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Supply chain disruptions and sourcing strategies ☆

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ABSTRACT

Supply chain disruptions have recently been at the center of both academic and policy debates. After reviewing some of the emerging literature on supply chain disruptions, we discuss the role of buyers' sourcing strategies in mediating responses to such shocks. We focus on two dimensions of a buyer's sourcing strategy: *relationality* (the extent to which the buyer concentrates its sourcing in a few core suppliers) and *just-in-time*. On the one hand, theoretical models of sourcing suggest that these are complementary practices and their adoption should be positively correlated in the data. On the other hand, the two dimensions have opposing implications for supply-chain resilience to shocks. We borrow an empirical proxy for a buyer's *relationality* from Cajal-Grossi et al. (2023) and introduce a new proxy for a buyer's adoption of *just-in-time* inventory systems. Using data from the apparel global value chain we compute the two proxies and present three results: (a) the variation in both *relationality* and *just-in-time* is mostly explained by across-buyer variation, rather than product or country variation, (b) consistent with the theoretical analysis in Taylor and Wiggins (1997), *relationality* and *just-in-time* are highly correlated with each other across buyers, (c) at the onset of the global Covid-19 pandemic, buyers' overall sourced values declined relatively less for *relational* buyers but not for buyers with *just-in-time* inventory systems.

1. Introduction

Many companies have recently seen their supply chains disrupted and tested more than ever before. As Grossman et al. (2021) simply put it, supply chain disruptions have become the new normal. For example, the 2021 Supply Chain Resilience report from BCI found that 25% of firms experienced more than ten disruptions in 2020 compared to less than 5% in 2019 (BCI, 2021). Similarly, Resilinc – a consulting company specialized in monitoring supply chains – reported a 67% increase in disruptions between 2019 and 2020 (Resilinc, 2022). The recently released GSCPI Index on supply chain disruptions was between 3 and 4 standard deviations above its long-term average on 2021 and 2022 (Benigno et al., 2022). Albeit an imprecise proxy, Fig. 1 reports the intensity of Google searches for "*Supply Chain Shortage*", "*Supply Chain Disruption*" and "*Supply Chain Problem*" from 2017 to 2022. For many people, supply chain disruptions have been top of mind more than ever before.

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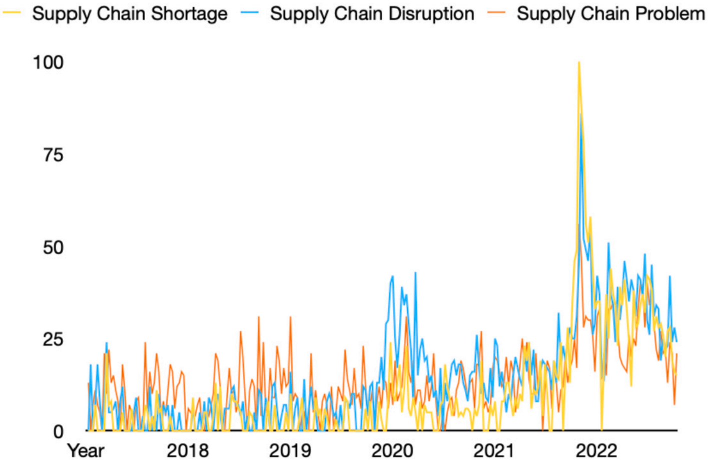

Fig. 1. Supply Chain Issues - Google Trends. The figure reports Google Trends searches for "*Supply Chain Shortage*", "*Supply Chain Disruption*" and "*Supply Chain Problem*" between 2017 and 2022. The vertical axis is the ratio between the search volume and the total number of searches completed in the time period considered, scaled on a range of 0-100.

As a result, supply chain disruptions and their economic consequences are nowadays at the center of the academic and policy debates (Baldwin and Freeman, 2022). On February 24, 2021, the U.S. president stated that "the United States needs resilient, diverse, and secure supply chains to ensure economic prosperity and national security." Similarly, to improve the resilience of supply chains, the European Union has promoted policies aimed at increasing domestic capacity, diversifying suppliers and supporting the multilateral rules-based trade environment. Both the U.S. (White House, 2021) and the E.U. (European Comission, 2021) recovery plans list supply chain resilience as one of the main policy goals.

This paper provides a preliminary exploration of the role played by buyers' sourcing strategies in mediating the response to supply-chain shocks. Understanding the drivers and consequences of different sourcing systems is a pre-requisite to evaluating the rationale for potential policy interventions aimed at boosting the economy's resilience to shocks (Baldwin and Freeman, 2022; Grossman et al., 2021). Inspired by the theoretical model in Taylor and Wiggins (1997), we focus on two dimensions of sourcing systems: *relationality* (the extent to which the buyer concentrates its sourcing in a few core suppliers) and *just-in-time* inventory systems. Taylor and Wiggins (1997) develop a model of two fundamentally different subcontracting systems that might arise to solve the moral hazard problem faced by a buyer sourcing an input. Their model emphasizes the complementarity between relying on a long-term relationship and a just-in-time inventory system to provide incentives to the supplier. In particular, the higher frequency of shipments in just-in-time systems facilitates the provision of relational incentives through repeated transactions. The model predicts that these complementary practices go hand in hand and their adoption will thus be positively correlated across buyers. At the same time, when evaluated through the perspective of supply-chain resilience, the two dimensions might have opposing implications. On the one hand, relational contracting is a sourcing strategy that might increase resilience against shocks. On the other hand, just-in-time practices entail lean inventories, leaving them more vulnerable to unanticipated supply chain disruptions.

We subject these hypotheses to empirical scrutiny in the context of the garment global value chain. Leveraging harmonized, transaction-level customs records from six garment–exporting countries (Bangladesh, Ethiopia, India, Indonesia, Pakistan and Vietnam) we characterize international buyers according to their sourcing strategies. After studying the nature and relationship between a buyer's strategies, we turn our attention to the interplay between supply-chain resilience and sourcing. We do so by characterizing the trade responses of buyers adopting different sourcing strategies, to a large-scale disruption to the garment supply chain – the Covid-19 pandemic. Our empirical results confirm the complementarity between *relationality* and *just-in-time* sourcing predicted by the theoretical implications discussed above, and find evidence for the opposing forces that *relationality* and *JIT* exert on the supply-chain, in the face of disruptions.

We deliver our main results in five steps, each presented in a section. Section 2 reviews some of the recent literature on the impact of supply chain disruptions. While the literature is still growing, certain common themes have begun to emerge. Among those, some studies have found that long-term relationships might help mitigate the impact of supply chain disruptions. This observation highlights the importance of sourcing strategies and brings us to the second part of the paper.

Section 3 introduces empirical proxies for two distinct dimensions of a buyer's sourcing strategy. A proxy for *relationality*, originally introduced in Cajal-Grossi et al. (2023), measures the extent to which buyers follow a *spot* versus a *relational* approach to sourcing. Holding sourced volumes constant, the proposed measure is akin to a measure of concentration in a buyer's supply base – with relational buyers having a more concentrated supply base. The second proxy, introduced here, measures the extent to which buyers follow a *just-in-time* (JIT) inventory system. Again, holding sourced volumes constant, the measure captures how frequent and chopped-up shipments are. An advantage of these proxies is that they can be computed using transaction-level data with information on buyer and supplier identities. These data are becoming increasingly available for both international (from customs records) and for domestic (from VAT records) transactions. The proxies can thus be used to map sourcing systems in other supply chains.

In Section 4, we implement the two proxies in the garment sector using customs records from several different sourcing origins and we present three sets of results. We begin studying both measures at a disaggregated level: we compute the buyer's relational sourcing at the level of the buyer b, product j and country of origin c (i.e., at the bjc-level), and the JIT measure at the level of the buyer b, product j, season h and country of destination d (i.e., at the $bjdh$-level). Our first result is that buyer b fixed effects – rather than product and country effects – account for the vast majority of the explained variability in sourcing strategies. Cajal-Grossi et al. (2023) already documented this finding for the relational proxy. We confirm this to be the case for JIT inventory systems as well. These findings suggest that the sourcing strategy of a buyer might depend on buyer-level investments in organizational capabilities. If the new environment requires a change in the approach to sourcing, this might be costly to implement for many organizations.

Second, we find that the two measures are highly correlated with each other. Across buyers, a JIT inventory system goes hand in hand with a relational approach to sourcing. This novel finding is consistent with the theoretical analysis in Taylor and Wiggins (1997). The result is also consistent with Cajal-Grossi et al. (2023) findings that relational buyers pay higher prices and markups to suppliers relative to spot buyers, in order to incentivize hard to contract upon actions, such as reliable JIT deliveries. At the same time, frequent supply chain disruptions likely call for a rethinking of JIT systems and their associated low inventories. This implies that "*relational contracts*" with core suppliers will need to be changed and new equilibria built to adjust to the landscape – a process that will also be difficult and will disrupt established routines in long-term relationships (see Gibbons and Henderson (2012) and Helper and Henderson (2014) on difficulties in adjusting relational contracts).

We also explore the extent to which buyers' characteristics correlate with the type of sourcing system. We find that buyer size and buyer's position in the supply chain correlate with the adoption of relational and JIT sourcing systems. Larger buyers are more likely to be relational and to use JIT. This is consistent with economies of scale or scope in the organization of sourcing. Buyers specialized in retail of branded garments – and thus further downstream – are also more likely to be relational and to use JIT. As these buyers need to be more responsive to changes in fashion trends, this provides further suggestive evidence that a relational strategy might be relatively more suitable in contexts that require frequent changes and adaptation – such as the new normal.

Section 5 explores whether buyers with different sourcing strategies exhibited different patterns of adjustment to the onset of the pandemic. On the extensive margin, *relational* buyers are less likely to permanently abandon their sourcing activities; in contrast, JIT buyers are more likely to do so. Both *relationality* and *just-in-time* correlate negatively with the likelihood of dropping existing suppliers in the year following the onset of the pandemic. On the intensive margin, buyers' overall sourced values declined relatively less for *relational* buyers. While the patterns are less clear-cut, it appears that buyers with *just-in-time* inventory systems suffered larger declines in their overall imported values once their *relationality* is accounted for. This underscores the importance of understanding sourcing practices as being part of a system of complementary practices.

We draw the reader's attention to two important aspects that are left beyond the scope of this paper. First, we focus on export transactions in the global apparel supply chain. We make no pretense that the garment chain is representative of other supply chains. This raises the question of whether our findings apply to other industries. Second, the paper focuses on buyers' sourcing strategies. In practice, however, buyers are not alone in having to make a strategic decision about the relationship-inventory bundle. Participating in the supply chain of buyers with different approaches to sourcing might also entail strategic choices on the part of suppliers.

These limitations notwithstanding, taking these first steps in the apparel value chain is motivated by several considerations. First, apparel production is an important sector for several developing countries. The production of garments is labor-intensive and, as a result, developing countries with abundant labor and low wages have a comparative advantage in garments production. The industry employs an estimated 60 million workers around the world, nearly 75% of whom are women. Garments destined to export markets are produced in large manufacturing plants in which developing countries get acquainted with modern management systems (Bloom and Van Reenen, 2010). As such, the industry has played a key role in the early phases of export-oriented industrialization (Baldwin and Martin, 1999; Gereffi, 1999). Moreover, the industry has been a driver of women's emancipation in several countries (Heath and Mobarak, 2015). Its historical relevance, size and societal role in developing countries make the garments global value chain one of intrinsic interest.

Second, the sector offers a rich laboratory to study issues of governance and supply-chain resilience. To benefit from the lower labor costs in emerging economies, most of the garments destined to high-income markets are sourced in China and other Asian countries. Information and contracting frictions, arguably pervasive in developing countries, make the management of cross-border transactions particularly complex, both in business-as-usual times, as well as in times of unexpected disruptions.[1] Garments provide the canonical example of a buyer-driven global value chain (Gereffi, 1999). In these chains, buyers "call the shots," which serves our purposes well given our focus on the critical –yet less studied– aspect of how international buyers organize their sourcing. Due to the ever-evolving fashion cycles and the high cost of inventories in high-income destination markets, a well-performing sourcing system is a key source of a buyer's competitive advantage in the industry. Buyers' choice of sourcing systems, however, also has profound implications for suppliers. Using detailed data from Bangladesh, Cajal-Grossi et al. (2023) finds that suppliers earn higher prices and margins on orders produced for relational buyers relative to (virtually identical) orders produced for buyers that source through short-term contracts. Supplying relational buyers thus represents a form of upgrading for developing countries' exporters. If relational buyers also adopt *just-in-time* inventory systems, such upgrading requires investments in capabilities on the sellers' side and implies sorting between buyers with certain sourcing systems and suppliers with certain capabilities. These considerations echo evidence that, more generally, exporting is associated with better management practices (Bloom et al., 2021). We thus hope that the limitations highlighted above will stimulate further research in this area.

[1] Boudreau et al. (2023) discusses in greater detail the garment supply chain and its governance challenges in developing countries.

2. Literature review

In this section we review some of the recent literature on supply chain disruptions. For reasons of space, our review is naturally selective and incomplete. Highly relevant and complementary reviews exist. First, Baldwin and Freeman (2022) provide a review on the literature that integrates perspectives from the international trade literature and the operations/supply chain literature. One important takeaway of the review is that evidence in the economics literature is relatively limited thus far, and possibly not adequate for informing policy debates around supply chain resilience. Second, Elliott et al. (2022) provides a theory-oriented overview of work on resilience and stability in networks, including supply chains. In particular, they analyze the conditions in which supply networks can be considered to be fragile, i.e., when aggregate output is very sensitive to small shocks. They derive results on phase transitions and highlight the role of diversification, link strength and depth of the chain in determining resilience.[2]

Transmission of shocks in supply chains A number of papers have used natural disasters to study how shocks propagate along supply chain links. Using the 2011 Tohoku earthquake, Boehm et al. (2019) find a high degree of complementarity between domestic inputs used by Japanese affiliates in the US and their imported inputs from Japan, consistent with a relationship close to Leontief; Carvalho et al. (2021) further document that these disruptions propagated upstream and downstream along supply chains, affecting both the direct and indirect suppliers, and customers of involved firms; Kawakubo and Suzuki (2023), however, find that buyers with suppliers located in the disaster area were actually able to shift their sourcing towards suppliers closer to headquarters, thereby limiting the negative effect of the shock. Using a wider range of natural disasters, Barrot and Sauvagnat (2016) analyze how suppliers affected by a shock in the U.S. induce output losses on their customers. They find that these losses are more substantial when the link involves customized products. This suggests that sourcing strategies developed to deal with contracting problems can play a potentially important role in shaping supply chain resilience to shocks – an issue upon which we return momentarily.

A growing literature analyzes the impact of the Covid-19 pandemic on Global Value Chains (henceforth, GVCs).[3] Fujiy et al. (2022), analyzing the impact of the Covid-19 crisis on Indian firm-to-firm trade, find a low degree of substitution between inputs. Such elasticity is one of the key parameters that drives the extent to which shocks propagate along networks in the macro literature. Khanna et al. (2022) show that during Covid-19 Indian firms that buy more complex products and that have fewer available suppliers were less likely to break links. Chacha et al. (2022) document that Kenyan importers and exporters adjust their domestic supply chains in response to international trade shocks. In developed countries, Heise (2020) examines the impact of the Chinese lockdown on U.S. imports, and finds that the sharp decline in the first quarter of 2020 was partially offset by growing imports from countries outside of China, such as Vietnam, India, and Bangladesh. Lafrogne-Joussier et al. (2023) study the firm-level propagation of the Covid-19 shock to exports and its heterogeneity across firms with different risk management strategies on French firm-to-firm data. They find that inventories are more effective at curbing supply shock than diversification strategies.[4]

The latter is a notable study that contributes much needed evidence on the role of inventories in supply chains. In general, the literature distinguishes whether the firm receives inventory only as needed for production – i.e., JIT –, or it opts for stocking up inventories ahead of time (Just-in-Case). In this literature, Feinberg and Keane (2006) and Keane and Feinberg (2007) show that the increase in intrafirm trade between US firms and their Canadian affiliates in the 1990s may be mainly attributable to JIT supply chain management. Pisch (2020), using French firm-level data, provides evidence that JIT is indeed a widespread strategy and that the JIT supply chains are more vertically integrated.

Supply-chain shocks, adaptation and governance form As noted by Williamson (2005), both Hayek – a firm defender of the efficiency of decentralized markets – and Barnard – the famous organization theorist – saw adaptation as the central problem of economic organization. Hayek proposed the idea that autonomous adaptation is accomplished by the decentralized market through prices. Barnard, instead, proposed that it was the firm, through its reliance on authority, that achieved conscious adaptation. Evidently, supply chain disruptions require adaptation – be it changes in prices, in the availability of trading partners and logistics, etc. – and, therefore, it might be useful to understand how the choice of governance forms mediates, and responds to, supply chain disruptions. For example, we might ask whether governance forms matter for the transmission of supply chain shocks, or whether governance forms are chosen in anticipation of future disruptions and – if so – whether these decentralized choices are efficient from a societal point of view.[5]

It is important to consider long-term relationships sustained by the prospect of ongoing trade – a "*hybrid*" form in between firms and markets, in Williamson's terminology – as a distinctive organizational form (Macchiavello, 2022). A significant share of trade takes place in long–term relationships between buyers and sellers. Many important aspects of trade – e.g., reliability, demand assurance, flexibility, quality, and payment terms – are non–contractible and potentially subject to opportunistic behavior. Even when a contract is in place, it is not expected to be enforced in court but is rather intended to guide parties about what to expect

[2] Grossman et al. (2021) is a noteworthy recent theoretical contribution that analyzes optimal policy in the face of uncertain supply chains.

[3] Bonadio et al. (2021), Meier and Pinto (2020), and Eppinger et al. (2021) investigate the role of input-output linkages at the sector level in the propagation of the Covid-19 shock. We focus on firm-level studies.

[4] See Blaum et al. (2023) for a discussion on shipping delays and the diversification of the supplier base.

[5] A large literature also has studied the firm decision to vertically integrate or outsoruce a particular stage of production (Baker et al., 2002; Antràs and Chor, 2013; Alfaro et al., 2016; Del Prete and Rungi, 2017; Alfaro et al., 2019; Berlingieri et al., 2021). Vertical integration is virtually absent in the stage of the apparel global value chain we focus on.

in the relationship. Under these circumstances, parties tend to stick with partners they trust. Long–term relationships are indeed ubiquitous in many contexts, including at the export gate. For example, recent studies found that the vast majority of U.S. imports occur in pre–existing relationships (Monarch and Schmidt-Eisenlohr, 2017; Monarch, 2018).

Shocks to specific industries have been used to better understand the functioning of relationships along supply chains. For example, Ksoll et al. (2021) investigates the mechanisms and costs of disruptions induced by the post-electoral violence in 2008 on the Kenyan floriculture industry. The violence induced a large negative supply shock that reduced exports primarily through workers' absence. The shock, however, had heterogeneous effects: larger firms and those exporting through long-term relationships suffered smaller production and losses of workers. Crucially, exporters with long-term buyers exerted significant effort to overcome the negative shock – e.g., setting up camps to host workers and stopping deliveries to more lucrative outside opportunities.

Macchiavello and Morjaria (2015) dig deeper into the nature and role played by long-term relationships in ensuring reliable deliveries in the Kenyan rose export sector. They test for the importance of reputation – defined as the buyer's beliefs about the seller's reliability – in these relationships. They document how, due to lack of enforcement, the volume of trade is constrained by the value of the relationship. They also quantify the value of these relationships and find it to be both substantial and increasing with the age of the relationship. During the shock, they find that deliveries are an inverted-U-shaped function of a relationship's age: exporters prioritize relationships that are already sufficiently valued, and receive insurance (here, in the form of slack) from more established partners with whom they have already gained sufficient trust. Less established partners are not prioritized and those relationships do not survive into the following season.

If different approaches to sourcing respond differently to shocks, firms should also adapt their choices of sourcing systems when the likelihood of facing a shocks changes. Heise et al. (2021) study the impact of trade policy *uncertainty* on the organization of supply chains using the US and China trade war. They find that when the probability of a trade war rises, firms become *less* likely to adopt "Japanese"-style procurement practices and form long-term relationships with foreign suppliers. To the extent that a trade war reduces permanently the value of future interactions, it can hinder parties' ability to develop and sustain long-term relationships – i.e., it lowers the *supply* of relationships. On the other hand, an increase in the likelihood of more short-lived disruptions, e.g., those associated with natural events, likely increases the *demand* for long-term relationships.

Given this evidence, we now try to make some progress in understanding where long-term relationships in supply chains come from. We will focus on sourcing systems, using the garment sector as a testing board. The analysis presented here borrows heavily on ongoing work (Cajal-Grossi et al., 2022). Besides the intrinsic interest of the industry noted in the introduction, buyers' sourcing strategies play a critical role in the industry. To take advantage of lower labor costs, the sourcing of garments destined for high-income markets has been relocated to developing countries – mainly to China and other Asian countries, such as Bangladesh, Pakistan, and Vietnam. Given ever-evolving fashion cycles and the high cost of inventories in high-income destination markets, a well-performing sourcing system is a critical source of competitive advantage in the industry. The industry was severely disrupted by Covid-19, as we further discuss in Section 5.

3. Measuring buyers' sourcing strategies

3.1. Data

We provide a succinct description of the data used in Cajal-Grossi et al. (2022). We harmonized transaction–level, exports customs records from six major garment–producing countries, namely Bangladesh, Ethiopia, India, Indonesia, Pakistan and Vietnam, over the period between January 2018 to March 2021. However, the sourcing metrics in this paper are computed using pre-2020 data, to avoid conflating sourcing strategies with responses to the pandemic. The countries in the sample account jointly for about one-quarter of the world exports of garments, which are led by China, with a global market share of 32%, and the European Union, all member countries together accounted for 28% in 2019.[6]

The data are disaggregated at the level of the transaction – a product code inside of a shipment. A transaction i is specific to a buyer or importer (b index) in a given destination (d), a seller or exporter (s) in an origin country (c), a product (j) and a date (τ).[7] The resulting dataset exceeds 28 million transactions. The data records for each transaction the weight (and in some cases units), value, destination, origin and the type of product (HS codes at 6-digits) – all within headings 61 and 62, corresponding to knit and woven garments. The data contain information on the international buyer and the seller (or exporter) in the transaction. Buyers are identified by name and address, and sellers are identified either by country–specific tax codes or by name and address. For 371 of the 500 largest buyers in our sample we were able to retrieve buyers' core activities and financial accounts from the Orbis database produced by the Bureau van Dijk (a Moody's Analytics company).[8]

6 Aside from their importance in international markets, garment exports represent a significant share of the total export earnings of the countries in our sample. For instance, about 80% and 40% of Bangladesh and Pakistan exports respectively, is accounted for by apparel. The importance of these sourcing origins notwithstanding, not observing the universe of the supplier base of the buyers in our data will induce measurement error in the sourcing metrics that we construct. This type of error will play *against* our ability to detect any differential responses to the pandemic shock, by buyers with different sourcing strategies.

7 In fact, transactions are more granular than a $-bdscj\tau$ combination, as in theory there may be multiple shipments of the same good traded by two parties on a given day, as the supplier may be shipping two orders, of the same product and same buyer, under two customs declarations.

8 Appendix A describes in detail the process of harmonization, cleaning, and buyer and seller identification.

3.2. Definitions and empirical measures

What is the *sourcing strategy* of a firm? We use this term to refer to the complex bundle of decisions a firm makes: *who* and *where* to buy from, *how* to source, i.e., the terms of purchases from suppliers. Besides standard volumes and prices, we are particularly concerned with the frequency and timing of transactions and whether the relationship is established or not. These sourcing decisions require coordination among multiple functions within the firm's organization, ranging from design to distribution and from communication to human resources (Milgrom and Roberts, 1990). Similarly, these decisions are often tied to the firm's and its partners' specific circumstances. The factors that enter the sourcing problem of the firm are typically not observed. Our approach is thus to use observed (equilibrium) outcomes that result from these choices, to construct proxies for buyers' sourcing strategies from transactions with their suppliers.

Taylor and Wiggins (1997) offer the canonical model of sourcing strategies. Their model emphasizes complementarities between bundles of practices and distinguishes between a *Japanese* and an *American* sourcing style. This distinction originated in the management literature on the automotive sector (Richardson, 1993; Nishiguchi, 1994; Helper and Sako, 1995; Helper and Henderson, 2014), but has proven useful in qualitative studies of other sectors, including electronics (De Toni and Nassimbeni, 2000) and aerospace (Masten, 1984). Under *Japanese* sourcing, buyers rely on long-term relationships with selected suppliers and implement JIT systems. Under *American* sourcing, instead, the buyer allocates larger, less frequent, orders to arm's length suppliers that compete in a form of procurement auction. In Taylor and Wiggins (1997)'s model, the more frequent, smaller, shipments in JIT facilitate the provision of incentives through higher prices in long-term relationships – the two practices are thus complementary. Alternatively, the buyer can pay lower prices and bear the cost of holding inventories and inspecting the goods. This is more efficient when shipments are larger and relatively infrequent.

While Taylor and Wiggins (1997) emphasize the complementarity between long-term sourcing relationships and just-in-time inventory systems, the two dimensions have different implications when evaluated through the perspective of supply-chain resilience. On the one hand, relational contracting is a sourcing strategy that might increase resilience against shocks. On the other hand, just-in-time practices entail that the buyer carries minimal or lean inventories, leaving them more vulnerable to unanticipated supply chain disruptions.

We therefore focus on two aspects of buyers' sourcing strategies: relationality – the extent to which the buyer relies on established or core relationships – and JIT – the extent to which goods are received from suppliers only as they are needed. For each dimension, we construct proxies for sourcing strategies at the buyer level. We follow Cajal-Grossi et al. (2023) and conceptualize the sourcing strategy as a buyer-level decision, rather than a variable that can be dialed up or down depending on the product, origin, or time of the transaction. This perspective builds on the idea that a sourcing system is sustained by several complementary practices in the organization. As a result, the strategy that a firm adopts is enabled by its organizational capabilities, which are costly to develop (Gibbons and Henderson, 2012; Helper and Henderson, 2014). An implication of this is that firms cannot easily adjust their sourcing strategy to adapt to local circumstances nor to accommodate unexpected changes in their sourcing environment. In this paper, we do not consider other potential aspects of a buyer's sourcing strategy. In particular, buyers may diversify the origin countries from which they source, thus spreading their supply base across different countries and increasing their resilience to country-specific idiosyncratic shocks. Similarly, buyers may choose product and destination market mixes to smooth or concentrate demand – again choices that would be highly complementary with the sourcing strategy. We explore these decision margins in Cajal-Grossi et al. (2022).

Relationality Cajal-Grossi et al. (2023) characterize buyers according to where they lie on the relationality spectrum. At one extreme, "spot" buyers spread purchases among multiple arm's–length suppliers, allocating short–term orders to the lowest bidders and bearing the costs of suppliers' non–performance. At the other extreme, "relational" buyers allocate orders to a few suppliers with whom they develop long–term relationships. We exploit the intuition that, conditional on sourced volumes, relational buyers concentrate sourcing among a small number of suppliers and define

$$Relational_b = \sum_{jc} \left[\frac{PQ_{bjc}}{PQ_b} \times Relational_{bjc} \right] \qquad \text{and} \qquad Relational_{bjc} = -\frac{N^s_{bjc}}{N^i_{bjc}},$$

where N^i_{bjc} is the number of shipments in the buyer–product–origin combination, and N^s_{bjc} is the number of suppliers in the buyer–product–origin combination. The (negative of the) ratio of sellers to shipments is aggregated at the level of the buyer by weighing each product-origin combination by their share in the buyer's imported values, denoted with PQ, in the data.

Cajal-Grossi et al. (2023) argue that this approach yields a cross–sectional characterization of buyers' relational sourcing that maps closely to qualitative accounts in the industry and also presents certain advantages relative to other intuitive alternatives. First, much of the empirical literature on buyer-seller relationships uses measures of relationship age (e.g., calendar time or number of past transactions) to proxy for relational trade (Macchiavello, 2010; Macchiavello and Morjaria, 2015; Heise, 2020; Martin et al., 2020). The advantage of relationship age as a proxy for relational trade is that it is observable in the data. There are disadvantages, however. First, panel data with information on the identities of trading parties are often shorter than the lifespan of many real-life business relationships. This creates problems of both right and left censoring in most applications. More fundamentally, relationship age is not a perfect proxy for relational contracting. Baker et al. (2002) defines relational contracts as informal arrangements sustained by the value of future interactions. Repeated trade, then, does not imply relational trade which, instead, relies on future rents used to provide incentives to parties to resist current temptations to deviate (see Macchiavello (2022) for a discussion). More pertinent to our application, using relationship age as a measure of relational contracting also requires implicit assumptions about the demand structure across buyers. For example, when start-to-end duration is used, this ignores that very frequent interactions and sporadic interactions may entail different implicit commitments by parties. On the other hand, when the count of interactions is used, one runs the risk of attributing relational contracting to buyer-specific seasonal patterns and demand characteristics. At any rate, using data from Bangladesh – for which a longer panel is available – Cajal-Grossi et al. (2023) show that the metric based on sellers-to-shipments ratios is well correlated with metrics based on relationship duration, as well as robust to perturbations to the set of partners or time periods that are considered.

Just-in-time JIT is a management system by which inventories and holding costs are minimized, and downstream demand is catered for in real-time, through the agile response of the supply chain (Ohno, 2019). Despite the current widespread use of JIT sourcing, records on firm-level adoption of these practices are rare. In the economics literature, those records are limited to industry-specific, case studies of a small number of firms at a time (Helper and Henderson, 2014), or build on survey-based data, typically containing some binary question on adoption (Bloom and Van Reenen, 2010; Pisch, 2020). In the accounting literature, and with high overlap with the definition introduced above, a commonly used proxy for JIT supply management is the firm's stock–to–turnover ratio, capturing the number of times the company has sold its total inventory (Kinney and Wempe, 2002). A related accounting measure of JIT sourcing is the days sales of inventory (DSI), a ratio that indicates the average time in days it takes a firm, to clear its inventory into sales (Kapanowski, 2016). While these metrics are very intuitive, they are not useful for industry-wide studies for two reasons. First, computing these measures of JIT requires (at least) balance sheet information of firms, which is typically available only for large firms. Moreover, since firms replenish stock at a more disaggregated level than the company's overall inventory, these data should be at the product/variety-level. Second, many different aspects of the firm-specific accounting system make the comparison of stocks-to-turnover or DSI hardly comparable across firms, let alone products, industries, or countries.

To overcome these limitations, we combine the intuition of the accounting literature – that JIT firms take fewer days to clear their inventory– with the observed timing of shipments in the customs records. We characterize the adoption of JIT by a buyer, using the time span between contiguous supply shipments, within the buyer's market. We operationalize this by assuming that buyers fulfill inventories of varieties defined at the level of the product, destination market and season.[9] Specifically, we compute the span in days between contiguous transactions of the buyer sourcing a product, for a given destination and in a given season ($-bjdh$): $Days^i_{bjdh} = Date^i_{bjdh} - Date^{i-1}_{bjdh}$ where transactions are ordered chronologically.[10] For each buyer–destination–product–season, we take the median span, across all the tuple's transactions. We normalize this by the total trade of the buyer in the product–destination–season, which allows us to re-express the time span per dollar (as in the accounting metrics). The resulting ratio is the shipment $Turnover_{bjdh}$ and holding size fixed, it is *low* when shipments are frequent. We re-express the turnover in relative terms with respect to the median shipment turnover across all buyers in the destination–product–season ($Med(Turnover)^b_{jdh}$). This mitigates concerns about the comparability of JIT measures across product categories or seasons. We aggregate at the level of the buyer, weighing each destination–product–season by their share over the buyer's trade, and multiplying by minus one, such that the measure is increasing in shipment frequency, or JIT. Formally,

$$JIT_b = \sum_{jdh} \frac{PQ_{bjdh}}{PQ_b} \times \left(- \frac{Turnover_{bjdh} - Med(Turnover)^b_{jdh}}{Med(Turnover)^b)_{jdh}} \right) \quad \text{and} \quad Turnover_{bjdh} = \frac{Med(Days)^i_{bjdh}}{PQ_{bjdh}}. \tag{1}$$

As we discuss in the next section, the resulting measure of JIT sourcing appears in line with industry accounts. To further validate our approach, we benchmark our metric with the stock–to–turnover accounting metric discussed above. The latter measures how often a company replaces inventory relative to its sales, with a higher ratio denoting high inventories relative to sales. This metric is constructed as the ratio between operating revenue and stocks (inventories) averaged over the period 2018-2019 and it is available for 371 buyers in our data, whose balance sheet information we can access from Orbis. For these buyers (not surprisingly, the largest buyers in our sample), we find a positive and significant correlation of 0.241 (S.E. 0.051) between our JIT measure and the Orbis stock–to–turnover ratio (see Fig. B.2).[11]

[9] For each product–destination combination, we organize the four quarters in a year into a high and a low season, and we index seasons with h.

[10] Two transactions within the same $-bjdh$ that happen on the same day are counted as the same transaction. We also note that the dates that we record are at the point of export (i.e., at exit from the exporting country) and, as such, do not count the shipping time to the destination. To see how this will affect the measure at the buyer level, consider two buyers whose orders at the point of export are biweekly, so in both cases we record as span 14 days. Assume that one buyer sources from an origin with low shipping times and the other buyer sources from an origin that implies high shipping times. So long as the shipping times are stable for the destination–origin pair, the shipping times and hence the point-of-entry dates will differ, but the time spans at the point of entry will be the same – still 14 days for both buyers. In this sense, observing either end of the shipment gives the same span.

[11] We note that negative skewness is a feature of our measure of JIT (skewness of -.2.6) as it is of the "off-the-shelf" stock-to-turnover measure (skewness of -7.7) and of other JIT measures. Intuitively, this is because there is a natural limit to how fast stock can be replenished, but there is no limit to how slow the process can be. This causes "bunching" at high levels of adoption of JIT and a long bottom tail for any linear measure. As our metric intends to approximate the measures in the supply chain management literature, but with data available at the industry scale (customs records), we purposefully stay as close as possible to these existing measures. This allows us to preserve the main intuition of what we are capturing, and also affords us the validation exercise in Fig. B.2.

Table 1
Top 25 Buyers.

Top 25 Buyers	Market Share %	Reported Activities					Sourcing Characteristics - Rankings			
		Manufac turing	Whole sale	Retail	Services	Special ized	$Relational_b$	JIT_b	Mix_b^j	Mix_b^d
Hennes & Mauritz	4.44	0	0	1	0	1	2	1	2	1
THe Gap	3.61	0	0	1	0	1	4	2	5	14
Hanes Brands	1.50	0	0	1	0	1	5	7	24	12
Inditex	1.42	1	0	0	0	1	24	10	4	21
Primark	1.37	0	0	1	0	1	15	5	9	4
Target	1.33	0	0	1	0	0	8	3	19	17
Adidas	1.16	1	0	0	0	1	3	4	7	3
Sae A	1.09	1	0	0	0	1	11	9	22	16
C & A	1.07	0	0	1	0	1	23	20	10	20
BYC	1.04	1	0	0	0	1	1	6	23	25
Marks & Spencer	0.97	0	0	1	0	0	16	16	1	18
Walmart	0.94	0	0	1	0	0	19	8	6	9
Phillips-VH	0.80	-	-	-	-	-	14	15	18	10
VF corporation	0.79	1	0	0	0	1	21	21	20	11
Uniqlo	0.74	0	0	1	0	1	13	14	15	5
Hansoll Textile	0.70	1	0	0	0	1	18	17	16	8
JC Penney Purchasing	0.70	-	-	-	-	-	17	19	13	22
Makalot Industrial	0.69	1	0	0	0	1	9	25	11	15
Kohls Department	0.67	0	0	1	0	0	20	24	3	23
Hansae	0.67	0	0	0	1	0	12	22	8	6
Bestseller	0.64	0	1	0	0	1	22	18	12	19
Levi Strauss	0.60	1	0	0	0	1	10	12	25	7
Apparel Trading	0.57	1	0	0	0	1	25	23	14	2
Toyobo STC	0.57	0	1	0	0	0	7	13	17	24
Under Armour	0.54	0	1	0	0	1	6	11	21	13

The table lists the largest 25 buyers in descending order based on their imports of garments preior to Covid. For each buyer, the table shows the buyer's market share (in all exports in our data harmonized over the six countries), the buyer's reported activities as collected by Orbis, and the ranking of the buyer based on different sourcing dimensions, in all cases one corresponding to the highest rank. The reported activities, based on the buyers' core activities as defined by Orbis, are, from left to right, manufacturing (NAICS codes 31 to 33), wholesale (NAICS code 42), retail (NAICS codes 44 and 45), service (NAICS codes from 51), and specialized (NAICS core codes: 3131, 3132, 3133, 3149, 3151, 3152, 3159, 3162, 4243, and 4481.) The sourcing characteristics are, from left to right, the relationality of the buyer ($Relational_b$), its just-in-time sourcing (JIT_b), its diversification across productcs (Mix_b^j) and across destinations (Mix_b^d). The definitions for the first to measures listed here are presented in Section 3.2, and the definitions of the diversification metrics are left for Appendix B.

4. How do buyers source?

Table 1 examines the 25 largest buyers of garments in our sample. The table presents buyers in descending order based on their in-sample market shares prior to Covid-19. H&M and The Gap lead the board with market shares of 4.44%, and 3.61% respectively, more than 5000 times larger than the median buyer in the sample.

Based on Orbis data, more than half of these top buyers are specialized in garments. A small fraction of them engage in in-house manufacturing, and a handful report wholesaling as part of their activities. Most leaders in the industry are specialized garment retailers (such as H&M, or The Gap), brand conglomerates (such as VF or PVH) or non-specialized mass retailers (like Walmart).

Even among this small set of large buyers, there are significant differences in their approach to sourcing. The rightmost panel of the table ranks buyers according to various sourcing metrics. Under the heading $Relational_b$, buyers are ranked by their relationality, the first rank corresponding to the most relational buyer. The order maps closely to qualitative accounts in the industry. For example, H&M and The Gap, ranked second and fourth, respectively are two large buyers known for their relational approach to sourcing, while Zara's owner Inditex, known for a spot sourcing strategy in Asia, is ranked lower. Similarly, the second column in the right panel of Table 1 shows buyers' rankings according to our measure of JIT. For instance, H&M and The Gap (including brands such as Athleta and Banana Republic), known for their frequent collection changes and their low inventory, lead the board with the highest JIT metrics. At the other end of the spectrum, Kohl's, with its large distribution and fulfillment centers in their consumer markets (in particular, in the U.S.), score at the bottom of the JIT list (see Wen et al. (2019) for a survey of operational models in the fashion retail supply chain).

4.1. What accounts for differences in sourcing?

We now present two results. First, we decompose disaggregated versions of the relational and JIT metrics, into different sources of variation. We show that most of the observed variability in sourcing strategies is accounted for by buyer-specific effects, as opposed to being driven by variation in product, origin or destination. Second, we show that relationality and JIT are indeed highly positively correlated, as implied by the model in Taylor and Wiggins (1997).

In a classic study, Monteverde and Teece (1982) test the key predictions of the transaction cost economics (TCE) theory of vertical integration developed in Williamson (1975). They first refine the theory and hypothesize that car assemblers will integrate when the

Table 2
Sources of Variability in Relationality.

Decomposition based on loss of fit (% of R^2)					
Fixed effects set:	I^1	I^2	I^3	I^3	I^4
Destination	16.90				
Buyer		71.58	64.25	58.72	41.24
Product	67.42	25.53			
Country	13.10	2.13			
Product-country			34.96	46.32	13.94
Product-destination					19.25
Sample		All		Multi-country	
Observations	261,029	260,749	260,701	114,927	111,909

Each entry reflects the loss of fit resulting from removing the fixed effects in the rows from a linear projection of $Relational_{bjc}$ on the set of fixed effects in each I specification (columns). The specifications are as follows: $I^1 = \{destination, product, country\}$, $I^2 = \{buyer, product, country\}$ and $I^3 = \{buyer, product - country\}$ and $I^4 = \{buyer, product - country, product - destination\}$. The loss of fit is computed as the share over the fit in the full model: $(R^2_I - R^2_{I-i})/R^2_I$. The first three columns of the table use all buyer–product–country triplets available in the global data. The last two columns restrict attention only to buyers present in two or more countries. I^1: destination = 148, product = 200, country = 6; I^2: buyer = 10,919, product = 200, country = 6; I^3, All: buyer = 10,919, product-country = 1,058; I^3, Multi-country: buyer = 2,903, product – country = 1,040; I^4: buyer = 2,886, product – country = 1,034, product – destination = 4,980.

production process of a component generates specialized, non-patentable, know-how. They then develop several empirical proxies for the transaction-specific know-how and test the predictions using data on the procurement of 133 components used by GM and Ford in 1976. In line with the prediction of TCE, they find that both GM and Ford were more likely to integrate into the production of specific components.

A less appreciated finding in Monteverde and Teece (1982) is that the buyer dummy turns out to be highly significant in explaining differences in vertical integration. That is, GM and Ford systematically differed in their vertical integration strategy for otherwise similar components. This suggests that organizational capabilities might also underpin the choice of governance form.

Cajal-Grossi et al. (2023) generalizes the approach in Monteverde and Teece (1982) and assess the quantitative relevance of TCE arguments versus organizational capabilities in explaining garments buyers' approach to sourcing. In our context, TCE would suggest that the choice of sourcing strategy should be driven by conditions in the sourcing market. For example, products that require customization, or that are sourced from countries in which contracts are harder to enforce, should be more likely sourced through a relational approach. Following this rationale, different buyers should choose similar sourcing strategies when sourcing the same product, from the same origin country. Accordingly, origin-product fixed effects should explain most of the variation in observed relationality. Similarly, destination-product effects proxy for conditions in the downstream market and therefore should also account for variation in sourcing. With regard to JIT, similar arguments apply. Products or seasons that exhibit high fashion turnover should see more JIT sourcing, as do destinations that are closer by or whose consumers demand high product turnover. In this case, we expect that product-destination-season effects explain most of the observed variation in JIT sourcing. In contrast, an organizational capability perspective would argue that a given buyer may adopt a similar sourcing strategy even when sourcing (and selling) different products from (and to) different countries. Conversely, within origins (or destinations) and product combinations, different buyers will behave differently. If this is the case, buyer fixed effects should explain the bulk of the observed variation in sourcing strategies.

We start by replicating Cajal-Grossi et al. (2023) and explore the margins that account for most of the observed variation in sourcing strategies, by means of a variance decomposition exercise. We quantify the relevance of the different margins of variability in the observed sourcing strategies by recovering the loss of fit from removing fixed effects from more saturated specifications. Table 2, which reproduces the results in Cajal-Grossi et al. (2023), decomposes the variability in relationality as captured by $Relational_{bjc}$ (see the definitions introduced in Section 3.2). Table 3 presents a novel decomposition of dispersion in JIT, by performing the loss-of-fit exercise on our disaggregated measure of days to restock, $Turnover_{bjdh}$.

Focusing on the most demanding specification in the decomposition of relationality (rightmost column of Table 2), the buyer accounts for 41% of the explained variability in sourcing strategies, vis-à-vis 13% and 19% that correspond to product-country (the origin of the garment) and product-destination (the country of the buyer), respectively. This pattern is consistent with the idea that buyer-level factors (capabilities) are quantitatively important drivers of sourcing behavior.[12]

Turning the attention to the decomposition of JIT, we note that, when buyer fixed effects are not taken into account, the destination country and the product account jointly for most of the explained variability in JIT (column 1 of Table 3). However, when

[12] Note that the result is not driven by the much larger number of buyer fixed effects relative to other dimensions. In the richer specifications we discuss in the text, the number of buyers is comparable to the number of groups in the other fixed effects sets.

Table 3
Sources of Variability in Just-in-Time.

Decomposition based on loss of fit (% of R^2)					
Fixed effects set:	I^1	I^2	I^3	I^3	I^4
Destination	44.15				
Buyer		97.39	73.75	65.44	65.42
Product	53.51	2.32			
Season	0.85	0.00	0.00		
Product-Destination			24.05		
Product-Destination-Season				31.74	31.74
Sample			All		Multi-Product
Observations	228,816	228,693	225,720	221,947	221,665

Each entry reflects the loss of fit resulting from removing the fixed effects in the rows from a linear projection of $Turnover_{bjdh}$ on the set of fixed effects in each I specification (columns). The specifications are as follows: $I^1 = \{destination, product, season\}$, $I^2 = \{buyer, product, season\}$ and $I^3 = \{buyer, season, product - destination\}$ and $I^4 = \{buyer, product - destination - season\}$. The loss of fit is computed as the share over the fit in the full model: $(R_I^2 - R_{I-i}^2)/R_I^2$. The first four columns of the table use all buyer (destination)–product–season triplets available in the global data. The last column restricts attention only to buyers present in two or more products. I^1: destination = 149, product = 200, season = 2; I^2: buyer = 10,937, product = 200, season = 2; I^3, All: buyer = 10,912, season = 2, product – destination = 7,617; I^3, Multi-country: buyer = 10,833, product – destination = 10,746; I^4: buyer = 10,695, product – destination – season = 10,740.

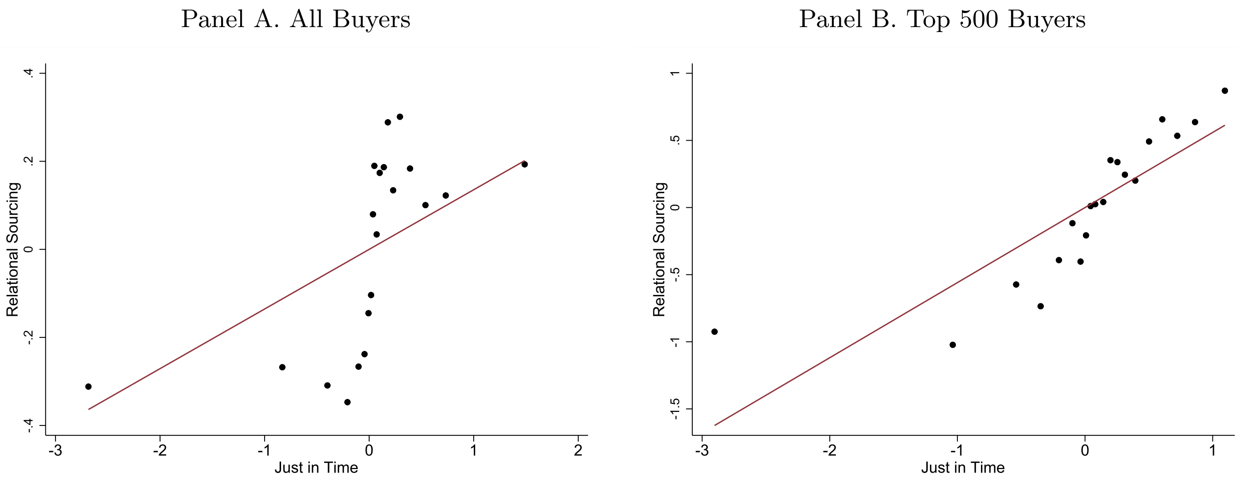

Fig. 2. Correlation between Relationality and Just-in-Time. The figure presents the correlation between the Relational and Just-in-Time metrics in our paper (as defined in Section 3.2). A unit of observation underlying this figure is a buyer. The scatter markers denote averages across all buyers within each of 20 equally-sized bins. The overlayed line corresponds to a linear fit of the underlying data, controlling for buyer size, in deciles of their imported value pre-Covid-19 and across all products. The estimated slope is 0.135 (S.E. 0.010) in Panel A, and 0.560 (S.E. 0.039) in Panel B.

buyer-specific intercepts are included in the model, the buyer accounts for 65% of the explained variation in JIT, while product-destination-season fixed effects account for 32% (columns 3-4).

The key take-away from our variance decomposition analysis is that the sourcing strategy of a buyer is mainly driven by organizational capabilities. If a new environment with frequent supply chain disruptions calls for a change in firms' approaches to sourcing, this will require costly, organization–wide adjustments.

4.2. *Are* relationality *and* JIT *complements?*

Fig. 2 tests, and finds support for, a key prediction in Taylor and Wiggins (1997). The figure shows that relationality and JIT are strongly positively correlated with each other across buyers. Using detailed data from Bangaldesh, Cajal-Grossi et al. (2023) find that relational buyers pay higher prices and markups to suppliers relative to spot buyers. This is consistent with the idea that they tend to incentivize actions that are hard to contract upon. Thus the two pieces of evidence combined provide strong support for the distinction between a *Japanese* sourcing system – based on JIT, long-term relationships, and high prices – and an *American* one – based on low prices, competitive bidding and short-term interactions to deliver large orders.

Table 4
Correlations Across Sourcing Characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			$Relational_b$					JIT_b	
$Size_b$	0.303***				0.196***	0.430***			0.319***
	(0.076)				(0.045)	(0.070)			(0.044)
JIT_b		0.588***			0.438***				
		(0.110)			(0.106)				
Mix_b^d			0.193***		0.135***		0.071		-0.076*
			(0.041)		(0.032)		(0.046)		(0.039)
Mix_b^j				-0.327***	-0.354***			-0.103**	-0.062
				(0.033)	(0.039)			(0.049)	(0.047)
$Relational_b$									0.463***
									(0.069)
R^2	0.11	0.35	0.04	0.11	0.47	0.23	0.01	0.01	0.44
Obs.	496	496	496	496	496	496	496	496	496

Standard errors in parentheses, robust to heteroskedasticity across observations. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). The table shows regressions of our metrics of sourcing, $Relational_b$ (columns (1) to (4)) and JIT_b (columns (5) to (8)) on buyer characteristics. The definitions of these outcomes are presented and discussed in Section 3. The regressors are the buyer size ($Size_b$) measured as the log values imported prior to Covid-19 across all countries in the data, and measures of the buyer's diversification in destinations (Mix_b^d) and products (Mix_b^j). The definitions of these variables are presented in Appendix B. All variables, except for $Size_b$ are standardized in the regression sample. The sample restricts attention to the top 500 buyers (accounting for over 75% of the exported values in our global data), of which 4 are discarded on account on at least one sourcing measure not being available. All variables in this regression table are constructed using pre-Covid-19 (2018 and 2019) transactions.

4.3. Sourcing strategies and buyer characteristics

Finally, Table 4 explore cross-sectional correlation patterns between buyers' characteristics and the two dimensions of sourcing. Beside being informative about potential drivers of sourcing strategies, the table also offers an additional test for the complementarity between the two sourcing practices. The standard way to test for complementarity in organizational practices is to identify factors that "move" practices together (Brynjolfsson and Milgrom, 2013). We thus expect relationality and JIT to have common drivers.

Table 4 confirms this hypothesis. Columns (1) and (6) show that the buyer's size is positively correlated with both relationality and JIT. As discussed above, this is consistent with economies of scale – likely driven by investments in organizational capabilities – associated with setting up *Japanese*-style procurement systems. Columns (3) and (7) show that *more* diversified buyers – in terms of number of downstream markets they sell to – have higher relationality and JIT (the latter for a p-value of 0.12). This is consistent with the idea that downstream diversification allows buyers to smooth out demand and guarantee more stability in orders (i.e., provide demand assurance) to their core suppliers – a likely key aspect of relational sourcing systems. Conversely, columns (4) and (8) show that *less* diversified buyers – in terms of number of products they source – also have both higher relationality and JIT indexes. Concentrating volumes in fewer product categories might allow buyers to guarantee larger volumes (and thus book a higher share of the capacity) of their suppliers, thus also facilitating relational sourcing. Columns (5) and (9) show that these patterns hold when all variables are considered together, and also confirm that relationality and JIT are strongly and positively correlated, conditional on the buyer's size and its product and market diversification.

5. Sourcing strategies and supply chain disruptions

We now provide a preliminary exploration of how the two dimensions of sourcing systems – relationality and just-in-time – correlate with differential changes in buyers' sourced volumes at the onset of the Covid-19 pandemic. The halt in production in China on February 2020 was followed by the closures of shops and factories around the world. In the early days of the pandemic, the apparel global value chain was hit by both demand and supply shocks. On the one hand, brands and retailers saw their in-store sales collapse due to lockdowns in destination markets. Many buyers simply canceled or postponed production orders, refusing, in several cases, to pay for clothing their supplier factories had already produced. Conversely, mandated restrictions in manufacturing countries also led to supply shortages. Even in the absence of restrictions in producing countries, the buyers' behavior resulted in partial or complete shutdowns of factories in souring countries (Anner, 2020). As a result of these events, in April 2020, the Sustainable Textile of Asian Region (STAR) Network, a body that brings together representatives of the producing associations from Bangladesh, Cambodia, China, Myanmar, Pakistan, and Vietnam, released a statement inviting global businesses to "support business partners in the supply chain as much as possible, and aim at a long-term strategy of business continuity, supply chain unity and social sustainability."[13]

[13] The statement can be accessed at the following link: http://www.asiatex.org/ennewss/393.html, accessed on 25^{th} June 2023.

Table 5
Buyers' Extensive and Sub-Extensive Margins of Adjustment.

	Extensive		Sub-extensive		
	(1) $Exit_b$	(2) $Exit_b^c$	(3) $Drop_b^s$	(4) $Drop_b^d$	(5) $Drop_b^j$
$Relational_b^D$	-0.036**	-0.099**	-0.094*	-0.022	-0.020
	(0.014)	(0.046)	(0.048)	(0.031)	(0.032)
JIT_b^D	0.052**	-0.111	-0.134**	-0.016	-0.055*
	(0.023)	(0.072)	(0.050)	(0.024)	(0.029)
Mean of Outcome	0.01	0.20	0.59	0.31	0.33
Buyer-level Controls	yes	yes	yes	yes	yes
FEs	d,y	d,y	d,y	d,y	d,y
R^2	0.03	0.09	0.29	0.15	0.16
Obs.	485	479	479	479	479

Standard errors in parentheses, clustered at the level of the main destination of the buyer. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. The sample restricts attention to the top 500 buyers and a unit of observation is a buyer. The table shows linear regressions of extensive and sub-extensive buyer outcomes and buyers' sourcing strategies, relationality and just-in-time, as defined in Section 3.2. For the purpose of these regressions, the sourcing variables are indicators that take value one for buyers above the 90^{th} percentile of the distribution of the (continuous) corresponding sourcing metric: $Relational_b^D$ and JIT_b^D. All sourcing variables in this regression table are constructed using pre-Covid-19 (2018 and 2019) transactions only. Columns (1) and (2)'s outcomes are indicators that take value one if the buyer stops importing from all countries ($Exit_b$) and from at least one country ($Exit_b^c$) in the last quarter of 2019 or the first quarter of 2020. Columns (3)–(5) condition on $Exit_b = 0$. Columns (3)–(5) study the share of pre-existing sellers (or destinations or products) of the buyer with whom trade stops at the onset of the pandemic. $Drop_b^s$ corresponds to the share of sellers that are dropped, $Drop_b^d$ studies the share of destinations the buyer stops shipping to, and $Drop_b^j$ looks at the share of products (HS6) the buyer stops importing. All columns control for fixed effects for the main destination the buyer serves and for the cohort of the buyer (here either 2018 or 2019), the pre-Covid-19 size of the buyer (in terms of imported values) and their diversification in products (Mix_b^j) and destinations (Mix_b^d).

We study whether buyers with different sourcing strategies exhibited different patterns of adjustment to the onset of the pandemic. Because of the pandemic, many smaller buyers stopped sourcing altogether or went into bankruptcy. Since we are interested in understanding how the sourcing strategy mediated the trade responses to the Covid-19 shock, we focus our attention on the 500 largest buyers in our sample, out of the 11,000+ buyers observed at least once in our data (see Table B.1 Panel B for the top 500 buyers' summary statistics). These buyers account for 75.4% of the pre-pandemic trade volumes in our sample and yield a relatively balanced panel over the course of the sample period.

5.1. Adjustments on the extensive and sub-extensive margins

We first analyze the *extensive* and *sub-extensive* margins of adjustment, the former referring to a buyer's exit from importing activities from all or some origins in our data, and the latter referring to a buyer's dropping suppliers, destinations or products from their portfolio, conditional on continuing importing from at least one country in our data.

We focus on five key outcomes, all measured at the level of the buyer. The first of these is an indicator that takes value one if a buyer imports from countries in our data for the last time on the last quarter of 2019 or the first quarter of 2020 – what we call the onset of the pandemic. We refer to these buyers as 'permanent' exiters, and label their indicator as $Exit_b$.[14] Second, conditional on remaining active (importing) from at least one origin country, we identify buyers that permanently exit at least one of their sourcing countries at the onset of the pandemic. We flag these buyers as country exiters with the indicator $Exit_b^c$. Third, for surviving buyers, we study the share of the buyer's pre-Covid-19 suppliers that are permanently dropped between 2020Q1 and 2021Q1 – $Drop_b^s$.[15] As the fourth and fifth measures, we define analogously the share of the buyer's destinations ($Drop_b^d$) and of their products ($Drop_b^j$) that are dropped at the start of the pandemic.

Table 5 correlates buyers' sourcing strategies with the likelihood of a buyer's exit or sub-extensive drops. For clarity and compatibility with the exercises of the following section, we capture sourcing strategies with discrete versions of the continuous measures of relationality and just-in-time introduced earlier: $Relational_b^D$ and JIT_b^D. The super-script D here indicates that the variable is a

[14] We note that what we call a 'permanent' exit implies a stance on censoring, as our data ends in 2021Q1. This means that if a buyer does not import at all between 2020Q1 and 2021Q1, but resumes importing at some point further down the line (unobservable to us), we erroneously classify the buyer as an exiter. While the probability of these 'false positives' is not zero, our focus on the top 500 buyers, who are typically active in all time periods assuages the concern.

[15] As such, this measure considers that a buyer–seller relationship ends if it is not observed trading for an entire year. The results presented here are based on all the relationships of the buyer, but our results are robust (and stronger) under more stringent definitions that focus on existing relationships of a minimum duration.

dummy, taking value one for the top 10% buyers in the distribution of the sourcing measure. For example, $Relational_b^D = 1$ marks the most relational buyers – i.e., buyers above the 90^{th} percentile of the distribution of relationality ($Relational_b$) among the top 500 buyers. Similarly, $JIT_b^D = 1$ identifies the most just-in-time buyers among the top 500. To mitigate the incidence of spurious correlations between the buyer's sourcing and the extensive and sub-extensive adjustments, we condition on fixed effects for the main destination the buyer serves and for the cohort of the buyer, the pre-Covid-19 size of the buyer (in terms of imported values) and their diversification in products (Mix_b^j) and destinations (Mix_b^d).

Column (1) shows that relational buyers were less likely to permanently exit our sample, while JIT buyers were slightly more prone to permanently stop importing from the sourcing countries in our sample. On this margin, we this find that the two practices are associated with different responses to the shock. Conditional on remaining active, relative to buyers that are neither relational nor adopt just-in-time, columns (2) and (3) show that both relational and JIT buyers are less likely to permanently cease importing activities from at least one origin country and to stop sourcing from an existing supplier following the onset of the pandemic. Columns (4) and (5) find some evidence that relational and JIT buyers are also less likely to permanently exit destination markets or products, although the estimates are small and not precisely estimated.

In sum, on the extensive margin: (i) relationality appears associated with greater stability in sourcing as evidenced by overall, country and supplier exits; (ii) JIT buyers are more prone to ceasing importing activities overall, but conditional on surviving, they tend to maintain their supplier base.

5.2. Intensive margin adjustments

We now turn our attention to *intensive* margin adjustments to the pandemic – i.e., the evolution of buyers' imported values, conditional on continuing to import. In this section, we study the evolution of log values (pq) imported by buyers with different sourcing strategies, following the specification

$$pq_{bt} = \delta_b + \delta_t + \sum_t \gamma_\tau Sourcing_b \times \boldsymbol{I}\{t = \tau\} + \epsilon_{bt}, \tag{2}$$

where a unit of analysis is a buyer–quarter pair, indicated with $-bt$. We have restricted the sample to quarters spanning from 2018Q1 to 2020Q4, and 2020Q1 is excluded as baseline for comparisons. The specification includes buyer fixed effects (δ_b) which capture average differences across buyers in their imported values and time effects (δ_t) which account for quarterly variation in imported values, for buyers adopting the baseline sourcing strategy, which we define momentarily. The regressor of interest, $Sourcing_b \in \{Relational_b^D, JIT_b^D\}$ corresponds to the indicator for relationality ($Relational_b^D$) or of just-in-time sourcing (JIT_b^D), defined in Section 5.1: $Relational_b^D = 1$ marks the most relational buyers and $JIT_b^D = 1$ identifies the most just-in-time buyers among the top 500. These sourcing metrics enter our specification interacted with quarter–specific indicators, such that γ_τ captures the differential performance of buyers adopting a certain sourcing strategy, $Relational_b^D$ or JIT_b^D, in a given point in time, as compared to other buyers. At this point, we remind the reader that the measures of relationality and just-in-time are constructed using pre-Covid-19 (2018 and 2019) trade exclusively (see Section 3.2). This allows us to study short-term post-Covid-19 responses of buyers that prior to the shock sourced relationally and/or just-in-time.

As discussed in Section 4, relationality, just-in-time and buyer size are correlated characteristics of the buyer. We start by studying each sourcing metric on its own, following equation (1), to then proceed with a richer specification in which both sourcing strategies enter the specification. We complete the analysis allowing for interactions of time and the buyer's size (log traded values) prior to the onset of the pandemic. The richest specification is then

$$\begin{aligned} pq_{bt} =& \delta_b + \delta_t + \sum_t \alpha_\tau^R Relational_b^D \times \boldsymbol{I}\{t = \tau\} \\ &+ \sum_t \alpha_\tau^J JIT_b^D \times \boldsymbol{I}\{t = \tau\} + \sum_t \beta_\tau Size_b \times \boldsymbol{I}\{t = \tau\} + \epsilon_{bt}. \end{aligned} \tag{3}$$

Table 6 presents short–term (quarter-by–quarter in 2020) differential responses of buyers with relational and JIT sourcing strategies. Column (1) follows the specification of equation (2) and has $Sourcing_b \equiv Relational_b^D$; column (2) follows the same specification with $Sourcing_b \equiv JIT_b^D$. The rest of table uses the specification of equation (3), without (column (3)) and with (column (4)) pre-Covid-19 size interactions.

Results show that garment buyers' overall sourced values declined relatively less for relational buyers (column (1)). The effect was particularly pronounced in the first two quarters that followed the onset of the pandemic. If anything, instead, we find that buyers with JIT inventory systems suffered larger declines in their overall imported values once we control for relationality (columns (3)-(4)). The results thus confirm that these two complementary sourcing practices are associated with quite different responses to shocks along the value chain.[16]

It is important to stress that these results do not disentangle the exact mechanism through which a relational approach to sourcing supported trade during the shock. On the one hand, this could be due to suppliers' increased efforts to preserve valuable relationships, as in Macchiavello and Morjaria (2015). On the other hand, relational buyers might have also kept to their promise

[16] These results must be interpreted cautiously because the aggregate imports of buyers with different characteristics display differential trends prior to the onset of the pandemic.

Table 6
Sourcing Strategies and Responses to Covid.

	(1)	(2)	(3)	(4)
	Imported Values: pq_{bt}			
Post-Covid-19 Quarters				
2020Q2	-0.660***	-0.620***	-0.653***	-0.656***
	(0.020)	(0.018)	(0.020)	(0.021)
2020Q3	-0.143***	-0.116***	-0.142***	-0.154***
	(0.028)	(0.029)	(0.030)	(0.035)
2020Q4	-0.196***	-0.185***	-0.197***	-0.228***
	(0.039)	(0.044)	(0.042)	(0.045)
Relationality				
2020Q2 × $Relational_b^D = 1$	0.520***		0.565***	0.572***
	(0.066)		(0.100)	(0.102)
2020Q3 × $Relational_b^D = 1$	0.430***		0.438***	0.458***
	(0.069)		(0.104)	(0.110)
2020Q4 × $Relational_b^D = 1$	0.201		0.194	0.235
	(0.173)		(0.215)	(0.215)
Just-In-Time				
2020Q2 × $JIT_b^D = 1$		0.113*	-0.117	-0.081
		(0.053)	(0.074)	(0.087)
2020Q3 × $JIT_b^D = 1$		0.152**	-0.027	0.105
		(0.052)	(0.086)	(0.102)
2020Q4 × $JIT_b^D = 1$		0.099	0.020	0.289**
		(0.059)	(0.098)	(0.113)
Size Interaction	.	.	.	yes
FEs	b,t	b,t	b,t	b,t
R^2	0.52	0.51	0.52	0.54
Obs.	6,272	6,272	6,272	6,272

Standard errors in parentheses, clustered at the level of the buyer and the quarter. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. The sample restricts attention to the top 500 buyers. The table shows regressions of the log values imported by a buyer b in a quarter t, on quarter dummies interacted with indicators for different sourcing strategies, as defined in Section 3.2. For the purpose of these regressions, the sourcing variables are indicators that take value one for buyers above the 90^{th} percentile of the distribution of the (continuous) corresponding sourcing metric. Column (1) follows the specification of equation (2) and has $Sourcing_b \equiv Relational_b^D$; column (2) follows the same specification with $Sourcing_b \equiv JIT_b^D$. The rest of table uses (3) with (column (3)) and without (column (4)) pre-Covid-19 size interactions. The size variable is constructed as the log of imported values prior to Covid-19, and the variable is standardized within sample. All sourcing variables in this regression table are constructed using pre-Covid-19 (2018 and 2019) transactions only. All specifications include buyer and quarter fixed effects, and the table displays the time fixed effects for the Post-Covid-19 period, for the benchmarking of the interacted time effects. The base category is always 2020Q1. We display post-shock coefficients for compactness.

of demand assurance, in the form of more stable and regular orders even when hit by a sudden change in demand. Anecdotally, the provision of a stable and predictable demand that enables regular capacity utilization is a buyer's attribute that is highly valuable in the industry. While we are not aware of empirical evidence demonstrating this force in the apparel context, Macchiavello and Miquel-Florensa (2017) and Blouin and Macchiavello (2019) find that long-term relationships do indeed provide demand assurance to processors and exporters in the coffee industry.

6. Conclusions

This paper provides a preliminary exploration of how buyers' sourcing strategies mediate responses to supply chain disruptions using data from the apparel global value chain. We focus on two dimensions of buyers' sourcing strategies: relationality – the extent to which the buyer relies on core relationships – and JIT – the extent to which goods are received from suppliers only as they are needed. Using export customs records for six garment-producing countries over the period January 2018 to March 2021, we presented three novel results.

First, the variation in both relationality and JIT is mostly explained by across-buyer variation, rather than product or country variation. This is consistent with a buyer's organizational capabilities playing a critical role in determining sourcing strategies. Therefore, if the new environment requires a change in the approach to sourcing, this might require costly adjustments for many organizations.

Second, and consistent with the theoretical analysis in Taylor and Wiggins (1997), we showed that relationality and JIT are highly correlated with each other across buyers. Furthermore, other buyer characteristics (e.g., overall size) correlate with the two proxies in a way that is consistent with the two sourcing practices being complementary.

Finally, we highlight how the two practices differ in their correlation with changes in the buyer's overall sourced values at the onset of the Covid-19 pandemic. Specifically, we find that sourced volumes declined relatively less for relational buyers. If anything, instead, we find that buyers with JIT inventory systems suffered larger declines in their overall imported values, once relationality is controlled for.

This paper provides a first step toward a more systematic understanding of the implications of supply chain disruptions for firms' relationships, in particular, and economic resilience, in general. The results in the paper are not sufficient to conclude whether a move away from *just-in-time* and towards *just-in-case* systems is warranted, particularly for those buyers that have invested or can invest, in long-term relationships with suppliers. Such an analysis would need to consider further dimensions of a buyer's sourcing strategy (e.g., diversification), how they relate to each other, and what are the forces behind their adoption. In the context of garments, we plan to tackle some of these issues in Cajal-Grossi et al. (2022). It would be important to explore the robustness of our evidence in other sectors and using other shocks. A fortiori, the evidence is also not sufficient to assess the extent to which buyers' choices of sourcing systems are socially efficient or if, instead, policy intervention might be required. Much research – theoretical, as well as empirical – remains to be done in this exciting area.

CRediT authorship contribution statement

All authors contributed equally to the project.

Data availability

The data that has been used is confidential.

Appendix A. Data sources and assembly

This section summarizes the procedure for the cleaning and curation of raw customs records for the consolidation of the cross–country, transaction–level dataset used in the paper.

Harmonization of firm identifiers

Customs records in our dataset have been obtained directly through customs authorities and through a private provider that collects data via independent agreements. In general, the main variables used in our analysis, i.e., the international buyer and seller names, net weight, value, and type of the product exported, are recorded in every custom office with various levels of detail and entries issues. Hence, after identifying the common variables, we harmonize values and checked for duplicates, with the result of a first version of the global dataset.

Secondly, since the fields recording the buyer and seller names are, in some countries, manually entered in string format by the customs officers, various sorts of data-entry typos and mistakes were found. Typically, the cleaning procedure consists of two steps: i) parsing a field into the relevant subcomponents and standardizing common character strings, and ii) matching the standardized names. Therefore, after a general cleaning of the strings to remove blanks, accents, full stops, hyphens and apostrophes within a string variable, and a substantial manual cleaning, we matched similar strings together by the means of a probabilistic record linkage algorithm.[17] We finally visually inspected the matched names to further check for potential mismatches. A number of rich cross-checking routines corrected false-positive and false-negative mistakes in the assignment of identifiers.

Other data processing

Daily transaction dates have been harmonized and converted to the format DD-MM-YYYY. Products classification follows the Harmonized System (HS) nomenclature. We first standardized the products into a 6-digit level string and then used a correspondence table to the 2017 HS classification, if different versions of the nomenclature are detected.

Destinations were manually harmonized to be able to assign each country its respective iso alpha-2 code.

Consolidation of the global data

This subsection provides a brief description of the steps conducted when consolidating customs records from the 6 countries considered in this analysis. The consolidation process includes a further cleaning and trimming to assemble a dataset, hereinafter global data, which contains 23,608,761 observations.

[17] We first calculate the Levenshtein distance between all pairwise combinations of buyer and seller names, and then we matched a string pair if their normalized edit distance is less than or equal to .25.

Table A.1
Global Data: Number of Transactions by Country.

Country	Count (1)
Bangladesh	5,119,453
Ethiopia	12,991
India	6,388,026
Indonesia	2,669,981
Pakistan	1,029,787
Vietnam	8,388,523
Total	23,608,761

The table presents the total number of transactions by country after cleaning, trimming and consolidation of the global data, following the procedures described above.

We start by discarding 489 observations from April 2021, as this was the last month available and it is not complete. The post-Covid-19 period considers all data (strictly) after quarter one of 2020. We proceed to discard observations for which any of the following essential variables is missing: value, product code, buyer or seller identities. 208 observations are dropped because of not reporting a value, 5,749 observations are dropped because they are missing a buyer identity and 8,916 observations are dropped because of not reporting a seller identity. None observations were missing product code. It is worth mentioning that missing identities could either come from the raw custom records or could also be a result of the cleaning routine. Nonetheless, cases in which the cleaning routine converts an identity into a missing entry correspond to misleading entries as *to the order of, inc, llc...*

Further cleaning on the buyer side was conducted. First, all buyer names showing less than three characters and those whose name starts with "&" are renamed as "Others." Names with less than three characters account for 141,997 observations, equivalent to 0.46% of the total export value. Names starting with "&" implied 4,770 changes. Moreover, buyers that report less than 100 transactions in the entire global data are as well re-labeled as "Others." We relabel 1,200,457 observations, which correspond to 112,271 different buyers, but explain only 3.8% of the exported values. At the end, we discard all buyers which were re-labeled as "Others", equal to 2,407,704 observations which are equivalent to 18.21% of the export value.

On the seller side, additional trimming takes place on firms reporting less than 10 transactions in the entire data. This implies a discard of 58,617 observations, which represent 16,339 different sellers and account for 0.4% of the exported values.

Transaction values, reported in dollars, are winsorized at 3% and 97%, within country of origin. Likewise, exported quantities are winsorized with the same cutoffs as values, within country of origin, when a measure of mass is available. When quantities are recorded in some other way (packages, units, etc.) quantities are winsorized within country of origin and measurement unit.

Table A.1 presents the total number of transactions by country after cleaning, trimming and consolidation of the global data from the 6 countries listed.

Appendix B. Further definitions and descriptives

Other buyer-level measures

The analysis in the main text makes use of buyer-level measures of diversification across products and destinations. In this appendix we introduce the formal definitions of the proxies we use to measure diversification along these margins.

We construct a measure of the buyer's diversification over products (Mix_b^j), using the buyer's trade prior to Covid-19. The measure is a weighted average (across destinations) of the negative of a normalized HHI of product concentration:

$$Mix_b^j = \sum_d \left[\frac{PQ_{bd}}{PQ_b} \times (-HHI_{bd}^j) \right] \quad \text{and} \quad HHI_{bd}^j = \left[\sum_j \left(\frac{PQ_{bjd}}{PQ_{bd}} \right)^2 - 1/N_{bd}^j \right] / \left[1 - 1/N_{bd}^j \right].$$

The normalization, which considers the number of products in the buyer-destination combination (N_{bd}^j), re-scales the standard HHI to span between 1 and 0, rather that $1/N$. The weight associated to each destination is given by the share of the destination in all exports accounted for by the buyer. This implies that buyers tend to serve more than one destination.

Similarly, we construct a measure of the buyer's diversification over destination markets (Mix_b^d) as a weighted average (across products) of the negative of a normalized HHI of destination concentration:

$$Mix_b^d = \sum_j \left[\frac{PQ_{bj}}{PQ_b} \times (-HHI_{bj}^d) \right] \quad \text{and} \quad HHI_{bj}^d = \left[\sum_d \left(\frac{PQ_{bjd}}{PQ_{bj}} \right)^2 - 1/N_{bj}^d \right] / \left[1 - 1/N_{bj}^d \right].$$

The normalization and weighing procedures for this measure are analogous to those described with reference to Mix_b^j.

Table B.1
Global Buyers' Descriptives.

	Count (1)	Mean (2)	P10 (3)	P25 (4)	P50 (5)	P75 (6)	P90 (7)
Panel A: All Buyers							
N_b^s	11,627	13.41	1.00	2.00	5.00	12.00	28.00
N_b^c	11,627	1.25	0.00	1.00	1.00	1.00	2.00
N_b^j	11,627	19.31	2.00	7.00	14.00	25.00	42.00
N_b^d	11,627	3.26	1.00	1.00	2.00	3.00	7.00
$Relational_b$	11,200	-0.15	-0.33	-0.21	-0.11	-0.05	-0.02
JIT_b	11,200	-2.51	-7.91	-2.39	-0.15	0.57	0.87
JIT_b^{Orbis}	231	-16.52	-22.38	-10.63	-6.68	-4.56	-3.34
Mix_b^j	11,200	-0.37	-0.76	-0.49	-0.30	-0.18	-0.12
Mix_b^d	11,200	-0.92	-1.00	-1.00	-1.00	-0.92	-0.72
Panel B: Top 500 Buyers							
N_b^s	500	88.00	3.00	12.00	38.50	103.00	207.50
N_b^c	500	2.75	1.00	1.00	3.00	4.00	5.00
N_b^j	500	60.91	13.00	30.00	52.00	90.00	120.00
N_b^d	500	14.11	1.00	3.00	8.00	18.00	38.00
$Relational_b$	496	-0.04	-0.10	-0.05	-0.02	-0.01	-0.00
JIT_b	496	0.88	0.72	0.85	0.93	0.97	0.99
JIT_b^{Orbis}	231	-16.52	-22.38	-10.63	-6.68	-4.56	-3.34
Mix_b^j	496	-0.26	-0.55	-0.34	-0.18	-0.11	-0.07
Mix_b^d	496	-0.79	-1.00	-1.00	-0.91	-0.61	-0.39

The table shows summary statistics at the buyer level for variables in the customs records and the sourcing measures introduced in this paper. Super- and sub-scripts are as follows: b corresponds to buyer, s to seller or exporter, j to HS6 product category, c to country of origin of the exports, with $c \in \{Bangladesh, India, Indonesia, Vietnam, Pakistan, Ethiopia\}$, and d to country of destination of the exports, where d may include countries other than c. $Orbis$ indicates the subset of observations for which Orbis data is available (see Section 3.1). The sourcing characteristics are the relationality of the buyer ($Relational_b$), its just-in-time sourcing (JIT_b), its diversification across products (Mix_b^j) and across destinations (Mix_b^d). The definitions for the first two measures are presented in Section 3.2, and the definitions of the diversification metrics are left for Appendix B.

Descriptives

Table B.1 reports summary statistics of customs records at the buyer level, including the sourcing measures introduced in this paper.

Supplementary materials

Relationality over time We compare the measure of relationality used in the paper, in three versions: (a) the baseline measure that pools together transactions and sellers in 2018 and 2019, (b) a measure that uses only the 2018 sellers and transactions, and (c) a measure that uses only the 2019 transactions of the buyer. Fig. B.1 shows scatter markers of the median relational measure for all buyers organized in 20 equally sized bins, with the measure constructed only with 2018 data (vertical axis) and only with 2019 data (horizontal axis):

As this figure suggests, constructing the relationality measure using either year of the data gives very similar results, as evidenced by the binned scatter markers here being mostly on the 45 degree line. The departures are small and mostly concentrated on the bottom tail of the relationality measure, populated by small buyers. The baseline measure in the paper is a weighted combination of the 2018 and 2019 alternatives discussed here, and exhibits high (0.725 and 0.781) unconditional correlations with the year–specific measures. This finding is in line with our arguments in Cajal-Grossi et al. (2023): the degree of relationality appears to be buyer–specific and fairly time invariant. As we argue in our other paper, changes in sourcing strategies are infrequent. In a seven year period in Bangladesh, we observe very few such changes, one of which we exploit in the paper. The rationale for the stability over time of buyers' sourcing strategies lies on the large number of complementary practices that are needed to support relational sourcing. These practices span several departments, from HR to procurement, from forecasting to compliance. As such, shifting sourcing strategies requires organization–wide changes.

Validation of JIT measure Fig. B.2 shows a positive correlation between our constructed measure of buyers' JIT sourcing, and the more standard measure based on stock–to–turnover. This pattern can only be established for only 231 buyers in our sample, for which inventory data is available via Orbis.

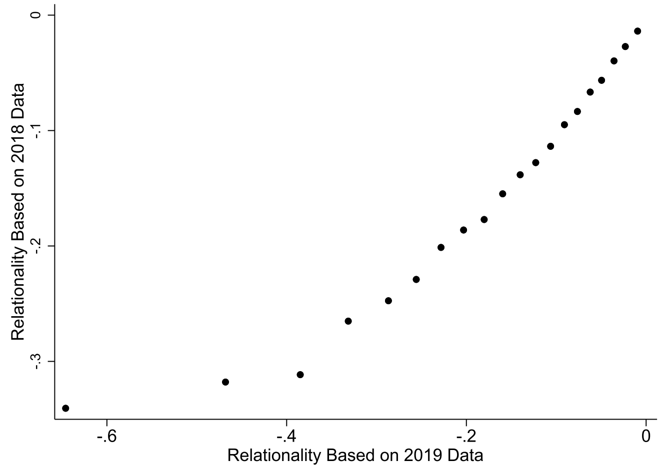

Fig. B.1. Relationality Over Time - 2018 & 2019. The figure shows the relationship between the relationality metric (see definitions in Section 3.2), constructed only with data from 2018 (vertical axis) and constructed only with data from 2019 (horizontal axis). A unit of observation underlying this figure is a buyer, and the scatter markers denote medians across all buyers within each of 20 equally-sized bins. The unconditional correlation between the relationality metric used in the body of the paper (pooling data from both 2018 and 2019) and these year–specific alternatives is 0.725 (with 2018) and 0.791 (with 2019).

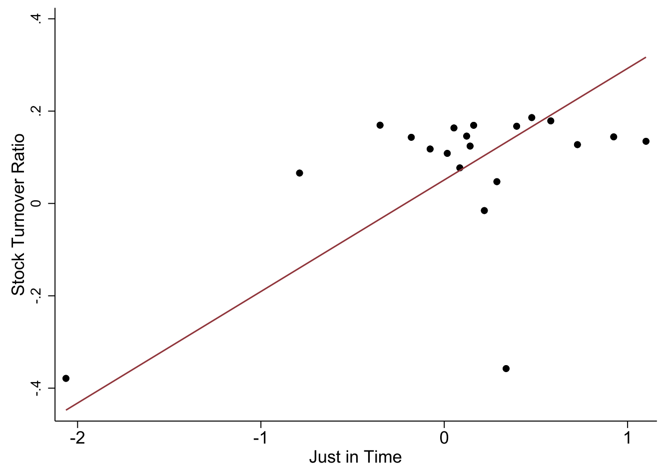

Fig. B.2. Correlation between Just-in-Time Metric and Stock-to-Turnover Ratio. The figure illustrates the correlation between the JIT metric in our paper (as defined in Section 3.2) and the stock-to-turnover ratio of the firm, obtained from Orbis and matched into our main data. A unit of observation underlying this figure is a buyer, and there are 371 for which the Orbis data is available, but only 231 of these record inventory-related data (including stock-to-turnover). Of these, we remove the outlying observations below the first percentile in the stock-to-turnover distribution. The scatter markers denote averages across all buyers within each of 20 equally-sized bins. The overlayed line corresponds to a linear fit of the underlying data, controlling for buyer size, in deciles of their imported value pre-Covid-19 and across all products. The estimated slope is 0.241 (S.E. 0.051).

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