THE IMPACT OF NEGATIVE INCOME SHOCKS ON THE PRICES OF PRIVATE LABEL PRODUCTS: THE COVID-19 EPISODE

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ABSTRACT

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In this study we show the causal 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. We exploit the sudden and unexpected income shock caused by Covid-19 measures within a difference in differences setting. Our results show that when households experience a negative income shock the relative prices of private label products increase significantly.

Keywords: Private Label Products, Retail Prices, Covid-19, Business Cycles, Cost of Living

ÖZ

NEGATİF GELİR ŞOKLARININ ÖZEL ETİKETLİ ÜRÜN FİYATLARINA ETKİSİ: COVİD-19 DÖNEMİ

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Bu çalışmada, hane halkının geliri ile ulusal markalara göre daha düşük kaliteli ve daha ucuz alternatifler olarak bilinen özel markalı ürünlerin göreli fiyatları (ulusal markalı ürünlerin fiyatlarına kıyasla) arasındaki nedensel ilişkiyi incelenmiştir. Bu amaçla Covid-19 ve ilgili önlemlerin sebep olduğu ani ve beklenmedik dışsal gelir şoku farkların farkı modeli çerçevesinde değerlendirilmiştir. Sonuçlarımız, hanelerin olumsuz bir gelir şoku yaşadığı durumda, özel etiketli ürünlerin göreli fiyatlarının önemli ölçüde arttığını göstermektedir.

Anahtar Kelimeler: Özel Etiketli Ürünler, Perakende Fiyatları, Covid-19, İş Çevrimleri, Yaşam Maliyeti

To My Family

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CHAPTER 1

INTRODUCTION

The Covid-19 pandemic and measures taken against it have 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 measures, nonfarm employment started to decline dramatically in March 2020 in Turkey. In addition to these employment losses, many employees lost some part of their income as they had been benefitting from the short-time work allowance. In May 2020, nonagricultural employment was 8.42 percent below its level in February. Taking into account the beneficiaries of the short-time working allowance as well, the number of employees who lost some or all of their income reached 22.77 percent in May of those employed in February. Moreover, considering that some employees had to take unpaid leave who were not able to benefit from the short-time working allowance, the real number is higher than the one stated above. These widespread income losses and uncertainty about the future income may have 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 the business cycles and are affected by households' 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, 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 mitigates the effect of demand conditions on the aggregate price level; second, during recessionary periods, it makes changes in the cost of living higher for lower-income consumers who already consume these lower quality products.

Our aim in this paper is to exploit the exogenous income shock to show the causal relationship between the households' 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 the shock. To this end, we first use the coarsened exact matching (CEM) algorithm to balance the sectoral composition of the comparison groups and then make the comparison within the difference-in-differences (DID) setting.

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[1]. 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 analyzed another episode in which the Turkish Lira experienced another sizable 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.

[1] Our dataset contains prices from 9 different chains. Only 3 of them, which are known as discount markets, sell PL products, while all the chains sell NB products

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 this behavior varies across different product groups. Our thesis also relates the studies about 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 the 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 the 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 impact of the Covid-19 on prices. Balleer et al. (2020) studied the impact of Covid-19 on producer prices, Hillen (2020) the behavior of online food prices during the pandemic, and Akter (2020) 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. Chapter 2 briefly summarizes the literature. Chapter 3 provides details on the Covid-19 experience in Turkey. Chapter 4 summarizes the dataset. Chapter 5 explains our identification strategy. Chapter 6 presents the results. Chapter 7 provides robustness checks. Chapter 8 contains the conclusion.

CHAPTER 2

LITERATURE

As the data on retail prices and household consumption became available to researchers, the literature on consumer behavior, retailers' pricing behavior, and their relation with 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 Turkey (Kara, Ogunc, & 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 into Turkey's official food price inflation. They report that a one percent depreciation in the Turkish Lira causes inflation to rise 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 Turkey 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 provide a detailed analysis on the impact of exchange rate developments.

We utilize micro price data collected from several retail chains. Nakamura (2008) uses data from 7000 different stores of 33 major chains in the US and analyzes the sources of variations in retail prices. Her results show that only 16 percent of price variations are common to all stores selling the same product and 65 percent of the variation is common to stores within the same supermarket chain (but not across the chains), while the remaining variation is idiosyncratic to specific stores and specific products. These findings show that only a small fraction of price variation is related to macroeconomic cost and demand shocks. The author argues that most of the price variations are temporary price changes caused by the dynamic pricing strategies of retailers. Similarly, Nakamura and Steinsson (2008) argue that sales may be independent of macroeconomic conditions. Coibion, Gorodnichenko, and Hong (2015) analyze whether temporary sales respond to local economic conditions. They report that neither the size nor the frequency of the temporary sales is sensitive to business cycles. Anderson et al. (2017) and Eichenbaum et al. (2011) show that once temporary price changes are excluded, a systematic relation between the cost changes and price changes becomes apparent. These findings indicate that comparing the observed prices from only two points in time may produce misleading results. In other words, prices from a single point of time may represent time-chain specific effects. Therefore, in our baseline estimates, we try to use prices averaged over a sufficient time period.

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 households' 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 generate an exogenous negative income shock suddenly and its effect on the prices becomes clear in a short time, our results are not affected by long-term trends and can be regarded as casual. 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 Brancelli (2020) reported. Our findings are also consistent with the literature studies 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 coupon use 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 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 the 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 the 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 behind this gap is that higher-income consumers have a better 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 a higher cost of living inflation. We claim that this kind of mechanism is likely to exert upward pressure on lower quality products' prices. Our results show that the relative prices of PLs during the high unemployment period caused by Covid-19 significantly increased, so households that were already consuming these products before the Covid-19 become even worse off.

Fourth, our work contributes to the rapidly growing literature on the economic impacts of Covid-19. Several studies 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.

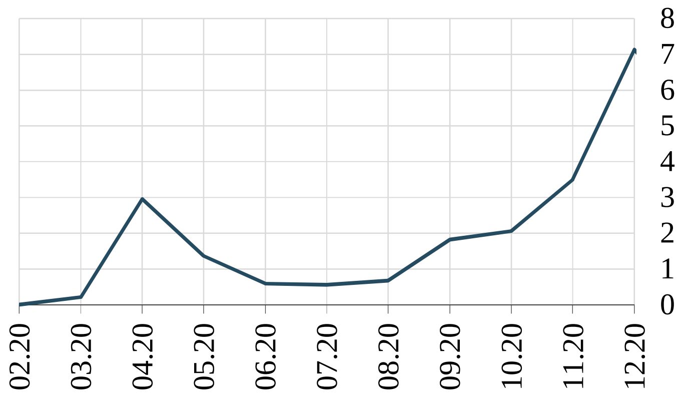
CHAPTER 3

BACKGROUND INFORMATION AND DATA

3.1. Background Information

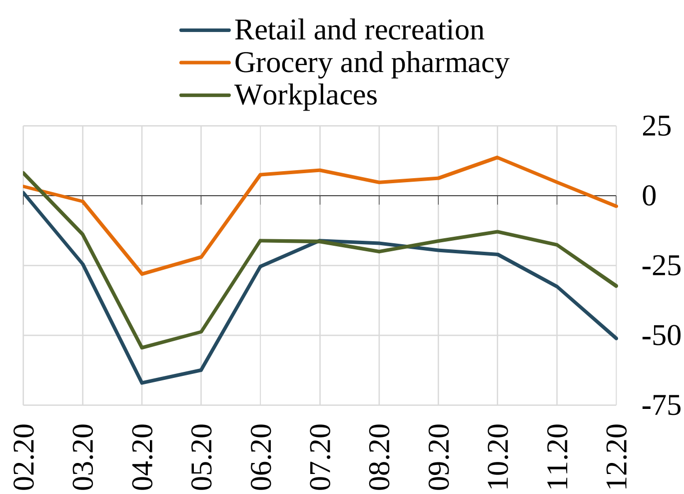
The Covid-19 pandemic emerged in China at the end of 2019 and spread to almost the entire world within a few months. Various measures were taken around the world to contain its spread. The first official step taken in Turkey was the establishment of the Coronavirus Scientific Advisory Board on January 10, 2020. Thereafter, some measures were implemented such as installing thermal cameras at airports, screening passengers arriving from countries that reported 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, Turkey's neighbor to the southeast. On February 23, Turkey closed its border with Iran, and thereafter the list of countries that 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. Health minister Fahrettin Koca announced the first Covid-19 case on March 11 and the first death on March 17 (Figure 3.1). 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 Turkey. After these measures, mobility in Turkey decreased sharply (Figure 3.2) and factory shutdowns caused electricity production to fall 20 percent below its pre-Covid level (Figure 3.3). 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.



Source: Ministry of Health

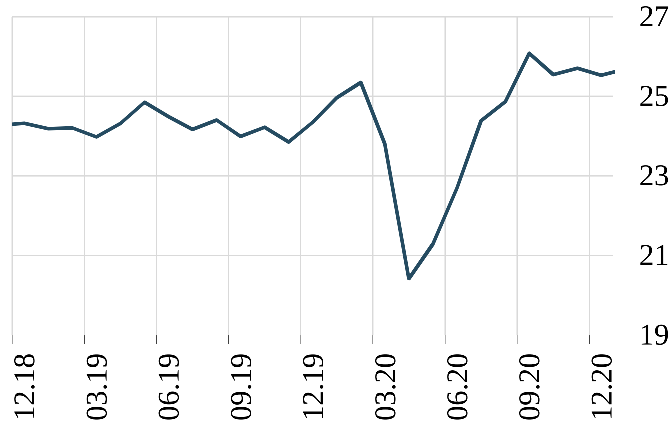
Figure 3.1: Monthly Number of Deaths due to Covid-19 in Turkey (Thousand)



Source: Google

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

Figure 3.2: Google Mobility Index for Turkey (Monthly Average)

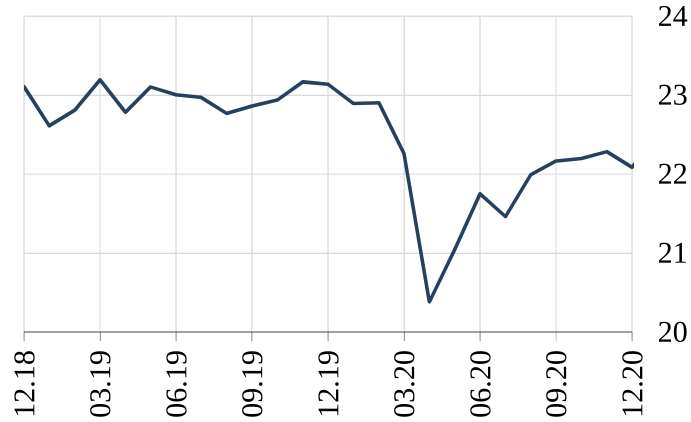


Source: Turkish Electricity Transmission Corporation

Figure 3.3: Monthly Electricity Production in Turkey (Seasonally Adjusted, Million MWh)

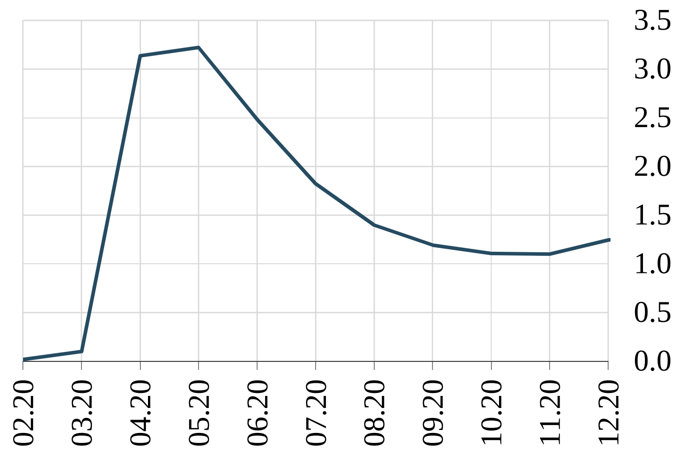
These measures had some serious effects on the labor market. In order to limit permanent damage, cancellation of labor contracts by firms was banned (Law #7244) on April 16, 2020 except for in some extreme cases. Therefore, after this date, firms could not cancel the contracts applied for short-time working pay or force their employees to take unpaid leave. In line with these developments, Figure 3.4 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 3.5).

Official employment statistics show that employment in May was 8.41 per cent 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 some part of their income increases to 22.77 percent of those employed in February. However, although we do not have statistics about it, it is known that there are 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.



Source: Turkstat

Figure 3.4: Nonfarm Employment in Turkey (Seasonally Adjusted, Million People)



Source: Iskur

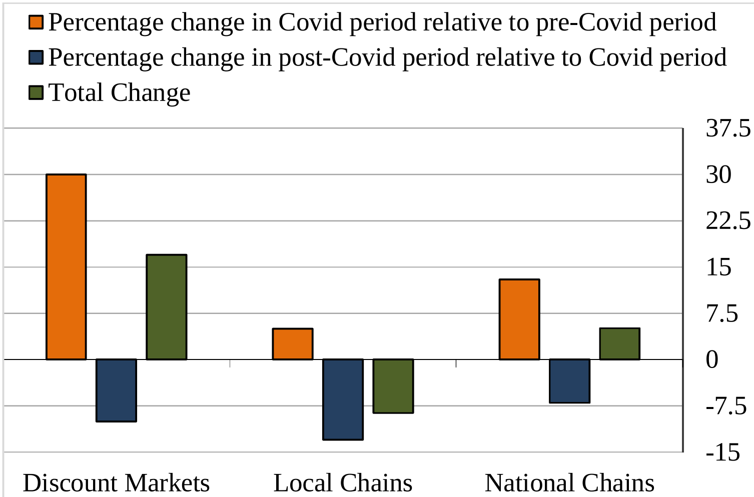
Figure 3.5: Beneficiaries of Short-Time Working Pay (Million People)

The Government of Turkey has taken a series of measures in order to limit the effects of Covid-19 on the economy. In an informative box of inflation report, the Central Bank of the Republic of Turkey (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 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[2], some of which are presented in Figure 3.6. Their data show that discount markets experienced bigger growth rates than other supermarket chains after the Covid-19 outbreak. Moreover, in their report it is stated that the share of PLs (for fast moving consumption goods) rose by 2 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 3.7 shows, monthly depreciations gained speed between March and May, and after a period of stabilization a second wave started in August.

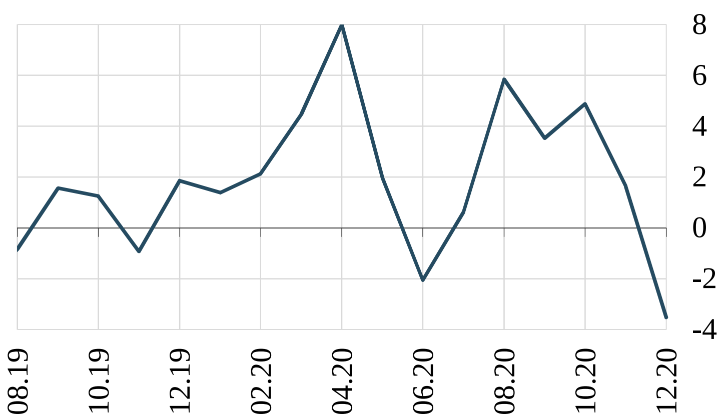
[2] Ipsos collects homescan data from a balanced panel of households in Turkey. Shared statistics are calculated from these homescan data.



Source: Ipsos

Notes: 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 3.6: Growth of Households' Supermarket Spending by Supermarket Type in Turkey



Source: CBRT

Note: Exchange rate basket is calculated as 0.5×TL/$ + 0.5×TL/€

Figure 3.7: Exchange Rate Basket (Monthly % Change)

3.2. Data

The data used in the present 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.

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[3] (COICOP classes) with products of discount markets. This selected part contain prices of 1404 products, classified in 84 different 11-digit classes, at a bi-weekly frequency for the period December 2019[4] 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 outliers[5], we have a balanced panel of data consisting of 1287 different product that are classified in 84 different 11-digit classes[6].

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[3] 11-Digit classes have quite narrow product definitions such as pasteurized milk, sterilized milk (UHT), corn oil, and sunflower seed oil.

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

[5] 17 different products are defined as outliers because of extreme price changes.

[6] 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.

Table 3.1: Number of Products by Markets and Product Label Type

Market	National Brand	Private Label	Total
A101	77	51	128
BİM	31	63	94
ŞOK	77	41	118
AKYURT	132	0	132
ALTUNBİLEKLER	125	0	125
CAĞDAŞ	145	0	145
CARREFOUR	140	0	140
MİGROS	261	0	261
YUNUS	144	0	144
Total	1132	155	1287

Our dataset consist of prices from 9 different supermarkets. Among these markets, Şok, A101, and Bim are classified as discount markets. These 9 chains can also be divided into two groups, from another angle, as national and local chains. Migros, Carrefour, Şok, A101, and Bim are considered national chains since they have stores in almost all cities in Turkey, while the other 4 chains are mostly concentrated in Ankara and surrounding provinces and are classified as local chains. Table 3.1 shows the numbers of products our dataset includes by markets and product label type (PL or NB). In Turkey only 4 chains sells considerable number of different PL products and our data cover PLs from 3 of them with sufficient number of products. Table 3.2 shows the content of the dataset within the wide product definitions of the 4-digit COICOP classification.

Table 3.2: 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

CHAPTER 4

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 measures create a sudden and large scale negative income shock, it gives a good opportunity to answer this question. Because households' 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 3.1, all PLs in our dataset are sold by discount markets. Therefore, estimation of the impact on PLs may also represent the common behavior in the pricing by 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[7].

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

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[7] 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.

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. The CBRT report (2021) states that seasonality is not present in the 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[8]. Therefore, our results are not expected to suffer from 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 into 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 rates differ across comparison groups.

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

4.1. Coarsened Exact Matching (CEM)

This is a nonparametric method designed to estimate the average treatment effect on treated[9] [10]. The aim of the method is to reduce model dependence by imitating fully

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[8] 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).

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

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

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 nonexperimental 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 0-2000 TL, 2001-5000 TL, and +5000 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 nontreateds that are elements of the same stratum as them. If a stratum does not contain any nontreated units while it does have treateds, those treateds 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[11] allow CEM to be used together with regression analysis. In brief, CEM allows us to compare treated units with nontreateds 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 level[12]. After the matching part, for example, the share of pasteurized milk is the same in both comparison groups.

[11] 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.

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

4.2. 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[13]. In the present 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 Turkey 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 is, if there is any. Our equation (4.1) for estimating the impact on the relative prices of NBs sold in discount markets and our equation (4.2) for the impact on the relative prices of PLs are as follows:

$$\ln\left(P_{i,t,m}\right) = \alpha + \delta * (Discount_m \times T_t) + \theta * T_t + f_i \qquad (4.1)$$

$$\ln\left(P_{i,t}\right) = \mu + \beta * (Private_i \times T_t) + \tau * T_t + f_i \qquad (4.2)$$

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

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

Here P is price and i, t, and m the 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

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

parameters of interest showing the impact on relative price of NBs sold in discount markets and PLs, respectively.

Abadie et al. (2017) state that standard errors should be clustered if individual units are assigned to treatment by clusters. In equation 5.2.1 the value of treatment variable changes with markets and in equation 5.2.2 the probability of assignment to treatment changes with markets[14]. In other words, only products of some markets are assigned or have probability of assignment to treatment. Therefore, following Abadie et al. (2017) we report standard errors clustered at market level.

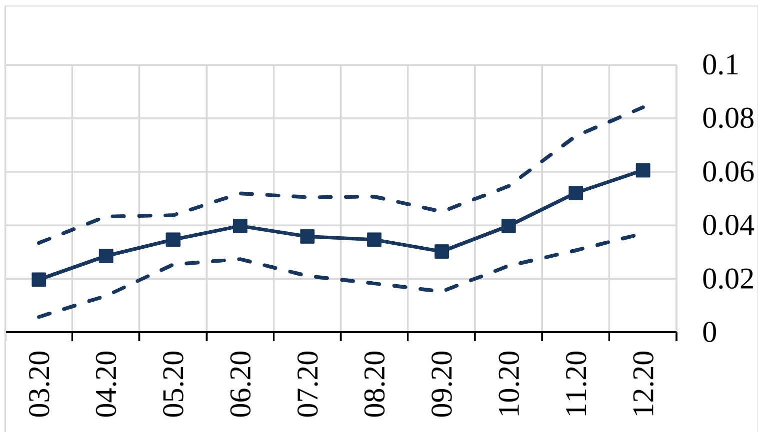
4.3. The Effects of Exchange Rate Depreciations

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 3.7). Because both income losses and exchange rate depreciations took place at similar times, the DID analysis cannot identify the possible impacts of both shocks separately. 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 posttreatment periods and estimate equations 4.1 and 4.2 for each definition separately. Figures 4.1 and 4.2 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

[14] As stated in section 3, all PLs in our dataset are sold by discount markets.

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, cumulative change in the relative price of PLs continued to fluctuate around 3.5 percent until the reintroduction of measures.



Note: Dashed lines show confidence interval at 95% confidence level.

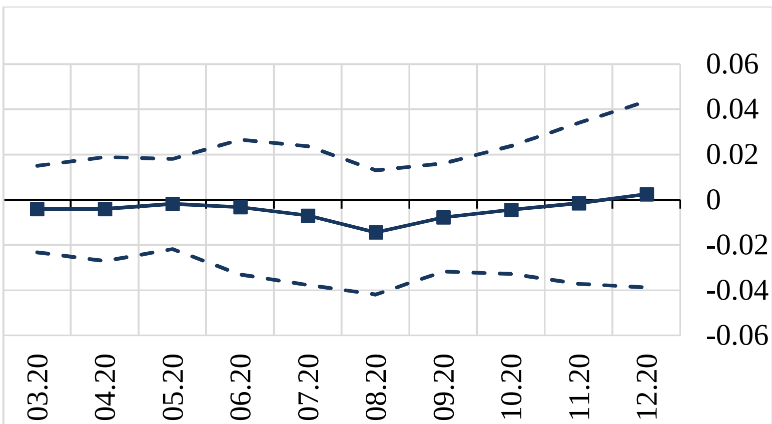
Figure 4.1 : Cumulated Impact on the Relative Prices of PL Products.

To formalize this finding, we estimate equation 4.2.2, defining the period May 2020-July 2020 as pretreatment and August 2020-October 2020 as posttreatment. The results show that exchange-rate pass-through into relative prices of PLs is statistically insignificant (Table 4.1). Figure 4.2 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.

Table 4.1: Impact of Exchange Rate on the Relative Prices of PLs

Impact (S.error)	-0.002 (0.003)
R^2	0.997
N of NB	862
N 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.



Note: Dashed lines show confidence interval at 95% confidence level.

Figure 4.2: Cumulated Impact on the Relative Prices of PL Products.

CHAPTER 5

RESULTS

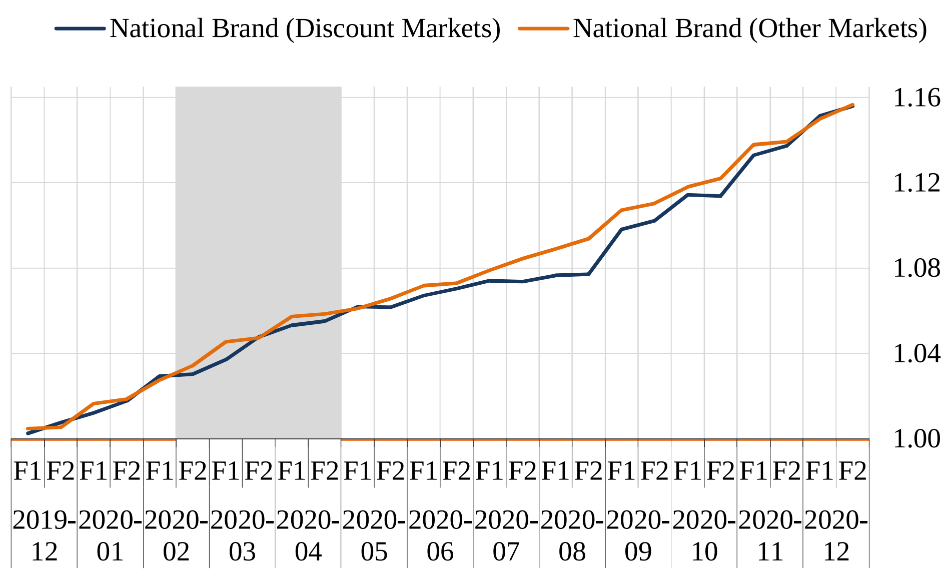
We start our analysis by estimating the impact on relative prices of NBs sold by discount markets. Next, we estimate the impact on the relative prices of PLs and interpret it with the support of the result on relative prices of discount markets. In both analyses, we first form our baseline results using 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 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 or not.

5.1. 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 dataset[15]. Figure 5.1 shows the average of the natural logarithm of the prices weighted by CEM

[15] 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.

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.



Note: 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.

Figure 5.1: Average Prices of National Brand Products (Natural logarithm , 2019-12 = 1)

In line with this observation, the results for our baseline analysis, presented in Table 5.1, 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 posttreatment period.

Table 5.2 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 they are negative.

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

	Postshock Period	
	I	II
Impact	-0.002 (0.007)	-0.011 (0.007)
R^2	0.997	0.996
N of products sold in discount markets	185	185
N 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.

Table 5.2: Impact on the Relative Prices of NBs Sold in Discount Markets by Product Classes

	Postshock Period		Numbers of products	
Product Class	I	II	Sold in discount markets	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, and 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. Numbers of products are reported in the tables. The sample contains 10 price observations for each of these products.

In the last step, we divide the treatment group into three by discount markets while keeping the control group the same. Table 5.3 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 posttreatment 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 5.3: Impact on the Relative Prices of NBs Sold in Discount Markets for Each Discount Market

	Treatment Group		
Postshock Period	**Bim**	**Şok**	**A101**
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)
N of products sold in discount markets	31	77	77
N 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.

5.2 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 5.2 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.

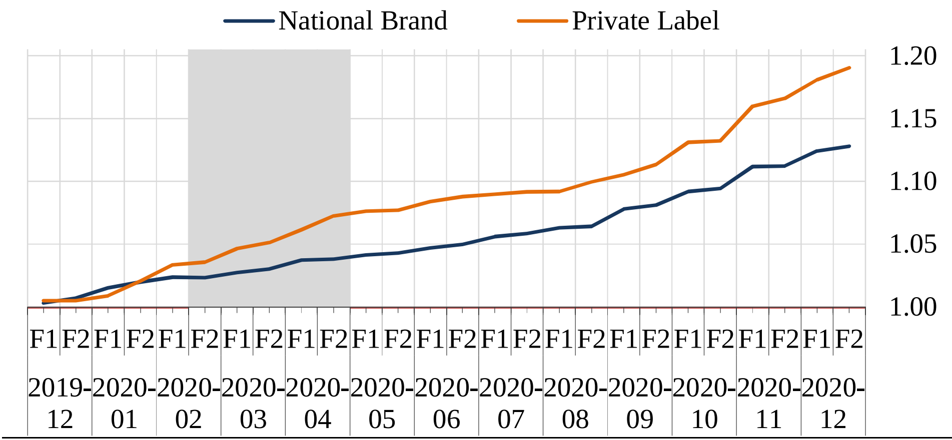
Table 5.4: Impact on the Relative Prices of PL Products

	Postshock Period	
	I	**II**
Impact	0.035*** (0.004)	0.031*** (0.005)
R^2	0.997	0.996
N of NB products	767	767
N 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.

This observation is supported by our baseline result, presented in Table 5.4, that the negative income shock caused PL prices to increase 3.5 percent more than NB prices. Estimation with the second posttreatment 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 5.5). 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).



Note: 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.

Figure 5.2: Average Prices of PL and NB Products (Natural logarithm , 2019-12 = 1)

Table 5.5: Impact on the Relative Prices of PLs by Product Classes

Product Class	Postshock Period I	Postshock Period II	Numbers of products: Sold in discount markets	Numbers of products: 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.

Table 5.6: Impact on the Relative Prices of PLs for Each Discount Market

	Treatment Group		
Postshock Period	**Bim**	**Şok**	**A101**
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)
N of products sold in discount markets	796	543	621
N 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.

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 PLs' 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 Brancelli (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.

CHAPTER 6

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.

6.1 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 3 comparison groups are balanced at the same time. Next we estimate equation 6.1.

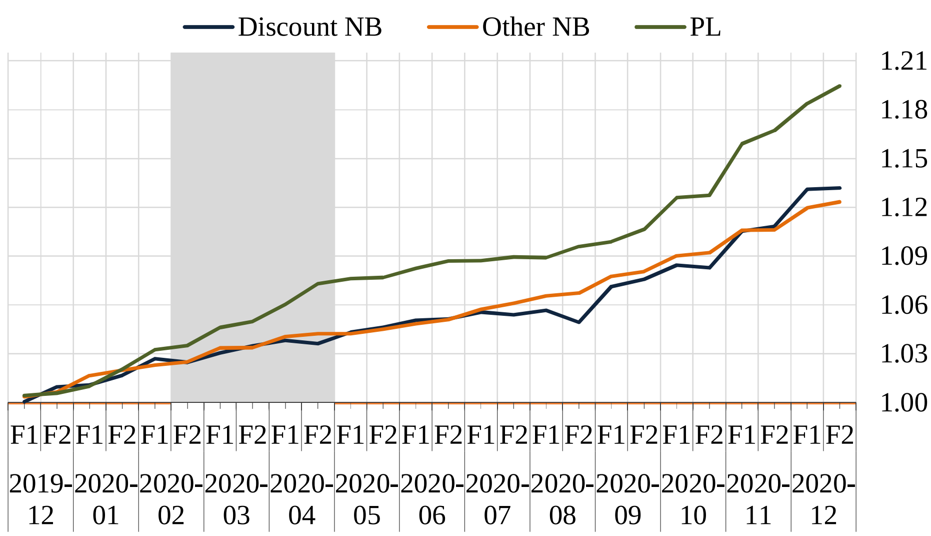
$$\ln(P_{i,t,m}) = \alpha + \beta * (PL_m \times T_t) + \delta * (NBD_m \times T_t) + \theta * T_t + f_i \tag{6.1}$$

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

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

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.

Average of the logarithm of prices for balanced groups is shown in Figure 6.1. In line with the baseline results, during the shock period the prices of NBs follow a similar trend, while the prices of PLs diverge.



Note: 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.

Figure 6.1: Average Prices of Comparison Groups (Natural logarithm , 2019-12 = 1)

Similarly, the result of the regression analysis, represented in Table 6.1, 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.

Table 6.1: Impact on the Relative Prices of PLs and NBs Sold in Discount Markets

	Posttreatment	
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)
N of NB sold in discount markets	129	129
N of PL	128	128
N 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.

6.2 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 6.2 and Table 6.3 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 6.2: Impact on the Relative Prices of NBs Sold in Discount Markets with Different Control Groups

	Control Group	
Postshock Period	**National Chains**	**Local Chains**
I	0.007 (0.006)	-0.008 (0.006)
II	-0.001 (0.007)	-0.017** (0.007)
N of NB products sold in discount markets	182	185
N 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.

Table 6.3: Impact on the Relative Prices of PLs with Different Control Groups

	Control Group	
Postshock Period	**National Chains**	**Local Chains**
I	0.04*** (0.005)	0.029*** (0.003)
II	0.041*** (0.003)	0.02*** (0.004)
N of NBs	455	455
N 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.

CHAPTER 7

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 sizable 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 consumer 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 PL 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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APPENDICES

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 4 of these are PLs (treated units) while other 6 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	N of product sold in discount markets	N of product 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 (mix of 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

Table B.1 (continued)

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
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

Table B.1 (continued)

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

Table B.2 (continued)

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
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

Table B.2 (continued)

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.

C. TURKISH SUMMARY / TÜRKÇE ÖZET

Covid-19 salgını ve buna karşı alınan tedbirler ekonomiler üzerinde ani ve büyük ölçekli etkiler yaratmıştır. Türkiye ekonomisi üzerindeki en büyük ve ani etkilerden biri hanehalklarının yaşadıkları gelir kayıpları olmuştur. Covid-19 salgını ve ilgili önlemlerin ardından Türkiye'de tarım dışı istihdam Mart 2020'de önemli ölçüde azalmaya başlamıştır. Bu istihdam kayıplarına ek olarak, birçok çalışan kısa çalışma ödeneğinden yararlanmış ve gelirlerinin bir kısmını kaybetmiştir. Mayıs 2020'de tarım dışı istihdam Şubat ayındaki seviyesinin yüzde 8,42 altında kalmıştır. Kısa çalışma ödeneğinden yararlananlar da dikkate alındığında, gelirinin bir kısmını veya tamamını kaybeden çalışan sayısı Mayıs ayında Şubat ayı istihdamının yüzde 22,77'sine ulaşmıştır. Ayrıca, kısa çalışma ödeneğinden yararlanamayan bazı çalışanların ücretsiz izin almak zorunda kaldığı da dikkate alındığında, gelir kaybına uğrayan hanelerin sayısının daha da büyük olduğu görülmektedir. Bu yaygın gelir kayıplarının, tüketicilerin davranışları ve tüketim mallarının fiyatları üzerinde önemli etkilerinin olabileceği düşünülebilir. Stroebel ve Vavra (2019), servet artışlarının tüketici davranışında değişikliklere neden olarak perakende fiyatlarında artışlara yol açtığına dair doğrudan kanıt göstermektedir. Coibion vd. (2015) ve Beraja vd. (2019), perakende fiyatlarının bölgesel işsizlik oranlarına önemli ölçüde tepki verdiğini göstermektedir. Birlikte ele alındığında bu çalışmalar, perakende fiyatlarının iş döngülerini takip ettiğini ve hanehalklarının gelir değişimlerinden etkilendiğini göstermektedir. Ancak fiyatlar üzerindeki bu etkiler, farklı kalite segmentlerine ait ürünler arasında heterojen olabilir.

Raporladıkları etkilerin büyüklüğü farklılaşsa da, Lamey vd. (2007), Lamey vd. (2012), Dube vd. (2018), Brancatelli vd. (2020), gelir kayıplarını takiben, ulusal markalı (UM) ürünlere göre daha ucuz ve kalitesiz alternatifler olarak bilinen özel etiketli (ÖE) ürünlerin pazar payının arttığını göstermektedir. Daha düşük kaliteli mallara yönelik tüketici talebindeki bu tür bir değişim, fiyatları üzerinde yukarı yönlü baskılar oluşturabilir. Böyle bir mekanizmanın iki önemli ekonomik sonucu olacaktır:

birincisi, talep koşullarının toplam fiyat seviyesi üzerindeki etkisini azaltacaktır; ikincisi, durgunluk dönemlerinde, bu düşük kaliteli ürünleri hâlihazırda tüketen düşük gelirli tüketiciler için yaşam maliyetindeki değişikliklerin daha yüksek olmasına neden olacaktır.

Bu çalışmadaki amacımız, Covid-19 tedbirlerinin yarattığı gelir şokundan yararlanarak, hanehalkı geliri ile ÖE ürünlerin göreli fiyatları arasındaki nedensel ilişkiyi göstermektir. Temel olarak, ÖE ve UM ürünlerinin Covid-19 öncesi ve sonrası fiyatları karşılaştırılmakta ve bu fiyat değişimleri arasındaki fark gelir şokunun etkisi olarak yorumlanmaktadır. Bu amaçla, öncelikle karşılaştırma gruplarının sektörel kompozisyonunu dengelemek amacıyla Coarsened Exact Matching (CEM) algoritmasını kullanılmış, ardından farkların farkı modeli (DID) çerçevesinde karşılaştırma yapılmıştır.

Tahmin sonuçları, Covid-19 ve ilgili önlemlerin ÖE fiyatlarında UM fiyatlarına kıyasla ortalamada yüzde 3,5 daha fazla artış olduğunu göstermektedir. Çeşitli ürün grupları ayrı ayrı değerlendirildiğinde ise bu etkinin farklılık gösterdiği tahmin edilmektedir. Ulaşılan bu sonuçların, ÖE fiyatlarına özgü etkiyi mi yoksa bu ürünlerin satıldığı marketlerde (ucuzluk marketleri) gözlenen genel fiyatlamayı mı yansıttığı da ayrıca test edilmiştir. Bu amaçla, ucuzluk marketlerinde satılan UM'lerin fiyat hareketleri ile diğer marketlerde satılan UM'lerin fiyat hareketleri de karşılaştırılmıştır. Sonuçlar, UM'lerin fiyatlarındaki değişikliklerin, her iki market çeşidinde de benzer olduğunu göstermektedir. Dolayısıyla, gelir etkisinin ucuzluk marketlerindeki fiyatların genelinde değil sadece ÖE fiyatlarında olduğu anlaşılmaktadır.

Bu çalışmada faydalanılan gelir şokunun yaşandığı dönemde, Türk Lirası önemli bir değer kaybı yaşamıştır ve dolayısıyla kur gelişmelerinin göreli fiyatlara yapacağı olası bir etki bu çalışmadaki tahmin kalitesini olumsuz etkileyecektir. Bu sebeple, Türk Lirası'nın önemli değer kaybı yaşadığı fakat hanehalklarının gelirinde önemli bir değişikliğin görülmediği bir başka dönemdeki fiyat gelişmeleri de incelenmiştir.

Sonuçlar ÖE ve UM ürün fiyatlarının döviz kuru gelişmelerine gösterdiği hassasiyetin benzer olduğunu göstermektedir. Dolaysıyla göreli fiyatların döviz kuru gelişmelerinden etkilenmediği ve bu çalışmada raporlanan bulgunun döviz kuru gelişmelerinin yansıması olmadığı anlaşılmaktadır.

Bu çalışma, literatürün çeşitli alanlarına katkıda bulunmaktadır. Çalışmamız, gelirin PL ürünlerine olan talep üzerindeki etkisine odaklanan çalışmalarla bağlantılıdır. Bu çalışmalar genellikle ÖE'lerin pazar payı veya hanehalklarının tüketim sepetindeki PL'lerin payı üzerindeki etkiyi tahmin etmeye çalışmaktadır. Lamey vd. (2007) ve Lamey vd. (2012) zaman serisi yöntemlerini kullanarak PL'lerin pazar paylarının iş çevrimlerinden etkilendiğini tahmin etmiştir. Elde ettikleri sonuçlar bizim bulgularımızla tutarlıdır, ancak toplu verilerle yapılan zaman serisi analizi nedensel ilişkileri göstermek için yeterli değildir. Dube vd. (2018) ABD'nin 2004-2012 dönemi için ev tarama paneli verilerini kullanarak, hanehalkı tüketimindeki özel etiketli ürün payının, gelir değişikliklerine nasıl tepki verdiğini tahmin etmektedir. Brancatelli vd. (2020), 2011-2018 dönemini kapsayan Hollanda ev tarama paneli verilerini kullanarak, aynı tahmin prosedürünü de izlemiştir. Her iki çalışma da ÖE'lerin toplam tüketim içindeki payı ile hanehalkı geliri arasındaki ters ilişkinin istatistiksel olarak anlamlı olduğunu raporlasa da bu ilişkinin boyutunun oldukça küçük olduğu tahmin edilmiştir. Bu çalışmalara iki ana eleştiri getirmek mümkündür. Birincisi, gelir değişikliklerinin ÖE'lerin payları üzerindeki etkisinin hane halkının gelir düzeyine göre değişebileceği hesaba katılmamıştır. Örneğin, yüksek gelirli bir hanenin yaşayacağını yüzde 10'luk bir gelir kaybının ÖE tüketimine yapacağı etkinin, orta ve düşük gelirli hanelerdekine kıyasla daha sınırlı olması beklenebilir. İkincisi, her iki çalışmada da, PL'lerin paylarının uzun vadeli artma eğilimi doğrusal bir değişken ile kontrol edilmiş ve bu değişkenin modele dahil edilmesinin tahmin sonuçlarını etkilediği belirtilmiştir. Buna karşın, PL'lerin Pazar payındaki uzun vadeli artış eğilimi doğrusal olmak zorunda değildir; örneğin, pazar payının azalan bir oranda artması beklenebilir. Bu nedenle, bu çalışmaların sonuçları hanehalkı gelirinin PL talebi üzerindeki nedensel etkisi olarak yorumlanamaz.

Bu çalışmada kullandığımız veri setimiz, hanelerin tüketimlerini içermediği için çalışmamızda gelir kayıplarının ÖE ürün talebine olan etkisini doğrudan gösterememekteyiz. Buna karşın çalışmamız da ÖE ürünlerin göreli fiyatlarının hanehalkı geliriyle ters negatif ilişkili olduğu ve ilişkinin gelir ile ÖE talebi arasındaki negatif ilişkiden kaynaklandığı tartışılmıştır. Covid-19 tedbirleri ani ve dışsal bir negatif gelir şoku yarattığı için fiyatlar üzerindeki etkisi kısa sürede belirginleşmiştir. Bu sebeple sonuçlarımızın uzun vadeli trendlerden etkilenmemekte ve nedensel ilişkiyi göstermektedir. Covid-19'un işgücü piyasası üzerindeki etkilerine paralel olarak, ÖE göreli fiyatlarındaki artışın şoktan sonraki iki buçuk ay içinde yüzde 3,5 seviyesine ulaştığını tahmin edilmektedir. Aynı dönem için ÖE ürünlerinin pazar payında herhangi bir düşüş olmadığını gösteren toplulaştırılmış veriyle (Ipsos, 2020) birlikte değerlendirildiğinde, sonuçlarımız, hane geliri ile ÖE talebi arasındaki ilişkinin Dube vd. (2018) ile Brancelli vd. (2020) tarafından raporlanandan daha güçlü olduğuna işaret etmektedir.

Çalışmamız, iş çevrimlerinin perakende fiyatları üzerindeki etkisine odaklanan literatüre de katkıda bulunmaktadır. Stroebel ve Vavra (2019), araç değişken (Instrumental variable) stratejisini kullanarak konut fiyatı artışlarının perakende fiyatları üzerindeki etkisini tahmin etmiştir. Elde ettikleri sonuçlar konut fiyatlarındaki artışın perakende fiyatlarında artışa yol açtığını ve bu etkinin ev sahibi yoğunluğunun yüksek olduğu mahallelerde daha güçlü olduğunu göstermektedir. Yazarlar, konut fiyatları arttıkça ev sahiplerinin daha fazla harcama yaptığını; ancak jenerik ürünlerin ve indirimden satın alının ürünlerin toplam tüketim içindeki payının azaldığını göstermektedir. Diğer bir deyişle, konut fiyatlarındaki artış, ev sahiplerinin servetini arttırarak onları perakende fiyatlarına daha az duyarlı hale getirmektedir. Çalışmada sunulan sonuçlar, tüketici davranışında gözlenen bu değişimin, perakendecilerin kar marjının ve dolayısıyla tüketici fiyatlarının artmasına sebep olduğunu göstermektedir. Coibion, Gorodnichenko ve Hong (2015) yerel ekonomik koşulların perakende fiyatları üzerindeki etkisini incelemiştir. Çalışmanın sonuçları perakende fiyatlarının yerel işsizlik oranlarına güçlü bir şekilde yanıt verdiğini göstermiştir. Hem Stroebel ve Vavra (2019) hem de Coibion, Gorodnichenko ve Hong (2015), iş döngülerinin tüketici davranışlarını aracılığıyla perakende fiyatlarını etkilediğini göstermektedir. Bizim çalışmamız bu etkinin farklı kalite segmentlerindeki ürünler arasında heterojen olduğunu gösterdiğini için bahsedilen çalışmaları tamamlayıcı niteliktedir. Sonuçlarımız, ekonomik koşullar kötüleştiğinde, düşük kaliteli ÖE'lerin daha yüksek kaliteli UM'lere göre daha fazla pahalılaştığını göstermektedir.

Çalışmamız, farklı gelir gruplarından hane halkları arasındaki yaşam maliyeti farklılıklarına odaklanan araştırmalarla da bağlantılıdır. Argente ve Lee (2017), farklı gelir gruplarındaki tüketiciler için ayrı ayrı fiyat endeksileri hesaplamış ve hesaplamayı yaparken tüketicilerin üzerinden ödeme yaptıkları nihayi fiyatları kullanmıştır. Elde ettikleri sonuçlar, düşük gelirli hanehalkları için geçim maliyeti enflasyonunun, yüksek gelirli hanehalklarına kıyasla 2008-2013 döneminde önemli ölçüde daha yüksek olduğunu göstermektedir. Araştırmacılar farklı gelir gruplarının enflasyon oranları arasındaki farkı bileşenlerine ayrıştırdıklarında, bu duruma sebebiyet veren belirleyici mekanizmanın yüksek gelirli tüketicilerin yaptığı kalite ikamesi olduğu görülmüştür. Buna göre gelir kaybı yaşandığında görece yüksek gelirli tüketiciler daha kalitesiz ürünlere yönelerek yaşam maliyetini sınırlandırmaktadır fakat hali hazırda kalitesiz ürün tüketen düşük gelir grubu için böyle bir marj bulunmamaktadır. Sonuçlarımız bu bulguyu tamamlayıcı niteliktedir. Argente ve Lee (2017) tarafından ortaya konan bulgular, ekonomik daralma dönemlerinde yüksek gelir grubundaki tüketicilerin görece daha düşük yaşam maliyeti enflasyonu ile karşılaştığı ve düşük kaliteli ürünlere olan göreli talebin arttığını işaret etmektedir. Bizim çalışmamız bu tip bir mekanizmanın düşük kaliteli ürün fiyatlarında yukarı yönlü bir baskı yaptığını göstermektedir. Buna göre artan taleple düşük kaliteli ürünlerin göreli fiyatlarında artış gözlenmiş ve bu durum hâlihazırda bu ürünleri tüketen düşük gelirli tüketicilerin yaşam maliyetini arttıran ilave bir kanal oluşturmuştur

Bu çalışmada hane halkı geliri ile ÖE ürünlerin göreli fiyatları arasındaki ilişki incelenirken Covid-19'a karşı alınan önlemlerin sebep olduğu gelir kayıplarından yararlanılmıştır. Tüm dünyada olduğu gibi Türkiye'de de Covid-19'un yayılımını kısıtlamak amacıyla bir takım önlemler alınmıştır. Türkiye'de atılan ilk resmi adım 10 Ocak 2020'de Koronavirüs Bilimsel Danışma Kurulu'nun kurulması olmuştur. Daha sonra havalimanlarına termal kamera takılması, çok vaka bildirilen ülkelerden gelen yolcuların taranması, Çin vb. ülkelerden tüm uçuşların durdurulması gibi önlemler alınmıştır. Buna karşın Covid-19, Türkiye’nin güneydoğu sınırındaki komşu ülke İran'da görülen vaka artışlarından sonra, Şubat 2020'nin ikinci yarısında ana akım medyada gündem haline gelmiştir. Türkiye 23 Şubat'ta İran'la olan sınırını kapatmıştır ve ardından giriş çıkışı yasaklanan ülkelerin listesi genişletilmiştir. Mart ayı başında halka açık yerlerde dezenfeksiyon çalışmaları yapılmaya başlanmış ve bazı özel sektör firmaları evden çalışmaya geçmiştir. Sağlık Bakanı Fahrettin Koca, 11 Mart'ta ilk Covid-19 vakasını ve 17 Mart'ta ilk ölümü açıklamıştır (Şekil 3.1). Mart 2020'nin sonraki günlerinde okullar kapatılarak uzaktan eğitime geçilmiş; restoranlar, kafeler ve eğlence yerleri geçici olarak kapatılmış; fabrikalar üretimlerini durdurmaya başlamış ve sokağa çıkma yasakları uygulanmıştır. Nisan ayı başında Türkiye'nin 31 şehrinde şehirlerarası seyahatler kısıtlanmıştır. Bu önlemlerin ardından Türkiye'deki hareketlilik keskin bir şekilde azalmış (Şekil 3.2) ve fabrikaların kapanması elektrik üretiminin Covid-19 öncesi seviyesinin yüzde 20 altına düşmesine neden olmuştur (Şekil 3.3). Bu önlemler Mayıs 2020'de kısmen kaldırılmıştır. Fabrikalar Mayıs ayında yeniden faaliyete geçerken, restoranlar, kafeler ve bazı eğlence mekanları Haziran ayında tekrar açılmıştır. Bu aylarda şehirlerarası seyahatlerle ilgili önlemler kademeli olarak kaldırılmıştır. Kasım 2020'de, artan Covid-19 vakalarına karşı yeni önlemler getirilmiş, restoranlar ve kafeler yalnızca paket yemek için hizmet verecek şekilde sınırlandırılmış ve sokağa çıkma yasaklarının daha gevşek bir versiyonu tekrar uygulamaya girmiştir. Bu tedbirler işgücü piyasası üzerinde önemli etkiler yaratmıştır. Bu gelişmelerin sebep olacağı kalıcı zararların sınırlandırılması amacıyla, iş sözleşmelerinin firmalar tarafından feshedilmesi 16 Nisan 2020 tarihinde yasaklanmıştır (7244 sayılı Kanun). Dolayısıyla bu tarihten sonra firmalar kısa süreli çalışma ücreti için yapılan sözleşmeleri iptal edememiş veya çalışanlarına ücretsiz izin vermiş veya kısa çalışma ödeneğine başvurmuştur. Bu gelişmelere paralel olarak, Şekil 3.4 tarım dışı istihdamın Mart ve Nisan 2020'de çarpıcı bir şekilde düştüğünü, ancak düşüşün Mayıs 2020'de yavaşladığını göstermektedir. Öte yandan, Nisan 2020'de önemli sayıda çalışan insan kısa süreli çalışma ücretinden yararlanmaya başlamıştır (Şekil 3.5).

Resmi istihdam istatistikleri, Mayıs ayındaki istihdamın Şubat ayındaki seviyesinin yüzde 8,41 altında olduğunu göstermektedir. Kısa çalışma ödeneğinden yararlananlar da dikkate alındığında, gelirlerinin en azından bir kısmını kaybeden çalışan sayısı Şubat istihdamının yüzde 22.77'sine ulaşmaktadır. Öte bu sayılara dahil olmayıp ücretsiz izin almak zorunda kalan veya kendi işini yapıp işini kaybeden önemli sayıda kişi bulunduğu bilinmektedir. Özetle, Covid-19 ve ilgili önlemler hanelerin önemli bir kısmının gelirlerinin en azından bir kısmını kaybetmesine neden olmuştur. Türkiye Hükümeti, Covid-19'un ekonomi üzerindeki etkilerini sınırlandırmak için bir dizi önlem almıştır. TCMB (2020) enflasyon raporunun bilgilendirici kutusunda bu önlemleri üç olarak sınıflandırmaktadır: 1) mali önlemler, 2) finansmana erişimi kolaylaştırmak için alınan önlemler ve (3) istihdamı sürdürmek ve dezavantajlı grupları korumak için sosyal önlemler. Son grup bizim bağlamımızda önemli bir yere sahiptir. Bu gruptaki hanelere doğrudan verilen başlıca parasal destekler şunlardır: Kısa süreli ödeneği, işsizlik sigortası ödemesi ve muhtaç ailelere sağlanan nakdi yardımlar. Aile, Çalışma ve Sosyal Hizmetler Bakanlığı'nın paylaştığı verilere göre, bu doğrudan ödemelerin toplamı 18 Mayıs'ta 11,6 milyar TL'ye (10 milyon kişiye / hane halkına ödenen) ulaşmıştır. Toplam destek tutarı Temmuz ayı sonunda 29,7 milyar TL'ye ve Aralık ayı sonunda 45,2 milyar TL'ye ulaşmıştır. Bu veriler, devlet desteklerine rağmen hanehalklarının pandemi nedeniyle ciddi gelir kayıpları yaşadığını göstermektedir.

Bu çalışmada kullanılan veriler, TCMB tarafından ay içi fiyat gelişmelerini takip etmek amacıyla toplanan fiyatlardan oluşmuş gizli veri setinin bir parçasıdır. Dolayısıyla, çalışmada kullanılan veriler resmi tüketici fiyatları verisini temsil edebilmektedir. Bu verilerin bir kısmı çevrimiçi kaynaklardan toplanırken, diğer kısmı süpermarketleri ve mağazaları ziyaret eden bir ekip tarafından toplanmaktadır.

Araştırma sorumuz doğrultusunda bu çalışmada, TCMB veri setinin bir alt kümesi kullanılmıştır. Bu alt küme, indirim marketlerinde satılan gıda ürünlerini ve bu ürünlerle aynı türde olup diğer marketlerde satılan ürünleri kapsamaktadır. Bu seçilmiş kısım, Aralık 2019'dan Aralık 2020'ye kadar olan dönem için 1404 farklı ürünün fiyatlarını iki haftalık frekansta içermektedir. Ancak, bu ürünlerin 99'unun fiyatları tüm dönem için mevcut değildir. Fiyatları eksik olan ve aykırı davranışlar sergileyen ürünler çıkarıldıktan sonra, 1287 farklı üründen oluşan dengeli bir panel veri setine ulaşılmıştır. Veri setimiz 9 farklı süpermarkete ait fiyatlardan oluşmaktadır. Bu marketler arasında Şok, A101 ve Bim indirim marketleri olarak sınıflandırmaktadır. Tablo 3.1, veri setimizin marketlere ve ürün etiketi türüne (ÖE veya UM) göre içerdiği ürün sayısını göstermektedir. Türkiye'de sadece 4 zincir önemli sayıda ÖE ürünü satmaktadır ve verimiz 3 markette satılan ÖE ürünleri kapsamaktadır.

Bu çalışmadaki amacımız, hane halkının gelirindeki değişikliklerin ÖE'lerin fiyatlarını (UM'lere göre) nasıl etkilediği sorusuna cevap vermektir. Covid-19‘a karşı alınan önlemler ani ve büyük ölçekli bir gelir şoku yarattığı için ilgili dönem bu soruya cevap vermek için uygun bir fırsat sunmaktadır. Hanehalkının gelir kaybı ve gelir kaybı beklentisi ani bir şekilde gerçekleştiği için, talepteki olası bir değişimin ve bu değişimin fiyatlara yansımasının da kısa sürede gerçekleşmesi beklenebilir. Bu sebeple gelir etkisini tahmin etmek için, ÖE ve UM ürünlerinin fiyatlarındaki değişim farkların farkı (difference in differences, DID) modeli çerçevesinde karşılaştırılmaktadır.

Tablo 3.1'de görüldüğü gibi veri setimizdeki tüm ÖE'ler ucuzluk marketleri tarafından satılmaktadır. Bu nedenle, ÖE'ler ve UM’lerin karşılaştırılmasıyla elde edilecek tahmin, ucuzluk marketlerindeki genel fiyatlama davranışını yansıtabilir. Bu sebeple öncelikle ucuzluk marketlerinde satılan UM’ler ile diğer marketlerde satılan UM’ler karşılaştırılmış, fiyat değişimleri arasında bir farkın olmadığı gözlendikten sonra ÖE ve UM karşılaştırılmasına geçilmiştir.

Bir DID analizindeki temel varsayım, şokun olmadığı durumda karşılaştırma gruplarının paralel bir eğilim izleyeceğidir. Bizim çalışmamızda bu varsayıma yönelik üç olası tehdit vardır. Öncelikle, karşılaştırma grupları farklı mevsimsel yapıya sahip olabilir ve tahminimiz gelir etkisi yerine bu mevsimsellikler arasındaki farklılığı gösteriyor olabilir. Veri setimiz bu durumu doğrudan kontrol etmek için yeterli değildir fakat grupların farklı mevsimsel yapılarının olacağı bir durumda bu grupları kapsayan toplu fiyat endeksinin de mevsimsellik göstermesi beklenebilir. TCMB raporu (2021), işlenmiş gıda enflasyonunda mevsimselliğin olmadığını belirtmektedir. Ayrıca, resmi TÜFE verileri ile hesaplanan toplam gıda ve alkolsüz içecekler fiyat endeksi (taze meyve ve sebze, patates ve kırmızı et hariç), istatistiksel olarak anlamlı bir mevsimsellik göstermemektedir. Bu sebeple sonuçlarımızın mevsimsellikten etkilenmediği değerlendirilmektedir. İkincisi, karşılaştırma gruplarımız arasında bazı sektörel farklılıklar olabilir, bu olası sektörel farklılıklar şokun olmadığı bir durumda bile karşılaştırma gruplarının farklılaşmasına sebep olabilecektir. Başka bir deyişle bu olası farklılık sektörlere özgü eğilimlerin tahmin sonuçlarımızı yanıltmasına neden olabilecektir. Bu sorunun üstesinden gelmek için, DID uygulamasından önce, karşılaştırma gruplarını dengelemek için ilk olarak Coarsened Exact Matching (CEM) prosedürünü (Iacus, King ve Porro, 2012) kullanılmıştır. Üçüncüsü, hanehalkı negatif gelir şokunu yaşarken, Türk Lirası önemli bir değer kaybı yaşadı. Nakamura ve Zerom (2010) ve Hong ve Li (2017), karşılaştırma gruplarımızın fiyatlarına döviz kuru geçişinin farklı olabileceğini ima etmektedir. Böyle bir durumda, DID tahminlerinin sadece gelir etkisini değil aynı zamanda döviz kuru etkisini de göstermesi beklenir. Bu nedenle, döviz kuru geçişinin karşılaştırma grupları arasında farklılık gösterip göstermediğini değerlendirmek için ek bir analiz yapılmıştır.

Ampirik analizimizde DID uygulaması öncesinde karşılaştırma grupları arasındaki sektörel farklılıkları yok etmek için CEM yöntemi kullanılmış böylece her 11-basamak ürün çeşidinin bu iki karşılaştırma grubunda aynı paya sahip olması sağlanmıştır. Örneğin CEM aşamasından sonra pastörize süt ürünlerin karşılaştırma gruplarındaki payı aynı olmuştur. Karşılaştırma gruplarını arasındaki denge sağlandıktan sonra gelir etkisi denklem 4.1 ve 4.2 aracılığıyla tahmin edilmiştir.

Yukarıda da anlatıldığı gibi ancak Şubat 2020'nin ikinci yarısında Türkiye de gündem olmuştur. Bu dönemin öncesinde fiyatlar üzerinde Covid-19 kaynaklı bir etki olmayacağı için 1 Aralık 2019 ve 15 Şubat 2020 dönemi Covid-19 öncesi dönem olarak tanımlanmıştır. Gelir şokunun fiyatları etkilemesi bir miktar zaman alacağından ötürü takip eden 2,5 aylık dönem analizden dışlanmıştır. 1 Mayıs ve sonrasındaki 2,5 aylık periyot ise Covid-19 sonrası dönem olarak tanımlanmıştır.

$$\ln\left(P_{i,t,m}\right) = \alpha + \delta * (Ucuzluk_m \times T_t) + \theta * T_t + f_i \quad (4.1)$$

$$\ln\left(P_{i,t}\right) = \mu + \beta * (\text{Ö}E_i \times T_t) + \tau * T_t + f_i \quad (4.2)$$

$$T_i = \begin{cases} 1, & Covid-19\ Sonrası \\ 0, & Covid-19\ \text{Ö}ncesi \end{cases} \qquad Discount_m = \begin{cases} 1, & Ucuzluk\ Marketi \\ 0, & Diğer \end{cases}$$

$$\text{Ö}E_i = \begin{cases} 1, & \text{Ö}zel\ Etiketli\ \text{Ürün} \\ 0, & Ulusal\ Markalı\ \text{Ürün} \end{cases}$$

Bu formülasyonda P değişkeni ürün fiyatlarını gösterirken i, t ve m sırasıyla ürünü, zamanı ve ürünün satıldığı marketi göstermekte ve f_i her bir ürün için kullanılan kukla değişkenleri göstermektedir. Denklemlerdeki δ ve β parametreleri sırasıyla ucuzluk marketlerinde satılan ulusal markalı ürünlerin (diğer marketlerde satılan UM'lere kıyasla) ve özel etiketli ürünlerin (UM'lere kıyasla) göreli fiyatları üzerindeki gelir etkisini göstermektedir. Regresyon sonuçları raporlanırken market bazında sınıflanmış standart hatalar kullanılmıştır.

Çalışmamızın sonuçlar kısmına geçilmeden önce döviz kurundan tüketici fiyatlarına geçişin karşılaştırma gruplarımız arasında farklılaşıp farklılaşmadığı test edilmiştir. Bunun için herhangi bir gelir şokunun yaşanmadığı fakat Türk Lirasının önemli bir değer kaybı gösterdiği Ağustos-Ekim 2020 dönemi denklem 4.2 çerçevesinde incelenmiştir. Tablo 4.1'de sunulan sonuçlara göre Ağustos-Ekim döneminde fiyatları ile Mayıs- Temmuz dönemi fiyatları karşılaştırıldığında fiyat değişimleri her iki karşılaştırma grubu için de benzerdir. Buna göre ÖE ürünlerin göreli fiyatlarının (UM ürünlere kıyasla) döviz kurundan etkilenmediği görülmektedir.

Yukarıda da bahsedildiği gibi çalışmamızda öncelikle ucuzluk marketlerinin geneline yansıyan bir gelir etkisi olup olmadığı test edilmiştir. Tablo 5.1, denklem 4.1 ile yapılan tahminleri sunmaktadır. Buna göre her iki market grubunda satılan ulusal markalı ürün fiyatları şok döneminde benzer değişimler göstermiştir ve göreli fiyatları üzerinde istatistiksel olarak anlamlı bir gelir etkisi bulunamamıştır. Denklem 4.1 çeşitli ürün grupları için ayrı ayrı tahmin edildiğinde de benzer bir sonuç görülmektedir (Tablo 5.2). Ayrıca her bir ucuzluk marketinde satılan UM'ler diğer marketlerde satılan UM'ler ile ayrı ayrı karşılaştırıldığında da istatistiksel olarak anlamlı ve pozitif bir etki görülmemektedir (Tablo 5.3).

Tablo 5.4, denklem 4.2 ile yapılan tahmin sonuçlarını sunmaktadır. Buna göre Covid-19 önlemleri sonucunda ortaya çıkan negatif gelir şoku, ÖE ürün fiyatlarının UM ürün fiyatlarından ortalama yüzde 3,5 daha fazla artmasına sebep olmuştur. Farklı ürün grupları ayrı ayrı incelendiğinde göreli fiyatlar üzerindeki gelir etkisinin ürün grubuna göre değişiklik gösterdiği gözlenmektedir (Tablo 5.5). Ayrıca her bir ucuzluk marketinde satılan ÖE ürünlerin göreli fiyatları ayrı ayrı incelendiğinde tahminlerin tamamında benzer bir etki görülmektedir (Tablo 5.6).

Covid-19 önlemleri hane halkının gelirlerinde önemli bir kayba sebep olmuştur. İlgili literatür bu tip gelir kayıpları sonucunda tüketicilerin kalite ikamesi yaparak görece daha ucuz ürünlere yöneldiğini göstermektedir. Bu çalışmada gelir kayıplarının görece daha kalitesiz olan ürünlerin göreli fiyatlarına etkisi incelenmiş ve bu etkinin talep kanalıyla kaynaklandığı tartışılmıştır. Sonuçlarımız Covid-19 tedbirlerinin sebep olduğu gelir kaybının, ÖE ürün fiyatlarının aynı türdeki UM fiyatlarına kıyasla ortalamada yüzde 3,5 daha fazla arttığını göstermektedir. Bulgularımız Ipsos (2020) verileriyle birlikte değerlendirildiğinde, Covid-19 ile birlikte ÖE ürünlere olan talebin arttığını göstermektedir. Bu sonuçlar, iki temel makroekonomik çıkarıma işaret etmektedir. Birincisi, ekonomik faaliyetin perakende fiyatları üzerindeki etkisi, farklı kalite segmentlerindeki ürünler arasında heterojenlik sergilemektedir. İkincisi, halihazırda daha düşük kaliteli ürünler tüketen düşük gelirli tüketiciler, yaşam maliyetlerinde daha yüksek artışlarla karşı karşıya kalmaktadır. Düşük gelirli tüketicilerinin göreli satın alma gücü azaldıkça, reel gelir dağılımı bozulma eğiliminde olacaktır. Bu nedenle, sonuçlarımız, gelir eşitsizliğine duyarlı politika yapıcıları için uyarıcı nitelikte olup, durgunluk dönemlerinde düşük gelirli tüketicilerin refah kaybı yaşadıklarına işaret etmektedir.

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