The Impact of Negative Income Shocks on the Relative Prices of Private Label Products: The Covid-19 Episode

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Abstract

In this study, we show the relationship between households' income and the relative prices of private label products (relative to the prices of national brand products), known as lower quality and cheaper alternatives to national brands. By employing retail-product level micro price data from nine different supermarket chains in Türkiye, we exploit the sudden and unexpected income losses caused by Covid-19 measures within a difference in differences setting. Our results show that when households experience income shocks, the relative prices of private label products increase significantly. Therefore, our results indicate that the relative prices of lower quality products are significantly affected by households' income.

Keywords: Difference-in-Differences, Private label products, Supermarket prices, Covid-19, Lower quality products

JEL Codes: C21, D22, E21, E31

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Non-Technical Summary

Although there are several empirical studies providing direct evidence that aggregate demand conditions significantly affect retail prices, heterogeneity of this effect across products of different quality segments is understudied. Related literature shows that economic downturns lead to significant changes in households' consumption behavior in such a way that consumers reallocate their consumption bundle towards lower-quality goods. This kind of synchronized change in consumers' behavior may increase overall demand for lower quality products and put upward pressure on their prices. Such a mechanism would worsen the real income inequality by increasing the cost of living for lower income households who already consume lower quality products. The aim of this paper is to show whether relative prices of lower-quality food products (relative to prices of higher-quality products) increase during the periods when households experience income losses.

In this study, we first define private label (PL) and national brand (NB) products as lower and higher quality product groups, respectively, and balance the content of each group through a coarsened exact matching algorithm. Then, we exploit the sudden and unexpected income losses caused by Covid-19 measures within a difference in differences setting. In other words, we compare pre- and post-Covid-19 outbreak prices of PL and NB product groups which consist of the same product types (e.g. milk, oil, tomato sauce etc.) and interpret the difference between the changes of these prices as the impact of income losses.

Our results indicate that relative prices of lower quality PL products (relative to prices of higher quality NB products) increased by 3.5 percent on average after sharp employment losses due to Covid-19 measures. This finding implies that the impact of aggregate demand conditions on the food prices varies across the products of different quality segments. Thus, households already consuming lower-quality food products lose more of their real income in the case of economic downturns and additional subsidies should be provided to lower-income households to prevent a worsening of real income inequality.

1. Introduction

The Covid-19 pandemic and measures taken against it had sudden and large-scale effects on economies. Undoubtedly, one of the biggest and most sudden impacts on the Turkish economy was households' income losses. Following the Covid-19 pandemic and the related restrictive measures in March 2020, non-farm employment started to decline dramatically in Türkiye. In addition, many employees lost part of their income as they had been benefitting from the short-time work allowance. In May 2020, non-agricultural employment was 8.42 percent points below its level in February. Considering the beneficiaries of the short-time working allowance as well, the number of employees who lost some or all of their income in May reached 22.77 percent of those employed in February. Moreover, considering that some employees had to take unpaid leave and were not able to benefit from the short-time working allowance, the real number is higher. These widespread income losses and uncertainty about future income may have had significant impacts on consumers' behavior and the demand for consumption goods. Stroebel and Vavra (2019) provide direct causal evidence that wealth increases cause changes in consumer behavior, leading to increases in retail prices. Coibion et al. (2015) and Beraja et al. (2019) show that retail prices respond significantly to local unemployment rates. Taken together, these studies show that retail prices follow business cycles and are affected by household income. However, these effects on prices may be heterogeneous across the products of different quality segments. Although they report different findings on sizes, Lamey et al. (2007), Lamey et al. (2012), Dubé et al. (2018) and Brancatelli et al. (2020) provide results showing that following income losses, the market share of private label (PL) products[1], known as lower quality and cheaper alternatives to national brand (NB) products, increases. This kind of a shift in consumer demand towards lower quality goods may put upward pressure on their prices. Such a mechanism has two important economic implications: First, it may mitigate the effect of demand conditions on the aggregate price level. Second, during recessionary periods, the cost of living rises for lower-income consumers who already consume these lower quality products.

Our aim in this paper is to exploit the exogenous Covid-19 shock to identify the relationship between household income and the relative prices of PL products. Basically, we compare pre- and post-Covid-19 outbreak prices of PL and NB products and interpret the difference between the changes of these prices as the impact of income losses. Although several supply-side shocks occurred simultaneously with the income shock, our identification strategy allows us to isolate the impact of income losses. In the empirical analysis part, we first employ a coarsened exact matching (CEM) algorithm to balance the composition of the comparison groups (PLs and NBs) according to product types. Since the same product types constitute equal shares in each comparison group, any supply-side shock is expected to show similar effects on the prices of each group.[2] On the other hand, because PL and NB products differ both in terms of quality and price level, any change in household income levels may cause demand shifts between these groups and affect their prices differently. Thus, application of difference in difference methodology to balanced data provides a clear estimate for the impact of income losses on the relative prices of PLs and NBs.

Our estimation results reveal that the Covid-19 measures caused PL prices to increase 3.5 percent more on average than NB prices, and this impact was heterogeneous across product types. We also assess whether the estimated impact is specific to PLs or caused by the general pricing behavior of the discount markets.[3] For this purpose, we compare the prices of NBs sold by discount markets with the prices of those sold by other chains. The results suggest that changes in the prices of NBs show similar patterns regardless of whether they are sold by discount markets or other chains. The period when households experienced income losses coincides with a considerable depreciation in the Turkish lira and our findings could be due to the impact of this depreciation. For this reason, we

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[1] Private labels refer to products whose brands are owned by retailers and are sold by only the retailer that owns the brand. These private label products are either manufactured by the retailers or by a third-party manufacturer. On the other hand, national brands refer to products whose brand is generally owned by the manufacturer and can be sold in any retailer. One main difference between private labels and national brands is that private labels are known to be both cheaper and lower quality products compared to national brands.

[2] For example, after the application of the CEM, both PL and NB groups contain same amount of milk, and any kind of supply side shock related to the milk sector is expected to affect prices of both groups similarly.

[3] Our dataset contains prices from nine different chains. Only three of them, known as discount markets, sell PL products, while all the chains sell NB products.

analyzed another episode in which the Turkish lira was exposed to a sizeable depreciation and found no significant change in the relative prices of PL products. We also conduct two different robustness analyses and show that our baseline results are robust to alternative definitions of the control groups.

Our study contributes to the literature in several ways. Stroebel and Vavra (2019), Coibion et al. (2015) and Beraja et al. (2019) report that retail prices exhibit cyclical behavior. Our results are complementary to these findings, as we show that this behavior varies across different product groups. Our study also relates to the studies on the impacts of income changes on demand for PLs. Lamey et al. (2007), Lamey et al. (2012), Dubé et al. (2018), and Brancatelli et al. (2020) show that demand for PLs exhibits cyclical behavior. Although we do not directly analyze demand for PLs, our results are consistent with these findings and we argue that income shocks affect prices through the demand channel. Our study is also related to the studies focusing on the inequality of cost-of-living inflation across income levels. Argente and Lee (2017) show that cost-of-living inflation is higher for the lower-income households during recessionary periods. They find that while higher-income consumers decrease their cost of living by making quality substitutions, lower-income consumers, who already consume lower quality products, do not have such a margin. We show that this kind of mechanism exerts additional upward pressure on the price of lower quality products and makes lower-income consumers even worse off. Finally, our paper is also related to studies that explore the economic impacts of Covid-19. There are several studies analyzing the impact of the Covid-19 pandemic on prices. Balleer et al. (2020) studied the impact of Covid-19 on producer prices, Hillen (2020) analyzed the behavior of online food prices during the pandemic, and Akter (2020) examined the impact of Covid-19-related 'stay-at-home' restrictions on food prices. However, to the best of our knowledge, there are no studies examining the impact of Covid-19 measures on the relative prices of low quality (or PL) products, and so our study is the first.

The rest of the paper is structured as follows. Section 2 briefly summarizes the literature, data and the contextual background. The subsequent section explains our identification strategy. Section 4 presents the results. Section 5 provides robustness checks. Finally, the last section presents concluding remarks.

2. Literature, Background Information and Data

2.1 Literature

As the data on retail prices and household consumption became available to researchers, the literature on consumer behavior, retailers' pricing behavior, and their relationship to macroeconomic conditions started to grow rapidly. In this section, we briefly summarize some of these studies that guide us during our empirical analysis or are closely related to our study.

We are interested in assessing whether the negative income shock caused by Covid-19 affects the relative prices of PLs through the demand channel. During the period when Turkish households experienced the income shock, the Turkish lira suffered a considerable depreciation. This exchange rate movement may be a possible threat to the identification of the income effect on the relative prices of PLs. Auer, Burstein and Lein (2021) showed that retail prices are sensitive to exchange rate developments. It is also known that the exchange rate is one of the main drivers of consumer price inflation in Türkiye (Kara, Öğünç and Sarıkaya, 2017), and food inflation is significantly affected by exchange rate movements. Özmen and Topaloğlu (2017) conducted a VAR analysis to estimate exchange-rate pass-through in Türkiye's official food price inflation. They report that a one percent depreciation in the Turkish lira causes inflation to rise by 23.5 and 27.1 basis points in unprocessed food and processed food prices, respectively. As the related literature points out that retail prices in Türkiye are likely to be affected by an exchange rate depreciation, understanding the dynamics behind the exchange-rate pass-through is crucial. Nakamura and Zerom (2010) analyzed coffee prices and reported that the pass-through of imported commodity prices and the exchange rate into consumer prices is incomplete. Their results show that the pass-through's incompleteness is mainly caused by the share of the local costs in the total cost of the final product and markup adjustments. In our study, we compare changes in prices of PL and NB products of the same type. Therefore, the shares of imported and local inputs are expected to be similar between the two product types. However, markups on PL and NB products may differ because of the degree of vertical integration in PL products or possible differences in producers' market power. Auer and Schoenle (2016), Berman, Martin and Mayer (2012), and Amiti, Itskhoki and Konings (2014) used microdata on import and export prices and showed that firms with higher market shares have lower exchange-rate pass-through in their prices. Hong and Li (2017) analyzed whether cost pass-through into retail prices is affected by vertical and horizontal market structure. Their dataset allows them to group products by three different vertical relationships: PLs manufactured by retailers, PLs externally produced but branded by retailers, and NBs. They analyzed how the pass-through of commodity costs into retail prices changes across these three groups. The results show that the pass-through for both PL groups is higher than that of NBs. While higher pass-through for PLs produced by retailers is highly significant and robust to alternative estimators, it is weaker for those that are externally produced. When the products' market shares are controlled for, higher pass-through rates for PL products become more apparent. Moreover, the coefficient for market shares takes a negative value, indicating lower pass-through for firms with greater market power. In short, while the exchange-rate pass-through is higher for vertically integrated firms and products with a higher share of imported inputs, it is lower for firms with higher market shares. As we compare changes in the prices of PL and NB products of the same type, exchange-rate pass-through into these groups is not expected to differ because of the share of imported inputs. However, possible differences in the markups of PL and NB products could cause the pass-through rate to differ partially. If pass-through rates into these two comparison groups are different, our empirical strategy will fail to identify the effect of income losses. Therefore, in section 5.3, we conduct a detailed analysis on the impact of exchange rate developments. Results show that relative prices of PLs and NBs in Türkiye are not affected by exchange rate developments.

The present study contributes to various strands of the literature. First, our work relates to the studies focusing on the impact of income on demand for PL products. In general, these studies try to estimate the impact on the market share of PL products or their share in household consumption baskets. Lamey et al. (2007) and Lamey et al. (2012) use time-series methodologies and state that PLs' market shares are affected by business cycles, and a part of the market share of PLs gained during contraction periods is permanent. Their results are consistent with ours, but time series analysis with aggregated data is not sufficient to show causal relationships. Dubé et al. (2018) estimate, using homescan panel data for the US over the period 2004-2012, how shares of PL consumption within the household change in response to income changes. Brancatelli et al. (2020) also apply, using Dutch homescan panel data for the period covering 2011-2018, almost the same estimation procedure. Both studies report that the negative impact of income on PL products' shares is statistically significant, but reported sizes are very small. It is possible to level two main criticisms at these studies. First, they do not consider that the impact of income changes on PL products' shares may vary with households' income level. For instance, it is expected that a 10 percent loss of income for a high-income household will have a more limited impact on the PL products' shares compared to middle- and low-income households. Second, in both studies, the long-term trend of increasing PL products' shares is controlled by a linear variable, and it is stated that the inclusion of this variable changes the conclusion. However, the long-term trend in the PL products' shares need not necessarily be linear: for example, shares may be expected to increase at a decreasing rate. Therefore, these studies' results cannot be interpreted as showing the causal impact of household income on PL product demand.

Our dataset does not contain the consumption bundles of consumers, and we only show the causal relationship between income and PL demand by analyzing the reaction of relative prices of PL products and prices of NB products sold by discount markets. As Covid-19 measures generated an exogenous negative income shock suddenly and its effect on prices became clear in a short time, our results are not affected by long-term trends and can be regarded as causal. In line with the effects of Covid-19 on the labor market, we estimate the increase in PL relative prices reached 3.5 percent in just two and a half months after the shock. Combining with aggregated homescan data that do not show any decline in the market share of PL products for the same period (Ipsos, 2020), our results imply that the relationship between household income and PL demand is stronger than what Dubé et al. (2018) and Brancatelli (2020) reported. Our findings are also consistent with the literature on the changes in consumer behaviors during economic downturns. Aguiar et al. (2013) use data from the American Time Use Survey and show that time spent on shopping activities such as grocery shopping, comparison shopping, and coupon clipping significantly increases during recessionary times. In line with these results, Nevo and Wong (2019), using homescan data from the US, find that the share of shopping with coupons and purchases of sale items increased during the Great Recession. Their study also shows that consumers increased the share of generic products and large-sized items in their spending and that they did more of their shopping at discount markets during the recession. Coibion, Gorodnichenko and Hong (2015) find that when local economic conditions are worsening, consumers exert more effort to find cheaper retailers, and they increase the share of their spending from those retailers. Increasing the share of cheaper PLs in total expenditure could complement these observed changes in consumer behaviors.

Second, our work contributes to the literature focusing on the effect of business cycles on retail prices. Stroebel and Vavra (2019) employed the instrumental variable strategy and estimated the causal impact of house price increases on retail prices. Their results suggest that a rise in house prices leads to increases in retail prices, and this effect is stronger in neighborhoods with a higher intensity of homeowners. The authors show that as house prices increase, homeowners start to spend more, but the share of generic products, the share of items bought in the sale, and the use of coupons decrease. In other words, a rise in house prices results in homeowners becoming wealthier and this makes them less sensitive to retail prices. In response to this change in consumer behaviors, retailers increase mark-ups and prices. Coibion, Gorodnichenko, and Hong (2015) examine the impact of local economic conditions on the posted and effective retail prices. They find that while effective prices respond to local unemployment rates strongly, cyclical behavior in the posted prices is modest. Both Stroebel and Vavra (2019) and Coibion, Gorodnichenko, and Hong (2015) show that business cycles affect retailer prices by changing consumer behaviors. Our work is complementary to these studies, as we show that the effect of business cycles on retail prices is heterogeneous across products of different quality segments. Our results show that lower quality PLs become more expensive relative to higher quality NBs when economic conditions deteriorate.

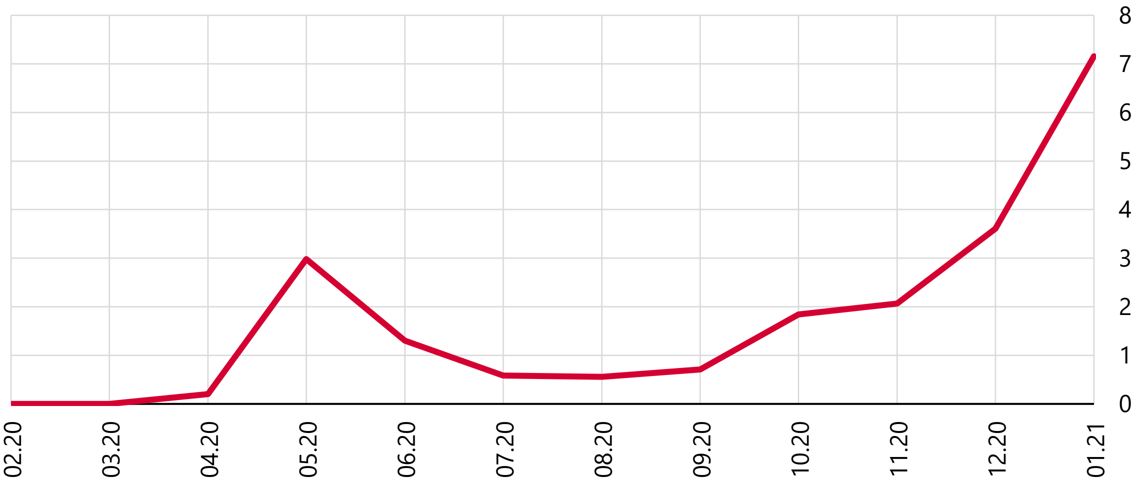
Third, our work relates to studies focusing on the differences in the cost of living across households of different income groups. Argente and Lee (2017) construct income group-specific price indexes, which allow both the share of different products within categories and the prices paid for each product to vary across income groups. Their results suggest that the cost-of-living inflation for lower-income households is significantly higher during the 2008-2013 period compared to higher-income households. By decomposing the gap between inflation rates, they showed that one main reason for this gap is that higher-income consumers have a wider margin to make a quality substitution and reallocate expenditures toward lower-priced retailers. Our results are complementary to this finding. They show that consumers try to limit the cost of living by switching their consumption to lower quality goods and buying from cheaper supermarkets during recessionary periods. However, as lower-income households already consume lower quality products and buy from cheaper stores, they cannot adjust their expenditures and face higher cost-of-living inflation. We claim that this kind of mechanism is likely to exert upward pressure on lower quality products' prices.

Fourth, our work contributes to the rapidly growing literature on the economic impacts of Covid-19. Several studies have analyzed its impact on prices. Balleer et al. (2020) studied the impact of Covid-19 on producer prices, Hillen (2020) examined the behavior of online food prices during the pandemic, and Akter (2020) studied the impact of Covid-19-related 'stay-at-home' restrictions on food prices. However, to the best of our knowledge, there are no studies yet examining the impact of Covid-19 and related measures on the relative prices of lower quality (or PL) products, and so our study is the first on this subject.

2.2 Background Information

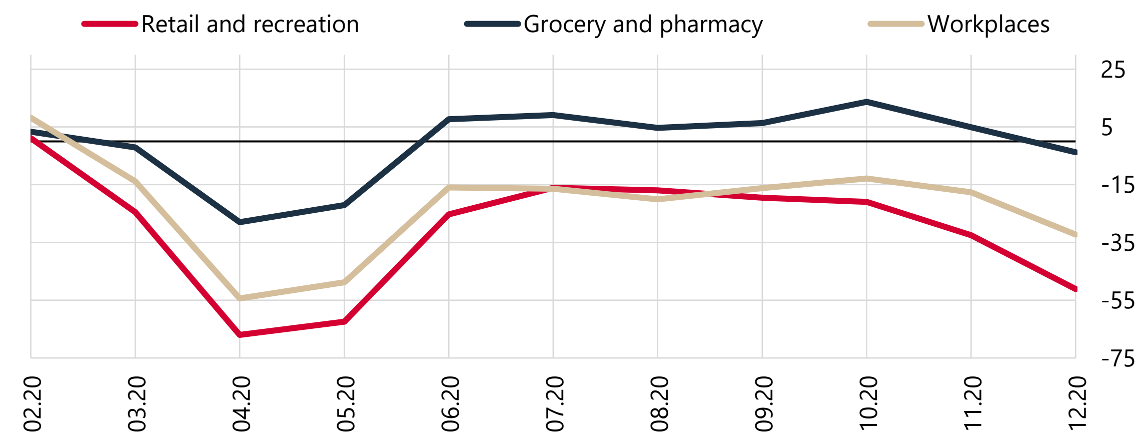
The Covid-19 pandemic emerged in China at the end of 2019 and spread to almost the entire world within a few months. Various measures were taken around the world to contain its spread. The first official step taken in Türkiye was the establishment of the Coronavirus Scientific Advisory Board on January 10, 2020. Thereafter, measures were implemented such as installing thermal cameras at airports, screening passengers arriving from countries that reported a high number of cases and stopping all flights from China. However, Covid-19 became a hot topic in the mainstream media in the second half of February 2020, following a spike in new cases in Iran, Türkiye's neighbor to the southeast. On February 23, Türkiye closed its border with Iran, and thereafter the list of countries with which flights to and from were banned was extended to countries with high numbers of cases. At the beginning of March disinfection was carried out in public places and some private sector companies started to switch to telecommuting. The Ministry of Health announced the first Covid-19 case on March 11 and the first death on March 17 (Figure 2.1). In the following days in March 2020, schools were closed and distance education started; restaurants, cafes, and entertainment venues were temporarily closed; factories started to shut down their production; lockdowns started; and all international flights were cancelled. At the beginning of April, intercity travel was restricted for 31 cities in Türkiye. After these measures, mobility in Türkiye decreased sharply (Figure 2.2) and factory shutdowns caused electricity production to fall 20 percent below its pre-Covid level (Figure 2.3). These measures were partially lifted in May 2020. Factories were reopened in May, while restaurant, cafes, and some entertainment venues were reopened in June. During these months restrictions on intercity travel were removed gradually. In November 2020, new measures were introduced, restaurants and cafes were restricted to serving only takeout food, and a relaxed version of lockdown was implemented again.

Figure 2.1: **Monthly Number of Deaths due to Covid-19 in Türkiye** (Thousand)



Source: Ministry of Health

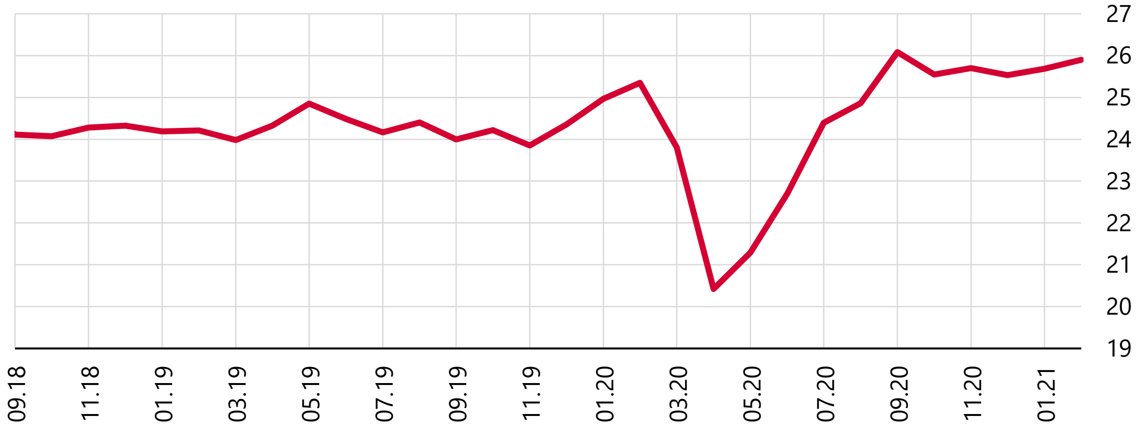
Figure 2.2: Google Mobility Index for Türkiye* (Monthly Average)



Source: Google

* Google provides the index at a daily frequency and in the form of percentage change from the baseline. This graph presents the monthly average of the data reported by Google.

Figure 2.3: Monthly Electricity Production in Türkiye (Seasonally Adjusted, Million MWh)

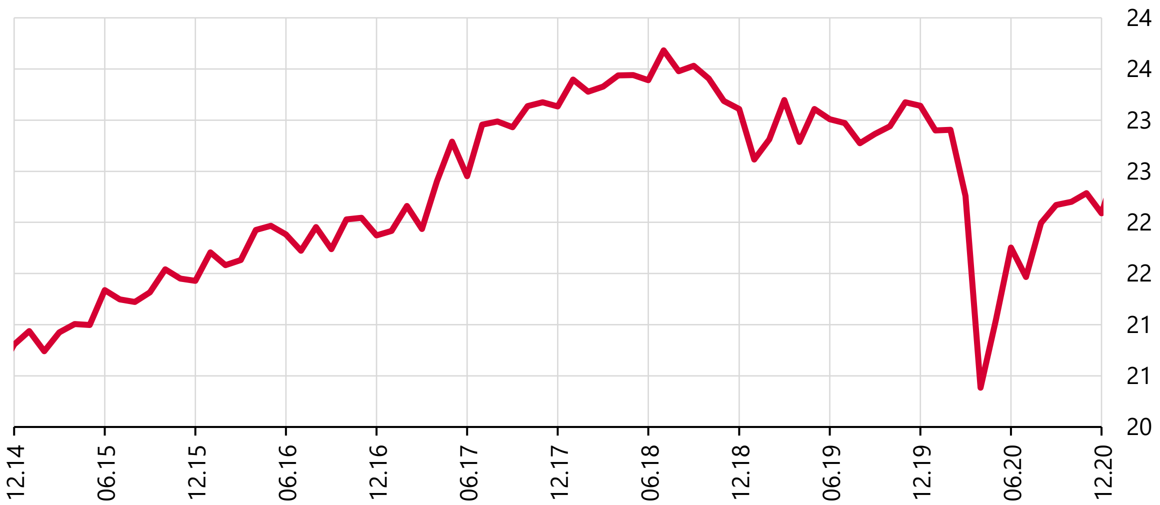


Source: Turkish Electricity Transmission Corporation

These measures had serious effects on the labor market. In order to limit permanent damage, on April 16, 2020 firms were banned from canceling labor contracts (Law #7244) except for in some extreme cases. Therefore, after this date, firms could not cancel the contracts for short-time working pay or force their employees to take unpaid leave. In line with these developments, Figure 2.4 shows that nonfarm employment declined dramatically in March and April 2020 but the decrease slowed down in May 2020. On the other hand, a considerable number of people started to benefit from short-time working pay in April 2020 (Figure 2.5).

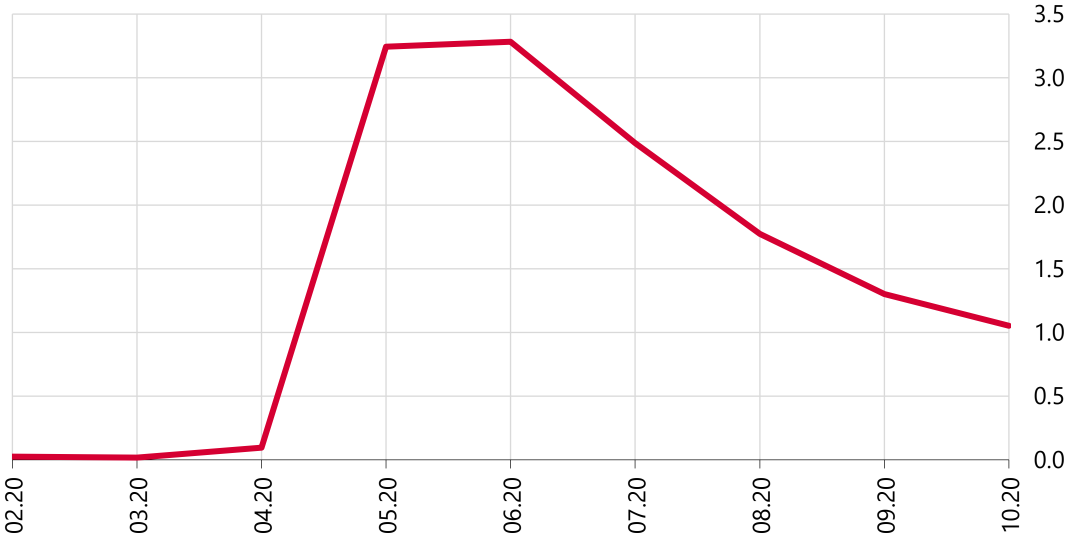
Official employment statistics show that employment in May was 8.41 percent below its level in February. When the beneficiaries of the short-time working pay are also considered, the number of employees who lost at least part of their income increases to 22.77 percent of those employed in February. However, although we do not have statistics on it, there is anecdotal evidence that there were also many employees who had to take unpaid leave and many self-employed people lost some part of their income. In sum, Covid-19 and the related measures caused a considerable number of households to lose at least some of their income.

Figure 2.4: **Nonfarm Employment in Türkiye** (Seasonally Adjusted, Million People)



Source: TURKSTAT

Figure 2.5: Beneficiaries of Short-Time Working Pay (Million People)



Source: Iskur

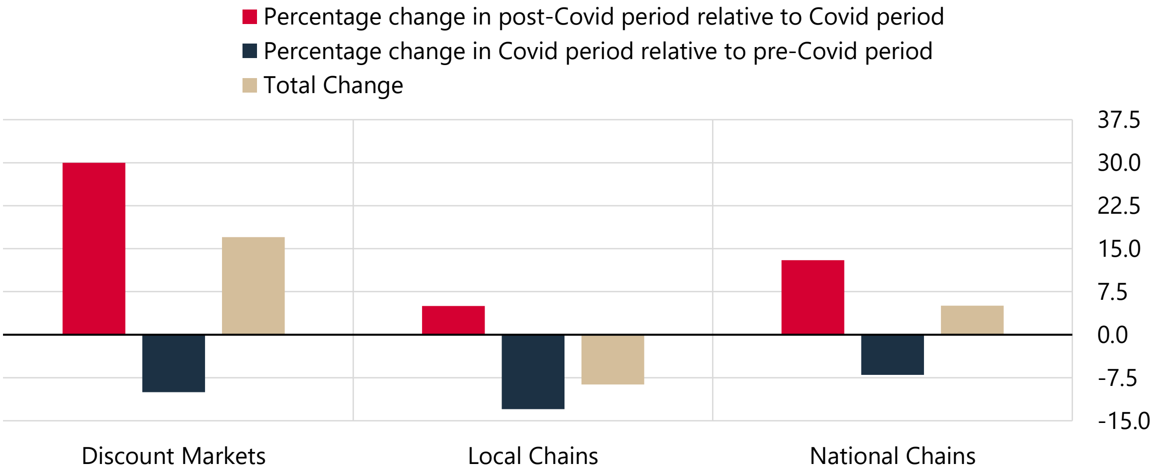
The Turkish Government has taken a series of measures to limit the effects of Covid-19 on the economy. In an informative box in its Inflation Report, the Central Bank of the Republic of Türkiye (CBRT) (2020) classifies these measures into three types: 1) fiscal measures, 2) financial measures to facilitate financial access, and (3) social measures to maintain employment and protect disadvantaged groups. The third has an important place in our context. The main forms of monetary support given directly to households in this group are short-time working pay, unemployment benefits, and in-cash assistance to families in need. According to data shared by the Ministry of Family, Labor, and Social Services, the total of these direct payments reached 11.6 billion Turkish lira (TL) (paid to 10 million people/households) on May 18. The total amount of support reached 29.7 billion TL and 45.2 billion TL by the end of July and December, respectively. These data show that, in spite of government support, households experienced serious income losses because of the pandemic.

Covid-19 and the related measures also affect households' supermarket spending. As people started to spend more time at home, supermarket spending increased in total. A report published by the research company Ipsos (2020) gives remarkable statistics[4], some of which are presented in Figure 2.6. Their data show that discount markets experienced bigger growth rates than other supermarket chains after the Covid-19 outbreak. Moreover, their report states that the share of PLs (for fast moving consumption goods) rose by 2 points to 22 percent during the Covid-19 period and then returned to its previous level in the post-Covid period. We interpret this positive performance of discount markets and PLs as showing households' reallocation of spending to cheaper markets and lower quality products as a result of income losses.

Covid-19 and the related measures were not the only critical economic developments for the Turkish economy in 2020. The Turkish lira experienced serious depreciations during the year. As Figure 2.7 shows, monthly depreciations gained speed between March and May, and after a period of stabilization a second wave started in August.

[4] Ipsos collects homescan data from a balanced panel of households in Türkiye. Shared statistics are calculated from these homescan data.

Figure 2.6: **Growth of Households' Supermarket Spending by Supermarket Type in Türkiye** *



Source: Ipsos

* Definitions of the periods used in the table are different from those used in our analysis. They define the periods January 1-March 15, March 16-May 31, and June 1-July 31 as the pre-Covid, Covid, and post-Covid periods, respectively (Ipsos, 2020).

Figure 2.7: Exchange Rate Basket* (Monthly % Change)

Source: CBRT

2.3 Data

The data used in this study are part of a confidential dataset constructed by the CBRT in order to follow monthly price developments before the official inflation rate is announced. Hence the dataset is representative of official consumer price statistics and when prices are grouped a purpose-based consumption classification (COICOP) is adopted as in the official statistics. Some portion of these data is extracted from online sources while the other portion is collected by a team visiting supermarkets and stores. In each price collection period, attempts are made to collect the prices of the same products. When a particular product is not available for one period, its price is assumed to be constant, but if this unavailability extends to more than one period, the product is substituted with a new one.

Table 2.1: Number of Products by Markets and Product Label Type

Market	National Brand	Private Label	Total
M1	77	51	128
M2	31	63	94
M3	77	41	118
M3	132	0	132
M5	125	0	125
M6	145	0	145
M7	140	0	140
M8	261	0	261
M9	144	0	144
Total	**1132**	**155**	**1287**

Table 2.2: Number of Products by Product Class (4-Digit COICOP Classes)

Product Class	NB products sold in discount markets	NB products sold in other markets	PL products	Total
Bread and cereals	34	165	29	228
Meat	14	75	7	96
Milk, cheese, and eggs	12	80	21	113
Oils and fats	11	48	10	69
Vegetables	11	63	13	87
Sugar, jam, honey, chocolate, and confectionery	26	151	26	203
Other processed foods	22	129	26	177
Coffee, tea and, cocoa	25	94	9	128
Mineral waters, soft drinks, and fruit and vegetable juices	30	142	14	186
Total	185	947	155	1287

In line with our research question, we used a subset of the CBRT's dataset. This subset includes food products sold in discount markets and products of other markets that are classified in the same 11-digit classes[5] (COICOP classes) as products of discount markets. This selected part contains prices of 1,404 products, classified in 84 different 11-digit classes, at a bi-weekly frequency for the period December 2019[6] to December 2020. However, the prices for 99 of these products are not available for the whole period. After removing the products with missing prices and

[5] 11-Digit classes have quite narrow product definitions such as pasteurized milk, sterilized milk (UHT), corn oil, and sunflower seed oil.

[6] CBRT's dataset does not contain any observation from discount markets before this date.

outliers[7] , we have a balanced panel of data consisting of 1,287 different product that are classified in 84 different 11-digit classes[8].

Our dataset consists of prices from nine different supermarkets. Among these markets, M1, M2, and M3 are classified as discount markets. These nine chains can also be divided into two groups, from another angle, as national and local chains. M8, M7, M1, M2, and M3 are considered national chains since they have stores in almost all cities in Türkiye, while the other four chains are mostly concentrated in Ankara and surrounding provinces and are classified as local chains. Table 2.1 shows the numbers of products our dataset includes by markets and product label type (PL or NB). In Türkiye only four chains sell a considerable number of different PL products and our data cover PLs from three of them with sufficient number of products. Table 2.2 shows the content of the dataset within the wide product definitions of the 4-digit COICOP classification.

3. Identification Strategy

Our aim in this study is to answer the question of how changes in households' income affect the prices of PLs (relative to NBs). As Covid-19 and the related restrictive measures created a sudden and large-scale negative income shock, it offers a good opportunity to answer this question. Because household income deteriorates significantly in a short time, a possible shift in demand is expected to show its impact on prices quickly. Therefore, we compare, within a difference in differences (DID) setup, pre-Covid and post-Covid prices of PLs with prices of NBs.

As seen in Table 2.1, all PLs in our dataset are sold by discount markets. Therefore, estimation of the impact on PLs may also represent the common pricing behavior of these discount markets. In order to separate this possible impact, we first assess a possible impact on the prices of discount markets by comparing the prices of NBs sold in discount markets with those of NBs sold in other markets. After observing that there is no significant impact on discount market prices in general, we confidently estimate the impact on PLs by comparing PLs with all NBs.[9]

The key assumption in DID analysis is that comparison groups should follow a parallel trend in the absence of the shock. There are three possible threats to this assumption in our case. First of all, the comparison groups may have different seasonal patterns and our estimation may represent the difference between these seasonal patterns instead of the income effect. Unfortunately, our data do not allow us to directly check whether this is the case or not. However, if the groups have different seasonal trends, then an aggregated price index that consists of these groups should have seasonality. Monthly Price Developments Report of the CBRT (CBRT, 2021) states that seasonality is not present in processed food inflation. Additionally, an aggregated price index of food and beverages (excluding fresh fruits and vegetables, potatoes, and red meat) calculated with official CPI data does not show statistically significant seasonal variation.[10] Therefore, our results are not expected to be subject to seasonality of comparison groups. Second, there may be some sectoral differences between our comparison groups, and this would cause sector-specific trends to confound our estimations. In order to overcome this issue, before the DID application, we first employed the CEM procedure (Iacus, King and Porro; 2012) to balance the comparison groups. Third, during the period when households experienced the negative income shock, the Turkish lira underwent a considerable depreciation. Nakamura and Zerom (2010) and Hong and Li (2017) imply that exchange rate pass-through to prices of our comparison groups may be different. If this is the case, then DID estimations are expected to show not only the income effect, but also the exchange rate effect. Therefore, we conduct additional analysis to assess whether pass-through ratios differ across comparison groups.

[7] Seventeen different products are defined as outliers because of extreme price changes.

[8] Some portion of these data will be pruned with a matching method that is explained in the next section. Detailed tables that contain the names of the 11-digit classes with the number of products remaining after pruning that fall into these classes are provided in appendix B.

[9] In section 6, as a robustness check, we compare prices of the three groups, i.e., PLs, NBs sold in discount markets, and NBs sold in other markets, within the same regression. This estimation also leads to results similar to baseline analysis.

[10] This and all other seasonality checks and seasonal adjustments in this study are conducted with automated procedures of the software JDemetra 2.2.0. The procedure conducts TRAMO-SEATS19 for seasonal adjustment (Gomez and Maravall, 1998).

The remainder of this section presents the CEM application, DID settings, and analysis on the effects of currency depreciations.

3.1 Coarsened Exact Matching (CEM)

This is a nonparametric method designed to estimate the average treatment effect on treated groups.[11, 12] The aim of the method is to reduce model dependence by imitating fully blocked experiments. When a fully blocked experiment is designed, first subjects are paired as observable covariates (i.e., education level, age etc.) that match exactly, and then these subjects are assigned to control and treatment groups randomly. In this way, conductors of the experiment make sure that the treatment and control groups are exactly balanced over the observables. The CEM method tries to capture, at least partially, this property of data generated via a fully blocked experiment from quasi-experimental or non-experimental data. As a first step, in the application of CEM, continuous explanatory variables are divided into coarsened groups (for example, the income of workers, which is a continuous variable, divided into groups of 0-2,000 TL, 2,001-5,000 TL, and +5,000 TL) so that all the observable covariates become categorical variables. Second, each possible combination of these categorical variables constitutes a stratum and treated units are only compared with nontreated units that are elements of the same stratum as them. If a stratum does not contain any nontreated units while it does have treated units, those treated units are excluded from the analysis and vice versa. Third, after the units are classified into stratums, for each unit a weight is calculated and these weights[13] allow CEM to be used together with regression analysis. In brief, CEM allows us to compare treated units to nontreated units with similar values of covariates. In our study, if we skip the CEM part and apply DID directly, the share of a specific product might be too much in one comparison group while it is limited in the other group. In this case, we might be comparing, for example, milk with corn oil, and our result may represent differences between sector-specific trends, instead of the impact of an income shock. Thus, we employ CEM to eliminate sectoral differences between our comparison groups. The only covariate we use is a categorical variable of products type. Categories of the variables are product definitions of the COICOP classification of 11-digit level14. After the matching part, for example, the share of pasteurized milk is the same in both comparison groups.

3.2 Difference in Differences (DID)

The DID setup is usually employed to estimate the impact of a treatment by comparing the differences of treated and nontreated units in pretreatment and posttreatment periods[15]. In this study, we are interested in estimating how the impact of a negative income shock on prices varies across different product groups that are expected to follow similar patterns in the absence of the shock. As explained in section 2, Covid-19 became a serious issue in Türkiye during the second half of February 2020. Therefore, before this date any impact on the prices is not expected to be seen and we defined the period December 1, 2019-February 15, 2020 as the pre-Covid period. After the effect of Covid-19 started to be seen, some time is needed for price adjustments to be completed. Thus, the two-and-a-half-month period following February 15 is excluded from the analysis. We set two consecutive periods of two and half months starting from May 1, 2020 as two different post-Covid periods. Estimation with the first gives the impact of the shock, while estimation with second shows how persistent the impact was, if at all. Our equation (3.1) for estimating the impact on the relative prices of NBs sold in discount markets and our equation (3.2) for the impact on the relative prices of PLs are as follows:

$$\ln\left(P_{i,t,m}\right) = \alpha + \delta * (Discount_m \times T_t) + \theta * T_t + f_i \tag{3.1}$$

$$\ln\left(P_{i,t}\right) = \mu + \beta * (Private_i \times T_t) + \tau * T_t + f_i \tag{3.2}$$

[11] For more details on theoretical aspects and application see (Iacus, King and Porro, 2012; King, Nielsen 2019).

[12] For all the applications of CEM in this paper, the R package CEM is used (Iacus, King and Porro, 2009).

[13] In order to explain how these weights are calculated in detail, we provide the same example given by Iacus et al. (2012) with an adjustment to make it compatible with our context.

[14] A detailed list of product types remaining after CEM is provided in the appendix (for each comparison)

[15] For more details, see Angrist and Pischke (2008) and Wooldridge (2010)

$$T_i = \begin{cases} 1, & if\ i\ in\ post - Covid \\ 0, & otherwise \end{cases} \qquad Discount_m = \begin{cases} 1, & if\ m\ is\ a\ discount\ Market \\ 0, & otherwise \end{cases}$$

$$Private_i = \begin{cases} 1, & if\ product\ i\ is\ PL \\ 0, & if\ product\ is\ NB \end{cases}$$

Here P is price and i, t, and m index product id, time, and market, respectively; f_i is a time invariant dummy controlling for each product. In these formulas, δ and β are parameters of interest showing the impact on relative price of NBs sold in discount markets and PLs, respectively.

3.3 The Effects of Currency Depreciations

Covid-19 became a hot topic of the mainstream media in the second half of February, and indicators on mobility and economic activity show dramatic declines for the following period. In addition to these developments, the Turkish lira experienced 2.1, 8, and 2 percent depreciations in March, April, and May, respectively (Figure 2.7). Because both income losses and currency depreciations took place at similar times, the DID analysis cannot identify the possible impacts of both shocks separately. Although we balance the sectoral composition of each comparison group via CEM, one may still claim that import content of the groups may be different so exchange rate fluctuation may affect each group differently. Therefore, understanding whether exchange rate movements affect relative prices is key to the interpretation of our estimations.

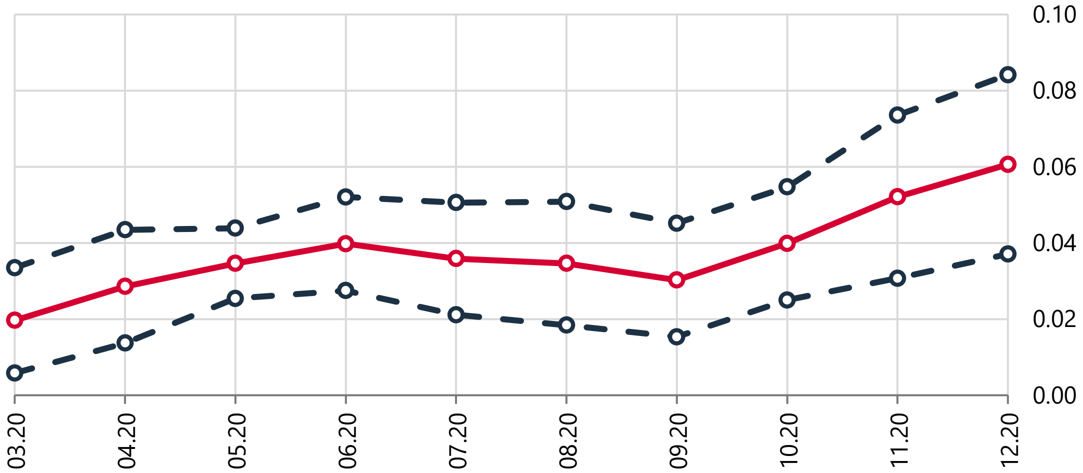
To understand the impact of exchange rate variations, we estimate how relative prices evolve month by month. To this end, we define each month between March and December as different post-treatment periods and estimate equations 3.1 and 3.2 for each definition separately. Figures 3.1 and 3.2 show the cumulative percentage changes in relative prices by months. Estimations for the impact on PLs show that the relative prices of PLs increased until May and reached 3.5 percent; then they fluctuated around this value until the reintroduction of Covid-19-related measures in November. While the Turkish lira depreciates by 8 percent in April, relative price increases in April and May and then stabilizes. Therefore, if the observed change was mostly caused by the exchange rate movements, then exchange-rate pass-through into the relative prices is completed in two months. However, although we observe another depreciation starting from August, the cumulative change in the relative price of PLs continued to fluctuate around 3.5 percent until the reintroduction of measures.

Table 3.1: Impact of Exchange Rate on the Relative Prices of PLs

Impact (Standard Error)	-0.002 (0.003)
R-squared	0.997
Number of NB	862
Number of PL	152

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights.

Figure 3.1: **Cumulative Impact on the Relative Prices of PL Products*,****



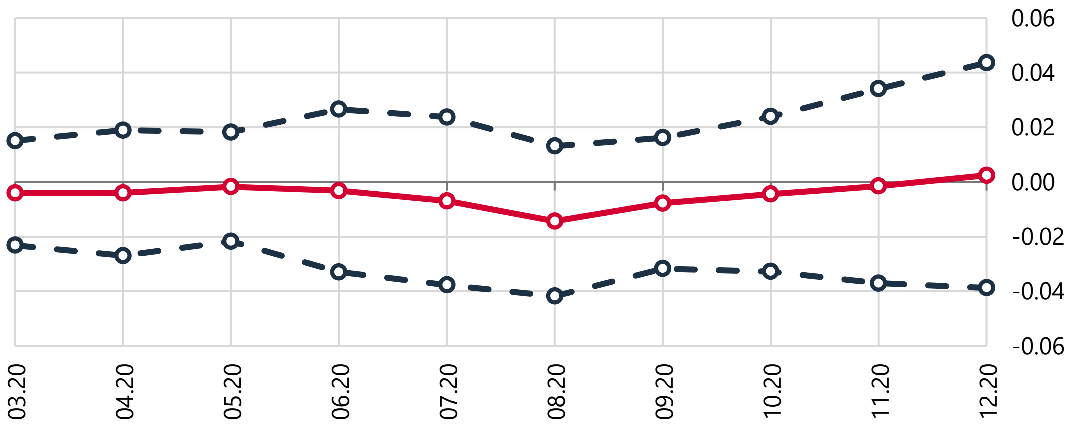
Source: Authors' calculations.

* Dashed lines show confidence interval at 95% confidence level.

** The graph shows the processed results of equation 3.2

To formalize this finding, we estimate equation 3.2, defining the period May 2020-July 2020 as pretreatment and August 2020-October 2020 as post-treatment. The results show that exchange-rate pass-through into relative prices of PLs is statistically insignificant (Table 3.1). Figure 3.2 shows that the relative prices of NBs that are sold in discount markets do not differ from those in the baseline period. This means that the relative prices of NBs also are not affected by exchange rate movements. As a result, we are confident in interpreting our findings from the baseline analysis as the impact of the negative income shock.

Figure 3.2: **Cumulative Impact on the Relative Prices of NB Products Sold in Discount Markets.*,****



Source: Authors' calculations.

* Dashed lines show the 95% confidence interval.

** The graph shows the processed results of equation 3.1

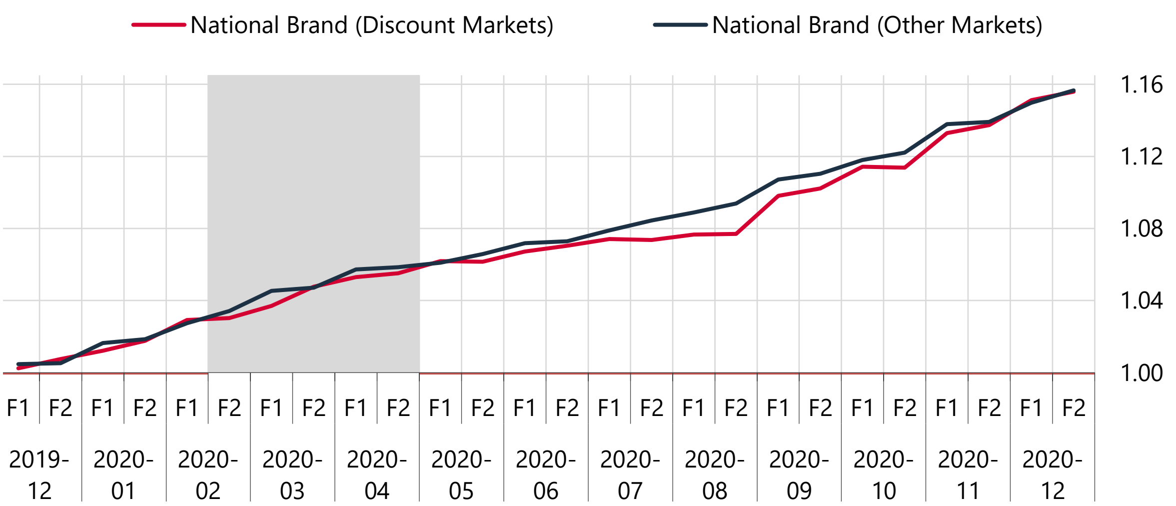
4. Results

We start our analysis by estimating the impact on relative prices of NBs sold by discount markets (relative to NBs sold in other markets). Next, we estimate the impact on the relative prices of PLs and interpret it with the support of the result on relative prices of discount markets. In both analyses, we first form our baseline results using all available data for our comparison groups and then we refine these results by conducting the same analysis for selected subsets. The first of these refinements is applying the same analysis to each 4-digit product class separately. If there are any significant impacts, this exercise may give us a better idea about the way an income shock works. For example, it may be the case that the relative prices of basic foods increase more than the prices of other products, as some people limit their consumption of products other than basic needs. Second, we form different treatment groups with the products of each discount market, while keeping the control group the same as in the baseline analysis. Estimation of the impact on each discount market separately will show whether the result from the baseline estimation is a general behavior or not. Additionally, estimations on these subsets also serve as robustness checks, because they show if a subgroup dominates the baseline results.

4.1. Impact on the Relative Prices of National Brands Sold in Discount Markets

After the products are matched by product types across the comparison groups and those that do not match are pruned via CEM, 807 products remain in our dataset16. Figure 4.1 shows the average of the natural logarithm of the prices weighted by CEM weights. Because both series are normalized to 1 for December 2019, the difference between the lines approximately shows the percentage changes in the relative prices of the comparison groups. Since the series do not diverge during the shock period (the shaded area in the graph), a visual inspection does not offer a significant impact on the relative prices.

Figure 4.1: **Average Prices of National Brand Products* (Natural logarithm , 2019-12 = 1)**



Source: Authors' calculations.

* Series show the weighted average prices in logarithms. The prices of each product are weighted by corresponding CEM weights that are produced to balance the comparison groups by product type.

[16] In the appendix, we provide a table on the definitions of product types, the number of products that meet these definitions, and the shares of each product type in the sample after the data are balanced with the weights produced via CEM.

In line with this observation, the results for our baseline analysis that are obtained from the estimation of equation 3.1 and presented in Table 4.1, show no significant impact of the income shock on the relative prices of NBs sold in discount markets and this result holds for both definitions of the post-treatment period.

Table 4.2 present the results for product classes, each of which is analyzed separately. In none of the subgroups was any significant and positive impact found; most of the estimated impacts are very close to zero or negative.

Table 4.1: Impact on the Relative Prices of NBs in Discount Markets *

	Post-Shock Period	
	I	**II**
Impact	-0.002 (0.007)	-0.011 (0.007)
R-squared	0.997	0.996
Number of products sold in discount markets	185	185
Number of products sold in other markets	850	850

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* Both columns show result of the same analysis with different definitions of the post-shock period. While post-shock I covers the period 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

In the last step, we divide the treatment group into three by discount markets while keeping the control group the same. Table 4.3 shows the results of the estimations when each of these treatment groups is used separately. In line with the previous results, no significant and positive impact is found in any of the post-treatment periods for any of the alternative treatment groups. Similar to previous estimations, the estimated coefficients are either very close to zero or negative. All three settings point to the same result of no significant increase in the relative prices of NBs. As explained above, Ipsos data (2020) show that the share of discount markets in the consumers' spending increased sharply relative to the other supermarkets. If this sharp increase is assumed to be caused by the income shock, our result leads to the conclusion that negative income shocks cause consumers to switch to cheaper markets.

Table 4.2 Impact on the Relative Prices of NBs Sold in Discount Markets by Product Classes*

Product Class	Post-Period I	Post-Period II	Number of products: Sold in discount markets	Number of products: Sold in other markets
Bread and cereals	0.003 (0.016)	0.003 (0.015)	34	148
Milk, cheese, eggs and meat products	-0.026*** (0.008)	-0.045*** (0.011)	26	133
Oils and fats	-0.013 (0.024)	-0.02 (0.027)	11	43
Sugar, jam, honey, chocolate and confectionery	0.005 (0.005)	0.002 (0.011)	26	138
Other processed foods	0.017 (0.015)	0.002 (0.015)	22	108
Coffee, tea and cocoa	0.007 (0.005)	0.006 (0.016)	25	94
Mineral waters, soft drinks, fruit and vegetable juices	-0.004 (0.015)	-0.022 (0.017)	30	142

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights.

* Both columns show result of the same analysis with different definitions of post-shock period. While the post-shock I covers the period 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

Table 4.3: Impact on the Relative Prices of NBs Sold in Discount Markets for Each Discount Market*

Post-Shock Period	Treatment Group: M2	Treatment Group: M3	Treatment Group: M1
I	0.005 (0.004)	0.002 (0.005)	-0.009** (0.004)
II	-0.004 (0.005)	-0.003 (0.005)	-0.021*** (0.004)
Number of products sold in discount markets	31	77	77
Number of products sold in other markets	320	722	720

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* While the post-shock I covers the period 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

4.2. Impact on the Relative Prices of Private Label Products.

This subsection presents the results about the impact of an income shock on prices of PLs relative to those of NBs. As indicated above, all PLs in our dataset are sold by discount markets. Therefore, an impact, identified by the comparison of PLs with NBs, may be examined regarding whether it is on PL products only or on products sold in discount markets in general. However, the results from the previous subsection clarify the situation and show that any significant impact estimated in this subsection does not represent the general behavior in discount markets. When presenting our findings about the relative prices of PLs, we follow the same strategy as in the previous subsection. Figure 4.2 shows average prices of comparison groups that are balanced by product type. Series started to follow different trends during the shock period and this difference seems to persist in the following periods. Hence, visual inspection points to a possible positive impact on the relative prices of PLs.

Table 4.4: Impact on the Relative Prices of PL Products*

	Post-Shock Period	
	I	**II**
Impact	0.035*** (0.004)	0.031*** (0.005)
R-squared	0.997	0.996
Number of NB products	767	767
Number of PL products	155	155

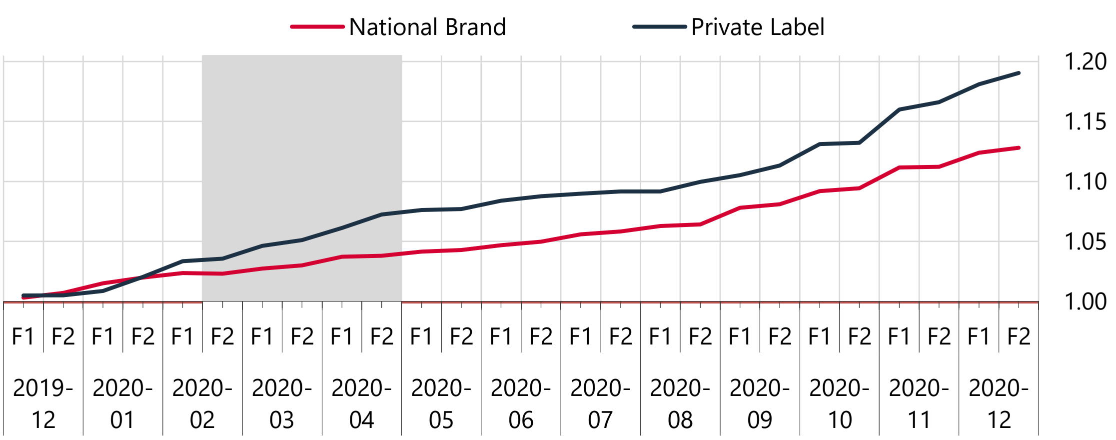
Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* Both columns show result of the same analysis with different definitions of post-shock period. While the post-shock I period covers the period 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

This observation is supported by our baseline result, presented in Table 4.4, that the negative income shock caused PL prices to increase 3.5 percent more than NB prices. Estimation with the second post-treatment period shows that the impact mostly persists in the subsequent months.

Estimation by subgroups confirms the statistical significance of the impact for half of the subgroups despite the decreasing number of observations (Table 4.5). Moreover, all estimated coefficients are either positive or very close to zero except for the beverages group. When the same analysis is conducted for each discount market separately, the results show that the impact is both persistent and statistically significant for the PL products of each discount market and their sizes are somewhat similar (Table 5.6).

Figure 4.2: Average Prices of PL and NB Products * (Natural logarithm, 2019-12 = 1)



Source: Authors' calculations.

* Series show weighted average prices in logarithms. The prices of each product are weighted by corresponding CEM weights that are produced to balance the comparison groups by product type.

Table 4.5: Impact on the Relative Prices of PLs by Product Classes

	Post-Shock Period		Numbers of Products	
Product Class	**I**	**II**	**Sold in discount markets**	**Sold in other markets**
Bread and cereals	0.044*** (0.014)	0.058*** (0.019)	163	29
Milk, cheese, eggs, and meat products	0.017 (0.011)	0.009 (0.013)	147	28
Oils and fats	0.009 (0.012)	-0.002 (0.01)	59	10
Vegetables (excluding fresh vegetables)	0.038*** (0.015)	0.047*** (0.017)	56	13
Sugar, jam, honey, chocolate, and confectionery	0.059*** (0.012)	0.058*** (0.014)	159	26
Other processed foods	0.039** (0.015)	0.014 (0.022)	145	26
Coffee, tea, and cocoa	0.082*** (0.014)	0.054*** (0.017)	57	9
Mineral waters, soft drinks, and fruit and vegetable juices	-0.017 (0.017)	-0.011 (0.016)	110	14

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* Both columns show result of the same analysis with different definitions of post-shock period. While the post-shock I period covers 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

Table 4.6: Impact on the Relative Prices of PLs for Each Discount Market

	Treatment Group		
Post-Shock Period	**M2**	**M3**	**M1**
I	0.030*** (0.005)	0.039*** (0.004)	0.037*** (0.003)
II	0.029*** (0.007)	0.034*** (0.004)	0.029*** (0.004)
Number of products sold in discount markets	796	543	621
Number of products sold in other markets	63	41	51

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* While the post-shock I period covers 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

Our results from various settings show that the prices of PLs increased, on average, 3.5 percent more than prices of NBs for corresponding product types. Argente and Lee (2017) show that consumers with higher incomes are better able to limit welfare losses by making quality substitutions, while lower income consumers do not have this margin as they already consume low quality products. Our results add to their findings and show that lower income households who already consume lower quality products (PLs in our case) face even higher food price inflation, since negative income shocks increase the relative prices of lower quality products. The Ipsos (2020) report states that the markets shares of PLs first increased during the Covid-19 pandemic and then returned to their pre-Covid levels. Combining these statistics with our results implies increasing demand for PLs during recessionary times. Although we do not estimate the impact of income shocks on PL demand directly, our results suggest that the relation between demand for PLs and household income is stronger than those reported by Dubé et al. (2018) and Brancatelli (2020). Our results also add to the findings reported by Stroebel and Vavra (2019), Coibion et al. (2015), and Beraja et al. (2019), and show that the cyclicality in retail prices changes across product groups.

5. Robustness Checks

We conduct two different exercises to ensure our results are robust to alternative settings. First, we perform a triple comparison of PLs, NBs sold by discount markets, and NBs sold by other markets, within the same estimation. Second, we divide the control group into two alternatives and repeat our baseline analysis with these alternative control groups. The results from both exercises confirm our baseline results.

5.1 Triple Comparison

Although all of the PLs in our sample are sold by discount markets, when we interpret our findings, we conclude that the impact on the relative prices of PLs is not a reflection of general behavior in discount markets, but is specific to PLs. While making this interpretation, we see that there was no significant impact on the relative prices of NBs sold by discount markets. If the trend of NBs' prices in discount markets does not diverge from the trend of corresponding NBs' prices sold by other markets, then this argument sounds logical. However, the content of the samples we used for our estimations may be different to some extent. Our dataset, for example, does not necessarily contain a PL product for each type of NB sold by discount markets. Therefore, we decided to restrict our sample to product types that are represented in all three comparison groups and repeat our baseline analysis. Our first step is again CEM, but this time the contents of all three comparison groups are balanced at the same time.

Next, we estimate equation 5.1.

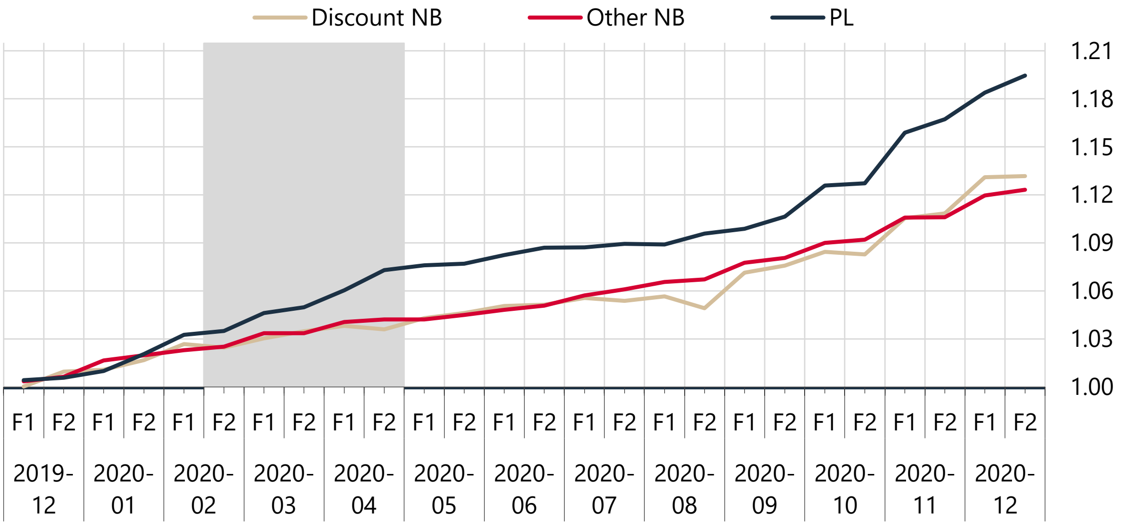
$$\ln\left(P_{i,t,m}\right) = \alpha + \beta \ * (PL_m \times T_t) + \ \delta \ \ * (NBD_m \times T_t) + \theta * T_t \ + f_i \qquad (5.1)$$

$$T_t = \begin{cases} 1, & t \ is \ in \ post-Covid \\ 0\ , & otherwise \end{cases} \qquad Private_i = \begin{cases} 1, & if \ product \ i \ is \ PL \\ 0, & if \ product \ is \ NB \end{cases}$$

$$NBD_{mi} = \begin{cases} 1, & if \ m \ is \ a \ Discount \ Market \ and \ i \ is \ a \ NB \\ 0, & otherwise \end{cases}$$

Here β and δ show the impact on the prices of PLs and NBs sold in discount markets, relative to the prices of NBs sold by other markets.

Figure 5.1: Average Prices of Comparison Groups (Natural Logarithm , 2019-12=1)



Source: Authors' calculations.

* Series show weighted averages of logarithm of prices. The prices of each product are weighted by corresponding CEM weights that are produced to balance the comparison groups by product type.

Table 5.1: Impact on the Relative Prices of PLs and NBs Sold in Discount Markets

	Post-treatment	
Treatment Groups	**I**	**II**
PL	0.032*** (0.004)	0.025*** (0.007)
NB sold in discount markets	0.002 (0.009)	-0.008 (0.01)
Number of NB sold in discount markets	129	129
Number of PL	128	128
Number of NB sold in other markets	670	670

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

* Both columns show result of the same analysis with different definitions of post-shock period. While the post-shock I period covers 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

Average of the logarithm of prices for balanced groups is shown in Figure 5.1. In line with the baseline results, during the shock period the prices of NBs follow a similar trend, while the prices of PLs diverge. Similarly, the result of the regression analysis, represented in Table 5.1, shows that the relative prices of PLs significantly increase after the income shock, while there is no significant impact on the relative prices of NBs.

5.2 Alternative Control Groups

We divide our control groups into two alternatives and repeat the same procedure used in the baseline analysis as a robustness check. For both analyses, we divide the control group into national and local chains. Table 5.2 and Table 5.3 report the results for the estimations, conducted with alternative control groups, for the relative prices of NBs sold by discount markets and PLs. Similar to the baseline results, analyses with different control groups also confirm the statistically significant and positive impact on the relative prices of PLs and no significant and positive impact on the NBs sold by discount markets.

Table 5.2: Impact on the Relative Prices of NBs Sold in Discount Markets with Different Control Groups

	Control Group	
Post-Shock Period	**National Chains**	**Local Chains**
I	0.007 (0.006)	-0.008 (0.006)
II	-0.001 (0.007)	-0.017** (0.007)
Number of NB products sold in discount markets	182	185
Number of NB products sold in other markets	360	490

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

** While the post-shock I period covers 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

Table 5.3: Impact on the Relative Prices of PLs with Different Control Groups

	Control Group	
Post-Shock Period	**National Chains**	**Local Chains**
I	0.040*** (0.005)	0.029*** (0.003)
II	0.041*** (0.003)	0.020*** (0.004)
Number of NBs	455	455
Number of PLs	155	155

Note: ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors clustered at market level are reported in parentheses. Observations are weighted by corresponding CEM weights. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

** While the post-shock I period covers 1 May 2020-15 July 2020, the post-shock II period covers 15 July 2020 - 30 September 2020.

6. Conclusion

The Covid-19 measures caused substantial declines in household incomes. We examined whether these deteriorations exerted upward pressure on the relative prices in discount markets and the relative prices of PLs. We find that these widespread income losses caused prices of PLs to increase 3.5 percent more on average than the prices of NBs, with no significant impact on the relative prices of NBs sold by discount markets. We argue that the main source of the impact is that households losing income switch their food consumption toward PLs. Indeed, combined with our results, the data shared by Ipsos (2020) point to a sizeable shift in demand towards PLs and discount markets.

These results lead to two main macroeconomic implications. First, the impact of economic activity on retail prices exhibits heterogeneity across products of different quality segments. Second, lower-income consumers who already consume lower quality products face higher inflation in their cost of living. As the purchasing power of lower-income consumers decreases further, real income distribution will tend to deteriorate. Therefore, our results serve as a warning to policymakers who are sensitive to income inequality that during recessionary periods lower-income consumers become worse off even if they do not experience any direct income loss.

This study has two limitations. First, our dataset contains prices of PLs only for the period after December 2019. Therefore, we cannot check the long-term trends in the prices of comparison groups. Second, we do not observe households' consumption bundles. Thus, we cannot directly identify the mechanism behind the increasing relative prices of PLs. A future study that utilizes price data together with data on households' consumption bundles will be beneficial to see the mechanism driving the increase in the relative prices of PLs clearly. In this paper, we analyze how the relative prices of different quality segments are affected by households' income change by focusing only on food prices. Future studies that assess this relationship in different product groups seem promising to provide new insights on the cyclical behavior of consumer prices.

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Appendix

A. An Example of Calculation of CEM Weights

Suppose we have prices of 10 different products from three product types (or 11-digit COICOP classes) and four of these are PLs (treated units) while the other six are NBs (control units) presented in Table A.1.

Table A.1: Simplified Sample for CEM Example

	COICOP 11-Digit Class (Product type)	Private Label	Price
1	1	1	2
2	1	0	3
3	1	0	5
4	2	1	5
5	2	1	7
6	2	0	10
7	2	0	8
8	3	1	32
9	4	0	4

For product type 1, difference between the price of PL and NB is calculated as the difference of arithmetic means of prices, -2, while for product type 2, the difference is -3. Because there are no NB and PL products from product types 3 and 4, respectively, price differences cannot be calculated and observations from these product types are omitted from the analysis. The difference in the sample is calculated as $\frac{(1\times-2)+(2\times-3)}{3}$, since we have one PL observation from product type 1, while two PL from product type 2.

It is also possible to calculate weights for each observation and have the same result by taking the difference between weighted means of comparison groups or running weighted regression. Before the weights are calculated observations 8 and 9 are removed from the sample. For the remaining data, weights of PLs are assigned as 1. For NBs, weights are calculated as $\frac{n_{NB}}{n_{PL}} * (w_s)$, where:

i) n_{PL} and n_{NB} are the numbers of PLs and NBs in the sample, respectively.

ii) $w_s = \frac{n_{PL}^s}{n_{NB}^s}$, where n_{PL}^s and n_{NB}^s are the numbers of PLs and NBs in the stratum, respectively.

Table A.2 shows the calculated weights for our simplified example.

Table A.2: Simplified Sample and Weights Calculated via CEM

Observation No	COICOP 11-Digit Class (Product type)	Private Label	Price	w_s	n_{NB}/n_{PL}	w
1	1	1	2	-	-	1
2	1	0	3	1/2	4/3	2/3
3	1	0	5	1/2	4/3	2/3
4	2	1	5	-	-	1
5	2	1	7	-	-	1
6	2	0	10	1	4/3	4/3
7	2	0	8	1	4/3	4/3
8	3	1	32	-	-	0
9	4	0	4	-	-	0

B. Number of Products and Weights by Product Types for Baseline Analysis

Table B.1: Number of products within each product type for the sample used in the estimation of the impact on relative prices of NBs sold in discount markets

Product type	Number of products sold in discount markets	Number of products sold in other markets	Share in the sample
Wheat Flour	1	7	0.01
Baby Food	5	12	0.03
Biscuit (plain)	2	13	0.01
Biscuit (for babies)	4	11	0.02
Biscuit (creamy)	3	14	0.02
Cracker (plain)	3	14	0.02
Wafer (chocolate covered)	3	14	0.02
Cream Cakes and Patisserie Products	1	3	0.01
Cake	2	14	0.01
Thin Dough	1	7	0.01
Macaroni (plain)	3	12	0.02
Vermicelli (plain)	2	13	0.01
Cereal (plain or with cocoa)	4	14	0.02
Garlic-Flavored Sausage (red meat)	4	14	0.02
Garlic-Flavored Sausage (red and white meat)	1	9	0.01
Sausage (mix of red)	3	13	0.02
Sausage (mix of red and white meat)	3	6	0.02
Salami (mix of red and white meat)	3	11	0.02
Yoghurt (plain)	2	14	0.01
Ready Made Milky Sweets	1	10	0.01
White Cheese (full-fat)	2	12	0.01
Kasar Cheese (fresh)	3	11	0.02
Tulum Cheese	1	11	0.01
Cream Cheese (plain)	1	9	0.01
Cream Cheese	2	13	0.01
Butter	3	10	0.02
Margarine	5	10	0.03
Olive Oil	1	10	0.01
Sunflower Oil	2	13	0.01
Canned Vegetables (Corn)	1	9	0.01
Tomato Sauce	1	11	0.01
Olive (black)	3	12	0.02
Potato and corn chips	6	12	0.03
Granulated Sugar	1	10	0.01
Sugar Cubes	2	13	0.01
Jam	1	13	0.01
Grape Molasses	2	7	0.01
Halvah	3	22	0.02
Peanut Butter	1	10	0.01
Tablet of Chocolate	2	19	0.01

Table B.1: Number of products within each product type for the sample used in the estimation of the impact on relative prices of NBs sold in discount markets (continued)

Chocolate Cream	4	11	0.02
Chewing Gum	5	13	0.03
Holiday Candy	1	6	0.01
Ice Cream	4	14	0.02
Condiment Spices	2	11	0.01
Salt	1	11	0.01
Baking Powder	3	12	0.02
Yeast	3	3	0.02
Vinegar	1	11	0.01
Ketchup	2	14	0.01
Mayonnaise	1	12	0.01
Sesame Oil	2	9	0.01
Packaged Soup	4	14	0.02
Pudding	3	11	0.02
Turkish Coffee	2	11	0.01
Instant Coffee (Classic)	4	10	0.02
Instant Coffee (3 in 1)	4	12	0.02
Tea (classic)	6	14	0.03
Tea (tea bag)	3	14	0.02
Herbal Tea	2	12	0.01
Cocoa	3	10	0.02
Cocoa Beverages	1	11	0.01
Water (0.5 lt)	2	12	0.01
Water (1 lt)	2	12	0.01
Mineral Water (Plain)	4	11	0.02
Carbonated Fruity Beverages	4	14	0.02
Carbonated Fruity Beverages	1	14	0.01
Coke (Canned)	3	11	0.02
Coke (1 lt)	3	12	0.02
Ice Tea (Canned)	2	8	0.01
Ice Tea (1 lt)	2	8	0.01
Ayran (1 lt)	2	13	0.01
Fruit Juice (Small)	2	14	0.01
Fruit Juice (1 lt)	3	13	0.02
Total	**146**	**661**	**1.00**

Note: Table shows the number of products remaining after CEM step balancing comparison groups by product type. Fourth column shows the share of each product type after CEM. This sample is used to conduct baseline analysis, the results of which are presented in Table 5.1.

Table B.2: Number of products within each product type for the sample used in the estimation of the impact on relative prices of PLs

Product type	N of NBs	N of PLs	Share in the sample
Wheat Flour	8	2	0.01
Bulgur Wheat	12	3	0.02
Biscuit (plain)	15	2	0.01
Biscuit (creamy)	17	3	0.02
Cracker (plain)	17	3	0.02
Wafer (chocolate covered)	17	3	0.02
Cookie	5	3	0.02
Cake	16	3	0.02
Thin Dough	8	1	0.01
Macaroni (plain)	15	3	0.02
Vermicelli (plain)	15	2	0.01
Cereal (plain or with cocoa)	18	1	0.01
Garlic-Flavored Sausage (mix of red and white meat)	10	1	0.01
Sausage (mix of red and white meat)	9	1	0.01
Salami (red meat)	10	2	0.01
Salami (mix of red and white meat)	14	1	0.01
Meatball (raw)	12	2	0.01
Yoghurt (plain)	16	3	0.02
Ready Made Milky Sweets	11	3	0.02
White Cheese (full-fat)	14	4	0.03
Kasar Cheese (fresh)	14	3	0.02
Tulum Cheese	12	1	0.01
Cream Cheese (plain)	10	4	0.03
Cream Cheese	15	3	0.02
Butter	13	3	0.02
Margarine	15	1	0.01
Olive Oil	11	2	0.01
Sunflower Oil	15	2	0.01
Corn Oil	5	2	0.01
Canned Vegetables (green peas)	10	2	0.01
Canned Vegetables (garniture)	9	3	0.02
Canned Vegetables (Corn)	10	3	0.02
Tomato Sauce	12	3	0.02
Olive (black)	15	2	0.01
Granulated Sugar	11	3	0.02
Sugar Cubes	15	3	0.02
Jam	14	3	0.02
Honey	13	4	0.03
Grape Molasses	9	2	0.01
Halvah	25	5	0.03
Peanut Butter	11	1	0.01

Table B.2: Number of products within each product type for the sample used in the estimation of the impact on relative prices of PLs (continued)

Tablet of Chocolate	21	1	0.01
Chocolate Cream	15	2	0.01
Chewing Gum	18	1	0.01
Holiday Candy	7	1	0.01
Black Pepper	9	3	0.02
Chili Pepper	12	3	0.02
Condiment Spices	13	1	0.01
Salt	12	3	0.02
Baking Powder	15	2	0.01
Vinegar	12	2	0.01
Ketchup	16	3	0.02
Mayonnaise	13	3	0.02
Sesame Oil	11	2	0.01
Packaged Soup	18	2	0.01
Pudding	14	2	0.01
Turkish Coffee	13	3	0.02
Tea (tea bag)	17	3	0.02
Herbal Tea	14	1	0.01
Cocoa	13	2	0.01
Mineral Water (Plain)	15	1	0.01
Carbonated Fruity Beverages	18	1	0.01
Carbonated Fruity Beverages	15	1	0.01
Coke (1 lt)	15	2	0.01
Ayran (1 lt)	15	3	0.02
Fruit Juice (Small)	16	3	0.02
Fruit Juice (1 lt)	16	3	0.02
Total	**896**	**155**	**1.0**

Note: Table shows the number of products remaining after CEM step balancing comparison groups by product type. Fourth column shows the share of each product type after CEM. This sample is used to conduct baseline analysis, the results of which are presented in Table 5.4.

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