

Borraz, Fernando; Livan, Giacomo; Rodríguez-Martínez, Anahí; Picardo, Pablo

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# Price, sales, and the business cycle: a time series principal component analysis\*

Fernando Borraz<sup>†</sup>      Giacomo Livan<sup>‡</sup>      Anahí Rodríguez-Martínez<sup>§</sup>

Pablo Picardo<sup>¶</sup>

## Abstract

The main contribution of this work consist on studying sales behaviour and their relationship with local market conditions like labor market indicators through a time series principal component analysis. We study the correlation structure of a large database on prices and found that all product sectors share a common correlation structure and the highest correlation and significance is achieved between employment variation and the first principal component, mostly in the second week of the following month. Sales or promotions, are a channel for price flexibility because firms can use them to change effective prices keeping sticky reference prices. We use a rich database of retail prices from Uruguay to characterize prices' flexibility, the behavior of sales, and their relationship with local market conditions like labor market indicators. Finally, we find a positive and significant relationship between sales and unemployment and perform a time series principal component analysis to study these relationships.

*Keywords:* price rigidity, sales, unemployment, principal component analysis

*JEL classification codes:* E31, E32, E24, C38

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\*Disclaimer: Any errors made in this paper are the sole responsibility of the authors. The authors' views do not necessarily reflect those of Banco Central del Uruguay, Banco de Mexico or CEMLA.

<sup>†</sup>Banco Central del Uruguay, Departamento de Economía de la Facultad de Ciencias Sociales de la Universidad de la República and Universidad de Montevideo. E-mail: fborraz@bcu.gub.uy.

<sup>‡</sup>University College London.

<sup>§</sup>Centro de Estudios Monetarios Latinoamericanos.

<sup>¶</sup>Banco Central del Uruguay.

# 1 Introduction

In the new Keynesian model of Galí (2008) price rigidity is relevant to explain the real effects of monetary policy on output. The seminal work of Blinder (1991) was followed by literature that estimates the degree of price rigidity (Bils & Klenow (2004), Klenow & Malin (2010), Nakamura & Steinsson (2008), Nakamura & Steinsson (2013) and Klenow & Kryvtsov (2008)). The consensus of this literature was that prices were not as flexible as previously thought. Thus, the discussion became about quantifying the degree of price rigidity and not so much whether it exists or not. Additionally, it is often argued that sales (temporarily and featured price reductions) are a channel for price flexibility. Firms can use them to change effective prices keeping sticky reference prices. However, the empirical work has the difficulty of defining sales because not all price reductions are a promotion. Nakamura & Steinsson (2008) use an algorithm to define sales to find that in the US promotions are an important source of price flexibility. Traditionally, from a macro point of view, the sales were not considered because they are not related to aggregate phenomena.

As new micro databases become available (micro CPI data, scanner data, web scrapping, etc) the literature started to analyze the relationship between prices and the business cycle at the micro-level. In particular, it was discussed how prices related to the economic cycle and how the price variations at the micro-level are related to macroeconomics variables as unemployment.

Coibion et al. (2015) for the US with micro-data of prices and quantities find that the prices paid by the consumers fall with unemployment (substitution for cheaper goods, and or buying in cheaper stores). They find that sales do not play an important role, and they are not related to unemployment. However, they conclude that: "a 2-percentage-point rise in the unemployment rate lowers inflation in effective prices by 0.2 to 0.3 percentage points relative to inflation in posted prices for a given UPC". In the 2008 crisis the unemployment rose 5 percentage points which implies that the reported official inflation was overestimated by at least 0.5 percentage points (the goal is 2%). However, Gagnon et al. (2017) find that the results of Coibion et al. (2015) are explained by the data management and in particular the censorship of price changes greater than 8% to mitigate the effect of outliers (nonstandard methodological choices). They conclude that the substitution effect is not important.

In contrast and using a different price base (CPI) to US and UK Kryvtsov & Vicent (2020) find that promotions are countercyclical. That is, promotions increase with unemployment. We have to take into account that the CPI generally does not capture this effect of promotions. Moreover, Anderson et al. (2017) find that promotions do not respond to economic shocks captured by the local unemployment rate. Therefore, the relationship between sales and unemployment is an open and interesting question to be answered empirically.

In this paper first, we use a rich dataset of retail prices from Uruguay to characterize prices' flexibility, the behavior of sales, and their relationship with local market conditions like labor market indicators. In our micro data set, the supermarket reports whether the product is on sale or not and it is not necessary an algorithm to identify it. Moreover, there may be sales that are not associated with price reductions such as mailing advertising or bundling. We find a positive and significant relationship between sales and unemployment. The firms' use sales in the lower part of the business cycle to increase revenue.

Second, we perform a novel time-series principal component analysis (PCA) to explore the relationships between sales and unemployment. We use PCA to reduce the dimensionality of the data set while retaining as much as possible the variation in the data set. The principal components (PCs) are linear transformations of the original set of variables, and are uncorrelated and ordered so that the first few components carry most of the variation in the original data set.

Principal component analysis procedure was used to analyze the correlation between the prices of different products of each sector based on the 2014-2019 price database from Uruguay. With PCA, we were able to reduce the dimensionality of the data and we figured out which sector has high average price changes of commodities and where unemployment had more impact.

We find that all sectors share a common correlation structure and that highest correlation and significance is achieved between employment and Principal Component in the second week of the following month, especially for food, fruit and vegetables, and personal care sectors. The main contribution of this work consist on studying sales behaviour and their relation with micro-economic variables such as unemployment indicator through a time series principal component analysis.

The rest of the paper is organized as follows: Section 2 explores the literature on price stickiness and their relationship with micro and macroeconomic variables whereas Section 3 describes the data used for the calculations. Section 4 explain the methodological aspects of the paper and shows the most relevant results of this work. Finally, Section 5 summarizes some of the main insights and explores further work.

## 2 Literature Review

Based on the increased availability of retailer micro price level data, the literature adopted a micro approach to traditional macroeconomics topics like the real effects of monetary policy, price stickiness or the relationship between inflation and unemployment. The discussion moved from the analysis of macro data to the study of micro data. Nakamura & Steinsson (2008), for example, use the consumer price index (CPI) and the producer price index (PPI) from the U.S. Bureau of Labor Statistics (BLS) for the period 1988-2005 to study price stickiness. Their results show that regular prices last between eight and eleven months, after excluding sale prices. Temporary sales are an important source of (downward) price flexibility. Moreover, roughly one-third of price changes, excluding sales, are price decreases. On the other hand, price increases correlate strongly with inflation, but price decreases do not; and price changes are highly seasonal, mainly in the first quarter. Otherwise, in Glandon (2018) scanner data is used to investigate temporary price reductions (*sales*) and its role in aggregate price adjustment. This paper shows evidence that sales are positively correlated with the local unemployment rate during recessions and the CPI indexes used to deflate nominal consumption expenditure do not fully account for variation in sales.

Regarding models that try to explain microeconomic price rigidity, Golosov & Lucas Jr (2007) built a model based on a monetary economy in which repricing of goods is subject to a menu cost (fixed cost) with the presence of idiosyncratic shocks. This model is used to examine the behavior of Phillips curves by analyzing the correlation between inflation rates and levels of production and employment. Their main finding consisted of a small and temporary responses of real variables as output, employment, and prices to an increase in nominal wages. The real effects are less persistent than in other economies with time-dependent pricing.

Similarly, Kehoe & Midrigan (2015) built a menu cost model in which firms can either change their prices permanently (from their regular price) or temporarily (sales). Timing and magnitude of sales are fully responsive to the state of economy. They found that sales price changes contribution is small to the response of aggregate prices to monetary shocks. In other words, there is a small long run impact on the aggregate price level due price changes than there is due to regular price changes. This result is due to the fact that sales price changes are transitory.

In the case of Nakamura & Steinsson (2013), it reviewed and discussed evidence on price

rigidity from the macroeconomics literature. They found that fiscal stimulus, taxes, and increased on uncertainty are potential sources of variation in demand. Also, a huge amount of heterogeneity in the frequency of price change across sectors have implications regarding movements in relative prices and relative inflation rates across sectors. They explained that sales have to be treated separately to analyze the responsiveness of the aggregate price level to various shocks because (i) sales are highly transitory, (ii) the incentive for retailers to stagger the timing of sales, and (iii) the possible unresponsive characteristic of sales to macroeconomic shocks. Firms' decisions to have sales may be independent of macroeconomic conditions. In the first case sales are more independent to macro conditions than the decisions to change prices regularly. The frequency and size of sales fall when unemployment rates rise, Coibion et al. (2015). When unemployment rate increases, households substitute more of their expenditures towards low-price retailers, consistent with significant expenditure reallocation across retailers by households.

Furthermore, Eichenbaum et al. (2011) assess the importance of nominal rigidities with weekly data and the implications of cost change in prices. They found that the nominal rigidities are important and take the same trend of reference prices and costs. Their results concluded that reference prices have an average duration of one year. The retailer chooses a reference price duration for each product to keep their markup within specific bounds that are similar among different products. Also, they found that volatility of prices generally is greater than the one for the marginal cost.

### 3 Data

The available database is a rich unbalanced weekly panel that includes prices of 23,902 products from August 5th, 2014 to December 25th, 2019. Not all products appear all the time; there are 2,759,261 observations (with almost 10,000 products constantly appearing throughout the period). In 2019, for example, there were 14,274 products.

The source of this data is a major retail business from Uruguay. It is updated on a regular weekly basis and it can also be scraped through the supermarket website. All products were classified into 8 sectors or categories, where the most common products are food. The categories are:

- Food
- Fruits and vegetables
- Drinks (sodas, water, etc.)
- Drinks with alcohol
- Cleaning products
- Personal care products
- Tobacco products
- Other products

Over time, the share of product categories have not changed too much. However, there is a growing trend in food and other products, that represent about half of the sample.

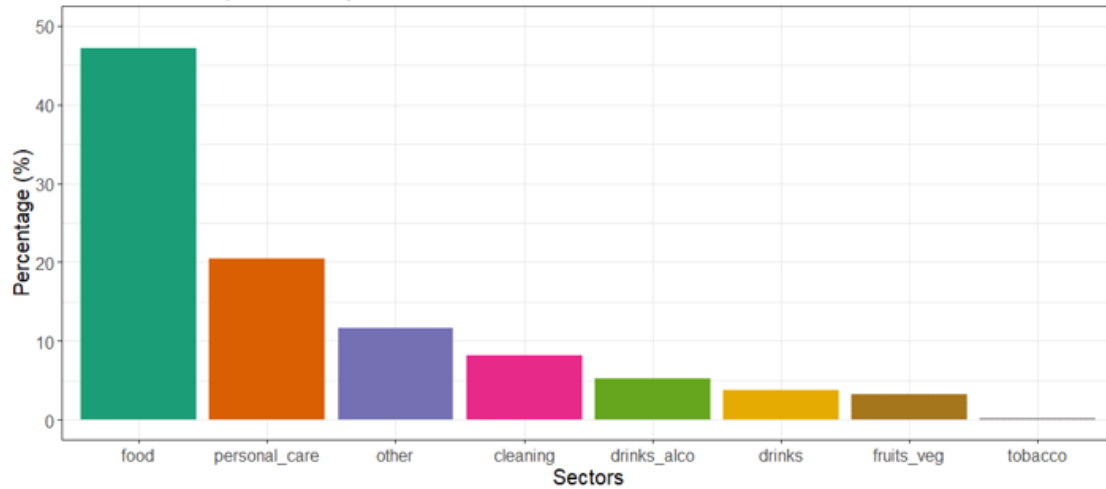


Figure 1: Distribution of product categories  
 Source: supermarket data, authors' classification.

Besides the description of the product, the price and date, there is a binary variable that indicates whether the product is on sale according to the supermarket. This is relevant because in the literature is usual to require an algorithm to define sales, Nakamura & Steinsson (2008). In our case we do not require the use of an algorithm. Also, in our sample a sale does not necessarily mean a reduction of the list price. It is possible that the item be included in the mailing list or bundling with another product. Moreover, the literature does not have a consensus regarding what defines a sale. Some commercial strategies as bundling and price discount can be considered as a sale even though there is not a price reduction. In our data, the store reports if the product is on sale and therefore we do not require the use of arbitrary algorithms to define a sale. On average, 6.7% of the products are indicated to be on sale on each month.

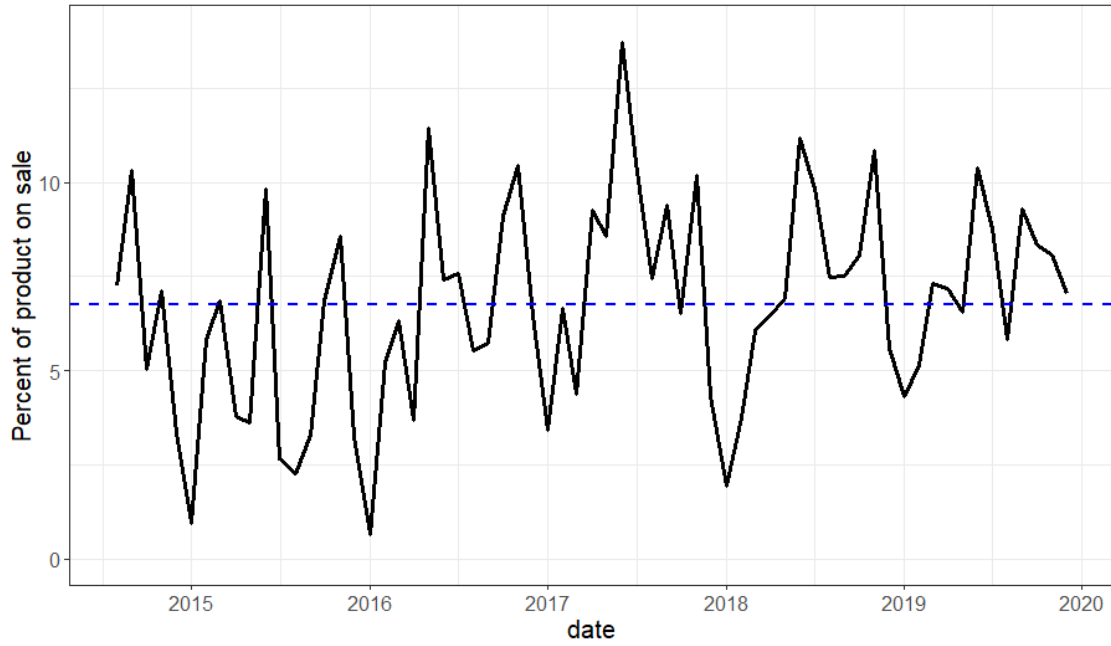


Figure 2: Monthly share of products labelled as *on sale*  
 Source: supermarket data.

Meanwhile, around 4.7% of products change its price within a month (3.4% up and 1.2% down). Also, there is a strong seasonality in all changes as well as in “sales” labelling. In 2015 and 2016, there are two price change outliers (11% and 16% respectively), after that most of the time this price flexibility is closer to 4%.

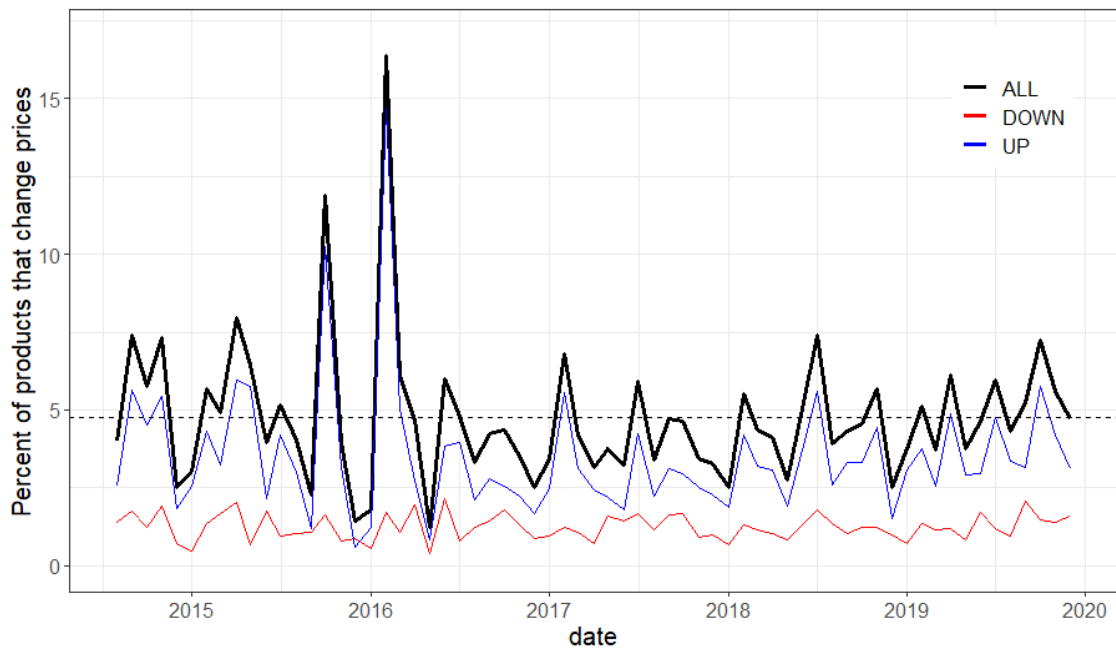


Figure 3: Monthly share of products whose price changed  
 Source: supermarket data.

As shown in the next figure, in June there are, on average, 10% of the products on sale. Similar peaks appear in November and, in January there is a minimum with 2.5% products on sale. For the one hand, regarding upward price changes, in February the share of products is almost 6% and In July and October, almost 5%. For the other hand, price reductions have its peak at the same time that sales (in June) with 1.7% of the products.



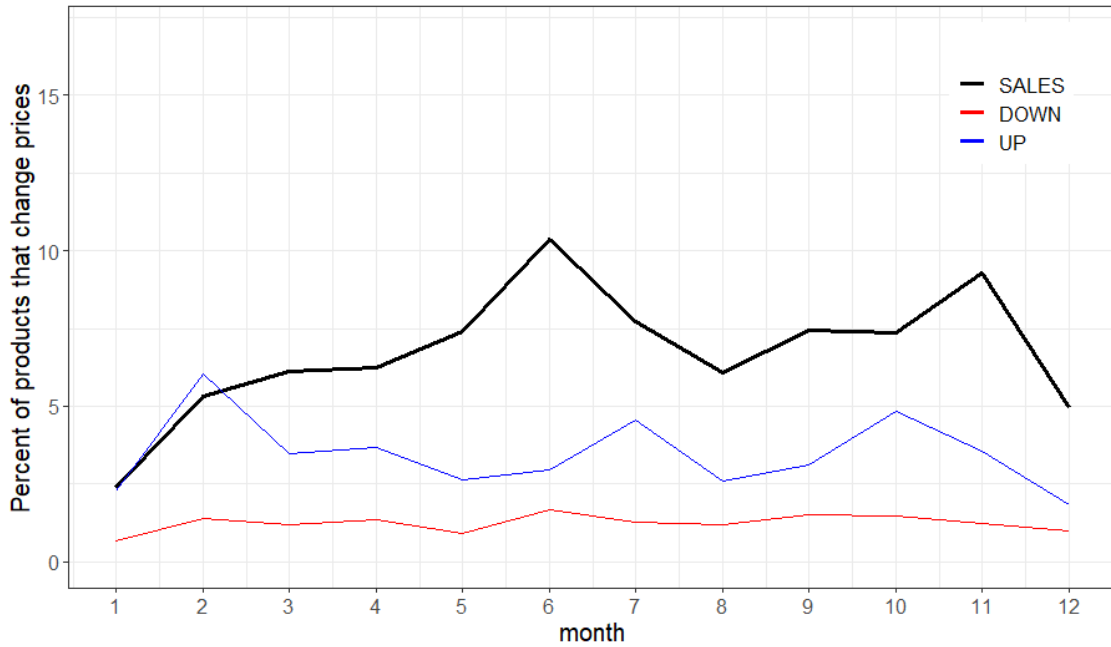


Figure 4: Seasonality of the share of products whose price changed  
Source: supermarket data.

If we consider only products on sale, only 13% refers to price changes, of which 9.2% refers to price decreases and 3.8% to a price increases. As the following figure shows, products on sale that changed its price go side by side with price decreases. However, when sales are removed, price decreases practically disappears.

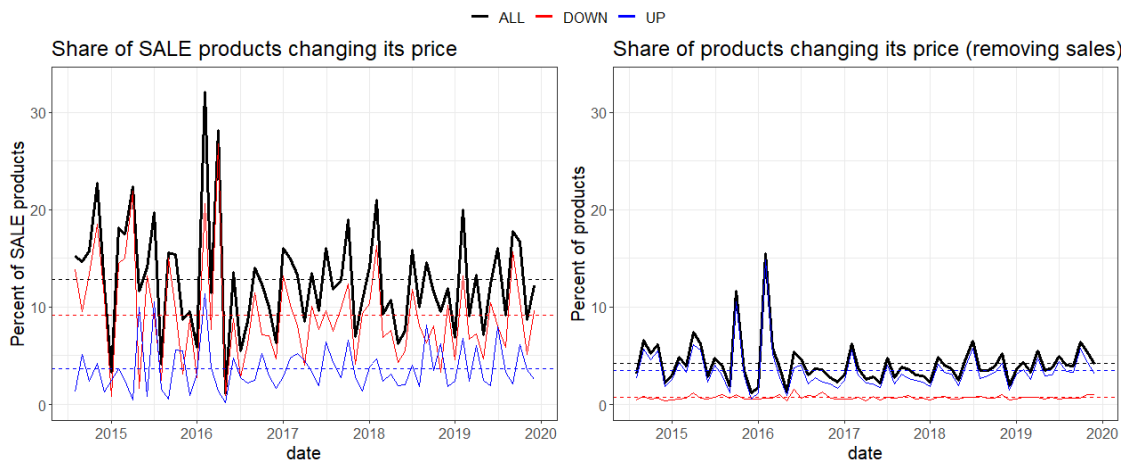


Figure 5: Monthly share of products, on sale or not, whose price changed  
Source: supermarket data.

Some of the products were directly linked to the official Consumer Price Index (CPI). These products represent 12.1% of the total (14.3% if we consider only products in 2019).

We consider data for employment and unemployment that are taken from the Uruguayan National Household Survey (ECH), conducted by the National Institute of Statistics (INE). The ECH is administered throughout the year with the purpose of generating an accurate picture of the urban Uruguayan employment situation along with socio-economic characteristics of that population. We use data from the survey from 2014 to 2019 for Montevideo, the capital of Uruguay. As the following figure shows, during the period of analysis (from August 2014 to December 2019), unemployment rate was rising and employment rate was falling, both persistently.

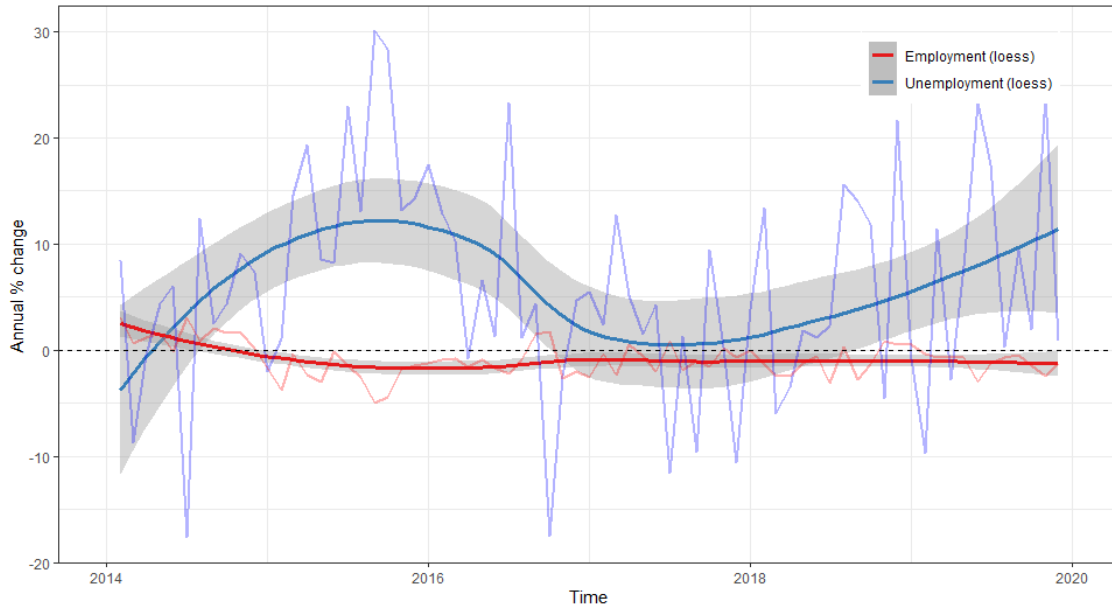


Figure 6: Percent change of rate of employment and unemployment in Montevideo, Uruguay  
 Source: Uruguayan National Household Survey (ECH), National Institute of Statistics (INE).

There is also a seasonality in these variables, especially in the unemployment rate. For example, in the period considered, unemployment grew more in the last two quarters. We perform a seasonal adjustment for these series. Therefore in the empirical analysis we use the seasonally adjusted series. In Figure 8a and 8b we analyzed the price dispersion for each product category with sales and without sales. We find no large differences between the analysis with and without sales except for the "other" product category, which has a larger price dispersion with sales. We find other slight differences in the fruits and vegetables and personal care categories.

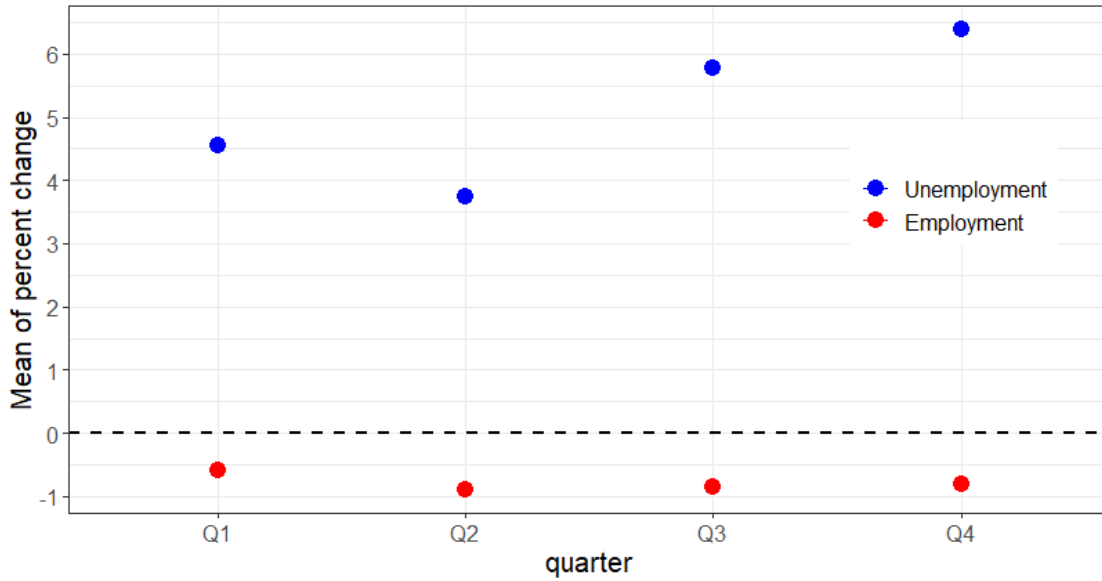
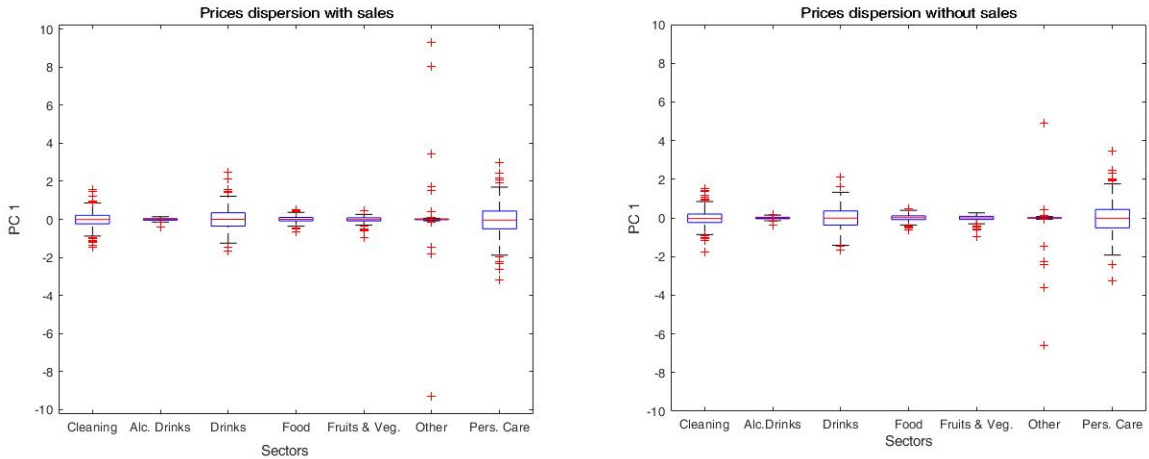


Figure 7: Mean of percent change of rate of employment and unemployment by quarters  
 Source: Uruguayan National Household Survey (ECH), National Institute of Statistics (INE).



(a) Price dispersion with sales

(b) Price dispersion without sales

Figure 8: Price dispersion with and without sales

Source: Uruguayan National Household Survey (ECH), National Institute of Statistics (INE).

## 4 Methodology and results

### 4.1 Sales and unemployment

We estimate the following fixed effects panel regression to analyze the relationship between sales and unemployment:

$$sale_{i,t} = \alpha_i + \alpha_t + \beta * unemployment_{i,t-3} + \varepsilon_{it} \quad (1)$$

where sale is the probability that a product  $i$  was labelled as on sale by the supermarket in the month  $t$ . In the right side there is a fixed effect for product ( $i$ ) and time ( $t$ ) and the unemployment index that is three months lagged (because the release of the index is three month after). Because of the correlation of the error term, we clustered the standard errors at the product and time level.

Table 1: Regression for the sale probability with product and time fixed effects

<i>Dependent variable:</i>	
Probability of being on sale	
Unemployment	0.006*** (0.001)
Observations	685,343
R <sup>2</sup>	0.279
Adjusted R <sup>2</sup>	0.253
Residual Std. Error	0.184 (df = 661377)
Controls:	FE (products & time). Clustered errors at product & time level in parentheses.
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 1 shows a positive and significant relationship at the micro-level between sales and unemployment. As the economy worsens with increases in unemployment, the supermarket uses sales to a greater extent as a mechanism for price flexibility and to stimulate revenue in a negative scenario. This result is in contrast with Coibion et al. (2015) who found that sales are not relevant from a macroeconomic perspective and they are not related to the business cycle.

We also estimate the same panel regression but with the price change probability as the dependent variables (instead of the sale probability).

Table 2: Regression for the price change probability with product and time fixed effects

<i>Dependent variable:</i>		
Probability of price change		
	All products	Without sales
Unemployment	-0.009*** (0.0003)	-0.010*** (0.0003)
Observations	685,343	668,624
R <sup>2</sup>	0.176	0.154
Adjusted R <sup>2</sup>	0.146	0.123
Residual Std. Error	0.107 (df = 661377)	0.124 (df = 644938)
Controls:	FE (products & time). Clustered errors at the product & time level in parentheses.	
Note:	*p<0.1; **p<0.05; ***p<0.01	

We find a negative and significant relationship between the probability of price change and unemployment (see Table 2). This result indicates that price changes become infrequent in the worst stage of the business cycle.

We also estimate equation (1) for each of the categories of products in our sample. Table 3 shows that the results remain the same for most of the products. Interestingly for the cleaning product category we observe a negative and significant relationship between sales and unemployment. This result could indicate that cleaning items are procyclical. One possible explanation may be that people stay longer in their homes when unemployment rises and they are more attentive to cleaning it.

Table 3: Regressions for the probability of being on sale by category, with unemployment

<i>Dependent variable:</i>							
Probability of being on sale							
	food	pers.care	cleaning	alc. drinks	drinks	fruitveg	other
unemp- loyment	0.008*** (0.001)	0.004** (0.001)	-0.006*** (0.002)	0.010*** (0.002)	0.023*** (0.002)	0.009*** (0.002)	-0.003** (0.002)
Obs.	366,936	133,807	55,294	49,059	28,670	18,722	31,243
R <sup>2</sup>	0.256	0.335	0.295	0.219	0.241	0.352	0.467
Adj.R <sup>2</sup>	0.232	0.309	0.268	0.197	0.215	0.322	0.414
Res. S.E.	0.181	0.201	0.194	0.176	0.207	0.103	0.115
df=	355581	128845	53274	47749	27691	17886	28401

Controls: FE (products & time). Clustered errors at the product & time level in parentheses.  
*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

One concern with the previous results is individuals can shift in recession from employment to inactive and the unemployment rate would not be a good measure on economic conditions. Therefore, as a robustness check we estimate the sales regression but against the employment rate (defined as the number of employed people divided by the total labor force). Table 4 shows the results when we use employment data (seasonal adjusted and with three lags) instead of unemployment.

Table 4: Regressions for the probability of being on sale for all and by category with **employment**

<i>Dependent variable:</i>								
Probability of being on sale								
	all	food	pers.care	cleaning	alc. drinks	drinks	fruitveg	other
employ- ment	-0.004*** (0.001)	-0.006*** (0.0005)	-0.003** (0.001)	0.004*** (0.001)	-0.007*** (0.001)	-0.016*** (0.002)	-0.006*** (0.002)	-0.002 (0.001)
Obs.	685,343	366,936	133,807	55,294	49,059	28,670	18,722	31,243
R <sup>2</sup>	0.279	0.256	0.335	0.295	0.219	0.241	0.352	0.467
Adj.R <sup>2</sup>	0.253	0.232	0.309	0.268	0.197	0.215	0.322	0.414
Res.S.E.	0.184	0.181	0.201	0.194	0.176	0.207	0.103	0.115
df=	661377	355581	128845	53274	47749	27691	17886	28401

Controls: FE (products & time). clustered errors at the product & time level in parentheses.

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 4.2 Principal component analysis

In this section we proceed to study the price correlation structure of the products introduced above. Given their partition in terms of sectors (i.e., food, drinks, etc.) such products are naturally organised in terms of clusters, and we reasonably expect correlations between prices to be stronger between the products belonging to the same clusters. Such a structure naturally lends itself to dimensionality reduction, which we will perform by means of Principal Component Analysis (PCA). In a nutshell, we shall extract from each sector time series (the principal components) whose dynamics over time are representative of the price dynamics of all or some of the products belonging to it. We will test whether such time series display significant correlations and/or causal relationships with our macroeconomic variables of interest.

Let us start by introducing PCA in general terms. Suppose we are interested in studying the statistical properties of  $N$  time series, each one made of  $T$  observations. Let us collect their standardized data (i.e., zero mean and unit variance)  $x_{it}$  – with  $i = 1, \dots, N$ , and  $t = 1, \dots, T$  – in an  $N \times T$  matrix  $\mathbf{X}$ , which we can then use to construct the  $N \times N$  Pearson correlation matrix  $\mathbf{C} = \mathbf{X}\mathbf{X}^T/T$ . By definition, such a matrix is symmetric and positive definite. Hence, it yields  $N$  non-negative eigenvalues  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_N \geq 0$ . The corresponding eigenvalue problem can be written as

$$\mathbf{C}\mathbf{V}^{(i)} = \lambda_i \mathbf{V}^{(i)} \quad (2)$$

where  $\mathbf{V}^{(i)} = (V_1^{(i)}, V_2^{(i)}, \dots, V_N^{(i)})$  is the normalized eigenvector for the  $i$ -th eigenvalue. Since  $\mathbf{C}$  is symmetric, the eigenvectors  $\mathbf{V}^{(i)}$  are mutually orthogonal (i.e.,  $\sum_{j=1}^N V_j^{(i)} V_j^{(\ell)} = 0$  for  $i \neq \ell$ ).

The main point about PCA is that the set of  $N$  time series  $x_{it}$  can be mapped onto a set of  $N$  *exactly uncorrelated* standardized time series  $e_{it}$ , called principal components (PCs). This is achieved with the following linear transformation:

$$e_{it} = \frac{1}{\sqrt{\lambda_i}} \sum_{j=1}^N V_j^{(i)} x_{jt} \quad (3)$$

where

$$x_{it} = \sum_{k=1}^N \sqrt{\lambda_k} V_i^{(k)} e_{kt} . \quad (4)$$

Exploiting eigenvector orthogonality one can immediately verify that the new variables introduced in Eq. (4) are indeed uncorrelated:

$$\frac{1}{T} \sum_{t=1}^T e_{it} e_{jt} = \delta_{ij} , \quad (5)$$

where  $\delta_{ij} = 1$  if  $i = j$  and  $\delta_{ij} = 0$  otherwise.

All in all, Eq. (4) shows that the result of the PCA mapping is to decompose the time evolution of each time series  $x_i$  into  $N$  uncorrelated contributions whose standard deviation is proportional to the square root of the eigenvalues of the empirical correlation matrix. Therefore, the ratios  $\lambda_i/N$  quantify the fraction of the overall variance in the original data explained by the  $i$ -th PC.

Now, suppose, that a few eigenvalues, e.g., the first  $M$ , are much larger than the remaining ones. Then, by virtue of equation Eq. (4), one could approximate each  $x_i$  as

$$x_{it} \sim \sum_{k=1}^M \sqrt{\lambda_k} V_i^{(k)} e_{kt} . \quad (6)$$

In the limiting case of a single eigenvalue being much larger than any other ( $\lambda_1 \gg \lambda_i$  for  $i = 2, \dots, N$ ) one could eventually approximate all variables with the first principal component  $e_1$ :

$$x_{it} \sim \sqrt{\lambda_1} V_i^{(1)} e_{1t} . \quad (7)$$

Despite being rather crude, the above approximation is a useful first step to understand the collective dynamics of multivariate time series. In particular, the inspection of the first eigenvector's components ( $V_1^{(1)}, \dots, V_N^{(1)}$ ) provides relevant insight into the role played by the first PC. In fact, when most components  $V_i^{(1)}$  share the same sign, then the first PC  $e_1$  acquires a clear meaning as a source of positive correlation in the system, as it “drives” most variables  $x_i$  in the same direction.

The first two columns of Table 5 show summary statistics for the first PCs of the price time series in the sectors we consider. We report the fraction of positive components in the first eigenvector of the sector's correlation matrix ( $n_+ = \sum_{i=1}^N \Theta(V_i^{(1)})/N$ , where  $\Theta$  denotes Heaviside's step function), and the fraction of variance explained by the corresponding PC ( $\lambda_1/N$ ). As it can be seen from the latter number, the first PC of each sector explains a considerably large fraction of the variance of its price dynamics, ranging from more than 30% to 55% in the case of alcoholic drinks. Furthermore, the values of  $n_+$  – all abundantly larger than 50% – show that the first PC is a clear source of positive correlation between the prices of most products in each sector.

Table 5: Summary statistics of the first two PCs of each sector.  $n_+$  denotes the fraction of positive components in the corresponding eigenvectors.

	1st PC		2nd PC	
	$n_+$	% of var. explained	$n_+$	% of var. explained
food	72.3%	45.6%	56.4%	11.6%
pers. care	68.8%	43.2%	50.8%	11.7%
cleaning	70.3%	43.9%	55.2%	10.3%
alc. drinks	68.1%	55.0%	55.2%	10.5%
drinks	68.1%	39.1%	53.8%	12.1%
fruits & veg.	75.5%	31.2%	55.1%	12.1%
other	60.2%	34.4%	68.1%	16.1%

If we extend the simple approximation in Eq. (7) to include the second PC we obtain

$$x_{it} \sim \sqrt{\lambda_1} V_i^{(1)} e_{1t} + \sqrt{\lambda_2} V_i^{(2)} e_{2t} . \quad (8)$$

The last two columns in Table 5 provide summary statistics for the second PC of each sector. As it can be seen, the percentage of the overall variance explained by the 2nd PC is still considerable, ranging between roughly 10% and 16% in all sectors. However, the values of  $n_+$  are all around 50% in this case (with the notable exception of the “other” sector), signaling that the 2nd PC does not have a clear interpretation as a source of correlation between products.

The stylized model in Eq. (8) explains more than *half* of the variance in price dynamics for each sector, which suggests that the first two PCs may hold relevant information in relation to the macroeconomic variables of interest to our study. In Table 6 we look at the correlation between monthly records of employment / unemployment and the values of each sector’s first PC in the final week of the same months. We observe a remarkably strong positive (negative) correlation between employment (unemployment) and the first PCs ( $p < 0.01$  in all cases). Correlations with second PCs are not statistically significant ( $p > 0.1$  in all cases) and are therefore not reported. The positive correlation between the first PCs of all sectors and employment is visually clear from Fig. 9, where the time evolution of all variables (after suitable standardization) is plotted.

Table 6: Pearson correlation between employment / unemployment and the value of the first PC of each sector in the final week of the month of the indicators’ publication.

	employment	unemployment
food	0.920***	-0.796***
pers. care	0.917***	-0.807***
cleaning	0.922***	-0.804***
alc. drinks	0.907***	-0.768***
drinks	0.913***	-0.797***
fruits & veg.	0.882***	-0.747***
other	0.901***	-0.802***

*Note:* \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$



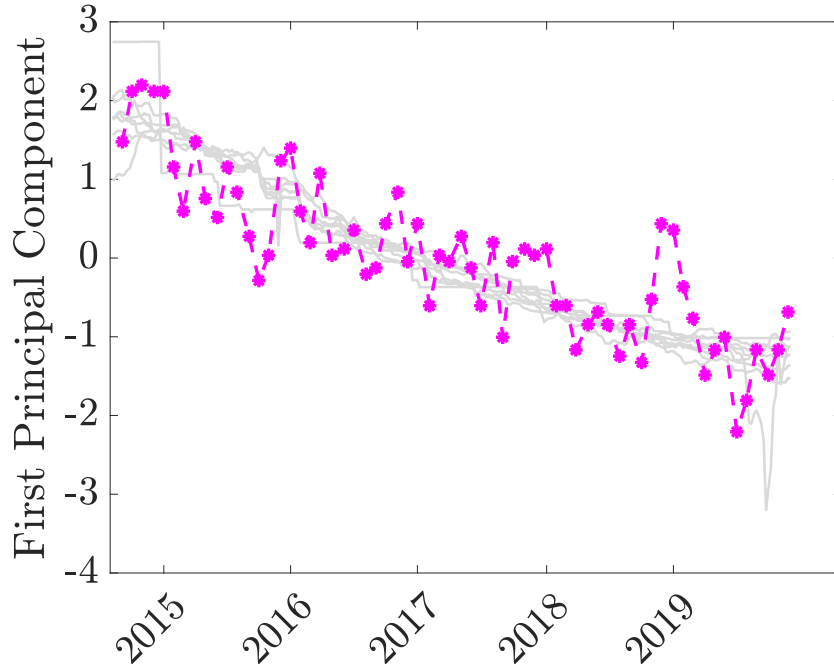


Figure 9: Time evolution of the PCs of the seven product sectors (grey solid lines) and of employment (purple dots and dashed line). The employment time series has been standardized for comparison purposes.

The above results clearly hint at a rather strong relationship between employment / unemployment and the price dynamics of the sectors we consider, as explained by the first PC. We further investigate this by measuring causal interactions. In Table 7 we report the results of Granger causality tests, which determine whether variation in one variable is explanatory of future variation in another variable with a certain time lag (for a complete description of the test see Granger (1969)). Here, we will test whether employment / unemployment Granger-cause the first two PCs of each sector in the final week of the second month after the publication of their values. We find substantial causality across board. In particular, we find that employment Granger-causes (with different levels of statistical significance) the first two PCs of all sector except for “other”. In addition, we find unemployment to Granger-cause the first PC of the alcoholic drinks and fruits & vegetables sectors, and the second PC of all sectors except for food and other. Similar results and similar levels of significance are obtained when testing Granger causality between macroeconomic variables and PC values in the final week of the first month after their publication. Also, the results are qualitatively unchanged when considering PC values in different weeks of the month. These results are available upon request.

Table 7: F-statistic of Granger causality tests between employment / unemployment and the values of the first / second PCs in the final week of the second month after the publication of the indicators.

	1st PC		2nd PC	
	employment	unemployment	employment	unemployment
food	5.07***	2.19	5.57**	2.48
pers. care	6.46**	2.71	5.27**	6.91***
cleaning	5.92***	1.45	6.98**	5.08***
alc. drinks	6.47**	8.07***	1.80***	1.50***
drinks	3.81**	9.86	1.59***	7.32***
fruits & veg.	1.75***	1.80***	1.79***	8.15***
other	0.16	8.69	2.52	1.67

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 5 Conclusions

The main contribution of this work consist on studying sales behaviour and their relation with microeconomic variables such as unemployment indicator through a time series principal component analysis. The time series principal component analysis shows that all of the product categories share a common correlation structure and the highest correlation and significance is achieved between employment variation and the first principal component, mostly in the second week of the following month. Additionally, we find substantial causality between unemployment and the first principal component of the alcoholic drinks and fruits and vegetables sectors.

We use a rich weekly price database from the biggest supermarket in Uruguay to analyze the relationship between prices, sales, and business cycle conditions captured by the unemployment rate. The results show a strong relationships between unemployment and price dynamics of the product categories we analyze. In particular, we find a positive and significant relationship between sales and unemployment.

We analyze the behavior for each product category, in particular, food, alcoholic drinks, drinks and fruits and vegetables have high and positive significant relationship between the probability of being on sale and unemployment. On the other hand, food, cleaning, alcoholic drinks, drinks and fruits and vegetables have a high and negative significant relationship between the probability of being on sale and employment.

Finally, it is still necessary to extend the analysis by including more microeconomic variables and more sectors of the Uruguayan economy. This would allow us to define wider policy implications in the Uruguayan economy.

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