Buyers' Sourcing Strategies and Suppliers' Markups in Bangladeshi Garments*

Julia Cajal-Grossi† Rocco Macchiavello‡ Guillermo Noguera§

December 6, 2020

Abstract

Do suppliers' margins in global value chains depend on buyers' approach to sourcing? We distinguish between international buyers adopting *relational* versus *spot* sourcing strategies in the Bangladeshi garment sector. Our data allow us to match inputs used by exporters to produce specific orders for different buyers. Within suppliers, we show that orders produced for relational buyers earn higher prices than comparable orders produced for spot buyers. These orders however do not differ in the type, prices, or efficiency of variable inputs. We interpret these patterns through the lens of a model of garment production that allows for capacity constraints, order-varying input prices, and a technology that is specific to the exporter, product, and time combination. The model yields a sufficient statistic for differences in markups across orders and, thus, across buyers. Within exporter-product-time triplets, we find that relational buyers pay approximately 11% higher markups relative to spot buyers for comparable export orders. Additional evidence suggests that these higher markups reflect, at least in part, incentives paid to suppliers to undertake non-contractible actions.

Keywords: Sourcing Strategies, Global Buyers, Buyer-Driven Value Chains, Markups.
JEL Codes: L11, L14, D23, F63

*We are particularly indebted to Chris Woodruff with whom this project was started and to Penny Goldberg and Nina Pavcnik for many suggestions. We thank David Atkin, Johannes Boehm, Laura Boudreau, Amit Khandelwal, Kalina Manova, Tristan Reed, Tim Schimdt-Einselhor, John Sutton, Catherine Thomas and Eric Verhoogen for helpful discussions. We also thank seminar participants at Aarhus, Barnard, Columbia-NYU, Düsseldorf, London School of Economics, Mannheim, Munich, Oslo, Oxford, Sciences Po, Warwick, World Bank, Yale, and conference participants at the 2019 ASSA Meeting, Bank of Italy, Kellogg-Northwestern Conference on Markets and Organizations in Emerging Economies, Workshop on International Economic Networks (WIEN), NYU Trade Jamboree, FREIT-EITI Japan, PEDL Inaugural Conference, CEPR/WB Conference on Global Values Chains, Trade and Development, Workshop on Firms, Markets and Development (McGill, IGC, Ortygia), GEP Imports and Global Value Chains conference, 2018 SAET conference, and CAGE Research day for helpful discussions and comments. We gratefully acknowledge financial support from the Centre for Competitive Advantage in the Global Economy (CAGE).

†Graduate Institute, Geneva. E-mail: julia.cajal@graduateinstitute.ch.
‡London School of Economics and CEPR. E-mail: r.macchiavello@lse.ac.uk.
§Yale University and CAGE. E-mail: guillermo.noguera@yale.edu.

1 Introduction

How a firm approaches sourcing is a key strategic decision (Baker et al., 2002; Gibbons and Henderson, 2012). Sourcing strategies are particularly critical in volatile contexts afflicted by lack of contract enforcement, such as international sourcing from emerging markets (Antràs, 2016; Atkin and Khandelwal, 2020; World Bank, 2020). Buyers may find it difficult to secure quality products (Banerjee and Duflo, 2000), obtain reliable deliveries (Macchiavello and Morjaria, 2015), or ensure social and environmental compliance (Amengual and Distelhorst, 2019; Boudreau, 2020).

There are two polar approaches to sourcing.[1] At one extreme, buyers may pursue a *spot* sourcing strategy in which short-term orders are allocated to the lowest bidders and the buyer bears any costs of non-compliance. At the other extreme, buyers may adopt a *relational* sourcing strategy in which orders are allocated to a few suppliers with whom the buyer develops long-term relationships.[2] Theoretical models (Taylor and Wiggins, 1997; Baker et al., 2002; Board, 2011) suggest that a buyer's approach to sourcing can have profound implications for its suppliers' performance. Under spot sourcing, suppliers' margins are squeezed by intense competition; under relational sourcing, higher markups are used to incentivize suppliers to deliver on aspects that are difficult to contract upon.[3] The buyer's approach to sourcing can thus be an important dimension of upgrading. As an implication, export promotion agencies, especially in developing countries, may benefit from promoting trade with buyers that source relationally.[4]

Despite its potential policy relevance, the relationship between suppliers' margins and buyers' approach to sourcing has not been examined empirically. The main challenge is that the exercise requires one to compare the costs that a given supplier incurs when producing the same product for buyers adopting different sourcing strategies. These costs are difficult to estimate in standard datasets since the amounts and prices of the variable inputs used to produce for a particular buyer are typically not observed.[5]

[1] A large body of work has documented differences in sourcing strategies across firms within narrowly defined industries. See, e.g., Richardson (1993), Nishiguchi (1994), Helper and Saki (1997) and Helper and Henderson (2014) for automotive; De Toni and Nassimbeni (2000) for electronics and machinery; Masten (1984) for aerospace and McMillan (1994) for textile and machine tools. These differences parallel those in the adoption of lean management practices (Bloom and Van Reenen, 2007; Bloom and Van Reenen, 2010). Unlike the management practices agenda, however, the literature on sourcing strategies is mostly qualitative and has not systematically explored how sourcing strategies correlate with firm performance.

[2] We refer to buyers as spot or relational when they adopt the corresponding sourcing strategy.

[3] Many forms of relational incentives result in higher markups for the supplier either directly through higher prices or indirectly through lower costs (e.g., through better capacity utilization).

[4] The rationale for policy interventions would parallel arguments in the "good jobs" versus "bad jobs" labor literature. For example, in Acemoglu (2001) the laissez-faire equilibrium generates too many low-wage, bad jobs relative to the social optimum.

[5] A comparison *across* suppliers producing for buyers with different sourcing strategies would be marred

This paper provides direct evidence on the relationship between buyers' sourcing strategies and their suppliers' markups. We compare spot versus relational sourcing by international buyers trading with Bangladeshi garment exporters. Besides the intrinsic interest of the context, special features of the data allow us to make progress on the empirical front.[6] In particular, we are able to match the type, prices and amounts of the main variable inputs (fabric and labor employed on sewing lines) used to produce specific orders for buyers that adopt different sourcing strategies.

We find that orders produced for relational buyers earn higher prices but are not different in the utilization and prices of inputs or in their technology. We interpret these patterns through the lens of a model in which garment manufacturers produce export orders for different buyers. Our main finding is that Bangladeshi exporters earn relatively higher markups on orders produced for relational buyers compared to spot buyers. This pattern is confirmed by a difference-in-differences analysis of the switch of a large international buyer from spot to relational sourcing. Considering several mechanisms that could account for these findings, additional evidence suggests that the higher markups paid by relational buyers incentivize, at least in part, suppliers' behaviors that are difficult to contract upon. In addition to contributing to our understanding of global value chains, our results indicate that foreign buyers' sourcing strategy may be an important dimension of exporters' upgrading, especially in developing countries.

Section 2 describes the garment production process and the features of our data that allow us to match variable inputs to orders and, in turn, to buyers. Woven garments are manufactured order by order through a common sequence of steps, organized in two stages: an inspection and cutting stage, and a sewing and finishing stage. The main variable inputs in the production of garments are fabric and labor employed on the sewing lines. For fabric, we exploit detailed transaction-level customs data. Besides standard information for each order on the output side (quantity, prices and type), our data include the amount, price and type of fabric used in the production of each export order. We thus observe order-level *buy-to-ship* ratios (defined as the weight of purchased fabric divided by the weight of shipped garments), which is a standard performance indicator in the industry and captures fabric efficiency over the two production stages. With regard to labor, we leverage daily records from a large sample of sewing lines, operating in 51 garment factories. Sewing is the most labor intensive step in garment production. We observe export-order-specific labor

by selection and other confounding factors.

[6] The garment industry has played a critical role in the early phases of export-oriented industrialization, most recently in East Asia (see, e.g., 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.

utilization and efficiency on the sewing lines. The two datasets that we use, from customs and from sewing lines, include the identity of the buyer for which an order is produced.[7]

Our analysis proceeds in five steps. In the first step, in Section 3.1, we describe the sourcing practices of international buyers in the Bangladeshi garment sector. Motivated by the literature, numerous business case studies, as well as our own interviews with buyers, we conceptualize the sourcing mode as a buyer-level strategic choice. Complementarities in organizational (Milgrom and Roberts, 1990) and procurement (Antràs et al., 2017) decisions imply dispersion in sourcing strategies even within narrowly defined market segments: different buyers source the same products, from the same suppliers under radically different sourcing strategies. By way of an example, Levi Strauss & Co. and J.C. Penney, two buyers with similar market shares in our sample, engage with suppliers in significantly different ways: in a given year, Levi Strauss & Co. sources from only 7 suppliers, whereas J.C. Penney sources from 25 suppliers. This discrepancy reflects substantially different approaches to sourcing at the two companies' global headquarters.[8]

The comparison between Levi Strauss & Co. and J.C. Penney lends intuition to the way in which we capture buyers' sourcing strategies in the data. Building on Heise et al. (2020), we compute, for each buyer and across product-year combinations, the average ratio between the number of suppliers and the number of transactions associated to the buyer. This gives us a cross-sectional metric across buyers that is consistent with theoretical predictions (see, e.g., Taylor and Wiggins, 1997) and which maps closely to accounts in industry publications.[9] We validate the metric using a variety of data sources, including customs data from another country (Myanmar), other corporate-level strategic decisions related to sourcing, and independently collected surveys on suppliers' perceptions about buyers.[10]

[7] The factory-level production data were collected as part of RCTs evaluating training programs (see Macchiavello et al., 2015). The customs data and the factory-level data, however, can only be matched via the buyer's name on the order. We are unable to match factories (or orders) across the two datasets.

[8] Building on historical production capabilities, Levi Strauss & Co. has relied on long-term relationships with a limited number of suppliers since it begun outsourcing production to foreign suppliers. At the core of their approach, "vendors [...] should be recognised and rewarded in ways that allow them to reinvest in [...] improve their sustainability performance" (Supply Management, Nov. 2014). In contrast J.C. Penney had a reputation for "squeezing cost out of the supply chain" (see, *Sourcing Journal*, January 11th, 2013) rather than developing relationships in sourcing countries. Section 3.1 elaborates on these and other examples.

[9] For instance, in our sample of more than 1,500 buyers, Levi Strauss & Co. ranks 2nd when buyers are ordered by our measure of relational outsourcing. The Gap and H&M, two buyers well-known for a relational approach to sourcing, rank 1st and 3rd respectively. Large continental European discount retailers (e.g., Kik Textilen and JCK), known for a spot sourcing strategy, appear lower in our ranking.

[10] In our regression analysis we take advantage of the fact that Bangladesh exports both woven and knitwear garments. Due to differences in production processes, the sets of woven and knitwear exporters are disjoint. The same buyers thus source in Bangladesh different products from different suppliers. To assuage concerns that our sourcing metric captures industry dynamics that are directly correlated with our outcomes of

In the second step of our analysis, in Section 3.2, we correlate buyers' sourcing strategies with output prices. We find that relational buyers pay higher prices than spot buyers. This correlation holds within seller-product-year combinations, and controlling for characteristics at the buyer (destination market, size, experience), buyer-seller (age, experience and proxies of bilateral market power) and order (volume, fabric type, price and origin) levels.

In the third step, in Section 3.3, we investigate whether the pattern in output prices reflects differences in variable costs that suppliers incur when producing orders for relational buyers compared to spot buyers. We find that there are no significant differences in the utilization of variable inputs across orders produced for buyers with different sourcing strategies. Conditional on seller-product-year fixed effects, the buyer's sourcing strategy does not correlate with fabric efficiency (the buy-to-ship ratio) nor with the price of fabric. The production line data confirm that garments produced for relational and spot buyers are sewed by comparable workers with similar labor efficiency. In addition, we exploit exogenous changes in cotton prices and in the minimum wage to show that, although fabric and labor are substitutes for each other (at least to an extent), there are no significant differences in the substitution pattern across orders produced for buyers with different sourcing strategies.

Higher prices paid by relational buyers could, in principle, reflect higher product quality. Several patterns in the data, however, suggest that differences in product quality are unlikely to account for the observed price differences. First, orders produced for relational and spot buyers display similar *Standard Minute Values* (SMVs), a measure of a garment's technical complexity. Second, output quality typically depends on input quality (see, e.g., Kugler and Verhoogen, 2012; Bastos et al., 2018). The lack of a difference in the price of fabric and in the sewing workers' skill composition further assuage concerns that quality differences might drive the price differences. Finally, the results hold when controlling for the price of fabric used to produce the order and other product attributes (e.g., the origin of imported inputs, the type of fiber, etc.) which arguably proxy for quality.

Do the higher prices paid by relational buyers reflect higher markups? Answering this question requires developing a theoretical framework to aggregate (observable) input utilization and prices and to estimate marginal production costs. We present such a framework in the fourth step of our analysis, in Section 4. We assume that (i) fabric enters the production function in a log separable way, and (ii) fabric is flexibly chosen by the manufacturer order by order.[11] The model reveals that *differences* in markups across orders that are produced with

interest, we use the sourcing metric in knitwear as our baseline measure to study woven exports.

[11] Both assumptions are consistent with the institutional environment and the garment production process as described in Section 2 and further detailed in Appendix B. Besides those assumptions, the model allows for different types of labor to enter the production function in unrestricted ways, to be subject to capacity constraints, and have different wages.

the same output-to-fabric elasticity only depend on the buy-to-ship ratios and the output and fabric prices, and are thus directly observable in our data.

In the final step of our analysis, in Section 5, we investigate the relationship between buyers' sourcing strategies and differences in markups across orders recovered from the model. Assuming that the output-to-fabric elasticity varies at the exporter-product-year level, we show that orders produced for relational buyers have no higher marginal costs, but earn higher markups compared to orders produced for spot buyers. The estimates are quantitatively relevant: a shift in sourcing strategy from a spot approach like Kik's to relational sourcing like H&M's is associated with an additional \$0.215 per kilogram of garment, equivalent to a 7.2% increase in the average markup.[12]

We complement our across buyers comparison with a detailed case study. We zoom in on the supply chain of VF Corporation, a large American multi-brand garment buyer that shifted its *global* approach to sourcing from spot to relational within our sample period. The results are consistent with the cross-sectional evidence. First, the transition is well-captured by our metric: as it moves from spot to relational sourcing, VF consolidates its Bangladeshi suppliers' base, trading with fewer partners each of whom is allocated more orders. Second, a difference-in-differences exercise (that controls for buyer fixed effects in addition to the baseline seller-product-year fixed effects) shows that, after the transition, suppliers earn higher markups on orders from VF relative to those from other buyers.

Going back to our main finding, different mechanisms could explain the higher markups that relational buyers pay relative to spot buyers. For example, relational buyers may have a weaker bargaining position due to higher switching or search costs (Monarch, 2019; Cajal-Grossi, 2019). Relational buyers may also have higher market power in downstream markets and may share their rents with suppliers (Halpern and Koren, 2007). Alternatively, relational buyers may require suppliers to undertake fixed costs investments which are then compensated with higher prices (Hallak and Sivadasan, 2013), or may pay higher prices as an incentive for suppliers to undertake non-contractible actions (Taylor and Wiggins, 1997).

Distinguishing across the different mechanisms that may drive relational markups is challenging.[13] To make progress, we explore the robustness of our results to different controls

[12]Our sourcing metric is continuous. The reported example is close to a shift from the 25^{th} to 75^{th} percentile in the buyers' sourcing metric, which produces a difference in markups of approximately 11%. This result exploits the *differences* in markups across orders within seller-product-time triplets. In order to benchmark our context to existing studies, Appendix B recovers the *level* of markups. Under stronger assumptions, we estimate the fabric output elasticity to be in the 0.55 - 0.62 range and essentially constant returns to scale at the order level. These estimates are closely aligned with industry reports and imply an average markup factor of 1.44. As a robustness check, we show that the estimated fabric output elasticity does not vary between orders produced for relational and spot buyers. It is important to reiterate that our main analysis *does not* rely on the assumptions required to estimate the level of markups.

[13]Any empirical metric of relational sourcing may capture a bundle of complementary practices that might

and study additional outcomes that can inform the discussion. We find that relational buyers pay higher markups even after we control for proxies for buyer's and seller's market power in the industry, for the buyer's share in downstream markets, and for seller destination-specific pricing strategies. Additional evidence on quality checks, lead times and shipping modes suggests that relational buyers pay higher markups to incentivize, at least in part, suppliers' non-contractible actions, such as internal processes for quality assurance and reliable and flexible deliveries. We discuss policy implications in the concluding section.

Related Literature To the best of our knowledge, this paper is the first to provide evidence on the equilibrium relationship between buyers' sourcing strategies and their suppliers' markups. The paper thus contributes to three strands of literature. First, international buyers' approach to sourcing has received significant attention in the literature on global value chains (see, e.g., Gereffi, 1999; Antràs, Forthcoming for reviews). An emerging body of work studies relationships between firms when contracts are hard to enforce (see, e.g., Macchiavello, 2010; Antràs and Foley, 2015; Macchiavello and Morjaria, 2015; Blouin and Macchiavello, 2019; Garcia-Marin et al., 2020). Like this literature, we exploit detailed data and contextual knowledge of a specific industry to investigate how business relationships matter. Those papers use observed responses to shocks to *infer* future rents in a *relationship*. In contrast, we focus on the buyer-level sourcing strategy and match variable inputs utilization to export orders to directly *measure* the higher markups earned when selling to relational buyers. We thus follow a distinct, but complementary, approach.[14] We also complement recent studies of international buyers in the garment industry. For example, Amengual and Distelhorst (2019) examine the impact of a change in the global sourcing approach at The Gap Inc. on suppliers' compliance. Boudreau (2020) evaluates an initiative led by international buyers aimed at enforcing a mandate for worker-manager safety committees in 84 Bangladeshi garment factories.[15]

Second, our paper contributes to a growing literature on firm upgrading and demand-side constraints in developing countries (see Verhoogen (2020) for a review).[16] For example,

mimic distinct economic mechanisms. For example, relational buyers might simultaneously offer higher markups to provide incentives *and* commit to switching costs that alter bargaining forces in the relationship.

[14]Our paper is also related to the empirical literature on relational contracts (see, e.g., Gibbons and Henderson (2012) for a review). Macchiavello and Morjaria (2019) document how relational sourcing practices with supplying farmers are associated with better performance across mills in the Rwanda coffee sector.

[15]Starting with Antràs (2003) seminal contribution, a large literature on global value chains has focused on vertical integration (see Alfaro and Charlton, 2009; Costinot et al., 2011; Antràs and Chor, 2013; and Boehm and Sonntag, 2019 for more recent contributions). We abstract from vertical integration as an alternative approach to sourcing as it is virtually nonexistent in our context.

[16]This literature builds upon a wide body of work on the relationship between exporting and firm productivity, see e.g., Pavcnik (2002) for earlier work and, more recently, Garcia-Marin and Voigtländer (2019)

Atkin et al. (2017) implements an RCT among Egyptian rug producers. Randomizing export orders across suppliers, they provide rigorous causal evidence of quality upgrading associated with export activity. Tanaka (2019) exploits the rapid opening of the Myanmar economy and exogenous firm and product variation to study the relationship between access to foreign markets and firm performance. Her results show that exporting has a positive impact on working conditions, firm size and management practices. Macchiavello and Miquel-Florensa (2019) study the impact of a large scale buyer-driven quality upgrading program in the Colombia coffee chain. The program, implemented through relational arrangements with the exporter, provides higher margins to the exporter and substantial benefits to upstream farmers. Our results highlight how the buyer's sourcing strategy can be an important dimension of upgrading for exporters in developing countries.[17]

Finally, our paper constributes to the literature studying markups in multi-product firms. Our contribution hinges on relaxing data constraints: to the best of our knowledge, this paper is the first to directly observe variable input utilization at the production order level. We focus on differences in prices, inputs and markups across orders produced for buyers with different sourcing strategies, holding constant seller-product-time varying effects.[18] Our industry-specific focus is similar to Atkin et al. (2015), who directly measure markups through survey questions in the Sialkot soccer ball cluster in Pakistan. De Loecker et al. (2016) estimate within-firm differences in markups across products. We instead estimate within firm-product-time differences in markups across orders sold to different buyers.

2 Industry Background and Data

Our analysis focuses on exports of woven garments, such as shirts and trousers. This section first describes the production process of this type of garment before introducing our sample and the main sources of data used in the analysis.

and Chor et al. (2020).

[17] Alfaro-Urena et al. (2019) show that after starting to supply multinational corporations (MNCs), Costa Rican suppliers experience persistent improvements in sales, employment and productivity.

[18] Brandt et al. (2018) links inputs to outputs across three stages of vertically integrated firms in the Chinese steel industry but focus on rather different questions. Studying a large Indian exporter, Adhvaryu et al. (2019) link the sorting of sewing operators and line supervisors to delivery pressures from large buyers. De Roux et al. (2020) explore the relationship between product quality and markups using data from a large Colombian coffee exporter.

2.1 Garment Production

Ready-made garment manufacturers in Bangladesh, entirely export-oriented, make production decisions about variable inputs based on the orders they receive from international buyers. Buyers provide their suppliers with a design and a set of technical specifications on the items to be produced. The manufacturer sources fabric and accessories, then cuts, sews and packages the garments. Bangladeshi exporters exclusively operate on an FOB basis and control the sourcing of all inputs.[19]

Fabric and labor employed on sewing lines are the two main variable inputs utilized in the production of a garment export order. 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 Appendix B.1 for details). With regard to fabric efficiency, there are two key performance indicators manufacturers focus on. The *buy-to-cut ratio* measures performance at the inspection and cutting stage. This is the ratio of purchased fabric to cut fabric, with lower values representing lower wastage and thus higher fabric efficiency in transforming purchased fabric into cut fabric bundles. The *cut-to-ship ratio* measures performance at the sewing and finishing stage. This is the ratio of cut fabric to shipped garments, with lower values representing lower wastage arising from defects and thus higher fabric efficiency at this stage. The product of these two metrics, the *buy-to-ship ratio* is a commonly used performance indicator that captures fabric efficiency over the two stages. It reflects the relationship between purchased fabric and shipped garments; lower values of the buy-to-ship ratio represent lower wastage and, thus, higher efficiency over the two stages of production. As explained below, the data we leverage in the analysis allow us to observe, for each export order, the buy-to-ship ratio.

Labor employed in the sewing section of the factory is the other main variable input in the production of garments. Analogously to the buy-to-ship ratio introduced above, 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 on the line multiplied by the line's runtime. 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. In turn, 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 a particular garment is supposed to take to be sewed together (see Macchiavello et al. (2015) for an application).

[19]This is different from CMT (cut-make-trim) systems common in other countries (e.g., China, Mexico and Myanmar) in which the buyer directly provides fabric and other material inputs to the manufacturer.

2.2 Data and Sample

Our main source of data consists of all the transaction-level export and import records from Bangladesh over the period 2005-2012. These records include information on the product transacted, its value, and its volume (in kilos), the date of the transaction, as well as unique identifiers for the Bangladeshi exporting/importing firms. For export transactions, the records also include the names of the international buyers. The main novelty of the data is that we can match material inputs usage to output at the transaction level.

As anticipated, we focus on woven garments. Two features of the Bangladeshi woven garment sector enable us to link material inputs use to output at the export order level. First, unlike other major garment exporters, like 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.[20] 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. If approved, a unique UD identifier is then assigned to all export and import transactions belonging to that export order.

Given these two features of the woven garment sector, we are able to identify the material inputs that correspond to a specific export order. In particular, each export and import customs record in our data contains a UD identifier alongside standard information as described above. We aggregate transaction-level records at the order (i.e., UD) level, producing, for each order, a single entry that contains information on: 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.[21]

To illustrate, a hypothetical observation in our dataset would look 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 3-thread or 4-thread twill, including cross twill, weighing not more than 200g/m^2, i.e., HS520813) at \$6 per kg from China on 01/20/2008 and to fulfill an order subsequently exported to *Walmart Inc.* of 450 kg of men's or boys'

[20] This feature does not apply to knitted garments, which account for about half of Bangladeshi garment exports. The production of knitted garments differs from that of woven garments in that it requires an additional production step from yarn to fabric. This step is performed by either vertically integrated or independent units. This precludes matching imported yarn material to output at the transaction level.

[21] In some cases, multiple types of fabric and additional material inputs (e.g., accessories like zippers and buttons) are imported for a given order. Our baseline estimation uses the total amount of fabric imported and abstracts from other material inputs as these may also be sourced domestically. We show that our results are robust to these choices.

woven cotton shirts (HS620520) on 03/01/2018 at \$10 per kg. The customs data thus allow us to compute the *buy-to-ship* ratio at the export-order level. As an illustration, for our hypothetical data observation on *Nice Apparel Co. Ltd.*, the buy-to-ship ratio corresponding to that order would be $400/450 \approx 0.89$. In our data, we find that the average order-level buy-to-ship ratio is 0.87; see Table 1.[22]

We expect significant variation in buy-to-ship ratios. Table 1 reports a coefficient of variation of the order-level buy-to-ship ratio of 33%. This observed dispersion may result from both differences in efficiency in the inspection and cutting or in the sewing and finishing stages of production as well as from the possibility of substituting fabric with other inputs, at least to a certain extent. Appendix B.2 provides evidence from within-firm studies documenting sources of variation in the buy-to-cut and cut-to-ship ratios due to efficiency. Using the customs records, we later leverage exogenous shocks to the prices of inputs to explore substitution patterns across labor and fabric.

We are able to match export and import transactions by UD identifier for 33,490 woven garment orders between 2005 and 2012. In the empirical analysis, we focus on the 17 six-digit HS codes in the two largest woven apparels: shirts and trousers. As we are primarily interested in exploring within exporter dispersion in prices, costs and markup, we restrict our analysis to the 500 largest exporters, accounting for 87% of the relevant sample.[23]

Table 1 provides descriptive statistics for our final sample. On average, orders last just over four months from the date of the first import of fabric to the date of the last export of apparel (Panel A). Sellers are active for an average of 6.65 years in the sample. The average seller exports 3.27 different woven products (six-digit HS codes) and trades with 5.88 buyers on average in a given year (Panel B). Buyers are more diversified both in terms of products sourced (4.24) and suppliers (22.05) on average in a given year (Panel C). Our sample contains trade interactions between 5,658 buyer-seller pairs. Many transactions occur within repeated buyer-seller relationships; the average buyer-seller relationship lasts almost two years and involves around 3.38 orders per year (Panel D).

We complement the customs records with daily production data on ≈1300 sewing lines operating within 51 garment factories. As described above, sewing lines are the most labor intensive step in garment production. The data records, for each sewing line on any given day, the quantity and type of garments produced, the utilization and efficiency of labor, and

[22] The buy-to-ship ratio is computed using net export volumes (kilos) that include accessories and packaging (garments are folded in plastic envelopes and then stored in carton boxes). This explains why the ratio in our data is typically below one. We have detailed data on the type and number of packages and verify that our results are unchanged when we control for packaging characteristics.

[23] Table A1 in the Appendix compares transactions in the UD system, with those outside of the UD system. More details on the sample construction can be found in Appendix A.

the international buyer whose order is being produced. We can thus match the buyers in the production line data with the buyers observed in the customs records.

The data, described in greater detail in Macchiavello et al. (2015), were collected as part of three RCTs that evaluated training programs for line operators and supervisors. Participating factories were recruited in collaboration with two large U.K. supermarkets and a large branded retailer. The supplier bases of the collaborating buyers overlap with those of many other international buyers. This provides the necessary variation to study labor utilization and efficiency in lines producing for different buyers.

When combined, the two sources of data allow us to explore within-firm differences in utilization and physical efficiency for the two main variable inputs: fabric (in the customs data) and labor (in the production line data).

3 Relational Buyers, Output Prices and Variable Costs

This section begins by characterizing the sourcing practices of international buyers in the Bangladeshi garment sector. We first describe the buyers, propose an empirical measure of their sourcing strategies and validate the metric using a variety of data sources, including customs records from another country (Myanmar), qualitative case studies and independently collected surveys on suppliers' perceptions about buyers. We then leverage the customs data to document that buyers that adopt relational sourcing practices pay higher prices. This correlation holds controlling for seller-product-year fixed effects, for the destination market, for buyer-level, buyer-seller-level and order-level characteristics. The higher prices paid by relational buyers might reflect higher (marginal) costs or higher markups at the order-level. To interpret the observed correlation, the section finally correlates utilization and prices of fabric and labor on the sewing lines to the sourcing strategy of the buyer for which the order is produced.[24]

3.1 Sourcing Strategies in the Garment Industry

This subsection describes the sourcing strategies of international buyers in the context we study. First, we document variation in buyers' approach to sourcing and introduce a metric of sourcing strategies along the lines of Heise et al. (2020). Second, we argue that the sourcing strategy is a corporate decision taken at the global headquarter level.

[24] Costs that are variable at the factory level, e.g., setting up a new production line or employing an additional quality supervisor, are fixed from the point of view of a single export order.

Measuring Sourcing Strategies International buyers sourcing garments in Bangladesh are extremely heterogeneous, ranging from dedicated apparel brands (e.g., The Gap), to non-specialized mass retailers (e.g., Walmart) and upscale branded marketeers (e.g., Tommy Hilfiger). The distribution of buyers' size is highly skewed: the largest 100 buyers account for 66% of the traded volumes. Table 2 provides a closer look at the 25 largest buyers in shirts and trousers. Column (1) ranks buyers according to their market shares in Bangladesh. H&M, Walmart, and the multi-brand apparel company VF Corporation lead the board with market shares of 5.22%, 5% and 4.14% respectively, more than 500 times larger than the median buyer in the sample.

Buyers exhibit significant differences in their approach to sourcing. Column (2) in Table 2 shows that even buyers of similar size can greatly differ in the number of suppliers they source from. For example, while Levi Strauss & Co. and J.C. Penney have similar market shares (2.21% and 1.96% respectively) in a typical year the former only sources from 7.4 suppliers whilst the latter does so from more than 25.7 sellers. This discrepancy reflects the radically different approach to sourcing of the two companies. During an interview conducted by one of the authors with a sourcing director for Levi Strauss & Co., it was reported that the company's origin as a manufacturer created a corporate culture centered around production capabilities. When the company started outsourcing production to foreign suppliers, it retained that focus by creating very strong partnerships with a limited number of suppliers. In exchange for loyalty and compliance, Levi Strauss & Co. transfers production capabilities to core suppliers (e.g., introducing new fabric material, assisting with planning and industrial engineering). In contrast, J.C. Penney has traditionally adopted a strategy of "squeezing cost out of the supply chain" (see, *Sourcing Journal*, January 11$^{\text{th}}$, 2013) and during our sample's years, "decimated [their] sourcing department and trampled on trusted relationships established in foreign countries" under the leadership of Ron Johnson (see, e.g., *Forbes*, April 25$^{\text{th}}$, 2014).

The difference between Levi Strauss & Co. and J.C. Penney reflects a broader distinction between two polar sourcing models in the apparel industry: *spot* interactions at one end and *relational* sourcing at the other (see, e.g., De Toni and Nassimbeni, 2000; Taylor and Wiggins, 1997; McMillan, 1990). Under *spot* procurement, suppliers are selected based on short-run cost minimization criteria exclusively: buyers source from multiple suppliers, with whom trade relationships tend to be short-lived and ended by out-bids from cheaper suppliers. Procurement orders tend to be large and either one-off or sporadic. In contrast, under *relational* sourcing buyers concentrate orders on a small number of suppliers on which they rely for the on-time and flexible delivery of shipments of consistent quality. The longer and more stable horizon of the relationship and, potentially, price premia mitigate the risks of opportunistic behavior on the supplier's side.[25]

Heise et al. (2020) use transaction-level U.S. import data to classify, through the lens of the model in Taylor and Wiggins (1997), importers according to their procurement styles. We build on their approach to measure buyers' sourcing strategies in our sample. We normalize the number of sellers the buyer trades with, by the number of shipments the buyer receives in each product-year, to construct a weighted average for each buyer across all its product-year combinations. This metric reflects that buyers reliant on spot sourcing tend to spread out their shipments across multiple suppliers, while relational buyers concentrate them in a set of core suppliers.[26]

The metric produces sensible results. First, column (3) in Table 2 ranks the largest buyers according to their sourcing strategies (1 being the most relational buyer). The ranking maps closely to qualitative accounts in industry publications. For example, Levi Strauss & Co. ranks 2nd, close to other large buyers known for their relational behavior, such as The Gap and H&M, ranked 1st and 3rd respectively. Large continental European discount retailers (e.g., Kik Textilen and JCK), known for a spot sourcing strategy, appear lower in our ranking.[27] Second, the metric captures the characterization of relational buyers in Taylor and Wiggins (1997). Appendix Table C2 shows that, conditional on seller-product-year fixed effects, orders from relational buyers are smaller and consist of more frequent shipments.[28]

The Sourcing Strategy as a Headquarters-Level Decision We now argue that the sourcing strategy is a buyer-level characteristic: although buyers can adapt to specific circumstances, the overall sourcing approach is a strategic decision taken at the headquarters level. Organizational complementarities across management practices in general (Milgrom and Roberts, 1990) and in procurement in particular (Antràs et al., 2017) provide a rationale for the sourcing strategy being a buyer-level decision that extends to different product lines, countries of sourcing and suppliers. This is confirmed by numerous industry accounts (see,

[25] These two models are sometimes referred to in the literature as 'adversarial' or 'American-style' sourcing in contrast to 'collaborative' or 'Japanese-style' sourcing (see, e.g., Kawasaki and McMillan, 1987; Richardson, 1993; and Helper and Saki, 1997).

[26] The relational sourcing metric captures a bundle of complementary practices (prices, promises of stable future orders, suppliers ranked into tiers, as well as other organizational measures, e.g., visits to the suppliers' premises and integration of IT systems). Some of these practices might alter price setting behavior in ways that look similar to changes in search costs or bargaining power. These considerations have implications for the interpretation of our results in Section 5.

[27] Inditex (the owner of Zara) appears relatively low in our relational ranking. During the sample period, Zara mostly sourced (relationally) from suppliers located near their headquarters in north-western Spain and relied on Bangladesh suppliers for more standard products sourced through the more traditional spot approach. For details, see HBS's case study 9-703-407 in Ghemawat and Nueno Iniesta (2006).

[28] Our analysis focuses on differences across export orders produced within seller-product-year combinations. Across sellers, Table C3 in Appendix C shows that exporters that sell to relational buyers are larger. Conditional on size, however, these sellers *do not* export more products or to more destination countries.

e.g., Gereffi, 1999) and business case studies.

For example, Nike's change in sourcing strategy is perhaps best known (see Harvard Business School's (HBS) case study in Nien-he et al., 2019). The HBS case study traces Nike's strategic shift towards a more relational approach to sourcing, which responded to an effort to reconcile competitive pressure on the demand side with the need to guarantee social compliance on the supply side. The transition involved several profound organizational changes at the headquarter level, starting with the establishment of a Code of Conduct on sourcing in the 1990s and culminating in 2009 in a company-wide reorganization entitled *Project Rewire*. At this point, a new corporate division, headed by a new Vice-President, merged the Social Compliance Team into the Global Sourcing Department.[29]

VF, a multi-brand U.S. apparel retailer, experienced a similar transformation (see HBS case study in Pisano and Adams, 2009). The company initiated a global transition from a spot-style of procurement in favor of a relational approach - the *Third Way* - in the mid-2000s.[30] The pivot begun slowly in 2005. By 2009, there were only five *Third Way* suppliers in VF's supply chain, but the shift was rapidly rolled out globally in 2010. In Section 5, we take advantage of VF's large supplier base in Bangladesh and the fact that the transition occurred half-way through our sample period to conduct a difference-in-differences analysis on the impact of a buyer's change in sourcing strategy on suppliers' outcomes.

If the sourcing decision is a buyer level policy, we expect that a buyer's propensity to source relationally is correlated (i) across products, (ii) across sourcing countries, (iii) with other corporate-level strategic decisions related to sourcing, and (iv) with suppliers' perceptions of the relationship. Table C1 provides supporting evidence along these four dimensions. The table reports correlation patterns between our baseline metric and different empirical counterparts to the buyers' sourcing strategy.

First, we take advantage of garment exports in Bangladesh being concentrated in two distinct sets of products: woven and knitwear. The production process of the two types of garments is significantly different and the sets of exporters in the two sub-sectors are largely

[29]In 1998, Nike stablished a CSR division reporting to the company's President but still separate from the Sourcing Department. Quoting from the case study: "*Sourcing decisions are often decoupled from the enforcement of private regulation [such as CoC], 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*".

[30]VF's earlier approach to sourcing is well summarized in the case study:"*Like its competitors, VF's outsourcing strategy emphasized flexibility*" and "*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.*"

disjoint.[31] In order to match fabric utilization to export orders, our analysis focuses on woven garments. However, for each buyer, we construct our metric of sourcing strategy in both woven and knitwear products. As expected, column (1) shows that the two metrics are strongly correlated across buyers: i.e., buyers that source woven relationally, also tend to source knitwear relationally from a disjoint set of suppliers. Note that, in the analysis in the rest of this paper, we use as the baseline metric of relational sourcing the metric constructed in *excluded* products, to avoid any mechanical correlation with order-level outcomes.

Second, we expect the buyer's sourcing approach to be correlated across countries. We have access to transaction-level customs data from Myanmar, a country that following up recent political reforms is becoming an important sourcing origin for several international buyers. For the sample of buyers that appear both in our Bangladeshi data and the Myanmar records, column (2) shows that the buyer's sourcing behavior is positively correlated across the two countries.

Third, the central panel of Table C1 shows that various measures of the average length of buyers sourcing relationships strongly correlate with our baseline metric of sourcing strategy. This is the case when we consider the duration of relationships in excluded products, exclusively in in-sample products, residualizing relationships' durations on the buyer's size and cohort and using trade relationships with suppliers in Myanmar - presented respectively in columns (3) to (6).[32]

Finally, we further validate our sourcing strategy metric by correlating it with information typically unobserved in customs records: the suppliers' perceptions of the relationship with the buyers. We are fortunate to have access to survey data (independently) collected in Bangladesh by the Better Work Program of the International Labor Organization. In the survey, managers of garment plants report on whether the relationship with specific buyers is strong or very strong, as opposite to neutral or weak. Column (7) of Table C1 shows that our baseline metric for relational sourcing is associated with a higher probability of being identified by suppliers as a strong or very strong partner.

In sum, taken together the evidence presented in this subsection establishes: (i) that sourcing strategies are, to a significant extent, buyer-level strategic decisions; (ii) that from

[31] Historically, the industry begun with woven in the 1980s and only later in the 2000s a significant number of knitwear manufacturers entered the industry. Relative to woven, knitwear manufacturing requires higher capital investments, so the pool of entrants in the two industries were rather different. Today, there are two separate business associations, BGMEA and BKMEA, catering for woven and knitwear respectively.

[32] We favor our baseline metric of sourcing over any alternative based on the duration of relationships for coverage reasons. The construction of duration-based metrics requires that a large number of relationships are discarded due to censoring in the data, at either the start or end of these relationships. We incur further losses of data by imposing a minimum number of relationships to construct the buyer-level metric. Despite this, the main results are robust to using the duration-based metrics, as shown in Table C4.

the point of view of sourcing relationships with specific Bangladeshi suppliers, a buyer's sourcing strategy can be taken to be a buyer-level characteristic; and (iii) that our empirical measure is a satisfactory proxy for a buyer's sourcing strategy. We now explore how this buyer characteristic correlates with the prices paid to Bangladeshi suppliers.

3.2 Relational Buyers and Export Prices

Buyers adopting relational sourcing strategies pay higher prices to Bangladeshi suppliers. Figure 1 illustrates this finding. Focusing on the market for men's shirts made of cotton in Bangladesh, the figure arranges buyers on the horizontal axis along bins, according to our relational metric: buyers that spread sourcing over a large number of suppliers (like J.C. Penney) are near the origin; relational buyers that concentrate shipments on few sellers (like Levi Strauss & Co.) are at the other end. The vertical axis reports the average price that the buyer pays for a cotton shirt for men. The figure shows a strong relationship between sourcing behavior and prices: relational buyers pay higher prices.

This strong correlation raises two questions. First, to what extent this correlation is robust to the inclusion of additional controls, and second, what underlying economic mechanisms account for this relationship. The reminder of this subsection tackles the first of these questions and the rest of the paper addresses the second one.

Consider the log unit price of garment order o, of product j (six digits HS code), manufactured by seller s for buyer b, p_{sbjo}. Our baseline specification is:

$$p_{sbjo} = \delta_{sjy} + \delta_d + \beta Relational_b + \varepsilon_{sbjo}, \tag{1}$$

where δ_{sjy} is a fixed effect that absorbs seller-product-year specific variation and allows us to study differences across buyers within sellers. Note that this set of fixed effects captures important, well-studied sources of variation in prices, including the manufacturer's inherent productivity, which might be time-varying and product-specific, like in models of core competences. Similarly, we condition on destination fixed effects, δ_d, to absorb differences explained by characteristics common to all buyers in a given country. These account for demand shifters that explain variation of average prices across destinations, such as differences in preferences, downstream competition or regulatory environments. The regressor of interest, $Relational_b$, is our baseline metric of buyers' sourcing, based on the ratio of sellers-to-shipments in *excluded* products and constructed in Section 3.1. Note that we use the metric in excluded products to avoid any mechanical correlation with order-level outcomes.

Column (2) of Table 3 reports the results of this specification and shows that a standard deviation increase in the sourcing metric (i.e. the more relational the buyer is) is associated to prices that are 2.4% higher when we compare orders within seller-product-year combinations, controlling for the destination of the order. This figure is slightly lower than the one displayed in column (1), which conditions simply on destination and product-year effects: the sorting of sellers with high average prices to buyers that adopt relational sourcing strategies induces a higher correlation between sourcing and prices, of 3.4%. Retaining the baseline fixed effects of column (2), columns (3) to (5) sequentially add controls that are buyer-, relationship- and order-specific. Across all of these specifications, the association between sourcing and prices remains quantitatively and qualitatively unchanged, ranging from 2.4% to 3%.

Column (3) controls for buyer-level characteristics. In particular, relational sourcing is unconditionally correlated with the buyer's size and its age in the market (see Table C1 and Panel B of Table C2). We therefore control for the cohort of the buyer, its overall size and the age of the buyer at the time of the order. In addition, we condition on whether the buyer is currently a member of the Accord or Alliance initiatives for health and fire safety in garment plants in Bangladesh. This indicator is a proxy for whether the buyer devotes resources to developing social compliance practices among their suppliers, a behavior that may affect prices and that is also associated to tighter relationships with a core set of sellers.

Column (4) adds controls for buyer-seller-pair characteristics. The size and age of the buyer-seller relationship could correlate with prices, for instance, due to reputation, scale effects or demand assurance mechanisms. To account for these and other potential confounders, column (4) controls for the cohort of the relationship, its size, the age of the relationship at the time of the order, the share of the seller in the buyer's trade and share of the buyer in the seller's trade.

Finally, column (5) also includes controls for order-level characteristics. Panel C of Table C2 suggests that relational buyers place more frequent, smaller orders. It is thus important to control for order size, as it might correlate with prices through other channels, such as scale effects and bulk discounts. In a similar vein, if the price of the main input, fabric, differed across buyers with different sourcing strategies, this could also explain the correlation between prices and buyers' sourcing strategy. Column (5) confirms the robustness of our results to the inclusion of the size of the order and the price of the fabric used in its production as controls. Table C4 reports further robustness checks, considering alternative samples and other order-level differences (Panel A) and alternative metrics for buyers' sourcing strategies (Panel B).

Taken together, the evidence indicates that buyers that adopt relational sourcing strategies pay significantly higher prices for the garments they purchase. The analysis here shows that this pattern is not explained by idiosyncratic characteristics of the seller, such as its productivity or differential competences in manufacturing specific products, or the country in which the buyer is located. Similarly, the observed higher prices do not follow from the size or age of the buyer or the relationship, its seasonality or specialization in certain products; nor does it emerge from specifics of the order being traded, such as its volume or the nature and price of its main input.

3.3 Variable Inputs and Relational Buyers

The finding that across orders produced by the same seller, in the same product, and at the same point in time, relational buyers pay higher prices could, in principle, follow from two different mechanisms. On the one hand, the higher prices might simply reflect higher costs, induced by efficiency and technology differences when producing for buyers adopting different sourcing strategies. On the other hand, the observed price differentials could respond to higher markups. In general, it is difficult to distinguish between these two channels. The main empirical challenge in establishing whether higher export prices follow higher costs or higher markups is that production costs for individual orders are unknown: in standard datasets, the inputs used to produce a particular order are not observed.[33]

This section makes empirical progress taking advantage of the two unique features of the data in our context. We explore the extent to which the higher prices paid by relational buyers are likely to reflect differences in (variable) costs across orders produced for different buyers by the same exporter, in the same product, at the same point in time. We first consider the fabric component of the costs, we then turn to labor and finally investigate substitution patterns between these two main variable inputs. The main takeaway of this analysis is that, conditional on exporter-product-time fixed effects, we *do not* detect any difference in the type, efficiency or utilization of fabric or labor across orders produced for relational and non-relational buyers.

Input Usage: Materials. We explore regressions following the same specification in equation (1) above, simply changing the outcome variable of interest. We analyze three outcomes related to the main material input, fabric.

The first outcome is the price of the fabric used in the production of the order. Column (1) of Table 4 shows that, conditional on seller-product-time fixed effects, the price of the fabric does not correlate with the sourcing strategy adopted by the buyer for whom the order is being produced. In particular, the unit price of fabric is not higher in orders manufactured for more relational buyers. Column (2) in the table explores the robustness of this result to the inclusion of buyer, relationship and order characteristics.

[33] More generally, in the estimation of production functions for multi-product firms, the allocation of inputs across multiple outputs is not observed. See De Loecker et al. (2016) for a discussion.

The second outcome is the buy-to-ship ratio, this is, the efficiency in the use of fabric. Column (3) of Table 4 shows that there is no correlation between fabric efficiency at the order level and whether the order is being produced for a buyer with a relational sourcing strategy. Column (4) shows this result remains unchanged after the inclusion of buyer, relationship and order characteristics.

Finally, we consider a measure of product complexity: the number of different types of fabric used for producing the order. Column (5) finds no statistically significant correlation between relational sourcing and the complexity in the assembly of the garment, as measured by the combination of different fabrics.

Taken together, these exercises suggest that the higher export prices paid by relational buyers are unlikely to reflect underlying differences in the type of fabric used, or differences in the efficiency with which suppliers turn fabric into garments when producing for buyer adopting different sourcing practices.

Input Usage: Labor. We now turn our attention to the other main variable input at the order level, labor employed in the sewing lines. We use daily production line-level data from a sample of garment factories. On any given calendar day τ, a seller s assigns line l to the production of garment for buyer b. For each day, we observe the number of workers, the composition of the workforce on the line (operators and helpers) and its efficiency in the use of labor. Labor efficiency is the standard industry metric described in Section 2.1 and constructed as the ratio between the minutes-equivalent of the output of the line and the minutes of labor input. The input minutes are directly observable from the number of workers present and the effective runtime of the line. The output minutes are calculated as the product between the Standard Minute Values (SMVs) and the number of pieces.

We investigate specifications like the following:

$$y_{slb\tau} = \delta_{sm(\tau)} + \delta_{\tau} + \delta_{sl} + \beta Relational_b + \varepsilon_{slb\tau}, \tag{2}$$

where $y \in \{Efficiency, \#Workers, Share\ Helpers\}$ is the outcome and $Relational_b$ is the main regressor of interest, i.e. the sourcing strategy of the buyer for which the line is producing on a given day. The specification includes several fixed effects. Specifically, $m(\tau)$ corresponds to the calendar month of date τ. As such, $\delta_{sm(\tau)}$ absorbs any variation in labor inputs that is specific to the plant and month and common across all production lines and buyers. δ_{τ} is a day fixed effect collecting common shocks that could affect production in all plants, such as hartals or festive days. Finally, production line fixed effects, δ_{sl}, condition on time-invariant idiosyncratic characteristics of production lines. These characteristics include the fixed assignment of employees to lines (e.g., line supervisors rarely move across lines) as well as potential differences in the vintage or operational conditions of sewing machines across lines. We report specifications with and without production line fixed effects. Those without production line fixed effects allow for the variation that arises if the factory allocates orders for relational buyers to lines with different characteristics. Such specifications are the empirical equivalent of our within exporter-product-time specifications in equation (1) above. Specifications that control for line fixed effects are also reported to investigate whether other unobservable inputs are allocated to lines differentially when they produce for buyers with different sourcing strategies.[34]

Table 5 reports the results for the three outcomes of interest excluding (odd columns) and including (even columns) the line fixed effects. Columns (1) and (2) show that orders produced for relational buyers are not characterized by higher efficiency on the sewing lines. Columns (3) and (4) show that orders produced for relational buyers do not have a significantly different number of operators working on the sewing line. Finally, columns (5) and (6) also show that orders produced for relational buyers employ the same share of helpers on the line (relative to more skilled sewing operators). In sum, the table reveals no significant differences in the efficiency or in the organization of labor when producing orders for buyers that adopt more relational sourcing strategies.[35]

Substitution Across Inputs. We explore whether the substitution between labor and materials differs across buyers adopting different sourcing strategies. To do so, we relate the amount of fabric imported at the order level, q^f_{sbjo}, to two exogenous sources of variation in input prices. First, we study the effects of changes in the international price of cotton, the most common material found in fabrics used for garment production in Bangladesh. Second, we consider the effects of a significant increase in the minimum wage in Bangladesh in November 2010. The specification is given by:

$$q^f_{sbjo} = \delta_{sj} + m(o) + \beta_1 Shock_{m(o)} + \beta_2 Relational^D_b + \beta_3 Shock_{m(o)} \times Relational^D_b + \beta_4 q_{sbjo} + \varepsilon_{sbjo}, \tag{3}$$

which includes seller-product fixed effects, δ_{sj}, and a linear time trend corresponding to the calendar month of the order, $m(o)$. All specifications control for the size of the order, q_{sbjo}. The two exogenous input price shifters are captured by the term $Shock_{m(o)} \in$

[34] The buyer-level controls from Table 3 are also included in the specification. As we cannot match the factories in the production data with the customs records, however, we cannot include the same set of relationship- and order-level controls.

[35] The imprecisely estimated *negative* coefficient in Column (3) implies *lower* variable labor costs on orders produced for relational buyers unless wages on lines that more often produce for those buyers were much higher. This would be inconsistent with Columns (5) and (6). Furthermore, since the average production line has ≈ 40 workers, wages would need to be $\approx 30\%$ higher to equalize labor costs and, given a labor cost share of $\approx 15\%$ for the typical garment, implausibly higher to explain price differences across orders.

$\{p^{cotton}_{m(o)}; m(o) \geq MinWageChange\}$. To assess the differential responses across buyers, we interact those shocks with a dummy indicating whether the buyer is in the top decile of the distribution of the sourcing metric, $Relational^D_b$.

Table 6 shows that fabric and labor are indeed substitutes and that the extent of the substitution does not differ across orders produced for buyers with different sourcing strategies. This suggests that the technology operated by a given seller, for a given product, at a given time, does not vary across orders shipped to buyers with different approaches to sourcing.

Column (1) in Table 6 shows that higher cotton prices translate into lower import volumes of fabric to produce orders of a given size. Conversely, column (2) shows that a significant increase in the minimum wage (which resulted into significant increases in wages of sewing operators) calls for higher volumes of fabric to produce orders of a given size. Column (3) shows that the two patterns hold within the same specification. Based on this evidence, to a certain degree, fabric and labor can be substituted. That is to say, a factory can employ more labor to reduce defects and save fabric.

The degree to which fabric and labor can be substituted for each other does not appear to be different across buyers that adopt different sourcing practices. This is illustrated by the results in columns (4), (5) and (6). Column (4) interacts the two price shocks in column (3) with the dummy for relational buyers. Both interactions terms render coefficients that are small and non-significant. The exercise is repeated in columns (5) and (6) on the sample of orders and adding the controls of our baseline specifications, to the effect of showing that results remain unchanged.[36]

Discussion. The analysis fails to detect any substantial difference in the price or use of fabric and labor across orders produced for buyers with different sourcing strategies. This suggests that observed differences in output prices across buyers are not explained by the type, price, efficiency of, and substitution between, the two main variable inputs.

The higher prices paid by relational buyers could, in principle, reflect higher product quality. Several patterns, however, suggest that differences in product quality are unlikely to account for the observed price differences. First, as noted above, orders produced for the two types of buyers display similar *Standard Minute Values* (SMVs), a measure of a garment's technical complexity. Second, the literature argues that output quality depends on input quality in general (see, e.g., Kugler and Verhoogen, 2012; Bastos et al., 2018) and in garments in particular (Medina, 2019). The lack of a difference in the price of fabric used to produce the order and in the workers' skill composition on the sewing lines further assuage

[36] Note that in column (6) the coefficients on input prices are statistically insignificant. This is because the inclusion of seller-product-year effects absorbs almost all the variation in the input price shocks.

concerns that differences in quality might drive the price differences. Finally, our results are robust to controls for the price of fabric and other product attributes that are arguably correlated with product quality. Table C4, Panel A, explores differences in specialization patterns, seasonality, and product complexity. We include an extensive set of dummies that capture the type and origin of the fabric most used in the order.[37] In addition, we also control for the complexity of the garment, proxied by the number of fabric types used for producing the order. Results are robust to the inclusion of these controls.

4 Theory: Differences in Order-Level Markups

The patterns uncovered in Section 3 lead to the question of whether the higher prices paid by relational buyers reflect higher markups or higher costs. Data alone cannot answer this question: a framework that aggregates (observable) input utilization and prices is necessary to net out (marginal) production costs from prices. This section develops such a framework.

Section 4.1 presents a model of garment production that captures the main aspects of the technology and the seller's cost minimization problem. Building on Hall (1988), and under mild assumptions, a sufficient statistic for the order-level marginal cost combines (i) the buy-to-ship ratio and fabric price and (ii) the fabric elasticity of output. The buy-to-ship ratio and price of fabric are observed in the data for each export order. Differences in marginal costs and markups across orders that are produced with the same fabric elasticity are thus also directly observed in the data. Section 5 explores differences in log markups and marginal costs across orders (and therefore buyers) under the assumption that the fabric elasticity flexibly varies across seller-product-time triplets using a regression framework akin to the baseline equation (1) in Section 3.

To benchmark our estimates to existing studies we also develop an approach that, under stronger assumptions, estimates *the* fabric elasticity and thus recovers the level of markups. The approach and the main findings are summarized in Section 4.2, with all the necessary details left to Appendix B.[38]

[37]An example of a category in this set of dummies reads as *Nice Ltd.'s men's shirts made of woven fabrics of cotton, containing 85% or more by weight of cotton, printed, plain weave, weighing more than 100g/m2 but not more than 200g/m2 sourced from India.*

[38]The additional assumptions required to recover markups in levels, as well as the empirical strategy deployed in Appendix B, are not necessary for our main analysis in Section 5.

4.1 Framework

We model trade between buyers indexed by b and sellers indexed by s. Sourcing and production in any period t are modeled as follows. First, buyers b and sellers s form links and sellers choose their production capacity. Second, each buyer's demand is realized and buyers place product orders. We impose no restrictions on the mechanism via which orders are allocated to sellers. 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 we denote the set of orders placed to seller s in period t (by all buyers and in all products) by O_{st}. Note that order o is seller-buyer-product-time specific (i.e., $sbjt$ specific); we omit these indices to ease the exposition. Each order specifies a volume Q_o and a unit output price P_o.

Set Up. The production of woven garments is organized at the level of the order and comprises two sequential stages: (i) inspection and cutting, and (ii) sewing and finishing. In the first stage, the fabric is cut into pieces which constitute the inputs into the labor intensive second stage, in which the garments are sewed together and finished. The inspection and cutting stage generates most of the variation in fabric waste. Conditional on the fabric fed onto the sewing lines, however, labor can also be used to reduce defects and fabric waste at the sewing and finishing stage (see Appendix B.1 for further details).

To approximate the two stages of production we assume an order-level production function that features log additive separability in the two main inputs, labor and fabric. Specifically, to produce an order o, a seller combines labor L_o^z of different types $z \in \{1, 2..., Z\}$ with fabric F_o. The different types of labor z capture the fact that orders are produced using workers of different skills, such as helpers, operators, supervisors and managers. We allow orders to vary in the way they combine the different types of labor and have idiosyncratic productivity ω_o. The production function can thus be written as:

$$Q_o = F_o^{\theta_o} H_o(\boldsymbol{L}_o, \omega_o) \tag{4}$$

where θ_o is the output elasticity with respect to fabric and $\boldsymbol{L}_o = \{L_o^1, L_o^2, ..., L_o^Z\}$.

The seller may face capacity constraints in labor type z. Specifically, seller s chooses how much labor of type z to use in each order $o \in O_{st}$ subject to the capacity constraint:

$$\overline{L}_{st}^z = \sum_{o \in O_{st}} L_o^z. \tag{5}$$

where summing over orders $o \in O_{st}$ is equivalent to summing over buyers, products, and orders for seller s in period t.

Seller s in period t chooses $\{\boldsymbol{L}_o, F_o\}_{o\in O_{st}}$ to minimize costs, subject to the technology constraint in (4) and capacity constraint (5), and taking order characteristics and prices as given. Denote the wages for labor of type z and the price of fabric with W_o^z and P_o^f respectively. We assume that fabric prices P_o^f do not depend on the size of the order.[39]

Cost Minimization. The Lagrangian for the seller's problem is

$$\mathcal{L}_{st} = \sum_o \left(\sum_z (W_o^z L_o^z) + P_o^f F_o \right) + \sum_o \lambda_o \Big(Q_o - F_o^{\theta_o} H_o(\boldsymbol{L}_o, \omega_o) \Big) + \sum_z \lambda_{st}^z \Big(\overline{L}_{st}^z - \sum_o L_o^z \Big).$$

The Lagrange multipliers λ_{st}^z reflect the value of relaxing the capacity constraint for labor of type z. Having an extra unit of labor of type z to be allocated across orders allow the seller to reduce fabric input use and thus costs. Note that orders $o \in O_{st}$ are interrelated only via the capacity constraints, as captured by the Lagrange multipliers λ_{st}^z. Naturally, the analysis also applies if labor of type z can be adjusted freely (in which case the multiplier λ_{st}^z is equal to zero).

The order-specific first order condition with respect fabric F_o yields

$$F_o = \theta_o \frac{Q_o}{P_o^f} \lambda_o, \tag{6}$$

By standard logic, the order-specific multipliers λ_o represent the increase in total cost associated with producing one additional unit of output in order o. That is, λ_o represents the short-run marginal cost for order o.

Knowledge of the marginal cost allows us to compute order-level markup factor M_o as the ratio between the order price P_o and the marginal cost λ_o:

$$M_o \equiv \frac{P_o}{\lambda_o} = \theta_o \frac{P_o Q_o}{P_o^f F_o}. \tag{7}$$

Equation (7) implies that the order-level markup M_o depends on the buy-to-ship ratio 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 F_o/Q_o, P_o and P_o^f are directly observed. The output fabric elasticity θ_o, however, is not. Denote $\alpha_o^{-1} = \frac{P_o Q_o}{P_o^f F_o}$ the term that is directly observed in the data. We can write the *difference* in (log) markups factors between two orders o and o' as:

$$\Delta_{oo'} \equiv \ln(M_o) - \ln(M_{o'}) = \underbrace{(\ln(\alpha_o^{-1}) - \ln(\alpha_{o'}^{-1}))}_{\text{Directly Observed in the Data}} - \underbrace{(\ln(\theta_o) - \ln(\theta_{o'}))}_{\text{Not Observed in the Data}}. \tag{8}$$

[39]We discuss the empirical validity of this assumption below.

The data thus allow us to directly observe differences in markups across orders that share the same fabric elasticity.

Taking the Model to the Data. Section 5 investigates differences in (log) markups factors across buyers with different sourcing strategies. The baseline specification allows for the output-to-fabric elasticity to vary at the seller-product-time level through the inclusion of the corresponding fixed effects. That is, in the empirical analysis, we assume $\theta_o = \theta_{sjt}$.

A fabric elasticity that varies at the seller-product-time level is more flexible than typically allowed for in the literature. A potential concern, however, is that within seller-product-time combinations, the fabric elasticity might also vary across orders produced for buyers that use different sourcing practices. Two considerations assuage this concern. First, in Section 3, we presented reduced form evidence that, conditional on seller-product-time fixed effects, substitution patterns between fabric and labor *do not* vary across buyers adopting different sourcing practices. Second, in Appendix B.3 we develop a framework to estimate the fabric elasticity and find no evidence of it differing across buyers with different sourcing strategies.

As is standard in the literature, our framework requires that fabric is flexibly chosen at the order level taking its price as given. The assumption is consistent with the context of our analysis. As noted in Section 2.1, through the UD system, Bangladeshi garment exporters import, on an FOB basis, fabric to produce a specific order. This ensures that fabric is sourced flexibly for each order. Still, two potential concerns arise. First, the fabric price could depend on the amount of fabric purchased - e.g., if the seller has market power over fabric suppliers and can negotiate discounts. Second, the price of fabric may depend on the buyer for which the order is produced. Even though buyers do not provide material inputs to their suppliers, they could influence its price - e.g., through relational sourcing with fabric suppliers.

Table C5 in the Appendix mitigates these concerns. First, the table shows that, conditional on seller-product-year fixed effects, the amount of fabric purchased in the order does not affect the fabric unit price. As expected, there is a negative correlation (all else equal, a garment manufacturer purchases more fabric when it is cheaper). Instrumenting for the amount of fabric purchased, however, we find no statistically significant relationship between the size of the fabric order and its price (see Appendix B.3 for details of the IV strategy). Second, if (relational) buyers negotiated price discounts with fabric manufacturers, we would expect that the price of fabric correlates with the buyer's sourcing practices and potentially with past volumes traded between the buyer and the garment manufacturer. We find no evidence for either.

4.2 Levels of Markups and Marginal Costs

Appendix B.3 estimates the *level* of markups for each export order. While the analysis in Section 5 *does not* require this estimation, the exercise allows us to benchmark our environment against other papers in the literature.

The main assumptions to recover the levels of markup are (i) a Cobb-Douglas production function; (ii) that both the first order conditions with respect to fabric and labor hold.[40] These assumptions yield a structural fabric demand equation at the order level. The equation identifies the fabric elasticity from the (linear) relationship between the buy-to-ship ratio, on the one hand, and the size of the order and the price of fabric, on the other, conditional on seller-product-time fixed effects. These fixed effects control for the (unobservable) labor prices and capacity constraints in the model.[41]

Across various specifications, the estimate of the output-to-fabric elasticity θ (our key outcome of interest) falls in the range $0.55 - 0.62$. All specifications also yield nearly constant returns to scale at the order level. These estimates are consistent with industry reports and costing sheets that show that fabric represents roughly two thirds of variable unit costs in garment production. Furthermore, in Appendix B.3 we find no statistically significant differences in the fabric elasticity for orders produced for relational relative to spot buyers.

Table B4 presents our estimates of the order-level marginal costs and markups, $\widehat{\lambda}_o$ and $\widehat{M}_o$. The table shows that, on average, the price per kilo of garment paid by buyers is \$13.65. This average price is composed by \$3.30 of markup and \$10.35 of marginal cost, where the latter is in turn composed by \$7.57 of fabric and a reminder of labor and other costs. The implied average markup factor is 1.44. This estimate is in line with the findings of De Loecker et al. (2016), who report mean and median (seller-product) markup factors of 1.57 and 1.33 for the textiles and apparel sector in India.[42] Table B4 shows that both markups and marginal costs exhibit significant dispersion. We find that order-level markup values are more dispersed than order-level marginal costs: the interquartile ratio is 6.29 for markups and 1.80 for marginal costs.

[40] We also need (iii) that wages (and capacity constraints) vary at the seller-product-time level, but not at the order level. This assumption *relaxes* conditions typically imposed in the literature.

[41] A concern in estimating the structural fabric demand equation is that the size of the order and the price of fabric might be endogenous to unobservables in the estimating equation. Appendix B.3 develops and implements an IV strategy that instruments for the size of the order exploiting information on the buyer-seller network and for the price of fabric using variation in the price of cotton and in fabric origins specific exchange rates. We also consider specifications that control for buyer fixed effects and that let the fabric elasticity to vary depending on the sourcing strategy of the buyer.

[42] Our estimates are also in line with annual reports available from sellers. For instance, Generation Next Fashions Ltd. and Beximco, both large Bangladeshi manufacturers of garments, report gross profit margins of 33 and 45% respectively in 2012. These margins are highly correlated with firm-wide measures of markups and are in the same range as the markups reported in Table B4.

The *within*-seller dispersion in markups (across buyers) is similar in magnitude to the dispersion *across* sellers. Figure 2 aggregates order-level markup factors for each seller-buyer-product-year combination. After residualizing these markups against product-year fixed effects, we construct the simple average, 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile residual markup for each seller. The horizontal axis arranges sellers ascendingly in percentiles according to their average markup. Across the full range of sellers, the within-seller interquartile range is everywhere wide. Moreover, the average within-seller interquartile range in markups is of comparable magnitude to the interquartile range observed across sellers.

After taking product and time variation into account, the buyer rather than the destination, appears to be a source of sizable within-seller dispersion in markups. In an unreported exercise, we decompose seller-buyer-product-year markups into a seller-product-year component and either a buyer or a destination component. Buyer effects account for about 30% of the total variation in markups explained by the decomposition. The alternative specification, replacing the buyer fixed effects with country fixed effects, shows that destinations account for less than 5% of the total explained variation in markups.[43]

While our main focus is on exploring within-seller variation in markups (charged to different buyers for the same product in the same year), it is useful to consider more aggregate patterns that can be compared with the findings of the literature. To this end, we aggregate order-level outcomes at the seller-product-year level and find that at this level, (i) markups are more dispersed than marginal costs, as in Atkin et al. (2015); (ii) exported quantities are negatively correlated with marginal costs and positively correlated with markups, in line with the results of De Loecker et al. (2016) for India and Atkin et al. (2015) for the soccer ball sector in Sialkot, Pakistan; and (iii) core products of multi-product firms exhibit lower marginal costs and higher markups than other products of these firms, consistent with the core product hypothesis discussed in Mayer et al. (2014).[44]

5 Relational Buyers and Markups

We take advantage of the framework developed in Section 4.1 to address two key questions. First, we ask whether the higher prices that relational buyers pay reflect higher marginal costs or higher markups. We establish the latter. Second, we explore different mechanisms

[43]For concreteness, we estimate specifications of the form $\mu_{sbjy} = \delta_\iota + \delta_{sjy} + \varepsilon_{sbjy}$, where δ_ι with $\iota \in \{b, d\}$ are fixed effects for the buyer or the destination. The decomposition on buyers gives a share over total explained variation of 0.296, computed as 16.80%/(16.80% + 39.89%), where 16.80% corresponds to the variation explained by the buyer fixed effect and 39.89% that accounted for by seller-product-year effects. The decomposition on destinations gives 0.047, as a result of 1.93%/(1.93% + 41.83%).

[44]These additional results are available upon request.

that could drive such pattern. We conclude that, at least in part, higher markups incentivize desirable, non-contractible behavior in garment suppliers.

5.1 Relational Buyers Pay Higher Markups

Using lower case to indicate logged variables, relabeling and rearranging equation (7) we obtain

$$mc_{sbjo} = p^{f}_{sbjo} + q^{f}_{sbjo} - q_{sbjo} - \ln(\theta_{sbjo})$$
$$\mu_{sbjo} = p_{sbjo} - mc_{sbjo}$$

where p^{f}_{sbjo} and q^{f}_{sbjo} are the (log) price and amount of fabric used by seller s for producing order o of (log) size q for buyer b in product j; θ_{sbjo} is the elasticity of output with respect to fabric. We estimate:

$$y_{sbjo} = \delta_{sjy} + \delta_d + \beta Relational_b + \gamma Z_{sbjo} + \varepsilon_{sbjo}, \tag{9}$$

where $y \in \{p, mc, \mu\}$ are log output prices p, marginal costs mc and markups μ. We assume that the output-to-fabric elasticity varies flexibly at the level of the seller-product-year: $\theta_{sbjo} = \theta_{sjy}$. The unobserved additive term $\ln(\theta_{sjy})$ in the expression for marginal costs mc and markups μ is then captured by the seller-product-time fixed effects, δ_{sjy}, in equation (9). Our main regressor of interest is the relational sourcing metric at the buyer level, $Relational_b$. As in the specifications of Table 3 we control for other buyer, relationship and order-level characteristics (Z_{sbjo}) and for destination (δ_d) fixed effects.

Table 7 presents the results. For comparison, column (1) replicates the result on prices reported in column (5) of Table 3. 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 follows from higher markups. These specifications control for the buyer's overall size, experience in the market and destination.[45]

The correlation between markups and relational sourcing is quantitatively sizable. To interpret the reported magnitude, we consider the average markup factor (1.43) and marginal cost ($10.39) in the sample of column (3) in Table 7. The estimated coefficient of 0.025 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 $0.215 per kilogram of garments, equivalent to a 7.2% increase in the average markup. Our sourcing metric is continuous and standardized. Considering the average buyer in the sample, a change in its sourcing strategy to mimic that of The Gap (a shift of one standard deviation approximately) yields a comparable

[45] Unreported exercises show qualitatively equivalent results in specifications that do not control for buyer's size and/or for destination fixed effects.

increase in markup values of approximately 11%. Comparing the 25^{th} (10^{th}) to 75^{th} (90^{th}) percentiles in the distribution of buyers' relational metric gives a 14.1% (28.3%) increase in the average markup value. Relational buyers source larger volumes than spot buyers from their suppliers. Suppliers' variable profits (i.e., gross of fixed costs) are thus considerably higher when supplying relational buyers relative to spot buyers.

The higher markups paid by relational buyers could in principle reflect differences in the physical quality of the garments. Several patterns suggest that this is unlikely to be the case. Inputs of higher quality are necessary to produce garments of higher quality (Medina, 2019). In contrast, Section 3.3 found no systematic differences in the price of the fabric or in the technical specifications (as captured by SMVs) of orders produced for relational buyers. Nor were there significant differences in the skill composition of the workforce in lines operating for relational buyers. Furthermore, the specifications in Table 7 control for the price of fabric used in each order. In the presence of complementarity across inputs in the production of quality, conditioning on the quality of one input controls for the quality of all inputs in a reduced form (see Verhoogen, 2008). Finally, Columns (4), (5) and (6) control for seasonality, specialization, the type of fabric (origin, fiber, etc.) and further proxies for product complexity.[46] Our results are robust to inclusion of these controls.

A Difference-in-Differences Analysis. The evidence that relational buyers pay higher markups is identified out of cross-sectional variation in sourcing strategies across buyers.[47] We leverage an event that allows us to exploit within-buyer variation in markups.

We zoom in on the Bangladeshi supplier base of VF, the large apparel buyer introduced in Section 3.1. During our sample period, VF shifted its global sourcing from a spot strategy to a relational approach. The events are described in detail in the HBS case study of Pisano and Adams (2009). The case documents several motives behind the transition, some related to sourcing, others driven by staffing and broader human resources considerations at the global headquarters level. The pivot towards the *Third Way* sourcing strategy begun in 2004 under the leadership of Chris Fraser, acting as President of Supply Chain International for VF Brands.[48] The transition was slow. Within a global supply network that counted over 1,000 suppliers, by 2009 there were only five *Third Way* suppliers (none among VF's

[46] The set of controls is as described in Panel A of Table C4.

[47] Unfortunately, it is difficult to systematically observe (exogenous) changes in buyers' sourcing strategies. Note that if buyers change sourcing strategies over time, our cross-sectional measure introduces measurement error in the main independent variable and thus biases the estimates towards zero.

[48] Quoting from the case: "*Fraser called this approach the Third Way sourcing strategy because it represented an alternative to both in-house manufacturing and traditional sourcing*". At the time of the case, VF sourced internally from its own plants and externally from a network of suppliers through short-term contracts to produce fixed volumes of specific garments.

Bangladeshi suppliers in our product categories).

The new approach ramped up globally in 2010. The change in sourcing strategy at VF is clearly visible in the Bangladeshi customs data. In 2010, at the onset of the transition, VF traded with 62 suppliers. The number quickly dropped to 56 in 2012. At the same time, the number of orders per supplier increased from approximately 160 in 2005 to close to 400 in 2012. That is, in line with our metric for relational sourcing practices, the switch in sourcing strategy implied a consolidation of VF's supplier base in Bangladesh.

The transformation in VF's sourcing strategy lends itself to a difference-in-differences approach. Among VF's suppliers, we compare the evolution over time of the markups earned in orders sold to VF relative to those sold to other buyers. We augment the specification in equation (9) to include buyer fixed effects and focus on interaction terms between an identifier for VF and year dummies. We estimate

$$\mu_{sbjo} = \delta_{sjy} + \delta_b + \sum_{r=2005}^{2012} \beta_s VF_o \times I_{\tau(o)=r} + \gamma Z_{sbjo} + \varepsilon_{sbjo}, \tag{10}$$

where VF_o is an indicator that takes value one if the order is sold to VF and zero otherwise, while $I_{\tau(o)=r}$ is a dummy for year r. We exclude the interaction with $r = 2009$. The inclusion of seller-product-year fixed effects, δ_{sjy} as in our baseline specification implies that we are comparing *changes* over time in the difference of order-level markups between VF and other buyers, holding constant seller-product-time varying specific attributes (such as production capabilities). The inclusion of buyer-specific fixed effects, δ_b, accounts for all unobservable, time-invariant buyer characteristics.

Figure 3 shows that the results of this exercise are consistent with the cross-sectional evidence presented above. Before VF's transition to relational sourcing we find no differential trend in markups in orders sold to VF relative to other buyers. After the transition, orders produced for VF start earning significantly higher markups relative to comparable orders produced for other buyers. The pattern persists until the end of our sample period. In the Appendix, Table C7 shows that the pattern in Figure 3 is driven by an increase in prices following VF's change in its approach to sourcing, rather than changes in marginal costs.

The difference-in-differences analysis confirms the patterns in Table 7 and provides reassurance that the higher markups paid by relational buyers reflect inherent differences between the economics of relational and spot sourcing.

5.2 Mechanisms

Relational buyers pay higher markups. What could account for this pattern? This section considers alternative explanations. A caveat to this exercise is that, as discussed in Section 2, the relational sourcing metric captures a bundle of complementary practices. These practices might induce differences in markups across buyers through distinct economic channels (e.g., changes in search and/or switching costs, rent sharing, etc.). To make progress, we explore robustness of our results to controls for alternative mechanisms and we directly study additional outcomes that can inform the discussion. The evidence suggests that higher markups paid by relational buyers incentivize, at least in part, suppliers' non-contractible behavior.

Bargaining Power. Relational buyers might have weaker bargaining power with suppliers. The specifications in Table 7 control for the buyer's size in the market, the age of the buyer-seller relationship and traded volumes between parties. In addition, we control for the share of the buyer (seller) in the seller's (buyer's) trade. Furthermore, column (7) (respectively (8)) discards orders sold to (bought from) the main buyer (supplier) and finds that the result 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 bargaining position of these buyers *vis-à-vis* their suppliers.

Pricing to Market. In our context, higher markups could also stem from sellers' discriminating pricing across markets. By controlling for destination fixed effects, Table 7 accounts for average differences across destinations. Table C6 in the Appendix further explores related confounders. For ease of comparison, column (1) reproduces column (3) of Table 7. Column (2) includes destination-product-year fixed effects while column (3) controls for seller-destination fixed effects. Column (4) includes country-product-year fixed effects, where country corresponds to where the order is shipped to (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 consumers' tastes across countries, products and time. These mechanisms do not explain the markup differentials across buyers, which remain robust throughout the exercise.

Buyers' Downstream Size and Rent Sharing. Relational buyers might have higher 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, which 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. Column (5) of Table C6 shows that our results are robust to controlling for the buyer's sales in the downstream market within this restricted sample.[49]

Fixed Costs. Higher markups could arise if suppliers are compensated for fixed costs incurred to produce for relational buyers. For example, relational buyers might demand certain investments in quality checks or in social compliance. Suppliers are then compensated by means of price premia as buyers compete for such scarce capabilities.

The production line records used in Section 3.3 offer a window to explore this hypothesis. Orders produced for relational buyers could be associated with organizational systems that allow for quality checks. In the data, not all exporters and, within exporters, not all production lines perform quality checks at the end of the production line. Suppliers might assign orders from relational buyers to those production lines in which systematic quality checks are conducted and recorded. Column (1) of Table 8 shows that the probability of a line in a given day collecting records on quality checks is positively associated to it producing for a relational buyer. This evidence holds within seller-month, for a given day and conditioning on other buyer characteristics.

The correlation, however, loses its significance when we control for production line fixed effects in column (2). That is, orders are sorted into production lines and quality checks are a fixed characteristic of the line rather than an additional variable cost of the order. Furthermore, the rest of Table 8 shows that, conditional on quality checks being performed, the incidence of defects (garments that may be repaired) and rejects (garments to be discarded) is uncorrelated with the buyer's sourcing strategy. The evidence suggests that suppliers allocate orders from relational buyers to lines that have the necessary quality control infrastructure. Conditional on that, quality standards are not higher. In other words, orders for relational buyers incur higher fixed costs but no higher variable costs.

Suppliers might also incur fixed costs to meet social compliance requirements. To the extent our data allow, we found no evidence that this explains differences in markups. First, relational buyers pay higher markups when we control for the buyer's participation in worker-safety initiatives (Accord and Alliance) that followed the Rana Plaza disaster. Second, we obtained access to surveys conducted as part of the monitoring process for the Better Work Program implemented by ILO in several countries. Unreported results show that, across plants, social compliance investments do not correlate with the share of output that plants sell to relational buyers. In addition, within plants, relational buyers do not appear to monitor social compliance more or less frequently relative to other buyers.

[49]Column (6) confirms that the baseline results are robust within the restricted sample of column (5), when we exclude the control for downstream size.

Incentives. Higher markups might incentivize suppliers to undertake costly actions that are difficult to contract upon. This is the essence of the Taylor and Wiggins (1997) model and in the spirit of relational contracting models more broadly. In the garment industry, relational buyers expect both *reliability* and *flexibility* from their core suppliers. *Reliability* refers to the supplier's ability to deliver orders with no delay and according to agreed upon specifications. *Flexibility* refers to the supplier's ability to accelerate production or allocate additional production capacity at short notice if needed.

Table 9 investigates proxies for flexibility and reliability in the customs data. Customs data record transactions that have happened, with no information on what was meant to happen. Flexibility and reliability therefore cannot be directly observed.[50] However, in the context of the garment industry, we have proxies for both. Flexibility is associated with shorter order lead-time. We construct a proxy for the order lead-time using the time elapsed between the incoming shipment of fabric and the outgoing shipment of garments at the customs point (akin to *through-put* time in production). To proxy for reliability, we exploit the fact that almost all garment orders are shipped by sea, with air shipments left reserved for urgent or last minute deliveries, due to the high costs of this mode of transport.[51]

If higher margins paid by relational buyers are used to incentivize flexibility and/or reliability using future rents, we should observe that (i) a buyer's relational sourcing strategy correlates with proxies for flexibility and/or reliability; (ii) proxies for flexibility and/or reliability correlate with markups at the order level; and (iii) conditional on the order proxies for flexibility and/or reliability, relational buyers still pay higher markups. Table 9 provides evidence consistent with these patterns. With respect to point (i), column (1) shows that orders sold to relational buyers have shorter lead-time and column (ii) shows that orders sold to relational buyers are *less* likely to be shipped by plane (higher reliability). With regard to points (ii) and (iii), column (3) shows that shorter lead-times are associated with higher markups. Furthermore, relational buyers pay higher markups, even conditional on lead-times. Similarly, column (4) shows that shipments by plane are compensated with higher markups and that, again, relational buyers pay higher markups even conditional on the mode of transport. Overall, the evidence is thus consistent with higher markups incentivizing -rather than merely compensating for costlier- flexible and reliable deliveries.

While both reliability and flexibility are desirable behaviors, there is a tension between

[50] In the absence of information on promises exchanged between parties and on contractual defaults, it is difficult to infer flexibility and reliability from transaction data. See Macchiavello and Morjaria (2015) and Blouin and Macchiavello (2019) for discussions.

[51] According to quotations obtained from three independent freight services (InterDirect, InterDepAir, InterCargo) in August 2015, shipping 50 kg. of garment from Dhaka to London in the most commonly used packaging in our data would range from \$483 to \$700 by air and \$321 by sea. The average port-to-port transport time from Dhaka to European destinations is 22 days by sea and 2 days by air.

the two. At full capacity, flexibility requires an exporter to divert resources engaged in other orders if needed: flexibility towards a buyer compromises reliability towards another one. An exporter that only supplies relational buyers cannot simultaneously guarantee flexibility and reliability to *all* of them. That being the case, we expect suppliers to spare some of their capacity for sporadic buyers so as to be able to shift additional capacity towards relational buyers when required. This logic is consistent with the pattern in Figure 4, which plots the distribution of production capacity that sellers dedicate to relational buyers. The figure shows that while sorting is substantial (many firms do not supply relational buyers at all), it is far from complete. Among firms that do supply relational buyers, very few *exclusively* supply relational buyers. If investments required to supply relational buyers were common across buyers and higher markups simply compensated for those investments, sellers should aim at exclusively selling to relational buyers in order to maximize profits. That does not appear to be the case.[52]

To summarize, the results in this section show that relational buyers pay higher markups. These could reflect different economic mechanisms. The evidence presented above suggests that the higher markups paid by relational buyers incentivize, at least in part, suppliers' non-contractible behavior.

6 Conclusions

This paper studied how order-level prices, marginal costs and markups vary with international buyers' sourcing strategies in the context of the Bangladeshi garment sector. We were able to do so by leveraging original data that allowed for the direct measurement of utilization and prices of the main variable inputs (fabric and labor) used to produce orders for different buyers. Our analysis revealed that exporters earn widely different markups for the same product, at the same point in time, from buyers adopting different sourcing strategies. Relative to buyers that use spot sourcing strategies, relational buyers pay higher prices and the difference reflects higher suppliers' margins, rather than higher (marginal) costs of producing for these buyers. Zooming in on the supply chain of a large buyer that switched from spot to relational sourcing half-way through our sample period, we confirmed that the difference in markups reflects the different economics of the two sourcing strategies. Additional evidence suggested that higher markups paid by relational buyers incentivize, at

[52]Relational buyers might set more stringent requirements with respect to garment defect rates. It appears difficult to write an enforceable contract specifying *how* the seller is supposed to undertake quality checks within the factory. As noted above, orders for relational buyers tend to have quality checks performed on the sewing line (as opposed to in a common finishing section). This pattern is thus also consistent with higher markups incentivizing hard to contract upon behavior.

least in part, suppliers' non-contractible behavior.

Besides its relevance for our understanding of global value chains, our analysis also hints at policy implications for export promotion agencies, particularly in developing countries. The results provide a quantitative underpinning to the view that international buyers' sourcing strategies are a potentially important dimension of upgrading for exporting firms in developing countries (see, e.g, Egan and Mody (1992) and Gereffi (1999) for qualitative accounts). The evidence is consistent with theoretical models (e.g., Taylor and Wiggins, 1997; Board, 2011) in which (some) buyers pay rents to incentivize hard-to-contract-upon behavior among their suppliers. These models echo theoretical frameworks distinguishing between "good jobs" - in which workers earn rents - versus "bad jobs". The laissez-faire equilibrium in markets with such dual structure is often inefficient. For example, in the model in Acemoglu (2001), an unregulated market generates too many low-wage, bad jobs relative to the social optimum. Applied to our context, this suggests the possibility that export promotion agencies might want to target their support programs to help firms establish relationships with relational buyers: besides *what* and *how much*, to *whom* a firm exports matters.

References

Acemoglu, Daron, "Good Jobs versus Bad Jobs," *Journal of Labor Economics*, 2001, *19* (1), 1–21.

Adhvaryu, Achyuta, Vittorio Bassi, Anant Nyshadham, and Jorge Tamayo, "No Line Left Behind: Assortative Matching Inside the Firm," *mimeo*, July 2019.

Alfaro, Laura and Andrew Charlton, "Intra-industry Foreign Direct Investment," *American Economic Review*, December 2009, *99* (5), 2096–2119.

Alfaro-Urena, Alonso, Isabela Manelici, and Jose Vasquez, "The Effects of Multinationals on Workers: Evidence from Costa Rica," *mimeo*, November 2019.

Amengual, Matthew and Greg Distelhorst, "Can Sourcing Help Enforce Global Labor Standards? Evidence from the Gap Inc Supply Chain," *mimeo*, 2019.

Antràs, Pol, "Firms, Contracts, and Trade Structure," *The Quarterly Journal of Economics*, 2003, *118* (4), 1375–1418.

_ , *Global Production: Firms, Contracts, and Trade Structure*, Princeton University Press, 2016.

_ , "Conceptual Aspects of Global Value Chains," *World Bank Economic Review*, Forthcoming.

_ **and Davin Chor**, "Organizing the Global Value Chain," *Econometrica*, 2013, *81* (6), 2127–2204.

_ **and Fritz Foley**, "Poultry in Motion: A Study of International Trade Finance Practices," *Journal of Political Economy*, 2015, *123* (4), 853–901.

_ **, Teresa Fort, and Felix Tintelnot**, "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," *American Economic Review*, 2017, *107* (9), 2514–64.

Atkin, David, Amit Khandelwal, and Adam Osman, "Exporting and Firm Performance: Evidence from a Randomized Experiment," *The Quarterly Journal of Economics*, 2017, *132* (2), 551–615.

_ **and** _ , "How Distortions Alter the Impacts of International Trade in Developing Countries," *Annual Review of Economics*, 2020, *12* (1).

_ **, Azam Chaudhry, Shamyla Chaudry, Amit Khandelwal, and Eric Verhoogen**, "Markup and Cost Dispersion across Firms: Direct Evidence from Producer Surveys in Pakistan," *American Economic Review*, May 2015, *105* (5), 537–544.

Baker, George, Robert Gibbons, and Kevin J. Murphy, "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 02 2002, *117* (1), 39–84.

Banerjee, Abhijit and Esther Duflo, "Reputation effects and the limits of contracting: a study of the Indian software industry," *Quarterly Journal of Economics*, 2000, *115*, 989 to 1017.

Bastos, Paulo, Joana Silva, and Eric Verhoogen, "Export Destinations and Input Prices," *American Economic Review*, February 2018, *108* (2), 353–392.

Bloom, Nicholas and John Van Reenen, "Measuring and explaining management practices across firms and countries," *Quarterly Journal of Economics*, 2007, *122* (4), 1341 to 1408.

_ **and** _ , "Why Do Management Practices Differ across Firms and Countries?," *Journal of Economic Perspectives*, March 2010, *24* (1), 203–24.

Blouin, Arthur and Rocco Macchiavello, "Strategic Default in the International Coffee Market," *The Quarterly Journal of Economics*, 01 2019, *134* (2), 895–951.

Board, Simon, "Relational Contracts and the Value of Loyalty," *American Economic Review*, December 2011, *101* (7), 3349–67.

Boehm, Johannes and Jan Sonntag, "Vertical Integration and Foreclosure: Evidence from Production Network Data," CEP Discussion Papers dp1641, Centre for Economic Performance, LSE August 2019.

Boudreau, Laura, "Multinational enforcement of labor law: Experimental evidence from Bangladesh's apparel sector," *mimeo*, 2020.

Brandt, Loren, Gueorgui Kambourov, and Kjetil Storesletten, "Barriers to Entry and Regional Economic Growth in China," 2018 Meeting Papers 954, Society for Economic Dynamics 2018.

Cajal-Grossi, Julia, "Searching for Trade Partners in Developing Countries," *mimeo*, August 2019.

Chor, Davin, Kalina Manova, and Zhihong Yu, "Growing Like China: Firm Performance and Global Production Line Position," Working Paper 27795, National Bureau of Economic Research September 2020.

Costinot, Arnaud, Lindsay Oldenski, and J. Rauch, "Adaptation and the Boundary of Multinational Firms," *Review of Economics and Statistics*, 2011, *93* (1), 298–308.

De Loecker, Jan, Pinelopi K Goldberg, Amit Khandelwal, and Nina Pavcnik, "Prices, Markups, and Trade Reform," *Econometrica*, 2016, *84* (2), 445–510.

De Roux, Nicolas, Rocco Macchiavello, Josepa Miquel-Florensa, and Eric Verhoogen, "Markups and Quality: Evidence from Colombian Coffee Exports," *mimeo* December 2020.

De Toni, Alberto and Guido Nassimbeni, "Just-in-Time Purchasing: an Empirical Study of Operational Practices, Supplier Development and Performance," *Omega-International Journal of Management Science*, December 2000, *28* (6), 631–651.

Dickerson, Kitty G, *Textiles and Apparel in the Global Economy*, Prentice Hall, 1999.

Egan, Mary Lou and Ashoka Mody, "Buyer-Seller Links in Export Development," *World Development*, March 1992, *20* (3), 321–334.

Euromonitor International, "GBO and GBN, sales, Apparel," *Passport Database, Accessed 2015: http://www.euromonitor.com/research-methodology-market-analysis* 2015.

Garcia-Marin, Alvaro and Nico Voigtländer, "Exporting and Plant-Level Efficiency Gains: It's in the Measure," *Journal of Political Economy*, 2019, *127* (4), 1777–1825.

_ , Santiago Justel, and Tim Schmidt-Eisenlohr, "Trade Credit, Markups, and Relationships," Working Paper 1303, Washington: Board of Governors of the Federal Reserve System September 2020.

Gereffi, Gary, "International Trade and Industrial Upgrading in the Apparel Commodity Chain," *Journal of International Economics*, 1999, *48*, 37–70.

Ghemawat, Pankal and Jose Luis Nueno Iniesta, "Zara: Fast Fashion," *Harvard Business School Case 9-703-407*, 2006.

Gibbons, Robert and Rebecca Henderson, "Relational Contracts and Organizational Capabilities," *Organization Science*, 2012, *23* (5), 1350–1364.

Hall, Robert E, "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 1988, *96* (5), 921–947.

Hallak, Juan Carlos and Jagadeesh Sivadasan, "Product and Process Productivity: Implications for Quality Choice and Conditional Exporter Premia," *Journal of International Economics*, September 2013, *91* (1), 53–67.

Halpern, László and Miklós Koren, "Pricing to Firm: an Analysis of Firm- and Product-level Import Prices," *Review of International Economics*, August 2007, *15* (3), 574–591.

Heise, Sebastian, Justin R Pierce, Georg Schaur, and Peter K Schott, "Tariff Rate Uncertainty and the Structure of Supply Chains," *mimeo*, 2020.

Helper, Susan and Mari Saki, "Supplier Relations in Japan and the United States: Are They Converging?," *MIT-Japan Program*, 1997.

_ **and Rebecca Henderson**, "Management Practices, Relational Contracts, and the Decline of General Motors," *Journal of Economic Perspectives*, February 2014, *28* (1), 49–72.

Houthakker, Hendrik, "The Pareto Distribution and the Cobb-Douglas Production Function in Activity Analysis," *Review of Economic Studies*, January 1955, *23* (1), 27–31.

Jones, Charles I, "The Shape of Production Functions and the Direction of Technical Change," *The Quarterly Journal of Economics*, May 2005, *120* (2), 517–549.

Kawasaki, Seiichi and John McMillan, "The Design of Contracts: Evidence From Japanese Subcontracting," *Journal of the Japanese and International Economies*, January 1987, *1* (3), 327–349.

Kugler, Maurice and Eric Verhoogen, "Prices, Plant Size, and Product Quality," *Review of Economic Studies*, February 2012, *79* (1), 307–339.

Macchiavello, Rocco, "Development Uncorked: Reputation Acquisition in the New Market for Chilean Wines in the UK," *mimeo*, June 2010.

_ **and Ameet Morjaria**, "The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports," *American Economic Review*, 2015, *105* (9), 2911–45.

_ **and** _ , "Competition and Relational Contracts in the Rwanda Coffee Chain," *mimeo*, 2019.

_ **and Josepa Miquel-Florensa**, "Improving Export Quality: The case of the Sustainable Quality Program in Colombian Coffee," *mimeo*, 2019.

_ **, Andreas Menzel, Atonu Rabbani, and Christopher Woodruff**, "Challenges of Change: An Experiment Training Women to Manage in the Bangladeshi Garment Sector," *mimeo*, December 2020.

Masten, Scott, "The Organization of Production: Evidence from the Aerospace Industry," *Journal of Law and Economics*, 1984, *27* (2), 403–17.

Mayer, Thierry, Marc J. Melitz, and Gianmarco I. P. Ottaviano, "Market Size, Competition, and the Product Mix of Exporters," *American Economic Review*, February 2014, *104* (2), 495–536.

McMillan, John, "Managing Suppliers: Incentive Systems in Japanese and U.S. Industry," *California Management Review*, July 1990, *32* (4), 38–55.

_ , "Reorganizing Vertical Supply Relationships," *in: Siebert, H. (ed.) Trends in business organization: Do participation and cooperation increase competitiveness?*, 1994, pp. 203–22.

Medina, Pamela, "Import Competition, Quality Upgrading and Exporting: Evidence from the Peruvian Apparel Industry," *mimeo*, December 2019.

Milgrom, Paul and John Roberts, "The economics of modern manufacturing: Technology, strategy, and organization," *The American Economic Review*, 1990, pp. 511–528.

Monarch, Ryan, ""It's Not You, It's Me": Prices, Quality and Switching in U.S.-China Trade Relationships," *mimeo*, November 2019.

Morlacco, Monica, "Market Power in Input Markets: Theory and Evidence from French Manufacturing," *mimeo*, 2019.

Nien-he, Hsieh, Michael Toffel, and Olivia Hull, "Global Sourcing at Nike," *Harvard Business School Case 619-008*, June 2019.

Nishiguchi, Toshihiro, *Strategic Industrial Sourcing: The Japanese Advantage*, Oxford University Press, 1994.

Pavcnik, Nina, "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants," *Review of Economic Studies*, 2002, *69*, 245–276.

Pisano, G. and P. Adams, "VF Brands: Global Supply Chain Strategy," *Harvard Business School Case 610-022*, November 2009.

Richardson, James, "Parallel Sourcing and Supplier Performance in the Japanese Automobile Industry," *Strategic Management Journal*, 1993, *14* (5), 339–350.

Tanaka, Mari, "Exporting Sweatshops? Evidence from Myanmar," *Review of Economics and Statistics*, 2019, pp. 1–44.

Tanvir, Saiful Islam and Tarique Mahmood, "Solid Waste for Knit Fabric: Quantification and Ratio Analysis," *Journal of Environmental and Earth Science*, 2014, *4* (12), 68–80.

Taylor, Curtis R and Steven N Wiggins, "Competition or compensation: Supplier incentives under the American and Japanese subcontracting systems," *The American Economic Review*, 1997, pp. 598–618.

Verhoogen, Eric, "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector," *The Quarterly Journal of Economics*, 2008, *123* (2), 489–530.

_ , "Firm-Level Upgrading in Developing Countries," *mimeo*, 2020.

World Bank, *World Development Report 2020: Trading for Development in the Age of Global Value Chains*, 0 International Bank for Reconstruction and Development, The World Bank, 2020.

Tables and Figures

Table 1: Summary Statistics

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

Super- and sub-scripts are as follows: o corresponds to orders, b to buyers, s to sellers, j to HS6 product categories, y to years. $Count^x_y$ is the number of x per y. For example, $Count^o_{sjy}$ 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 dataset. 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. $Share^x_y$ is the share of x in y expressed in percentage terms. For example, for $Share^s_{by}$, 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 B, corresponding to $Count^o_{by}$ shows that there are 4,478 buyer-year combinations in the data; across these, the average number of orders is 13.37.

Table 2: Buyers' Concentration and Sourcing

Top 25 Buyers	Market Share % (1)	Sellers per Year Average (2)	Relational Ranking (3)	Price (Residuals) Ranking (4)
H&M Hennes And Mauritz	5.22	55.25	3	2
Wal Mart Stores	5.00	57.50	17	16
VF Corporation	4.14	23.75	5	17
The Gap Inc	3.44	26.13	1	1
C & A Buying	3.17	41.00	8	9
K Mart Corporation	3.08	59.25	16	14
PVH Corporation	3.11	39.00	7	15
Levi Strauss & Co	2.21	7.38	2	7
J.C. Penney	1.96	25.75	11	10
Primark	1.42	22.75	10	24
Kik Textilen	1.32	49.88	25	22
Tesco	1.25	23.00	12	19
Kohls Department Stores Inc	1.25	16.13	13	5
Asda	1.21	19.50	6	8
Marks& Spencer	1.15	9.88	4	11
Carrefour	1.13	26.38	14	18
G. Gueldenpfennig Gmbh	0.87	30.88	24	20
Tema Magazacilik	0.91	41.63	21	4
Public Clothing Company Inc	0.84	24.75	23	23
Target Stores	0.85	19.38	15	12
Zara	0.81	32.25	20	3
Auchan S.A.	0.71	29.00	19	21
Charles Vogele	0.69	17.25	18	13
The Children's Place	0.68	11.13	9	6
IFG Corporation	0.65	14.13	22	25
Top 100 (Market Share = 66%)				
Mean	0.66	17		
Median	0.29	12		
St. Deviation	0.99	13.74		
Coeff. Variation	1.49	0.81		
All Buyers (N = 1,578)				
Mean	0.06	4.55		
Median	0.01	3		
St. Deviation	0.30	5.95		
Coeff. Variation	5.04	1.31		

The top panel 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.

Table 3: Buyers' Sourcing and Prices

	(1)	(2)	(3)	(4)	(5)
			p_{sbjo}		
$Relational_b$	0.034***	0.024***	0.030***	0.024***	0.024***
	(0.009)	(0.007)	(0.008)	(0.009)	(0.008)
FEs	jy,d	sjy,d	sjy,d	sjy,d	sjy,d
Controls	.	.	B	B,R	B,R,O
R^2	0.31	0.60	0.60	0.64	0.73
Obs.	21,259	18,399	18,261	15,476	15,476

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. The outcome in all regressions is the log price of an order between a seller and a buyer in a given product category, p_{sbjo}. The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. Column (1) includes fixed effects at the level of the product-year and the destination (jy, d). Columns (2) to (5) account for seller-product-year and destination effects (sjy, d). While columns (1) and (2) do not include any other controls, columns (3) to (5) sequentially add buyer-, relationship- and order-level covariates, as follows. Buyer controls (B): 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), a dummy indicating whether the buyer is a signatory of the Accord or Alliance 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 buyer's trade, share of the buyer in all of seller's trade. Order controls (O): size of order (log volume), log price of fabric of the order.

Table 4: Buyers' Sourcing and Fabric Usage

	(1)	(2)	(3)	(4)	(5)	(6)
	p^f_{sbjo}		$(F/Q)_{sbjo}$		$Complex_{sbjo}$	
$Relational_b$	0.007	0.008	-0.003	-0.004	0.019	-0.005
	(0.006)	(0.007)	(0.006)	(0.008)	(0.013)	(0.011)
FEs	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d
Controls	.	B,R,O	.	B,R,O	.	B,R,O
R^2	0.65	0.69	0.38	0.45	0.47	0.58
Obs.	18,399	15,476	18,399	15,476	18,399	15,476

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. 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 as the regression outcome, p^f_{sbjo} (columns (1) and (2)), the buy-to-ship ratio of the order, $(F/Q)_{sbjo}$ (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 and destination fixed effects. Even numbered columns also include buyer-, relationship- and order-level controls, as described in the notes of Table 3.

Table 5: Buyers' Sourcing and Labor Usage

	(1)	(2)	(3)	(4)	(5)	(6)
	$Efficiency_{slb\tau}$		$\#Workers_{slb\tau}$		$Share\ Helpers_{slb\tau}$	
$Relational_b$	-0.003	0.015	-10.324	-0.091	0.003	0.006
	(0.033)	(0.026)	(7.214)	(0.771)	(0.004)	(0.005)
FEs	sm(τ),τ	sm(τ),sl,τ	sm(τ),τ	sm(τ),sl,τ	sm(τ),τ	sm(τ),sl,τ
R^2	0.28	0.39	0.73	0.97	0.94	0.95
Obs.	17,183	17,183	26,606	26,599	26,606	26,599

Standard errors in parentheses, clustered at the level of the buyer and production line. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. 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 labor efficiency of a particular line in a plant, producing for a buyer on a given day, $Efficiency_{slb\tau}$. Labor efficiency is a standard industry metric constructed as the ratio between the minutes-equivalent of the output and the minutes of labor input. In turn, the output is calculated Standard Minute Values times the number of pieces and the input is calculated using the number of workers times the runtime. See main text for a comprehensive description. The outcome in columns (3) and (4) is the number of workers active on the line, $\#Workers_{slb\tau}$, and in columns (5) and (6) it is the share of such workers that are line helpers, $Share\ Helpers_{slb\tau}$. 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 or Alliance agreements 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).

Table 6: Buyers' Sourcing and Inputs' Substitution

	(1)	(2)	(3)	(4)	(5)	(6)
			q^f_{sbjo}			
$p^{cotton}_{m(o)}$	-0.020**		-0.074***	-0.073***	-0.090***	-0.009
	(0.010)		(0.011)	(0.015)	(0.018)	(0.023)
$m(o) \geq MinWage$		0.088***	0.117***	0.128***	0.136***	0.027
		(0.010)	(0.011)	(0.014)	(0.018)	(0.033)
$Relational^D_b{=}1 \times p^{cotton}_{m(o)}$				-0.001	0.014	-0.004
				(0.022)	(0.026)	(0.031)
$Relational^D_b{=}1 \times m(o) \geq MinWage$				-0.020	-0.028	-0.031
				(0.020)	(0.023)	(0.029)
FEs	sj	sj	sj	sj	sj	sjy,d
R^2	0.95	0.95	0.95	0.95	0.95	0.96
Obs.	21,986	21,986	21,986	20,841	15,476	15,476

Standard errors in parentheses, clustered at the seller-product level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. All specifications have the log of the quantity of fabric used in the order, q^f_{sbjo}, as the outcome. All specifications include a control for the size of the order, in log kilos of garment, q_{sbjo} and a monthly linear time trend. Columns (1) to (5) include seller-product fixed effects (sj) and column (6) uses the baseline seller-product-year and destination effects (sjy, d). $p^{cotton}_{m(o)}$ is the log of the international price of cotton in the first month of the order. $m(o) \geq MinWage$ is a dummy that takes value one if the order started after the implementation of the minimum wage increase in November 2010. The analogous exercise (not reported here) using the wage inflation update in November 2006 shows the same pattern, but with an effect on the outcome smaller in magnitude, consistent with the size of the wage increase. The richer fixed effects in column (6) restrict the size of the sample. Column (5) reproduces the specification of column (4), in the restricted sample of column (6). $Relational^D_b$ is a dummy that takes value one if the buyer is in the top 10% of the distribution of the relational souring metric. The linear term is not reported for compactness.

Table 7: Buyers' Sourcing, Markups and Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	p_{sbjo}	mc_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}
$Relational_b$	0.024***	-0.001	0.025***	0.025***	0.025***	0.032***	0.028***	0.031***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.010)	(0.008)	(0.011)
FEs	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d	sjfoy,dq	sjy,d	sjy,d
Controls	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O
Robustness	.	.	.	Season	Product	Quality	Small b	Small s
R^2	0.73	0.63	0.41	0.41	0.41	0.59	0.41	0.44
Obs.	15,476	15,476	15,476	15,476	15,476	10,103	15,021	7,454

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10), **(p < 0.05), * * *(p < 0.01)$. The outcome in column (1) is the log price of an order between a seller and a buyer in a given product category, p_{sbjo}. The outcome in column (2) is the estimated log marginal cost of the order, mc_{sbjo}. In all other columns, the outcome is the log markup factor, μ_{sbjo}. The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. All columns include buyer-, relationship- and order-level covariates, as described in the notes of Table 3. All columns but (6) include seller-product-year and destination fixed effects. As such, column (1) simply reproduces the results of column (5) in Table 3 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 μ_{sbjo}. Columns (4) to (6) include rich sets of controls to condition on seasonality patterns, product specialization features and the physical quality of the order. These controls are described in detail in the notes of Table C4. 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.

Table 8: Sourcing and Reliability in Quality Provision

	(1)	(2)	(3)	(4)	(5)	(6)
	$Records_{slb\tau}$		$Defects\ Rate_{slb\tau}$		$Rejects\ Rate_{slb\tau}$	
$Relational_b$	0.083**	0.006	-0.002	-0.001	-0.001	-0.001
	(0.037)	(0.021)	(0.006)	(0.007)	(0.002)	(0.001)
FEs	sm(τ),τ	sm(τ),sl,τ	sm(τ),τ	sm(τ),sl,τ	sm(τ),τ	sm(τ),sl,τ
R^2	0.61	0.70	0.55	0.68	0.33	0.50
Obs.	66,401	66,397	17,214	17,212	18,894	18,893

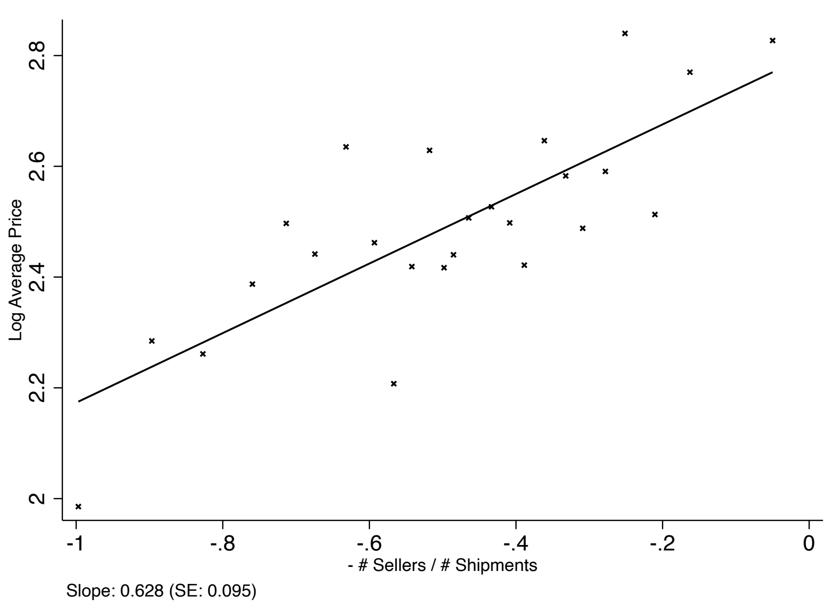
Standard errors in parentheses, clustered at the level of the buyer and production line. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. Across all specifications, the regressor of interest is the relational sourcing characteristic of the buyer (standardized). The outcome in columns (1) and (2) is an indicator that takes value one if the line keeps an administrative record of the quality control along the production process, $Records_{slb\tau}$. The outcome in columns (3) and (4) is the number of pieces recorded as defective divided by the total number of pieces produced by the line, $Defects\ Rate_{slb\tau}$, and in columns (5) and (6) it is the number of pieces recorded as rejected (or discarded) divided by the total number of pieces produced by the line, $Rejects\ Rate_{slb\tau}$. Note that columns (3) to (6) by construction condition on $Records_{slb\tau} = 1$. The discrepancies in sample size across columns (3) to (6) are due to the fact that not all plants keep the same administrative records with respect to quality assessment. All specifications include as controls for relevant buyer characteristics, its size and year of entry as a garment importer in Bangladesh and whether the buyer is a signatory of the compliance Accord or Alliance agreements as of 2019. 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).

Table 9: Sourcing and Reliability in Delivery

	(1) $Lead_{sbjo}$	(2) $Plane_{sbjo}$	(3) μ_{sbjo}	(4) μ_{sbjo}	(5) μ_{sbjo}	(6) μ_{sbjo}
$Relational_b$	-0.040**	-0.017*	0.024***	0.026***		
	(0.016)	(0.010)	(0.007)	(0.007)		
$Lead_{sbjo}$			-0.036***		-0.040***	
			(0.003)		(0.005)	
$Plane_{sbjo}$				0.038***		0.033**
				(0.010)		(0.014)
$Relational_b^D$					0.014	0.042***
					(0.028)	(0.016)
$Relational_b^D$=1 $\times$ $Lead_{sbjo}$					0.007	
					(0.007)	
$Plane_{sbjo}$=1 $\times$ $Relational_b^D$=1						0.011
						(0.019)
FEs	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d
Controls	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O
R^2	0.36	0.44	0.42	0.41	0.42	0.41
Obs.	15,476	15,476	15,476	15,476	15,476	15,476

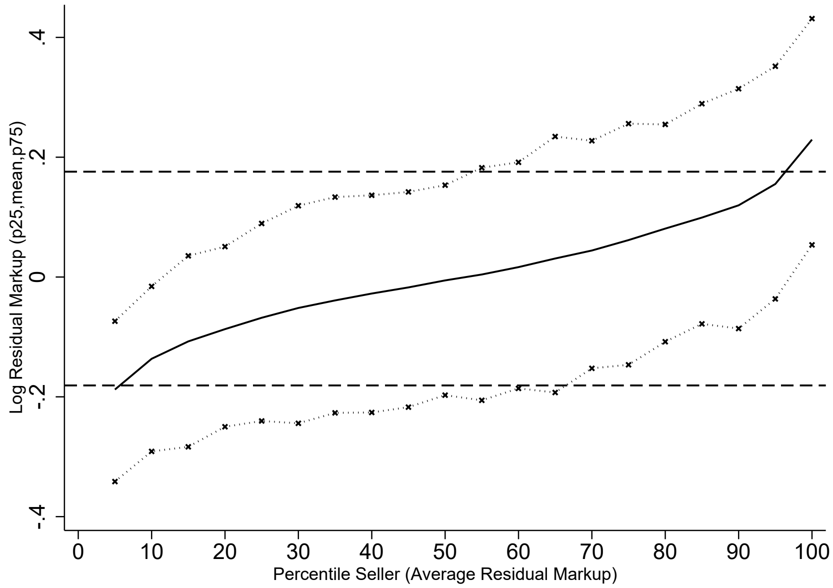
Standard errors in parentheses, clustered at the level of the buyer. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. The outcomes in the first two columns are, respectively, the 'lead time' of the order, $Lead_{sbjo}$, and whether the order was shipped by air, $Plane_{sbjo}$. $Lead_{sbjo}$ is constructed as the log number of days elapsed between the shipment into the country containing imported fabric for the order and the first shipment out of the country containing garment fulfilling the order. $Plane_{sbjo}$ is an indicator that takes value one if at least one export shipment in the order reports 'air' as mode of transport. These two variables are used as regressors in all other specifications. Across columns (1) to (4) the regressor of interest is the measure of sourcing of the buyer - continuous, standardized, increasing in the relational characteristic of the buyer. This is turned into an indicator collecting the top 10% of the distribution of the sourcing metric in columns (5) and (6), for ease of interpretation of the interactions. The outcome in columns (3) to (6) is the log markup factor, μ_{sbjo}. All specifications feature seller-product-year and destination fixed effects and include buyer-, relationship- and order-level covariates, as described in the notes of Table 3. In all cases, the estimation is via OLS.

Figure 1: Buyers' Prices and Sourcing of Men's Cotton Shirts



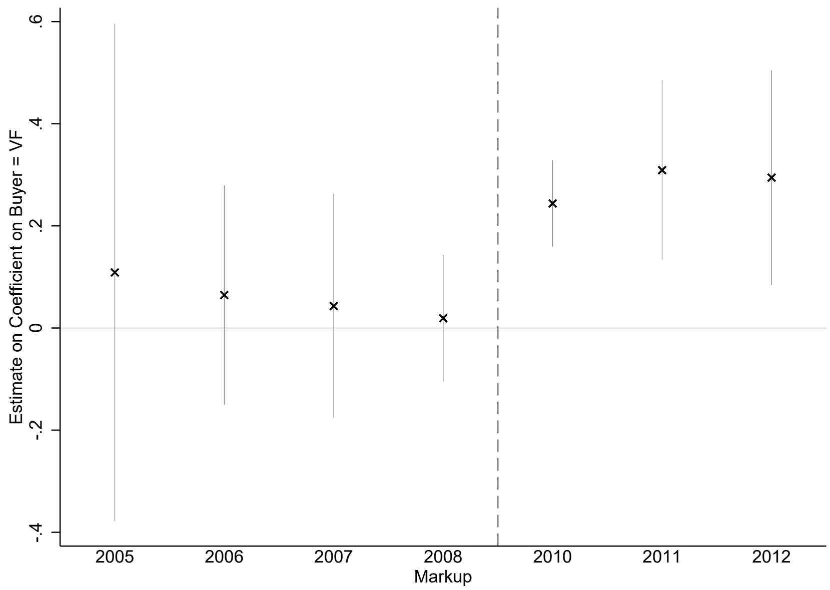
We consider the market for men's shirts made of cotton (HS code 620520). The horizontal axis captures (minus) the ratio between the number of sellers and the number of shipments that buyers have, throughout the data, in this product category. The vertical axis collects the log average price the buyer pays across all its shipments in the product category. The scatter markers correspond to averages of the underlying data partitioned in 25 quantiles (N=696). The solid line depicts the linear fit after a regression of prices on the sellers-to-shipments ratio, conditional on the destination of the buyer and its imported volume of cotton shirts. The note presents the estimated slope coefficient on the (minus) sellers-to-shipment ratio accompanied by its standard error. We note that the sourcing measure in the ratio of sellers to shipments (horizontal axis) is multiplied by -1 for consistency with the rest of this paper, where the sourcing metric is increasing on the relational characteristic of the buyer.

Figure 2: Dispersion in Markups across Buyers



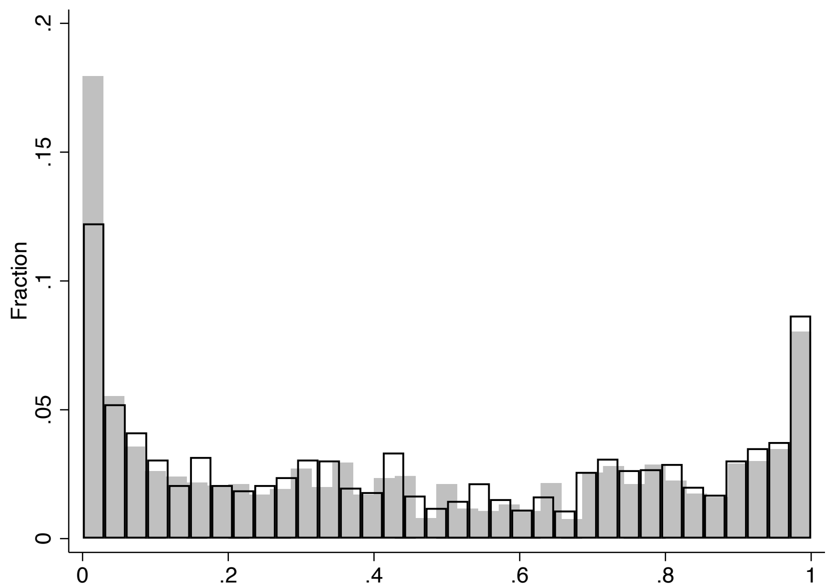
We aggregate order-level log markup factors for each seller-buyer-product-year combination, as weighted averages, where the weights are given by order volumes. We residualize these against product-year fixed effects. For each seller, we construct the simple average, 25^{th} and 75^{th} percentile markup across those residuals (discarding any seller with less than 10 data points). The horizontal axis arranges sellers ascendingly in percentiles according to their average markup. The solid line connects the average residualized markup in bins of 20 sellers. The dotted lines represent the 25^{th} and 75^{th} percentiles. The dashed horizontal lines correspond to the average interquartile range of residualized markups across sellers, centered around the average residualized markup of the median seller.

Figure 3: A Change in Sourcing Strategy



The figure plots estimated year-specific coefficients, β_r, on a dummy that takes value one when the buyer is VF, following specification (10). The excluded category corresponds to $VF \times I_{\tau(o)=2009}$. 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 on the first difference (time) in order level markups. The specification also includes buyer fixed effects, which absorb all buyer level controls (see, for example, Table 3) and the first difference in markups, comparing buyers with VF. Finally, we include relationship- and order-level covariates, as described in the notes of Table 3. The vertical bars correspond to 95% confidence intervals, when standard errors are clustered at the buyer-year level.

Figure 4: Share of Volumes Sold to Relational Buyers



The histogram shows the fraction of the volume of woven garments that each seller-year combination sells to relational buyers. Relational buyers are defined as those located in the top 10% of the distribution of the relational sourcing characteristic. The grey bars represent data for the 3,165 seller-year duplets in our sample. Across them, the average (median) share of volumes sold to relational buyers is 0.43 (0.37). The bars with black contours represent data for the subset of 2,934 that sell at least some volume to relational buyers. On this subsample, the average (median) share is 0.47 (0.42). Further trimming to this subsample, restricts the histogram to the 2,880 seller-year combinations that trade both with relational and non-relational. In that subsample, the average (median) is 0.46 (0.42). The histogram on this subset of observations is not reported in the graph for visual clarity.

A Sample Construction

In the empirical analysis, we focus on a subset of woven garment export products, comprising 17 six-digit HS codes, grouped more broadly into *trousers* and *shirts*. These account for approximately 86% of the exported volume in woven garments in our data. We discard export orders whose quality of underlying data is low, preventing a clean import-export matching exercise.[53] To mitigate sparseness in the data for our analysis, we only consider the top-500 exporters (out of approximately 1,500), who jointly account for 87% of the exported volumes in the subsample. Our final sample of 21,577 export orders accounts for approximately 37% of the Bangladesh's exports in the relevant product categories.

The order-level regressions that make use of the instrument for the size of the export order constructed as explained in the main text, necessitate a slightly more restrictive sample. In particular, the instrumentation strategy requires that the exporter is trading in the same quarter with *other* buyers, who in turn trade with *other* sellers. Together with use of fixed effects as granular as seller-product-year (where product is an six-digit HS code), this restriction renders a sample of 486 sellers with 16,500 export orders.[54]

Table A1 compares key shipment, buyer, seller, and relationship characteristics between the original sample and the two sub-samples described above.

Table A1: Sample Comparisons

Panel A: Average Shipment Characteristics

Shipments:	Count	Price (USD/kg)	Size (tonnes)
Under UD System	613,826	16.99	2.70
Outside UD System	5,181	15.35	1.76

Panel B: Firm and Relationship Characteristics

Orders:	Buyer Vol. (tonnes)	N_b^s	Seller Vol. (tonnes)	N_s^b	Rel. Vol. (tonnes)
Used in Analysis	228.96	13.71	504.83	20.09	75.40
Used in Estimation	368.80	21.44	500.40	21.47	93.07

The top panel compares shipments from orders in the UD system and shipments outside the UD system for buyers and sellers active in relevant products of the sub-sample used in the empirical analysis. A test of equal means finds that both average price and shipment size are not significantly different across samples. The bottom panel compares buyer, seller, and relationship characteristics for the two sub-samples used in the paper. Volumes are constructed as averages of yearly traded volume.

[53] Specifically, we work with export shipments that are channeled via the UD system, therefore ignoring isolated or stand-alone export transactions. Within this sub-sample, we exclude orders characterized as outliers (lower than 3% and larger than 97%) in the distribution of relevant observables: the buy-to-ship weight ratio, the output price, the input price, the cost share of fabric with respect to the order revenue. These conditions are satisfied for almost half of the volume exported in the relevant product categories.

[54] The instrument construction does not drop any individual seller, but discards some orders of these sellers, such that there is not enough variation within narrow clusters.

B Discussion on the Estimation of Markups and Costs

B.1 Garment Production Stages

The production of woven garments comprises two sequential stages: (i) inspection and cutting, and (ii) sewing and finishing. This section describes the processes that take place in each of these stages and explains the ways in which the plant might substitute fabric with other inputs.

Inspection and cutting. In the first stage, manufacturers inspect the quality and quantity of the purchased fabric, plan fabric utilization, and then proceed to cutting. To cut the fabric, manufacturers make markers, which are thin sheets of paper with diagrams indicating the pattern pieces to be cut for the specific style and sizes of an order. Manufacturers then spread the fabric on the cutting tables, cut the patterns, and finally ticket and bundle the pieces. Each of these tasks has a direct impact on fabric efficiency and relative labor, capital, and fabric input use. For example, manufacturers may use fabric inspection machines to check for fabric and print defects and shading. The markers for cutting can be made either by hand or by using software that automatically arranges the pattern pieces to reduce fabric waste. Spreading can also be done by hand (using a spreading table with roll racks, tracks, clamps, lifters, and end cutters) or by automatic spreading machines. Finally, cutting can be performed using manual, semi-automatic, or automatic systems, employing a variety of portable cutters (rotary or straight knives) or stationary cutters (band, die, laser, etc.), and either manually handling the fabric or holding it in place using a vacuum to avoid distortions and misalignment in the spread.

Sewing and finishing. In the second stage, cut fabric is sent to the sewing department, where cut fabric pieces are sewn together along production lines. Depending on the type of garments, fabric, and machines, production lines typically employ between 30 and 70 sewing operators and one or more line supervisors. The quality of the machines, the number and quality of sewing operators, and the effort of supervisors all affect the efficiency with which garments are sewn together. From the point of view of fabric use, there can be fabric losses at the sewing stage due to quality defects such as stains or garments sewn incorrectly. These losses can be reduced by including additional quality-control workers alongside the sewing lines. Factories can organize one or more inspection points along and at the end of the production line, or simply inspect quality in the finishing section, when the garment is pressed or ironed, finished, and packed.

B.2 Modeling Garment Production

Our description of the two stages of garment production provides insight into the possible sources of variation in the buy-to-ship ratio. To understand these further and guide our estimation framework, we next elaborate on important characteristics of the garment production process and discuss how to model them.

Dispersion in buy-to-ship ratios. We describe further evidence from within-firm studies documenting the sources of variation in buy-to-cut and cut-to-ship ratios.

The engineering study of Tanvir and Mahmood (2014) examines 30 Bangladeshi factories producing single jersey standard shirts. This study finds that fabric wastage is on average 8%; that is, out of 100 kilos of fabric that enter a factory, on average only 92 leave the factory in the form of garments. This metric varies significantly across factories, ranging between 1.6% and 19.2%. The authors find that most of this dispersion originates in the inspection and cutting stage, namely in differences in the buy-to-cut ratios (see Table B1).

Using data on reject rates and other defects from Macchiavello et al. (2015), we find that there is also variation in the sewing and finishing stage, namely in the cut-to-ship ratios. We examine a sub-sample of 6,000 orders that are included in the daily production records from the 51 factories (1,344 sewing lines) studied in Macchiavello et al. (2015). The reject rates at the final inspection point on the sewing line vary from 0% to 5% across these orders. This figure however is only a lower bound for the actual dispersion in the cut-to-ship ratios. One reason is that, while rejections lead to a complete waste of the garment's fabric, there is also partial fabric waste at this stage due to defects. A piece of garment that passes the end-of-line quality control may have required fabric-wasting corrections or alterations at intermediate points in the sewing process. A second reason is that data on end-of-line inspection points are available for relatively better managed factories, which tend to have inspection points alongside some of (usually not all) the sewing lines. Other factories instead only inspect quality in the finishing section, and given related observations in Tanvir and Mahmood (2014), we may expect these factories to exhibit even higher dispersion in wasted fabric.

Input substitutability. To reduce production costs, garment manufacturers have flexibility to substitute, to a certain extent, between fabric and other inputs. This can also contribute to the variation in buy-to-ship ratio observed in the data. An increase in the price of fabric incentivizes manufacturers to adopt fabric-saving practices, whereas an increase in the wage of sewing line operators incentivizes them to cut worker hours. Table 6 provides supportive evidence on the presence of this input substitutability. We relate the (logged) amount of fabric imported at the order level to two exogenous sources of variation in input prices (while controlling for order size, firm-product fixed effects, and a time trend). First, we study the effects of changes in the international price of cotton, noting that cotton is the most common material found in fabrics used for garment production in Bangladesh. Columns (1) to (3) of Table 6 show that, as anticipated, higher cotton prices translate into lower import volumes of fabric to produce orders of a given size. Second, we consider the effects of a policy that significantly increased the minimum wage in Bangladesh in November 2010. Also as expected, we find that the increase in labor costs translated into higher import volumes of fabric. While these correlations should be interpreted with caution, the results are in line with accounts of the industry.

In sum, we find that a model of garment production should accommodate three important characteristics: (1) a production process that operates at the order level (also see description of the UD system in Section 2), (2) fabric efficiency that may differ across orders, and (3) a technology that allows for substitution across inputs. The framework we propose in Section 4.1 incorporates these characteristics into a technology that transforms material fabric inputs and labor into garments. We address (1) by specifying this production function at the order level. We address (2) by allowing for a productivity shock at the order level. Finally, we address (3) with a flexible specification in which fabric enters production in a log additive separable fashion, can be substituted for labor of different types, subject to capacity constraints accounting for the possibility of fixed or quasi-fixed factors of production.

In Section B.3 we restrict the production function to be Cobb-Douglas for the purpose of estimating the elasticity of output to fabric, needed for the recovery of markups in levels. While there are different formulations that could be used to address (1)-(3), the Cobb-Douglas has at least two features that we find appealing. The first one is that a Cobb-Douglas function can emerge from the aggregation of production stages when the stage-level technology is either also Cobb-Douglas or is Leontief with Pareto distributed technical coefficients (see, e.g., Houthakker, 1955 and Jones, 2005). This is fitting for our context, where, as we have documented, the production process involves a number of sequential stages. In fact, as a microfoundation, if this process is partitioned into sufficiently small activities, then the technology for each such activity could be represented as one with fixed proportions, and as such our Cobb-Douglas function may be suitable to model the aggregate process. This aggregate process is the one that we observe in our data.[55]

The second convenient feature of the Cobb-Douglas function relates to our estimation strategy. As we explain in detail in the sections to follow, to obtain the levels of markups and marginal costs, we need to first estimate output elasticities. The Cobb-Douglas production functional form assumes constant output elasticities for a given disaggregation level of the production function parameters. This allows us to perform our estimation even though we observe fabric use and not the usage of labor or capital, which would be necessary if allowing for a more flexible production function like the translog. It is however important to stress that we need the elasticity of output to fabric only to compute the levels of markups. Our main results, which focus on exploring difference in markups across buyers within seller-product-time combinations, *do not* rely on the measurement of the output elasticities and are consistent with very flexible production functions in which the output elasticity varies at the seller-product-year level, for any production function.

B.3 Estimating Fabric-Output Elasticity: A Framework

In Section 4.1 we develop a parsimonious model of garment production that allows us to recover deviations in markups, across orders, within seller-product-time combinations. We can directly map the components of these markup deviations to readily available information in our data. In this section we extend this framework with the purpose of recovering, from our data, the level of markups and marginal costs in each order.

Naturally, the estimation of orders' markups and marginal costs in levels requires an estimate of θ, the elasticity of output to fabric. This section derives a structural input demand equation that identifies the fabric elasticity. We assume a Cobb-Douglas production function with fabric (labor) output elasticity θ (β).[56]

[55] More broadly, a more flexible production function, such as a translog, can be approximated to a first-order with a Cobb-Douglas function.

[56] For clarity, the rest of this section presents derivations for the case $Z = 1$, i.e. one type of labor z only.

We introduce two additional assumptions:

1) we assume that wages can vary by product, time period, and seller, but not across orders or buyers for the same product-time-seller combination (i.e., we assume $W_o = W_{sjt}$).[57] This significantly relaxes assumptions commonly made in the literature.

2) we require that the first order condition for the labor input, L_o, also holds exactly. This takes the form

$$L_o = \frac{\beta}{\widetilde{W}_{sjt}} Q_o \lambda_o, \tag{B1}$$

with $\widetilde{W}_{sjt} \equiv W_{sjt} + \lambda^L_{st}$.

We combine the Cobb-Douglas structure in production, the first order condition for fabric (see Section 4.1) and (B1), and solve for the observable buy-to-ship ratio, F_o/Q_o. Taking logs, we obtain a structural equation that relates an order's buy-to-ship ratio to the order's size, the price of fabric used for producing the order, and two additional terms:

$$\ln \frac{F_o}{Q_o} = \frac{1-\beta-\theta}{\beta+\theta} \ln Q_o - \frac{\beta}{\beta+\theta} \ln P^f_o + \frac{\beta}{\beta+\theta} \ln\left(\frac{\theta \widetilde{W}_{sjt}}{\beta}\right) - \frac{1}{\beta+\theta}\omega_o. \tag{B2}$$

In principle, the framework allows for flexible production function parameters θ_o and β_o. In practice, in estimating (B2) we are constrained by the amount of variation in the data and we obtain more precise estimates when we restrict the elasticity to be common across all orders.[58] Exercises in which we allow for further disaggregation reveal nearly identical estimates.

The following relabeling is convenient: $\gamma_1 \equiv \frac{1-\beta-\theta}{\beta+\theta}$, $\gamma_2 \equiv -\frac{\beta}{\beta+\theta}$. The third term in (B2) reflects a seller-product-time-specific shifter, whenever the production function elasticities vary at most at that level of disaggregation, i.e. $\theta_o = \theta_{sjt}$ and $\beta_o = \beta_{sjt}, \forall o \in O_{sjt}$. Let this shifter be denoted $\delta_{sjt} \equiv -\gamma_2 \ln(\theta \widetilde{W}_{sjt}/\beta)$, and $\varepsilon_o \equiv -\omega_o/(\beta+\theta) + \nu_o$, where ν_o is an econometric error. Allowing for this error and simplifying terms in (B2) by means of the proposed notation yield the estimating equation:

$$\ln \frac{F_o}{Q_o} = \gamma_1 \; q_o + \gamma_2 \; p^f_o + \delta_{sjt} + \varepsilon_o, \tag{B3}$$

where lowercase letters denote logged variables.

The dependent variable in (B3) is the buy-to-ship ratio at the order level, which is directly observed in our data. The first two explanatory variables on the right-hand side are also observable; these are the order size q_o and the price of fabric p^f_o. Instead, the third explanatory term, δ_{sjt}, is not observable in our data. It is a function of the wage W_{sjt}, which is common across orders for a given seller-product-time combination, and the

The extension to any number of Cobb-Douglas inputs is immediate.

[57]In the presence of this assumption, it continues to be possible to extend the model to multiple production factors, flexible or subject to capacity constraints, without altering the structural equation derived below. Sellers in our model could be allowed to choose different bundles of operators, supervisors, and machines across different products, provided that the prices of these inputs vary at the seller-product-time level only.

[58]Note that this assumption, i.e. $\theta_o = \theta \; \forall o$, is significantly stronger than the assumption $\theta_o = \theta_{sjt}$ $\forall o \in O_{sjt}$ used to recover differences in markups in Section 5.

Lagrange multiplier λ^L_{st}, which varies at the seller-time level. We remind the reader that this multiplier is a sufficient statistic capturing the interdependence in input choices across orders arising from prices and capacity constraints. We can flexibly control for δ_{sjt} by including seller-product-time (i.e., sjt) fixed effects: while we lack information on labor and capital, our order-level data allows us to circumvent this challenge by exploiting the structural equation of order-level buy-to-ship ratios. The sjt fixed effects control not only for the interdependence across orders but also for unobservable factors and productivity shocks that affect buy-to-ship ratios and are common across orders at the sjt level.[59] Finally, the fourth explanatory variable on the right-hand side of (B3) includes an order-specific productivity deviation, which is not observable.

Estimating equation (B3) allows us to construct our variables of interest in levels: specifically, from the estimated coefficients $\widehat{\gamma}_1$ and $\widehat{\gamma}_2$, we compute the estimated elasticities $\widehat{\theta} = (1+\widehat{\gamma}_2)/(1+\widehat{\gamma}_1)$ and $\widehat{\beta} = -\widehat{\gamma}_2/(1+\widehat{\gamma}_1)$. We then combine $\widehat{\theta}$ with observable prices and quantities to obtain estimated marginal costs and markups at the order level, $\widehat{\lambda}_o = P^f_o F_o/(\widehat{\theta} Q_o)$ and $\widehat{M}_o = P_o/\widehat{\lambda}_o$. We next discuss the approach that we use for estimating equation (B3).

B.4 Estimation of Elasticities

The recovery of elasticity θ by means of estimation of equation (B3) poses a number of challenges. Our baseline approach is an OLS estimation of a unique θ across all orders. We explore alternatives to this approach, to accommodate variations to our modeling assumptions that would lead to specification problems in equation (B3). We discuss each of these concerns, before presenting the alternative estimation approaches.

First, since quantities q_o are obtained from customs records, measurement error is likely present in our data. In its classical form, measurement error would bias our estimate of $\gamma_1 \equiv \frac{1-\beta-\theta}{\beta+\theta}$ towards zero, thus yielding $\beta + \theta = 1$ even when the production technology does not exhibit constant returns to scale. Second, a similar concern applies to measurement error in the price of fabric p^f_o after which, other things equal, θ would be biased upwards towards $(1+\gamma_1)^{-1}$. Third, we derived equation (B3) under the assumption that productivity and the shadow price of labor are captured by a seller-product-year-specific shifter of the buy-to-ship ratio. Systematic deviations of productivity or the underlying production constraints that are correlated with volumes would bias our estimate of γ_1. In particular, misspecified productivity can overstate the scale coefficient and bias our estimates of θ upwards. Similarly, a fourth and related concern arises if the price of fabric is correlated with the error term. Such scenario appears relevant in the presence of omitted inputs whose prices vary order by order concomitantly with the cost of fabric or if bargaining power upstream is not fully captured by seller-product-time effects (e.g., if fabric prices are negotiated by the buyer).

We address these issues performing a range of different estimation exercises. Across various specifications described momentarily, the estimate of the output-to-fabric elasticity θ is always around 0.6. All specifications also yield nearly constant returns to scale at the order level. The estimate of θ is thus remarkably consistent with industry reports and costing sheets, which show that fabric represents roughly two thirds of variable unit costs in garment

[59] Note also that the inclusion of sjt fixed effects in the estimating equation allows us to recover the relevant elasticity even in the presence of exporters' market power upstream as described in Morlacco (2019).

production. We also find that the availability of detailed information on the heterogeneous input prices and varying allocation of fabric across orders is crucial for the recovery of θ: estimating equation (B3) ignoring these features of our data yields implausible large output fabric elasticities.

An IV strategy mitigates issues arising from measurement error and/or endogeneity of the order size with respect to unobservables governing the buy-to-ship ratio. The center of Panel A in Table B2 presents the estimate of θ after instrumenting the size of the order in (B3) with volumes traded by third parties connected through the network of buyers and sellers. A full description of the construction of this instrument is included below and diagnostics showing a strong first stage are presented in column (1) of Table B3. The estimated elasticity is 0.615, very close to the point estimate under OLS, 0.623 (leftmost column in Panel A of Table B2). The similarity between the OLS and IV estimates suggests that productivity shocks that correlate with the buy-to-ship ratio and with the size of the order are well captured by the seller-product-time fixed effects. Additional order-specific productivity shocks (e.g., worker absenteeism due to hartals, power cuts, etc.) are plausibly *ex-post*, this is, revealed after the size of the order has been set.

As described above, another set of concerns arises from the fact that there might be (unobservable) factors that correlate with both the price of fabric and with the buy-to-ship ratio, even conditional on seller-product-year fixed effects. Of particular interest is the possibility that garment buyers have market power upstream. The discussion and evidence presented in the main text suggest this mechanism is not supported by our data. Here we propose two approaches to address this issue directly. First, we instrument for fabric prices in the structural equation (B3). We pursue this strategy exploiting data on international prices of cotton in the main origin from which the fabric is sourced. The exclusion restriction requires that the unobservables in equation (B3) are uncorrelated with shifts in the international price of cotton and with exchange rates (details on the construction of the instrument are included in the text below). The rightmost columns of Panel A in Table B2 present the estimate of θ after instrumenting for both the size of the order (as described above) and the price of fabric. The elasticity is slightly lower (0.544) than the one obtained via the OLS approach, but is accompanied by much higher standard errors, inherited from a borderline first stage (see column (3) of Table B3).

The inclusion of the sjt fixed effects, however, yields a weak first stage. Given this, we also address the potential endogeneity of fabric prices to unobserved buyer-specific characteristics via a second approach. We augment equation (B3) to include buyer-specific fixed effects (see equation (B4) below). Panel B of Table B2 presents the elasticities obtained from estimating this augmented equation for the buy-to-ship ratio, by OLS (left side) and IV on quantities (right side). The elasticities obtained under these are 0.591 and 0.583 respectively (first stage diagnostics for the IV included in column (2) of Table B3). These estimates are very close to those obtained in estimations without buyer fixed effects. This assuages the concern that buyers of garment have market power two tiers upstream or that choices of fabric at the order-level (e.g., with respect to fabric type) are influenced by the buyer in ways that correlate with order-level efficiency.

Our main interest in this paper is the study of dispersion in marginal costs and markups across orders sold to different buyers. The estimation approaches considered in this appendix constrain the elasticity of output to materials to take a unique value across all orders, products, buyers and sellers. If the true parameter was not constant along all those dimensions, our estimation would understate the amount of dispersion in the level of marginal costs and markups by underestimating heterogeneity in technology.[60] Given our focus, a relevant concern is that the elasticities vary with the sourcing strategy of the buyer. Panel C of Table B2 presents estimates of elasticities that are specific to whether the buyer is relational or not (i.e. is, spot). These follow the specification in equation (B5) described below, which is estimated by OLS and IV. The inclusion of fixed effects at the $sjt\bar{b}$, with $\bar{b} \in \{Relational, Spot\}$ depending on the sourcing strategy of the buyer, yields a weak first stage: including seller-product-time-sourcing fixed effects absorbs most of the relevant identifying variation in the instrument.[61] The elasticities that we obtain are 0.592 for relational buyers and 0.638 for spot buyers in the OLS and, respectively, 0.590 and 0.618 in the IV. Very close to each other, we cannot reject the null hypothesis that the elasticity of output to fabric is the same across the two types of buyers. This result reinforces the earlier evidence on suppliers not operating significantly different technologies when producing for buyers of different sourcing characteristics.

The following paragraphs develop in detail the alternative estimation approaches described here. All relevant results are presented in Tables (B2) and (B3).

Instrumenting for quantities. To assuage measurement error and endogeneity concerns in the regressor capturing quantities, we instrument for the size of the order, q_o. Our IV strategy leverages the observed network of trade partnerships. The key identifying assumption is that buyers cannot adjust their orders in response to shocks that are realized after orders have been allocated with sellers. Put differently, buyers take into account any information they have on the demand and seller-product-year characteristics when placing their orders, but they cannot respond to ex-post production shocks (for example, unexpected disruptions on the sewing line) that occur after orders have been assigned and production decisions have been made. This assumption does not appear to be too restrictive in light of the actual timing of events in the negotiation, production and delivery of a typical order.

Specifically, consider an example in which buyer b places an order with seller s, where we denote the order size by q_{sb}. Suppose that b also sources from another seller, s', who in turn sells to another buyer, b'. Importantly, in this example, b' is not a trade partner of s. We thus use the volume traded between s' and b', which we can label $q_{s'b'}$, as an instrument for q_{sb}. The argument for relevance is as follows. If b' receives a positive demand shock in its domestic market at the time of allocating orders, then it will order a large volume $q_{s'b'}$ from seller s'. Under capacity constraints, this means that seller s' will not be able to accept large volumes from buyer b, who, as a result, will tend to allocate a larger volume to seller s. To understand the exclusion restriction, note that since orders are allocated before production shocks occur, $q_{s'b'}$ is not a function of ω_o (or, in our example, ω_{sb}), the order-specific shocks

[60]Note that this limitation only applies to the recovery of markups and marginal costs in levels. The rest of the paper (in particular Section 5) is compatible with elasticities that vary flexibly at the level of the seller-product-time combination.

[61]As explained in this Appendix, the mechanics of the construction of the instrument are such that, while the potentially endogenous regressor, q_{sbjo} varies with each order, the instrument is only seller-buyer-time specific. To the extent that a seller might be trading with one buyer of each type $\bar{b}$ at a time, the fixed effect absorbs the instrument.

that s faces in the production of the order for buyer b.

More generally, take an order o of size q_o placed by buyer b with seller s in quarter τ. We identify the sellers other than s who trade with b, and we use as an instrument for q_o the volume that these sellers trade in quarter τ with buyers other than b who are not trading with s. That is, for any firm (buyer or seller) i, denote by $\mathcal{N}_i$ the set of i's trade partners in quarter τ, and let $\mathcal{N}_i \backslash \{k\}$ be this set excluding partner k. Then the instrument for q_o is the log of:

$$z_{sb\tau} = \frac{1}{\#\{\mathcal{N}_b \backslash \{s\}\}} \sum_{m \in \mathcal{N}_b \backslash \{s\}} \frac{1}{\#\{\mathcal{N}_m \backslash \mathcal{N}_s\}} \sum_{n \in \mathcal{N}_m \backslash \mathcal{N}_s} Q_{mn\tau},$$

where $\#\{\cdot\}$ is the cardinality of the set in the argument. Note that while the instrumented regressor q_o is an order-level variable, the instrument is constructed at the seller-buyer-quarter-level. This higher level of aggregation is needed due to sparsity in our data but has almost no impact on our estimation in practice since our sample is dominated by buyer-seller-quarter triplets with unique orders.

Instrumenting for the price of fabric. To address measurement error and potential endogeneity of input prices in equation (B3), we instrument for the price of the fabric, p_o^f. To this end, we leverage the rich information we have on the dates of import shipments relevant to the order and the origins of each fabric shipment. Specifically, we use the international price of cotton in the month of the order, converted from dollars to the relevant currency using the exchange rate between the main country of origin of the fabric and the US dollar, in the corresponding month.[62]

Buyer Fixed effects. Equation (B3) includes a seller-product-time-specific term, capturing the market and shadow prices of inputs other than fabric. The baseline estimation absorbs this term, unobservable to us, in a fixed effect that removes variability in the error term at that level of aggregation. This device mitigates several concerns with the specification at hand. In particular, it allows for the unobservable productivity to be specific to a seller-product-time combination. This nests the standard assumptions the literature puts in place when estimating production functions in manufacturing, normally at higher levels of aggregation. The fixed effect also captures rich bargaining protocols upstream. For example, it allows for garment manufacturers negotiating prices with a textile supplier for all the orders to be produced in, say, a product-year combination. A remaining concern specific to our context, however, is that the international buyer directly negotiates the fabric price with the foreign fabric supplier. To overcome this concern we estimate a version of (B3), including buyer fixed effects:

$$\ln \frac{F_o}{Q_o} = \gamma_1 \ q_o + \gamma_2 \ p_o^f + \delta_{sjt} + \delta_b + \varepsilon_o, \tag{B4}$$

[62]In practice, we also include an interaction between the price of cotton in local currency and an indicator that takes value one if the order uses fabric from one origin only. This allows for the slope of the international price of cotton in the first stage regression to differ for orders in which the main origin is the only relevant one, relative to orders sourcing from multiple origins and for which the currency conversion might be noisier.

Buyer's Sourcing Strategy and Elasticities. In principle, the framework presented in Section 4.1 allows for flexible production function parameters θ and β. In practice, when estimating elasticities in (B3) we are constrained by the amount of variation in the data. In the baseline specification, we fix these elasticities to be common across all orders in the data. We introduce one relevant extension to this specification, following

$$\ln \frac{F_o}{Q_o} = \gamma_{1\bar{b}}\; q_o + \gamma_{2\bar{b}}\; p_o^f + \delta_{sjt\bar{b}} + \varepsilon_o, \tag{B5}$$

where the two coefficients of interest, γ_1 and γ_2, are allowed to vary at a disaggregation level of $\bar{b}$. Given the structural components collected in δ, allowing the elasticities to vary at level $\bar{b}$ requires that we introduce richer fixed effects of the form $\delta sjt\bar{b}$. Specifically, $\bar{b}$ reflects the relational characteristic of the buyer of the order, i.e. $\bar{b} \in \{Relational_b, Spot_b\}$. Like in the rest of the paper, we define a buyer to be *Relational* if it falls in the top 10^{th} percentile of the distribution of the relational characteristic. All other buyers are defined as *Spot*, for the purpose of this discrete classification. The extension here, allowing for sourcing-specific elasticities is particularly relevant, given the focus of the analysis in the main text.

Naïve estimation with insufficient data. To illustrate the importance of the data on input utilization at the order-level, we conclude by estimating equation (B3) by OLS ignoring the available information. First, we ignore the information on order-specific input prices. In this exercise, we assume that all sellers pay the average price of fabric (across all orders and sellers) when producing a product (HS6 code) in a given month. This severely underestimates the responses of buy-to-ship ratios to changes in the price of fabric and, with this, overstates the elasticity of output to materials, which is now estimated to be 0.99. In the second exercise, we ignore the information on the allocation of inputs to outputs. We assume that we observe the total volume of fabric purchased by the seller-buyer combination in a year, F_{sbt}, but not the amount of fabric devoted to each order, F_o. We split the volume in F_{sbt} across orders proportionally to the share of the order in the $-sbt$ combination, i.e. Q_o/Q_{sbt}. As expected, the loss of informative identifying variation produces coefficients on the order size and the price of fabric that approach zero; θ is biased towards one and estimated to be 0.86. When combined with cost shares, these elasticities would result in significantly larger estimates of markups.

References

Houthakker, H S, "The Pareto Distribution and the Cobb-Douglas Production Function in Activity Analysis," *Review of Economic Studies*, January 1955, *23* (1), 27–31.

Jones, Charles I, "The Shape of Production Functions and the Direction of Technical Change," *The Quarterly Journal of Economics*, May 2005, *120* (2), 517–549.

Macchiavello, Rocco, Andreas Menzel, Atonu Rabbani, and Christopher Woodruff, "Challenges of Change: An Experiment Training Women to Manage in the Bangladeshi Garment Sector," *mimeo*, December 2015.

Tanvir, Saiful Islam and Tarique Mahmood, "Solid Waste for Knit Fabric: Quantification and Ratio Analysis," *Journal of Environmental and Earth Science*, 2014, *4* (12), 68–80.

Table B1: Fabric Input and Waste over Production Stages

Factory Number	Input Quantity (KG)	Inspection Loss (KG)	Cutting Loss (KG)	Sewing Loss (KG)	Finishing Loss (KG)	Total Waste (KG)	% of waste
	$A1$	(1)	(2)	(3)	(4)	$A2$	$(A1/A2) \times 100$
1	700	35	50	20	10	115	16.25
2	750	30	40	25	15	110	14.67
3	780	40	50	15	10	125	16.03
4	800	25	30	30	20	105	13.13
5	820	20	45	30	15	110	13.42
6	880	25	40	35	20	120	13.63
7	910	50	70	30	25	175	19.24
8	950	45	65	25	20	155	16.34
9	990	25	35	35	15	110	11.12
10	1,000	50	50	30	10	140	14
11	1,100	25	40	25	5	95	8.64
12	1,900	100	100	50	40	290	15.27
13	2,000	80	60	30	50	120	6
14	2,300	110	100	50	20	280	12.18
15	2,500	25	20	10	5	60	2.4
16	3,000	20	40	30	10	100	3.34
17	3,200	60	35	20	20	135	4.26
18	3,600	50	30	10	15	105	2.9
19	3,900	90	35	30	20	175	4.49
20	4,000	80	30	25	25	160	4
21	4,100	40	25	50	20	135	3.3
22	4,250	35	30	30	10	105	2.48
23	4,400	55	25	50	5	135	3.06
24	4,700	70	30	30	5	135	2.89
25	5,000	65	25	50	10	150	3
26	14,000	50	120	20	45	235	1.68
27	1,100	25	15	25	10	75	6.8
28	24,200	220	200	50	40	470	2
29	23,100	140	180	45	30	385	1.6
30	1,600	10	10	25	5	50	3.1
Total	136,930	1,585	1,325	930	540	4,240	

This table is taken from Tanvir and Mahmood (2014) and shows data on fabric wastage from 30 Bangladeshi garment factories surveyed in their study.

Table B2: Elasticities and Returns to Scale

Panel A: OLS and IV, sjy fixed effects						
	OLS		IV: Quantities		IV: Quantities, Fab. Price	
	Coeff	SE	Coeff	SE	Coeff	SE
Materials: θ	0.623	0.016	0.615	0.016	0.544	0.28
Labor: β	0.445	0.016	0.343	0.026	0.453	0.273
RTS: $\theta+\beta$	1.068	0.003	0.958	0.025	0.998	0.013

Panel B: OLS and IV, sjy, b fixed effects				
	OLS		IV: Quantities	
	Coeff	SE	Coeff	SE
Materials: θ	0.591	0.017	0.583	0.017
Labor: β	0.48	0.017	0.398	0.073
RTS: $\theta+\beta$	1.071	0.004	0.981	0.076

Panel C: OLS and IV, $sjy\bar{b}$ fixed effects, sourcing-specific elasticities ($\bar{b} \in \{R, S\}$)				
	OLS		IV: Quantities	
	Coeff	SE	Coeff	SE
Materials: θ^R	0.592	0.028	0.59	0.028
Labor: β^R	0.471	0.029	0.301	0.029
RTS: $\theta^R+\beta^R$	1.064	0.005	0.891	0.005
Materials: θ^S	0.638	0.023	0.618	0.023
Labor: β^S	0.438	0.022	0.341	0.022
RTS: $\theta^S+\beta^S$	1.076	0.005	0.961	0.005
Test $\theta^R=\theta^S$ (χ^2)	1.70; pval: 0.192		0.73; pval: 0.392	

Panel D: Naïve Estimations, OLS, , sjy fixed effects				
	OLS: Naïve Allocations		OLS: Naïve Prices	
	Coeff	SE	Coeff	SE
Materials: θ	0.865	0.011	0.999	0.024
Labor: β	0.164	0.011	0.058	0.023
RTS: $\theta+\beta$	1.029	0.002	1.057	0.003

The table reports detailed results of the main estimation strategies used for computing the elasticities of output to materials and labor, θ and β, respectively, on the sample of 16,500 garment orders. Panel A shows the elasticities resulting from the estimation of equation (B3) using our data. The underlying specification includes seller-product-time fixed effects. The leftmost panel performs the estimation using OLS. The central block reports the results of the IV strategy when only the size of the order, q_{sbjo}, is instrumented for. The rightmost block presents results from the IV strategy when both quantities and the price of fabric, p^f_{sbjo} are instrumented for. The first stages of all IV (2SLS) procedures, in all panels of this table, are reported in Table B3. Panel B shows the elasticities using the augmented specification in equation (B4), which to (B3) adds buyer-specific fixed effects. The estimation is again performed via OLS (left) and IV instrumenting the size of the order (right). Panel C presents elasticities that are specific to the sourcing strategy of the buyer, obtained via the OLS and IV estimation of equation (B5). At the bottom of this panel we include the test statistic for the null hypothesis that the elasticity of output to fabric is no different across buyers with the different sourcing strategies. Panel D presents the elasticities obtained via the OLS estimation of equation (B3), with data that we artificially restrict to mimic limitations present in commonly available datasets: the unobservability of the allocation of inputs to output and the setting of input prices to be common to all orders and manufacturers. We present the results on this under the headings of "OLS: Naïve Allocations" and "OLS: Naïve Prices". Please refer to the text in Appendix B.3 for further details. The standard errors in all panels are bootstrapped drawing, with replacement, the entire vector of export orders for each seller (in all products and time periods).

Table B3: First Stage Regressions and Diagnostics

Panel A: Unique Elasticity

	(1)		(2)		(3)			
Instrumentation:	Quantities Only		Quantities Only		Quantities and Fabric Price			
Equation:	q_{sbjo}		q_{sbjo}		q_{sbjo}		p^f_{sbjo}	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
$z_{sb\tau}$	0.095	0.010	0.055	0.012	0.085	0.010	0.004	0.002
p^f_{sbjo}	-0.568	0.051	-0.509	0.049				
p^c_{sbjo}					0.125	0.014	0.012	0.002
$p^c_{sbjo} \times \mathbf{1}\{\#fabric = 1\}$					-0.223	0.013	-0.001	0.002
Fixed effects	sjy		sjy,b		sjy			
First Stage K-P (F weak)	113.55		23.16		9.04			
First Stage K-P (LM underid)	103.77		24.06		26.87			

Panel B: Sourcing-specific Elasticities

	(1)			
Instrumentation:	Quantities Only			
Equation:	q_{sbjo}		$q_{sbjo} \times Relational^D_b$	
	Coeff	SE	Coeff	SE
$z_{sb\tau}$	0.091	0.014	0.000	0.000
$z_{sb\tau} \times Relational^D_b$	-0.002	0.030	0.089	0.027
p^f_{sbjo}	-0.472	0.073	0.000	0.000
$p^f_{sbjo} \times Relational^D_b$	-0.108	0.107	-0.581	0.080
Fixed effects	sjy$\bar{b}$			
First Stage K-P (F weak)	6.27			
First Stage K-P (LM underid)	13.00			

The table reports results of the first stage estimations corresponding to the IV strategies used for recovering elasticitie, as reported in Panels A, B and C of Table B2. In all cases, the first stage equations include seller-product-year fixed effects. The specifications whose header read 'Quantities only' treat the price of fabric, p^f_{sbjo}, as exogenous and the size of the order, q_{sbjo}, as endogenous; those reading 'Quantities and Price of Fabric' instrument both variables. The instruments are the competitors' trade variable constructed using the trade network instrument described in the text of Appendix B.3, $z_{sb\tau}$ and the international price of cotton in the month of the order, p^c_{sbjo}, as the exogenous shifter (see text for further details). The coefficient on this instrument is allowed to vary when the order uses only one type of fabric. Panel A reports the first stages corresponding to the exercises that recover a unique elastiity for all orders. In this panel, column (1) is the IV estimation instrumenting for quantities only, column (2) augments the specification to include buyer-specific effects and column (3) corresponds to the IV of both quantities and fabric prices. Panel B reports the first stages corresponding to the exercises that recover elasticities specific to the souring strategy of the buyer. $Relational^D_b$ corresponds to a dummy taking value one if the buyer is in the top 10^{th} percentile of the distribution of the sourcing characteristic. In the specification of the fixed effects, $\bar{b} \in \{Relational^D_b = 1, Relational^D_b = 0\}$ such that $-sjy\bar{b}$ correspond to seller-product-time-sourcing fixed effects. For each estimation in this table we report test statistics for underidentification (LM) and weak instruments (F), allowing for clustering of the standard errors. The LM test corresponds to the Kleibergen-Paap rank test and in all cases all exogenous regressors, including the seller-product-year (and, when suitable, buyer) fixed effects) are partialled out (χ^2-distributed). The standard errors reported in the table are bootstrapped drawing, with replacement, the entire vector of export orders for each seller.

Table B4: Order-Specific Markups and Marginal Costs

	But-to-Ship Ratio (Kg/Kg)	Price Garment (USD/Kg)	Price Fabric (USD/Kg)	Marginal Cost (USD/Kg)	Markup Factor (Units of Mc)	Markup Value (USD/Kg)
	(1)	(2)	(3)	(4)	(5)	(6)
Mean	0.87	13.65	7.57	10.35	1.44	3.30
Median	0.86	13.06	7.25	9.52	1.31	2.94
10^{th} Percentile	0.51	8.62	4.64	5.55	0.95	-0.64
25^{th} Percentile	0.67	10.43	5.64	7.13	1.08	0.86
75^{th} Percentile	1.04	16.32	9.15	12.83	1.67	5.38
90^{th} Percentile	1.22	19.77	11.03	16.36	2.14	7.80
St. Deviation	0.29	4.21	2.41	4.30	0.47	3.32
Coeff. Variation	0.33	0.31	0.32	0.42	0.33	1.01
$90^{th}/10^{th}$ Ratio	2.39	2.29	2.38	2.95	2.25	-12.24
$75^{th}/25^{th}$ Ratio	1.56	1.57	1.62	1.80	1.55	6.29
Number of orders			22,741			

All statistics are computed over all orders for which a markup was computed. Columns (1) to (3) are directly observed in the data, while columns (4) to (6) are constructed using the elasticities recovered as described in the body of the text and presented in Table B2, Panel A, unique θ estimated by OLS. The markup factor is defined as Price/Marginal Cost while the markup value is (Markup Factor - 1) $\times$ Marginal Cost.

C Appendix Tables and Figures

Table C1: Metrics of Buyers' Sourcing Strategies

	Sellers-to-Shipments		Duration of Relationships				Strength Rel.
	In-sample Products	Myanmar	Excluded Products	In-sample Products	Resid.	Myanmar	ILO Managers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Relational_b$	0.316***	0.312**	0.542***	0.321***	0.196***	0.207***	0.050*
	(0.028)	(0.148)	(0.021)	(0.027)	(0.029)	(0.072)	(0.029)
R^2	0.10	0.04	0.28	0.09	0.03	0.04	0.73
Obs.	3,238	113	3,193	2,826	2,313	113	159

Standard errors in parentheses, clustered at the destination level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. The main regressor across all specifications is the metric of buyers' relational sourcing, based on sellers-to-shipments in excluded products. It is increasing in the relational nature of the buyer. This metric is standardized using the mean and standard deviation across all buyers. All columns report OLS regressions of alternative measures of relational sourcing on the baseline metric. All outcomes in columns (1) to (6) are also standardized. Columns (1) and (2) use sellers-to-shipments metrics, constructed in the products of the analysis sample - woven shirts and trousers - and constructed using the customs records of Myanmar. The sample size reflects the limited overlap of the buyers' in the records of the two countries. Columns (3) to (6) use metrics based on the weighted average length of the buyers' relationships with sellers, as captured by the number of months of effective interaction. The averages are generated over relationships in excluded product categories (column (3)), product categories in the analysis sample (column (4)), in excluded products having residualized the duration of relationships against imported volumes, seller fixed effects and buyer's cohort effects (column (5)) and using the duration of relationships the buyer sustains with suppliers in Myanmar. The outcome in column (7) is a buyer-seller metric. It is based on data supplied by the ILO's Better Work Program and constitutes a dummy that takes value one if a manager in a garment plant identifies the relationship with the buyer as *strong or very strong*. This specification includes plant fixed effects and conditions on buyer size. Standard errors in this case are clustered by plant.

Table C2: Sourcing Strategies and Destination, Buyer and Order Characteristics

Panel A: Destination Characteristics (Cross-Section 2010)

	(1)	(2)	(3)	(4)
		$Relational_b$		
$Distance_d$	-0.271***			
	(0.103)			
GDP_d		0.023		
		(0.025)		
$Population_d$			-0.002	
			(0.028)	
$GDPpc_d$				0.165**
				(0.067)
R^2	0.01	0.00	0.00	0.01
Obs.	918	918	918	918

Panel B: Buyer Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	q_{by}	$Med\ Share^s_{by}$	$Max\ Share^s_{by}$	$Count^o_{by}$	$Count^{ship}_{by}$	$Count^j_{by}$
$Relational_b$	0.639***	-0.123***	-0.041***	0.011	0.148***	0.082***
	(0.054)	(0.020)	(0.009)	(0.016)	(0.016)	(0.013)
R^2	0.11	0.56	0.40	0.70	0.87	0.52
Obs.	5,569	5,569	5,569	5,569	5,569	5,569

Panel C: Order Characteristics

	(1)	(2)	(3)	(4)
	q_{sbjo}	$\overline{q}^{ship}_{sbjo}$	N^{ship}_{sbjo}	N^{ship}_{sbjo}
$Relational_b$	-0.042**	-0.164***	0.122***	0.150***
	(0.018)	(0.013)	(0.017)	(0.012)
R^2	0.56	0.52	0.61	0.83
Obs.	18,399	18,399	18,399	18,399

Standard errors in parentheses, clustered at the buyer level in Panels B and C, heteroskedasticity-robust in Panel A. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. Panel A has the baseline standardized buyer-specific metric of relational sourcing as the outcome and it runs in the cross-section of active buyers in 2010. All gravity variables are in logs and correspond to the distance from the buyer's county to Bangladesh ($Distance_d$), the GDP of the destination in the selected year (GDP_d), its population ($Population_d$) and GDP per capital (GDP_{pc}). Panel B regresses on the standardized buyer-specific souring characteristic, a number of outcomes: the buyer's size of trade (q_{by}), the log share the median seller of the buyer has in the buyer's yearly trade ($Med\ Share^s_{by}$), the log share that the largest seller of the buyer has in the buyer's yearly trade ($Max\ Share^s_{by}$), the log number of orders the buyer has in the year ($Count^o_{by}$), the log number of shipments the buyer has in the year ($Count^{ship}_{by}$) and the log number of products (HS6 codes) the buyer purchases in the year ($Count^j_{by}$). All columns (1)-(6) include year fixed effects and columns (2)-(6) also control for the size of the buyer's trade, q_{by}. Panel C's main regressor of interest is again the standardized sourcing characteristic of the buyer on order-level and the outcomes are: the log size of the export order (q_{sbjo}), the log average size of the shipments in the order ($\overline{q}^{ship}_{sbjo}$) and the log number of shipments in the order (N^{ship}_{sbjo}). All specifications (1)-(4) include seller-product-year and destination fixed effects. They also control for the size of the buyer's trade, q_{by}. Column (4) further controls for the size of the order (q_{sbjo}).

Table C3: Sourcing Strategies and Sellers' Characteristics

Panel A: Seller Characteristics

	(1) q_{sy}	(2) $Count^j_{sy}$	(3) $Count^d_{sy}$	(4) $Count^b_{sy}$	(5) $Count^o_{sy}$
$Trades\ w/Relational_s$	0.371***	0.090	0.226***	0.271**	0.316***
	(0.125)	(0.058)	(0.086)	(0.115)	(0.103)
R^2	0.03	0.01	0.02	0.01	0.02
Obs.	3,248	3,248	3,241	3,248	3,248

Panel B: Seller Characteristics (conditional on size)

	(1) $Count^j_{sy}$	(2) $Count^d_{sy}$	(3) $Count^b_{sy}$	(4) $Count^o_{sy}$	(5) $Med\ Share^b_{sy}$	(6) $Max\ Share^b_{sy}$
$Trades\ w/Relational_s$	0.023	0.154	0.174	0.117	-0.202**	-0.109*
	(0.064)	(0.094)	(0.126)	(0.105)	(0.101)	(0.060)
R^2	0.14	0.12	0.14	0.44	0.03	0.03
Obs.	3,248	3,241	3,248	3,248	3,248	3,248

Panel C: Order Characteristics

	(1) q_{sbjo}	(2) $\overline{q}^{ship}_{sbjo}$	(3) N^{ship}_{sbjo}	(4) N^{ship}_{sbjo}
$Trades\ w/Relational_s$	-0.229***	0.009	-0.239***	-0.073**
	(0.064)	(0.040)	(0.059)	(0.036)
R^2	0.49	0.57	0.56	0.84
Obs.	18,030	18,030	18,030	18,030

Standard errors in parentheses, clustered at the seller level in Panels A and B and seller-product-year level in Panel AC. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. Across all panels, the regressor of interest is a dummy that takes equal one if the seller trades at least once, in any product, at any point in time, with a buyer classified as relational (i.e. in the top 10 percentile of the distribution of the continuous sourcing characteristic). Panel A studies a number of outcomes at the level of the seller-year: the seller's log export volume in the products of interest (q_{sy}), the log count of products, destinations, buyers and orders of the seller-year combination (respectively $Count^j_{by}$, $Count^d_{by}$, $Count^b_{by}$, $Count^o_{by}$). In all cases, panel A conditions on year fixed effects. In columns (1) to (4), Panel B repeats the exercises on the counts of products, destinations, buyers and orders, but in addition to the year fixed effects it also controls for the seller-year's size (q_{sy}). Columns (5) and (6) retains the same controls, and studies as outcomes the log share the median buyer of the seller in its yearly trade ($Med\ Share^b_{sy}$) and the log share that the largest buyer of the seller has ($Max\ Share^b_{sy}$). Panel C studies order-level outcomes: the log size of the export order (q_{sbjo}), the log average size of the shipments in the order ($\overline{q}^{ship}_{sbjo}$) and the log number of shipments in the order (N^{ship}_{sbjo}). All specifications (1)-(4) include buyer-product-year fixed effects and control for the size of the seller's trade, q_{sy}. Column (4) further controls for the size of the order (q_{sbjo}).

Table C4: Buyers' Sourcing and Prices: Robustness

Panel A: Robustness to samples and further controls

	(1) p_{sbjo}	(2) p_{sbjo}	(3) p_{sbjo}	(4) p_{sbjo}	(5) p_{sbjo}
$Relational_b$	0.035***	0.109***	0.023***	0.024***	0.021**
	(0.006)	(0.026)	(0.008)	(0.008)	(0.008)
FEs	sjy,d	sjy,d	sjy,d	sjy,d	sjfoy,d
Controls	.	.	B,R,O	B,R,O	B,R,O
Robustness	.	.	Season	Product	Quality
Sample	All Orders	Production Data	.	.	.
R^2	0.57	0.70	0.73	0.73	0.79
Obs.	47,912	7,039	15,476	15,476	10,434

Panel B: Robustness to sourcing metrics

	(1) p_{sbjo}	(2) p_{sbjo}	(3) p_{sbjo}	(4) p_{sbjo}	(5) p_{sbjo}
$Relational_b^D$	0.045***				
	(0.015)				
Duration-based metrics:					
Excluded Prod.		0.015***			
		(0.005)			
In-sample Prod.			0.007		
			(0.004)		
Residualized				0.010**	
				(0.005)	
Myanmar					0.056*
					(0.033)
FEs	sjy,d	sjy,d	sjy,d	sjy,d	sjy,d
R^2	0.60	0.60	0.60	0.60	0.76
Obs.	18,399	18,017	18,225	16,949	3,257

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. Panel A studies robustness of the results presented in Table 3 to using different samples of orders and to including further controls to the richest specification in Table 3. In panel A, the main regressor in all cases is the baseline, buyer-specific metric of sourcing and it is standardized Column (1) uses all export orders in woven trousers and shirts in the data (of sellers of any size) and column (2) restricts the baseline sample to only include orders from buyers that are also present in the production line data. Both columns condition on seller-product-year and destination fixed effects (sjy, d). Columns (3) to (5) augment the richest specification of Table 3, featuring buyer-, relationship- and order-level controls, to include further controls accounting for seasonal specialization, product specialization and physical quality. These additional controls are as follows. Season: Herfindhal 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 $Complex_{sbjo}$) and a fixed effect for the seller-product-year-fabric-type-origin $(sjfoy)$, 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 100g/m2 but not more than 200g/m2 sourced from India in 2010.* Panel B shows robustness of the baseline result in Table 3 to the use of alternative metrics of relational sourcing. The regressions use a dummy that collects the top 10% buyers in the distribution of the continuous sourcing metric (column (1)) and using alternative metrics based on the duration of relationships as described in Table C1 (columns (2) to (5)).

Table C5: Price of Fabric, Relationship Dynamics and Fabric Quantities

Panel A: Price of Fabric and Relationship Dynamics

	(1)	(2)	(3)	(4)
		p^f_{sbjo}		
$Relational_b$	0.010			
	(0.007)			
$Past\ Trade_{sbo}$	0.003	0.002	0.006	0.005
	(0.003)	(0.003)	(0.005)	(0.004)
$Relational_b \times Past\ Trade_{sbo}$	-0.001	0.002	0.000	
	(0.002)	(0.003)	(0.004)	
$Relational^D_b{=}1 \times Past\ Trade_{sbo}$				-0.002
				(0.004)
FEs	sjy,d	sjy,sb	sjy,sb	sjy,sb
Controls	B,R,O	B,R,O	B,R,O	B,R,O
Relationships	All	All	Main	All
R^2	0.69	0.78	0.79	0.78
Obs.	18,261	16,002	7,373	16,002

Panel B: Price and Quantity of Fabric

	(1)	(2)	(3)	(4)	(5)	(6)
	p^f_{sbjo}	q^f_{sbjo}	p^f_{sbjo}	p^f_{sbjo}	q^f_{sbjo}	p^f_{sbjo}
q^f_{sbjo}	-0.050***		0.020	-0.039***		0.049
	(0.004)		(0.030)	(0.002)		(0.031)
$z_{sb\tau}$		0.109***			0.092***	
		(0.016)			(0.012)	
FEs	sjy	sjy	sjy	sjy,fo	sjy,fo	sjy,fo
Fabric	Single	Single	Single	All	All	All
Specification	OLS	First Stage	IV	OLS	First Stage	IV
KP F-Stat	.	44.188	.	.	57.880	.
R^2	0.66	0.53	-0.05	0.71	0.55	-0.15
Obs.	6,754	6,754	6,754	16,209	16,209	16,209

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10)$, $**(p < 0.05)$, $***(p < 0.01)$. In Panel A, the outcome of all specifications is the log price of the fabric used in the order, p^f_{sbjo}. Columns (1), (2) and (4) correspond to regressions in the entire sample, while column (3) performs robustness of column (2) to restricting the sample to orders the buyer places with the seller with the highest share of its imports in the product-year combination, i.e. its *main* partner. The key regressors in all specifications are: the baseline, buyer-specific metric of relational sourcing and it is standardized, $Relational_b$; the experience in the relationship measured as the log cumulative traded volumes until the date of the order, $Past\ Trade_{sbo}$; the interaction between the two. All columns include buyer-, relationship- and order-level controls, as described in the notes of Table 3. Column (1) includes the baseline seller-product-year and destination fixed effects, therefore exploiting variation across buyers. Columns (2), (3) and (4) include seller-product-year and seller-buyer effects (so the coefficient on the buyer-level variable $Relational_b$ is not identified). Column (4) simply reproduces the exercise in columns (2), replacing the continuous relational metric with a dummy variable indicating the buyers in the top 10% of the relational characteristic, $Relational^D_b$. These specifications using the dummy are included for ease of interpretation and to match our practice in other tables that feature interactions in this paper. Panel B presents OLS and IV estimations of regressions of the price of fabric, p^f_{sbjo}, on the quantity of fabric used in the order, q^f_{sbjo}, both in logs. Columns (1), (2) and (3) use a sample of orders that use a unique fabric type (a unique HS code), as the specification in this trimmed sample more closely resembles an inverse-demand relationship. The specifications in these first three columns include seller-product-year fixed effects. Columns (4), (5) and (6) use all orders (including multi-fabric orders) and augment the specification to include fabric-origin fixed effects. The specifications correspond to the OLS (columns (1) and (4)), the first stage regression of q^f_{sbjo} on the excluded instrument $z_{sb\tau}$ (columns (2) and (5)) and the second stage in the 2SLS (columns (3) and (6)). Please, see Section B.3 for details on the construction of the instrument. For columns (2) and (5) the Kleibergen-Paap F statistic is reported.

Table C6: The Downstream Market

	(1)	(2)	(3)	(4)	(5)	(6)
	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}	μ_{sbjo}
$Relational_b$	0.025***	0.030***	0.035**	0.023***	0.133*	0.121*
	(0.007)	(0.008)	(0.014)	(0.007)	(0.070)	(0.071)
$Downstream_{by}$					-0.058	
					(0.040)	
FEs	sjy,d	sjy,djy	sjy,sd	sjy,cjy	sjy,d	sjy,d
Controls	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O	B,R,O
R^2	0.41	0.50	0.51	0.44	0.44	0.44
Obs.	15,476	14,910	14,536	15,288	5,451	5,451

Standard errors in parentheses, clustered at the buyer level. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. In all columns the outcome is the log markup factor, μ_{sbjo}. The main regressor in all cases is the baseline, buyer-specific metric of relational sourcing and it is standardized. All columns include buyer-, relationship- and order-level covariates, as described in the notes of Table 3. All columns but include seller-product-year fixed effects. Column (1) also includes destination fixed effects and as such, simply reproduces the results of column (3) in Table 7. Column (2), instead, allows for destination-product-year fixed effects. Column (3) allows for seller-destination effects. Column (4) instead of the destination of the buyer uses the country to which the order is shipped, here denoted with c and allows for country-product-year fixed effects. Columns (5) and (6) use the specification of column (1) on a sub-sample of orders for which we have data on the total sales in clothing of the buyer in the year. These data were obtained from Euromonitor and covers all years in our sample, 2005-2012. Column (5) includes as a regressor $Downstream_{by}$, the log annual sales of clothing of the buyer in its main country of operations, defined by the size of its retail sales. Column (6) reproduces the baseline regression of column (1) in the restricted sample of column (5). We note that the relational metric is re-standardized in columns (5) and (6) over the buyers in the smaller sample of these columns. While the sample size is considerably reduced in columns (5) and (6) we note that the raw correlation between the variable $Downstream_{by}$ and the buyer size control that we use as baseline in the paper (i.e. the total volume of garments imported by the buyer) is positive and high (0.52). Moreover, conditional on destination and year, that correlation is 0.79.

Table C7: A Change in Sourcing Strategy - VF's Case

	(1) p_{sbjo}	(2) $(F/Q)_{sbjo}$	(3) mc_{sbjo}	(4) μ_{sbjo}
$VF_b \times I_{\tau(o)>2010}$	0.120***	-0.081	-0.062	0.182**
	(0.042)	(0.071)	(0.096)	(0.092)
FEs	sjy,b	sjy,b	sjy,b	sjy,b
Controls	R,O	R,O	R,O	R,O
R^2	0.78	0.50	0.66	0.42
Obs.	1,215	1,215	1,215	1,215

Standard errors in parentheses, clustered at the level of the buyer and year. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$. We focus on export orders in the products of interest, manufactured by sellers that traded at some point with VF. Among those orders, we consider the orders placed by VF or by a main buyer of the seller. The estimated equation is in all cases $y_{sbjo} = \delta_{sjy} + \delta_b + \beta VF_o \times I_{\tau(o)>2010} + \gamma Z_{sbjo} + \varepsilon_{sbjo}$. Outcomes are the log price of the order, p_{sbjo}, in column (1), the buy-to-ship ratio, $(F/Q)_{sbjo}$, in column (2), the log marginal cost, mc_{sbjo}, in column (3) and, in column (4), the log markup factor, μ_{sbjo}. Across all specifications, the regressor of interest is a treatment variable that takes value one for all orders placed by VF after its 2010 change in sourcing strategy. All specifications include seller-product-year fixed effects, buyer fixed effects and relationship- and order-level covariates, as described in the notes of Table 3.

The table complements the results presented in Figure 3. Column (1) of Table C7 shows that, relative to other buyers, the prices paid by VF increased after the transition. Column (2) detects a reduction in the buy-to-ship ratio which results in a decrease in marginal costs, as presented in column (3). These estimates are, however, noisy and we cannot reject a zero effect. Consequently, column (4) shows that the markup factor increases following VF's transition to relational sourcing. The difference between the price increase ($\approx$ 12%) and the markup increase ($\approx$ 18%) arises from the (imprecisely estimated) increase in efficiency through a reduction of the buy-to-ship ratio. The potential increase in fabric efficiency is consistent with knowledge transfers from VF to its core suppliers after the switch to relational sourcing. Quoting from the case study referred to in the main text, this would be consistent with Fraser stating "*that a company like VF, with its strong internal manufacturing capabilities, had expertise that it could share with suppliers in order to improve processes and reduce costs*".