

BUYERS' SOURCING STRATEGIES AND SUPPLIERS' MARKUPS IN BANGLADESHI GARMENTS*

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We study differences in markups earned by Bangladeshi garment exporters across buyers with different sourcing strategies and make three contributions. First, we distinguish buyers with a relational versus a spot sourcing strategy and show that a buyer's sourcing strategy is correlated across products and origins. Buyer fixed effects explain most of the variation in sourcing strategies, suggesting that these depend on organizational capabilities. Second, we use novel data that match quantities and prices of the two main variable inputs in the production of garments (fabric and labor on sewing lines) to specific export orders. We derive conditions under which these data allow measurement of within exporter-product-time differences in markups across orders produced for different buyers. Third, we show that exporters earn higher markups on otherwise identical orders produced for relational, as opposed to spot, buyers. A sourcing model with imperfect contract enforcement, idiosyncratic shocks to exporters, and buyers that adopt different sourcing strategies trading off higher prices and reliable supply rationalizes this and other observed facts in the industry. We discuss alternative explanations and policy implications. *JEL codes*: L11, L14, D23, F63.

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I. INTRODUCTION

Firm-level decisions play a critical role in explaining aggregate productivity (Goldberg et al. 2010; Van Reenen 2018) and the structure of trade flows (Gereffi, Humphrey, and Sturgeon 2005; Bernard et al. 2007; Antràs 2016). The diffusion of just-in-time inventory systems and outsourcing—including across borders—have turned firms' approaches to sourcing into a particularly important strategic decision (Dyer, Cho, and Cgu 1998). Different ways of organizing sourcing must be coordinated with other operational processes (Cooper and Ellram 1993) and require appropriate internal structures and management practices (Milgrom and Roberts 1990, 1995). Firms, even within narrowly defined industries, end up developing distinctive approaches to sourcing (Helper and Henderson 2014). At one extreme (which we label spot sourcing), the buyer's purchases are spread among multiple suppliers to "improve the firm's bargaining power" (Porter 1980, 123). Buyers keep suppliers at arm's length, avoid any type of commitment, allocate short-term orders to the lowest bidders, and bear the costs of suppliers' nonperformance. At the other extreme (which we label relational sourcing), orders are allocated to a few suppliers with whom the buyer develops long-term relationships to incentivize behavior that might otherwise be difficult to contract on.

Buyers' approaches to sourcing can have far-reaching implications for suppliers. In particular, existing theories highlight the role of markups: under spot sourcing, suppliers' markups are squeezed by intense competition; under relational sourcing, buyers may pay higher markups to incentivize suppliers (see Taylor and Wiggins 1997). To our knowledge, this hypothesis has not been tested empirically. Do suppliers indeed earn higher markups from relational buyers? If so, are buyers' choices of sourcing socially efficient, or is there scope for policy intervention? Answering these questions is important—particularly with respect to developing economies, where buyers can act as potent vehicles for upgrading (World Bank 2020)—but challenging. The first challenge is that measuring the markups earned from different buyers requires knowledge of the prices obtained—and the costs incurred—from supplying a specific buyer. While information on prices at the required level of detail is increasingly available, costs remain difficult to estimate since the amounts and prices of inputs used to produce for specific buyers are typically unobserved. The second challenge is that buyers' sourcing strategies

are not directly observed, either. As a result, one must construct proxies based on observable sourcing behavior, which, may correlate with prices and markups through multiple channels.

This article studies differences in markups that Bangladeshi woven garment exporters earn from foreign buyers with different sourcing strategies. In addition to the intrinsic interest of this context, its unique features allow us to make progress on the empirical front.¹ For woven garments, we observe the type, prices, and amounts of the main variable inputs (fabric and labor employed on sewing lines) used to produce specific export orders for different buyers, thereby overcoming the first challenge. In addition, many buyers source both woven garments and knitwear from Bangladesh. Due to differences in production processes, woven garments and knitwear are produced by different exporters. We use transactions in knitwear to characterize buyers' sourcing strategies and correlate those with prices and markups across woven garments export orders, thereby overcoming the second challenge.²

To fix ideas, [Section II](#) presents a model of buyers' sourcing. Relational sourcing is generally used to incentivize suppliers to undertake costly actions that are hard to contract on. Conversations with exporters and buyers suggest that shocks to suppliers' ability to deliver orders on time are common in our context, and therefore, for concreteness, we focus on this aspect. In the model, buyers seek to secure reliable supplies from sellers who face idiosyncratic shocks. Spot sourcing adequately ensures delivery under "business as usual" conditions but fails to incentivize sellers to undertake costly actions and avoid delivery failures when shocks occur. This creates a rationale for relational sourcing. In equilibrium, ex ante identical buyers choose different sourcing strategies: some buyers invest in organizational capabilities and become relational—that is, are able to make clear and credible promises of higher prices and markups in exchange for reliable deliveries from their suppliers. Other buyers do not

1. The garment industry has played a critical role in the early phases of export-oriented industrialization, most recently in East Asia (see [Dickerson 1999](#); [Gereffi 1999](#)). Bangladesh is the world's second largest exporter of garments (after China), and the industry, which accounts for over 80% of the country's exports and an estimated 12% of its GDP, employs over four million workers, mostly women.

2. In the article, we use "buyer" to refer to the firm that purchases ready-made garments from Bangladesh. Similarly, we use "seller", "supplier", or "exporter" to refer to the local garment manufacturer.

invest, source through spot contracts at low prices, but are unable to secure reliable supplies.

The main prediction of the model is that relational buyers pay higher prices and markups to suppliers than do spot buyers sourcing the same product from the same supplier at the same time. Two ingredients are needed to test this prediction: (i) a characterization of buyers' sourcing strategies and (ii) information on the prices and markups earned by the same seller for the same products from different buyers. [Section III](#) characterizes international buyers' sourcing strategies in the garment sector and provides the first ingredient. We introduce an intuitive proxy for buyers' sourcing strategies, building on the fact that relational buyers concentrate their sourcing among a small number of suppliers. Specifically, we compute the weighted average across product-year combinations of the number of suppliers from whom a buyer sources, normalized by scale. This yields a cross-sectional characterization of buyers' sourcing strategies that maps closely to qualitative accounts in the industry. Computing the proxy for other sourcing countries reveals that a buyer's approach to sourcing is correlated across origins and products, with buyer-level fixed effects explaining a large share of the variation in sourcing strategies. This observation underpins our buyer-level—as opposed to buyer–seller-level—characterization of sourcing strategies.

[Section IV](#) tests and validates the main prediction of the model. Within seller-product-year combinations, the pattern that relational buyers pay higher prices is indeed extremely robust. We take advantage of the unique features of our data to investigate differences in variable costs that suppliers incur when producing orders for relational buyers in comparison to spot buyers. In addition to standard information on the output side (quantity, prices, and product type), we observe the amount, price, and type of fabric used in the production of each export order. Conditional on seller-product-year fixed effects, the buyer's sourcing strategy does not correlate with the order-level buy-to-ship ratio (a measure of fabric efficiency) or with the price of fabric. For a sample of factories, we also observe labor utilization and efficiency on the sewing lines—the most labor-intensive step in garment production—and can exploit worker surveys that contain information on labor characteristics and wages. These data confirm that orders produced for relational and spot buyers are sewed by workers of comparable skill, earning similar wages, and working with similar efficiency.

The evidence on fabric and sewing labor is consistent with the model's prediction that the higher prices paid by relational buyers reflect a higher markup. However, there might be unobserved order-level variable costs that systematically vary between orders produced for relational and spot buyers. We develop an empirical framework, compatible with our theoretical model, that clarifies the conditions under which the available data allow us to recover within seller-product-time differences in markups across orders and precisely test the model's main prediction.³ We show that exporters earn higher markups from orders produced for relational buyers relative to spot buyers.

Section V discusses alternative mechanisms, provides a quantification of the value of supplying relational buyers, and sets forth policy implications. First, we revisit our approach to characterizing the sourcing strategy at the buyer—as opposed to the buyer-seller-level. We then complement our cross-buyer analysis with an event study around the shift from spot sourcing to relational sourcing rolled out in the global supply chain of VF Corporation, a large buyer of garments. Both exercises confirm that a buyer's relational approach to sourcing is associated with higher supplier markups. We also discuss in greater detail the reliability mechanism as well as alternative mechanisms (including differences in market power, search behavior, product quality, and demand assurance) that could yield differences in markups earned from different buyers. The value of supplying relational buyers is substantial. A conservative estimate is that a shift in sourcing strategy from the average buyer in the sample to the relational sourcing adopted by The Gap Inc. (a shift of about one standard deviation in our empirical proxy) is associated with an 11% increase in the average markup value. A back-of-the-envelope calculation suggests that the net present value of supplying a relational buyer is equal to at least 30% of the yearly profits in the relationship.

The model suggests that relative to the social optimum, too few buyers choose a relational strategy. Due to contracting

3. The main condition is a production function that features (log-)separability of fabric relative to other costs—an assumption justifiable in light of the two-step production process for garments. Other than that, the framework allows for an elasticity of output with respect to fabric that varies at the seller-product-time level and for an arbitrary number of other inputs that sellers might be able to choose freely (e.g., casual labor, bribes) or subject to capacity constraints (e.g., managerial labor and attention).

problems, relational buyers exert a positive pecuniary externality on other market participants—a planner may thus want to subsidize their entry. In light of this, our conceptualization of the sourcing strategy as a buyer-level attribute—as opposed to an exclusive emphasis on the relational nature of the buyer-seller pair—is of practical relevance. Even though organizational-level capabilities underpin a buyer’s ability to establish long-term relationships with suppliers, the relational contract with a particular supplier remains deeply rooted in both parties’ specific circumstances (Baker, Gibbons, and Murphy 2002; Gibbons and Henderson 2012). It is thus unlikely that policy makers can improve specific relationships between exporters and buyers. If certain buyers have organizational capabilities that make them valuable relational partners, and if such capabilities generate benefits for suppliers, an actionable margin for policy opens up. It might be possible to attract such buyers, for example, by subsidizing visits to the country or targeting factors that favor their entry.

In sum, this article makes three key contributions. First, it provides an empirical characterization of sourcing strategies and novel evidence on the sourcing strategy as a buyer-level characteristic. Second, we mobilize novel data to match quantities and prices of variable inputs used to produce specific orders. This allows—for the first time, to the best of our knowledge—measurement of the differences in markups across orders produced for different buyers. The third contribution is to show that exporters earn significantly higher markups from relational buyers—the sourcing strategy of the buyer can be an important dimension of upgrading. Understanding buyers’ choices of sourcing strategy, drivers of selection into the supply chain of relational buyers, and other contracting problems alleviated by relational sourcing are important areas for future research.⁴

I.A. Related Literature

Differences in sourcing strategies appear in many narrowly defined industries, including the automotive (Richardson 1993;

4. The online appendices present supplementary material. [Online Appendix A](#) provides the details for the model; [Online Appendix B](#) describes the data sources; [Online Appendix C](#) presents additional evidence that supports the model; [Online Appendix D](#) discusses various robustness exercises pertaining to our main empirical findings; and [Online Appendix E](#) extends our econometric approach to the estimation of markups in levels.

Nishiguchi 1994; Helper and Sako 1997), electronics (De Toni and Nassimbeni 2000), aerospace (Masten 1984), and apparel (Gereffi 1999) industries. These differences echo those in the adoption of lean management practices (Bloom and Van Reenen 2007, 2010). Unlike the evidence on management practices, accounts of sourcing strategies are mostly qualitative.⁵ We characterize sourcing strategies by introducing an empirical measure that builds on recent developments by Heise et al. (2021).⁶ We test the hypothesis that organizational capabilities are key drivers of sourcing strategies, showing that a buyer's sourcing strategy is correlated across products and origins. We also use "excluded" products to assuage endogeneity concerns when testing the prediction that a buyer's sourcing strategy correlates with suppliers' prices and markups.

Sociologists (see Gereffi 1999; Ponte, Gereffi, and Raj-Reichert 2019) and economists (see Antràs 2016, 2020; Macchiavello 2022 for reviews) alike have emphasized the relational nature of global value chains. Macchiavello and Morjaria (2015) show that Kenyan rose exporters hit by an unanticipated shock prioritized buyers with whom they had valuable relationships. Exploiting unanticipated surges in international coffee prices, Blouin and Macchiavello (2019) show that supplier opportunism—as opposed to force majeure—causes many delivery failures. These papers test the reliability mechanism at the heart of our model and infer the value of relationships from observed responses to shocks. We borrow the idea that buyers' concerns over reliability are important drivers of relational contracting and apply it to our context. In contrast to these earlier works, we directly measure the higher markups earned from supplying relational buyers, and we characterize the sourcing strategy at the buyer level rather than focusing on buyer-seller relationships. Besides the novelty, this distinction has practical policy relevance. Recent contributions on

5. Exceptions include Macchiavello and Morjaria's (2021) study of relational sourcing and firm performance across coffee mills in Rwanda and Helper and Munasib's (2022) analysis of differences in the use of relationships to import parts into the United States between Japanese versus American and European car manufacturers.

6. Heise et al. (2021) derive a measure of relational sourcing from a model based on Taylor and Wiggins (1997), characterizing spot and relational sourcing strategies. Startz (2021) also estimates a model along the lines of the approach of Taylor and Wiggins (1997) using tailored surveys on the sourcing decisions of Nigerian importers.

buyers' role in global value chains include [Amengual and Dis-telhorst's \(2019\)](#) study on the impact of a change in the global sourcing approach at The Gap Inc. on supplier compliance; [Boudreau's \(2021\)](#) evaluation of a buyer-driven initiative aimed at enforcing worker-manager safety committees in Bangladeshi garment factories; and [Macchiavello and Miquel-Florensa's \(2019\)](#) analysis of a buyer-driven quality upgrading program in the Colombian coffee chain.⁷

A vast body of work studies firms' upgrading from export-ing and foreign direct investment in developing economies (see [Verhoogen forthcoming](#) for a review). For example, [Atkin et al. \(2017\)](#) show that randomly assigned export orders induced quality upgrading among Egyptian rug producers (see also [Pavcnik 2002](#); [Chor, Manova, and Yu 2021](#)). [Alfaro-Ureña, Manelici, and Vasquez \(2022\)](#) find that Costa Rican suppliers increase sales, employment, and productivity after starting to supply multinational corporations. We highlight buyers' sourcing strategies as an up-grading dimension. We do so by relaxing data constraints that have hindered progress in the estimation of markups in multi-product firms ([De Loecker et al. 2016](#)).⁸

II. CONCEPTUAL FRAMEWORK

To fix ideas, we begin with a brief discussion of sourcing sys-tems, present illustrative case studies from the apparel sector, and describe the key elements and predictions of a model of sourc-ing in the apparel sector. This model underpins our empirical characterization of buyers' sourcing strategies in [Section III](#). The main prediction is that relational buyers pay higher prices and markups than do spot buyers sourcing the same product from the same supplier at the same time. We test this prediction in [Section IV](#). [Online Appendix A](#) presents the model in detail and

7. The literature has also studied vertical integration in global value chains (see [Antràs 2003](#); [Costinot, Oldenski, and Rauch 2011](#)). [Macchiavello and Miquel-Florensa \(2018\)](#) compare integrated and relational sourcing in the coffee sector. We abstract from vertical integration, as it is virtually nonexistent in our context.

8. Recent contributions that use within-firm data and that are closely related include [Brandt, Kambourov, and Storesletten's \(2020\)](#) analysis of vertical inte-gration in the Chinese steel industry; [Adhvaryu et al.'s \(2020\)](#) study of workers' allocation across production lines in a large Indian garment exporter; [De Roux et al.'s \(2020\)](#) analysis of the relationship between product quality and markups in a large Colombian coffee exporter; and [Atkin et al.'s \(2015\)](#) survey-based study of markups in the Sialkot soccer ball cluster in Pakistan.

discusses additional implications. [Online Appendix C](#) presents further evidence consistent with the model.

II.A. Sourcing Garments

We argue that (i) two polar approaches to sourcing—spot and relational—can be distinguished and (ii) the adoption of each system requires distinct organizational capabilities. This leads buyers to adopt consistent sourcing strategies across their supplier base, justifying our buyer-level approach to sourcing strategies in the empirical analysis.

The introduction of lean management practices and just-in-time inventory systems has enhanced the importance of sourcing as a key strategic function ([Dyer, Cho, and Cgu 1998](#)). Reliability of supply—the ability to guarantee supply in due time and form under most contingencies—is a key source of competitive advantage in many industries. Reliability, however, is hard to contract on—especially in developing economies and in the context of international sourcing. Buyers generally deal with this limitation by pursuing either one of two stylized approaches to sourcing: a spot sourcing strategy, at one end, or a relational sourcing strategy, at the other. Under spot sourcing, buyers purchase from multiple suppliers, relationships tend to be short-lived (often ending as a result of out-bids from cheaper suppliers), and orders tend to be one-off or sporadic. Under relational sourcing, buyers concentrate orders on a small number of suppliers with whom they develop relational contracts—defined as “informal agreements sustained by the value of future relationships” ([Baker, Gibbons, and Murphy 2002](#), 39).⁹

Implementing one or the other sourcing strategy requires adopting a set of complementary management practices and structures ([Milgrom and Roberts 1990](#)) and organization-wide capabilities ([Helper and Henderson 2014](#)). The literature on supply chain management highlights how the processes of sourcing, making, and delivering must be coordinated across functions in the firm ([Cooper and Ellram 1993](#)). Under relational sourcing, such coordination requires adequate human resource policies, such as rotation of personnel across functions, avoiding

9. The distinction originated in the literature comparing the sourcing practices of U.S. versus Japanese car manufacturers. The two models are sometimes referred to as “adversarial” or “American-style” in contrast to “collaborative” or “Japanese-style” sourcing (see [McMillan 1990](#); [Helper and Sako 1997](#)).

excessively high-powered incentives conducive to conflict between functions, and stability of purchasing agents. By contrast, under spot sourcing, purchasing agents are given high-powered incentives and rotate frequently to avoid capture by suppliers. Postprocurement functions, such as in-house quality control and product cycle integration, are critical. The capabilities that support one or the other sourcing strategy create economies of scale and scope in the formation of relationships: a buyer with the organizational capabilities that enable relational sourcing tends to trade relationally across its supply base. In the empirical analysis, we posit that the sourcing strategy is a buyer-level attribute.

The contrast between the two sourcing systems appears clear in the garment sector (see Gereffi 1999). Several case studies document differences across firms and within-firm, organization-wide restructurings of sourcing strategies. For example, VF Corporation, a multibrand U.S. apparel retailer, shifted its approach to sourcing globally from a spot style of procurement to a relational approach—the third way—in the mid-2000s (see Pisano and Adams 2009). According to the case study, “historically, apparel companies and apparel suppliers showed little loyalty to one another. Contracts were short-term (typically one season). In their aggressive pursuit of low costs, apparel companies drove hard bargains on pricing and freely shifted production from one supplier to another. There were no guarantees in either direction. Every year, suppliers had to bid to get new business from a company and never guaranteed production capacity beyond a very short time horizon... They also took on products from as many companies as possible (often competitors) to diversify their risks” (Pisano and Adams 2009, 9). Similarly, Nike shifted toward a more relational approach to sourcing. This culminated in 2009 in a company-wide reorganization in which a new corporate division merged the Social Compliance Team into the Global Sourcing Department (see Nien-he, Toffel, and Hull 2019). According to Distelhorst, Hainmueller, and Locke’s (2017, 710) study of Nike’s supply chain, “Sourcing decisions are often decoupled from the enforcement of private regulation... resulting in a tension between the two functions,” and it is “not uncommon to hear complaints from [Social Compliance] managers that their mission is not taken seriously by their colleagues in purchasing departments.” The merging of two previously distinct functions at the headquarters level is an organizational change that affects sourcing across Nike’s global supplier base.

II.B. A Model of Sourcing

We present a model in which sellers are hit by idiosyncratic shocks: in some states of the world, a seller's capacity is scarce, and not all buyers can be prioritized. While buyers and sellers can transact at market prices under normal conditions, it is not possible to formally enforce contracts that prevent delivery failure when shocks occur. Buyers can invest in organizational capabilities that enable relational contracts with suppliers. In such contracts, the buyer promises a higher price (and markup) in exchange for reliable supply.

Formally, we assume that an exogenous measure $B = 1$ of ex ante identical buyers and a measure $S < 1$ of ex ante identical sellers interact over an infinite sequence of periods $t = 0, 1, \dots$ with common discount factor $\delta \in (0, 1)$. In each period, buyers need to source one order of fixed quantity $q = 1$. A fulfilled order yields a gross payoff v to the buyer. An unfulfilled order yields zero to the buyer. Sellers can also sell completed orders to an external market at price $\underline{v} < v$. After contracts have been negotiated, idiosyncratic shocks (assumed to be i.i.d. over time and across sellers) hit sellers' capacity with probability $\alpha \in (0, 1)$. When hit by a shock, the seller can produce only one order at cost c_1 instead of two orders at cost $c_0 < c_1$ each. We assume $c_0 < \underline{v} < c_1 < v$. The efficient trade is thus for a seller to serve one buyer when hit by a shock and to supply two buyers otherwise. When hit by a shock, a seller that has agreed to produce two orders with different buyers must decide which buyer to prioritize. In such circumstances, the seller would not produce for the external market. After production, order delivery and payments take place.

A sourcing contract is an exchange of promises: the buyer promises to pay a certain price upon delivery; the seller promises to deliver at the agreed price. We rule out ex ante transfers between parties. There are two types of contracts: spot and relational. A spot contract is simply a price p_t^S to be paid to the seller on delivery in the current period. Buyers and sellers with a spot contract do not expect to continue trading in the future, so these contracts are offered at the beginning of each period. Sourcing contracts are not perfectly enforced by courts: sellers cannot be penalized for failing to deliver, and buyers cannot be fully penalized for withholding payment. We assume that if a buyer does not pay the promised price after delivery, a court is unable to adjudicate whether the order was appropriately delivered. The seller

is, however, able to prevent the buyer from withholding payment completely, for example, because of a letter of credit. For simplicity, we assume that the court enforces a payment equal to the market value of the order, \underline{v} .

Given these assumptions, a buyer always reneges on a spot contract with price $p_t^S > \underline{v}$. Thus, all spot contracts promise $p_t^S = \underline{v}$. Sellers do not fulfill orders under spot contracts when hit by a shock. Buyers sourcing through spot contracts can source only from sellers that have not been hit by a shock. This captures the idea that spot contracts are useful under business as usual but are ineffective to induce sellers to undertake costly actions during unusual, difficult-to-contract-on circumstances. Buyers that source through spot contracts thus suffer delivery failures with probability $(1 - \sigma)$. This probability is endogenous and depends on buyers' choices of sourcing strategy in equilibrium.

The possibility of delivery failures creates a rationale for relational contracts. A relational contract between buyer b and seller s is a plan that specifies deliveries and prices for each period $t = 1, 2, \dots$ as a function of the past history of play and the current state. For simplicity, we focus on stationary relational contracts (and drop the time subscript in what follows) and assume that the buyer promises to pay a price p^R regardless of the shock.¹⁰ The relational contract is rooted in parties' specific circumstances that cannot be verified by courts. We maintain the assumption that a defaulting buyer is forced to pay \underline{v} and a court does not enforce any additional promised payment ($p^R - \underline{v}$).

Credibility and clarity are necessary features of successfully managed relationships (Gibbons and Henderson 2012). Credibility refers to self-enforcement: a relational contract is self-enforcing if it constitutes a subgame-perfect equilibrium of the repeated game between the buyer and the seller. In equilibrium, it must be that parties do not want to deviate from the agreed plan. Credibility is thus captured by dynamic incentive constraints for the buyer and the seller. Clarity is about understanding (and selecting) what equilibrium is played. Even when dynamic incentive constraints can be satisfied, different equilibria, including inefficient ones, can emerge. We thus assume that in period $t = 0$,

10. In practice, prices cannot easily be adjusted in response to production conditions (see Carlton 1986 for a discussion and empirical evidence). The assumption captures in a parsimonious way the common insight that rents must be paid to induce suppliers to undertake costly, noncontractible actions. The assumption can be microfounded and relaxed (see Online Appendix A for a discussion).

buyers can invest in organizational capabilities, at cost F , to become able to make credible promises to sellers. Only buyers that invest can offer relational contracts. We say that a buyer is relational if he invests and is spot otherwise. Let ρ denote the (endogenous) share of buyers who invest.

We construct an equilibrium in which sellers always deliver to relational buyers regardless of the shock and relational buyers pay the promised price p^R . We assume that if a seller fails to deliver, no buyer will source relationally from her in the future. Similarly, we assume that if a buyer reneges on a promised payment, no seller will believe his promises in the future. Thus, upon renegeing, the buyer would be able to source only through spot contracts. These drastic assumptions can be relaxed and are meant to capture the idea that there must be some reputational loss from renegeing on a relational contract. No relational equilibrium could be sustained if following a deviation, buyers and sellers could immediately rematch with a partner offering an identical relational contract.

For the relational contract to be self-enforcing, the price, p^R , must be sufficiently high to induce the seller to deliver even when there is a shock, that is, $p^R \geq \underline{p}^R \equiv (1 - \delta)c_1 + \delta[\alpha c_1 + (1 - \alpha)\underline{v}]$. Conversely, the price must not be too high, otherwise the buyer would prefer to renege on the promised payment, $p^R \leq \bar{p}^R \equiv \delta[v - \sigma(v - \underline{v})] + (1 - \delta)\underline{v}$. Denote with $V = \Delta\pi_s^R + \Delta\pi_b^R$ the expected joint surplus created by the relationship, with $\Delta\pi_i^R$ the difference in payoffs between the relational contract and the outside option for party $i \in \{b, s\}$. A necessary condition for the relational contract to be self-enforcing is that in each state, the net present value of the expected surplus is larger than the sum of the seller's and buyer's temptations to deviate. Intuitively, in the absence of a shock, the incentive constraint cannot be binding if the relationship generates value. The relevant dynamic incentive constraint is given by

$$\frac{\delta}{1 - \delta}V \geq c_1 - \underline{v}.$$

Note that the relational price p^R is a transfer between parties, and it thus drops out from the relationship value, V , and the sum of temptations to deviate, $c_1 - \underline{v}$. There exists a continuum of prices $p^R \in [\underline{p}^R, \bar{p}^R]$ that satisfy the incentive compatibility constraints.

OBSERVATION 1. A seller that supplies a relational buyer and a spot buyer earns higher prices and markups on orders produced for the relational buyer. Moreover, a seller earns higher profits from a relational buyer than from spot buyers: the higher markups under no shock more than compensate for the cost of delivering under the shock.

We complete the derivation of the equilibrium by studying buyers' investment decisions. Recall that spot buyers pay a price $p^S = \underline{v} < \underline{p}^R$. An interior equilibrium in which $\rho \in (0, S)$ features sellers competing to attract relatively few relational buyers (and therefore $p^{R^*} = \underline{p}^R$) and requires buyers to be indifferent between the sourcing strategies, that is,

$$\delta[v - p^{R^*} - \sigma(\rho^*)(v - \underline{v})] = (1 - \delta)F.$$

II.C. Summary of Takeaways

1. *Relational Buyers Pay Higher Prices and Markups.* The main prediction of the model is that relational buyers pay a higher price, and thus a higher markup, than spot buyers. Two ingredients are needed to test this prediction: (i) a characterization of buyers' sourcing strategies, and (ii) information on prices and markups earned by the same seller at the same time for the same products from different buyers. [Section III](#) characterizes international buyers' sourcing strategies in the garment sector and provides the first ingredient. [Section IV](#) delivers the second ingredient and tests the prediction exploiting the unique features of our data. We discuss alternative mechanisms and policy implications in [Section V](#).

2. *Relational Buyers Trade with Fewer Sellers than Spot Buyers.* Relational buyers always buy from the same seller (only one seller, given our simplifying assumptions on unit demands), whereas spot buyers switch between partners over time. [Section III](#) builds on this observation to construct an empirical proxy for buyers' sourcing strategies.¹¹

11. Because the costs of becoming relational are fixed, an extension of the model in which buyers demand two units per period instead of one implies that relational buyers source relationally from both suppliers.

3. *Additional Implications.* The model assumes ex ante identical buyers that endogenously adopt different sourcing strategies and therefore provides a rationale for the large unexplained variation in sourcing strategies documented in [Online Appendix C.1](#). The model assumes ex ante identical sellers for simplicity and endogenously derives that sellers supply a mix of relational and spot buyers, as documented in [Online Appendix C.2](#). Finally, the model implies that exporters prioritize orders for relational buyers when unexpected supply disruptions occur. [Online Appendix C.3](#) provides suggestive evidence that, indeed, sellers prioritize relational buyers during strikes that make it harder to fulfill orders on time.

III. BUYERS' SOURCING STRATEGIES

This section characterizes the sourcing strategies of international garment buyers. [Section III.A](#) introduces our measure of relational sourcing. [Section III.B](#) presents novel evidence on international sourcing of garments and provides a formal test that justifies our empirical approach in [Section IV](#).

III.A. Measuring Buyers' Sourcing Strategies

A distinctive feature of relational buyers is the concentration of sourcing in a small number of suppliers. We thus measure the sourcing strategy according to how concentrated a buyer's sourcing is on a small number of suppliers. To lend intuition, [Table I](#) examines the 25 largest buyers of woven garments in Bangladesh. Column (1) ranks buyers according to their market shares in the country. H&M, Walmart, and the multibrand apparel company VF Corporation lead the board with market shares of 5.22%, 5%, and 4.14%, respectively—each more than 500 times larger than the median buyer in the sample. Even among these large buyers, there are large differences in their approach to sourcing. For example, Levi Strauss & Co. has a reputation for developing long-term collaborative relationships with suppliers; J.C. Penney has traditionally adopted a strategy of “squeezing cost out of the supply chain” (see [Casabona 2013](#)) and during our sample years, “decimated [their] sourcing department and trampled on trusted relationships established in foreign countries” under the leadership of Ron Johnson (see [Loeb 2014](#)). [Table I](#), column (2) shows that Levi Strauss & Co. and J.C. Penney have similar market

TABLE I
BUYERS' CONCENTRATION AND SOURCING

	Market share %	Sellers per year average	Relational ranking	Price (residuals) ranking
Top 25 buyers	(1)	(2)	(3)	(4)
H&M Hennes and Mauritz	5.22	60.75	3	2
Wal Mart Stores	5.00	59.75	17	16
VF Corporation	4.14	25.50	5	17
The Gap Inc.	3.44	27.13	1	1
C & A Buying	3.17	43.38	8	9
K Mart Corporation	3.08	62.13	16	14
PVH Corporation	3.11	39.88	7	15
Levi Strauss & Co	2.21	7.50	2	7
J.C. Penney	1.96	25.88	11	10
Primark	1.42	23.00	10	24
Kik Textilien	1.32	51.88	25	22
Tesco	1.25	23.50	12	19
Kohls Department Stores Inc.	1.25	16.50	13	5
Asda	1.21	19.63	6	8
Marks & Spencer	1.15	10.25	4	11
Carrefour	1.13	26.88	14	18
G. Gldenpfennig GmbH	0.87	32.38	24	20
Tema Magazacilik	0.91	44.13	21	4
Public Clothing Company Inc.	0.84	25.25	23	23
Target Stores	0.85	19.50	15	12
Inditex (Zara)	0.81	33.13	20	3
Auchan S.A.	0.71	30.63	19	21
Charles Vogele	0.69	17.38	18	13
The Children's Place	0.68	11.13	9	6
IFG Corporation	0.65	14.38	22	25
Top 100 (market share = 66%)				
Mean	0.66	17.53		
Median	0.29	13.00		
Std. deviation	0.99	14.58		
Coeff. variation	1.49	0.83		
All buyers ($N = 1,578$)				
Mean	0.06	4.60		
Median	0.01	3.00		
Std. deviation	0.30	6.16		
Coeff. variation	5.04	1.34		

Notes: The top part lists the largest 25 buyers in descending order based on their imports of woven garments (trousers and shirts). For each of them, it reports the buyer's market share (column (1)), the number of sellers the buyer trades with on average every year (column (2)), the ranking according to the buyer's relational characteristic in woven products (column (3)), and the ranking of the buyer according to the average price it pays for its orders, residualized against the size of the order and seller-product-year fixed effects (column (4)). The bottom panels of the table report summary statistics of the corresponding variables in columns (1) and (2) across the top 100 buyers and across all buyers.

shares (2.21% and 1.96%, respectively) but differ in the number of suppliers they source from: in a typical year, the former sources from only 7.5 suppliers, while the latter does so from 25.9 suppliers.

Guided by these observations, we construct the buyer-level measure of relational sourcing as the weighted average of the negative of the number of sellers divided by the number of shipments at the product–year level. Specifically, we define

$$\begin{aligned}
 \text{Relational}_b &= \sum_{jt \in \mathcal{J}_b} \left[\frac{Q_{bjt}}{Q_b} \times \text{Relational}_{bjt} \right] \quad \text{and} \\
 (1) \quad \text{Relational}_{bjt} &= - \frac{\#\text{Sellers}_{bjt}}{\#\text{Shipments}_{bjt}},
 \end{aligned}$$

where Q_{bjt} is the overall volume of garment sourced by buyer b in product j (an HS6 code) in year t and \mathcal{J}_b is the set of all product–year combinations jt sourced by buyer b . We normalize the number of sellers by the number of shipments so that, other things equal, a buyer with a higher number of shipments per seller, or equivalently with fewer sellers per shipment, is assigned a higher value on the relational metric. Relative to a normalization based on volumes or values, the number of shipments is observed with less error and is better aligned to our model in [Section II](#) (and to the model in [Taylor and Wiggins 1997](#)). [Online Appendix D.2](#) shows that the results in this article are robust to the use of alternative measures of sourcing strategies, including those that normalize the number of partners using traded volumes or values and those based on the average duration of a buyer's relationships.¹²

The Relational_b metric produces a sensible ordering of buyers. [Table I](#), column (3) ranks the largest 25 buyers according to their sourcing strategies (the first one being the most relational buyer). The ranking maps closely to qualitative accounts in

12. Relational contracts—informal arrangements sustained by the value of future interactions—are not directly observable in the data (see [Macchiavello 2022](#)). Much of the existing empirical work thus resorts to relationship age—which is instead observable—to proxy for relational trade. There are a number of drawbacks to this approach. First, repeated trade does not imply relational trade, which instead critically hinges on the promise of future rents to induce parties to resist temptations to engage in opportunist behavior. Second, measures based on a relationship's age require a stance on censoring and assumptions about the demand structure across buyers.

industry publications. For example, Levi Strauss & Co. ranks second, close to other large buyers known for their relational approach to sourcing, such as The Gap Inc. and H&M, ranked first and third, respectively. Large European discount retailers (e.g., Kik Textilien and JCK), known for a spot sourcing strategy, appear lower in the ranking. Zara's owner Inditex is ranked slightly lower: during the sample period, Zara sourced relationally from suppliers located near its headquarters in northwestern Spain and sourced from Bangladeshi suppliers through the traditional spot approach (see Ghemawat and Nueno Iniesta 2006).

In the empirical analysis in Section IV, we correlate buyers' sourcing strategies with order-level outcomes, such as prices and markups. A potential source of concern is that our proxy for sourcing strategy relies on features of the buyers' transactions that might be correlated with these outcomes of interest other than through the relational or spot nature of sourcing. To assuage such concerns, the empirical analysis takes advantage of the fact that garment exports in Bangladesh are concentrated in two distinct sets of products—woven garments and knitwear (see Online Appendix B.1). The production process of the two types of garments is radically different, and the sets of exporters in the two subsectors are largely disjoint. Our analysis focuses on woven garments (for which we can match inputs and output at the order level). We thus construct our metric separately for products included in our analysis, \mathcal{J}^+ , and for products excluded from our analysis, \mathcal{J}^- , with $\mathcal{J} = \mathcal{J}^+ \cup \mathcal{J}^-$ and $\mathcal{J}^+ \cap \mathcal{J}^- = \emptyset$. The metric of relational sourcing that we take to the data is then

$$(2) \quad \textit{Relational}_b = \sum_{jt \in \mathcal{J}^-} \left[\frac{Q_{bjt}}{Q_{b\mathcal{J}^-}} \times \textit{Relational}_{bjt} \right].$$

Online Appendix Figure D.1 shows that the sourcing of the buyer is strongly correlated between included and excluded products. This is reassuring for our approach and, as we show below, illustrates a more general pattern.

Online Appendix Figure C.1 presents the distribution of the proxy for sourcing strategies across woven garment buyers in Bangladesh, computing the metric defined in equation (2) on excluded products. By construction, the measure ranges in the interval $[-1, 0)$, with -1 indicating the greatest reliance on spot and $\rightarrow 0$ on relational sourcing. The median of this distribution is -0.344 , meaning that the median buyer has just over 34

suppliers for every 100 transactions. The most relational buyers, conversely, have one supplier for every 100 transactions on average. To fix ideas, we consider two large buyers presented in [Table I](#). Across the main woven product categories, H&M trades with 157 different sellers throughout our sample period, allocating an average of 847 shipments to each. In contrast, Kik Textilien trades with 206 sellers, allocating an average of 26 shipments to each of them. As a result, H&M is located at the top end of the distribution of our sourcing metric ($Relational_{H\&M} = -0.021$), and Kik Textilien is almost 1 (0.83) standard deviation below ($Relational_{Kik} = -0.241$). We return to this comparison as an illustrative example in our quantification in [Section V.D](#).

Our empirical analysis studies how export order-level outcomes vary with the sourcing strategy of the buyer. By construction, the proxy for buyers' sourcing strategies includes several potential forms of measurement error that may lead to attenuation bias—that is, making differences across buyers harder to detect in the data. First, buyers may tailor their sourcing practices to specific suppliers. Second, buyers might change their sourcing strategy over time. If that is the case, our reliance on a time-invariant measure makes identification elusive. We address both issues in [Section V](#). Third, in some cases, buyers might source through specialized sourcing intermediaries (such as Li & Fung). Collaborations with buyers revealed that on occasion, buyers use both direct sourcing and intermediaries. In Bangladesh, these intermediaries rarely take ownership of the good and thus might not appear in the customs data, introducing measurement error. Finally, our strategy to focus on excluded products alleviates endogeneity concerns but introduces measurement error.

III.B. Sourcing Strategies as a Buyer-Specific Characteristic

Having introduced an empirical measure for buyers' sourcing strategies, this subsection provides a test of the idea that buyer-level capabilities are important drivers of sourcing strategies. We measure buyers' sourcing strategies using transaction-level customs records of garment exports (defined at the HS6 level—as in the rest of the article) from Bangladesh, Ethiopia, India, Indonesia, Pakistan, and Vietnam. Taken together, these countries account for 36% of garment exports from developing countries into

the United States and the European Union.¹³ Our working sample contains approximately 16.5 million transactions, across the six countries, corresponding to almost 10,000 buyers and 29,000 sellers. For each buyer-product-country, we construct our proxy $Relational_{bjc}$ analogously to the definition in equation (1), where $c \in \{BD, ET, IN, ID, PK, VN\}$ and j is an HS6 code.

Figure I shows (stylized) scatter plots of $Relational_{bjc}$ and $Relational_{bjc'}$ for all pairwise combinations c and c' . A positive slope indicates that a buyer b that sources product j relationally in country c tends to do so in country c' as well. This is the slope that we find in all but one pair of countries—the sole exception being the pair Vietnam (the most advanced garment producer in our sample) and Ethiopia (which only recently began exporting large volumes of garments). For example, in HS 610442, H&M is classified at the 99th percentile of the relational metric in both Bangladesh and Pakistan and at the 96th percentile in Indonesia. In HS 620459, H&M is above the 95th percentile in Bangladesh, Indonesia, Pakistan, and Vietnam. In contrast, J.C. Penney is below the 25th percentile in HS 610520 in Vietnam and Ethiopia and in HS 620429 in Bangladesh and Vietnam.

We can formally test the hypothesis that buyers' sourcing strategies are largely driven by buyer-level capabilities, justifying our approach to model them at the buyer level. Our test is inspired by and generalizes Monteverde and Teece's (1982) classic study of vertical integration for 133 components used by Ford and GM. The authors test and find empirical support for the transaction cost economics theory of vertical integration by showing that car assemblers integrate components whose production processes generate quasi-rents in the form of specialized, nonpatentable know-how. A perhaps less appreciated finding in this classic study is that the buyer dummy accounts for a substantial share of the observed variation in vertical integration across components. This suggests that—when a component's technical specification is held constant—Ford and GM differ in their overall approach to sourcing.

Returning to our context, transaction cost economics (Williamson 1971, 1975, 1985) predicts that the choice of governance form—in our case, the choice between spot versus

13. The data, described in detail in Online Appendix B.3, come from ongoing work in Cajal-Grossi, Del Prete, and Macchiavello (2023). We are grateful to Davide Del Prete for letting us use the data in this paper.

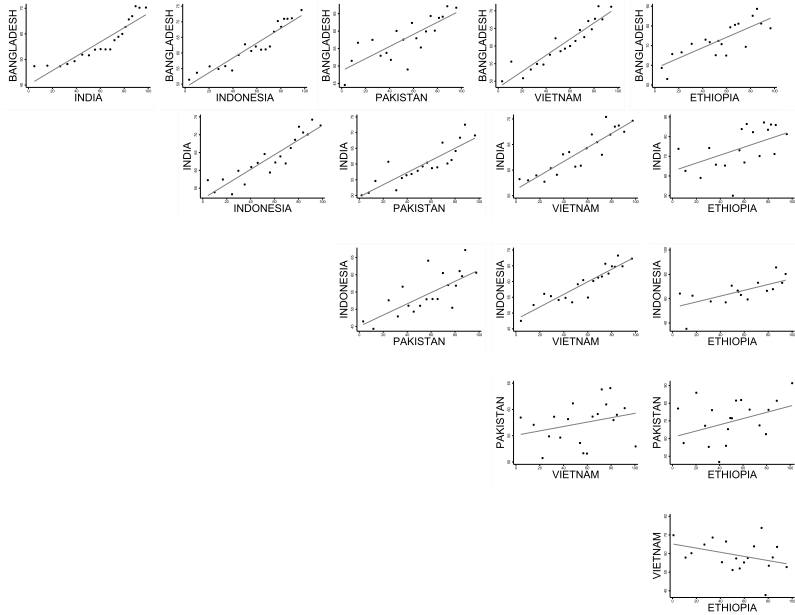


FIGURE I

Buyers' Sourcing Strategies in Different Countries

The graphs show two-way comparisons of buyers' sourcing strategies in different countries using data from [Cajal-Grossi, Del Prete, and Macchiavello \(2023\)](#). A datapoint used for the construction of these graphs is a buyer-product-country combination in each pre-COVID year, where the buyer-product is active in the two countries in the corresponding plot. The variable being plotted measures the sourcing strategy of the buyer in the product-country, $Relational_{bjc}$, and it is measured as (minus) the ratio between the number of sellers and the number of shipments. These measures are standardized in product-country pairs, and arranged in 100 quantiles in each country. The scatter markers correspond to averages in a partition over 20 bins. The solid line depicts the linear fit after a regression of the sourcing metric of buyers in the country indicated on the vertical axis, over the sourcing metric of these buyers in the country of the horizontal axis, conditional on product fixed effects. Each graph is produced on a different number of observations (buyer-product combinations present in both the horizontal axis and vertical axis countries). We report here the number of observations, point estimate of the slope coefficient, and standard errors (clustered by product), corresponding to each graph. Bangladesh-India (top-left) : $N = 12,862$, coeff. = 0.280, std. err. = 0.009. Bangladesh-Indonesia: $N = 4,217$, coeff. = 0.238, std. err. = 0.015. Bangladesh-Pakistan: $N = 3,158$, coeff. = 0.174, std. err. = 0.018. Bangladesh-Vietnam: $N = 5,159$, coeff. = 0.229, std. err. = 0.015. Bangladesh-Ethiopia: $N = 193$, coeff. = 0.264, std. err. = 0.051. India-Indonesia: $N = 5,136$, coeff. = 0.206, std. err. = 0.013. India-Pakistan: $N = 3,718$, coeff. = 0.193, std. err. = 0.016. India-Vietnam: $N = 5,697$, coeff. = 0.137, std. err. = 0.013. India-Ethiopia: $N = 203$,

FIGURE I

(Continued) coeff. = 0.203, std. err. = 0.056. Indonesia-Pakistan: $N = 908$, coeff. = 0.163, std. err. = 0.034. Indonesia-Vietnam: $N = 5,628$, coeff. = 0.199, std. err. = 0.014. Indonesia-Ethiopia: $N = 119$, coeff. = 0.240, std. err. = 0.073. Pakistan-Vietnam: $N = 1,012$, coeff. = 0.041, std. err. = 0.032. Pakistan-Ethiopia: $N = 70$, coeff. = 0.176, std. err. = 0.085. Vietnam-Ethiopia (bottom-right): $N = 173$, coeff. = -0.112 , std. err. = 0.058.

relational sourcing—is driven by characteristics of the product and the market in which it is being sourced. For example, products that are more differentiated (Rauch 1999), that have different fashion cycles (Woodruff 2002), or that are sourced from countries in which contracts are harder to enforce (Antràs and Foley 2015) are more likely to be sourced relationally. Similarly, conditions in the downstream market might also influence the choice of sourcing strategy. This logic implies that origin-product fixed effects and destination-product fixed effects should account for most of the observed variation in sourcing strategy. If instead organizational capabilities—as opposed to transaction costs—are a key driver of sourcing strategy choices, a buyer’s sourcing strategy should be correlated across the different products and origin countries that the buyer sources from (as seen in Figure I), and quantitatively, a buyer’s identity should explain a significant proportion of the variation in how sourcing is organized.

We implement a loss-of-fit exercise to quantify the relative importance of buyer fixed effects versus other factors in driving variation in sourcing strategies $Relational_{bjc}$. Online Appendix Table C.1 reports the results. We regress $Relational_{bjc}$ on a set of fixed effects $\{\delta_i\}_{i \in I}$ and obtain the loss in model fit from removing each component from model I . We denote by b , j , c , and d —as in the rest of the article—the buyer, product, country of origin, and destination, respectively. Focusing on the most saturated specification with $I = \{b, jc, jd\}$, we find that buyer fixed effects account for over 40% of the explained variation in sourcing strategies, vis-à-vis 16% and 14% explained by product-country (the origin of the garment) and product-destination (the country of the buyer), respectively. We conclude that organizational capabilities at the buyer level appear to play a key role in driving a buyer’s approaches to sourcing in the industry.

IV. EVIDENCE

This section tests the main prediction of the model: relational buyers pay higher markups. Before presenting the main results, we describe the garment production process and our data. The customs data reveal that within seller-product-year combinations, orders produced for relational buyers earn higher prices. These higher prices may reflect higher markups (as predicted by the model) or higher costs of producing for relational buyers. Disentangling the two is challenging, as the allocation of inputs to output is not typically observed. Our customs data and the internal records from factories, however, allow us to link inputs to specific orders and reveal that within seller-product-year combinations, orders produced for relational buyers do not differ in the type, price, or efficiency of fabric and sewing labor. We derive conditions under which the data recover differences in markups across orders produced for different buyers and confirm the model's main prediction.

IV.A. Buyer-Specific Inputs and Outputs

1. *Garment Production.* Ready-made garment manufacturers in Bangladesh, who are entirely export oriented, make production decisions based on orders received from international buyers. Buyers provide suppliers with a design and a set of technical specifications on the items to be produced. Unlike cut-make-trim systems (like those in China, Mexico, and Myanmar), in which buyers provide fabric and other material inputs to the manufacturer, Bangladeshi exporters source fabric and inputs before cutting, sewing, and packaging the garments according to the buyers' specifications.

Fabric and labor employed on sewing lines are the two main variable inputs used in the production of a garment export order and jointly account for 85%–90% of the variable costs of producing a typical garment. Fabric utilization choices are made order by order. Once the fabric is available at the manufacturing plant, two sequential production stages take place: (i) inspection and cutting, and (ii) sewing and finishing (see [Online Appendix E.1](#) for details). Fabric efficiency is tracked by two performance indicators. The buy-to-cut ratio—the ratio of purchased fabric to cut fabric that is fed to the sewing lines—measures performance at the inspection and cutting stage. The cut-to-ship ratio—the ratio of cut fabric to shipped garments—measures performance at

the sewing and finishing stage. The product of these two metrics, the buy-to-ship ratio, is a commonly used performance indicator. Lower values represent lower levels of waste and thus higher efficiency over the two stages of production.

Labor employed in the sewing section of the factory is the other main variable input in the production of garments. Like the buy-to-ship ratio, labor efficiency is a standard performance indicator in the industry. It is measured as the ratio between the minutes-equivalent output of the production line and the minutes of labor input. On a given day, the input minutes on a line are given by the number of sewing operators multiplied by the line's run time. The output minutes are calculated as the product between the garment's standard minute values (SMVs) and the number of pieces produced by the line. The SMV is a measure computed by the factory's industrial engineers—often based on international libraries of SMVs of elemental sewing processes—and captures the amount of time required to sew a particular garment.

2. Data and Sample. Our main source of data consists of transaction-level export and import customs records from Bangladesh over the period 2005–2012. We complement these data with internal production records and worker surveys from a sample of factories. These additional data were collected as part of a series of randomized controlled trials (see [Macchiavello and Woodruff 2014](#); [Ashraf et al. 2015](#); [Macchiavello et al. 2020](#)). The main novelty of the data is that they allow us to explore differences in the price and efficiency of the two main variable inputs—fabric (in the customs data) and labor (in the production line data)—across export orders produced for different buyers. We offer a brief description here and refer the reader to [Online Appendices B.1 and B.2](#) for details.

3. Customs Records. We focus on woven garments. Two features of the Bangladeshi woven garment sector enable us to link the use of material inputs to output at the export order level. First, unlike other major garment exporters (including China, India, and Pakistan), Bangladesh lacks a domestic woven textile industry. Woven products exported by Bangladeshi firms are thus produced using imported fabric (e.g., woven cotton fabric) exclusively, as there are no suitable domestic substitutes. Second, to participate in a customs bonded warehouse regime that

allows duty-free import of material inputs, exporters must indicate the export order for which the imported fabric will be used. Specifically, after receiving an order from an international buyer, the manufacturer submits a utilization declaration (UD) to the Bangladesh Garment Manufacturers and Exporters Association. A unique UD identifier is assigned to all export and import transactions belonging to that export order. These features enable us to identify the material inputs that correspond to an export order. We aggregate transaction-level records at the order (UD) level, producing a single entry for each order that denotes the following information: the buyer's identity and destination country, garment product code, value and volume of garment exported, seller's identity, fabric product code, value and volume of fabric imported, and country of origin of fabric. As an example, a hypothetical observation in our data set is as follows: based on UD 2/124/46/902, Nice Apparel Co. Ltd. imported 400 kg of unbleached woven fabric (containing 85% or more by weight of cotton, in three-thread or four-thread twill, including cross twill, weighing not more than 200g/m², i.e., HS520813) at \$6 per kg from China on January 20, 2008, to fulfill an order subsequently exported to Walmart Inc. of 450 kg of men's or boys' woven cotton shirts (HS620520) on March 1, 2008, at \$10 per kg.

We focus on woven garment orders channeled through the UD system in the 17 six-digit HS codes in the two largest woven apparels: shirts and trousers. Cross-order variation within export-product-time combinations is needed to test the model's prediction. We thus restrict our analysis to the 500 largest exporters, accounting for 78% of the relevant sample. [Online Appendix](#) Table B.1 compares the analysis sample with the broader population.

Table II provides descriptive statistics. Panel A reveals that the average order has a buy-to-ship ratio of 0.87—similar to $\frac{400}{450} \approx 0.89$ for our hypothetical order exported by Nice Apparel Co. Ltd. to Walmart Inc. The buy-to-ship ratio is often less than one because it is computed using the net export volumes (kilos) that in addition to fabric include accessories and packaging (garments are folded in plastic envelopes and then stored in carton boxes). Our results are robust to including controls for accessories and packaging characteristics. Buy-to-ship ratios at the order level are also quite dispersed, with a coefficient of variation of 0.33. This dispersion is consistent with differences in efficiency—at the inspection and cutting and/or at the sewing and finishing stages

TABLE II
SUMMARY STATISTICS

	Obs.	Mean	Std. dev.	P10	P25	P50	P75	P90
Panel A: Orders								
<i>Buy-to-Ship_o</i>	22,741	0.87	0.29	0.51	0.67	0.86	1.04	1.22
<i>Length_o</i> (months)	22,741	4.24	3.25	1.47	2.17	3.3	5.23	8.03
Panel B: Sellers								
<i>Count_{st}^o</i>	3,165	14.60	13.07	3	6	11	19	29
<i>Count_{s jt}^o</i>	6,872	6.03	7.53	1	2	3	7	14
<i>Count_{st}^j</i>	3,165	3.27	1.88	1	2	3	4	6
<i>Share_{st}^j</i>	3,165	57.76	34.92	6.40	24.29	62.30	92.67	100
<i>Count_s^b</i>	500	20.97	17.10	4	8.5	17	28	42.5
<i>Count_{st}^b</i>	3,165	5.88	4.86	1	2	5	8	12
<i>Count_{s jt}^b</i>	6,872	2.91	2.91	1	1	2	4	6
<i>Share_{st}^b</i>	3,165	43.98	36.91	1.71	8.50	34.67	82.18	100
<i>Length_s</i> (years)	500	6.65	1.54	4.08	5.75	7.63	7.75	7.75
Panel C: Buyers								
<i>Count_{bt}^o</i>	4,478	13.37	29.75	1	2	5	13	27
<i>Count_{b jt}^o</i>	8,070	5.75	11.54	1	1	2	5	12
<i>Count_{bt}^j</i>	4,478	4.24	3.83	1	2	3	5	9
<i>Share_{bt}^j</i>	4,478	59.47	35.71	5.96	26.41	63.58	100	100
<i>Count_b^s</i>	2,529	54.40	50.06	9	18	37	72	137
<i>Count_{bt}^s</i>	7,569	22.05	20.52	4	7	14	30	58
<i>Count_{b jt}^s</i>	11,942	8.80	9.07	1	3	5	12	21
<i>Share_{bt}^s</i>	4,478	48.62	37.97	0	11.72	42.08	92.28	100
<i>Length_b</i> (years)	1,578	5.48	2.42	1.58	3.58	6.42	7.67	7.75
Panel D: Relationships								
<i>Count_{sbt}^o</i>	10,448	3.38	4.58	1	1	2	4	7
<i>Count_{s bjt}^o</i>	12,858	2.52	3.14	1	1	1	3	5
<i>Count_{sbt}^j</i>	10,448	1.46	0.85	1	1	1	2	2
<i>Length_{sb}</i> (years)	5,658	1.87	2.03	0.08	0.25	1.17	2.75	5.08

Notes. Super- and subscripts are as follows: *o* corresponds to orders, *b* to buyers, *s* to sellers, *j* to HS6 product categories, and *t* to years. $Count_y^x$ is the number of *x* per *y*. For example, $Count_{s jt}^o$ is the number of orders per seller-product-year combination. $Length_o$ is the number of months between the first import shipment and the last export shipment of the order. $Length_{sb}$, $Length_b$, and $Length_s$ are the number of years the buyer-seller pair, buyer, and seller are observed trading in the dataset, respectively. A value of 7.75 in these variables implies censoring, given the time span of our data set. That is, more than 25% of the sellers under study and more than 10% of international buyers are active in all years of our panel. $Share_y^x$ is the share of *x* in *y* expressed in percentage terms. For example, for $Share_{bt}^s$, the average seller's share in buyer's trade in a year is 48.62%. The column under the heading Obs. reports the count of cells relevant to the level of aggregation of the variable in the row. For example, the first row of Panel C, corresponding to $Count_{bt}^o$ shows that there are 4,478 buyer-year combinations in the data; across these, the average number of orders is 13.37.

of production—and in the substitution between fabric and other inputs (see [Online Appendix E.1](#) for a discussion and evidence). Panels B, C, and D provide descriptive statistics at the exporter, buyer, and buyer-seller pair levels. Our baseline specification

explores differences across orders within seller-product-year—denoted sjt —combinations. There are 6,872 seller-product-year sjt combinations. Across these, the median (mean) number of buyers in the triplet is 2 (2.91). There are 4 (6) buyers at the 75th (90th) percentile.

4. *Internal Plant Production Records.* We complement the customs records with daily production data on approximately 1,300 sewing lines from 51 garment factories. Sewing lines are observed for approximately 340 days. The data record the utilization, composition, and efficiency of labor, including the SMVs. Recordkeeping varies across plants and in plants over time. The buyer for whom the line is producing on a specific day is observed for 46% of the observations. [Online Appendix Table B.3](#) shows that there are no significant differences between observations with and without information on the buyer. We observe the buyer whose order is being produced for almost 200,000 production line–day combinations (see [Online Appendix Table B.2, Panel A](#)). This allows us to compare labor usage for buyers with different sourcing strategies. [Online Appendix Table B.5](#) reports summary statistics on the labor data and shows that there is significant variation (coefficient of variation of approximately 0.5) on the sourcing characteristic of the buyers for which lines are producing. The production records do not contain information on the skills and wages of workers on the lines. We thus complement the data with surveys of over 1,000 workers employed at these plants ([Online Appendix Table B.2, Panel C](#)) and internal HR records for over 35,000 workers in 11 factories ([Online Appendix Table B.2, Panel B](#)).

IV.B. Relational Buyers and Export Prices

The model predicts that relational buyers pay higher prices than spot buyers for otherwise identical orders produced by a given supplier under identical conditions. We estimate

$$(3) \quad p_{sbjo} = \delta_{sjt} + \beta \text{Relational}_b + \varepsilon_{sbjo},$$

where p_{sbjo} is the log unit price of garment order o of product j (six-digit HS code) manufactured by seller s for buyer b and δ_{sjt} is a fixed effect that absorbs seller-product-year variation. These fixed effects allow us to compare differences across orders produced for different buyers as in the model. The regressor of interest, Relational_b , is our baseline metric of buyers' sourcing defined in [Section III](#). Throughout the analysis, we use the metric

TABLE III
BUYERS' SOURCING AND PRICES

	P_{sbjt}			
	(1)	(2)	(3)	(4)
<i>Relational_b</i>	0.020 ^{***} (0.008)	0.023 ^{***} (0.008)	0.019 ^{**} (0.009)	0.021 ^{***} (0.008)
FEs	<i>sjt</i>	<i>sjt, d</i>	<i>sjt, d</i>	<i>sjt, d</i>
Controls	.	B	B,R	B,R,O
R^2	0.57	0.59	0.63	0.73
Obs.	18,664	18,513	15,647	15,647

Notes. Standard errors are in parentheses, clustered at the buyer level. The outcome in all regressions is the log price of an order between a seller and a buyer in a given product category, p_{sbjt} . The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. Column (1) includes our baseline fixed effect, defined at the level of the seller-product-year triplet. Columns (2)–(4) sequentially add buyer-, relationship-, and order-level covariates, as follows. Buyer controls (B): fixed effect for the main destination of the buyer, cohort of the buyer (year first observed in the data), size (log volume imported by the buyer throughout our data and across all woven products), age of the buyer at the time of the order (log number of months elapsed since first observed in the data), and a dummy indicating whether the buyer is a signatory of the accord as of 2019. Relationship controls (R): Cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order controls (O): size of order (log volume) and log price of fabric of the order. * $p < .10$. ** $p < .05$. *** $p < .01$.

in excluded products to assuage endogeneity concerns and avoid mechanical correlations with order-level outcomes.

Table III reports the results. Column (1) shows that a standard deviation increase in the sourcing metric (i.e., a greater reliance on relational sourcing by the buyer) is associated with 2% higher prices. Columns (2) to (4) sequentially add controls that are buyer-, relationship-, and order-specific. Across all specifications, the estimated coefficient remains quantitatively and qualitatively unchanged, ranging from 1.9% to 2.3%.

Relational sourcing is unconditionally correlated with the buyer's size (see Online Appendix Table C.2, Panel A). Column (2) includes controls for buyer-level characteristics and destination fixed effects, δ_d , to absorb differences explained by characteristics common to all buyers in a given country. Column (3) adds buyer-seller controls: the age and cohort of the relationship, its size, the share of the seller in the buyer's trade, and the share of the buyer in the seller's trade. Finally, relational buyers place more frequent, smaller orders (Online Appendix Table C.2, Panel B) and might demand garments of different quality. Column (4) controls for the size of the order and the price of the fabric used in its production.

The pattern is extremely robust. We explore robustness by relaxing controls and using alternative time period definitions. We consider combinations that (i) let the set of covariates feature none, some, or all sets of controls (i.e., buyer-, relationship- and/or order-level controls); (ii) include one-, two-, and three-way combinations of fixed effects (s for seller, j for product, d for destination, and t for period); and (iii) define the period t at either the month m , quarter q , or year y . Figure II reports estimates from the 522 resulting specifications.¹⁴ All point estimates fall in the interval [0.005, 0.046], with our baseline specification (corresponding to Table III, column (4)) below the midpoint.¹⁵

The baseline specifications likely underestimate the differences in prices paid by relational and spot buyers. Leaving aside Figure II, *Relational_b* exploits only cross-buyer variation. To the extent that buyers tailor sourcing behavior to suppliers' circumstances (e.g., some relational buyers might source spot from some suppliers) or buyers change sourcing strategies over time, our approach induces attenuation bias. We return to both issues in the next section. Furthermore, Online Appendix D explores additional departures from our baseline specifications, including the use of 15 alternative definitions of relational sourcing (Online Appendix Table D.3) and different estimation samples (Online Appendix Tables D.4 and D.5). The results are robust and often larger in magnitude than those in our baseline specification.

IV.C. Relational Buyers and Variable Inputs

We turn to the two main variable inputs—fabric and labor on the sewing lines. The main takeaway is that conditional on inclusion of exporter-product-time fixed effects, we do not detect any difference in the type, efficiency, price, or utilization of the two

14. We restrict attention to specifications that have no more than two sets of additive fixed effects and combinations of fixed effects that feature sufficient within-bin variability. Extensive explorations of excluded specifications (available upon request) support our findings.

15. The 36 specifications with coefficients not significantly different from zero (albeit positive) correspond to specifications that include either seller-month (or seller-product-month) fixed effects or destination-seller fixed effects alongside product-month fixed effects, and no order-level controls. These fixed effects leave insufficient variation either because not enough exporters ship multiple orders of the same product within a month or have multiple buyers with a different sourcing strategy in the same destination market.

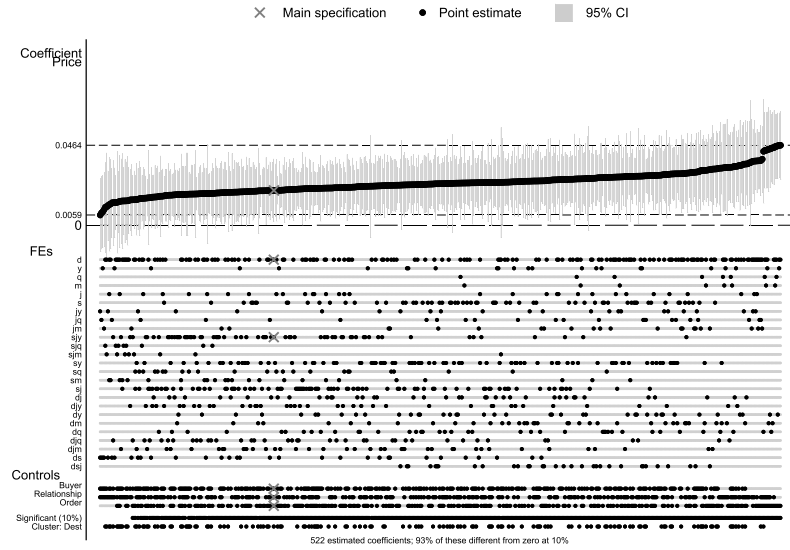


FIGURE II

Robustness of Price Result to Alternative Fixed Effects and Controls

The graph presents 522 estimates of the coefficient on the buyer-specific relational metric in the regression of order prices following specifications with alternative controls and fixed effects. Our baseline, highlighted by gray crosses in the graph, includes seller-product-year fixed effects, destination fixed effects, and buyer-, relationship-, and order-level controls. These controls are as follows. Buyer: cohort of the buyer (year first observed in the data), size (log volume imported by the buyer throughout our data and across all woven products), age of the buyer at the time of the order (log number of months elapsed since first observed in the data), and a dummy indicating whether the buyer is a signatory of the accord as of 2019. Relationship: cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order: size of order (log volume) and log price of fabric of the order. The fixed effects are labeled following the notation of the article: *s* for seller, *j* for product, *y* for year, *d* for destination, *m* for month, and *q* for quarter. The scatter marks in black present the point estimates and the bars in gray show 95% confidence intervals. The bottom panel reflects the set of fixed effects and controls used for the corresponding estimation. For example, a point estimate that has a black marking in *dy*, *sjq*, and *Buyer* corresponds to a price regression on the relational metric, with destination-year and seller-product-quarter fixed effects, as well as buyer-level controls. All possible combinations of fixed effects and controls give an intractably large set of estimates to report. The specifications presented here exclude (i) redundant combinations (for example, seller-product-quarter and year in the same specification), (ii) combinations with more than two sets of additive fixed effects and three multiplicative effects. Still, in the nonredundant specifications with up to two sets

FIGURE II

(Continued) of additive fixed effects, we are forced to reduce the state space, for clarity. We select specifications that we believe are interesting (feature relevant margins of variation) and where there is sufficient richness in the data. For example, we exclude specifications that have only s, j , or only j, t fixed effects, as well as those with sd_y, sd_q , or sd_m fixed effects, where the data becomes sparse. The results on excluded combinations of fixed effects (which are in line with what we present here) are available on request. We note that the number of observations may vary across specifications, as the change in the fixed effects structure gives rise to different singleton nests. The average specification runs on 17,453 orders. The largest sample runs on 21,577 orders, and the smallest sample includes only 6,483 orders. This sample reduction is associated with the use of seller-product-month fixed effects (alongside different forms of destination fixed effects and controls). Standard errors are clustered at the level of the buyer in most specifications. In 148 cases, very granular fixed effects (namely, destination-month, destination-product-month, destination-quarter, destination-quarter-month) and buyer-level clustering give variance matrices that are close to singular. In these cases, the standard errors are clustered by destination (which is a conservative solution in general). This is indicated at the bottom of the figure. There are 36 out of the 522 point estimates (6.8% of all estimations) that are not significantly different from zero. Of these, two-thirds correspond to computations of the standard errors clustering at the level of the destination. The remaining 14 (out of the 36) nonsignificant point estimates correspond to buyer-level clustering of the standard errors. The 36 specifications with coefficients not significantly different from zero (albeit positive), in general correspond to two types of specifications: (i) seller-product-month, seller-month, or seller-product-quarter fixed effects, alongside destination fixed effects and no order-level controls; (ii) destination-seller fixed effects, alongside product-month, product-quarter, or product-year fixed effects and no order-level controls.

variable inputs across orders produced for relational and nonrelational buyers.

1. *Input Usage: Fabric.* We use the specification in [equation \(3\)](#) and consider three outcomes: the price of the fabric used in the production of the order; the order-level buy-to-ship ratio; and a proxy for product complexity given by the number of different types of fabric used to produce the order. [Table IV](#) reports the results. Odd columns estimate the specification in [Table III](#), column (1); even columns include buyer-, relationship-, and order-level controls as in [Table III](#), column (4). Columns (1) and (2) show that the price of the fabric does not correlate with the sourcing strategy adopted by the buyer for whom the order is being produced. Columns (3) and (4) show that there is also no correlation between fabric efficiency—as measured by the order's buy-to-ship ratio—and whether the order is produced for a relational buyer. Finally, column (5) shows a small positive correlation between a proxy for product complexity (the number of different fabric types used in the order) and the buyer's sourcing strategy, but the

TABLE IV
BUYERS' SOURCING AND INPUT USAGE

	p_{sbjo}^f		$\left(\frac{F}{Q}\right)_{sbjo}$		$Complex_{sbjo}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Relational_b</i>	0.008 (0.006)	0.003 (0.007)	-0.004 (0.006)	-0.007 (0.007)	0.021* (0.012)	-0.003 (0.011)
FEs	<i>sjt</i>	<i>sjt, d</i>	<i>sjt</i>	<i>sjt, d</i>	<i>sjt</i>	<i>sjt, d</i>
Controls	.	B,R,O	.	B,R,O	.	B,R,O
R^2	0.64	0.69	0.36	0.44	0.46	0.58
Obs.	18,664	15,647	18,664	15,647	18,664	15,647

Notes. Standard errors are in parentheses, clustered at the buyer level. The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. Outcomes are: the log weighted average price of fabric in the order, p_{sbjo}^f (columns (1) and (2)), the buy-to-ship ratio of the order, $\left(\frac{F}{Q}\right)_{sbjo}$ (columns (3) and (4)), and a measure of complexity of the garment order (the log of the number of fabric types used for producing the order), $Complex_{sbjo}$ (columns (5) and (6)). All columns feature seller-product-year fixed effects. In addition, even-numbered columns also include buyer-, relationship-, and order-level controls, as follows. Buyer controls (B): fixed effect for the main destination of the buyer, cohort of the buyer (year first observed in the data), size (log volume imported by the buyer throughout our data and across all woven products), age of the buyer at the time of the order (log number of months elapsed since first observed in the data), and a dummy indicating whether the buyer is a signatory of the accord as of 2019. Relationship controls (R): Cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order controls (O): size of order (log volume) and log price of fabric of the order. * $p < .10$, ** $p < .05$, *** $p < .01$.

correlation vanishes once controls (in particular, the size of the order) are included in column (6).

Taken together, these results suggest that the higher export prices paid by relational buyers are unlikely to reflect differences in the fabric's type, price, or efficiency when suppliers produce for buyers with different sourcing strategies. Before turning our attention to labor on the sewing lines, we note that the extent to which labor and fabric can be substituted also does not differ across buyers adopting different sourcing strategies. Exploiting time variation in cotton prices (the main input to produce fabric) and a large increase in the minimum wage, [Online Appendix Table E.2](#) shows that when the price of fabric (labor) increases, exporters use less (more) fabric to produce orders of a given size. These substitution patterns, however, do not differ across orders produced for buyers with different sourcing strategies. See [Online Appendix E.1](#) for details.

2. Input Usage: Labor. We now turn to labor employed on the sewing lines. To the extent possible, we would like to study labor

usage using the same specification as in [equation \(3\)](#). Differences in the nature of the customs and production data, however, require us to impose certain adjustments. To fix notation, let τ , s , l , and b denote a calendar day, seller, production line, and buyer, respectively. We estimate

$$(4) \quad y_{slb\tau} = \delta_{sm(\tau)} + \delta_{\tau} + \delta_{sl} + \beta \text{Relational}_b + \varepsilon_{slb\tau},$$

where $y \in \{\#Workers, Share\ Helpers, SMVs, Efficiency\}$ is the outcome and the main regressor of interest is Relational_b —the sourcing strategy of the buyer for which the line is producing on a given day. Denoting with $m(\tau)$ the calendar month of date τ , fixed effects $\delta_{sm(\tau)}$ absorb factory-month-specific variation common across all production lines and buyers. δ_{τ} is a day fixed effect capturing common shocks that could affect production in all plants (e.g., strikes or festive days), and δ_{sl} are production line fixed effects.

There are four main differences in the structure of the production line data from that of the customs records, and these induce small discrepancies between [equations \(3\)](#) and [\(4\)](#). First, the production line data do not include information on the product. It is thus not possible to directly include the product j dimension and replicate the seller–product–time fixed effects in [equation \(3\)](#). The fixed effects $\delta_{sm(\tau)}$ in [equation \(4\)](#) are thus akin to st fixed effects in the customs data. In practice, this might not be a significant departure because (i) most factories specialize in a narrow range of products, with exporters typically using multiple factories to offer a broader range of products to their buyers, and (ii) [Figure II](#) and [Online Appendix D](#) show that the customs data results are robust to specifications with st —as opposed to sjt —fixed effects. A second potential departure pertains to the inclusion (or not) of production line fixed effects. Because the allocation of orders to lines is part of the cost-minimization problem solved by the sellers and production lines are not observed in the customs records, consistency would suggest that we exclude line fixed effects in the production data. At the same time, it is interesting to explore whether orders from relational buyers are systematically allocated to more/less efficient lines. Furthermore, factories that produce multiple products tend to assign dedicated lines to specific product types. Including production line fixed effects therefore helps deal with the unobserved j dimension in the production data. For these reasons, we report the results with and without line fixed effects. A third potential source of discrepancy is that

the higher frequency of the production data—a day, as opposed to a more sporadic export order—suggests a narrower definition of the time period relative to that in the customs data (a month $m(\tau)$ instead of a quarter, or a year). Nevertheless, [Online Appendix Tables D.1 and D.2](#) show that the results are robust to different definitions of the time period in either data set. Finally, the specification includes the buyer-level controls added in [Table III](#), column (2). As we cannot precisely match the factories in the production data with the customs records, we cannot include relationship- or order-level controls.

[Table V](#) reports the results for the four outcomes of interest excluding (odd columns) and including (even columns) the line fixed effects. Columns (1)–(4) show that orders produced for relational buyers have similar SMVs and efficiency on the sewing lines.¹⁶ Columns (5) and (6) show that orders produced for relational buyers do not have a significantly different number of operators working on the sewing line. Finally, columns (7) and (8) show that factories use a similar mix of helpers and skilled sewing operators when producing for relational buyers. In sum, the table reveals no significant differences in the efficiency or type of labor when suppliers produce orders for buyers with different sourcing strategies.

The production data do not contain information on the skills or pay of workers on the production lines. If orders produced for relational buyers employ more skilled workers who earn higher wages, physical efficiency will fail to detect differences in labor costs. To investigate this possibility, we leverage workers' surveys and administrative HR data from (some of) the factories. A sample of 704 workers were asked whether they have rotated lines on a temporary or permanent basis (in the entirety of their job history at the factory). Considering permanent rotations, 93.6% of the workers responded that they had never rotated, and 98% reported at most one rotation in their work history at the plant. Considering temporary rotations, 73.5% of the workers answered that they had never rotated, and 95% of the workers had at most three rotations in their history. In other words, workers do not rotate frequently across lines. These patterns are confirmed by HR

16. Column (3) estimates a negative coefficient that is statistically different from zero at conventional levels. The estimated coefficient is, however, economically small and corresponds to an increase in variable costs of approximately 0.25%—nearly one-tenth of our conservative estimate for prices.

TABLE V
BUYERS' SOURCING AND LABOR USAGE

	SMV _{slτ}		Efficiency _{slτ}		#Workers _{slτ}		Share Helpers _{slτ}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Relational _b	-0.084 (0.353)	-0.024 (0.320)	-0.010* (0.006)	-0.005 (0.005)	0.428 (0.534)	0.396 (0.335)	0.001 (0.002)	-0.002 (0.001)
FES	$sm(\tau), \tau$	$sm(\tau), sl, \tau$	$sm(\tau), \tau$	$sm(\tau), sl, \tau$	$sm(\tau), \tau$	$sm(\tau), sl, \tau$	$sm(\tau), \tau$	$sm(\tau), sl, \tau$
R ²	0.77	0.85	0.20	0.23	0.80	0.92	0.92	0.94
Obs.	155,723	155,723	116,905	116,896	125,940	125,932	125,940	125,932

Notes: Standard errors are in parentheses, clustered at the level of the buyer and production line. Across all specifications, the regressor of interest is the metric on relational sourcing, standardized and increasing in the relational characteristic of the buyer. The outcome in columns (1) and (2) is the standard minutes value (SMV), defined as the amount of time a particular garment is supposed to take to be sewed together, computed by the factory's industrial engineers (often based on international libraries of SMVs of elemental sewing processes). Columns (3) and (4) study labor efficiency of a particular line in a plant, producing for a buyer on a given day, $Efficiency_{sl\tau}$. Labor efficiency is constructed as the ratio between the minutes-equivalent of the output and the minutes of labor input. In turn, the output is calculated as standard minute values times the number of pieces and the input is calculated using the number of workers times the run time. See the main text for a comprehensive description. The outcome in columns (5) and (6) is the number of workers active on the line, $\#Workers_{sl\tau}$, and in columns (7) and (8) it is the share of such workers that are line helpers, $ShareHelpers_{sl\tau}$. The discrepancies in sample size across columns are due to the fact that not all plants keep administrative records of all labor usage metrics studied here. All specifications include as controls for relevant buyer characteristics: its size as a garment importer in Bangladesh; whether the buyer is a signatory of the compliance accord as of 2019; and the cohort of the buyer. Odd-numbered columns condition on fixed effects corresponding to the seller-month ($sm(\tau)$) and the day (τ). Even-numbered columns, in addition, include a fixed effect for the production line of the seller (sl). *, **, *** $p < .05$, *** $p < .01$.

records on production line assignment for almost 20,000 operators in a more limited set of factories. Although it is possible that these records underreport the movement of workers across lines, 79% of the workers are always on the same line; 99.5% are assigned to at most two lines. In light of this, the line fixed effects in [Table V](#) effectively control for differences in worker composition across orders.

Furthermore, the worker surveys provide information on demographics for 1,500 line operators, line supervisors, and line chiefs. A subset of the workers (approximately 700) were also asked about wages and pay. Details on the line on which the worker was working at the time of the survey allow us to construct a variable, $Relational_{sl}$, that measures the share of days during which that worker was likely producing for a relational buyer. We are able to construct this variable for approximately 1,000 workers in the overall sample and for 560 workers in the sample for which we have information on compensation. Although the construction of $Relational_{sl}$ inevitably entails measurement error, [Online Appendix Table C.3](#) shows that conditional on factory and workers' position fixed effects, $Relational_{sl}$ does not correlate with the wage, whether the worker is paid piece rates, quality bonuses, or other types of bonuses (Panel A). Furthermore, $Relational_{sl}$ does not correlate with worker gender, education level, or experience or a measure of cognitive skills (Panel B). This evidence assuages concerns that differences in skills could be driving differences in prices. In sum, we find no differences across relational and nonrelational buyers in terms of labor costs.¹⁷

IV.D. Relational Buyers and Markups

The evidence presented so far is consistent with the model's prediction that the higher prices paid by relational buyers reflect a higher markup. However, there might be order-level unobserved costs that systematically vary across orders produced for

17. Using HR records, in [Online Appendix Table C.13](#), we study within-worker variation in wages, overtime, and absenteeism. We show that these do not significantly correlate with how much the plant is producing for relational buyers. The results hold for workers of any type, for nonline workers only, and for managers only. As overtime is a sensitive issue that factories might misreport in their HR records, we complement these results using the run time observed in the production data to confirm our findings (see [Online Appendix Table C.14](#)).

relational and nonrelational buyers. We develop an empirical framework that clarifies the conditions under which the available data recover within seller-product-time differences in markups across orders, thereby allowing for a precise test of the model's main prediction.

It turns out that these conditions are quite mild: they boil down to a production function that features (log-)separability of fabric use relative to other costs. This condition appears justifiable in light of the two-step production process for garments (see [Section III](#) and [Online Appendix E.1](#)). Other than that, the framework allows for an elasticity of output with respect to fabric that varies at the seller-product-time level and for an arbitrary number of other inputs that sellers may choose freely (e.g., casual labor) or subject to capacity constraints (e.g., managerial labor and attention). We sketch the main elements of the framework. [Online Appendix E.2](#) provides the details. [Online Appendix E.3](#) estimates markup levels.

1. Estimating Differences in Order-Level Markups. Following the model in [Section II](#) (see in particular [note 1](#)), let the timing of events in a period t be as follows. First, buyers b and sellers s form links (and sellers choose their production capacity). Second, each buyer's demand is realized, buyers place orders, and shocks to sellers' capacity are realized. Finally, each seller s produces the orders it received and delivers them to the respective buyers. We index products by j and orders by o and denote the set of orders placed to seller s in period t (by all buyers and in all products) by O_{st} . Order o is seller-buyer-product-time specific (i.e., $sbjt$ specific). Each order specifies a volume Q_o and a unit output price P_o .

To produce an order o , a seller combines labor L_o^z (of potentially different types $z \in \{1, 2, \dots, Z\}$) with fabric F_o . We allow orders to vary in how they combine the different types of labor and to have idiosyncratic productivity ω_o . We denote as θ_o the output elasticity with respect to fabric and as $\mathbf{L}_o = \{L_o^1, L_o^2, \dots, L_o^Z\}$ the available capacity in labor of type z .

Seller s in period t chooses $\{\mathbf{L}_o, F_o\}_{o \in O_{st}}$ to minimize costs, subject to technology and capacity constraints, taking order characteristics and prices as given. Denote the wages for labor of type z and the price of fabric as W_o^z and P_o^f , respectively. The order-specific Lagrange multiplier λ_o represents the increase in cost associated with producing one additional unit of output in order

o , that is, the short-run marginal cost for order o . Denoting the order-level markup factor M_o , the (order-specific) first-order condition with respect to fabric F_o yields

$$(5) \quad \lambda_o = \frac{P_o^f F_o}{\theta_o Q_o} \text{ and } M_o \equiv \frac{P_o}{\lambda_o} = \theta_o \frac{P_o Q_o}{P_o^f F_o}.$$

Equation (5) implies that the order-level markup M_o depends on the buy-to-ship ratio $\frac{F_o}{Q_o}$, the unit price of garment P_o and fabric P_o^f , and the output fabric elasticity θ_o . The unique feature of our data is that $\frac{F_o}{Q_o}$, P_o , and P_o^f are directly observed. The output fabric elasticity θ_o , however, is not. Denote as $\psi_o = \frac{P_o Q_o}{P_o^f F_o}$ the term that is directly observed in the data. We can write the difference in (log) markup factors between two orders o and o' as:

$$(6) \quad \begin{aligned} \Delta_{oo'} \equiv \ln(M_o) - \ln(M_{o'}) = & \underbrace{(\ln(\psi_o) - \ln(\psi_{o'}))}_{\text{Directly Observed in the Data}} \\ & + \underbrace{(\ln(\theta_o) - \ln(\theta_{o'}))}_{\text{Not Observed in the Data}}. \end{aligned}$$

The data allow us to directly observe the differences in markups across orders that share the same fabric elasticity. We assume that the output-to-fabric elasticity varies at the seller-product-time level, that is $\theta_o = \theta_{sjt}$. Under this assumption, we can directly explore differences in (log) markup factors across buyers within a seller-product-time combination using ψ_o as the dependent variable in our baseline regression in equation (3). Denote with μ and mc the log markup factor and marginal cost, respectively, and note that $\mu_{sbjto} \equiv p_{sbjto} - mc_{sbjto}$. The seller-product-time fixed effects, δ_{sjt} , flexibly control for differences in the (log of the) output-to-fabric elasticity $\ln(\theta_{sjt})$ —the only unobserved component of markups. A potential concern is that the fabric elasticity might vary across orders produced for buyers that use different sourcing practices. Evidence in Online Appendix E.1 assuages such concerns.

2. Relational Buyers Pay Higher Markups. Figure III replicates Figure II and reports the results from 522 regressions using μ as the dependent variable. All point estimates in the markup regressions are bounded in [0.009, 0.048], with our baseline specification—explored in Table VI—estimating a coefficient of 0.026. For ease of comparison, column (1) replicates the result

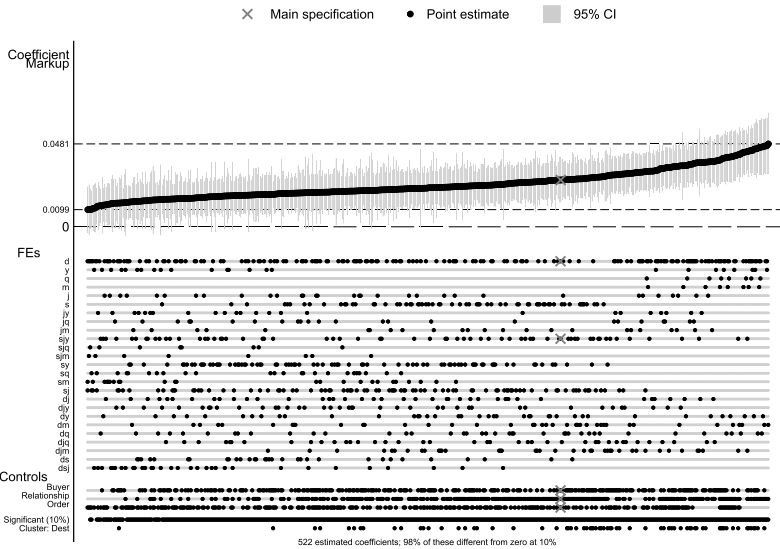


FIGURE III

Robustness of Markups Result to Alternative Fixed Effects and Controls

The graph presents 522 estimates of the coefficient on the buyer-specific relational metric in the regression of order-level markup factors following specifications with alternative controls and fixed effects. Our baseline, highlighted by gray crosses in the graph, includes seller-product-year fixed effects, destination fixed effects, and buyer-, relationship-, and order-level controls. These controls are as follows. Buyer: cohort of the buyer (year first observed in the data), size (log volume imported by the buyer throughout our data and across all woven products), age of the buyer at the time of the order (log number of months elapsed since first observed in the data), and a dummy indicating whether the buyer is a signatory of the accord as of 2019. Relationship: cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and the seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order: size of order (log volume) and log price of fabric of the order. The fixed effects are labeled following the notation of the paper: *s* for seller, *j* for product, *y* for year, *d* for destination, *m* for month, and *q* for quarter. The scatter marks in black present the point estimates and the bars in gray show 95% confidence intervals. The bottom panel reflects the set of fixed effects and controls used for the corresponding estimation. For example, a point estimate that has a black marking in *dy*, *sjq*, and *Buyer* corresponds to a price regression on the relational metric, with destination-year and seller-product-quarter fixed effects, as well as buyer-level controls. All possible combinations of fixed effects and controls give an intractably large set of estimates to report. The specifications presented here exclude (i) redundant combinations (for example, seller-product-quarter and year in the same specification), (ii) combinations with more than two sets of additive fixed effects and three multiplicative effects. Still, in the nonredundant specifications with up

FIGURE III

(Continued) to two sets of additive fixed effects, we are forced to reduce the state space, for clarity. We select specifications that we believe are interesting (feature relevant margins of variation) and where there is sufficient richness in the data. For example, we exclude specifications that have only s, j , or only j, t fixed effects, as well as those with sd_y , sd_q , or sd_m fixed effects, where the data becomes sparse. The results on excluded combinations of fixed effects (which are in line with what we present here) are available on request. We note that the number of observations may vary across specifications, as the change in the fixed effects structure gives rise to different singleton nests. The average specification runs on 17,453 orders. The largest sample runs on 21,577 orders and the smallest sample includes only 6,483 orders. This sample reduction is associated with the use of seller-product-month fixed effects (alongside different forms of destination fixed effects and controls). Standard errors are clustered at the level of the buyer in most specifications. In 75 cases, very granular fixed effects (namely, destination-month, destination-product-month, destination-quarter, destination-quarter-month) and buyer-level clustering give variance matrices that are close to singular. In these cases, the standard errors are clustered by destination (which is a conservative solution in general). This is indicated at the bottom of the figure. There are 11 out of the 522 point estimates (2.1% of all estimations) that are not significantly different from zero. The 11 specifications with coefficients not significantly different from zero (albeit positive), in general correspond to two types of specifications: (i) seller-product-month or seller-month fixed effects, alongside destination fixed effects; (ii) destination-seller-product fixed effects, alongside product-year or year fixed effects.

on prices reported in Table III, column (4). Columns (2) and (3) decompose the difference in prices into marginal costs and markup factors. Orders produced for relational buyers do not have higher marginal costs, and therefore the price difference reflects a higher markup. Only 11 of the 522 estimates are not significantly different from zero at 10% significance.¹⁸ The results are also robust to the use of different estimation samples and proxies for relational sourcing (see Online Appendix D). In sum, relational buyers pay higher prices and markups.

V. DISCUSSION AND FURTHER EVIDENCE

This section revisits our characterization of the sourcing strategy at the buyer—as opposed to the buyer-seller—level, complements the baseline analysis with an event study exploiting a shift in VF Corporation’s global sourcing strategy, discusses the reliability mechanism, alongside alternative channels, explores

18. As with prices, these 11 specifications generally include either seller-product-month or destination-seller-product fixed effects that absorb most of the cross-order variation in the data.

TABLE VI
BUYERS' SOURCING, MARKUPS, AND COSTS

	$P_{s,ijto}$ (1)	$mc_{s,ijto}$ (2)	$\mu_{s,ijto}$ (3)	$\mu_{s,ijto}$ (4)	$\mu_{s,ijto}$ (5)	$\mu_{s,ijto}$ (6)	$\mu_{s,ijto}$ (7)	$\mu_{s,ijto}$ (8)
<i>Relational_b</i>	0.021 ^{****} (0.008)	-0.005 (0.007)	0.026 ^{****} (0.007)	0.026 ^{****} (0.007)	0.026 ^{****} (0.007)	0.032 ^{****} (0.010)	0.039 ^{****} (0.010)	0.027 ^{****} (0.012)
FEs	<i>sjt, d</i> B,R,O	<i>sjt, d</i> B,R,O	<i>sjt, d</i> B,R,O	<i>sjt, d</i> B,R,O	<i>sjt, d</i> B,R,O	<i>sjfof, dq</i> B,R,O	<i>sjt, d</i> B,R,O	<i>sjt, d</i> B,R,O
Robustness	.	.	.	Season	Product	Quality	Small b	Small s
R^2	0.73	0.62	0.41	0.41	0.41	0.59	0.43	0.44
Obs.	15,647	15,647	15,647	15,647	15,647	10,103	10,780	7,479

Notes. Standard errors are in parentheses, clustered at the buyer level. The outcome in column (1) is the log price of an order between a seller and a buyer in a given product category, $P_{s,ijto}$. The outcome in column (2) is the estimated log marginal cost of the order, $mc_{s,ijto}$. In all other columns the outcome is the log markup factor, $\mu_{s,ijto}$. The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. All columns but (6) include seller-product-year and destination fixed effects. As such, column (1) simply reproduces the results of column (4) in Table III and columns (2) and (3) use the same specification to study marginal costs and markups. All remaining columns report the results of different robustness exercises, for brevity, shown only on $\mu_{s,ijto}$. All columns in the table include buyer- (B), relationship- (R), and order-level (O) covariates, as follows. Buyer controls (B): fixed effect for the main destination of the buyer, cohort of the buyer (year first observed in the data), size (log volume imported by the buyer throughout our data and across all woven products), age of the buyer at the time of the order (log number of months elapsed since first observed in the data), and a dummy indicating whether the buyer is a signatory of the accord as of 2019. Relationship controls (R): Cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order controls (O): size of order (log volume) and log price of the order. Columns (4)-(6) control for seasonality patterns, product specialization, and the physical quality of the order measured as follows. Season: Herfindahl index describing how concentrated the trade in a relationship is in one season, the share of the largest season in the seller-buyer-year combination, and an indicator that picks up orders in such season. Product: defined analogously to controls described for seasonality. Quality: measure of complexity of the garment order (the log of the number of fabric types used for producing the order, elsewhere labeled as $Complex_{s,ijto}$) and a fixed effect for the seller-product-year-fabric-type-origin (*sjfof*), exploiting the type and origin of fabric to define the variety of the order; a category is as specific as Nice Ltd.'s men's shirts made of wov. fab, containing > 85% cotton, printed, plain weave, weighing more than 100 g/m² but not more than 200 g/m² sourced from India in 2010. Column (7) trims the sample to drop all the orders of the largest buyer of the seller-year-product. Column (8), analogously, drops all orders of the largest seller of the buyer in the product-year combination. * $p < .10$, ** $p < .05$, *** $p < .01$.

the quantitative implications of our estimates, and, finally, discusses policy implications.

V.A. *Relational Buyers versus Relational Relationships*

A distinctive feature of our analysis is that we consider the sourcing strategy to be a buyer-level characteristic, as opposed to a relationship feature. We subject this approach to further empirical scrutiny. We start by quantifying the role of buyer- vis-à-vis relationship-specific effects in explaining variation in prices and markups and then revisit our baseline specification introducing a measure of relationality at the buyer-seller level.

[Section III](#) argued that buyer-level factors (capabilities) are key drivers of observed sourcing patterns. This does not preclude a buyer's sourcing behavior from varying across different suppliers. For example, a relational buyer might source relationally from a core set of suppliers but also source spot from a fringe of suppliers that are used at times of especially high demand. As already noted, this would imply that our approach underestimates the influence of relational sourcing on prices and markups.

We borrow from the employer-employee literature (see [Card et al. 2012](#)) to assess the relative importance of buyer and buyer-seller effects in explaining order-level prices and markups. We compare the explanatory power of a model that includes buyer fixed effects with one that includes buyer-seller fixed effects, conditional on the baseline fixed effects δ_{sjt} . [Online Appendix Table C.4](#) shows that between 96.5% (89.7%) and 96.3% (90.0%) of the fit in a model of prices (markups) with bilateral buyer-seller fixed effects can be explained by a model with buyer effects only. In both cases, we cannot reject the null hypothesis that the model with buyer effects explains as much variation as the one with relationship effects.

To investigate buyer-seller sourcing in a manner consistent with our measure of relational sourcing at the buyer level, we construct an analogous metric of relationality at the buyer-seller level. [Taylor and Wiggins's \(1997\)](#) model implies that when sourced volumes are held constant, relational trade is associated with more frequent shipments. This suggests that we proxy the relational nature of buyer-seller pairs using traded volumes per shipment. Formally,

$$(7) \quad \text{Relational}_{sb} = -1 \times \sum_{jt \in sb} \left[\frac{q_{sbjt}}{q_{sb}} \times \frac{1}{\#Shipments_{sbjt}} \right].$$

This measure has three appealing features. First, it is consistent with our approach to measuring sourcing practices in the rest of the article. Second, it is empirically correlated with measures of relational sourcing at the buyer-seller level (such as relationship duration; see [Online Appendix Table C.5](#)). Finally, it can be aggregated over relationships to give a buyer-level measure of sourcing comparable to our baseline, as

$$(8) \quad \widetilde{Relational}_b = \sum_{s \in b} \left[\frac{q_{sb}}{q_b} \times Relational_{sb} \right].$$

This feature allows us to write the relationship-level metric as $\widetilde{Relational}_{sb} = -1 \times (|Relational_{sb}| - |\widetilde{Relational}_b|)$ and decompose the sourcing strategy into a relationship-specific component and a buyer-level one.

[Online Appendix Table C.6](#) reports the results from our baseline specification with seller-product-year (δ_{sjt}) fixed effects and buyer- and order-level controls. We omit the controls at the buyer-seller pair level included in the baseline specification to focus on bilateral relationality. To ease comparison, column (1) reports the baseline relational sourcing metric, $Relational_b$, in levels.¹⁹ Column (2) reports the buyer's relational metric, $\widetilde{Relational}_b$, in excluded products. This metric benchmarks the estimates once we introduce buyer-seller-specific metrics. The results confirm both positive correlations. Column (3) uses the relationship-specific measure, $Relational_{sb}$. There is a positive correlation between the bilateral metric and both prices and markups. Of course, endogeneity concerns prevent us from interpreting these correlations as causal: the bilateral sourcing metric could be correlated with unobserved aspects that are also correlated with our outcomes of interests—a further reason to favor our buyer-level approach.

Column (4) provides our main test. It includes both the buyer-level metric and the bilateral metric, centered on the buyer's mean ($\widetilde{Relational}_b$). The buyer-level metric has a positive coefficient in the prices and markups regressions that is, if anything, larger than in column (2). This is expected: as noted, omitting

19. For ease of interpretation, everywhere in the article we present results standardizing the relational sourcing metric. In [Online Appendix Table C.6](#), column (1), the metric is, instead, included in levels. This is for consistency with the rest of the table. To present the exact decomposition of column (4), $\widetilde{Relational}_b$ and $Relational_{sb}$ need to be in levels.

the relationship-level metrics introduces measurement error and biases our estimates toward zero.

The bilateral proxy for relationality is positively correlated with markups but not with prices. This suggests that sellers incur lower marginal costs to produce for buyers with whom they trade relationally. This result, however, is difficult to interpret. On the one hand, suppliers might be more efficient—either through learning by doing or from transfers of capabilities from the buyer—when producing orders for more stable partners. On the other hand, orders for which the supplier has lower costs are more likely to result in more stable matches with buyers. The difficulty in interpreting the results with proxies for relationality at the buyer-seller level provides further justification for our approach that considers the buyer-level proxies for relational sourcing computed in excluded products. Removing these concerns facilitates interpretation.

V.B. An Event Study

Our evidence is identified out of cross-sectional variation in sourcing strategies across buyers. We leverage an event to probe whether the patterns are robust to within-buyer changes in sourcing strategies over time. We zoom in on the Bangladeshi supplier base of VF Corporation, the large apparel buyer mentioned in [Section III](#). In 2004, VF began a shift in its global sourcing from a spot strategy to a relational approach (see [Pisano and Adams 2009](#) for details). The approach was called the third way “because it represented an alternative to both in-house manufacturing and traditional sourcing.” VF used to source internally from its own plants and externally from suppliers through short-term contracts. The transition was slow: in a global supply network of over 1,000 suppliers, by 2009, there were only 5 third-way suppliers (none among VF’s Bangladeshi suppliers in our product categories). The new approach ramped up globally in 2010.

The data confirm the profound supply-chain restructuring brought about by the transition to the third way. The transition induced a significant degree of churning—with terminations of many suppliers and fewer new ones added after the transition. At the same time, VF expanded the volumes sourced from suppliers: the number of orders per supplier increased from around 160 in 2005 to close to 400 in 2012. Before the transition, VF accounted for 27%–28% of the volumes exported by its suppliers in 2007 and

2008 on average. That share jumped to 44%–47% in 2010 and 2011. This is consistent with VF's (continuing) suppliers dropping buyers that they had previously supplied. On average, VF's continuing suppliers dropped 2.6 more buyers and begun supplying 2.1 fewer new buyers after VF's transition than in the preperiod. In line with our metric for relational sourcing, VF consolidated its supplier base in Bangladesh. The transition, however, also implied a reorganization of the suppliers' set of buyers.

We compare the evolution of the markups earned in orders sold to VF relative to that of other buyers within a difference-in-differences framework,

$$(9) \quad \mu_{sbjo} = \delta_{sjt} + \delta_b + \sum_{r=2005}^{2012} \beta_r VF_b \times I_{t(o)=r} + \gamma Z_{sbjo} + \varepsilon_{sbjo},$$

where VF_b is an indicator that takes value 1 if the buyer in the order is VF and 0 otherwise while $I_{t(o)=r}$ is a dummy for year r ($r = 2009$ is the excluded year). We include seller-product-year fixed effects, δ_{sjt} , as in our baseline specification and thus compare changes in the differences in order-level markups between VF and other buyers. The inclusion of buyer fixed effects, δ_b , accounts for unobservable, time-invariant buyer characteristics.

The churning of trade partners resulting from the transition implies that a simple before-and-after comparison of orders is marred by selection effects. The most likely form of selection is that in the post period, continuing suppliers likely dismissed (and avoided forming new relationships with) less profitable buyers, that is, those from which they earned lower markups. This implies that a difference-in-differences coefficient estimated on the entire sample would be biased downward. We restrict the sample to include only the main buyers of the supplier—defined as those accounting for at least 20% of the sellers' non-VF exports in each year—and include relationship cohort fixed effects because these buyers change over time.

The difference-in-differences analysis confirms the cross-sectional evidence in Section IV. Figure IV reveals no differential trends in markups in orders sold to VF and those on orders sold to other buyers before VF's transition. After the transition, orders produced for VF start earning significantly higher markups than comparable orders produced for other buyers. The pattern persists until the end of our sample period. Online Appendix

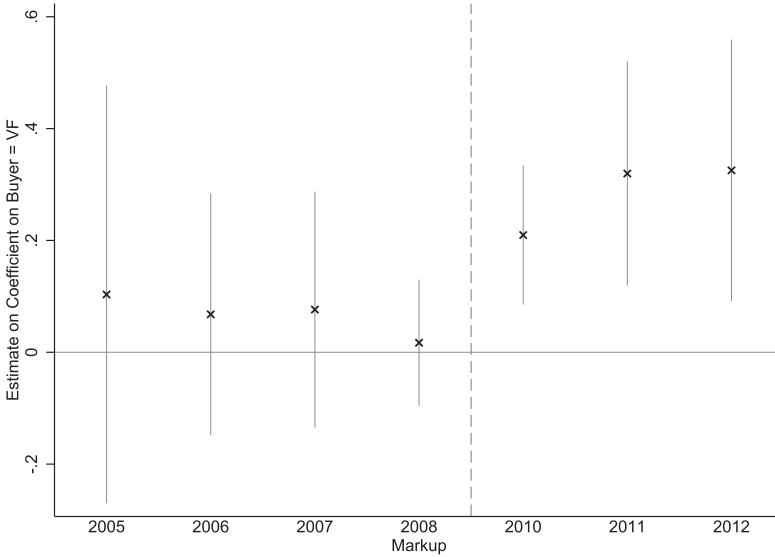


FIGURE IV

A Change in Sourcing Strategy

The figure plots estimated year-specific coefficients, β_r , on a dummy that takes value 1 when the buyer is VF, following specification (9). The excluded category corresponds to $VF \times I_{r=2009}$. We focus on export orders manufactured by sellers that traded at some point with VF. Among those, we consider the orders placed by VF or by another main buyer of the seller. A main buyer is either the largest buyer (in volumes) of the supplier over the entirety of the sample period, before 2010 or after 2010. The regression includes seller-product-year fixed effects. This controls already for the first difference (time) in order-level markups. The specification also includes buyer fixed effects, which absorb all buyer-level controls included elsewhere (see Table III) and the first difference in markups, comparing buyers with VF. Finally, we include relationship- and order-level covariates, defined as follows. Relationship: cohort of the relationship (year first observed in the data), size (log volume traded by the buyer and seller throughout our data and across all woven products), age of the relationship at the time of the order (log number of months elapsed since first observed in the data), share of the seller in all of the buyer's trade, and share of the buyer in all of the seller's trade. Order: size of order (log volume) and log price of fabric of the order. The vertical bars correspond to 95% confidence intervals, when standard errors are clustered at the buyer-year level.

Table C.7 shows that the pattern in Figure IV is driven by an increase in prices following VF's change in its approach to sourcing, rather than changes in marginal costs. Furthermore, alternative samples that deal with selection restricting attention to continuing buyers and to surviving suppliers yield similar estimates.

Including all buyers, however, leads to lower estimates that are statistically not different from zero, consistent with the selection effect discussed above.

V.C. Mechanisms

Relational buyers pay higher markups. Supported by motivating evidence presented in [Online Appendix C.3](#), our model rationalizes this fact through a particular mechanism: the buyer's (noncontractible) need to ensure reliable deliveries. Although we believe this mechanism to be relevant in our context, we do not contend that it is the only mechanism that might be at play. We discuss in greater detail the reliability mechanism before turning to other potential alternative explanations for our main finding.

1. *Reliability.* The model—akin to a pure moral hazard model—conceptualizes reliability as a costly action that is difficult to contract on. This is motivated by suggestive evidence in [Online Appendix C.3](#) indicating that disruptions caused by hartals lead to shorter delays (conditional on order size) for orders produced for relational buyers.²⁰ Indeed, as shown in [Online Appendix Table C.8](#), a shorter order throughput time is associated with higher markups and relational buyers, suggesting that on-time deliveries are an important aspect of relational sourcing.²¹

An interesting question is whether reliability could instead be considered a (possibly hidden) type, whereby only some suppliers are able to be reliable. Our empirical analysis includes seller(-product-time) fixed effects. These fixed effects thus control for the seller's type—whether observed or not. A model in which reliability is purely a type is thus difficult to reconcile with the different prices and markups charged by the same seller to different buyers. An alternative formulation in which reliability is the

20. Hartals—a form of mass protest that often involves factory and workplace shutdowns—are common in Bangladesh (see [Ashraf et al. 2015](#)).

21. In the presence of demand shocks, flexibility—meaning the supplier's ability to accelerate production or allocate additional production capacity at short notice—can also be important. In such cases, we also expect the order lead time (the time elapsed between the incoming shipment of fabric and the outgoing shipment of garments) (i) to correlate (negatively) with relational sourcing and (ii) to correlate (positively) with higher markups, and (iii) sourcing to still display a positive correlation with markups, conditional on lead times. [Online Appendix Table C.8](#) finds support for these three patterns and thus supports flexibility as an additional mechanism.

result of hidden types and actions is also possible. In such a reputation model, buyers' beliefs matter for how the seller responds to shocks. For example, [Macchiavello and Morjaria \(2015\)](#) develop and test such a model. In their model, uncertainty over the seller's type (whether she is reliable) and the seller's actions (whether she exerts effort to prioritize the buyer) influence buyers' beliefs about the value of future interactions with the seller. A common feature of such models is that uncertainty over types is needed to preserve reputational incentives. They find an inverted-U pattern in sellers' responses to an unanticipated supply shock: sellers prioritize relationships that are neither too young nor too old. Young relationships are not valuable enough; in old relationships, there is nothing left to prove. The findings in [Macchiavello and Morjaria \(2015\)](#) suggest that during hartals, relational buyers may be prioritized but may also give slack to the exporter depending on circumstances that are unobservable to us. Furthermore, unlike the shock in [Macchiavello and Morjaria \(2015\)](#) (which is large, unanticipated, and observable), the hartals discussed in [Online Appendix C.3](#) are relatively small, frequent, and measured with significant error. These considerations limit our ability to replicate their analysis to untangle a pure moral hazard model from a model with both moral hazard and hidden types.

To close, we do not contend that reliability is the only mechanism that generates a rationale for relational contracting in this industry—nor that reliability should be conceptualized in a pure moral hazard framework with no hidden types. Reliability appears to be an empirically plausible mechanism that, once formalized, is consistent with several facts reported here. We turn to discussing alternative mechanisms that are consistent with some—but not all—the facts in the paper.

2. *Demand Assurance.* Not all models with relational contracts imply that relational buyers pay higher prices than spot buyers. With demand uncertainty (see, e.g., [Carlton 1978](#); [Dana 1998](#)), for instance, suppliers face uncertain capacity utilization. Relational buyers may promise reliable capacity utilization and offer relational rents to sellers in the form of lower costs. Indeed, in industries where demand uncertainty is important, prices tend to be lower in long-term relationships (see [Pirrong 1993](#); [Macchiavello and Miquel-Florensa 2018](#)). Furthermore, in such industries, buyers might adopt a dual sourcing strategy in which they keep a few “reliable” suppliers to serve the stable part

of demand and then use a fringe of spot suppliers to cover unforeseen spikes. Based on our understanding of the sector and interviews in the field, demand assurance is likely also an important aspect of relationships in this context. However, our results suggest that this is quantitatively outweighed by alternative mechanisms—such as the reliability mechanism in our model—that imply higher prices. Our estimates thus understate the value of relational buyers to exporters if demand assurance is at play.²²

3. *Costly, Seller-Specific Capabilities.* Sellers might need to undertake, and be compensated for, specific investments to supply relational buyers. To the extent that our data allow it, we do not find evidence for such differences. However, we cannot rule out other, unobservable costs, fixed from the perspective of an export order, that are necessary to build capabilities to supply relational buyers. If the ability to supply relational buyers was a seller capability, however, the higher markups paid by relational buyers would induce sellers that have acquired such capabilities to specialize in supplying relational buyers. In contrast, the evidence in [Online Appendix C.2](#) reveals that sellers supply a mix of relational and spot buyers—a pattern that is naturally explained by the mechanism in our model.

4. *Product Quality.* Differences in the physical quality of products are unlikely to account for the observed differences in markups across buyers. The—rather limited—existing empirical evidence suggests that higher-quality products are associated with higher markups (see [Atkin et al. 2015](#); [De Roux et al. 2020](#)). However, buyers with different sourcing strategies do not appear to differ in the quality of the garments that they source. [Table V](#) shows no differences in the SMV—a direct measure of a garment's technical complexity—between orders produced for a relational and spot buyers. Although this is suggestive, other dimensions of quality are unobserved. Two pieces of evidence assuage such concerns. First, higher-quality garments are produced using higher-quality inputs (see [Kugler and Verhoogen 2012](#))—they are made with better fabric and sewed by

22. Our model could be extended to consider flexibility. At full capacity, flexibility requires an exporter to divert resources from other orders: flexibility toward one buyer compromises reliability toward another one. An exporter that only supplies relational buyers thus cannot simultaneously guarantee flexibility and reliability to all of them. This is consistent with the evidence in [Online Appendix C.2](#).

more skilled operators. We find no differences in the price and type of either fabric or labor across orders produced for buyers with different sourcing strategies. Furthermore, [Table VI](#) reports the results from additional specifications that further control for proxies for physical quality, including specialization, seasonality, proxies for product complexity, and dummies for the type and origin of the most used fabric in the order. The results are robust to including these different proxies for product quality.

5. Bargaining Power. Differences in bargaining power are unlikely to explain our results. Before we discuss the evidence for this assertion, we introduce an important distinction between *ex ante* and *ex post* bargaining power. The former refers to the relative strength of parties as they negotiate their initial agreement. Note that in our model, relational buyers do have *ex ante* bargaining power and indeed negotiate a relational price that is the most favorable price that still satisfies the supplier's incentive compatibility constraints. Even so, they still pay higher prices and markups than spot buyers. To rationalize the evidence without introducing incentive compatibility constraints, an alternative model would thus need to assume that relational buyers have lower *ex ante* bargaining power. When we control for common proxies for bargaining power, however, we find that our results remain robust. All specifications in [Table VI](#) control for the buyer's size in the market, the age of the buyer-seller relationship and the traded volumes between parties. In addition, they control for the share of the buyer (seller) in the seller's (buyer's) trade. Furthermore, column (7) (respectively, column (8)) discards orders sold to (bought from) the main buyer (supplier) and finds that the results remain largely unchanged in the sample of orders in secondary relationships. These patterns suggest that the higher markups paid by relational buyers are unlikely to solely reflect a weaker *ex ante* bargaining position of these buyers vis-à-vis their suppliers.

Ex post bargaining power refers instead to parties' relative negotiating position once the relationship has been formed. By design, relational buyers choose to have lower *ex post* bargaining power vis-à-vis their suppliers: according to [Sako and Helper \(1998\)](#) "a deliberate strategy of locking oneself into a relationship, thus raising switching costs, may facilitate the creation and maintenance of trust." In other words, lower *ex post* bargaining power should not be considered an alternative explanation to be ruled out—it is a quintessential feature of relational sourcing systems.

6. *Search and Switching Costs.* As in the previous discussion, it is useful to distinguish between search and switching costs. Search costs are relevant at the ex ante stage, that is, when a buyer is searching for and negotiating with adequate suppliers. Differences in search costs are unlikely to explain our evidence. Buyers may differ in their costs of searching for a supplier. Certain buyers may be more patient (or have lower search costs) and thus be “pickier”: they search longer to find a suitable supplier, and when they find one, they establish long-lasting relationships, thus mimicking relational behavior. In standard models, however, more patient buyers have stronger bargaining power and negotiate a lower price—we find instead that relational buyers with more stable relationships pay higher prices. The prediction, however, could be reversed if “picky” buyers attain higher-value matches. These buyers would form lasting relationships that generate more surplus—potentially shared with the supplier in the form of higher prices. The evidence in [Section V.A](#), however, suggests that match-specific components are unlikely to quantitatively account for our patterns and that controlling for proxies at the buyer-seller pair level strengthens our results.²³

Switching costs, instead, refer to the cost of finding alternative suppliers ex post, that is, once the relationship is established. As with bargaining power, it is a deliberate strategy to introduce higher switching costs to support the relationship. Switching costs are an attribute of relational sourcing systems rather than an unobserved confounder to be ruled out.

7. *Pricing to Market and Rent Sharing.* In our context, higher markups could also stem from seller price discrimination across markets. By including destination fixed effects, [Table VI](#) accounts for average differences across destinations. [Online Appendix Table D.6](#) further explores related confounders. For ease of comparison, column (1) reproduces [Table VI](#), column (3). Column (2) includes destination-product-year fixed effects, and column (3) includes seller-destination fixed effects. Column (4) includes country-product-year fixed effects, where the

23. In the same context as this article, [Cajal-Grossi \(2022\)](#) develops and tests a model in which buyers sensitive to the risk of reputational losses due to supplier misconduct may have both higher search costs and higher values from being matched with suppliers of a higher type. She finds that these buyers experiment with different suppliers, but do so to a lesser extent when reputational risks are high.

country corresponds to where the order is shipped (which could differ from the main destination of the buyer). These fixed effects control for differences in markups following sellers' pricing-to-market behavior and from heterogeneous consumer tastes across countries, products, and time. These mechanisms do not explain the markup differentials across buyers, which remain robust throughout the exercise.

Relational buyers might also have greater market power downstream and pass through some of their profits to upstream suppliers. In this case, the higher markups paid by relational buyers might reflect profit sharing. To explore this possibility, we match the buyers in our sample with data from Euromonitor that capture the sales of the buyer in the destination market (Euromonitor International 2015). We find 53 buyers for which the downstream market share is observed for every year in our sample. Online Appendix Table D.6, columns (5) and (6) show that our results are robust to controlling for the buyer's sales in the downstream market in this restricted sample.

V.D. How Valuable Are Relational Buyers?

We explore the quantitative implications of our estimates—and their limitations—through a back-of-the-envelope calculation. The estimated correlation between markups and relational sourcing is quantitatively sizable. Our baseline specification reveals that a one standard deviation increase in the buyer's measure of relationality is associated with a 0.026 increase in the (log) markup factor. To interpret this magnitude, consider the average markup factor (1.44) and marginal cost (\$10.35) estimated in Online Appendix E.5. The estimated coefficient implies that a shift in sourcing strategy from a spot approach like Kik's to relational sourcing like H&M's is associated with an additional \$0.32 per kg of garments, equivalent to a 9.8% increase over the average markup value (\$3.32). Put differently, a change in sourcing strategy from the average buyer for The Gap Inc. (a shift of about one standard deviation) yields an increase in markups of approximately 11%. Comparing the 25th (10th) to 75th (90th) percentiles in the distribution of buyers' relational metric gives a 15.3% (30.6%) increase over the average markup value.²⁴

24. Relational contracts are plausibly more time-consuming for contract managers/procurement managers, as they are expected to offer a more personalized service to relational buyers. Although these administrative costs are not

To our knowledge, there are no other estimates of markups earned from specific buyers in the literature—it is thus difficult to benchmark our results. [Macchiavello and Morjaria \(2015\)](#) and [Blouin and Macchiavello \(2019\)](#) estimate the net present value of a relationship through a revealed preference approach. From a seller's point of view, the relationship with a buyer is worth at least as much as the seller's "temptations to deviate"—which is directly observed in those papers. Both studies find that the relationships with buyers are highly valuable. For example, [Macchiavello and Morjaria \(2015\)](#) find that to the typical Kenyan rose dealer, the average relationship is worth 161% of their weekly turnover. Assuming a profit margin of 10%, this translates into a net present value of $\frac{161\%}{10\% \times 52} \approx 30\%$ of the yearly profits from that relationship. To benchmark these estimates to ours, we need to discount the estimated markup increase. Conditional on the buyer and the seller trading for at least one year, the average duration of relationships with relational buyers is $D = 3.71$ years. Assuming an annual interest rate of 15% gives an effective discount factor $\delta = \frac{1}{1+0.15} \times (1 - \frac{1}{D}) \approx 0.635$. This yields a net present value in the range of $\frac{9.8\%}{1-0.635} \approx 26.8\%$ to $\frac{11\%}{1-0.635} = 30.15\%$.

The reduced-form results in our article, however, likely underestimate the value of relational buyers. First, our proxy for the buyer's relational strategy is conservative and suffers from attenuation bias. Using alternative definitions ([Online Appendix Table D.3](#)) often yields higher estimates; controlling for a bilateral proxy for relationality increases our buyer-level estimate by one-tenth ([Online Appendix Table C.6](#)). Second, we do not take into account two potentially important sources of value from supplying relational buyers: higher volumes and demand assurance. Relational buyers source larger volumes than spot buyers from their suppliers—a typical supplier thus earns significantly higher variable profits when supplying relational buyers relative to spot buyers. Relational buyers are also likely to provide more stable demand, thus allowing better capacity planning and utilization

variable at the order level, they could potentially erode the extra profits that suppliers earn from relational buyers. The average annual gross salary of managing directors and chief executives in manufacturing in Bangladesh's Labor Force Survey of 2017 is \$4,755 (34,133 BDT per month for 12 months). The average size of orders from relational buyers in our analysis sample is over 64,500 kg. The extra \$0.32 markup thus amounts to almost \$20,000 in the average order, almost four times the annual gross pay of a managing director in manufacturing.

and lower costs. On the other hand, in our model, suppliers incur a loss when delivering to relational buyers while hit by the shock. The within seller-time comparison of our baseline thus might overestimate the difference in average markups between relational and spot buyers. Given this limitation, we see the development of structural models to estimate the value of relationships as an important avenue for future research.

V.E. Policy Implications

Because of contracting problems, the spot market is not efficient: when suppliers are hit by shocks, they sell to relational buyers but not to spot buyers, despite the fact that their cost is lower than buyers' valuation. Some capacity thus remains inefficiently underutilized, and overall market efficiency is increasing in the share of relational buyers. In deciding whether to implement a relational strategy, a buyer takes into account only his private returns, not the rents that his investment generates for other market participants. As a result, there is insufficient entry of relational buyers in equilibrium. In such circumstances, a planner may want to intervene and subsidize the entry cost of relational buyers.

In [Online Appendix A.4](#), we formally show that provided that the equilibrium share of relational buyers under no subsidy is sufficiently small, a subsidy is justified. This is the case for a planner that cares only about sellers' profits and the cost of public funds and—a fortiori—for a planner that also values buyers' profits. Our model has assumed away ex ante lump-sum transfers between sellers and buyers. This implies that sellers earn rents in equilibrium. While the assumption provides a rationale for policy intervention when the planner cares only about exporters' surplus, this assumption is not needed to rationalize a subsidy to the entry of relational buyers under more general planner preferences. It can be shown that even if buyers could capture all the rents from relational trade by charging suppliers an ex ante lump-sum fee, a planner that equally values exporters' and buyers' surplus would subsidize entry of relational buyers if the equilibrium share of relational buyers and cost of public funds are sufficiently low. The reason is that spot buyers are better off when there are more relational buyers in the market, and thus a buyer investing in relational capabilities exerts a positive externality on spot buyers.

These observations provide a practical justification for our approach of considering the sourcing strategy a buyer-level—as opposed to a buyer-seller pair-level—attribute. Even though organizational capabilities are important to build relational arrangements with suppliers, a particular relational contract between a buyer and one of their suppliers will still be rooted in a mutual understanding of the specific circumstances of that individual pair (Gibbons and Henderson 2012; Baker, Gibbons, and Murphy 2002). It is thus difficult for policy makers—for example, export promotion agencies in developing economies—to directly improve specific relationships between exporters and buyers. On the other hand, if certain buyers possess organizational capabilities that make them valuable relational partners, an actionable margin for policy opens up. It might be possible to attract such buyers by, for example, subsidizing visits to the country or understanding the specific factors that favor their entry.

VI. CONCLUSION

This article studied how order-level prices, variable costs, and suppliers' markups vary with the sourcing strategies of international buyers in the Bangladeshi garment sector. We contributed novel evidence that sourcing strategies are largely driven by buyer-level capabilities, leading us to propose a model in which *ex ante* identical buyers endogenously choose different sourcing strategies in equilibrium. The main prediction of the model is that to induce suppliers' reliable deliveries under bad contingencies, relational buyers pay higher markups than spot buyers for otherwise identical orders from the same supplier. We tested and found empirical support for this prediction by leveraging original data that allow the direct measurement of utilization and prices of the main variable inputs (fabric and labor) used for producing orders for different buyers.

Interpreted through the lens of the model, the empirical results have policy implications for export promotion agencies, particularly in developing economies. The results provide quantitative support to the view that international buyers' sourcing strategies are a potentially important dimension of upgrading for exporting firms in developing economies (see Egan and Mody 1992; Gereffi 1999). Similarly to models that distinguish between “good jobs”—in which workers earn rents—versus “bad jobs” (see Acemoglu 2001), the *laissez-faire* equilibrium generates too few

relational buyers relative to the social optimum. This gives rise to the possibility that export promotion agencies might want to target programs to assist exporters in establishing relationships with relational buyers.

This study provides a first step toward a more systematic understanding of the implications of sourcing practices for economic performance and international trade. Much research remains to be done, however, and we hope that our results will spur further work on this important topic. Two areas appear to be particularly pressing. First, while we have focused on suppliers' markups, buyers' sourcing strategies likely affect other important aspects of supply chains' performance, such as their resilience to and transmission of shocks and transfers of capabilities to suppliers—especially in developing economies. Second, we have documented, rationalized, and then taken as given substantial unexplained variation in sourcing strategies across firms in a narrowly defined sector. The discussion of the policy implications of our results, however, suggests that exploring drivers of buyers' choices of sourcing strategy should be a priority in future research.

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SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

DATA AVAILABILITY

The code underlying this article is available in the Harvard Dataverse, <https://doi.org/10.7910/DVN/CHMSZG> (Cajal-Grossi, Macchiavello, and Noguera 2023).

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