Exchange Rate Shocks and Quality Adjustments*

Daniel Goetz
University of Toronto Mississauga
Rotman School of Management

Alexander Rodnyansky
University of Cambridge

First Version: August 10, 2016
This Version: August 6, 2019

Abstract

Do firms respond to cost shocks by reducing the quality of their products? Using micro-data from a large Russian retailer that refreshes its product line twice-yearly, we document that higher quality products are more profitable than lower quality ones before a large ruble devaluation in 2014, but are stocked relatively less frequently after the devaluation. We reconcile these facts with a simple model that features consumer expenditure switching between high and low qualities, and show that reallocation to lower quality products reduces average pass-through by 12%.

JEL Codes: E30, F14, F31, L11, L15, L16, L81, M11.

*We are grateful to Mark Aguiar, Markus Brunnermeier, Vasco Carvalho, Giancarlo Corsetti, Jan de Loecker, Mikhail Golosov, Bo Honoré, Oleg Itskhoki, Sergei Izmalkov, Myrto Kalouptsidi, Jakub Kastl, Atif Mian, Virgiliu Midrigan, David Sraer, Claudia Steinwender, Motohiro Yogo, as well as multiple seminar participants at the Barcelona GSE Summer Forum, University of Cambridge, the annual conference of the CEA, New Economic School, Princeton University, Stockholm School of Economics, and University of Toronto for valuable advice. Rodnyansky gratefully acknowledges financial support from the Alfred P. Sloan Foundation, the CME Group Foundation, Fidelity Management & Research, and the MFM initiative. Goetz: Department of Management, Kaneff Centre, Rm 233, 1833 Inner Circle Rd., UTM, Mississauga, ON L5L 1C6, Canada. Email: daniel.goetz@rotman.utoronto.ca. Rodnyansky: Faculty of Economics, Austin Robinson Building, Sidgwick Avenue, Cambridge, CB3 9DD, UK. Email: a.rodnyansky@gmail.com.

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 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 (2015), and Medina (2018), 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 high frequency 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 particular

[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 (2017).

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

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, 2015). Third, we have a directly observable measure of quality for each product, whose utility to consumers is validated in Khandelwal (2010) regressions on pre-shock data; while we do not claim that our measure captures all of the multi-faceted nature of quality, it is important to consumers and consistent with the quality literature above.

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 a canonical trade model (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 after the Russian ruble devaluation increases import costs in 2014. A 1% ruble devaluation causes a roughly 0.35% differential reduction in the fraction of natural fabrics in imported versus domestically produced items. The analysis relies on a difference-in-differences identification strategy with Russian manufactured products as a control group, which rules out common shocks or global trends in material input prices as the explanation for the compositional shift. Our robustness checks include looking at raw numbers of products and documenting downgrading across product groups.

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. We rule out "flight from quality" due to falling incomes as the primary mechanism by exploiting a concurrent oil price shock, which affects labor earnings differentially across oil-producing regions of Russia.[6] We also find that there is no differential pass-through across qualities, and indeed no changes in multiplicative markups above wholesale cost for any product after the shock.

To explain the data we build a simple model of consumer demand and import sourcing where high quality products can be ex ante more profitable, but can also be dropped more quickly after a cost shock. The key ingredient is the Fieler (2011) demand system that supports expenditure switching between CES nests of high and low quality products. The parameter conditions that

[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]Such 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.

allow quality downgrading in response to a cost shock—namely, that high quality products have a larger CES substitution parameter—are exactly those required by Medina (2018) to achieve quality upgrading in response to an import competition shock. Expenditure switching and higher demand sensitivity for high quality have also been used successfully to explain how trade responds to differences in incomes and are a feature of linear and logit demand in general;[7] we use the CES system to match our reduced form facts on constant multiplicative markups.

The model induces incomplete exchange rate pass-through via an old mechanism—that of compositional bias, with higher priced goods within narrow categories being dropped after a shock. The novel insight is that those higher priced goods can also be more profitable, as in the quality sorting literature. As Chen and Juvenal (2015) note in their data on wine, firms sell an order of magnitude more distinct products than would be implied by even the HS12 trade data categorization, with potentially large quality variation within each category; compositional bias is thus almost certainly relevant in practice.

To assess whether quality reallocation can explain incomplete exchange rate pass-through, we use our reduced form results to construct counterfactual pass-through at the product group level. We find that, on average, pass-through would increase from 0.43 to 0.48 if there were no quality downgrading; however, there is substantial heterogeneity across products. Pass-through increases from 0.3 to 0.52 for sport shoes—the firm's highest sales category—if there is no downgrading, while it only increases from 0.51 to 0.53 for dresses, the firm's second highest sales category. The baseline numbers are well in the range of those found in the literature (Nakamura and Steinsson, 2012).

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., HS-8 or HS-10) level prices (Knetter, 1989; Goldberg, Knetter, et al., 1997; Auer and Chaney, 2009; Berman, Martin, and Mayer, 2012; Amiti, Itskhoki, and Konings, 2014, 2016). Our result that quality downgrading can lead to incomplete price pass-through is most applicable to price stickiness within product categories, since our evidence relates to product adding and dropping and not direct replacement. However, the model is consistent with within-firm-product upgrading and downgrading, and thus remains relevant to the within-

[7] See, for example, Fajgelbaum, Grossman, and Helpman (2011); Levchenko, Lewis, and Tesar (2011); Auer, Chaney, and Sauré (2018).

firm-product long run pass-through findings. 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.[8] Medina (2018) 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, and quantifying what that implies for demand. In an influential paper, Khandelwal (2010) pioneers using a demand residual, while Medina (2018), Levchenko, Lewis, and Tesar (2011) and Alessandria and Kaboski (2011) make an assumption based on the description of the goods (e.g., pima cotton versus other fabrics, and fresh versus frozen fruit) and Crozet, Head, and Mayer (2012) rely on expert opinions. Our paper bridges these approaches 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. This approach is similar to the one used by Auer, Chaney, and Sauré (2018), who find that quality heterogeneity affects price pass-through, as do Ludema and Yu (2016) and Chen and Juvenal (2016).

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 (2015) and Bems and di Giovanni

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

(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 (2018).[9]

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.[10] 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 counterfactuals. Section 6 concludes.

2 Background and Data

Our data come from a large, online apparel retailer that sells across all of Russia.[11] 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

[9] 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)).

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

[11] 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, wielding significant market power in many of Russia's regions, and employing more than 4,000 people as of December 2015.

the quantity sold in each province (oblast) in each month.[12] 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 inventory, fabric composition, country of manufacture, brand (e.g., Adidas), product group (e.g., shoes), wholesale cost in rubles, and which currency the the firm used to purchase each SKU.[13] 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 choose pricing.[14]

We associate the Spring season with the period from March through August, and Fall with September through February of the following year.[15] Figure 1 shows that the majority of revenue for a season's SKUs happens 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.[16]

There are two features of the store worth mentioning. First, for most SKUs the firm does all

[12] Even though the data is sufficiently granular to facilitate the tracking of purchases for each consumer over time, we aggregate up to the regional level and exploit shocks to local GDP to identify any potential income induced demand reallocation. We find no evidence of an income-shock induced "flight from quality" in section 3.3.

[13] 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 (2019)).

[14] 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. We also find that, on average, the retailer charges a markup of two (i.e., doubling wholesale costs) until the goods are put on sale and phased out as the season draws to an end.

[15] 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.

[16] 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.

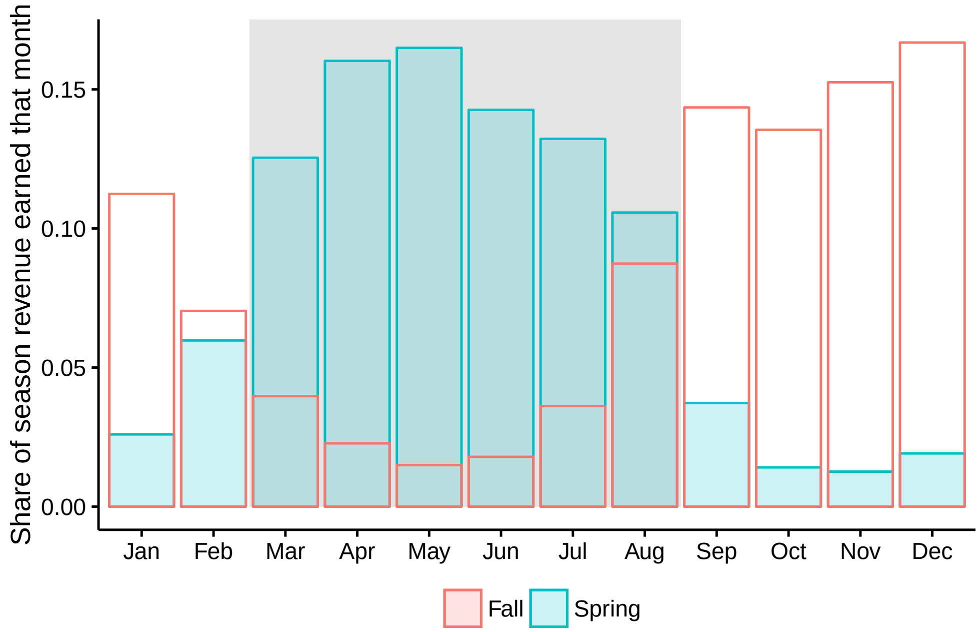


Figure 1: **Monthly revenue shares for SKUs by season**
Note: This figure shows histograms of the distribution of Fall and Spring introductions by revenue. The gray area covers the months we choose to associate with Spring goods of March-August.

of its stocking up in one initial wave, before the season starts, at a prearranged unit wholesale cost from existing brands. 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 fabrics but prevents us from tracking SKUs over long periods.[17]

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 fabrics 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) and Alessandria and Kaboski (2011) and classify products as high or low quality based on their product description, and specifically based on the primary material used in the product. To proceed, we first code polyester, plastic polymers, and any fabric with the word "artificial" as low quality. We assume an SKU containing a low qual-

[17]Related features of the 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)).

ity material is a low quality product, except SKUs containing polyester, in which case we require that polyester is the only component for it to be low quality. Where an artificial fabric appears overwhelmingly as part of a blend and is included to provide a specific property—for instance, elastane, which provides stretchiness—it is coded as high quality. Our precise mapping from the 30 most commonly occurring fabrics, present in 97% of SKUs and accounting for all materials in 93% of SKUs, into the high/low quality categories is given in Table A.1 in Appendix A. As in the fabric quality upgrading analysis of Medina (2018), our split reflects that naturally-derived materials such as leather, silk, and cotton have superior attributes compared to fake leather, polymers, and polyester.

To validate our quality measure, we run a Khandelwal (2010) style regression to recover product-specific fixed effects in Appendix A.1. We then project these fixed effects on our quality dummy; the dummy has a positive, significant effect that implies high quality products sell 9% more than low quality products, all else equal. We do not claim that material content is a perfect measure of quality—brand, design, workmanship, and many other features play a role—but it is clearly relevant for consumers, and may serve as a useful indicator of expected sales (conditional on price) for the firm when deciding whether to stock new products it has never sold before.[18]

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. column gives the fraction of Russian manufactured products.[19]

Our panel analysis focuses on the season level SKU stocking choices of the firm, so we aggregate SKUs sales and prices 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.[20] 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.[21] Total sales and num-

[18]Operationally, the firm likely does not perfectly anticipate each SKU's demand shifter a season in advance, especially for new brands. Our measure is equivalent to the firm taking the expectation of the Khandelwal (2010) shifter conditional on the quality dummy.

[19]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.

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

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

Table 1: Cross-sectional summary statistics

Group	Share	Quality	Rus.	Group	Share	Quality	Rus.
Ankle Boots	0.012	0.727	0.091	Outwear	0.060	0.577	0.031
Bags	0.080	0.468	0.060	Sandals	0.019	0.500	0.041
Ballerina Shoes	0.016	0.600	0.039	Scarves	0.022	0.813	0.091
Blazers and Suits	0.011	0.866	0.052	Shirts	0.056	0.769	0.037
Boots	0.039	0.823	0.036	Shoes	0.048	0.787	0.058
Dresses	0.078	0.774	0.117	Shorts	0.018	0.834	0.015
Flip Flops	0.011	0.369	0.068	Skirts	0.020	0.769	0.087
Headwear	0.025	0.894	0.225	Sport Shoes	0.062	0.645	0.014
Heeled Sandals	0.033	0.668	0.057	Sweatshirts	0.032	0.890	0.036
High Boots	0.044	0.775	0.076	Polos	0.114	0.950	0.039
Jeans	0.022	0.988	0.005	Jumpsuits	0.046	0.880	0.051
Knitwear	0.068	0.949	0.039	Underwear	0.016	0.952	0.005
Moccasins	0.018	0.853	0.040	Vests and Tops	0.026	0.793	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.

Table 2: Time-varying summary statistics

Season	Quality	No. SKUs	Units Sold	Price	Raw Cost	Avg. RUB/USD
2012-03-01	0.816	27,089	339,747	3,874	1,775	31.170
2012-09-01	0.804	33,592	421,807	4,164	1,957	30.840
2013-03-01	0.772	63,584	1,232,188	3,285	1,433	31.947
2013-09-01	0.776	60,638	1,233,759	4,750	1,914	33.225
2014-03-01	0.764	69,945	1,895,759	3,631	1,465	35.324
2014-09-01	0.777	74,885	2,082,531	4,578	1,941	51.704
2015-03-01	0.738	88,122	2,826,627	4,512	1,898	56.898
2015-09-01	0.708	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.

ber of SKUs are on a sharp upward trend, as the firm is expanding during this time period. It is also worth pointing out that the fraction of high-quality products clearly decreases from its previous steady state during the first 2015 season, which is the initial post-devaluation period and is indicative of quality downgrading in the aggregate. While this happens, the unweighted average wholesale cost for this 2015 Spring season rises to $1,898$ rubles, far exceeding values of $1,433$ and $1,465$ rubles for Spring 2013 and Spring 2014, respectively. Since Table 1 shows that different product groups have very different mean levels 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.[22] In response, Russia implemented a wide-ranging food import ban against the EU, 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.[23] Incidentally, the food import ban, oil price shock, and financial sanctions 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, which is before any of the quality downgrading is observed.

Besides documenting the exchange rate shock, Figure 2 also provides for an initial look at how the firm responded to the devaluation. A number of patterns are revealed: first, there is a lot of periodicity in the average wholesale cost of goods sold, with Spring/Summer items always being cheaper on average than goods associated with Fall/Winter seasons; second, the steep nominal devaluation at the end of 2014 led to an increase in average wholesale costs during the subsequent Spring 2015 season (mean COGs). 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

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

[23] 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.

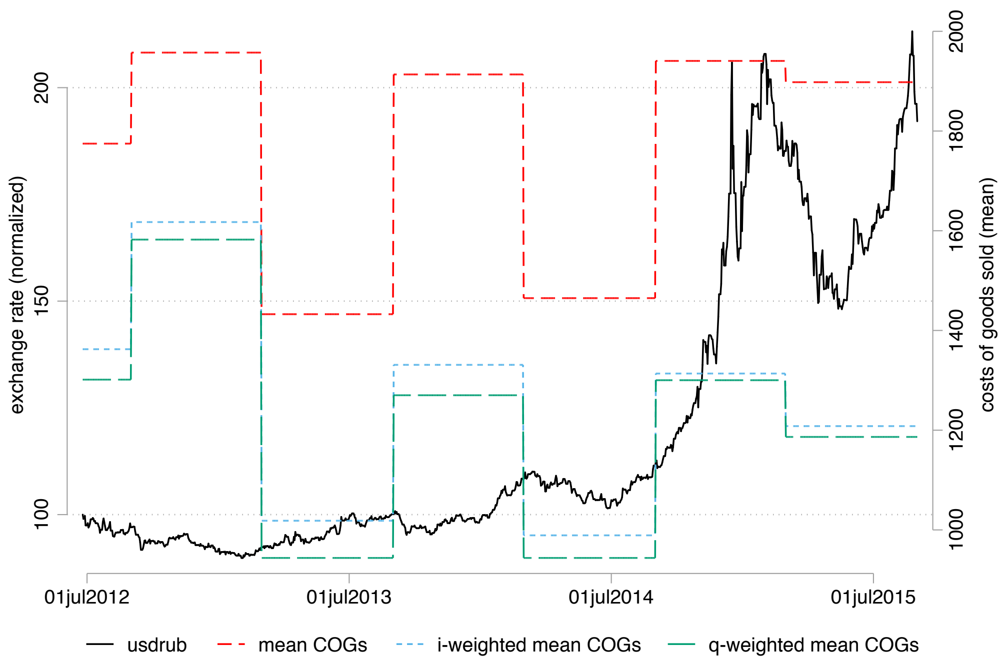


Figure 2: **Cost of goods sold**
Note: This figure shows the normalized U.S. dollar to ruble exchange rate (black solid line), the mean seasonal (red dashed line), the inventory-weighted mean seasonal (blue short-dashed line), and the purchase quantity-weighted mean seasonal (green long-dashed line)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

average stocking quantities per SKU increased in relative terms for cheaper, lower quality goods, which hints at non-homothetic adjustment mechanisms.[24]

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 four empirical facts in our data:

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

2. Imported goods experience a greater quality reduction compared to Russian-produced

[24]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.

goods, and goods for which quality is more costly to provide experience the greatest quality reduction.

3. Regions in Russia that experience greater income shocks do not differentially reallocate consumption to lower quality goods.

4. High-quality goods do not experience differential pass-through.

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). Facts 2 and 3 establish that the exchange rate shock induces quality downgrading, and rule out an income shock induced "flight from quality" à la Burstein, Eichenbaum, and Rebelo (2005) as the sole explanation for quality downgrading. Fact 4 suggests that differential movements in the relative markups of high and low quality goods cannot explain the disproportionate exit of high quality goods.

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 $\pi_j = q_j(p_j - c_j)$.[25] 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:

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

where y_{jgt} is either the profit, revenue, quantity sold, price or wholesale cost of SKU j, in product group g, in season t, and $\mathbf{D}_{gt}$ are product group-season fixed effects. Standard errors are clustered at the group-season level to allow for serial correlation across time and within season. The results are reported in Table 3; high quality goods are found to be about 5.2% more profitable on average. Controlling for brand and product group fixed effects, so that only within brand variation is used, implies a similar estimated magnitude significant at the 0.1% level (see Appendix B.1).

[25]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)
	(1)	(2)	(3)	(4)	(5)
Natural$_j$	0.052**	0.046**	-0.337***	0.384***	0.374***
	(0.020)	(0.019)	(0.036)	(0.039)	(0.041)
Group $\times$ Season FE	✓	✓	✓	✓	✓
Observations	304,577	304,577	304,577	304,577	304,577
R^2	0.379	0.392	0.180	0.394	0.371

*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.*

Note from the quantity regression in Table 3 that high quality goods sell fewer 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. Our identification strategy relies on a difference-in-differences (DiD) approach, where imported SKUs are the treatment and domestically produced SKUs are the control group. The fraction of products that are high quality (natural fabric) 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;[26] if quality adjustment is an important margin for passing through the ruble cost increase, then there will be a negative, significant coefficient for the foreign sourced goods post-shock.

In our first specification, we aggregate within seasons to the product group-origin level.[27] For each of the 26 product groups, we will have two observations in each of the eight seasons: the

[26]We confirm that this is true in pass-through regressions in Section 3.4.

[27]While this aggregation helps to transform the data into a tractable format for regression analysis, the results hold for alternative levels of firm stocking choices.

fraction of high quality SKUs for products with a domestic origin, and the fraction of high quality SKUs for imported products. In order not to impose a timing assumption on when the firm passes through the shock, we run a specification with time-varying treatment effects:

$$natfrac_{grt} = \sum_{t>1} \delta_t \left(nonrus_{gr} \cdot \mathbf{D}_t \right) + \sum_{gr} \alpha_{gr} \mathbf{D}_{gr} + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{grt} \tag{2}$$

where g indexes a product group (e.g., high boots), r indicates either foreign or domestic manufacturing origin, and t is a season. $natfrac_{grt}$ is the fraction of offered SKUs that use a natural fabric for product group g, origin r, in season t, δ_t are the time-varying treatment effects, $nonrus_{gr}$ is an indicator with a value of one for the set of non-Russian (imported) products in group g, $\mathbf{D}_{gt}$ are product group-season specific dummies, and $\mathbf{D}_{gr}$ are dummies for each product group-origin combination. The latter sets of indicators are included to account for systematic differences in quality across product groups, as well as for changes in this quality level within groups over time and by origin.

Specification 2 uses only within group-origin variation to identify downgrading. Because the specification includes group-origin and group-season dummies, it is equivalent to running a separate DiD within each product group, using foreign-sourced products as the treatment in each case, and then averaging the treatment effects across product groups. Treatment effects that are the result of seasonal reallocations from high $natfrac$ to low $natfrac$ product groups are therefore ruled out, as are explanations that are common across the treatment and control within a product group, such as changing tastes, changing incomes, or changing commodity/raw fabric costs that are contemporaneous with the devaluation.

The estimated coefficients δ_t from equation 2 are plotted in Figure 3, along with their associated standard errors, clustered at the group$\times$origin level to allow for within-group-origin serial correlation over time. The results indicate that there is no statistically significant differential reduction in quality within product groups for non-Russian (imported) goods until the March 2015 season, after the peak of the devaluation. That is, there was a significant reduction in the quality of imported products, and it 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 validates the use of domestic products as a control group as part of our identification strategy, and rules out a pre-trend as the explanation for the effect.

To quantify the impact of the devaluation on imported products, we next run specifications

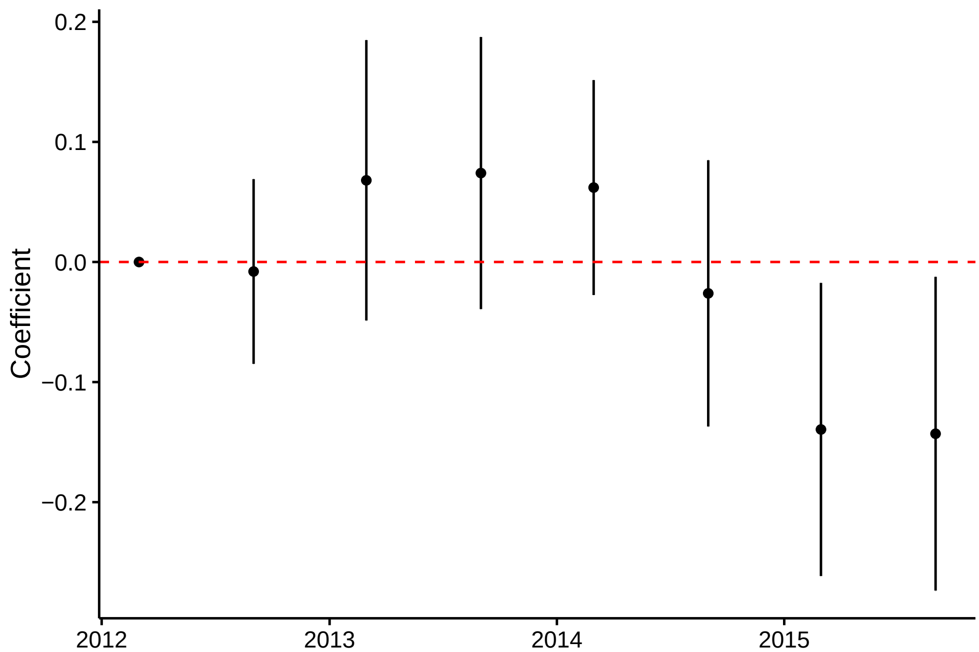


Figure 3: **Quality downgrading**

Note: This figure plots the estimated δ_t coefficients of equation 2 with 95% confidence intervals around them. Fixed effects are at the product group$\times$country of origin and season level. Standard errors are clustered by group$\times$origin to allow within-group-origin serial correlation.

that allow the magnitude of the lagged exchange rate movement to play a role:

$$natfrac_{grt} = \delta \left(nonrus_{gr} \cdot \log(ER_{t-1}) \right) + \sum_{gr} \alpha_{gr} \mathbf{D}_{gr} + \sum_{gt} \alpha_{gt} \mathbf{D}_{gt} + \epsilon_{grt} \tag{3}$$

$\log(ER_{t-1})$ is the average U.S. dollar to ruble exchange rate during the prior season. The coefficient δ no longer has a t subscript, and can be approximately interpreted as the percent change in $natfrac_{grt}$ that results from a one percent change in the lagged exchange rate. We express the dependent variable in levels in our baseline specification, but all results go through if we use $\log(natfrac_{grt})$ instead.[28]

We run equation 3 for three different levels of aggregation: i) one that does not distinguish between product groups at all (no g), so that each season has one observation for the imported high quality fraction and one for the domestic high quality fraction; ii) one where g indicates product groups as in equation 2; iii) and one where g indicates specific brands within a product group.[29]

[28]We also run regressions using the number of high and low quality SKUs instead of the fraction, which we discuss in the robustness section. The results are available in Appendix B.

[29]For example, Adidas and Puma are two brands within sport shoes, but here a brand will have different fixed effects for all the product groups where it sells items.

Table 4: Differential quality downgrading

	Dependent variable:			
	$natfrac_{grt}$			
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.285**	-0.347***	-0.321**	0.204
	(0.059)	(0.064)	(0.115)	(1.029)
Origin FE	✓			
Season FE	✓	✓		
Group × Origin FE		✓	✓	
Group × Season FE			✓	✓
Brand × Origin FE				✓
Observations	16	395	395	24,820
R^2	0.911	0.692	0.864	0.999

*Note: This table presents coefficient estimates from specification 3, aggregating SKUs within non-Russian (imported) or Russian origin in column (1), within product group-origin in columns (2) and (3), and within brand-origin in column (4). The outcome is the fraction of offered SKUs that use a natural fabric for group or brand 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.*

These specifications are saturated with fixed effects and therefore allow for quality reallocations between product groups, within product groups and between brands, and within brands only for the three regressions, respectively.

Our base specification in columns (2) and (3) of Table 4 correspond to the within-product group model, and imply that a one percent devaluation in the prior season leads to a roughly 0.35% reduction in the fraction of high quality offerings. In column (1), we recover a negative, significant δ coefficient that is not statistically different from the estimates in (2) and (3), suggesting that reallocation between product groups with different average quality levels is not a key margin for quality downgrading for the firm. In column (4), δ is estimated as insignificant, implying that within-brand reallocations are less important for downgrading.[30]

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

[30] Results for specification 3 using the logged fraction of natural offerings, and results dropping the last season of incomplete data are reported in Appendix B. Both are qualitatively and quantitatively similar to our baseline findings.

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 3 to vary by product group in our product group level specification:

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

For each product group, we recover the quality premium 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 (20 out of 26), quality is costly.

We plot the estimated coefficients δ_g against the quality premium in Figure 4.[31] The strong 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.

Quality downgrading robustness

Our 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. Since Russian products may use imported intermediates combined with Russian labor this is to be expected, and suggests that our quality downgrading coefficient in Table 4 is a lower bound since the control group experiences a cost shock as well.

One concern is that the treatment effects are driven by quality upgrading or idiosyncratic movements in the control group, rather than downgrading in the treatment group, especially since the control group is relatively small. We perform several checks to address this issue.

We first run a DiD using only imported goods, treating the logged number of high or low

[31] The full regression results from equation 4 are available in Table B.2 in Appendix B.

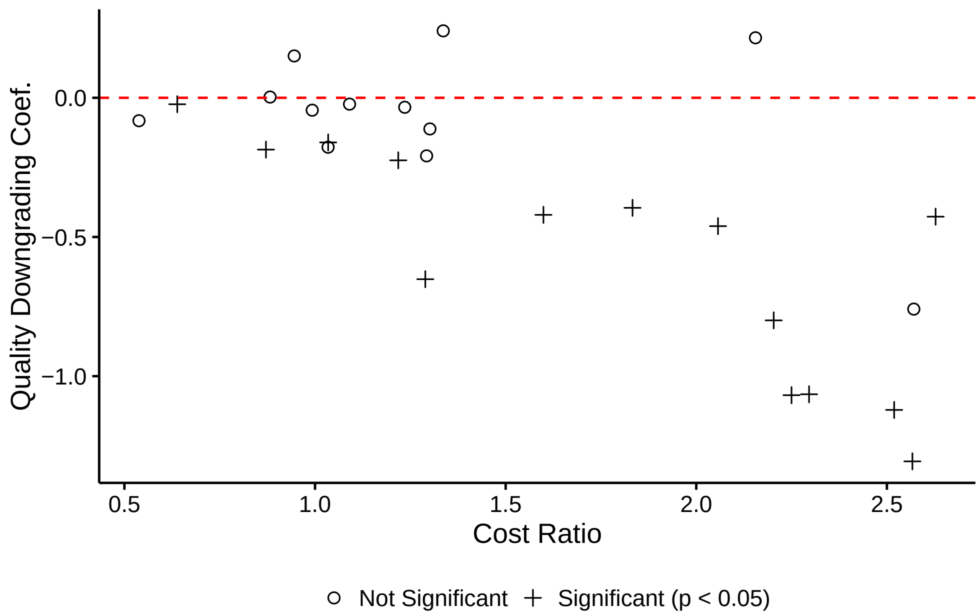


Figure 4: **Cross-group variation in downgrading**
Note: This figure plots the estimated δ_g coefficients of equation 4. Fixed effects are at the group$\times$origin and season level. Standard errors are clustered by group$\times$origin level to allow within-group-origin serial correlation.

quality SKUs within a group as our dependent variable. Our main specification is:

$$\log(N_{mgt}) = \gamma_1 \log(ER_{t-1}) + \gamma_2 \log(ER_{t-1}) \cdot Nat_{mgt} + \gamma_3 t + \sum_{mgs} \alpha_{mgs} \mathbf{D}_{mgs} + \epsilon_{mgt} \tag{5}$$

where the time trend is included to account for the firm's growth over this time, from Table 2, and quality, product group, season of year dummies are included. Results reported in Appendix B indicate a negative and significantly estimated $\hat{\gamma}_2$, so that Table 4 reflects that imports' natural fabric share is actually shrinking, and not simply growing less quickly than Russian products' natural fabric share. We also perform the regression without time controls but including a dummy for product group, season (e.g, Spring/Summer 2014) combinations.

Moreover, we also provide in Appendix B a raw DiD data graph for polymers (Figure B.1), which appear as a rubber and leather substitute in product groups using leather (approx. 40% of total SKUs). Polymers have a significant presence by end of sample (in 8% of SKUs) and show a clear differential trend, with imports increasing their share while domestic products keep the share roughly constant. This check provides some assurance that the DiD is picking up differential downgrading in the treatment group.

3.3 Demand channel

One might suspect that the observed compositional changes stem from a large demand shift towards cheaper or lower quality goods as a result of an income shock to consumers, rather than a cost shock to the importer. In this section we assess the quantitative importance of this mechanism by looking at regions that were more adversely affected during the crisis and comparing their demand patterns to regions that had higher economic growth. We find little evidence of differential consumption reallocation toward cheaper goods in Russian regions (oblasts) suffering from extremely low or even negative economic growth in 2015. The basic approach entails a DiD estimation strategy of the following form:

$$\log(Qual_{it}) = \alpha_i + \sum_t \gamma_t \mathbf{D}_t + \sum_t \delta_t \left(\mathbf{D}_t \cdot Growth_i\right) + X_{it}'\theta + \sum_t \psi_t \left(\mathbf{D}_t \cdot X_{it}\right) + \epsilon_{it} \quad (6)$$
$$\forall i,\ \forall t \in \{2012m1, \ldots, 2015m9\} \setminus \{2014m12\}$$

where $Qual_{it}$ is either the median or mean quality ($natfrac$) in region i at time t, α_i are region fixed effects, $Growth_i$ is the nominal regional GDP growth in 2015, $\mathbf{D}_t$ is an indicator for the time period (year-month), with $2014m12$ taken as the omitted category, $(\mathbf{D}_t \cdot Growth_i)$ represents an interaction term between the time indicators and a region's economic performance in 2015, and X_{it} is a matrix of control variables that includes total regional sales (in logs), as well as regional unemployment and income levels.[32] All standard errors are clustered at the region-level to allow for serial correlation across time.

The Russian currency crisis had a vastly differential impact on various regions of the country. This provides for a clean distinction between exposed (low growth) and unexposed (high growth) oblasts that can be utilized when estimating specification 6. Panel (A) of Figure 5 shows a map with geographic regions that grew relatively fast (in dark colors) as well as slowly (in light colors) in 2015. Exclusively devoting attention to oblasts with positive retail sales, the steepest contraction saw regional GDP growth of -10.1% whereas the oblast with the highest growth expanded by 16.1%. The standard deviation of income growth was 3.26 over this period.

As would be necessary with any DiD estimation approach, this specification also provides evidence on the parallel trends assumption in all outcome variables. That is, in the absence of treatment the unobserved disparities between high- and low-growth regions should be constant

[32]The results are unaffected by inclusion of these additional controls and interaction terms. Appendix B.4 further presents estimates for the median and mean regular prices in region i at time t as alternative outcome variables.

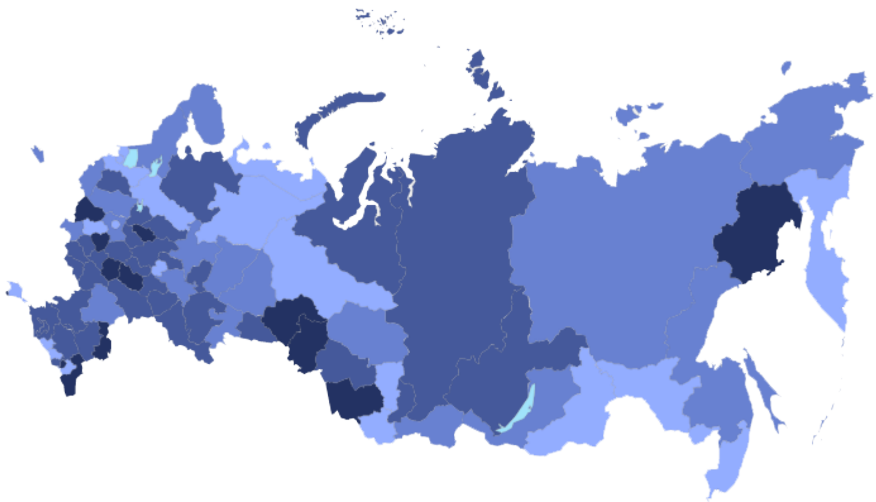
over time—the validity of the estimation procedure relies on outcome variables that would have continued to develop as they did before the economic shock in all regions. Unless this assumption is valid, the estimated treatment effects would be biased versions of the true impact. As an additional robustness check on the identification strategy, all control variables are interacted with the $\mathbf{D}_t$ indicators to allow for possible heterogeneous responses to negative economic shocks across distinct regions (e.g., poor versus rich oblasts could react differently to the crisis).

The main parameters of interest are the δ_t since they capture the difference between crisis exposed and relatively unscathed regions over time. The estimated fixed-effects model includes leads going back to early 2012 and lags reaching the last available month, September 2015. The specification allows for any causal direction of the findings and assesses if the effects grow or fade over time.

One may also entertain a causal interpretation of the δ_t estimates in equation 6 for other important reasons. Firstly, about 93% of goods sold by the retailer are not produced in Russia, and even when the good is home made it is almost never manufactured in the region under consideration. Hence the specification will not suffer from endogeneity issues typically associated with regressions of prices on economic activity. For instance, unobserved productivity innovations for a specific SKU are unlikely to be correlated with local growth rates. In principle, aggregate shocks could lead to simultaneous movements in prices of goods and local economic growth. But since time fixed effects are included, they should eliminate this endogeneity issue too. Finally, the retailer does not price discriminate across geographic regions within Russia and thus any observed divergence in regional median and mean quality can only be explained by changes in quantities (purchases).

The findings are summarized in Figure 5, which plots the key estimated parameters of interest, $\widehat{\delta_t}$, with 95% confidence intervals around them. As would be consistent with the parallel trends assumption, the estimates in Panel (B) show no robust differences between the positively exposed (high growth) and negatively hit (low growth) regions in the months prior to the onset of Russia's currency crisis. Then, starting around mid-2014, there is increasingly more volatility in the treatment effects for all outcome variables. However, the results are insignificant and hardly moving in the expected positive direction. Together with unreported but similarly robust evidence suggesting no differential effects on total regional sales, this leads us to conclude that income shocks across Russian regions had a marginal role in the observed compositional shifts in the affordable fashion industry and that endogenous amplification channels on the firm-side

(A) Regional growth (2015)



(B) Income effect

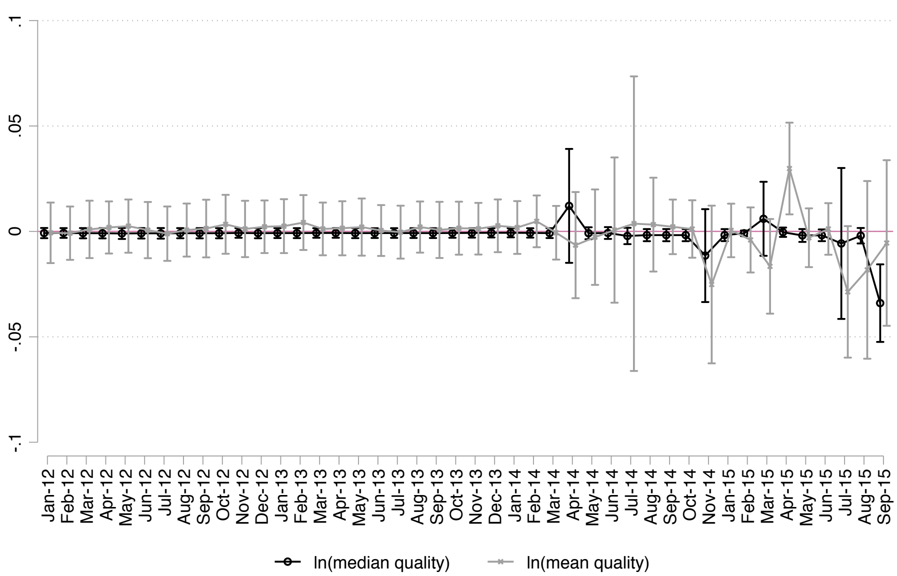


Figure 5: **Demand channel**

Note: Panel (A) depicts regional GDP growth rates across Russian oblasts in 2015, with darker colors representing higher economic growth; Panel (B) plots the estimated δ_t coefficients of equation 6 with 95% confidence intervals around them. Results for two distinct outcome variables are displayed over time: the log median regional quality (black), and the log mean regional quality (grey). Time is measured on a monthly basis.

must be driving most of the quality downgrading.

3.4 Price pass-through

Having documented quality downgrading in the previous section, in this section we explore pass-through. If the firm is stocking fewer high-quality goods, then they must have become relatively less profitable; since profit is simply markup multiplied by quantity sold, either high quality markups, quantities, or both must have experienced a relative decline after the shock.

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 material-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:

$$\begin{aligned}\log(y_{jmbgt}) = {} & \beta_1 \log(ER_{t-1}) + \beta_2 \log(ER_{t-1}) \cdot Nat_{jmbgt} + \beta_3 \log(ER_{t-1}) \cdot Rus_{jmbgt} \\ & + \sum_{mbgs} \alpha_{mbgs} \mathbf{D}_{mbgs} + \sum_{bgr} \alpha_{bgr} \mathbf{D}_{bgr} + \epsilon_{jmbgt}\end{aligned} \tag{7}$$

where y_{jmbgt} is either p_{jmbgt}, the first observed price of SKU j of material 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 $\times$ brand $\times$ product group $\times$ season of year level (f), so for instance, high quality Adidas sport shoes in Spring/Summer have their own intercept. Dummies are also included at the brand $\times$ product group $\times$ origin level, to allow Russian and non-Russian products to have different intercepts.

Results from the regression are presented in Table 5. Pass-through into prices in column (1) is incomplete, as the coefficient on the lagged exchange rate for pass-through into prices is roughly 0.75 and statistically different from 1. However, using the raw data on wholesale costs, this imperfect pass-through does not correspond to lowered markups: the pass-through on cost is very similar in column (2).[33] Importantly, the differential change in prices and wholesale

[33]From discussions with the firm's operations staff, they describe negotiating a "50-50" split of the cost increase (in rubles) with their wholesale suppliers. The coefficient on the lagged exchange rate in column (2) is higher than

Table 5: Pass-through coefficients

	Dependent variable:			
	log(p)	log(c)	log(p)	log(c)
	(1)	(2)	(3)	(4)
$\log(ER_{t-1})$	0.754***	0.746***	0.751***	0.742***
	(0.032)	(0.043)	(0.033)	(0.042)
$\log(ER_{t-1}) \cdot Nat$	0.024	-0.046	0.028	-0.040
	(0.031)	(0.040)	(0.038)	(0.048)
$\log(ER_{t-1}) \cdot Rus$	-0.143**	-0.208***		
	(0.053)	(0.050)		
Quality × Brand × Group × SoY FE	✓	✓	✓	✓
Brand × Group × Origin FE	✓	✓		
Observations	393,916	393,916	371,559	371,559
R^2	0.890	0.886	0.890	0.886

*Note: This table presents coefficient estimates from specification 7 at the brand-group-fabric level. The dependent variable is either (1) the first observed price of SKU j or (2) 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 fixed effect level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

costs for high quality goods is not significantly different from zero, implying no differential pass-through for these products. While the prices of Russian-sourced products do increase following the devaluation—perhaps due to strategic complementarities in price setting—those goods still exhibit significantly lower pass-through than imported items, validating their use in the previous section as a control group that is less exposed to the cost shock. Additional regressions that drop the domestically sourced Russian products in columns (3) and (4) yield similar results.

We address concerns that within material-brand-group selection on low-performing SKUs may be biasing pass-through in Appendix B.3. 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.

Even with no differential pass-through there may have been a differential reduction in demand. With demand that exhibits expenditure switching, a proportionate price increase can imply a disproportionate reduction in quantity sold of the more expensive, higher quality product. Indeed, we find that within product groups, the aggregate quantity sold of high quality products

0.5, which may reflect that larger brands with more SKUs negotiated higher pass-through into costs.

decreases disproportionately more relative to low quality products. Those results are reported in Appendix B.3.

4 Model

This section develops a simple model of firm quality choice. We write a model capable of matching the facts that high quality products are more profitable pre shock, dropped at a faster rate post shock, and that the multiplicative markup over marginal cost did not change for either type of product; that is, there was no differential pass-through. The model provides insights on what demand assumptions are necessary for quality downgrading.

4.1 Setup

There are M_t identical consumers in season t, each of whom has Y_t to spend on products from the retailer. Products can be high (h) or low (ℓ) quality, denoted by subscript $k \in \{h, \ell\}$, and consumers have preferences for each good.[34] The retailer decides in season $t-1$ how many products of each quality type to offer in period t.

Demand

We follow Fieler (2011) and Medina (2018) in our utility specification:

$$U_t = \alpha_h \int_{\nu_h \in \Omega_h} Q_{ht}(\nu_h)^{\frac{\sigma_h - 1}{\sigma_h}} \partial \nu_h + \alpha_\ell \int_{\nu_\ell \in \Omega_{\ell t}} Q_{\ell t}(\nu_\ell)^{\frac{\sigma_\ell - 1}{\sigma_\ell}} \partial \nu_\ell \tag{8}$$

α_h and α_ℓ are quality shifters, Ω_{mt} is the set of varieties of type m available at t, and $\sigma_m > 1$ measures the elasticity of substitution across varieties of type m goods. We also define $\Omega_t \equiv \{\Omega_{ht}, \Omega_{\ell t}\}$.

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

[34] We follow Levchenko, Lewis, and Tesar (2011) and Alessandria and Kaboski (2011) and our reduced form in treating quality as a 0-1 dummy corresponding to material. In their analysis of the 2008 income shock, Levchenko, Lewis, and Tesar (2011) find more evidence of a quality response when using explicit, 0-1 measures of quality instead of demand residuals as in Khandelwal (2010).

usual CES form for demand of product ν_m:

$$Q_{mt}(\nu_m) = M_t \frac{X_{mt} P_{mt}(\nu_m)^{-\sigma_m}}{P_{mt}^{1-\sigma_m}} \tag{9}$$

where X_{mt} is the total expenditure on products of quality m at time t by any given consumer, and P_{mt} is the CES price index for goods of quality m, $P_{mt} \equiv \left(\int_{\nu_m} P(\nu_m)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}$. The formula for X_{mt} is $X_{mt} = \lambda^{-\sigma_m} \alpha_m P_m^{1-\sigma_m}$, where λ is the marginal utility of income.

Pricing

Products are priced to maximize profit, given consumer demand and marginal costs. Assume that the marginal cost of a m quality product is c_m in units of foreign currency, which is converted to rubles via an exchange rate. In our setup, sourcing and pricing decisions are made one season in advance, so that the variable profits of product ν_m are therefore:

$$\pi_t(\nu_m) \equiv Q_{mt}(\nu_m)(P_{mt}(\nu_m) - ER_{t-1} c_m) \tag{10}$$

The optimal price will depend on whether the firm internalizes the effect of changing the price of the product ν_m on all of its other products. Prices are given by:

$$P_{mt}(\nu_m) = \frac{\sigma_m}{\sigma_m - 1} ER_{t-1} c_m + \mathbf{1_M} \cdot \Phi(\Omega_h, \Omega_\ell, ER_{t-1}), \tag{11}$$

where $\mathbf{1_M}$ is an indicator function equal to one if the firm is pricing as a monopolist, and Φ is a non-negative function that depends on the set of offered goods and parameters. In what follows we set the indicator to 0, since in our reduced form we find a constant proportional markup that does not change following the shock. With an indicator equal to 1, the model would counterfactually predict changing markups.

All products of a given quality type face the same costs and exchange rate, so we look for a symmetric equilibirum where products of the same quality have the same price, $P_{mt} = \frac{\sigma_m}{\sigma_m - 1} ER_{t-1} c_m$.

Quality choice

To close the model, we specify how the firm chooses its product mix each season. We assume the firm faces a fixed, per-product cost of sourcing. Given the form of the utility function, having the firm jointly maximize profits of all products by picking the optimal numbers of high and low qualities would lead to a corner solution.

Instead, we assume that each SKU sourcing decision is under the control of a purchasing manager, indexed by ν. There are a fixed number of managers, and each manager chooses between stocking a high quality SKU, a low quality SKU, or not stocking anything that season. Given anticipated optimal prices P^*_{mt}, the profit from choice $m \in \{h, \ell, 0\}$ is

$$\pi_{mt}(\Omega_t) - f - \epsilon_{mt}(\nu), \tag{12}$$

where f is a fixed per-SKU cost of sourcing, and $(\epsilon_{ht}(\nu), \epsilon_{\ell t}(\nu), \epsilon_{0t}(\nu))$ is a vector of stochastic fixed costs associated with each option.

Managers do not observe each others' stochastic fixed costs, and therefore do not perfectly observe each others' choices. They can, however, anticipate strategies in equilibrium given the cost parameters, exchange rate, and demand. The solution of the sourcing problem is a set of choice probabilities and beliefs about strategies that are mutually consistent in a Bayesian Nash equilibrium. Assuming that $\pi_t(\nu_0) = 0$ and the stochastic fixed costs take a logit form, we have:

$$\rho_{mt}(\nu, \Omega_t(\boldsymbol{\rho}_t)) = \frac{\exp(E_{\Omega_t}[\pi_t(\nu_m, \Omega_t(\boldsymbol{\rho}_t))] - f)}{1 + \exp(E_{\Omega_t}[\pi_t(\nu_h, \Omega_t(\boldsymbol{\rho}_t))] - f) + \exp(E_{\Omega_t}[\pi_t(\nu_\ell, \Omega_t(\boldsymbol{\rho}_t))] - f} \tag{13}$$

where $\boldsymbol{\rho}_t = (\rho_{ht}, \rho_{\ell t}, \rho_{0t})$ is the equilibrium vector of sourcing probabilities *and* the equilibrium vector of manager beliefs about those sourcing probabilities. Profit expectations are taken over the possible sets of stocked products induced by the choice probabilities of the other managers.

Although the assumption on independently acting managers is extreme, we believe it is justified. Qualitatively, we know that the firm does devolve responsibility for product sourcing to quasi-independent managers; while precise combinations of inputs are needed for production in manufacturing, for retail stocking this level of coordination may be too costly to be worthwhile. Quantitatively, the model still allows for product sourcing interrelationships, but vastly simplifies the computation of the optimal sourcing problem, and would be immediately applicable to static sourcing problems that do have independently acting firms which is the usual situation in the literature.[35]

[35]Models of sourcing sets of discrete products that affect each other through product or demand interrelationships are combinatorial optimization problems (Antras, Fort, and Tintelnot, 2017). Our model requires demand interrelationships be taken into account, since inward shifting residual demand curves are the only limit on the size of the firm; we thus cannot use the quality sourcing models of Fan, Li, and Yeaple (2018) or Manova and Yu (2017), which

4.2 Model predictions

Consider the more general utility function:

$$U_t = g\left(\alpha_h \int_{\nu_h \in \Omega_h} Q_{ht}(\nu_h)^{\frac{\sigma_h - 1}{\sigma_h}} \partial \nu_h, \quad \alpha_\ell \int_{\nu_\ell \in \Omega_{\ell t}} Q_{\ell t}(\nu_\ell)^{\frac{\sigma_\ell - 1}{\sigma_\ell}} \partial \nu_\ell\right) \tag{14}$$

Our exposition above was with $g(x, y) = x + y$, as in Fieler (2011). We compare the predictions using this aggregator compared to more standard trade models that use $g(x, y) = x^\xi y^{1-\xi}$, $\xi \in (0, 1)$; i.e., CES nests with a Cobb-Douglas aggregator, which fix consumer expenditure shares across product nests.

Theorem 1. *For a currency devaluation represented by an increase in ER_{t-1}, we have that*

1. *For $g(x, y) = x + y$ with $\sigma_h > \sigma_\ell$ and $\alpha_h > \alpha_\ell$, there exist parameters such that $\partial(\rho_h/\rho_\ell)/\partial ER_{t-1} < 0$*
2. *For $g(x, y) = x + y$, with $\sigma_h = \sigma_\ell$, $\partial(\rho_h/\rho_\ell)/\partial ER_{t-1} = 0$*
3. *For $g(x, y) = x^\xi y^{1-\xi}$ with $\xi \in (0, 1)$, $\partial(\rho_h/\rho_\ell)/\partial ER_{t-1} = 0$*

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 high quality products to low quality products. Part 2 shows that to get this reallocation, it is necessary that demand for high quality products is more sensitive to price increases ($\sigma_h > \sigma_\ell$), and part 3 shows that it is necessary for consumers to be able to reallocate expenditures across product categories. The requirement that $\alpha_h > \alpha_\ell$ is simply to ensure that h products are more profitable than ℓ ones by having larger demand shifters in spite of lower markups.

The downgrading result comes purely from the demand model, using an identical specification to Medina (2018) and Fieler (2011). The result would also be generated by the linear demand curves of Melitz and Ottaviano (2008) or Eckel, Iacovone, Javorcik, and Neary (2015) with variable markups, or the logit model with constant additive markups of Khandelwal (2010). Both the logit and linear demand can feature expenditure switching and higher demand elasticities for the high price, high quality product.

rely on single product firms or abstract from interrelationships. Our method implies a tractable sourcing model that is very easy to solve and estimate (< 1 sec to compute an equilibrium, vs. roughly 1 day for Jia (2008)).

Note that if there were no reallocation from high to low quality, then given constant multiplicative markups, price pass-through would be equal to the pass-through into costs. With a reduction in high price, high quality products in favour of low price, low quality ones, the result implies that the average price increase is dampened by quality downgrading. We explore the empirical relevance of this prediction to 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."

For pass-through into prices, we run the following modified version of specification 7:

$$\log(p_{jmbgt}) = \sum_{g} \beta_g \mathbf{D}_g \log(ER_{t-1}) + \sum_{mbgs} \alpha_{mbgs} \mathbf{D}_{mbgs} + \epsilon_{jmbgt} \tag{15}$$

We drop all Russian products, restrict pass-through to be the same for natural and non-natural products as indicated in the reduced form, and allow each product group to have its own pass-through.[36] Fixed effects are at the material-brand-product group-season of year level as before. From this specification we will recover the predicted log price, which we exponentiate to recover $\hat{p}_{jmbgt}$ for each SKU.

For pass-through into the numbers of high and low quality products stocked by the firm, we run a modified version of specification 5 from the quality downgrading robustness section:

$$\log(N_{mgt}) = \sum_{g} \gamma_{1,g} \mathbf{D}_g \log(ER_{t-1}) + \sum_{g} \gamma_{2,g} \mathbf{D}_g \log(ER_{t-1}) \cdot Nat_{mgt} + \tag{16}$$

$$\sum_{g} \gamma_{3,g} \mathbf{D}_g t + \sum_{mgs} \alpha_{mgs} \mathbf{D}_{mgs} + \epsilon_{mgt}. \tag{17}$$

[36] A robustness check where pass-through is allowed to vary by material within group is reported in Appendix C.

As before, we drop Russian products, and allow natural and artificial material products to be affected differently by the exchange rate. To reflect the company's growth over this time period, we include a linear time trend. Lastly, we allow the mean number of products to vary by material, group, and season-of-year. From this we recover the predicted number of each type of product in each product group as a function of the exchange rate, $\hat{N}_{mt}(ER)$. The results of this regression, as well as the pricing regression, are reported in Appendix D.

Within a product group and given an exchange rate ER, we compute the average price in a season as:

$$\bar{p}_{gt}(ER) = \frac{\hat{N}_{ht}(ER) \cdot \hat{p}_{ht}(ER) + \hat{N}_{\ell t}(ER) \cdot \hat{p}_{\ell t}(ER)}{\hat{N}_{ht}(ER) + \hat{N}_{\ell t}(ER)}.$$

The counterfactual will compare baseline predicted pass-through to predicted pass-through if the number of goods behaved as if the exchange rate did not increase. In light of the seasonality present in our data, the counterfactual compares the predicted average price in Spring/Summer 2014 to Spring/Summer 2015. Our two key objects for each product group are therefore:

$$\text{Act}_g \equiv \frac{\bar{p}_{g,SS2015}(ER_{FW2014})/\bar{p}_{g,SS2014}(ER_{FW2013}) - 1}{ER_{FW2014}/ER_{FW2013} - 1}$$
$$\text{Cfac}_g \equiv \frac{\bar{p}_{g,SS2015}(ER_{FW2013})/\bar{p}_{g,SS2014}(ER_{FW2013}) - 1}{ER_{FW2014}/ER_{FW2013} - 1}$$

where the first object is the ratio of the percent average price increase for the observed exchange rates, divided by the percent increase in the exchange rate; the second object is the same ratio but using the counterfactual numbers of products in the numerator. For reference, the denominator is 0.556, reflecting an increase from 33.2 rubles/USD in Fall/Winter 2013 to 51.7 rubles/USD in Fall/Winter 2014.

Plots of 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 pass-through number from running the analysis across all product groups simultaneously, which is from the baseline price and quantity pass-through specifications 7 and 5 in the reduced form section.

First, with quality downgrading average pass-through is approximately 0.43, while without quality downgrading that number increases to 0.48, almost 12% higher. 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 (Naka-

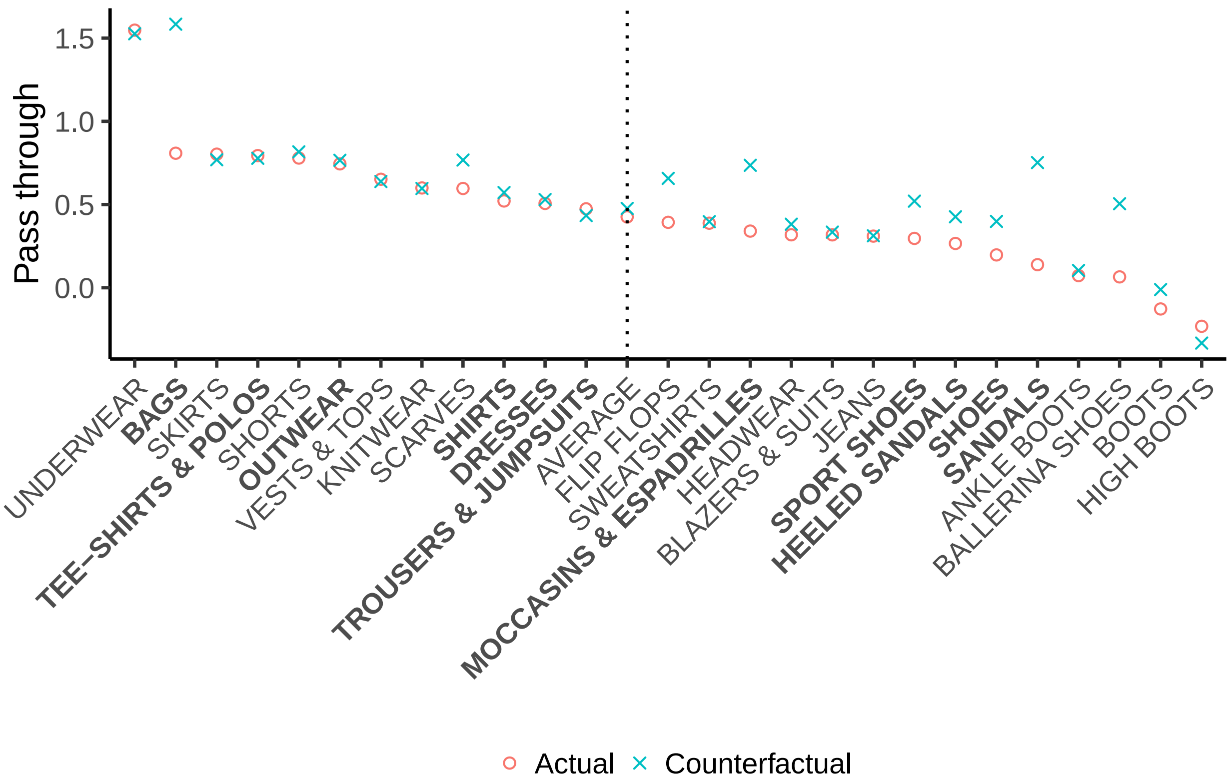


Figure 6: **Counterfactual pass-through by product group**
Note: Bolded product group names comprise 80% of sales during the 2014 Spring/Summer season.

mura and Steinsson, 2012), which suggests external validity.

Second, this main effect is not driven by unusual behavior in categories with very few SKUs. Bolded 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 dampener 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 fell from 0.52 to 0.30.

6 Conclusion

We use a novel and unique online retail dataset that spans Russia's enormous currency depreciation in late 2014 as a laboratory to analyze how firms respond to cost shocks. We document that changes to product quality allocations figure prominently following the exchange rate shock. We further show that increasing costs—not an income-driven flight from quality—motivates the downgrading, and that markups do not change post-shock. A simple demand model with expenditure switching can rationalize the downgrading. Counterfactual analysis indicates that, on average, downgrading dampened price changes, reducing pass-through from 0.48 to 0.43. Our paper complements a long literature on incomplete exchange rate pass-through by showing direct evidence of another margin of adjustment for firms, and introduces an endogenous firm reallocation margin to the literature on expenditure switching in demand systems.

Our study looks at the effects of the exchange rate shock on quality holding consumer preferences fixed. Yet reductions in quality may deplete firms' relationship capital with consumers, 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 those 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

Material	High Quality	Num. SKUs	Blend Fraction
Cotton	1	140,665	0.508
Polyester	0	104,400	0.653
Leather	1	71,173	0.057
Elastane	1	51,757	0.999
Viscose	1	42,806	0.774
Nylon	1	31,613	0.814
Artificial Leather	0	28,637	0.062
Polymer	0	27,614	0.323
Textile	1	17,618	0.334
Acrylic	0	17,480	0.657
Wool	1	17,411	0.842
Suede	1	10,344	0.028
Spandex	1	8,089	1
Nubuck	1	4,776	0.004
Velour	1	4,046	0.0002
Silk	1	4,024	0.450
Artificial	0	3,256	0.233
Lycra	1	2,751	0.998
Linen	1	2,745	0.765
Rubber	1	2,729	0.715
Angora	1	2,111	0.998
Modal	1	1,924	0.866
Artificial Suede	0	1,900	0.001
Cashmere	1	1,678	0.931
Split	1	1,511	0.001
Artificial Nubuck	0	933	0.002
District	1	852	0.826
Mohair	1	767	0.982
Acetate	0	676	0.934

Note: This table presents the mapping from the 30 most commonly occurring fabrics, 97% of SKUs and accounting for all materials in 93% of SKUs, into the high/low quality dummy.

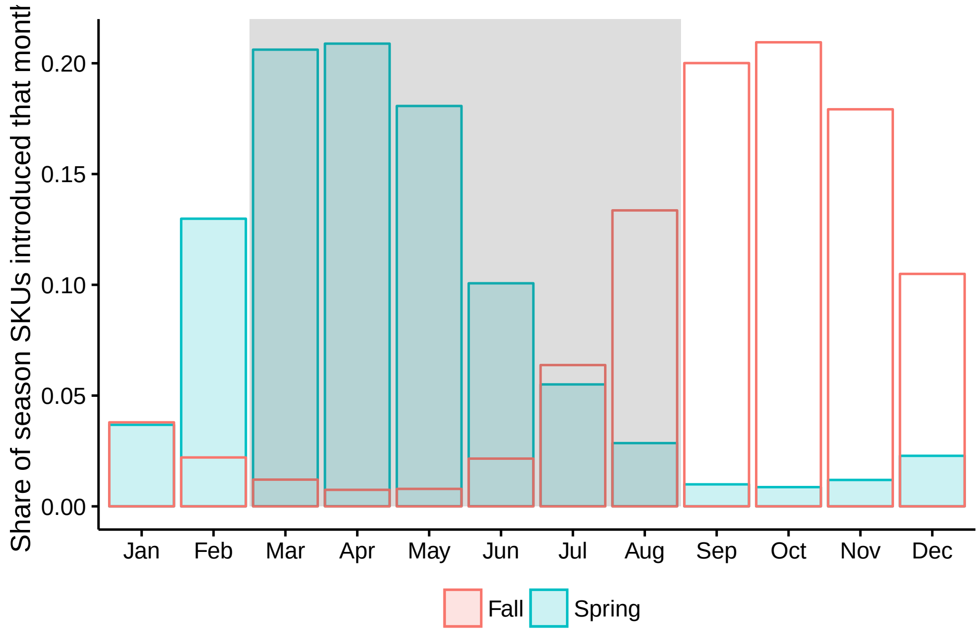

Figure A.1: **Month of first appearance for new SKUs by season**
Note: This figure shows histograms of the distribution of Fall and Spring introductions by month. The gray area covers the months we choose to associate with Spring goods of March-August.

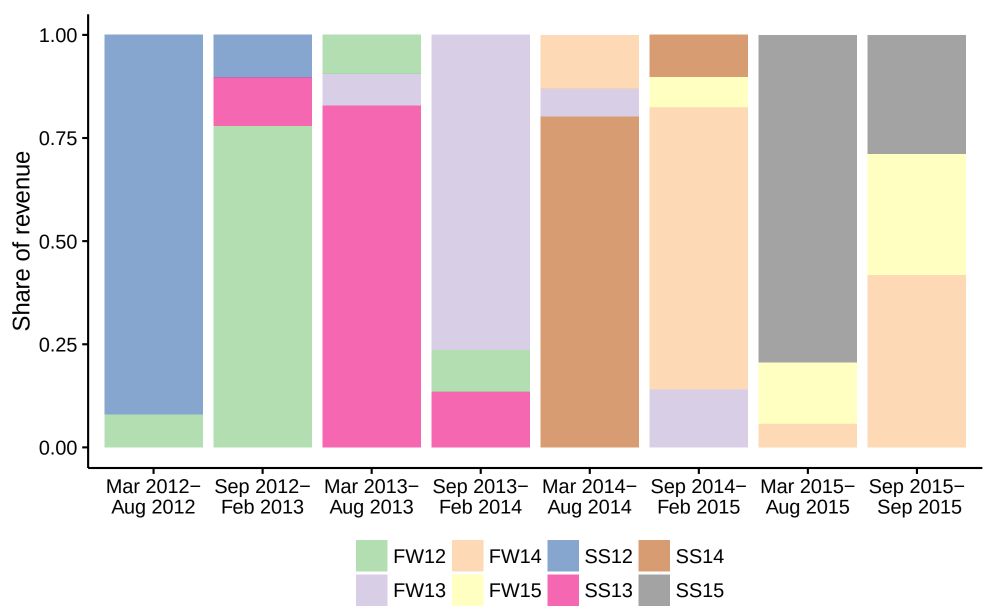

Figure A.2: **Overlapping generations of goods**
Note: This figure plots the revenue shares (between 0 and 1) for each generation of goods over subsequent Fall and Spring seasons.

A.1 Quality measure validation

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

We observe price and consumption variation within a season across months, and indeed this is the primary source of our price variation for a product since products only last one season. We therefore run the regression at the monthly level with product (j) and month (τ) fixed effects, denoted by $\lambda_{1,j}$ and $\lambda_{2,\tau}$:

$$\ln(s_{j\tau}) - \ln(s_{0\tau}) = \lambda_{1,j} + \lambda_{2,\tau} + \alpha p_{j\tau} + h(j,\tau) + \lambda_{3,j\tau}. \tag{A.1}$$

Our specification differs from that of Khandelwal (2010) in two ways: first, we do not control for "hidden varieties" with 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, third, or fourth 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.

Once we have recovered the fixed effects $\hat{\lambda}_{1,j}$ we project them onto product characteristics, along with brand product group season fixed effects:

$$\lambda_{1,j} = \beta_1 Natural_j + \beta_2 Premium_j + \sum_{bgs} \alpha_{abs} \mathbf{D}_{bgs} + \epsilon_{bgs}, \tag{A.2}$$

where $Natural_j$ is the quality dummy, and $Premium_j$ is a signifier assigned by the firm indicating a "premium" product.

Results from Equation A.1 and Equation A.2 are presented in Tables A.2 and A.3. We try Khandelwal (2010) specifications using both prices and log prices. The project of demand residuals on the quality dummy yields coefficients around 0.09, indicating that conditional on brand, product group, season, and prices, natural material SKUs have sales roughly 9% higher than non-natural SKUs.

Table A.2: Logit demand regression results

	Dependent variable: $\log(s_j) - \log(s_0)$ (1)	(2)
$\log(p)$	-1.506***	
	(0.076)	
p		-0.324***
		(0.014)
t_2	0.205***	0.199***
	(0.019)	(0.018)
t_3	0.092***	0.087***
	(0.014)	(0.012)
Product FE	✓	✓
Month FE	✓	✓
Observations	1,073,026	1,073,026
R^2	0.855	0.850

*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 Product and Month levels. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

Table A.3: Quality shifter decomposition

	Dependent variable: Product FE (1)	(2)
Natural	0.093***	0.092***
	(0.008)	(0.009)
Premium	0.068	0.065
	(0.268)	(0.317)
Brand $\times$ Group $\times$ Season FE	✓	✓
Observations	339,318	339,318
R^2	0.831	0.826

*Note: This table presents coefficient estimates from specification A.2. The unit of observation is at the level of an SKU j in season t. Standard errors are clustered at the Brand$\times$Group$\times$Season level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

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. Standard errors are clustered at the brand$\times$product group level to allow for serial correlation across time. The results are similar to before: high quality goods are about 5% more profitable, and sell at a 5.1% 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)
	(1)	(2)	(3)	(4)	(5)
Natural	0.048***	0.050***	-0.001	0.051***	0.052***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Brand $\times$ Group $\times$ Season FE	✓	✓	✓	✓	✓
Observations	304,577	304,577	304,577	304,577	304,577
R^2	0.695	0.685	0.660	0.899	0.900

*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$\times$group$\times$season level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

B.2 Quality downgrading

Number of SKU quality downgrading regressions

In this section, we assess quality downgrading using the logged raw number of SKUs as a dependent variable, instead of the high quality share of SKUs. Regressions in this section include material quality, product group, season of year dummies, drop the last season with incomplete observations, and drop Russian products. The unit of observation is a product group $\times$ quality $\times$ season count of SKUs. The estimated specification is written out below for clarity:

Table B.2: Heterogeneous downgrading coefficients

Group	Cost Ratio	Coef.	SE	p-val
Ankle Boots	2.571	-1.404	0.152	0
Bags	2.155	0.409	0.204	0.045
Ballerina Shoes	2.296	-1.065	0.430	0.013
Blazers And Suits	1.235	0.153	0.076	0.044
Boots	2.057	-0.383	0.171	0.025
Dresses	1.218	-0.258	0.063	0.00004
Flip Flops	1.833	-0.395	0.084	0.00000
Headwear	1.090	0.139	0.276	0.614
Heeled Sandals	2.250	-1.068	0.209	0.00000
High Boots	2.567	-1.114	0.309	0.0003
Jeans	0.639	-0.056	0.024	0.018
Knitwear	1.034	-0.120	0.057	0.036
Moccasins	2.628	-0.427	0.073	0
Outwear	1.293	-0.625	0.224	0.005
Sandals	2.203	-0.800	0.317	0.012
Scarves	1.599	-0.659	1.090	0.546
Shirts	1.301	-0.145	0.117	0.212
Shoes	2.519	-1.038	0.264	0.0001
Shorts	1.336	0.241	0.225	0.285
Skirts	1.034	-0.116	0.194	0.551
Sport Shoes	1.289	-0.609	0.413	0.140
Sweatshirts	0.993	-0.019	0.068	0.778
Tee-Shirts And Polos	0.945	0.537	0.066	0
Trousers And Jumpsuits	0.871	-0.130	0.054	0.017
Underwear	0.538	-0.051	0.050	0.302
Vests And Tops	0.882	-0.150	0.072	0.036

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. Standard errors are clustered at the product group$\times$origin and product group$\times$season levels.

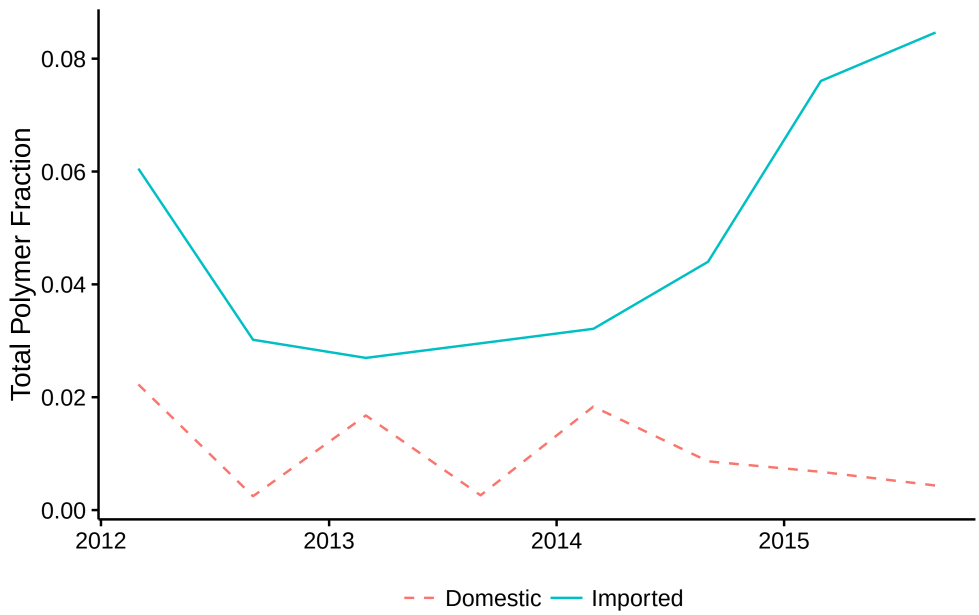

Figure B.1: **Polymer presence by manufacturing origin**
Note: This figure shows the fraction of SKUs where "polymer" is listed as a component over time by domestic (red dashed line) and imported (blue solid line) goods.

$$\log(N_{mgt}) = \gamma_1 \log(ER_{t-1}) + \gamma_2 \log(ER_{t-1}) \cdot Nat_{mgt} + \gamma_3 t + \sum_{mgs} \alpha_{mgs} \mathbf{D}_{mgs} + \epsilon_{mgt} \tag{B.2}$$

where $Natural_{mg}$ 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 $t-1$, and a time trend is included to account for the firm's growth over time. Standard errors are clustered at the fixed effect level. Estimated coefficients are reported in Table B.5

B.3 Price pass-through 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

Table B.3: Differential quality downgrading robustness: logged dependent variable

	Dependent variable:			
	$\log(natfrac_{grt})$			
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.360**	-0.662***	-0.595**	0.095
	(0.072)	(0.133)	(0.212)	(1.909)
Origin FE	✓			
Season FE	✓	✓		
Group × Origin FE		✓	✓	
Group × Season FE			✓	✓
Brand × Origin FE				✓
Observations	16	393	393	22,945
R^2	0.915	0.647	0.853	0.999

*Note: This table presents coefficient estimates from specification 3, but with a logged dependent variable, aggregating SKUs within non-Russian (imported) or Russian origin in column (1), within product group-origin in columns (2) and (3), and within brand-origin in column (4). The outcome is the fraction of offered SKUs that use a natural fabric for group or brand 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.*

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 (σ_p/μ_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

Table B.4: Differential quality downgrading robustness: dropped final season

	Dependent variable:			
	$natfrac_{grt}$			
	(1)	(2)	(3)	(4)
$nonrus_{gr} \cdot \log(ER_{t-1})$	-0.237*	-0.355***	-0.348*	0.244
	(0.088)	(0.074)	(0.156)	(1.254)
Origin FE	✓			
Season FE	✓	✓		
Group × Origin FE		✓	✓	
Group × Season FE			✓	✓
Brand × Origin FE				✓
Observations	14	347	347	23,423
R^2	0.858	0.695	0.864	0.999

*Note: This table presents coefficient estimates from specification 3, but dropping the last season (2015-09), aggregating SKUs within non-Russian (imported) or Russian origin in column (1), within product group-origin in columns (2) and (3), and within brand-origin in column (4). The outcome is the fraction of offered SKUs that use a high quality material for group or brand 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.*

regressions through selection.

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

$$\begin{aligned} \mathrm{CV}^x_{mbgt} = \beta_1 \log(ER_{t-1}) + \beta_2 \log(ER_{t-1}) \cdot Nat_{mbgt} + \log(ER_{t-1}) \cdot Rus_{mbgt} \\ + \sum_{bgr} \alpha_{bgr} \mathbf{D}_{bgr} + \sum_{mbg} \alpha_{mbg} \mathbf{D}_{mbg} + \epsilon_{mbgt}, \end{aligned} \tag{B.3}$$

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, and can be estimated when the fixed effects do not control for season. Results in Table B.6 show no significance for β_2, implying that the dispersion in prices and costs did not change differentially for high 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. These results suggests that differential dropping

Table B.5: Number of SKUs quality downgrading results

	Dependent variable:		
	$\log(N)$		
	(1)	(2)	(3)
$\log(ER_{t-1}) \cdot Nat_{mgt}$	-1.017***	-1.139**	-1.139***
	(0.273)	(0.344)	(0.337)
$\log(ER_{t-1})$		2.515***	-0.273
		(0.272)	(0.341)
t			0.288***
			(0.028)
Group × Quality FE	✓		
Group × Season FE	✓		
Group × Quality × SoY FE		✓	✓
Observations	364	364	364
R^2	0.985	0.906	0.944

*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. $Natural_{mgt}$ 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 $t-1$. Standard errors (in brackets) are clustered at the fixed effect level. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

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:

$$\Delta\overline{p}_{i,t} = \beta_1 \Delta_{\tau_1} e_t + \beta_2 \Delta_{\tau_2} e_{t-\tau_1} + \eta_i + \epsilon_{i,t} \tag{B.4}$$

Table B.6: No change in within-brand-fabric price dispersion

	Dependent variable:	
	CV(p)	CV(cog)
	(1)	(2)
$\log(ER_{t-1})$	-0.006	-0.006
	(0.012)	(0.013)
$\log(ER_{t-1}) \cdot Nat$	-0.016	-0.012
	(0.014)	(0.015)
$\log(ER_{t-1}) \cdot Rus$	-0.010**	-0.012***
	(0.004)	(0.003)
Brand $\times$ Origin FE	✓	✓
Brand $\times$ Quality FE	✓	✓
Observations	21,533	21,429
R^2	0.815	0.772

*Note: This table presents coefficient estimates from specification B.3 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$\times$origin and brand$\times$quality-level to allow for serial correlation across time. ***, **, * indicate significance at the 0.1%, 1% and 5% levels, respectively.*

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.7 reports the results from estimations of regression B.4. 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

Table B.7: 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.4. 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.*

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.

Differential quantity reduction

We test whether there was a differential reduction in shares for high material quality goods. At the material-group-season level, we run:

$$\log(q_{mgt}) = \sum_t \delta_t \left(Nat_{mg} \cdot \mathbf{D}_t\right) + \sum_{mg} \alpha_{mg}\mathbf{D}_{mg} + \sum_{gt} \alpha_{gt}\mathbf{D}_{gt} + \epsilon_{mgt} \tag{B.5}$$

where q_{mgt} is the aggregate quantity sold of material m, product group g, in season t. We restrict our sample to imports only. A consumption reallocation away from high quality towards low quality would be reflected in a negative, significant δ_t, starting in March 2015. The results are plotted in Figure B.2 and show a relative reduction in the quantity share of high-quality goods right after the steep ruble devaluation. We also estimate the regression using expenditures (price multiplied by quantity sold) as the dependent variable and find very similar results; since we use within product group variation this makes our results comparable to the within group switching in Bems and di Giovanni (2016).

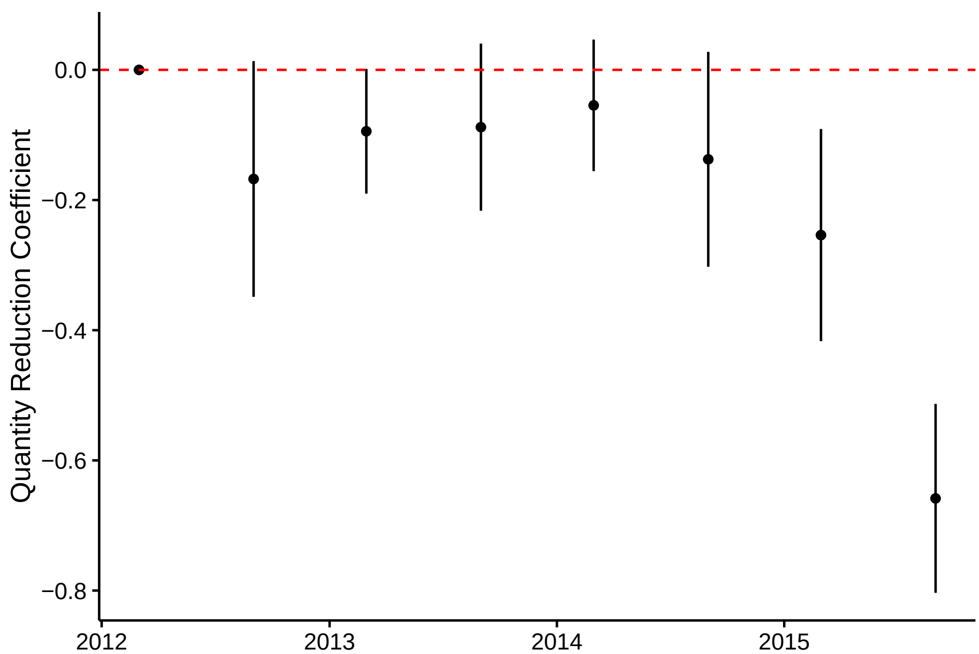

Figure B.2: **Differential quantity reduction**
Note: This figure plots the estimated δ_t coefficients of equation B.5 with 95% confidence intervals around them. The unit of observation is the quantity sold of material m, in product group g, in season t. Fixed effects are at the product group$\times$material and product group$\times$season level. Standard errors are clustered at product group$\times$material level to allow within-group-material serial correlation. Results are similar when only using a season, instead of group$\times$season fixed effect.

This section highlights that differential demand responses play a key role in the reallocation towards lower quality products, as even with no relative change in prices or markups high quality products disproportionately decrease in quantity purchased. There is also supporting evidence that the quality downgrading was not completely in response to an income shock, since if that were true one might expect some reallocation in Figure B.2 towards low quality when the income shock hit in the Fall 2014 season. The fact that significant reallocation only occurred after the firm passed through higher costs into consumer prices suggests that the cost shock played a dominant role in product quality downgrading.

B.4 Demand channel robustness

Prices as outcome variables

Regression model 6 is estimated using the median and mean regular prices in region i at time t as the outcome variables instead. The results are displayed in Figure B.3. Again, the parallel trends assumption seems to hold. The estimated $\hat{\delta}_t$ are somewhat more volatile but insignificant, and not moving in the expected positive direction. This suggests that product quality downgrading is driven by an endogenous amplification channel on the part of the firm rather than by an income-induced "flight from quality" phenomenon originating from consumers.

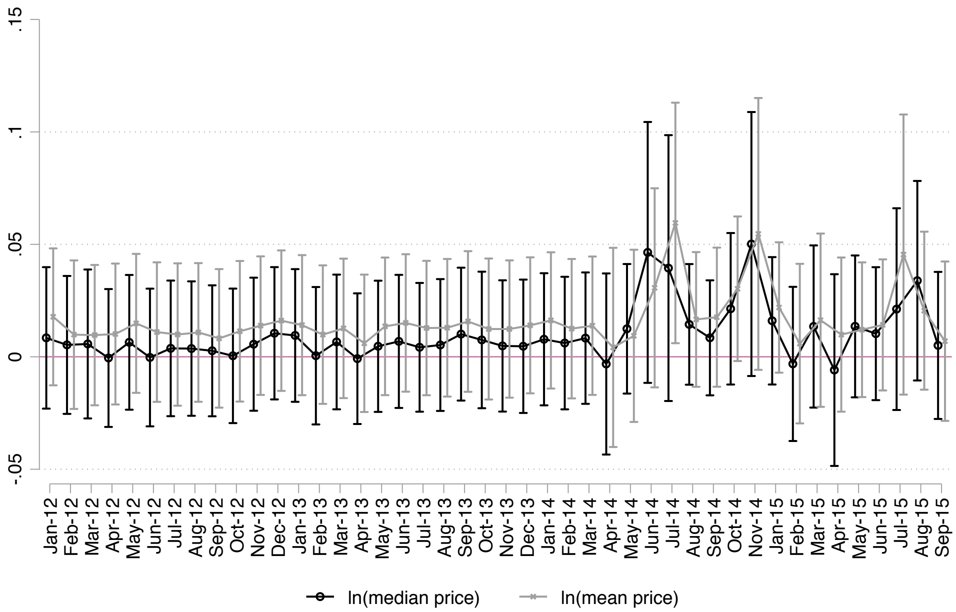

Figure B.3: **Income effect**

Note: This figure plots the estimated δ_t coefficients of equation 6 with 95% confidence intervals around them. Results for two distinct outcome variables are displayed over time: the log median regional purchase price (black), and the log mean regional purchase price (grey). Time is measured on a monthly basis.

C Structural Model

C.1 Proof of Theorem 1

C.1.1 Proof of Part 1

To prove part 1 of the theorem, we need only find parameters such that $\partial(\rho_h/\rho_\ell)/\partial ER < 0$. We prove that such parameters exist by simulation. To solve the model for a given set of parameters $\theta \equiv (\sigma_h, \sigma_\ell, c_h, c_\ell, ER, \alpha_h, \alpha_\ell, Y, S, f)$ we implement Algorithm 1.

S is the total number of potential entrants, and ε is a tolerance parameter. Note that we make an approximation with regards to Jensen's inequality when evaluating expected profits, see Appendix C.2

For $\theta = (3, 2.5, 3, 2.5, ER, 7, 2.5, 10, 20, 0.1)$, 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

Algorithm 1 Model Solution

1: Guess $(\rho_h^{(r)}, \rho_\ell^{(r)}, \rho_0^{(r)})$
2: Compute $N_m^{(r)} = S \cdot \rho_m^{(r)}$
3: Recover prices $P_m = \frac{\sigma_m}{\sigma_m - 1} ERc_m$
4: Recover the marginal utility of income λ by solving

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

5: Recover $Q_m^{(r)} = \alpha_m \lambda^{-\sigma_m} P_m^{-\sigma_m}$
6: Recover $\pi_m^{(r)} = Q_m^{(r)}(P_m^{(r)} - ER \cdot c_m)$
7: Compute

$$\rho_m^{(r+1)} = \frac{\exp(\pi_m^{(r)} - f)}{1 + \exp(\pi_h^{(r)} - f) + \exp(\pi_\ell^{(r)} - f)}$$

8: Return to 1, loop until $\max_m \left| \rho_m^{(r)} - \rho_m^{(r+1)} \right| < \varepsilon$

products to low quality ones as the former becomes less profitable. Note that the increase and decrease in probabilities are offsetting; if there was an outside nest in the utility function that was not experiencing a cost increase, the sum of entry probabilities for high and low would be decreasing as consumers substitute their expenditure to the outside option.

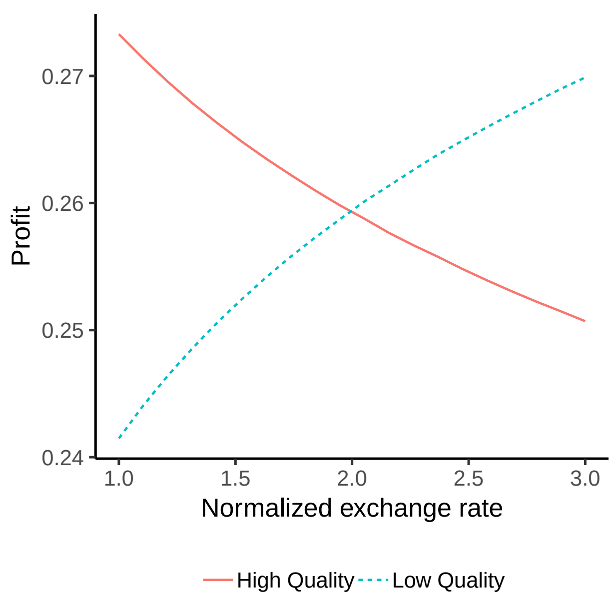

Figure C.1: **Simulated Profits**
Note: This figure plots the simulated profits for high and low quality products in response to increasing the normalized exchange rate from 1 to 3.

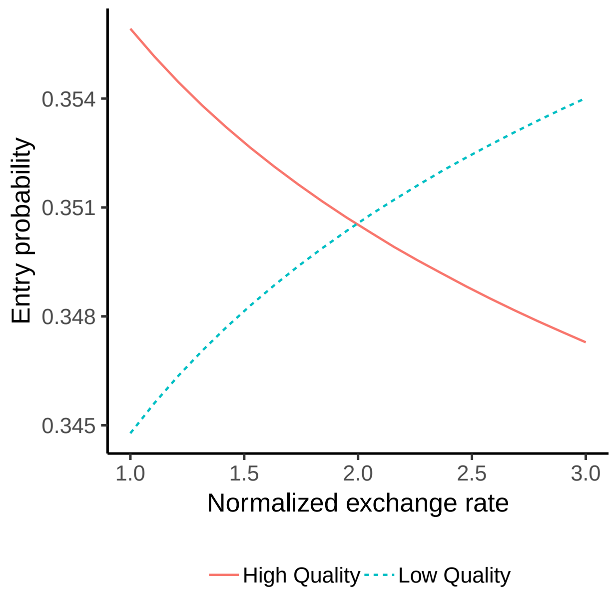

Figure C.2: **Simulated Entry**
Note: This figure plots the simulated choice probabilities for a manager picking between high quality, low quality and no entry in response to increasing the normalized exchange rate from 1 to 3.

C.1.2 Proof of Part 2

Suppose $\sigma_h = \sigma_\ell = \sigma$. Writing out the consumer's budget constraint, substituting in $Q_m = \lambda^{-\sigma}\alpha_m P_m^{-\sigma}$, and rearranging yields:

$$\lambda = \left(\frac{Y}{\alpha_h P_h^{1-\sigma} + \alpha_\ell P_\ell^{1-\sigma}}\right)^{-\frac{1}{\sigma}}$$

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

$$\pi_m = \frac{\frac{\alpha_m}{\sigma} Y \cdot P_m^{1-\sigma}}{\alpha_h P_h^{1-\sigma} + \alpha_\ell P_\ell^{1-\sigma}}$$

Note that since $P_m(\nu) = \frac{\sigma}{\sigma-1} ER \cdot c_m$, substituting into the price indexes would lead ER to cancel in both top and bottom, implying that profits—and hence, entry probabilities—are not a function of ER. There is thus no incentive for quality downgrading.

C.1.3 Proof of Part 3

Suppose we have a Cobb-Douglas utility function with CES aggregators over varieties of high and low quality products:

$$U = \left(\alpha_h \int_{\nu_h \in \Omega_h} Q_{ht}(\nu_h)^{\frac{\sigma_h - 1}{\sigma}} \partial \nu_h \right)^{\xi} \left(\quad \alpha_\ell \int_{\nu_\ell \in \Omega_{\ell t}} Q_{\ell t}(\nu_\ell)^{\frac{\sigma_\ell - 1}{\sigma_\ell}} \partial \nu_\ell \right)^{1-\xi} \tag{C.1}$$

Solving for demand, $Q_m = \beta Y \alpha_m P_m^{-\sigma_m}(\nu)/P_m^{1-\sigma_m}$. Profits are:

$$\pi_m = \frac{\frac{\alpha_m}{\sigma_m}\beta Y \cdot P_m^{1-\sigma_m}(\nu)}{P_m^{1-\sigma_m}}$$

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

C.2 Expected profit approximation

Formally, $\pi^e_{jmt}(\hat{\boldsymbol{P}}_{-jt}, \theta_s) = \mathbb{E}\left[\pi^v_m(\boldsymbol{a}_{-jt}, \cdot)\right] - f_m$, where the expectation is over the multinomial distribution:

$$\mathbb{E}\left[\pi^v_m(\boldsymbol{a}_{-jt}, \cdot)\right] = \sum_{N_\ell, N_h | N_{\ell t} + N_{ht} \leq \tilde{N}_t} \frac{\tilde{N}_t!}{N_{\ell t}! N_{ht}! (\tilde{N}_t - N_{ht} - N_{\ell t})!} \cdot \\ P_{\ell t}^{N_{\ell t}} P_{ht}^{N_{ht}} (1 - P_{ellt} - P_{ht})^{\tilde{N}_t - N_{ht} - N_{\ell t}} \cdot \pi^v_m(N_{ht}, N_{\ell t}, \cdot)$$

Since N_{ht} and $N_{\ell t}$ are typically quite large, we approximate the expectation of the profit with the profit of the expectations as in Ershov (2018). This implies:

$$\mathbb{E}[\pi^v_m(\boldsymbol{a}_{-jt}, \cdot)] \approx \pi^v_m(\tilde{N}_t \hat{P}_{ht}, \tilde{N}_t \hat{P}_{\ell t}, \cdot),$$

which is straightforward to calculate. Simulations using the multivariate normal approximation to the multinomial and integration using sparse quadrature suggest the error from violating Jensen's inequality is not substantial.

D Counterfactuals

Table D.1: Pass-through into prices, aggregate and first 13 groups

	Dependent variable: $\log(price)$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$\log(ER_{t-1})$	0.773^{***}	0.595^{***}	0.909^{***}	0.786^{***}	0.906^{***}	0.662^{***}	0.826^{***}	0.926^{***}	0.749^{***}	0.852^{***}	0.601^{**}	0.754^{***}	0.926^{***}	0.765^{***}
	(0.016)	(0.153)	(0.047)	(0.081)	(0.069)	(0.093)	(0.042)	(0.126)	(0.088)	(0.061)	(0.197)	(0.058)	(0.046)	(0.062)
Brand × Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	371,559	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	0.890	0.895	0.833	0.911	0.849	0.861	0.873	0.866	0.822	0.903	0.850	0.892	0.844	0.902

Note: This table shows the effect of the exchange rate on log prices by product group, from specification 15. The unit of observation is a SKU j in season t. The first column is for all groups together, while the remaining 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 prices, aggregate and second 13 groups

	Dependent variable: $\log(price)$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$\log(ER_{t-1})$	0.773^{***}	0.804^{***}	0.802^{***}	0.764^{***}	0.886^{***}	0.820^{***}	0.582^{***}	0.694^{***}	0.649^{***}	0.604^{***}	0.716^{***}	0.695^{***}	0.778^{**}	0.775^{***}
	(0.016)	(0.042)	(0.048)	(0.106)	(0.039)	(0.068)	(0.054)	(0.070)	(0.061)	(0.072)	(0.051)	(0.068)	(0.260)	(0.077)
Brand × Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	371,559	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	0.890	0.797	0.895	0.780	0.853	0.908	0.831	0.880	0.830	0.856	0.808	0.811	0.672	0.758

Note: This table shows the effect of the exchange rate on log prices by product group, from specification 15. The unit of observation is a SKU j in season t. The first column is for all groups together, while the remaining 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 number of SKUs, aggregate and first 13 groups

	Dependent variable: $\log(N)$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
t	0.288***	0.309*	0.265**	0.195	0.565**	-0.039	0.457***	-0.034	0.218***	0.186	0.168	0.238*	0.402**	0.402**
	(0.028)	(0.113)	(0.061)	(0.093)	(0.131)	(0.108)	(0.084)	(0.127)	(0.035)	(0.165)	(0.104)	(0.082)	(0.111)	(0.091)
$\log(ER_{t-1})$	-0.273	-1.816	-1.315	0.052	-1.853	0.825	-1.810	1.791	0.713	0.488	-0.701	0.331	-0.554	0.861
	(0.341)	(1.578)	(0.861)	(1.297)	(1.842)	(1.512)	(1.179)	(1.778)	(0.492)	(2.318)	(1.455)	(1.148)	(1.553)	(1.275)
$\log(ER_{t-1})\cdot Nat$	-1.139***	-0.617	-0.797	-1.798	-1.410	-1.504	-0.290	0.128	-0.340	-1.901	-0.814	-1.552	-1.993	-3.008
	(0.337)	(1.616)	(0.882)	(1.329)	(1.886)	(1.549)	(1.207)	(1.822)	(0.504)	(2.374)	(1.490)	(1.176)	(1.591)	(1.306)
Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	364	14	14	14	14	14	14	14	14	14	14	14	14	14
R^2	0.944	0.896	0.794	0.951	0.908	0.904	0.924	0.961	0.992	0.962	0.953	0.988	0.963	0.981

Note: This table shows the effect of the exchange rate on the log number of SKUs by product group, from specification 17. The unit of observation is a material quality m for product group g in season t. The first column is for all groups together, while the remaining 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 number of SKUs, aggregate and second 13 groups

	Dependent variable: $\log(N)$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
t	0.288***	0.364***	-0.190	0.286	0.393**	0.236*	0.385***	0.501***	0.246**	0.462***	0.417***	0.421***	0.181	0.466***
	(0.028)	(0.058)	(0.164)	(0.144)	(0.081)	(0.086)	(0.067)	(0.068)	(0.049)	(0.078)	(0.045)	(0.060)	(0.126)	(0.076)
$\log(ER_{t-1})$	-0.273	-0.597	3.542	-0.915	-0.937	-0.569	-2.867*	-1.278	-0.010	-1.290	-1.274	-1.329	4.422*	-1.012
	(0.341)	(0.809)	(2.303)	(2.016)	(1.133)	(1.212)	(0.943)	(0.951)	(0.680)	(1.097)	(0.633)	(0.842)	(1.763)	(1.072)
$\log(ER_{t-1})\cdot Nat$	-1.139***	-0.449	-1.501	-0.471	-1.144	-1.351	1.045	-0.539	-1.103	-0.887	-1.201	-0.617	-3.771	-1.744
	(0.337)	(0.829)	(2.359)	(2.065)	(1.160)	(1.241)	(0.966)	(0.975)	(0.697)	(1.123)	(0.648)	(0.862)	(1.806)	(1.098)
Group × Quality × SoY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Observations	364	14	14	14	14	14	14	14	14	14	14	14	14	14
R^2	0.944	0.958	0.951	0.804	0.925	0.915	0.972	0.961	0.941	0.968	0.993	0.976	0.965	0.956

Note: This table shows the effect of the exchange rate on the log number of SKUs by product group, from specification 17. The unit of observation is a material quality m for product group g in season t. The first column is for all groups together, while the remaining 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, $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.