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

Anatoli Colicev, Joris Hoste, and Jozef Konings[1]

University of Liverpool Management School, GBR; University of Cambridge, GBR; Nazarbayev University GSB, KAZ, CEPR, GBR and KU Leuven, BEL

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Abstract

We use retailer scanner data to analyze the impact of a large and sudden exchange rate shock on the cost of living of consumers. We document an increase in the marginal cost of foreign varieties relative to local varieties, a decrease in retail markups on foreign varieties relative to local varieties, and increased entry and exit of both foreign and local varieties around the depreciation. As richer consumers spend relatively more on foreign varieties, they are disproportionally affected by the change in marginal costs but benefit from the reduction in retail markups and increased product variety relative to poor consumers.

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1 Introduction

Developing countries often experience important terms of trade and exchange rate volatility. In response, a growing literature has tried to understand how such volatile international shocks affect the aggregate cost of living and how consumers across the income distribution are differently affected.

The lack of detailed consumer-level price and quantity data has, however, precluded the literature from studying how international shocks are transmitted into consumer prices and the cost of living. First, while there is abundant evidence that distribution margins matter for explaining the disconnect between consumer and border prices (Burstein et al. (2003), Hellerstein (2008) and Berger et al. (2012)), considerably less is known about how distribution margins change in response to international shocks. In particular, it is unclear whether changes in distribution margins dampen the relative price adjustment following a currency depreciation and alter the distributional price effects of international price changes. Second, given the available data, the literature on the distributional effects of international shocks has focused predominantly on quantifying how heterogeneity in expenditure shares across product categories leads to distributional cost-of-living effects (e.g. Fajgelbaum and Khandelwal (2016) and Cravino and Levchenko (2017)). However, category-level price effects originate from both price changes of continuing varieties and changes in the underlying set of available varieties. If consumers have heterogeneous preferences over foreign and local varieties, relative price changes and changes in product availability will affect rich and poor consumers differently.

This paper studies how consumer prices, costs, retail margins, and product availability change following a large nominal exchange rate shock and how these adjustments induce distributional cost-of-living effects. Against the backdrop of falling international commodity prices in August 2015, the Kazakh National Bank was forced to switch from a fixed to a floating exchange rate regime. This episode provides us with an intriguing setting for three reasons. First, the depreciation was sudden, allowing us to demarcate a clear pre- and post-depreciation period. Second, the depreciation was substantial, trumping most concurrent shocks, and came after a period of foreign exchange stability due to the fixed exchange rate that was in place before the depreciation.[2] Third, we can study the distributional effects of foreign exchange shocks on consumer prices in the context of an emerging economy. Data availability has forced most of the literature to either study advanced economic settings in a very detailed manner (e.g. Borusyak and Jaravel (2021)) or to focus predominantly on heterogeneity across product categories in developing economies (see Cravino and Levchenko (2017)).[3] Since rich and poor countries tend to be very imbalanced in terms of the average quality of their imports and exports, the exposure of rich and poor consumers to international shocks could be quite different as well (e.g. Schott (2004)).

We draw on highly detailed scanner data from a supermarket chain, Metro, 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. Observing both price and cost at the product level enables us to examine how retail margins behave in response to a currency depreciation without resorting to strong structural assumptions on demand, supply, or market structure. We use the accompanying transaction-level data to subdivide consumers into different income groups by levering quality Engel curves, i.e. the fact that richer consumers tend to purchase products with higher unit prices. In doing so, we study how the cost-of-living effects differ for different consumers.

We focus on purchases of food and non-alcoholic beverages and provide three pieces of reduced-form evidence. First, within detailed product categories, rich consumers spend on average more

[2]After one, three, and six months, the currency had lost 36.9%, 55.9%, and 78.5% of its value to the US Dollar. Auer et al. (2021) study a similar setting with the sudden appreciation of the Swiss Franc in 2015.

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

on foreign varieties relative to poor consumers. This heterogeneity in expenditure shares implies that within product categories rich consumers in Kazakhstan were more exposed to changes in the relative price of foreign varieties.

Second, consumer prices rose on average by 20% following the depreciation. However, within detailed product categories, consumer prices of foreign varieties increased only by 3 to 4 percent more relative to local varieties. While marginal costs increased by 7 to 8 percent more for foreign varieties than for local varieties, retail margins on foreign varieties fell by 3 to 4 percent. Using an additional data source, we show that different types of stores adjusted prices very similarly in response to the depreciation. Instead, markup adjustments were more likely the result of price adjustments across foreign and local varieties by a multiproduct retailer that limited and altered the transmission of the shock into consumer prices.

Third, even though consumer price adjustment was fairly weak, we document considerable changes on the extensive margin. Following the substantial depreciation, we document a break in the entry and exit patterns for foreign and local varieties. In particular, following the depreciation, we show that the exit rate of foreign varieties and the entry rate of local varieties increased. In case rich and poor consumers differed in how substitutable they perceived these varieties, the depreciation would have had distributional effects through changes at the extensive margin as well.

To understand whether changes in relative prices and product availability induced distributional cost-of-living effects, we model consumer preferences according to a nested mixed-CES demand system. The mixed-CES specification is well-suited to capture the three pieces of reduced-form evidence. First, by allowing parameters and budget shares to vary across income groups, it provides a non-parametric way to account for preference heterogeneity between rich and poor consumers (e.g. Atkin et al. (2018), Jaravel (2019), and Argente and Lee (2021)). Second, mixed-CES systems are consistent with relative shifts in markups following relative changes in marginal costs (see Redding and Weinstein (2020)). Finally, the CES-family of demand systems is the workhorse framework to quantify the effect of product entry and exit (e.g. Feenstra (1994) and Broda and Weinstein (2006)).

Next, we decompose changes in the cost of living into three channels: (1) the price channel, consisting of a markup and a cost effect, (2) the substitution channel, and (3) the product variety channel. The decomposition highlights the three ways in which consumers can be differently affected following an international shock. First, if consumers differ in their pre-shock expenditure shares on varieties whose prices adjust differently following the depreciation, their cost of living adjusts differently. Second, if consumers differ in their responsiveness to price changes, it will change their exposure ex-post.[4] Finally, the variety channel captures that if consumers differ in how substitutable they perceive varieties or if they switch differently from existing varieties towards entering varieties, they will also be differently affected. To quantify the different channels, we estimate the elasticities of substitution by making use of the variety-level price and quantity data. We document substantial differences between rich and poor consumers. Across all specifications, we estimate that the price elasticity of demand is, on average, twice as high for poor consumers compared to rich consumers.

We find that, one year after the depreciation, the cost of living for the same basket of food and non-alcoholic beverages increased by 20%. While the cost of living went up by 24% for poor consumers, it only went up by 16% for rich consumers. First, consistent with the reduced-form evidence, rich consumers experienced a larger increase in the marginal cost of food and beverages, but this was offset by a reduction in the average retail markup. Second, because poor consumers have higher elasticities of substitution, they reallocated expenditure more toward varieties that experienced a smaller price increase following the depreciation. This dampened the increase in their cost of living somewhat. Finally, whereas the relative expenditure share on entering and exiting varieties was similar for rich and poor consumers, the lower elasticities of substitution for the rich imply that they experienced a

[4] This coincides with the unequal expenditure switching channel highlighted in Auer et al. (2023).

lower increase in the cost of living. Altogether, because the price and substitution channels offset each other and render the intensive margin distributionally neutral, we find that the extensive margin drove the distributional effects.

This paper contributes to two streams of literature in several ways. First, we contribute to the literature on the exchange pass-through. The literature on exchange rate pass-through into import prices is vast (e.g. Gopinath and Rigobon (2008), Gopinath et al. (2010), Berman et al. (2012), Amiti et al. (2014), and Amiti et al. (2019)) but so far did not extensively connect currency movements to consumer prices. Most papers either rely on price indices (e.g. Burstein et al. (2005) and Goldberg and Campa (2010)) or link import and consumer prices at the product category level (Berger et al. (2012) and Auer et al. (2021)). Using data on consumer prices, retail markups, and marginal retail costs for foreign and local products at the variety level, we contribute to this literature in two ways. First, we provide novel evidence on how changes in retail markups offset the relative cost increase for foreign varieties. Second, recent work by Nakamura and Steinsson (2012), Cavallo et al. (2014), Goetz and Rodnyansky (2023) and Crowley et al. (2024) shows how firms use product introductions and replacements as a source of price flexibility in response to currency fluctuations. We document considerable changes in product availability and show how they are a crucial ingredient to understanding how the cost of living changes following exchange rate fluctuations.

Second, we contribute to the literature on distributional cost-of-living effects in response to international shocks, such as trade liberalization (Porto (2006), Faber (2014), and Fajgelbaum and Khandelwal (2016)) and currency devaluations (Cravino and Levchenko (2017) and Auer et al. (2023)). Cravino and Levchenko (2017) distinguish between distributional effects stemming from differential exposure across product categories and stemming from heterogeneity in the adjustment of prices within product categories. This paper contributes to this second strand in the literature in two ways. First, this literature has mostly focused on the role of heterogeneity in expenditure shares across varieties in generating distributional effects across rich and poor consumers. Like, Auer et al. (2023), we also consider the implications of differences in the price sensitivity across rich and poor consumers for evaluating the impact of international shocks on consumer welfare. Whereas Auer et al. (2023) focuses on differences in substitution across consumer groups, this paper emphasizes that if consumers differ in their elasticities of substitution, they will also be differently affected through changes on the extensive margin. Second, data limitations have mostly precluded the literature from studying how international shocks transmit into final consumer prices and how they might affect them in heterogeneous ways. This paper relies on data on consumer prices, retail markups, and costs to document how international cost shocks are (partially) offset in final consumer prices through adjustments in the retail markups and the extensive margin of product varieties.

The rest of this paper is organized in the following way. Section 2 introduces the datasets. Section 3 documents the three pieces of reduced form evidence that motivate the study of the distributional cost of living effects. In section 4, we develop the framework, and section 5 presents the changes in the cost of living. Finally, section 6 concludes.

2 Data

We use matched store-level and consumer-level scanner data from a large retailer, Metro, in Kazakhstan. 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. The data are collected through daily price scans between September 2014 and November 2017. Metro's product assortment covers product categories, such as Food and Non-alcoholic beverages, Tobacco and Alcoholic Beverages, Household equipment (cleaning, cooking tools, decoration, and toys), and Clothing. In the analysis, we restrict the sample to the consumer level by only including frequently shopping households and to the product level by focusing on food and non-alcoholic beverages. We provide more details below.

2.1 Transaction level data

A transaction contains a unique customer ID, the product that was bought the total expenditure associated with the transaction, the number of units bought, the store at which the product was bought, and the time stamp. To shop at the stores, store policy dictates that customers are required to have a loyalty card. We rely on consumer-level transaction data to subdivide consumers into different income groups based on quality Engel curves.

Income definition Ideally, we subdivided consumers based on their reported income. As the retailer did not collect this information, we do not observe consumer-level income. There is, however, substantial evidence that richer consumers tend to consume the higher-priced varieties within product categories. In other words, consumers adhere to so-called quality Engel curves. Deaton (1988) shows this regularity for food purchases in Ivory Coast and Bils and Klenow (2001) confirms this for US households. This pattern also holds in more recent data as shown by Handbury (2021), Argente and Lee (2021) and Faber and Fally (2022) for the US and by Cravino and Levchenko (2017) for Mexico.

We build on this evidence and subdivide consumers into three income groups based on the observed consumption patterns. Doing so, we proceed in four steps. First, we select the transaction data before the depreciation to avoid introducing a bias in the income group classification.[5] Second,

[5] 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 who start buying after the depreciation. This 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

we use package size information from the article name to express consumer prices in equivalent units (e.g. KZT per ml or kg). Table A.7 shows the share in terms of total expenditure and the 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" are in grams.[6] Third, within each product group, we rank varieties according to their median pre-depreciation unit price and categorize varieties into four types: (1) very cheap, (2) cheap, (3) expensive, and (4) very expensive varieties based on the product group-specific quartiles:

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

where $p_{i,g}^{\text{med}}$ is the pre-depreciation median unit price of a variety i in product group g and P_g is the random variable representing the product group's pre-depreciation unit price. Finally, we compute for each consumer an index that is the weighted average of how expensive her consumption basket is:

$$\text{Index}_j = \frac{\sum_g \sum_i \sum_{t \leq 2015Q2} f(p_{i,g}^{\text{med}}; P_g) \cdot p_{i,g,t} \cdot q_{j,i,g,t}}{\sum_g \sum_i \sum_{t \leq 2015Q2} p_{i,g,t} \cdot q_{j,i,g,t}}$$

We define poor consumers as consumers who have an index value in the first quintile, while rich consumers have an index value in the fifth quintile. Figure 1 shows the distribution of the index

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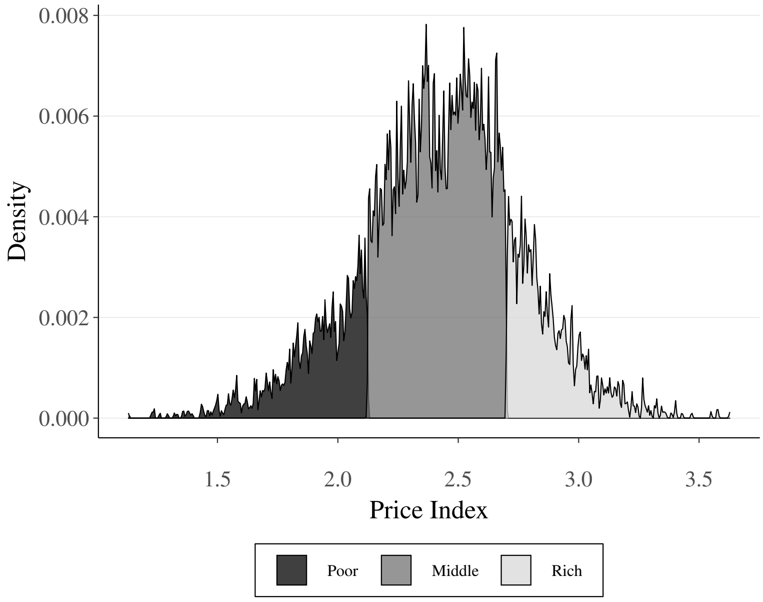
these consumers anyhow.

[6]There are 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) (see infra). We have chosen to conduct the exercise at the product group level to make sure that we have a sufficient number of articles to compute the distributions.

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



Notes: This figure displays the distribution of the index that captures the weighted average of how expensive consumers' consumption basket is. Poor consumers are defined as consumers that have an index in the lowest quintile of this distribution. Rich consumers are defined as consumers with an index in the highest quintile of the distribution. The index is constructed by only including expenditure before the depreciation and is pooled across regions.

and indicates the different income groups in separate colors.[7] Below, we check the robustness of the distribution results by computing the effects for different cut-off percentiles.

An alternative way to infer income would be to classify consumers based on expenditure per capita (e.g. Faber and Fally (2022)). Although we observe total expenditure, we do not have information about the size of the household. As a consequence, it is unclear whether higher expenditure reflects higher income or larger household size. For this reason, we rely on quality Engel curves. Below, we show that the main results of the paper are nonetheless robust to using total expenditures as the income classification method.

[7] In the construction of these income groups, we pool across consumers shopping in the different stores. Figure A.5 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.

Households The customer pool of Metro comprises both households and small business owners, such as restaurants and small shops. To isolate households from small business owners, we discard expenditures that are unlikely to be made by households. Table A.5 shows the average expenditure per month and the corresponding average expenditure per week in local currency and in US dollars. 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 distribution of the average monthly expenditures.[8] Besides, because we study the evolution of the cost of living through the depreciation episode, we remove all consumers who did not shop at the retailer before the depreciation.[9].

Frequently shopping households To quantify the effect of the currency depreciation on the cost of living of different consumers, we need to track the consumption patterns of the same consumers over time. Therefore, we only focus on consumers who frequently shop at the store. To be part of the frequent sample, we require consumers to shop at the retailer for at least 8 months out of the 11 months before the depreciation and at least 9 months in the 12 months directly after the depreciation. Tables A.8 and A.9 compare the frequent and full samples on a set of observable characteristics. The frequent sample contains 5,040 consumers, who jointly account for 27% of total expenditures. Table A.9 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 by including both frequent and infrequent shoppers and find that the results are even more pronounced.

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

[9]Table A.6 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.

2.2 Product level data

We have access to rich product-level data that covers the full universe of products sold by the retailer. We observe the quantity and the price for each purchase made by the customers on a given day.[10] 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, the inventory information enables us to compute variety-level replacement or marginal costs. When registering sales and inventory restocking, the retailer uses a First-in-First-Out (FIFO) inventory principle. We combine this knowledge with the inventory data and back out the cost that is attributed to the latest inventory restocking.[11] This inventory cost includes the most recent wholesale price paid and the variable distribution costs necessary to put products on the store's shelves. We will refer to this cost measure as the marginal costs as the costs associated with buying and selling products are the most important part of retailers' cost structure. Like Gopinath et al. (2011), Eichenbaum et al. (2011), and Goetz and Rodnyansky (2023), we use this cost measure and define retail markups as the ratio of prices and replacement costs. Second, the inventory data provide direct information about which product varieties are available to consumers and thus which products enter and exit the choice of consumers at the store.

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

[11]Knowing the inventory principle is necessary to map the data on inventory costs to replacement costs or marginal costs (e.g. Peltzman (2000)).

Food and non-alcoholic beverages The analysis focuses on purchases of food and non-alcoholic beverages. To maximize the external validity of the results, we concentrate solely on product categories that exhibit a comparable price evolution to the corresponding Consumer Price Index (CPI) component. To this end, Figure A.3 contrasts the aggregate price evolution of the categories Food and Non-alcoholic beverages, Tobacco and Alcoholic beverages, Household products, and Clothing with the price evolution of their corresponding CPI component.[12] Looking at Figure A.3, only the Food and Non-alcoholic beverage categories show a price evolution that is similar before and after the depreciation. The other categories either miss the mark before, after, or before and after the depreciation. While the sample coverage inevitably reduces, column 3 of Table A.11 shows that Food and Non-alcoholic beverages are the most important source of revenue for the retailer representing 61% of its revenue. Moreover, Table Table A.10 indicates that Food and Non-alcoholic beverages carry a 34% expenditure weight in the CPI basket, making it the most important category in the overall CPI construction.

Foreign and local varieties We match the retailer's proprietary product identification number with the product's EAN code provided by the retailer.[13] We follow Bems and Giovanni (2016) and subdivide products into foreign and local based on the EAN code: if the article's EAN code starts with "487", Kazakhstan's country code, the product is labeled as "local"; for any other code, the product is labeled as "foreign". Table 1 shows the foreign share that we obtain for different subcategories and the share of varieties that we can identify as either foreign or local. Apart from meat, vegetables, and fruits, we classify around 80% to 90% of total expenditures as being local or

[12]We compute a category-level price index from variety-level prices by computing a Törnqvist price index.

[13]In the EAN classification system, each barcode has 13 digits. The first 3 digits identify the country of registration of the manufacturer, the next 5 digits indicate the manufacturer and the final 5 digits reflect the product.

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 provides 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 combinations in the dataset. The column "Observations" indicates the number of months in which there were 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 quality" 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 and all stores.

foreign.[14] Apart from the estimation of the event studies in section 3, we include all varieties even if we cannot determine their origin.[15]

One potential problem with this approach is that foreign manufacturers might relabel their products or change the barcode of the product when they sell to a different market. One way to check the performance of the barcode-based classification method is to evaluate its accuracy in classifying varieties that are differentiated by their origin (see Bems and Giovanni (2016)). To this end, we retrieved the from the barcode descriptions the origin country of wines and found that the barcode classification method classified 97% of expenditure on foreign wines as foreign and 99% of expenditure on local wines as local.

[14]These product categories are notoriously hard to classify and other papers usually discard these categories altogether Cravino and Levchenko 2017; Auer et al. 2021.

[15]To conduct the event studies, we need to allocate a variety to the treated, i.e. foreign varieties, or the control group, i.e. local varieties, and therefore we have to discard varieties whose origin we cannot determine.

Frequency To focus on the short- to middle-run effects of the depreciation, we aggregate the data to monthly data by computing average consumer prices and costs and total sales and quantities within each month. Given that we focus on the consumption of food and non-alcoholic beverages by households, we deem a monthly frequency as reasonable to be able to abstract from very short-run anticipatory effects before the depreciation. For the decomposition results, we will present results at the quarterly level but the decomposition results are very similar when we use monthly data instead.

Representativeness of the store Our results are based on data from one retailer. To support the external validity of our results, we provide an extensive analysis of the entire Kazakh retail sector in Appendix A.1. To this end, we use scanner data on the whole Kazakh retail sector from AC Nielsen and data from the Kazakh National Bank to address two concerns regarding our approach. The AC Nielsen data contains information about the forty highest-selling barcodes in each category.[16] First, we show that prices for the same products at small and large stores, which together make up 85% of the retail sector, did not respond differently after the shock.[17] Second, when studying the distributional consequences of 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 suggesting that sorting of consumers across varieties within a store is likely more important than across stores.

[16] The AC Nielsen dataset contains barcode descriptions but does not contain EAN codes. Hence, we could not match AC Nielsen data to our Metro data.

[17] Metro has an overall market share of 10%.

3 Reduced-form evidence

In this section, we discuss the depreciation of the Kazakh Tenge in August 2015 and its effect on consumer prices. We also provide three pieces of reduced-form evidence that motivate the estimation of changes in the cost of living for rich and poor consumers later on. First, rich consumers spend on average more on foreign varieties compared to poor consumers. Second, consumer prices of foreign varieties rose little relative to consumer prices of local varieties because changes in retail markups compensated for changes in costs. Finally, there was a substantial adjustment on the extensive margin with the increased entry of local varieties and exit of foreign varieties.

3.1 The depreciation and consumer price inflation

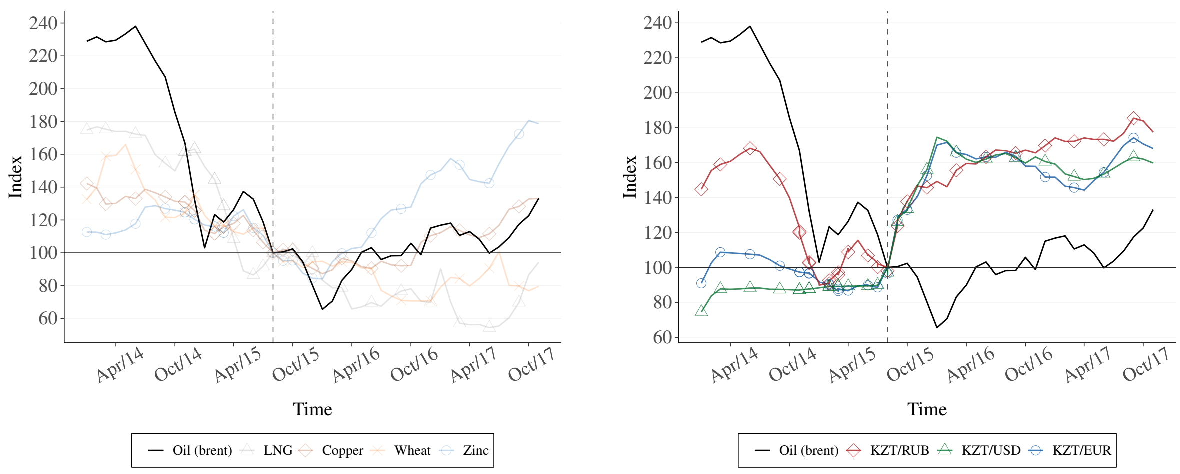
Kazakhstan is an emerging economy that primarily exports commodities and takes world prices as given (see Table A.12).[18] Because the economy strongly relies on commodity exports, the Kazakh National Bank (KNB) implemented a fixed exchange rate regime and pegged the Tenge to the Euro and the US Dollar before August 2015. Following the collapse of global commodity prices and the appreciation of the Tenge relative to the Russian Ruble in 2015, the KNB switched to a floating exchange rate regime on August 20th, 2015. As a result, the Kazakh Tenge sharply depreciated between 40% and 80% versus all major currencies within 6 months as shown in Figure 2b.

This episode provides an intriguing setting to study the transmission of exchange rate shocks into consumer prices and the cost of living for three reasons. First, the depreciation was sudden and persistent. Figure 2b shows that the Tenge depreciated immediately after the policy shift and stabilized at a much lower value after six months. This allows us to identify a clear pre- and

[18] Oil is Kazakhstan's largest exported commodity. The country's production only accounts for one or two percent of global oil production.

Figure 2: Depreciation 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). Table A.12 shows that these commodities collectively made up around 80% of exports in 2015. 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.

post-event window. Second, the monetary policy shift was a response to external events. To support its fixed exchange rate policy, the KNB relied heavily on foreign currency inflows through the country's exports of commodities that tend to be denominated in foreign currency.[19] However, Figure 2a shows that world prices of the economy's five most exported commodities started falling in late 2014. This made it increasingly difficult for the KNB to keep the nominal exchange rate at parity.[20] Eventually, the KNB was forced to let go of the pegged exchange rate and decided to float the exchange rate, resulting in substantial exchange rate variation as can be seen from Figure 2b. Finally, the disaggregated nature of our dataset makes it possible to plausibly demarcate the depreciation from other concurrent, and potentially confounding, events. We execute the analysis

[19]Gopinath (2015) and Boz et al. (2022) provide evidence that world prices of most commodities tend to be denominated in USD.

[20]The drawdown of foreign currency reserves is confirmed in reports on the evolution of the Kazakh National Bank's balance sheet. In response, the National Bank increasingly borrowed foreign currency from other central banks to defend the fixed exchange rate as shown in Figure A.6.

using granular scanner data at the individual variety and consumer level for which we obtain data on the origin of product varieties. As foreign varieties are exogenously more exposed to the depreciation, we can examine whether consumer prices, costs, retail markups, and product availability changed differently for foreign versus local varieties.

To stress the substantial effect of the depreciation on consumer prices, we estimate the following hedonic price regression:

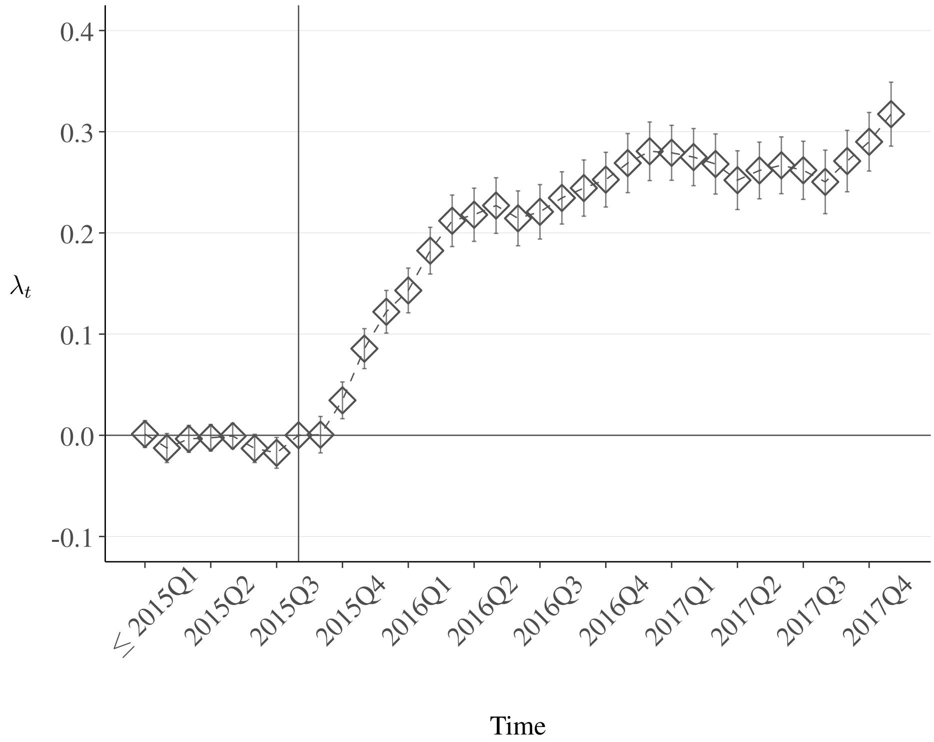
$$\ln\left(p_{i,st}\right) = \theta_{p(i)o(i)} + \theta_{p(i),s} + \lambda_t + \varepsilon_{i,st}. \tag{2}$$

where $\ln\left(p_{i,st}\right)$ is the natural logarithm of the consumer price of a variety i in a store s at time t. We include category-origin fixed effects, $\theta_{p(i)o(i)}$, to filter out persistent price differences between products and origins.[21] We also add category-store fixed effects, $\theta_{p(i),s}$, that control for persistent differences across locations within product categories. Finally, we include λ_t which are time fixed effects that are normalized relative to August 2015. Figure 3 plots these time effects and underscores the inflationary effect of the depreciation. Consumer prices rose by 20% after six months and reached a new mid-to-long equilibrium level that was 25% higher after roughly one year. Because prices converged after 12 to 15 months, we focus on the first five quarters after the depreciation when we quantify the cost-of-living effects below.[22]

[21]The category refers to the finest level of aggregation which is the product level. We interact category fixed effects with product origin fixed effects as Table A.1 shows that there are large price differences between foreign and local varieties.

[22]Table A.14 shows that the Ruble, the Euro, and the US Dollar are the three main currencies of invoicing used by the retailer. Therefore, we considered whether there is interesting heterogeneity in the level of pass-through across currencies of invoicing. When we re-estimate equation (2) for different currencies of invoicing in Figure A.7, we find that there is some heterogeneity across currencies in the transition towards the medium- to long-run pass-through level. Because the medium- to long-run pass-through level is very similar, we do not explore this dimension any further in the following sections.

Figure 3: Consumer prices response



Notes: This figure shows the evolution of consumer price following the depreciation. More specifically, we plot the coefficients λ_t which are obtained from estimating equation (2). Note that we have bunched the effects prior to January 2015 into the effect for January 2015 and the effects after September 2016 into the effect of September 2016. Whiskers are 95% confidence intervals around the point estimates computed from standard errors which are clustered at the product-store level.

3.2 Heterogeneity in foreign expenditure shares

If there was meaningful variation in the spending share on foreign varieties across rich and poor consumers, the depreciation could have generated distributional effects if the relative price of foreign varieties rose considerably. Indeed, richer consumers had on average a significantly higher expenditure share on foreign varieties both across and within detailed product categories.

Figure 4 shows the conditional distribution of the total expenditure share spent on foreign varieties for rich and poor consumers separately. There is a substantial shift in the distribution towards more spending on foreign varieties by rich consumers. Moreover, parametric and non-parametric tests reject the null hypothesis that the conditional distributions are stochastically equivalent (see Table

A.20 and A.21 respectively).[23] Figure A.11 shows the disparities in the conditional distributions also monotonically increase when we move from looser toward stricter definitions of rich and poor consumers.

Figure A.12 illustrates that the same pattern also persists within the detailed product categories. Figure A.12 displays the conditional distributions of the share spent on foreign varieties across product categories for rich, poor, and in-between consumers. The distribution of category-level of the foreign expenditure share is shifted upwards for rich consumers and Tables A.20-A.21 confirm that pattern is statistically significant for all the different income group definitions. Like before, the pattern monotonically strengthens when we move from a loose to a strict income classification.

Classifying consumers based on total expenditure does not overturn this pattern. Figure A.13 illustrates that the conditional distribution of foreign shares for rich consumers still stochastically dominates the one for poor consumers when we subdivide consumers according to total expenditures.[24]

3.3 Relative consumer price stability

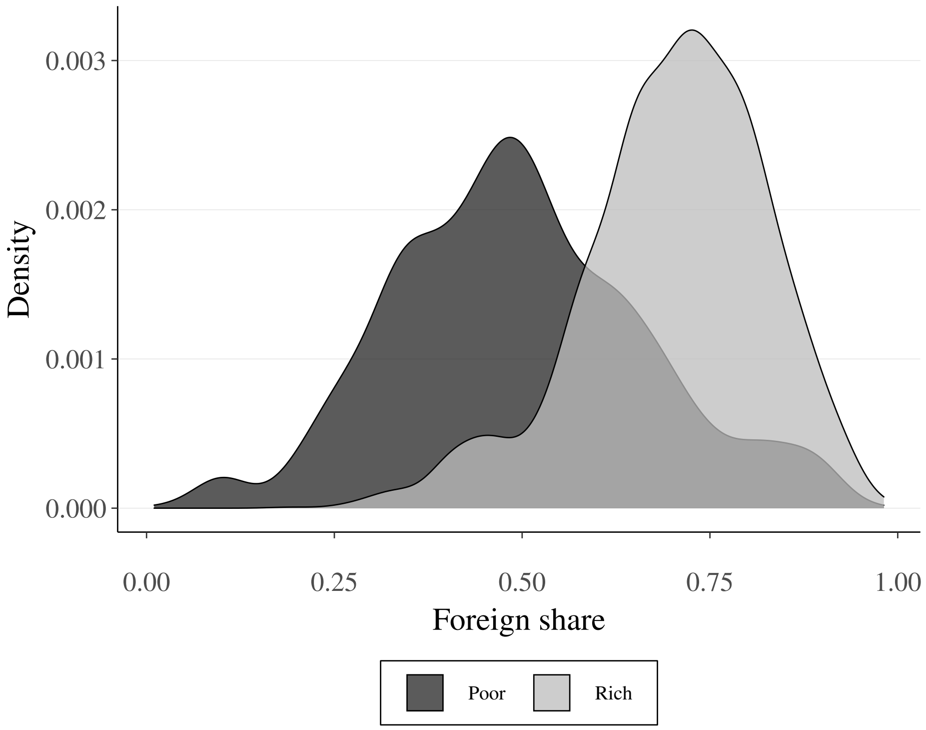
Next, we estimate whether and by how much consumer prices of foreign varieties increased relative to consumer prices for local varieties. We also estimate how cost and retail markup for foreign varieties adjusted relative to local alternatives. To this end, we augment equation (2) and estimate the following difference-in-difference specification:

$$y_{i,st} = \sum_t \beta_{q(t)} \Big(\mathbb{1}\left(o(i) = \text{Foreign}\right) \times \mathbb{1}\left(q(t) \neq 2015Q3\right) \Big) + \theta_{p(i)o(i)} + \lambda_{p(i),t} + \varepsilon_{i,st} \tag{3}$$

[23] We consider a parametric Kolmogorov-Smirnov and a non-parametric Paired-Rank-Sum-Wilcoxon test.

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

Figure 4: Foreign share - Per income group (20%-80% split)



Notes: 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.

where $y_{i,st}$ is either the log price, log cost, or log retail markup of a variety i in a store s at time t, $\mathbb{1}\left(o(i) = \text{Foreign}\right)$ is one when the origin of variety i is foreign and zero otherwise, and $\mathbb{1}\left(q(t) \neq 2015Q3\right)$ is one for all quarters apart from 2015Q3.[25] In this way, we estimate a pre-treatment effect for each quarter before 2015Q3 and a post-treatment effect for each quarter from 2015Q4 until 2016Q4. After 2016Q4, we collect the effects into one estimate.[26] We include two other sets of fixed effects. We keep the category-origin fixed effects $\theta_{p(i)o(i)}$ that control for persistent differences between foreign and local varieties at the category level. We substitute the time-fixed effects for more detailed category-time fixed effects $\lambda_{p(i)t}$ that control for common

[25]To include as many observations as possible, we consider observations at the store level as well. Below, we check the robustness of the results when we also consider fixed effects at the store level.

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

changes at the category level for foreign and local varieties over time. To capture adjustment for continuing varieties, we only include continuing products and weigh their importance using pre-depreciation expenditure shares.

The coefficients of interest are the time-varying treatment effects, $\beta_{q(t)}$. Through foreign intermediate input sourcing or changes in manufacturing markups, local varieties were very likely affected by the depreciation as well. For this reason, the time-varying treatment effects only measure the differential adjustment of foreign varieties relative to local varieties and not the full effect of the depreciation on the prices of foreign varieties. Given that we are interested in how consumer prices of foreign varieties adjusted relative to local varieties, this difference-in-difference estimator is still suitable.

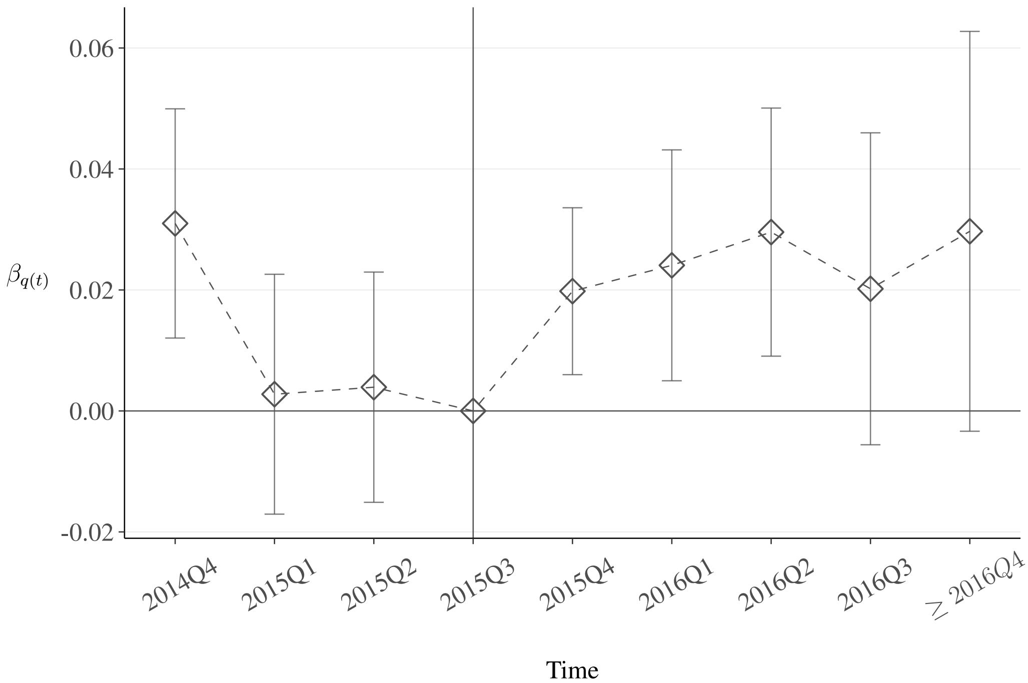
Consumer prices Figure 5 shows the results when we estimate equation (3) for final consumer prices. We note that prices of foreign varieties were on a downward trend before the depreciation as one of the pre-depreciation treatment effects is statistically significant and positive. We believe this does not compromise the interpretation of the results for two reasons. First, the post-depreciation effects are not a continuation of the pre-depreciation trend as the depreciation induced a break from the pre-depreciation trend. The downward trend before the depreciation and increase in the relative price of foreign varieties after the depreciation is also consistent with the appreciation-depreciation cycle of the KZT relative to the RUB (see Figure 2b). Second, we focus on non-durable items that are frequently restocked. Therefore, it is unlikely that the appreciation of the Kazakh Tenge before the depreciation affected the post-depreciation adjustment.

We find that the increase in relative consumer prices of foreign varieties relative to local varieties was small. In the baseline specification, the change in relative consumer prices peaks at a mere 3% three quarters after the depreciation and is not statistically significant at the 95% level from that point onwards. Figure A.8 and Table A.17 show that this result is robust across different specifications. First, the results are robust to replacing the category-origin fixed effects with more detailed product variety fixed effects. In this specification, relative foreign prices increase by around 3% throughout the first four quarters after the depreciation and reach their peak at around 5% in the quarters thereafter. Second, we consider a specification that interacts category fixed effects with origin fixed effects and the category-time fixed effects with store fixed effects. The baseline specification treats the price evolution of foreign varieties relative to local alternatives similarly across the two store locations. This is problematic if there is heterogeneity in the assortment of local and foreign varieties across locations or if these locations experience different concurrent unobserved shocks. When we control for store-specific effects, we find that relative foreign prices increase by around 5.5% shortly after the shock and remain 4.25% higher after four quarters. Finally, relative foreign prices increase to around 6% after four quarters when we account for variety- and store-level effects simultaneously. However, the relative price increase remains small in magnitude compared to the size of the depreciation and we unpack it by separately looking at how relative marginal costs and retail markups changed.

Marginal costs Figure 6 shows the relative marginal cost of foreign varieties experiences increases by 3% on impact, reaches its peak in the second quarter at about 6.8% and settles at around 5%. Figure A.9 and Table A.18 show that these results are also robust when we include more flexible fixed effects. Like before, the estimated effects are slightly larger, between 7% and 9% after four quarters, when we control for persistent differences in costs across foreign and local varieties (i.e. variety fixed effects), for store-specific effects (i.e. category-origin–store and category-time-store fixed effects) or for both variety- and store-level effects at the same time.

Several mechanisms can potentially explain this modest relative cost increase. First, in response

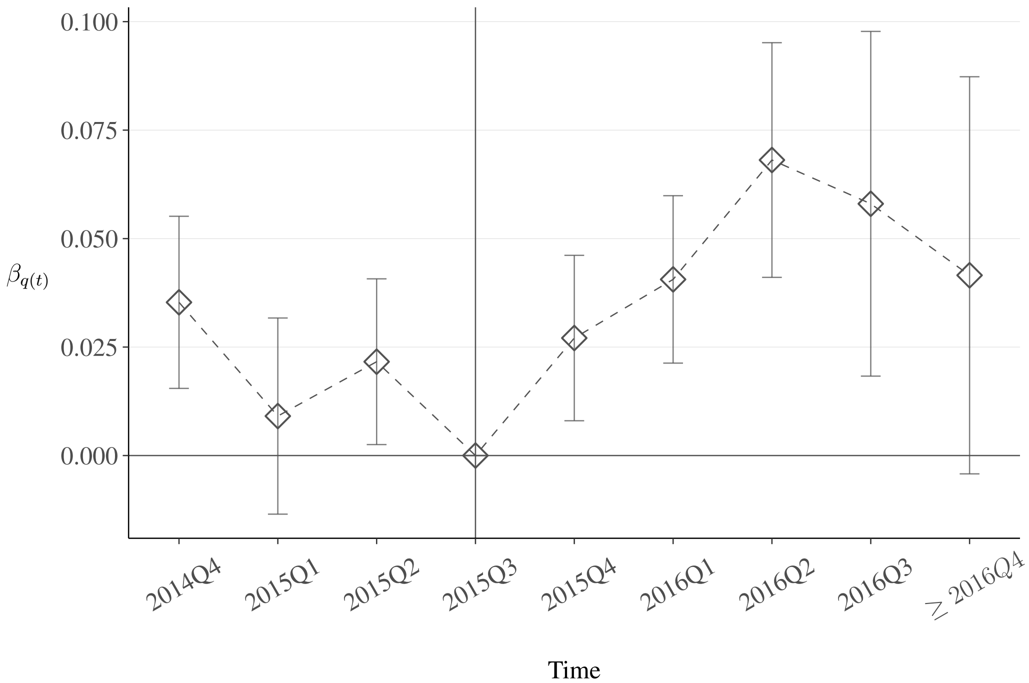
Figure 5: Difference-in-difference: Consumer Prices



Notes: This figure shows the results from estimating equation (3) for consumer prices for setup with category-origin and 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% confidence intervals based on standard errors that are clustered at the category-origin level.

to the depreciation, exporters could have lowered markups on foreign varieties (e.g. Berman et al. (2012) and Fitzgerald and Haller (2014)) and manufacturers of local varieties might have increased markups on local varieties (e.g. Amiti et al. (2019)). Second, sharply rising production costs for local alternatives due to rising nominal wages (see Figure A.4) and more expensive imported intermediate inputs in production (e.g. Amiti et al. (2014)) are other possible explanations. Third, as explained in section 2, our cost measure includes the wholesale price paid and distribution costs. If the distribution costs were very large and paid in terms of domestic labor, they would naturally dampen changes in relative costs. Unfortunately, our data does not report the wholesale price and the distribution costs separately. A final reason could be measurement error in the determination of local versus foreign varieties. There are two reasons why measurement error might not be a big concern. On the one hand, the classification works very well for a category in which varieties are differentiated by origin. On

Figure 6: Difference-in-difference: Costs

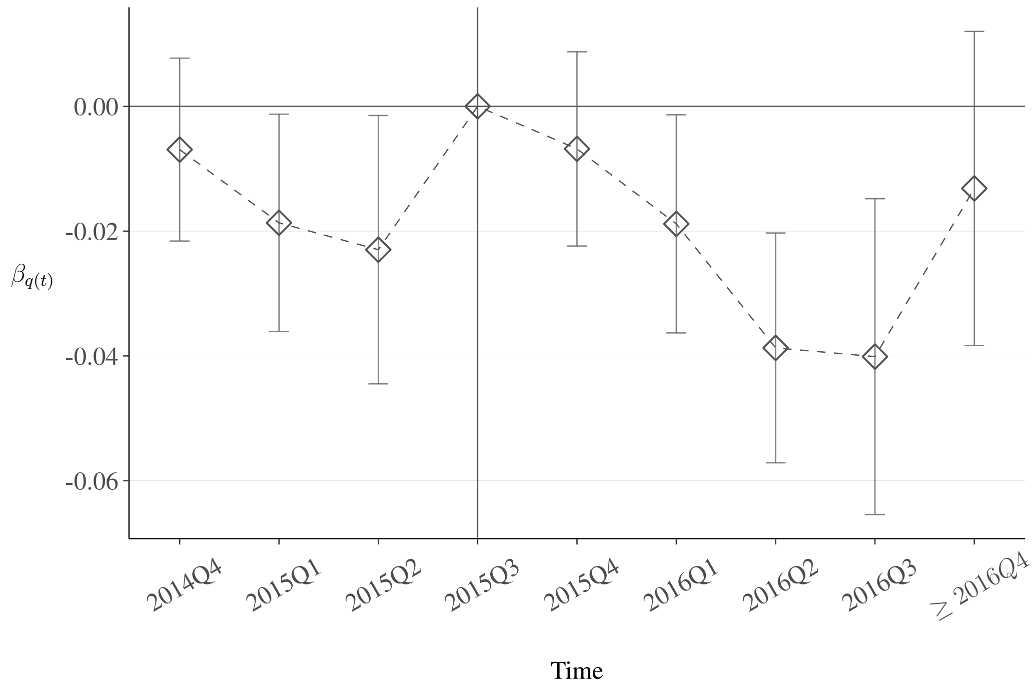


Notes: This figure shows the results from estimating equation (3) for costs for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are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

the other hand, if measurement error was important, it would imply that our results are a lower bound on the relative adjustment in final consumer prices, costs, and retail markups. Hence, the qualitative insights would not be overturned.

Retail markups Figure 7 illustrates that retail markups fell for foreign varieties relative to local ones and thus counteracted the relative cost increase experienced by foreign varieties. In our baseline specification, we find that four quarters after the depreciation markups on foreign varieties fell by around 4% relative to local varieties. While relative markups are insignificantly different from zero on impact, they gradually drop and reach their trough after four quarters. Retail markups on foreign and local varieties are not different statistically anymore four quarters after the depreciation, which explains the jump in relative prices over this same period. Figure A.10 and Table A.19 show that

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 median pre-depreciation retail markup was 1.13. The dots indicate the point estimate and the whiskers are 95% confidence intervals based on standard errors that are clustered at the category-origin level.

these results are both qualitatively and quantitively very robust to including alternative and more detailed sets of fixed effects that account for persistent differences across varieties and locations and for location-specific time effects across product categories.

To understand the decrease in retail markups on foreign varieties relative to local varieties, we distinguish three possible mechanisms. First, in response to competitive pressure from local stores with fewer foreign products, the retailer might have reduced markups on foreign varieties. However, using more aggregated data from AC Nielsen[27], we show in Table A.3 that prices of food and non-alcoholic beverages did not change differently in small and large stores after the depreciation.[28] In

[27]The data from AC Nielsen covers a much broader sample of stores that sell food and non-alcoholic beverages but provides information on only the forty best-selling products in each category.

[28]Columns (2) and (3) of Table A.3 show the results from a difference-in-difference estimation where we compare the price evolution in large stores relative to small stores for the same category and the same products respectively. These

addition, Figure A.1 plots the expenditures shares across different store types and illustrates that these shares remained very stable after the depreciation. Both elements point to a relatively stable retail market, making it unlikely that this is the main force acting on relative markups.

Second, the reduction in retail markups for foreign varieties could alternatively be rationalized in demand systems that provide a link between the elasticity of demand and real income. [29] However, if a decrease in real income was responsible for the reduction in retail markups on foreign varieties, we should see the same for retail markups on local varieties. In contrast, the data shows that, on average, retail markups on local varieties slightly increased.

We argue that the fall in retail markups on foreign varieties relative to local varieties is consistent with optimal pricing by a multi-product retailer that faces oligopolistic competition and heterogeneous consumers, such as in a mixed-CES demand.[30] First, the assumption of oligopolistic competition is necessary because the combination of CES demand with perfect or monopolistic competition leads to constant markups. Second, heterogeneity in consumer preferences is necessary as well. This is because in a CES-demand system without consumer heterogeneity substitution between products only depends on the market shares of those respective products. Importantly, when products are sold by the same firm, markups only depend on parameters and the firm-level market share (see Hottman et al. (2016)). Hence, relative markups on products sold by the same firm are unaffected by changes in relative costs. In contrast, in a CES-demand system with consumer heterogeneity, i.e. consumer-specific taste or elasticities of substitution, substitution between products is governed by a weighted average of consumer-specific elasticities of substitution with

regressions yield a precisely estimated zero effect.

[29]This could happen through an increase in search intensity (e.g. Stroebel and Vavra (2019) and Sangani (2023)) or through changes in the marginal utility of consumption (e.g. Mongey and Waugh (2024))

[30]This way of modeling the retail sector is very standard in the industrial organization literature (e.g. Hellerstein (2008) Crawford and Yurukoglu (2012), Miller and Weinberg (2017)).

weights that depend on consumer-specific consumption levels. Consequently, when the composition of consumer-specific consumption levels changes in response to changes in relative costs, variety-level elasticities of demand and, thus, equilibrium markups change accordingly.

Crucially, our data also points towards important heterogeneity in consumer preferences across rich and poor consumers. First, section 3.2 shows that rich consumers spent significantly more on foreign varieties even though they faced the same consumer prices, which is direct evidence of a higher taste for foreign varieties. Second, section 5 shows that rich consumers have significantly lower elasticities of substitution compared to poor consumers. This heterogeneity in price sensitivity is a second source of consumer heterogeneity that supports an interpretation of the data through the lens of a mixed-CES preference system.

3.4 Changes in product availability

Besides changes in final consumer prices, marginal costs, and retail markups, the depreciation also induced substantial adjustments in the set of varieties that were available to consumers. To see this, Table A.16 shows for different subcategories the share of entering, exiting, and continuing varieties in terms of the number of varieties and the expenditure share allocated to them. In this Table, we define continuing varieties as varieties that were present before the depreciation and were still present in the sample one year after the depreciation. Exiting products are products that were present before the depreciation, but were not present anymore after one after the depreciation. Entering products were not present before the depreciation, but entered within one year after the depreciation. Across virtually all product categories, the share of continuing varieties in terms of number of varieties is below 50% and is around 70% in terms of expenditure.

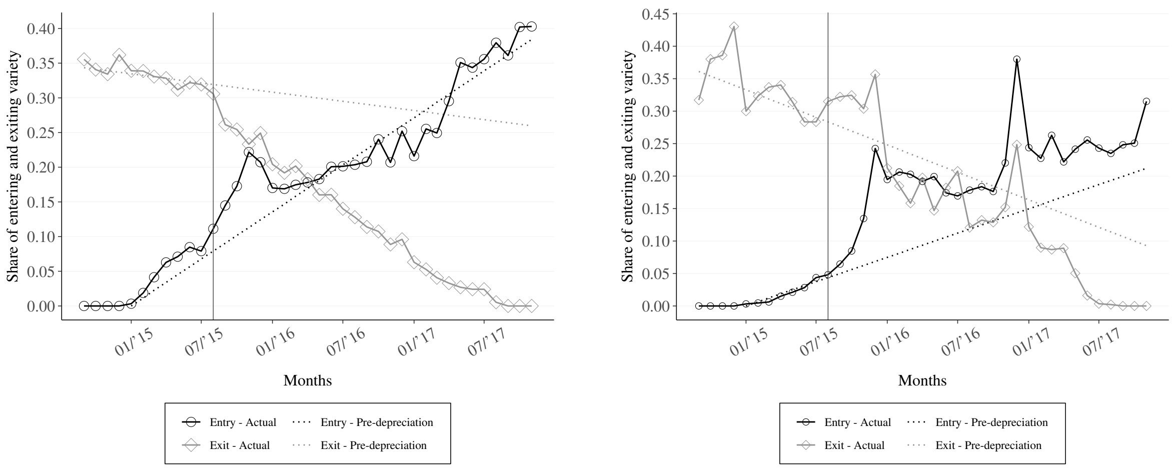
However, non-trivial product churning, i.e. simultaneous entry and exit of varieties, happens even in more tranquil environments (see Bernard et al. (2010), Broda and Weinstein (2010), and

Argente et al. (2024)).[31] This begs the question of whether such changes arose because there was a structural break around the depreciation or because of product churning that would have happened regardless of the depreciation. To discriminate between both explanations, we follow Kehoe and Ruhl (2013) and plot in Figure 8 the expenditure on entering (exiting) varieties, defined as product varieties not available in the first (last) three months of the sample period, as a share of total expenditure over time. As varieties progressively enter (exit) the sample the expenditure share on this group of varieties gradually increases (decreases). Yet, if continuous product churning was behind changes at the extensive margin, the reallocation of expenditure towards/away from these varieties would not have changed markedly around the depreciation and would have followed the pre-depreciation trend lines. However, we find that after the depreciation increasingly more expenditure was reallocated away from foreign varieties that eventually exited. Also, right after the depreciation, increasingly more expenditure was allocated to entering local varieties. These patterns align well with workhorse models such as Melitz (2003) and Bernard et al. (2011) in which foreign firms or varieties exit and domestic firms or varieties enter following an increase in trade barriers. As the depreciation permanently re-aligned the nominal exchange rate closer to the underlying economic fundamentals of the Kazakh economy, it resembled an increase in trade barriers for foreign inducing increased entry of local varieties and exit of foreign varieties.

[31] Steady-state product churning can be quite substantial. In particular, Argente et al. (2024) show that, on average, 12% of sales is accounted for by products that were introduced in the same year and that sales of existing products decrease by around 30% per year.

Figure 8: Extensive margin

(a) Foreign varieties **(b)** Local varieties



Notes: This figure plots the share spent on entering varieties and exiting varieties separately for foreign and local varieties. The trend lines are computed as a linear extrapolation from the pre-depreciation trend in the shares.

4 Framework

4.1 Conceptual approach

In response to price increases and real income changes after the depreciation, consumers adjust their spending patterns, altering their utility obtained from consumption. To estimate the impact of the depreciation on consumers' welfare, we compute the compensating variation which is the hypothetical income required to keep a consumer's utility unchanged after being subjected to the depreciation:

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

where $\boldsymbol{P}^t$ is the price vector, u^h is the utility of consumer h, and $e(\cdot)$ is the unit expenditure function. The compensating variation of consumer h depends on how her nominal income, y^h, changed and how her cost of living, $e(\boldsymbol{P}, u^h)$ changed. As we do not observe the nominal income of consumers, we abstract from changes in the nominal income of households and focus on how the cost of living changed.

To obtain a closed-form solution for $e\left(\boldsymbol{P}, u^h\right)$, we model consumer preferences as a nested mixed-CES demand system for two reasons. First, as explained in the previous section, by allowing for heterogeneity in consumer preferences, the mixed-CES demand system features variable elasticities of demand and generates the empirical facts documented in section 3. Second, The CES framework is the workhorse framework to quantify the welfare effects of changes in the set of available varieties. Doing so, we follow Atkin et al. (2018), Jaravel (2019) and Argente and Lee (2021) and capture heterogeneity in consumer preferences by allowing budget shares and elasticities of substitution to vary non-parametrically between income groups while households within an income group share the same preferences.

4.2 Preferences

There are four levels of aggregation in the data: (1) the category level (e.g. Food), (2) the subcategory level (e.g., Fruit), (3) the product group level (e.g. Stonefruit), and (4) the product level (e.g. Peaches).[32] Each product comes in different varieties, which can be local or foreign. Per category, we define two nests.[33] The upper nest captures substitution across products (e.g. rice versus bread) and the lower nest substitution across varieties within the same category (e.g. Basmati rice versus Jasmin rice). We choose to define the upper nest at the product level for two reasons. First, we want to allow for substitution between products after the depreciation. For instance, if the depreciation causes bread prices to increase relative to rice, consumers might choose to substitute

[32]To compare the level of aggregation with the widely used Nielsen HomeScan database Hottman et al. 2016; Jaravel 2019; Argente and Lee 2021, 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.

[33]We execute the analysis for one category, i.e. food and non-alcoholic beverages. We are silent on the way we aggregate across categories. For instance, a Cobb-Douglas aggregator would be suitable.

bread for rice. The degree of substitution is governed by the elasticity of substitution σ_c^h.[34] Second, the product level is the finest level of aggregation without meaningful product entry or exit after the depreciation. There are products that either enter or exit after the depreciation, but their sales share in total category spending is around 0.1%. The lowest nest is defined at the variety level where the elasticities, η_p^h, govern how consumers substitute between varieties of the same product. More formally, the aggregator in the upper nest is given by[35]:

$$U_t^h = \left[\sum_{p \in \Omega_t} \xi_p^h Q_{p,t}^{h\,\frac{\sigma^h}{\sigma^h - 1}} \right]^{\frac{\sigma^h - 1}{\sigma^h}}$$

where $Q_{p,t}^h$ is the aggregate consumption of product p by households in income group h at time t, ξ_p is a product level demand shifter, which may differ across income groups, Ω, is the set of available products and σ_p^h is the elasticity of substitution. The product-specific quantity, $Q_{p,t}^h$ is a CES aggregator over individual varieties:

$$Q_{p,t}^h = \left[\sum_{i \in \Omega_{p,t}} \xi_{pi}^h Q_{pi,t}^{h\,\frac{\eta_p^h}{\eta_p^h - 1}} \right]^{\frac{\eta_p^h - 1}{\eta_p^h}}$$

where $Q_{pi,t}^h$ is the consumption of a variety i by households in income group h at time t, ξ_{pi}^h is a variety-level demand shifter, $\Omega_{p,t}$ is the set of varieties available at time t within product p and η_p^h is the elasticity of substitution between varieties. In this way, consumers of the same income group have the same elasticity of substitution across foreign and local varieties. Local and foreign varieties directly compete within highly detailed product categories and face the same elasticity of substitution within

[34]The model captures this type of substitution through the product level Sato-Vartia weight which is constructed from the pre-and post-depreciation expenditure shares.

[35]For notational simplicity, we drop the category index c.

income groups.[36] At the same time, consumer taste is allowed to differ between foreign and local varieties and between consumers of different income groups. In this way, the preference structure rationalizes differences in expenditure shares between foreign and local varieties and rich and poor consumers. Given this structure, the category-level and product-level unit expenditure functions are given by:

$$P_t^h = \left[\sum_{p \in \Omega_t} \xi_p^h {P_{p,t}^h}^{1-\sigma^h} \right]^{\frac{1}{1-\sigma^h}}, \qquad P_{p,t}^h = \left[\sum_{i \in \Omega_{p,t}} \xi_{pi}^h {P_{pi,t}}^{1-\eta_p^h} \right]^{\frac{1}{1-\eta_p^h}}$$

where $P_{pi,t}^h$ is the price of variety i at time t.

4.3 Price index decomposition

Because the income-group-specific utility functions are homothetic, the change in the cost of living coincides with the change in the unit expenditure function:

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

where $\omega_{p,t}^h$ are the Sato-Vartia weights which are given by:

$$\omega_{p,t}^h \equiv \frac{\frac{\phi_{p,t}^h - \phi_{p,t-1}^h}{ln\phi_{p,t}^h - ln\phi_{p,t-1}^h}}{\sum_{p \in \Omega} \frac{\phi_{p,t}^h - \phi_{p,t-1}^h}{ln\phi_{p,t}^h - ln\phi_{p,t-1}^h}}, \qquad \phi_{p,t}^h \equiv \frac{\sum_{i \in \Omega_{p,t}} P_{pi,t} \cdot Q_{pi,t}^h}{\sum_{p \in \Omega} \sum_{i \in \Omega_{p,t}} P_{pi,t} \cdot Q_{pi,t}^h}$$

The change in the product level unit expenditure function can be further decomposed into a term that depends on changes in variety-level prices for continuing products and a term that captures changes

[36] This is in contrast to international trade applications where interactions between foreign and local goods at an aggregate level, see for instance Schmitt-Grohé and Uribe (2018) and Fajgelbaum et al. (2020).

in product availability at the variety level (see Feenstra (1994)):

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

where $\omega_{pi,t}^h$ are the variety-level Sato-Vartia weights given by:

$$\omega_{pi,t}^h \equiv \frac{\frac{\phi_{pi,t}^h-\phi_{pi,t-1}^h}{ln\phi_{pi,t}^h-ln\phi_{pi,t-1}^h}}{\sum_{i\in\Omega_p^{t-1\cap t}}\frac{\phi_{pi,t}^h-\phi_{pi,t-1}^h}{ln\phi_{pi,t}^h-ln\phi_{pi,t-1}^h}}, \qquad \phi_{pi,t}^h \equiv \frac{P_{pi,t}\cdot Q_{pi,t}^h}{\sum_{i\in\Omega_p^{t-1\cap t}}P_{pi,t}\cdot Q_{pi,t}^h}$$

and $\phi_{pi,t}^h$ is the expenditure share of variety i at time t and $\Omega_p^{t-1\cap t} \equiv \Omega_{p,t-1}\cap\Omega_{p,t}$. The variety effect is defined as the ratio of the expenditure share of continuing products relative to all available varieties at time t and the expenditure share of continuing products relative to all available varieties weighted by the elasticity of substitution at time $t-1$:

$$\frac{\lambda_{p,t}^h}{\lambda_{p,t-1}^h} \equiv \frac{\frac{\sum_{i\in\Omega_p^{t-1\cap t}}P_{pi,t}\cdot Q_{pi,t}^h}{\sum_{i\in\Omega_{p,t}}P_{pi,t}\cdot Q_{pi,t}^h}}{\frac{\sum_{i\in\Omega_p^{t-1\cap t}}P_{pi,t-1}\cdot Q_{pi,t-1}^h}{\sum_{i\in\Omega_{p,t-1}}P_{pi,t-1}\cdot Q_{pi,t-1}^h}}$$

Finally, use the definition of retail markups as the ratio of the final consumer price and the marginal cost, $P_{pi,t}\equiv M_{pi,t}\cdot C_{pi,t}$ to arrive at the final decomposition:

$$\frac{CLE_t^h}{e(\boldsymbol{P}^0, u_0^h)} = \prod_{p\in\Omega_p}\Bigg[\underbrace{\prod_{i\in\Omega_p^{t-1\cap t}}\underbrace{\left(\frac{C_{pi,t}}{C_{pi,t-1}}\right)^{w_{pi,t-1}^h}}_{\text{Cost effect}}\cdot\prod_{i\in\Omega_p^{t-1\cap t}}\underbrace{\left(\frac{M_{pi,t}}{M_{pi,t-1}}\right)^{w_{pi,t-1}^h}}_{\text{Markup effect}}}_{\text{Price channel}}\cdot \tag{4}$$

$$\underbrace{\prod_{i\in\Omega_p^{t-1\cap t}}\left(\frac{P_{pi,t}}{P_{pi,t-1}}\right)^{\omega_{pi,t}^h-w_{pi,t-1}^h}}_{\text{Substitution channel}}\cdot\underbrace{\left(\frac{\lambda_{p,t}^h}{\lambda_{p,t-1}^h}\right)^{\frac{1}{\eta_p^h-1}}}_{\text{Variety channel}}\Bigg]^{\omega_{p,t}^h} - 1$$

This final step shows that we can decompose the cost of living of consumer h into three different channels: (1) the price channel, which further decomposes into a cost and markup effect, (2) the substitution channel, and finally (3) the variety channel.

The price channel is defined as the covariance between changes in consumer prices and pre-depreciation expenditure shares of continuing varieties. It gives rise to distributional effects if different income groups have different expenditure shares on different varieties. For example, if rich consumers spend relatively more on foreign varieties and if foreign varieties experience a greater price increase, then the price channel will increase more for rich consumers and have distributional effects. By further decomposing the price channel into a cost and markup effect, we provide more insight into the transmission of the depreciation into final consumer prices and move beyond previous work that mostly focuses on models with constant markups (e.g. Fajgelbaum and Khandelwal (2016) and Borusyak and Jaravel (2021)). Since rich consumers had larger expenditure shares on foreign varieties before the depreciation, we expect the cost channel to increase the cost of living relatively more for rich consumers and the markup channel to offset this increase as markups of foreign varieties fell relative to local varieties.

The substitution channel is defined as the covariance between changes in final consumer prices and the difference in the variety-level Sato-Vartia weights and variety-level pre-depreciation expenditure shares. Intuitively, if consumers reallocate expenditure away from varieties with higher price increases, the cost of living will be lower. If low-income consumers have higher elasticities of substitution, we expect stronger substitution away from varieties with higher price increases for poor consumers, attenuating their increase in the cost of living relative to rich consumers.[37]

The variety channel quantifies how changes at the extensive margin translate into changes in the

[37] As the substitution channel captures differences in the way rich and poor consumers substitute in response to the depreciation, it coincides with the unequal expenditure switching channel emphasized in Auer et al. (2023).

cost of living. It is composed of the ratio of the expenditure share on continuing varieties after and before the depreciation and the variety-level elasticity of substitution. If the ratio of expenditure shares is below one, the appeal of the varieties that entered must have been greater compared to the appeal of varieties that exited. The extent to which this reallocation of expenditure translates into changes in the cost of living depends on the elasticity of substitution. When the elasticity is high, products are perceived as good substitutes, and adding new varieties increases utility only marginally. Whether the variety effect will have distributional cost-of-living effects as well, depends on the relative magnitude of the elasticity of substitution and the difference in the observed reallocation of expenditure from exiting to entering varieties between rich and poor consumers.

5 Quantifying changes in the cost of living

Before we can estimate how the cost of living changes, we need to estimate the variety-level elasticities of substitution. We start by discussing the empirical strategy we rely on. Next, we present both average and income-group-specific elasticities of substitution. Finally, we document how the cost of living changed following the depreciation and how rich and poor consumers were differently affected.

5.1 Estimating the elasticities of substitution

Applying Shephard's lemma to the product-level unit expenditure function, we obtain the residual demand for variety i:

$$Q^h_{pi,t} = \left(\xi^h_{pi,t}\right)^{\eta^h_p - 1} \left(\frac{P_{pi,t}}{P^h_{p,t}}\right)^{-\eta^h_p} Q^h_{p,t} \tag{5}$$

After taking logs, equation 5 becomes:

$$q^h_{pi,t} = -\eta^h_p p_{pi,t} + \eta^h_p p^h_{p,t} + q^h_{p,t} + \left(\eta^h_p - 1\right) ln(\xi^h_{pi,t})$$

where lowercase letters indicate logarithmic transformations. The crucial parameters of interest are the elasticities of substitution η^h_p. To consistently estimate the elasticity, we need to overcome a set of econometric challenges. First, the product-level price index $P^h_{p,t}$ and quantity index $Q^h_{p,t}$ depend on the demand shifters and are unobserved. To deal with this potential simultaneity issue, we flexibly account for them using product-income-time fixed effects.[38] Second, the demand shifters, $\xi^h_{pi,t}$, are also unobserved. If firms have prior knowledge of $\xi^h_{pi,t}$, prices are likely set with $\xi^h_{pi,t}$ in mind. To overcome this issue, we decompose the demand shifters into a variety-income group fixed effect and a residual term as follows: $ln(\xi^h_{pi,t}) = \theta^h_{pi} + \varepsilon^h_{pi,t}$. In this way, our estimating equation becomes:

$$q^h_{pi,st} = \beta^h_{pi} p_{pi,st} + \theta^h_{pi} + \lambda^h_{pi,t} + \varepsilon^h_{pi,st} \tag{6}$$

where we have added the subscript s to indicate that we observe prices and quantities at the variety-store-income group-time level. While the category-income-time fixed effects, $\lambda^h_{p,t}$, take care of the potential omitted variable bias, there may still be unobserved time-varying demand shifters that are correlated with prices. To address this concern, we exploit the spatial dimension of our data. We use the price of variety i in location s' as an instrument for the price of the same variety in location s. We believe this is an appropriate instrument as Metro is using near uniform pricing across the two stores in Almaty and Astana.[39] More specifically, Figures A.14 and A.15 replicate some of the

[38]See Atkin et al. (2018), Arkolakis et al. (2019) and Faber and Fally (2022) for a similar strategy.

[39]This identification strategy was first introduced in Hausman (1996) and was subsequently used by Nevo (2001), Dellavigna and Gentzkow (2019) and Faber and Fally (2022).

evidence presented in Dellavigna and Gentzkow (2019) and indicate that across the two stores prices of the same variety tend to be highly correlated in both the cross-section and in the time dimension. By employing uniform pricing across locations, it is much more likely that retailers adjust prices in response to common shocks, e.g. changes in costs, than in response to idiosyncratic local demand shocks. Because we study a period in which the depreciation of the Tenge induced large changes in the prices and costs of both local and foreign varieties, price variation in our sample likely stems from such a common cost shock.

Nevertheless, the crucial assumption underpinning the consistent estimation of the elasticities is that the Hausman instrument is not contaminated by common demand shocks. Two possible common cost shocks come to mind. First, if the devaluation also induced changes in real income and shifted relative demand across varieties, e.g. by affecting the demand for foreign varieties relatively more, the elasticities might be inconsistently estimated. While we cannot account for variety-specific shifts over time, below we consider specifications that control for shifts between local and foreign varieties within product categories. Second, the estimation strategy also rules out demand shocks driven by national advertising. To partially address this concern, we follow Dellavigna and Gentzkow (2019) and show that the results are robust to controlling for seasonal variety-specific demand shocks.

5.2 Estimates of the elasticity of substitution

To estimate the elasticities of substitution, we regress monthly purchased quantities on consumer prices (inclusive of sales and coupons) and we include all periods. 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 category-store level. We first provide estimates that average across income groups and then estimate elasticities of substitution for each income group separately.

Average elasticity of substitution Columns (1) to (4) of Table 2 present the OLS estimates of the average elasticity of substitution and Columns (5) to (8) present the IV-estimates. Column (1) shows the result when we include the most basic set of fixed effects, being product-quarter fixed effects that filter out the price and quantity indices and variety fixed effects to account for the demand shifters. In this setup, we recover a negative and statistically significant estimate of -2.24. 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. When we allow the demand shifters and price indices to also differ across locations in columns (3) and (4), the estimated elasticities decrease to -1.43 and -1.31 respectively but remain below the theoretical constraint of -1.

Looking at columns (5) to (8), we first note that the Hausman-type instrument is strong as the first-stage F-statistics are always substantially above the conventional critical values, which is consistent with the presence of near uniform pricing. Second, the IV estimates are statistically significant and deliver more elastic demand curves to their respective OLS estimates. For example, in our most basic fixed effect setup, the IV estimate is -3.17 while its corresponding OLS estimate is -2.24. Third, the estimates reported in columns (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 product categories sold by US retailers and report an average elasticity of substitution for food products of around -2.8. 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.

Consumer heterogeneity To understand whether consumers of different income groups might have different elasticities of substitution, we re-estimate equation 6 separately for each income group. We

Table 2: Elasticity of substitution - Aggregate

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{pi,st}$	-2.24 ***	-2.15 ***	-1.43 ***	-1.32 ***	-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	348.0	6,778.3	5,823.4
R sq.	0.056	0.070	0.055	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. Columns (1) - (4) are OLS estimates and columns (5) - (8) are estimated using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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.

estimate one regression for each income group to ensure 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 reports the results for the same fixed effect specifications as Table 2 and Panels (a), (b), and (c) show the results for the relatively low-, middle- and high-income groups respectively.

Table 3 shows that the instruments remain strong and that the IV-estimates are statistically significant and negatively estimated. Also, the IV estimates again deliver more elastic demand curves relative to their corresponding OLS estimates. More importantly, regardless of the specification, we find that consumers of rich consumers have lower elasticities of substitution compared to poor consumers. This indicates that rich consumers consider the alternatives in their choice set as less substitutable and will value changes in product variety more relative to poor consumers. The finding that high-income consumers have lower elasticities of substitutions is in line with a substantial IO literature (e.g.Berry et al. (1995) for cars, Nevo (2001) for breakfast cereal, and Dellavigna and Gentzkow (2019) for many grocery categories). Also, they are quantitatively in line with the differences in elasticities of substitution across income groups reported in Handbury (2021)

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

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot \mathbb{1}(\text{Low})$	-3.65 ***	-3.51 ***	-2.35 ***	-2.27 ***	-5.2 ***	-5.18 ***	-2.51 ***	-2.53 ***
	(0.243)	(0.252)	(0.146)	(0.160)	(0.467)	(0.536)	(0.184)	(0.215)
First stage F-stat	-	-	-	-	292.6	170.8	2,920.1	2,213.8
R sq.	0.034	0.054	0.018	0.043	-	-	-	-
Nr. obs	190,063	190,063	190,063	190,063	151,759	151,759	151,759	151,759
$p_{i,p,t} \cdot \mathbb{1}(\text{Middle})$	-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	415.3	7,571.5	6,232.5
R sq.	0.104	0.120	0.100	0.120	-	-	-	-
Nr. obs	329,014	329,014	329,014	329,014	264,839	264,839	264,839	264,839
$p_{i,p,t} \cdot \mathbb{1}(\text{Top})$	-1.24 ***	-1.14 ***	-0.964 ***	-0.825 ***	-2.22 ***	-2.17 ***	-1.22 ***	-1.06 ***
	(0.155)	(0.158)	(0.089)	(0.095)	(0.263)	(0.288)	(0.106)	(0.115)
First stage F-stat	-	-	-	-	443.7	295.3	5,413.4	4,578.2
R sq.	0.052	0.069	0.045	0.066	-	-	-	-
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 separately, 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 consumers classified in the middle-income group. from estimating equation Columns (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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.

and Auer et al. (2023). For instance, Auer et al. (2023) study how rich and poor consumers differentially adjust their expenditures across local and imported products. In their baseline estimates, they find that a tripling of the household income leads to a fall in the elasticity of substitution between 2.12 and 2.42.

Robustness We consider four robustness checks. First, we consider the possibility that the depreciation not only acted as a cost shock but also changed relative demand across foreign and local varieties through its effect on real income. To investigate this, we follow Bems and Giovanni (2016) and consider a specification in which we interact the category-time fixed effects with origin fixed effects. In this way, we account for changes in the demand for foreign varieties relative to local varieties. We find that the elasticities are still precisely estimated and are slightly more inelastic compared to the baseline estimates (see Table A.23). Crucially, the difference between the elasticities for rich and poor consumers remains quantitatively important.

Second, the baseline estimates do not control for changes in variety-level demand over time that are common between the two store locations. To assess the robustness of the results in controlling for seasonal demand shocks, we follow Dellavigna and Gentzkow (2019) and consider a specification in which we replace the variety-store fixed effects with variety-store-year and variety-store-month-of-the-year fixed effects. In this way, we control for seasonal variety-specific demand shocks that are common across stores and are allowed to differ every year. Table A.24 and Table A.30 show that the estimates we recover are very close to the ones we recover with only variety-store fixed effects, both on average and between groups of consumers.

Third, we also consider clustering the standard errors at the monthly level to account for systematic cross-sectional correlation across varieties induced by the depreciation. Tables A.22 and A.27 show that the aggregate and income-specific elasticity estimates remain precisely estimated.

Finally, when we classify consumers according to their total expenditure instead of the average price of the expenditures in Table A.28, we find that the difference between the elasticities of substitution across rich and poor consumers is both qualitatively and quantitatively preserved.

5.3 Cost-of-living effects

This section presents how the cost of living changed in the four quarters following the depreciation. To have a sense of the average change in the cost of living, we start with the aggregate results. Hereafter, we show that the change in the cost of living differed between rich and poor consumers.

Aggregate effects To obtain the aggregate decomposition results, we first compute each of the four components: (1) cost channel, (2) markup channel, (3) substitution channel, and (4) product variety channel separately and combine them to obtain the overall cost of living effect.[40] To calculate the components, we fix period t-1 to be equal to the pre-depreciation quarter and compute for each of the ensuing quarters the cumulative difference relative to the pre-depreciation.[41]

Figure 9 shows the aggregate cost-of-living and the decomposition into the different channels.[42] 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%. The transmission of the exchange rate shock into prices was gradual as the cost of living increased by 5% after one quarter and steadily grew to a little under 25% after 5 quarters. This is qualitatively in line with Figure 3 which also showed that pass-through converged after 12 to 15 months and is also consistent with other large devaluation episodes as described in Burstein et al. (2005) and Alessandria et al. (2010).

The increase in costs for continuing varieties was the main driver of the cost of living increase. Two quarters after the depreciation, the marginal cost of food and beverages went up by more than 15% and by 28% after four quarters. This corresponds roughly to an aggregate pass-through rate into marginal costs of 40% to 50% which is quantitatively in the range of estimates provided by Goldberg and Campa (2010) and recent work on dominant currencies in international trade (e.g. Gopinath et al. (2020)). In the aggregate, the markup and substitution channels do not significantly dampen the increase in the cost of living.

Four quarters after the depreciation, the variety channel had dampened the increase in the cost of

[40]To compute the variety effect we use the estimate in column (5) of Table 2 We use these estimates as they yield the most conservative results for the variety effect.

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

[42]The same results are also displayed in Table A.25.

living by about 6%. This implies that the taste-adjusted price of entering varieties was superior to the taste-adjusted price of the varieties that exited. As mentioned before, the fact that the variety effect is quantitatively important is consistent with the closed economy literature on product churning in which relatively less appealing are frequently replaced by relatively more appealing varieties (e.g. Bernard et al. (2010), Broda and Weinstein (2010), and Argente et al. (2024)). In addition, Argente and Lee (2021) shows that the variety channel also had a dampening effect on the cost of living for all US income groups during the Great Recession in the US, potentially speeding up the cleansing of older and less appealing for more appealing varieties. While the effect of changes in product assortment on pass-through into prices has been studied before (e.g. Nakamura and Steinsson (2012), Cavallo et al. (2014) and Goetz and Rodnyansky (2023)), our results show that accounting for changes in product variety and measuring their welfare impact is important to translate pass-through estimates into welfare terms.

Distributional effects To obtain the distributional effects, we apply the same steps as for the aggregate effects but now with income group-specific expenditure shares and elasticities.[43] To assess the distributional effects, we take 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).

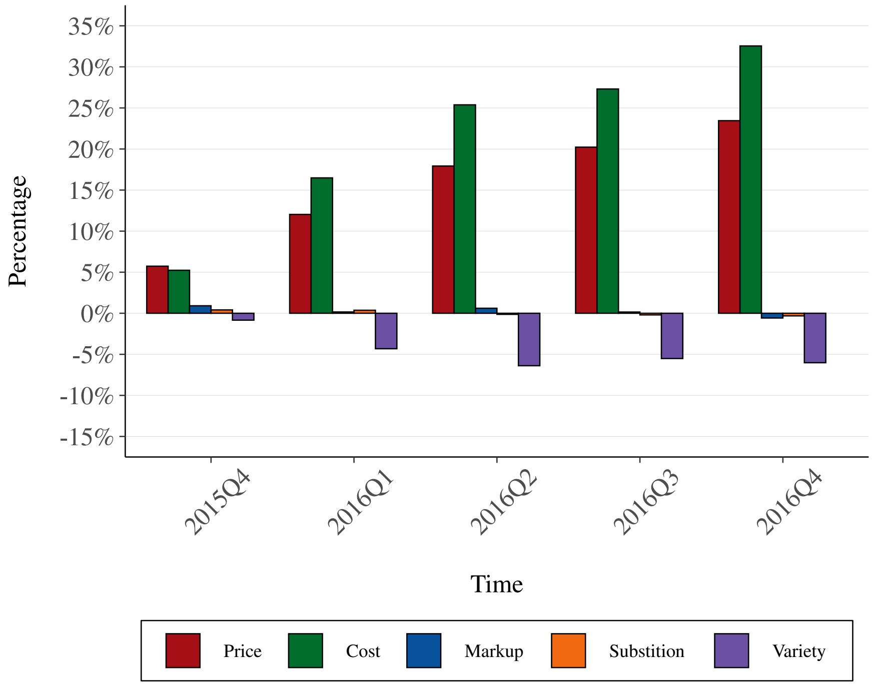
Figure 10 presents the distributional effects of the depreciation for the income definition based on quintiles.[44] Overall, we find that the cost of living went up by less for rich consumers compared to poor consumers as the cost-of-living increase is 5% and up to 10% lower for rich consumers compared to poor consumers two and five quarters after the depreciation respectively.

Notably, due to offsetting intensive margin channels, the majority of the distributional effects did

[43]For the elasticities of substitution, we use the IV estimates displayed in column (5) of Table 3 as they yield conservative results for the variety effect.

[44]The same results are also displayed in Table A.35.

Figure 9: Cost-of-living - Aggregate Effects

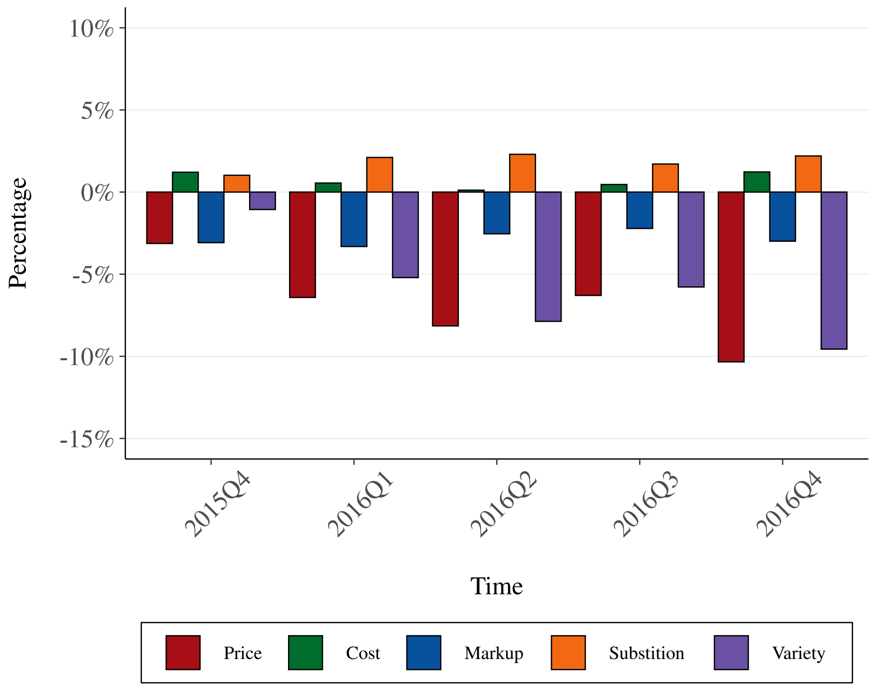


Notes: These figures show the aggregate results from the nested CES decomposition which are also presented in A.25. The results are obtained after pooling across all income groups and estimating the variety effect when we restrict the elasticity of substitution to be the same across all product categories. 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 A.25.

not arise from changes associated with the set of continuing products. First, the cost and markup channels, which collectively make up the price channel, moved in opposite directions. Depending on the horizon we consider, the baseline results show that the cost channel led to a 0.1% - 1.2% increase in the cost of living of rich consumers compared to poor consumers. At the same time, the markup channel moved in the opposite direction and attenuated the cost-of-living increase by 2%-2.8% for rich consumers. As the cost and markup channels diverged, they made consumer prices go up by less for rich consumers relative to poor consumers. This observation is congruent with the fact that rich consumers have on average a higher expenditure share on foreign varieties whose costs increased more and retail markups declined after the depreciation.

Second, whereas consumer prices on average increased by less for rich consumers, the substitu-

Figure 10: Cost-of-living: Distributional effects - Per income group (20%-80% split)



Notes: This figure shows the distributional results from the nested CES decomposition for the quintiles definition of the income distribution. These results are also presented in Table A.35. 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 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 A.35. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

tion channel led to a greater cost-of-living increase for rich consumers. Our baseline results point to a relative increase in their cost of living through the substitution channel by 2.1% and 2.3% after two and four quarters respectively. As the substitution channel measures how intensely consumers substitute away from continuing varieties that become relatively more expensive, this is consistent with the fact that we estimate that poor consumers have higher elasticities of substitution. This is also in line with Bems and Giovanni (2016) and Auer et al. (2023) who find that poor consumers reduced the cost-of-living increase by substituting more towards cheaper continuing products. Taken together, the distributional effects we document did not arise from changes associated with the set of continuing products because the price channel was quantitatively offset by the substitution channel.

Adjustments on the extensive margin, however, were the main driver of the distributional effects of the depreciation. Figure 10 illustrates that rich consumers benefitted more from the changes in variety after the depreciation. After two and four quarters, changes in product variety subdued the cost-of-living increase by 2.5% and 3% for poor consumers and 7.5% and 8.6% for rich consumers. This translates into a cost of living inequality of 5.2% after two quarters and by 5.7% after four quarters. Despite its quantitative importance in other settings, the extensive margin has not been incorporated before to study the aggregate and distributional welfare consequences of large depreciation. Our results show that accounting for changes in the choice set of consumers is paramount to determine whether relatively rich or relatively poor suffer more from depreciation.

The differences in the variety effect for rich and poor consumers can be driven by differences in substitution towards new varieties and away from varieties that exited, by differences in elasticities of substitution, or both. First, to understand differential switching, Figure A.19 shows the distribution of the ratio of the expenditure share on continuing varieties after the depreciation relative to before the depreciation across product categories for rich and poor consumers separately. These ratios measure the extent to which rich and poor consumers substituted new varieties for varieties that exited. When we test equality between these distributions with a parametric and non-parametric test, we are unable to reject the null hypothesis of equal switching. Second, differences in the elasticities of substitution imply that for the same level of switching, the associated welfare effect will differ. This is because lower elasticities of substitution imply that varieties are perceived to be more differentiated such that the same level of switching implies a larger change in utility. As Table 3 provides robust evidence that rich consumers have lower elasticities of substitution, heterogeneity in the elasticities of substitution across income groups seems to be the key driver of the distributional effects stemming from the variety effect.

Alternative cutoffs The baseline distributional results stem from categorizing rich and poor consumers as those consumers whose consumption basket ranks within the top and the bottom quintile in terms of the unit cost respectively. To ensure that our results do not depend on this particular cut-off, we replicate the analysis by considering terciles, quartiles, and deciles as alternative cut-offs. Figures A.17a-A.17d and Tables A.33-A.36 show that the results are robust across these alternative definitions. Importantly, the differences between rich and poor consumers in terms of the total cost-of-living effect and the cost-of-living components generally grow when we start from the loosest definition, i.e. terciles, and move to the strictest definition, i.e. deciles.

Heterogeneity across categories The results presented so far are based on the assumption that the elasticities of substitution are the same across different product categories. However, if changes in product variety are more concentrated in product categories with higher elasticities of substitution, using homogeneous elasticities could lead to overstating the variety effects. For this reason, we consider heterogeneity in the elasticities of substitution.

Starting with the aggregate cost-of-living effects, we re-estimate equation 6 separately for each subcategory and obtain an elasticity of substitution for each of the 14 subcategories.[45] Table A.31 presents the IV results and shows that the distribution is indeed quite dispersed.[46] Figure A.16 and Table A.26 presents the aggregate cost-of-living effects when we account for heterogeneity in the elasticities of substitution. Relative to the homogeneous case, the product variety channel strengthens and exerts a greater dampening effect on the aggregate cost of living increase. In this setup, changes in the choice set of consumers subdue the rise in the cost of living between 8% and 10% depending

[45]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.

[46]Judging from our preferred specification (which is column 3 of Table A.31), the elasticities range from -1.4 to -4.79.

on the horizon we look at.

To check the robustness of the distributional effects, we adjust equation 6 in two ways. First, we not only estimate category-level elasticities of substitution but also interact prices with income group levels. In this way, we estimate 42 different elasticities that vary at the subcategory–income group level. Second, we interact the category-time and variety fixed effects with income group fixed effects to allow for income group-specific price indices, expenditure levels, and demand shifters. We present the estimates in Table A.32. Tables A.37 - A.40 and Figures A.18a - A.18d show the distributional cost-of-living results. First, in line with the aggregate results, accounting for between-category heterogeneity in the elasticities of substitution tends to strengthen the welfare effects of changes in product variety. In particular, for both low-income and high-income consumers, the product variety channel dampened the cost-of-living increase by more. Second, rich consumers still experienced slower growth in the cost of living in the year following the depreciation. In particular, rich consumers experienced a 3%, 5%, and 7% slower increase in their cost of living one, two, and three quarters after the depreciation and this pattern is consistent across the different income group definitions. At the same time, the heterogeneous results are less persistent as the gains from changes in product variety seem to be roughly equal across high-income and low-income consumers after four quarters. 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 analyzes the impact of the depreciation of the Kazakh Tenge in August 2015 on consumer prices, costs and retail markups of local and foreign products and how these adjustments induce distributional cost-of-living effects. To this end, we leverage novel scanner data from a supermarket, Metro, in Kazakhstan at the product and transaction level. The depreciation had a potentially considerable welfare effect as it pushed up the final consumer prices by 25% after one year and induced substantial changes in the set of available products one year after the depreciation.

We document that rich consumers have substantially larger expenditure shares on foreign varieties relative to poor consumers within highly detailed product categories before the depreciation. In principle, this exposed rich consumers more to changes in the final consumer prices of foreign varieties. However, through an event study design, we show that the relative consumer price increase of foreign products compared to local alternatives was very muted. While marginal costs of foreign products increased by 6 to 8% more relative to local varieties, this increase was offset by a decrease in the retail markups of foreign varieties by 3 to 4% relative to local varieties.

To analyze the change in the cost of living, we make assumptions about consumer preferences and decompose changes in the cost of living in (1) the price channel, (2) the substitution channel, and (3) the product variety channel. We estimate that the aggregate cost of living increased by 25 percent after four quarters. We also explore the distributional effects on the cost of living and show that the impact of the depreciation was less severe for rich consumers. In line with the event study, we show that 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. We estimate that rich consumers have lower elasticities of substitution which made them substitute away less intensively from varieties whose prices rose by more but it also means that they benefitted more from changes in product variety that occurred in the year following the depreciation.

Our results shed new light on the transmission mechanisms of exchange rate shocks to consumer prices and how offsetting movements in markups can dampen relative price adjustment after the depreciation. Furthermore, we show that heterogeneity in the price sensitivity of rich and poor consumers can translate into substantial cost-of-living inequality in the presence of large changes in product variety following international shocks.

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

ONLINE APPENDIX

A Appendix

A.1 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 the retailer compares to other stores and how it might have responded differently after the shock. To this end, we complement the store-level scanner data with two additional data sources. First, we add product-level scanner data from AC Nielsen Kazakhstan on the same set of products observed across multiple stores. From 2014 until 2016, the dataset covers the 40 top-selling barcodes in each category and records prices and sales for the same product at different stores of different sizes aggregated across regions.[47][48] Second, we use disaggregated 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 in our dataset from the National Bank of Kazakhstan.[49]

Market share. 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 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

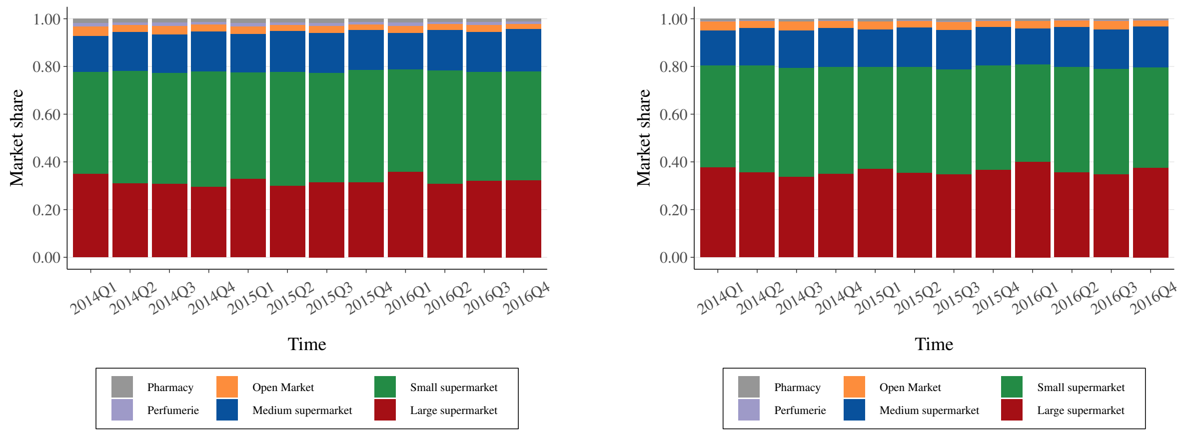
[47] Stores are classified as large, medium, small or other (including open market stores, pharmacies, and perfumeries) based on whether they sell both food and non-food and based on the physical size of the stores. Table A.4 provides a mapping from the store types in the data to the classification we use in this section.

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

[49] We retrieve information about food and non-alcoholic beverages, tobacco and alcoholic beverages, clothing items, and household supplies.

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 store types for each quarter from 2014 until 2016. Panel (a) includes all product categories and Panel (b) only food and non-alcoholic beverages.

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.

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 two versions of the following regression:

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

where $p_{i,st}$ is natural logarithm of the consumer prices of variety i which is part of category p sold at storetype s at time t. The function $\mathbb{1}(\mathrm{s} = \mathrm{k})$ is an indicator function that is equal to one when the store is either large, medium, or residual.[50] Hence, we consider small stores as the baseline

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

in these regressions. By including category-time $\lambda_{p(i),t}$, we estimate the price difference between small stores and a store type k stemming from price differences for identical varieties and assortment differences. In contrast, by including variety-time $\lambda_{i,t}$, the estimated price differences only result from differences in the price for identical products. 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 particular, in column (1) we include only category-time fixed effects and find that prices within the same 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.[51]

Next, we turn to document 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:

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

where $y_{i,st}$ is either the log consumer price, log cost or log retail markup of product i, sold in store s in month t, $\mathbb{1}(\text{o(i)} = \text{foreign})$ 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 category, we add $\theta_{p(i),s}$ which are category-store fixed effects. To focus on the cross-sectional dispersion within product categories, we include $\lambda_{p(i),t}$ which category-time 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 of the relative cost change induced

[51]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 large stores increase by roughly 50%.

Table A.1: Price disperion

$p_{i,st}$	Food & Non-alc. Beverages (1)	(2)	(3)	(4)	All products (5)	(6)	(7)	(8)
$\mathbb{1}(s = \text{Large})$	0.227 ***	0.115 ***	0.222 ***	0.0938 ***	0.325 ***	0.244 ***	0.32 ***	0.205 ***
	(0.016)	(0.012)	(0.016)	(0.012)	(0.015)	(0.013)	(0.015)	(0.013)
$\mathbb{1}(s = \text{Medium})$	0.0711 ***	0.0428 ***	0.0681 ***	0.0345 ***	0.0714 ***	0.0893 ***	0.0692 ***	0.0769 ***
	(0.010)	(0.008)	(0.011)	(0.007)	(0.011)	(0.009)	(0.011)	(0.009)
$\mathbb{1}(s = \text{Other})$	0.18 ***	0.148 ***	0.181 ***	0.121 ***	0.407 ***	0.385 ***	0.383 ***	0.327 ***
	(0.017)	(0.015)	(0.017)	(0.013)	(0.015)	(0.017)	(0.016)	(0.016)
Category x Time FE	✓		✓		✓		✓	
Variety x Time FE		✓		✓		✓		✓
R sq.	0.333	0.509	0.368	0.584	0.371	0.482	0.396	0.553
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, while 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.

by the depreciation. The first three columns of Table A.2 show 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 the store- or region-specific time variation and to interacting the category-store fixed effects with store-month fixed effects.[52] 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.

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 of 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.[53] This figure shows that the two series closely track each other in the period around the depreciation.[54]

Second, using the AC Nielsen data we check whether large stores adjusted prices differently

[52]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 Giovanni (2016) find a 28% foreign premium using scanner data from a Latvian retailer and Goetz and Rodnyansky (2023) 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 and Rogoff 2001 or by a literature on vertical specialization which predicts that richer (poorer) countries tend to specialize more in high-(low-)quality varieties Schott 2004; Fajgelbaum et al. 2011.

[53]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.

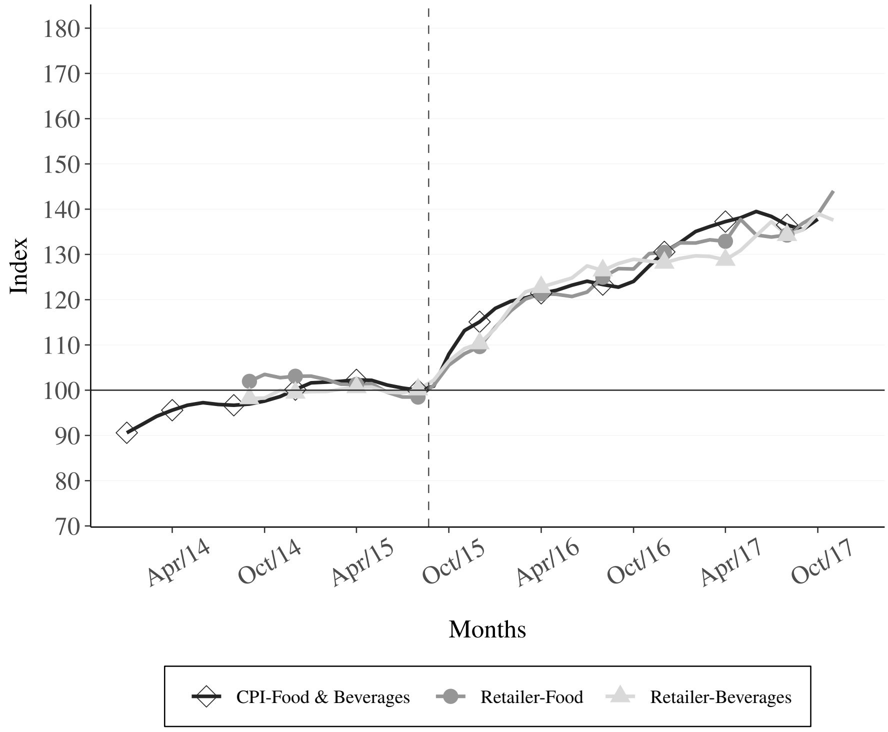
[54]Figure A.3 shows that the co-movement between the overall price evolution in other product categories of our retailer and the corresponding CPI component is much weaker. In addition, we show below that large stores increased prices by more after the depreciation compared to small stores.

Table A.2: Foreign Premium: Food & Beverages

	Price			Cost			Margin		
$y_{i,st}$	(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. The pre-depreciation median retail markup was 1.13. 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.

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 closely as possible, these series are constructed using only continuing products. More precisely, for this exercise, 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 computed from expenditure on these products before the devaluation.

compared to small stores after the depreciations by estimating:

$$p_{i,st} = \sum_{k \in \mathcal{S}} \beta_k \Big(\mathbb{1}\,(\mathrm{s} = \mathrm{k}) \times \mathbb{1}\,(t > 2015\mathrm{Q}3) \Big) + \theta_{i,s} + \lambda_{i,t} + \varepsilon_{i,st} \tag{A.3}$$

where $p_{i,st}$ is still the natural logarithm of the consumer prices of variety i sold at store type 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 $\lambda_{i,t}$ 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.[55]

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

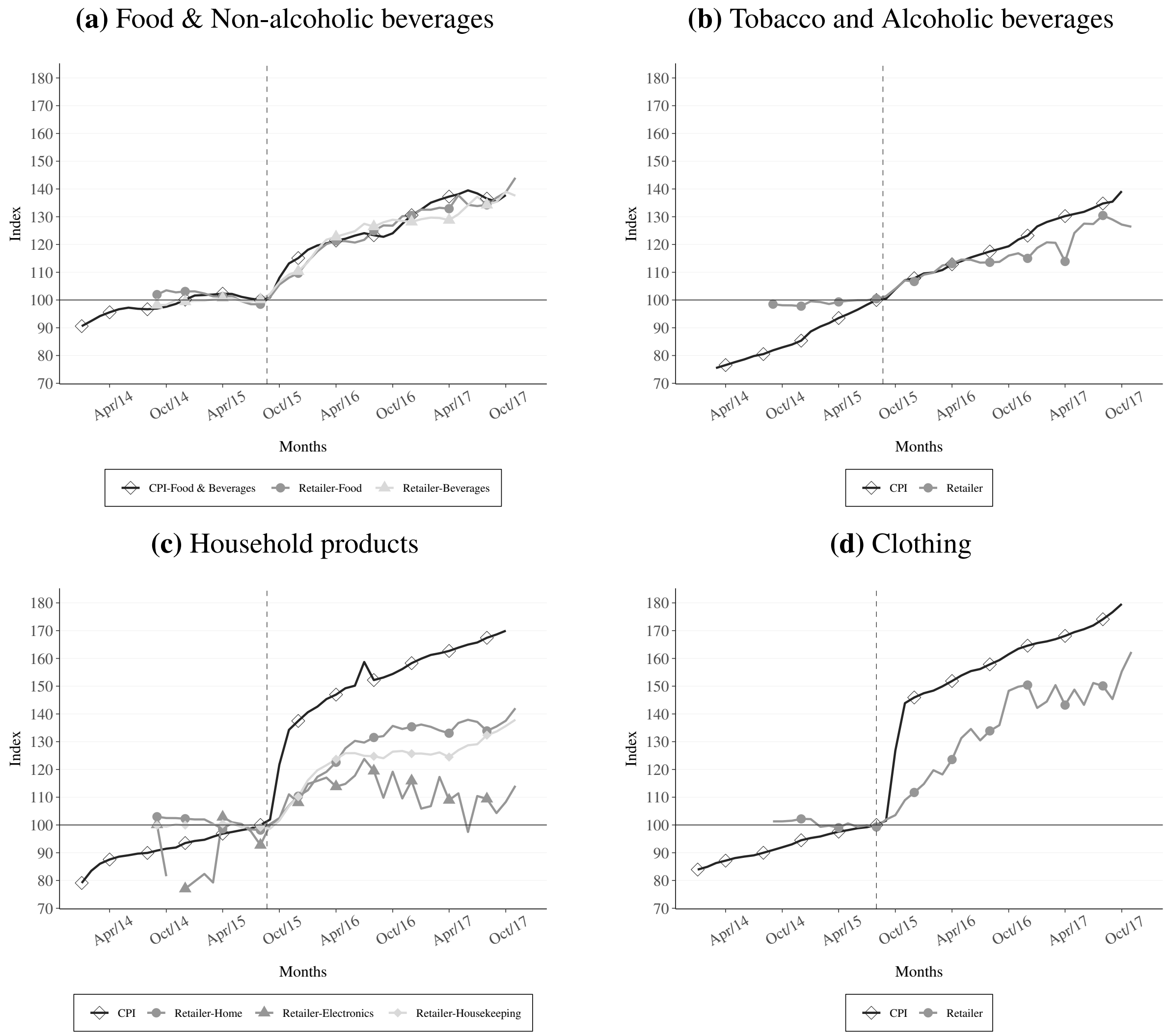
Table A.3: Differential Price adjustment

	Food & Non-alc. Beverages			All products		
$p_{i,st}$	(1)	(2)	(3)	(4)	(5)	(6)
$\nVdash(s = \text{Large}) \cdot \nVdash(t > 2015Q3)$	0.0203 **	-0.00248	0.00867	0.0141 *	0.105 ***	0.0677 ***
	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.007)
$\nVdash(s = \text{Medium}) \cdot \nVdash(t > 2015Q3)$	0.0171 **	0.1 ***	-0.00418	0.0169 **	-0.0269 **	-0.0449 ***
	(0.007)	(0.012)	(0.012)	(0.007)	(0.012)	(0.012)
$\nVdash(s = \text{Other}) \cdot \nVdash(t > 2015Q3)$	-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.

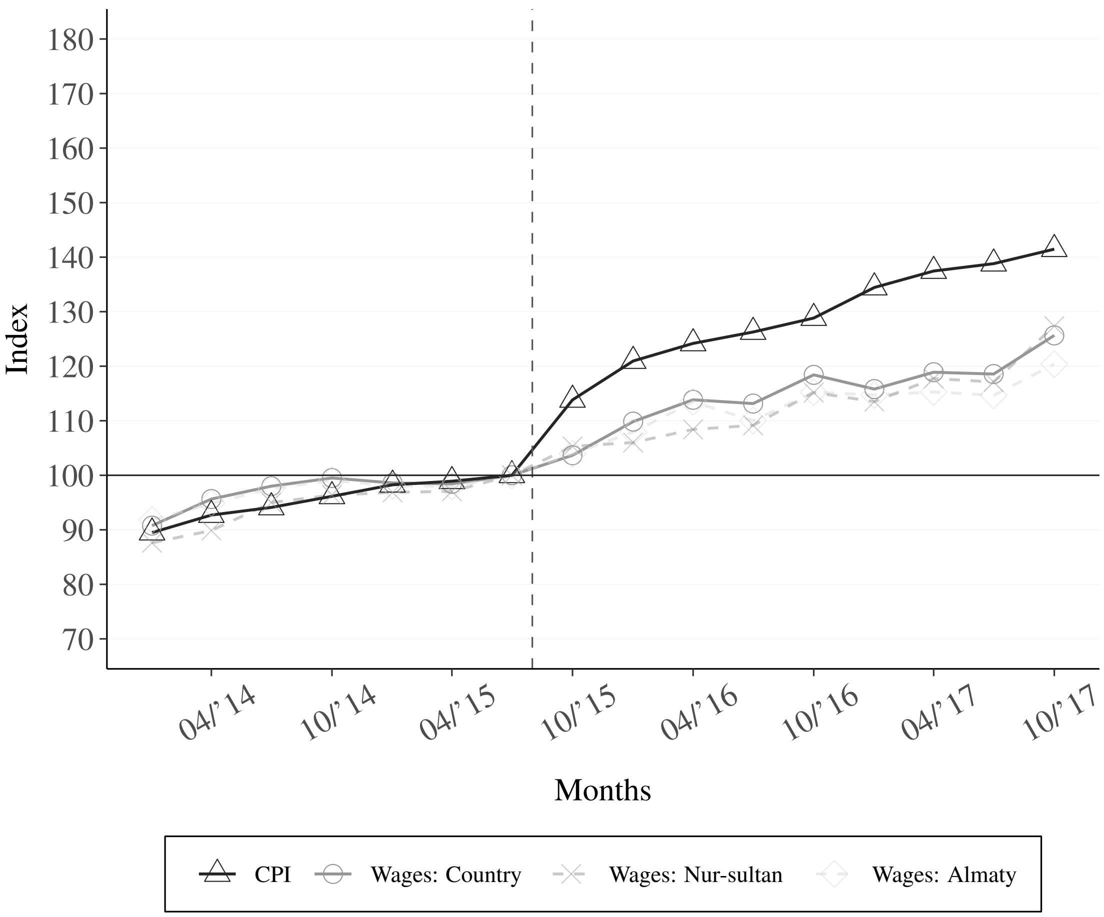
A.2 Figures

Figure A.3: Price evolution comparison: Retailer vs CPI



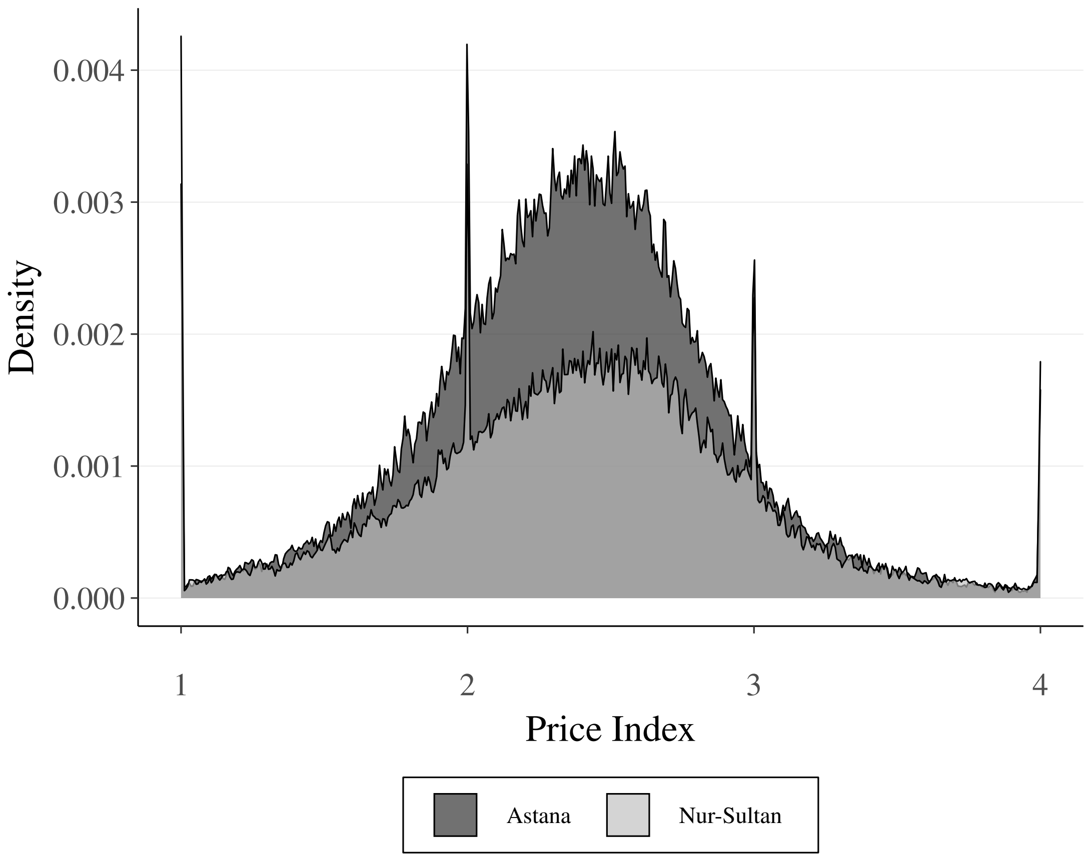
Notes: This figure compares the aggregate price evolution of the subset of broad expenditure categories that are covered by the retailer and the CPI. To mimic the construction of the CPI index as closely as possible, these series are constructed using only continuing products, products that were present before and after the devaluation. More precisely, for this exercise, 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 computed from expenditure on these products before the devaluation.

Figure A.4: CPI and Nominal Wage evolution



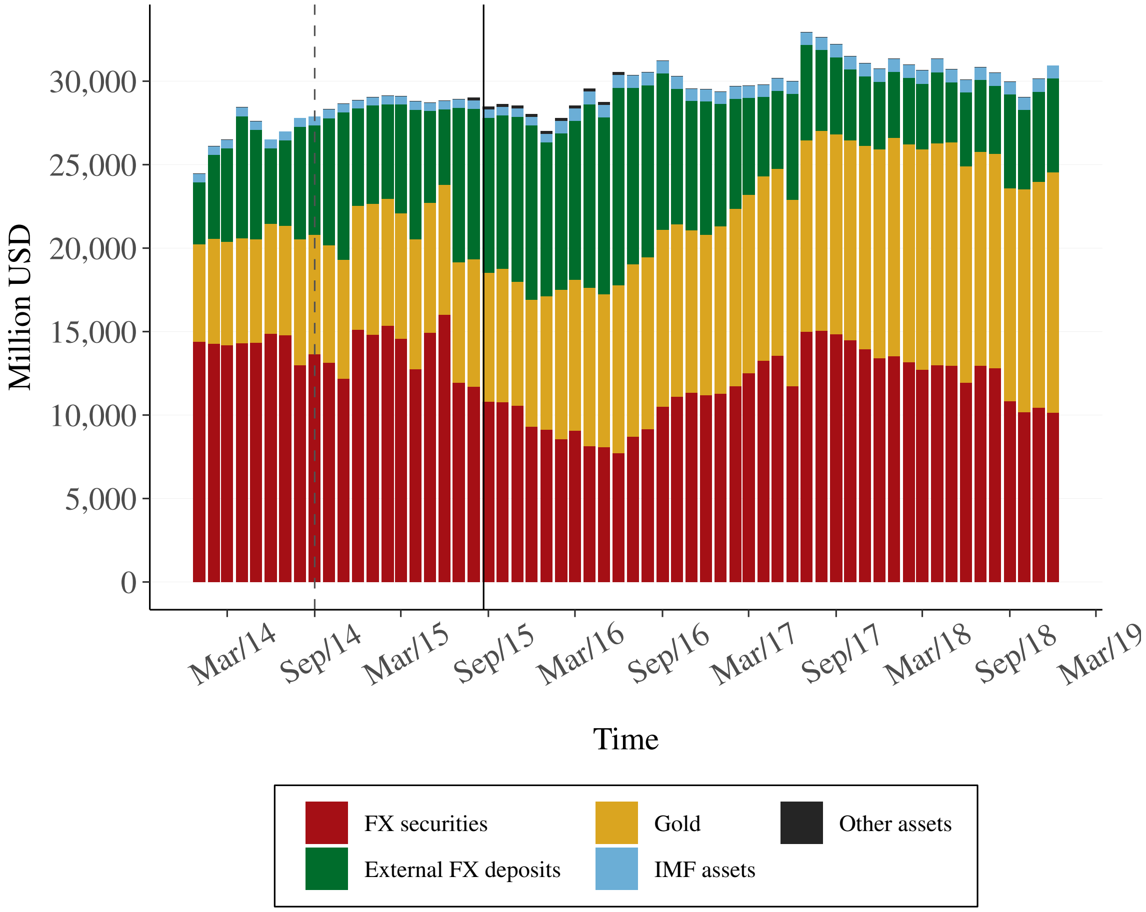
Notes: This figure displays the evolution of the overall CPI and of the average nominal wage in Kazakhstan. In addition, it also provides the evolution of nominal wages in Almaty and Astana.

Figure A.5: Distribution of Index across stores



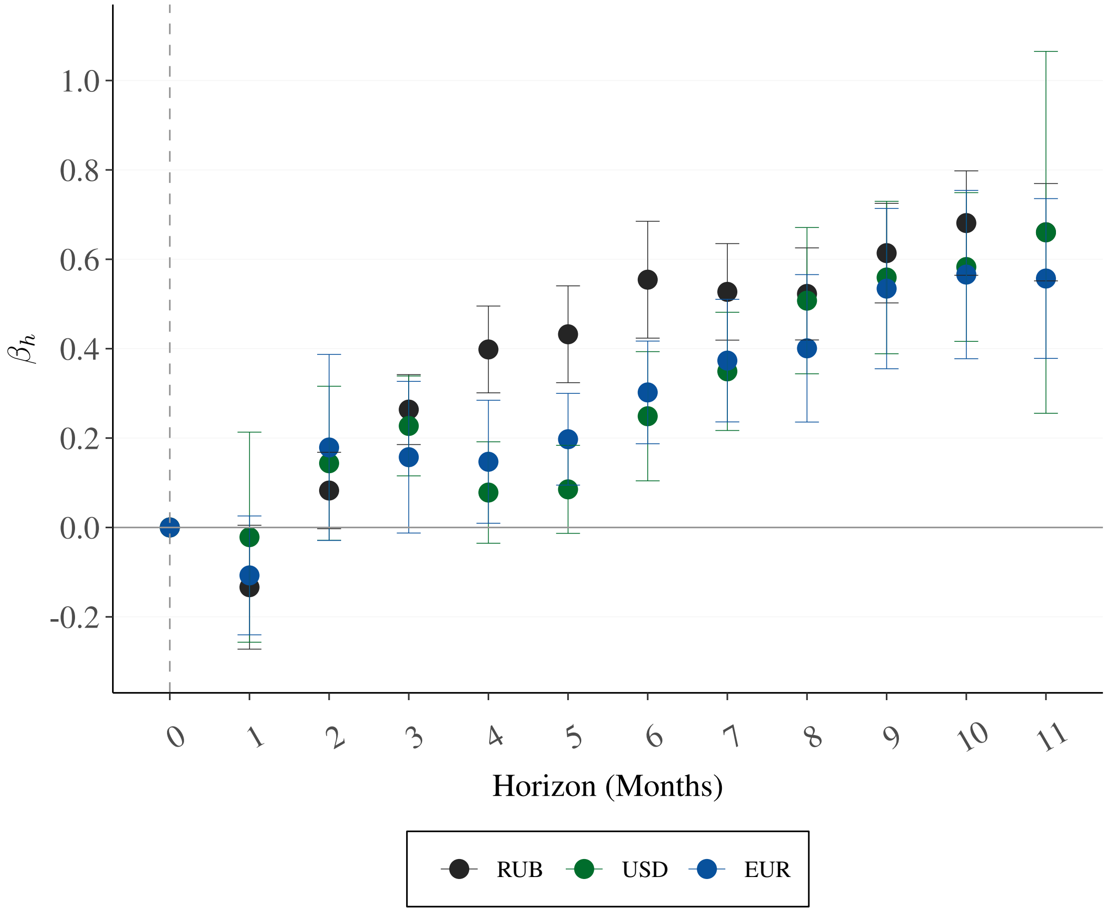
Notes: This figure displays the distribution of the expensiveness index across the stores in Almaty and Astana.

Figure A.6: Foreign currency reserves



Notes: This figure shows the evolution of the foreign currency reserves of the Kazakh National Bank by their type. We distinguish between the reserves owned by the Bank itself, the reserves it borrowed from other Central Banks or reserves that were made available by other Banks, reserves of Gold, and other foreign currency reserves. These reserves may be in the form of hard currency or safe foreign currency-denominated debt. Data is obtained from the IMF's International Reserve and Foreign Currency Liquidiy database.

Figure A.7: Exchange Rate Pass-through: Currency of invoicing

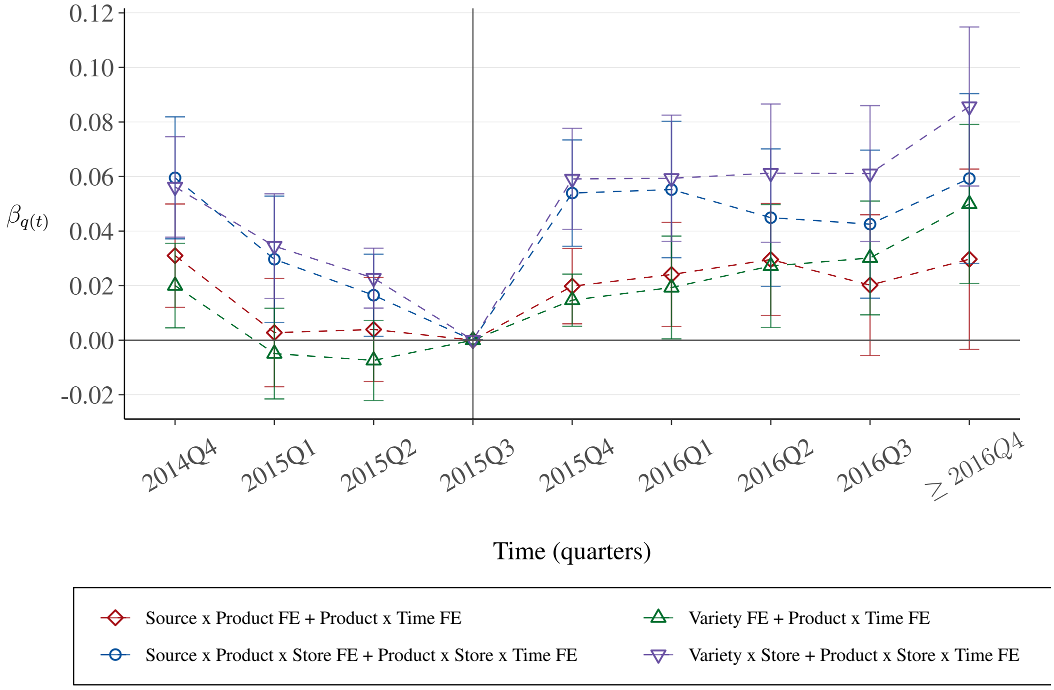


Notes: This figure shows the evolution of exchange rate pass-through into prices separately for different currencies of invoicing. More specifically, we plot the coefficients β_h which are obtained from estimating equation

$$\Delta_h \ln(p_{ist}) = \Delta_h \ln(e_{ist}) + \varepsilon_{ist}$$

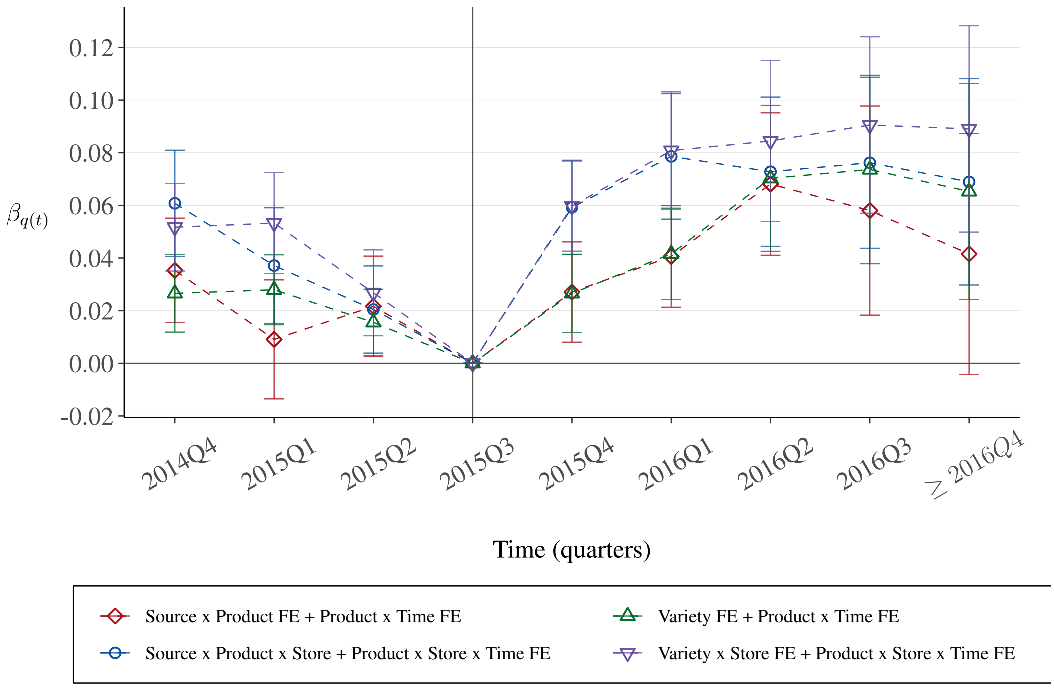
Whiskers are 95% confidence intervals around the point estimates computed from standard errors which are clustered at the product-store level.

Figure A.8: Difference-in-difference: Consumer Prices



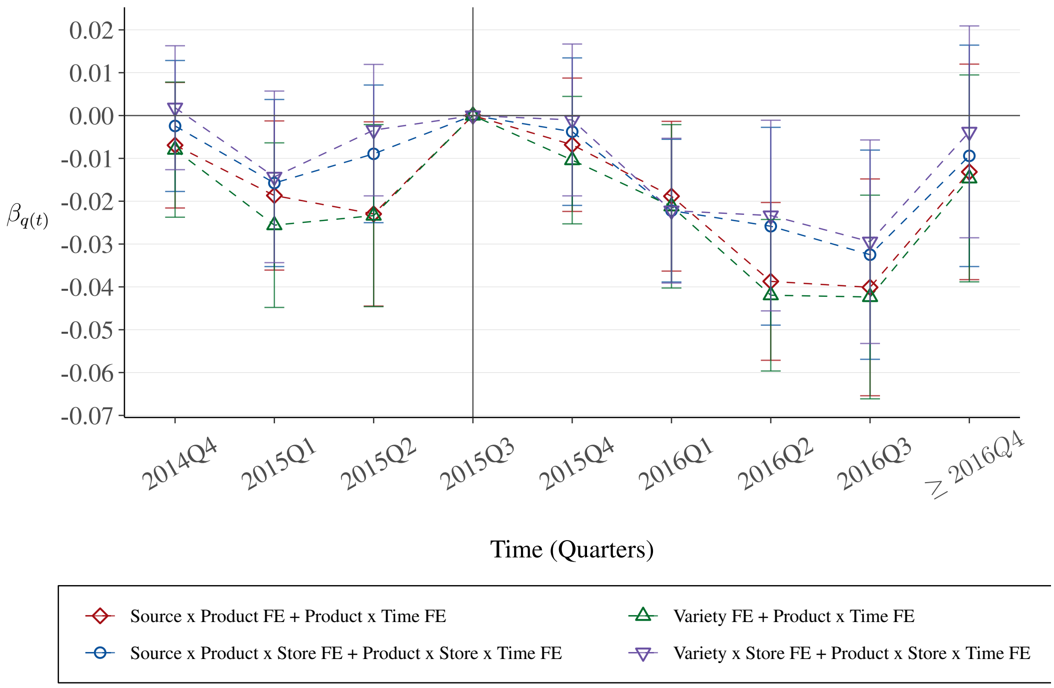
Notes: This figure shows the results from estimating equation 3 for consumer prices for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers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

Figure A.9: 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% confidence intervals based on standard errors that are clustered at the category-origin level.

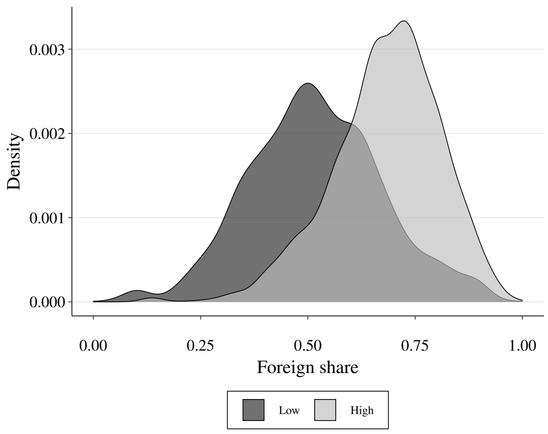
Figure A.10: Difference-in-difference: Markups



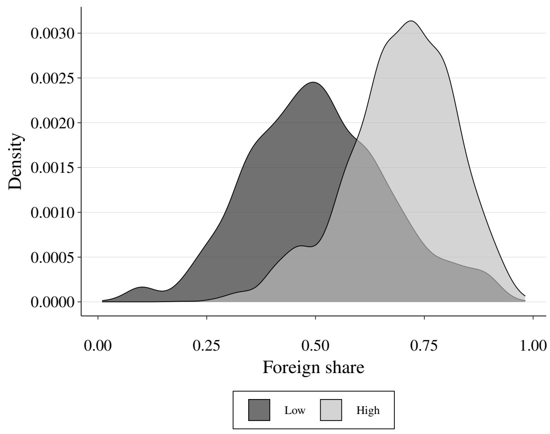
Notes: This figure shows the results from estimating equation 3 for markups for different specifications of the fixed effects. We include only continuing products in the estimation and weight observations by pre-depreciation expenditure shares. The dots indicate the point estimate and the whiskers are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

Figure A.11: Foreign share across consumers

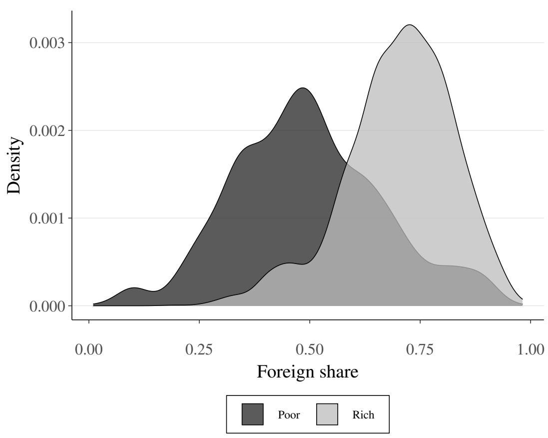
(a) Terciles: 33%-66% split



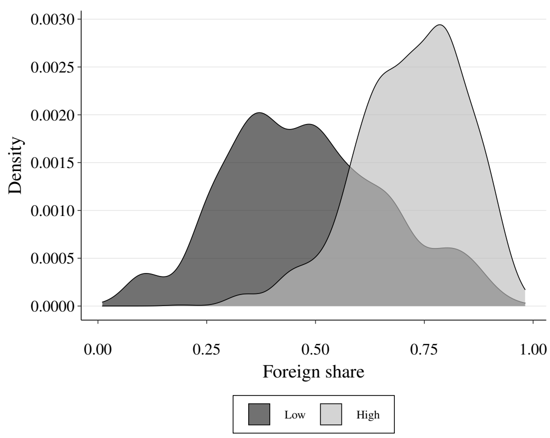
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split



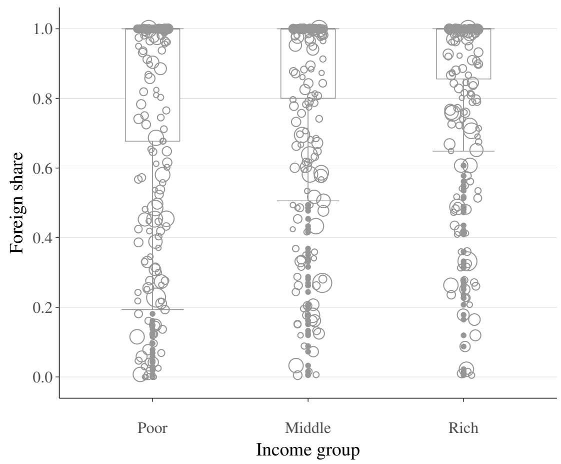
(d) Deciles: 10%-90% split



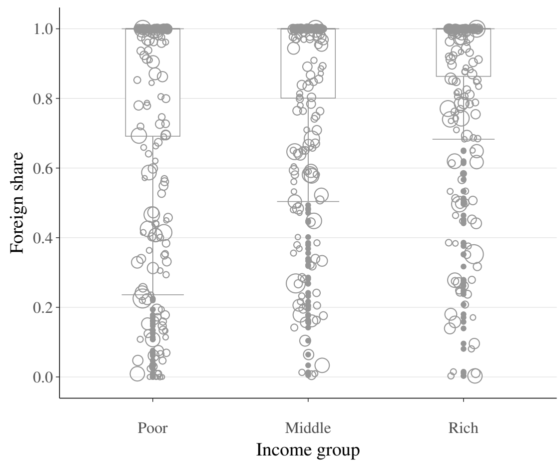
These figures display the distribution of the expenditure share on foreign varieties across rich and poor consumers. We compute the income classification based on the expensiveness index. We include food & non-alcoholic beverages and the frequent sample of consumers in the construction of these graphs. We show the same figure for different definitions of the income groups: (a) terciles, (b) quartiles, (c) quintiles, and (d) deciles.

Figure A.12: Foreign share across products: Food & Non-alcoholic Beverages

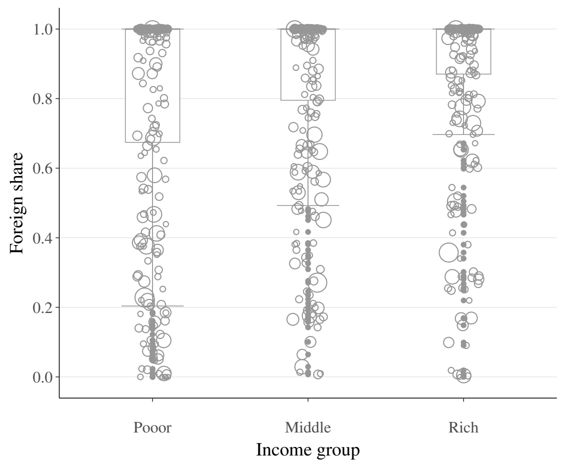
(a) Terciles: 33%-66% split



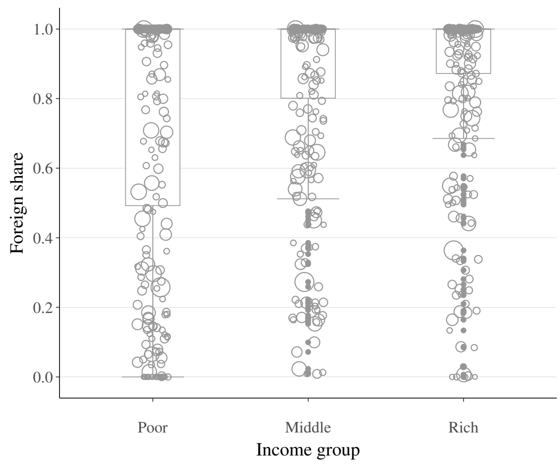
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split

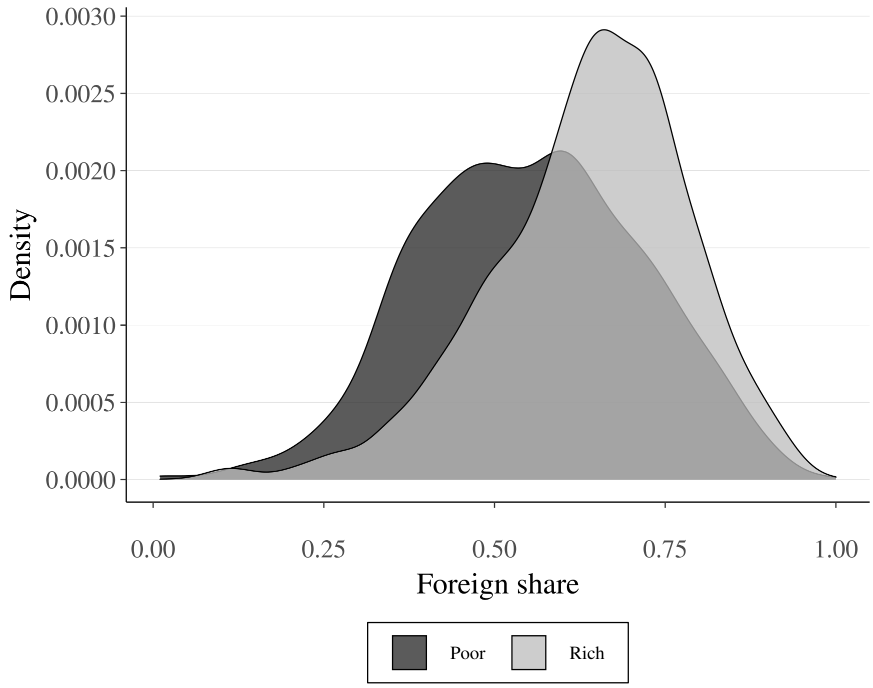


(d) Deciles: 10%-90% split



These figures display the distribution of the expenditure share on foreign varieties across detailed products separately 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 A.13: Foreign share across income groups: Total Expenditures

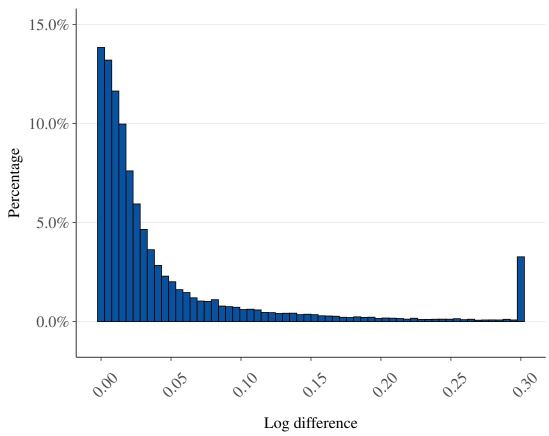


This figure displays the distribution of the expenditure share on foreign varieties across rich and poor consumers separately. Income classification was executed using total expenditures. We include food & non-alcoholic beverages and the frequent sample of consumers in the construction of these graphs.

Figure A.14: Absolute log price difference

(a) Dellavigna and Gentzkow (2019)

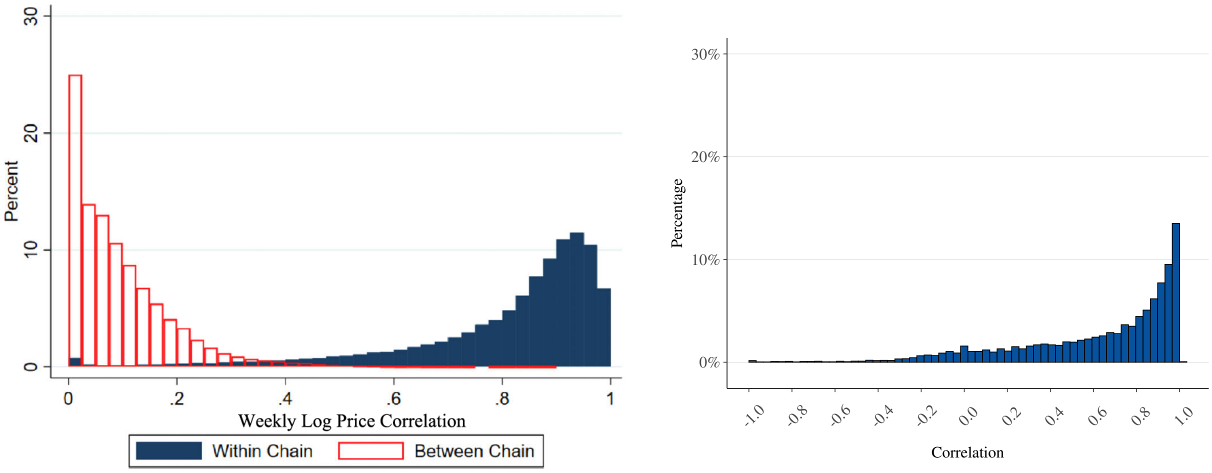
(b) Own retailer



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) is Figure IIA from Dellavigna and Gentzkow (2019). 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 A.15: Log price correlation

(a) Dellavigna and Gentzkow (2019) **(b)** Own retailer

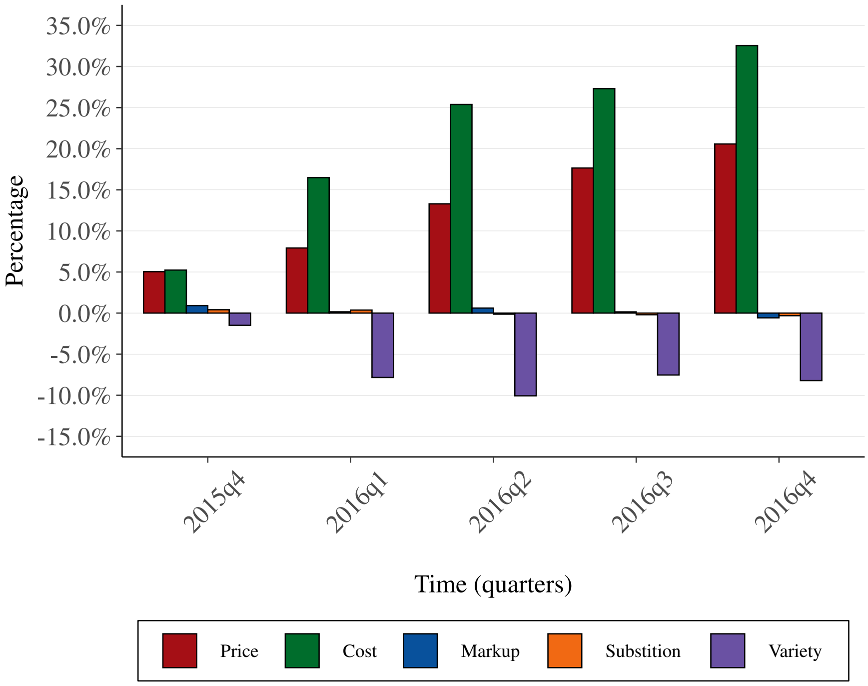


Notes: This figure plots the distribution of the weekly correlation of log prices. This is obtained from purging the residuals from the following regression:

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

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) is Figure IIB from Dellavigna and Gentzkow (2019). 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).

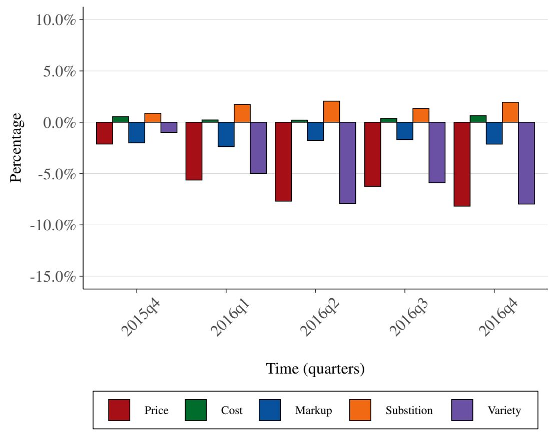
Figure A.16: Cost-of-living: Aggregate Effects - Heterogeneous



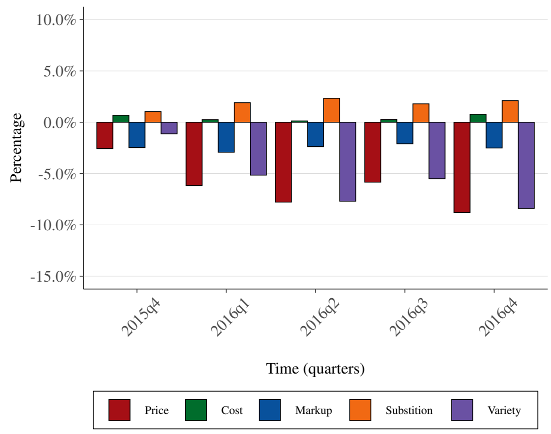
Notes: These figures show the aggregate results from the nested CES decomposition which are also presented in A.26. The results are obtained after pooling across all income groups and estimating the variety effect when we allow the elasticity of substitution to vary across subcategories categories. To be precise, we use the estimate of column (3) in Table A.31. 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 A.26.

Figure A.17: Cost-of-living: Distributional Effects - Homogeneous

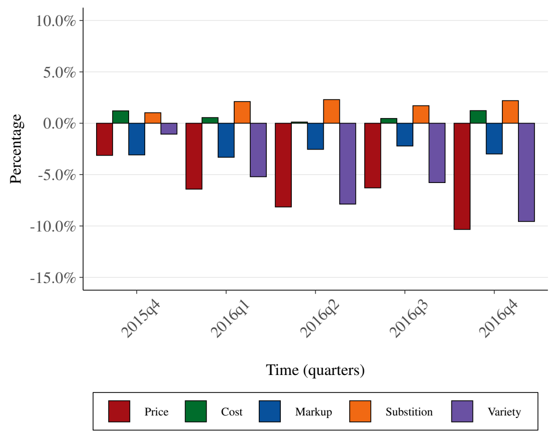
(a) Terciles: 33%-66% split



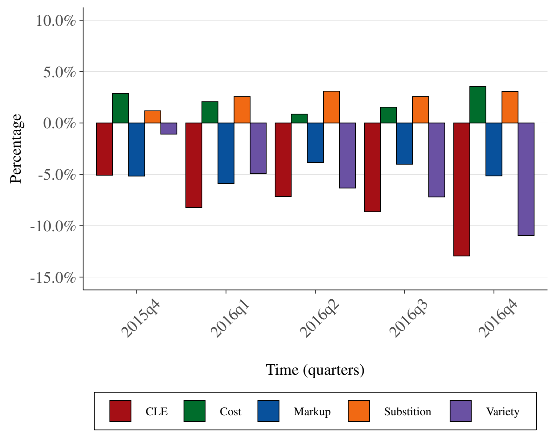
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split



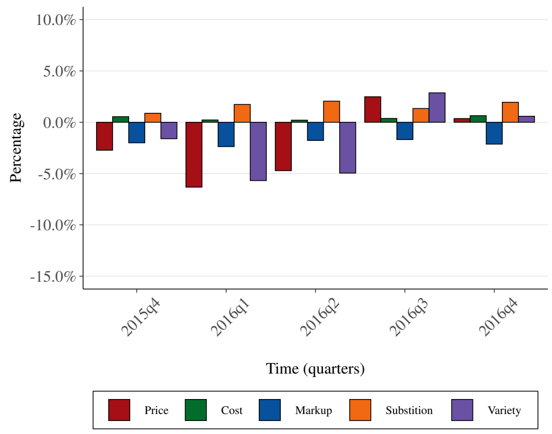
(d) Deciles: 10%-90% split



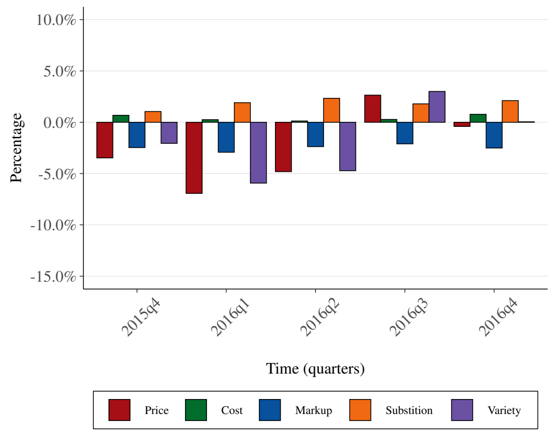
Notes: This table shows the distributional results from the nested CES decomposition which are also presented in Tables A.33 - A.36. The results are obtained by computing each of the components separately for each income group. Each of the panels shows the result for a different definition of the income 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$^{\text{th}}$ 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$^{\text{th}}$ 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 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 A.33 - A.36. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

Figure A.18: Cost-of-living: Distributional Effects - Heterogeneous

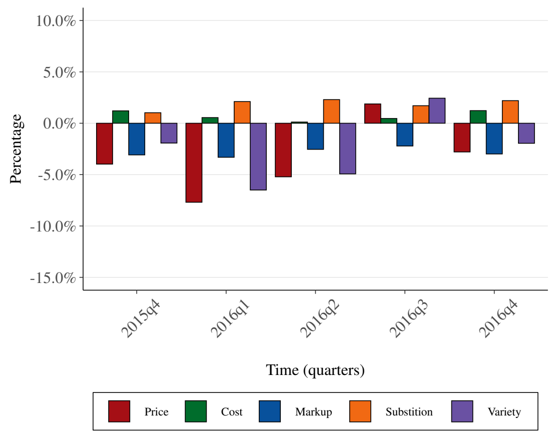
(a) Terciles: 33%-66% split



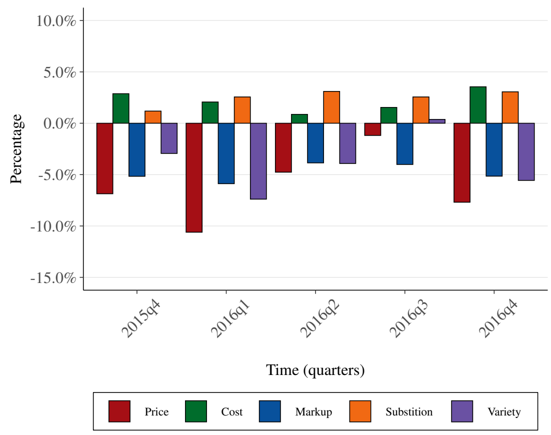
(b) Quartiles: 25%-75% split



(c) Quintiles: 20%-80% split

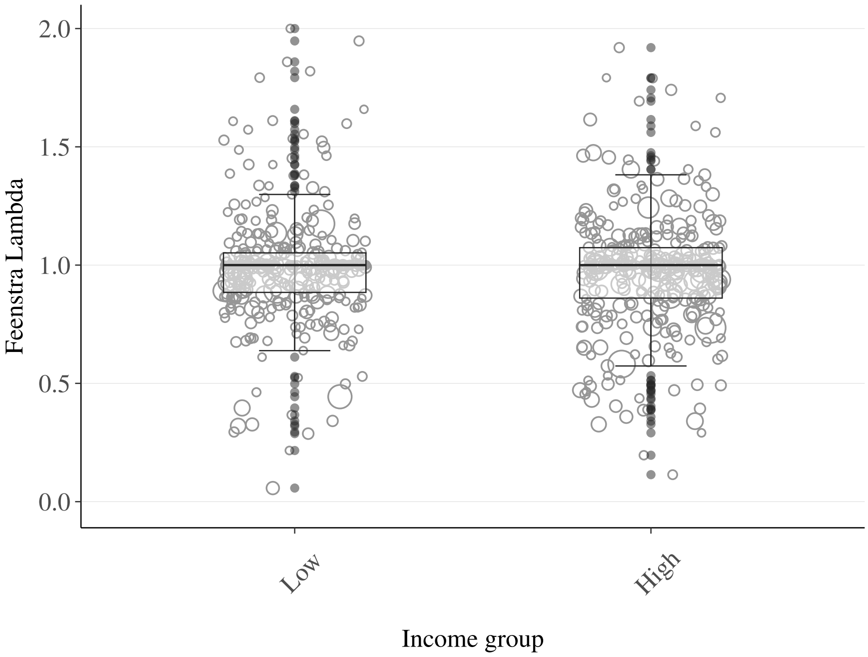


(d) Deciles: 10%-90% split



Notes: This table shows the distributional results from the nested CES decomposition which are also presented in Tables A.37 - A.40. The results are obtained by computing each of the components separately for each income group. Each of the panels 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$^{\text{th}}$ 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$^{\text{th}}$ 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 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 A.33 - A.36. The size of each bar is calculated by subtracting 1 and multiplying by 100 each of the numbers in the corresponding tables.

Figure A.19: 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: This figure plots the conditional distributions of the ratio of the expenditure share on continuing varieties after and before the depreciation across product categories separately for rich and poor consumers. As in the main body of the text, we compute these ratios at the product level. We overlay the scatterplots with boxplots.

A.3 Tables

Table A.4: Mapping Table AC Nielsen 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 are kiosks and pavilions which are small stores without a fixed physical structure, pharmacies and perfumeries that focus on non-food, and open markets which are small vendors selling in market halls. In addition to these individual types 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 and 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 A.5: 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 who 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 of $12/52$.

Table A.6: 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") and 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 the number of transactions. All the statistics are computed by pooling across all periods and all categories.

Table A.7: 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. Columns 2 to 4 do so by weighting the distribution by sales and columns 5 to 7 do so by counting the number of articles per type of unit.

Table A.8: 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 transactions. All the statistics are computed by pooling across all periods and all categories.

Table A.9: 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 characteristics across consumers who are in the frequent sample (Frequent) and the ones who are left out of the frequent sample (Complete). These statistics are computed solely based on purchases of food and beverages but are qualitatively the same when we include food and beverage consumption.

Table A.10: 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 A.11: 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 A.10 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 A.10 divided by 0.55.

Table A.12: 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 the most exported commodities by Kazakh companies in 2015. The share and cumulative share are calculated for the total export of Kazakhstan in 2015 as reported by UN Comtrade.

Table A.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 period. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table A.14: 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 A.15: 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:

$$\Delta_h \ln(p_{ist}) = \Delta_h \ln(e_{ist}) + \varepsilon_{ist}$$

for each invoicing currency separately. which are also shown in Figure A.7. Standard errors are clustered at the category level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table A.16: 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 terms of sales (columns 2 to 5) and the 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 A.17: 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 category-origin level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table A.18: 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 category-origin level. Significance levels are denoted at the 10% (*), 5% (**) and 1% (***) level.

Table A.19: 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 category-origin level. Significance is denoted at the * 10%, ** 5 % and *** 1% level.

Table A.20: Foreign share across income groups: Kolmogorov-Smirnov 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 share across products are 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 A.21: 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 products are 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 A.22: Elasticity of substitution: Aggregate - Clustered by month

	OLS				IV			
$q_{i,p,t}$	(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. Columns (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.23: Elasticity of substitution: Aggregate - Origin time fixed effects

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t}$	-2.24 ***	-2.15 ***	-1.64 ***	-1.49 ***	-3.17 ***	-3.08 ***	-1.73 ***	-1.52 ***
	(0.133)	(0.133)	(0.087)	(0.086)	(0.214)	(0.224)	(0.100)	(0.104)
Product x Quarter FE	✓				✓			
Product x Month FE		✓				✓		
Product x Quarter x Origin FE			✓				✓	
Product x Month x Origin FE				✓				✓
Variety FE	✓	✓			✓	✓		
Variety x Origin FE			✓	✓			✓	✓
First stage F-stat	-	-	-	-	516.8	347.4	4,226.7	3,639.2
R sq.	0.056	0.070	0.052	0.068	0.056	0.070	0.053	0.069
Nr,. obs	769,717	769,717	656,348	656,348	620,806	620,806	548,258	548,258

Notes: This table shows the estimates of the elasticities of substitution pooled across product categories and pooled across consumers. Columns (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.24: Elasticity of substitution: Aggregate - Seasonal fixed effects

	OLS						IV					
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$p_{pi,st}$	-2.24 ***	-2.15 ***	-1.43 ***	-1.32 ***	-1.4 ***	-1.16 ***	-3.17 ***	-3.08 ***	-1.55 ***	-1.41 ***	-1.48 ***	-1.3 ***
	(0.133)	(0.133)	(0.068)	(0.071)	(0.090)	(0.100)	(0.214)	(0.224)	(0.077)	(0.085)	(0.116)	(0.127)
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			✓	✓					✓	✓		
Variety x Store x Year FE					✓	✓					✓	✓
Variety x Store x Quarter-of-Year FE					✓						✓	
Variety x Store x Month-of-Year FE						✓						✓
First stage F-stat	-	-	-	-	-	-	516.8	348.0	6,778.3	5,823.4	4,073.5	4,438.7
R sq.	0.056	0.070	0.055	0.071	0.048	0.104	-	-	-	-	-	-
Nr,. obs	769,717	769,717	769,717	769,717	769,717	769,717	620,806	620,806	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. Columns (1) - (6) are OLS estimates and columns (7) - (12) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.25: Cost-of-living: 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 which are also presented in 9. The results are obtained after pooling across all income groups and estimating the variety effect 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 A.26: Cost-of-living: 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 which are also presented in A.16. The results are obtained after pooling across all income groups and estimating the variety effect when we allow the elasticity of substitution to vary across subcategories categories. To be precise, we use the estimate of column (3) in Table A.31. 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 A.27: Elasticity of substitution: Per Income Group (20% - 80% split) - Clustered by month

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot \mathbb{1}(\text{Low})$	-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
$p_{i,p,t} \cdot \mathbb{1}(\text{Middle})$	-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
$p_{i,p,t} \cdot \mathbb{1}(\text{Top})$	-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 separately, 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 consumers classified in the middle-income group. from estimating equation Column (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.28: Elasticity of substitution: Per Income Group (20% - 80% split) - Total expenditures

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot \mathbb{1}(\text{Low})$	-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
$p_{i,p,t} \cdot \mathbb{1}(\text{Middle})$	-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
$p_{i,p,t} \cdot \mathbb{1}(\text{Top})$	-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 separately, 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 consumers classified in the middle-income group. from estimating equation Columns (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.29: Elasticity of substitution: Per Income Group (20% - 80% split) - Origin time fixed effects

	OLS				IV			
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p_{i,p,t} \cdot \mathbb{1}(\text{Low})$	-3.65 ***	-3.51 ***	-2.78 ***	-2.57 ***	-5.2 ***	-5.18 ***	-3.18 ***	-2.97 ***
	(0.243)	(0.252)	(0.204)	(0.213)	(0.467)	(0.537)	(0.263)	(0.287)
First stage F-stat	-	-	-	-	292.6	170.7	1,711.7	1,368.2
R sq.	0.034	0.054	0.016	0.043	0.033	0.056	0.012	0.041
Nr. obs	190,063	190,063	160,194	160,194	151,759	151,759	132,484	132,484
$p_{i,p,t} \cdot \mathbb{1}(\text{Middle})$	-2.34 ***	-2.29 ***	-1.82 ***	-1.69 ***	-3.17 ***	-3.15 ***	-1.89 ***	-1.69 ***
	(0.139)	(0.145)	(0.100)	(0.101)	(0.244)	(0.274)	(0.130)	(0.137)
First stage F-stat	-	-	-	-	619.2	414.6	4,835.2	4,056.2
R sq.	0.104	0.120	0.102	0.122	0.108	0.127	0.107	0.129
Nr. obs	329,014	329,014	281,906	281,906	264,839	264,839	235,319	235,319
$p_{i,p,t} \cdot \mathbb{1}(\text{Top})$	-1.24 ***	-1.14 ***	-1.06 ***	-0.896 ***	-2.22 ***	-2.17 ***	-1.31 ***	-1.1 ***
	(0.155)	(0.158)	(0.112)	(0.111)	(0.263)	(0.288)	(0.134)	(0.139)
First stage F-stat	-	-	-	-	443.7	294.7	3,366.7	2,882.0
R sq.	0.052	0.069	0.046	0.068	0.056	0.073	0.049	0.070
Nr. obs	250,640	250,640	214,248	214,248	204,208	204,208	180,455	180,455
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 separately, 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 consumers classified in the middle-income group. from estimating equation Columns (1) - (4) are OLS estimates and columns (5) - (8) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.30: Elasticity of substitution: Per Income Group (20% - 80% split) - Seasonal fixed effects

	OLS						IV					
$q_{i,p,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$p_{i,p,t} \cdot \mathbb{1}(\text{Low})$	-3.65 ***	-3.51 ***	-2.35 ***	-2.27 ***	-2.72 ***	-1.97 ***	-5.2 ***	-5.18 ***	-2.51 ***	-2.53 ***	-2.97 ***	-2.79 ***
	(0.243)	(0.252)	(0.146)	(0.160)	(0.261)	(0.400)	(0.467)	(0.536)	(0.184)	(0.215)	(0.370)	(0.588)
First stage F-stat	-	-	-	-	-	-	292.6	170.8	2,920.1	2,213.8	1,107.4	544.0
R sq.	0.034	0.054	0.018	0.043	-0.106	-0.007	-	-	-	-	-	-
Nr. obs	190,063	190,063	190,063	190,063	190,063	190,063	151,759	151,759	151,759	151,759	151,759	151,759
$p_{i,p,t} \cdot \mathbb{1}(\text{Middle})$	-2.34 ***	-2.29 ***	-1.57 ***	-1.43 ***	-1.48 ***	-1.3 ***	-3.17 ***	-3.15 ***	-1.7 ***	-1.52 ***	-1.53 ***	-1.36 ***
	(0.139)	(0.145)	(0.077)	(0.083)	(0.110)	(0.142)	(0.244)	(0.274)	(0.100)	(0.113)	(0.153)	(0.214)
First stage F-stat	-	-	-	-	-	-	619.2	415.3	7,571.5	6,232.5	3,934.5	3,134.8
R sq.	0.104	0.120	0.100	0.120	0.061	0.144	-	-	-	-	-	-
Nr. obs	329,014	329,014	329,014	329,014	329,014	329,014	264,839	264,839	264,839	264,839	264,839	264,839
$p_{i,p,t} \cdot \mathbb{1}(\text{Top})$	-1.24 ***	-1.14 ***	-0.964 ***	-0.825 ***	-0.859 ***	-0.601 ***	-2.22 ***	-2.17 ***	-1.22 ***	-1.06 ***	-1.15 ***	-1.01 ***
	(0.155)	(0.158)	(0.089)	(0.095)	(0.136)	(0.185)	(0.263)	(0.288)	(0.106)	(0.115)	(0.200)	(0.284)
First stage F-stat	-	-	-	-	-	-	443.7	295.3	5,413.4	4,578.2	2,199.1	1,388.7
R sq.	0.052	0.069	0.045	0.066	-0.040	0.061	-	-	-	-	-	-
Nr. obs	250,640	250,640	250,640	250,640	250,640	250,640	204,208	204,208	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			✓	✓					✓	✓		
Variety x Store x Year FE					✓	✓					✓	✓
Variety x Store x Quarter-of-Year FE					✓						✓	
Variety x Store x Month-of-Year FE						✓						✓

Notes: This table shows the estimates of the elasticities of substitution pooled across product categories and pooled across consumers. Columns (1) - (6) are OLS estimates and columns (7) - (12) are IV estimates using the Hausman instrument as the instrument. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.31: Elasticity of substitution - 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
Bakery/Cereal	-2.73 ***	53,028	126.4	0.028	-2.64 ***	53,028	111.5	0.041	-2.74 ***	53,028	223.0	0.029	-3.1 ***	53,028	198.7	0.045
	(0.546)				(0.592)				(0.441)				(0.482)			
Candy	-4.44 ***	104,131	76.0	0.044	-4.02 ***	104,131	62.2	0.060	-3.4 ***	104,131	108.8	0.044	-3.23 ***	104,131	94.6	0.060
	(0.610)				(0.639)				(0.402)				(0.445)			
Dairy	-2.73 ***	92,540	89.1	0.079	-3.17 ***	92,540	68.6	0.092	-2.72 ***	92,540	218.1	0.086	-2.78 ***	92,540	143.4	0.100
	(0.409)				(0.490)				(0.269)				(0.343)			
Dry food	-3.35 ***	58,904	93.7	0.045	-3.2 ***	58,904	60.3	0.058	-2.74 ***	58,904	732.2	0.048	-2.79 ***	58,904	554.2	0.062
	(0.582)				(0.559)				(0.434)				(0.435)			
Fish	-2.49 ***	31,018	239.0	0.022	-2.14 ***	31,018	199.6	0.041	-1.86 ***	31,018	375.5	0.018	-2.14 ***	31,018	288.5	0.042
	(0.435)				(0.546)				(0.333)				(0.471)			
Fruit	-2.62 ***	15,329	78.7	0.085	-2.49 **	15,329	25.4	0.127	-2 ***	15,329	196.6	0.080	-2.47 ***	15,329	135.0	0.122
	(0.757)				(1.032)				(0.542)				(0.618)			
Meat	-0.177	30,949	4.5	0.080	2.19	30,949	1.4	0.091	-2.34 ***	30,949	82.7	0.092	-1.89 **	30,949	62.9	0.110
	(2.405)				(5.243)				(0.695)				(0.875)			
Ready-made	-11.5 *	9,790	2.4	-0.044	-23.1	9,790	0.6	-0.305	-2.56 ***	9,790	109.0	0.031	-3.53 ***	9,790	135.1	0.056
	(6.161)				(27.887)				(0.422)				(0.399)			
Savoury	-1.73 *	20,745	482.9	0.030	-1.7	20,745	375.7	0.046	-1.59 *	20,745	657.7	0.029	-1.84 *	20,745	551.8	0.047
	(1.008)				(1.099)				(0.934)				(0.983)			
Seasoning	-1.87 ***	64,948	45.4	0.053	-1.24 *	64,948	33.2	0.069	-1.7 ***	64,948	405.8	0.053	-1.39 ***	64,948	306.7	0.074
	(0.657)				(0.693)				(0.408)				(0.487)			
Vegetables	-1.47 ***	33,404	38.8	0.071	-1.58 ***	33,404	16.2	0.093	-1.4 ***	33,404	696.1	0.070	-1.57 ***	33,404	498.7	0.093
	(0.454)				(0.559)				(0.253)				(0.312)			
Coffee/Tea	-4.56 ***	43,860	71.3	0.035	-4.45 ***	43,860	69.3	0.043	-3.85 ***	43,860	89.2	0.034	-3.94 ***	43,860	74.9	0.041
	(0.671)				(0.629)				(0.639)				(0.644)			
Soft drinks	-5.46 ***	51,476	301.5	0.058	-5.15 ***	51,476	281.2	0.068	-4.79 ***	51,476	806.0	0.058	-4.83 ***	51,476	766.2	0.069
	(0.672)				(0.706)				(0.533)				(0.618)			
Water	-2.6 **	10,684	90.7	0.092	-2.31 **	10,684	85.9	0.099	-3.14 **	10,684	473.4	0.103	-2.77 **	10,684	416.2	0.114
	(1.132)				(1.023)				(0.957)				(0.844)			
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 IV estimator. The results per income group are obtained by estimating 6 separately for each subcategory. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.32: Elasticity of substitution - Per Subcategory and income group (20%-80% split)

	(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)										

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	(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
	-1.28				-1.29				-				-			
	(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 IV estimator. The results per income group are obtained by estimating 6 separately for each subcategory. The first stage F-statistic refers to the effective first-stage F-statistic developed by Montiel-Olea and Pflueger (2013) which is valid under non i.i.d. distributed errors. 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 A.33: Cost-of-living: Distributional 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 which are also presented in A.17a. 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$^{\text{th}}$ 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$^{\text{th}}$ 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 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 A.34: Cost-of-living: Distributional 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 which are also presented in A.17b. 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$^{\text{th}}$ 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$^{\text{th}}$ 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 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 A.35: Cost-of-living: Distributional 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 which are also presented in A.17c. 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$^{\text{th}}$ 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$^{\text{th}}$ 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 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 A.36: Cost-of-living: Distributional 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 which are also presented in A.17d. 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 10th 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 90th 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 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 A.37: Cost-of-living: Distributional 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 which are also presented in A.17a. 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 33th 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 66th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income groups. We use the estimates of the elasticity of substitution reported in column (1) of Table A.32 (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 the elasticities are 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 A.38: Cost-of-living: Distributional 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 which are also presented in A.17a. 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 25th 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 75th percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income groups. We use the estimates of the elasticity of substitution reported in column (1) of Table A.32 (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 the elasticities are 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 A.39: Cost-of-living: Distributional 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 which are also presented in A.17a. 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$^{\text{th}}$ 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$^{\text{th}}$ percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income groups. We use the estimates of the elasticity of substitution reported in column (1) of Table A.32 (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 the elasticities are 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 A.40: Cost-of-living: Distributional 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 which are also presented in A.17a. 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$^{\text{th}}$ 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$^{\text{th}}$ percentile in this distribution. The variety effect is computed by allowing the elasticity of substitution to vary across product categories and income groups. We use the estimates of the elasticity of substitution reported in column (1) of Table A.32 (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 the elasticities are 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.