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JEL Classification: F4

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The Impact of a Large Depreciation on the Cost of Living of Rich and Poor Consumers*

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Abstract

This paper shows that a large exchange rate depreciation affects the cost of living of rich and poor consumers differently. Interestingly, we show that rich consumers are less affected by the depreciation. This is because the depreciation introduces a large variety of products to the market which are more accessible to rich than for poor consumers. We exploit scanner data tracking consumer purchases before and after the large depreciation of the Kazakh Tenge, when it switched from a fixed to a floating exchange rate regime, in August 2015. We use an event study design to show that marginal costs increase more for foreign products than for local products after the depreciation. However, the retail margins on foreign products decrease by more than the retail margins on local products. Thus, the retailer limits relative price movement by adjusting its margins, which helps explain the low sensitivity of domestic absorption to changes in relative border prices. To examine the cost-of-living effect we decompose it into a cost, a retail markup, a substitution and a variety effect. As richer consumers spend, on average, more on foreign varieties, we find that they are disproportionally affected by the cost effect. However, lower retail markups after the shock offset this relative cost increase. Since richer consumers benefit more from changes in product variety, their cost of living increases by less after the depreciation.

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1 Introduction

Nominal exchange rate volatility has been commonplace since the breakdown of the Bretton Woods system. The extent to which currency shocks transmit into domestic prices is central to understanding external adjustment and optimal monetary policy. An extensive literature has focused on the apparent disconnect between exchange rate shocks and fluctuations in nominal prices, known as the exchange rate disconnect puzzle.[1] Itskhoki (2021) illustrates that the degree of home bias in tradeable consumption is one of the key factors explaining this puzzle. If the local content of tradeable consumption is larger, then prices in local currency respond less to exchange rate changes. One specific source of home bias is a large distribution margin on foreign products purchased by domestic consumers (Burstein, Neves, & Rebelo, 2003). This is exacerbated when local distributors set large margins, which has a large impact on the final consumer price. Another potential force behind large home bias in tradeable consumption is the importance of local products. Burstein, Eichenbaum, and Rebelo (2005) show that because many tradeable varieties are in fact never traded, we should not expect the aggregate price of tradeable products to respond fully to an international shock.[2] Using highly detailed scanner data, this paper studies how the retail margin on products and product variety are affected after a large and sudden nominal exchange rate shock and how these adjustments induce distributional cost-of-living effects.

We contribute to a large literature on exchange rate pass-through in a two ways. First, distribution margins usually consist of a cost component (e.g., transport and marketing costs) and a markup component (Burstein et al., 2005; Hellerstein, 2008; Burstein & Gopinath, 2014). While there is abundant evidence that distribution margins matter for explaining the disconnect between consumer and border prices (Burstein et al., 2003; Hellerstein, 2008; Berger, Faust, Rogers, & Steverson, 2012), considerably less is known about how distribution margins change in response to currency shocks. In contrast to mixed evidence from the US[3], we exploit a large depreciation in an emerging economy and find that retail margins of foreign products face a larger decrease compared to local products. Moreover, this adjustment partially offsets the relative cost increase experienced by foreign products. This is yet another explanation of why the elasticity of domestic absorption with respect to changes in consumer prices is substantially larger than the

[1] See Rogoff (1996), Obstfeld and Rogoff (2000), Amiti, Itskhoki, and Konings (2014) and references therein.

[2] Other mechanisms that give rise to home bias in tradeable consumption are trade costs, the use of imported intermediate inputs and a preference which are biased towards local tradeable goods (Itskhoki, 2021).

[3] Hellerstein (2008) finds that retail markup adjustment accounts for about 10% of incomplete exchange rate pass-through. In contrast, Nakamura and Zerom (2010) and Gopinath and Itskhoki (2011) find that retail margins are largely unresponsive to currency changes.

same elasticity with respect to border prices (Auer, Burstein, & Lein, 2021).

Second, standard exchange rate pass-through estimates quantify the change in the price of continuing products following an exchange rate shock. However, Nakamura and Steinsson (2012) show that when varieties are often replaced and prices are sticky that standard pass-through estimates are biased.[4] Relatedly, we find that accounting for changes in product variety leads to a year-on-year change in the cost-of-living that is 5% lower compared to a standard exchange rate pass-through measure that only focuses on the adjustment for continuing products.

We advance an emerging literature on the distributional consequences of international shocks by exploring how relative cost and markup adjustments and changes in product variety affected rich and poor consumers differently. When studying distributional cost of living effects, it is useful to distinguish between an intensive margin and an extensive margin: the intensive margin measures the price response of continuing products to the shock and the extensive margin quantifies the response of product variety to the shock. The intensive margin can be further decomposed into an *across effect* and a *within effect*. The *across effect* originates from heterogeneity in consumer budget shares across different product categories while the *within effect* measures how consumers are affected when they consume different varieties within a product category. For example, Fajgelbaum and Khandelwal (2016) and Cravino and Levchenko (2017) show that poor consumers tend to have higher budget shares on tradeable goods. Therefore, these consumers tend to be more affected when international shocks change the relative price of tradeable goods.[5] In contrast, the *within effect* is largely unexplored[6] and potentially very relevant in developing and emerging countries where richer consumers tend to consume higher-quality foreign varieties (see Deaton (1988) for an early treatment). Standard international trade and international macroeconomic models that rely on demand and market structures that give rise to constant markups[7]

[4]When varieties are often replaced and prices are sticky, varieties might be replaced following an exchange rate shock before any price change is observed. Therefore, estimated pass-through would be zero whereas aggregate prices could react through the introduction of more expensive varieties.

[5]Simply put, poorer (richer) consumers tend to spend relatively more on tradeable goods (services). As international shocks tend to affect the prices of tradeable goods more compared to services, the poor have a higher exposure to the products that change more in response to international shocks.

[6]In addition to the across effect, Cravino and Levchenko (2017) also study the within effect. However, they only discuss the intensive within margin and they have to rely on strong assumptions to estimate the intensive within effect. Besides assuming that retail margins do not change following the devaluation, they also have to assume that rich consumers always consume the high-priced varieties in all categories. In our analysis, we allow for changing retail margins and only assume that rich consumers pay on average higher unit prices while taking the shares from the data.

[7]Workhorse trade models are usually founded on a Ricardian model à la Eaton and Kortum (2002) with perfect competition or a Melitz (2003)-type of model with CES demand and monopolistic competition. Both family of models cannot account for variable markups. Also, Fajgelbaum and Khandelwal (2016) model the supply side of the economy parsimoniously as an Armington (1969) model and Cravino and Levchenko (2017) assume constant retail

predict that richer consumers should be disproportionally affected when foreign varieties' relative cost rises. We show that high-income consumers are disproportionally affected by the relative cost change, but the retail margins adjustment largely offsets this effect. Moreover, a growing literature in international macro (e.g., (Nakamura & Steinsson, 2012; Gopinath & Neiman, 2014; Corsetti, Crowley, Han, & Song, 2021)) shows that the extensive margin, namely how many products are imported, explains a considerable fraction of trade responses to currency changes in the short-run. To account for such extensive margin adjustments, we model consumer demand in a similar way as Atkin, Faber, and Gonzalez-Navarro (2018) and Jaravel (2019) and adjust the common variety cost-of-living change with a term that is composed of the Feenstra (1994)-ratio and the elasticity of substitution. By doing so, we provide novel evidence on how consumers pertaining to different income classes experience different cost-of-living effects from currency shocks as they are differently affected by cost, markup, and product variety effects.

We exploit scanner data tracking consumer purchases before and after the large depreciation of the Kazakh Tenge, when Kazakhstan switched from a fixed to a floating exchange rate regime in August 2015. The depreciation of the Tenge provides us with a unique setting. First, the unanticipated nature of the depreciation allows us to treat it as an event study. The depreciation was substantial[8] trumping most concurrent shocks, and came after a period of relative foreign exchange stability due to the fixed exchange rate policy that was in place before the depreciation.[9] Second, the Kazakh depreciation allows us to study the distributional effects of foreign exchange shocks on consumer prices in the context of an emerging economy. This is important because data availability has forced most of the literature to either study advanced economic settings in a very detailed manner or to focus predominantly on the across effect in developing economies.[10] Moreover, there is substantial literature in international trade showing how differences in the income level across countries drive vertical specialization across and trade patterns between countries (Schott, 2004; Fajgelbaum, Grossman, & Helpman, 2011). This makes poor (rich) countries import predominantly high (low) quality products, directly affecting how the within margin will operate across countries.[11]

margins.

[8] After one, three and six months, the currency had lost 36.9%, 55.9% and 78.5% of its value to the US Dollar.

[9] Auer et al. (2021) study a similar setting with the sudden appreciation of the Swiss Franc in 2015.

[10] Nevertheless, Atkin et al. (2018) is a very nice recent exception to this rule. Using very detailed data, they study the aggregate and distributional welfare effects of retail FDI in Mexico.

[11] This is because in Fajgelbaum et al. (2011) richer countries have more internal demand for high quality products due to non-homotheticities in preferences. This home market effect induces a comparative advantage in producing high-quality products and makes the richer country specialize in the production of high-quality products.

We draw on highly detailed scanner data from a supermarket chain, Metro, both at the product and the transaction level. The product level data provides us with price, quantity, and cost data for both local and foreign products within highly detailed product categories. Importantly, observing both price and cost at the product level grants us the opportunity to examine how retail margins behave in response to the depreciation without having to resort to strong structural assumptions on demand, supply, or market structure. We rely on the accompanying transaction level data to subdivide consumers into different income groups. This rare feature of the data allows us to move beyond a representative agent interpretation and study how the cost of living effects differ for different consumers. We focus on food and beverages as they carry a 34% weight in the Kazakh CPI and are the most important income source for Metro. Even though we focus on one large retailer, we show that there was a uniform response following the depreciation across the retail sector and that prices at retailer closely tracked the corresponding CPI component after the depreciation.

To examine the aggregate and distributional cost of living effects, we follow the recent international economics literature and model consumer preferences according to a nested CES demand system. For instance, Hottman, Redding, and Weinstein (2016) exploit this structure to shed light on the sources of firm heterogeneity and Atkin et al. (2018) use such a setup to quantify the welfare effects of retail FDI in Mexico. However, due to the lack of data in earlier work on both prices and quantities consumed by different consumers, this approach has not been applied to study the distributional effects of currency fluctuations. The CES-specification provides a closed-form solution for the exact cost of living effect and is very flexible in dealing with certain features of our data. First, it can generate variable markups under a wide variety of both static and dynamic market structures (Atkeson & Burstein, 2008; Amiti, Itskhoki, & Konings, 2019) which is essential given the overwhelming evidence on markup adjustment in response to currency shocks (Gopinath, Itskhoki, & Rigobon, 2010; Berman, Martin, & Mayer, 2012; Amiti et al., 2019). Second, it is well suited to account for and quantify the effect of product entry and exit following the devaluation (Feenstra, 1994; Broda & Weinstein, 2006). Finally, by allowing parameters and budget shares to vary across income groups, it provides a non-parametric way to account for non homotheticities governing demand (Atkin et al., 2018; Jaravel, 2019; Argente & Lee, 2020). We exploit this demand structure and decompose the resulting cost of living into four components: (1) a cost effect, (2) a markup effect, (3) a substitution effect, and (4) a product variety effect and assess their contribution to the differential effects across the consumers.

Our main results are two-fold. First, using an event study design, we show that marginal costs increase more for foreign products than for local products. However, the retail margin on foreign products decrease by more than the retail margin on local products. Thus, the retailer limits relative price movement by adjusting its margins, explaining the low sensitivity of domestic absorption to changes in relative border prices. Second, we combine these relative adjustments and the observation that high-income consumers spend more on foreign varieties to explore the distributional cost of living effects of large depreciations. While we find that the depreciation pushed up the cost associated with food and beverages by 20% after four quarters on average, the cost associated with obtaining a basket of food and beverages went up by 24% for the lower-income consumers and only by 16% for the higher-income consumers. On the one hand, lower-income consumers experience a smaller increase in the marginal cost of food and beverages and are able to reallocate expenditure more to lower-priced varieties. On the other hand, after the depreciation, they face higher markups compared to high-income consumers and benefit less from increased product variety. As the cost and markup effects offset each other and render the intensive within margin largely neutral, we find that the extensive within effect drives the distributional effects. The extensive within effect itself is determined by the fact that low-income consumers have higher elasticities of substitution, implying that poorer consumers benefit less from increased variety relative to high-income consumers.

This paper connects with the vast literature on exchange rate pass-through into consumer prices (Burstein et al., 2005; Campa & Goldberg, 2010; Cravino & Levchenko, 2017). By studying the effect on both foreign and local alternatives, we provide novel evidence that the relative price of foreign products is quite unresponsive to the currency shock, which is consistent with no or limited expenditure switching. Moreover, as suggested by Auer et al. (2021) and Cavallo, Gopinath, Neiman, and Tang (2021), we provide new causal evidence that retail margin adjustment dampens the relative price movement of foreign products following a currency depreciation. Also, this literature shows that pass-through is heterogeneous and depends on firm size (Berman et al., 2012; Amiti et al., 2014, 2019) and the currency of invoicing (Berman et al., 2012; Amiti et al., 2014, 2019), among other dimensions. We extend this literature by studying how currency shocks can have different welfare effects across consumers. Second, this paper is related to recent literature on the distributional cost of living effects of international shocks, such as trade liberalization (Porto, 2006; Faber, 2014; Fajgelbaum & Khandelwal, 2016; Jaravel, 2019), currency devaluations (Cravino & Levchenko, 2017) and retail FDI (Atkin et al., 2018). These papers mostly focus on the across effect (Porto, 2006; Fajgelbaum & Khandelwal, 2016) and usually do not study the effect of changes in retail margins in response to these shocks. Hellerstein (2008) does consider the distributional effects of currency shocks but focuses on the distribution between producers and consumers. We focus on distributive effects between different types of consumers. Finally, our study relates to an extensive literature that identifies changes in product variety as vital ingredients in judging the welfare effects of international shocks (Feenstra, 1994; Broda & Weinstein, 2006). Moreover, recent work by Nakamura and Steinsson (2012), Cavallo, Neiman, and Rigobon (2014) and Goetz and Rodnyansky (2021) shows how firms use product introductions and replacements as a source of price flexibility in response to currency fluctuations. Our paper incorporates this idea and shows that changes in product variety are important in determining both the overall and distributional cost of living consequences of the currency depreciation.

The rest of this paper is organized in the following way. Section 2 introduces the data set that we use. Section 3 documents relative price movements using an event study design. Section 4 develops the framework we use to study the distributional cost of living effects, and section 5 presents the structural estimates. Finally, section 6 concludes.

2 Data

We use scanner data of products of a large retailer, Metro, in Kazakhstan.[12] Metro entered the Kazakh market in 2009 and currently operates eight stores across the country. The data cover two stores, one in Almaty (the economic capital) and one in Nur-Sultan (the official and administrative capital), with daily price scans between September 2014 until November 2017.[13] The products cover the typical consumption categories such as Food and Non-alcoholic beverages, Tobacco and Alcoholic Beverages, Household equipment (cleaning, cooking tools, decoration, and toys), and Clothing. We focus on purchases of food and non-alcoholic beverages as they are the most important categories in the CPI and the most important source of revenue for Metro. We match the product level data with transaction level data that track purchases at the individual consumer level.

[12]Our approach is similar to Bems and Di Giovanni (2016) who study consumption patterns throughout the Latvian crisis of 2008-2009 using data from one retailer.

[13]Nur-Sultan is the name of the capital city was adopted in 2019. Previously it was known as Astana.

2.1 Transaction level data

A transaction contains a unique customer ID, the product that was bought[14] the total expenditure associated with the transaction, the number of units bought, the store at which the product was bought, and the time stamp. Observing both the expenditure and the number of units purchased by a consumer allows us to infer the price each consumer paid for the product.

Income definition. To subdivide consumers into different income groups, we use the observed purchases of each consumer. Ideally, we would like to know each consumer's income level, but we do not have access to income data. Still, there is substantial evidence that richer consumers tend to consume higher-priced varieties within product categories. For example, Deaton (1988) shows for food purchases in Cote d'Ivoire that richer consumers tend to consume higher unit value products. This pattern also holds in more recent data as shown by Broda, Leibtag, and Weinstein (2009) and Faber and Fally (2021) for the US and Cravino and Levchenko (2017) for Mexico. Thus, our approach captures the income ranking of customers based on their observed consumption basket

To do so, we proceed as follows. First, we only use transaction data before the depreciation to avoid introducing a bias in the income group classification.[15] Second, we express the prices in equivalent units, which avoids misclassification of consumers as high-income when they buy larger package sizes. To this end, we scrape the article names to obtain the relevant product units (e.g. ml or kg) and the size (e.g. 750 ml). Table C.4 shows the share in total expenditure and number of varieties of each unit across product categories. For example, varieties in the subcategories "soft drinks" and "water" are almost solely expressed in milliliters, while subcategories "fish" and "meat" in grams[16] Third, we rank varieties according to their median[17] unit equivalent prices and obtain a distribution of unit equivalent pre-depreciation median prices within each product group. In turn, this allows us to categorize varieties into four types: (1) very cheap,

[14]The product is identified by an internal product ID, which corresponds to the internal product ID provided in the product level dataset.

[15]As the depreciation increased, the price of foreign products, including the prices of products after the deprecation, could bias the income group classification. One implication of this choice is that we cannot compute this index for consumers that start buying after the depreciation. This is restriction is not problematic for our purposes as we are interested in the evolution of the cost of living relative to the cost of living before the depreciation. Thus, we would need to exclude these consumers anyhow.

[16]There are essentially four different levels of categorization in the dataset: (1) Categories (e.g. food), (2) Subcategories (e.g. fruit), (3) Product groups (e.g. stonefruit) and (4) Products (e.g. peach). We have chosen to conduct the exercise at the product group level to make sure that we have sufficient number of articles to compute the distributions.

[17]Median of the unit price over the time period before the devaluation.

(2) cheap, (3) expensive, and (4) very expensive varieties based on the product group-specific quartiles. Formally, we classify varieties as follows:

$$f(p^{\text{med}}_{i,g}; P_g) = \begin{cases} 1 & \text{if} \quad P(p^{\text{med}}_{i,g} \geq P_g) \leq 0.25 \\ 2 & \text{if} \quad 0.25 < P(p^{\text{med}}_{i,g} \geq P_g) \leq 0.5 \\ 3 & \text{if} \quad 0.5 < P(p^{\text{med}}_{i,g} \geq P_g) \leq 0.75 \\ 4 & \text{if} \quad P(p^{\text{med}}_{i,g} \geq P_g) > 0.75 \end{cases} \tag{1}$$

here $p^{\text{med}}_{i,g}$ is the pre-depreciation median unit equivalent price of variety i in product group g and P_g is the random variable representing the product group pre-depreciation unit equivalent price. Finally, armed with this product group level classification, we compute for each consumer an index that reflects how expensive his or her consumption basket is on average at our retailer by weighting each transaction by the type in which the variety is classified. Doing so, this index for consumer j is calculated as:

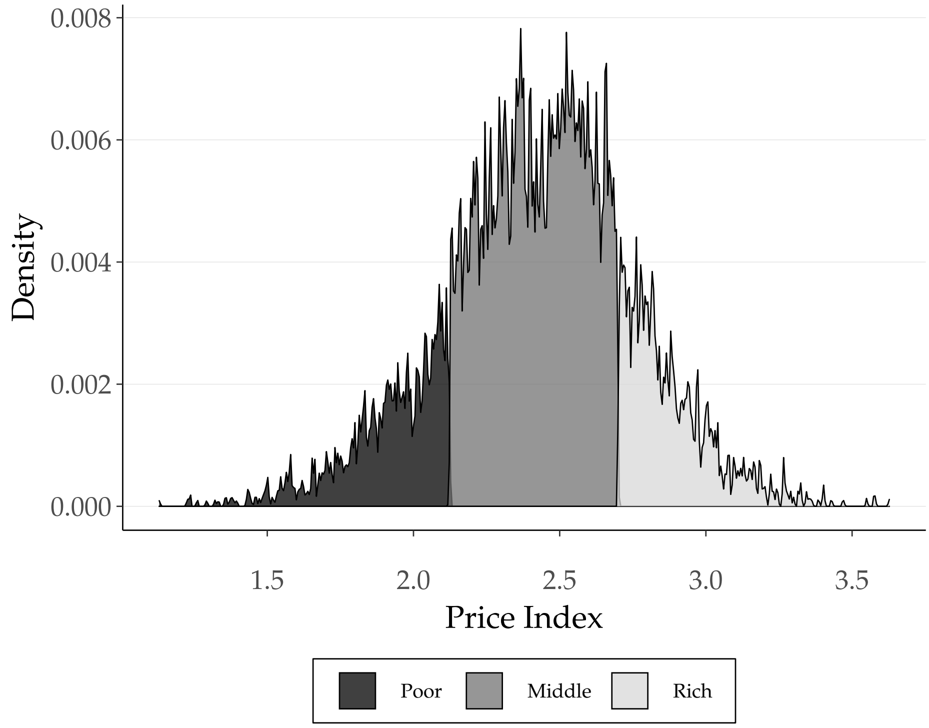
$$Index_j = \frac{\sum_g \sum_i \sum_t f(p^{\text{med}}_{i,g}; P_g) \cdot p_{i,g,t} \cdot q_{j,i,g,t}}{\sum_g \sum_i \sum_t p_{i,g,t} \cdot q_{j,i,g,t}}$$

We define low-income consumers as consumers that have an index value in the first quintile, while high-income consumers have an index value in the fifth quintile. Figure 1 illustrates this income definition graphically by showing the distribution of the index and by indicating the difference income groups in separate colors.[18] When we compute the distributional cost-of-living effects, we check the robustness of the results and compute the effects for different income percentiles.[19] An alternative way of classifying consumers as rich or poor consumers is to classify them based on their expenditure per capita (see for instance Faber and Fally (2021)). One reason we prefer the price index approach is because, even though we observe total expenditure, we do not have information about the size of the household. Therefore, the quality of this classification method crucially depends on the correlations between household size and income and household size and total expenditure, which are unobserved. Nevertheless, we document below that the main results of the paper are robust to using total expenditures as the classification method.

[18]We note that in the construction of these income groups we pool across consumers shopping in the different stores. Figure B.2 shows that the distribution of this index is very similar across stores and therefore we can safely aggregate across stores without losing interesting spatial variation in the income distribution across stores.

[19]Specifically, we also compute the results for a cut-off equal to 33% (terciles), 25% (quintiles) and 10% (deciles) and find that the distributional effects grow starker when we consider more extreme income definitions.

Figure 1: Distribution of Index (Quintiles: 20%-80% split)



Notes: This figure displays the distribution of the expensiveness index across consumers.

Households. We exclude small business owners, such as restaurants and small shops, which are also in the customer pool of Metro. Since we cannot distinguish between households and small business customers, we discard expenditures which are unlikely to be made by households and assume that customers who spend in the highest percentiles are likely to be small business owners. In particular, Table C.2 shows the average expenditure per month and the corresponding average expenditure per week in both local currency and in US dollar. Given that average monthly wages in Kazakhstan were 126,021 KZT (or 568 USD) in 2015, we exclude from the sample customers who rank above the 99% percentile of the average monthly expenditures' distribution.[20] Because we study the evolution of the cost of living through the depreciation episode, we remove all consumers that did not shop at the retailer before the depreciation.[21].

Frequently shopping households. To compute income specific expenditure weights and income specific elasticities of substitution, we focus on a group of consumers that shop frequently

[20]Data was taken from the International Labor Organization (ILO).

[21]Table C.3 shows that in this way we remove about one-third of the consumers, but that this group accounts only for 23% in total sales and for 14% in all transactions.

at the store. We aim to measure to what extent consumers react to changes in relative prices of different product varieties in the same store. Therefore, we only need to use the variation in demand stemming from within-store-across-variety substitution and not from across-store substitution. Our approach is conservative as we find lower elasticities of substitution on the full sample. To be part of the frequent sample, we require consumers to shop at the retailer in at least 8 months out of the 11 months before the depreciation and in at least 9 months in the 12 months directly after the depreciation. Tables C.5 and C.6 compare the frequent and full samples on a set of observable characteristics. The frequent sample contains 5,040 consumers, which account for 27% of total sales. Table C.6 shows that the consumers in the frequent and complete sample are almost identical in terms of price and composition of the consumption basket. We check the robustness of our results using the full sample and find that our results are even more pronounced.

2.2 Product level data

We have access to rich product-level data that covers the full universe of products sold by the retailer. More precisely, we observe the quantity and the price for each purchase made by the customers on a given day.[22] Moreover, we also observe the inventory value and inventory quantity for each purchased variety at each point in time.

Variable construction. Observing the inventory value and quantity for each purchased variety, is crucial to our analysis for two reasons. First, it allows us to track inventories over time and compute the replacement cost (i.e. the most recent price paid to the supplier) for each product separately at any point in time. Since the costs associated with buying and selling products is the most important part of any retailer's cost structure, we will refer to this cost measure as the marginal costs. We take a similar approach as (Gopinath & Itskhoki, 2011; Eichenbaum, Jaimovich, & Rebelo, 2011; Goetz & Rodnyansky, 2021) and use this cost measure in our computation of the retail markups which is then defined as the ratio of prices and replacement costs. Second, the inventory data provides direct information about which product varieties are available to consumers and thus which product enter and exit the choice of consumers at the store.

[22] Many papers identify a product by recording data at the barcode or UPC level (Hottman et al., 2016; Jaravel, 2019). Instead, like in Anderson, Jaimovich, and Simester (2015) we identify products at the stock keeping unit which is at least as diaggregated as the UPC or EAN level as in practice the same UPC may be associated with more than one SKU.

Frequency. We aggregate the data to monthly data by computing the price and cost variables as average prices and costs in a given month and by summing sales and quantities[23] The aggregation allows us to focus on the mid-to-long-run effects of the depreciation and abstract away from anticipatory effects that may have occurred shortly before and after the depreciation and be comparable to previous research (e.g. (Bems & Di Giovanni, 2016; Cravino & Levchenko, 2017; Atkin et al., 2018)).[24]

Food and non-alcoholic beverages. We focus on purchases of food and non-alcoholic beverages for three reasons. First, Table C.7 indicates that they are the most important category in the CPI construction, carrying a 34% expenditure weight. In addition, Column 3 of Table C.8 shows that Food and Non-alcoholic beverages is the most important source of revenue for the retailer (61% expenditure share). Second, we rely on a static utility maximization by the consumer to compute the cost-of-living effects. Therefore, we focus on a set of consumption goods for which anticipatory behavior, such as stockpiling, on the part of the consumer is unlikely. Finally, the prices of food and non-alcoholic beverages closely mimic the overall price evolution of food and non-alcoholic beverages throughout Kazakhstan, which we document below.

Foreign and local varieties. We match the retailer's proprietary product identification number with the product's EAN-code provided by the retailer.[25] Based on these EAN-codes, we follow Bems and Di Giovanni (2016) and subdivide products into foreign and local. Specifically, if the article's EAN-code starts with "487", Kazakhstan's country code, the product is labeled as "local" while for any other code the product is labelled as "foreign". One potential problem with this approach of classifying products is that foreign manufacturers might relabel their products or change the barcode of the product when they sell to a different market. To see if this a problem in our dataset, we can check whether the barcode classification coincides with the foreign/local denomination that can be established for varieties that are differentiated by their origin. In particular, we retrieved the differentiation by origin for wines from barcode description and found that

[23] We note that when there is no expenditure on a product at a certain point in time, we cannot compute the average price. We treat this simply as a missing observation and do not attempt to impute prices to obtain a more balanced panel.

[24] Given that we will focus on consumption of food and non-alcoholic beverage consumption by households, we deem a monthly frequency as sufficient to abstract from anticipatory effects. Moreover, for the decomposition results we present results at the quarterly level. We also note the decomposition results are very similar when we use monthly data instead.

[25] The EAN-classification system is the Eurasian alternative to the Anglo-Saxon UPC classification system. An EAN code is a 13 digit unique product level identification number of which the first 3 digits identify the country of registration of the manufacturer, the next 5 digits the manufacturer and the final 5 digits the product.

the barcode classification method classify 97% of expenditure on foreign wines as foreign and 99% of expenditure on local wines as local. Table 1 provides an overview of this classification. Apart from meat, vegetables and fruits,[26] we classify around 80% to 90% of total expenditures as being local or foreign.

Table 1: Product sample: Overview

Subcategory	Sales share	Variety x Store units	Observations	Foreign share	Classification quality
Bakery/Cereal	0.05	3,115	46,650	0.87	0.55
Candy	0.08	4,395	60,683	0.89	0.68
Coffee/Tea	0.06	1,208	25,120	0.97	0.82
Dairy	0.17	3,292	57,447	0.82	0.55
Dry food	0.07	1,933	34,406	0.88	0.49
Fish	0.05	1,641	24,206	0.80	0.67
Fruit	0.04	1,125	11,249	0.36	0.81
Meat	0.20	2,384	27,009	0.05	0.39
Ready-made	0.01	541	8,089	0.97	0.55
Savoury	0.01	644	11,669	0.99	0.94
Seasoning	0.09	2,347	40,407	0.88	0.54
Soft drinks	0.06	1,606	30,106	0.99	0.73
Vegetables	0.07	1,808	23,366	0.56	0.91
Water	0.03	231	5,855	1.00	0.48

Notes: This table shows an overview of different subcategories in the Food and Non-alcoholic Beverages category we consider in the analysis. The column ”Sales share” indicates the share of each subcategory in total sales for the whole Food and Non-alcoholic Beverages category. The column ”Variety x store” indicates the number of unique variety x store combination in the dataset. The column ”Observations” indicates the number of months in which there was a registered sales for a variety x store combination. The column ”Foreign share” shows the share of foreign products in total sales for that subcategory. Finally, the column ”Classification uality” indicates the percentage of sales in each subcategory we can classify as either foreign or local. All statistics are computed by pooling across the full sample period.

Representativeness of the store. To support the external validity of our results, we provide an extensive analysis of the Kazakh retail sector in Appendix A. In particular, using scanner data on the whole Kazakh retail sector from AC Nielsen and data from the Kazakh National Bank, we address two concerns regarding our approach in which we focus on one large retailer. First, we show that prices for the same products at small and large stores, which make up 85% of the retail sector[27], did not respond differently after the shock. Second, when studying the distributional consequences of the depreciation, we need to make sure that we capture both rich and poor consumers at the store. We show that while small stores are cheaper and stock cheaper products, the price differences between varieties within our retailer are three times larger implying that sorting

[26] Note that these product categories are notoriously hard to classify and other papers usually discard these categories all together (Cravino & Levchenko, 2017; Auer et al., 2021).

[27] The retailer we focus on has an overall market share of 10%.

of consumers across varieties within a store is likely more important than across stores.

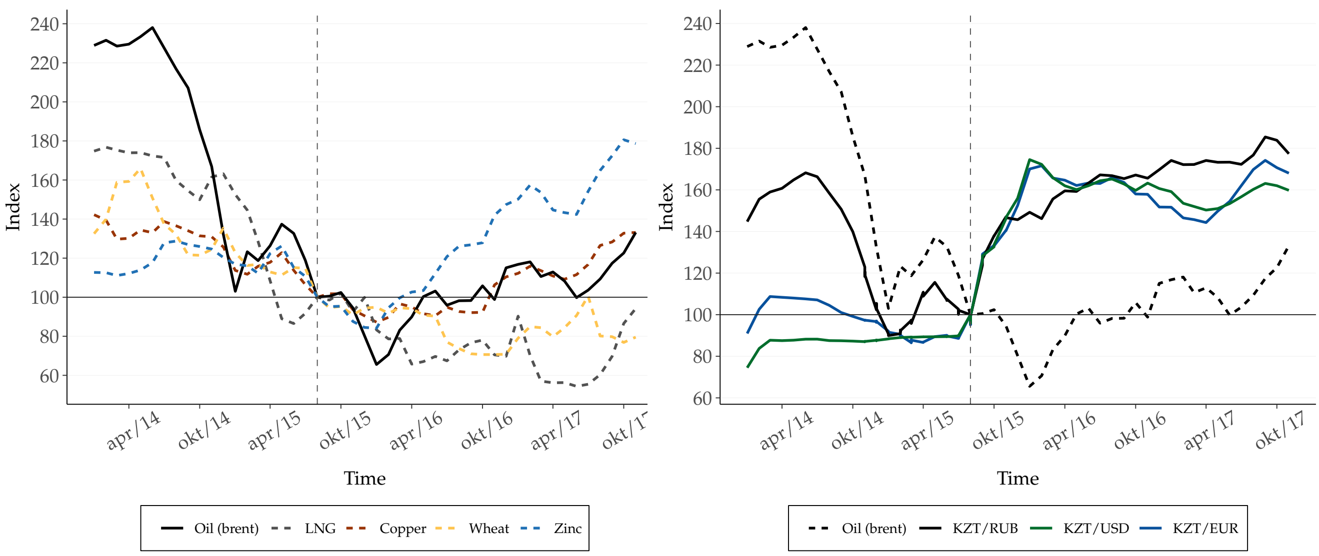
3 Reduced-form Evidence

3.1 The Depreciation and exchange rate pass-through

Kazakhstan is an emerging economy that made great economic strides through an export-led expansion[28] based on its rich natural resources.[29] Because of its reliance on commodity exports (see Table C.9), the Kazakh National Bank had implemented a fixed exchange rate regime pegging the Kazakh Tenge to the Euro and the US Dollar before August, 2015. However, with the collapse of global commodity prices, particularly of crude oil, and with the strong depreciation of the Russian Ruble, the government switched to a floating exchange rate regime on August 20th, 2015. Figure 2a shows that this decision led to a sharp depreciation of the Kazakh Tenge, losing between 40% and 80% versus all major currencies within 6 months.

Figure 2: Devaluation of 2015

(a) Commodity slump **(b)** Foreign exchange markets



Notes: Panel (a) shows the evolution of the price for Brent crude Oil, liquified natural gas (LNG), copper and zinc ore and the global price for wheat. All series are normalized to their August 2015 level and were obtained from the St. Louis Federal Reserve database (FRED Database). In panel (b) we repeat the series for Brent crude Oil and show the evolutions of the Kazakh Tenge (KZT) versus the US Dollar (USD), the Euro (EUR) and the Russian Ruble (RUB). The foreign exchange series are taken from the IMF Financial database.

[28] According to the UNCTAD database, from 2002 to 2011 Kazakhstan nominal export growth averaged 28% per year.

[29] Kaiser and Pulsipher (2007) argue that Kazakhstan has vast endowments of oil, natural gas and metals such as zinc, lead and iron ore. Moreover, according to Trademap.com Kazakhstan is now the 10th largest oil exporter in the world.

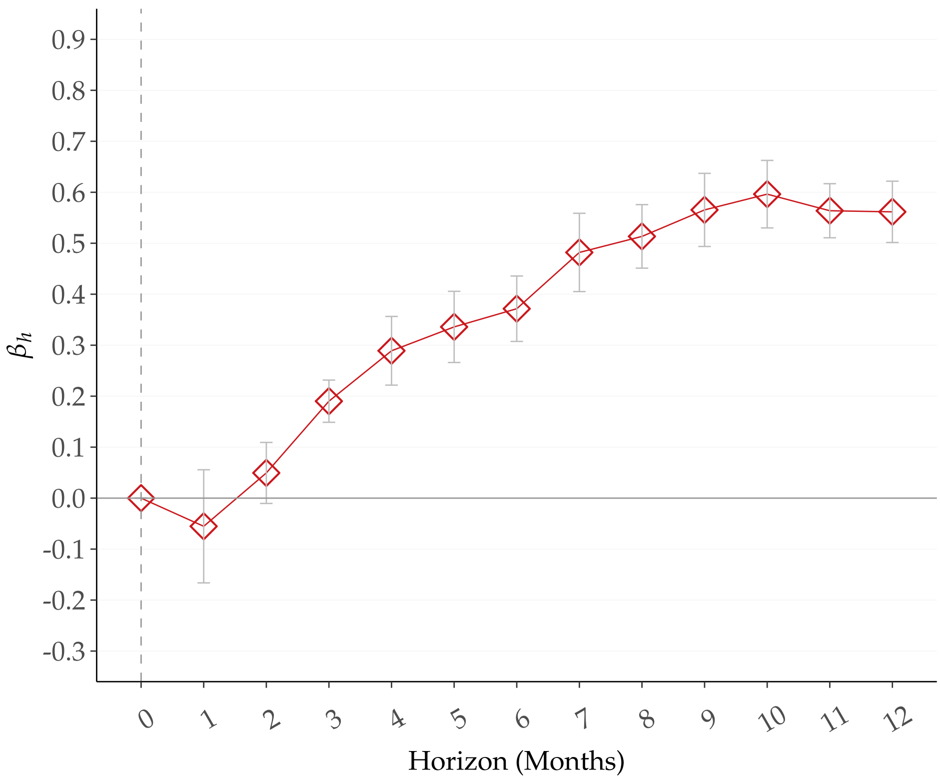
This large depreciation of the Kazakh Tenge provides a unique setting to study the reaction of retail margins in response to exchange rate fluctuations and their distributional consequences. First, it induced a potentially large relative cost shock to foreign product varieties. After one, three and six months, the currency had lost 36.9%, 55.9% and 78.5% of its value to the US Dollar, respectively, which clearly demarcated the currency shock from other confounding events. Moreover, by obtaining data on the origin of product varieties, we analyze the extent of exchange rate pass-through and compare the evolution of prices, costs, and margins of local versus foreign varieties within disaggregated product categories. Second, studying an overnight (vs. gradual) depreciation creates the possibility to treat the depreciation as an event study with a sharp pre- and post-event window. This is evident from Figure 2b, which shows how the initial shocks caused a sharp depreciation of the Tenge, which stabilized after 12 months. Third, since we use granular scanner data at the detailed product level and at the level of consumers, we can treat the shock as exogenous to answer our research question. This is in line with other work that uses firm-product level data to analyze exchange rate pass through (Gopinath & Itskhoki, 2011; Burstein & Gopinath, 2014; Amiti et al., 2019). This argument relies on the seminal paper of Meese and Rogoff (1983) in which the authors could not reject the random walk hypothesis of the nominal exchange rate. In fact, when we test for a unit root in the level of individual exchange rates (KZT/USD, KZT/EUR and KZT/RUB), we cannot reject the null hypothesis of a unit root. Since we focus on the impact of the depreciation on the cost of living of consumers and not on the optimal response of firms' prices, we can confidently treat the ensuing variation in exchange rates and prices as given.

The depreciation had potentially large welfare effects as it was followed by sharply rising prices of food and non-alcoholic beverages. We estimate pass-through in a reduced way. Formally, we estimate

$$\Delta_h p_i = \beta_h \Delta_h e_i + \varepsilon_i \qquad \forall h = \{0, 1, \dots 12\}. \tag{2}$$

where $\Delta_h p_i = ln(p_{i,t+h}) - ln(p_{i,t})$ is a long difference, taken from period $t-1$ until period $t+h$, of the log consumer price of variety i. We set the period t-1 equal to July, 2015. Also, $\Delta e_{i,t}$ is the long difference of the nominal exchange rate and is defined analogously. In this way, β_h measures to what extent prices have adjusted to the exchange rate change after h months. Figure 3 shows the results for the different horizons when we pool across both local and foreign products. The pass-through into consumer prices is around 60% after 12 months which means that the depreciation has potentially very large cost of living effects, which we quantify in section 5. The pass-through converges after around 12 months after the devaluation to its medium- to long-run level. For this reason, we focus on the first year after the depreciation.

Figure 3: Exchange Rate Pass-through: Consumer Prices



Notes: This figure shows the evolution of exchange rate pass-through into prices. More specifically, we plot the coefficients β_h which are obtained from estimating equation 2. Whiskers are 95% confidence intervals around the point estimates computed from standard errors which are clustered at the product-store level.

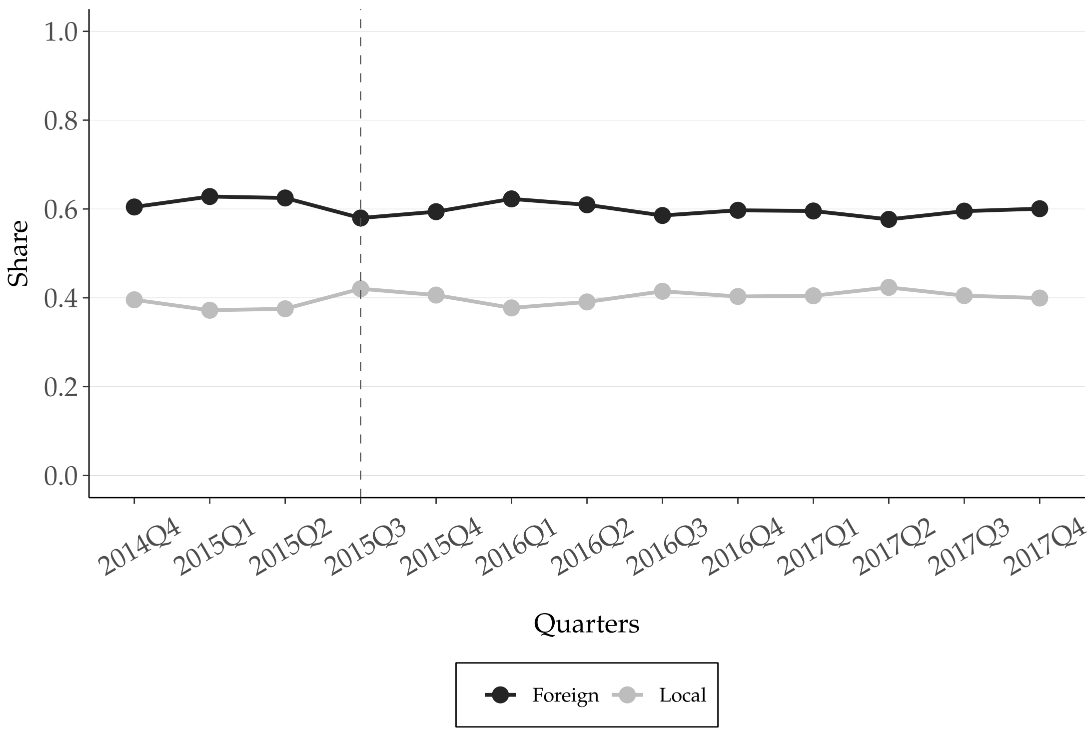
Table C.10 shows that the Ruble, the Euro and the US Dollar are the three main currencies of invoicing used by the retailer. Given the recent interest in the relation between pass-through and the currency of invoicing (Gopinath et al., 2020; Amiti, Itskhoki, & Konings, 2020), we investigate whether there is interesting heterogeneity in the level of pass-through across currencies of invoicing. To this end, we re-estimate equation 2 for different currencies of invoicing and present the results in Figure B.3. While we do find that there is some heterogeneity across currencies in the transition towards the medium- to long-run pass-through level, the medium- to long-run pass-through level is very similar. For this reason, we do not explore this dimension any further in the following sections.

3.2 Expenditure Switching and Changes in Product Variety

One of the key functions of nominal exchange rate adjustment is to allow for relative price changes in case of real shocks, even when prices are sticky in producer currency (Engel, 2002). In this way, an exchange rate depreciation could help a country in their external adjustment if the depreciation makes domestic goods relatively cheaper compared to foreign goods and if it induces a switch in expenditure from foreign to local goods. Therefore, an important empirical question is whether the relative price of foreign products indeed rises and whether foreign products' expenditure share falls. In a recent application, Auer et al. (2021) find that the share spent on foreign products rose from 26% of 27% after the Swiss Franc appreciated by about 15% in 2015.

In Figure 4 and Table C.13 we investigate whether the Kazakh depreciation induced significant expenditure switching from foreign varieties of food and non-alcoholic beverages towards local varieties. To this end, we follow Auer et al. (2021) and compute the expenditure share and quantity of foreign and local varieties by only including continuing products. We find that the expenditure share on foreign varieties is surprisingly stable after the depreciation (see **??**). The expenditure share on foreign varieties is 0.1%, 2.5% and 1.3% percentage points lower three, four, and five quarters after the depreciation, respectively, compared to the average value before the depreciation. While these numbers are in line with the numbers reported in Auer et al. (2021), the swiss Franc appreciated only 15%, whereas the Kazakh Tenge lost around 60% to 80% over a span of one year.

Figure 4: Expenditure switching



Notes: Panel (a) shows the evolution of the share of expenditures on foreign and local varieties and panel (b) shows the evolution of the units sold expressed in physical units. We only include varieties that where present before and after the depreciation.

In contrast to the limited degree of expenditure switching, we find that there were substantial changes in the set of available products. In Table C.14 we subdivide different product varieties as continuing products, entering products and exiting products depending on whether they were available to consumers before the depreciation and whether they were still available one year after the depreciation.[30] In fact, there is substantial entry and exit after the depreciation. For instance, for the food category, only 34% of the existing products were still on offer one year after the depreciation and the sales shares of both exiting and entering products are non-trivial for all categories. Importantly, the sales share on entering varieties tends to be higher than the sales share on exiting varieties which will be important when we compute and interpret the change in the cost-of-living.[31]

[30]Hence, we loosely define continuing products as products that were present before and one year after the depreciation. Few "temporary" products were not present before the depreciation but briefly were on the shelves during the first year after the depreciation (and exited before the one year window).

[31]Note that we have loosely defined entering and exiting using one year after the depreciation as a hard cut-off. In the quantification exercise later on, we will refine this definition and account for the timing of entry and exit and ensure the periods over which sales shares are computed are comparable.

3.3 Relative Price Stability

Next, we explain why the depreciation did not induce important shifts in the relative share of foreign varieties. We explain this limited expenditure switching through the lens of consumer price stability. While we find that consumer prices of foreign varieties do increase relative to local varieties, this only happened to a limited extent. When we decompose this relative consumer price stability into its components, we find that a relative decrease in markups partly offsets the increase in relative costs of foreign varieties.

To this end, we estimate relative price, cost, and markup adjustments after the depreciation using a difference-in-difference type of estimation. In particular, we compare the evolution of prices, costs and markups of foreign varieties to the evolution in prices, costs and markups for local varieties within the same detailed product category. In particular, we estimate the following regression:

$$y_{i,s,p,t} = \sum_{t>2015Q3} \beta_{QY(t)} \cdot \mathbb{1}(i = \text{foreign}) + \theta_{s,p} + \theta_{p,t} + \varepsilon_{i,s,p,t} \tag{3}$$

Where $y_{i,s,p,t}$ is either the price, cost or markup of variety i in store s which is part of product category p at time t which is a month. $\mathbb{1}(i = \text{foreign})$ is an indicator function that is one when the variety is foreign and zero otherwise. The coefficients of interest are $\beta_{QY(t)}$ which are time-varying treatment effects that measure for each quarter-year combination ($QY(t)$) after the devaluation the differential adjustment in prices, costs and markups for foreign varieties relative to local varieties. Consistent with the evidence in section 3.1, which shows that pass-through converges after 12 months, we estimate a time-varying treatment effect for each quarter from 2015Q4 until 2016Q4.[32] We include two sets of fixed effects. First, we include $\theta_{s,p}$ which are origin - product category fixed effects, and which control for persistent differences in the level of prices, costs or markups between foreign and local varieties at the product category level.[33] We add product category - time fixed effects which control for changes in costs and markups over time at the product category level. By adding detailed time – product category fixed effects, we ensure that the treatment effects are identified from comparing local and foreign varieties of the same detailed product category and are not driven by granular price trends at product category level.

Figure 5 shows the results when we estimate equation 3 for consumer prices. Consistent with the results on expenditure switching, we only include continuing products and weight their im-

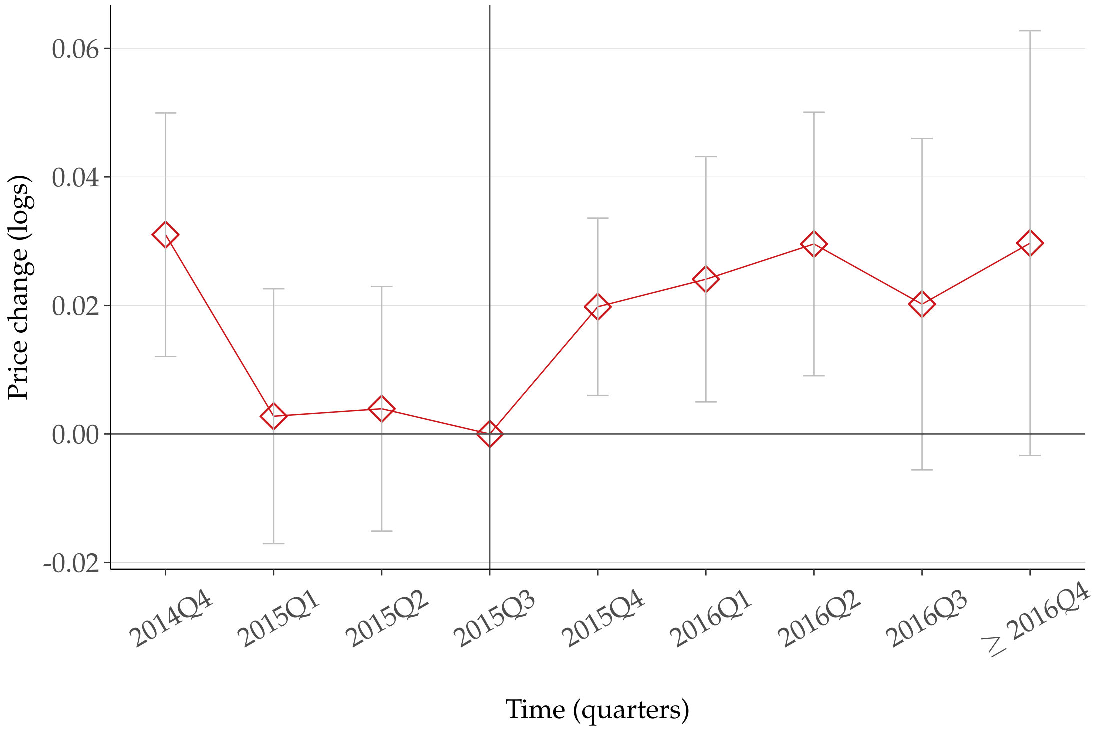
[32]Similar to Atkin et al. (2018)), we group the effect for 12016Q4 and the ensuing quarters into one coefficient.

[33]The product category refers to the finest level of aggregation which is the product level.

portance using pre-depreciation expenditure shares.[34] Before discussing the results, we highlight that the pre-depreciation treatment effects are positive and significantly different from zero indicating a downward trend in the relative price of foreign products. The fact that the relative price of foreign products was on a downward trend is consistent with the appreciation of the KZT relative to the USD prior to the depreciation (see Figure 2b). Moving on to our baseline estimation, we include our baseline set of fixed effects and find that the increase in relative consumer prices of foreign varieties relative to local varieties is small. More specifically, the increase in the relative consumer price peaks at 3% after three quarters after the depreciation is not statistically significant at the 95% from that point onwards. In Figure B.4 and Table C.15, we show that this result is largely unaltered when we replace the product category-origin fixed effects with more detailed fixed effects. First, when we replace the product category-origin fixed effects with more detailed product variety fixed effects, relative prices of foreign varieties increase by around 3% throughout the first four quarters after the depreciation and reach their peak at around 5% in the quarters thereafter. Second, when we interact the product category-origin and product category-time fixed effects with store fixed effects and compare only foreign and local varieties of the same product category sold in the same store, we find a slightly larger relative price increase. In this specification, the relative price increase is faster and peaks already in the second quarter after the devaluation at around 5.5%. Hereafter, the increase tapers off and settles at around 4.25% after four quarters which is roughly twice as large as the point estimate in the baseline specification. Third, when we add even more detailed fixed effects by replacing the product category–origin–store fixed effects by variety-store fixed effects then the relative price increase rises further to around 6% after four quarters. Altogether, we find that there is a relative price increase after the large depreciation, but that this increase is rather small in magnitude, compared to the size of the depreciation, and that the magnitude of the point estimate depends on the specification.

[34] The results are very similar when we weight observations using sales values that vary over time.

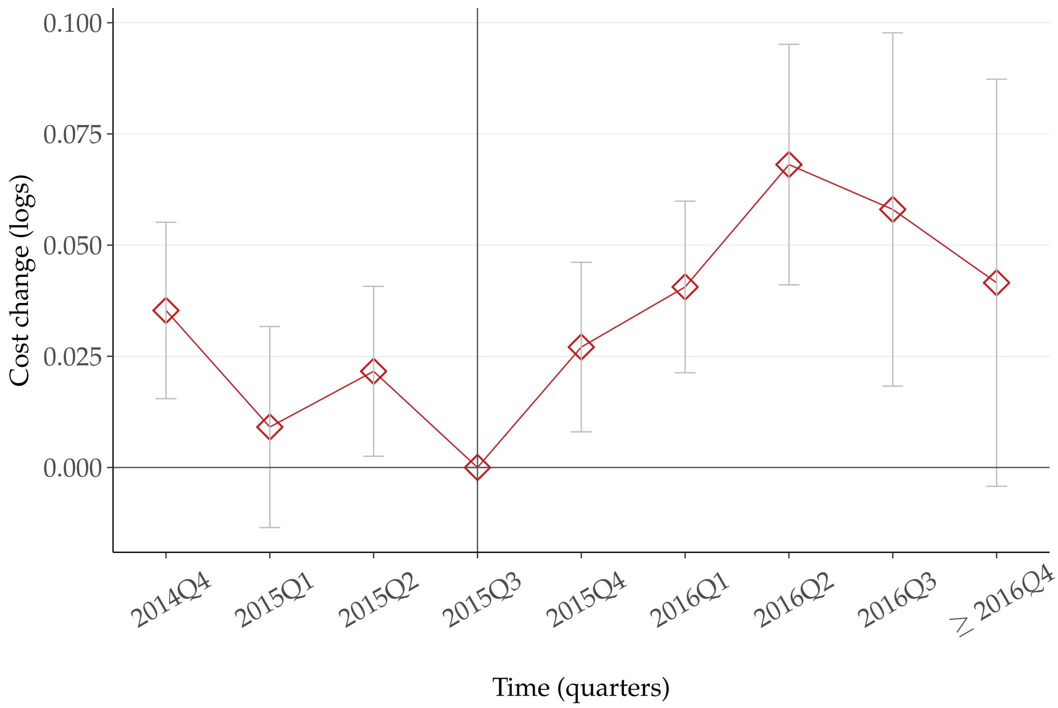
Figure 5: Difference-in-difference: Consumer Prices



Notes: This figure shows the results from estimating equation 3 for consumer prices for setup with product category-source and product category-time fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

Next, we unpack the small increase in relative consumer prices by separately looking at relative costs and relative markups. First, depending on the specification, we find that relative costs of foreign varieties increases between 6% and 9% after four quarters after the depreciation. We present the baseline results in Figure 6 and report the specifications increasingly with increasingly detailed sets of fixed effects in Figure B.5 and Table C.16. In our baseline specification, foreign varieties experience a relative cost increase on impact that amounts to 3%. The relative cost difference increases in the ensuing quarters and reaches its peak in the second quarter of 2016 with a comparable cost difference of about 6.8% and settles at around 5.8% after four quarters. In addition, Figure B.5 show that the results are robust to including more flexible fixed effects which control for persistence spatial differences in costs across foreign and local varieties within product categories (i.e. product category–origin–store fixed effects) and more granular relative cost trends (i.e. product category–store–time fixed effects). In line with the results for prices, the treatment effect is slightly larger and is between 7% and 9% after four quarters in these specifications.

Figure 6: Difference-in-difference: Costs



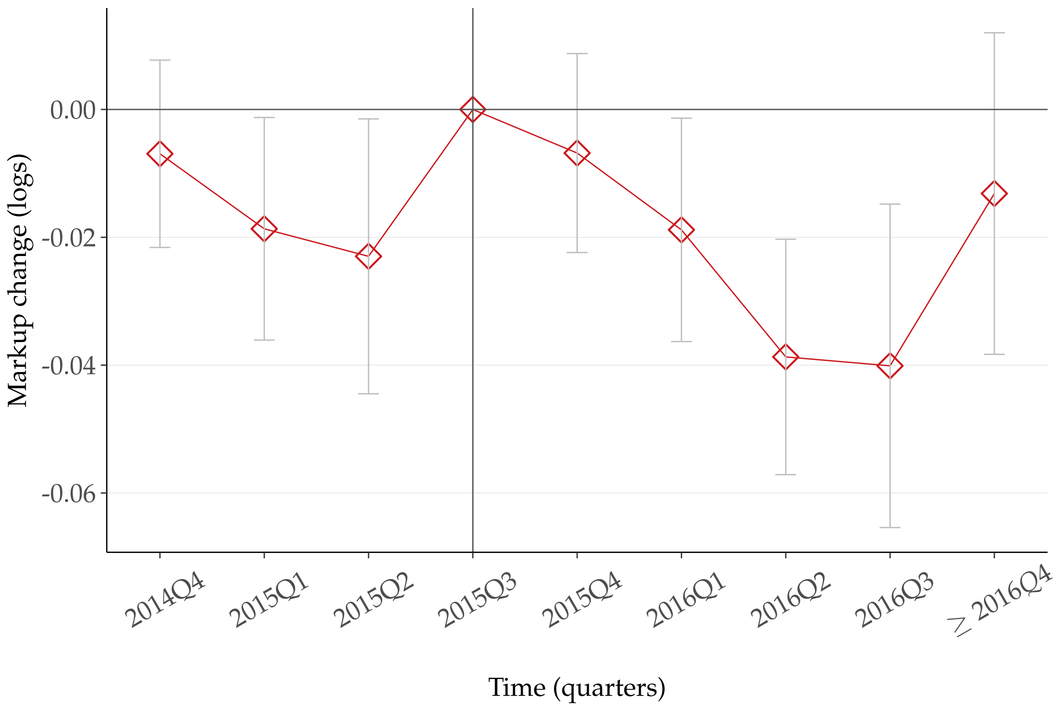
Notes: This figure shows the results from estimating equation 3 for costs for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

Second, Figure 7 show that relative markups fall and counteract the relative cost increase experienced by foreign varieties. In our baseline specification, we find that markups on foreign varieties fall around 4% relative to local varieties after 4 quarters after the depreciation. While relative markups are insignificantly different from zero on impact, they gradually drop and reach their trough after four quarters. After more than four quarters after the depreciation, markups on foreign and local varieties are not different statistically anymore which explains the jump in relative prices over this same period. Figure B.6 and Table C.17 show that these results are both qualitatively and quantitively very robust to including alternative and more detailed sets of fixed effects.[35]

In sum, we conclude that relative consumer prices do not increase markedly because relative costs do not increase considerably and because this relative cost increase is at least partially offset by a fall in the relative markup.

[35] Because Figure A.2 shows that the market share of large stores remained very stable after the depreciation and because Figure A.1 showed that the retailer adjusted its prices in accordance with the CPI, it is unlikely that the fall in relative markups for foreign products can be explained by an overall decrease in markups.

Figure 7: Difference-in-difference: Markups



Notes: This figure shows the results from estimating equation 3 for markups for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

3.4 Heterogeneity in foreign expenditure shares

In the previous section, we showed that there is meaningful heterogeneity in the reaction of relative cost and markups after the depreciation. Moreover, if there is also meaningful variation in the spending shares across rich and poor consumers, then different consumers are potentially differently affected by the depreciation. This is what we explore in this section and we find that high-income households spend more on foreign varieties compared to low-income consumers.

First, Figure 8 shows the raw distribution of the total expenditure share spend on foreign varieties across consumers for the low- income and high-income group separately. This figure shows that there is a clear shift in the distribution towards more spending on foreign varieties by the high-income group. Moreover, the fact that the distribution for rich consumers stochastically dominates the one for poor consumers is statistically significant[36] and increases when we move towards more extreme definitions of high- and low-income in as shown Figure B.7.

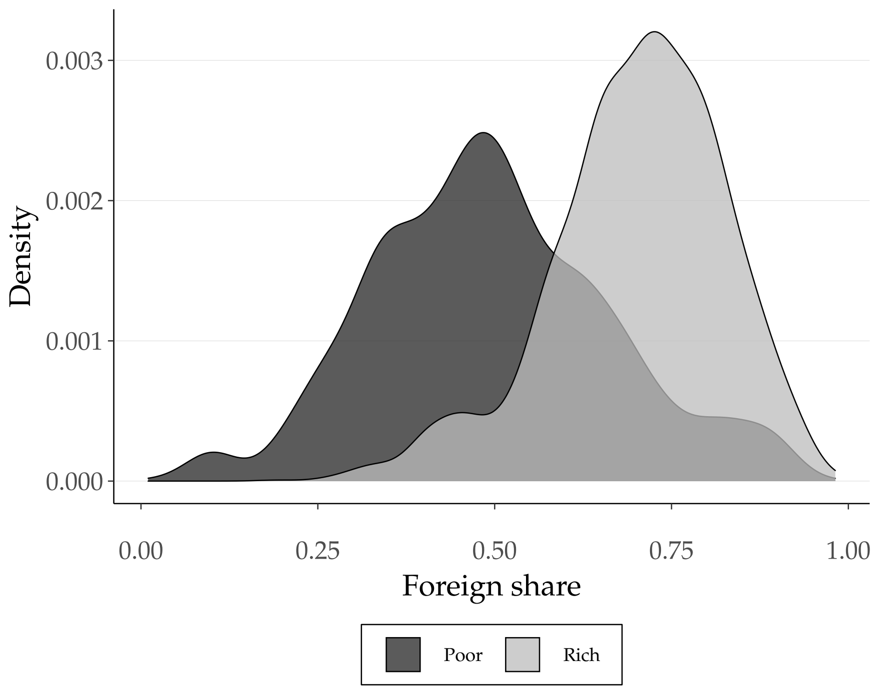
Second, Figure B.8 illustrates that the same pattern also persists within the detailed product

[36]We conduct a one-sided Kolmogorov-Smirnov test and find overwhelming evidence of stochastic domination.

categories. Figure B.8 displays the distribution of the share spend on foreign varieties across product categories for the three different income groups. Each of the panels repeats this exercise for different definitions of the income groups. Again, we see that for relatively low (high)-income consumers there are relatively more product categories with a low (high) share spend on foreign varieties. Moreover, Tables C.18-C.19 implement a parametric t-test and a non-parametric Paired-Rank-Sum-Wilcoxon test respectively to test whether these patterns are statistically significant. In fact, they indicate that this pattern is statistically significant for all the different income group definitions and that the pattern tends to strengthen with more extreme income group classifications.

Finally, Figure B.9 illustrates that the distribution of foreign shares for rich consumers still stochastically dominates the one for poor consumers when we subdivide consumers according to total expenditures.[37]

Figure 8: Foreign share across consumers (Quintiles: 20%-80% split)



This figure displays the distribution of the expenditure share on foreign varieties across rich and poor consumers separately. Income classification was executed using the expensiveness index. We include food & non-alcoholic beverages and the frequent sample of consumers in the construction of these graphs.

[37]Using this classification method, a one-sided Kolmogorov-Smirnov test still rejects null hypothesis that the distributions are the same for rich and poor consumers.

4 Framework

4.1 Conceptual approach

Following Cravino and Levchenko (2017) and Atkin et al. (2018), we apply a compensating variation approach to estimate the impact of the depreciation on consumers' welfare. In particular, we compute the income compensation required to keep a consumer's utility unchanged after the depreciation. In response to price increases and real income changes after the depreciation, consumers adjust their spending patterns, altering their utility obtained from consumption. In turn, this allows us to compute the required hypothetical additional income a social planner would need to provide to bring them back to their original utility level from i:

$$CV^h = \underbrace{e(\boldsymbol{P}^1, u_0^h) - e(\boldsymbol{P}^0, u_0^h)}_{\text{Cost of living effect (CLE)}} \qquad + \qquad \underbrace{y_1^h - y_0^h}_{\text{Nominal income effect (NI)}}$$

The compensating variation of a consumer of income group h depends on two effects: the nominal income effect (y^h) and the cost of living effect $e(\boldsymbol{P}, u^h)$, where $\boldsymbol{P}$ is the price vector, u^h is the utility of consumer h, and e is the expenditure associated with consumption. The nominal income effect represents the change in the nominal income of consumers of income group h.[38]. In turn, the cost of living effect, which is our focus, represents the change in the cost associated with the consumers's consumption basket, summarized by the change in the expenditure level.[39]

To obtain a closed-form solution for $e(\boldsymbol{P}, u^h)$, we model consumer preferences as a nested Constant Elasticity of Substitution (CES) demand system as in Atkeson and Burstein (2008) and Amiti et al. (2019). This nested CES demand system presents the following advantages. First, it is able to assess changes in product variety. In our data, firms can withdraw existing products, introduce new varieties, or replace existing varieties at different quality levels. Nakamura and Steinsson (2012) show that ignoring such replacements can severely bias aggregate pass-through rates for US border prices.[40] As in Feenstra (1994) and Broda and Weinstein (2006), we rely on the CES structure and quantify the variety effect across income groups by the relative shares of continuing products before and after the depreciation weighted by the elasticity of substitution. [41]

[38]We abstract from changes in the nominal income of households as we do not directly observe the nominal income of consumers.

[39]Apart from Atkin et al. (2018) who can match income and consumption data at the individual level, few papers have been able to do so and either focus on income effects or cost of living effects.

[40]They show that aggregate import and export price indices show substantial rigidity in response to exchange rate shocks because many products are withdrawn or replaced even before experiencing a price change.

[41]Jaravel (2019) argues that measuring product variety at the article level should be reassuring to assume that

Second, the CES demand system is consistent with variable markups in response to cost shocks. This is important as previous research has shown that exporters actively change their markups in response to exchange rate changes to remain competitive relative to local substitutes (Gopinath & Itskhoki, 2011; Berman et al., 2012; Amiti et al., 2019). Moreover, Section 3.3 provides evidence that retailers adjust the relative margin of foreign to local varieties in response to the exchange rate shock. The nested CES demand system can generate variable markups under plausible market structures. For example, Atkeson and Burstein (2008) and Amiti et al. (2019) show that combining a nested CES demand system with oligopolistic competition (either Cournot or Bertrand competition) is sufficient to generate these patterns.

Finally, because we want to investigate the distributional effects of the depreciation, the standard CES demand system can be easily adjusted to account for non-homotheticities in demand. As we do not observe income levels, we cannot rely on approaches that explicitly allow budget shares on different products to vary with income levels (Deaton & Muellbauer, 1980; Fajgelbaum & Khandelwal, 2016). Instead, we follow the approach taken in Atkin et al. (2018), Jaravel (2019), and Argente and Lee (2020) and capture non-homotheticities in a non-parametric way by allowing budget shares and elasticities of substitution to vary by income group. In line with this literature, we assume that all households in a particular income group share the same underlying preferences. Nevertheless, by allowing the preference parameters to vary across these income groups, we can still flexibly account for non-homethecities in demand.

4.2 Preferences

In our data, product varieties can be aggregated on four different levels: (1) category level (e.g. Food), (2) subcategory level (e.g., Fruit), (3) product group level (e.g. Stonefruit), and (4) Product level (e.g. Peaches).[42] In addition, each product comes in different varieties, which can be both local and foreign varieties. Following Broda and Weinstein (2006), Hottman, Redding and Weinstein (2016) and Argente and Lee (2020), we define two nests per product category.[43] The upper

quality is constant over time for a given article. This is when quality would be altered after the depreciation, having the same article at different quality levels would interfere with the inventory systems of retailers. Therefore, we are reasonably certain that if the quality of a product would be altered, it would appear as a new article in our data.

[42]To compare the level of aggregation with the widely used Nielsen HomeScan database (Hottman et al., 2016; Jaravel, 2019; Argente & Lee, 2020), this dataset contains 184 different product groups and 900 different products which are comparable in their level of aggregation to the “Product Groups” and “Product Modules” in the Nielsen HomeScan database.

[43]The retailer sells in seven different broad product categories: Food, Non-alcoholic beverages, Alcoholic beverages and Tobacco, Electronics, Housekeeping products, Household furnishings and Clothing.

nest models substitution across products (e.g. rice versus bread) and the lower nest accounts for substitution across varieties within the same product category (e.g. Basmati rice versus Jasmin rice). We choose to define the upper nest on the product level for two reasons. First, we want to account for the fact that households may substitute between different kinds of products after the depreciation. For instance, if the depreciation causes bread prices to increase relatively to rice, consumers might choose to substitute to rice to compensate for these relative price changes. This degree of substitution is governed by the elasticity of substitution σ_c^h.[44] Second, the product level is the finest level of aggregation without meaningful product entry or exit after the depreciation.[45] Therefore, we don't have to quantify the welfare impact of entry and exit of products, nor do we have to estimate the elasticities of substitution at the product level. The lowest nest is defined on the variety level where the elasticities, η_p^h, govern how consumers substitute across varieties of the same product. Given the substantial entry and exit on the product variety level (see Table C.14), we will estimate the η_p^h's to account for the welfare impact of the extensive margin adjustments on the variety level.

While we conduct the analysis at the product category level, we drop the index c for notational simplicity.[46] For the upper nest of the utility function, consumers derive utility from consumption in category c according to:

$$U_t^h = \left[\sum_{p \in \mathcal{P}_t} \alpha_p^h Q_{p,t}^h{}^{\frac{\sigma^h}{\sigma^h - 1}} \right]^{\frac{\sigma^h - 1}{\sigma^h}}$$

where $Q_{p,t}^h$ is aggregate consumption of product p by households in income group h at time t, α_p^h is a product level demand shifter, which differs across income groups, $\mathcal{P}_t$ is the set of products available at time t and σ_p^h is the elasticity of substitution aggregating across products $p \in \mathcal{P}_t$. This specification of the upper nest gives rise to the following aggregate (category level) price index P_t^h:

[44]In the analysis, this type of substitution will be accounted for by the product level Sato-Vartia weight which is constructed from the pre- and post depreciation sales share.

[45]There are a handful of products that either enter of exit after the depreciation, but their sales share in total product category spending is around 0.1% and therefore we can safely discard product attrition on this level of aggregation.

[46]To aggregate across product categories, one could assume a cobb-douglas aggregator like in Hottman et al. (2016), but we are silent on the way we aggregate across categories. This is because we will execute the analysis for one product category being food and non-alcoholic beverages which carried a 34% CPI weight in 2015.

$$P_t^h = \left[\sum_{p \in \mathcal{P}_t} \alpha_p^h {P_{p,t}^h}^{1-\sigma^h} \right]^{\frac{1}{1-\sigma^h}}$$

which aggregates across quality adjusted product level prices $P_{p,t}^h$. In turn, the product specific quantity, $Q_{p,t}^h$ and price, $P_{p,t}^h$, aggregates are given by CES functions themselves:

$$Q_{p,t}^h = \left[\sum_{i \in \mathcal{I}_{p,t}} \beta_{i,p}^h {Q_{i,p,t}^h}^{\frac{\eta_p^h}{\eta_p^h - 1}} \right]^{\frac{\eta_p^h - 1}{\eta_p^h}}$$

where $Q_{i,p,t}^h$ is aggregate consumption of variety $i \in p$ by households in income group h at time t, $\beta_{i,p}^h$ is an variety level demand shifter, $\mathcal{I}_{p,t}$ is the set of varieties available at time t for product p and η_p^h is the elasticity of substitution between varieties in product $p \in \mathcal{P}_t$. Again, we write the product price index as $P_{p,t}^h$:

$$P_{p,t}^h = \left[\sum_{i \in \mathcal{I}_{p,t}} \beta_{i,p}^h {P_{i,p,t}}^{1-\eta_p^h} \right]^{\frac{1}{1-\eta_p^h}}$$

aggregating indiviudal varieties level prices $P_{i,p,t}$. One implication of the way we model consumer preferences is that consumers have the same elasticity of substitution across foreign and local varieties.[47] This is because, just like Bems and Di Giovanni (2016) and Auer et al. (2021), our data allows us to study substitution across local and foreign varieties within very detailed product categories. Therefore, the assumption of an equal elasticity of substitution between foreign and local varieties is much more likely to hold compared to other settings that make use of international trade data in which the domestic good can only enter at the most aggregate level (e.g. Schmitt-Grohé and Uribe (2018); Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020)).

4.3 Price index decomposition

Next, we exploit the CES structure to write down the theoretically consistent price index which we use to decompose the cost of living effect.

Since the set of available products $\mathcal{P}_t$ is extremely stable over time, we do not have to account for changes in the set of available products in our analysis.[48] From Diewert (1976), Sato (1976)

[47]Because we allow tastes to differ between foreign and local varieties and across consumers of different income group, our preference structure rationalizes differences in expenditure shares either through differences in consumer prices for foreign and local varieties or differences in tastes for foreign and local varieties across income groups.

[48]In fact, the sales share on new products is less than 0.1%. For this reason, not allowing for attrition at the product

and Vartia (1976), this feature of the data implies that we can express the cost of living effects at the product level as:

$$\frac{CLE_t^h}{e(\boldsymbol{P}^0, u_0^h)} = \frac{e(\boldsymbol{P}^t, u_0^h)}{e(\boldsymbol{P}^{t-1}, u_0^h)} - 1$$
$$= \prod_{p \in \mathcal{P}} \left[\frac{P_{p,t}^h}{P_{p,t-1}^h} \right]^{\omega_{p,t}^h} - 1$$
$$= \prod_{p \in \mathcal{P}} \left[\bar{P}_{p,t}^h \right]^{\omega_{p,t}^h} - 1$$

where $P_{p,t}^h$ is the income group-specific price level for product p and time t[49] $\omega_{p,t}^h$ are the Sato-Vartia weights which are given by:

$$\omega_{p,t}^h = \frac{\frac{\phi_{p,t}^h - \phi_{p,t-1}^h}{ln\phi_{p,t}^h - ln\phi_{p,t-1}^h}}{\sum_{p \in \mathcal{P}} \frac{\phi_{p,t}^h - \phi_{p,t-1}^h}{ln\phi_{p,t}^h - ln\phi_{p,t-1}^h}}$$

where $\phi_{p,t}^h = \frac{\sum_{i \in \mathcal{I}_p} P_{i,p,t} \cdot Q_{i,p,t}^h}{\sum_{p \in \mathcal{P}} \sum_{i \in \mathcal{I}_p} P_{i,p,t} \cdot Q_{i,p,t}^h}$ is the expenditure share of product p at time t.

The CES structure allows us to further decompose the cost of living effect by providing an expression for the product level price index $\bar{P}_{p,t}^h$ that depends on the variety level prices for continuing products and a term that adjusts this product level price index for the effect of changes in product variety:

$$\frac{CLE_t^h}{e(\boldsymbol{P}^0, u_0^h)} = \frac{e(\boldsymbol{P}^1, u_0^h)}{e(\boldsymbol{P}^0, u_0^h)} - 1 = \prod_{p \in \mathcal{P}} \left[\bar{P}_{p,t}^h \right]^{\omega_{p,t}^h} - 1$$
$$= \prod_{p \in \mathcal{P}} \left[\prod_{i \in \mathcal{I}_p} \underbrace{\left(\frac{P_{i,p,t}}{P_{i,p,t-1}} \right)^{\omega_{i,p,t}^h}}_{\text{PI continuing}} \cdot \underbrace{\left(\frac{\lambda_{p,t}^h}{\lambda_{p,t-1}^h} \right)^{\frac{1}{\eta_p^h - 1}}}_{\text{Variety effect}} \right]^{\omega_{p,t}^h} - 1$$

level is not of first order concern.

[49]The income group specificity follows from the fact that the weights used to aggregate article level price changes are income group specific.

where $P^h_{i,p,t}$ is the price of variety i at time t, $\omega^h_{i,p,t}$ are the Sato-Vartia weights obtained by:

$$\omega^h_{i,p,t} = \frac{\frac{\phi^h_{i,p,t} - \phi^h_{i,p,t-1}}{ln\phi^h_{i,p,t} - ln\phi^h_{i,p,t-1}}}{\sum_{i \in \mathcal{I}^{\cap}_{p,t}} \frac{\phi^h_{i,p,t} - \phi^h_{i,p,t-1}}{ln\phi^h_{i,p,t} - n\phi^h_{i,p,t-1}}}$$

and $\phi^h_{i,p,t} = \frac{P_{i,p,t} \cdot Q^h_{i,p,t}}{\sum_{i \in \mathcal{I}^{\cap}_{p,t}} P_{i,p,t} \cdot Q^h_{i,p,t}}$ is the expenditure share of variety i at time t and $\mathcal{I}^{\cap}_{p,t} = \mathcal{I}_{p,t-1} \cap \mathcal{I}_{p,t}$. The variety effect is captured by the expenditure share of continuing products in terms of all available varieties at time t relative to the sales share in all available varieties at time $t-1$ weighted by the elasticity of substitution.[50] This ratio is given by:

$$\frac{\lambda^h_{p,t}}{\lambda^h_{p,t-1}} = \frac{\frac{\sum_{i \in \mathcal{I}^{\cap}_{p,t}} P_{i,p,t} \cdot Q^h_{i,p,t}}{\sum_{i \in \mathcal{I}_{p,t}} P_{i,p,t} \cdot Q^h_{i,p,t}}}{\frac{\sum_{i \in \mathcal{I}^{\cap}_{p,t}} P_{i,p,t} \cdot Q^h_{i,p,t}}{\sum_{i \in \mathcal{I}_{p,t-1}} P_{i,p,t} \cdot Q^h_{i,p,t}}}$$

Using the identity: $P_{i,p,t} \equiv C_{i,p,t} - \mathcal{M}_{i,p,t}$, we further decompose the inner product as:

$$\begin{aligned}
\frac{CLE^h_t}{e(\boldsymbol{P}^0, u^h_0)} &= \prod_{p \in \mathcal{P}} \left[\prod_{i \in \mathcal{I}_p} \left(\frac{P_{i,p,t}}{P_{i,p,t-1}} \right)^{\omega^h_{i,p,t}} \cdot \left(\frac{\lambda^h_{p,t}}{\lambda^h_{p,t-1}} \right)^{\frac{1}{\eta^h_p - 1}} \right]^{\omega^h_{p,t}} - 1 \\
&= \prod_{p \in \mathcal{P}} \left[\prod_{i \in \mathcal{I}_p} \underbrace{\left(\frac{C_{i,p,t}}{C_{i,p,t-1}} \right)^{w^h_{i,p,t-1}}}_{\text{Cost effect}} \cdot \prod_{i \in \mathcal{I}_p} \underbrace{\left(\frac{\mathcal{M}_{i,p,t}}{\mathcal{M}_{i,p,t-1}} \right)^{w^h_{i,p,t-1}}}_{\text{Markup effect}} \cdot \right. \\
&\qquad \left. \prod_{i \in \mathcal{I}_p} \underbrace{\left(\frac{P_{i,p,t}}{P_{i,p,t-1}} \right)^{\omega^h_{i,p,t} - w^h_{i,p,t-1}}}_{\text{Substitution effect}} \cdot \underbrace{\left(\frac{\lambda^h_{p,t}}{\lambda^h_{p,t-1}} \right)^{\frac{1}{\eta^h_p - 1}}}_{\text{Variety effect}} \right]^{\omega^h_{p,t}} - 1
\end{aligned} \tag{4}$$

This final step shows that we can decompose the cost of living of consumer h into four different margins: (1) a cost effect, (2) a markup effect, (3) a substitution effect and finally (4) a variety effect.

First, the cost and markup effects are essentially covariances between pre-depreciation budget share weights and the evolution of variety level costs and markups, respectively. As all consumers

[50] Intuitively, when this ratio is very small (high), this means that relatively more (fewer) well-perceived varieties have entered the chocie set compared to the varieties that have left the choice set. Hence, the cost index provided overestimates (underestimates) the true cost of living change and is adjusted downwards (upwards). In addition, the extent to which we should adjust the price index crucially depends on the elasticity of substitution. When this is high, products are already perceived good substitutes and adding new varieties will increase utility all that much. When this elasticity is low, the currenct varieties are well-differentiated and adding new varieties has a high probability to match the preferences of consumers in a better way.

face the same in-store prices, these two margins will give rise to distributional effects if different income groups have different weights on different varieties. For example, if relatively richer consumers spend relatively more on foreign varieties which, experience a greater cost or markup increase, then the cost or markup effect will affect the distribution of welfare. The decomposition of price adjustment into a cost and markup component is novel to the international economics literature. This is because workhorse international trade and macroeconomics literature are built on models that give rise to constant markups and thus assume that all cost changes translate into price changes. Section 3 showed that this assumption does not hold in the data. Moreover, given that relatively rich consumers have larger expenditure shares on foreign varieties, we expect the cost margin to go up more for relatively rich consumers. Accordingly, we expect the markup effect to counteract this as markups of foreign varieties fell relative to local varieties.

Second, since the substitution effect is computed using a similar formula as the cost and markup effect, it can also be interpreted as a covariance. It is the covariance between variety level price evolutions and the difference in the variety level sato-vartia weight and the pre-depreciation budget share. Intuitively, the substitution effect will be negative and drecrease the overall cost of living effect whenever there is a reallocation of expenditure towards varieties (the difference in sato-vartia weigth and the pre-depreciation weight is positive) with a relatively lower price increase. This margin echoes the idea of flight from quality that was first introduced in Burstein et al. (2005) and later in Bems and Di Giovanni (2016) and measures this in terms of substitution from higher priced, higher quality continuing varieties to lower priced lower quality continuing varieties. [51] Following, Burstein et al. (2005) we expect that relatively low income consumers will substitute more towards cheaper varieties.

Finally, the variety effect quantifies any substitution towards (away from) entering (exiting) varieties and corrects the cost of living effect arising purely from price changes of continuing products depending on whether changes in the choice set are well or badly perceived by consumers. The variety effect may differ across consumers of different income groups either because their substitution patterns following changes in their choice set are different or because they differ in the way they appreciate these changes in the choice set, which is measured by the elasticity of substitution.

[51] This margins only captures substitution away from high to low priced products for the continuing products. Any substitution to (away) enetering (exiting) products is captured by the variety effect.

4.4 Empirical Strategy

In order to quantify the variety effect following the depreciation, we require estimates of the elasticity of substitution. To this end, we exploit the CES structure which implies the following demand for variety i of product category p at time t:

$$Q^h_{i,p,t} = \beta^h_{i,p,t}\left(\frac{P_{i,p,t}}{P^h_{p,t}}\right)^{-\eta^h_p} E^h_{p,t} \tag{5}$$

where

$$P^h_{p,t} = \left[\sum_{i\in\mathcal{I}_{p,t}} \beta^h_{i,p,t} {P_{i,p,t}}^{1-\eta^h_p}\right]^{\frac{1}{1-\eta^h_p}}$$

and $E^h_{p,t} \equiv Q^h_{p,t} \cdot P^h_{p,t}$. After taking logs, equation 5 becomes:

$$q^h_{i,p,t} = ln(\beta^h_{i,p,t}) - \eta^h_p p_{i,p,t} + \eta^h_p p^h_{p,t} + e^h_{p,t}$$

where $q^h_{i,p,t} = ln(Q^h_{i,p,t})$, $p_{i,p,t} = ln(P_{i,p,t})$, $p^h_{p,t} = ln(P^h_{p,t})$ and $e^h_{p,t} = ln(E^h_{p,t})$.

In this equation, the crucial parameter of interest is the elasticity of subsitution η^h_p which is allowed to vary across consumer groups and product categories. In order to identify this parameter, we need to solve a set of econometric challenges. First, the price index $P^h_{p,t}$ and the expenditure level $E^h_{p,t}$ are two constructs that depend on the prices of individual varieties $p_{i,p,t}$. Since they are unobserved and determine the quantity level $q^h_{i,p,t}$, we face a potential simultaneity issue. To solve this, we follow Atkin et al. (2018) and Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (2019) and flexibly account for them using product-income-time fixed effects. Second, the rest of the unexplained variance in the demand equation comes from the demand shifter $ln(\beta^h_{i,p,t})$, which is also unobserved. We decompose the demand shifter into a variety-income group fixed effect and an error term as follows: $ln(\beta^h_{i,p,t}) = \theta^h_{i,p} + \varepsilon^h_{i,p,t}$.In this way, our estimating equation becomes:

$$q^h_{i,p,t} = \beta^h_p p_{i,p,t} + \theta^h_i + \theta^h_{p,t} + \varepsilon^h_{i,p,t} \tag{6}$$

here θ^h_i are the variety-income group fixed effects and $\theta^h_{p,t}$ are the product category-income-time fixed effects. The addition of these detailed sets of fixed effects addresses the problem that certain variables are unobserved, but there is still a possibility that time-varying demand shifters, captured by the error term $\varepsilon^h_{i,p,t}$, are correlated with the price variable. To address this residual identification concern, we utilize the spatial variation in our dataset and instrument the price of variety i at time t in one store, (i.e. the store in Almaty), with the price of the same variety i at the same time t in the other store (i.e. the store in Nur-Sultan). This identification strategy was first introduced in Hausman (1996) and builds on a recent literature that establishes that retailers broadly apply uniform pricing rules across different localities (Dellavigna & Gentzkow, 2019; Anderson, Rebelo, & Wong, 2019). For instance, Dellavigna and Gentzkow (2019) provide evidence that prices of the same article co-move very closely across two stores of the same retail chain, both in the cross-section and in the time series. By applying this identification strategy, we filter out local variation that can affect both prices and quantities and only utilize variation in prices at the country level. To provide additional support for our instrument, we replicate the main motivating evidence in Dellavigna and Gentzkow (2019) for uniform pricing rules and show the results in Figures B.10 and B.11. Specifically, we show that prices of the same article tend to be highly correlated in both the cross-section and in the time dimension across the two stores that make up our dataset.

5 Results

In this section we present the decomposition results. We start by providing the average elasticities of substitution and by decomposing the aggregate cost of living increase into a cost, markup, substitution and variety effect. Herefafter, we present the elasticities of substitution across the different income groups and investigate whether there were distributional effects on the cost of living following the depreciation.

5.1 Aggregate results

5.1.1 Elasticities

To assess the size of the elasticities of substitution, we regress monthly purchased quantities on consumer prices (inclusive of sales and coupons) as in equation 6. In the estimation, we include all time periods and assume that the elasticities are constant over time. Also, we include all varieties in the estimation, so we do not distinguish between continuing, entering and exiting varieties for this purpose. We report unweighted regressions and cluster standard errors at the product category-store level. Given that we are interested in the aggregate cost of living effect, we restrict the elastitcity to be equal across income groups.

We present the estimates in Table 2. Columns (1) to (4) report the OLS estimates for different sets of fixed effects. Column (1) shows the result when we include the most basic setof fixed effects that is implied by our framework in section 4.4: (a) product−quarter fixed effects that filter out the product category level price indices and expenditure levels, and (b) a variety fixed effect to account for the demand shifter. In this setup, we recover a negative and statistically significant estimate of −2.24, which satisfies the theoretical constraint imposed by our CES demand system. When we replace the product-quarter fixed effects with more detailed product−month fixed effects in column (2), we find that the elasticity is almost the same and is estimated at −2.15. In our framework of section 4, we allowed for differences along the income distribution, but we did not account for spatial differences in consumption patterns.[52] Given that we observe most varieties in Almaty and Nur-Sultan, columns (3) and (4) examine whether our results change when we allow the demand shifters and price indices to also differ across locations. In fact, the estimated elasticities decrease in magnitude, but remain comfortably above the theoretical constraint of 1.

As mentioned in the previous section, the OLS estimates potentially suffer from an upward bias if there are time-varying demand shocks at the variety level[53] that induce a positive correlation between prices and quantities. To address this endogeneity concern, we leverage the spatial variation in our data and re-estimate equation 6 by instrumenting the price of variety i in one store with the price of the same variety i in the other store. Columns (5) to (8) report the 2SLS estimates for the same fixed effect setups as in columns (1) to (4). First, the Hausman-type instrument is strong as the first stage F-statistics are very large and are always substantially above the conventional critical values of 10 to 15. The fact that our instrument is highly correlated with the endogenous variable is consistent Figures B.10 and B.11. Second, in line with our expectations, the 2SLS estimates are always larger (in absolute value) compared to their respective OLS estimates and statistically significant.[54] For example, in our most basic fixed effect setup, the 2SLS estimate is −3.17 while its corresponding OLS estimate is −2.24. Third, the estimates reported in column (5) to (8) are well in the range of previous estimates in the literature. Using a similar empirical strategy, Dellavigna and Gentzkow (2019) estimate elasticities of demand for similar

[52]Such differences may arise due to differences in the composition of consumers across the two stores. According to the 2009 Census, Kazakhstan is characterized by substantial differences in ethnicity (the north of Kazakhstan is mostly populated by Ethnic Russians and the south by ethnic Kazakhs) and in religion (Ethnic Russians are predominantly Orthodox Christian and Ethnic Kazakhs are generally Muslim).

[53]Note that product-quarter or product-month fixed effects already account for time-varying demand shocks at the more aggregated product category level.

[54]The statistical significance of the results is unaffected when we cluster at the monthly level.

product categories sold by US retailers and report an average elasticity of substitution for food products of around -2.8.[55] These estimates are also close to own-price elasticities for food products that have been reported in the discrete-choice literature. Nevo (2001) estimates own-price elasticities of demand for breakfast cereal that range between -2.34 and -4.25 and Hendel and Nevo (2013) find own-price elasticities of demand between -2.46 and -2.94 for soft drinks.

Table 2: Aggregate elasticity of substitution

	OLS				2SLS			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t}$	-2.24 ***	-2.15 ***	-1.43 ***	-1.31 ***	-3.17 ***	-3.08 ***	-1.55 ***	-1.41 ***
	(0.133)	(0.133)	(0.068)	(0.071)	(0.214)	(0.224)	(0.077)	(0.085)
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Store FE			✓				✓	
Product x Month x Store FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Store FE			✓	✓			✓	✓
First stage F-stat	-	-	-	-	516.8	347.4	6,778.3	5,808.9
R sq.	0.056	0.070	0.055	0.071	0.056	0.070	0.056	0.071
Nr,. obs	769,717	769,717	769,717	769,717	620,806	620,806	620,806	620,806

Notes: This table shows the estimates of the elasticities of substitution pooled across product categories and pooled across consumers. Column (1) - (4) are OLS estimates and column (5) - (8) are 2SLS estimates using the Hausman-instrument as an instrument. Standard errors are reported below the coefficient in brackets and are clustered at the store-product level. Significance is at the * 10%, ** 5 % and *** 1% level.

5.1.2 Aggregate cost of living effects

The aggregate decomposition results are graphically displayed in Figure 9 and reported in more detail in Table C.21. These results are obtained by computing first each of the four components: (1) cost effect, (2) markup effect, (3) substitution effect and (4) product variety effect separately. We then combine them and obtain the overall cost of living effect. Each of the components is calculated relative to the pre-depreciation quarter which we define as June 2015, July 2015 and August 2015. In other words, in equation 4 we fix period t-1 to be equal to the pre-depreciation quarter[56] and compute for each of the ensuing quarters the different components. We compute the product variety effect by pooling across income groups and we restrict the elasticity of substi-

[55] In Figure 15 of the online appendix in Dellavigna and Gentzkow (2019) most of the mass of the distribution of demand elasticities falls between -5 and -1. Hence, our estimate falls in the lower part of their distribution.

[56] We define the pre-depreciation quarter as June 2015, July 2015 and August 2015. We proceed in this way because the depreciation was in August 20th and Figure 3 indicates that prices did not respond at all in August 2015.

tution to be the same across product categories. We draw the following conclusions from Figure 9 in Table C.21.

First, Figure 9 clearly shows that the cost of living went up considerably after the depreciation. After one year the cost of living increased a little under 25%. Nevertheless, the transmission of the exchange rate shock into prices was quite gradual: the cost of living increased by 5% after one quarter and steadily grew to a little under 25% after 5 quarters. This gradual evolution of the cost of living is in line with Figure 3 which also showed that pass-through converged after 10 to 12 months and is also consistent with other large devaluation episodes as described in Burstein et al. (2005) and Alessandria, Kaboski, and Midrigan (2010).

Second, the cost component almost entirely drives the increase in the cost of living that stems from inflation of continuing products. We find that after two quarters the marginal cost of food and beverages went up by more than 15% and by 28% after four quarters. This closely mimics the response of the corresponding CPI component (see Figure A.2) and corresponds roughly to an aggregate pass-through rate into marginal costs of 40% to 50%. Even though this effect is large in magnitude, it is in the range of estimates provided by Campa and Goldberg (2010) and consistent with recent work on the presence of dominant currencies in international trade. This literature has established that exchange rate pass-through into prices is expected to be larger in emerging countries as most of final goods and intermediate inputs are priced in a foreign currency (Gopinath, 2015; Gopinath et al., 2020). In fact, Table C.10 shows that almost all products which are directly imported by the retailer are invoiced in either Ruble, Euro or US Dollar.

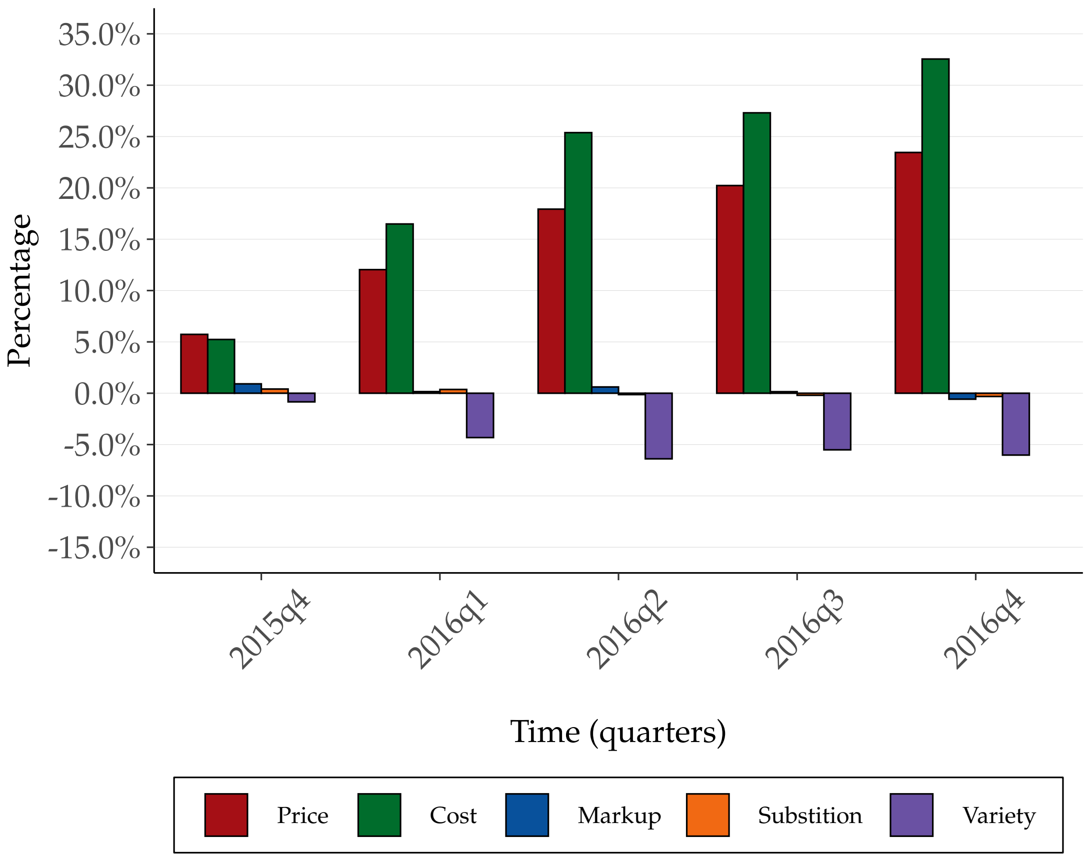
Third, we do not find much evidence that the markup and substitution channels are very important drivers of the aggregate cost of living evolution. The stability of average retail markups is in line Nakamura and Zerom (2010) and Gopinath and Itskhoki (2011) who fail to find important retail markup adjustment on aggregate in the US.[57] The observation that the substitution margin does not matter considerably for the aggregate cost fo living effect aligns well with Hausman (2003) who points out that not accounting for substitution is usually of second order importance to obtain a correct cost of living number. The isignificant role for the substitution effect is also consistent with the limited expenditure switching we documented in section 3.2.

Fourth, the product variety term is an important driver in lowering the overall impact of the depreciation on the cost of living. We calculate that after four quarters enhanced product variety dampened the overall increase in the cost of living by about 6%. This is qualitatively consistent

[57] In section 5, we will distinguish between local and foreign varieties and show that retail markups may not have changed much overall, but there are clear relative effects.

with Argente and Lee (2020) who show that across all US income groups product variety mitigated the cost of living increase during the great recession in the US. While Nakamura and Steinsson (2012), Cavallo et al. (2014) and Goetz and Rodnyansky (2021) provide evidence that product replacement may be an important source of price flexibility in response to currency shocks, the literature on exchange rate pass through usually does not account for this margin due the unavailability of expenditure shares. In contrast, our results show that accounting for changes in product variety and measuring their welfare impact are important to translate pass-through estimates into a welfare metric.

Figure 9: Decomposition: Aggregate Effect



Notes: These figures show the aggregate results from the nested CES decomposition from equation 4 which are also presented in C.21. The results are obtained after pooling across all income groups and estimating the variety effects when we restrict the elasticity of substitution to be the same across all product categories. To be precise, we use the estimate of column (5) in Table 2. These effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015. The size of each bar is expressed in percentage differences and is obtained by subtracting 1 and multiplying by 100 each of the numbers in Table C.21.

Our previous results are based on the assumption that the elasticities of substitution are the same across varieties of different product categories. This assumption is not innocuous given that changes in product variety might be more concentrated in product categories with higher elasticities of substitution. If such a correlation was present in the data, then we would be overstating the welfare effects of changes in product variety. For this reason, we estimate the elasticities of substitution on the subcategory level [58] To this end, we estimate equation 6 separately for each subcategory and obtain one elasticity of substitution for each of the 14 subcategories. We present the 2SLS-results in Table C.24 and from this table it is clear that elasticities of substitution are quite dispersed.[59] Figure B.12 and Table C.25 present the results when we account for heterogeneity in the elasticities of substitution. The key takeaway from this figure is that the product variety effects strenghten and that they exert a greater dampening effect on the cost of living increase. In this setup, changes in the choice set of consumers lower the increase in the cost of living between 8% and 10% depending on the horizon we look at. So, not only is it important to account for changes in product variety, it is also important to account for heterogeneity across product categories to infer the aggregate welfare effect of exchange rate shocks.

5.2 Distributional results

5.2.1 Elasticities

In this section we tune in on the distributional cost of living effects resulting from a large depreciation. When quantifying the variety effect for different income groups, we need to account for the possibility that consumers of different income groups might have different elasticities of substitution. Hence, we re-estimate equation 6 separately for each income group and report the results for the same fixed effect specifications as before in Table 3. Panels (a), (b) and (c) show the results for the relatively low-, middle- and high-income groups respectively. By estimating one equation for each income group, we make sure that the fixed effects vary at the income group level and that they filter out income group-specific price indices and variety level demand shifters.

Table 3 shows that all 2SLS-estimates are statistically significant[60] and negatively estimated. Also, the first stage F-statistics are large in all specifications and the 2SLS-estimates are again above their corresponding OLS-estimates in all specifications. More importantly, we find that consumers of higher income groups have lower elasticities of substitution compared to the con-

[58] The subcategory level contains 14 different categories: Bakery/Cereal, Candy, Dairy, Dry Food, Fish, Fruit, Meat, Ready-made, Savory edibles, Seasonings, Vegetables, Coffee/Tea, Soft Drinks and Waters.

[59] Judging from our preferred specification (which is column 3 of Table C.24), the elasticities are quite heterogenous and range from -1.4 to -4.79..

[60] The statistical significance of the results is unaffected when we cluster at the monthly level.

sumers from the lower-income group. This result is important as it indicates that high-income consumers tend to value new product variety to a greater extent than lower-income consumers. This is because the lower elasticity of substitution indicates that richer consumers consider the alternatives in their choice set as less substitutable compared to the low-income consumers. Therefore, when faced with the introduction of new product variety, high-income consumers will value this new variety more than low-income consumers who already considered their current choice set to contain good substitutes. The finding that low-income consumers have higher elasticities of substitutions is in line with a substantial IO literature. This literature usually finds that high income consumers tend to be less price elastic (Berry, Levinsohn, and Pakes (1995) for cars and Nevo (2001) for breakfast cereal). Also, Dellavigna and Gentzkow (2019) and Faber and Fally (2021) find that demand elasticity is lower in absolute value in richer US commuting zones.[61] Table C.23 shows that the difference between the elasticities of substitution across rich and poor consumers is both qualitatively and quantitatively preserved when we classify consumers according to their total expenditure.

[61] In principle, these differences could also be driven by heterogeneity in budget shares on subcategories within food & non-alcoholic beverages with heterogenous elasticities of substitution. However, the budget shares across more disaggregated categories within food & beverages are very similar across income groups and across different definitions of those income group. Also, when we estimate the effect of changes in product variety for different income groups, we explicitly account for this possibility and estimate the elasticities of substitution for each income group and subcategory separately when we compute the welfare effects of product variety.

Table 3: Elasticity of substitution (20% - 80% split) - Per Income Group

	OLS				2SLS			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (a): Low income								
$p_{i,p,t}$	-3.65 ***	-3.51 ***	-2.35 ***	-2.28 ***	-5.2 ***	-5.18 ***	-2.51 ***	-2.53 ***
	(0.243)	(0.252)	(0.146)	(0.160)	(0.467)	(0.537)	(0.184)	(0.215)
First stage F-stat	-	-	-	-	292.6	170.7	2,920.1	2,213.2
R sq.	0.034	0.054	0.018	0.043	0.033	0.056	0.014	0.041
Nr. obs	190,063	190,063	190,063	190,063	151,759	151,759	151,759	151,759
Panel (b): Middle income								
$p_{i,p,t}$	-2.34 ***	-2.29 ***	-1.57 ***	-1.43 ***	-3.17 ***	-3.15 ***	-1.7 ***	-1.52 ***
	(0.139)	(0.145)	(0.077)	(0.083)	(0.244)	(0.274)	(0.100)	(0.113)
First stage F-stat	-	-	-	-	619.2	414.6	7,571.5	6,217.6
R sq.	0.104	0.120	0.100	0.120	0.108	0.127	0.106	0.128
Nr. obs	329,014	329,014	329,014	329,014	264,839	264,839	264,839	264,839
Panel (c): High income								
$p_{i,p,t}$	-1.24 ***	-1.14 ***	-0.964 ***	-0.82 ***	-2.22 ***	-2.17 ***	-1.22 ***	-1.06 ***
	(0.155)	(0.158)	(0.089)	(0.095)	(0.263)	(0.288)	(0.106)	(0.116)
First stage F-stat	-	-	-	-	443.7	294.7	5,413.4	4,557.8
R sq.	0.052	0.069	0.045	0.066	0.056	0.073	0.047	0.068
Nr. obs	250,640	250,640	250,640	250,640	204,208	204,208	204,208	204,208
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Store FE			✓				✓	
Product x Month x Store FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Store FE			✓	✓			✓	✓

Notes: This table shows the estimates of the elasticities of substitution for each income group seperately, but pooled across product categories. The results per income group are obtained by estimating 6 separately for each income group. Panel (a) shows the results for the relatively low income group, panel (c) for the relatively high income group and panel (b) for consumer classified in the middle income group. from estimatin equation Column (1) - (4) are OLS estimates and column (5) - (8) are 2SLS estimates using the Hausman-instrument as an instrument. Standard errors are reported below the coefficient in brackets and are clustered at the store-product level. Significance is at the * 10%, ** 5 % and *** 1% level.

5.2.2 Distributional cost of living effects

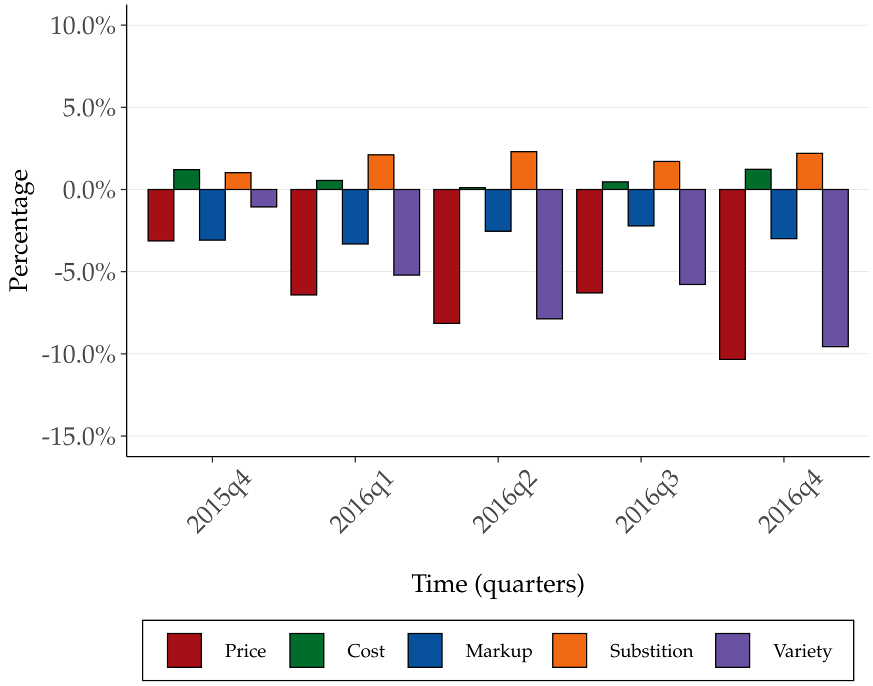
Figure 10 present the distributional effects of the depreciation for the quintiles income distribution. We present the results for the other income definitions alongside the baseline definition in Figures B.13a-B.13d and in Tables C.27-C.30. Each of these results are calculated in two steps. First, we compute for each income group separately the components by applying the income group specific weights and the income group specific elasticity of substitution to the expressions in equation 4. Second, for each component we assess the distributional effect across income groups by taking the ratio of the value for the high-income group (H) relative to the component value of the low-income group (L) and obtain a component specific ratio (H/L)[62] We compute the variety effect by allowing for different elasticities of substitution across income groups and restrict them to be same across product categories.

Overall, we find that the cost-of-living goes up less for relatively high-income consumers compared to relatively low-income consumers. Using our baseline definition of the income groups[63], we find that the cost-of-living increase is 5% (after two quarters) and up to 10% (after five quarters) lower for relatively high-income consumers. Also, we find that the results are robust across different definitions for income groups and that the overall quantitative magnitude of the different channels increases when we start from the most conservative income group definition (terciles) and move to more extreme definitions of the income groups (deciles). Furthermore, the decomposition shows that the differential cost-of-living effects are driven mostly by the extensive within margin and not by inflation from the intensive within margin. We investigate each of these two channels more in detail below.

[62] For the elasticities of substitution, we use the 2SLS estimates displayed in column (5) of Table 3. We use these estimates as they yield the most conservative results for the variety effect.

[63] Recall that we use the quintiles or the 20%-80% definition as our baseline definition.

Figure 10: Decomposition: Distributional Effect (Quintiles: 20%-80% split)



Notes: This figure shows the distributional results from the nested CES decomposition in equation 4 for the quintiles definition of the income distribution. These results are also presented in Table C.29. The results are obtained by computing each of the components separately for each income group. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. These effects are cumulative effects relative to the quarter before the devaluation, which is defined as June, July and August 2015 and coincide with the ratio column for each channel as displayed in Table C.29. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

Intensive within margin. The reason why price from the intensive within margin is not the main driver of the distributional cost-of-living effects is because it originates from offsetting forces: while the cost and substitution margins drive up the cost-of-living more for high-income consumers and decrease inflation inequality[64], the markup effect offsets this relative increase in the cost-of-living for the high-income as they benefit from lower retail margins after the depreciation.

(1) Costs and Markup effects. Across all definitions of the income groups and at each horizon, we observe that the cost component tends to increase consumer prices relatively more for high-income consumers compared to low-income consumers. In our baseline results, the cost margin

[64]We refer to decreasing inflation inequality if the margin decreases differences the cost-of-living increase for poor consumers relative to rich consumers.

led to a 0.1% - 1.2% increase in the cost of living of high-income consumers compared to the low-income consumers depending on the horizon we consider. Even though the magnitude of the cost margin is quite small, its sign is positive across all definitions of the income groups and decreases inflation inequality.

While the cost effect decreases inflation inequality, the markup effect increases inflation inequality. This is because high-income experience on average lower margins after the depreciation compared to the low-income consumers. According to our baseline results, the markup channel increases inflation inequality by 2%-2.8% as high-income consumers experience lower markups while low-income consumers experience relatively higher markups. In other words, the markup channel offsets the relative cost of living increase that high-income consumers would have experienced in case that there was perfect cost pass-through and margins did not adjust to the shock. Again, these results are robust across different definitions of the income groups and tend to grow when we move towards more extreme classifications: the markup effect would induce inflation inequality amounting to 1.9%-2.4% in the quartiles definition and between 3.4%-5.1% in the decile definition depending on the horizon we consider.

(2) Substitution effect. Across all income group definitions, the substitution margin leads to a greater cost of living increase for the high-income consumers compared to low-income consumers. The substitution margin is defined as the covariance between price changes and the difference between the post-depreciation Sato-Vartia weights and the pre-depreciation expenditure weights (see equation 4). Therefore, it measures to what extent consumers substitute away from continuing varieties that become relatively more expensive towards other continuing varieties within the same category. In this way, this margin resembles the so-called "flight-from-quality" from Burstein et al. (2005) where consumers substitute towards cheaper alternatives to dampen the overall cost of living increase. Consistent with Bems and Di Giovanni (2016), we find that low-income consumers do indeed lower the overall cost of living increase by substituting towards continuing products that increase less in price. Whereas the substitution margin is not central to understand the aggregate cost of living evolution, it does matter to infer the distributional effects relatively low-income consumers did substitute more to varieties with lower inflation and mitigate the cost of living increase compared to high-income consumers.

Extensive within margin. Figures B.13a – B.13d demonstrate that extensive within margin is the main driver of the distributional effects of the depreciation and that relatively high-income consumers benefit more from the changes in product variety that occur after the depreciation. First, our baseline specification indicates that changes in product variety dampen the cost of living increase for all consumer groups. We find that changes in the choice set contribute to a 2.5% (after two quarters) and 3% (after four quarters) lower cost of living level for relatively low-income consumers (see Table C.29). However, Table C.29 also shows that relatively high-income consumers benefit more from increased product variety as they experience a lower cost of living of 7.5% (after two quarters) and 8.6% (after four quarters) compared to the situation without changes in product variety. Hence, changes in product variety lead to an increase in cost of living inequality of 5.2% (after two quarters) and 5.7% (after four quarters). Second, Figures B.13a – B.13d and Tables C.27 - C.30 illustrate that these results are both qualitatively and quantitatively very stable across different definitions of the income groups. For example, cost of living inequality increases by 5.2% (after two quarters) and by 5.5% (after four quarters) in the quartile definition and by 4.9% (after two quarters) and by 7.2% (after four quarters) in the decile definition.

This result aligns well with a recent literature on the distributional consequences of economic shocks. In particular, Atkin et al. (2018) and Jaravel (2019) have emphasized that extensive margin adjustments are central to fully understand the cost of living effects of economic shock across the income distribution. For instance, Atkin et al. (2018) show that because high-income consumers tend to switch more towards foreign retail stores after they entered in Mexico, they have access to lower prices and more variety. Also, Jaravel (2019) shows that product innovations directed towards the rich US consumers lead to a substantially lower cost of living increase for high-income consumers in the long run. Despite its quantitative importance, the extensive within margin has not been incorporated before to study the aggregate and distributional welfare consequences of large currency shocks. In fact, our results show that accounting for changes in the choice set of consumers are paramount to determine whether relatively rich or relatively poor suffer more from the depreciation. Hence, we contribute to the literature on the distributional consequences of large currency shocks by pointing out that changes in product variety are a key driver to understand such distributional, and in our case unequal, effects.

Mechanism. The fact that the extensive within margin differs for rich and poor consumers can be driven by two forces: (1) differences in the extent to which rich and poor consumers substitution towards (away from) entering (exiting) varieties and (2) differences in elasticities of substitution. First, Figure B.15 shows the distribution of Feenstra-ratios across product categories for rich and poor consumers separately. The Feenstra-ratios measure the extent to which rich and poor consumers substitute towards (away from) entering (exiting) varieties. To test whether differential switching is responsible for the difference in benefits from the extensive margin, we conduct both a paired t-test and a non-parametric paired Wilcoxon rank sum test. However, for both tests we are unable to reject the null hypothesis of equal switching. Second, if rich consumers have lower elasticities of substitution, then for each level of switching the associated welfare effect will be larger for rich consumers. This is because they consider varieties to be more differentiated and therefore receive a larger change in utility whenever the same level of switching is observed. As we illustrated in the previous section, Table 3 provides robust evidence that rich consumers have lower elasticities of substitution and therefore experience larger welfare changes for the same level of switching.

Heterogeneity. Similarly to the aggregate results, we check the robustness of our results when we allow the elasticities of substitution to vary not only across income groups, but now also across product categories. For this purpose, we adjust equation 6 in two ways. First, we still estimate the elasticities of substitution separately for each subcategory level[65] , but now interact the price variable with an income group dummy to obtain 42 different elasticities that vary on the subcategory – income group level. Second, we interact the product category-time and variety fixed effects with income groups to ensure that we control for income group specific price indices, expenditure levels and demand shifters. We present the 2SLS-estimates in Table C.26. In turn, Tables C.31 - C.34 and Figures B.14a - B.14d show the results when we account for very rich heterogeneity in the elasticities of substitution. First, in line with the aggregate results, we find that accounting for heterogeneity in the elasticities of substitution tends to strengthen the welfare effects of changes product variety. Comparing Tables C.31 - C.34 with their respective homogenous elasticities counterparts illustrates that increased product variety dampened the rise in the cost of living for both relatively low-income and high-income consumers at almost each horizon and income group definition. Second, the heterogenous results still indicate that rich consumers experienced slower growth in their cost of living in the year following the depreciation. In our baseline specification rich consumers experienced a 3%, 5% and 7% slower increase in their cost of living after one, two and three quarters after the depreciation. This pattern is consistent across the different across the different income group definitions. However, we do note that the results do

[65] The subcategory level contains 14 different categories: Bakery/Cereal, Candy, Dairy, Dry Food, Fish, Fruit, Meat, Ready-made, Savory edibles, Seasonings, Vegetables, Coffee/Tea, Soft Drinks and Waters.

not seem as persistent as in the homogenous setup. This is because it seems that after four quarters, the gains from changes in product variety seem to be roughly equal across high-income and low-income consumers. Altogether, the heterogenous results suggest that there was still a substantially lower growth in the cost of living of relatively high-income over the first three quarters after the depreciation but that these growth paths seem to have converged after four quarters.

6 Conclusion

This paper uses a novel scanner dataset of consumer products and characteristics from a large supermarket, METRO, in Kazakhstan. We analyze the impact of the large and sudden currency depreciation of the Kazakh Tenge in August 2015 on consumer prices, costs and retail markups of local and foreign products. Aggregate exchange rate pass-through into consumer prices is incomplete and persistent. Even after 12 months and despite the large cost shock, exchange rate pass-through into consumer prices was only 60%. Surprisingly, the depreciation did not induce substantial expenditure switching as the expenditure share of foreign products decreased by less than 3% after one year. We explain this limited expenditure switching by conducting an event study design where we compare the evolution in the relative price, cost and markup of foreign varieties to local varieties. The analysis unveils that the relative consumer price increase of foreign products compared to local alternatives was very muted. This is because relative costs for foreign products only increased by 6 to 8%, and this increase was further offset by a decrease in their relative retail markups of 2 to 3%.

While we measure that the aggregate cost of living increased by 30 percent, we also explore the distributional effects on the cost-of-living and show that the impact of the depreciation hurts high-income consumers less. We establish this result by decomposing the cost-of-living effect of the depreciation into a (1) cost, (2) markup, (3) substitution and (4) product variety effect. At first sight high-income consumers are more exposed to the relative cost shock because they allocate a larger share of their budget to foreign varieties, but they experience relatively lower retail markups after the shock. In addition, they benefit more from changes in product variety that occur in the year following the depreciation.

Our results shed new light on the transmission mechanisms of exchange rate shocks to consumer prices, which is important for conducting monetary policy an economy that has to accommodate large currency swings. In particular, we show that expenditure switching is limited, that retail markups partially offset relative price adjustment and that distributional cost-of-living effects following aggregate shocks can occur even within product categories.

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A Representativeness of the Store

While our dataset is very rich in many dimensions, it only covers one chain. To support the external validity of our results, we now show how our retailer, and large stores in Kazakhstan in general, compare to other stores and how they might have responded differently after the shock. To this end, we complement insights from our scanner data with two additional data sources. First, we add product-level scanner data from AC Nielsen Kazakhstan on the same set of products across different types of stores. From 2014 until 2016, the dataset covers the 40 top-selling barcodes in each product category and records prices and sales for the same product at different stores of different sizes[66], but aggregate across regions.[67] Second, we use disaggregate information on the construction of the CPI in Kazakhstan. Specifically, we retrieve the expenditure weights and evolution in the index of different CPI components that correspond to categories[68] in our dataset from the National Bank of Kazakhstan.

Market share. Based on the AC Nielsen data and anecdotal evidence from our retailer, the retailer has a non-trivial overall market share of around 10%. Figure A.1b plots the evolution of the market share of small, medium, large and other stores over time for all categories in the AC Nielsen dataset and for food and non-alcoholic beverages separately. Focusing on the cross-section, this figure shows that the group of large stores, to which our retailer belongs, has on average a market share of around 35%, independent of the sample of product categories. From conversations with the retailer, we know that they have a 25% market in the segment of large stores. Combining these two numbers, we arrive at a total market share of around 10% which highlights that it is an important competitor in the Kazakh retail market.

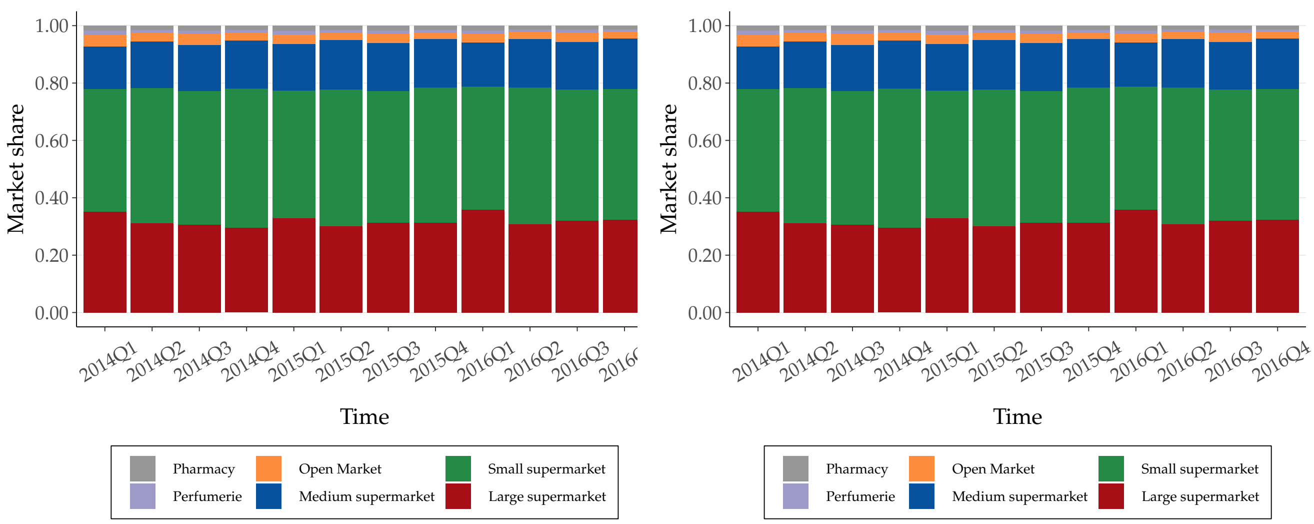
[66]Stores are classified as large, medium, small or other (including open market stores, pharmacies and perfumeries) based on whether they sell both food and non-food and based on the physical size of the stores. Table C.1 provides a mapping from the store types in the data to the classification we use in this section.

[67]Depending on the product category, the frequency of the data is at the monthly or bimonthly level. Therefore, we aggregate the data to the quarterly level.

[68]We retrieve information on: Food and Non-Alcoholic beverages, Tobacco and Alcholic beverages, Clothing items and household supplies (i.e. detergents, ...).

Figure A.1: Market share distribution across storetypes

(a) All Products **(b)** Food and Non-alcoholic beverages



Notes: Using the AC Nielsen scanner data, this figure shows the market share across storetypes for each quarter from 2014 until 2016. Panel (a) includes all product categories and Panel (b) only food and non-alcholic beverages.

Price differences across and within stores. Whereas large stores charge higher prices for the same varieties and have a more expensive product assortment, such price differences are much lower compared to price differences across local and foreign varieties offered by our retailer. To compare consumer prices across stores, we use the AC Nielsen data and estimate the following regression:

$$p_{i,s,p,t} = \sum_{k \in \mathcal{S}} \beta_k \cdot \mathbb{1}(\mathrm{s}=\mathrm{k}) + \theta_{p,t} + \theta_{i,t} + \varepsilon_{i,s,p,t} \tag{A.1}$$

where $p_{i,p,s,t}$ is natural logarithm of the consumer prices of variety i which is part of product category p sold at storetype s at time t. The function $\mathbb{1}(\mathrm{s}=\mathrm{k})$ is an indicator function which is equal to one when the store is either a large store, a medium store or a residual store.[69] Hence, we consider small stores as the baseline in these regressions. By including either only category-time $\theta_{p,t}$ and variety-time $\theta_{i,t}$ fixed effects or only category-time $\theta_{p,t}$ fixed effects, we estimate the price difference between small stores and a store type k stemming from price differences for identical varieties solely and stemming from both price differences for identical varieties and from assortment differences. Columns (1) and (2) of Table A.1 show the results when estimating the previous regression for varieties that are part of the food and non-alcoholic beverage category. In

[69] Residual stores are either pharmacies, perfumeries or other stores.

particular, in column (1) we include only category-time fixed effects and find that prices within the same product category are on average 22% higher in large stores. When we add variety-time fixed effects in column (2), the coefficient on the foreign dummy roughly halves, indicating that product assortment and price differences for identical varieties each account for roughly half of this average price difference.[70]

Table A.1: Price disperion

	Food & Non-alc. Beverages				All products			
$p_{i,s,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}(s = \text{Large})$	0.227 ***	0.114 ***	0.222 ***	0.0943 ***	0.325 ***	0.174 ***	0.32 ***	0.135 ***
	(0.016)	(0.010)	(0.016)	(0.010)	(0.015)	(0.010)	(0.015)	(0.010)
$\mathbb{1}(s = \text{Medium})$	0.0711 ***	0.0344 ***	0.0681 ***	0.0275 ***	0.0714 ***	0.0309 ***	0.0692 ***	0.0228 ***
	(0.010)	(0.006)	(0.011)	(0.006)	(0.011)	(0.007)	(0.011)	(0.006)
$\mathbb{1}(s = \text{Other})$	0.18 ***	0.0753 ***	0.181 ***	0.0604 ***	0.407 ***	0.216 ***	0.383 ***	0.16 ***
	(0.017)	(0.010)	(0.017)	(0.009)	(0.015)	(0.010)	(0.016)	(0.009)
Category x Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Variety x Time FE		✓		✓		✓		✓
R sq.	0.333	0.650	0.368	0.720	0.371	0.640	0.396	0.709
Nr. obs	77,954	77,954	41,850	41,850	116,242	116,242	62,768	62,768

Notes: This table presents the results from estimating equation . Columns (1), (2), (5) and (6) estimate this regression for the full sample, columns (3), (4), (7) and (8) consider only pre-devaluation data, i.e. from the first quarter of 2014 until the third quarter of 2015. Standard errors are clustered at the variety level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Next, we turn to documenting price differences across foreign and local varieties within our retailer. To see this, we turn back to our detailed scanner data and estimate the following regression:

$$y_{i,s,p,t} = \beta \cdot \mathbb{1}(\text{i = foreign}) + \theta_{s,p} + \theta_{p,t} + \varepsilon_{i,s,p,t} \tag{A.2}$$

where $y_{i,p,s,t}$ is either the log consumer price, log cost or log retail markup a of product i, sold in store s, which is part of product group p[71], in month t, $\mathbb{1}(\text{i = foreign})$ is an indicator function that is one when the product is a foreign product and zero otherwise. To compare foreign and local products within the same product category, we add $\theta_{s,p}$ which are product category - store fixed effects. In this regression we are careful to only include pre-depreciation observations. This is because including data after the depreciation is likely to yield a positive estimate simply because

[70] The other columns in Table A.1 show that the results are consistent when we only focus on the pre-depreciation period. When we include all products in the regression, the price differences across small and lare stores increase by roughly 50%.

[71] We define the product category at the lowest level of aggregation in our dataset.

of the relative cost change induced by the depreciation. The first three columns of Table A.2 shows the results for consumer prices. We find that foreign products have around 60% higher consumer prices and costs within product categories. The results are invariant to adding store - month fixed effects that flexibly control for store- or region-specific time variation and to interacting the product category - store fixed effects with store - month fixed effects.[72] In addition, columns (4) to (9) show these price differences are due to cost differences and not due to differences in retail markups.

Combining the results from above, we conclude that while there exists non-trivial price dispersion across stores, there is even greater price dispersion within stores. In other words, whereas different consumers might sort across different stores, there is even more scope for sorting across varieties within stores, which is the variation that we focus on in this paper.

[72] The observation that foreign varieties tend to be more expensive compared to local alternatives is in line with recent evidence for other emerging economies. Bems and Di Giovanni (2016) find a 28% foreign premium using scanner data from a Latvian retailer and Goetz and Rodnyansky (2021) estimate a 40% price difference between local and foreign varieties sold by a Russian clothing retailer. This finding be rationalized by the presence of substantial trade costs (Obstfeld & Rogoff, 2000) or by a literature on vertical specialization which predicts that richer (poorer) countries tend to specialize more in high-(low-)quality varieties (Fajgelbaum et al., 2011; Feenstra & Romalis, 2014).

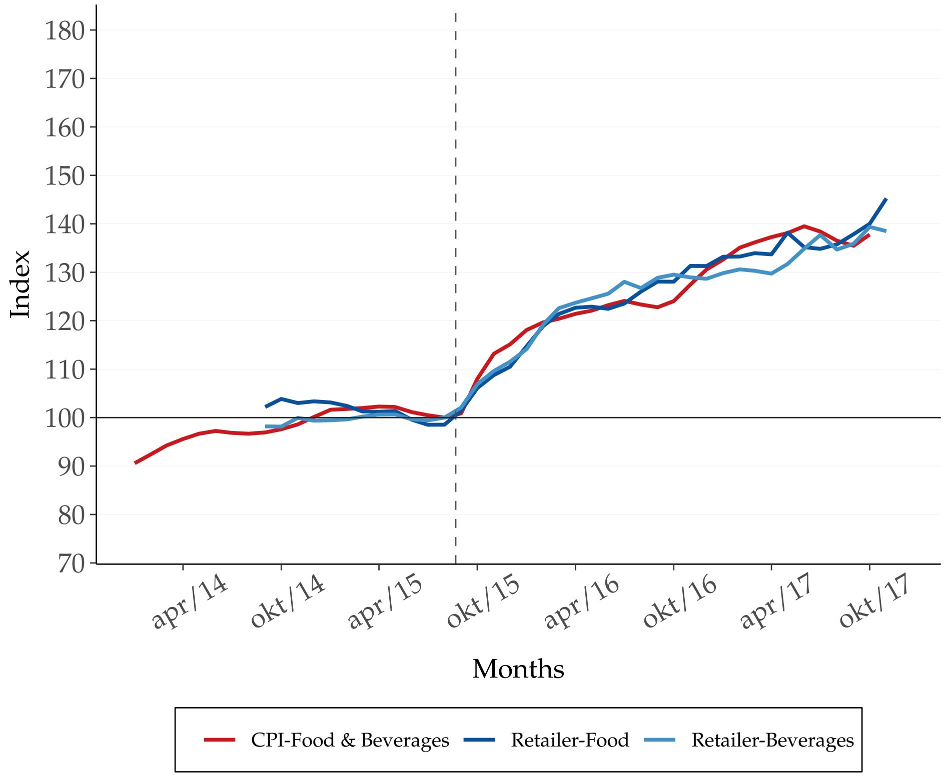
Table A.2: Foreign Premium: Food & Beverages

	Price			Cost			Margin		
$y_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(i = foreign)	0.616 ***	0.616 ***	0.62 ***	0.606 ***	0.606 ***	0.608 ***	0.00967	0.0101	0.0122
	(0.042)	(0.042)	(0.043)	(0.042)	(0.042)	(0.043)	(0.008)	(0.008)	(0.008)
Product x Store FE	✓	✓		✓	✓		✓	✓	
Store x Month FE		✓			✓			✓	
Product x Store x Month FE			✓			✓			✓
R sq.	0.697	0.698	0.686	0.689	0.689	0.676	0.097	0.101	0.155
Nr. obs	109,148	109,148	109,148	109,110	109,110	109,110	109,110	109,110	109,110

Notes: This table shows the result of a regression of log consumer prices, log wholesale prices or costs and log retail margins respectively on a foreign dummy on a sample including only food % beverages. Therefore, the coefficient on the foreign dummy indicates the percentage difference between foreign and local products or the foreign premium. Standard errors are reported below the coefficient in brackets and are clustered at the store-product level. Significance is at the * 10%, ** 5 % and *** 1% level.

Price adjustment after the shock across stores. Small and large stores changed consumer prices almost uniformly following the depreciation. To corroborate this claim, we provide two pieces evidence. First, Figure A.2 plots the aggregate price evolution of food and beverages in our dataset and compares this to the price evolution of the corresponding CPI component.[73] This figure shows that the two series closely track each other in the period around the depreciation.[74]

Figure A.2: Price evolution for Food & Non-alcoholic beverages: Retailer vs CPI



Notes: This figure compares the aggregate price evolution of the subset of broad expenditure categories that are covered by the retailer and the CPI. To mimic the construction of the CPI index as close as possible, these series are constructed using only continuing products, products that were present before and after the - devaluation. More precisely, for this excercise a continuing product is a product that had positive inventories before the devaluation and still had positive inventories one year after the devaluation. Also, we use product weights are computed from expenditure on these products before the devaluation.

Second, using the AC Nielsen data we check whether large stores adjusted prices differently compared small stores after the depreciations by estimating:

$$p_{i,s,p,t} = \sum_{k \in \mathcal{S}} \beta_k \cdot \mathbb{1}(\mathrm{s} = \mathrm{k}) \cdot \mathbb{1}(t > 2015Q3) + \theta_{i,s} + \theta_{i,t} + \varepsilon_{i,s,p,t} \tag{A.3}$$

[73] To be consistent with the construction of the CPI, we compute this aggregate price evolution using a Laspeyres index with expenditure weights computed from pre-devaluation expenditure data.

[74] Figure B.1 shows that the co-movement between the overall price evolution in other product categories of our retailer and the corresponding CPI component is much weaker. In addition, we show below that large stores increased prices by more after the depreciation compared to small stores.

where $p_{i,p,s,t}$ is still the natural logarithm of the consumer prices of variety i which is part of product category p sold at storetype s at time t. The function $\mathbb{1}(\mathrm{s} = \mathrm{k})$ is still the indicator function which is equal to one when the store is either a large store, a medium store or a residual store and $\mathbb{1}(t > 2015\mathrm{Q}3)$ is an indicator function that is one for all periods after the depreciation. In our preferred specification, we include $\theta_{i,s}$ and variety-store $\theta_{i,t}$ variety-time fixed effects to focus differential price adjustment between different store types for the same product variety relative to small stores. Column (3) of Table A.3 shows that we cannot reject the null hypothesis that large stores adjusted consumer prices differently compared to small stores for food and non-alcoholic beverages.[75]

Table A.3: Differential Price adjustment

	Food & Non-alc. Beverages			All products		
$p_{i,s,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(s = \text{Large}) \cdot \mathbb{1}(t > 2015Q3)$	0.0203 **	-0.00248	0.00867	0.0141 *	0.105 ***	0.0677 ***
	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.007)
$\mathbb{1}(s = \text{Medium}) \cdot \mathbb{1}(t > 2015Q3)$	0.0171 **	0.1 ***	-0.00418	0.0169 **	-0.0269 **	-0.0449 ***
	(0.007)	(0.012)	(0.012)	(0.007)	(0.012)	(0.012)
$\mathbb{1}(s = \text{Other}) \cdot \mathbb{1}(t > 2015Q3)$	-0.0468 **	0.0792 ***	0.0783 **	0.0728 ***	0.423 ***	0.33 ***
	(0.023)	(0.027)	(0.034)	(0.019)	(0.019)	(0.026)
Store FE	✓			✓		
Store-Category FE		✓			✓	
Store-Variety FE			✓			✓
Time FE	✓			✓		
Time-Category FE		✓			✓	
Time-Variety FE			✓			✓
R sq.	0.057	0.476	0.818	0.106	0.515	0.792
Nr. obs	77,954	77,954	77,954	116,242	116,242	116,242

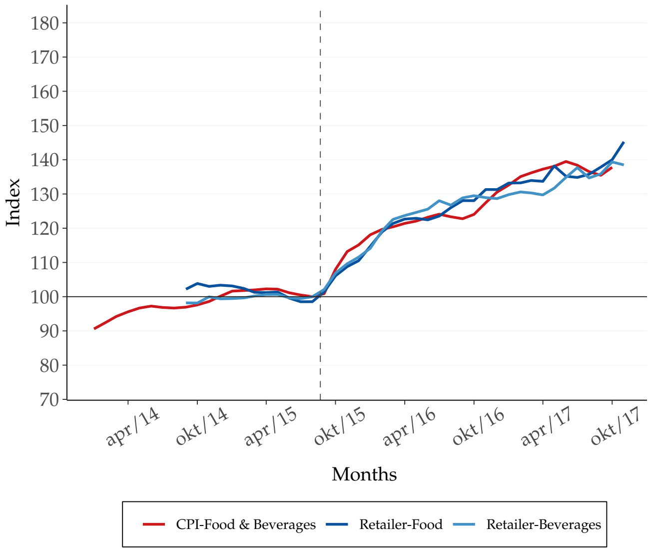
Notes: This table presents the results from estimating equation A.3. Standard errors are clustered at the variety level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

[75] These results are robust to including alternative sets of fixed effects.

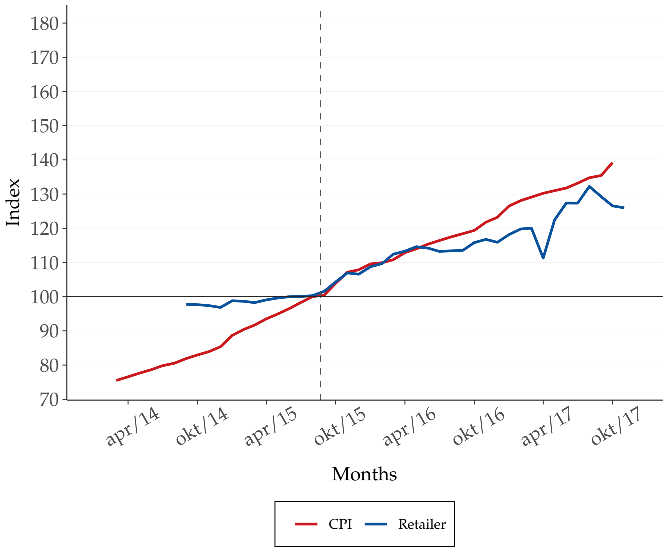
B Figures

Figure B.1: Price evolution comparison: Retailer vs CPI

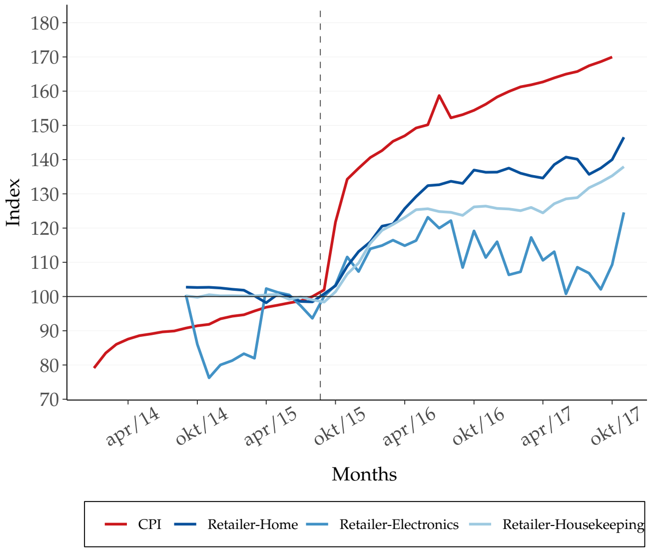
(a) Food & Non-alcoholic beverages



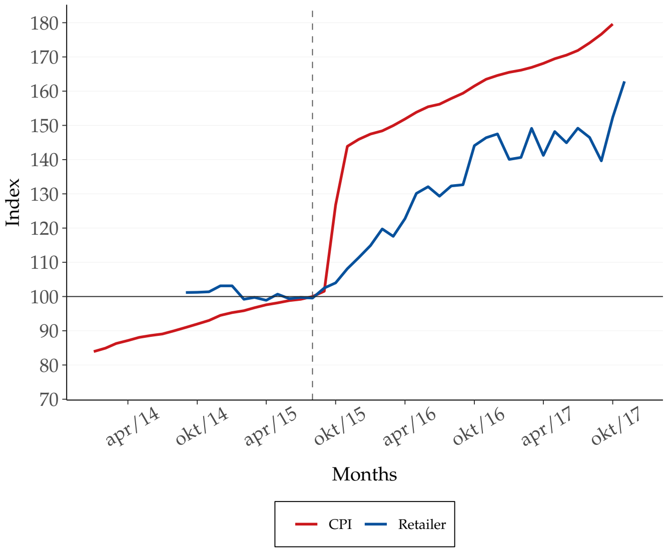
(b) Tobacco and Alcoholic beverages



(c) Household

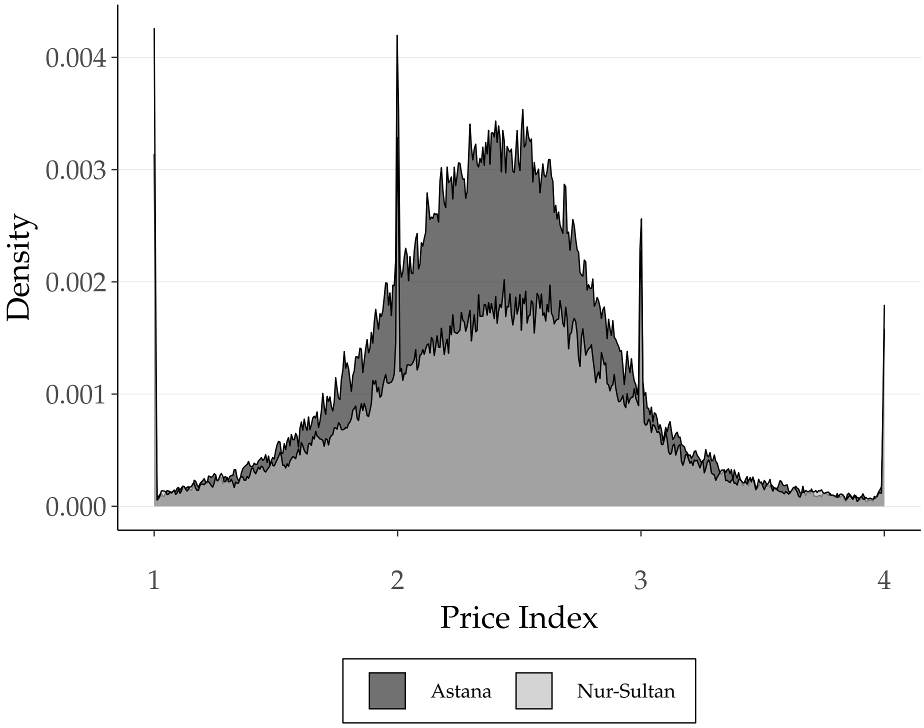


(d) Clothing



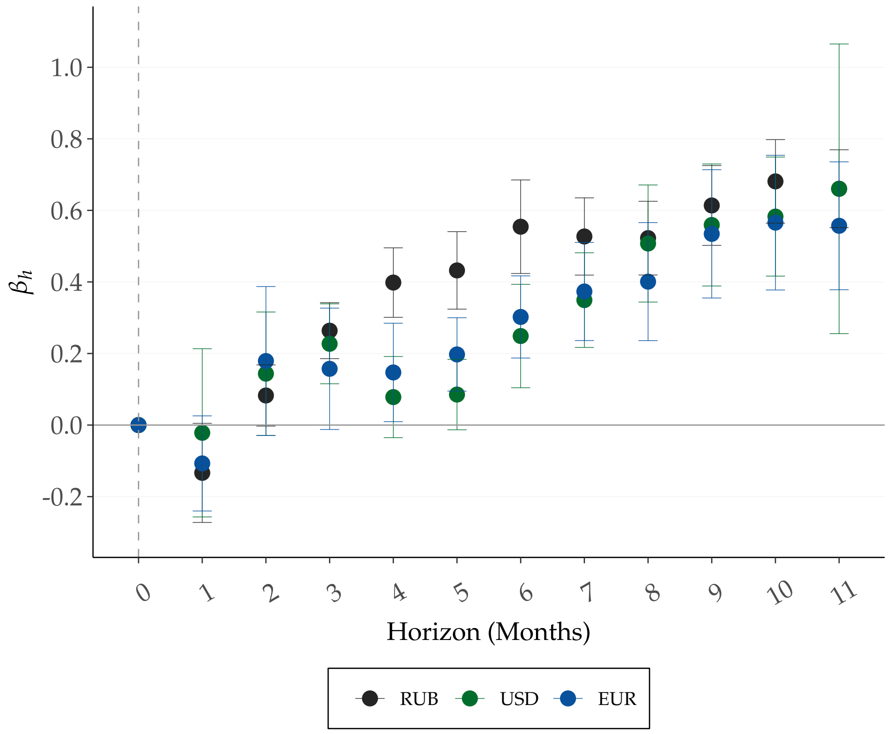
Notes: This figure compares the aggregate price evolution of the subset of broad expenditure categories that are covered by the retailer and the CPI. To mimic the construction of the CPI index as close as possible, these series are constructed using only continuing products, products that were present before and after the - devaluation. More precisely, for this excercise a continuing product is a product that had positive inventories before the devaluation and still had positive inventories one year after the devaluation. Also, we use product weights are computed from expenditure on these products before the devaluation.

Figure B.2: Distribution of Index across stores



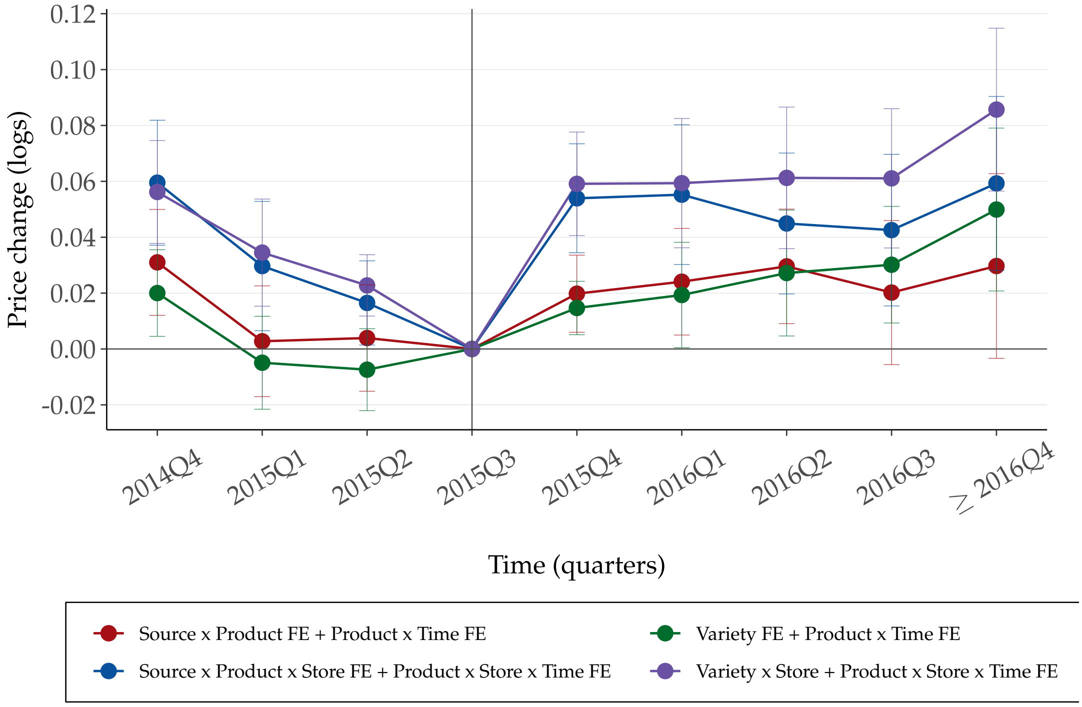
Notes: This figure displays the distribution of the expensiveness index across the stores in Almaty and Astana.

Figure B.3: Exchange Rate Pass-through: Currency of invoicing



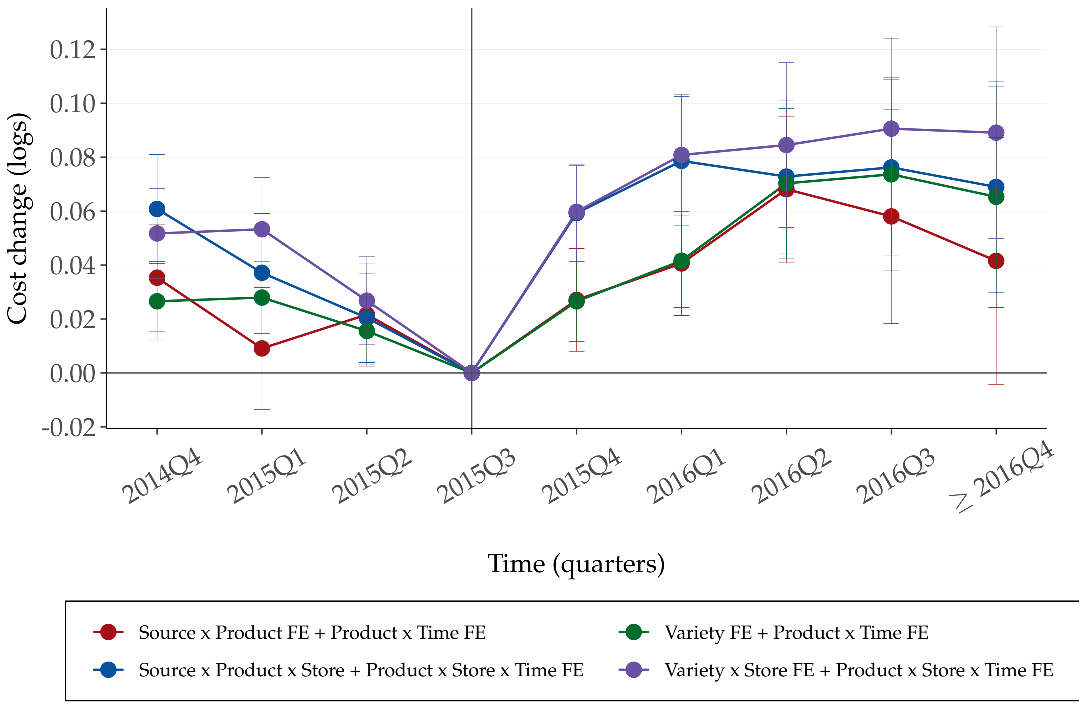
Notes: This figure shows the evolution of exchange rate pass-through into prices seperately for different currencies of invoicing. More specifically, we plot the coefficients β_h which are obtained from estimating equation 2. Whiskers are 95% confidence intervals around the point estimates computed from standard errors which are clustered at the product-store level.

Figure B.4: Difference-in-difference: Consumer Prices



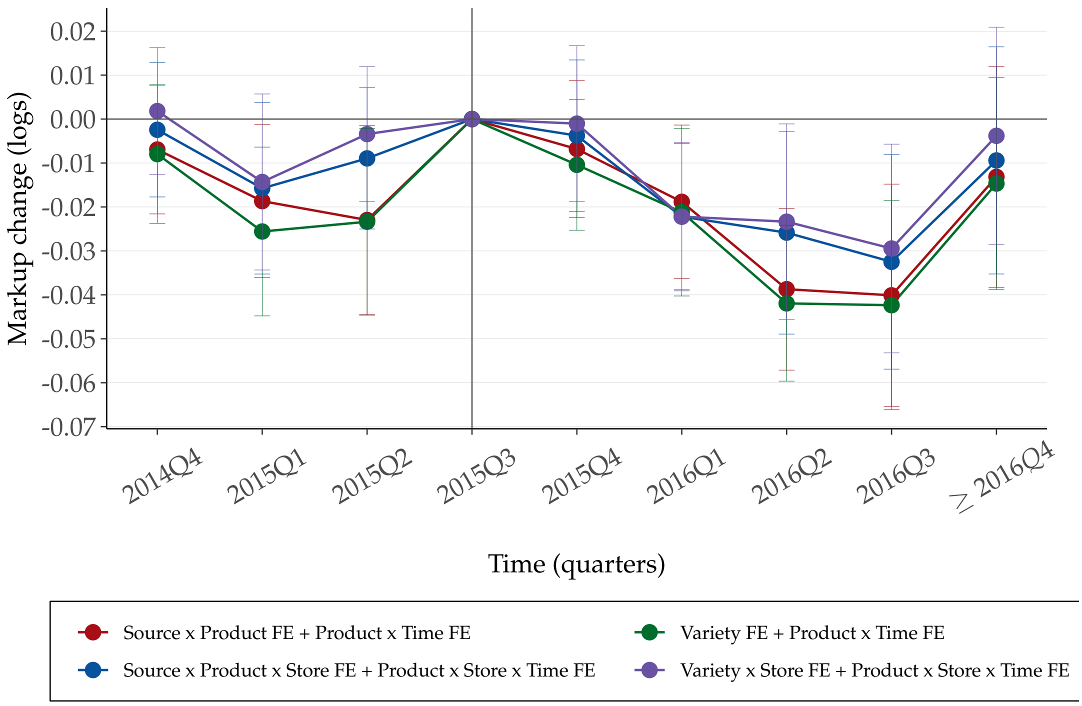
Notes: This figure shows the results from estimating equation 3 for consumer prices for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

Figure B.5: Difference-in-difference: Costs



Notes: This figure shows the results from estimating equation 3 for costs for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

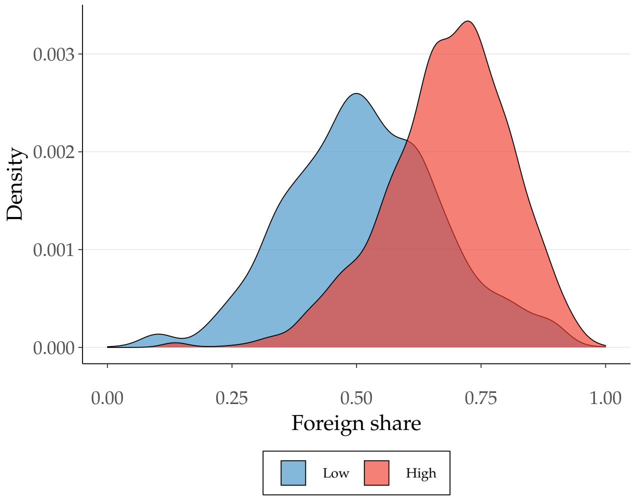
Figure B.6: Difference-in-difference: Markups



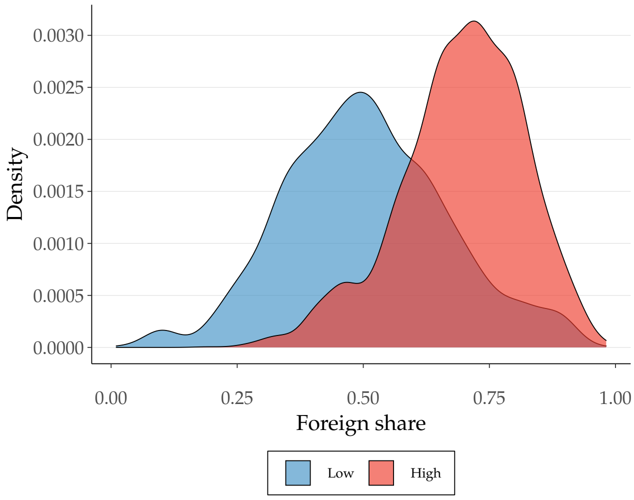
Notes: This figure shows the results from estimating equation 3 for markups for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are 95% condifence intervals based on standard errors that are clustered at the product category-origin level.

Figure B.7: Foreign share across consumers

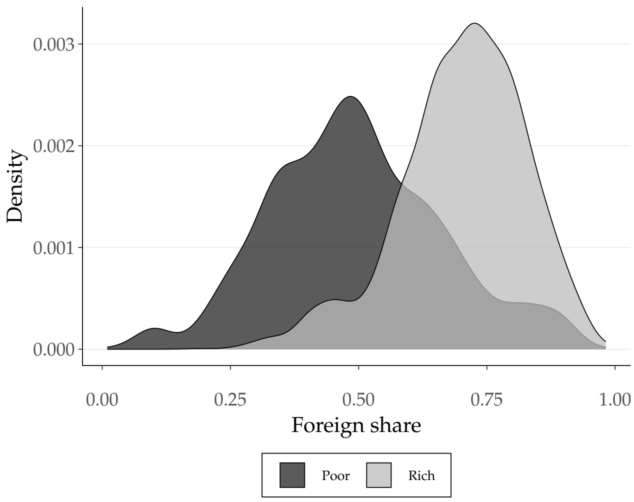
(a) Terciles: 33%-66% split



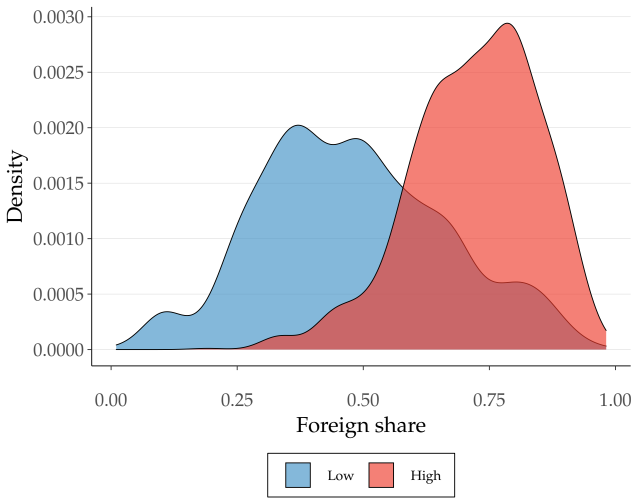
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split



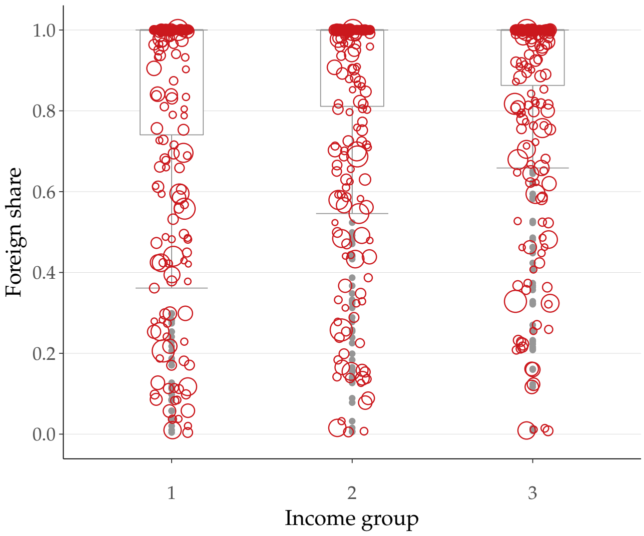
(d) Deciles: 10%-90% split



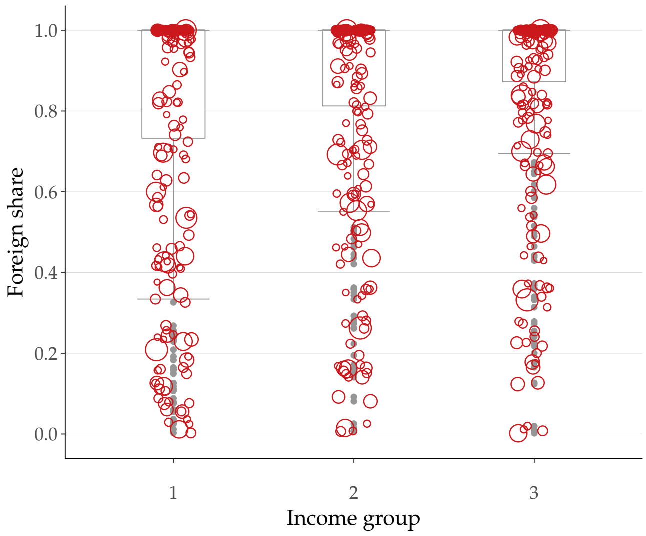
These figures display the distribution of the expenditure share on foreign varieties across consumers of the relatively low-income group (in blue) and for the relatively high-income group. We include food % non-alcoholic beverages and the frequent sample of consumers in the construction of these graphs. We show the same figure for different definitions of the income groups: (a) terciles, (b) quartiles, (c) quintiles and (d) deciles.

Figure B.8: Foreign share across products: Food & Non-alcoholic Beverages

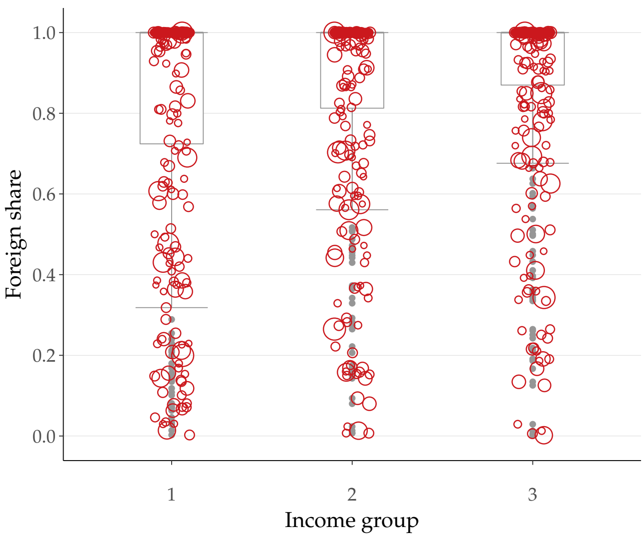
(a) Terciles: 33%-66% split



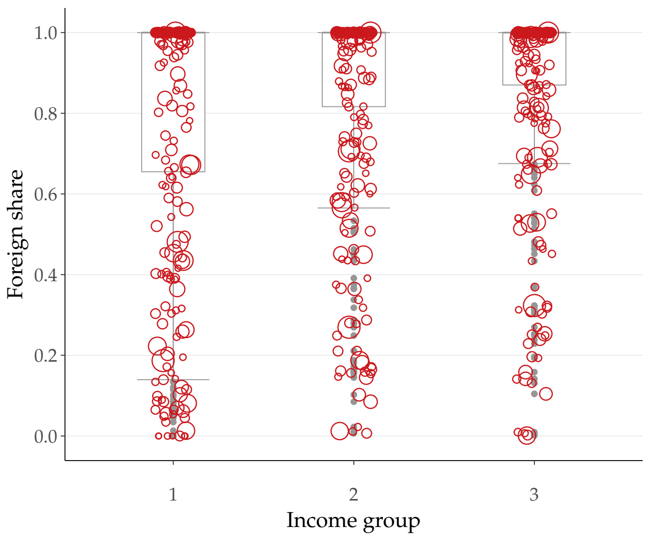
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split

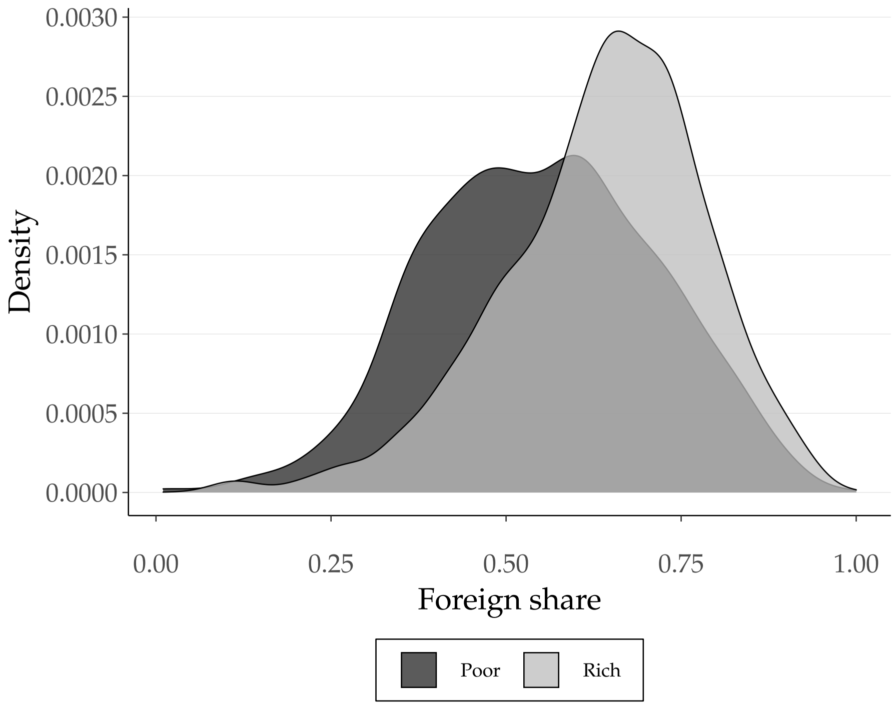


(d) Deciles: 10%-90% split



These figures display the distribution of the expenditure share on foreign varieties across detailed products seperately for three income groups: (1) relatively low-income consumers, (2) relatively middle income consumers and (3) relatively high income consumers. We include food % non-alcoholic beverages and the full sample of consumers in the construction of these graphs. We show the same figure for different definitions of the income groups: (a) terciles, (b) quartiles, (c) quintiles and (d) deciles.

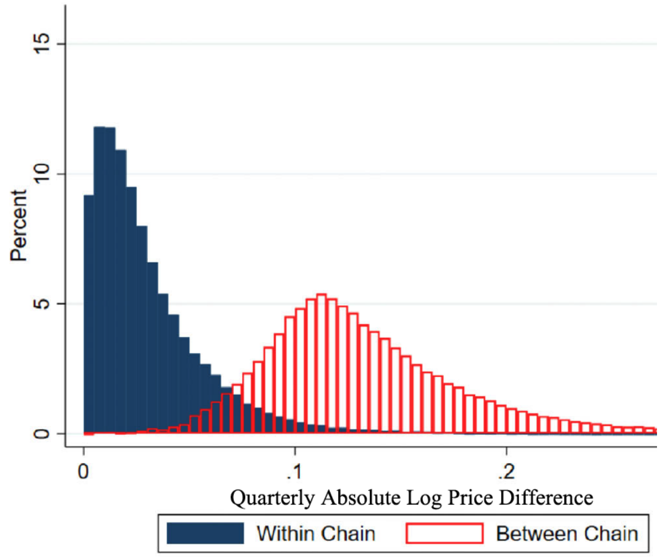
Figure B.9: Foreign share across income groups: Total Expenditures



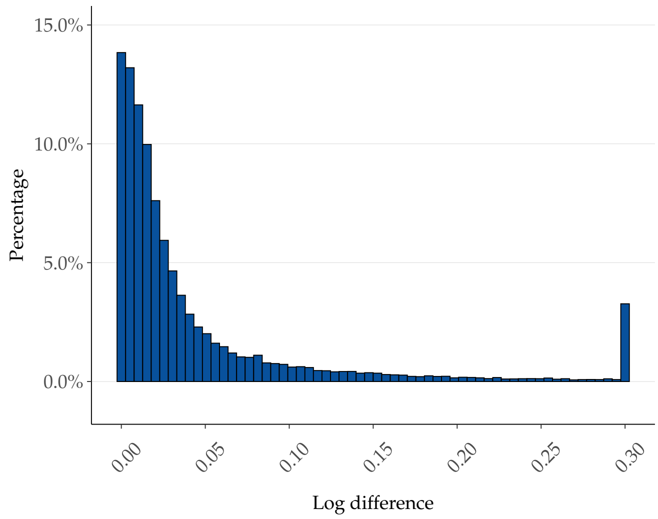
This figure displays the distribution of the expenditure share on foreign varieties across rich and poor consumers separately. Income classification was executed using total expenditures. We include food & non-alcoholic beverages and the frequent sample of consumers in the construction of these graphs.

Figure B.10: Absolute log price difference

(a) Dellavigna and Gentzkow (2019)



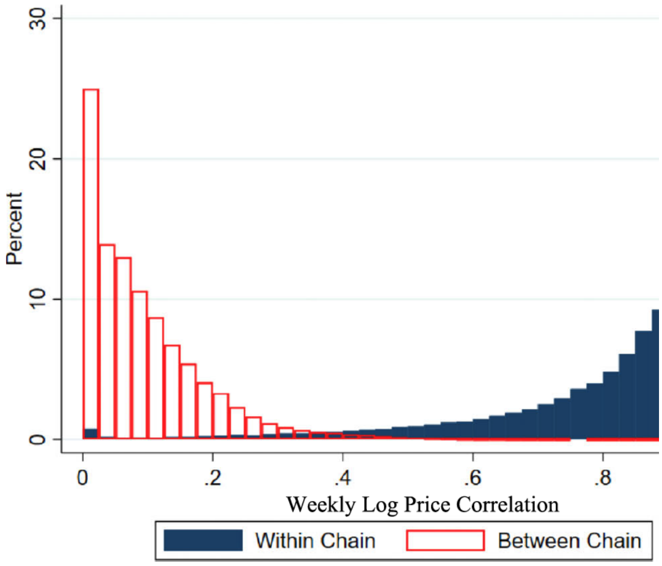
(b) Own retailer



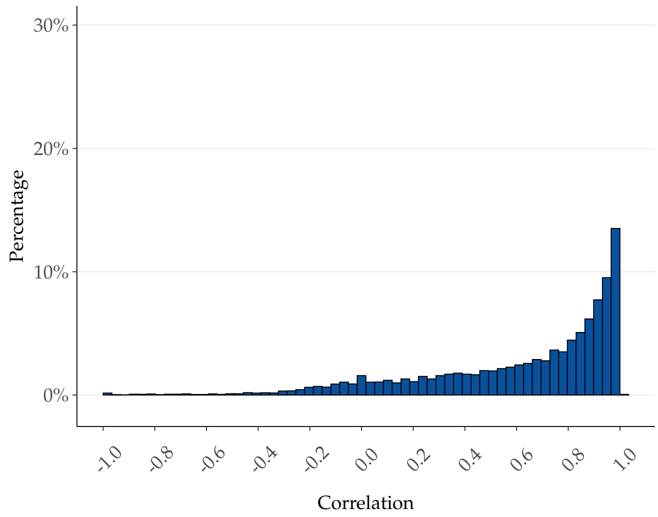
Notes: This figure plots the distribution of the average quarterly absolute difference in the price of an article in one store compared to the price of the same article in the other store. Panel (a) corresponds to Figure IIA from Dellavigna and Gentzkow (2019) and is taken directly from the paper. The blue graph corresponds to the distribution across two stores of the same retail chain and the red distribution is obtained from comparing prices of the same article across stores of two different retail chains. Panel (b) plots the same distribution for our dataset and shows a stark similarity with the blue distribution of panel (a).

Figure B.11: Log price correlation

(a) Dellavigna and Gentzkow (2019)



(b) Own retailer

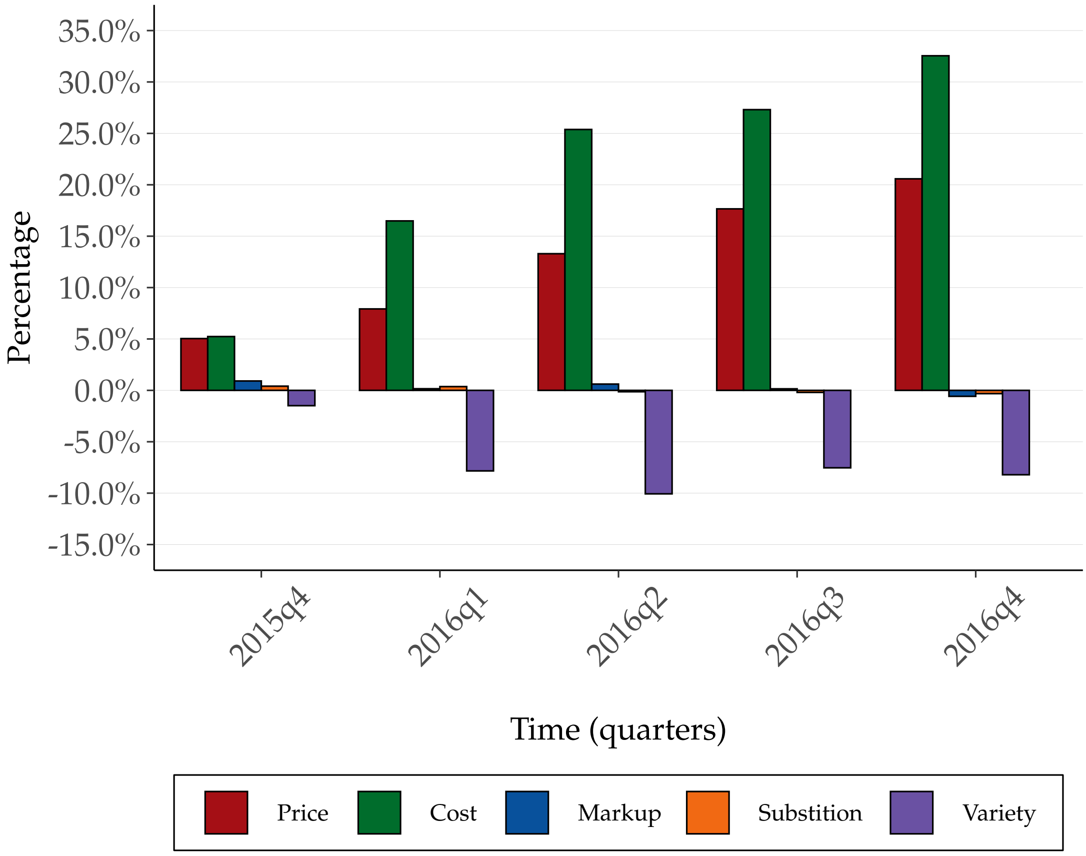


Notes: This figure plots the distribution of weekly correlation of log prices. This is obtained from purging the residuals from the following regression:

$$ln(p_{i,s,t}) = \alpha_{i,s,y} + \varepsilon_{i,s,t}$$

where $\alpha_{i,s,y}$ are store-article-year fixed effects and computing the correlation in $\varepsilon_{i,s,t}$ for each article. Panel (a) corresponds to Figure IIB from Dellavigna and Gentzkow (2019) and is taken directly from the paper. The blue graph corresponds to the distribution across two stores of the same retail chain and the red distribution is obtained from computing the correlation across stores of two different retail chains. Panel (b) plots the same distribution for our dataset using monthly data and shows a stark similarity with the blue distribution of panel (a).

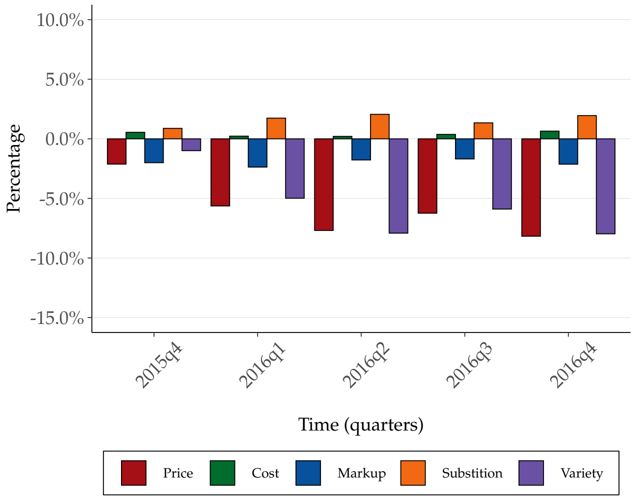
Figure B.12: Decomposition: Aggregate Effects - Heterogeneous



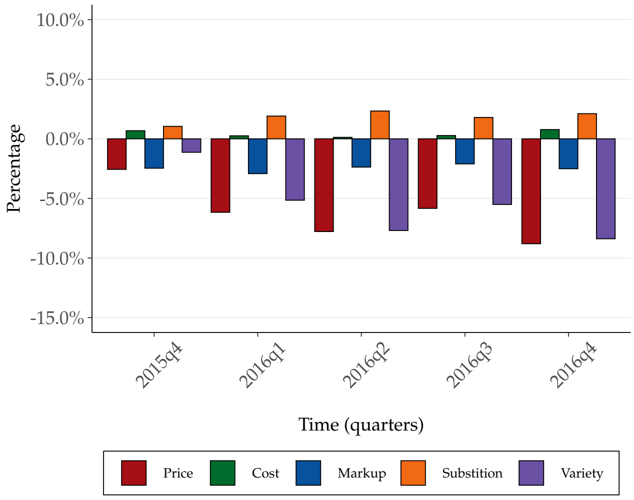
Notes: These figures show the aggregate results from the nested CES decomposition from equation 4 which are also presented in C.25. The results are obtained after pooling across all income groups and estimating the variety effects when we allow the elasticity of substitution to vary across subcategories categories. To be precise, we use the estimate of column (3) in Table C.24. We choose these results as the F-statistics are consistently above critical values of 10 or 15 and the elasticities are sensible across all subcategories. These effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015. The size of each bar is expressed in percentage differences and is obtained by subtracting 1 and multiplying by 100 each of the numbers in Table C.25.

Figure B.13: Decomposition: Distributional Effect

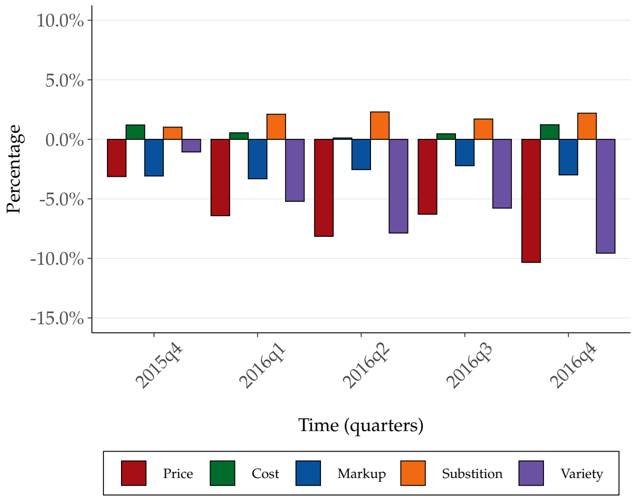
(a) Terciles: 33%-66% split



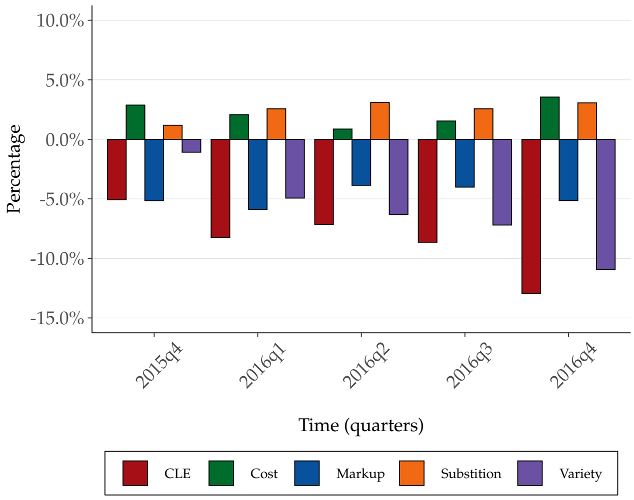
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split



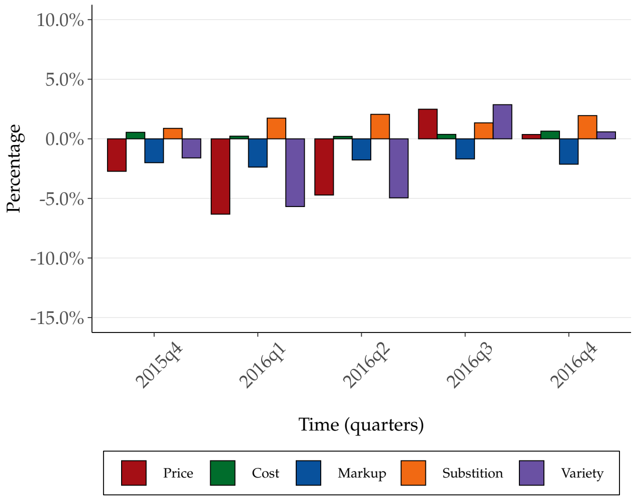
(d) Deciles: 10%-90% split



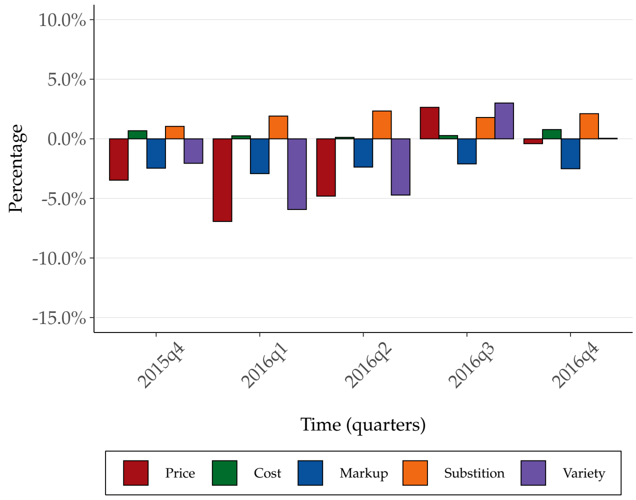
Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in Tables C.27 - C.30. The results are obtained by computing each of the components separately for each income group. Each of the panel shows the result for a different definition of the income groups. For instance, in panel (a) the relatively low-income group is defined as the set of consumers whose average expenditure is below the 33%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 66%-th percentile in this distribution. Panel (b), panel (c) and panel (d) do the same for the 25%-75%, 20%-80% and 10%-90% splits respectively. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. These effects are cumulative effects relative to the quarter before the devaluation, which is defined as June, July and August 2015 and coincide with the ratio column for each channel as displayed in Tables C.27 - C.30. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

Figure B.14: Decomposition: Distributional Effects - Heterogeneous

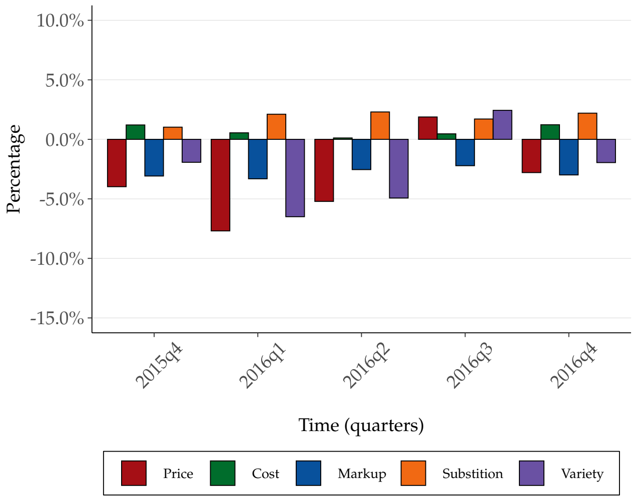
(a) Terciles: 33%-66% split



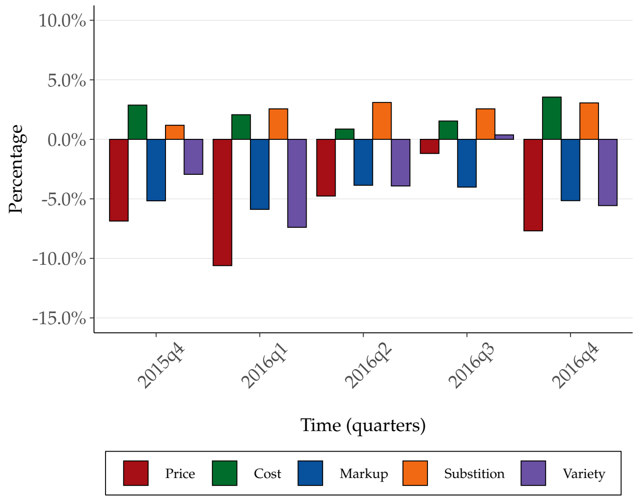
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split

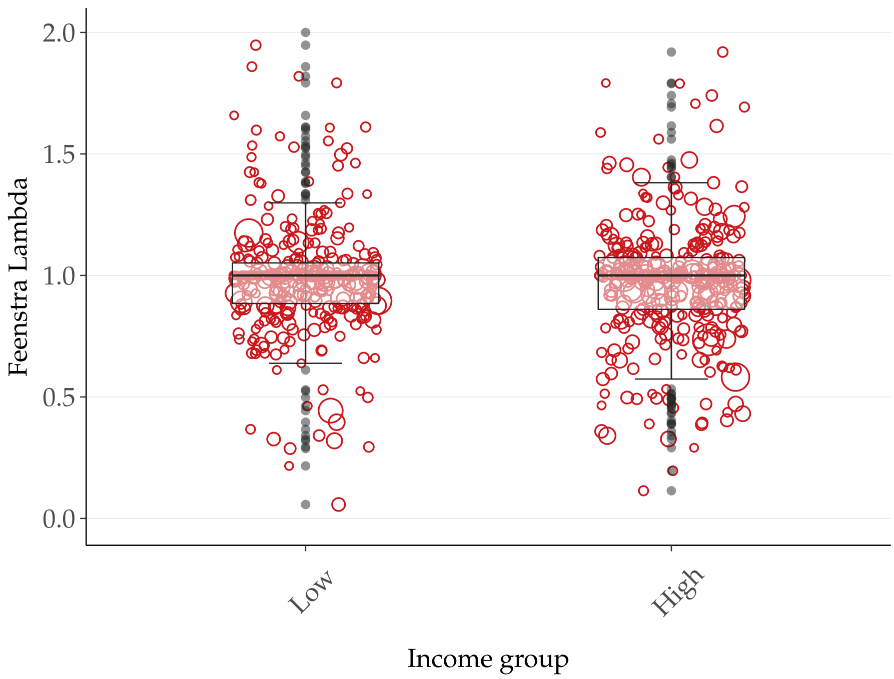


(d) Deciles: 10%-90% split



Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in Tables C.31 - C.34. The results are obtained by computing each of the components separately for each income group. Each of the panel shows the result for a different definition of the income groups. For instance, in panel (a) the relatively low-income group is defined as the set of consumers whose average expenditure is below the 33%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 66%-th percentile in this distribution. Panel (b), panel (c) and panel (d) do the same for the 25%-75%, 20%-80% and 10%-90% splits respectively. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. These effects are cumulative effects relative to the quarter before the devaluation, which is defined as June, July and August 2015 and coincide with the ratio column for each channel as displayed in Tables C.27 - C.30. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

Figure B.15: Feenstra ratios - Low vs High Income



p-value of Paired t-test of differences: 0.223. p-value of Paired Wilcoxon Rank Sum test of differences: 0.165

Notes:

C Tables

Table C.1: Mapping Table AC Nieslen to store type

AC Nielsen name	Store type
Urban Small Food & Mixed Stores	Small supermarket
Urban Kazakhstan RA+OM	Aggregate
Kazakhstan Urban RA+OM	Aggregate
Urban Large Food & Mixed Stores	Large supermarket
Urban Medium Food & Mixed Stores	Medium supermarket
Urban Kazakhstan RA (Retail)	Aggregate
URBAN KAZAKHSTAN RA+OMA	Aggregate
URBAN SMALL&KIOSKS&PAVILIONS&OMA	Small supermarket
Drug Kazakhstan RA+OM (with Pharm)	Aggregate
DRUG Kazakhstan RA+OM	Aggregate
Super/ Large Mixed stores	Large supermarket
Urban Open Markets	Open market
URBAN MEDIUM FOOD&MIXED STORES	Medium supermarket
Pharmacies	Pharmacy
PAV&NewsAg&Kiosks&OM Urban	Small supermarket
URBAN LARGE FOOD&MIXED STORES	Large supermarket
Perfumeries	Perfumerie
Medium/ Small Mixed Stores	Medium supermarket
Kiosks & Pavilions Urban	Small supermarket
Household Stores	Aggregate
Food Groceries	Aggregate
Households	Aggregate
Urban Petrol Stations	Small supermarket
Urban Kiosks & Pavilions	Small supermarket
Total Kazakhstan OM	Open market
Medium/Small Mixed Groceries	Small supermarket
Total Kazakhstan Groceries	Aggregate

Notes: AC Nielsen divides stores into the following categories: Large stores are stores with a floorspace above $100m^2$, medium stores between $25m^2$ and $100m^2$ and small stores as stores below $25m^2$ in floorspace. In addition, there kiosks and pavillions which are small stores without a fixed physical structure, pharmacies and perfumeries which focus on non-food and open markets which are small vendors selling in markethalls. In addition to these individual type of stores, the dataset also contains aggregates across different store types, e.g. RA+OM, which we denote as aggregates and which we omit from the analysis. We also omit food groceries, household (stores) as there is not enough information to classify these types of stores. Nevertheless, these omitted store types account for less than 0.5% of total expenditure.

Table C.2: Expenditure/month distribution

Quantile	KZT/month	USD/month	KZT/(week in a month)	USD/(week in a month)
Min	0.00	0.00	0.00	0.00
33 %	8,354.49	27.85	1,927.96	6.43
Median	13,455.55	44.85	3,105.13	10.35
66 %	20,147.18	67.16	4,649.35	15.50
90 %	46,475.09	154.92	10,725.02	35.75
95 %	68,538.47	228.46	15,816.57	52.72
99 %	202,443.19	674.81	46,717.66	155.73
99.9 %	1,435,570.09	4,785.23	331,285.41	1,104.28
Max	25,662,100.03	85,540.33	5,922,023.08	19,740.08

Notes: This table provides percentiles for the distribution of consumer expenditure per month across consumers that make at least one purchase over the sample period in one of the two stores that are covered in our database. We convert KZT into USD by dividing by 300 which is roughly the KZT/USD exchange rate after the devaluation. We convert expenditure per month into expenditure per week by multiplying the monthly figures by a factor 12/52.

Table C.3: Old versus new consumers

Before	Nr. consumers	Nr. Share	Exp. Share	Trans. share
No	53564	0.34	0.23	0.14
Yes	102886	0.66	0.77	0.86

Notes: This table shows the importance of the set of consumers that did shop ("Yes") did not shop ("No") at the retailer before the depreciation. The column "Nr. consumers" shows the number of consumers in each group and the column "Nr. share" expresses this statistic as a share. The columns "Exp. share" and "Trans. share" indicate the importance of each group of consumers when measured in terms of total expenditure and in terms of total transaction. All the statistics are computed by pooling across all time periods and all categories.

Table C.4: Sanity check on units

	Sales			Nr.		
Category	gr	ml	pc	gr	ml	pc
Bakery/Cereal	0.94	0.00	0.06	0.88	0.01	0.11
Candy	0.90	0.03	0.07	0.86	0.05	0.09
Coffee/Tea	0.98	0.00	0.02	0.92	0.00	0.08
Dairy	0.68	0.26	0.07	0.77	0.18	0.04
Dry food	1.00	0.00	0.00	0.99	0.00	0.01
Fish	0.99	0.00	0.01	0.98	0.00	0.02
Fruit	0.75	0.03	0.23	0.73	0.05	0.22
Meat	0.99	0.00	0.01	0.96	0.00	0.04
Ready-made	0.93	0.01	0.06	0.95	0.01	0.04
Savoury	0.98	0.02	0.00	0.94	0.06	0.00
Seasoning	0.49	0.49	0.02	0.76	0.21	0.03
Soft drinks	0.00	1.00	0.00	0.01	0.99	0.00
Vegetables	0.75	0.09	0.16	0.76	0.11	0.13
Water	0.00	1.00	0.00	0.00	1.00	0.00

Notes: This table provides an overview of the distribution across possible units: (1) volume (ml), (2) weight (gr) and (3) per piece (pc) for each subcategory in food & non-alcoholic beverages. Column 2 to 4 do so by weighting the distribution by sales and columns 5 to 7 do so by counting the number articles per type of unit.

Table C.5: Frequent versus Full sample: Importance

Sample	Nr. consumers	Nr. share	Sales share	Trans. share
Out	97208	0.95	0.73	0.73
In	5040	0.05	0.27	0.27

Notes: This table shows the importance of the set of consumers that are in the frequent and outside of the frequent sample. The column "Nr. consumers" shows the number of consumers in each group and the column "Nr. share" expresses this statistic as a share. The columns "Exp. share" and "Trans. share" indicate the importance of each group of consumers when measured in terms of total expenditure and in terms of total transaction. All the statistics are computed by pooling across all time periods and all categories.

Table C.6: Frequent versus Full sample: Statistics

	Frequent		Complete	
Statistic	Mean	Std.	Mean	Std.
Consumers (nr)	5,040	-	94,838	-
Index	2.44	0.32	2.44	0.41
Foreign share	0.60	0.15	0.61	0.24
Branded share	0.96	0.05	0.95	0.09
Categories (nr)	2.00	0.04	1.86	0.34
Subcategories (nr)	13.66	0.80	9.52	3.93
Product groups (nr)	62.26	13.16	26.85	18.92
Products (nr)	134.74	47.46	42.42	38.13
Exp. per visit (KZT)	18,829.68	18,369.24	10,077.76	12,052.20
Volume per visit (Units)	39.60	43.75	21.40	33.61
Exp. per visit and per category (KZT)	9,418.21	9,185.71	5,334.96	6,714.39
Exp. per visit and per subcategory (KZT)	1,366.51	1,327.23	1,144.62	2,987.20

Notes: This table compares certain observable characteristic across consumers which are in the frequent sample (Frequent) and the ones which are left out of the frequent sample (Complete). These statistic are computed solely based on pruchases of food and beverages, but are qualitatively the same when we include food and beverages consumption.

Table C.7: CPI expenditure weights

Component	CPI
Food & Beverages	0.34
Alcohol & Tobacco	0.04
Clothing	0.12
Household	0.05
Housing	0.17
Education	0.03
Healthcare	0.03
Transportation	0.09
Communaction services	0.03
Recreative activities	0.04
Bar, Restaurants and Hotels	0.02
Miscallenous services	0.05

Notes: This table shows the publicly available expenditure weights across broad categories used to compute the Kazakh CPI. The weights are obtained from the Kazakh National bank and represent averages over the years 2014 and 2015.

Table C.8: Comparison: Retail sales shares and CPI expenditure weights

Component	CPI	Retailer
Food & Beverages	0.62	0.61
Alcohol & Tobacco	0.07	0.12
Clothing	0.22	0.02
Household	0.09	0.24

Notes: This table compares the sales share of the retailer to the expenditure share of the corresponding CPI categories. In this table the expenditure shares of the CPI are reweighted according to the total share of this subset of categories in the CPI. More concretely, Table C.7 shows that these categories make up around 55 % of all CPI expenditure and thus the numbers in column 2 correspond to the shares in column 2 of Table C.7 divided by 0.55.

Table C.9: Kazakhstan - Exports

Nr.	Commodity	SITC (3-Digit)	Share (%)	Cumm. Share (%)
1	Crude and Bituminous Oil	333	58.26	58.26
2	Gas, natural and manufactured	341	5.19	63.45
3	Radioactive Material	524	5.12	68.57
4	Copper	682	4.27	72.84
5	Refined Petroleum Products	334	3.01	75.85
6	Iron and Ferro-Alloys	671	2.96	78.8
7	Ores and concentrates of base metals, nes	287	2.14	80.95
8	Iron and Steel plates/sheets	674	1.66	82.61
9	Wheat and meslin, unmilled	41	1.5	84.1
10	Zinc	686	1.25	85.36
11	Meal/Flour of wheat/meslin	46	1.08	86.43
12	Silver and Platinum metals	681	1.06	87.49
13	Coal, lignite and peat	322	1.06	88.55
14	Iron ore and concentrates	281	.88	89.43
15	Aluminium	684	.87	90.3
16	Oxides and Halogen Salts	522	.77	91.07
17	Sulphur and unroasted iron pyrites	274	.71	91.78
18	Iron and Steel (primary forms)	672	.61	92.4
19	Gold (not ores or concentrates)	971	.46	92.86
20	Lead	685	.41	93.27

Notes: The data is taken from UN Comtrade. The table presents the top 20 of most exported commodities by Kazakh companies in 2015. The share and cummulative share are calculated with respect to the total export of Kazakhstan in 2015 as reported by UN Comtrade.

Table C.10: Currency shares of Imported Products

USD	RUB	EUR	GBP
0.17	0.61	0.22	0.00

Notes: This table provides the sales weighted distribution (including all products) across the currencies of invoicing used by the retailer on direct imports.

Table C.11: Pass-through: Consumer Prices

Horizon	β_h	SE	N	R^2
h=1	0.0494	(0.031)	21,261	0.002
h=2	0.19***	(0.021)	20,437	0.049
h=3	0.289***	(0.034)	19,969	0.102
h=4	0.336***	(0.036)	19,508	0.101
h=5	0.372***	(0.033)	18,288	0.159
h=6	0.482***	(0.039)	17,554	0.180
h=7	0.513***	(0.032)	17,191	0.234
h=8	0.565***	(0.037)	16,784	0.309
h=9	0.596***	(0.034)	16,210	0.308
h=10	0.564***	(0.027)	15,674	0.360
h=11	0.562***	(0.031)	15,171	0.305
h=12	0.599***	(0.053)	14,684	0.120

Notes: This table shows the results from estimating equation 2 which are also shown in Figure 3. Standard errors are clusted at the product category level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table C.12: Pass-through: Currency of Invoicing

	RUB				EUR				USD			
Horizon	β_h	SE	N	R^2	β_h	SE	N	R^2	β_h	SE	N	R^2
h=1	-0.134*	(0.071)	3,463	0.004	-0.0217	(0.119)	273	-0.003	-0.107	(0.068)	763	0.017
h=2	0.0827*	(0.044)	3,187	0.004	0.144	(0.087)	232	0.074	0.179*	(0.106)	648	0.028
h=3	0.264***	(0.040)	3,070	0.068	0.227***	(0.057)	211	0.322	0.157*	(0.086)	581	0.036
h=4	0.398***	(0.050)	2,957	0.106	0.0781	(0.058)	217	0.057	0.147**	(0.070)	547	0.048
h=5	0.432***	(0.055)	2,722	0.136	0.0852*	(0.050)	190	0.082	0.197***	(0.052)	469	0.135
h=6	0.554***	(0.067)	2,535	0.166	0.249***	(0.073)	170	0.336	0.302***	(0.058)	437	0.259
h=7	0.527***	(0.055)	2,367	0.207	0.349***	(0.067)	216	0.413	0.373***	(0.070)	424	0.279
h=8	0.523***	(0.053)	2,280	0.220	0.507***	(0.083)	249	0.464	0.401***	(0.084)	379	0.219
h=9	0.614***	(0.057)	2,162	0.254	0.559***	(0.087)	259	0.524	0.534***	(0.091)	348	0.335
h=10	0.681***	(0.060)	2,052	0.307	0.583***	(0.085)	257	0.512	0.566***	(0.096)	324	0.370
h=11	0.661***	(0.056)	1,974	0.325	0.66***	(0.206)	245	0.123	0.557***	(0.091)	309	0.394
h=12	0.695***	(0.052)	1,961	0.362	0.498***	(0.094)	218	0.492	0.525***	(0.089)	300	0.361

Notes: This table shows the results from estimating equation 2 which are also shown in Figure B.3. Standard errors are clusted at the product category level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table C.13: Foreign share

Quarter	Quantity	Sales
2014Q4	0.474	0.605
2015Q1	0.500	0.628
2015Q2	0.527	0.625
2015Q3	0.474	0.580
2015Q4	0.491	0.594
2016Q1	0.520	0.623
2016Q2	0.502	0.609
2016Q3	0.461	0.585
2016Q4	0.458	0.597
2017Q1	0.446	0.595
2017Q2	0.422	0.577
2017Q3	0.441	0.595
2017Q4	0.447	0.601

Notes: This table shows the expenditure share on foreign and local products over time. These shares are computed as the ratio of total sales on foreign or local products divided by total sales on all products in the same time period. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table C.14: Sample attrition

	Sales				Nr.			
Subcategory	Continuing	Exit	Entry	Temporary	Continuing	Exit	Entry	Temporary
Bakery/Cereal	0.77	0.08	0.15	0.01	0.35	0.23	0.37	0.05
Candy	0.74	0.08	0.16	0.02	0.31	0.22	0.42	0.04
Dairy	0.82	0.05	0.13	0.00	0.40	0.28	0.30	0.02
Dry food	0.68	0.10	0.22	0.00	0.38	0.34	0.26	0.02
Fish	0.77	0.09	0.13	0.01	0.40	0.38	0.19	0.04
Fruit	0.64	0.10	0.24	0.02	0.24	0.38	0.30	0.08
Meat	0.57	0.12	0.30	0.00	0.24	0.36	0.36	0.05
Ready-made	0.67	0.16	0.17	0.00	0.31	0.40	0.27	0.01
Savoury	0.80	0.04	0.16	0.00	0.39	0.19	0.40	0.02
Seasoning	0.70	0.14	0.15	0.00	0.38	0.31	0.28	0.03
Vegetables	0.70	0.09	0.16	0.06	0.34	0.32	0.26	0.08
Coffee/Tea	0.92	0.02	0.06	0.00	0.50	0.16	0.32	0.02
Soft drinks	0.90	0.05	0.06	0.00	0.44	0.25	0.30	0.02
Water	0.89	0.08	0.03	0.00	0.61	0.10	0.27	0.01

Notes: This table shows the expenditure shares measured in sales (columns 2 to 5) and in number of products (columns 6 to 9) across subcategories for the full sample of consumers. In this table, we loosely define continuing products as products that were present before the devaluation and were still present in the sample one year after the devaluation. Exiting products are products that were present before the devaluation, but were not present anymore after one after the devaluation. Entering products were not present before the devaluation, but entered within one year after the devaluation. Finally, there is a small group of temporary products which are products that were not present before the devaluation, entered within one year after the devaluation, but also exited within one year after the devaluation. The presence of a product is determined by its first and last period in which we observe a change in the inventory for that article.

Table C.15: Difference-in-difference results: Consumer prices

$p_{i,p,t}$	(1)	(2)	(3)	(4)
2014Q4 x Foreign	0.031***	0.0595***	0.02**	0.0562***
	(0.010)	(0.011)	(0.008)	(0.009)
2015Q1 x Foreign	0.00276	0.0297**	-0.00492	0.0345***
	(0.010)	(0.012)	(0.008)	(0.010)
2015Q2 x Foreign	0.00392	0.0165**	-0.0074	0.0228***
	(0.010)	(0.008)	(0.007)	(0.006)
2015Q3 x Foreign	-	-	-	-
2015Q4 x Foreign	0.0198***	0.0539***	0.0147***	0.0591***
	(0.007)	(0.010)	(0.005)	(0.009)
2016Q1 x Foreign	0.0241**	0.0552***	0.0193**	0.0594***
	(0.010)	(0.013)	(0.010)	(0.012)
2016Q2 x Foreign	0.0296***	0.0449***	0.0272**	0.0612***
	(0.010)	(0.013)	(0.011)	(0.013)
2016Q3 x Foreign	0.0202	0.0425***	0.0302***	0.0611***
	(0.013)	(0.014)	(0.011)	(0.013)
$\geq$ 2016Q4 x Foreign	0.0297*	0.0593***	0.0499***	0.0857***
	(0.017)	(0.016)	(0.015)	(0.015)
Product x Source FE	✓			
Product x Source x Store FE		✓		
Variety FE			✓	
Variety x Store FE				✓
Product x Month FE	✓		✓	
Product x Month x Store FE		✓		✓
R sq.	0.712	0.710	0.984	0.983
Nr. obs	210,757	210,757	210,757	210,757

Notes: This table shows the difference-in-difference estimates after estimating equation 3 for consumer prices. Regressions are weighted by pre-devaluation expenditure shares and standard errors are clustered at the product category-origin level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table C.16: Difference-in-difference results: Cost

$c_{i,p,t}$	(1)	(2)	(3)	(4)
2014Q4 x Foreign	0.0353***	0.0608***	0.0266***	0.0517***
	(0.010)	(0.010)	(0.008)	(0.008)
2015Q1 x Foreign	0.0091	0.0371***	0.0279***	0.0533***
	(0.012)	(0.011)	(0.007)	(0.010)
2015Q2 x Foreign	0.0216**	0.0204**	0.0156**	0.0268***
	(0.010)	(0.008)	(0.006)	(0.008)
2015Q3 x Foreign	-	-	-	-
2015Q4 x Foreign	0.0271***	0.0593***	0.0266***	0.0597***
	(0.010)	(0.009)	(0.008)	(0.009)
2016Q1 x Foreign	0.0406***	0.0786***	0.0416***	0.0808***
	(0.010)	(0.012)	(0.009)	(0.011)
2016Q2 x Foreign	0.0681***	0.0728***	0.0703***	0.0845***
	(0.014)	(0.014)	(0.014)	(0.016)
2016Q3 x Foreign	0.058***	0.0762***	0.0736***	0.0905***
	(0.020)	(0.017)	(0.018)	(0.017)
$\geq$ 2016Q4 x Foreign	0.0415*	0.0689***	0.0653***	0.0891***
	(0.023)	(0.020)	(0.021)	(0.020)
Product x Source FE	✓			
Product x Source x Store FE		✓		
Variety FE			✓	
Variety x Store FE				✓
Product x Month FE	✓		✓	
Product x Month x Store FE		✓		✓
R sq.	0.678	0.676	0.962	0.968
Nr. obs	208,883	208,883	208,883	208,883

Notes: This table shows the difference-in-difference estimates after estimating equation 3 for costs. Regressions are weighted by pre-devaluation expenditure shares and standard errors are clustered at the product category-origin level. Significance levels are denoted at the 10% (*), 5% (**) and 1% (***) level.

Table C.17: Difference-in-difference results: Markups

$\mu_{i,p,t}$	(1)	(2)	(3)	(4)
2014Q4 x Foreign	-0.00693	-0.00244	-0.00797	0.00183
	(0.007)	(0.008)	(0.008)	(0.007)
2015Q1 x Foreign	-0.0187**	-0.0158	-0.0256***	-0.0143
	(0.009)	(0.010)	(0.010)	(0.010)
2015Q2 x Foreign	-0.023**	-0.00894	-0.0234**	-0.00341
	(0.011)	(0.008)	(0.011)	(0.008)
2015Q3 x Foreign	-	-	-	-
2015Q4 x Foreign	-0.00682	-0.00376	-0.0104	-0.00103
	(0.008)	(0.009)	(0.008)	(0.009)
2016Q1 x Foreign	-0.0188**	-0.0222***	-0.0212**	-0.0222***
	(0.009)	(0.008)	(0.010)	(0.009)
2016Q2 x Foreign	-0.0387***	-0.0258**	-0.0419***	-0.0234**
	(0.009)	(0.012)	(0.009)	(0.011)
2016Q3 x Foreign	-0.0401***	-0.0325***	-0.0424***	-0.0295**
	(0.013)	(0.012)	(0.012)	(0.012)
$\geq$ 2016Q4 x Foreign	-0.0132	-0.00941	-0.0147	-0.00381
	(0.013)	(0.013)	(0.012)	(0.013)
Product x Source FE	✓			
Product x Source x Store FE		✓		
Variety FE			✓	
Variety x Store FE				✓
Product x Month FE	✓		✓	
Product x Month x Store FE		✓		✓
R sq.	0.229	0.242	0.470	0.562
Nr. obs	208,883	208,883	208,883	208,883

Notes: This table shows the difference-in-difference estimates after estimating equation 3 for markups. Regressions are weighted by pre-devaluation expenditure shares and standard errors are clustered at the product category-origin level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table C.18: Foreign share across income groups: t-test

Level	Statistic	Low vs. Middle	Low vs. High	Middle vs. High
Terciles	stat	(-5.11)***	(-6.82)***	(-5.99)***
	p	0.000	0.000	0.000
	nr	287	287	287
Quartiles	stat	(-5.39)***	(-7.01)***	(-6.5)***
	p	0.000	0.000	0.000
	nr	287	287	287
Quintiles	stat	(-5.65)***	(-7.24)***	(-4.18)***
	p	0.000	0.000	0.000
	nr	287	287	287
Deciles	stat	(-6.69)***	(-6.89)***	(-2.05)
	p	0.000	0.000	0.123
	nr	287	287	287

Notes: This table provides the results from a t-test to test whether the distributions of the foreign hare across product is different for the different income groups. The definition of the income group classification is the baseline 20%-80% split. Standard errors are reported below the coefficients and are corrected for multiple testing by applying the Bonferroni correction. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.19: Foreign share across income groups: Paired Wilcoxon Rank Sum test

Level	Statistic	Low vs. Middle	Low vs. High	Middle vs. High
Terciles	stat	(804)***	(378)***	(753)***
	p	0.000	0.000	0.000
	nr	287	287	287
Quartiles	stat	(901)***	(386)***	(709)***
	p	0.000	0.000	0.000
	nr	287	287	287
Quintiles	stat	(795)***	(392)***	(730)***
	p	0.000	0.000	0.000
	nr	287	287	287
Deciles	stat	(729)***	(725)***	(1100)***
	p	0.000	0.000	0.000
	nr	287	287	287

Notes: This table provides the results from a non-parametric Paired Wilcoxon Rank Sum test to test whether the distributions of the foreign share across product is different for the different income groups. The definition of the income group classification is the baseline 20%-80% split. Standard errors are reported below the coefficients and are corrected for multiple testing by applying the Bonferroni correction. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.20: Aggregate elasticity of substitution

	OLS				2SLS			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t}$	-2.24 ***	-2.15 ***	-1.43 ***	-1.31 ***	-3.17 ***	-3.08 ***	-1.55 ***	-1.41 ***
	(0.120)	(0.117)	(0.100)	(0.086)	(0.204)	(0.189)	(0.122)	(0.097)
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Store FE			✓				✓	
Product x Month x Store FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Store FE			✓	✓			✓	✓
First stage F-stat	-	-	-	-	822.1	682.7	5,278.2	5,243.1
R sq.	0.056	0.070	0.055	0.071	0.056	0.070	0.056	0.071
Nr,. obs	769,717	769,717	769,717	769,717	620,806	620,806	620,806	620,806

Notes: This table shows the estimates of the elasticities of substitution pooled across product categories and pooled across consumers. Column (1) - (4) are OLS estimates and column (5) - (8) are 2SLS estimates using the Hausman-instrument as an instrument. Standard errors are reported below the coefficient in brackets and are clustered at the monthly level. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.21: Decomposition of Aggregate effect - Homogeneous

Quarter	Price	Cost	Markup	Substitution	Variety
2015q4	1.06	1.05	1.01	1.00	0.99
2016q1	1.12	1.16	1.00	1.00	0.96
2016q2	1.18	1.25	1.01	1.00	0.94
2016q3	1.20	1.27	1.00	1.00	0.94
2016q4	1.23	1.33	0.99	1.00	0.94

Notes: This table shows the aggregate results from the nested CES decomposition in equation 4 which are also presented in 9. The results are obtained after pooling across all income groups and estimating the variety effects when we restrict the elasticity of substitution to be the same across all product categories. To be precise, we use the estimate of column (5) in Table 2. These effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.22: Elasticity of substitution (20% - 80% split) - Per Income Group

	OLS				2SLS			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot I(\text{Low})$	-3.65 ***	-3.51 ***	-2.35 ***	-2.28 ***	-5.2 ***	-5.18 ***	-2.51 ***	-2.53 ***
	(0.164)	(0.172)	(0.135)	(0.120)	(0.431)	(0.495)	(0.234)	(0.214)
First stage F-stat	-	-	-	-	512.8	377.7	2,882.9	2,561.9
R sq.	0.034	0.054	0.018	0.043	0.033	0.056	0.014	0.041
Nr. obs	190,063	190,063	190,063	190,063	151,759	151,759	151,759	151,759
$p_{i,p,t} \cdot I(\text{Middle})$	-2.34 ***	-2.29 ***	-1.57 ***	-1.43 ***	-3.17 ***	-3.15 ***	-1.7 ***	-1.52 ***
	(0.151)	(0.146)	(0.116)	(0.108)	(0.238)	(0.217)	(0.137)	(0.114)
First stage F-stat	-	-	-	-	862.3	715.1	5,487.0	5,233.7
R sq.	0.104	0.120	0.100	0.120	0.108	0.127	0.106	0.128
Nr. obs	329,014	329,014	329,014	329,014	264,839	264,839	264,839	264,839
$p_{i,p,t} \cdot I(\text{Top})$	-1.24 ***	-1.14 ***	-0.964 ***	-0.82 ***	-2.22 ***	-2.17 ***	-1.22 ***	-1.06 ***
	(0.132)	(0.142)	(0.105)	(0.096)	(0.262)	(0.277)	(0.150)	(0.156)
First stage F-stat	-	-	-	-	773.3	641.0	4,712.5	4,510.6
R sq.	0.052	0.069	0.045	0.066	0.056	0.073	0.047	0.068
Nr. obs	250,640	250,640	250,640	250,640	204,208	204,208	204,208	204,208
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Store FE			✓				✓	
Product x Month x Store FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Store FE			✓	✓			✓	✓

Notes: This table shows the estimates of the elasticities of substitution for each income group seperately, but pooled across product categories. The results per income group are obtained by estimating 6 separately for each income group. Panel (a) shows the results for the relatively low income group, panel (c) for the relatively high income group and panel (b) for consumer classified in the middle income group. from estimatin equation Column (1) - (4) are OLS estimates and column (5) - (8) are 2SLS estimates using the Hausman-instrument as an instrument. Standard errors are reported below the coefficient in brackets and are clustered at the monthly level. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.23: Elasticity of substitution (20% - 80% split) - Per Income Group

	OLS				2SLS			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot I(\text{Low})$	-2.99 ***	-2.76 ***	-2.26 ***	-2.26 ***	-4.91 ***	-4.71 ***	-2.9 ***	-3.24 ***
	(0.304)	(0.328)	(0.233)	(0.263)	(0.562)	(0.686)	(0.305)	(0.370)
First stage F-stat	-	-	-	-	253.2	145.6	1,250.3	891.2
R sq.	-0.005	0.016	-0.021	0.007	-0.008	0.014	-0.028	0.004
Nr. obs	132,768	132,768	132,768	132,768	104,803	104,803	104,803	104,803
$p_{i,p,t} \cdot I(\text{Middle})$	-2.47 ***	-2.45 ***	-1.66 ***	-1.55 ***	-3.46 ***	-3.51 ***	-1.87 ***	-1.76 ***
	(0.142)	(0.148)	(0.079)	(0.084)	(0.266)	(0.292)	(0.107)	(0.116)
First stage F-stat	-	-	-	-	527.6	354.9	6,676.4	5,591.4
R sq.	0.094	0.111	0.092	0.114	0.097	0.115	0.097	0.120
Nr. obs	318,488	318,488	318,488	318,488	256,303	256,303	256,303	256,303
$p_{i,p,t} \cdot I(\text{Top})$	-1.96 ***	-1.92 ***	-1.27 ***	-1.17 ***	-2.69 ***	-2.7 ***	-1.39 ***	-1.24 ***
	(0.141)	(0.146)	(0.078)	(0.083)	(0.253)	(0.282)	(0.102)	(0.115)
First stage F-stat	-	-	-	-	590.7	387.8	8,041.0	6,597.5
R sq.	0.081	0.097	0.074	0.093	0.084	0.101	0.078	0.097
Nr. obs	298,994	298,994	298,994	298,994	242,512	242,512	242,512	242,512
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Store FE			✓				✓	
Product x Month x Store FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Store FE			✓	✓			✓	✓

Notes: This table shows the estimates of the elasticities of substitution for each income group seperately, but pooled across product categories. The income group definition is determined based on total expenditure shares. The results per income group are obtained by estimating 6 separately for each income group. Panel (a) shows the results for the relatively low income group, panel (c) for the relatively high income group and panel (b) for consumer classified in the middle income group. from estimatin equation Column (1) - (4) are OLS estimates and column (5) - (8) are 2SLS estimates using the Hausman-instrument as an instrument. Standard errors are reported below the coefficient in brackets and are clustered at the product-store level. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.24: Elasticity of substitution (20% - 80% split) - Per Subcategory

	(1)				(2)				(3)				(4)			
Categories	Coef	N	F-stat	R^2	Coef	N	F-stat	R^2	Coef	N	F-stat	R^2	Coef	N	F-stat	R^2
$p_{i,p,t} \cdot I(\text{Low})$	-3.65 ***	-3.51 ***	-2.35 ***	-2.28 ***	-5.2 ***	-5.18 ***	-2.51 ***	-2.53 ***								
	(0.164)	(0.172)	(0.135)	(0.120)	(0.431)	(0.495)	(0.234)	(0.214)								
First stage F-stat	-	-	-	-	512.8	377.7	2,882.9	2,561.9								
R sq.	0.034	0.054	0.018	0.043	0.033	0.056	0.014	0.041								
Nr. obs	190,063	190,063	190,063	190,063	151,759	151,759	151,759	151,759								
$p_{i,p,t} \cdot I(\text{Middle})$	-2.34 ***	-2.29 ***	-1.57 ***	-1.43 ***	-3.17 ***	-3.15 ***	-1.7 ***	-1.52 ***								
	(0.151)	(0.146)	(0.116)	(0.108)	(0.238)	(0.217)	(0.137)	(0.114)								
First stage F-stat	-	-	-	-	862.3	715.1	5,487.0	5,233.7								
R sq.	0.104	0.120	0.100	0.120	0.108	0.127	0.106	0.128								
Nr. obs	329,014	329,014	329,014	329,014	264,839	264,839	264,839	264,839								
$p_{i,p,t} \cdot I(\text{Top})$	-1.24 ***	-1.14 ***	-0.964 ***	-0.82 ***	-2.22 ***	-2.17 ***	-1.22 ***	-1.06 ***								
	(0.132)	(0.142)	(0.105)	(0.096)	(0.262)	(0.277)	(0.150)	(0.156)								
First stage F-stat	-	-	-	-	773.3	641.0	4,712.5	4,510.6								
R sq.	0.052	0.069	0.045	0.066	0.056	0.073	0.047	0.068								
Nr. obs	250,640	250,640	250,640	250,640	204,208	204,208	204,208	204,208								
Product x Quarter FE	✓				✓											
Product x Month FE		✓				✓										
Product x Quarter x Store FE			✓				✓									
Product x Month x Store FE				✓				✓								
Variety FE	✓	✓			✓	✓										
Variety x Store FE			✓	✓			✓	✓								

Notes: This table shows the estimates of the elasticities of substitution for each subcategory separately, but pooled across different consumers. All coefficients are estimated using the 2SLS estimator. The results per income group are obtained by estimating 6 separately for each subcategory. Standard errors are reported below the coefficient in brackets and are clustered at the monthly level. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.25: Decomposition of Aggregate effect - Heterogeneous

Quarter	Price	Cost	Markup	Substitution	Variety
2015q4	1.05	1.05	1.01	1.00	0.99
2016q1	1.08	1.16	1.00	1.00	0.92
2016q2	1.13	1.25	1.01	1.00	0.90
2016q3	1.18	1.27	1.00	1.00	0.92
2016q4	1.21	1.33	0.99	1.00	0.92

Notes: This table shows the aggregate results from the nested CES decomposition in equation 4 which are also presented in B.12. The results are obtained after pooling across all income groups and estimating the variety effects when we allow the elasticity of substitution to vary across subcategories categories. To be precise, we use the estimate of column (3) in Table C.24. We choose these results as the F-statistics are consistently above critical values of 10 or 15 and the elasticities are sensible across all subcategories. These effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.26: Price - Baseline

	(1)				(2)				(3)				(4)			
Categories	Coef	Test	N	R^2	Coef	Test	N	R^2	Coef	Test	N	R^2	Coef	Test	N	R^2
Bakery/Cereal	-3.55 ***	-1.39	53,028	0.051	-	-	-	-	-3.41 ***	-0.43	53,028	0.044	-	-	-	-
	(0.606)	(0.871)							(0.456)	(0.387)						
	-2.57 ***				-				-3.06 ***				-			
	(0.564)								(0.443)							
	-2.16 ***				-				-2.98 ***				-			
	(0.765)								(0.445)							
Candy	-2.94 ***	-0.119	104,131	0.068	-2.6 ***	0.0579	104,131	0.084	-2.56 ***	-0.0556	104,131	0.058	-2.19 ***	0.0747	104,131	0.077
	(0.380)	(0.0945)			(0.409)	(0.0931)			(0.293)	(0.0592)			(0.284)	(0.0588)		
	-2.8 ***				-2.51 ***				-2.23 ***				-1.85 ***			
	(0.395)				(0.431)				(0.293)				(0.282)			
	-2.83 ***				-2.66 ***				-2.5 ***				-2.26 ***			
	(0.399)				(0.399)				(0.306)				(0.285)			
Dairy	-2.68 ***	-0.544 ***	92,540	0.118	-	-	-	-	-2.75 ***	-0.373 ***	92,540	0.121	-2.59 ***	-0.335 ***	92,540	0.138
	(0.395)	(0.102)							(0.312)	(0.0625)			(0.420)	(0.0627)		
	-2.06 ***				-				-2.39 ***				-2.23 ***			
	(0.368)								(0.308)				(0.416)			
	-2.14 ***				-				-2.38 ***				-2.26 ***			
	(0.358)								(0.298)				(0.393)			
Dry food	-3.12 ***	0.365	58,904	0.074	-3.27 ***	0.667 **	58,904	0.088	-2.76 ***	0.511 ***	58,904	0.069	-	-	-	-
	(0.435)	(0.261)			(0.484)	(0.26)			(0.427)	(0.135)						
	-2.5 ***				-2.7 ***				-2.4 ***				-			
	(0.471)				(0.453)				(0.428)							
	-3.49 ***				-3.94 ***				-3.27 ***				-			
	(0.516)				(0.529)				(0.433)							
Fish	-	-	-	-	-1.9 **	-0.419	31,018	0.042	-	-	-	-	-	-	-	-
					(0.900)	(0.814)										
	-				-1.6 ***				-				-			
					(0.614)											
	-				-1.48 ***				-				-			
					(0.562)											
Fruit	-3.08 ***	-0.949 *	15,329	0.079	-3.2 ***	-0.88	15,329	0.102	-2.5 ***	-0.614 **	15,329	0.051	-	-	-	-
	(0.919)	(0.541)			(1.118)	(0.575)			(0.626)	(0.265)						
	-2.32 ***				-2.68 ***				-2.21 ***				-			
	(0.685)				(0.844)				(0.618)							
	-2.13 ***				-2.32 ***				-1.89 ***				-			
	(0.726)				(0.882)				(0.637)							
Meat	-3.75	-3.65	30,949	0.100	0.964	0.411	30,949	0.111	-2.6 ***	0.087	30,949	0.105	-1.39	0.159	30,949	0.122
	(3.123)	(4.04)			(5.670)	(3.75)			(0.926)	(0.618)			(1.203)	(0.632)		
	0.351				1.27				-2.43 ***				-1.21			
	(1.935)				(3.721)				(0.921)				(1.204)			
	-0.106				0.553				-2.69 ***				-1.55			
	(1.898)				(3.665)				(0.939)				(1.251)			
Ready-made	-4.69	1.38	9,790	0.040	-14.9	-6.71	9,790	0.002	-3.22 ***	-1.79	9,790	0.045	-5.74 ***	-5.1 ***	9,790	0.078
	(3.912)	(5.27)			(11.017)	(4.5)			(0.555)	(1.42)			(0.978)	(1.48)		
	-3.53 *				-10.5 ***				-2.91 ***				-5.38 ***			
	(1.974)				(3.950)				(0.585)				(1.014)			
	-6.07				-8.2				-1.44				-0.636			
	(4.892)				(5.596)				(0.921)				(0.917)			
Savoury	-1.6 *	-0.133	20,745	0.057	-1.75 *	0.266	20,745	0.072	-	-	-	-	-	-	-	-
	(0.865)	(0.542)			(0.903)	(0.529)										
	-1.28				-1.29				-				-			

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Categories	(1) Coef	Test	N	R^2	(2) Coef	Test	N	R^2	(3) Coef	Test	N	R^2	(4) Coef	Test	N	R^2
	(1.014)				(1.145)											
	-1.47				-2.01 *				-				-			
	(1.226)				(1.109)											
Seasoning	-1.71 ***	-0.249	64,948	0.075	-1.35 **	-0.00902	64,948	0.096	-1.64 ***	-0.0389	64,948	0.067	-	-	-	-
	(0.494)	(0.43)			(0.640)	(0.387)			(0.376)	(0.217)						
	-1.34 ***				-1.09 *				-1.35 ***				-			
	(0.501)				(0.621)				(0.383)							
	-1.46 **				-1.34 *				-1.6 ***				-			
	(0.663)				(0.767)				(0.456)							
Vegetables	-0.164	0.0374	33,404	0.081	0.692	1.46	33,404	0.105	-1.82 ***	-0.923 ***	33,404	0.071	-1.63 ***	-0.415	33,404	0.098
	(0.777)	(0.931)			(1.019)	(0.961)			(0.292)	(0.349)			(0.410)	(0.358)		
	-2.27 ***				-2.22 ***				-1.55 ***				-1.35 ***			
	(0.397)				(0.513)				(0.285)				(0.406)			
	-0.201				-0.771				-0.894 **				-1.22 **			
	(0.680)				(0.795)				(0.379)				(0.473)			
Coffee/Tea	-4.52 ***	-0.355	43,860	0.060	-4.77 ***	-0.406 *	43,860	0.069	-4.29 ***	-0.31 ***	43,860	0.057	-	-	-	-
	(0.670)	(0.232)			(0.739)	(0.229)			(0.679)	(0.115)						
	-4.55 ***				-4.83 ***				-4 ***				-			
	(0.658)				(0.711)				(0.688)							
	-4.16 ***				-4.36 ***				-3.98 ***				-			
	(0.716)				(0.742)				(0.579)							
Soft drinks	-5.86 ***	-0.767 **	51,476	0.083	-5.63 ***	-0.541 *	51,476	0.093	-5.32 ***	-0.725 ***	51,476	0.077	-5.03 ***	-0.6 ***	51,476	0.087
	(0.561)	(0.325)			(0.646)	(0.314)			(0.443)	(0.182)			(0.556)	(0.184)		
	-5.57 ***				-5.29 ***				-4.88 ***				-4.59 ***			
	(0.616)				(0.727)				(0.425)				(0.543)			
	-5.09 ***				-5.09 ***				-4.6 ***				-4.43 ***			
	(0.705)				(0.771)				(0.393)				(0.531)			
Water	-3.8 ***	-2.02	10,684	0.136	-2.49 **	0.183	10,684	0.141	-4.47 ***	-1.56	10,684	0.142	-3.9 ***	-1.12	10,684	0.151
	(0.822)	(1.89)			(1.122)	(1.8)			(0.883)	(1.1)			(0.808)	(1.12)		
	-3.71 **				-3.08 **				-3.87 ***				-3.29 ***			
	(1.533)				(1.289)				(0.842)				(0.780)			
	-1.79 **				-2.67 ***				-2.91 ***				-2.78 ***			
	(0.779)				(1.000)				(0.678)				(0.598)			
Product x Quarter x IG FE	✓															
Product x Month x IG FE					✓											
Product x Quarter x Store x IG FE									✓							
Product x Month x Store x IG FE													✓			
Variety x IG FE	✓				✓											
Variety x Store x IG FE									✓				✓			

Notes: This table shows the estimates of the elasticities of substitution for each subcategory separately, but pooled across different consumers. All coefficients are estimated using the 2SLS estimator. The results per income group are obtained by estimating 6 separately for each subcategory. Standard errors are reported below the coefficient in brackets and are clustered at the store-product level. Significance is at the * 10%, ** 5 % and *** 1% level.

Table C.27: Decomposition of Distribution effect (33% - 66% split) - Homogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.07	1.05	0.98	1.05	1.06	1.01	1.02	1.00	0.98	1.00	1.01	1.01	1.00	0.99	0.99
2016q1	1.14	1.08	0.95	1.16	1.17	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.98	0.93	0.95
2016q2	1.21	1.12	0.93	1.25	1.25	1.00	1.01	1.00	0.98	0.99	1.01	1.02	0.97	0.89	0.92
2016q3	1.23	1.16	0.94	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.00	1.01	0.97	0.91	0.94
2016q4	1.27	1.17	0.92	1.32	1.33	1.01	1.00	0.98	0.98	0.99	1.01	1.02	0.97	0.89	0.92

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13a. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 33%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 66%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.28: Decomposition of Distribution effect (25% - 75% split) - Homogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.07	1.05	0.98	1.05	1.06	1.01	1.02	1.00	0.98	1.00	1.01	1.01	1.00	0.98	0.99
2016q1	1.15	1.08	0.94	1.16	1.17	1.00	1.02	0.99	0.97	0.99	1.01	1.02	0.98	0.93	0.95
2016q2	1.21	1.12	0.92	1.25	1.26	1.00	1.02	0.99	0.98	0.99	1.01	1.02	0.96	0.89	0.92
2016q3	1.23	1.16	0.94	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.97	0.91	0.94
2016q4	1.27	1.17	0.92	1.32	1.33	1.01	1.01	0.98	0.97	0.99	1.01	1.02	0.97	0.89	0.92

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13b. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 25%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 75%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.29: Decomposition of Distribution effect (20% - 80% split) - Homogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.07	1.05	0.98	1.05	1.06	1.01	1.03	0.99	0.97	1.00	1.01	1.01	1.00	0.98	0.99
2016q1	1.14	1.08	0.94	1.16	1.17	1.01	1.02	0.98	0.97	0.99	1.01	1.02	0.98	0.92	0.95
2016q2	1.22	1.12	0.92	1.25	1.26	1.00	1.02	0.99	0.97	0.99	1.01	1.02	0.97	0.89	0.92
2016q3	1.24	1.16	0.94	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.97	0.91	0.94
2016q4	1.28	1.16	0.91	1.32	1.34	1.01	1.01	0.98	0.97	0.98	1.01	1.02	0.97	0.88	0.90

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13c. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 20%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 80%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.30: Decomposition of Distribution effect (10% - 90% split) - Homogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.08	1.06	0.98	1.04	1.07	1.03	1.05	0.99	0.95	1.00	1.01	1.01	1.00	0.99	0.99
2016q1	1.15	1.08	0.94	1.15	1.18	1.02	1.04	0.98	0.94	0.99	1.01	1.03	0.97	0.92	0.95
2016q2	1.22	1.14	0.94	1.25	1.27	1.01	1.03	0.99	0.96	0.98	1.01	1.03	0.97	0.90	0.94
2016q3	1.24	1.15	0.93	1.27	1.29	1.02	1.02	0.98	0.96	0.98	1.01	1.03	0.97	0.90	0.93
2016q4	1.28	1.15	0.90	1.31	1.35	1.04	1.02	0.97	0.95	0.98	1.01	1.03	0.98	0.87	0.89

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13d. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 10%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 90%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across income groups and using the estimates of the elasticity of substitution in reported in column (5) of Table 3. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.31: Decomposition of Distribution effect (33% - 66% split) - Heterogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.06	1.03	0.98	1.05	1.06	1.01	1.02	1.00	0.98	1.00	1.01	1.01	0.99	0.97	0.98
2016q1	1.10	1.03	0.94	1.16	1.17	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.93	0.88	0.94
2016q2	1.14	1.09	0.95	1.25	1.25	1.00	1.01	1.00	0.98	0.99	1.01	1.02	0.91	0.86	0.95
2016q3	1.17	1.20	1.03	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.00	1.01	0.92	0.95	1.03
2016q4	1.23	1.24	1.01	1.32	1.33	1.01	1.00	0.98	0.98	0.99	1.01	1.02	0.94	0.94	1.01

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13a. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 33%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 66%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income grpup. We use the estimates of the elasticity of substitution in reported in column (1) of Table C.26 (this corresponds to column (5) of Tables 2 and 3). In case, we are unable to estimate the elasticities (due to multicollinearity with the detailed fixed effects) or if of the elasticities is above -1, we take the elasticities of column (3) or column (2) if the estimates in column (2) do not satisfy the previous criteria. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.32: Decomposition of Distribution effect (25% - 75% split) - Heterogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.06	1.03	0.97	1.05	1.06	1.01	1.02	1.00	0.98	1.00	1.01	1.01	0.99	0.97	0.98
2016q1	1.10	1.03	0.93	1.16	1.17	1.00	1.02	0.99	0.97	0.99	1.01	1.02	0.94	0.88	0.94
2016q2	1.13	1.08	0.95	1.25	1.26	1.00	1.02	0.99	0.98	0.99	1.01	1.02	0.90	0.86	0.95
2016q3	1.17	1.20	1.03	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.92	0.95	1.03
2016q4	1.22	1.23	1.00	1.32	1.33	1.01	1.01	0.98	0.97	0.99	1.01	1.02	0.94	0.94	1.00

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13a. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 25%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 75%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income grpup. We use the estimates of the elasticity of substitution in reported in column (1) of Table C.26 (this corresponds to column (5) of Tables 2 and 3). In case, we are unable to estimate the elasticities (due to multicollinearity with the detailed fixed effects) or if of the elasticities is above -1, we take the elasticities of column (3) or column (2) if the estimates in column (2) do not satisfy the previous criteria. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.33: Decomposition of Distribution effect (20% - 80% split) - Heterogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.06	1.03	0.97	1.05	1.06	1.01	1.03	0.99	0.97	1.00	1.01	1.01	0.99	0.97	0.98
2016q1	1.10	1.02	0.93	1.16	1.17	1.01	1.02	0.98	0.97	0.99	1.01	1.02	0.94	0.88	0.94
2016q2	1.14	1.08	0.95	1.25	1.26	1.00	1.02	0.99	0.97	0.99	1.01	1.02	0.90	0.86	0.95
2016q3	1.17	1.20	1.02	1.27	1.28	1.00	1.01	0.99	0.98	0.99	1.01	1.02	0.92	0.94	1.02
2016q4	1.24	1.22	0.98	1.32	1.34	1.01	1.01	0.98	0.97	0.98	1.01	1.02	0.95	0.93	0.98

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13a. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 20%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 80%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income grpup. We use the estimates of the elasticity of substitution in reported in column (1) of Table C.26 (this corresponds to column (5) of Tables 2 and 3). In case, we are unable to estimate the elasticities (due to multicollinearity with the detailed fixed effects) or if of the elasticities is above -1, we take the elasticities of column (3) or column (2) if the estimates in column (2) do not satisfy the previous criteria. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.

Table C.34: Decomposition of Distribution effect (10% - 90% split) - Heterogeneous

Quarter	Price			cost			Markup			Substitution			Variety		
	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$	L	H	$\frac{H}{L}$
2015q4	1.09	1.04	0.96	1.04	1.07	1.03	1.05	0.99	0.95	1.00	1.01	1.01	1.00	0.97	0.97
2016q1	1.11	1.01	0.91	1.15	1.18	1.02	1.04	0.98	0.94	0.99	1.01	1.03	0.94	0.87	0.93
2016q2	1.13	1.09	0.96	1.25	1.27	1.01	1.03	0.99	0.96	0.98	1.01	1.03	0.90	0.86	0.96
2016q3	1.18	1.19	1.00	1.27	1.29	1.02	1.02	0.98	0.96	0.98	1.01	1.03	0.93	0.93	1.00
2016q4	1.27	1.21	0.96	1.31	1.35	1.04	1.02	0.97	0.95	0.98	1.01	1.03	0.97	0.92	0.94

Notes: This table shows the distributional results from the nested CES decomposition in equation 4 which are also presented in B.13a. The results are obtained by computing each of the components separately for each income group. In this case, the relatively low-income group is defined as the set of consumers whose average expenditure is below the 10%-th percentile of the distribution that measures how expensive consumers' consumption basket at the store is. The relatively high-income group is the set of consumers that are above the 90%-th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income grpup. We use the estimates of the elasticity of substitution in reported in column (1) of Table C.26 (this corresponds to column (5) of Tables 2 and 3). In case, we are unable to estimate the elasticities (due to multicollinearity with the detailed fixed effects) or if of the elasticities is above -1, we take the elasticities of column (3) or column (2) if the estimates in column (2) do not satisfy the previous criteria. All the effects are cumulative effects relative to the quarter before the depreciation, which is defined as June, July and August 2015.