We use the Stata command `xtreg, fe vce(cluster firmid)` to run the estimation.

In the full model (columns 3–11), consistent with the past studies, we find positive and significant coefficient for gross margin, and negative and significant coefficient for sales surprise. Similar to the estimation results of simultaneous equation model (Table 3), in certain specifications we find positive and significant coefficient for capital intensity, which is in contrast to past studies (see the discussion in §7). However, compared to the simultaneous equation model results there are two interesting departures. One, although the estimate of the product variety is positive, it loses significance in a majority of specifications. Perhaps the positive impact of product variety on demand (Kadiyali et al. 1998) leads to this drop in significance as the dependent variable in these specifications captures a firm's inventory level relative to its demand. Second, we find that the coefficient of demand uncertainty is negative and significant. This is in contrast to what the theory predicts, but it is consistent with the results obtained by Rumyantsev and Netessine (2007) for the retail sector, which constitutes about 65% of observations in our panel data. This intriguing departure merits future research and investigation. From here on, we focus on the first two rows of Table 6, which show the impact of the extent and dispersion of global sourcing (WGSS and WSD) on inventory investment.

We find a positive and significant impact of the extent of global sourcing on the inventory investment variable across eight out of nine potential relative inventory models described above. Further, in *all* nine relative inventory models, we find significant support for a decrease in inventory investment with the increase in supplier dispersion. These results are in line with the insights derived from the absolute inventory three-equation system and provide further support for our main findings. We note that, like the absolute inventory model, the relative inventory model can potentially have an endogeneity effect because of simultaneous determination of margins and relative inventory level. However, we do not find support for such an endogeneity in our data. The two-step endogeneity test (see Wooldridge 2006, pp. 532–533) fails to reject that there is no endogeneity in the relative inventory model with  $p = 0.65$ .

## 9. Managerial Implications

### 9.1. Economic Significance of Effects

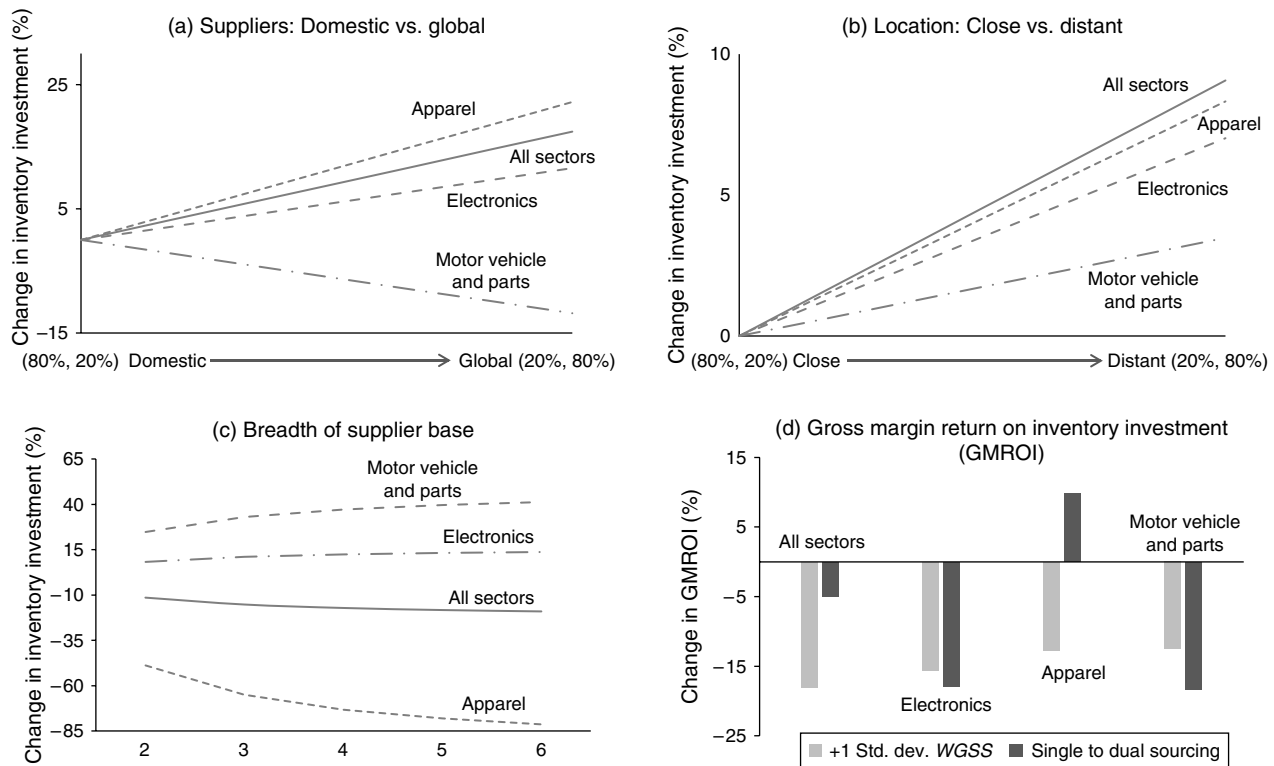
Our results highlight that a company increasing its global sourcing must be prepared to see more capital tied up in inventory unless it simultaneously increases the diversity of its supplier base. To understand the economic significance of our estimation results, we performed several counterfactual experiments. Our measure of global sourcing WGSS, captures both the extent of global sourcing and the lead

time mix of the global supplier portfolio. We first study the marginal impact of these two constituents, examining scenarios in which one variable changes but the other is kept fixed. A typical firm in our sample that shifts 10% of its sourcing from domestic to global suppliers, while keeping the original mix and share of global locations, will require 8.8% higher inventory investments, which corresponds to US\$104 MM more in the capital tied up in inventory. Figure 4(a) elaborates this effect for three industry segments: apparel, electronics, and motor vehicles and parts and illustrates the expected change in inventory investments when a firm shifts from 80% domestic sourcing to as much as 80% global sourcing. Like the typical firm, firms in the apparel and electronics sector experience an increase in inventory, but motor vehicles and parts firms are atypical. Differences between the input costs, scale, and specialization of local and global suppliers can perhaps explain this effect.

Next, we consider a typical firm that sources from two equal-cost locations:<sup>18</sup> a close location C, with a lead time of 18 days, which is typical of sourcing from Mexico to the U.S. East Coast, and a distant location D with a lead time of 53 days, which is typical of sourcing from China to the U.S. East Coast. Figure 4(b) illustrates the change in inventory as the firm moves from a “80% close–20% distant” mix of its global sourcing to the opposite scenario “20% close–80% distant.” An increase in the share of the distant location by 10% increases the firm's inventory investment by 1.51% but the impact varies across industry segments. For example, firms in the apparel, electronics, and auto sectors suffer less than the average firm does on account of a shift to distant locations.

Finally, we calculate the impact of the increase in supplier dispersion by considering a hypothetical sole-sourcing firm. If such a firm adopts dual sourcing and distributes its business equally between two suppliers, we find a decrease of 11.40% (US\$134 M) in inventory investment (Figure 4(c)). Whereas increasing supplier dispersion can limit the inventory increase for apparel and typical firms, this is not the case for atypical sectors like electronics and motor vehicles. Perhaps the different levels of complexity for the products sourced by these industries explain the varying role of supplier dispersion between different sectors. These counterfactual experiments indicate that the two elements of the global sourcing strategy that we study, the extent of global sourcing and supplier portfolio management strategies, both have a high, economically significant impact on inventory investments. Awareness, estimation, and management of this impact is thus key to managing global sourcing.

<sup>18</sup> We use direct effect estimates here to capture equal cost locations.

**Figure 4** Examples of Managerial Implications

Apparel: NAICS 4243, 4481. Motor vehicle and parts: NAICS 4231, 4411. Electronics: NAICS 4236, 4251, 4431.

## 9.2. Global Sourcing and Operational Performance (GMROI)

Our estimates can also be used to predict the impact of a global sourcing on operational performance. We illustrate the application of our estimates to predict changes in gross margin return on inventory investment, a metric widely used by retailers that aggregates the profitability and inventory efficiency of the product assortment (Pradhan 2006), with all variables driven by sourcing strategy. Figure 4(f) shows the impact of changes in global sourcing on GMROI. We find that, for an average firm in our sample, the GMROI decreases with an increase in sourcing from global suppliers. The firm can partially defray this decrease by employing a higher supplier dispersion strategy. Although increases in global sourcing always decrease GMROI, the effectiveness of a high supplier dispersion strategy varies across industries.

## 10. Discussion

Our results provide the first empirical evidence linking firm-level global sourcing to inventory investments. Although there are well-established competing theories that relate global sourcing to inventory investments (e.g., longer lead times but lower purchase costs when sourcing globally), there is an open debate around the net impact of the extent and

dispersion of global sourcing on inventory investments. We find that more global sourcing leads to a higher inventory investment, and diversification among global suppliers leads to a lower inventory investment. Ignoring these investments may lead a firm to grossly overestimate the benefits of global sourcing or, even worse, to employ global sourcing with an inferior supplier dispersion strategy.

Our empirical analysis rigorously demonstrates the association between the global sourcing strategy employed by the firm and the inventory investment. There are three potential interpretations of this association. The effect on inventory investment could be interpreted as a result of the global sourcing strategy, as a cause of the global sourcing strategy, or alternatively, both global sourcing and inventory investment could be caused by some third variable, such as a firm characteristic, a time characteristic, or some firm-epoch varying economic characteristic such as margins, demand level, product variety, etc. Of these interpretations, the first, i.e., elements of the global sourcing strategy *cause* the change in inventory investment, seems most appropriate. Let us consider the other alternative explanations: potentially higher inventory investment causes firms to change their global sourcing strategy (reverse causality). For example, if firms have too much inventory, they might for some reason decide to change their supplier



management strategy. To us, this is less plausible than the explanation that it is the choice of supplier management strategy that impacts inventory investments. Further, if this were true, we would expect the effects to be less contemporaneous, but perhaps more with lags that are not found in our data. Another alternative explanation for our association relates to the existence of other variables that simultaneously influence both the inventory investment and the global sourcing strategy. Here, note that the inclusion of firm-level and time dummies exclude the possibility of any firm or time-specific variables serving this role. Further, the most viable candidates for this role are demand, margins, and assortment of product categories imported, which are all interdependencies that we explicitly include in our estimation model. Finally, we use our simultaneous equation model to control for the indirect relationship between global sourcing strategy and inventory investment via the global-sourcing-induced changes in demand and procurement costs.

Taken together, these arguments suggest that although the latter two explanations are somewhat plausible, they are far less probable than the explanation that our observed association, in fact, represents a causal effect. While only a controlled experiment can unambiguously establish contemporaneous causality, in the light of the above arguments we feel quite confident in proposing here that an increase in global sourcing *causes* an increase in inventory investment, an increase that can be mitigated by supplier diversification.

Although the data that we analyze are extremely rich, limitations around the generalizability of our empirical results apply. First, we only study public firms, firms that are required to report their inventory investment. It is possible that private firms have different global sourcing strategies and consequences. Second, despite our efforts to identify all import transactions, it is possible some smaller transactions are not accurately recorded in customs manifests. If the misreporting or underreporting of imports is substantial and systematic, our results may be biased. The key problem here is correct identification of foreign suppliers, which are numerous and there does not exist precise data about them. Third, although we have detailed transactional data on global sourcing, we have only quarterly financial data, which limits our analysis. Fourth, our data has a very short horizon of just three years, which happens to cover the financial crisis. As such, it is very difficult for us to study the impact of global sourcing on financial performance of companies, or to understand the original reasons for global sourcing. Relaxing all of these restrictions offers viable avenues for future research.

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