Abstract

This paper shows that an income effect can drive expenditure switching. We use a unique Latvian scanner-level dataset for food and beverages, covering the 2008–09 financial crisis, to study (i) relative price movements, and (ii) expenditure switching between domestic and imported goods during a ‘sudden stop’ episode. We begin by documenting several empirical findings. First, imports contracted by 26%, with expenditure switching accounting for one third of the fall, while the relative price of foreign goods viz. the food CPI increased by 4.4% during the crisis. Next, we show that the majority of the switching took place between goods within narrowly defined product groups, while the relative price adjustment was across product groups. This puzzling asymmetry in expenditure and price adjustments, combined with a finding that the unit values of domestic goods were on average lower than those of comparable foreign ones, motivate us to model non-homothetic consumer demand. Over the crisis period, the estimated model explains one half of the observed expenditure switching, which was driven almost entirely by an income effect.

JEL Classifications: F1; F3; F4

Keywords: Sudden stops; relative price adjustment; expenditure switching; non-homothetic preferences
1 Introduction

Conventional international macroeconomics theory posits that changes in the relative price between domestic and foreign goods is the sole driver of expenditure switching. For example, following a currency devaluation, a country’s imports would fall and its exports rise in proportion to its relative price change vis-à-vis that of the rest of the world. This paper revisits external adjustment and relative price changes during a sudden stop episode empirically, and shows that an income effect can also play an important role in expenditure switching.

We examine the 2008–09 sudden stop crisis in Latvia, during which the country had limited nominal exchange rate flexibility, using a unique goods-level dataset. First, we quantify how much expenditure switching took place between domestic and imported goods. Second, we exploit these detailed data to examine at what margins did expenditure switching and relative price movements take place. Finally, we ask whether the observed relative price changes explained the observed expenditures switching through the lens of ‘standard’ economic models, or are other channels required in order to match the data.

We are able to measure relative price and consumption changes across goods by using a scanner-level dataset on food and beverages, which covers the 2006Q2–2011Q2 period, where Latvia experienced a boom-bust episode.1 These data provide both prices and quantities at the individual good level, and crucially identify the country origin of each good, and detailed product groups to which items belong to. Using the data, we find that during the crisis period real consumption of imports fell by 26%. We then use the item-level dimension of the data to present four main findings, which help explain this fall, and motivate the modeling and estimation strategy in the remainder of the paper.

First, we find that expenditure switching from imported to domestic goods accounted for one-third of the total fall in imports observed in the dataset.2 The majority of this expenditure switching was driven by substitution between goods within narrowly defined product groups. Second, this expenditure switching was accompanied by a 4.4% rise in the price of imports relative to the food CPI, where this change was almost entirely driven by changes in prices across product groups. Third, within product groups, consumers substituted towards cheaper items during the crisis. Furthermore, imported items exhibited higher unit values than comparable domestic ones within product groups on average. Fourth, the aggregate

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1See Blanchard et al. (2013) for a forensic account of Latvia’s boom, bust, and recovery over 2000–13.
2The other two-thirds is due to a proportional fall in domestic and imported goods in response to the crisis-induced fall in aggregate income.
dynamics of expenditure switching were primarily driven by the intensive margin (i.e., due to continuing goods), and not the extensive margin (i.e., due to entry and exit of goods).

The asymmetry in adjustment of expenditures and relative prices within and across product groups (Findings 1 and 2), along with the average domestic/foreign price differential (Finding 3), motivates us to set up a demand-side model of the economy, where a household’s consumption decision not only depends on the good’s relative price, but also on other item characteristics. We follow the framework in Hallak (2006), where a non-homothetic term enters the utility function via a good’s quality, such that the consumer’s intensity for demand of quality varies with her income level. Though we do not explicitly model quality, we follow the literature and allow for the unit value of an item to proxy for this “quality” term. What is crucial is that we want to capture the possibility for a consumer to substitute between comparable cheap and expensive goods, irrespective of their relative price change, when hit by an income shock, such as the one consumers faced during Latvia’s crisis.

We estimate the model using item-level data, and use the estimated parameters to predict each good’s expenditure share, which we then aggregate in order to measure total expenditure switching over the sample period. The results are quite striking. First, the baseline CES model, which only allows for a relative price change channel, and which underlies the workhorse models in international macroeconomics, performs poorly: though the estimated relative price parameters are significant, the model’s predicted expenditure switching does not match the switching observed in the data, particularly during the sudden stop episode. Second, the non-homothetic model, which nests the baseline model, is better able to match observed expenditure switching during the crisis – it captures one-half of what is observed in the data. Therefore, allowing for an income channel, where consumers can substitute towards cheaper goods when their income falls, helps explain Latvia’s expenditure switching on the import side during the crisis.

Note that neither the theoretical model nor the estimation differentiate between domestic or foreign goods at the item level. Therefore, what is the intuition for the aggregate results on expenditure switching and the role of relative prices and income? Finding 3 points to one possible answer: foreign goods are on average more expensive than domestic ones in Latvia. Therefore, given the non-homothetic channel, when Latvian consumers substituted to cheaper goods during the crisis, they also moved away from foreign goods. This finding is consistent with the “flight from quality” hypothesis put forth in Burstein et al. (2005).

The literature to which this paper most directly contributes to has focused on relative price adjustment as the driver of the external adjustment after sudden stops. Our contribu-
tions are twofold. First, we provide evidence for relative price adjustment under a pegged regime. There is a large literature examining international prices and exchange rates (see Burstein and Gopinath, 2013, for a recent survey), but only limited evidence has been provided examining price movements under a fixed exchange rate (e.g., see Parsley and Popper, 2006, for the case of Hong Kong), though recent work has contrasted real exchange rate adjustments in and outside the Eurozone (Berka et al., 2012). Second, we measure expenditure switching and assess its drivers. Though the theoretical literature on expenditure switching and the role of the exchange rate policy is large (see Engel, 2003, for a review), the empirical literature on measuring the impact of relative price changes on expenditure switching using both domestic and foreign quantity and price data at the microeconomic level is, to the best of our knowledge, non-existent.3

Diaz Alejandro (1965) is an early study of how income effects can affect external real-balancing.4 However, the author considers how consumption behavior differences across the income distribution within the economy – specifically the difference between wage and non-wage earners – can affect the demand of different sectors’ imports. Unfortunately, we do not have household data to match to our scanner data in order to examine how Engel’s Law played a role in Latvia’s external adjustment. Finally, a potential “flight from quality,” which would show up as income driven expenditure switching for a small emerging market, like Latvia, may have been a more general phenomenon across countries during crises – some recent work has pointed to a fall in the quality composition of large EU countries’ exports during the financial crisis (Berthou and Emlinger, 2010; Esposito and Vicarelli, 2011).5

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents empirical findings, which are used to motivate the modeling and empirical analysis of the Latvian experience. Section 4 presents the model. Section 5 estimates the model, and quantifies the contribution of relative price changes and income effects in explaining the observed expenditure switching. Section 6 concludes.

3Of course, there is a long-standing literature that estimates import elasticites, which has more recently highlighted the importance of heterogeneity across sectors. See, Imbs and Méjean (2009) and Feenstra et al. (2012) for two recent contributions.

4We thank Chang-Tai Hsieh for bringing Diaz Alejandro’s work to our attention.

5Bems et al. (2013) are currently examining the potential for an asymmetry in the adjustment for a broad set of countries, which depends on whether a country is a net exporter of high or low quality goods.
2 Data Description

The analysis is based on detailed scanner-level data, which contain monthly information on quantities sold and the average price level charged for 13-digit UPC items sold by one of Latvia’s largest retailers. The data are collected across three types of stores that the retailer owns and runs: (i) a ‘Hypermarket’ (HM) (ii) a ‘Supermarket’ (SM) and a ‘Discounter’ (D). Each store type’s data are aggregated across the respective type’s sales-per-item across the country, so there is no geographical distinction by type of store. In total, there are over 100,000 UPC-store pair items, and 64,000 unique items, covering the six-year period May 2006–May 2011. The coverage of goods is primarily for food and beverages (F&B), but the dataset also contains other consumer non-durables, such as toiletries. Besides quantity and price information, the dataset also provides information on the type of unit and the net content of each UPC item.

The retailer provides 2-, 3-, and 4-digit classifications of the items into product groups. An example of a 2-digit product group would be ‘hot drinks,’ which at the 3-digit level is further broken down into ‘tea,’ ‘coffee,’ and ‘cacao.’ The 3-digit group ‘tea’ is further broken down at the 4-digit level into types of tea. For example, there is ‘unflavored black tea,’ ‘flavored black tea,’ ‘herbal tea,’ ‘fruit tea,’ etc.

The retailer also provides an item description with an accompanying retailer assigned ‘material’ code. An example would be “SOY SAUCE BLUE DRAGON LIGHT 150ML; ‘material’ code: 111455.” A given ‘material’ code can be assigned to multiple UPC items. This would be the case, for example, if a good’s label is updated, but there is no change in the item’s name or net content.

The UPC is crucial for the analysis because it allows us to identify the domestic/foreign origin of each item. In particular, the first three digits of the bar code identify the country in which the label was applied for. Because Latvia is a small market, foreign suppliers usually do not relabel their goods in Latvian. Instead, imported items carry a source country label or a label intended for a larger destination market. This allows us to use the item’s label to identify domestic/foreign origin. However, for items of foreign origin the label does not necessarily identify the country of production.

An alternative approach to identifying the origin suggests that the UPC is a valid proxy. We zoom in on domestic/imported origin for a subset of 4-digit product groups that

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6The SM and HM carry a wider variety of goods than the D, and the same good can vary in price across the three types of stores.

7For example, the UPC of a bottle of tequila produced in Mexico, but labeled in the United States, and then shipped to Latvia would identify the bottle as originating from the United States.
explicitly group items by origin (e.g., imported and domestic beer). Such product groups account for 11.6% of total F&B expenditures in our sample, 6.2% of which are identified as local and 5.4% as foreign. We find that for product groups that are identified as local, 97.3% of expenditures carry local UPCs. For product groups that are identified as imported, 97.2% of expenditures carry foreign UPCs. This suggests that for a small market, such as Latvia, UPCs can correctly identify the origin for more than 97% of expenditures.

One set of items for which we cannot identify the origin is store products. Such items are produced/labeled by the retailer, with the bulk of the goods falling into product groups such as 'store bake,' ‘fruits and berries,' ‘vegetables and root crops,’ and ‘fresh/processed meat and fish.’ The UPC identifies such items as ‘store products,’ but provides no information about the origin of ingredients. Store items account for 18% of total food expenditures in the data. Over time there is a gradual decline in the weight of such items, from 20% in 2006 to 16% in 2011, but we find no evidence that this weight is affected by the crisis. Because we cannot identify the origin of ‘store products,’ we are forced to drop all such items.

We also exclude items with Estonian and Lithuanian product labels and product groups dominated by such items, because the two economies went through a crisis very similar in magnitude to Latvia’s. For the purpose of this paper one might expect items from these neighboring economies to behave like domestic rather than imported products. These two countries together account for 6% of expenditures with no significant trend over time.

Altogether these exclusions reduce the scanner data expenditures by 34%, out of which 24% is due to dropping store products and goods from Estonia and Lithuania, and the remaining 10% is due to dropping whole product groups dominated by such items. This leave us with 37 2-digit product groups.

2.1 Data Cleaning and Merging

As with any large micro dataset, data cleaning is needed. First, we drop items without a UPC. Second, we drop items where either quantity or price is less or equal to zero. Third, we drop items with the 0.05% largest price changes. Imposing these three conditions left total revenue virtually unchanged, decreasing it by 0.3%.

We next consolidate scanner data for homogeneous items, which improves the measurement of items’ prices and entry/exit rates. We start by consolidating data by the triplet of (i) UPC \( (i) \), (ii) store type \( (s) \), and (iii) time period \( (t) \), because information pertaining to a given triplet can be reported in multiple entries. The consolidation is done by summing quantities \( q_{ist} \) and expenditures \( x_{ist} \) over identical triplets and then re-computing the unit.
values from aggregated data. As a check that the data we consolidate pertain to homo-
geneous items, we compare prices for all identical triplets and find that in 99.7% of cases
prices are indeed identical.

On some occasions the UPC is an “overly” unique identifier of homogeneous items. For
example, this would be the case if an item’s label is frequently updated. Two such cases
are presented in the panel below, which shows data entries as they appear in the dataset
before aggregation:

<table>
<thead>
<tr>
<th>4-digit product code</th>
<th>Description code</th>
<th>Description code</th>
<th>Description code</th>
<th>Description code</th>
<th>Description code</th>
</tr>
</thead>
<tbody>
<tr>
<td>6439</td>
<td>Other dental care</td>
<td>404199</td>
<td>DENTAL FLOSS ORAL</td>
<td>25 M</td>
<td>3056922039741</td>
</tr>
<tr>
<td>2101</td>
<td>Fat-free milk</td>
<td>211961</td>
<td>MILK VALMIERA 0.5%</td>
<td>1L</td>
<td>4750770600562</td>
</tr>
</tbody>
</table>

Items identified by the retailer’s ‘material’ codes 404199 and 211961 have identical (i)
product description, (ii) net content, (iii) average monthly prices, and (iv) producer code
(identified by the first 6 digits of the UPC), but have varying 13-digit UPCs. For the
purpose of this paper such items can be treated as homogeneous.

Motivated by this example, we consolidate data by the pair of (i) ‘material’ code and (ii)
store type, when prices are identical in all periods for overlapping pairs. This consolidation
decreases the number of unique UPCs in our sample by 12%.\(^8\)

Lastly, we examine item homogeneity across the three store types. We find that for
SMs and HMs, 70% of overlapping monthly prices of identical UPCs are identical, i.e.,
\(p_{i,s=SM,t} = p_{i,s=HM,t}\), and in 97% of cases the deviation is less than 5%. The mean of this
price differential is 0.0007, and the median of the distribution is 0. Thus, there is strong
evidence that items with identical UPCs in these two types of stores are homogeneous for
our purpose. We therefore aggregate these UPC-store item pairs into a common UPC item.
This consolidation does not change the number of unique UPCs in our sample, but reduces
the store types to two – market (M) and discounter (D) – and decreases the number of
unique UPC-store pairs by 29% percent. Price levels in Ds differ from the Ms. The mean
of this price differential is –0.13, while the median is –0.11. Therefore, in this case, we
continue to treat identical UPCs as different items, depending on whether the item is sold
in the aggregated M stores or D stores.

\(^8\)This aggregation across items can be used to shed further light on the quality of the scanner dataset. If
the UPC identifies unique items, then the multiple entries for the same UPC should all be assigned to the
same 4-digit product group and have the same net content. We find that this is the case for 98.8-99.5% of
aggregated items, depending on the store type.
2.2 Summary Statistics

Table 1 presents annual data on total sales for all products, as well as domestic and foreign goods separately. Given the sample period, we drop the first month of the sample, and define a year as June to May. So, for example, 2006 would be the year covering June 06–May 07. Looking at Columns (1) and (2), one sees that the value of sales increased until 2008–09 when the crisis hit, and there is then a pick up in 2010–11 as the Latvian economy began to recover. The same pattern holds for both domestic and foreign sales. The foreign share of total sales is approximately 37% on average, and drops by 3% over the crisis period.

Next, Table 2 presents summary statistics for 2-digit product groups over the whole sample period. The ‘Share’ column presents the share of each product groups sales viz. total sales over the period, while the ‘Foreign Share’ column measures the foreign content of a given product group. There is considerable heterogeneity in both the size and foreign content of product groups at this relatively high level of aggregation. ‘Alcoholic products’ make up the largest value of total sales, accounting for 14.97% of aggregate revenue, while foreign content ranges from as lows such as 0 (‘Eggs’) to a high of 0.99 (‘Baby food’). Though the food and beverage sector is generally considered a tradable sector (Berka and Devereux, 2011; Crucini et al., 2005), there is considerable heterogeneity in import intensity among product groups.

2.3 Aggregating Data into Macroeconomic Indicators

Food and beverages account for approximately 30% of total household expenditures in Latvia,\(^9\) therefore the scanner data cover an important component of total consumption. Furthermore, given the size of the retailer, the scanner dataset directly adds up to 15% of aggregate household expenditure on F&B over the period. In order to draw aggregate implications from the dataset, we next compare key aggregate statistics on F&B with equivalent series constructed from the scanner data.

First, as Figure 1 shows, the constructed aggregate price index closely mimics F&B’s CPI.\(^10\) Second, retail market share data, kindly provided to us by IGD Retail Analysis, show that during 2007–11 the retailer maintained a stable grocery retail market share of around 20% (see Table 3). Finally, Figure 2 plots the total revenue of foreign products

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\(^9\)According to the Latvian CPI calculations, food has a 35% weight, but in the national income accounts data, F&B account for 25% of household expenditures. We therefore take a simple average to arrive at the 30%.

\(^{10}\)The CPI is constructed using the GEKS methodology, which will be discussed below in Section 3.2, and which is described in detail in Appendix A.
across all stores and aggregate F&B imports used for final consumption.\textsuperscript{11} The two series are highly correlated, and the scanner data pick up the large fall in imports over the crisis period.\textsuperscript{12}

Why use scanner data rather than macroeconomic data for the purpose of this study? Scanner data allow us to measure expenditures on domestic and imported goods consistently within a single large dataset using final consumer prices. In contrast, macroeconomic data would require combining data on trade flows with household expenditure data, which would create multiple issues for the measurement of expenditures on domestic/foreign goods. One issue is that household expenditures are measured in final consumer prices and include domestic retail services, while trade flows are measured at the dock (Berger et al., 2009; Burstein et al., 2005). Another issue is that inventories can drive a wedge between final expenditures and trade flows, especially during sudden stop episodes (Alessandria et al., 2010). As a result, studies that use macro data have focused on relative price movements between domestic/imported goods, while with scanner data we can empirically examine both relative prices as well as expenditure switching between domestic and foreign goods and study the impact of relative price movements on consumption behavior.\textsuperscript{13}

We should also stress the limitations of the scanner dataset for studying expenditure switching. One obvious shortcoming is that the data only contain demand for domestic and imported F&B, though as noted above, our scanner data are representative of aggregate prices and expenditures on F&B, and consumption of F&B make up a significant portion of aggregate household expenditures in Latvia. We also unfortunately cannot match these data with supply-side data in order to capture the impact on exports. Thus, our results only speak to one facet of external sector adjustment – imports.

\textsuperscript{11}We rely on the Global Trade Information Services (http://www.gtis.com), and the UN Broad Economic Classification (http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=10) in order to calculate the aggregate numbers.

\textsuperscript{12}Aggregate F&B imports in customs data drop more quickly than in the store data and also show a more rapid recovery. This could be due to an inventory effect (e.g., such as argued by Alessandria et al., 2010). Though interesting for future research, this finding does not impact the analysis of the current paper given that we are interested in studying the total impact of the crisis, and not the dynamics per se.

\textsuperscript{13}Another advantage is that scanner data report prices and quantities at the detailed item level, allowing for a breakdown of relative prices and expenditures into narrow product groups of homogeneous items. Furthermore, scanner data directly record quantities purchased for each good, while NIA data estimate quantities indirectly using surveys, which are bound to be less reliable.
3 Empirical Findings

The Latvian economy experienced a sharp contraction during the sudden stop, and this contraction was felt across all sectors of the economy, including consumption in food and beverages. Figure 3 uses quarterly data to plot the year-on-year (y-o-y) log change in real aggregate food consumption in the scanner data. The figure depicts a classic “boom-bust” episode, where consumption was growing before the crisis, at which point it experienced a substantial drop, bottoming out at $-16\%$ in real terms over Q4:08–Q4:09, which we define as our crisis period.

The scanner data allow us to document four empirical findings pertaining to expenditure switching during the crisis, with a focus on the relative movements of the domestic and foreign components of consumption and prices within and across narrowly defined product groups. These findings underpin the main results of the paper, as well as motivate the modeling and estimation methodology we use below.

The four empirical findings are:

1. Expenditure switching from imported to domestic food accounted for one third of the contraction of imports during the crisis and was driven mainly by switching between goods within narrowly defined product groups.

2. The expenditure switching was accompanied by a 4.4% rise in the relative price of foreign goods to total food CPI, where the relative price change was driven almost entirely by changes in prices across product groups.

3. Within product groups imported goods exhibited higher unit values than comparable domestic ones on average.

4. The aggregate dynamics of expenditure switching were primarily driven by the intensive margin (i.e., due to continuing goods), and not the extensive margin (i.e., due to entry and exit of goods).

3.1 Finding 1: Expenditure Switching

We first examine the role of expenditure switching in the total fall of imports during the crisis by considering a simple decomposition. We begin by defining $X$ as total expenditures on F&B, and $X^F$ as expenditures on imported F&B. Then, define $\Delta x \equiv \ln (X_{Q4:09}/X_{Q4:08})$.

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14The sample begins at the second quarter of 2006, which is defined as May–July in order to maximize observations. Using y-o-y changes helps avoid seasonality issues.
and $\Delta x^F \equiv \ln \left( \frac{X_{Q4:09}^F}{X_{Q4:08}^F} \right)$ as the respective growth rates of expenditures. We can then decompose the fall in imports as

$$\Delta x^F \equiv \Delta x + (\Delta x^F - \Delta x),$$

where the first term on the RHS is the contribution due to an across-the-board contraction in food consumption, which is proportional to the fall in total consumption of F&B, and the second term is a residual that captures the contribution of expenditure switching. This term captures the finding that expenditures on imports contracted more than proportionally with aggregate expenditures on food, and as a result, there was expenditure switching from imported to domestic food. In scanner data imports fell by 26%, while total food expenditures fell by 18% during the crisis. Therefore, the expenditure switching term accounted for 8 percentage points, or one third, of the fall in imports.

Figure 4 provides an alternative way of quantifying the size of the expenditure switching, by plotting the y-o-y percentage point change in the import expenditure share, $\Delta \left( \frac{X^F}{X} \right)$. The figure shows that at the trough (i.e., Q4:09), 3.5 percent of expenditures were reallocated from imports towards domestically produced food.

We next exploit the data at both the product group and item level in order to distinguish between two sources of expenditure switching due to consumers reallocating expenditures either (i) across product groups, or (ii) between domestic and foreign items within product groups. The within margin can contribute directly to expenditure switching, as consumers substitute between similar domestic and foreign items. The across margin can contribute indirectly to expenditure switching as long as product groups have different import shares. For example, if the dairy product group is mainly composed of domestic items, while the alcohol product group has a large foreign content, then substitution from alcohol to dairy, holding all else equal, would result in aggregate expenditure switching.

Begin by defining a product group $g \in \{1, \ldots, G\}$, an item $i \in I_g$ and expenditure share $s_{igt}$ for item $i$ in product group $g$ in period $t$, so that $\sum_i \sum_g s_{igt} = 1$. Further, denote $s_{jgt} = \sum_{i \in I_j} s_{igt}$ as the expenditure share for a subset $j$ of items in product group $g$. With this notation one can express expenditure share of a product group as $s_{gt} = \sum_{i \in I_g} s_{igt}$ and total expenditure share on imports is $s_{Ft} = \sum_g \sum_{i \in I_g} s_{igt}$, where $F$ refers to imported items.

Next, define the share of imports within a product group as $\varphi_{gt}^F = s_{Fgt}/s_{gt}$. Then $s_{igt}^F = s_{igt}\varphi_{gt}^F$, and aggregate expenditure switching between any two periods $k$ and $t$ can be decomposed into the two components of interest – expenditure switching within and
across product groups – as follows:

\[
s^F_t - s^F_k = \sum_g s_{gt} \phi^F_{gt} - \sum_g s_{gk} \phi^F_{gk} \\
= \sum_g s_{gk} (\phi^F_{gt} - \phi^F_{gk}) + \sum_g \phi^F_{gk} (s_{gt} - s_{gk}) + \sum_g (\phi^F_{gt} - \phi^F_{gk}) (s_{gt} - s_{gk}).
\] (1)

Figure 4 plots this decomposition for y-o-y changes in \(s^F_t\), where a product group \(g\) is defined at the 4-digit level. We find that the bulk of expenditure switching took place within sectors, as consumers substituted from foreign to domestic goods, while maintaining relatively constant shares of expenditures across product groups throughout the sample. The within-switching is a crucial empirical finding that our analysis incorporates below. To the best of our knowledge, there is no previous empirical work that either quantifies the magnitude of expenditure switching during a crisis, or decomposes expenditure switching within and across product groups. Therefore, we view these results as novel.

### 3.2 Finding 2: Relative Price Adjustment

We next examine price movements of domestic and imports goods at the aggregate and product group level. In order to do so, we must construct comparable price indexes across product groups from the UPC-level data on unit values and quantities. To avoid well-documented biases for price indexes based on supermarket scanner data (Ivancic et al., 2011), we follow a multilateral index number method proposed by the authors and compute GEKS price indexes – see Appendix A for details.

We first apply the GEKS methodology to compute price indexes for domestic (\(D\)) and imported (\(F\)) F&B in each product group \(g\), which we define as \(P^D_{gt}\) and \(P^F_{gt}\), respectively, using individual UPC prices \(\{p^t_{igt}\}_{i \in I_{gt}}\) and expenditure shares \(\{s^t_{igt}\}_{i \in I_{gt}}\) of domestic and foreign origin.

We then use these indexes to construct aggregate price indexes as expenditure-weighted geometric averages:

\[
P^j_t = \prod_g \left( P^j_{gt} \right)^{s^j_{gt}/s^j_t},
\]

where \(j \in \{F, D\}\). The aggregate F&B price index is then a geometric mean of the aggregate domestic and foreign price indexes:

\[
P_t = (P^F_t)^{s^F_t} (P^D_t)^{1-s^F_t}.
\]

The relative price is defined as \(P^F_t / P_t\) in order to link it to our measures of expenditure switching. The solid blue line in Figure 5 plots the y-o-y change in \(\ln(P^F_t / P_t)\). The relative
price increases by 4.4% y-o-y during the crisis period (Q4:08–Q4:09), and by 6% from trough to peak.

As with expenditure switching, it is instructive to decompose the change in the relative price into across and within product-group components. First, note that the (log) relative price can be written as a weighted sum of product-group relative prices:

$$\ln \frac{P_t}{P_t} = \sum_g \frac{s^F_{gt}}{s^F_t} \ln \frac{P^F_{gt}}{P_t} = \sum_g \frac{s^F_{gt}}{s^F_t} \left( \ln \frac{P^F_{gt}}{P_t} + \ln \frac{P^F_t}{P_t} \right),$$

which implies that the growth rate of the relative price between periods $k$ and $t$ can be expressed as

$$\ln \frac{P^F_t}{P^F_k} - \ln \frac{P^F_k}{P^F_k} = \sum_g \frac{s^F_{gt}}{s^F_t} \left( \ln \frac{P^F_{gt}}{P_t} + \ln \frac{P^F_t}{P_t} \right) - \sum_g \frac{s^F_{gt}}{s^F_t} \left( \ln \frac{P^F_{gt}}{P_t} + \ln \frac{P^F_t}{P_t} \right)
\quad + \sum_g \frac{s^F_{gt}}{s^F_t} \left( \ln \frac{P^F_{gt}}{P_t} - \ln \frac{P^F_{gt}}{P_t} \right)$$

$$\approx 0.$$  (2)

In Figure 5, again using 4-digit product groups, one can see that the increase in the relative price of imports was almost exclusively driven by price movements across product groups. Within product groups, relative prices did not exhibit any systematic deviations. This result is the opposite of what occurred for expenditure shares, where switching took place within, not across product groups.

To examine this finding in more detail, Figure 6 zooms in on the across and within relative price decomposition for the y-o-y changes over Q4:08–Q4:09 by plotting each component, $\ln \left( \frac{P^F_{g,Q4:09}/P_{g,Q4:09}}{P^F_{g,Q4:09}/P_{g,Q4:09}} \right)$ and $\ln \left( \frac{P^F_{g,Q4:09}/P_{g,Q4:09}}{P^F_{g,Q4:09}/P_{g,Q4:09}} \right)$, against the product group’s import share viz. total expenditures on imports in Q4:08, $s^F_{g,Q4:09}/s^F_{Q4:09}$. First, looking at the across decomposition in Figure 6a, we see that relative prices increased during the crisis precisely for those product groups that have larger import shares. This result is consistent with what Burstein et al. (2005) find during the 2002 Argentinean devaluation. Second, Figure 6b depicts the within decomposition during the crisis. Here, one sees no systematic deviation in relative price changes for product groups that have non-trivial import shares; while the ones whose shares are approximately zero do not impact the aggregate measure given they will influence aggregate expenditure switching very little.
These findings can be related to the extensive literatures on relative price adjustment during crises/sudden stops. Appendix B presents a methodology to define tradability based on a products shelf-life, and provides a decomposition of price changes along the tradability and home/foreign dimensions. We can then reinterpret Finding 2 in a standard two-sector macroeconomic framework by relabeling the across component as the *internal margin*, and the within component as the *external margin*. In doing so, we find that bulk of the relative price adjustment during the crisis took place between the relative price of tradables and nontradables (i.e., a change along the internal margin).

### 3.3 Finding 3: Unit Values

We next investigate whether there is any systematic differences in the unit values across comparable goods, as well as between comparable imported and domestic goods, by examining price differences within detailed 4-digit product groups. In order to document whether such differences exist, we need to further restrict the data in order to have comparable unit values.

We first drop product groups where ‘pieces’ are used as the measure of units, because such units are not comparable across items. This leads to the dataset’s total revenues dropping by 7.6%. Next, we identify the most frequent units for each product group and drop items that are not measured in such units (for example, some product groups might report both L and KG unit values). This decreases total revenues by a further 2.1%.

There is a great deal of heterogeneity in the dispersion of unit values across product groups. Figure 7 plots the distribution of interquartile ranges of unit values for each product group, where the interquartile range of a given product group is defined as the difference between the unit value of the goods at the 75th and 25th percentiles of the product group’s distribution of unit values. We find that for the median product group, the unit value at the 75th percentile is 70% above that of the 25th percentile.

Given the dispersion of prices within product groups, there is clearly scope for expenditure switching to be driven by substitution from high value to low value items, irrespective of relative price changes. To have a better view on this, we next calculate unit values for domestic and imported components for the quarters for which data are available.\(^\text{15}\) In

\[^{15}\text{For the domestic-foreign unit value comparison we identify product groups that account for at least 0.01% of total revenues and where both domestic and imported components account for at least 5% of the product group’s expenditures. When doing so, we are left with a sample of 265 4-digit product groups.}\]
particular, we compute the domestic and import unit values of product group \( g \), \( V_{gt}^{j} \) as

\[
V_{gt}^{j} = \frac{\sum_{i \in I_{gt}^{j}} V_{igt} Q_{igt}}{\sum_{i \in I_{gt}^{j}} Q_{igt}} = \sum_{i \in I_{gt}^{j}} \phi_{igt} V_{igt},
\]

(3)

where \( j = \{F, D\} \), \( \phi_{igt} = Q_{igt} / \sum_{i \in I_{gt}^{j}} Q_{igt} \) is a quantity-based weight, and \( V_{igt} \) is the unit value for item \( i \in I_{gt}^{j} \).

Figure 8 plots the distribution of the resulting unit value differences. The within product groups unit value of the imported component is on average 33% higher than that of the domestic component. The median difference is 30%. Therefore, over the whole sample, foreign goods tend to be more expensive than comparable domestic ones.

We have thus far shown the dispersion of unit values by pooling all the data over time. We next characterize how households changed their consumption behavior over “cheap” and “expensive” items within product groups over the boom-bust cycle. Figure 9 plots, for the median product group, the within-product group ratio of unit values for items that gain quantity share over those that lose quantity share relative to their respective quantity shares a year ago, calculated using the year ago unit values. Formally, for quarterly data, we use (3) to define \( V_{gt}^{-} \) and \( V_{gt}^{+} \), where \( I_{gt}^{-} \) includes all the items such that \( \phi_{igt+4} - \phi_{igt} < 0 \), and \( I_{gt}^{+} \) includes all the items such that \( \phi_{igt+4} - \phi_{igt} > 0 \). We use the unit values of products at time \( t \) for calculating the \( V_{gt}s \). In other words, we fix \( V_{igt} \) at its \( t \) value for both \( t \) and \( t+4 \) in calculation (3), but allow quantities to vary in the two time periods. For example, if \( t \) is Q4:08, then the values of \( V_{gt}^{j} \) will be computed based on the change in quantity shares over the crisis period Q4:08–Q4:09, using unit value data from Q4:08. As can be seen in the figure, as income begins to fall during the crisis, the median ratio of \( V_{t}^{+}/V_{t}^{-} \) also falls, meaning that the unit values of the items that gain quantity share within a product group tend to be lower on average than those which lose quantity share. In other words, consumers switched to items with lower unit values during the crisis.

This finding that there is switching towards items with lower unit values during crises is consistent with earlier findings by Burstein et al. (2005). To the best of our knowledge, however, there is no evidence on differences in the unit values of domestic and imported goods given the lack of available data.\(^{16}\) Work examining scanner data in the U.S. has noted that consumers search for cheaper goods by switching stores during recessions (Coibion et al., 2012), as well as differences in consumption across cities and household income levels.
(Handbury, 2012), but no one has examined the international dimension yet. The finding that imported goods tend to be more expensive than domestic ones in Latvia is an important result, which we build on below in helping to explain the observed expenditure switching.

3.4 Finding 4: Intensive and Extensive Margins

Finally, given that we are using detailed item level data, we wish to investigate the potential impact of entry and exit of goods on the dynamics of expenditures, both for domestic and foreign goods. There are two important reasons to do so. First, as recently shown by Corsetti et al. (2013), it is theoretically possible to have expenditure switching without a corresponding relative price change if there is substantial entry and exit of goods. Second, our modeling and estimation strategies implicitly rely on continuing goods as the source of identification.

In order to examine the importance of entry and exit in our data, we follow two different strategies. First, we consider a “gross” concept, and look at the time series of products, aggregated at the domestic and foreign sector level, for continuing, entering and exiting goods. Figure 10 plots these time series for y-o-y data. The top panel graphs the count of products, while the bottom panel plots the time series based on total expenditures. Regardless of the measure, continuing goods make up the largest component of total of goods, both for domestic and foreign items, over time. Moreover, it is also interesting to note that for entry, simply looking at the count measure can be misleading: there is an uptick in entry of the number of domestic products during the crisis, but in terms of total expenditures, entry remains considerably more flat throughout the time series.

Second, we are also interested in looking at how entry/exit contributes to the change in total growth over time – i.e., what happens on “net.” We therefore follow di Giovanni et al. (2012) and decompose the growth rate of total expenditures on domestic and foreign goods into an intensive and an extensive margin. The intensive component at date $t$ is defined as the growth rate of sales that had positive sales in both $t-1$ and $t$. The extensive margin is defined as the contribution to total sales of the appearance and disappearance of goods over the same time period.

We calculate the overall, intensive and extensive growth rates at the quarterly level, and then sum them over a four-quarter overlapping rolling window, in order to keep track of entry and exit of goods from quarter to quarter. Figure 11 plots these measures for domestic and foreign goods. One observes a boom-bust cycle for domestic goods and imports, with imports having a steeper decline during the crisis. What is striking, however, is that the
intensive component tracks overall sales growth very closely for both sectors, and that the extensive margin is relatively flat and does not contribute significantly to the dynamics of overall sales growth over the whole period, though there is a small increase in its contribution during the crisis period.

This decomposition helps assuage our concern that ignoring the extensive margin in our analysis may lead to any biases. Given the relatively short horizon of our analysis, it is not that surprising that the extensive margin does not play a large role in the crisis dynamics. Furthermore, our findings are consistent with those of the recent trade collapse literature, which also finds that the extensive margin played a small role (see Bems et al., 2012, for a recent review), as well recent evidence on the import behavior of firms during the Argentinean crisis Gopinath and Neiman (Forthcoming, 2013).

3.5 Discussion

We next turn to a modeling and estimation methodology to use in explaining the observed aggregate expenditure switching in our data. Before doing so, however, we summarize the important take-away messages from the findings we showed above.

First, to understand the observed expenditure switching for aggregate consumption in the data one needs to focus on explaining variation in expenditure shares within product groups, since there was no systematic variation in expenditure shares across product groups. Second, the within component of product groups’ relative prices of imported goods did not vary systematically. These findings do not bode well for relative prices being a major driver of expenditure switching. Finally, if consumers switched to cheaper domestic substitutes within product groups, it may be possible to generate aggregate expenditure switching, even in the absence of relative price changes.

4 Model

To formally quantify the importance of relative prices and income on expenditure switching, we next model the consumer’s expenditure allocation for F&B. The conventional approach in the international macroeconomics literature is to explicitly model the consumer’s choice between goods of domestic and foreign origin in a model that also distinguishes between tradable and nontradable goods (see Obstfeld and Rogoff, 2005, for example). However, given the item-level data is at our disposal, we find it more intuitive to model the consumer as basing her consumption decisions on the characteristics of goods, such quality or potential calories per unit (since we are considering food). These characteristics in turn
may be reflected in a product’s relative price or unit value. *A priori*, it is not clearly why a consumer would explicitly discriminate between geographical origin of a good given these other characteristics.

We therefore follow the literature that uses scanner data and model the expenditure allocation as a two-stage decision, where a consumer first allocates expenditures *across* grocery product groups (tea, coffee, cacao, etc), and then allocates expenditures between UPC items *within* product groups. Given the documented heterogeneity in unit values within product groups (see Finding 3), we also build in a channel through which consumers may substitute between low and high priced goods when faced with an income shock, such as the one experienced by Latvia during its sudden stop. In particular, we borrow from the setup of Hallak (2006)’s model, which allows goods to vary by quality, and for the consumer’s intensity of demand for quality to depend on her income level. These modifications of the standard CES demand system introduce a non-homotheticity at the bottom layer of the utility function. The higher the income the more the consumer values the higher quality items. Though we are not modeling quality formally here, since other factors may drive the difference in prices across domestic and foreign goods (e.g., transport costs), this modeling strategy captures an important potential channel that we wish to test; i.e., that consumers substituted to cheaper goods during the crisis, irrespective of relative price changes.

Introducing a “quality” parameter into the model allows for non-homothetic preferences to play a role in expenditure switching is novel, and has not been explored in the international macroeconomics literature in general. The few applications of non-homothetic preferences in macroeconomics usually rely on Stone-Geary type utility functions (Herrendorf et al., Forthcoming, 2013; Kongsamut et al., 2001; Ravn et al., 2008).

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17 See, Broda and Weinstein (2010) or Handbury (2012) for recent contributions using nested utilities and scanner data. Blackorby et al. (1978) is an early contribution that uses nested utility, and which also allows for non-homothetic preferences.

18 Hallak (2006) takes the supply of quality and income as exogenous in a partial equilibrium setting, like ours. See Feenstra and Romalis (2012) for a general equilibrium model, where quality is an endogenous outcome.
4.1 Setup

Define the expenditure allocation problem over F&B for a representative consumer as

\[ U_t = \left( \sum_{g=1}^{G} \omega_g c_{gt}^\rho \right)^{\frac{1}{\rho}} \]

\[ c_{gt} = \left( \frac{1}{\sigma_g} \sum_{i \in I_{gt}} \tilde{c}_{igt}^{\frac{1}{\sigma_g-1}} \right)^{\frac{\sigma_g-1}{\sigma_g}}, \text{ where } \tilde{c}_{igt} = \theta_{tg} c_{igt} \]

s.t.

\[ \sum_{g} \sum_{i} p_{igt} c_{igt} = C_t. \]

Utility is defined over \( G \) product groups with the familiar CES aggregator. Within each product group \( g \) a consumer chooses between a group-specific set of items (there are \( N_g \) items), each denoted \( \tilde{c}_{igt} \), measured in ‘utils,’ and constructed as \( \tilde{c}_{igt} = \theta_{tg} c_{igt} \), where \( c_{igt} \) is measured in common physical units (e.g., KG or L) and \( \theta_{tg} \) is a factor that converts physical units into ‘utils.’ In Hallak (2006), \( \theta_{tg} \) is as a proxy for quality differences and is measured using export unit values. We follow the same strategy using the UPC-level unit values, though as discussed above, there might be other factors driving the difference in unit values than just quality. Furthermore, as in Hallak (2006), we allow \( \theta_{tg} \) to vary with income level (measured as total expenditures \( C_t \)), so that “quality differences” within a product group matter more when income is high. Specifically, \( \lambda_g(C_t) \) captures the consumer’s intensity for demand of an item’s “quality” in a given group \( g \), and varies with income \( C_t \) such that \( \partial \lambda_g(C_t) / \partial C_t > 0 \). It is worth stressing again that the specified model does not differentiate between domestic and foreign goods within a product group.

4.2 Characterization of the Model Solution

Given prices, \( p_{igt} \), total expenditure, \( C_t \), qualities, \( \theta_{tg} \), and parameter values, the consumer optimally allocates food expenditures in each period. Because modifications to the standard CES utility function rely entirely on exogenous parameters, the familiar f.o.c’s hold both at the top and bottom levels of the utility. Specifically, at the top level we have

\[ c_{gt} = \omega_g p_{gt}^{-\rho} C_t, \]

and consistent with the expenditure share notation in the previous section, group \( g \)’s expenditure share can be written as

\[ s_{gt} = \frac{p_{gt} c_{gt}}{C_t} = \omega_g p_{gt}^{1-\rho}. \]
The utility-based aggregate price index, which we use as a numéraire, is

\[ P_t = \left( \sum_{g=G} \omega_g P_{gt}^{1-\rho} \right)^{\frac{1}{1-\rho}}. \]

At the bottom level of the utility, i.e., within product groups, the demand equation is

\[ c_{igt} = \frac{1}{N_g \theta_{igt}^{\lambda_g(C_t)}} \left( \frac{p_{igt}}{p_{gt}} \right)^{1-\sigma_g} c_{gt}, \]

so that an item’s within-group expenditure share is

\[ \varphi_{igt} \equiv \frac{p_{igt} c_{igt}}{p_{gt} c_{gt}} = \frac{1}{N_g} \left( \frac{p_{igt}}{p_{gt}} \right)^{1-\sigma_g}, \quad (5) \]

and the item’s expenditure share in total F&B expenditures is

\[ s_{igt} \equiv \varphi_{igt} s_{gt} = \frac{1}{N_g} \left( \frac{p_{igt}}{p_{gt}} \right)^{1-\sigma_g} \omega_g P_{gt}^{1-\rho}. \quad (6) \]

Finally, the utility-based price index for a product group is

\[ p_{gt} = \left( \frac{1}{N_g} \sum_i \left( \frac{P_{igt}}{\theta_{igt}^{\lambda_g(C_t)}} \right)^{1-\sigma_g} \right)^{\frac{1}{1-\sigma_g}}. \]

It is instructive to note that if the income level considerations are switched off, i.e., \( \lambda_g(C_t) = 0 \), then the equation for \( s_{igt} \) collapses to

\[ s_{igt} = \frac{1}{N_g} \left( \frac{p_{igt}}{p_{gt}} \right)^{1-\sigma_g} \omega_g P_{gt}^{1-\rho}, \]

which is the standard CES expression for the item’s expenditure share in total expenditures. However, more generally income affects the expenditure share, so that the demand system is non-homothetic.

**Equilibrium:** Given prices, \( p_{git} \), total expenditure, \( C_t \), qualities, \( \theta_{igt} \), and parameter values, consumer optimally allocates food expenditures in each period. The solution of the demand system can be is characterized by a system of expenditure share equations \( s_{igt} \), combined with group and aggregate price indexes and the budget constraint. One can solve the system to obtain the optimal consumption quantities for each item, \( c_{igt} \).
5 Estimation and Results

This section estimates the model presented above using the item-level data. We first show how to arrive at the estimating equation using the theoretical expenditure model, where we focus on exploiting the within-product group variation of the data. Then, given the estimated parameters, we predict an item’s share in a given product group, and aggregate all predicted shares of imported goods in order to calculate the predicted import share of total F&B, and the corresponding expenditure switching over periods, which we compare to the data.

5.1 Setting up the Estimation Equation

The key equation that characterizes the solution of the model presented in the previous section is (6). In order to take the model to the data, we make two simplifying assumptions so that estimation is tractable. First, we set \( \rho = 1 \), which is a reasonable approximation given the data.\(^{19}\) Second, rather than using the model implied prices to derive group-level price indexes as a function of the item level prices, we compute the price indexes at the group level with the GEKS methodology explained in Section 3.\(^{20}\)

Given these assumptions, (6) can be written as

\[
S_{igt} = \omega_g \left( \frac{p_{igt}}{p_{gt}} \right)^{1-\sigma_g} \left( \frac{1}{\theta^{\lambda_g(C_t)}} \right)^{1-\sigma_g} \equiv \omega_g \varphi_{igt}.
\]

Therefore, an item’s total expenditure share can be explained by its product-group expenditure share, up to the constant \( \omega_g \), which does not vary with time. Therefore, since we are interested in explaining the within variation of expenditure shares, it is sufficient to empirically model the variation in \( \varphi_{igt} \). Taking the logarithm of both sides of (5) we have

\[
\ln \varphi_{igt} = \ln \left( \frac{1}{N_g} \right) + (1 - \sigma_g) \ln \left( \frac{p_{igt}}{p_{gt}} \right) + (\sigma_g - 1) \lambda_g(C_t) \ln \theta_{ig}
\]

\[
= \ln \left( \frac{1}{N_g} \right) + (1 - \sigma_g) \ln \left( \frac{p_{igt}}{p_{gt}} \right) + (\sigma_g - 1) (\eta_g + \mu_g C_t) \ln \theta_{ig},
\]

where the last line follows from the assumption that \( \lambda_g(C_t) = \eta_g + \mu_g C_t \).

\(^{19}\)A regression of product group shares on the relative price (in log-log), following from (4) yields an estimate of \( \rho \) of 0.975 with a standard error of 0.054 at the 4-digit product group level.

\(^{20}\)The reason for this deviation from the model is that fixed weight indexes perform very poorly with scanner data. Furthermore, we follow a long tradition of the empirical literature that estimates demand systems by taking prices as given (e.g., Deaton and Muellbauer, 1980).
5.2 Taking the Model to the Data

To estimate the model using item-level data, we begin by re-writing (7) as

\[
\ln \varphi_{igt} = \alpha_g + \beta_{1g} \ln \left( \frac{p_{igt}}{\bar{p}_{igt}} \right) + \beta_{2g} \ln \bar{p}_i C_t + \varepsilon_{igt},
\]

(8)

where \( \alpha_g \) is a 4-digit product group fixed effect, and we proxy the quality parameters \( \theta_{ig} \) as the mean unit value of item \( i \) in the sample, \( \bar{p}_{igt} \), and \( \varepsilon_{igt} \) is as random disturbance term.

As in the model, we interact the “quality” term \( \ln \bar{p}_i t \) with income, \( C_t \). Since, the aggregate price index, \( P_t \), is the numéraire, we simply divide \( C_t \) by 1 to express it in real terms.

The inclusion of product group fixed effects implies that the \( \beta \) parameters will be identified from variation across items within their product groups and over time. This within variation is crucial for the identification of \( \beta_{2g} \), since the unit value of a given item (\( \bar{p}_{ig} \)) is only comparable within a group.\(^{21}\)

In order to estimate (8), we use the same data sample as used in Section 3, though we drop seven 4-digit product groups given that they do not contain enough data to identify the coefficients of interest, and we do not trim the data based on import shares as we did in Section 3.3. The final regression sample comprises of 293,162 item×time observation, and 437 product groups.\(^{22}\)

We estimate two versions of (8). The first model, which we call the ‘CES’ model, restricts all \( \beta_{2g} \) to 0. Therefore, only changes in prices will affect an item’s share. The second model, which we call the ‘NH’ (non-homothetic) model, runs (8) unrestricted. Table 4 presents summary statistics of the distribution of the estimated \( \beta \)s for each product group for the two models. Column (1) presents the CES model, where we restrict \( \beta_{2g} \) to be 0. The mean value of \( \beta_{1g} \) is \(-0.2170\), while the median value is somewhere larger in absolute value, at \(-0.3657\), which implies values of 1.22 and 1.37 for \( \sigma_g \), respectively. There is quite a bit of dispersion in the estimated coefficients, as well as their standard errors,\(^{23}\) but in total, 309 coefficient are significant at the 10% level; of these 272 are significant at the 5% level, while 225 are significant at the 1% level. Columns (2) and (3) present summary statistics for the

\(^{21}\)Note that by not including item-level fixed effects, we are restricting \( \eta_g \) to be zero across all groups. We do this for tractability purposes, as well as the fact that we are not able to separately identify this parameter and other product group parameters in the data given collinearity issues. This omission is innocuous, since this parameter does not vary over time, and we are ultimately interested in explaining the within variation of expenditure switching.

\(^{22}\)We also experimented with restricting the sample so that each product groups contains a minimum of 500 observations over the whole sample period. This is equivalent to requiring that there are at least 11 item-quarter observations for each product group, which cuts the sample to 172 product groups. Results were robust to these restrictions, and are available upon request.

\(^{23}\)Not reported to conserve space, but available from the authors upon request.
\(\beta_{1g}\) and \(\beta_{2g}\), respectively, for the unrestricted model. The mean and median values of \(\beta_{1g}\) are larger (in absolute value) than those of the restricted model, with values of \(-0.9912\) and \(-0.8811\), respectively. The estimated income coefficients, \(\beta_{2g}\), are on average positive, as we would expect, with mean and median values of \(0.0149\) and \(0.0081\), respectively. Again, there is considerable heterogeneity in the estimated coefficients across groups, but the majority of the price coefficients are significant at the 5% level, as are the income coefficients. Both models fit the data reasonably well, with an \(R^2\) of 0.2937 and 0.3054, respectively. Finally, it is interesting to note that the \(\beta_{1g}\)s increase substantially when including the income effect variables. Therefore, it is possible that relative price changes help explain the observed expenditure switching once controlling for an income effect. We investigate this possibility below by decomposing the predicted expenditure switching into income and price effects.

5.3 Predicted Expenditure Switching

It is possible to back out the structural parameters of the model for every product group. However, we are only interested in the predicted shares, \(\hat{\phi}_{igt}\), from which we can generate the predicted import shares of each group \(g\): \(\hat{\varphi}^F_{igt} = \sum_{i \in I_i} \hat{\phi}_{igt}\). We then use these predicted shares to calculate measures of expenditure switching for aggregate F&B consumption. Specifically, as Finding 1 above shows, the majority of expenditure switching occurred within product groups, so we focus on this measure. Further, to better match the actual data we use actual product group expenditure shares \(s_{gk}\) observed each period in order to calculate the within component of (1), and compare these values to the actual data (constrained to the same sample that is used for the regression). That is, we calculate

\[
\sum_g s_{gk} (\hat{\varphi}^F_{gt} - \hat{\varphi}^F_{gk}),
\]

for the two regression models.

Figure 12 plots the actual and predicted within y-o-y expenditure switching. Two standard error confidence bands for the aggregate predicted shares are calculated from a non-parametric stratified bootstrapping procedure. In particular, in each iteration of the bootstrap, we redraw with replacement the sample for each product group (the “strata”), and re-estimate the regression model (8) for the CES and NH specifications, and then calculate the aggregated predicted shares based on the new estimates. We repeat this

\footnote{A chi-square test rejects no systematic difference in the coefficients of the two models. Furthermore, what is crucial, is the implication of including these additional explanatory variables for predicting aggregate expenditure switching, which will be discussed in the following section.}
procedure 1001 times, and calculate the standard errors of the predicted shares using the distribution of predictions for each time period.

The first fact to note is that the within expenditure switching observed in the data (the solid line) has very similar dynamics compared to the within component plotted in Figure 4, which was calculated using a slightly larger data sample. Next, turning to comparing the two models’ predicted expenditure switching to that of the data in Figure 12, the predicted expenditure switching for the CES model does a very poor job in tracking the actual within expenditure switching observed in the data, and particularly during the crisis period when income dropped substantially. However, one can see that the non-homothetic model predicted values appear to track the data better throughout the sample, and picks up the switching during the pre-crisis boom period, as well as the switching during the crisis. In particular, the within component of expenditure switching between Q4:08–Q4:09 implied by data is −0.026, while the CES model predicts a value of only 0.004, and the non-homothetic model predicts a value of −0.0134. Therefore, the CES model barely predicts any expenditure switching between domestic and imported goods at the aggregate level (and in fact goes in the wrong direction), while the non-homothetic model is able to explain a little over 50% of what is observed in the data during the crisis period.

Finally, Figure 13 decomposes predicted expenditure switching of the non-homothetic model into separate price and income effects. We calculate these by keeping either prices or income set at their initial values, and then predict item’s shares, and aggregate up. It is clear that the income effect is responsible for almost all of the predicted expenditure switching.

6 Conclusion

This paper measures what drove expenditure switching in Latvia during a sudden stop episode in 2008–09, using a scanner-level dataset of food and beverages. Contrary to conventional theory, relative price changes did not drive expenditure switching. Instead, this paper’s findings show that the fall in income during the crisis led consumers to substitute from foreign to domestic goods, where this substitution was driven by the finding that foreign goods were on average more expensive than domestic ones. This non-homothetic channel is estimated using a simple model that allows for quality differences across goods, where the consumer’s intensity of demand for quality varies with income.

The analysis in this paper only focuses on substitution between domestic goods and imports for a particular sector of the economy for a country that maintained a peg during
its crisis. Future work should investigate how relevant the non-homothetic channel is in a more general setting, which incorporates exports as well as other sectors of the economy, as well as how results vary across exchange rate regimes.
Appendix A  Construction of Price Indexes

Price indexes are a key ingredient for the empirical analysis of this paper. They underlie both the aggregated relative price and aggregated quantity data that we use. This section summarizes the methodology for computing an aggregate price index for a given set of supermarket items.

Traditional ‘fixed-base’ indexes used to compute CPIs have a major disadvantage when applied to scanner data. Such indexes quickly become unrepresentative of the population of items sold, because (i) scanner items have a significant level of churn – this holds true in our data where the median sample item has 14 monthly observations out of 61 (see Figure A1 for the distribution of UPC item lifespans) and (ii) it is hard to match exiting items with their replacements. To give some idea about the extent of this problem in our dataset, Figure A2 reports the fraction of items sold in the first month (May06) that were also sold in each subsequent month. The green line plots the product-life hazard function in the sample. It shows that 70% of the items are still being sold after one year, while only 25% goods are sold after 5 years. The relevance of the initial consumption basket diminishes at a somewhat slower pace if items are weighted by revenues, as depicted by the blue line. Still, at the 5-year horizon more than half of the consumed items are new. This feature of scanner data remains broadly unchanged when data are aggregated to an annual frequency.

To keep the consumption basket relevant over time one would normally use chained (superlative) price indexes. However, in scanner data chained indexes suffer from ‘chain drift,’ which is likely caused by price oscillations and accompanying quantity shifts (see Ivancic et al., 2011, for further discussion). Aggregating data over time should diminish the chain drift. However, Ivancic et al. (2011) find that aggregation from monthly to quarterly frequency might not be sufficient to eliminate the chain drift in scanner data. Further aggregation to an annual frequency would be preferable, but is excessively costly for our purposes, as we would have to aggregate over key adjustment dynamics and, more generally, would be left with too few time-series observations (5 to be precise).

To keep the consumption basket representative of the full population of items being sold over time and, at the same time, avoid the chain drift, Ivancic et al. (2011) advocate a multilateral index number method for construction of price indexes for scanner data. These

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25ILO (2004, 445) defines chain drift as price index “does not return to unity when prices in the current period return to their levels in the base period.”
authors define a price index as:

\[ GEKS_{1,t} \equiv \prod_{k=1}^{T} (P_{1,k}P_{k,t})^{\frac{1}{T}}, \]

where,

\[ P_{1,k} = \left( \sum_i s_{i1} \left( \frac{p_{ik}}{p_{i1}} \right) \left[ \sum_i s_{ik} \left( \frac{p_{i1}}{p_{ik}} \right) \right]^{-1} \right)^{\frac{1}{2}} \]

\[ P_{k,t} = \left( \sum_i s_{ik} \left( \frac{p_{it}}{p_{ik}} \right) \left[ \sum_i s_{it} \left( \frac{p_{ik}}{p_{it}} \right) \right]^{-1} \right)^{\frac{1}{2}} \]

are Fisher price indexes, which in turn are geometric means of the Laspeyres and Paashe indexes, with \( s_{ij} \) representing good \( i \)'s expenditure share in period \( j \).

The GEKS price index does not suffer from the ‘fixed-basket’ problem, because price changes between any two periods are computed using a superlative Fisher price index. At the same time, Ivancic et al. (2011) show that the resulting index is also free of the chain drift. Intuitively, this is the case because GEKS uses ‘fixed-base’ comparisons between all possible matches for the time period under consideration, each of which is free of chain drift, and then averages over all comparisons to keep the consumption basket relevant.

To further motivate the GEKS price index, Table A1 compares inflation rates as computed with the GEKS and chained-Fisher indexes at various levels of product aggregation. Consistent with the literature, we find that the Fisher index underestimates inflation. For the aggregate level we find that over the 5-year horizon the Fisher index underestimates food inflation by 0.08 percentage points, or 0.015 percentage points a year. The bias is larger, but still small at higher levels of disaggregation. At the 4-digit level, the median bias is 1.6 percentage points over the 20 quarters (i.e., 0.3 percentage points per year). However, the bias can vary substantially across the different product groups, as indicated by the standard deviation of 14.3% at the 4-digit level. This is our main motivation for using GEKS.

**Appendix B  Interpretation of Finding 2 in a Two-Sector Model with Tradables and Nontradables**

The modeling and quantitative approach of the paper focuses on the detailed micro-level data in order to identify the margins at which expenditure switching took place, and then
aggregate the results to draw conclusions about expenditure switching at the macroeconomic level. One downside of this micro-approach in studying the crisis/sudden stop is that our findings cannot be easily compared to the extensive existing literature (e.g., see Burstein et al., 2005; Kehoe and Ruhl, 2008; Mendoza, 2005; Obstfeld and Rogoff, 2005) that emphasizes the distinct roles of tradable and nontradable goods during the crisis.

To facilitate such a comparison, this appendix recasts Finding 2 of Section 3 from the perspective of a two-sector economy with tradable and nontradable goods. In order to do so, we must define whether a given 4-digit product group belongs to the tradable or nontradable sector. Though F&B as a whole is commonly considered a tradable sector in the international macroeconomic literature (Berka and Devereux, 2011; Crucini et al., 2005), Table 2 reveals that many product groups within F&B have a negligible import content. We aggregate F&B product groups into tradables/nontradables based on the shelf-life of a typical product in each 4-digit product group (REF TO SHELF-LIFE PAPER). In the baseline case, a 4-digit product group is defined as nontradable, if its shelf-life is less than 180 days and as tradable if the shelf-life is equal to or exceeds 180 days. With this classification 40% of expenditures on F&B are tagged as nontradables and import share in nontradables is mere 4%. Remaining 60% of expenditures are classified as tradables, with an import share in tradables exceeding 50%. For sensitivity purposes we also examine a case whereby a product group is defined as nontradables, if its shelf-life is less than 60 days. In this case nontradables constitute 28% of F&B expenditures and only 1% of nontradables F&B expenditures fall on imports.26

We re-apply the price decomposition formula from Section 3.2 to the two-sector case with tradables and nontradables, i.e., \( g \in \{ T, N \} \). Adjustments within and across sectors can now be cast in more familiar terms. Price adjustment within sectors amounts to an adjustment between prices of domestic and imported tradables within the tradable sector, commonly referred to in the macro literature as the external margin. This is the case because import content in the nontradable sector is negligible. Price adjustment across sectors captures changes in the relative price between tradable and nontradable F&B, or the internal margin.

Price decomposition results, presented in Figure A3, are broadly the same as at the level of the 4-digit product groups, presented in Figure 5. Plotted in Figure A3, in addition

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26 An alternative commonly pursued approach in the literature to distinguish between tradables/nontradables is to label a product group as tradables, if expenditures on imports in the group exceed 10%. Decomposition results for this approach were similar to the ‘shelf-life’ approach. However, we find import intensity to be a less appealing measure, as low import content might merely signal a comparative advantage of the domestic producers.
changes in the relative price of imports $P^F_t/P_t$, is contribution from the external margin of adjustment, when nontradables are defined as product groups with shelf-life of $<180$ days and $<60$ days. In the former case (180 days) the relative price adjustment during the crisis took place almost entirely at the internal margin, i.e., between the relative price of tradables and nontradables. In the latter case (60 days) the contribution of the external margin is increased, but still amounts to only 1/4 of the total price adjustment during the crisis. Bulk of the adjustment in relative prices took place at the internal margin. This finding is consistent with results from other crisis episodes (e.g., see Burstein et al., 2005; Mendoza, 2005).

An important implication for the Engel (1999)-type decomposition is that during the sudden stop episode in Latvia the relative price of imported tradables to all tradables, $P^F_t/P_T$, increased by a mere 0.5% (over Q4:09/Q4:08). For this price adjustment to explain the observed expenditure switching from foreign to domestic tradables, the price elasticity would have to be around 14, which is a very large value for this level of aggregation. Therefore, even at this aggregate level analysis, a further channel is needed to explain the observed expenditure switching. The introduction of a non-homothetic channel, like in the model of Section 4, in macroeconomic models could be one potential way to help explain the observed expenditure switching in a standard two-sector macroeconomic framework.
References


Table 1. Aggregate Sales and Product Summary Statistics

<table>
<thead>
<tr>
<th>Year</th>
<th>(1) Sales</th>
<th>(2) Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>2.23E+08</td>
<td>–</td>
</tr>
<tr>
<td>2007</td>
<td>2.80E+08</td>
<td>0.2297</td>
</tr>
<tr>
<td>2008</td>
<td>3.18E+08</td>
<td>0.1259</td>
</tr>
<tr>
<td>2009</td>
<td>2.80E+08</td>
<td>-0.1257</td>
</tr>
<tr>
<td>2010</td>
<td>2.82E+08</td>
<td>0.0075</td>
</tr>
</tbody>
</table>

II. Domestic Products

<table>
<thead>
<tr>
<th>Year</th>
<th>(1) Sales</th>
<th>(2) Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>1.37E+08</td>
<td>–</td>
</tr>
<tr>
<td>2007</td>
<td>1.71E+08</td>
<td>0.2247</td>
</tr>
<tr>
<td>2008</td>
<td>1.98E+08</td>
<td>0.1494</td>
</tr>
<tr>
<td>2009</td>
<td>1.83E+08</td>
<td>-0.0822</td>
</tr>
<tr>
<td>2010</td>
<td>1.85E+08</td>
<td>0.0132</td>
</tr>
</tbody>
</table>

III. Foreign Products

<table>
<thead>
<tr>
<th>Year</th>
<th>(1) Sales</th>
<th>(2) Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>8.62E+07</td>
<td>–</td>
</tr>
<tr>
<td>2007</td>
<td>1.09E+08</td>
<td>0.2375</td>
</tr>
<tr>
<td>2008</td>
<td>1.19E+08</td>
<td>0.0881</td>
</tr>
<tr>
<td>2009</td>
<td>9.75E+07</td>
<td>-0.2024</td>
</tr>
<tr>
<td>2010</td>
<td>9.72E+07</td>
<td>-0.0033</td>
</tr>
</tbody>
</table>

Notes: This table presents summary statistics for all products aggregated across all types of stores at an annual level, where a year is defined from June-May (e.g., June06-May07) in order to maximize coverage. Column (1) presents total sales in euros. Column (2) presents the annual growth rate of sales.
Table 2. Product Group Summary Statistics

<table>
<thead>
<tr>
<th>Code</th>
<th>Name</th>
<th>Share</th>
<th>Foreign Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Meat, fresh and frozen</td>
<td>0.010</td>
<td>0.01</td>
</tr>
<tr>
<td>11</td>
<td>Fish</td>
<td>0.020</td>
<td>0.12</td>
</tr>
<tr>
<td>12</td>
<td>Processed meat</td>
<td>0.043</td>
<td>0.03</td>
</tr>
<tr>
<td>13</td>
<td>Prepared food</td>
<td>0.011</td>
<td>0.03</td>
</tr>
<tr>
<td>14</td>
<td>Fresh bread</td>
<td>0.077</td>
<td>0.02</td>
</tr>
<tr>
<td>21</td>
<td>Dairy products</td>
<td>0.085</td>
<td>0.02</td>
</tr>
<tr>
<td>20</td>
<td>Eggs and eggs preparations</td>
<td>0.020</td>
<td>0.00</td>
</tr>
<tr>
<td>22</td>
<td>Yogurts &amp; dairy snacks</td>
<td>0.049</td>
<td>0.12</td>
</tr>
<tr>
<td>23</td>
<td>Edible fats</td>
<td>0.016</td>
<td>0.18</td>
</tr>
<tr>
<td>24</td>
<td>Cheese</td>
<td>0.046</td>
<td>0.15</td>
</tr>
<tr>
<td>25</td>
<td>Frozen foods</td>
<td>0.018</td>
<td>0.40</td>
</tr>
<tr>
<td>26</td>
<td>Ice cream</td>
<td>0.014</td>
<td>0.08</td>
</tr>
<tr>
<td>30</td>
<td>Grain products</td>
<td>0.026</td>
<td>0.36</td>
</tr>
<tr>
<td>31</td>
<td>Biscuits and wafers</td>
<td>0.016</td>
<td>0.17</td>
</tr>
<tr>
<td>32</td>
<td>Canned (jarred) foods</td>
<td>0.023</td>
<td>0.34</td>
</tr>
<tr>
<td>33</td>
<td>Juices</td>
<td>0.023</td>
<td>0.21</td>
</tr>
<tr>
<td>34</td>
<td>Hot drinks</td>
<td>0.044</td>
<td>0.86</td>
</tr>
<tr>
<td>35</td>
<td>Baby foods and drinks</td>
<td>0.009</td>
<td>1.00</td>
</tr>
<tr>
<td>36</td>
<td>Baby care products</td>
<td>0.015</td>
<td>0.91</td>
</tr>
<tr>
<td>37</td>
<td>Pet foods</td>
<td>0.013</td>
<td>0.86</td>
</tr>
<tr>
<td>38</td>
<td>Pet accessories</td>
<td>0.002</td>
<td>0.85</td>
</tr>
<tr>
<td>40</td>
<td>Dry ingredients</td>
<td>0.006</td>
<td>0.68</td>
</tr>
<tr>
<td>41</td>
<td>Seasoning &amp; preserve</td>
<td>0.046</td>
<td>0.43</td>
</tr>
<tr>
<td>42</td>
<td>Sweets</td>
<td>0.047</td>
<td>0.66</td>
</tr>
<tr>
<td>43</td>
<td>Snacks</td>
<td>0.009</td>
<td>0.45</td>
</tr>
<tr>
<td>44</td>
<td>Dried fruit and nuts</td>
<td>0.009</td>
<td>0.18</td>
</tr>
<tr>
<td>45</td>
<td>Natural &amp; pharm. prods.</td>
<td>0.002</td>
<td>0.76</td>
</tr>
<tr>
<td>48</td>
<td>Brewery + mild alc. bevs.</td>
<td>0.053</td>
<td>0.16</td>
</tr>
<tr>
<td>49</td>
<td>Alcoholic products</td>
<td>0.150</td>
<td>0.65</td>
</tr>
<tr>
<td>50</td>
<td>Soft drinks</td>
<td>0.037</td>
<td>0.47</td>
</tr>
<tr>
<td>60</td>
<td>Tissues</td>
<td>0.013</td>
<td>0.73</td>
</tr>
<tr>
<td>62</td>
<td>Disposable tableware, etc.</td>
<td>0.007</td>
<td>0.71</td>
</tr>
<tr>
<td>63</td>
<td>Intimate hygiene</td>
<td>0.007</td>
<td>0.98</td>
</tr>
<tr>
<td>64</td>
<td>Body wash and care</td>
<td>0.027</td>
<td>0.98</td>
</tr>
<tr>
<td>65</td>
<td>Cosmetics</td>
<td>0.006</td>
<td>0.89</td>
</tr>
<tr>
<td>66</td>
<td>Jewelry &amp; optical prods.</td>
<td>0.002</td>
<td>0.81</td>
</tr>
<tr>
<td>68</td>
<td>Detergents</td>
<td>0.001</td>
<td>0.56</td>
</tr>
</tbody>
</table>

Notes: This table presents summary statistics for two-digit product groups, aggregated across stores over the sample period May 2006–May 2011. The ‘Share’ column presents a product group’s share of total sales over the sample period. The ‘Foreign Share’ column presents the share of foreign sales within a product group over the sample period. The ‘Aggregate’ foreign share is a ‘Share’-weighted average of product groups’ foreign shares.
### Table 3. Grocery Retail Market Share

<table>
<thead>
<tr>
<th>Year</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market share, %</td>
<td>20.0</td>
<td>21.7</td>
<td>22.5</td>
<td>22.4</td>
<td>21.5</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates of the total grocery retail market share in Latvia for stores covered by the scanner data. Source: IGD Retail Analysis

### Table 4. CES and Non-Homothetic Models’ Regression Results

<table>
<thead>
<tr>
<th></th>
<th>CES Model</th>
<th>NH Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\beta_{1g}$</td>
<td>$\beta_{1g}$</td>
<td>$\beta_{2g}$</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.2170</td>
<td>-0.9912</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>2.9358</td>
<td>3.6637</td>
</tr>
<tr>
<td>5th pctile</td>
<td>-2.2284</td>
<td>-4.2707</td>
</tr>
<tr>
<td>10th pctile</td>
<td>-1.6796</td>
<td>-3.4329</td>
</tr>
<tr>
<td>25th pctile</td>
<td>-1.0253</td>
<td>-1.9854</td>
</tr>
<tr>
<td>50th pctile</td>
<td>-0.3657</td>
<td>-0.8811</td>
</tr>
<tr>
<td>75th pctile</td>
<td>0.2116</td>
<td>0.0000</td>
</tr>
<tr>
<td>90th pctile</td>
<td>1.0297</td>
<td>0.8882</td>
</tr>
<tr>
<td>95th pctile</td>
<td>1.7246</td>
<td>1.9749</td>
</tr>
<tr>
<td>Group effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Obs.</td>
<td>293,162</td>
<td>293,162</td>
</tr>
<tr>
<td>Groups</td>
<td>437</td>
<td>437</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.2937</td>
<td>0.3054</td>
</tr>
<tr>
<td>$\chi^2_{437}$: 4931.30</td>
<td>Prob $&gt; \chi^2 = 0.0000$</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table presents summary statistics on the distribution of estimated coefficients of the regression model (8). Column (1) presents the price coefficients for the CES model, while Columns (2) and (3) present the price and income coefficients, respectively, for the non-homothetic model. The magnitude of the coefficients in Column (3) reflects income being expressed in millions. All specifications are run with product group fixed effects. The $\chi^2$ statistic tests the null of no difference in coefficients being systematic across the two models, which is rejected. In Column (1), 309 coefficients are significant at the 10% level; of these 272 are significant at the 5% level, while 225 are significant at the 1% level. In Column (2), the number of coefficients that are significant at the 10, 5, and 1% level are 284, 249, and 199, respectively. In Column (3), the number of coefficients that are significant at the 10, 5, and 1% level are 249, 249, and 199, respectively.
**Figure 1.** Food and Beverages CPI and Aggregate Price Index from Scanner Data for Latvia

![Figure 1](image)

Notes: This figure plots the Latvian aggregate CPI for F&B, and an aggregate price index constructed using the scanner data. Sources: Central Statistical Bureau of Latvia and authors’ calculations.

**Figure 2.** Food and Beverages Imports: Customs and Scanner Data

![Figure 2](image)

Notes: This figure plots value indexes of (i) aggregate imports of F&B for final goods (based on UN BEC classification), and (ii) expenditures on foreign goods in the scanner data. Note that both series are scaled such that 2008Q1 value is zero. Sources: Global Trade Information Services (http://www.gtis.com), UN Broad Economic Classification (http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=10), and authors’ calculations.
**Figure 3.** Food and Beverages Fall During the Crisis

![Graph showing year-on-year log change in real food consumption.](image)

Notes: This figure plots the year-on-year log change of total F&B expenditures over the whole sample as measured using the scanner data. Source: authors' calculations.

**Figure 4.** Expenditure Switching: Total, Within and Across Product Groups

![Graph showing year-on-year change in import expenditure share.](image)

Notes: This figure plots the year-on-year change of the import share of total F&B expenditures over the whole sample as measured using the scanner data. The total change in the import share is broken into the contribution due to switching expenditures 'across' product groups and 'within' product groups (i.e., by substituting between goods), calculated using (1).
Figure 5. Relative Price Change: Total, Within and Across Product Groups

Notes: This figure plots the year-on-year change of the relative price of foreign goods for F&B expenditures over the whole sample as measured using the scanner data. The total change in the relative price is broken into the contribution due to changes ‘across’ product groups and ‘within’ product groups (i.e., by substituting between goods), calculated using (2).
Figure 6. Across and Within Relative Price Change and Import Penetration: Across Sectors

Notes: This figure plots the across and within components of the relative price change, used to calculate the aggregate components in (2), for each product group over Q4:08–Q4:09 against the groups’ average import shares.
**Figure 7.** Distribution of Within Product Group Interquartile Range Unit Values at the 4-Digit Product Code Level

Notes: This figure plots the within product group interquartile range unit values across all 4-digit product groups over the entire sample.

**Figure 8.** Distribution of Relative Unit Values at the 4-Digit Product Code Level

Notes: This figure plots the natural logarithm of the relative unit values of foreign to domestic goods, $\ln(p_F/p_D)$, at the four-digit product code level. The histogram is constructed using relative prices for goods over the whole sample period, May 2007–May 2011. Prices are constructed by unit, where units are either kilograms or liters, and relative prices are computed within each unit group by 4-digit product code.
Figure 9. Switching Between Low and High Unit Value Items

Notes: This figure plots, for the median 4-digit product group, the within-product group ratio of unit values for items that gain quantity share over those that lose quantity share relative to their quantity shares a year ago. The unit value for the subset of items that gained market share is denoted by $V^+$, and $V^-$ denotes the unit value for the losers. The unit value ratios are computed using items’ start-of-period unit values. For example, the $V^+/V^-$ computed at 2008:Q4 uses unit values of 2007:Q4 given that we are looking at year-on-year changes of shares to define + or – groups. Note that quantity shares can be computed at the 4-digit product group because at this level of detail all items within a group have the same unit (e.g., KG or L).
Figure 10. Domestic and Import Goods: Continuing, Entry, and Exit

Notes: This figure plots the time series of products that (i) continue, (ii) enter and (iii) exit from one year to the next (based on quarterly y-o-y measure) for domestic and foreign goods. The top two panels presents the count of UPC, while the bottom two panels presents total expenditures on the types of goods.
Figure 11. Domestic and Import Expenditure Growth: Total and Intensive and Extensive Margins

Notes: This figure plots the growth rate of total expenditures on domestic and imported goods, as well as the contribution to growth due to changes for continuing goods – the ‘intensive margin’ – and due to net entry and exit of goods – the ‘extensive margin’. Growth rates are calculated using quarterly data and are then accumulated over a four-quarter overlapping rolling window.
Notes: This figure plots the within component of expenditure switching observed in the data and estimated using the model based on (8), for the CES and Non-homothetic models. The shaded areas are two standard error bands, calculated using a non-parametric stratified bootstrapping procedure.
**Figure 13.** Non-Homothetic Model’s Within Components of Expenditure Switching: Income and Price Effects

Notes: This figure plots the estimated within component of expenditure switching predicted by the Non-homothetic model, breaking it down into contributions due to (i) a price effect, and (ii) an income effect. The model is estimated using the full model (8). The shaded areas are two standard error bands, calculated using a non-parametric stratified bootstrapping procedure.
Table A1. Fisher-GEKS Differentials for Inflation Rates

<table>
<thead>
<tr>
<th>Level of Product Group Aggregation</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.084</td>
<td>-2.522</td>
<td>-3.445</td>
</tr>
<tr>
<td>Median</td>
<td>-0.084</td>
<td>-0.615</td>
<td>-1.572</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>–</td>
<td>10.583</td>
<td>14.334</td>
</tr>
<tr>
<td>Obs.</td>
<td>1</td>
<td>37</td>
<td>512</td>
</tr>
</tbody>
</table>

Notes: This table presents the differences in 5-year inflation rates, expressed in percentage points, when price indexes are calculated using the Fisher and GEKS formulas. The difference is measured as Fisher – GEKS. Column 1 presents this differential when aggregating all goods; Column 2 presents summary statistics for inflation differentials at the level of 2-digit product groups; Column 3 presents summary statistics for inflation differentials at the level of 4-digit product groups.
**Figure A1.** Distribution of UPC Item Lifespan

![Distribution of UPC Item Lifespan](image)

Notes: This figure plots the monthly distribution of UPC item lifespans for all products in the dataset over May 2006–May 2011.

**Figure A2.** Items Survival Hazard

![Items Survival Hazard](image)

Notes: This figure plots the fraction of items sold in the first month that were also sold in each subsequent month, i.e., a hazard function of a product in the dataset. The green line plots the unweight product-life hazard function in the sample. The blue line plots the revenue-weighted hazard function.
Figure A3. Relative Price Change in a Two-Sector Model: Total and Contribution from External Margin

Notes: This figure plots the y-o-y change of the relative price of foreign goods for F&B expenditures over the whole sample as measured using the scanner data. The total change in the relative price is broken into the contribution due to the ‘internal margin’ or changes in the relative price of tradables to nontradables and the ‘external margin’ or changes in the relative price of domestic and imported tradables. Only the latter contribution is plotted in the figure. Two definitions of nontradables are considered: (i) 4-digit product groups with a shelf-life of <180 days and (ii) 4-digit product groups with a shelf-life of <60 days.