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Recovering from Supply Interruptions: The Role of Sourcing Strategy

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Fast recovery from supply interruptions is a key objective of supply chain and business continuity professionals. This paper provides the first rigorous and large-scale empirical evidence that relates the use of different supply chain strategies—supplier diversification and the use of long-term relationships—with the ability of a supply chain to recover from supply interruptions. We develop an estimator of a supply-chain's recovery rate that can be constructed using the limited available data—only the time series of firms' actual sourcing behavior. Using more than two million import manifests, we extract firms' sourcing transactions and use these data to estimate recovery rates of different firm-category supply chains of publicly traded US firms. We find that supplier diversification is associated with slower recovery from supply 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.

Keywords: Supply Interruption; Supply Chain Management; Supplier Diversification; Long-term Relationships; Empirical Analysis; Time to Recovery

RECOVERING FROM SUPPLY INTERRUPTIONS: THE ROLE OF SOURCING STRATEGY

ABSTRACT. Fast recovery from supply interruptions is a key objective of supply chain and business continuity professionals. This paper provides the first rigorous and large-scale empirical evidence that relates the use of different supply chain strategies—supplier diversification and the use of long-term relationships—with the ability of a supply chain to recover from supply interruptions. We develop an estimator of a supply-chain's recovery rate that can be constructed using the limited available data—only the time series of firms' actual sourcing behavior. Using more than two million import manifests, we extract firms' sourcing transactions and use these data to estimate recovery rates of different firm-category supply chains of publicly traded US firms. We find that supplier diversification is associated with slower recovery from supply 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.

1. INTRODUCTION

The complexity and diversity of global supply chains exposes them to a variety of logistical, industrial, geopolitical and natural events that can temporarily constrain sourcing (for example: labor strife (Rao, 2014), political activity (Victory, 2011), bad weather (Gledhill et al., 2014) and industrial accidents (Simchi-Levi et al., 2014) have all led to significant interruptions in sourcing for firms). 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; Miklovic and Witty, 2013).

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). This literature proposes various strategies for limiting the incidence and consequences of supply-interruptions. Yet to the best of our knowledge, there is no empirical complement that validates and/or compares the efficacy of these mechanisms. Fast-recovering supply chains have also received significant attention in the popular press on supply chains (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 supply-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 those 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 and what it was actually able to source, where differences between the two, the mismatch, would reflect the effect of interruptions. The time to decay of this 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 address both the data availability issues. First, we use legislatively mandated public data on import transactions to compile a large-scale, high-frequency data set on the actual global sourcing of firms; these data enable us to portray accurately the actual sourcing of different categories of imported goods by firms with global supply chains. We parse more than 45 million import manifests (bills of lading) issued during the period 2006–2011 to build a set of data on the global sourcing of public US retail, wholesale, and manufacturing firms, much expanding such data used in previous work (Jain et al., 2013). The second component, unobserved information on the firm's sourcing target, is more challenging to handle.

To surmount this challenge, we extend existing models on inventory management to compute the optimal sourcing policy for a firm that faces uncertain demand and uncertain supply. The resulting model structure relates a firm's demand and supply patterns to its target sourcing which has a specific form that can enable the necessary identification. Recall that we quantify supply 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. This estimator can be used to recover the relationships between the recovery rate and the firms' sourcing strategies using appropriate controls, fixed effects and "augmented instruments" or instruments which satisfy an additional exclusion condition that accounts for the compound nature of the recovery rate estimator.

Next, we use our data on actual sourcing to construct the recovery rate estimator, the augmented instruments and metrics for supply chain strategies—the extent of supplier diversification, the extent of long-term sourcing and the extent of sourcing from logistically efficient locations—all at the firm times category-of-sourced-goods level. We then identify the effects of supply chain strategy on the supply chain recovery rate using instruments in a model that incorporates both firm and category fixed effects. Effectively, this estimation exploits the differences between firms in their differences between categories. 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 narrower, 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, 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 and under a variety of alternate variable constructions.

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 supply chain's time to recover from interruptions. This 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 supply interruptions due to inventory record inaccuracy and under-staffing. There has not been much large-data research that investigates recovery from supply 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 supply interruptions: dual or multiple sourcing (e.g. Yang et al., 2012), emergency sourcing (Yang et al., 2009), passive acceptance and inventory build-up (Tomlin, 2006), process flexibility and improvement (Mizgier et al., 2015), indirect procurement using intermediaries (Yang and Babich, 2014), supply chain collaboration that improves supplier reliability (Wang et al., 2010), and collaborative investments by otherwise competing members of the supply chain (Bakshi and Kleindorfer, 2009). Iyer et al. (2005) study our key metric, recovery time, and its dependence both on contractual arrangements and on the existence of alternate suppliers. Bendoly et al. (2016) studies the effect of differences in suppliers' recovery-abilities on a retailer's sourcing policy. Although there is an extensive theoretical literature on the relationship between operational strategies and supply 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, industrial, geopolitical and natural 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 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 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. 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 (i.e., when multiple firms are competing for the slack capacities of unaffected suppliers). Moreover, suppliers typically have varying ability to recover from interruption events (Bendoly et al. (2016)). Fewer suppliers make it easier for the buyer firm to identify those that are better managed and that can recover most quickly from a supply interruption. Managing relationships and undertaking collaborative efforts to improve supply resilience is also easier when there are fewer suppliers involved (Wang et al., 2010).

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. *Supply chains with more diversified sourcing have **slower** recovery.*

Hypothesis 1b. *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). Deep relationships are typically characterized by "evergreen" or long-term sourcing contracts that lead to relationship-specific investments, information sharing, cross-shareholding, and in general, cooperative value enhancing actions as opposed to a individualistic myopic profit-maximizing behavior (Isaacson, 1994; Belavina and Girotra, 2012).

Long-term relationships typically involve inter-temporal trade-offs (Beth et al., 2003; Taylor and Plambeck, 2007) 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.[1]

Although there are many advantages to long-term sourcing, there are some arguments against them. 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. Yet anecdotal evidence suggests that the benefits outweigh the costs, which leads to our next hypothesis.

Hypothesis 2. *Supply Chains with longer-term relationships have **faster** recovery.*

[1]According to the 2014 "supply chain resilience" survey conducted by the Business Continuity Institute, just over half (51%) of interruptions occur at tier-2 or at other upstream tiers. The survey sample consisted of 525 business continuity specialists and other relevant respondents from 71 countries (bit.ly/1O7IYaP, accessed August 20, 2015).

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. Overall, however, we conjecture (as follows) that the benefits outweigh the costs.

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

4. Sample and Data Sources

We focus our study on US public firms covered by the 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 4000 candidate firms.

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 US	Texas Instruments, 7800 Banner drive, Dallas, TX 75251, US 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 4.1. Sample Bill of Lading

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.

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 4.1, 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 United States. 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 expanded sample; we add manufacturing firms to the sample and also expand the time-period to cover transactions from June 2006 to June 2011. We Web-crawled the data service to obtain more than 45 million bills of lading for imports during that five-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[2]) 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–1549 out of over 4000–actually participate in global sourcing. Altogether we obtain 2,037,459 import transactions for these 1,549 firms.

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*" dataset (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 U.S. 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; Wu, 2016). 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 supply 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 supply interruptions in the supply chain and the spillover of such mismatches

[2]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.

in preceding periods. Given the many 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,

$$\begin{aligned} m_t &= \sum_{s=0}^{t-1} \alpha^{t-s} \zeta_s + \zeta_t, \\ &= \alpha m_{t-1} + \zeta_t. \end{aligned} \tag{5.1}$$

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. 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. At times this theoretical construct is not even clear to the managers at the firm itself because at times of interruption managers tend to focus on the feasible sourcing options that respond to the interruption rather than on the counter-factual quantity that they would have sourced had there been no interruption. 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 an 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 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 (5.1) described previously imparts unique properties to the delivered-quantity process that facilitate our identification of the 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. At the same time, 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:

$$D_t = \mu + \theta_1 D_{t-1} + \cdots + \theta_p D_{t-p} + \epsilon_t + \phi_1 \epsilon_{t-1} + \cdots + \phi_q \epsilon_{t-q}, \tag{5.2}$$

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 auto-correlation 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:

$$S_t \quad = \quad K + \sum_{i=1}^{\infty} \boldsymbol{w}_i^T \boldsymbol{\epsilon}_{t-i} + \sum_{i=1}^{\infty} \boldsymbol{w}_i'^T \boldsymbol{\zeta}_{t-L-1-i}, \tag{5.3}$$

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:

$$C([K, \boldsymbol{w}_i, \boldsymbol{w}_i']) = E\Bigg[h\Bigg(\Bigg(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\Bigg) - \sum_{i=0}^{L} D_{t+i}\Bigg)^+ + p\Bigg(\sum_{i=0}^{L} D_{t+i} - \Bigg(S_t - \sum_{i=0}^{L} m_{t-L-1+i}\Bigg)\Bigg)^+\Bigg], \tag{5.4}$$

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*

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

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 lemma. 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.

The order-up-to levels S_t, the realized demand D_t, the realized mismatches m_t, and the leftover inventory together establish q_t, the order that the firm would like to place. When there are supply interruptions, the difference between inventory levels at the start and the end of a period is determined not only by the demand realized during the period but also by the mismatch incurred with respect to the order, placed L periods ago, that is scheduled to be delivered during the period. More specifically, the desired order quantity is then $q_t = S_t - (S_{t-1} - m_{t-L-2}) - D_{t-1}$ and the corresponding delivered ordered quantity is $d_t = q_t - m_t = S_t - (S_{t-1} - m_{t-L-2}) - D_{t-1} - m_t$.

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 5.3), demand D and mismatch extent m at different time instances. This inter-linking 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 the above proposition.

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 $\bar{\theta}_1$.

5.3. **Using the Compound Estimator with 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

$$R = \psi_0 + \psi_S S + \psi_X \boldsymbol{X} + \delta, \tag{5.5}$$

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

$$\psi_S \rightarrow \hat{\psi}_S^{OLS(\bar{R}_{DM})} = \frac{\mathrm{Cov}(\tilde{\bar{R}}_{DM}, \tilde{S})}{\mathrm{Var}(\tilde{S})}, \tag{5.6}$$

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:

$$\begin{aligned} \hat{\psi}_S^{\prime OLS(\bar{R})} &= \frac{\mathrm{Cov}(\tilde{\bar{R}}, \tilde{S})}{\mathrm{Var}(\tilde{S})} \\ &= \psi_S - \frac{\mathrm{Cov}(\tilde{\bar{\theta}}_1, \tilde{S})}{\mathrm{Var}(\tilde{S})}, \end{aligned} \tag{5.7}$$

by substituting $\bar{R} = \bar{R}_{DM} - \bar{\theta}_1$ and eq (5.6). That is the 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 $\mathrm{Cov}(\tilde{\bar{\theta}}_1, \tilde{S}) \neq 0$. In other words, using the compound measure will lead to biased relationships when the covariates $\boldsymbol{X}$ do not account for all the sources of correlation between the autocorrelation in a firm's demand for a category of products and its sourcing strategy in that category. We next illustrate how we can still recover unbiased relationships by the use of 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 $\mathrm{Cov}(Z, \tilde{S}) \neq 0$ (relevance) and *two* exclusion conditions: $\mathrm{Cov}(Z, \tilde{\theta}_1) = 0$ and $\mathrm{Cov}(Z, \delta) = 0$.

An IV estimation of $\tilde{\bar{R}} = \psi_0' + \psi_S' \tilde{S} + \delta'$ using augmented instrument Z can estimate the relationships without bias:

$$\begin{aligned}
\hat{\psi}_S^{\prime IV(\bar{R})} &= \frac{\mathrm{Cov}(\tilde{\bar{R}}, Z)}{\mathrm{Cov}(\tilde{S}, Z)} \\
&= \frac{\mathrm{Cov}(\tilde{\bar{R}}_{DM}, Z)}{\mathrm{Cov}(\tilde{S}, Z)} - \frac{\mathrm{Cov}(\tilde{\bar{\theta}}_1, Z)}{\mathrm{Cov}(\tilde{S})} \\
&= \psi_S, \qquad (5.8)
\end{aligned}$$

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

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. 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 (for e.g., HS code 521 which denotes "woven cotton fabric" based components, HS code 950 denotes "toys, games and equipment", etc.).

6.1. **Compound Measure of Recovery Rate.**

We start by building the monthly time series of the delivered quantity 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.[3] 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.

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 6.1, Panel (a) shows the distribution of this measure.

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. 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:

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

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

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.

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

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:

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

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 is sourced from supplier j, and Count of Nonzero Imports Month_{fc} is 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 Index for different sourcing locations, where the respective weights are set equal to the values of imports from each location. Thus we have

$$\text{Month Level Logistics Efficiency}_{fct} = \sum_{j=1}^{\mathrm{SL}_{fct}} \frac{\text{Supplier Import Value}_{fctj} \times \text{Logistics Performance Index}_{jt}}{\text{Cummulative Import Value}_{fct}},$$

$$\mathrm{LEL}_{fc} \equiv \frac{1}{|\mathrm{NZ}_{fc}|} \sum_{t \in \mathrm{NZ}_{fc}} \text{Month Level Logistics Efficiency}_{fct},$$

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 6.1, 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

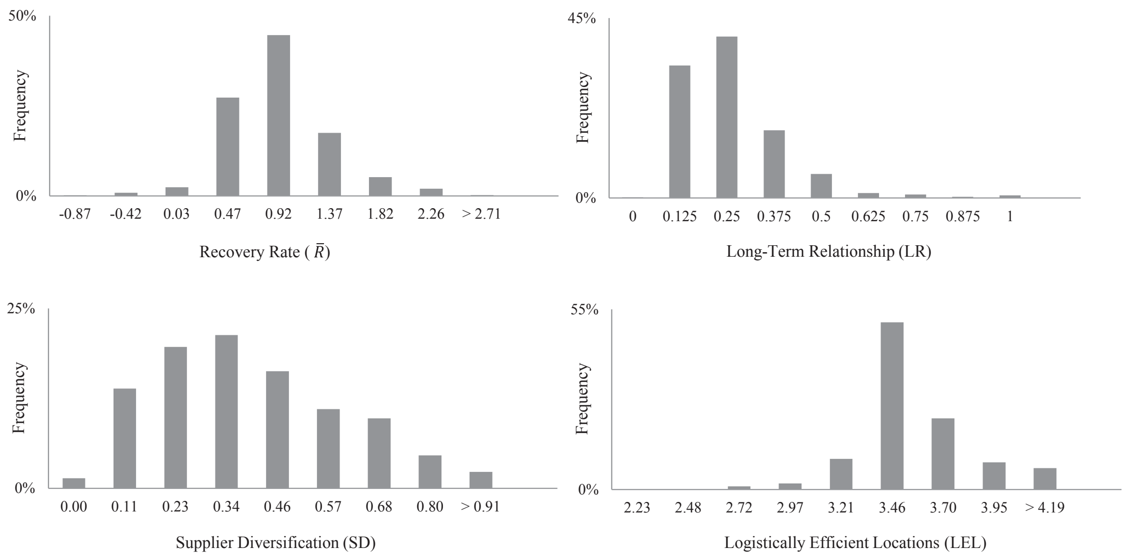


Figure 6.1. Sample Distribution of Recovery and Sourcing Strategy Variables

weights are set equal to the respective imports' 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,

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

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

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.

		All 1008 Firm × Components		**Manufacturing** 458 Firm × Components		**Retail/Wholesale** 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

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; this implies that there is enough variation in our data to potentially identify separate impacts of diversification and relationships.

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:

$$\overline{\mathrm{R}}_{fc} = \beta_0 + \beta_1 \mathrm{SD}_{fc} + \beta_2 \mathrm{logLR}_{fc} + \beta_3 \mathrm{LEL}_{fc} + \beta_4 \mathrm{SLT}_{fc} + \mathrm{F} + \mathrm{C} + \psi_{fc}. \tag{7.1}$$

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 6.1, Panel (b)).

The two-way fixed-effects model allows us to adopt a difference-in-differences identification strategy. The first difference is applied across supply chains for different categories of sourced goods within a firm, which eliminates firm fixed effects. That is, the first difference transforms Equation (7.1) into

$$\triangle^f_{c_i c_j}\overline{\mathrm{R}} = \beta_1 \triangle^f_{c_i c_j}\mathrm{SD} + \beta_2 \triangle^f_{c_i c_j}\mathrm{logRS} + \beta_3 \triangle^f_{c_i c_j}\mathrm{LEL} + \beta_4 \triangle^f_{c_i c_j}\mathrm{SLT} + (\mathrm{P}_i - \mathrm{P}_j) + \triangle^f_{c_i c_j}\psi, \tag{7.2}$$

where $\triangle^{f}_{c_i c_j}(\cdot)$ is a firm-level operator that differences out category j's value for a variable from the corresponding value of category i. The second difference is applied across firms within a category pair; this procedure removes the category pair fixed effects that were introduced in the first-difference–transformed model of Equation (7.2). The final model after the second difference is

$$\triangle^{f^k f^l}_{c_i c_j}\overline{\mathrm{R}} = \beta_1 \triangle^{f^k f^l}_{c_i c_j}\mathrm{SD} + \beta_2 \triangle^{f^k f^l}_{c_i c_j}\log\mathrm{RS} + \beta_3 \triangle^{f^k f^l}_{c_i c_j}\mathrm{LEL} + \beta_4 \triangle^{f^k f^l}_{c_i c_j}\mathrm{SLT} + \triangle^{f^k f^l}_{c_i c_j}\psi, \tag{7.3}$$

where $\triangle^{f^k f^l}_{c_i c_j}(\cdot)$ denotes a category pair–level operator that differences out firm l's values for a variable from the corresponding value for firm k. Based on the second-difference–transformed model of Equation (7.3), we find it instructive to interpret the coefficients β for any sourcing strategy variables S as follows:[4]

$$\beta = \frac{E\Big[\big(\bar{\mathrm{R}}_{ki} - \bar{\mathrm{R}}_{kj}\big) - \big(\bar{\mathrm{R}}_{li} - \bar{\mathrm{R}}_{lj}\big)\Big]}{E\Big[\big(\mathrm{S}_{ki} - \mathrm{S}_{kj}\big) - \big(\mathrm{S}_{li} - \mathrm{S}_{lj}\big)\Big]} \tag{7.4}$$

for $S \in \{\mathrm{SD}, \mathrm{RS}, \mathrm{LEL}\}$. That is β captures the dependence of the differences in recovery rates between firms (k and l) in their differences between overlapping categories i and j, $(\bar{\mathrm{R}}_{ki} - \bar{\mathrm{R}}_{kj})$ based on the corresponding differences in sourcing strategy (S). Effectively this estimation exploits the differences between firms in their differences between categories.

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 or category-level characteristics. For example, any unobserved endogenous firm characteristic (for example, management's risk aversion, information system quality, etc.) that affects both sourcing strategy and recovery rate will not bias our results. Similarly, the specific nature of a category (for example seasonality in supply of a raw material, complexity of imported goods, etc.) that affects both the sourcing strategy and the recovery rate will not bias our estimates of the effect of sourcing strategy on 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.

[4]The exact formula for these β coefficients incorporates an adjustment for the presence of additional covariates.

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 auto-correlation 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 our 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. (see for ex. Berry et al. 1995; Suarez et al. 2013). Specifically, we instrument the supply chain strategy employed in the focal firm×category by the aggregate strategy employed in other categories by the same firm:

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

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

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

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 dataset) 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. 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–the idiosyncratic firm×category component of the recovery rate) is unlikely to be correlated with the recovery rate for a different category of products. Likewise, the sourcing strategy for other categories is unlikely to be correlated with the demand auto-correlation for the focal products. For example, how a department store sources toys is unlikely to be correlated with the unexplained component of the autocorrelation in that retailer's demand for apparel, 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 three issues that can arise when estimating the two-way fixed-effects model in Equation (7.1), 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. Our inclusion of two-way fixed effects only partially corrects for such clustering (Petersen, 2009), so we must incorporate these two-way clustered errors into our estimation procedure. If unaccounted for, these may cause under estimation of standard-errors which may result in inflated significance levels ((Bertrand et al., 2002; Petersen, 2009; Cameron et al., 2011)). The problem is known to be acute for panels with two-way clustering. For example, Cameron et al. (2011) finds that ignoring the two-way clustered errors may result in as much as 50% higher chance of reporting spurious effects if the number of clusters in each dimension is more than 50 (as in our case).

Taken together, these first two issues entail the existence of two distinct sources of heteroskedasticity in error terms. The third possible issue concerns the presence of *partial* overlap but not complete overlap in product categories sourced by different firms. Effectively, this makes our data similar to an unbalanced panel wherein firms have observations spanning different time periods. The unbalanced structure of data significantly impedes the estimation of two-way models using the fixed-effects (within) estimator, and including numerous dummies makes the estimation computationally intensive (Guimaraes and Portugal, 2010). Even so, the relatively modest size of our data set renders the computational issue moot and we are able to execute the fixed-effects estimator in a reasonable time, which considerably simplifies our correction for the other two issues.

We employ five different estimation approaches, all of which are based on fixed-effects estimators with firm- and category-level dummy variables. As just discussed, the relatively small number of firms (142) and product categories (67) makes this approach computationally feasible. 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 $\times$ 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 E1 reveals that accounting for heteroskedasticity rather than homoskedasticity 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.[5] 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. This suggests that our model covariates, specially the firm and category fixed effects, are sufficient to account for all the sources of correlation between autocorrelation in a firm's demand for a category of products and its sourcing strategy in that category. As such there is no bias introduced on account of the compound recovery rate estimator.

[5]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; Kleibergen and Paap, 2006).

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)	0.80** (0.038)	0.80** (0.039)	0.80** (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	1008	1008	1008	1008	1008	1008
R-sq	27.6%	27.6%	27.6%	30.1%	30.1%	
Adjusted R-sq	8.3%			11.4%		

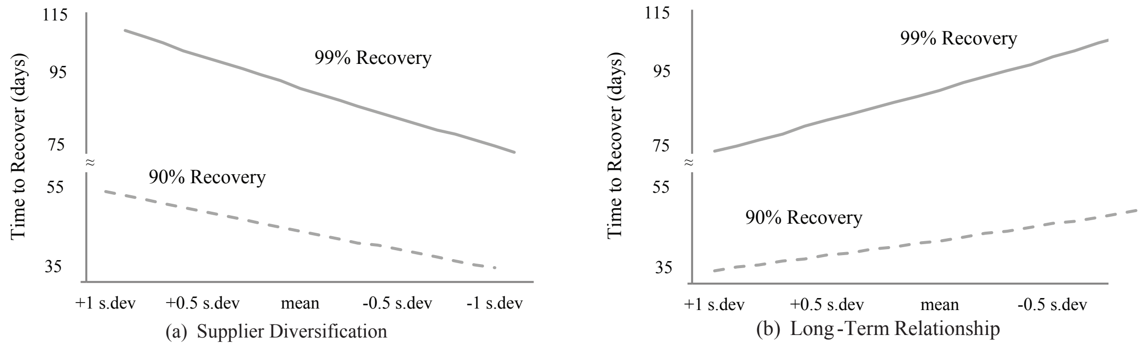
*** -- 1% level, ** -- 5% level, * -- 10% level

Table 2. Estimation Results

This is not surprising as autocorrelation in a firm's category demand series is largely determined by the category's characteristics (such as seasonal vs non-seasonal, long vs short life cycle) and by the business cycles experienced by the firm (Gaur et al., 2005; Chopra and Meindl, 2001; Nahmias, 1993).

We find a negative and significant effect of supplier diversification on the recovery rate; all else being equal, *a supply chain with more dispersed sourcing takes longer to recover from an interruption*. The benefits of ordering from fewer suppliers (volume leverage, better supplier selection, etc.) dominate those of ordering from more suppliers (access to alternate sources, supplier competition, etc.). This result complements research identifying the beneficial 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 supply chain with more long-term relationships recovers faster from an* interruption. The better alignment of incentives in long-term relationships outweighs any complacency introduced on account of such relationships.



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 7.1. Impact of Sourcing Strategies on Recovery Rate

We find a negative and insignificant effect of sourcing from logistically efficient locations on recovery. Thus there is insufficient evidence either to support or to reject the assertion that, in terms of facilitating recovery from a supply chain interruption, some locations are better than others. This outcome could be due to the small amount of variation in our constructed measure or to the opposing effects of logistically efficient locations, which cancel each other out and thus lead to a small net change. We note here that the logistically efficient locations variable exhibits significant correlation with the sourcing lead time variable which perhaps has reduced our ability to identify significant effects of the two.

Panels (a) and (b) of Figure 7.1 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-recovery by 16%. Similarly, a one standard deviation increase in long-term relationship reduces time-to-recover by 20%.

7.4. **Robustness Tests.** We next examine how robust our analysis is to the use of different subsamples of data and to alternative ways of constructing variables. Table 3 reports the results. To facilitate comparisons, we show the original estimates in Row 1. Each subsequent row provides estimates for variants of our original analysis. As in that main analysis, estimation results incorporate both weights and the two-way clustered correlation of errors.

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

	#	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***	0.10***	1000	Unit Root Test: Phillips-Perron (Non-Parametric) White Noise Test: Portmanteau
	5	-0.30***	0.07**	1147	Unit Root Test: Augmented Dickey Fuller White Noise Test: Bartlett
	6	-0.30***	0.06*	1177	Unit Root Test: Phillips-Perron (Non-Parametric) White Noise Test: Bartlett
Alternate Variable Construction	7	-0.06***	0.10***	1008	Supplier Diversification based on Number of Suppliers
	8	-0.11	0.04**	1008	Weighted Long-Term Relationship by import share
	9	-0.14**	0.08**	1004	Sourcing strategies measured over 90 days window
	10	-0.22**	0.03	1034	Component-category definition at 4 digit HS-Code level
	11	-0.26***	0.06**	967	ARMA best fit criterion: Bayesian Information Criterion (BIC)
	12	-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 3. Robustness Tests

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 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.

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 results using two popular alternate tests: the Phillips–Perron test for stationarity (Phillips and Perron, 1988) in Row 4 of the table, and a white-noise test due to (Bartlett, 1978) in Row 5; both tests are incorporated into the values reported by Row 6.

We find that, irrespective of the sample used, the coefficient's signs are the same as in our original results. The significance of those results also remain—except for the long-term relationship variable in the lower-power manufacturing subsample. The magnitude of all effects is generally close to our original estimates.

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 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 thus 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 7).

In Row 8, 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 captured 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 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. We define the alternate measure as,

$$\mathrm{LR}_{fc} \equiv \frac{1}{\mathrm{NS}_{fc}} \sum_{j=1}^{\mathrm{NS}_{fc}} \frac{\left(\frac{\text{Supplier Import Value}_{fcj}}{\text{Total Import Value}_{fc}}\right) \times \text{Count of Non-Zero Supplier Import Months}_{fcj}}{\left|\text{Count of Non-Zero Import Months}_{fc}\right|},$$

where Supplier Import Value$_{fcj}$ is the value of imports received by firm f in category c from supplier j, and Total Import Value$_{fc}$ is the cumulative import value across all suppliers.

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 9 of Table 1 we report estimation results using sourcing strategy measures that are constructed over 90-day windows.

Row 10 of the table gives estimation results under an alternate definition of category of imported goods. On the one hand, a relatively coarser definition reduces 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 10 reports the results when categories are defined (less coarsely) using 4-digit HS codes.

Finally, Rows 11 and 12 of Table 1 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 11). 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 12 of the table 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: $d_t = \alpha_0 + \alpha_1 t + \text{Quarter-level dummies} + \tilde{d}_t$.

Results of the 11 robustness tests described in this section can be summarized as follows. We confirm the negative and significant effect of supplier diversification on recovery across 10 of the tests, and the effect of long-term relationship is positive and significant across 9 of them. In addition, the signs of our coefficients are unchanged across all 22 tests. Altogether, these tests strongly support the robustness of our main findings.

8. Conclusion

This paper provides the first rigorous and large-scale empirical evidence that relates a firm's particular supply chain strategy to the ability of that supply chain to recover from interruptions. 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 for 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 investigation. Although existing theoretical work has shown how diversification reduces the incidence of interruptions, we demonstrate that there is also a downside to diversification vis-a-vis recovery. Together, there is now ambiguity on the preferred strategy for building resilient supply chains—future work might investigate the relative efficacies and value of using supplier diversification to reduce the incidence and consequences of interruptions. 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 another interesting avenue for future work.

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Appendix A. Proofs

PROOF OF PROPOSITION 1. We solve for the optimal parameters $[K^*, \boldsymbol{w}_1^*, \dots \boldsymbol{w}_1'^*, \dots]$ in two-steps. First, for a fixed weight vectors $\boldsymbol{w}_i$'s and $\boldsymbol{w}_i'$'s, we solve $\arg\min_K C\left(K, \boldsymbol{w}_1, \dots \boldsymbol{w}_1', \dots\right)$ to obtain optimal $K^*(\cdot)$ as a function of the weight vectors. Next, we solve $\arg\min_{(\boldsymbol{w}_1,\dots \boldsymbol{w}_1',\dots)} C\left(K^*(\cdot)\ , \boldsymbol{w}_1, \dots \boldsymbol{w}_1', \dots\right)$ to obtain the optimal weight vectors $(\boldsymbol{w}_1^*, \dots \boldsymbol{w}_1'^*, \dots)$. 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. (5.4)) as:

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

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

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

$$m_t = \sum_{i=0}^{\infty} \mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}. \tag{A.2}$$

Next, using the definition of order-up-to level S_t (eq. 5.3), ordered-delivered mismatch quantity process m_t (eq. 5.1), and demand process D_t (eq. 5.2) 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

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

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

$$C(K^*(\cdot), \boldsymbol{w}_1, \ldots \boldsymbol{w}'_1, \ldots) \quad = \quad (h+p)\phi(z)\sqrt{\triangle_w^D + \triangle_u^D + \triangle_{w'}^m + \triangle_u^m}, \tag{A.3}$$

where $\phi(\cdot)$ is the standard normal density function. Equation (A.3) 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 $\triangle_u^m = \mathrm{Var}\big(\sum_{i=0}^{L}\sum_{j=0}^{i}\zeta_{t-L-1+i-j,t-L-1+i}\big) = \sum_{i=0}^{L}\mathrm{Var}\big(\sum_{j=0}^{L-i}\zeta_{t-L-1+i,t-L-1+i+j}\big) = \sigma_m^2\sum_{i=0}^{L}\big(\sum_{k=0}^{i}\alpha^k\big)^2$ as $\zeta_{t,t+k} = \alpha^k\zeta_{t,t}$ and $\zeta_t \sim N(0,\sigma_m^2)$.

Finally, substituting optimal weights in (A.3), we obtain the square of optimal cost expression as:

$$C(\cdot)^2 \quad = \quad g \times \left(\triangle_u^D + \sigma_d^2\sum_{i=0}^{L}\left(\sum_{k=0}^{i}\alpha^k\right)^2\right), \tag{A.4}$$

where $g = (h+p)^2\phi(z)^2$. Differentiation of both the sides of equation with respect to spill-over rate α (A.4) gives:

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

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:[6]

$$q_t = S_t - \left(S_{t-1} - m_{t-L-2}\right) + D_{t-1}. \tag{A.5}$$

In the absence of interruptions eq. (A.5) 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. (5.3), (A.1), (A.2), and eq. (A.5) we get

$$d_t = \mu + \sum_{i=1}^{\infty}\left(\boldsymbol{w}_i - \boldsymbol{w}_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\epsilon}_{t-i} + \sum_{i=1}^{\infty}\left(\boldsymbol{w}'_i - \boldsymbol{w}'_{i-1} + \mathbf{e}_i^T\right)\boldsymbol{\zeta}_{t-L-1-i} - \sum_{i=0}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}. \tag{A.6}$$

[6]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; Cui et al., 2015).

Eq. (A.6) implies that the delivered quantity process is the sum of two sub-processes $d_t = \mathbb{P}^1_t + \mathbb{P}^2_t$, where $\mathbb{P}^1_t = \mu + \sum_{i=1}^{\infty}\big(\boldsymbol{w}_i - \boldsymbol{w}_{i-1} + \mathbf{e}_i^T\big)\boldsymbol{\epsilon}_{t-i}$ and $\mathbb{P}^2_t = \sum_{i=1}^{\infty}\big(\boldsymbol{w}'_i - \boldsymbol{w}'_{i-1} + \mathbf{e}_i^T\big)\boldsymbol{\zeta}_{t-L-1-i} - \sum_{i=0}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i}$, that are driven by mutually independent demand ϵ and mismatch shocks ζ. Further, note that $\mathbb{P}^1_t$ 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 $\mathbb{P}^1_t$ 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 $\mathbb{P}^1_t$ are the same as that of the demand process D_t. For the sub-process $\mathbb{P}^2_t$, under the optimal parameters $\boldsymbol{w}^*_i = e^{i+L+1}_{i+1}$ and $\boldsymbol{w}'^*_i = e^{i+L+1}_{i+1}$, we obtain

$$
\begin{aligned}
\mathbb{P}^2_t - \alpha\mathbb{P}^2_{t-1} \;&=\; \big(e_1^{L+2}\big)^T\boldsymbol{\zeta}_{t-L-2} + \big(\mathbf{e}_2 + \mathbf{e}_{L+3}\big)^T\boldsymbol{\zeta}_{t-L-3} + \sum_{i=3}^{\infty}\big(\mathbf{e}_i + \mathbf{e}_{i+L+1}\big)^T\boldsymbol{\zeta}_{t-L-1-i} - \zeta_t - \sum_{i=1}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i} \\
&\quad -\alpha\big(e_1^{L+2}\big)^T\boldsymbol{\zeta}_{t-L-3} - \alpha\sum_{i=1}^{\infty}\big(\mathbf{e}_i + \mathbf{e}_{i+L+1}\big)^T\boldsymbol{\zeta}_{t-L-2-i} - \alpha\sum_{i=0}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-1-i}, \\
&=\; \big(e_1^{L+2}\big)^T\boldsymbol{\zeta}_{t-L-2} + \big(\mathbf{e}_2 + \mathbf{e}_{L+3}\big)^T\boldsymbol{\zeta}_{t-L-3} + \sum_{i=3}^{\infty}\big(\mathbf{e}_i + \mathbf{e}_{i+L+1}\big)^T\boldsymbol{\zeta}_{t-L-1-i} - \zeta_t - \sum_{i=1}^{\infty}\mathbf{e}_{i+1}\boldsymbol{\zeta}_{t-i} \\
&\quad -\big(e_2^{L+3}\big)^T\boldsymbol{\zeta}_{t-L-3} - \sum_{i=2}^{\infty}\big(\mathbf{e}_{i+1} + \mathbf{e}_{i+L+2}\big)^T\boldsymbol{\zeta}_{t-L-2-i} - \sum_{i=0}^{\infty}\mathbf{e}_{i+2}\boldsymbol{\zeta}_{t-1-i},
\end{aligned} \tag{A.7}
$$

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 $\sum_{i=2}^{\infty}\big(\mathbf{e}_{i+1} + \mathbf{e}_{i+L+2}\big)^T\boldsymbol{\zeta}_{t-L-2-i} \equiv \sum_{i=3}^{\infty}\big(\mathbf{e}_i + \mathbf{e}_{i+L+1}\big)^T\boldsymbol{\zeta}_{t-L-1-i}$ 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. (A.7), we obtain

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

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

$$
(1 - \theta_1 B - \cdots - \theta_p B^p)\mathbb{P}^1_t \;=\; (1 - \phi'_1 B - \cdots - \phi'_{q'} B^{q'})\epsilon_t, \tag{A.8}
$$

$$
(1 - \alpha B_1)\mathbb{P}^2_t \;=\; \Bigg(1 - B + \Bigg(\sum_{i=1}^{L+2}\alpha^{i-1}\Bigg)B^{L-2} - \Bigg(\sum_{i=3}^{L+2}\alpha^{i-1}\Bigg)B^{L-3}\Bigg)\zeta'_t, \tag{A.9}
$$

where B denotes the backward operator, q' equals the length of moving-average part of $\mathbb{P}_t^1$ and ϕ' denote the moving-average coefficients. Computing the sum $(A.8) \times (1 - \alpha L_1) + (A.9) \times (1 - \theta_1 L_1 - \cdots - \theta_p L^p)$ gives:

$$\begin{aligned} (1 - \theta_1 L_1 - \cdots - \theta_p L^p)(1 - \alpha L_1)(\mathbb{P}_t^1 + \mathbb{P}_t^2) &= (\cdot)\epsilon_t + (\cdot\cdot)\zeta_t, \\ (1 - (\theta_1 + \alpha)B - (\theta_2 + \theta_1 \alpha)B^2 - \cdots)d_t &= (\cdot)\epsilon_t + (\cdot\cdot)\zeta_t. \end{aligned} \tag{A.10}$$

Eq. (A.10) implies the coefficient of first auto-regressive term B of the delivered quantity process is $(\theta_1 + \alpha_1)$.