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Keywords: Quality, exchange rate pass-through, Devaluations, crisis, Demand estimation

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Exchange Rate Shocks and Quality Adjustments*

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1 Introduction

How do firms respond to cost shocks and what are the most relevant margins of adjustment? Economists[1] and the business press[2] have long speculated that companies may reallocate towards lower quality product offerings instead of raising prices in response to adverse exchange rate movements. This hypothesis complements a long literature on incomplete price pass-through in international finance by providing another margin of adjustment for firms.[3]

While swapping out high quality products for low quality ones may offer an explanation for long-run incomplete price pass-through, there are two challenges in testing the hypothesis: first, it has been difficult to accurately measure quality; second, any positive evidence of quality downgrading must be reconciled with the quality sorting literature, which shows that higher quality products tend to be more profitable.[4] Since a cost shock that hits all imports proportionately will typically not change product profit rankings, quality sorting would seem to rule out quality downgrading. Our contribution is to directly test for quality downgrading using new and uniquely granular microdata, to reconcile quality downgrading with quality sorting, and to quantify the implications for price pass-through.

We use data from a large Russian online apparel retailer as a laboratory for studying changes to the quality assortment of offered products during an exchange rate shock. We directly observe the fabric and materials used in hundreds of thousands of individual products offered by the firm, as well as prices, quantities and unit costs. Following Crozet, Head, and Mayer (2012), Levchenko, Lewis, and Tesar (2011), Chen and Juvenal (2018), and Medina (2020), who use expert opinions or product descriptions to classify goods as high or low quality, we combine intuitive restrictions on which fabrics are high quality with regular seasonal changes in firm product stocking to identify the effect of the 2014 Russian currency crisis on the quality configuration of offered products.

Our dataset is well-suited to analyzing whether and why quality reallocation is an operative margin for firms. First, the firm refreshes its entire product line twice-yearly on a fixed schedule in line with fashion-industry standards, implying substantial product reallocation tied to partic-

[1]Feenstra (1988) argues that firms may upgrade their products through changing the design or adding extra features when there is a decline in the quantity sold, in his example as a result of quotas.

[2]In the aftermath of Brexit, the devalued pound was cited as a reason for shrinking candy bars. See, for example, the Financial Times article "Food groups embrace 'shrinkflation' to cope with rising costs" on December 2 of 2016.

[3]For recent entries on incomplete price pass-through see, for example, Goldberg and Campa (2010), Gopinath and Itskhoki (2010a,b), Amiti, Itskhoki, and Konings (2014), and Auer, Burstein, and Lein (2020).

[4]See, for instance, Manova and Zhang (2012); Crozet, Head, and Mayer (2012).

ular exchange rates.[5] Second, because the data contains individual products this reallocation is perfectly observable, which may not be true even at the HS12 level in standard trade data (Chen and Juvenal, 2018). Third, we have an observable measure of quality for each product, whose utility to consumers is validated in Khandelwal (2010) demand regressions. While we do not claim that our measure captures all of the multi-faceted nature of quality, it is important to consumers and can provide direct evidence of quality changes, unlike quality proxies recovered from more aggregated trade data.

To begin our analysis, we confirm that high quality imports tend to be more profitable and more expensive in our data, as in the quality sorting literature. Since the profit ranking of different products does not change in response to a proportional cost shock in canonical trade models (e.g., Crozet, Head, and Mayer (2012)), quality sorting suggests there should not be a reallocation towards lower quality products.

We then show that high quality imports are dropped more quickly relative to low quality ones within narrow product categories as a direct result of the Russian ruble devaluation. A 1% depreciation causes a roughly 0.32 percentage point differential reduction in the fraction of natural materials in imported versus domestically produced items. We argue that our identification strategy rules out an income shock driven "flight from quality" and isolates the part of the exchange rate shock that operates through import costs; we also provide further evidence against the income shock mechanism by exploiting a concurrent oil price shock, which affects consumer incomes differentially across oil-producing regions of Russia.[6]

Our quality downgrading result generalizes to alternative definitions of quality and to other sectors beyond fast-fashion. Using Khandelwal (2010) residuals instead of our quality measure, we document both in our data and in the universe of Russian imports at the HS6 level that greater ruble devaluation in associated with lowered product quality, with the effect operating through the cost-shock channel. While there are caveats to the generalization, it suggests that macroeconomic implications of our findings are more broadly applicable.

Having documented quality downgrading, we next turn to the question of why the firm would react to the exchange rate shock by reallocating towards lower quality products. Pass-through into prices and into wholesale costs is the same across qualities in the data, so differentially

[5]Typically, menu costs (Goldberg and Hellerstein, 2013), inventories (Alessandria, Kaboski, and Midrigan, 2010), or other adjustment costs can make it unclear when exchange rate pass-through is occurring.

[6]"Flight from quality" phenomena are well-known in the literature (see Burstein, Eichenbaum, and Rebelo (2005)), and similar mechanisms have been emphasized by Coibion, Gorodnichenko, and Hong (2015), who find that consumers reallocate expenditure across stores in response to economic conditions.

shrinking markups cannot explain the reallocation. We do find that relative consumer expenditure on high quality products shrinks post shock, suggesting expenditure switching across product qualities in response to the proportional price increase.

To rationalize our empirical facts, we build a simple model of consumer demand and multi-product firm import sourcing where high quality products can be ex ante more profitable, but can also be dropped more quickly after a cost shock. For our model to generate quality reallocation, consumer demand must feature expenditure switching between high and low qualities, as well as a larger price elasticity for high qualities. While non-homothetic demand systems generally allow for expenditure switching, some such systems feature different demand elasticities for different qualities (Fieler, 2011) while others do not (Bems and di Giovanni, 2016). We verify that higher qualities have larger price elasticities in our data using both a formal, model-derived regression estimated with supply-side data, and also using the same Khandelwal (2010) regressions on demand data that we employ to validate our quality dummy.

Using our reduced form estimates, we find that quality reallocation can help explain incomplete exchange rate pass-through via compositional changes: high price, high quality products are dropped in favour of low price, low quality products within the same product category. On average, pass-through would increase from 0.50 to 0.59 if there were no quality reallocation; both numbers lie within the range of those found in the literature (Nakamura and Steinsson, 2012). Since firms sell an order of magnitude more distinct products than would be implied by even the HS12 categorization (Chen and Juvenal, 2018) compositional bias is almost certainly relevant for computing pass-through at any aggregation level of trade data.

Assuming our findings generalize to different cost shocks and countries, there are several macroeconomic implications. First, while an exchange rate depreciation can act to correct a current account deficit, our paper shows that it may also lead to an unintended increase in lower quality imports as the composition of trade changes. A poorer country or one that specializes in lower qualities might therefore find its domestic industries facing more competition than expected after a devaluation. Second, countries that move up the quality ladder in certain industries are not necessarily insulated from import partners' currency shocks—or other cost shocks such as tariffs—as their partners' incentive may be to reallocate to lower qualities. Finally, long-run incomplete pass-through for cost shocks in general, and for exchange rate shocks in particular, has very different welfare implications for consumers if the lower pass-through reflects falling quality rather than shrinking markups.

This paper contributes to a large literature that explores why pass-through from exchange rate shocks into prices is incomplete. A variety of consistent explanations for incomplete pass-through have been tested using both firm-product (Gopinath and Rigobon, 2008; Gopinath and Itskhoki, 2010a,b) and firm-category (e.g., HS8 or HS10) level prices (Knetter, 1989; Goldberg, Knetter, et al., 1997; Auer and Chaney, 2009; Berman, Martin, and Mayer, 2012; Amiti, Itskhoki, and Konings, 2014, 2019). While our empirical evidence speaks directly to price stickiness within aggregated categories, the theoretical mechanism is consistent with disaggregated product upgrading and downgrading. Indeed, Nakamura and Steinsson (2012) find that firms often replace products instead of changing prices, giving firms ample opportunity to adjust quality levels.

The present work is also linked to research that focuses on quality sorting of products and quality upgrading. Manova and Zhang (2012) and Crozet, Head, and Mayer (2012) demonstrate cross-sectional quality sorting within firms: high quality products are exported to more destinations and have higher trade values, which in their frameworks is rationalized by the products being more profitable. Fan, Li, and Yeaple (2015), Bas and Strauss-Kahn (2015), Manova and Yu (2017) show that firms may upgrade quality after a trade shock given production function complementarities; their focus is not on price pass-through, but rather how trade affects firm level residuals, either quality or productivity.[7] Medina (2020) addresses the same focus, but relies on an expenditure switching demand system to induce firms to change their input quality mix in response to an import price shock. While we draw on this literature's robust finding that higher quality products tend to be more profitable—especially in wealthier countries—we do not speak to the trade literature on how firms produce quality or productivity as our firm purchases its products from wholesalers.

A key difficulty in the trade literature on quality has been actually identifying which goods are high quality. The first standard approach is to use prices and unit values, as in Bastos, Silva, and Verhoogen (2018) for instance. However, nominal prices that do not move in response to an exchange rate shock could reflect many forces that generate incomplete pass-through, and do not necessarily imply quality changes. Ludema and Yu (2016) find indirect support for quality changes in response to trade shocks using a model that links quality ladders, firm heterogeneity, and prices; Chen and Juvenal (2016); Auer, Chaney, and Sauré (2018) also show how quality affects price pass-through. The second approach to measuring quality uses demand residuals, as pioneered by Khandelwal (2010); however, while flexible, the residual approach is susceptible

[7] For productivity see, e.g., Bustos (2011).

to mismeasurement induced by hidden varieties. The third approach is to use product descriptions (Medina, 2020; Alessandria and Kaboski, 2011) or expert opinions (Chen and Juvenal, 2018; Crozet, Head, and Mayer, 2012). Our paper bridges the second and third approach by separating out goods into natural and artificial fabrics using their descriptions, but then also quantifying the effect of natural fabrics in a demand regression.

Other papers have studied the role of quality in a macroeconomic and international finance setting. A recent paper by Jaimovich, Rebelo, and Wong (2019) shows how non-homotheticities in demand can lead to quality downgrading (or "trading-down") and thereby amplify business cycle fluctuations as high-quality goods tend to be more labor intensive. One prominent strand, including Levchenko, Lewis, and Tesar (2011), Chen and Juvenal (2018) and Bems and di Giovanni (2016), has found some evidence that the disproportionate drop in the value of trade after the global negative income shock in 2008 was caused by the higher quality of traded goods combined with non-homotheticity of demand. Previous work has also examined the relationship between trade distances and quality (Alchian and Allen (1964), Hummels and Skiba (2004), and Feenstra and Romalis (2014)). Another strand has shown that firms may choose to upgrade the quality of their exported products, either because exchange rate shocks make exporting to richer countries more attractive (Bastos, Silva, and Verhoogen, 2018) or because competing with inexpensive imports drives firms to upgrade, as in Medina (2020).[8]

Finally, this paper complements other structural IO papers that evaluate exchange-rate shocks in particular industries such as beer (Goldberg and Hellerstein, 2013) and coffee (Nakamura and Zerom, 2010) but which do not allow for quality downgrading or entry and exit.[9] We also connect to Gopinath, Gourinchas, Hsieh, and Li (2011) and Burstein and Jaimovich (2012) insofar as both papers use the decision-making of a single retailer to answer empirical questions in a trade context—in their cases, pricing to market.

The paper proceeds as follows. Section 2 provides an overview of the data and institutional background. Section 3 presents direct evidence on quality downgrading in the Russian online apparel industry. Section 4 describes a model of quality choice and provides insights on what demand assumptions are necessary for quality downgrading. Section 5 provides details on the

[8]Other trade shocks that can drive firms to quality upgrade include rising competition from low-wage countries (as in Martin and Mejean (2014)), cheaper intermediate inputs (see Verhoogen (2008), Fieler, Eslava, and Xu (2014) and Bas and Strauss-Kahn (2015)) or access to larger markets (see Bustos (2011), Lileeva and Trefler (2010), and Aw, Roberts, and Xu (2011)).

[9]Feenstra, Gagnon, and Knetter (1996) look at pass-through for cars, and note that quality adjustments may affect price pass-through numbers.

counterfactuals. Section 6 concludes.

2 Background and Data

Our data come from a large, online apparel retailer that sells across all of Russia.[10] The retailer offers clothing, shoes, and accessories. At the retailer-assigned stock-keeping unit (SKU) level, we observe the price, which is constant across Russia but can vary month to month, as well as the quantity sold in each province (oblast) in each month. SKUs are comparable to UPCs in that each one describes a specific product—e.g., a particular variety of Adidas running shoe—aggregating only over different colors and sizes of the same product. The data cover January 2012 through September 2015; from September 2014 to March 2015 the ruble devalued by over 50% after holding roughly steady against the U.S. dollar since the early 2000s.

In addition to prices and quantities of SKUs, we observe a product's fabric composition, country of manufacture, brand (e.g., Adidas), product group (e.g., shoes), inventory, wholesale cost in rubles, and which currency the firm used to purchase each SKU.[11] A more precise description of these variables and how they are used in the analysis is provided below.

2.1 Store features

The store operates by ordering SKUs at a wholesale cost from both large and small brands and then reselling to Russian consumers with a markup. Most SKUs are uniquely associated by the firm with the Fall/Winter or Spring/Summer season within a year, which are the two main seasons in the fashion industry (Bhardwaj and Fairhurst, 2010). Before a season begins, the firm chooses which brands and SKUs to include, and, once the goods start being offered, the firm is free to put products on sale.[12]

We associate the Spring season with the period from March through August, and Fall with

[10]The company is owned by a publicly traded German enterprise, listed on the Frankfurt Stock Exchange. As of today, the retailer operates in four countries (Belarus, Kazakhstan, Russia, and Ukraine), although the present study focuses exclusively on the largest market, which is Russia. The firm is one of two leading online apparel retailers in Russia, and employed more than 4,000 people as of December 2015.

[11]Most imported SKUs are invoiced either in Euros or the U.S. dollar, and the ruble depreciated almost one-for-one against both. The prevalence of dominant currencies in international transactions is consistent with recent evidence from international finance (e.g., see Gopinath, Boz, Casas, Díez, Gourinchas, and Plagborg-Møller (2020)).

[12]As far as we are aware from interviews with the management team, the firm is not bound by any resale-price maintenance agreements with the manufacturers. Empirically, the retailer charges an average markup of 100% over wholesale costs until the goods are put on sale and phased out as the season draws to an end.

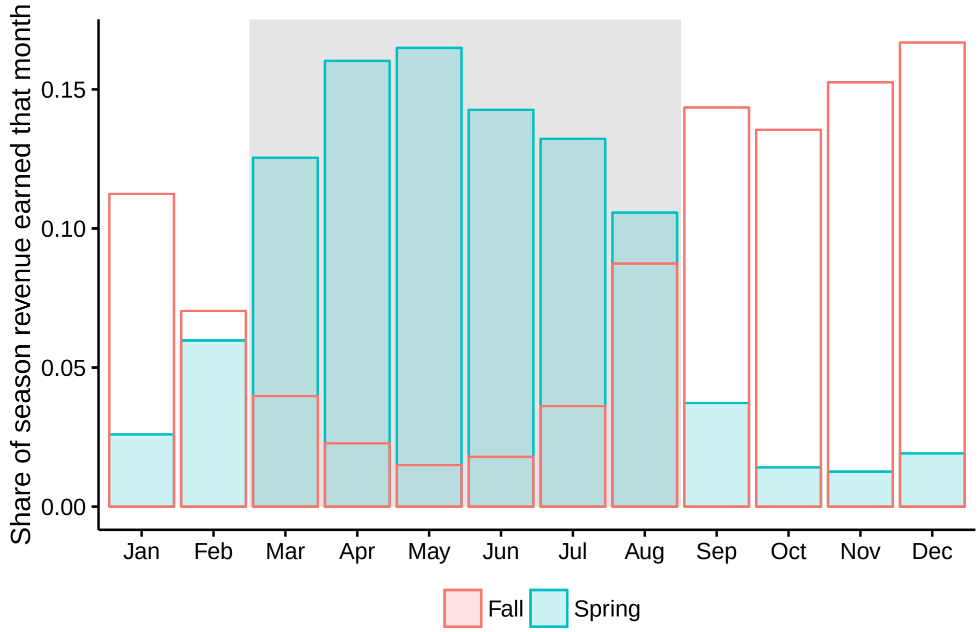

Figure 1: **Monthly revenue shares for SKUs by season**
Note: This figure shows histograms of the distribution of Fall and Spring introductions by revenue. The gray area covers the months we choose to associate with Spring goods of March-August.

September through February of the following year.[13] Figure 1 shows that the majority of revenue for a season's SKUs is earned during the six month window associated with that season. The only slight discrepancy from this pattern occurs in the Fall 2015 season since we only observe 17 full days in September of 2015 after which our data end.[14]

There are two features of the store worth mentioning. First, in line with U.S. fashion industry norms, for most SKUs the firm does all of its stocking up in one initial wave, before the season starts, at a prearranged unit wholesale cost (Şen, 2008). We thus expect any exchange rate pass-through or quality changes to occur with a lag. Second, the product line is almost completely refreshed each season with new SKUs that are associated with the new season, which gives the firm the scope to reallocate between qualities but prevents us from tracking SKUs over long periods.[15]

[13] 78% of Spring SKUs and 75% of Fall SKUs are introduced in our designated Spring and Fall months, respectively. 83% of Spring revenue and 78% of Fall revenue are earned in our designated Spring and Fall months, respectively. Additional graphs of the distribution of Fall and Spring introductions and revenue shares are available in Appendix A.

[14] Since a season's SKUs continue to be introduced beyond the first month of the season, the Fall 2015 revenue share appears low for the final bar of Figure A.2 in Appendix A.

[15] Product portfolio choice microdata have recently been emphasized in work studying how firms grow through the introduction of new product lines (e.g., Argente, Lee, and Moreira (2018)).

2.2 Product quality and summary statistics

We have price, quantity, material and origin information for 444,629 SKUs spread over 1,583 brands and 26 product groups. The most common materials are presented in Appendix A. Cotton, polyester, and leather dominate, with at least one of the three present in 50% of SKUs.

We follow Levchenko, Lewis, and Tesar (2011), Alessandria and Kaboski (2011) and Medina (2020) and classify products as high or low quality based on their product description, and specifically based on the materials used in the product. To proceed, we code synthetic materials—including polyester, plastic polymers, acrylic, and any fabric with the word "artificial"—as low quality.[16] We then assume SKUs comprised solely of low quality materials are low quality products, and all other SKUs are high quality products. This categorization implies that blended fabrics are high quality, which is consistent with a literature that tracks consumer perceptions of different textiles (Schutz, Cardello, and Winterhalter, 2005; Forsythe and Thomas, 1989).

We validate our binary quality indicator in Khandelwal (2010) demand regressions, reported in Table A.3, Appendix A.1. Projecting sales on prices, a rich set of fixed effects, and product characteristics, high quality products sell between 3.7% and 13.5% more than low quality ones, depending on specification. Material content is only a rough measure of quality—brand, design, workmanship, and many other features play a role—but it is relevant for consumers in our data, and likely serves as a useful indicator of expected sales for the firm (conditional on price) when deciding whether to stock new products it has never sold before.

As an additional check, we explore what intuitively valuable features of products our measure is capturing by estimating product group-specific quality shifters in Figure A.3, Appendix A.1. 19 of 26 product category-specific shifters are positive, with statistical significance for utilitarian products—such as underwear and headwear—that make direct skin contact, likely reflecting the comfort and odor-resistance of natural materials. The quality shifter is also large and significant for footwear with a leather/artificial leather split, in line with intuition about the superior durability and aesthetics of natural leather compared to plastic substitutes.

Table 1 presents summary statistics by product group. The Share column gives the number of SKUs in that group divided by the total number of SKUs offered over the whole sample period, the Quality column gives the high quality fabric SKU share of each product group, and the Rus.

[16] Our quality mapping for the 30 most commonly occurring fabrics, present in 97% of SKUs and accounting for all materials in 93% of SKUs, is given in Table A.1 in Appendix A. Table A.2 in Appendix A for the top three fabrics by product group.

Table 1: Cross-sectional summary statistics

Group	Share	Quality	Rus.	Group	Share	Quality	Rus.
Ankle Boots	0.012	0.725	0.091	Outwear	0.060	0.408	0.031
Bags	0.080	0.447	0.060	Sandals	0.019	0.497	0.041
Ballerina Shoes	0.016	0.598	0.039	Scarves	0.022	0.702	0.091
Blazers and Suits	0.011	0.850	0.052	Shirts	0.056	0.765	0.037
Boots	0.039	0.816	0.036	Shoes	0.048	0.786	0.058
Dresses	0.078	0.765	0.117	Shorts	0.018	0.818	0.015
Flip Flops	0.011	0.365	0.068	Skirts	0.020	0.764	0.087
Headwear	0.025	0.686	0.225	Sport Shoes	0.062	0.633	0.014
Heeled Sandals	0.033	0.666	0.057	Sweatshirts	0.032	0.887	0.036
High Boots	0.044	0.769	0.076	Tee-Shirts and Polos	0.114	0.948	0.039
Jeans	0.022	0.988	0.005	Jumpsuits	0.046	0.870	0.051
Knitwear	0.068	0.874	0.039	Underwear	0.016	0.934	0.005
Moccasins	0.018	0.853	0.040	Vests and Tops	0.026	0.787	0.045

Note: This table presents summary statistics by product group. The Share column gives the fraction of SKUs in a group compared to all SKUs offered over the whole sample period, the Quality column lists the high quality fabric SKU share of each product group, and the Rus. column contains the fraction of Russian manufactured products.

column gives the fraction of Russian manufactured products.[17]

Our panel analysis focuses on the season level SKU stocking choices of the firm, so we aggregate SKUs sales and prices within seasons and associate the aggregated values with our assigned time windows. Our baseline results use the first observed price as that SKU's within-season price.[18] Summary statistics at the season level are presented in Table 2. The number of SKUs drops precipitously in the September 2015 season, which reflects the fact that our data end in September, but SKUs associated with a season continue to be introduced after the first month.[19] Total sales and number of SKUs are on an upward trend, as the firm is expanding during this time period. The fraction of high-quality products exhibits seasonality, and at first glance there seems to be a decrease in Spring/Summer 2015 compared to the same season in 2014 and 2013, which is the initial post-devaluation period and potentially indicative of quality downgrading in the aggregate. Since Table 1 shows that different product groups have very different mean levels

[17]The Russian apparel industry is made up of numerous manufacturers that tend to be quite labor intensive, with the sector employing around 236,158 workers in medium to large enterprises in 2015 (according to BvD's Amadeus data). For comparison, and according to the U.S. Department of Labor, apparel manufacturers in the United States employed about 142,860 workers in 2014.

[18]The results are robust to using a within-season sales-weighted average.

[19]See Figure A.1 in the Appendix A.

Table 2: Time-varying summary statistics

Season	Quality	No. SKUs	Units Sold	Price	Raw Cost	Avg. RUB/USD
2012-03-01	0.805	27,089	339,747	3,874	1,775	31.170
2012-09-01	0.747	33,592	421,807	4,164	1,957	30.840
2013-03-01	0.759	63,584	1,232,188	3,285	1,433	31.947
2013-09-01	0.719	60,638	1,233,759	4,750	1,914	33.225
2014-03-01	0.751	69,945	1,895,759	3,631	1,465	35.324
2014-09-01	0.729	74,885	2,082,531	4,578	1,941	51.704
2015-03-01	0.726	88,122	2,826,627	4,512	1,898	56.898
2015-09-01	0.667	13,100	411,986	4,590	1,983	69.885

Note: This table presents summary statistics at the season level over time. The Season column contains the start date of each respective season, the Quality column lists the fraction of high-quality goods for each season, the number of units sold per season is contained in the fourth column, the average SKU price is in the fifth, the wholesale cost is in the Raw Cost column, and the average U.S. dollar to ruble exchange rate over a season is shown in the last column.

of quality, to assess the magnitude of downgrading accurately we will control for reallocation between product groups in Section 3.

2.3 Macroeconomic environment

In 2014, a decline in investor confidence led to a rapid fall in the value of the Russian ruble. Falling confidence in the Russian economy stemmed from two major sources: first, the price of crude oil, a key Russian export, declined by nearly 50% from June 2014 to December 2014; second, the annexation of Crimea in March 2014 precipitated Western asset freezes on Russian energy and banking sectors that were implemented by July 2014.[20] In response, Russia implemented a selective food import ban against the EU and several other western countries, although no other trade was restricted.

Figure 2 shows how these developments were mirrored in a steep ruble depreciation against the U.S. dollar between July and December 2014. From the vantage point of our firm, which earns revenue in rubles but buys wholesale in foreign currencies, this abrupt movement represents an exogenous cost shock that was fully realized by the time the company was sourcing products for its Spring/Summer 2015 season.[21] The food import ban, oil price shock, and financial sanctions

[20]See, for example, the New York Times article “Raising Stakes on Russia, U.S. Adds Sanctions” on July 17 of 2014.

[21]As is well-known from the broader exchange rate disconnect puzzle, nominal exchange rates follow a volatile random walk process that is uncorrelated with macroeconomic fundamentals and is hence largely unpredictable.

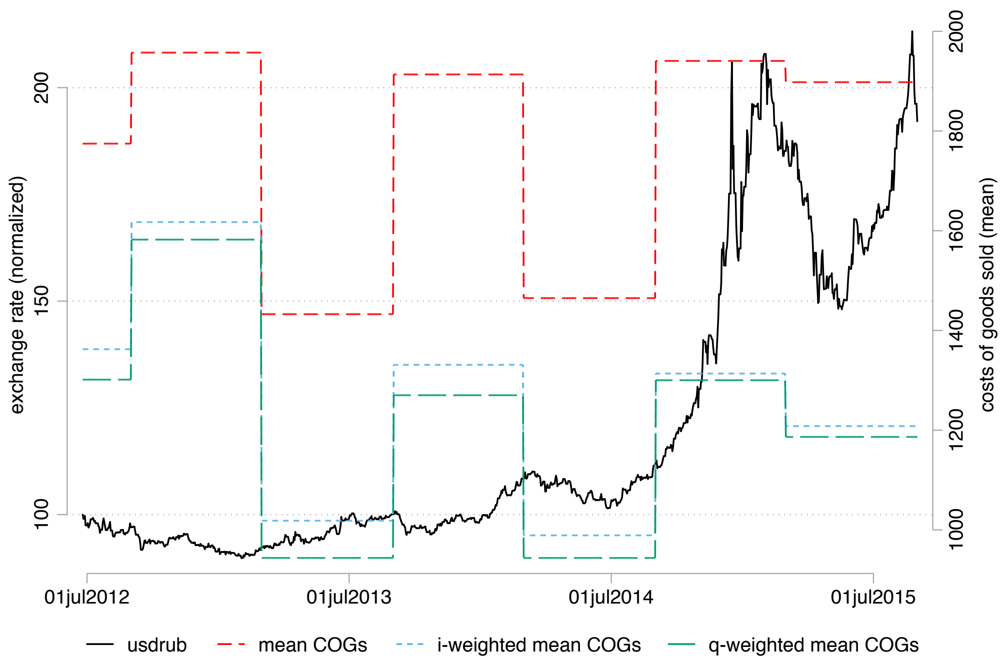

Figure 2: **Cost of goods sold**
Note: This figure shows the normalized U.S. dollar to ruble exchange rate (black solid line), the mean seasonal (red dashed line), the inventory-weighted mean seasonal (blue short-dashed line), and the purchase quantity-weighted mean seasonal (green long-dashed line) wholesale costs of all SKUs from mid-2012 until 1 Sept 2015.

on the Russian economy that began in July 2014 may also have represented a substantial income shock to consumers as early as during the Fall 2014 season.

Besides documenting the exchange rate shock, Figure 2 also provides an initial look at how the firm responded to the devaluation. Conditional on the seasonal periodicity in wholesale costs, the average cost of goods (COGs) in rubles increased substantially in the Spring 2015 season following the nominal devaluation at the end of 2014. Yet costs did not go up nearly as much as one might expect under complete pass-through into import prices. Furthermore, inventory-weighted wholesale costs increased even less in percentage terms than unweighted mean costs. This reflects that average stocking quantities per SKU increased in relative terms for cheaper, lower quality goods.[22]

[22]This pattern is not driven by a large scale removal of high cost goods from the retailer's warehouses (which could be rationalized with consumers moving forward consumption), but rather by a disproportionate amount of stocking-up on low cost goods—the close association between average *quantity*- and *inventory*-weighted wholesale costs confirms this interpretation.

3 Reduced Form Evidence

In this section we provide evidence that the firm reacted to the nominal exchange rate shock by reducing the quality of the products it imported for resale. In particular, we identify three empirical facts in our data:

1. High-quality goods are more profitable than low-quality goods.

2. The nominal exchange rate shock causes a greater reduction in the high quality share for imported goods compared to Russian-produced goods, independent of shocks to income, tastes, or firm costs.

3. High-quality goods do not experience differential pass-through, but do experience differential expenditure reductions.

Fact 1 implies that our data exhibits the same features as the quality sorting literature where high quality goods are more profitable (Manova and Zhang, 2012). In workhorse models of international trade, this would imply that high quality goods would not be dropped after an adverse shock (Crozet, Head, and Mayer, 2012). Fact 2 establishes that the exchange rate shock induces quality downgrading, and rules out an income shock induced "flight from quality" à la Burstein, Eichenbaum, and Rebelo (2005) as the sole explanation. Fact 3 shows that expenditure switching between qualities—not relative markup adjustments—is needed to explain the disproportionate exit of high quality goods.[23]

3.1 Quality and profitability

Since we observe wholesale costs of a product c_j directly, we can approximate the variable profits of a good j as $\pi_j = q_j(p_j - c_j)$.[24] In all following sections, we will refer to high quality products interchangeably as "natural," in line with our classification method. We run the following regression at the SKU-level using pre-shock data:

$$\log(y_{jgt}) = \beta \cdot Natural_j + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{jgt} \tag{1}$$

[23] In Appendix E, we replicate all three empirical findings using only the subset of product groups which have a positive estimated quality shifter from the Khandelwal (2010) regressions discussed in the data section.

[24] Price varies over a product's life within season; we use sales prices that are actually observed and faced by consumers to compute profits.

Table 3: Mean differences for high quality products

	Dependent variable:					
	log(π)	log(pq)	log(q)	log(p)	log(c)	log(p/c)
	(1)	(2)	(3)	(4)	(5)	(6)
Natural$_j$	0.074***	0.066***	-0.326***	0.392***	0.379***	0.013*
	(0.022)	(0.020)	(0.034)	(0.037)	(0.039)	(0.006)
Group $\times$ Season FE	✓	✓	✓	✓	✓	✓
Observations	304,577	304,577	304,577	304,577	304,577	304,577
R^2	0.379	0.392	0.180	0.394	0.371	0.048

*Note: This table presents coefficient estimates from specification 1. The outcome variables is either the profit, revenue, quantity sold, price or cost of SKU j, in product group g, in season t. Only products with non-missing values for all dependent variables are included. Product group-season fixed effects are included. Prices are sales-weighted within SKUs, and standard errors are clustered at the group level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

where y_{jgt} is either the profit, revenue, quantity sold, price, wholesale cost or multiplicative markup of SKU j, in product group g, in season t, and $\mathbf{D}_{gt}$ are product group-season fixed effects. Results reported in Table 3 indicate that high quality goods are 7.4% more profitable on average. Regressions that use variation only within a brand-product group-season give similar estimates and significance, except for quantity and markups which become insignificant and close to zero (see Appendix B.1).

Note from the quantity regression in Table 3 that high quality goods do not sell more units than low quality goods. Higher quality goods will therefore still be more profitable than low quality ones even if there is an unobserved per-unit, constant additive cost (e.g., distribution or storage) contributing to the marginal cost.

3.2 Quality downgrading

We show in this section that the share of high-quality goods on offer was reduced in response to the exchange rate shock. We use a difference-in-differences (DiD) approach, where imported SKUs are the treatment group that experiences the shock, domestically sourced SKUs are the control, and the fraction of products that are high quality (natural material) from each origin is the dependent variable. Intuitively, items manufactured abroad and purchased by the firm in a foreign currency will have a larger increase in ruble costs post-shock than domestically produced items purchased in rubles; if quality adjustment is an important margin for passing through the ruble cost increase, then there will be a negative, significant effect on the quality share of foreign sourced goods post-shock.

In our main specification, we aggregate within seasons to the product group-origin level. For each of the 26 product groups, in each of the eight seasons from 2012 through 2015, we observe the share of high quality SKUs for non-Russian goods and the share of high quality SKUs for domestically sourced goods. In line with the firm's one-season-ahead stocking decisions, we run the following regression that allows the exchange rate in season $t-1$ to affect the quality share of non-Russian goods in season t:

$$natfrac_{grt} = \delta \left(nonrus_{gr} \cdot \log(ER_{t-1}) \right) + \sum_{gr} \alpha_{gr} \mathbf{D}_{gr} + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{grt} \tag{2}$$

where $natfrac_{grt}$ is the number of high quality goods $N_{h,grt}$ divided by the sum of high and low quality goods $N_{h,grt} + N_{\ell,grt}$ in product group g, origin r, and season t, $nonrus_{gr}$ is a dummy indicating a non-Russian origin, and $\log(ER_{t-1})$ is the average U.S. dollar to ruble exchange rate during the prior season from Table 2. $\mathbf{D}_{gr}$ and $\mathbf{D}_{gt}$ are group-origin and group-season dummies, respectively, which rules out seasonal reallocation from high $natfrac$ to low $natfrac$ product groups as an explanation for downgrading.

Identification of the cost effect of the exchange rate shock via δ in specification 2 is robust to numerous confounding factors. Time-varying shocks that affect products in the same way regardless of import origin—such as changing tastes for quality or raw material costs—will not affect the quality share in a product group differentially across Russian and non-Russian products, and so will be absorbed by the $\mathbf{D}_{gt}$ dummy. Shocks that affect the difficulty of sourcing that do not vary across qualities within an origin—such as changing finance terms due to inflation in Russia—will not affect the ratio of high to low qualities within each origin. Meanwhile, constant differences in the average taste, input costs, or sourcing costs for different qualities by origin will be absorbed by $\mathbf{D}_{gr}$.

Importantly, the DiD will identify the exchange rate effect even if there is an income-shock driven "flight from quality"; provided the income shock affects the quality share of Russian and non-Russian products in the same proportion, its effect will be absorbed by $\mathbf{D}_{gt}$. In Section 4, we show formally in a non-homothetic demand and supply model that identification in specification 2 is robust to a contemporaneous income shock, and all other shocks described above, when

Table 4: Differential quality reallocation

	Dependent variable:			
	$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.342***	-0.320***	-1.583**	-1.500*
	(0.082)	(0.095)	(0.610)	(0.650)
Group × Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	395	395	395	395
R^2	0.695	0.859	0.664	0.834

*Note: This table presents coefficient estimates from specification 2. The outcome in the first two columns is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t, and in the last two columns is the log ratio of the number of natural SKUs to artificial SKUs within grt. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group ×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

using $\log(N_{h,grt}/N_{\ell,grt})$ as the dependent variable. In a robustness section below, we also provide further checks against the income-shock channel using cross-sectional variation in GDP growth.

Our results from specification 2 are reported in Table 4: we find a negative, significantly estimated δ, with a 1% devaluation at $t-1$ mapping to a 0.32 percentage point reduction in the quality share of imports at t in our preferred specification in column (2). The formally identified coefficient in column (4) gives a consistent result, implying a 1.5% reduction in the ratio of high to low quality SKUs stocked. Results are stable when dropping the incomplete Fall 2015 season, when weighting by start-of-season inventory, and when interacting product group-origin fixed effects with the season-of-year—Fall/Winter and Spring/Summer—which would account for predictable, within group-origin seasonal demand shifts for natural vs. artificial materials. We also find an insignificant δ when restricting reallocations to be only within brand, suggesting that within-brand quality downgrading is not an important margin, see Appendix B.2 for details.

To validate our assumption of one-season-ahead stocking choices in specification 2 and to rule out a pre-trend, we allow the quality share of imports to vary flexibly by season and origin

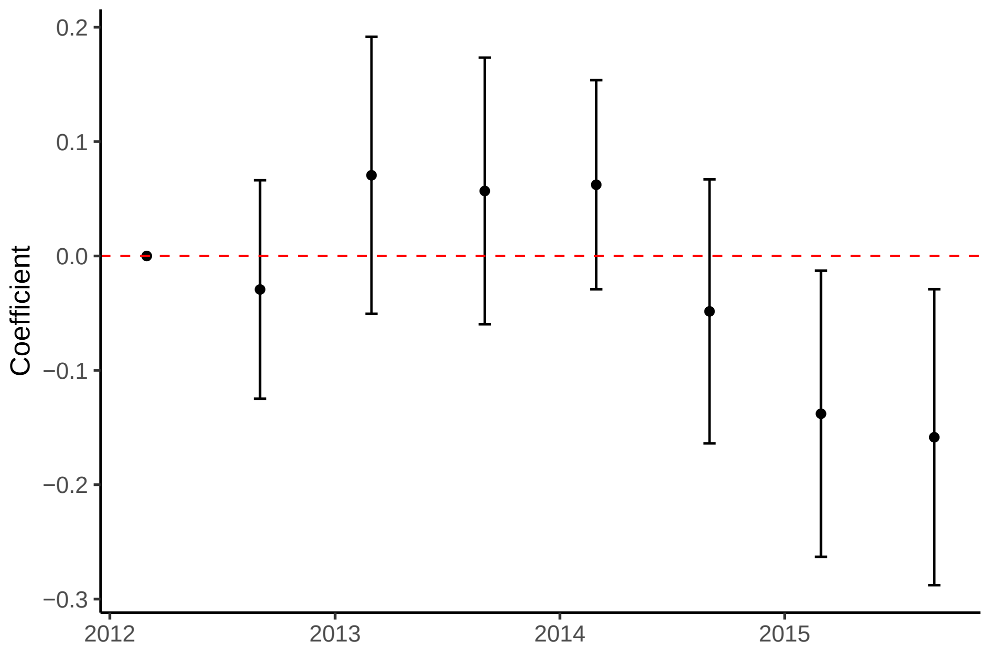

Figure 3: **Quality downgrading**
Note: This figure plots the estimated δ_t *coefficients of equation 3 with* 95% *confidence intervals around them. Fixed effects are at the product group×country of origin and season level. Standard errors are clustered by group×origin to allow within-group-origin serial correlation.*

in a DiD timing test:

$$natfrac_{grt} = \sum_{t>1} \delta_t \left(nonrus_{gr} \cdot \mathbf{D}_t \right) + \sum_{gr} \alpha_{gr} \mathbf{D}_{gr} + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{grt} \tag{3}$$

The estimated coefficients δ_t from equation 3 are plotted in Figure 3, along with their associated standard errors, clustered at the group-origin level to allow for within group-origin serial correlation over time. There is no statistically significant differential reduction in quality within product groups for non-Russian goods until the March 2015 season, after the peak of the devaluation. That is, the significant reduction in the quality of imported products happened on a time frame consistent with the firm's one-season-ahead stocking decisions. The lack of a significant treatment effect prior to March 2015 also provides evidence against a pre-trend in reallocations.

If the increase in costs from the exchange rate shock—rather than an income shock or a change in the nature of demand—is causing quality downgrading, one might expect that for product groups where quality is more expensive to provide, there will be more downgrading. We test this relationship by allowing for the treatment coefficient in equation 2 to vary by product group in our product group level specification:

$$natfrac_{grt} = \sum_g \delta_g \left(nonrus_{gr} \cdot \log(ER_{t-1}) \right) + \sum_{gr} \alpha_{gr} \mathbf{D}_{gr} + \sum_t \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{grt} \tag{4}$$

For each product group, we recover the cost premium of quality by dividing the average wholesale cost for high versus low quality goods in the seasons prior to March 2015. A value greater than one indicates that high quality goods cost more on average than low quality goods in that product group. For most product groups (19 out of 26), quality is costly. Full regression results, including those using $\log(N_{h,grt}/N_{\ell,grt})$ as the dependent variable, are available in Appendix B.

We plot the estimated coefficients δ_g against the quality premium in Figure 4. The negative relationship between the costs of providing quality and the amount of quality downgrading supports the hypothesis that costs played a central role in the firm's decision to quality downgrade after the devaluation. Our result that product groups with the highest costs downgrade the most after a proportional increase in input wholesale costs agrees with the evidence in Fan, Li, and Yeaple (2018), who find that firms with the highest costs upgrade the most after a proportional reduction in input prices.

Our key finding from this section is that the firm chooses to reduce the quality of goods in response to the cost shock, on a timeframe consistent with its stocking decisions, and independently of a range of concurrent shocks. In the sections below we provide additional robustness checks, first with respect to the measurement of quality and identification of the DiD, second with respect to ruling out an income shock driven "flight from quality," and lastly with supplementary data that generalizes our findings.

Quality downgrading robustness check: DiD and quality assumptions

Our DiD identification is based on the assumption that the exchange rate shock does not affect the wholesale cost of Russian-manufactured products as much as foreign-manufactured products. We provide evidence that pass-through from the devaluation into Russian product wholesale costs is lower but still positive in Table 5 in the next section. This pass-through result is to be expected since Russian products may use imported intermediates combined with Russian labor, and suggests that the quality downgrading coefficient in Table 4 may understate the true effect as the control group experiences a cost shock as well.

To check that our results are not being driven by our particular choice of quality coding, we

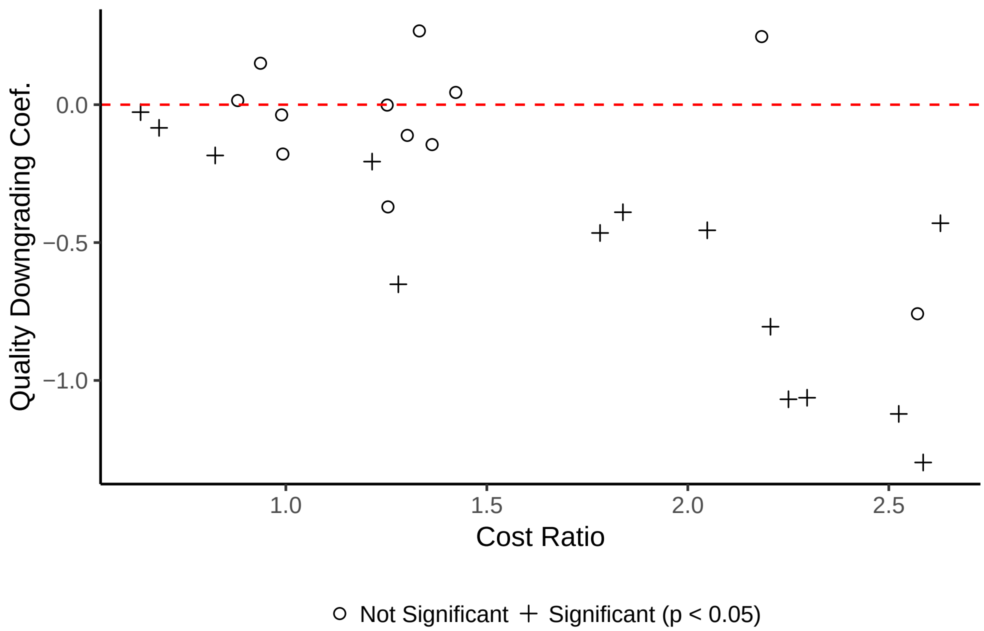

Figure 4: **Cross-group variation in downgrading**
Note: This figure plots the estimated δ_g coefficients of equation 4. Fixed effects are at the group$\times$origin and season level. Standard errors are clustered by group$\times$origin level to allow within-group-origin serial correlation.

re-run specification 2 with the Khandelwal (2010) measure. We average the SKU-level estimated quality residuals from the Khandelwal (2010) regression discussed in Section 2.2 within a group-origin-season, and use this average as the dependent variable instead of $natfrac_{grt}$.[25] Output in Appendix B.2 confirms the negative, significant effect of the exchange rate on average quality of imports. Estimated product group level coefficients have a correlation of 0.34 with their counterparts from specification 4, implying that both approaches are capturing the same variation within groups, see Figure B.1.

We also verify that downgrading is driven by quality reallocation in the treatment group, rather than upgrading or idiosyncratic movements in the domestically-sourced control group. We run a DiD using only imported goods, treating the logged number of SKUs within a quality-group-season combination as our dependent variable, and find a relative decrease in the number of imported goods using natural materials. Moreover, we also provide a raw DiD graph for polymers, which have a significant presence by end of sample (8% of SKUs) as a lower quality rubber and leather substitute. There is a clear differential trend, with imports increasing their polymer share

[25]See Appendix A.1 for the Khandelwal (2010) regression formulation and output.

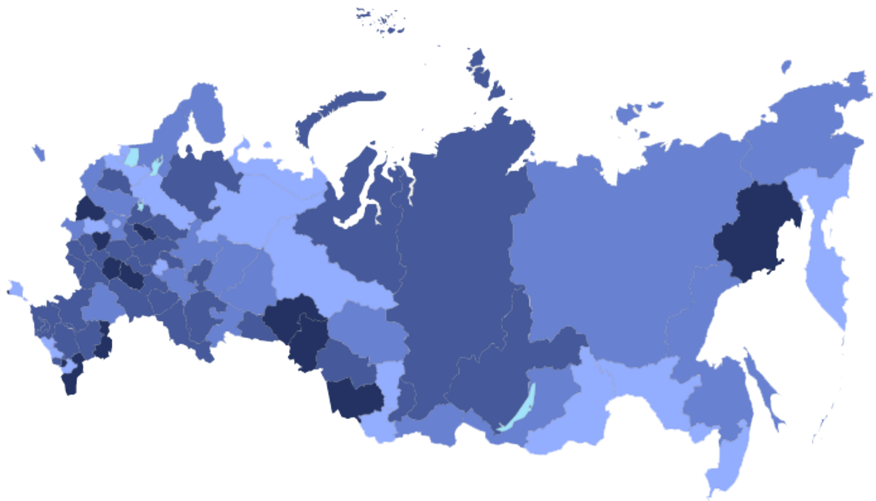

Figure 5: **Regional growth, 2014-2015**
Note: This figure depicts gross regional product growth rates across Russian oblasts in 2015, with darker colors representing higher economic growth.

while domestic products keep the share roughly constant. Results are reported in Appendix B.2.

Quality downgrading robustness check: flight from quality

While our DiD design should control for an income-shock driven flight from quality, in this section we provide a further robustness check that the realized income shock did not induce consumption reallocation towards lower quality goods.

We leverage the substantial variation in gross regional product (GRP) growth across Russian regions (oblasts), seen in Figure 5, to test whether the demand for quality varied across high growth and low growth oblasts. A flight from quality will appear as a positively estimated ϕ in the regression below, which follows Chen and Juvenal (2018):

$$\Delta \ln X_{mgcy} = \phi \Delta \ln \left(\frac{GRP}{cap} \right)_{cy} \cdot Nat_m + \sum_{gcy} \alpha_{gcy} \mathbf{D}_{gcy} + \sum_{mgy} \alpha_{mgy} \mathbf{D}_{mgy} + \sum_{mgc} \alpha_{mgc} \mathbf{D}_{mgc} + \epsilon_{mgcy},$$

where X_{mgcy} measures expenditures on SKUs of quality m in product group g in oblast c in year y. As in Chen and Juvenal (2018), we aggregate sales to the yearly level (e.g., Spring/Summer 2012 and Fall/Winter 2012 are combined into 2012), since this is the time interval at which we observe GRP per capita growth in each oblast.

We find an insignificantly estimated $\hat{\phi}$, reported in Appendix B.3. Results are similar when taking average price as the dependent variable, and when we further disaggregate the data by brands. We also run a flexible DiD specification in Appendix B.3 where the share of high quality products consumed within an oblast each season is regressed on GRP per capita growth from 2014-2015 interacted with season dummies. We find no evidence of differential movement in quality shares related to income changes.

Quality downgrading robustness check: generalization

To provide evidence that our results are not specific to one firm and industry, we use publicly available data on the universe of Russian imports at the HS6$\times$country$\times$quarter level from 2013 through 2015 from the UN's Comtrade dataset.

We treat each observation as a product, and test whether quality downgrading was greater for imported products from countries against whose currencies the ruble depreciated substantially, such as China and the United States, compared to imports from countries against whose currencies the ruble depreciated little, such as Kazakhstan and Belarus.[26] Intuitively, all imports face the potential concurrent income shock in Russia but only imports from countries where the ruble did not hold its value experience the cost shock, which allows us to separate out the effect of the cost shock even without the domestic control group present in our baseline estimation.

Our data sources, data selection, estimation procedure, and results are reported in Appendix B.4; briefly, we use Khandelwal (2010) to recover product quality, and run a regression similar to specification 2 to test downgrading. We find evidence that greater relative ruble depreciation against a country's currency is associated with lower quality of imports from that country, with statistical significance for lagged exchange rates, implying that quality takes time to adjust. The results suggest that our main findings are not unique to our firm or to fast-fashion. The primary caveat to this robustness check is that the Khandelwal (2010) approach will measure a quality reduction if the number of actual, unobserved varieties within an HS6$\times$country category decreases—even if there is no quality reallocation.

[26] Our firm has almost no imports from countries against which the ruble did not depreciate substantially, which is why we do not leverage cross-country exchange rate variation in our main regressions.

3.3 Price pass-through and expenditure switching

In this section, we explore why the firm would react to the cost shock by reallocating towards lower quality products. Intuitively, the firm will only reallocate if higher quality products experience a relative reduction in markups, or if consumers move their expenditures away from high quality products after the shock, leading to a differential quantity reduction.

Price pass-through

A differential reduction in markups would imply lower pass-through of the shock into high than low quality goods. We run pass-through regressions to determine whether high quality goods experienced a change in relative prices. Since we do not observe most SKUs for longer than one season, our main results are not within SKU; rather, we treat a quality-brand-group choice as a consistent product over time through the inclusion of eponymous fixed effects. Meanwhile, we still use SKUs as our unit of observation in the regression. Our specification is:

$$\begin{aligned}\log(y_{jmbgt}) = \beta_1 \log(ER_{t-1}) + \beta_2 \log(ER_{t-1}) \cdot Nat_{jmbgt} + \beta_3 \log(ER_{t-1}) \cdot Rus_{jmbgt} \\ + \beta_4 \log(ER_{t-1}) \cdot Nat_{jmbgt} \cdot Rus_{jmbgt} + \sum_{mbgs} \alpha_{mbgs} \mathbf{D}_{mbgs} + \sum_{bgr} \alpha_{bgr} \mathbf{D}_{bgr} + \epsilon_{jmbgt}\end{aligned} \tag{5}$$

where y_{jmbgt} is either p_{jmbgt}, the first observed price of SKU j of quality m for brand b in product group g in season t, or c_{jmbgt}, the constant (within season) wholesale cost of j. ER_{t-1} is the lagged average U.S. dollar to ruble exchange rate, and Nat_{jmbgt} and Rus_{jmbgt} are dummies for whether SKU j has a natural fabric and Russian origin, respectively. The specification includes fixed effects at the quality-brand-product group-season of year level ($mbgs$), so for instance, high quality Adidas sport shoes in Spring/Summer have their own price or cost intercept. Dummies are also included at the brand-product group-origin level (bgr), to allow Russian and non-Russian products to have different intercepts.

We first run specification 5 only on imports (i.e., $\beta_3 = \beta_4 = 0$) and report results in columns (1) and (2) of Table 5. The first row indicates that pass-through is incomplete: a 1% depreciation leads to a roughly 0.75% increase in both import prices (column 1) and wholesale costs (column 2).[27] That the price and wholesale cost coefficients are statistically indistinguishable implies no

[27]The firm's operations staff describe negotiating a "50-50" split of the cost increase (in rubles) with their wholesale suppliers. Our larger estimate may reflect that larger brands with more SKUs negotiated higher pass-through into costs, or that the percent-increase interpretation of log-log coefficients overstates the true elasticity for non-

baseline change in markups. The second row shows no differential price pass-through for high quality products and no differential wholesale cost pass-through, implying no relative change in high quality markups post-shock. Note that these regressions do not imply markups are the same across qualities, only that markups are constant within a quality over time.

Expanding the sample to include Russian-sourced products, the full specification 5 coefficients are reported in columns (3) and (4) of Table 5 for prices and wholesale costs respectively. Russian products in general have significantly lower pass-through and an increase in markups—perhaps due to strategic complementarity in price setting—but with no difference between high and low qualities. These results validate the use of Russian products as a control group that is less exposed to the cost shock in the baseline Section 3.2 DiD.

We address concerns that within material-brand-group selection on low-performing SKUs may be biasing pass-through in Appendix B.5. We also perform standard within-SKU pass-through regressions on the small set of SKUs we observe for longer than one season, and find no evidence of differential pass-through for natural fabric products.

Expenditure switching

In a demand system that exhibits expenditure switching, a proportionate price increase can imply a disproportionate reduction in quantity demanded of the more expensive, higher quality product, rationalizing the firm's product reallocation even with no change in relative markups.

We run a regression in the spirit of Bems and di Giovanni (2016) to examine within product group expenditure switching, where $expfrac_{grt}$ is the share of spending on high quality in group g, origin r and season t:[28]

$$\log(expfrac_{grt}) = \delta^e(nonrus_{gr} \cdot \log(ER_{t-1})) + \sum_{gr} \alpha_{gr}\mathbf{D}_{gr} + \sum_{gt} \alpha_{gt}\mathbf{D}_{gt} + \epsilon_{grt}. \tag{6}$$

The coefficient δ^e will be negative if high quality imported products experience a relative reduction in expenditure after the devaluation. Identification of the exchange rate effect, versus concurrent changes in income, taste, or costs, proceeds as in Section 3.2.

Results reported in Table 6 imply substantial within-product-group differential switching for

infinitesimal underlying changes; we revisit this point in Section 5.

[28]Note that $expfrac_{grt} = \left(\sum_j Nat_{jgrt} \cdot p_{jgrt} \cdot q_{jgrt}\right) / \left(\sum_j p_{jgrt} \cdot q_{jgrt}\right)$, where sums are taken over all SKUs j in product group g, origin r, season t.

Table 5: Pass-through coefficients

	Dependent variable:			
	log(p)	log(c)	log(p)	log(c)
	(1)	(2)	(3)	(4)
log(ER_{t-1})	0.757***	0.734***	0.760***	0.739***
	(0.032)	(0.039)	(0.031)	(0.040)
log(ER_{t-1})$\cdot Nat$	0.021	-0.031	0.017	-0.036
	(0.037)	(0.045)	(0.030)	(0.038)
log(ER_{t-1})$\cdot Rus$			-0.141*	-0.200***
			(0.060)	(0.057)
log(ER_{t-1})$\cdot Nat \cdot Rus$			-0.005	-0.012
			(0.023)	(0.022)
Quality × Brand × Group × SoY FE	✓	✓	✓	✓
Brand × Group × Origin FE			✓	✓
Observations	371,559	371,559	393,916	393,916
R^2	0.891	0.887	0.891	0.887

*Note: This table presents coefficient estimates from specification 5 at the brand-group-fabric level. The dependent variable is either the first observed price of SKU j or the within season wholesale cost of j. ER_{t-1} is the lagged averaged U.S. dollar to ruble exchange rate, and Nat and Rus are indicators for whether SKU j has a natural fabric and is of Russian origin, respectively. Standard errors (in brackets) are clustered at the quality, brand, group, season of year level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

imports, with a 1% devaluation leading to an approximately 0.32 percentage point reduction in the share of expenditures on high quality products for imports relative to domestic products in our preferred specification in column (2). Timing tests and alternative specifications using imports only are reported in Appendix B.5.

Our results are similar to Bems and di Giovanni (2016) who also find within-group expenditure switching in scanner data from a large Latvian grocery chain; however, they demonstrate expenditure switching away from imports in response to an income shock, while we show switching away from high quality goods within imports due to a cost shock. In Section 4, we explore what features of consumer demand are required for the firm to engage in quality reallocation.

4 Model

This section develops a simple model of a multiproduct firm choosing its quality mix. We use the model to structurally rationalize our difference-in-differences identification strategy, and to

Table 6: Differential expenditure switching

	Dependent variable:			
	$expfrac$			
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.348***	-0.316**	-0.367**	-0.372*
	(0.094)	(0.115)	(0.125)	(0.147)
Group $\times$ Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group $\times$ Season FE		✓		✓
Observations	395	395	349	349
R^2	0.651	0.847	0.644	0.846

*Note: This table presents coefficient estimates from specification 6. The outcome is the fraction of expenditure on natural fabric products in group g, origin r, in season t. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (1) and (2) include all periods, and (3) and (4) drop the final, incomplete season. Standard errors (in brackets) are clustered at product group $\times$origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

show what demand assumptions are necessary to match our facts on quality sorting and quality downgrading with constant proportional markups.

4.1 Setup

M_t identical consumers in season t each have Y_t to spend on products. Products can be high (h) or low (ℓ) quality, denoted by subscript $m \in \{h, \ell\}$, and consumers have preferences for each good. A mass J of homogeneous multiproduct retailers decide in season $t-1$ how many products of each quality type to offer next season and whether to source domestically from Russia ($r = 1$) or from abroad ($r = 0$).

Demand

We follow Fieler (2011) in our utility specification:

$$U_t = \int_{\nu_h \in \Omega_{ht}} \alpha_{rht}^{\frac{1}{\sigma_h}}(\nu_h) Q_{rht}(\nu_h)^{\frac{\sigma_h - 1}{\sigma_h}} \partial \nu_h + \int_{\nu_\ell \in \Omega_{\ell t}} \alpha_{r\ell t}^{\frac{1}{\sigma_\ell}}(\nu_\ell) Q_{r\ell t}(\nu_\ell)^{\frac{\sigma_\ell - 1}{\sigma_\ell}} \partial \nu_\ell$$

$\Omega_{mt} = J \times \Omega_{jmt}$ is the set of varieties of quality m available at t; each of the homogeneous retailers $j \in J$ will offer differentiated varities of the same set of products Ω_{jmt}. The set of products may include both domestically sourced and foreign varieties. $\alpha_{rmt}(\nu_m)$ is a quality shifter for variety ν_m, and $\sigma_m > 1$ measures the elasticity of substitution across varieties of quality m goods.

Consumers take prices as given in each season and choose among varieties to maximize utility, subject to their budget constraint $\int_{\nu_h \in \Omega_{ht}} P_{rht}(\nu_h) Q_{rht}(\nu_h) \partial \nu_h + \int_{\nu_\ell \in \Omega_{\ell t}} P_{r\ell t}(\nu_\ell) Q_{r\ell t}(\nu_\ell) \partial \nu_\ell = Y_t$. This leads to the following demand for product ν_m:

$$Q_{rmt}(\nu_m) = M_t \frac{X_{rmt} P_{rmt}(\nu_m)^{-\sigma_m}}{P_{mt}^{1-\sigma_m}} \tag{7}$$

where X_{rmt} is the expenditure on a variety ν_m from r at time t by any given consumer, and P_{mt} is the CES price index for goods of quality m, $P_{mt} \equiv \left(\int_{\nu_m} \alpha_{rmt}(\nu_m) P_{rmt}(\nu_m)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}$. Expenditure is $X_{rmt} = \lambda_t^{-\sigma_m} \alpha_{rmt} P_{mt}^{1-\sigma_m}$, where λ_t is the marginal utility of income at time t, and we have assumed identical tastes α_{rmt} for varieties with the same source r and material m in season t.

Pricing

Prices are chosen to maximize profit, given consumer demand and marginal costs. In our application, sourcing and pricing decisions are made one season in advance. The marginal cost in rubles of a m quality product sourced from r for sale at t is $ER_{r,t-1} \cdot c_{rm,t-1}$, where $ER_{r,t-1}$ is the exchange rate at $t-1$ and equals one for a domestically sourced product. As with tastes, we assume identical marginal costs for all varieties with the same source r and material m in season $t-1$.

Since each firm's products are a measure zero fraction of a double continuum of products, firms are too small to affect consumer expenditures or the price index. Each therefore sets a multiplicative CES markup of $\sigma_m/(\sigma_m - 1)$ over marginal cost for a good of quality m.

Quality choice

To close the model, we specify how a firm chooses its product mix. The mass of products sourced from each location and quality will be independent since the firm is small relative to the mass of competitors. However, assuming firms are small implies no equilibrium constraints limiting the optimal number of products. We therefore impose sourcing costs that are quadratic in the mass of each type of product, so that at time $t-1$ the firm chooses $\boldsymbol{N_t} = (N_{1ht}, N_{1\ell t}, N_{0ht}, N_{0\ell t})$ to solve:[29]

$$\max_{\boldsymbol{N_t}} \sum_{rm} N_{rmt}\pi_{rmt} - \sum_{rm} \frac{f_{rm,t-1}}{2} N_{rmt}^2$$

Substituting in for profit, the optimal mass of products sourced from r of type m is:[30]

$$N_{rmt} = M_t \frac{\lambda_t^{-\sigma_m} \cdot \alpha_{rmt} \cdot (ER_{r,t-1} \cdot c_{rm,t-1})^{1-\sigma_m} \cdot \theta_m}{f_{rm,t-1}} \tag{8}$$

This closed form for the optimal number of products implies our first lemma, which justifies the DiD strategy used in the empirical section:

Lemma 1. *If $\alpha_{rmt} = \alpha_{rm} \cdot \alpha_{rt} \cdot \alpha_{mt}$, $c_{rmt} = c_{rm} \cdot c_{mt}$, and $f_{rmt} = f_{rm} \cdot f_{rt} \cdot f_{mt}$, then the log ratio of high to low quality products sourced for season t can be written as:*

$$\log \frac{N_{rht}}{N_{r\ell t}} = (\sigma_\ell - \sigma_h) \log ER_{r,t-1} \times \mathbf{D}_r + \sum_r \beta_r \mathbf{D}_r + \beta_t \mathbf{D}_t \tag{9}$$

Proof. See Appendix C □

The regression using specification 2 is exactly equation 9, with the caveats that we allow time and origin coefficients to vary by product group in the empirical implementation, and introduce a non-structural error.

Our assumptions on tastes α_{rmt}, marginal costs $c_{rm,t-1}$, and sourcing costs $f_{rm,t-1}$ make it clear how shocks must be restricted to identify the effect of the exchange rate movement on the import quality mix. For instance, tastes and sourcing costs can move arbitrarily in any two of the three dimensions of origin, quality, and time—Russian products may be suddenly preferred in Spring/Summer 2015 or easier to source, or high quality goods may be suddenly less preferred or more difficult to source—and it will not affect the relative movement of the high quality share for Russian products versus imports. Marginal costs can also move arbitrarily in two dimensions except the origin×season dimension, which would be conflated with the exchange rate movement.

Note that in addition to a range of taste, cost, and sourcing shocks, the effect of the exchange rate shock on the import quality mix is identified even if the firm expects a shock to Y_t. That shock

[29]We assume that the firm is able to perfectly forecast spending Y_t and taste shocks α_{rmt} for t at $t-1$.

[30]Note that $\theta_m \equiv \left(\frac{\sigma_m^{-\sigma_m}}{(1-\sigma_m)^{-(\sigma_m-1)}}\right)$.

would affect the demand for high versus low qualities through the shadow value of income λ_t, but it will not differentially affect the Russian share versus the imported product share, and so will be differenced out over time. Our identification result holds even if markups are not set optimally, but are multiplicative and constant over time (see Appendix C).

4.2 Model predictions

Consider the more general utility function:

$$U_t = g\left(\int_{\nu_h \in \Omega_{ht}} \alpha_{rht}^{\frac{1}{\sigma_h}}(\nu_h) Q_{rht}(\nu_h)^{\frac{\sigma_h - 1}{\sigma_h}} \partial \nu_h, \int_{\nu_\ell \in \Omega_{\ell t}} \alpha_{r\ell t}^{\frac{1}{\sigma_\ell}}(\nu_\ell) Q_{r\ell t}(\nu_\ell)^{\frac{\sigma_\ell - 1}{\sigma_\ell}} \partial \nu_\ell\right)$$

Our baseline uses $g(x, y) = x + y$ as in Fieler (2011). Our next theorem shows that several workhorse alternate specifications cannot deliver quality reallocation, but that there exist parameters for our baseline that can match the quality sorting and reallocation we observe. We focus on a pure importer with no domestic sourcing to simplify exposition and therefore drop the r subscript below, see Appendix C for a discussion of domestic sourcing.

Theorem 1. *For a currency devaluation represented by an increase in ER_{t-1}:*

1. *For $g(x, y) = x+y$ there exist $\sigma_h > \sigma_\ell$ and $\alpha_{ht} > \alpha_{\ell t}$ such that $\frac{\partial \log N_{ht}/N_{\ell t}}{\partial ER_{t-1}} < 0$ and $\pi_{ht} > \pi_{\ell t}$.*
2. *For $g(x, y) = x + y$ and $\sigma_h = \sigma_\ell$, $\frac{\partial \log N_{ht}/N_{\ell t}}{\partial ER_{t-1}} = 0$. This holds even if α_{ht} is a function of Y_t as in Bems and di Giovanni (2016).*
3. *For $g(x, y) = x^\xi y^{1-\xi}$ with $\xi \in (0, 1)$, $\frac{\partial \log N_{ht}/N_{\ell t}}{\partial ER_{t-1}} = 0$.*

Proof. See Appendix C. □

Part 1 of the theorem states that a proportional import cost shock can lead the firm to reduce the ratio of imported high quality products to low quality products, even if those high quality products are more profitable. Parts 2 and 3 show that to get this reallocation, demand for high quality products must be more price sensitive ($\sigma_h > \sigma_\ell$), and consumers must be able to reallocate expenditures across product categories.

There are two pieces of empirical evidence that $\sigma_h > \sigma_\ell$ in our setting. First, Lemma 1 provides a structural interpretation of the δ coefficient in specification 2 with $log(N_{h,grt}/N_{\ell,grt})$ as the dependent variable as $\sigma_\ell - \sigma_h$. This coefficient is estimated negative and significant in Table 4, implying that $\sigma_h > \sigma_\ell$. Second, in the Khandelwal (2010) regressions we use to recover quality we allow high quality products to have a different elasticity, and estimate that high quality products are more price sensitive; see Appendix A.

While the applied theory literature provides conditions under which $\sigma_h > \sigma_\ell$ (Coibion, Einav, and Hallak, 2007), of particular note is the observation that in empirical settings, the nested logit demand system of Khandelwal (2010) will often imply that more expensive products are also more price sensitive (Björnerstedt and Verboven, 2016). Given that high quality products tend to be more expensive, many quality regressions in the trade literature may thus have the implicit implication that high quality products are more price elastic.

The downgrading result comes purely from the demand model, using an identical specification to Medina (2020) and Fieler (2011). The linear demand in Melitz and Ottaviano (2008) or Eckel, Iacovone, Javorcik, and Neary (2015), or the logit demand in Khandelwal (2010), can also exhibit expenditure switching and greater price sensitivity for the high quality good, but would generate shrinking relative markups.

The model implies that after a devaluation, the average price increase in a product group is dampened by the reallocation away from high price, high quality products. We explore the empirical relevance of this prediction for explaining incomplete pass-through in the next section.

5 Counterfactuals

To what extent does quality downgrading affect exchange rate pass-through into average prices? The literature focuses on pass-through within aggregated HS6 categories (Knetter, 1989) or within much finer HS10-importer categories that are often treated as a product (Gopinath and Itskhoki, 2010a). Our product groups are similar to HS6 (e.g., shirts) or in some cases HS10 categories (e.g., flip-flops or heeled sandals), and so the results in this section can be interpreted as the contribution to incomplete pass-through from quality downgrading either within category or "product."

The price of imports within a product group is the weighted average of the prices of high and low quality products, where weights correspond to the shares of each type of product. We write the quality share and the product prices as functions of potentially different exchange rates, ER^N and ER^p respectively, to set up our counterfactual where the quality ratio will be held constant at a pre-shock exchange rate while prices will reflect the post-shock exchange rate:

$$\bar{p}_{gt}(ER^N, ER^p) = nat\hat{frac}_{gt}\left(ER^N\right) \cdot \hat{p}_{hgt}(ER^p) + \left(1 - nat\hat{frac}_{gt}\left(ER^N\right)\right) \cdot \hat{p}_{\ell gt}(ER^p)$$

For pass through into the predicted share of high quality products, we use the results from our downgrading DiD specification 4 that allows coefficients to vary by product group. For pass-through into prices, we recover predicted prices at the SKU-brand-season level from our pass-through regression specification 5—restricted to imports as in column (1) of Table 5—and take the average of predicted prices within each quality-group-season, giving $\hat{p}_{hgt}$ for high quality products and $\hat{p}_{\ell ht}$ for low quality products.

The counterfactual will compare baseline predicted pass-through to predicted pass-through if the quality share behaved as if the exchange rate did not increase. In light of the seasonality present in our data, we compare the predicted average price in Spring/Summer 2015 (t^*) to Spring/Summer 2014 ($t^* - 2$). Our two key objects for each product group are therefore:

$$\begin{aligned} \text{Actual}_g &\equiv \left(\frac{\bar{p}_{g,t^*}(ER_{t^*-1}, ER_{t^*-1})}{\bar{p}_{g,t^*-2}(ER_{t^*-3}, ER_{t^*-3})} - 1\right) / \left(\frac{ER_{t^*-1}}{ER_{t^*-3}} - 1\right) \\ \text{Counterfactual}_g &\equiv \left(\frac{\bar{p}_{g,t^*}(ER_{t^*-3}, ER_{t^*-1})}{\bar{p}_{g,t^*-2}(ER_{t^*-3}, ER_{t^*-3})} - 1\right) / \left(\frac{ER_{t^*-1}}{ER_{t^*-3}} - 1\right) \end{aligned}$$

As a reference, the denominator is 0.556, reflecting an increase from 33.2 rubles/USD in Fall/Winter 2013 (affecting Spring/Summer 2014) to 51.7 rubles/USD in Fall/Winter 2014 (affecting Spring/Summer 2015).

Plots of the two objects are reported in Figure 6, with product groups sorted in order of decreasing predicted baseline pass-through. The vertical dotted line indicates the average of the estimated coefficients across all product groups.

With quality downgrading average pass-through is approximately 0.50, while without quality downgrading that number increases to 0.59; quality downgrading thus reduces pass-through by roughly 15%.[31] While quality downgrading cannot fully explain incomplete price pass-through, it moves in the right direction. Our pass-through numbers are also reasonable in the context of estimates from the literature (Nakamura and Steinsson, 2012).

This main effect is not driven by unusual behavior in categories with very few SKUs. Bolded

[31]Without downgrading, one might expect average pass-through to be 0.75 as in Table 5; however, since the underlying depreciation is large, the linear approximation to the log-log specification 5 overstates the percentage change. Computing pass-through exactly yields $0.75 \log(51.7/33.2) \div 0.556 = 0.59$.

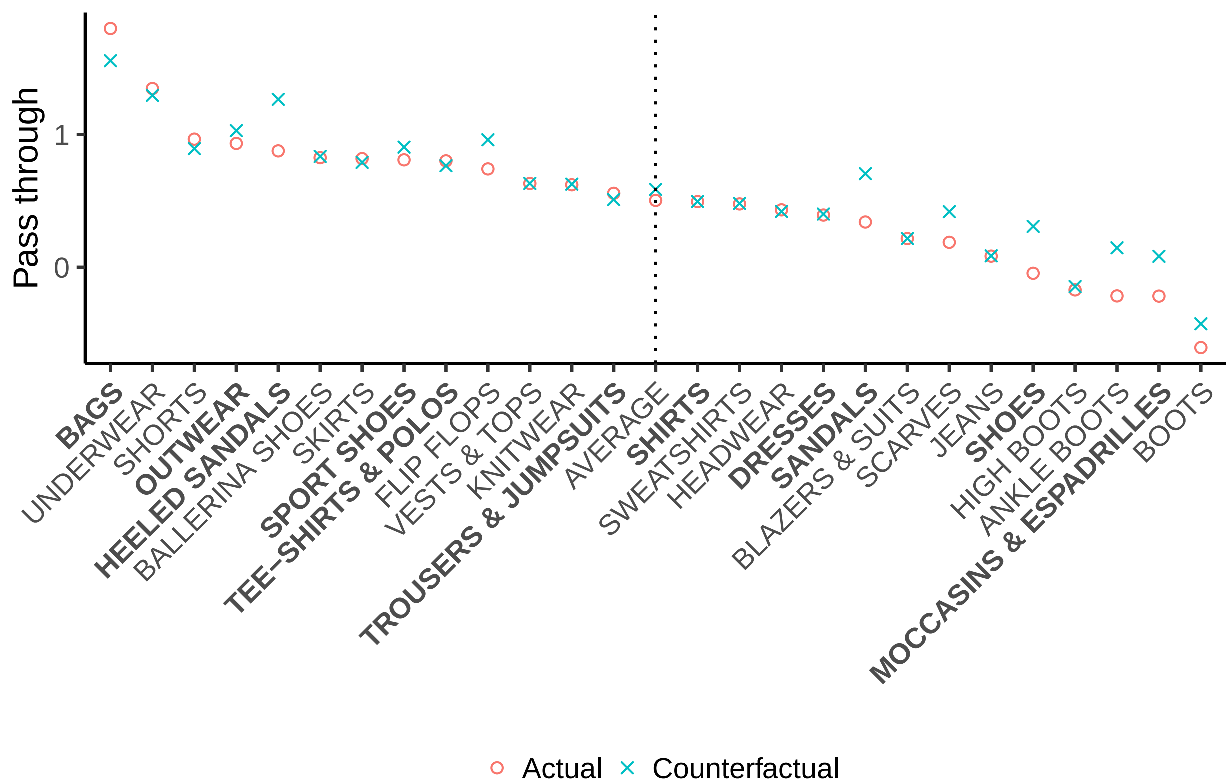

Figure 6: **Counterfactual pass-through by product group**
Note: Bolded product group names comprise 80% of sales during the 2014 Spring/Summer season.

product group names in Figure 6 comprise 80% of sales during the 2014 Spring/Summer season; there are many such product groups for which quality downgrading acts as a substantial damper on price increases. For instance, sport shoes are the most important category in Spring/Summer 2014 with almost 15% of total sales; with quality downgrading pass-through falls from 0.90 to 0.81. We also show in Appendix D that allowing greater flexibility in predicting the components of the average price $\bar{p}_{gt}$ does not qualitatively change our findings.

6 Conclusion

Using rich data on hundreds of thousands of globally-sourced products from a fast-fashion retailer, we show that Russia's currency depreciation in late 2014 led the retailer to reallocate towards lower quality products. We provide evidence that a proportionate increase in marginal ruble costs is the causal channel, and argue that a simple model featuring non-homothetic utility and quality-specific demand elasticities is consistent with the data. Our paper is the first to directly document quality downgrading in response to a currency devaluation and to provide an empirically-supported mechanism for this phenomenon.

Our study looks at the effects of the exchange rate shock on quality holding downstream preferences fixed. Yet reductions in quality may deplete firms' relationship capital with customers, be they households or businesses (Hong, 2017), leading to larger long-run demand elasticities and less reallocation. Conversely, consumers' tastes may adapt to the suddenly more-prevalent low quality goods, implying further future reallocation. We leave questions regarding the long-run demand consequences of adjusting quality in response to cost shocks for future research.

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Online Appendix: Not For Publication

A Data

Table A.1: Material quality mapping

Quality	Material	Num. SKUs	Blend Fraction
High	Cotton	140,665	0.495
	Leather	71,173	0.050
	Viscose	42,806	0.773
	Textile	17,618	0.299
	Wool	17,411	0.836
	Suede	10,344	0.027
	Nubuck	4,776	0.004
	Velour	4,046	0.0002
	Silk	4,024	0.440
	Linen	2,745	0.762
	Rubber	2,729	0.715
	Angora	2,111	0.998
	Modal	1,924	0.865
	Cashmere	1,678	0.930
	Split	1,511	0.001
	District	852	0.826
	Mohair	767	0.982
Low	Polyester	104,400	0.632
	Nylon	31,613	0.812
	Artificial Leather	28,637	0.051
	Polymer	27,614	0.308
	Acrylic	17,480	0.655
	Artificial	3,256	0.233
	Artificial Suede	1,900	0.001
	Artificial Nubuck	933	0.002
	Acetate	676	0.933
	Lurex	610	1
Dropped	Elastane	62,574	0.999

Note: This table presents the quality mapping for the 30 most commonly occurring fabrics, at least one of which is present in 97% of SKUs and accounting for all materials in 93% of SKUs. Elastane almost always appears in blends as a negligible fraction, so we exclude it.

Table A.2: Top Three Fabrics by Product Groups

Group	Material	Quality	Share	Group	Material	Quality	Share
Ankle Boots	Leather	High	0.400	Outwear	Polyester	Low	0.360
	Artificial Leather	Low	0.130		Nylon	Low	0.160
	Suede	High	0.120		Cotton	High	0.080
Bags	Leather	High	0.340	Sandals	Leather	High	0.370
	Polymer	Low	0.210		Artificial Leather	Low	0.250
	Artificial Leather	Low	0.210		Polymer	Low	0.180
Ballerina Shoes	Leather	High	0.340	Scarves	Polyester	Low	0.160
	Artificial Leather	Low	0.220		Silk	High	0.130
	Textile	High	0.110		Acrylic	Low	0.110
Blazers And Suits	Cotton	High	0.180	Shirts	Cotton	High	0.440
	Polyester	Low	0.160		Polyester	Low	0.250
	Polyester/Viscose	High	0.140		Viscose	High	0.100
Boots	Leather	High	0.500	Shoes	Leather	High	0.520
	Artificial Leather	Low	0.110		Artificial Leather	Low	0.110
	Nubuck	High	0.100		Suede	High	0.090
Dresses	Polyester	Low	0.330	Shorts	Cotton	High	0.540
	Cotton	High	0.120		Polyester	Low	0.200
	Viscose	High	0.110		Cotton/Polyester	High	0.090
Flip Flops	Polymer	Low	0.320	Skirts	Polyester	Low	0.270
	Artificial	Low	0.200		Cotton	High	0.190
	Rubber	High	0.110		Polyester/Viscose	High	0.110
Headwear	Acrylic	Low	0.200	Sport Shoes	Leather	High	0.260
	Cotton	High	0.160		Textile	High	0.190
	Acrylic/Wool	High	0.120		Artificial Leather	Low	0.170
Heeled Sandals	Leather	High	0.450	Sweatshirts	Cotton/Polyester	High	0.420
	Artificial Leather	Low	0.190		Cotton	High	0.340
	Polymer	Low	0.100		Polyester	Low	0.140
High Boots	Leather	High	0.450	Tee-Shirts And Polos	Cotton	High	0.690
	Artificial Leather	Low	0.150		Cotton/Polyester	High	0.090
	Suede	High	0.140		Polyester	Low	0.060
Jeans	Cotton	High	0.660	Trousers And Jumpsuits	Cotton	High	0.350
	Cotton/Polyester	High	0.220		Polyester	Low	0.170
	Cotton/Cotton	High	0.030		Cotton/Polyester	High	0.140
Knitwear	Cotton	High	0.210	Underwear	Nylon	Low	0.400
	Acrylic	Low	0.070		Cotton	High	0.350
	Nylon/Viscose	High	0.060		Polyester	Low	0.080
Moccasins And Espadrilles	Leather	High	0.430	Vests And Tops	Cotton	High	0.280
	Textile	High	0.140		Polyester	Low	0.270
	Suede	High	0.090		Viscose	High	0.130

Note: This table shows the top three materials and their coding by product group. Two materials separated by a slash indicate a blend (in any combination). Shares are the share of SKUs in that group comprised of that material over the entire sample.

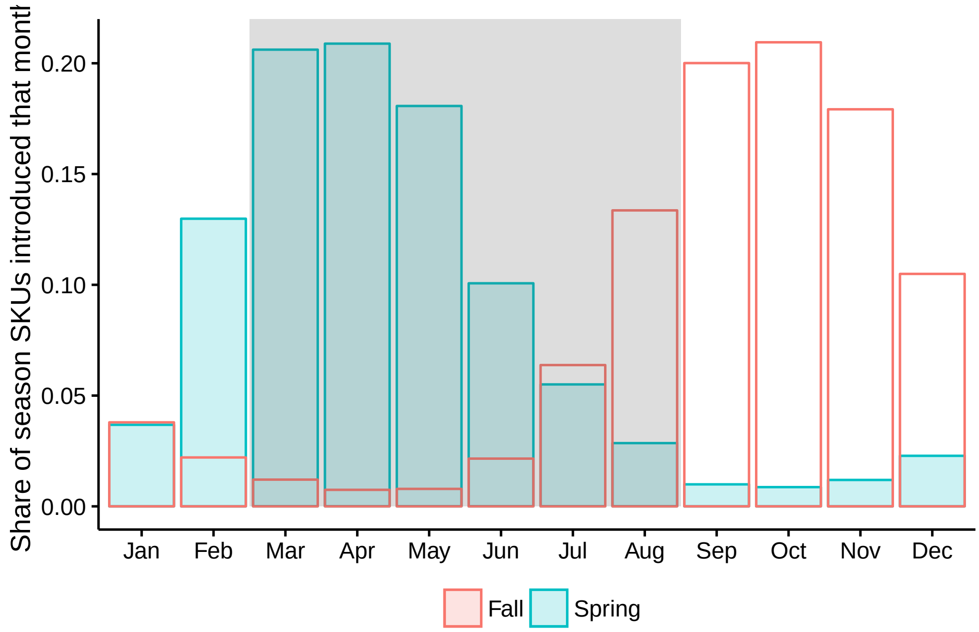

Figure A.1: **Month of first appearance for new SKUs by season**
Note: This figure shows histograms of the distribution of Fall and Spring introductions by month. The gray area covers the months we choose to associate with Spring goods of March-August.

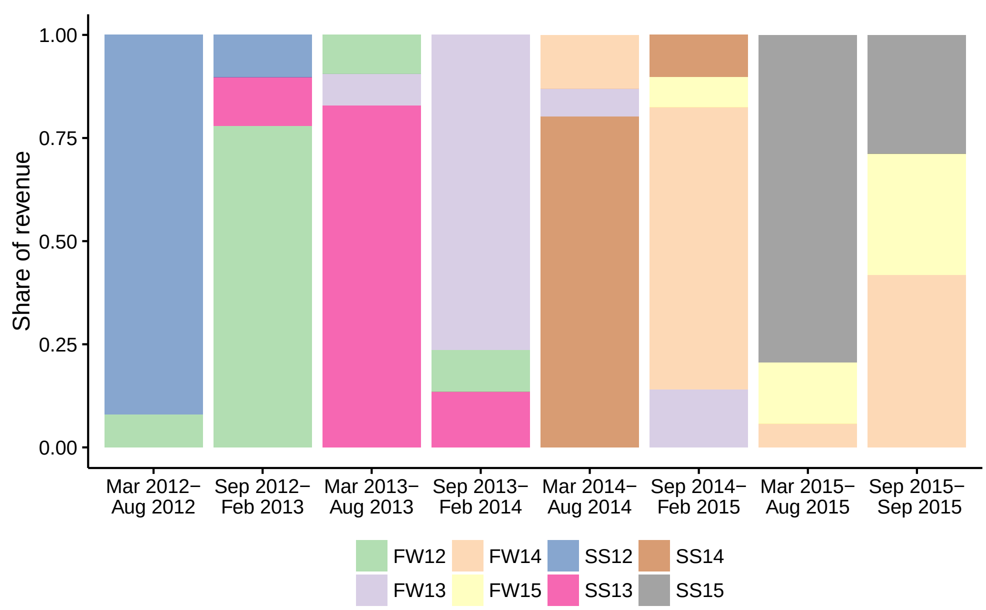

Figure A.2: **Overlapping generations of goods**
Note: This figure plots the revenue shares (between 0 and 1) for each generation of goods over subsequent Fall and Spring seasons.

A.1 Quality measure validation

In this section we validate our choice of the quality dummy using a characteristics-based Khandelwal (2010) style regression. This involves projecting log sales shares for each SKU onto prices, fixed effects and product characteristics, with the logic being that higher quality products are those with higher sales conditional on prices. We recover a positive, significant coefficient on our quality dummy.

We observe price and consumption variation within a season across months, and across products within a season. We therefore run the regression at the monthly level, with monthly SKU sales and prices our unit of observation. Our primary specification closely follows Khandelwal (2010):

$$\ln(s_{j\tau}) - \ln(s_{0\tau}) = \lambda_{1,j} + \lambda_{2,\tau} + \alpha_j p_{j\tau} + h_j(\tau) + \sigma \log(ns_{j\tau}) + \lambda_{3,j\tau}, \tag{A.1}$$

where $s_{j,\tau}$ is the share of SKU j in month τ, $s_{0,\tau}$ is the share of spending on the outside good, $p_{j,\tau}$ is the sales-weighted price of j in month τ, and $ns_{j\tau}$ is the share of SKU j within its product group (i.e., the nest share).

We make four changes compared to Khandelwal (2010). First, we do not control for hidden varieties with GDP based proxies as we observe demand at the level of a precise variety. Second, we include the $h_j(\tau)$ term, which for product j tracks whether τ is the first, second, or third month of it being sold. This term is necessary to take account of consumers' dynamic behavior: prices for a SKU within a season are lowered over time but demand does not necessarily increase—purchasing a product late in the season for which it is intended (e.g., buying winter boots in March) decreases utility from the purchase.

Third, we assume $\lambda_{1,j} = \boldsymbol{x}_j{}'\boldsymbol{\beta}$, with x_j including the product group-brand-season fixed effect, as well as variables for Russian/non-Russian origin, premium status as labelled by the retailer, and the high/low quality dummy. We do not include a fixed effect at the SKU level since our price instrument is wholesale cost, and it does not vary from month to month within an SKU.

Lastly, we allow the price coefficient α_j to vary between high and low quality products. Our mechanism for quality downgrading will require different price sensitivities across high and low quality. To treat the data as consistently as possible, we thus use the same demand system to recover the quality dummy, the quality residuals, and price sensitivities.

Results from equation A.1 are presented in Table A.3. We try specifications using both prices and log prices. Our instrument is highly significant, and price coefficients increase in magnitude under 2SLS as expected.

Coefficients on the quality dummy in columns (2) and (4) indicate that high quality products sell between 3.7% and 13.5% percent more conditional on price. The negative, significant coefficient on the interaction between price and quality implies that high quality products are more price sensitive. Although recovered elasticities are low, they are well within the interquartile range of estimated elasticities reported in Table 3 of Khandelwal (2010).

Table A.3: Logit demand regression results

	Dependent variable:			
	$\log(s_j) - \log(s_0)$			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$p_{j\tau}$	-0.021***	-0.026***		
	(0.001)	(0.001)		
$p_{j\tau} \times \text{Nat}_j$	-0.001	-0.003***		
	(0.001)	(0.001)		
$\log(p_{j\tau})$			-0.124***	-0.140***
			(0.004)	(0.004)
$\log(p_{j\tau}) \times \text{Nat}_j$			-0.010**	-0.014***
			(0.003)	(0.003)
Nat_j	0.028***	0.037***	0.100***	0.135***
	(0.005)	(0.005)	(0.023)	(0.025)
Rus_j	0.004	0.004	0.005	0.006
	(0.018)	(0.018)	(0.017)	(0.016)
$\text{Nat}_j \times \text{Rus}_j$	-0.003	-0.002	-0.0001	0.001
	(0.014)	(0.014)	(0.013)	(0.013)
Premium_j	-0.067	-0.069	-0.070	-0.072
	(0.120)	(0.121)	(0.123)	(0.124)
$\log(ns_{j\tau})$	0.703***	0.702***	0.701***	0.700***
	(0.002)	(0.002)	(0.002)	(0.002)
Mean Elasticity: Low Quality	-0.21	-0.26	-0.42	-0.47
Mean Elasticity: High Quality	-0.24	-0.33	-0.45	-0.51
First-Stage F Stat		664		669
$h_j(\tau)$	✓	✓	✓	✓
Group-Brand-Season FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Observations	853,187	853,187	853,187	853,187
R^2	0.941	0.941	0.941	0.941

*Note: This table presents coefficient estimates from specification A.1. The unit of observation is at the level of an SKU j in month τ. Standard errors are clustered at the Group-Brand-Season level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively. Nested logit elasticites are computed by SKU as $\frac{\partial s_{jt}}{\partial p_{jt}} \frac{p_{jt}}{s_{jt}} = \hat{\alpha}_j \cdot p_{jt} \cdot \left(\frac{1}{1-\hat{\sigma}} - \frac{\hat{\sigma}}{1-\hat{\sigma}} \cdot ns_{jt} - s_{jt}\right)$ and averaged across SKUs.*

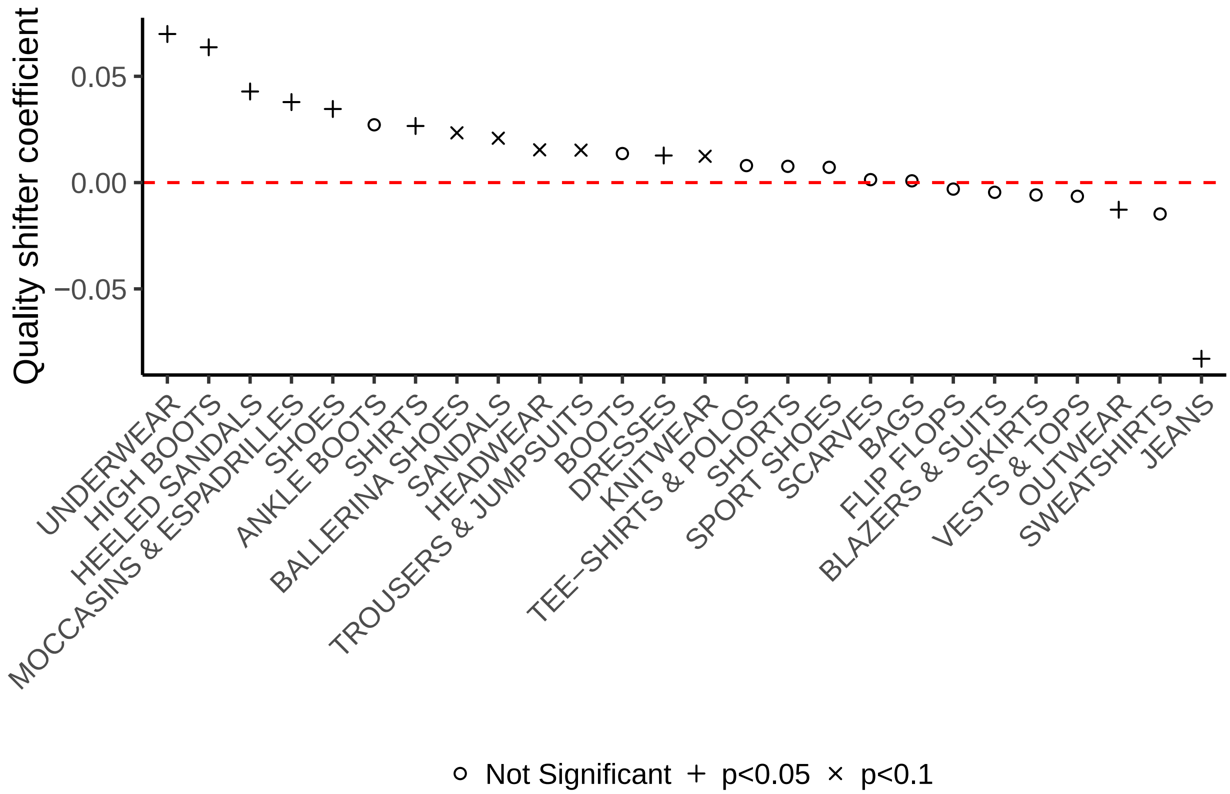

Figure A.3: **Product group-specific quality shifters**
Note: This figure plots the estimated partial effects of the quality dummy from equation A.1. Fixed effects and error clustering are as in Table A.3.

B Reduced Form Evidence

B.1 Profit and quality

We run the following regression on the entire set of pre-shock products (Fall 2014 and earlier) and report the results in Table B.1:

$$\log(y_{jbgt}) = \beta \cdot Natural_j + \sum_{bgt} \alpha_{bgt}\mathbf{D}_{bgt} + \epsilon_{jbgt} \tag{B.1}$$

where y_{jbgt} is either the profit, quantity sold, or price of SKU j, in product group g, in season t, $\mathbf{D}_{bgt}$ is a brand $\times$ product group $\times$ season fixed effect. The results are similar to Table 3: high quality goods are about 5.8% more profitable, and sell at a 6.1% higher price on average.

Table B.1: Mean differences for high quality products

	Dependent variable:					
	log(π)	log(pq)	log(q)	log(p)	log(c)	log(p/c)
	(1)	(2)	(3)	(4)	(5)	(6)
Natural	0.058***	0.059***	-0.002	0.061***	0.061***	0.0002
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.001)
Brand × Group × Season FE	✓	✓	✓	✓	✓	✓
Observations	304,577	304,577	304,577	304,577	304,577	304,577
R^2	0.695	0.685	0.660	0.899	0.900	0.869

*Note: This table presents coefficient estimates from specification B.1. The outcome variables is either the profit, quantity sold, or price of SKU j, in product group g, in season t. Brand, product group, season fixed effects are included. Prices are sales-weighted within SKUs, and standard errors are clustered at the brand×group×season level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

B.2 Quality downgrading

Table B.2: Differential quality downgrading robustness: dropped final season

	Dependent variable:			
	$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.334**	-0.334**	-2.211**	-2.158*
	(0.109)	(0.122)	(0.811)	(0.862)
Group × Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	349	349	349	349
R^2	0.691	0.857	0.671	0.839

*Note: This table presents coefficient estimates from specification 2, but dropping the last season 2015-09. The outcome in the first two columns is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t, and in the last two columns is the log ratio of the number of natural SKUs to artificial SKUs within grt. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group or brand×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.3: Differential quality downgrading robustness: inventory weighting

	Dependent variable:			
	$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.327**	-0.302*	-3.197**	-2.998*
	(0.105)	(0.125)	(1.117)	(1.225)
Group × Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	395	395	395	395
R^2	0.720	0.870	0.637	0.822

*Note: This table presents coefficient estimates from specification 2, but weighting each SKU by its initial stock-up inventory in the dependent variable construction. The outcome in the first two columns is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t, and in the last two columns is the log ratio of the number of natural SKUs to artificial SKUs within grt. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group or brand×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.4: Differential quality downgrading robustness: season-of-year controls

	Dependent variable:			
	$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.359**	-0.356**	-2.218**	-2.153*
	(0.114)	(0.123)	(0.811)	(0.838)
Group × Origin × Season-of-Year FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	395	395	395	395
R^2	0.777	0.900	0.762	0.887

*Note: This table presents coefficient estimates from specification 2, but interacting the group-origin fixed effect with the season-of-year, e.g. Fall/Winter and Spring/Summer. The outcome in the first two columns is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t, and in the last two columns is the log ratio of the number of natural SKUs to artificial SKUs within grt. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group or brand×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.5: Differential quality downgrading robustness: logged $natfrac_{grt}$

	Dependent variable:	
	log($natfrac_{grt}$)	
	(1)	(2)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.665***	-0.606***
	(0.168)	(0.173)
Group × Origin FE	✓	✓
Season FE	✓	
Group × Season FE		✓
Observations	393	393
R^2	0.644	0.852

*Note: This table presents coefficient estimates from specification 2, but using the log of $natfrac$ as the outcome, where $natfrac$ is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group or brand×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.6: Differential quality downgrading robustness: different levels of aggregation

	Dependent variable:			
	$natfrac$		log(N_h/N_ℓ)	
	(1)	(2)	(3)	(4)
$nonrus_r \cdot \log(ER_{t-1})$	-0.293**	0.151	-1.873**	1.680
	(0.074)	(1.213)	(0.490)	(6.777)
Origin FE	✓		✓	
Season FE	✓		✓	
Group × Origin × Brand FE		✓		✓
Group × Season × Brand FE		✓		✓
Observations	16	24,820	16	23,423
R^2	0.903	0.999	0.899	0.999

*Note: This table presents coefficient estimates from specification 2, but aggregating to the origin×season level in columns (1) and (3), and aggregating to the origin×group×brand×season level in columns (2) and (4). The outcome either the fraction of offered SKUs that use a natural fabric within each level of aggregation, or the ratio of the number of high to low quality SKUs. $nonrus_r$ is an indicator with a value of one for the non-Russian products, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at the group×brand×origin level in columns (2) and (4) to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.7: Heterogeneous downgrading coefficients

		Dependent Variable:			
		$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
Group	Cost Ratio	Coef.	SE	Coef.	SE
Ankle Boots	2.572	-0.758	0.441	-4.006	1.761
Bags	2.184	0.247	0.197	2.315	1.585
Ballerina Shoes	2.297	-1.063	0.413	-5.723	2.602
Blazers And Suits	1.252	-0.001	0.148	1.517	0.524
Boots	2.048	-0.456	0.121	-2.998	0.844
Dresses	1.215	-0.206	0.038	-2.466	0.340
Flip Flops	1.839	-0.390	0.081	-2.763	1.096
Headwear	1.423	0.044	0.397	0.975	3.069
Heeled Sandals	2.250	-1.068	0.205	-5.164	0.848
High Boots	2.586	-1.298	0.277	-5.938	2.001
Jeans	0.639	-0.027	0.002	0.344	1.062
Knitwear	1.364	-0.145	0.087	-0.309	1.407
Moccasins And Espadrilles	2.628	-0.430	0.071	-6.850	1.774
Outwear	1.254	-0.371	0.305	-1.619	1.596
Sandals	2.206	-0.805	0.311	-3.921	1.280
Scarves	1.782	-0.465	0.223	-2.362	1.925
Shirts	1.302	-0.111	0.073	-0.544	0.901
Shoes	2.525	-1.121	0.201	-7.242	2.642
Shorts	1.332	0.268	0.229	0.638	0.856
Skirts	0.993	-0.179	0.154	-0.388	0.878
Sport Shoes	1.280	-0.651	0.293	-3.180	2.661
Sweatshirts	0.989	-0.037	0.054	0.475	1.757
Tee-Shirts And Polos	0.937	0.150	0.281	4.277	2.119
Trousers And Jumpsuits	0.824	-0.184	0.054	-2.083	0.635
Underwear	0.685	-0.084	0.040	-1.497	1.104
Vests And Tops	0.880	0.015	0.113	1.701	1.461

Note: This table presents estimated quality downgrading coefficients δ_g from specification 4 for the various product categories along with their levels of statistical significance. The unit of observation in the regressions is at the product group g, origin r, season t level, and the dependent variable is the share of high quality SKUs or the log ratio of the number of high to low quality SKUs. Standard errors are clustered at the product group$\times$origin level.

Khandelwal (2010) DiD robustness checks

Table B.8: Differential quality reallocation

	Dependent variable:			
	Linear price res.		Log price res.	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.160	-0.198*	-0.188	-0.222*
	(0.180)	(0.085)	(0.180)	(0.086)
Group × Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	344	344	344	344
R^2	0.943	0.996	0.943	0.996

*Note: This table presents coefficient estimates from specification 2, but using the Khandelwal (2010) residuals from specification A.1 averaged within a group g, origin r, season t. The first two columns use the linear price and the second two use the log price versions of the Khandelwal (2010) specification. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group ×origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

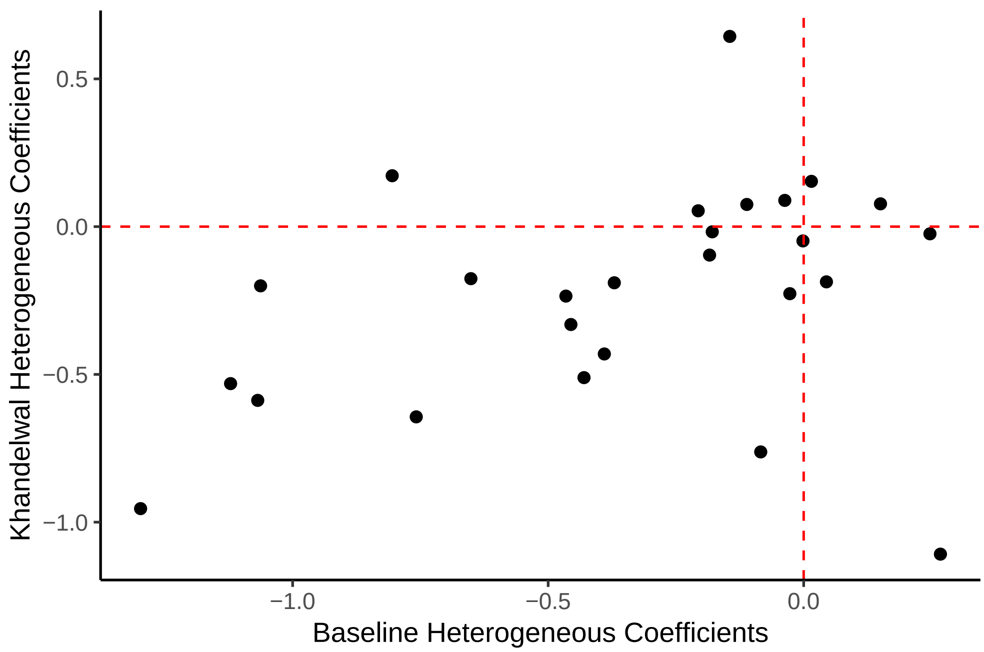

Figure B.1: **Correlations in cross-group variation in downgrading**
Note: This figure plots the estimated δ_g coefficients of equation 4 against the same, but using the averaged Khandelwal (2010) residuals as the dependent variable. Fixed effects are at the group$\times$origin and group$\times$season level.

Relative decrease in number of high-quality imported SKUs

In this section, we confirm that the baseline DiD results reflect quality downgrading among imports, and not quality upgrading in the control group. To do so, we use the logged raw number of SKUs within a product group$\times$quality$\times$season as the dependent variable, and look at the differential stocking of high relative to low qualities in the following regression:

$$\log(N_{mgt}) = \delta \log(ER_{t-1}) \cdot Nat_{mgt} + \sum_{mg} \alpha_{mg}\mathbf{D}_{mg} + \sum_{gt} \alpha_{gt}\mathbf{D}_{gt} + \epsilon_{mgt} \tag{B.2}$$

where m indexes high or low quality, and Nat_{mgt} indicates whether SKUs of quality m in group g at season t are high quality or not.

Results are reported in Table B.9, and indicate that the numbers of high quality imported SKUs decrease relative to the numbers of low quality imported SKUs after the exchange rate shock. We also report results in Table B.10 from a model where material$\times$product group fixed effects are allowed to vary by season-of-year, so that any measured reduction does not simply reflect constant differences in the appeal of high and low quality products between Fall and Spring seasons within a group.

These results imply that there is quality downgrading among imports, but unlike the baseline DiD they do not provide evidence about the mechanism. In particular, without the domestic control group these regressions do not disentangle the role of the income shock versus the cost shock.

Table B.9: Relative decrease in number of imported high quality SKUs

	Dependent variable:			
	log(N)			
	(1)	(2)	(3)	(4)
$\log(ER_{t-1}) \cdot Nat_{mgt}$	-1.065***	-1.065***	-0.766	-0.766***
	(0.295)	(0.216)	(0.518)	(0.215)
Group × Quality FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	416	416	364	364
R^2	0.666	0.982	0.637	0.984

*Note: This table presents coefficient estimates from specification B.2. The outcome is the log number of SKUs in a material quality m, product group g, season t. Nat_{mgt} is an indicator equal to 1 for high quality products in group g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (3) and (4) drop the final incomplete season. Standard errors (in brackets) are clustered at the group×quality level to allow serial correlation over time within a group and quality. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.10: Relative decrease in number of imported high quality SKUs, with seasonality controls

	Dependent variable:			
	log(N)			
	(1)	(2)	(3)	(4)
$\log(ER_{t-1}) \cdot Nat_{mgt}$	-1.000**	-1.000***	-0.964**	-0.964***
	(0.369)	(0.244)	(0.337)	(0.197)
Group × Quality × SoY FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	416	416	364	364
R^2	0.933	0.986	0.953	0.989

*Note: This table presents coefficient estimates from specification B.2, but with an additional season of year (SoY) interaction with the group×quality fixed effect. The outcome is the log number of SKUs in a material quality m, product group g, season t. Nat_{mgt} is an indicator equal to 1 for high quality products in group g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (3) and (4) drop the final incomplete season. Standard errors (in brackets) are clustered at the group×quality level to allow serial correlation over time within a group and quality. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

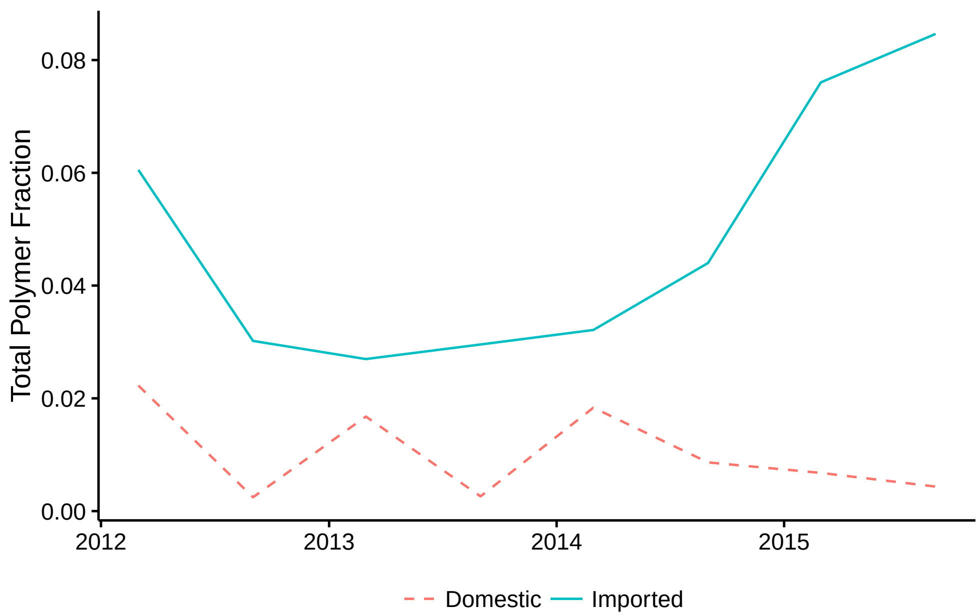

Figure B.2: **Polymer presence by manufacturing origin**
Note: This figure shows the fraction of SKUs where "polymer" is listed as a component over time by domestic (red dashed line) and imported (blue solid line) goods.

B.3 Demand channel ("flight from quality") robustness

Output from Chen and Juvenal (2018) regression

The following regression from Chen and Juvenal (2018) is repeated from the main text:

$$\Delta \ln X_{mgcy} = \phi \Delta \ln \left(\frac{GRP}{cap}\right)_{cy} \cdot Nat_m + \sum_{gcy} \alpha_{gcy} \mathbf{D}_{gcy} + \sum_{mgy} \alpha_{mgy} \mathbf{D}_{mgy} + \sum_{mgc} \alpha_{mgc} \mathbf{D}_{mgc} + \epsilon_{mgcy}, \tag{B.3}$$

where X_{mgcy} measures expenditures on SKUs of quality m in product group g in oblast c in year y, $y \in \{2012, \ldots, 2015\}$. Results are reported in the first column of Table B.11. A positive, significant $\hat{\phi}$ would indicate a flight-from-quality mechanism at work; we find a positive, insignificantly estimated coefficient.

We also run the regression using average prices within a quality-product group-oblast-year as a dependent variable. A positive, significant coefficient would indicate that high-quality products in areas with greater growth contraction experience disproportionate reductions in price. Results in the second column of Table B.11 show an insignificant coefficient, which accords with the firm's stated policy of maintaining the same price across all of Russia.

We replicate the regression on disaggregated data, so that g indexes not just product groups but product group-brands. Results in Table B.12 agree with the findings in Table B.11.

Alternative "flight from quality" regression

Our alternative regression is as follows:

$$natfrac_{gct} = \sum_t \delta_t \Delta \ln(GRP/cap2015)_c \cdot \mathbf{D}_t + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \sum_{gc} \alpha_{gc} \mathbf{D}_{gc} + \epsilon_{gct}, \tag{B.4}$$

where $natfrac_{gct}$ is the share of high quality (natural fabric) SKUs in product group g, oblast c, in season t, and $\Delta \ln(GRP/cap2015)_c$ is the change in log gross regional product per capita from 2014 to 2015 in oblast c.

The benefit of specification B.4 is that it keeps observations at the season level since it does not use changes in $\ln(GRP/cap)_{ct}$, which are only available at the yearly level. Conceptually, the specification is a difference-in-differences with continuous treatment based on growth from

Table B.11: No flight from quality, product group level

	Dependent variable:	
	$\Delta \ln X_{mgcy}$	$\Delta \ln P_{mgcy}$
	(1)	(2)
$\Delta \ln(GRP/cap)_{cy} \cdot Nat_m$	0.412	0.136
	(0.341)	(0.219)
Group × Oblast × Year FE	✓	✓
Quality × Group × Year FE	✓	✓
Quality × Group × Oblast FE	✓	✓
Observations	10,104	10,104
R^2	0.951	0.793

*Note: This table presents coefficient estimates from specification B.3. The dependent variable is either (1) the change in log expenditure on SKUs of quality m, group g, oblast c, from year $y-1$ to year y (2) the change in log average price for SKUs within mgc from year $y-1$ to year y. Standard errors (in brackets) are clustered at the quality-group-oblast level to allow for serial correlation across years. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.12: No flight from quality, product group-brand level

	Dependent variable:	
	ΔX_{mgcy}	$\Delta \ln P_{mgcy}$
	(1)	(2)
$\Delta \ln(GRP/cap)_{cy} \cdot Nat_m$	-0.008	0.001
	(0.158)	(0.048)
Group × Brand × Oblast × Year FE	✓	✓
Quality × Group × Brand × Year FE	✓	✓
Quality × Group × Oblast FE	✓	✓
Observations	181,178	181,178
R^2	0.955	0.945

*Note: This table presents coefficient estimates from specification B.3. The dependent variable is either (1) the change in log expenditure on SKUs of quality m, group-brand g, oblast c, from year $y-1$ to year y (2) the change in log average price for SKUs within mgc from year $y-1$ to year y. Standard errors (in brackets) are clustered at the quality-group-oblast level to allow for serial correlation across years. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

2014 to 2015, and flexible timing.

The δ_t coefficients plotted with 95% confidence bars in Figure B.3 show that there is no differential change in the share of high quality products sold in oblasts that experienced greater growth contractions.

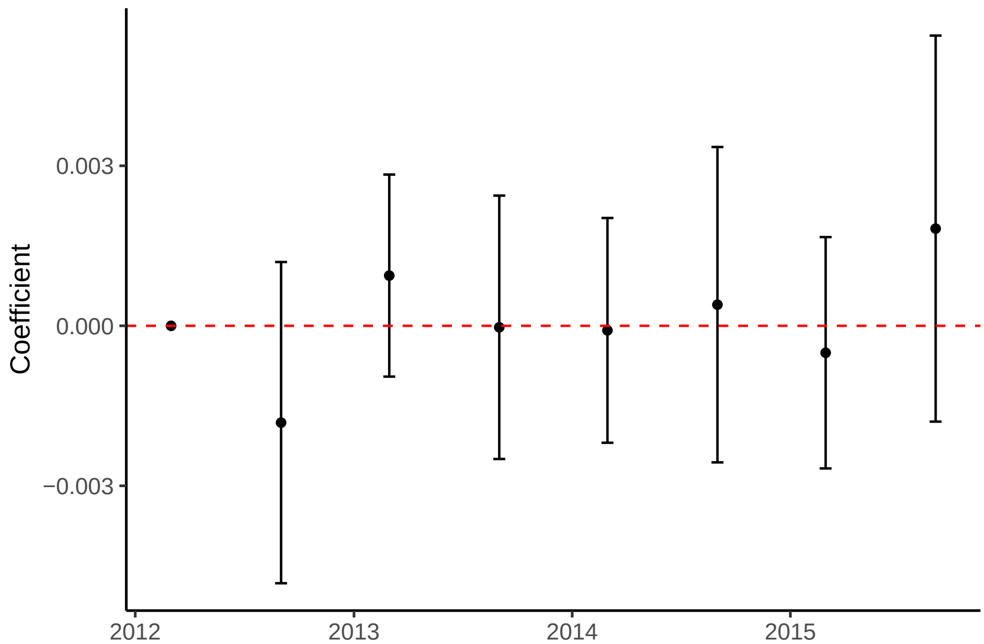

Figure B.3: **No differential reduction in quality share in low-growth oblasts**
Note: This figure plots the estimated δ_t coefficients of equation B.4 with 95% confidence intervals around them. The unit of observation is the share of high quality products purchased in product group g, oblast c, in season t. Fixed effects are at the product group$\times$oblast and product group$\times$season level. Standard errors are clustered at product group$\times$oblast level to allow within-group-oblast serial correlation.

B.4 Quality downgrading generalization

Supposing we can observe a measure of product quality at the HS6×country×quarter level, our goal is to run the following regression:

$$\bar{\lambda}_{cHq} = \delta ER_{cq} + \sum_{cH} \alpha_{cH} \mathbf{D}_{cH} + \sum_{Hq} \alpha_{Hq} \mathbf{D}_{Hq} + \epsilon_{cHq} \tag{B.5}$$

where c is a country, H is an HS4 category, and q is a quarter. $\bar{\lambda}_{cHq}$ is the average quality of HS6 products within HS4 category H imported from c in quarter q, while ER_{cq} is the nominal exchange rate in rubles per unit of currency for country c in quarter q.

We look at average quality within an HS4 category to mimic our baseline regression, where we allow reallocation amongst SKUs in a product group; here, we allow reallocation amongst HS6 products within an HS4 category. Our dummy variables will ensure that δ is identified by reallocation within a country×HS4 product group, conditional on quarterly, HS4-level shocks that affect the quality of imports from all countries in the same way.

To estimate λ_{cHq}, we follow Khandelwal (2010) and Zhu and Tomasi (2020) to estimate qualities at the HS6 level and take the average within an HS4 category. We start with the following regression—which is identical to equation (15) in Khandelwal (2010)—at the HS6×country×quarter level:

$$\ln s_{chq} - \ln s_{0q} = \lambda_{1,ch} + \lambda_{2,q} + \alpha p_{ch,q} + \sigma \ln ns_{ch,q} + \gamma \ln pop_{cq} + \lambda_{3,chq},$$

where s_{chq} is the market share of product h from country c, s_{0q} is the outside share, $p_{ch,q}$ is the unit value in USD, found by dividing the CIF traded value by the weight in kilograms, $ns_{ch,q}$ is the share of imports in HS6 category h accounted for by country c, and pop_{cq} is the population of country c in quarter q.

We do not observe the total market size (the denominator of s_{chq}), which is the sum of quantities of imports and domestically manufactured products in the HS4 category to which the HS6 product belongs; however, this will not be an issue for our application. Because market size and s_{0q} vary at the HS4×quarterly level, we can include only the logged numerator of s_{chq}—the quantity of country c's imports for HS6 h in quarter q, Q_{chq}—and the omitted components of the LHS variable will be absorbed by each regression's $\lambda_{2,q}$ fixed effect if we interact it with an HS4 dummy. In effect, we replace $\lambda_{2,q}$ with $\lambda_{2,Hq}$. The HS4×quarterly dummy in our downgrading specification B.5 will then fully absorb the variation in quality due to variation in $\lambda_{2,q}$, and this component of quality will therefore play no role in identifying δ.

To add additional flexibility, we run the regression separately for different HS2 product categories; Bernini and Tomasi (2015) run their HS6×firm level regression separately across HS4 categories, while Khandelwal (2010) runs their HS10 level regression for different SITC (rev. 2) industries. Our actual estimating equation for each HS2 category is therefore:

$$\ln Q_{chq} = \lambda_{1,ch} + \lambda_{2,Hq} + \alpha p_{ch,q} + \sigma \ln ns_{ch,q} + \gamma \ln pop_{cq} + \lambda_{3,chq}, \tag{B.6}$$

where α and σ will vary by HS2 category.

There are standard issues of endogeneity for the identification of both α and σ, which we resolve in the usual way. Prices are instrumented for by exchange rate movements (from the IMF), and oil prices (from the U.S. Energy Information Administration) interacted with distances between capitals as in Khandelwal (2010), as well as with MFN tariffs (from the WTO) as in Zhu and Tomasi (2020). We lack data on FOB unit values which could be used to recover transport and duty costs for the CIF unit values. Nest shares are instrumented for by the count variables in Khandelwal (2010) (see that paper for details). In total we have information on 76 importing partners and 1407 HS6 products, comprising 122 173 observations, with which to estimate quality residuals.

We construct quality as $\hat{\lambda}_{chq} = \hat{\lambda}_{1,ch} + \hat{\lambda}_{2,q} + \hat{\lambda}_{3,chq}$ using the estimates from specification B.6, average it within an HS4×country×quarter, and then estimate specification B.5. We exclude some HS2×country combinations whose exports were restricted by Russia in mid-2014, in retaliation for actions taken by those countries after Russia's annexation of Crimea. The countries include all EU member nations as well as Australia, Canada, Norway, and the United States; banned HS2 categories include 02, 03, 04, 07, 08, 16, 19 and 21, which cover processed and unprocessed agricultural products (Kutlina-Dimitrova, 2017). We also exclude imports from Ukraine, based on the ongoing conflict between Russia and that country which began in February 2014.

Results are reported in Table B.13. Coefficients are estimated negative, implying that countries against which the ruble depreciated more (a greater number of rubles per unit currency) experienced a larger drop in quality. The first column runs specification B.5, while the second one uses a 2 quarter lagged exchange rate to mimic the 6 month lag in our baseline quality downgrading regressions. The lagged exchange rate coefficient is larger in magnitude and significant,

Table B.13: Quality downgrading generalization

	Dependent variable:			
	$\bar{\lambda}_{cHq}$			
	(1)	(2)	(3)	(4)
log(ER$_{c,q}$)	-0.244		-0.247	
	(0.167)		(0.175)	
log(ER$_{c,q-2}$)		-0.388*		-0.221
		(0.171)		(0.169)
HS4 × Country FE	✓	✓		
HS6 × Country FE			✓	✓
HS4 × Season FE	✓	✓	✓	✓
Observations	122,173	122,173	122,173	122,173
R^2	0.999	0.999	0.999	0.999

*Note: This table presents coefficient estimates from specification B.5 at the HS4-country-quarter level. The dependent variable is the average quality, and ER_{cq} is the country c currency to ruble exchange rate (rubles per unit currency). Standard errors (in brackets) are clustered at the HS4×country level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

suggesting that quality takes time to adjust. The third and fourth columns repeat the exercise but introduce an HS6×country fixed effect to show that "within-product" downgrading does not seem to be driving the results.

Our ability to recover product quality from aggregated trade data faces the usual caveats. In particular, an HS6×country bucket likely contains many products, and quantity may decrease conditional on price not because quality has decreased, but because products are dropped at the extensive margin within the bucket. We use the usual population-based proxy to attempt to control for these hidden varieties, but it is not appropriate here as extensive margin changes are likely occuring rapidly in response to the shock. Even an HS12×firm category likely suffers from aggregation bias (Chen and Juvenal, 2018), and so even with finer trade data available in other papers this would be an issue, which highlights the benefits of using our dataset where all products are observed.

B.5 Price pass-through, expenditure switching and quantity switching

Differential pass-through dispersion

A concern with the main price pass-through regressions is that since we are not measuring price changes within SKUs, but within material×brand×product groups, there may be differential selection of products after the exchange rate shock in a way that biases the results. For instance, if there are different types of high quality products for a particular brand, and if some of them reduce markups more in response to the devaluation, it stands to reason that those high quality goods would drop out by more as they become less profitable. Our regression would thus find more pass-through for high quality goods than there should be.

We evaluate the role within-brand-material SKU heterogeneity plays by checking the second moments of the price and wholesale cost distributions for high and low quality goods. Suppose demand is such that a brand's least expensive high quality goods have more scope for incomplete pass-through compared to its other high quality goods; if the markup contraction makes these goods unprofitable to stock after the cost shock, then the coefficient of variation for a brand's high quality goods' prices ($\text{CV}^p \equiv \sigma_p/\mu_p$) should decrease, as lower priced SKUs from the bottom of the brand's price distribution of high quality SKUs drop out. The coefficient of variation for a brand's high quality goods' prices would also decrease if it is a brand's most expensive high quality goods that have more scope for incomplete pass-through. If the coefficient of variation for a brand's high quality goods prices does not decrease after the cost shock, then even if there is heterogeneity in pass-through within-brand-material it will not bias the average pass-through regressions through selection.

We run the following specification at the material-brand-season level to check for differential reductions in the coefficient of variation for a brand's high quality SKUs:

$$\begin{aligned}\text{CV}^x_{mbgt} &= \beta_1 \log(ER_{t-1}) + \beta_2 \log(ER_{t-1}) \cdot Nat_{mbgt} + \log(ER_{t-1}) \cdot Rus_{mbgt} \\ &\quad + \log(ER_{t-1}) \cdot Nat_{mbgt} \cdot Rus_{mbgt} + \sum_{mbg} \alpha_{mbg} \mathbf{D}_{mbgs} + \sum_{bgr} \alpha_{bgr} \mathbf{D}_{bgr} + \epsilon_{mbgt},\end{aligned} \tag{B.7}$$

where $\beta_2 \neq 0$ would indicate a differential effect of the exchange rate on the coefficient of variation of either the prices or wholesale costs for fabric quality m for brand b in season s, and $\beta_1 \neq 0$ indicates a baseline effect of the exchange rate on dispersion. Results in Table B.14 show no significance for β_2, implying that the dispersion in prices and costs did not change differentially for high

Table B.14: No change in within-brand-fabric price dispersion

	Dependent variable:			
	CV^p	CV^c	CV^p	CV^c
	(1)	(2)	(3)	(4)
$\log(ER_{t-1})$	0.003	-0.00000	0.001	-0.001
	(0.019)	(0.021)	(0.018)	(0.020)
$\log(ER_{t-1}) \cdot Nat$	-0.003	-0.002	-0.004	-0.003
	(0.022)	(0.024)	(0.021)	(0.023)
$\log(ER_{t-1}) \cdot Rus$			-0.004	-0.001
			(0.009)	(0.009)
$\log(ER_{t-1}) \cdot Nat \cdot Rus$			-0.008	-0.012
			(0.010)	(0.010)
Quality × Brand × Group × SoY FE	✓	✓	✓	✓
Brand × Group × Origin FE			✓	✓
Observations	20,753	20,615	21,767	21,660
R^2	0.775	0.744	0.771	0.742

*Note: This table presents coefficient estimates from specification B.7 at the fabric-brand-season level. The dependent variable is either (1) the within brand-quality coefficient of variation of prices or (2) the same but for wholesale costs. ER_{t-1} is the lagged averaged U.S. dollar to ruble exchange rate, and Nat and Rus are indicators for whether SKU j has a high quality material and is of Russian origin, respectively. Standard errors (in brackets) are clustered at the brand×origin and brand×quality-level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

quality goods. Moreover, β_1 itself is not significantly different from zero, suggesting no effect of the cost shock on the baseline within-brand pricing dispersion. When including Russian-sourced products, there is again no effect of the exchange rate on price dispersion within a material-brand-group-origin bucket. These results suggests that differential dropping of low margin, high quality goods in response to the cost shock is not biasing our pass-through results.

Micro-dynamics of price adjustments

Conditioning on price adjustments, the next section shows that within-SKU pass-through is very high for imported goods. Even though the number of products that live across seasons is small relative to the overall volume, one can use those observations to ask if natural items experienced any differential exchange rate pass-through.

At the SKU-level, we estimate pass-through into prices of exchange rate shocks realized during the most recent period of price non-adjustment and of those that were realized prior to the previous price adjustment. As discussed in the literature (Gopinath and Itskhoki (2010a)), in the absence of real rigidities, all adjustment should take place at the first instance of price change and hence the coefficient on the exchange rate change prior to the previous price adjustment should be zero. More precisely, the following regression is estimated:

$$\Delta \overline{p}_{i,t} = \beta_1 \Delta_{\tau_1} e_t + \beta_2 \Delta_{\tau_2} e_{t-\tau_1} + \eta_i + \epsilon_{i,t} \tag{B.8}$$

where i indexes the SKU, t stands for the date, the outcome variable, $\Delta \overline{p}_{i,t}$, is the change in the log ruble price of a good, *conditional on price adjustment*, and $\Delta_{\tau_1} e_t \equiv e_t - e_{t-\tau_1}$ is the the cumulative change in the log of the nominal exchange rate over the duration when the previous price was in effect (denoted as τ_1). Analogously, τ_2 denotes the duration of the previous price of the firm so that $\Delta_{\tau_2} e_{t-\tau_1} \equiv e_{t-\tau_1} - e_{t-\tau_1-\tau_2}$ is the cumulative exchange rate change over the previous period of non-adjustment, i.e., the period prior to the previous price change. Solely within-SKU variation is exploited via the inclusion of good-specific fixed effects, η_i, and standard errors are clustered at the SKU-level to allow for serial correlation across time.

Table B.15 reports the results from estimations of regression B.8. The number of SKUs is much smaller than in previous regressions due to the fact that there are very few goods that live across seasons. Still, the findings in columns (1) and (3) show that pass-through high after the cost shock. Compared to the Euro, the estimated coefficients are larger and more significant for the U.S. dollar to ruble exchange rate. This is because most trade is invoiced in U.S. dollars rather than in Euros. Columns (2) and (4) present very similar results, but allowing for exchange rate pass-through to differ across natural versus non-natural SKUs, which means that the model is augmented with interaction terms between the exchange rate change and the natural dummy. None of the multiplicative terms are statistically distinguishable from zero, suggesting yet again that pass-through does not vary across high quality and low quality goods.

Table B.15: Within-SKU pass-through

	Dependent variable: $\Delta\log(p_{i,t})$			
	(1)	(2)	(3)	(4)
Δ_{τ_1} usdrub$_{i,t}$	0.993***	0.921**		
	[0.279]	[0.409]		
Δ_{τ_2} usdrub$_{i,t-\tau_1}$	0.649***	0.553		
	[0.203]	[0.410]		
Δ_{τ_1} usdrub$_{i,t} \cdot Nat$		0.894		
		[0.975]		
Δ_{τ_2} usdrub$_{i,t-\tau_1} \cdot Nat$		-0.410		
		[0.923]		
Δ_{τ_1} eurrub$_{i,t}$			0.500*	0.383
			[0.270]	[0.383]
Δ_{τ_2} eurrub$_{i,t-\tau_1}$			0.461**	0.190
			[0.217]	[0.437]
Δ_{τ_1} eurrub$_{i,t} \cdot Nat$				0.948
				[0.766]
Δ_{τ_2} eurrub$_{i,t-\tau_1} \cdot Nat$				-0.272
				[0.935]
SKU FE	✓	✓	✓	✓
Observations	1,391	1,055	1,391	1,055
No. SKUs	1,126	839	1,126	839
R^2	0.028	0.035	0.009	0.023

*Note: This table presents pass-through coefficient estimates at the first and second rounds of price adjustment, respectively, estimated from regression B.8. The outcome variable is the change in the log ruble price of a good, conditional on price adjustment. All specifications include SKU fixed effects and standard errors [in brackets] are clustered at the SKU-level to allow for serial correlation across time. The estimation results are based on daily observations between Jan 1, 2014 and April 1, 2015. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.*

Differential expenditure and quantity reduction

Our timing test regression for expenditure switching follows specification 3:

$$expfrac_{grt} = \sum_{t>1} \delta_t \left(nonrus_{gr} \cdot \mathbf{D}_t\right) + \sum_{gr} \alpha_{gr}\mathbf{D}_{gr} + \sum_{gt} \alpha_{gt}\mathbf{D}_{gt} + \epsilon_{grt}. \tag{B.9}$$

Results are reported in Figure B.4.

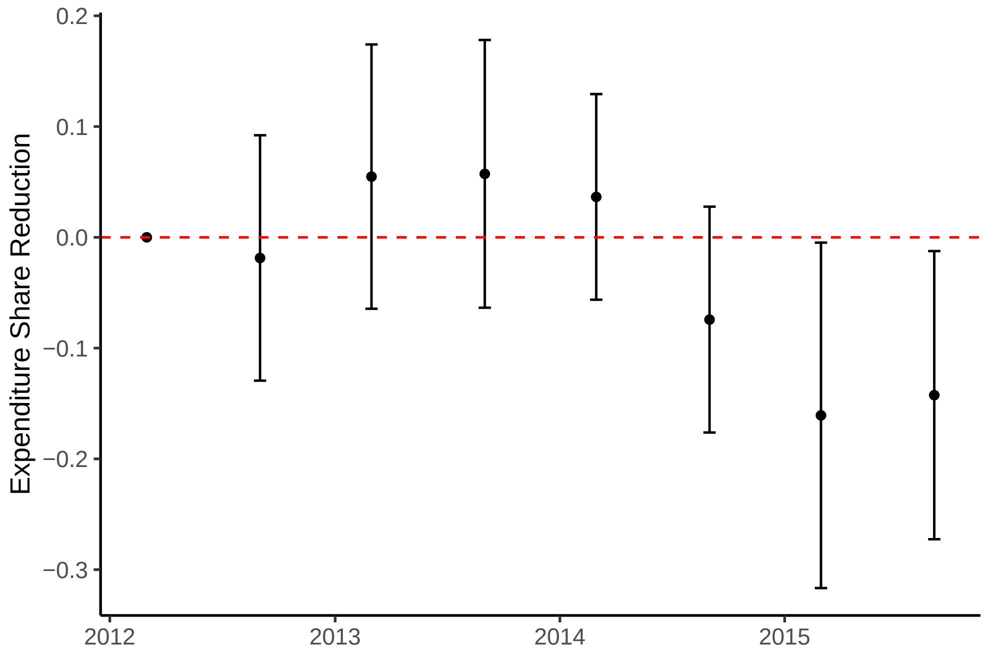

Figure B.4: **Differential expenditure reduction**
Note: This figure plots the estimated δ_t coefficients of equation B.9 with 95% confidence intervals around them. The unit of observation is consumers' expenditure share spent on high quality products with origin r, in product group g, in season t. Fixed effects are at the product group$\times$origin and product group$\times$season level. Standard errors are clustered at product group$\times$origin level to allow within-group-origin serial correlation. Results are similar when only using a season, instead of group$\times$season fixed effect.

Our regression for looking at the effect of the exchange rate shock on expenditures at the material-product group-season level using imports only follows specification B.2, using logged Y_{mgt}—the total spending on SKUs of quality m in product group g in season t—as the dependent variable:

$$\log(Y_{mgt}) = \delta \log(ER_{t-1}) \cdot Nat_{mg} + \sum_{mg} \alpha_{mg} \mathbf{D}_{mg} + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{mgt}. \tag{B.10}$$

Results are reported in Table B.16. We also use the same specification B.10 with summed quantities, results are reported in Table B.17.

Table B.16: Relative decrease in expenditures on imported high quality SKUs

	Dependent variable:			
	$\log(Y)$			
	(1)	(2)	(3)	(4)
$\log(ER_{t-1}) \cdot Nat_{mgt}$	-1.099**	-1.099***	-0.907	-0.907***
	(0.383)	(0.250)	(0.542)	(0.249)
Group × Material FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	416	416	364	364
R^2	0.691	0.980	0.686	0.982

*Note: This table presents coefficient estimates from specification B.10. The outcome is total spending on SKUs with material quality m, product group g, in season t. Nat_{mg} is an indicator equal to 1 for the high quality category in group g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (3) and (4) drop the final incomplete season. Standard errors (in brackets) are clustered at the group×quality level to allow serial correlation over time within a group and quality. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table B.17: Relative decrease in quantities of imported high quality SKUs

	Dependent variable:			
	log(q)			
	(1)	(2)	(3)	(4)
$\log(ER_{t-1}) \cdot Nat_{mgt}$	-0.918*	-0.918***	-0.823	-0.823***
	(0.368)	(0.220)	(0.535)	(0.241)
Group $\times$ Material FE	✓	✓	✓	✓
Season FE	✓		✓	
Group $\times$ Season FE		✓		✓
Observations	416	416	364	364
R^2	0.659	0.982	0.649	0.983

*Note: This table presents coefficient estimates from specification B.10. The outcome is total quantity of items sold with material quality m, product group g, in season t. Nat_{mg} is an indicator equal to 1 for the high quality category in group g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (3) and (4) drop the final incomplete season. Standard errors (in brackets) are clustered at the group$\times$quality level to allow serial correlation over time within a group and quality. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

C Structural Model

C.1 Proof of Lemma 1

We modify the expressions for the optimal numbers of products from the main text slightly, to allow that the markup may not be $\frac{\sigma_m}{\sigma_m - 1}$ for an m product, but instead an arbitrary μ_{rm}. Evidence suggests that markups do not vary over time or by material (see Table 3 and Table 5), similar to the findings of Nakamura and Zerom (2010) for the coffee industry. We thus have that:

$$\frac{N_{rht}}{N_{r\ell t}} = \frac{M_t \frac{\lambda_t^{-\sigma_h} \cdot \alpha_{rht} \cdot \left(ER_{r,t-1} \cdot c_{rh,t-1}\right)^{1-\sigma_h} \cdot \mu_{rh}^{-\sigma_h}(\mu_{rh}-1)}{f_{rht}}}{M_t \frac{\lambda_t^{-\sigma_\ell} \cdot \alpha_{r\ell t} \cdot \left(ER_{r,t-1} \cdot c_{r\ell,t-1}\right)^{1-\sigma_\ell} \cdot \mu_{r\ell}^{-\sigma_\ell}(\mu_{r\ell}-1)}{f_{r\ell t}}}$$

$$\frac{N_{rht}}{N_{r\ell t}} = \lambda_t^{\sigma_\ell - \sigma_h} \cdot \left(\frac{\alpha_{rht}}{\alpha_{r\ell t}}\right) \cdot ER_{r,t-1}^{\sigma_\ell - \sigma_h} \frac{c_{rh,t-1}^{1-\sigma_h}}{c_{r\ell,t}^{1-\sigma_\ell}} \frac{\mu_{rh}^{-\sigma_h}(\mu_{rh}-1)}{\mu_{r\ell}^{-\sigma_\ell}(\mu_{r\ell}-1)} \frac{f_{r\ell t}}{f_{rht}}$$

Imposing the restrictions $\alpha_{rmt} = \alpha_{rm} \cdot \alpha_{rt} \cdot \alpha_{mt}$, $c_{rmt} = c_{rm} \cdot c_{mt}$, and $f_{rmt} = f_{rm} \cdot f_{rt} \cdot f_{mt}$ and rearranging terms, we have

$$\frac{N_{rht}}{N_{r\ell t}} = ER_{r,t-1}^{\sigma_\ell - \sigma_h} \cdot \underbrace{\left(\frac{\alpha_{rh}}{\alpha_{r\ell}} \frac{c_{rh}}{c_{r\ell}} \frac{f_{rh}}{f_{r\ell}}\right) \frac{\mu_{rh}^{-\sigma_h}(\mu_{rh}-1)}{\mu_{r\ell}^{-\sigma_\ell}(\mu_{r\ell}-1)}}_{\text{origin-varying}} \cdot \underbrace{\left(\lambda_t^{\sigma_\ell - \sigma_h} \frac{\alpha_{ht}}{\alpha_{\ell t}} \frac{c_{h,t-1}^{1-\sigma_h}}{c_{\ell,t-1}^{1-\sigma_\ell}} \frac{f_{ht}}{f_{\ell t}}\right)}_{\text{time-varying}}$$

and therefore

$$\log \frac{N_{rht}}{N_{r\ell t}} = (\sigma_\ell - \sigma_h) \log ER_{r,t-1} \times D_r + \sum_r \alpha_r \mathbf{D}_r + \alpha_t \mathbf{D}_t$$

where α_r and α_t are the coefficients on origin and season dummies.

C.2 Proof of Theorem 1

C.2.1 Proof of Part 1

We specialize to a setting where $f_{mt} = f$, $c_{mt} = c_m$ with $c_h > c_\ell$, and $\alpha_{mt} = \alpha_m$. We assume $Y_t = 1$, $M_t = 1$, and $J = 1$. Our goal is to show that there is some $(f, c_h, c_\ell, \alpha_h, \alpha_\ell, \sigma_h, \sigma_\ell)$ with $\sigma_h > \sigma_\ell$ such that $\pi_h > \pi_\ell$ for at least some values of ER_{t-1}. This is because the lemma guarantees that an exchange rate depreciation will imply a reallocation to lower quality as long as $\sigma_h > \sigma_\ell$.

We prove that such parameters exist by simulation. To solve the model for a given set of parameters $\theta \equiv (\sigma_h, \sigma_\ell, c_h, c_\ell, ER, \alpha_h, \alpha_\ell, f)$ we implement Algorithm 1, where ε is a tolerance parameter.

Algorithm 1 Model Solution

1: Guess $(N_h^{(k)}, N_\ell^{(k)})$
2: Recover prices $P_m = \frac{\sigma_m}{\sigma_m - 1} \cdot ERc_m$
3: Recover the marginal utility of income λ by solving

$$\lambda^{-\sigma_h} \alpha_h J N_h^{(k)} P_h^{1-\sigma_h} + \lambda^{-\sigma_\ell} \alpha_\ell J N_\ell^{(k)} P_\ell^{1-\sigma_\ell} - Y = 0$$

4: Recover $Q_m^{(k)} = \alpha_m \lambda^{-\sigma_m} P_m^{-\sigma_m}$
5: Recover $\pi_m^{(k)} = MQ_m^{(k)}(P_m^{(k)} - ER \cdot c_m)$
6: Compute $N_m^{(k+1)} = \pi_m^{(k)}/f$
7: Return to 1, loop until $\max_m \left| N_m^{(k)} - N_m^{(k+1)} \right| < \varepsilon$

For $\theta = (3, 2.5, 3, 2.5, ER, 7, 2.5, 5)$, varying ER between 1 and 3 (in the neighborhood of the range it takes during our devaluation) yields the optimal values for profits and entry probabilities reported in Figure C.2, which clearly indicates a shift away from high quality products to low quality ones as the former becomes less profitable. Note that the increase and decrease in the number of each product type are offsetting; if there was an outside nest in the utility function that was not experiencing a cost increase, the sum of types for high and low would be decreasing as consumers substitute their expenditure to the outside option.

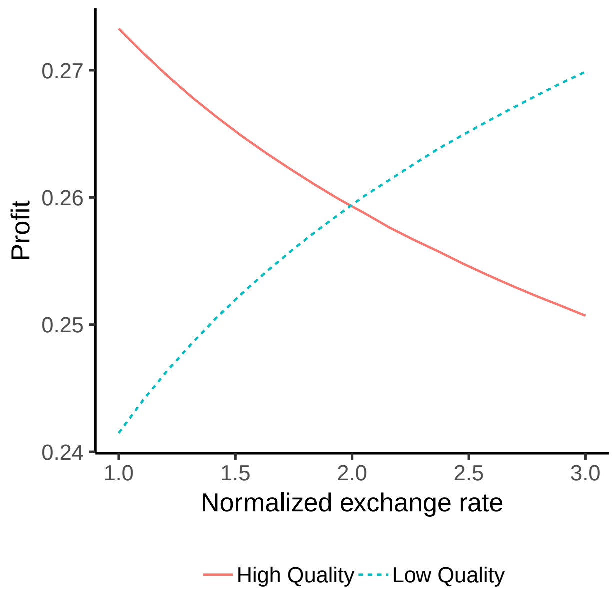

Figure C.1: **Simulated profits**
Note: This figure plots the simulated profits for high and low quality products in response to increasing the normalized exchange rate from 1 to 3.

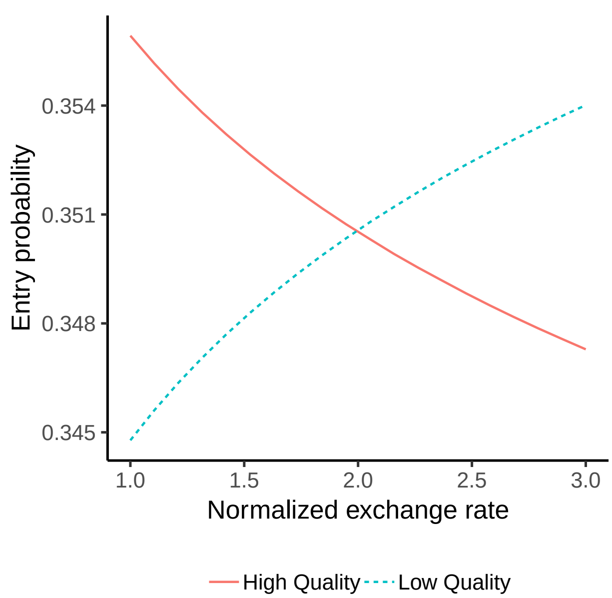

Figure C.2: **Simulated entry**
Note: This figure plots the simulated choice probabilities for a manager picking between high quality, low quality and no entry in response to increasing the normalized exchange rate from 1 to 3.

C.2.2 Proof of Part 2

Suppose $\sigma_h = \sigma_\ell = \sigma$. Writing out the consumer's budget constraint, substituting in $Q_{mt} = \lambda_t^{-\sigma}\alpha_{mt}P_{mt}^{-\sigma}$, and rearranging yields:

$$\lambda_t = \left(\frac{Y_t}{\alpha_{ht}P_{ht}^{1-\sigma} + \alpha_{\ell t}P_{\ell t}^{1-\sigma}}\right)^{-\frac{1}{\sigma}}$$

Substituting this expression for λ_t into the firm's profit function for a variety ν_m of good of type m:

$$\pi_{mt} = \frac{\frac{\alpha_m}{\sigma}Y_t \cdot P_{mt}^{1-\sigma}}{\alpha_{ht}P_{ht}^{1-\sigma} + \alpha_{\ell t}P_{\ell t}^{1-\sigma}}$$

Note that since $P_{mt}(\nu_m) = \frac{\sigma}{\sigma-1}ER_{t-1} \cdot c_{m,t-1}$, substituting into the price indexes would lead ER_{t-1} to cancel in both top and bottom, implying that profits—and hence, entry probabilities—are not a function of ER_{t-1}. There will thus be no quality downgrading in response to an exchange rate shock.

C.2.3 Proof of Part 3

Suppose we have a Cobb-Douglas utility function with CES aggregators over varieties of high and low quality products. Solving for demand, $Q_{mt} = \beta Y_t \alpha_{mt} P_{mt}(\nu_m)^{-\sigma_m}(\nu)/P_{mt}^{1-\sigma_m}$. Profits are:

$$\pi_{mt} = \frac{\frac{\alpha_{mt}}{\sigma_m}\beta Y_t \cdot P_{mt}^{1-\sigma_m}(\nu)}{P_{mt}^{1-\sigma_m}} \tag{C.1}$$

As above, substituting in $P_{mt}(\nu) = \frac{\sigma_m}{\sigma_m-1}ER_{t-1} \cdot c_{m,t-1}$ will lead ER_{t-1} to cancel from top and bottom, implying that profits and hence, entry probabilities will not depend on ER_{t-1}. Note that with Cobb-Douglas, the relative magnitudes of the α_m and σ_m is not important.

C.2.4 Bems and di Giovanni (2016) non-homothetic demand

The consumer's problem in Bems and di Giovanni (2016), first developed in Hallak (2006), is described in the Online Appendix to the former paper. We modify it slightly to make it directly comparable to our results. Specifically, we only look at CES demand for one product category instead of having CES nests for each category, and consider a double continuum of products offered by multiproduct firms within that group instead of an arbitrary countable number of products.

A representative consumer has utility

$$U_t = \left(\int_{\nu \in \Omega_t} \alpha_{mt}^{\frac{\lambda(Y_t)}{\sigma}}(\nu) Q_{mt}(\nu)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

which she maximizes by choosing quantities subject to $\int_{\nu \in \Omega_t} P_{mt}(\nu) Q_{mt}(\nu) \leq Y_t$.

Demand is non-homothetic in that if $\alpha_{ht} > \alpha_{\ell t}$ and $\lambda_{Y_t} = \eta + \mu \ln Y_t$ with $\mu > 0$, then as income increases, the demand shifter on h goods increases by more than the shifter on ℓ goods. Since the marginal utility of high quality goods increases in income, larger incomes will imply more spending on h goods.

This system will not imply quality downgrading in response to an exchange rate shock. Profits do not depend on a proportional cost shifter, for the same reason as in prior examples that impose the same elasticity of substitution between high and low qualities. Profits will be as in equation C.1, except $\beta = 1$ and α_{mt} will be raised to the power of $\lambda(Y_t)$. Neither of these modifications changes that profits are independent of the exchange rate.

C.2.5 Adding domestic sourcing

Domestic sourcing will not change the no downgrading result in instances where $\sigma_m = \sigma$. For Cobb-Douglas utility with CES aggregators and $\sigma_h > \sigma_\ell$, among imports there will be reallocation in response to the exchange rate shock, and $\partial \log N_{0ht}/N_{0\ell t} < 0$ as long as $N_{1ht} > 0$ and $N_{1\ell t} > 0$.

The mechanism still relies on there being relatively more expenditure reallocation for high quality products; however, now that reallocation is within nests, so there is relatively more reallocation of expenditure towards domestically sourced high qualities within the high quality nest, than reallocation of expenditure towards domestically sourced low qualities within the low quality nest. In our setting there are relatively few domestic varieties, so relying entirely on this within-nest margin is not attractive for explaining reallocation since $\partial \log N_{0ht}/N_{0\ell t} \to 0$ as $N_{1ht}, N_{1\ell t} \to 0$, unlike in the case with Fieler (2011) utility, which does not rely on domestic varieties for quality reallocation.

D Counterfactuals

Alternative predicted prices and quality shares

For pass-through into the share of high quality products, for maximum flexibility we recover pass-through into the numbers of high and low quality products with a modified version of specification B.2 from the quality downgrading robustness section:

$$\log(N_{mgt}) = \sum_g \gamma_{1,g}\mathbf{D}_g \log(ER_{t-1}) + \sum_g \gamma_{2,g}\mathbf{D}_g \log(ER_{t-1}) \cdot Nat_{mgt} + \sum_g \gamma_{3,g}\mathbf{D}_g t + \sum_{mgs} \alpha_{mgs}\mathbf{D}_{mgs} + \epsilon_{mgt} \tag{D.1}$$

We cannot include the $\mathbf{D}_{gt}$ dummy since we want to predict the counterfactual number of low-quality SKUs. Instead we include a linear time trend to control for the company's growth over this time period, and a season-of-year interaction with the material-group dummy to account for seasonality. Results are reported in Tables D.1 and D.2.

For pass-through into prices, we run the following modified version of specification 5 on imports:

$$\log(p_{jmbgt}) = \sum_g \beta_{1,g}\mathbf{D}_g \log(ER_{t-1}) + \sum_g \beta_{2,g}\mathbf{D}_g \log(ER_{t-1}) \cdot Nat_j + \sum_{mbgs} \alpha_{mbgs}\mathbf{D}_{mbgs} + \epsilon_{jmbgt} \tag{D.2}$$

The predicted log price is exponentiated to recover $\hat{p}_{jmbgt}$ for each SKU and averaged across SKUs within a material-group-season. Results are reported in Tables D.3 and D.4.

The actual and counterfactual average pass-through numbers are presented in Figure D.1. Without downgrading average pass-through is 0.58, with downgrading it is 0.45; downgrading thus reduces average pass-through by 22%.

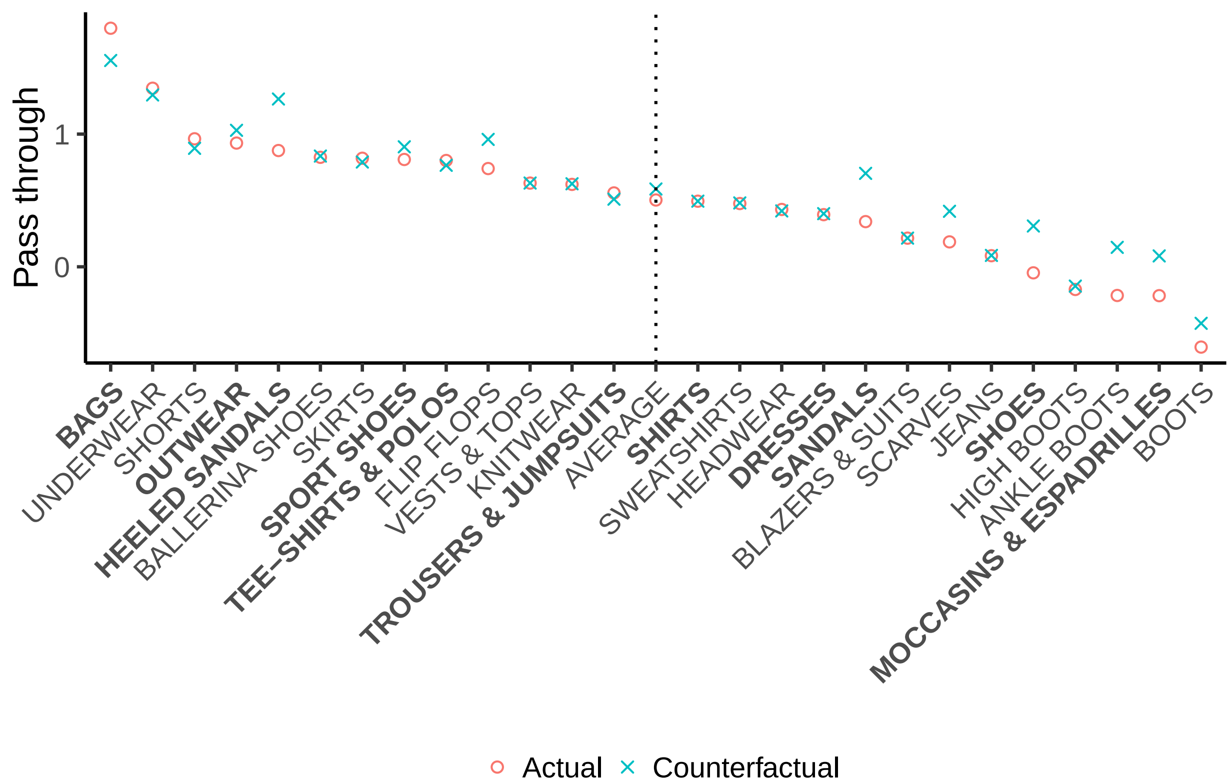

Figure D.1: **Counterfactual pass-through by product group**
Note: Bolded product group names comprise 80% of sales during the 2014 Spring/Summer season.

Table D.1: Pass-through into number of SKUs, first 13 groups

	Dependent variable: $\log(N)$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
t	0.310*	0.265**	0.193	0.562**	-0.043	0.447**	-0.038	0.245***	0.184	0.166	0.240*	0.381**	0.404**
	(0.112)	(0.062)	(0.092)	(0.144)	(0.109)	(0.084)	(0.121)	(0.037)	(0.165)	(0.104)	(0.084)	(0.096)	(0.093)
$\log(ER_{t-1})$	-1.814	-1.410	0.092	-2.043	0.832	-1.767	1.790	-0.015	0.491	-0.706	0.258	-0.966	0.867
	(1.576)	(0.867)	(1.292)	(2.018)	(1.524)	(1.172)	(1.699)	(0.521)	(2.308)	(1.464)	(1.182)	(1.350)	(1.303)
$\log(ER_{t-1})\cdot Nat$	-0.623	-0.602	-1.835	-1.163	-1.484	-0.221	0.188	0.271	-1.887	-0.787	-1.494	-1.413	-3.043
	(1.614)	(0.888)	(1.324)	(2.067)	(1.561)	(1.200)	(1.740)	(0.533)	(2.365)	(1.500)	(1.210)	(1.382)	(1.334)
Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	364	14	14	14	14	14	14	14	14	14	14	14	14
R^2	0.896	0.803	0.951	0.883	0.899	0.919	0.965	0.988	0.962	0.952	0.987	0.957	0.981

Note: This table shows the effect of the exchange rate on the log number of SKUs by product group, from specification D.1. The unit of observation is a material quality m for product group g in season t. Columns are for Ankle Boots, Bags, Ballerina Shoes, Blazers & Suits, Boots, Dresses, Flip Flops, Headwear, Heeled Sandals, High Boots, Jeans, Knitwear, Moccasins & Espadrilles, respectively. Standard errors are clustered at the level of the fixed effect, $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table D.2: Pass-through into number of SKUs, second 13 groups

	Dependent variable: $\log(N)$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
t	0.367***	-0.190	0.297	0.391**	0.236*	0.383**	0.499***	0.240**	0.462***	0.415***	0.406***	0.124	0.460***
	(0.054)	(0.164)	(0.144)	(0.080)	(0.086)	(0.073)	(0.067)	(0.045)	(0.081)	(0.045)	(0.062)	(0.092)	(0.076)
$\log(ER_{t-1})$	-0.776	3.550	-1.185	-0.940	-0.560	-2.895*	-1.241	-0.009	-1.417	-1.300	-1.267	3.171*	-1.048
	(0.754)	(2.303)	(2.021)	(1.127)	(1.205)	(1.020)	(0.943)	(0.628)	(1.131)	(0.632)	(0.874)	(1.288)	(1.070)
$\log(ER_{t-1})\cdot Nat$	-0.243	-1.517	-0.221	-1.122	-1.368	1.137	-0.560	-1.053	-0.744	-1.156	-0.522	-1.962	-1.639
	(0.772)	(2.359)	(2.070)	(1.154)	(1.234)	(1.045)	(0.965)	(0.644)	(1.159)	(0.647)	(0.896)	(1.319)	(1.096)
Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Observations	364	14	14	14	14	14	14	14	14	14	14	14	14
R^2	0.961	0.951	0.760	0.924	0.915	0.967	0.960	0.946	0.965	0.993	0.972	0.969	0.954

Note: This table shows the effect of the exchange rate on the log number of SKUs by product group, from specification D.1. The unit of observation is a material quality m for product group g in season t. Columns are for Outwear, Sandals, Scarves, Shirts, Shoes, Shorts, Skirts, Sport Shoes, Sweatshirts, Tee-Shirts & Polos, Trousers & Jumpsuits, Underwear, Vests & Tops, respectively. Standard errors are clustered at the level of the fixed effect, $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table D.3: Pass-through into prices, first 13 groups

	Dependent variable: $\log(price)$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\log(ER_{t-1})$	0.153	0.896***	0.717***	1.090***	0.709***	0.858***	1.035***	0.760***	0.695***	0.536**	0.830***	0.964***	1.002***
	(0.132)	(0.055)	(0.154)	(0.127)	(0.158)	(0.068)	(0.173)	(0.166)	(0.079)	(0.163)	(0.132)	(0.131)	(0.063)
$\log(ER_{t-1}) \cdot Nat$	0.603**	0.042	0.108	-0.213	-0.048	-0.042	-0.322	0.001	0.215	0.043	-0.077	-0.039	-0.258**
	(0.228)	(0.097)	(0.180)	(0.149)	(0.189)	(0.085)	(0.197)	(0.192)	(0.110)	(0.271)	(0.144)	(0.140)	(0.091)
Brand × Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,725	28,932	6,437	4,309	12,481	28,370	4,347	6,941	13,332	12,735	8,525	25,618	7,384
R^2	0.896	0.835	0.911	0.850	0.862	0.873	0.868	0.827	0.904	0.858	0.892	0.846	0.902

Note: This table shows the effect of the exchange rate on log prices by product group, from specification D.2. The unit of observation is a SKU j in season t. Columns are for Ankle Boots, Bags, Ballerina Shoes, Blazers & Suits, Boots, Dresses, Flip Flops, Headwear, Heeled Sandals, High Boots, Jeans, Knitwear, Moccasins & Espadrilles, respectively. Standard errors are clustered at the level of the fixed effect, $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table D.4: Pass-through into prices, second 13 groups

	Dependent variable: $\log(price)$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\log(ER_{t-1})$	0.794***	0.827***	0.798***	0.926***	0.597***	0.440***	0.794***	0.516***	0.334*	0.325**	0.564***	0.618	0.695***
	(0.056)	(0.060)	(0.209)	(0.079)	(0.155)	(0.105)	(0.119)	(0.088)	(0.145)	(0.121)	(0.126)	(0.651)	(0.133)
$\log(ER_{t-1}) \cdot Nat$	0.008	-0.042	-0.032	-0.049	0.263	0.158	-0.124	0.198	0.294	0.411**	0.151	0.166	0.102
	(0.083)	(0.094)	(0.243)	(0.090)	(0.171)	(0.121)	(0.145)	(0.108)	(0.164)	(0.132)	(0.147)	(0.701)	(0.162)
Brand × Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	22,517	7,817	7,832	22,162	17,414	7,460	7,589	23,659	12,320	44,746	17,721	6,694	10,492
R^2	0.805	0.895	0.778	0.853	0.909	0.833	0.880	0.831	0.857	0.809	0.813	0.674	0.759

Note: This table shows the effect of the exchange rate on log prices by product group, from specification D.2. The unit of observation is a SKU j in season t. Columns are for Outwear, Sandals, Scarves, Shirts, Shoes, Shorts, Skirts, Sport Shoes, Sweatshirts, Tee-Shirts & Polos, Trousers & Jumpsuits, Underwear, Vests & Tops, respectively. Standard errors are clustered at the level of the fixed effect, $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

E Replication on a Subset of Products

We replicate our three main empirical facts—that high quality products are more profitable, that they experience quality downgrading, and that they experience expenditure switching but not differential pass-through—using a subset of product groups. In particular, we use only product groups that have a positive estimated quality shifter in Figure A.3, Appendix A.1, a subset that includes Underwear, High Boots, Heeled Sandals, Moccasins & Espadrilles, Shoes, Ankle Boots, Shirts, Ballerina Shoes, Sandals, Headwear, Trousers & Jumpsuits, Boots, Dresses, Knitwear, Tee-Shirts & Polos, Shorts, Sport Shoes, Scarves and Bags.

Fact 1: High quality products are more profitable

Table E.1: Mean differences for high quality products

	Dependent variable:					
	log(π)	log(pq)	log(q)	log(p)	log(c)	log(p/c)
	(1)	(2)	(3)	(4)	(5)	(6)
Natural$_j$	0.077**	0.071**	-0.375***	0.446***	0.435***	0.011
	(0.025)	(0.023)	(0.037)	(0.042)	(0.044)	(0.007)
Group $\times$ Season FE	✓	✓	✓	✓	✓	✓
Observations	248,534	248,534	248,534	248,534	248,534	248,534
R^2	0.391	0.407	0.201	0.383	0.363	0.051

*Note: This table presents coefficient estimates from specification 1, using a subset of product groups. The outcome variables is either the profit, revenue, quantity sold, price or cost of SKU j, in product group g, in season t. Only products with non-missing values for all dependent variables are included. Product group-season fixed effects are included. Prices are sales-weighted within SKUs, and standard errors are clustered at the group level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Fact 2: The share of high qualities in imports decreases differentially compared to the share of high qualities in domestically sourced products.

Table E.2: Differential quality reallocation

	Dependent variable:			
	$natfrac_{grt}$		$\log(N_{h,grt}/N_{\ell,grt})$	
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.546***	-0.477**	-3.256***	-2.968**
	(0.129)	(0.170)	(0.758)	(0.951)
Group × Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group × Season FE		✓		✓
Observations	179	179	179	179
R^2	0.600	0.800	0.614	0.791

*Note: This table presents coefficient estimates from specification 2, using a subset of product groups. The outcome in the first two columns is the fraction of offered SKUs that use a natural fabric for group g, origin r, in season t, and in the last two columns is the log ratio of the number of natural SKUs to artificial SKUs within grt. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Standard errors (in brackets) are clustered at product group $\times$origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Fact 3: There is no differential price pass-through for high qualities, but there is differential expenditure switching away from high qualities.

Table E.3: Pass-through coefficients

	Dependent variable:			
	log(p)	log(c)	log(p)	log(c)
	(1)	(2)	(3)	(4)
log(ER_{t-1})	0.784***	0.802***	0.786***	0.803***
	(0.034)	(0.038)	(0.035)	(0.041)
log(ER_{t-1})$\cdot Nat$	0.040	-0.036	0.038	-0.037
	(0.042)	(0.050)	(0.036)	(0.038)
log(ER_{t-1})$\cdot Rus$			-0.270***	-0.310***
			(0.057)	(0.068)
log(ER_{t-1})$\cdot Nat \cdot Rus$			0.028	0.021
			(0.022)	(0.019)
Quality × Brand × Group × SoY FE	✓	✓	✓	✓
Brand × Group × Origin FE			✓	✓
Observations	172,625	172,625	185,750	185,750
R^2	0.890	0.890	0.891	0.890

*Note: This table presents coefficient estimates from specification 5 at the brand-group-fabric level. The dependent variable is either the first observed price of SKU j or the within season wholesale cost of j. ER_{t-1} is the lagged averaged U.S. dollar to ruble exchange rate, and Nat and Rus are indicators for whether SKU j has a natural fabric and is of Russian origin, respectively. Standard errors (in brackets) are clustered at the quality, brand, group, season of year level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table E.4: Differential expenditure switching

	Dependent variable:			
	$expfrac$			
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.573***	-0.501*	-0.539***	-0.535**
	(0.148)	(0.194)	(0.153)	(0.194)
Group $\times$ Origin FE	✓	✓	✓	✓
Season FE	✓		✓	
Group $\times$ Season FE		✓		✓
Observations	179	179	159	159
R^2	0.565	0.809	0.549	0.809

*Note: This table presents coefficient estimates from specification 6, using a subset of product groups. The outcome is the fraction of expenditure on natural fabric products in group g, origin r, in season t. $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian products in group or brand g, and $\log(ER_{t-1})$ is the average exchange rate during season $t-1$. Columns (1) and (2) include all periods, and (3) and (4) drop the final, incomplete season. Standard errors (in brackets) are clustered at product group $\times$origin level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*