

# Policy Uncertainty and Daily Consumer Card Payments

by G. Ardizzi, <u>S. Emiliozzi</u>, J. Marcucci and L. Monteforte<sup>\*</sup> (Banca d'Italia and UPB<sup>\*</sup>)

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\* The views expressed are those of the authors only and do not involve the responsibility of the Banca d'Italia and of UPB.

### Motivation

- The Great Moderation period was broken by the burst o the Global Financial Crisis of 2007-2008 in US and the Sovereign Debt Crisis in Europe
- Since then, uncertainty was considered one of the key factors in driving the recession
- Measuring Economic policy uncertainty (EPU) and investigating its economic impact took a center stage in the academic and policy debate
- Can daily Payment System data help us in investigating economic consequences of EPU innovations?

### The paper in one chart



# Main Findings

- Interesting seasonal pattern in payment data
- **Positive innovations in EPU** at the **daily frequency**:
  - Generate a temporary reduction in debit card transactions (consumer spending)
    - Precautionary savings
       Pistaferri-Jappelli,2010; Giavazzi-MacMahon,2013; Bayer et al., 2018
    - -Change in the quality of consumed goods Wong-Jaimovich-Rebelo, 2019; Michelacci-Pozzi-Paciello, 2020
  - Induce a temporary increase in Cash withdrawals Frenkel-Jovanovic, 1980; Bayer et al., 2018
- At monthly frequency we find significant and temporary effects of EPU innovations on payments coherently with daily frequency results

### Literature Review

#### **Economic Policy Uncertainty and macro**

Bloom & al. (2007); Bloom (2009); Bachmann & Bayer (2013); Bachmann, Elstner & Sims (2013); Jurado, Ludvigson & Ng (2015); Baker, Bloom & Davis (2016); Fernández-Villaverde, Guerron-Quintana & Kuester (2015); Caldara & Iacoviello (2018); Caldara, Iacoviello, Molligo & Prestipino (2019); Baker, Bloom & Terry (2020); Bloom & many al. (2020)

#### Payment systems data (Structural analysis)

Gelman, Kariv, Shapiro & Silverman (2014); Wang & Wolman (2016); Baker & Yannelis (2017); Baker (2018); Olaffson & Pagel (2018); Baugh, Ben-David & Park, Parker (2020); Chetty, Friedman, Hendren & Stepner (2020); Carvalho, Garcia, Hansen, Ortiz, Rodrigo, Rodriguez Mora & Riuz (2020); Dunn & Gholizadeh (2020); Huynha, Hob, Morin & Paarsch (2020); Baker, Farrokhnia, Meyer, Pagel, & Yannelis (2020)

#### Precautionary saving, income risk, and consumption

Jappelli & Pistaferri (2010); Giavazzi & McMahon (2012); Bayer, Lutticke, Pham-Do & Tjaden (2018); McKay (2017)

#### Payment systems data (Forecasting)

Carlsen & Storgaard (2010); Esteves (2009); Rodrigues & Esteves (2010); Galbraith & Tkacz (2013); Duarte, Rodrigues & Rua (2017); Aprigliano, Ardizzi & Monteforte (2018)

#### **Big data and economic/financial applications**

Giannone, Lenza & Primiceri (2017); Angelico, Marcucci, Miccoli & Quarta (2020); Buono, Kapetanios, Marcellino Mazzi & Papailias (2017); Bok, Caratelli, Giannone, Sbordone & Tambalotti (2018)

# Roadmap

- 1) Daily payments data
- 2) Seasonal Adjustment
- 3) EPU, E(P)U, EU
- 4) Econometric framework
- 5) Empirical results (Daily & Monthly freq.)
- 6) Conclusion

# Payment System Data

 BI-COMP: Bank of Italy's clearing and settlement system with daily aggregate info about value and number of transactions

 $\frac{BI - COMP \ tot.value \ 2018}{Italian \ nom.GDP \ 2018} = 1.1$ 

i) Debit card; ii) Checks; iii) Direct Debit; iv) Credit Transfers

- **Features**: 1) Collected in real time; 2) No revisions or observation errors
- According to the Bank of Italy's Survey of Household Income and Wealth (SHIW) in 2016:
  - 76% of Italian households own a debit card (main payment tool) (56 millions in 2018)
  - **30%** hold a **credit card** (15 millions in 2018)
  - 25% hold a prepaid card (postal services)
- **Good indicator for the whole Italian market:** around **66% of debit card** payments at POS are settled *through the BI-COMP system*.

# Payment System Data (Cont.)

- POS dynamics at quarterly frequency squares well with NA consumption expenditure in non durable consumption + services [figure] (Duarte et al., 2017)
  - Av. Daily payment: 60 euros with POS; 160 euros ATM withdrawal
  - POS+ATM values in BI-COMP = 100 / 110 billions per year

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$$\frac{POS + ATM \text{ values in BI-COMP}}{NON - DUR \text{ Consumption} + Services} = 12.5\%$$

 $\frac{ATM}{POS}$  a measures of consumers' **preference for cash** is **countercyclical**, consistently with literature on cash demand (Stix, 2004, Ardizzi et al., 2014) [figure]

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# POS purchases at daily frequency



- **Daily POS purchases** from **BI-comp system:** 
  - Sample: Apr. 2, 2007 Sep. 30, 2016
- Caveat: strong seasonal patterns and calendar effects.

# Seasonality of Payment Data (2)

Seasonality is a salient feature of our daily data on payments (we could use dummies, but too many parameters to be estimated):

- Day-of-the-week
- Day-of-the-month
- Day-of-the-year
- **Fixed Holidays** (e.g. Christmas, June 1<sup>st</sup>, May 1<sup>st</sup>);
- Moving Holidays (e.g. Easter).
- Two approaches for daily seasonal adjustment:
  - **TBATS**, by De Livera, Hyndman and Snyder (JASA 2011) is based on state space models, as in Harvey, Koopman and Riani (1997) but allows for a larger parameter space
  - Prophet, by Taylor and Lethman (2017) from Facebook research, is a flexible bayesian model that decomposes the time series with complex seasonal patterns in a) trend, b) seasonal components and c) calendar effects.

### Seasonality of POS in TBATS



6000000 4000000 2000000 0 -2000000 -4000000 -6000000 -8000000 Mon Tue Wed Thu Fri Sat Sun (b) POS daily series - weekly seasonality

Weakly seasonality









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### EPU, E(P)U Indexes for Italy

We follow the methodology proposed in Bloom, Baker and Davis (2016) selecting articles(/tweets) in Bloomberg (/Twitter) through keywords related to 3 broad categories: (E)conomic (P)olicy (U)ncertainty

 $EPU index_t = \frac{\# of \ articles \ satisfying \ EPU \ keywords \ in \ day \ t}{Total \ \# \ of \ articles \ in \ day \ t}$ 

 We construct 5 daily indexes for Italy ranging from 1 January 2007 to 31 September 2016

	Source	
Language	Bloomberg	Twitter
Italian	EPU	-
	EU	EU
English	EPU	-
	EU	-

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KeyBloombergIT
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**KeyBloombergEN** 

KevTwitterIT

# Daily EPU & E(P)U for Italy (Bloomberg, EN)

**EPU Italy** 

E(P)U Italy



Notes: indexes computed with Bloomberg. E(P)U contains at least the keywords (E) and (U) AND "ITAL\*" (English language). The dotted red line shows the 99 percentile. "External" EPU

# Daily E(P)U in Italian (Twitter) (HPT API)

#### E(P)U (in Italian) using the HPT API



### Monthly EPU indexes (standardized): Comparison with BBD (2016)



Consistent with the **monthly** series of BBD (2016); Correlations: E(P)U-TW 0.50, EPU 0.60 E(P)U 0.43.

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# Econometric framework

 We build daily impulse response functions (IRFs) with Local Projections (LP-OLS, Jordà, AER 2005), with the following specification:

$$y_{t+h} - y_t = \alpha_h Index_t^{EPU} + \sum_{i=1}^{I} \beta_i y_{t-i} + \sum_{i=1}^{J} \gamma_i Index_{t-j}^{EPU} + \dots$$

$$\dots + det_t + \varepsilon_{t+h}, \quad h = 1, \dots, H.$$

- We fully exploit our data set, using daily data =>
  - Around 2400 observations (02/04/2007 30/09/2016);
  - No need of mixed frequency models; no time aggregation issues; negligible concerns for endogeneity.
- LP are rather flexible and more robust than VAR to misspecification, the more for large horizons of the IRFs => given the lack of macroeconomic daily observables.

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# EPU $\rightarrow$ POS: whole sample (2007m4-2016m9)



# EPU $\rightarrow$ POS: subsample (2007m4-2013m12)



- EPU generates a non negligible reduction in purchases in the first subsample.
- The effects tend to vanish after 2 months. No Twitter-based E(P)U.

# EPU $\rightarrow$ POS: subsample (2014m1-2016m9)





- Not significant effect on POS when using E(P)U from Bloomberg in the 2° sub-sample
- Marginally significant results when Using Twitter

# EPU $\rightarrow$ ATM : whole sample (2007m4-2016m9)



# Robustness at Daily frequency

EPU is a relevant source of uncertainty other than Financial Uncertainty

- Results remain robust after controlling for :
  - proxies of daily Financial Uncertainty (daily Realized Vol. of the FTSEMIB)
  - -Stock market returns for Italy
  - -10y Sovereign debt spread ITA-GER and **5y CDS** for Italy

EPU jumps can be a proxy of bad news in the economy...

- We use **daily surprises** from several Italian **macro variables**
- **Daily suprises** = data released Bloomberg median forecast
  - **Quarterly:** such as GDP, Private Consumption
  - Monthly: Unemployment rate, Consumer confidence, Industrial production, Manufacturing and services PMI

# Monthly estimates

#### **Monthly Local Projections**

- It is crucial to identify shocks at daily frequency in order to rule endogeneity problems.
- To construct the monthly EPU shocks we follow the methodology put forward in Gazzani & Vicondoa (2019)
- 1. At the daily freq. we regress EPU indicators on EPU lags, POS lags, macro surprises and financial market variables
- 2. The monthly EPU shocks are the residuals in **step 1** aggregated at the monthly frequency
- We estimate the impact of EPU shocks on POS using LP-OLS adding other monthly controls such as Industrial production and Consumer confidence measures

# POS ← EPU: monthly level



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# Conclusions

- We use **daily debit card payments data** (adjusted for complex daily seasonal patterns)
- We build **EPU and E(P)U indexes** for Italy from different sources (Bloomberg, Twitter) all consistent with those of BBD (2016)
- We show that EPU shocks have temporary but not negligible contractionary effects on purchases made by Italian consumers, mainly during our first subsample characterized by the financial crisis (asymmetry). ATM withdrawals increase
- The effects found are temporary and short-lived, as theory predicts
- Monthly frequency results are consistent with the daily frequency ones

# Thanks!!!



# **Background slides**

# POS sales YOY and consumption



The correlation is close to 66%



# ATM/POS is counter-cyclical



The correlation is about -0.50%



### Seasonality of ATM in Prophet

Figure 8: POS daily series fitted with Prophet.



### EPU Index in Italian

 Computed from Bloomberg (EPU - story counts normalized by the # of all news a la Google Trends) containing

### Keywords:

- (E): «Economia» or «Economico» or «Economica» or «Economici» or «Economiche»
- (P): «Tassa» or «Tasse» or «Politica» or «Regolamento» or «Regolamenti» or «Spesa» or «Spese» or «Deficit» or «Banca Centrale» or «Banca d'Italia» or «Budget» or «Bilancio» or «BCE»
- (U): «Incerto» or «Incerta» or «Incerti» or «Incerte» or «Incertezza»

As in BBD (2016)

- If E(P)U, policy keywords (P) not included to match Twitter
- Sort of Internal EPU, i.e how Italians perceive EPU



# EPU-I Index in English with country Identifier

 Computed from Bloomberg (EPU - story counts normalized by the # of all news a la Google Trends) containing

### <u>Keywords</u>:

- (E): «Economic» or «Economy»
- (P): «Congress» or «Bank of Italy» or «Legislation» or «Regulation» or «Parliament» or «Government» or «Deficit» or «Central Bank» or «Budget» or «ECB»
- (U): «Uncertain» or «Uncertainty»
- (IT): AND «Ital\*»

As in **BBD (2016)** but adapted to the Italian case

 Kind of external EPU (how the rest of the world perceive EPU in Italy)



# E(P)U Index in Italian from Twitter

 Computed from Twitter (EPU - Tweet counts standardized by the max) containing

### Keywords:

- (E): «Economia» or «Economico» or «Economica» or «Economici» or «Economiche»
- (U): «Incerto» or «Incerta» or «Incerti» or «Incerte» or «Incertezza»

#### As in BBD (2016)

- (P) part excluded for limited number of tweets. Remember: a tweet has max 140 characters (around 12/13 words) including emoji, tiny urls, #hashtags (this until Nov. 7, 2017)
- No normalization because we couldn't get the total number of tweets (sensible figure for Twitter)



# Payment System Data (Cont.)

- How do people pay? If Francesco (an Italian guy) buys:
  - Grocery shopping, Restaurants, Gym, Movies, Hair cut, etc.
- Francesco can pay with the following 4 options:

1. Cash (ATM)	2. Debit Card	
– "not-on-us"	— Pagobancomat	
— "on-us"	<ul> <li>Maestro</li> </ul>	
3. Credit Card	4. Pre-paid debit card	

# Daily EPU & E(P)U for Italy (Bloomberg, IT)

#### **EPU in Italian**

#### E(P)U in Italian



Notes: indexes computed with Bloomberg. E(P)U contains at least the keywords (E) and (U) (Italian language). The dotted red line shows the 99 percentile. " Domestic" EPU