

# Price rigidity with microeconomic data

Fernando Borraz<sup>1</sup>    Giacomo Livan<sup>2</sup>    Pablo Picardo<sup>1</sup>    Anahí Rodríguez<sup>3</sup>

<sup>1</sup>Banco Central del Uruguay

<sup>2</sup>University College London

<sup>3</sup>CEMLA

Financial Technologies and Central Banking  
Mexico City, November 12-14, 2019



BCU



CEMLA  
CENTRO DE ESTUDIOS MONETARIOS LATINOAMERICANOS

---

The opinions expressed here are those of the authors and do not reflect the views of CEMLA, University College London or the Central Bank of Uruguay.

# Summary

- Understand price rigidity
- Characterize *sales* and explore its role in price flexibility
- Relate sales and retail price changes with unemployment and other macroeconomic variables
- Dataset: + 2.5 million observations
  - 1 +20,000 retail product prices
  - 2 Weekly basis
  - 3 Macroeconomic data
  - 4 From 2014 to *now*

# Structure

- 1 Motivation
- 2 Literature review
- 3 Data
- 4 PCA
- 5 Forthcoming

## Why retail data?

- Price forecasting, e.g.: fruits and vegetables
- Study price flexibility → PM models and analysis
- Possibility to manage and process big databases with a panel structure

## Why retail data?

- Price forecasting, e.g.: fruits and vegetables
- Study price flexibility → PM models and analysis
- Possibility to manage and process big databases with a panel structure

## Why sales?

- Mechanism of price rigidity
- Correlation with local business cycle

## Why retail data?

- Price forecasting, e.g.: fruits and vegetables
- Study price flexibility → PM models and analysis
- Possibility to manage and process big databases with a panel structure

## Why sales?

- Mechanism of price rigidity
- Correlation with local business cycle

## Why Uruguay?

- Small and open country
- Rich dataset to exploit

# Literature review

# Literature review

- **Nakamura and Steinsson (2006)**. *Five facts about prices: a reevaluation of menu cost models.*
- **Nakamura and Steinsson (2013)**. *Informational rigidities and the stickiness of temporary sales.*
- **Eichenbaum and Jaimovich (2011)**. *Reference prices, costs and nominal rigidities.*
- **Coibion, Gorodichenko and Hee Hong (2013)**. *The cyclicalty of sales, regular and effective prices: business cycle and policy implications.*
  - ▶ **Gagnon, López-Salido, Sockin (2017)**. *Comment.*
- **Glandon (2018)**. *Sales and the (mis)measurement of price level fluctuations.*



# Data description

# Data

- Retail prices: **weekly** from August 2014 to *now* (October 2019)
  - ▶ Classification by *sectors*:
    - ① Drinks
    - ② Alcoholic drinks
    - ③ Food (sample)
    - ④ Fruit and vegetables
    - ⑤ Tobacco
    - ⑥ Personal care
    - ⑦ Other (stationery, pet food, toys, etc.)
  - ▶ Dummy variable for *sales* (1 on sale, 0 normal price).
  - ▶ Currency (Uruguayan pesos)
- Macrodata: **monthly** from May 2013 to September 2019
  - ▶ Cpi index
  - ▶ Employment rate
  - ▶ Unemployment rate

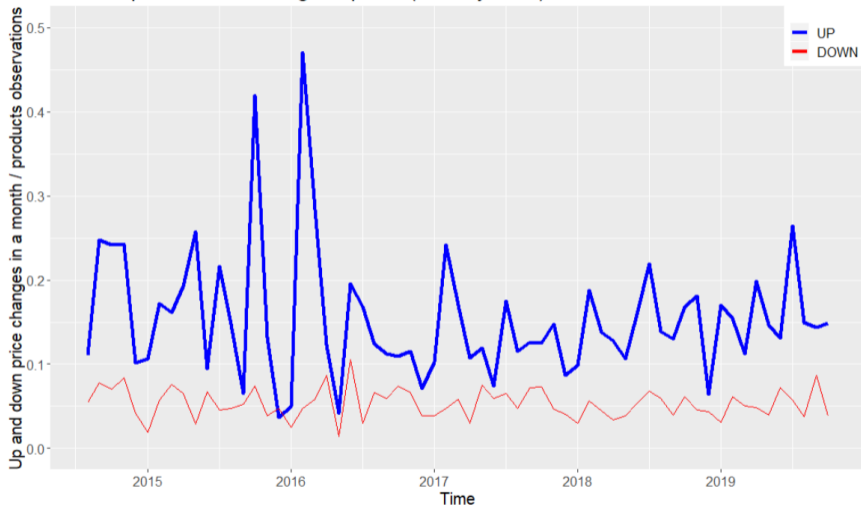
# Data

- Data cleaning for the PCA
  - ▶ Few constant prices were removed
  - ▶ Missing values were filled by assuming the last previous observation
  - ▶ Few multiple price cases, where a product reported multiple prices in the same week, we took the minimum price observed
- Softwares: **MATLAB + R**



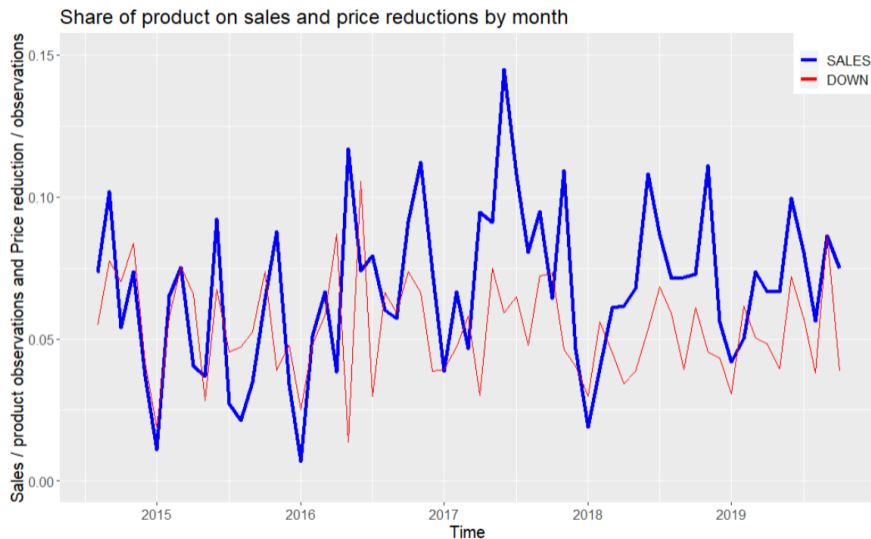
# How many products changed its price?

Share of products that change its price (monthly basis)



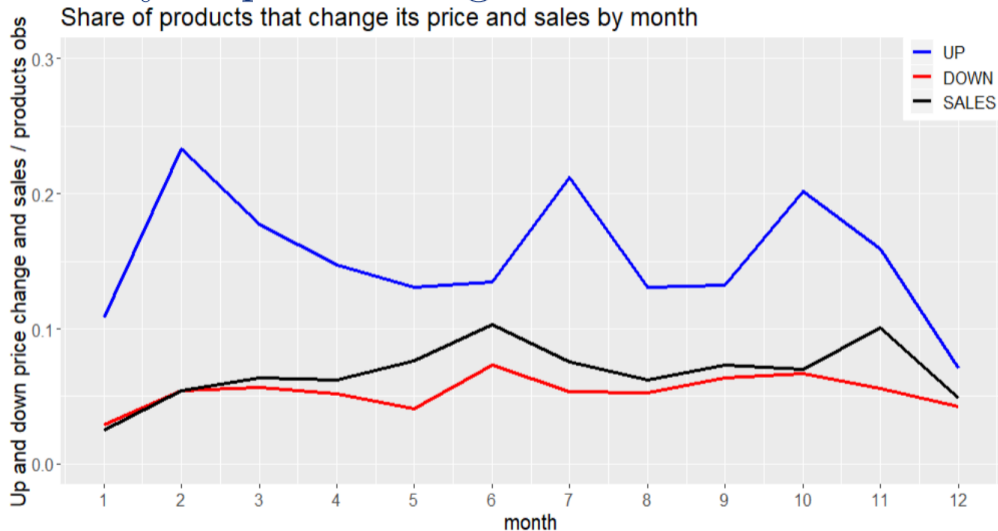
Source: Banco Central del Uruguay from supermarket data

# Price reductions and sales



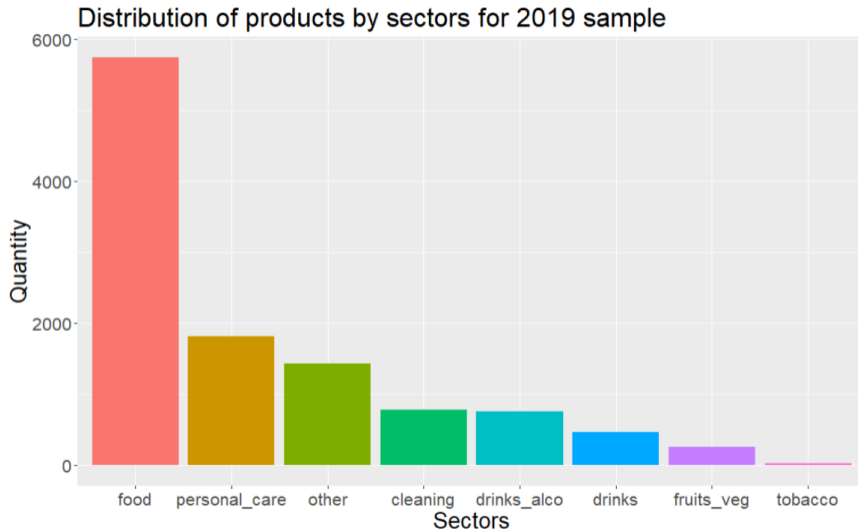
Source: Banco Central del Uruguay from supermarket data

# Seasonality of price changes and sales



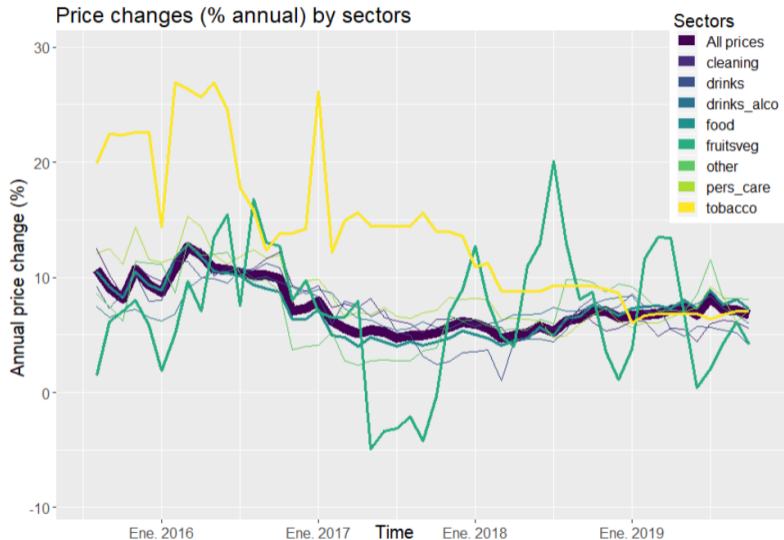
Source: Banco Central del Uruguay from supermarket data

# Product sectors



Source: Banco Central del Uruguay from supermarket data

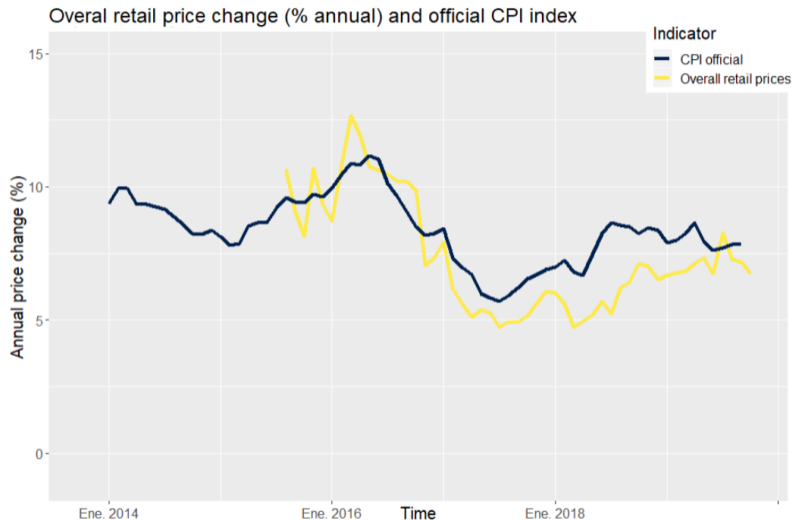
# Price variation: all sectors



Source: Banco Central del Uruguay from supermarket data

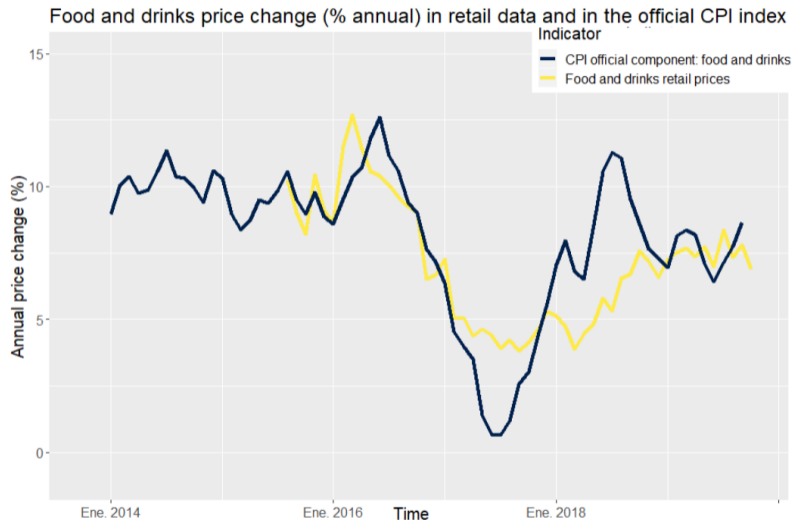


# Price variation: retail data vs. official CPI



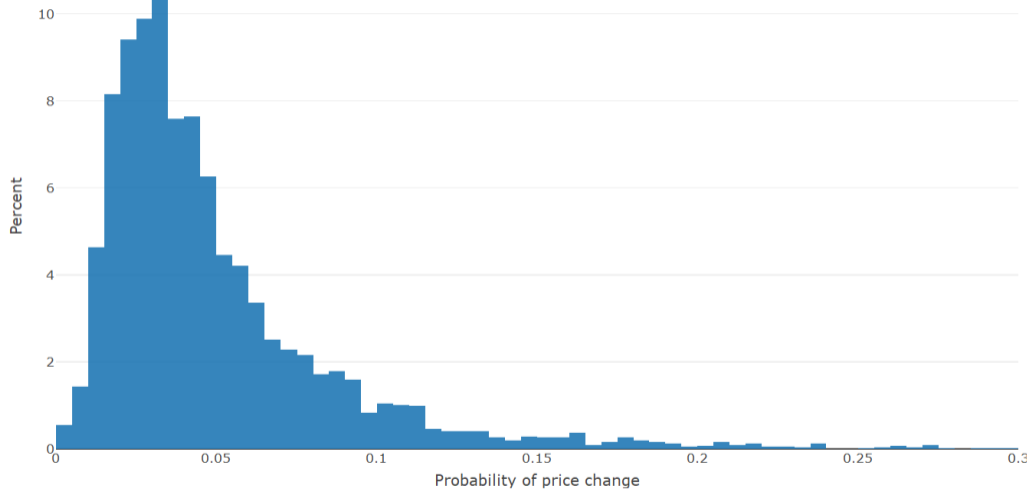
Source: Banco Central del Uruguay from supermarket data and National Institute of Statistics

# Price variation: food and drinks



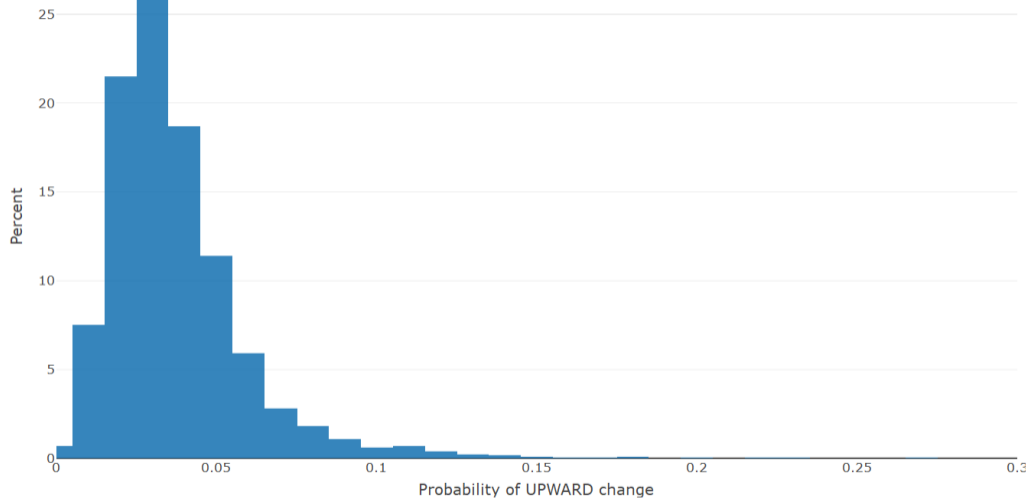
Source: Banco Central del Uruguay from supermarket data and National Institute of Statistics

# Price change probability



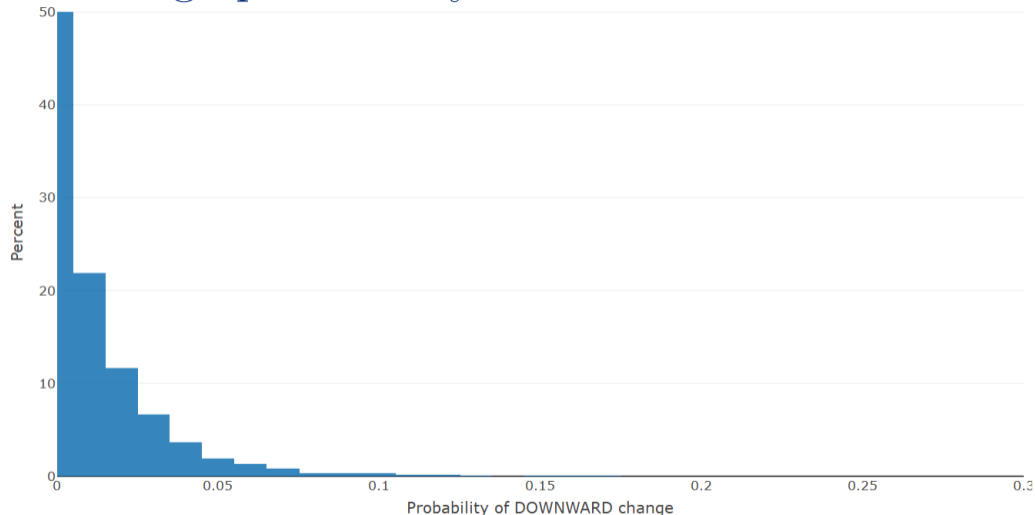
Source: Banco Central del Uruguay from supermarket data

# Price change probability: upward



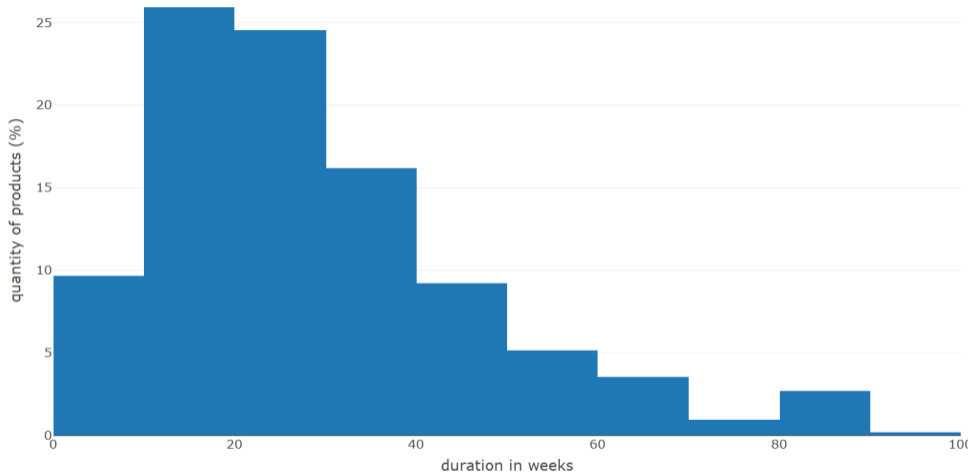
Source: Banco Central del Uruguay from supermarket data

# Price change probability: **downward**



Source: Banco Central del Uruguay from supermarket data

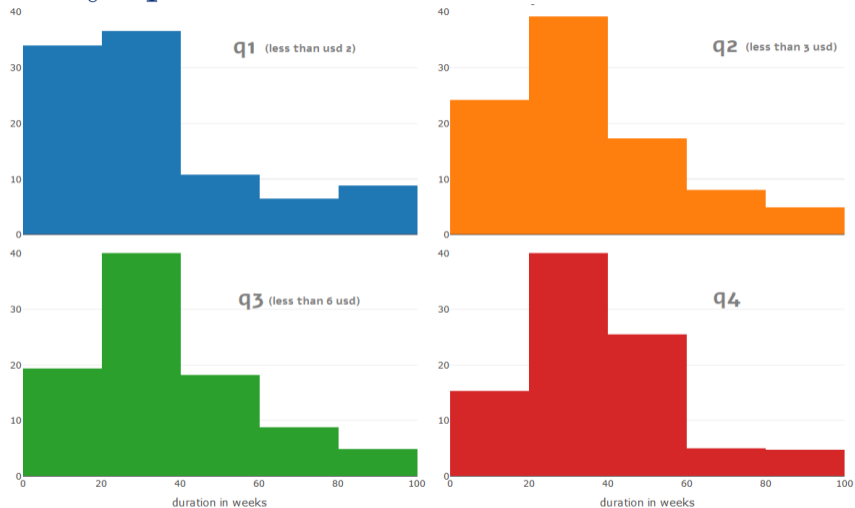
# Duration



$$\text{Duration in weeks} = \frac{-1}{1 - \log(\text{prob}(\text{price\_change}))}$$

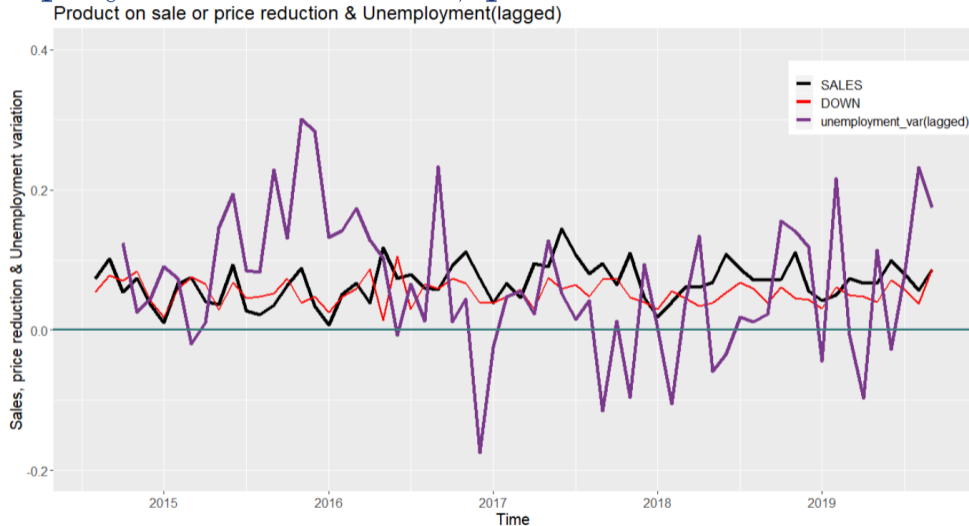
Source: Banco Central del Uruguay from supermarket data

# Duration by quantiles



Source: Banco Central del Uruguay from supermarket data

# Unemployment variation, price reduction and sales



Source: Banco Central del Uruguay from supermarket data and National Institute of Statistics



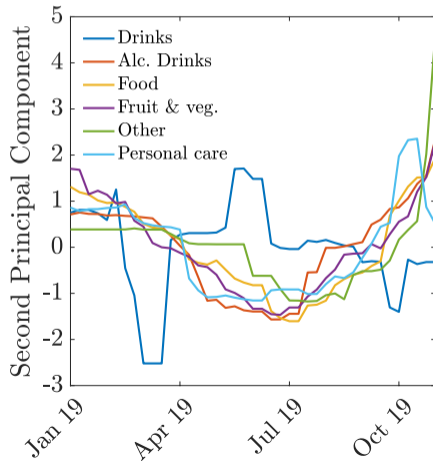
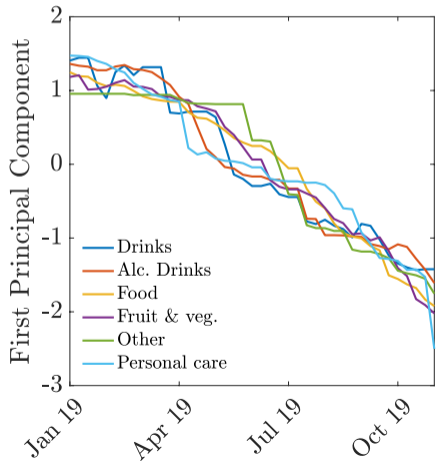
# Principal Component Analysis

## Data and PCs

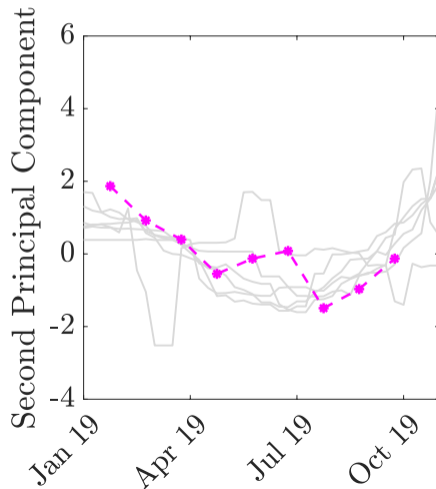
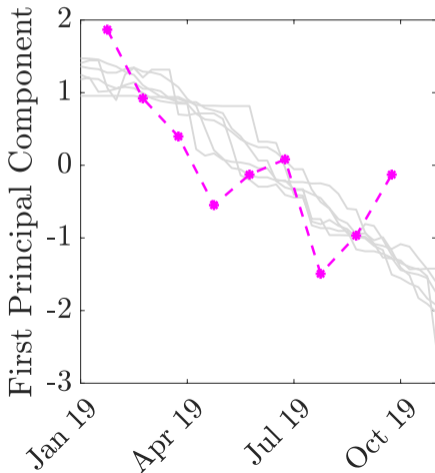
- January - October 2019 (41 weeks)
- Sectors:

<input type="checkbox"/> Drinks	$N = 132; \lambda_1/N = 34.8\%; \lambda_2/N = 14.0\%$
<input type="checkbox"/> Alc. drinks	$N = 608; \lambda_1/N = 53.6\%; \lambda_2/N = 12.5\%$
<input type="checkbox"/> Food	$N = 896; \lambda_1/N = 49.4\%; \lambda_2/N = 10.7\%$
<input type="checkbox"/> Fruit	$N = 140; \lambda_1/N = 38.1\%; \lambda_2/N = 16.9\%$
<input type="checkbox"/> Other	$N = 317; \lambda_1/N = 61.0\%; \lambda_2/N = 12.8\%$
<input type="checkbox"/> Personal	$N = 1601; \lambda_1/N = 45.9\%; \lambda_2/N = 14.3\%$

## 1st and 2nd PCs



## PCs and employment



## Correlations

- Highest correlation and significance is achieved between employment and PCs in 2nd week of the following month (especially with 2nd PC)

	1st PC	2nd PC
Drinks	0.74*	0.17
Alc. drinks	0.69*	0.60*
Food	0.64*	0.92***
Fruit & veg.	0.67*	0.82**
Other	0.60*	0.79*
Personal care	0.75*	0.75**

- Much lower correlation and significance in the case of unemployment

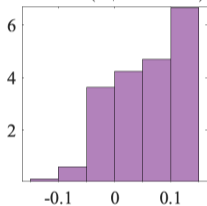
## Granger causality

- Granger causality (at 5% significance level, 1 time lag) of PCs by employment

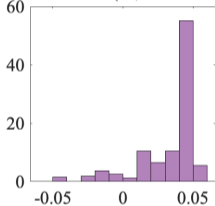
	1st PC	2nd PC
Drinks	×	×
Alc. drinks	✓	×
Food	✓	✓
Fruit & veg.	×	×
Other	×	×
Personal care	×	×

## 1st eigenvectors

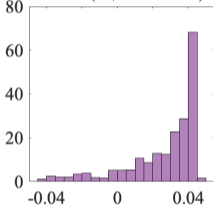
Drinks ( $n_+ = 78.0\%$ )



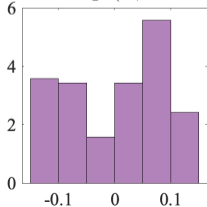
Alc. drink ( $n_+ = 89.6\%$ )



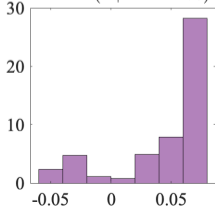
Food ( $n_+ = 88.4\%$ )



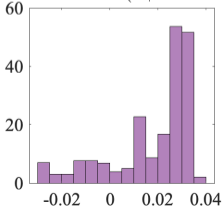
Fruit & veg. ( $n_+ = 57.1\%$ )



Other ( $n_+ = 83.6\%$ )

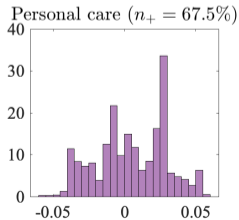
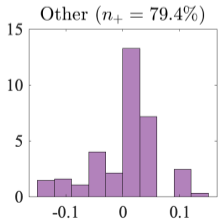
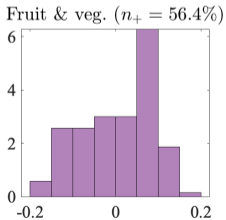
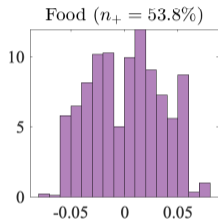
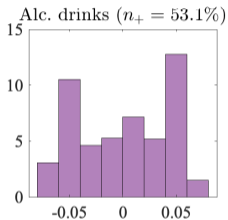
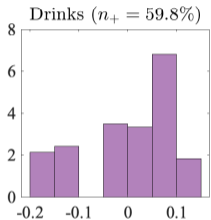


Personal care ( $n_+ = 82.3\%$ )



In 4 out of 5 cases there is a clear interpretation of 1st PC as a source of positive correlation between products, driven by employment (“sector mode” / “employment mode”)

## 2nd eigenvectors



Roughly 50-50 splits in 4 out of 5 sectors: possible interpretation as a source of negative correlation between groups of products w.r.t. 1st PC (different responses w.r.t. changes in employment)



## (Very preliminary) Conclusions

- All sectors share a **common correlation structure** as revealed by PCA
- 1st PC: “**employment mode**”
- 2nd PC: correlations with respect to employment mode, describing different product sensitivity
- Some **causality** (especially in the case of **food**)

# Forthcoming

# Forthcoming

- PCA with all the data
- More MACRO variables
- More MICRO variables
- Seasonality
- Price forecasting
  - ▶ **Nowcasting**
  - ▶ Martingale prediction market methodology

¡Gracias! / Thanks!

# Price rigidity with microeconomic data

Fernando Borraz<sup>1</sup>   Giacomo Livan<sup>2</sup>   Pablo Picardo<sup>1</sup>   Anahí Rodríguez<sup>3</sup>

<sup>1</sup>Banco Central del Uruguay

<sup>2</sup>University College London

<sup>3</sup>CEMLA

Financial Technologies and Central Banking  
Mexico City, November 12-14, 2019



BCU



CEMLA  
CENTRO DE ESTUDIOS MONETARIOS LATINOAMERICANOS

---

The opinions expressed here are those of the authors and do not reflect the views of CEMLA, University College London or the Central Bank of Uruguay.