Recovering Global Supply Chains from Sourcing Interruptions: The Role of Sourcing Strategy

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Problem definition: Fast recovery from sourcing interruptions is a key objective for global supply chains and for business continuity professionals. In this paper, we study the impact of different supply chain strategies—supplier diversification and the use of long-term relationships—on the ability of a supply chain to recover from sourcing interruptions.

Academic/Practical relevance: Improving supply chains' recovery ability has been an important focus area for both practitioners and academics. Collectively, available anecdotal evidence and theoretical analyses provide ambiguous recommendations driven by competing effects of different sourcing strategies. Our paper provides the first rigorous and large-scale empirical evidence relating the use of different supply chain strategies to the ability of a supply chain to recover from supply-interruptions.

Methodology: We develop a compound estimator of a supply-chain's recovery rate that can be constructed using limited available data (only the time series of firms' actual sourcing behavior). Using more than two and half million import manifests, we extract firms' maritime sourcing transactions and we use this data to estimate recovery rates of different firm-category supply chains of publicly traded US firms.

Results: We find that supplier diversification is associated with slower recovery from sourcing interruptions, while the use of long-term relationships is associated with faster recovery. A one standard deviation decrease in the former is associated with a 16% faster recovery, and a like increase in the latter is associated with a 20% faster recovery.

Managerial implications: Our paper brings important empirical evidence to the hitherto theoretical debate on the impact of sourcing strategies on faster recovery in supply chains. We therefore provide actionable advice on supply chain design for faster recovery.

Key words: supply chain, sourcing interruption, supplier diversification, long-term relationships, empirical analysis, time to recovery

1. Introduction

The complexity and diversity of global supply chains exposes them to a variety of logistical, natural, geopolitical and industrial events that can temporarily constrain sourcing (for example: labor strike (Lopez 2017), political activity (Victory 2011), and industrial accidents (Simchi-Levi et al. 2014) have all led to interruptions in sourcing for firms). In addition to these supply-side incidents, demand-side interruptions — either a huge surge or abysmal drop — can also lead to a gap between what a firm want to source and what is actually able to source. Many of these events occur for reasons beyond the firm's control, and little can be done to alter their frequency; however, good supply chain management practices can reduce the negative consequences of such interruptions. For example, a more resilient supply chain may be able to recover faster from an interruption, returning to its native state sooner than a less resilient one. It is for this reason that building resilient and faster-recovering supply chains has been a key focus of such world-beating firms as Toyota and Cisco, among many others (SCDigest, 2012).

Improving supply chain resilience has likewise been a long-time focus of theoretical analyses of supply chains (see for example Wang et al. (2010) and the references therein). Fast-recovering supply chains have also received significant attention in the popular press (Sheffi 2005, Simchi-Levi et al. 2014). Anecdotal evidence is provided for the role of sourcing practices, with supplier diversification and the use of long-term relationships identified as key strategies that influence the recovery-rate of a supply chain. It is worth noting that neither the theoretical analyses nor the anecdotal accounts provide clear recommendations for practitioners; theoretical explanations and anecdotal evidence can be found for competing effects of these strategies. For example, supplier diversification is cited as a way to build alternate supply sources, even though the strategy of volume-leverage—which requires supplier concentration instead—is also recommended for incentivizing suppliers to make investments that facilitate faster recovery. Our paper provides the first rigorous and large-scale empirical evidence relating the use of different supply chain strategies to the ability of a supply chain to recover from supply-interruptions.

A serious challenge to the study of supply chain recovery is the limited availability of data. Any study based on public announcements of interruptions is likely to suffer from several limitations. First, public announcements and media reports are more likely to involve the most significant and newsworthy interruptions. As a result, such samples of interruptions will likely over-represent interruptions that arise due to weather and geopolitical events while under-representing much more numerous interruptions due to logistical and industrial accidents, supply bottlenecks, and the like. Second, and perhaps more importantly, whereas the occurrence of such events receives considerable

attention, the restoration of a supply chain is seldom announced by the firm, and is rarely covered by the press. For these reasons, directly compiling data on the time to recovery for a large representative sample of supply-chains is practically impossible.

An ideal metric for the recovery process would be based on high-frequency time-series data on what the firm wanted to source from each possible route (sea, air, etc.) and what it was actually able to source. The differences between the two—the mismatch—would reflect the effect of interruptions. The time to decay of the mismatch series is the metric of interest—the speed of recovery (or recovery rate). However, neither component of that metric—the firm's target or actual sourcing—is publicly available. We overcome these data challenges by building on the central notion of recovery that captures the ability of a firm to restore sourcing levels to their pre-interruption native state.[1] In other words, although as a near-term response to manage the interruption, a firm may rely on high-cost sourcing alternatives (such as air shipments or emergency sourcing from high-cost suppliers), yet optimally the firm would like to recover, at the earliest, to the pre-interruption native sourcing plan. Combining this notion with the growing availability of transaction-level data on maritime shipments (Jain et al. 2013), we study the role of different supply chain strategies in the recovery ability of a supply chain by focusing on the primary sea-based global sourcing routes.[2]

We compile a large-scale, high-frequency data set on the actual sea-based global sourcing of firms by using legislatively mandated public data on import transactions. This data set enables us to portray accurately the actual sourcing of different categories of imported goods by firms with global supply chains. We parse more than 60 million import manifests (bills of lading) issued during the period 2004–2011 to build a set of data on the actual sourcing of public US retail, wholesale, and manufacturing firms, greatly expanding such data used in previous work (Jain et al. 2013).[3]

The data issue related to unobserved information on the firm's sourcing target is more challenging to handle. To surmount this challenge, we extend existing models of inventory management to compute the optimal sourcing policy for a firm that faces uncertain demand and supply. The resulting model structure relates a firm's demand and supply patterns to its target sourcing, which has a

[1] In rare circumstances, an interruption can lead to a chance discovery of a new, better sourcing option, or to a rethink of overall strategy, hence deviating from the pre-interruption native state to a new preferred sourcing plan.

[2] Maritime freight accounts for 90% of ***all*** world trade (IMO 2008). In US, the land-based imports from Canada and Mexico account for 26% to 27% of total imports. Overall, maritime freight accounts for a larger share of the sourcing by US publicly traded firms. Public firms are larger than all firms, and larger firms tend to use more maritime routes. Further, US firms source largely from Asia, and the US–Asia route is more than 95% serviced by maritime freight. As such, our focus on maritime shipping gives us an accurate description of sourcing.

[3] Based on the total weight (in kilograms) of imports, our compiled data set is within 0.3% of the cumulative weight reported by the US Census Bureau.

specific form that enables construction of a recovery measure. Recall that we quantify sourcing interruptions as the difference between the target and actual sourcing, and we are especially interested in the *decay rate* of this difference or the recovery rate. We demonstrate under general conditions that one can use the time-series properties of the actual sourcing to construct a compound estimator of the recovery rate. The estimator can be used to retrieve the relationships between the supply chain's recovery rate and the firms' sourcing strategies when using appropriate controls, fixed effects and "augmented instruments" or instruments that satisfy an additional exclusion condition that accounts for the compound nature of the recovery rate estimator.

Next, we use our data on actual sourcing and the above estimation approach to link supply chain recovery to the extent of supplier diversification, the extent of long-term sourcing and the extent of sourcing from logistically efficient locations—all at the firm× category-of-sourced-goods level. We then identify the effects of the supply chain strategy on the supply chain recovery rate using instruments in a model that incorporates both firm and category fixed effects. Together, our approach eliminates biases due to unobserved endogenous firm characteristics (management's risk aversion, information system quality, etc.), unobserved endogenous category properties (seasonality of raw material supplies, complexity of imported goods, etc.), and those due to the use of the compound estimator of the recovery rate.

We find that supply chains with supplier diversification are, in fact, slower at recovering from interruptions than are supply chains with a more concentrated supplier base. On average, the volume and other benefits of supplier concentration outweigh those of diversification. A one standard deviation decrease in supplier diversification is associated with a 16% faster recovery to 99% of the supply-chain's native state. This finding complements theoretical research that identifies the beneficial effect of diversification on the *likelihood* of facing interruptions; diversification may reduce that likelihood (Sheffi 2005, Yang et al. 2012), but it also impedes the firm's recovery from those that do occur.

We also find that supply chains with long-term supplier-relationships recover faster from interruptions. A one standard deviation increase in the use of long-term relationships leads to a 20% faster recovery to 99% of the supply-chain's native state. We find no support for the impact of sourcing from logistically efficient locations on recovery. Our results persist in sector subsamples, under a variety of alternate variable constructions, and with use of alternate set of instruments.

This paper provides the first (to our knowledge) rigorous and large-scale empirical evidence relating supplier diversification and the use of long-term relationships to a global supply chain's time

to recover to its desired sourcing state. It brings important empirical evidence to the hitherto theoretical and anecdotal debate on the strategies to build fast recovering supply chains and also offers actionable evidence for supply chain managers and other business continuity professionals.

2. Literature Review

Our work is related to past empirical work on supply chain interruptions and also to theoretical work that has studied supply chain strategies for managing supply uncertainty.

The pioneering empirical work of Hendricks and Singhal (2005a,b) first identified the highly significant financial consequences of unreliable supply chains by focusing on disruptions and glitches at the firm level. DeHoratius and Raman (2008) and Mani et al. (2015) have studied supply uncertainty indirectly by quantifying the negative consequences of interruptions due to inventory record inaccuracy and under-staffing. Kalkanci (2017) shows, using controlled lab experiments, that buyers are more effective in managing unreliable suppliers with the single sourcing strategy compared to the dual sourcing strategy. There has not been much large-data research that investigates recovery from interruptions and remediation, but there is a large stream of case-based work. Sheffi (2005) defines the notion of "recovery" in this context and provides case-based evidence on the use of supplier diversification, sourcing with long-term relationships, redundant resources, and other supply strategies. Todo et al. (2015) use Japanese survey data to study the recovery time of firms after Japan's 2011 Tohoku earthquake. Simchi-Levi et al. (2014) employ the "time to recover" notion to identify vulnerabilities in the supply chain of Ford Motor Company. Our own paper's focus on recovery time follows this emergent trend in case-based research. In particular, we extend and facilitate rigorous study of this key measure by building an estimator based on public data and then using this estimator to provide the first large-data evidence on the relationship between recovery time and sourcing strategies.

The theoretical literature has analyzed a variety of operational strategies to deal with sourcing interruptions: dual or multiple sourcing (e.g. Yang et al. 2012), passive acceptance and inventory buildup (Tomlin 2006), and supply chain collaboration that improves supplier reliability (Wang et al. 2010). Iyer et al. (2005) study our key metric—recovery time—and its dependence on contractual arrangements and on the existence of alternate suppliers. Bendoly et al. (2016) study the effect of differences in suppliers' recovery-abilities on a retailer's sourcing policy. Although there is extensive theoretical literature on the relationship between operational strategies and sourcing interruptions, we offer the first empirical complement to this literature by providing large-data evidence that validates the existence—and compares the efficacy—of the mechanisms posited by theoretical work.

3. Theory and Hypotheses

Logistical, natural, geopolitical and industrial events can temporarily constrain a firm's sourcing, preventing a buyer firm from sourcing at desired levels. Such constraints to sourcing might persist for many time periods after the event. Reducing this time—that is, the time required to return the supply chain to its original, pre-interruption native state—is essential for limiting the financial effects of such interruptions. Strategic sourcing choices such as supplier diversification, building long-term supplier relationships, and choosing suppliers that are located in logistically efficient locations potentially play an important role in enabling faster recovery; we hypothesize on potential mechanisms and the direction of these effects next.

Diversified Sourcing

In the event of idiosyncratic supply-side interruptions, a diversified supplier base—i.e., a product being sourced from many different suppliers—allows a firm to shift sourcing from the affected suppliers to other suppliers. For instance, a March 2000 fire at the Philips manufacturing plant in Albuquerque, New Mexico, impacted supplies of radio-frequency chips to both Nokia and Ericsson. Nokia had access to other suppliers and was able to recover quickly; Ericsson could not do the same because its supplier pool was smaller (Sheffi 2005). Using multiple suppliers has the further advantage of creating competition that motivates suppliers to make investments that facilitate recovery, such as breakdown management procedures and backup capacity (Iyer et al. 2005).

That being said, sourcing from fewer suppliers—that is, from a less diversified supplier pool—also has some compelling advantages for recovery. If there are fewer suppliers then more will be purchased, on average, from each one. Higher purchase volumes give the buyer firm more leverage, which can be used to encourage investments in recovery and in securing additional sourcing after an interruption. Moreover, suppliers typically have varying ability to recover from interruption events (Bendoly et al. 2016). In this respect, having fewer suppliers makes it easier for the buyer firm to identify those that can recover most quickly from a supply interruption. In comparison, in a multi-supplier sourcing program the coordination complexity may hinder the recovery efforts.

In short, there are good reasons to prefer both fewer suppliers and more suppliers. Because the preferred strategy should depend on which set of mechanisms dominates, we offer two competing hypotheses as follows:

Hypothesis 1a. *Global supply chains with more diversified sourcing have* ***slower*** *recovery.*

Hypothesis 1b. *Global supply chains with more diversified sourcing have* ***faster*** *recovery.*

Long-Term Relationships

Irrespective of how many suppliers are used, the buyer firm can develop relatively deep or shallow relationships with those suppliers (Sheffi 2005).

Long-term relationships typically involve inter-temporal trade-offs (Beth et al. 2003) whereby some gains are forgone now so that more shared value can be created later. A supplier's capacity to make such trade-offs advantages both the supplier and the buyer firm in the aftermath of an event that interrupts supply. For instance, the affected supplier and/or other suppliers can work beyond their contractually obligated levels in the interests of faster recovery. In 1997, a major fire at an Aisin Corp. production facility interrupted the supply of P-valves to Toyota. Motivated by its strong relationship with the auto firm, Aisin collaborated closely with other members of the supply network to ensure Toyota a continuing supply of P-valves. The result was a much faster recovery than observed in the case of other, comparable events (Sheffi 2005).

Aligned incentives in long-term relationships have been shown to encourage value-enhancing investments. Some such investments can facilitate faster recovery; for example, the supplier may invest in recovery management equipment and backup capacity. Long-term relationships also facilitate information sharing, which is crucial for firms recovering from interruptions that originate with tier-2 or higher-tier suppliers. Improved information sharing (Ren et al. 2010) with the tier-1 supplier renders the buyer-firm to anticipate and remediate upstream interruptions.[4]

Although there are many advantages to long-term sourcing, there are some arguments against it. For one, long-term relationships can lead to supplier complacency (Anderson and Jap 2005). An assured stream of future business may disincentivize suppliers to invest in systems that foster fast recovery. Alternatively, long-term contracts may also bind a firm with a minimum or maximum purchase quantity per period which, in turn, constrains the firm's ability to quickly recover from past mismatches. Reflecting these positive and negative aspects of a long-term relationship, we conjecture two competing hypotheses as follows:

Hypothesis 2a. *Global supply chains with longer-term relationships have* ***faster*** *recovery.*

Hypothesis 2b. *Global supply chains with longer-term relationships have* ***slower*** *recovery.*

[4] According to the 2018 "supply chain resilience" survey conducted by the Business Continuity Institute, about half (48%) of interruptions occur at tier-2 or at other upstream tiers. The survey sample consisted of 589 business continuity specialists and other relevant respondents from 76 countries (bit.ly/3jY4C7r, accessed August 20, 2020).

Sourcing from Logistically Efficient Locations

Countries worldwide differ markedly in their logistics capabilities owing to their respective quality of infrastructure, different customs procedures, and varying complexity of the bureaucratic machinations involved with cargo transport (Hausman et al. 2005). Sourcing from suppliers based in the most logistically efficient countries may yield better supply chain performance under normal circumstances, but logistical efficiency can prove to be a double-edged sword when interruptions occur.

On the one hand, it is conceivable that the benefits of better infrastructure, fewer bureaucratic procedures, and other factors that increase the efficiency of a country's logistics services also help the firm to attain faster recovery. On the other hand, a rational response to efficiency and reliability is to *reduce* investment in redundant resources and to build lean, just-in-time systems. For instance, ports with low variability in customs clearance times need to build smaller storage areas and fewer redundant inspection facilities. Although redundant resources may seem like a burden in most circumstances, in the event of an interruption they can serve as a backup and provide some service continuity while the affected resources are being repaired or replaced. Thus, systems that are normally efficient and lean may be less capable (than more "redundant" systems) of dealing with perturbations and so take longer to recover (Hollnagel 2012):

Thus logistical efficiency is associated both with benefits and with costs with respect to recovery; thus, we make following competing hypothesis

Hypothesis 3a. *Global supply chains with a higher propensity to source from logistically efficient locations have* ***faster*** *recovery.*

Hypothesis 3b. *Global supply chains with a higher propensity to source from logistically efficient locations have* ***slower*** *recovery.*

4. Sample and Data Sources

We focus our study on US public firms covered by Standard & Poor's Compustat Industrial Quarterly database that are classified as manufacturing (NAICS sectors: 31-33), wholesale (NAICS: 42) or retail firms (NAICS: 44-45). These sectors are the primary participants in global sourcing (Bernard et al. 2009) and, as such, the relevant sample for our study. We exclude energy sector firms (NAICS: 324, 4247, 4543) from our sample. The procurement decisions at these firms are driven by commodity price variability, geopolitical risks and the buildup of strategic inventories. These primary

factors likely confound the supply chain structure-related impacts that are the focus of our study (Jain et al. 2013). We are left with just over 4,000 candidate firms.

Our data set is built primarily based on a proprietary transaction-level data set covering all US sea imports, which we combine with information on logistical efficiency—namely, shipping and customs clearance times—from the World Bank.

For a variety of robustness analyses, we also augment our data set with value of annual imports and exports at the level of imported goods category (HS Code[5]); extracted from the US Census Bureau online portal (usatrade.census.gov). Finally, we append data on sales (code: SALEQ) extracted from Standard & Poor's Compustat Industrial Quarterly database.

4.1. US Sea Imports Data

All US firms are required to report details of each sea import transaction to the Federal Customs and Border Protection Agency (Department of Homeland Security) using a document known as the *bill of lading*. This document is 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). As shown in Figure 1, the bill of lading includes transaction-specific information such as the supplier's (and buyer's) name and address, a description of the goods, and the quantity imported. We process such documents to construct our data on sourcing.

As in Jain et al. (2013), we use a commercial "supplier intelligence data service" to access bill of lading forms for *every* import transaction into the US. The sample in Jain et al. (2013) is based on import transactions by retail and wholesale firms in the period July 2007 to July 2010. Our study is based on a much more expanded sample; we add manufacturing firms to the sample and also expand the time-period to cover transactions from June 2004 to May 2011. We obtain more than 60 million bills of lading for imports during that seven-year period. The unindexed and unstructured nature of data in the bill of lading documents poses challenges related to uniquely identifying importing and supplier entities due to the use of various trade names, subsidiaries, widespread spelling mistakes, transliterated entries for non-English names, and so on. We follow Jain et al. (2013) to tackle these issues and extract supplier, goods-category (HS code) and value information for imports by our candidate firms. As in other studies on global sourcing (e.g., Bernard et al. 2009, Jain et al. 2013), we find that only a minority of candidate firms—1,549 out of over 4,000—actually participate in

[5] The Harmonized Commodity Description and Coding System is an international standardized system of names and numbers used to classify traded goods for purposes of assessment and customs. It was developed and is maintained by the World Customs Organization, an independent intergovernmental organization with over 170 member countries.

Bill of Lading	House/Master	Estimated Arrival	Mode of Transport
DMAL1SX061825	House	18/11/2009	11
Vessel: Ever Champion *(Code: 9293765)*	**Carrier:** DMAL **MC:** EGLV	**Actual Arrival:** 20/11/2009	**Voyage:** 031E
Shipper	**Consignee**	**Notify**	**Notify 2**
Epak Multi Products Factory, Jianlong Int'l Estale, Henggang Longgang district, Shenzhen, China, cs 0755-28621335	Texas Instruments, 7800 Banner drive, Dallas, TX 75251, US	Texas Instruments, 7800 Banner drive, Dallas, TX 75251, US	
Port: 57078 - Yantian, China	**Port:** 2704 - Long Beach Seaport, CA	**Weight:** 5131 (KG)	**HSCODE†:** 392310
Place Receipt: Yantian, China (cn) (Asia)	**US Dist Port:**	**Quantity:** 468 (PCS)	**Value†:** $12989
InBond:	**Foreign Port:**	**Measurement:**	**TEU:** 1.63
Container Number (Info)	**Product Description**	**Marks & Numbers**	
EISU9831031, FCIU2572469, FSCU9882017, TCKU9409536, TCNU9911615 (Qty: 1807, FCL)	468ctns on 46 plastic pallets 1. plastic boxes for ic/wafer shipment 2. plastic ring	epak	

† Similar to Jain et al (2013), we use the Journal of Commerce's Port Import Export Reporting Service to supplement imports data with proprietary data on the dollar value and component-cateogry of imported goods

Figure 1 Sample Bill of Lading

global sourcing. We split the seven-year data into groups of two-year (June 2004 to May 2006) and five-year (June 2006 to May 2011) periods. The sample for main analysis is constructed using the five-year data set. Altogether we obtain 2,037,459 import transactions for the 1,549 firms. The two-year data set (comprising of 814,983 transactions) is used for constructing lagged measures of sourcing strategies to test the robustness of the main findings.

4.2. Two Data Sets from the World Bank: Doing Business and Logistics Performance Index

Following Jain et al. (2013), we combine import transactions with data on sea-shipping distances (www.sea-distances.com) and the *Doing Business* data set (www.doingbusiness.org) from the World Bank to construct a measure of the lead time in each sourcing transaction. We use data on sea-shipping distances to compute shipping times between the supplier countries and US ports using an average continuous-travel ship speed of 14 nautical mph. The *Doing Business* data set provides customs clearing time for 152 countries, accounting for 81% of the transactions in our sample. We are left with 1,670,378 transactions for which the sourcing lead time can be derived.

Finally, to each import transaction, we assign a score based on the source country's performance in terms of logistic efficiency. These data are also obtained from the World Bank, which makes public its Logistics Performance Index (LPI) data set (lpi.worldbank.org).

5. Recovery Rate: Definition and Estimation

5.1. Supply Chain Recovery Rate

Mismatches between a firm's target sourcing and its actual sourcing arise due to interruptions affecting tier-1 suppliers or any one of the multiple suppliers in upstream tiers (Li et al. 2015). Furthermore, the effect of an individual interruption often lasts multiple periods. So in a given period, the mismatch between a buyer firm's sourcing desire and ability depends not only on the joint effect of interruptions in all upstream suppliers during that period, but also on the spillover effects due to all such interruptions in preceding periods.

Formally, we conceptualize sourcing interruptions in terms of the mismatch between the desired sourcing quantity q_t and the quantity actually delivered d_t. This mismatch, $m_t \equiv q_t - d_t$, is the net result of all contemporaneous sourcing interruptions in the supply chain and the spillover of such mismatches in preceding periods. Given the many supply- and demand-side factors contributing to this mismatch, we model the contemporaneous effect of interruptions ζ_t as a sequence of independent and identically distributed (i.i.d.) random variables drawn from a *normal* distribution with variance σ_m^2. Without loss of generality, we normalize its mean to zero $\zeta_t \sim N(0, \sigma_m^2)$. We also assume that the effects of past interruptions spill over to subsequent periods at a stationary rate $\alpha \in (0,1)$. Thus,

$$\begin{aligned} m_t &= \sum_{s=0}^{t-1} \alpha^{t-s} \zeta_s + \zeta_t, \\ &= \alpha m_{t-1} + \zeta_t. \end{aligned} \tag{1}$$

Here the first term (αm_{t-1}) captures the spillover from previous periods, and the second term (ζ_t) captures any new interruptions.

Clearly, the spillover rate α is a measure of how long supply is constrained due to a supply-interrupting event. Higher (resp. lower) values of α correspond to an interruption's effects lasting a long (resp. short) time; for example, $\alpha = 0$ implies a near instantaneous recovery whereas $\alpha \to 1$ implies that the effect of the interruption persists indefinitely. Hence we define a supply chain's *recovery rate* as $R = 1 - \alpha$. Our subsequent analysis develops a model that demonstrates, under very general conditions, that the firm's profits are increasing in the recovery rate—a finding that reinforces the intuitive and theoretical appeal of this measure. Furthermore, the recovery rate R measures ability to restore sourcing, across all suppliers, to the pre-interruption level and is not tied to restoring sourcing from a particular (or a set of) supplier(s). We shall now address the issue of estimating a supply chain's recovery rate.

5.2. A Compound Estimator for the Recovery Rate of a Supply Chain

The most direct way of estimating the recovery rate would be to infer it from time-series observations of the mismatch process. Although one element of the mismatch process, the quantity delivered (d_t) is observable to the empiricist, the desired sourcing quantity (q_t) is not observable to any external party. Thus, direct observation of the mismatch process across different firms in a large-scale data set is simply not possible. Yet, as we will demonstrate shortly, under reasonable assumptions, it is still possible to construct a compound estimator of the recovery rate that is based only on the observation of the delivered-quantity time-series.

The missing component—that is, the desired sourcing quantity—is not entirely unknown because it actually follows a certain structure. Namely, it is the quantity the firm should acquire to maximize its profits when both demand and supply are uncertain (the latter because of supply-side interruptions). We therefore extend the general analysis of optimal inventory management policies under uncertain demand from Chen and Lee (2009) to the case of uncertain demand *and uncertain supply*. Doing so reveals some structural regularities in the process for sourcing desired supply levels. Combining the process for desired sourcing with the mismatch process (1) imparts unique properties to the delivered-quantity process that facilitate construction of a compound estimate of recovery rate.

The Desired Sourcing Quantity Consider a firm that sources while facing uncertain demand and uncertain supply. At every sourcing instance t: (i) the firm places an order q_t, and (ii) the supplier(s) deliver quantity d_{t-L-1}, which is based on the quantity ordered $L+1$ periods ago (here L is the lead time) and on the interruption-induced mismatch; thus $d_{t-L-1} \equiv q_{t-L-1} - m_{t-L-1}$. Finally, the demand D_t is realized and the inventory on hand is used to meet that demand. Any unmet demand is backlogged and the firm incurs a penalty cost of p dollars per unit of backlogged demand. Leftover inventory has a per-period holding cost of h dollars per unit. This sequence of order replenishment, order arrival, and demand realization follows widely studied periodic review models of inventory management (Cachon and Terwiesch 2009).

Following Gaur et al. (2005), we assume that demand is an autoregressive moving-average (ARMA) process—ARMA(p,q) for $p,q \geq 1$—that unfolds as follows:

$$D_t = \mu + \theta_1 D_{t-1} + \cdots + \theta_p D_{t-p} + \epsilon_t + \phi_1 \epsilon_{t-1} + \cdots + \phi_q \epsilon_{t-q}, \tag{2}$$

where μ is the process mean, ϵ_t is an i.i.d. normal demand shock of mean zero and variance σ_D^2, the θ_i are the autoregressive coefficients, and the ϕ_i are the moving-average coefficients. The autocorrelation structure of the demand and mismatch process implies that, in each time period, the firm

partially learns about the future demand and the mismatch extent using respective contemporaneous shocks. The firm can leverage this partial learning to make inventory replenishment decisions based on a class of stationary and affine *generalized order-up-to policies* or GOUTP (Chen and Lee 2009, Bray and Mendelson 2015). Under these policies, partial knowledge of future demand and mismatch levels is mapped onto order-up-to levels using a time-invariant and linear (affine) mapping structure. Formally, under these properties, the order-up-to level for a period t is:

$$S_t = K + \sum_{i=1}^{\infty} \boldsymbol{w}_i^T \boldsymbol{\epsilon}_{t-i} + \sum_{i=1}^{\infty} \boldsymbol{w}_i'^T \boldsymbol{\zeta}_{t-L-1-i}, \tag{3}$$

where K is a constant, $\boldsymbol{w}_i$ and $\boldsymbol{w}_i'$ are the constant time-invariant weight vectors ($\boldsymbol{w}_i^T = [w_{i1}, w_{i2}, \ldots]$, $\boldsymbol{w}_i'^T = [w_{i1}', w_{i2}', \ldots]$) for $i > 0$ and where $\boldsymbol{w}_0 = 0$ (notational assumption), and $\boldsymbol{\epsilon}_t$ and $\boldsymbol{\zeta}_t$ are forecast revision vectors for demand and for interruption-induced mismatches, respectively. The demand revision vector is $\boldsymbol{\epsilon}_t = [\epsilon_{t,t}, \epsilon_{t,t+1}, \epsilon_{t,t+2}, \ldots]$, the mismatch revision vector is $\boldsymbol{\zeta_t} = [\epsilon_{t,t}, \epsilon_{t,t+1}, \epsilon_{t,t+2}, \ldots]$, and $\epsilon_{t,s}$ is the new information learned about demand in subsequent periods $s \geq t$ through the realized demand shock in period t. Finally, $\zeta_{t,s}$ is the equivalent quantity for the mismatch.

We follow Chen and Lee (2009) in assuming that the forecast revision vectors $\boldsymbol{\epsilon}_t$ and $\boldsymbol{\zeta_t}$ are i.i.d. with respective multivariate and normal distributions $N(0, \Sigma_\epsilon)$ and $N(0, \Sigma_\zeta)$ and respective variance–covariance matrices $\Sigma_\epsilon = E\{\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t^T\}$ and $\Sigma_\epsilon = E\{\boldsymbol{\zeta}_t \boldsymbol{\zeta}_t^T\}$. Finally, given the vast geographical separation between a firm's global suppliers and its customer locations, we assume that demand ϵ and mismatch shocks ζ are mutually independent.

The optimal GOUTP terms $(K^*, \boldsymbol{w}_i^*, \boldsymbol{w}_i'^*)$ are such that they minimize the firm's long-run average cost:

$$C([K, \boldsymbol{w}_i, \boldsymbol{w}_i']) = E\left[h\left(\left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right) - \sum_{i=0}^{L} D_{t+i}\right)^+ + p\left(\sum_{i=0}^{L} D_{t+i} - \left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right)\right)^+\right], \tag{4}$$

where $\left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right)$ denotes the inventory available to meet the demand $\sum_{i=0}^{L} D_{t+i}$ during a replenishment cycle. $\sum_{i=0}^{L} m_{t-L-1+i}$ denotes the *cumulative* interruption-induced mismatch between ordered and delivered quantities over the replenishment cycle.

Proposition 1. *Optimal Ordering Policy under Uncertain Demand and Uncertain Supply.*

1. *The cost-minimizing optimal policy parameters are*

$$[K^*, \boldsymbol{w}_i^*, \boldsymbol{w}_i'^*] = \left[(L+1)\mu + z\sqrt{\triangle_u^D + \triangle_u^m}, \sum_{j=i+1}^{i+L+1} e_i, \sum_{j=i+1}^{i+L+1} e_i\right],$$

   where $z = \Phi^{-1}(p/(h+p))$, $\Phi(\cdot)$ *is the standard normal distribution function,* $\triangle_u^D = Var(\sum_{i=0}^{L} \sum_{j=0}^{i} \epsilon_{t+i-j,t+i})$, *and* $\triangle_u^m = \sigma_m^2 \cdot \left(\sum_{i=0}^{L} \left(\sum_{k=0}^{i} \alpha^i\right)^2\right)$.

2. *The optimal long-run average cost is*

$$C([K^*, \boldsymbol{w}_i^*, \boldsymbol{w}_i'^*]) = (h+p)\phi(z)\sqrt{\triangle_u^D + \triangle_u^m},$$

   where $\phi(\cdot)$ *is the standard normal density function.*

3. *The firm's optimal long-run average cost C^* is increasing in the spillover rate α; that is, $\frac{\partial C^*}{\partial \alpha} > 0$ for all $\alpha \in (0,1)$.*

PROOF: All proofs are provided in the Appendix.

Part (1) of the proposition shows that, similar to a safety stock buffer against demand uncertainty $\triangle_u^D$ (see Chen and Lee 2009), the buyer firm maintains additional inventory $\triangle_u^m$ to buffer against the supply side uncertainty on account of interruptions. The level of this supply-side safety stock $\triangle_u^m$ is increasing in the spillover rate α. In turn, such increases raise the firm's long-run average cost $C^*(\cdot) = (h+p)\phi(z)\sqrt{\triangle_u^D + \triangle_u^m}$; this is the gist of parts (2) and (3) of the Proposition. Thus we have formal validation that our intuitive measure of the recovery rate does, in fact, relate directly to the firm's financial performance in a predictable way.

Though the abovementioned recovery rate metric provides an important measure for supply chain recovery that directly affects long-term cost, it is important to realize that supply chain recovery is a multidimensional notion. For example, a complementary approach to the current recovery rate focus could be to measure post-interruption recovery efforts in terms of mitigating losses proportional to the extent of supply deviation. Likewise, we focus on the cost-minimization objective. Alternatively, a firm may prefer to focus on demand-side performance measures such as fill-rate and, thus, may prefer recovering to pre-interruption production plan rather than the pre-interruption sourcing level.

The Compound Estimator Note that the demand and mismatch process signals (ϵ and ζ) are deeply embedded into the delivered-quantity series through the order-up to levels S (Equation 3), demand D and mismatch extent m at different time instances. This interlinking makes identification of the recovery rate using the delivered-quantity series challenging. Nevertheless, the delivered-quantity series has two properties that are particularly salient and the key to identification of the recovery rate.

PROPOSITION 2. *Under the optimal policy parameters $[K^*, \boldsymbol{w}_i^*, \boldsymbol{w}_i'^*]$, the following statements hold.*

1. *The delivered quantity $d_t = q_t - m_t$ evolves as an ARMA(p', q') process: $d_t = \mu' + \gamma_1 d_{t-1} + \cdots + \gamma_{p'} d_{t-p'} + \eta_t + \phi_1 \eta_{t-1} + \cdots + \phi_{q'} \eta_{t-q'}$.*
2. *The coefficient of the first autoregressive term is the sum of the corresponding term in the demand process θ_1 and the spillover rate α: $\gamma_1 = \theta_1 + \alpha$.*

Careful examination and manipulation of the delivered-quantity time-series reveals that interlinked demand and mismatch signals can be disentangled, and the delivered-quantity series can be reformulated as the sum of two independent ARMA series. This reformulation is at the center of the proof of Proposition 2.

A careful reading of part (2) of Proposition 2 will reveal that γ_1, the first autoregressive term, includes the recovery rate ($R = 1 - \alpha$) and the AR(1) parameter of the demand series θ_1. This first autoregressive term γ_1 can be estimated from data by identifying the ARMA model that best fits the time-series observations of the delivered quantity (Box et al. 2013). Let $\bar{\gamma}_1$ denote the estimated value of γ_1 in this best-fit ARMA model. Now, $\bar{R} = 1 - \bar{\gamma}_1 = 1 - \bar{\alpha} - \bar{\theta}_1$ is a "compound-estimator" of the recovery rate as it includes the direct estimator of the recovery rate $\bar{R}_{DM} = 1 - \bar{\alpha}$ and the demand autocorrelation coefficient $\bar{\theta}_1$.

Here, it is important to note that the compound estimate does not allow for *any* direct comparison of supply chains with respect to their *recover* abilities since it also includes a demand parameter. Nevertheless, we can estimate the relationship between a supply-chain's recovery-rate and its sourcing strategies, albeit with some identification challenges. Essentially, the compound estimate poses challenges similar to those involved in regressions on a dependent variable with a measurement error (Roberts 2011). We next show how we overcome these challenges.

5.3. Estimation Strategy with Compound Estimator: Augmented Instruments

The presence of the demand autocorrelation coefficient θ_1 in the recovery rate measure may result in biased estimation of the relationship between a supply-chain's recovery-rate R and its sourcing strategies. Consider the following simple specification to estimate the impact of sourcing strategy S on the recovery rate R

$$R = \psi_0 + \psi_S S + \psi_X \boldsymbol{X} + \delta, \tag{5}$$

where $\boldsymbol{X}$ is the vector of relevant covariates, including fixed effects. With the direct measure, the relationship between the sourcing strategy and recovery rate could be simply estimated without bias as:

$$\psi_S \rightarrow \hat{\psi}_S^{OLS(\bar{R}_{DM})} = \frac{\mathrm{Cov}(\tilde{\bar{R}}_{DM}, \tilde{S})}{\mathrm{Var}(\tilde{S})}, \tag{6}$$

where $\tilde{\bar{R}}_{DM}$ and $\tilde{S}$ are the residuals of the respective regressions of $\bar{R}_{DM}$ and S on the covariates $\boldsymbol{X}$. On the other hand, with the compound estimator of recovery rate $\bar{R}$ we get:

$$\begin{aligned} \hat{\psi}_S^{\prime OLS(\bar{R})} &= \frac{\mathrm{Cov}(\tilde{\bar{R}}, \tilde{S})}{\mathrm{Var}(\tilde{S})} \\ &= \psi_S - \frac{\mathrm{Cov}(\tilde{\bar{\theta}}_1, \tilde{S})}{\mathrm{Var}(\tilde{S})}, \end{aligned} \tag{7}$$

by substituting $\bar{R} = \bar{R}_{DM} - \bar{\theta}_1$ and eq (6). Eq (7) implies that estimated coefficient would be biased *if* there is a correlation between the residual demand autocorrelation parameter $\tilde{\theta}_1$ and the residual sourcing strategy $\tilde{S}$, i.e., when $\text{Cov}(\tilde{\bar{\theta}}_1, \tilde{S}) \neq 0$. We next illustrate how we can still recover unbiased relationships by using variables akin to instruments in a typical setting.

Consider a variate Z that is correlated with the residual sourcing strategy but uncorrelated with the unexplained component of the recovery-rate δ *and* the residual demand autocorrelation parameter. That is, this "augmented instrument" must satisfy an additional exclusion condition—no correlation with the residual demand autocorrelation–in addition to the usual conditions for an instrument. Formally, the augmented instrument Z satisfies $\text{Cov}(Z, \tilde{S}) \neq 0$ (relevance) and *two* exclusion conditions: $\text{Cov}(Z, \tilde{\theta}_1) = 0$ and $\text{Cov}(Z, \delta) = 0$.

An IV estimation of $\tilde{\bar{R}} = \psi'_0 + \psi'_S \tilde{S} + \delta'$ using augmented instrument Z can estimate the relationships without bias:

$$\begin{aligned} \hat{\psi}_S^{\prime IV(\bar{R})} &= \tfrac{\text{Cov}(\tilde{\bar{R}}, Z)}{\text{Cov}(\tilde{S}, Z)} \\ &= \tfrac{\text{Cov}(\tilde{\bar{R}}_{DM}, Z)}{\text{Cov}(\tilde{S}, Z)} - \tfrac{\text{Cov}(\tilde{\bar{\theta}}_1, Z)}{\text{Cov}(\tilde{S})} \\ &= \psi_S, \end{aligned} \tag{8}$$

since $\text{Cov}(Z, \tilde{\theta}_1) = 0$, $\bar{R}_{DM} = \psi_1 + \psi_S \tilde{S} + \delta$ and $\text{Cov}(Z, \delta) = 0$.

To summarize, one can use the properties of the delivered-quantity series to construct a compound estimator of the recovery rate of a supply chain.[6] Estimation with the compound recovery-rate estimator may result in biased estimates *when* the covariates included in the regression model do not account for all the sources of correlation between the autocorrelation in a firm's demand for a category of goods and its sourcing strategy in that category. Nevertheless, use of appropriate covariates and augmented instruments can be used to compute unbiased estimates of the relationship between the recovery rate and supply chain strategies. We identify such augmented instruments and covariates in subsequent analysis.

6. Variable Construction

We construct all variables at the firm×category level, where the category of the sourced good is coded using the 3-digit Harmonized System (HS) code (e.g., HS code 521 which denotes "woven cotton fabric" based components, HS code 950 denotes "toys, games and equipment", etc.).

[6] Our estimator estimates a supply chain's recovery ability with a measurement error around it. So, the estimator cannot be used, for example, to rank supply chains as per their recovery abilities.

6.1. Compound Measure of Recovery Rate

We start by building the monthly time series of the delivered quantity—measured as weight (kilograms) imported—of each category of sourced good using information from each firm's bills of lading. We limit our sample to firms and categories for which (i) we have at least two years of data and (ii) there are *fewer* than five instances of two or more consecutive zero-import months during our five-year study period (June 2006 to June 2011). There are 1,675 such firm×category supply chains in our data set. We identify the best-fit ARMA model for each such delivered-quantity time series in three steps as follows (following Box et al. 2013).

First, we remove any trends and seasonality to obtain the corresponding stationary series.[7] We test for stationarity of the transformed series via the augmented Dickey–Fuller (ADF) unit root test, and we include only those supply chains for which the null hypothesis of a non-stationary series can be rejected with a p-value of 10% or less. There are 1,614 such stationary series. The drop in 3.6% of firm×category supply chains due to the presence of non-stationary elements can be attributed to multiple scenarios, including instances where an interruption led to a chance discovery of a new, better sourcing option, thus, resulting in a permanent change in sourcing strategy. Similarly, obligations of minimum quantity procurement under long-term contracts can also embed non-stationary elements as these obligations would effectively yield a flat delivered-quantity series.

In the second step, we iterate over different values of (p', q') to identify the ARMA(p, q) model that minimizes the Akaike information criterion (AIC). Finally, we test for whether the estimated residuals of the best-fit ARMA model amount to white noise via the portmanteau (Q) test and exclude supply chains for which the likelihood of white-noise residuals is rejected with a p-value of 10% or less. This step leaves us with 1,463 series.

Our empirical model will include firm- and category-level fixed effects, so we restrict our final sample to firms with at least three category supply chains and to categories that are sourced by at least three firms. Our final sample consists of 1,008 firm×category supply chains. The recovery rate variable $\bar{R}$ is measured as $1 - \bar{\gamma}_1$, where $\bar{\gamma}_1$ is obtained from the identified best-fit ARMA model. Figure 2, Panel (a) shows the distribution of this measure. In Table A1 of the online appendix, we compare distribution of firms and categories included in the regression sample vis-a-vis universe of all firms and categories observed in our 5-year imports dataset. We find that regression sample comprises of firms from all sectors and products from all categories except for HS 1 that refers to livestock and animal products. Such a wide representation in regression sample mitigates the concern of our findings being relevant to only selective industry sectors and product categories.

[7] We obtain the stationary delivered-quantity series $\tilde{d}_t$ using a linear trend model: $d_t = \alpha_0 + \alpha_1 t +$ month-level dummies $+ \tilde{d}_t$.

6.2. Diversification

We operationalize the extent of supplier diversification SD_{fc} in firm f's supply chain for category c as the temporal average of dispersion in monthly imports. Our category-level measure enables us to capture the notion of diversifying sourcing of a given part (and not that of the overall spend) across multiple suppliers. Dispersion in imports is measured as one minus the Herfindahl index based on share of imports (by value) across suppliers. Further, often a supplier's establishments in different countries function as independent profit centers, resulting in establishment-level business engagement for a buyer firm. So we treat a supplier's establishments in two different countries as two distinct suppliers. Formally:

$$\text{Herfindahl Index}_{fct} = \sum_{j=1}^{\mathrm{N}_{fct}} \left(\frac{\text{Supplier Import Value}_{fctj}}{\text{Cumulative Import Value}_{fct}} \right)^2, \tag{9}$$

$$\mathrm{SD}_{fc} \equiv \frac{1}{|\mathrm{NZ}_{fc}|} \sum_{t \in \mathrm{NZ}_{fc}} \left(1 - \text{Herfindahl Index}_{fct}\right),$$

where N_{fct} is the total number of suppliers from which category c is sourced by firm f in month t, Supplier Import Value_{fctj} are the imports by firm f from supplier j, Cumulative Import Value_{fct} is the total value of imports under category c, NZ_{fc} is the set of indices for months with nonzero imports in the supply chain's time-series data, and $|\cdot|$ is used to denote the cardinality of a set. Here, we would like to note that the SD measure captures diversification only among the global suppliers and not the overall diversification that would be determined by the domestic sourcing strategy.

6.3. Long-Term Relationships

We measure the longevity of the relationships LR_{fc} in firm f's supply chain for category c, as the across-supplier average of the longevity of a supplier–component relationship. That longevity is simply measured as the ratio of the number of months in which the category is sourced from the supplier to the total number of months in which the category is sourced from any supplier:

$$\mathrm{LR}_{fc} \equiv \frac{1}{\mathrm{NS}_{fc}} \sum_{j=1}^{\mathrm{NS}_{fc}} \frac{\text{Count of Nonzero Supplier Imports Month}_{fcj}}{\left|\text{Count of Nonzero Imports Month}_{fc}\right|}, \tag{10}$$

where NS_{fc} is the total number of suppliers from which category c is sourced by firm f, Count of Nonzero Supplier Imports Month_{fcj} is the total number of months in which category c is sourced from supplier j, and Count of Nonzero Imports Month_{fc} is the total number of months in which category c is imported by firm f from any supplier.

6.4. Logistically Efficient Locations

We operationalize the use of logistically efficient locations (LEL) in a firm f's supply chain for category c as the temporal average of the weighted average of the World Bank's Logistics Performance

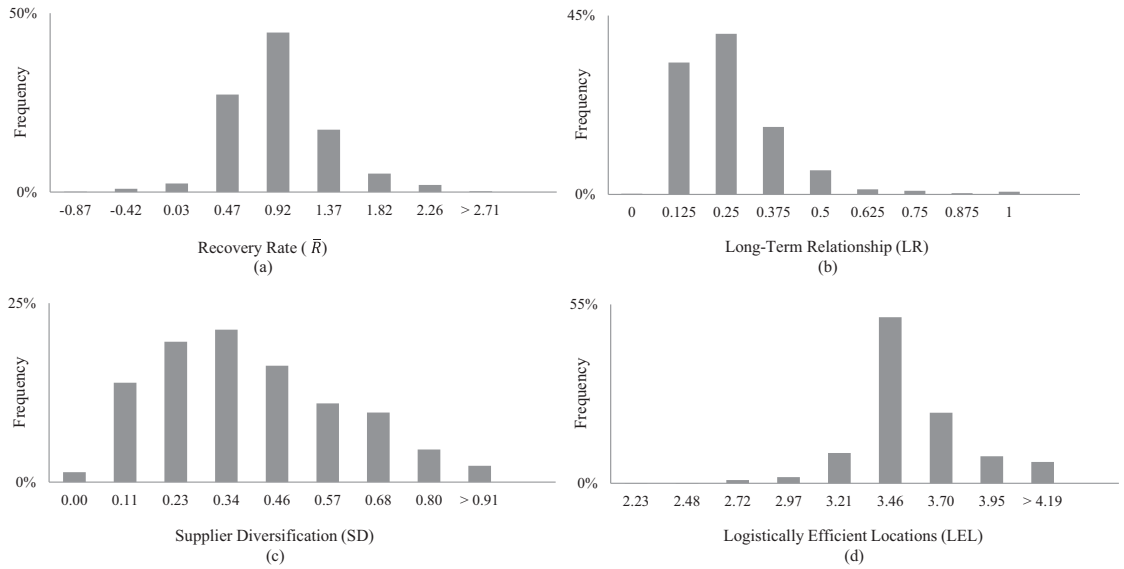


Figure 2 Sample Distribution of Recovery and Sourcing Strategy Variables

Index for different sourcing locations, where the respective weights are set equal to the values of imports from each location. Thus we have

$$\text{Month Level Logistics Efficiency}_{fct} = \sum_{j=1}^{\text{SL}_{fct}} \frac{\text{Supplier Import Value}_{fctj} \times \text{Logistics Performance Index}_{jt}}{\text{Cumulative Import Value}_{fct}},$$
$$\text{LEL}_{fc} \equiv \frac{1}{|\text{NZ}_{fc}|} \sum_{t \in \text{NZ}_{fc}} \text{Month Level Logistics Efficiency}_{fct}, \tag{11}$$

where SL_{fct} is the number of sourcing locations (countries) from which category c is sourced by firm f in month t and where Logistics Performance Index$_{jt}$ is the performance index's rank value for location j in month t. During our 2006–2011 study period, the World Bank compiled Logistics Performance Index surveys in 2007 and 2010. We use the rank value from the 2007 survey for categories imported during 2006–2009 and use the 2010 survey for all subsequent months.

Figure 2, Panels (b)-(d) show the distribution of supply chain strategy variables. Except for the long-term relationship variable, which has a log-normal distribution in our sample, all other variables have distributions close to the normal distribution. In addition to these main explanatory variables, we include a control variable on sourcing lead time because an increase in such time can constrain recovery efforts and, also, drive the endogenous choice of diversification sourcing strategy.

6.5. Control Variable: Sourcing Lead Time

We measure the sourcing lead time (SLT) of firm f's supply chain for category c as the weighted average lead time of different sea routes, where the weights are set equal to the respective imports'

		All		Manufacturing		Retail/Wholesale	
		1,008 Firm × Components		458 Firm × Components		550 Firm × Components	
Variables		**Mean**	**S.Dev**	**Mean**	**S.Dev**	**Mean**	**S.Dev**
Recovery Rate (R)	-	0.69	0.44	0.66	0.45	0.72	0.43
Supplier Dispersion (SD)	*ratio*	0.34	0.21	0.29	0.20	0.37	0.2
Long-Term Relationship (LR)	*ratio*	0.20	0.14	0.28	0.16	0.14	0.08
Logistcally Eff. Locs (LEL)	#	3.44	0.26	3.55	0.29	3.34	0.19
Sourcing Lead Time (SLT)	*months*	1.10	0.21	1.01	0.21	1.18	0.18
# Component Categories per Firm	#	7.10	5.38	5.26	2.97	10	6.9
# Firms per Component Category	#	15.05	12.38	7.39	6.84	9.02	8.1
Number of firms	#	142		87		55	
Number of products	#	67		62		61	

Table 1 Summary Statistics

values over the focal route. Following Jain et al. (2013), we define a *sea route* as a pair—consisting of a supplier country and a US port—and we measure the *lead time* of a sea route as a sum of (i) the average time required to obtain customs clearance in the supplier country and (ii) the travel time based on the sea route's distance. Customs clearance times are obtained from the *Doing Business* data set maintained by the World Bank. Travel time is computed based on the sea distance between US port and supplier country (obtained from www.sea-distances.com) and an average transport ship speed of 14 nautical mph. Formally,

$$\text{Month Lead Time}_{fct} = \frac{1}{30} \sum_{j=1}^{\text{SR}_{fct}} \frac{\text{Supplier Import Value}_{fctj} \times \text{Lead Time}}{\text{Cumulative Import Value}_{fct}},$$

$$\text{SLT}_{fc} \equiv \frac{1}{|\text{NZ}_{fc}|} \sum_{t \in \text{NZ}_{fc}} \text{Month Lead Time}_{fct},$$

where SR_{fct} is the number of sea routes over which category c is sourced by firm f in month t, and Lead Time_{jt} is the lead time associated with the sea route j.

6.6. Variables: Summary Statistics

Table 1 provides summary statistics of the recovery rate and the sourcing strategy variables in our final sample. The sourcing strategy variables differ along the expected lines between manufacturing and trading (retail/wholesale) firms: on average, manufacturing firms source fewer categories, have less diversified supply chains, and build more long-term relationships than do trading firms. The correlation between our metrics for sourcing lead times and logistically efficient locations is on the higher side (0.62), probably driven by the presence of customs clearance time in both of these variables. This suggests that potential multicollinearity issues may bias us against finding effects for these two variables. Notably, the correlation between the supplier diversification metric SD and the long-term relationship metric LR is low (<0.2). So, at any level of supplier diversification, the

firms in our data set exhibit wide variation in their choice of long-term relationship, thus enabling separate identification of impacts of diversification and relationship length.

7. Model Specification and Results

7.1. Model and Identification

We test our hypotheses using a firm×category-level model that includes both firm and category fixed effects, i.e., with a two-way fixed effects model:

$$\overline{\mathrm{R}}_{fc} = \beta_0 + \beta_1 \mathrm{SD}_{fc} + \beta_2 \mathrm{logLR}_{fc} + \beta_3 \mathrm{LEL}_{fc} + \beta_4 \mathrm{SLT}_{fc} + \mathrm{F} + \mathrm{C} + \psi_{fc}. \tag{12}$$

where f and c are the firm and category indices. F and C are firm and category dummies, respectively. The relationship variable is included with a log-transformation as its distribution was found to be log-normal (see Figure 2, Panel (b)).

The inclusion of firm and category fixed effects ensures that our estimates do not suffer from an endogeneity bias on account of either unobserved endogenous firm (for example, management's risk aversion, information system quality, etc.) or category-level characteristics (for example, seasonality in the supply of a raw material, complexity of imported goods, etc.) that could affect both the sourcing strategy and the recovery rate. In addition to these two fixed effects, we also control for sourcing lead time SLT as it likely influences recovery rate and may also be driving the choice of sourcing strategy. For example, an increase in sourcing lead time is expected to make it harder for a firm and its suppliers to coordinate after an interruption, resulting in delayed recovery. An increase in sourcing lead times might also lead the firm to diversify its supplier base, given that sourcing from multiple suppliers reduces the variability in realized lead times (Ramasesh et al. 1993). Taken together, these covariates provide a comprehensive control for a supply chain's aspects that can jointly influence its recovery rate and sourcing strategy choices.

7.2. Augmented Instruments

Recall from Section 5.3 that our augmented instruments must satisfy three conditions: (i) they should be correlated with the unexplained components of sourcing strategy that they are instrumenting (relevance); (ii) they should be uncorrelated with the unexplained components of the recovery rates (exclusion 1); and (iii) they should be uncorrelated with the unexplained component of the autocorrelation coefficient of the sourcing need or demand for the category (exclusion 2). The first two are the standard conditions, while the third arises due to the use of compound recovery rate measure.

Our instruments follow the tradition in past literature of constructing instruments using other units in the data that are adjacent to the focal unit, yet further away (e.g., Berry et al. 1995, Suarez

et al. 2013). Thus, in our context, we use the average sourcing strategy of the neighboring categories as an instrument for the focal category supply chain. In our sample, we find that firms typically import multiple categories with distinct part characteristics. For example, we find that the average distance (measured as a difference between the largest and smallest 3-digit HS code) between the imported categories is 292, and for half of the firms this distance is greater than or equal to 210. Specifically, we instrument the supply chain strategy $S \in \{SD, LR, LEL\}$ employed in the focal firm×category by the aggregate strategy employed in other categories by the same firm:

$$Z_{fc}^{S} = \frac{1}{|NC_f| - 1} \sum_{i \in NC_f \setminus \{c\}} S_{fi},$$

where NC_f is the set of component indices for firm f and $|\cdot|$ denotes the cardinality of the set $(\cdot)$.

The strategies employed by a firm in the focal firm×category likely bear resemblance to those employed by the firm in other categories. While large firms (like those in our data set) often allow sourcing-category managers to employ somewhat different sourcing strategies for different categories of products, there are typically some broad guidelines and limits on these choices that a group of category managers should follow. These guidelines ensure that our instruments are related to the sourcing strategy for the focal variable. Empirically, we find this to be the case, our instruments turn out to be highly relevant, as reported in subsequent sections.

Next, while firms might have some common guidelines, the degree of specialization typical of modern suppliers, and our use of broad 3-digit HS codes to identify categories, ensures that the different categories are sourced from very different suppliers, often in different countries. For example, the sample includes firms that import quite distinct categories such as "*Essential oils and resinoids; perfumery; cosmetic or toilet preparations*" (HScode: 330) and "*Textiles, made up articles, sets, worn clothing and worn textile articles, rags*" (HScode: 630). This ensures that the unexplained component of the recovery rate for a firm×category supply chain (that is, the part that is not captured by firm, category fixed effects and controls) is unlikely to be correlated with the recovery rate for a different category of products (thus, satisfying the exclusion 1 condition). Likewise, the sourcing strategy for other categories is unlikely to be correlated with the demand auto-correlation for the focal products (thus, satisfying the exclusion 2 condition). For example, how a firm sources "essential oil" category products is unlikely to be correlated with the unexplained component of the autocorrelation in that firm's demand for "textiles" category products, or the unexplained component of the recovery rate of the apparel supply chain. Together, this suggests that our instruments likely satisfy all three conditions required for computing unbiased estimates.

7.3. Model Estimation

There are two issues that can arise when estimating the two-way fixed-effects model in Equation (12), with or without instruments. The first of these is the varying precision in our dependent variable (the estimated recovery rate $\bar{R}$), which results in heteroskedastic error terms. The second issue arises owing to common firm- and category-level shocks that lead to clustered correlation in error terms at both the firm and the category level. We correct for these estimation issues using multiple approaches.

We employ five different estimation approaches, all of which are based on fixed-effects estimators with firm- and category-level dummy variables. Table 2 reports the estimated coefficients for the various approaches. Column E1 of the table is a benchmark model that ignores the correlation structure of its errors; for this we use a standard ordinary least-squares (OLS) estimator with homoskedastic errors. Column E2 shows estimation results obtained with heteroskedastic errors, but ignores the source of the heterogeneity and hence the specific embedded structure. In particular, we use Huber-White robust standard errors.

Column E3 in Table 2 shows the results obtained when we treat two-way clustered correlation as the sole source of heteroskedastic errors. Following Cameron et al. (2011), we compute the variance–covariance matrix of two-way clustered errors as $V = V(C_1) + V(C_2) - V(C_1 \cap C_2)$, where $V(C.)$ is the variance–covariance matrix when errors are correlated at the cluster level $C.$. This computation does not account for the heteroskedasticity due to the estimated nature of our dependent variable. In comparison, column E4 reports the results obtained when the varying precision of the estimated dependent variable is taken to be the sole source of heteroskedasticity. We employ the weighted least-squares (WLS) estimator, where each firm×category observation is weighted using the *reciprocal* of the standard error of the supply chain's recovery rate.

Column E5 shows the results of our approach to correct for inflated standard errors. It combines the approaches of estimations 3 and 4 and so accounts for both sources of heteroskedasticity. The estimation uses the weighted estimator *and* follows Cameron et al. (2011) in computing two-way clustered standard errors. Finally, column E6 of the table shows the results of IV estimation with the correction for both sources of heteroskedasticity.

We find consistent support (or lack thereof) for our key hypotheses across all these estimation approaches. The coefficients of the three OLS estimators (E1, E2, E3) are quantitatively equivalent, as are those of the two WLS estimators (E4 and E5). However, the standard errors of these coefficients differ across these estimators. Comparing the standard errors under E2 and E3 to those under

Variables	E1	E2	E3	E4	E5	E6
Estimation Approach	OLS	OLS, Robust SE	OLS, Two-Way Clustered SE	WLS	WLS, Two-Way Clustered SE	IV, Weights, Two-Way Clustered SE
Supplier Dispersion (SD)	-0.27*** (0.091)	-0.27*** (0.094)	-0.27*** (0.093)	-0.26*** (0.093)	-0.26*** (0.093)	-0.19** (0.104)
Long-Term Relationship (LR)	0.08** (0.038)	0.08** (0.039)	0.08** (0.041)	0.09** (0.040)	0.09** (0.040)	0.09* (0.058)
Logistically Eff. Locs (LEL)	-0.04 (0.105)	-0.04 (0.098)	-0.04 (0.128)	-0.08 (0.104)	-0.08 (0.139)	-0.08 (0.153)
Sourcing Lead time (SLT)	-0.12 (0.135)	-0.12 (0.141)	-0.12 (0.150)	-0.20* (0.138)	-0.20 (0.179)	-0.20 (0.162)
Firm Fixed Effects (F)	Yes	Yes	Yes	Yes	Yes	Yes
Component Category Fixed Effects (C)	Yes	Yes	Yes	Yes	Yes	Yes
N_observations	1,008	1,008	1,008	1,008	1,008	1,008
R-sq	27.6%	27.6%	27.6%	30.1%	30.1%	
Adjusted R-sq	8.3%			11.4%		

*** -- 1% level, ** -- 5% level, * -- 10% level

E1, E2, and E3 show results using the numerically equivalent estimator but different assumptions about error terms, similarly, E4 and E5. Finally, E6 same error assumption as E5 but uses a different estimator. E1 assumes homoskedastic errors. E2 and E4 assume heteroskedastic errors. E3, E5 and E6 assume two-way cluster correlated errors.

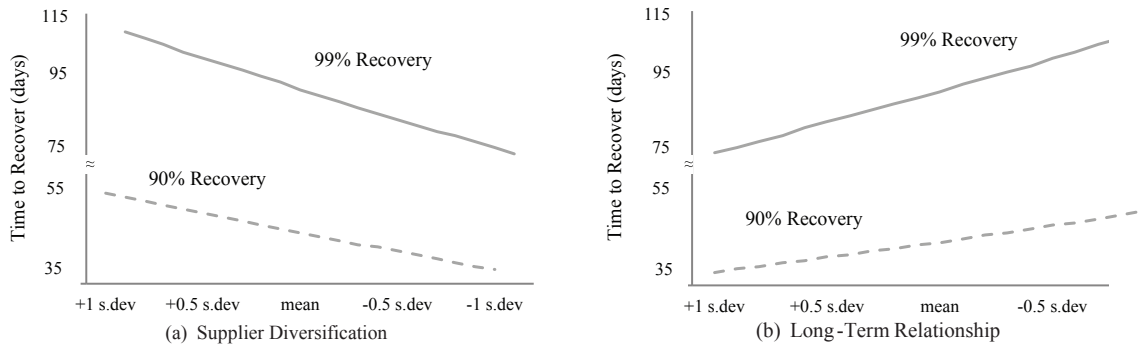
Table 2 Estimation Results

E1 reveals that accounting for heteroskedasticity results in marginally larger standard errors irrespective of the source of it. Comparing E3 to E2 and E5 to E4, we see that accounting for two-way clustering in errors results in marginally larger standard errors in three of the four estimates.

In the IV estimation analysis (E6), we find strong rejection for the under-identification test (p-value $< 0.1\%$) and the weak instruments test (F statistic > 10) for the chosen set of instruments.[8] Moreover, we find no significant difference between the IV estimates (E6) and OLS estimates (E5); the endogeneity test cannot be rejected at a p-value of 0.86.

We find a negative and significant effect of supplier diversification on the recovery rate; all else being equal, *a global supply chain with more dispersed sourcing takes longer to recover to the pre-interruption maritime sourcing level.* The benefits of ordering from fewer suppliers (volume leverage, better supplier selection, etc.) dominate the benefits of ordering from more suppliers (access to alternate sources, supplier competition, etc.). This result complements research identifying the beneficial

[8] We use Kleibergen-Paap rk statistics for evaluation of these tests as we rely on robust standard errors to account for various sources of heteroskedastic errors in our estimation (Kleibergen 2002).



The effects are illustrated for a typical firm-component supply chain i.e. with a sample average supplier diversification level of 0.34, long-term relationship of 0.20, and time to 99% recovery of 3 months. Estimates based on model E5 (WLS, Two-way Clustered SE).

Figure 3 Impact of Sourcing Strategies on Recovery Rate

effects of diversification on the *likelihood* of facing interruptions; so even as supplier diversification may reduce the likelihood of an interruption, it also makes recovery more difficult when they do occur.

We find a positive and significant effect of relationships on the recovery rate; all else being equal, *a global supply chain with more long-term relationships recovers faster to the pre-interruption maritime sourcing level.* The better alignment of incentives in long-term relationships outweighs any complacency introduced on account of such relationships.

We find a negative and insignificant effect of sourcing from logistically efficient locations on recovery. This outcome could be due to the small amount of variation in our constructed measure or to the competing effects associated with logistically efficient locations (see 'Sourcing from logistically efficient locations' in Section 3), which cancel each other out and thus lead to a small net change. We note here that the LEL variable exhibits significant correlation with the SLT variable, which perhaps has reduced our ability to identify significant effects of the two.

Collectively, our focal sourcing strategy variables marginally improve the explained variation in recovery rate by 56%. The Adjusted R-sq improves to 11.4% (see model E4) from 7.3% obtained in specification that includes all covariates of equation (12) except SD, LR and LEL sourcing strategy variables. Here, it is important to note that our findings are relevant for firms that prefer recovering to the pre-interruption global sourcing level. Our analysis does not include firms that enact significant change in sourcing strategy post an interruption.

Panels (a) and (b) of Figure 3 plot the effect of (respectively) supplier diversification and long-term relationships on recovery *duration*. The horizontal axis shows different levels of supplier diversification and the prevalence of long-term relationships. The vertical axis shows the time to recover (in days). The solid curve captures time required to attain 99% recovery, and the dashed line captures

time required to attain 90% recovery. We find that a one standard deviation decrease in supplier diversification reduces time-to-recover to the pre-interruption maritime sourcing level by 16%. Similarly, a one standard deviation increase in long-term relationship reduces time-to-recover by 20%.

7.3.1. Correlated Recovery Rates Across Product Categories The approach of constructing instrument variables (IV) using neighboring units to the focal unit, though commonly used, can be vulnerable to creating imperfect instrument variables (IIV) by failing to satisfy the required exclusion condition (Nevo and Rosen 2012). For instance, in the studied context, if the recovery rates across neighboring component categories are correlated, then the IV, Z, constructed using neighboring units' sourcing strategies will also be correlated with the focal unit's unexplained recovery rate component δ, i.e., $\text{Cov}(Z, \delta) \neq 0$. Recovery rates of neighboring component categories can be correlated for a variety of reasons, including an interruption of a common upstream supplier or a common port. Although we employ a broad definition to classify sourced component categories (HS codes at 3 digit level), the theoretical possibility of correlated recovery rates across neighboring units cannot be ruled out. To evaluate whether our main findings on SD and LR strategies are sensitive to this concern, we adapt the imperfect instrument analysis framework laid by Nevo and Rosen (2012) to provide a single-sided bound on the true value of SD and LR coefficients (β_1 and β_2 in eq(12)).

The imperfect instrument analysis builds on two aspects: (i) theory driven assessment on the sign of correlation between the unexplained component of the dependent variable and IIV, $\text{Cov}(Z, \delta)$; and (ii) sample-based covariance between IIV and residual value of endogenous variable, $\text{Cov}(\tilde{S}, Z)$. On the former aspect, it is reasonable to assume that neighboring entities that are impacted by common interruption events will exhibit a positive correlation due to the factors that are omitted in our model.[9] Lemma 1 below builds on this assumption and the sign of $\text{Cov}(\tilde{S}, Z)$ to formalize characteristics of bounds on the true value of SD and LR:

Lemma 1. *If $Cov(Z, \delta) > 0$ then the IIV estimate provides*

(i) a lower bound on true coefficients if the sample covariance between $\tilde{S}$ and Z is negative ($Cov(\tilde{\delta}, Z) < 0$),

(ii) an upper bound on true coefficients if the sample covariance between $\tilde{S}$ and Z is positive ($Cov(\tilde{\delta}, Z) > 0$).

[9] Nevo and Rosen (2012) show that, by adding an assumption on the sign of correlation between the error term and the endogeneous regressor $Cov(X, \delta)$, one can provide tighter bounds by leveraging the OLS estimate.

	#	Supplier Diversification	Long-Term Relationship	# of obs	Robustness Test Description
Original Assumptions	1	-0.26***	0.09**	1008	Unit Root Test: Augmented Dickey Fuller White Noise Test: Bartlett
Sub Samples	2	-0.30***	0.13**	550	Retailers/ Wholesaler (NAICS 2-digit code 42, 44, 45)
	3	-0.25*	0.07	458	Manufacturers (NAICS 2-digit code 31-33)
	4	-0.27***	0.04*	1258	Sampling Period Interval: 60 days
Alternate Variable Construction	5	-0.06***	0.10***	1008	Supplier Diversification based on Number of Suppliers
	6	-0.24***	0.09**	1008	Weight-based operationalization of Supplier Diversification and Logisitically Efficient Location sourcing variables
	7	-0.11	0.04**	1008	Weighted Long-Term Relationship by import share
	8	-0.22**	0.03	1034	Component-category definition at 4 digit HS-Code level
	9	-0.27*	0.11**	798	Lagged measures as instrument variables

All models are esimated like model E5 in the main results (WLS, Two-way Clustered SE), on account of the same estimates as model E6 and higher efficiency of the estimator
*** -- 1% level, ** -- 5% level, * -- 10% level

Table 3 Robustness Tests

In our sample, we find $\text{Cov}(\tilde{SD}, Z) = -0.19$ and $\text{Cov}(\tilde{LR}, Z) = -0.10$. This, together with Lemma 1, imply that our IIV estimates (presented in Table 2, column E6) provide a *lower bound* on the true impact of SD and LR strategies on recovery ability.

To summarize, the concern of commonly used neighboring entities' approach to construct IVs resulting in imperfect instruments—despite the use of a broad category classification—does not weaken the interpretation of our main findings.[10]

7.4. Robustness Tests

We next demonstrate the robustness of our analysis to the use of different subsamples of data, to alternative ways of constructing variables and to alternate set of instruments. Table 3 reports the results. To facilitate comparisons, we show the original estimates in Row 1.

Different Subsamples: Our sample consists of firms in the manufacturing and retail/wholesale sectors. These sectors differ considerably in the nature of components sourced from global suppliers and so may have distinct preferences with respect to particular sourcing strategies. It can be seen in Table 1 that, for example, firms in retail/wholesale sectors rely more on diversified sourcing than do firms in the manufacturing sector. Motivated by this observation, we test the robustness of our

[10] We also find qualitatively consistent results using a more stringent definition of a neighboring entities instrument that ignores immediate neighbors sharing a common 2-digit HS code.

results to each of these sectors separately; Row 2 gives our estimates for the retail/wholesale sector while Row 3 gives those for the manufacturing sector.

For the main analysis, we set the sampling interval to one month (30 days) for converting longitudinal data on imports to an equally spaced time series. Though this approach of analyzing operations related time series (demand series, order series and so on) as an equally spaced series—in the absence of information about true frequency—follows the existing literature (Gaur et al. 2005), the findings may be sensitive to the choice of sampling interval length. We report in Row 4 robustness of our findings with sampling interval length set to 60 days.

Alternative Constructions of Main Explanatory Variables: Supplier diversification has multiple effects on the recovery rate as a result of various mechanisms, which include competition-induced incentives for suppliers to invest in recovery abilities, and alternate opportunities for sourcing. Like any other operationalization, our Herfindahl-index-based construction of the measure asymmetrically captures the strength of these various mechanisms. In particular, the Herfindahl index (based on market shares) captures competition more effectively than alternate opportunities for sourcing which are better captured with a metric based on the number of distinct suppliers. We also test our hypotheses with an alternate measure, specifically we consider diversification as a temporal average of the number of suppliers, $\mathrm{SD} = \frac{1}{|\mathrm{NZ}_{fc}|} \sum_{t \in \mathrm{NZ}_{fc}} \mathrm{N}_{fct}$ (in Row 5). In Row 6, we show robustness to the choice of dollar-value-based operationalizaton of our focal sourcing strategy variables by reconstructing the SD and LEL measures using weight (kilograms) of the imported quantity – the unit of delivered-quantity series.

In Row 7, we show estimation results with an alternate measure for the use of long-term sourcing. Arguably, along with the extent of repeat business, a firm's relationship strength with a supplier is also influenced by the amount of business allocated to the supplier. We capture this by measuring relationships as a weighted average of the extent of repeat business across suppliers where the weights are set equal to the share of global sourcing accounted by respective suppliers. Our original measure sets these weights to one, i.e., provides equal importance to each supplier irrespective of the extent of business allocated to him.

Row 8 of the table gives estimation results under an alternate definition of category of imported goods. On the one hand, a relatively coarser definition reduces the number of supply chains per firm, which in turn leads to reduced identification power because our strategy relies on across-firm differences in the differences among categories. On the other hand, a more refined definition of category runs the risk of generating a sparse time series for the delivered quantity. Whereas our

original results were based on 3-digit HS codes, Row 8 reports the results when categories are defined (less coarsely) using 4-digit HS codes.

Row 9 presents the robustness of our findings to the choice of instrument variables. Although our main analysis uses instruments constructed using the commonly employed neighboring entities approach, it is impossible to claim that those IVs perfectly meet the relevance and exclusion conditions. In Row 9, we report estimates using another widely used approach to construct IVs: lagged measures of endogenous variables. We use two-year past data (from June 2004 to May 2006) to construct these lagged measures. We find strong evidence to reject the under-identification test (p-value $< 0.1\%$) and the weak instruments test (F statistic > 10) for these instruments.

In Appendix 1, we present eight more robustness tests that examine sensitivity of our findings to alternate unit-root tests (number of tests 3), one- and both-sided truncated sample (2), and sourcing strategies measures (3). Collectively, the results of these 16 robustness tests can be summarized as follows. We confirm the negative and significant effect of supplier diversification on recovery across 15 of the tests, and the effect of long-term relationship is positive and significant across 14 of them. In addition, the signs of our coefficients are unchanged across all 32 tests. Altogether, these tests strongly support the robustness of our main findings.

Finally, our data has limitations in not providing a detailed view of domestic suppliers, imports through non-sea-based routes, on the nature of an interruption: supply or demand side. Similar, we do not have a granular definition of product category. In Appendix 1, we present additional analyses to ascertain whether our main findings are sensitive to these limitations of our data.[11]

8. Conclusion

This paper provides the first rigorous and large-scale empirical evidence that relates a firm's supply chain strategies to the ability of that supply chain to recover from interruptions. Our empirical analysis focuses on U.S. maritime shipments. We show that supplier diversification is associated with slower recovery from interruptions, while the use of long-term relationships is associated with faster recovery. Our findings advance the academic understanding of supply chain resilience and provide actionable evidence to modern-day supply chain and business continuity professionals.

The evidence reported in this paper—namely, that a firm's supplier diversification reduces the supply chain's post-interruption recovery rate—offers several avenues for future research. Although existing theoretical work has shown how diversification reduces the incidence of interruptions, we

[11] We thank the review team for suggesting these robustness tests.

demonstrate that there is also a downside to diversification vis-a-vis recovery. Together, it leads to ambiguity on the preferred strategy for building resilient supply chains—future work can investigate the relative efficacies and value of using diversification-building supply chain resilience. Further, our data limitations constrain us from identifying the underlying mechanism that results in slower recovery of a diversified supply chain. For instance, is it on the account of a firm experiencing challenges (such as coordination across multiple suppliers) when implementing a multi-supplier sourcing program or is it because of the lack of incentives at the suppliers' end? Identification of such underlying mechanisms is a fruitful avenue of future research. Our study focuses on post-interruption recovery speed using the lens of a cost-minimization objective; it would be interesting to explore other important dimensions of supply chain recovery, including strategies that account for the extent of deviations, and a demand-side objective that may entail recovery to the pre-interruption production levels. Our analysis is agnostic to the source/nature of the supply interruption, separating different causes and identifying the best supply-chain strategies to deal with each source of interruptions is an interesting avenue for future work.

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Online Appendix for Recovering Global Supply Chains from Sourcing Interruptions: The Role of Sourcing Strategy

Firm Distribution			Product Category Distribution		
NAICS	All Importing Firms†	Regression Sample‡	Product Category	All Importing Firms†	Regression Sample‡
31	9.2	9.2	1	6.3	0.0
32	18.3	7.8	2	14.9	7.5
33	57.0	44.4	3	9.5	7.5
42	5.3	6.3	4	11.3	14.9
44	5.8	15.5	5	9.9	6.0
45	4.5	16.9	6	8.6	13.4
			7	13.5	11.9
			8	17.1	26.9
			9	9.0	11.9

† *Captures distribution of firms and product-categories that have at least one transaction in the 5-year import period (June, 2006 to May, 2011)*
‡ *Captures distribution of firms and product-categories in the regression sample which comprise of firm x category supply chains satisfying the criteria of longitudinal period, non-zero import periods, and stationarity (for details refer to Section 6.1 for regression sample details).*

Table A1 Distribution Coverage: Population vs Regression Sample

1. Additional Robustness Tests

In this section, we provide the results of additional robustness tests that examine our findings' sensitivity to alternate unit-root tests, one- and both-sided truncated sample, and sourcing strategies measures. Table A2 reports the results. To facilitate comparisons, we show the original estimates in Row 1.

As discussed in Section 5.1, a firm×category supply chain is included in our analysis only if (i) we can convincingly transform the delivered-quantity time series into a stationary series and (ii) our fitted ARMA model leads to white-noise residuals. The first criterion is checked using the Augmented Dickey-Fuller test for stationarity, and the second is checked using the Portmanteau test for white noise. We also report the results using two popular alternate tests: the Phillips–Perron test for stationarity (Phillips and Perron 1988) in Row 2 of the table, and a white-noise test (Bartlett 1978) in Row 3; both tests are incorporated into the values reported by Row 4.

Our data provides a truncated view of a firm-supplier relationship, as we do not observe the actual start of a supplier relationship. It is conceivable that relationship strength with suppliers before the start of our study period can also affect a firm's recovery ability. To ascertain that our findings are not driven by a limited view of firm–supplier relationships, we re-estimate our model using alternate measures of the LR variable over two truncated windows. Row 5 shows the results of a left truncated window wherein we exclude 20% of the available quarters for a firm-category supply chain at the start. Row 6 presents the results for a both-sided truncated window constructed by excluding 10% of the quarters at both the start and end of import period.

In our main analysis, we constructed the sourcing strategy variables using imports information gleaned from month-level transactions. For example, we use the allocation of imports across suppliers over a 30-day time window to construct the supplier diversification variable. On the one hand, this approach is preferable in that it comports with the temporal unit of our delivered-quantity time series, which is used to estimate the dependent variable. On the other hand, 30-day windows may not leave firms enough time to engage repeatedly with suppliers, especially those requiring longer lead times. We therefore test for the robustness of our results to relaxing this assumption: in Row 7 of Table A2 we report estimation results using sourcing strategy measures that are constructed over 90-day windows.

Finally, Rows 8 and 9 of Table A2 give the estimates derived when using alternative measures of the post-interruption recovery rate. As discussed in Section 5.1, we construct our main recovery measure using estimated coefficient values of the best-fit ARMA model for the observed delivered quantity. In particular, we select the model that minimizes the Akaike Information Criterion (AIC) as the best-fit model. Alternatively, one can also use Bayesian information criterion (BIC) to select the best-fit model (Row 8). An important step in constructing the recovery measure is the removal of seasonality from the observed non-stationary delivered-quantity time-series data to obtain the corresponding stationary series. Row 9 shows the estimation results with a recovery measure constructed using quarter-level instead of month-level seasonality. For that purpose, we derive the stationary delivered-quantity series $\tilde{d}_t$ using a linear trend model with quarter-level dummies: $d_t = \alpha_0 + \alpha_1 t + \text{Quarter-level dummies} + \tilde{d}_t$.

1.1. Sensitivity to the Extent of Maritime Shipments

We note that our data set comprises only of maritime shipments—a primary constituent of global sourcing—but excludes alternate shipments such as through air/land or from domestic suppliers. Such an exclusion can result in bias in our estimates if, post an interruption, firms in our sample

	#	Supplier Diversification	Long-Term Relationship	# of obs	Robustness Test Description
Original Assumptions	1	-0.26***	0.09**	1008	Unit Root Test: Augmented Dickey Fuller White Noise Test: Bartlett
Sub Samples	2	-0.27***	0.10***	1000	Unit Root Test: Phillips-Perron (Non-Parametric) White Noise Test: Portmanteau
	3	-0.30***	0.07**	1147	Unit Root Test: Augmented Dickey Fuller White Noise Test: Bartlett
	4	-0.30***	0.06*	1177	Unit Root Test: Phillips-Perron (Non-Parametric) White Noise Test: Bartlett
Alternate Variable Construction	5	-0.26***	0.10**	1008	Left-side truncated window: excluded 20% of quarters at the start of import period
	6	-0.26***	0.10**	1008	Both-side truncated window: excluded 10% of quarters at the start and end of import period
	7	-0.14**	0.08**	1004	Sourcing strategies measured over 90 days window
	8	-0.26***	0.06**	967	ARMA best fit criterion: Bayesian Information Criterion (BIC)
	9	-0.29***	0.08*	1098	Quarter level control for seasonality

All models are esimated like model E5 in the main results (WLS, Two-way Clustered SE), on account of the same estimates as model E6 and higher efficiency of the estimator
*** -- 1% level, ** -- 5% level, * -- 10% level

Table A2 Additional Robustness Tests

do not strive to return to their pre-interruption steady state sourcing composition, but instead shift to a new desired sourcing composition. This can happen, for example, if the interruption results in a chance discovery of a new, better sourcing option, or a rethink of overall sourcing strategy. To overcome concerns about this potential source of bias, we perform a robustness test to ascertain whether our main findings are sensitive to the absence of non-sea-based shipment data.

Using the US Census Bureau data on the value of annual imports and exports between 2006 to 2011, we classify component categories into two groups. First, we identify categories in which firms have higher chances of relying on air/land routes using these categories' five-year average share of non-sea-based imports, $\text{Share}_c^{\text{non-sea}}(\frac{1}{5}\sum_{t=2006}^{2011}(\text{Imports-via-air-and-land}_t/\text{Total-Imports}_t)$. Specifically, we define a dummy variable, HNONSEAIMP=1 for categories with higher than the 50th percentile of $\text{Share}_c^{\text{non-sea}}$ distribution (mean = 0.38, std.dev = 0.19). Second, we classify categories that have a strong domestic supplier market by using the five-year average of the ratio of exports to imports, $\text{REtoI}_c(\frac{1}{5}\sum_{t=2006}^{2011}(\text{Total-Exports}_t/\text{Total-Imports}_t)$. Intuitively, availability of domestic suppliers will be higher in product categories for which the US firms exhibit relatively higher export level compared to imports level. We define a dummy variable, HDOMESTIC=1 for categories with higher than the 50th percentile of REtoI_c distribution (mean = 248, std.dev = 1149). Next, we test the impact of the potential of alternate sourcing options on our findings by estimating two variants of the following model:

$$\overline{\text{R}}_{fc} = \beta_0 + \beta_1\text{SD}_{fc} + \beta_2\text{logLR}_{fc} + \beta_3\text{LEL}_{fc} + \beta_4\text{SLT}_{fc}$$

$$+\beta_5 \text{SD}_{fc} \times \text{DUMMY\_VARIABLE} + \beta_6 \text{logLR}_{fc} \times \text{DUMMY\_VARIABLE} + \text{F} + \text{C} + \psi_{fc}, \tag{A1}$$

where DUMMY_VARIABLE$\in$ {HNONSEAIMP, HDOMESTIC}. The interaction coefficients capture the impact of the varying potential of alternate sourcing options on the main effects of the respective sourcing strategy variables. For both HNONSEAIMP and HDOMESTIC, we find sourcing strategies main effects to be sign consistent and significant. The coefficient of SD and LR variables is -0.22^{**} (resp., -0.38^{***}) and 0.09^{*} (resp., 0.07^{*}) in estimation with HNONSEAIMP (resp., HDOMESTIC) dummy variable. Furthermore, we find both the interaction terms to be insignificant across the two estimations. The coefficient of the interaction term with SD and LR variables is -0.12 (resp., 0.23) and 0.01 (resp., 0.05) in estimation with HNONSEAIMP (resp., HDOMESTIC) dummy variable. Together, these results imply that our main findings are not sensitive to the absence of data on non-sea-based shipments.

1.2. Sensitivity to the Source of Interruptions: Demand or Supply

We do not have direct data to distinguish between the sources of interruption, i.e., whether an observed decrease in a delivered-quantity series is on account of demand- or supply-side interruption. It is conceivable that the effectiveness of the studied sourcing strategies on recovery ability is sensitive to interruption type. For example, constrained by long-term contractual commitments towards minimum quantity purchase, a firm would be constrained to respond to demand interruptions. In such a case, long-term relationships would negatively impact the supply chain recovery. To examine whether our findings are sensitive to the source of interruptions, we group firms in our sample based on their extent of demand volatility. Firms with higher demand volatility are more likely to experience frequent demand interruptions. We measure demand volatility using the coefficient of variance (CV). Following Rumyantsev and Netessine (2007), we construct measures of mean demand and standard deviation using sales data covering our study period. Next, we define a dummy variable, HDEMVOL=1 for firms with higher than the 50th percentile of CV distribution across firms. We estimate the impact of demand volatility using the interaction model specified in Section 1.1 (eq (A1) with DUMMY_VARIABLE=HDEMVOL. The coefficient of interaction terms (SD$\times$HDEMVOL and logLR$\times$HDEMVOL) captures the varying impact of demand volatility level on the main effects of respective sourcing strategy variables. We find that the main effects of sourcing strategies are sign consistent and significant ($\beta_1 = -0.31^{**}$, $\beta_2 = 0.09^{**}$), but the interaction effects are insignificant ($\beta_5 = 0.06$, $\beta_6 = -0.03$). These results imply that the net impact of the studied sourcing strategies on a supply chain's recovery ability is not sensitive to the source of interruptions (demand or supply).

1.3. Multiple Suppliers Within a Product Category: Supplier Diversification or Sourcing Different Goods?

Given the product-category aggregation level choice (HS 3-digit), it is possible that different suppliers – associated with a product category – are engaged to source different goods, and not for attaining diversification in sourcing. We perform an additional analysis to see whether our results are sensitive to the potential of sourcing different goods within the chosen category-level definition. We construct a measure of "potentially different goods are sourced" by a firm f within a HS-3 category c by counting the average number of HS-6 sub-product categories sc sourced by the firm f during our study period. Formally, we define Potential of Different Goods being Sourced ($PDGS$) as

$$\text{Month Level } PDGS_{fct} = \text{Count of distinct } sc \text{ sourced in month t by firm f in category } c$$
$$PDGS_{fc} = \frac{1}{|\mathrm{NZ}_{fc}|} \sum_{t \in \mathrm{NZ}_{fc}} \text{Month Level } PDGS_{fct}, \tag{A2}$$

where NZ_{fc} is the set of indices for months t with nonzero imports in the supply chain's time-series data, and $|\cdot|$ is used to denote the cardinality of a set. We estimate the impact of potential of sourcing different goods within a product-category using the interaction model specified in Section 1.1 (eq (A1)), but by replacing the DUMMY_VARIABLE with $PDGS$ (mean = 2.5, std.dev = 2.2) variable. The coefficient of interaction terms (SD×PDGS and logLR × PDGS) captures the varying impact of potential of sourcing different goods with a product-category on the main effects of respective sourcing strategy variables. We find that the main effects of sourcing strategies are sign consistent and significant ($\beta_1 = -0.26^{***}$ and $\beta_2 = 0.13^{***}$), but the interaction effects are insignificant ($\beta_5 = -0.013$ and $\beta_6 = 0.018$). These results imply that though in our data we cannot ascertain whether the different suppliers used for a category c provide diversification or distinct goods, our results do not seem to be sensitive to this aspect of data limitation.

2. Proof of Lemma 1

PROOF OF PROPOSITION 1. We solve for the optimal parameters $[K^*, \boldsymbol{w}_1^*, \ldots \boldsymbol{w}_1'^*, \ldots]$ in two-steps. First, for a fixed weight vectors $\boldsymbol{w}_i$'s and $\boldsymbol{w}_i'$'s, we solve $\arg\min_K C(K, \boldsymbol{w}_1, \ldots \boldsymbol{w}_1', \ldots)$ to obtain optimal $K^*(\cdot)$ as a function of the weight vectors. Next, we solve $\arg\min_{(\boldsymbol{w}_1, \ldots \boldsymbol{w}_1', \ldots)} C(K^*(\cdot), \boldsymbol{w}_1, \ldots \boldsymbol{w}_1', \ldots)$ to obtain the optimal weight vectors $(\boldsymbol{w}_1^*, \ldots \boldsymbol{w}_1'^*, \ldots)$. Taken together, this approach provides us with the optimal values of GOUTP policy parameters. Finally, we compute the firm's long-run average cost under these optimal policy parameters. Using $(a-b)^+ = (a-b) + (b-a)^+$, we re-write the cost function (see eq. (4)) as:

$$C = E\left[h\left(\left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right) - \sum_{i=0}^{L} D_{t+i}\right) + (h+p)\left(\sum_{i=0}^{L} D_{t+i} - \left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right)\right)^+\right].$$

Note that in terms of forecast revision vectors, we can re-write demand and mismatch processes as:

$$D_t = \mu_D + \sum_{i=0}^{\infty} \mathbf{e}_{i+1} \boldsymbol{\epsilon}_{t-i}, \tag{A3}$$

$$m_t = \sum_{i=0}^{\infty} \mathbf{e}_{i+1} \boldsymbol{\zeta}_{t-i}. \tag{A4}$$

Next, using the definition of order-up-to level S_t (eq. 3), ordered-delivered mismatch quantity process m_t (eq. 1), and demand process D_t (eq. 2) as well as some algebraic manipulations, we expand and re-write the term $\left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right) - \sum_{i=0}^{L} D_{t+i}$ as

$$\begin{aligned}\left(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\right) - \sum_{i=0}^{L} D_{t+i} \;=\; & K - \mu_D(L+1) + \sum_{i=1}^{\infty} (\boldsymbol{w}_i - e_{i+1}^{i+L+1})^T \boldsymbol{\epsilon}_{t-i} - \sum_{i=0}^{L}\sum_{j=0}^{i} \epsilon_{t+i-j,t+i} \\ & + \sum_{i=1}^{\infty} (\boldsymbol{w}'_i - e_{i+1}^{i+L+1})^T \boldsymbol{\zeta}_{t-L-1-i} - \sum_{i=0}^{L}\sum_{j=0}^{i} \zeta_{t-L-1+i-j,t-L-1+i}.\end{aligned}$$

Note that the terms $\sum_{i=1}^{\infty} (\boldsymbol{w}_i - e_{i+1}^{i+L+1})^T \boldsymbol{\epsilon}_{t-i}$ and $\sum_{i=1}^{\infty} (\boldsymbol{w}'_i - e_{i+1}^{i+L+1})^T \boldsymbol{\zeta}_{t-L-1-i}$ respectively capture information about replenishment period demand and ordered-delivered quantity mismatch, that is reflected in past demand $\{\epsilon_{t-1}, \epsilon_{t-2}, \ldots\}$, and mismatch signals $\{\zeta_{t-L-1-1}, \zeta_{t-L-1-2}, \ldots\}$, observed before period t. In contrast, the terms $\sum_{i=0}^{L}\sum_{j=0}^{i} \epsilon_{t+i-j,t+i}$ and $\sum_{i=0}^{L}\sum_{j=0}^{i} \zeta_{t-L-1+i-j,t-L-1+i}$ capture information reflected in the future demand $\{\epsilon_t, \epsilon_{t+1}, \ldots\}$ and deviation $\{\zeta_{t-L-1}, \zeta_{t-L}, \ldots\}$ signals. The implication is that these terms are mutually independent as they do not have overlapping signals. Building on this observation, we solve $\arg\min_K C\left(K, \boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots\right)$ using the newsvendor solution approach and we obtain $K^*(\cdot)$ as

$$K^*(\boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots) = \mu_D(L+1) + z\sqrt{\triangle_w^D + \triangle_u^D + \triangle_{w'}^m + \triangle_u^m},$$

where $z = \Phi^{-1}(p/(h+p))$ with $\Phi(\cdot)$ being the standard normal cumulative distribution,

$\triangle_w^D = \mathrm{Var}\left(\sum_{i=1}^{\infty} (\boldsymbol{w}_i - e_{i+1}^{i+L+1})^T \boldsymbol{\epsilon}_{t-i}\right)$, $\triangle_u^D = \mathrm{Var}(\sum_{i=0}^{L}\sum_{j=0}^{i} \epsilon_{t+i-j,t+i})$,

$\triangle_{w'}^m = \mathrm{Var}\left(\sum_{i=1}^{\infty} (\boldsymbol{w}'_i - e_{i+1}^{i+L+1})^T \boldsymbol{\zeta}_{t-L-1-i}\right)$ and $\triangle_u^m = \mathrm{Var}\left(\sum_{i=0}^{L}\sum_{j=0}^{i} \zeta_{t-L-1+i-j,t-L-1+i}\right)$. The resulting optimal cost is

$$C(K^*(\cdot), \boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots) \;=\; (h+p)\phi(z)\sqrt{\triangle_w^D + \triangle_u^D + \triangle_{w'}^m + \triangle_u^m}, \tag{A5}$$

where $\phi(\cdot)$ is the standard normal density function. Equation (A5) implies

$\min_{(\boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots)} C\left(K^*(\cdot) \;\; , \boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots\right) \geq (h+p)\phi(z)\sqrt{\triangle_u^D + \triangle_u^m}$ as $\triangle_u^D$ and $\triangle_u^m$ are not dependent on weight vectors $(\boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots)$. Therefore, optimal weight vectors are $\boldsymbol{w}_i^* = e_{i+1}^{i+L+1}$ and $\boldsymbol{w}_i'^* = e_{i+1}^{i+L+1}$ as they set $\triangle_w^D = \triangle_{w'}^m = 0$ and, consequently, attain the lower bound on cost, i.e., $C(K^*(\cdot), \boldsymbol{w}^*{}_1, \ldots \boldsymbol{w}_1'^*, \ldots) = (h+p)\phi(z)\sqrt{\triangle_u^D + \triangle_u^m}$. Next, we expand $\triangle_u^m$ to derive the optimal cost as a function of spill-over rate α. Note that $\mathrm{Cov}(\zeta_{t+i}, \zeta_{t+j}) = 0$ for $i \neq j$. This implies $\triangle_u^m = \mathrm{Var}\left(\sum_{i=0}^{L}\sum_{j=0}^{i} \zeta_{t-L-1+i-j,t-L-1+i}\right) = \sum_{i=0}^{L} \mathrm{Var}\left(\sum_{j=0}^{L-i} \zeta_{t-L-1+i,t-L-1+i+j}\right) = \sigma_m^2 \sum_{i=0}^{L} \left(\sum_{k=0}^{i} \alpha^k\right)^2$ as $\zeta_{t,t+k} = \alpha^k \zeta_{t,t}$ and $\zeta_t \sim N(0, \sigma_m^2)$.

Finally, substituting optimal weights in (A5), we obtain the square of optimal cost expression as:

$$C(\cdot)^2 \;=\; g \times \left(\triangle_u^D + \sigma_d^2 \sum_{i=0}^{L} \left(\sum_{k=0}^{i} \alpha^k\right)^2\right), \tag{A6}$$

where $g = (h+p)^2\phi(z)^2$. Differentiation of both the sides of equation with respect to spill-over rate α (A6) gives:

$$2C(\cdot)\frac{\partial C(\cdot)}{\partial \alpha} = = \frac{\partial}{\partial \alpha} g \times \left(\triangle_u^D + \sigma_d^2 \sum_{i=0}^{L} \left(\sum_{k=0}^{i} \alpha^k \right)^2 \right) = g\sigma_d^2 \sum_{i=0}^{L} 2 \sum_{k=0}^{i} \alpha^k \sum_{k=1}^{i-1} (k+1)\alpha^k,$$

by swapping the differentiation and summation. This implies $\frac{\partial C(\cdot)}{\partial \alpha} > 0$, since $C(\cdot) > 0$, $K > 0$,$\sigma_d > 0$, and$\alpha > 0$. ■

PROOF OF PROPOSITION 2. The delivered-quantity process is a convolution of order-quantity process and the interruption-induced mismatch process, $d_t = q_t - m_t$. By the law of material conservation, we obtain order quantity for a period t as:[12]

$$q_t = S_t - \left(S_{t-1} - m_{t-L-2}\right) + D_{t-1}. \tag{A7}$$

In the absence of interruptions eq. (A7) reduces to the conventional order-quantity expression $q_t = S_t - S_{t-1} + D_{t-1}$. The additional term m_{t-L-2} adjusts for the mismatch realized in quantity delivered in period $t-1$, corresponding to the order placed $L-1$ periods ago. By the definition of delivered quantity, eq. (3), (A3), (A4), and eq. (A7) we get

$$d_t = \mu + \sum_{i=1}^{\infty} \left(\boldsymbol{w}_i - \boldsymbol{w}_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\epsilon}_{t-i} + \sum_{i=1}^{\infty} \left(\boldsymbol{w}'_i - \boldsymbol{w}'_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\zeta}_{t-L-1-i} - \sum_{i=0}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}. \tag{A8}$$

Eq. (A8) implies that the delivered-quantity process is the sum of two sub-processes $d_t = \mathbb{P}_t^1 + \mathbb{P}_t^2$, where $\mathbb{P}_t^1 = \mu + \sum_{i=1}^{\infty} \left(\boldsymbol{w}_i - \boldsymbol{w}_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\epsilon}_{t-i}$ and $\mathbb{P}_t^2 = \sum_{i=1}^{\infty} \left(\boldsymbol{w}'_i - \boldsymbol{w}'_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\zeta}_{t-L-1-i} - \sum_{i=0}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}$, that are driven by mutually independent demand ϵ and mismatch shocks ζ. Further, note that $\mathbb{P}_t^1$ mimics an order-quantity process for a firm that faces no interruptions in sourcing (cf. Chen and Lee 2009). Building on this observation, it can be shown that $\mathbb{P}_t^1$ evolves as an ARMA process under the optimal policy parameters characterized in Proposition 1 and that, similar to previous studies including Zhang (2004), the auto-regressive terms of $\mathbb{P}_t^1$ are the same as that of the demand process D_t. For the sub-process $\mathbb{P}_t^2$, under the optimal parameters $\boldsymbol{w}_i^* = e_{i+1}^{i+L+1}$ and $\boldsymbol{w}_i'^* = e_{i+1}^{i+L+1}$, we obtain

$$\begin{aligned}
\mathbb{P}_t^2 - \alpha\mathbb{P}_{t-1}^2 = {} & \left(e_1^{L+2}\right)^T \boldsymbol{\zeta}_{t-L-2} + \left(\mathbf{e}_2 + \mathbf{e}_{L+3}\right)^T \boldsymbol{\zeta}_{t-L-3} + \sum_{i=3}^{\infty} \left(\mathbf{e}_i + \mathbf{e}_{i+L+1}\right)^T \boldsymbol{\zeta}_{t-L-1-i} - \zeta_t - \sum_{i=1}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i} \\
& -\alpha\left(e_1^{L+2}\right)^T \boldsymbol{\zeta}_{t-L-3} - \alpha \sum_{i=1}^{\infty} \left(\mathbf{e}_i + \mathbf{e}_{i+L+1}\right)^T \boldsymbol{\zeta}_{t-L-2-i} - \alpha \sum_{i=0}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-1-i}, \\
= {} & \left(e_1^{L+2}\right)^T \boldsymbol{\zeta}_{t-L-2} + \left(\mathbf{e}_2 + \mathbf{e}_{L+3}\right)^T \boldsymbol{\zeta}_{t-L-3} + \sum_{i=3}^{\infty} \left(\mathbf{e}_i + \mathbf{e}_{i+L+1}\right)^T \boldsymbol{\zeta}_{t-L-1-i} - \zeta_t - \sum_{i=1}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i} \\
& -\left(e_2^{L+3}\right)^T \boldsymbol{\zeta}_{t-L-3} - \sum_{i=2}^{\infty} \left(\mathbf{e}_{i+1} + \mathbf{e}_{i+L+2}\right)^T \boldsymbol{\zeta}_{t-L-2-i} - \sum_{i=0}^{\infty} \mathbf{e}_{i+2}\boldsymbol{\zeta}_{t-1-i},
\end{aligned} \tag{A9}$$

[12] The assumption of normality of demand and deviation shocks may lead to negative order quantities. Restricting demand and deviation shocks to positive domain leads to intractability of exact analysis. Therefore, in line with the past literature, we allow for negative order quantities in our analysis, with the assumption that the firm can freely return unlimited amounts of excess inventory to the supplier (Kahn 1987, Chen and Lee 2009).

since $\boldsymbol{\zeta_t} = [\epsilon_{t,t}, \epsilon_{t,t+1}, \epsilon_{t,t+2}, \ldots] = [\epsilon_{t,t}, \alpha\epsilon_{t,t}, \alpha^2\epsilon_{t,t}, \ldots]$. Note that $\sum_{i=2}^{\infty}\left(\mathbf{e}_{i+1}+\mathbf{e}_{i+L+2}\right)^T\boldsymbol{\zeta}_{t-L-2-i} \equiv \sum_{i=3}^{\infty}\left(\mathbf{e}_i + \mathbf{e}_{i+L+1}\right)^T \boldsymbol{\zeta}_{t-L-1-i}$ and $\sum_{i=0}^{\infty}\mathbf{e}_{i+2}\boldsymbol{\zeta}_{t-1-i} \equiv \sum_{i=1}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}$. Using these equivalent expressions and eq. (A9), we obtain

$$\begin{aligned}\mathbb{P}_t^2 &= \alpha\mathbb{P}_{t-1}^2 + \left(e_1^{L+2}\right)^T\boldsymbol{\zeta}_{t-L-2} + \left(\mathbf{e}_2+\mathbf{e}_{L+3}\right)^T\boldsymbol{\zeta}_{t-L-3} - \zeta_t - \left(e_2^{L+3}\right)^T\boldsymbol{\zeta}_{t-L-3},\\ &= \alpha\mathbb{P}_{t-1}^2 + \left(\sum_{i=1}^{L+2}\alpha^{i-1}\right)\zeta_{t-L-2} - \left(\sum_{i=3}^{L+2}\alpha^{i-1}\right)\zeta_{t-L-3} - \zeta_t.\end{aligned}$$

This implies that $\mathbb{P}_t^2$ follows an ARMA evolution as $\zeta_i \sim N(0,\sigma_m^2)$. Taken together, this implies that delivered-quantity process evolves as an ARMA process as it is the sum of two independent ARMA sub-processes:

$$(1-\theta_1 B - \cdots - \theta_p B^p)\mathbb{P}_t^1 = (1-\phi_1' B - \cdots - \phi_{q'}' B^{q'})\epsilon_t, \tag{A10}$$

$$(1-\alpha B_1)\mathbb{P}_t^2 = \left(1 - B + \left(\sum_{i=1}^{L+2}\alpha^{i-1}\right)B^{L-2} - \left(\sum_{i=3}^{L+2}\alpha^{i-1}\right)B^{L-3}\right)\zeta_t', \tag{A11}$$

where B denotes the backward operator, q' equals the length of moving-average part of $\mathbb{P}_t^1$ and ϕ' denotes the moving-average coefficients. Computing the sum $(A10)\times(1-\alpha L_1) + (A11)\times(1-\theta_1 L_1 - \cdots - \theta_p L^p)$ gives:

$$\begin{aligned}(1-\theta_1 L_1 - \cdots - \theta_p L^p)(1-\alpha L_1)(\mathbb{P}_t^1 + \mathbb{P}_t^2) &= (\cdot)\epsilon_t + (\cdot\cdot)\zeta_t,\\ (1-(\theta_1+\alpha)B - (\theta_2+\theta_1\alpha)B^2 - \cdots)d_t &= (\cdot)\epsilon_t + (\cdot\cdot)\zeta_t.\end{aligned} \tag{A12}$$

Eq. (A12) implies the coefficient of first auto-regressive term B of the delivered-quantity process is $(\theta_1+\alpha_1)$. ■

PROOF OF LEMMA 1. Following the augmented instrument analysis presented in Section 5.3, the IV estimate for a sourcing strategy S can be written as:

$$\hat{\psi}_S'^{IV(\bar{R})} = \frac{\mathrm{Cov}(\tilde{\bar{R}}, Z)}{\mathrm{Cov}(\tilde{S}, Z)}, \tag{A13}$$

where Z is the augmented instrument and $\tilde{\bar{R}}$ and $\tilde{S}$ are the residuals of the respective regressions of $\bar{R}$ and S on the covariates $\boldsymbol{X}$. By substituting $\bar{R} = \bar{R}_{DM} - \bar{\theta}_1$ where $\bar{R}_{DM}$ is the direct measure on recovery rate ($\bar{R}_{DM} = \psi_1 + \psi_S\tilde{S} + \delta$) and $\bar{\theta}_1$ is the demand auto-correlation parameter, eq (A13) expands to be:

$$\hat{\psi}_S'^{IV(\bar{R})} = \psi_S + \tfrac{\mathrm{Cov}(\tilde{\delta},Z)}{\mathrm{Cov}(\tilde{S},Z)} - \tfrac{\mathrm{Cov}(\tilde{\bar{\theta}}_1,Z)}{\mathrm{Cov}(\tilde{S},Z)}. \tag{A14}$$

Note that when both the exclusion conditions are met (i.e., $\mathrm{Cov}(\tilde{\delta}, Z) = 0$ and $\mathrm{Cov}(\tilde{\bar{\theta}}_1, Z) = 0$) eq (A14) implies that the IV estimator yields a consistent estimate of the sourcing strategy coefficient ($\hat{\psi}_S'^{IV(\bar{R})} = \psi_S$). In case the IV is imperfect ($\mathrm{Cov}(\tilde{\delta}, Z) \neq 0$), the IV estimate reduces to:

$$\hat{\psi}_S'^{IV(\bar{R})} = \psi_S + \tfrac{\mathrm{Cov}(\tilde{\delta},Z)}{\mathrm{Cov}(\tilde{S},Z)}. \tag{A15}$$

Eq (A15) implies:

$$\hat{\psi}_S'^{IV(\bar{R})} < \psi_S \text{ if } \mathrm{Cov}(\tilde{S}, Z) < 0, \tag{A16}$$

$$\hat{\psi}_S'^{IV(\bar{R})} > \psi_S \text{ if } \mathrm{Cov}(\tilde{S}, Z) > 0, \tag{A17}$$

Since $\mathrm{Cov}(\tilde{\delta}, Z) > 0$. ■