BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working Papers)

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October 2019

Number 1233

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Number 1233 - October 2019

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

NEWS AND CONSUMER CARD PAYMENTS

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Abstract

We exploit a unique daily data set on debit card expenditures to study the reaction of consumers to daily news relating to Economic Policy Uncertainty (EPU). Payments with debit cards are a proxy for consumption in the quarterly national accounts. Using big data techniques we construct daily EPU indexes, using either articles from Bloomberg news-wire or tweets from Twitter. Our empirical analysis at high frequency required estimates of daily seasonal components, finding strong patterns both within the week and within the month. Using local projections we find that daily shocks to EPU temporarily reduce debit card purchases, especially during the recent crisis; the main results are confirmed using monthly data and controlling for financial uncertainty and macroeconomic surprises. Furthermore, economic policy uncertainty affects the ratio between ATM withdrawals and debit card purchases, signaling an increase in households' preference for cash.

JEL Classification: C11, C32, C43, C52, C55, E52, E58.
Keywords: consumption, payment system, policy uncertainty, big data, daily seasonality, local projections.

Contents

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1 Introduction[1]

The global financial crisis of 2007-08 broke the long calm of the Great Moderation and made the world economy more volatile. Geopolitical risks have also increased due to institutional factors such as Brexit, but also for other aspects such as terrorism or climate change (Caldara and Iacoviello, 2017). Following these recent developments there is a strong interest among private agents and central bankers in finding ways to measure the macroeconomic impact of risks related to policy uncertainty (Visco, 2017).

Our paper investigates how households reacts to news concerning economic policy uncertainty (EPU henceforth). We tackle this issue using a novel data set for Italy on debit card payments, settled on the clearing systems of the Bank of Italy, where electronic transactions are observed with a short delay and time series may be extracted at high frequencies. To the best of our knowledge, our paper is the first one to provide a quantitative assessment of the effects of EPU on consumption at the daily frequency. This is relevant to avoid the bias related to the endogeneity between consumption and news, that we consider negligible within a day, while it may be serious with monthly or quarterly observations.

The first contribution of our paper is the construction of a variety of EPU measures based on prominent sources, both for professionals and private agents, such as Bloomberg news-wire and the social network Twitter; the indexes on EPU are computed according to the methodology put forward in Baker et al. (2016). The second contribution is the seasonal adjustment of the daily time series of debit card payments (POS henceforth) and Automatic Teller Machine (ATM henceforth) withdrawals, which are characterized by an extremely pronounced seasonality. For the sake of robustness, we apply two approaches that have been proposed in the literature very recently. Third, we investigate the reaction of consumption and preference for cash, both measured through payment data, to policy uncertainty. The empirical results are shown using impulse response functions (IRFs), based on the local projections approach proposed by Jordà (2005).

[1]We would like to thank two anonymous referees, Marco Bernardini, Nicholas Bloom, Dario Caldara, Laurent Calvet, Christopher D. Carroll, Luca Fanelli, Jesus Fernandez-Villaverde, Andrea Gazzani, Eric Ghysels, Òscar Jordà, Massimiliano Marcellino, Stefano Neri, Javier J. Pérez, John Rogers, Stefano Siviero, Alex Tagliabracci, Carin Van der Cruijsen-Knoben as well as participants to the CFE-2017 conference, the ECB workshop *"Household Heterogeneity and Macroeconomics"*, the Bank of Italy workshop *"Harnessing Big Data & Machine Learning Technology for Central Banks"*, the SITE 2018 workshop on "Macroeconomics of Uncertainty and Volatility" held at Stanford University, the 2019 ICEEE Conference and the 2019 Royal Economic Society Annual Conference for very helpful comments and suggestions on previous drafts of the paper. We are grateful to Luca Arciero from the Markets and Payment System department at Bank of Italy for providing the BI-COMP data. The views expressed in this paper are those of the authors and do not involve the responsibility of the Bank of Italy. All remaining errors are our own. Corresponding author: Simone Emiliozzi, Banca d'Italia, Via Nazionale, 91, 00184, Rome, Italy. Email: simone.emiliozzi@bancaditalia.it

We find that daily increases in EPU have temporary but statistically significant negative effects on purchases, mainly concentrated during the double-dip crisis. The adverse effect of policy uncertainty is confirmed when using monthly data and controlling for financial uncertainty and macroeconomic surprises. We also find a negative impact of EPU on the use of electronic money, because uncertainty tends to increase the preference of agents for cash (as a safe asset).

This paper sits at the intersection of two strands of literature. The first one relates to the big data studies on the effects of EPU, following the seminal work of Baker et al. (2016). However, while these papers study the impact of monthly EPU shocks, we use daily data in order to avoid endogeneity issues and time aggregation bias (Marcellino, 1999). In fact, at the monthly frequency, the effects of EPU shocks could be contaminated by other kinds of exogenous innovations happening during the month, such as fiscal or monetary policy shocks. Moreover, while these papers investigate the impact on the supply side, measured by industrial production and employment, we focus on the reaction of households.[2] Our paper is also related to the research on the use of payment data for macroeconomic studies. Clearing system data are an extremely timely and reliable source of information for tracking the business cycle, but they have been exploited only recently for empirical studies mainly on forecasting GDP (Galbraith and Tkacz, 2018; Aprigliano et al., 2019) and consumption (Duarte et al., 2017). Given the increasing digitalization of the retail payment ecosystem and the recent diffusion of electronic money and cryptocurrencies (such as Bitcoin or Ethereum), it is reasonable to expect that there will be a growing interest by researchers in payment data in the near future.

The rest of the paper is organized as follows. To put in perspective our empirical results, Section 2 contains a short review of the theory of optimal consumption and precautionary savings. Section 3 describes the data, the debit card series and our EPU indexes, while Section 4 describes the daily seasonality of our payment data. Section 5 highlights the econometric framework adopted, whereas Section 6 assess the macroeconomic effects on consumption of shocks to EPU. The two following Sections present some robustness analyses, on the exogeneity of EPU at daily (Section 7) and monthly frequency (Section 8). Section 9 concludes.

[2] He (2017) finds that negative news transmitted by the media had a crucial role in depressing employment in the US during the Great Recession. Basu and Bundick (2017) find that the uncertainty shock, measured by the implied stock market volatility, causes significant declines in output, consumption, investment, and hours worked.

2 EPU indicators as a proxy for increase in labor income risk

Positive innovations in EPU are associated with income risks of the households. For instance, uncertainty about electoral outcomes (Giavazzi and McMahon, 2012; Gillitzer and Prasad, 2018), government tax policies (Baker et al., 2016; Fernández-Villaverde et al., 2015), Social Security benefits (Luttmer and Samwick, 2018) may be interpreted as increases in the labor income risk, because agents face difficulties in predicting their disposable income. In this Section we borrow from consumption theory to put in perspective our empirical findings on the economic impact of EPU shocks on payments.

EPU indexes are countercyclical (Bloom, 2009, 2014) and increase during recessions, expanding the risks of future long-term earnings for consumers (see Guvenen et al. (2014) and Davis and Wachter (2011)). Since the labor income risk is difficult to insure, even temporary innovations can generate a rise in precautionary savings, through a contraction in current consumption (McKay, 2017; Challe et al., 2017; Bayer et al., 2018; Bloom et al., 2018).

EPU indicators have two nice properties that we exploit to identify the effects of policy uncertainty shocks on payments. First they display strong positive jumps around major economic policy events that can be considered exogenous and unpredictable by consumers (see Figure 4a, 4b and 5). Secondly, strong increases in EPU anticipate transitory surge in volatility of both POS payments (Figure 6a) and non-durable consumption (Figure 6b), its low-frequency analogue.

Motivated by this evidence, daily EPU indicators are used in the empirical specification (Section 5) as proxies for temporary unexpected jumps in income risk. In Section 6 we use POS payments, a unique high frequency proxy of non-durable consumption, to test whether EPU shocks generate fluctuations in consumption expenditure. While De Giorgi and Gambetti (2017) study their impact on the distribution of aggregate consumption at business cycle frequencies, we investigate the response of daily consumers expenditure. The high-frequency of our data-set is key in order to limit endogeneity concerns, due to reverse causality between uncertainty and consumption at lower frequencies (such as monthly or quarterly).

Jumps in EPU foster surge in future income streams volatility and, via the precautionary saving channel, generate a contraction of current consumption in order to save for *"the rainy days"* as predicted by equation 1 (Jappelli and Pistaferri, 2010; Carroll, 2001):

$$\Delta \ln c_t = \frac{\gamma}{2} var_{t-1}(\Delta \ln c_t) + \varepsilon_t \tag{1}$$

where γ is the coefficient of relative risk aversion, and ε_t is a forecast error.[3] In equilibrium, an unexpected (and temporary) sudden increase in EPU magnifies both consumers' perceived future income risk and the conditional variance of consumption growth, pushing up precautionary savings (the first term in equation 1), hence decreasing current consumption.

The theoretical prediction that we test in Section 6 is that after a strong positive innovation in the daily EPU indicators, POS payments, our proxy for high-frequency non-durable consumption, should display a temporary slowdown.

2.1 Consumption reaction after an EPU shock in a toy model

The importance of economic policy uncertainty for consumption decisions may be sketched with a simple toy model where the uncertainty refers to taxation. We consider a representative agent facing a stochastic tax rate τ that can assume three values, $\tau_{low} \leq \tau_{med} \leq \tau_{high}$, according to the following discrete distribution:

$$\tau = \begin{cases} \tau_{low}, & \text{with probability} \quad p \\ \tau_{\text{med}}, & \text{with probability} \quad 1-2p \\ \tau_{\text{high}}, & \text{with probability} \quad p \end{cases} \tag{2}$$

We define an EPU shock as a mean preserving spread of the distribution of the tax rate τ, that does not alter its future expected value moving from a low to a high uncertainty environment; the parameter p drives the probability mass on the tail of the distribution (p) and therefore the uncertainty (Figure 1a).

The representative agent, with log-utility, lives two periods and pays taxes τ proportional to its income y in the second period. For simplicity, income is assumed to be constant and the discount factor is set equal to one. She solves:

$$\max_{c_1, c_2} \log(c_1) + \log(c_2)$$
$$\text{s.t.} \quad c_1 + c_2 = y + (1-\tau)y$$

The optimal consumption path of the risk-averse agent after an EPU shock is shown in Figure 1b, for three possible scenarios. Under no uncertainty in the tax rate τ the agent can completely smooth consumption in the two periods (blue line). The tax rate uncertainty, obtained via an increase in p, steepens the consumption path via a precautionary

[3] When an isoelastic utility function is used, the precautionary saving term (the first term on the right-hand side of equation (1) is always positive and depends on the coefficient of relative prudence $(1+\gamma)$.

saving motive (from the red to the yellow line). The reaction of daily payments after an increase in EPU presented in Section 6 are qualitatively consistent with the theoretical implication drawn from this toy model.

3 Data

3.1 Payment data

A payment system is the set of instruments, procedures, settlement channels, rules and intermediaries that enable money to be transferred from one agent to another. In theory payment system data trace the economic transactions and therefore following the seminal equation of the quantity theory of money by Fisher (1912) they should also track economic activity. The New Monetarist Economics literature (Williamson and Wright, 2010; Schneider and Piazzesi, 2015) highlights the importance of the payment system, jointly with banking and asset markets, in order to understand theoretically the functioning of a monetary economy.

Payment data also have interesting empirical properties for macroeconomic analysis. The data are collected in real time and are free of observation errors, as they come from the clearing systems, inter-bank procedures, specialized according to the type of retail payment instrument (i.e., payment cards, checks, credit transfers) used to settle commercial transactions.

We use the data base of the clearing and settlement system BI-COMP, managed by the Bank of Italy, which includes information on the value and number of operations made by households and firms for each type of instrument (POS, ATM, low value checks, direct debits, and credit transfers).[4]

We concentrate our analysis on debit card payments data (POS), as they are a major tool used by Italian consumers for daily purchases of goods and services. The banking statistics report about 55 millions of debit cards in circulation at the end of 2016, against 14 million of credit cards and 25 million of prepaid cards. The debit card market is also rapidly growing in Italy: in 2016 over 1.8 billion of POS transactions were executed (around 38 per card) compared with approximately 0.8 billion in 2007 (about 24 per card). Further, according to the Survey of Household Income and Wealth (SHIW) of the Bank of Italy, conducted in 2016, 76% of the households in Italy hold a "*bancomat*" (i.e. a debit card), versus 30% for credit cards and 25 for prepaid cards. Our data-set is a

[4]BI-COMP is the retail settlement system managed by the Bank of Italy, which is composed by two sub-systems: i) the local clearing sub-system for paper-based transactions (such as high value checks, cashiers draft, bills); and ii) the (more relevant) retail sub-system for paperless transactions (debit cards, credit transfers, direct debit, other electronic payments). On average, BI-COMP handles around 5-6 million payments per day (i.e. around EUR 4-5 billion per year).

large sample of the whole Italian market of debit card payments, since about two third of the POS operations in Italy are settled through the Bank of Italy's BI-COMP system.[5]

Moreover, data on cards can also be used to study consumers' payment habits, as cards can be used both to buy goods and services through POS or to withdraw money at automated teller machines (ATM). Typically, cash transactions are not recorded in the clearing systems, but ATM operations may be a proxy of the demand for cash for retail payments (Carbó-Valverde and Rodríguez-Fernández, 2014), especially in our dataset where they only refer to 'not-on-us' operations (i.e. the issuing bank of the card is different from the ATM bank where the withdrawal is executed) which imply an additional fee for the consumer. Given this extra cost in our sample the ratio of the ATM withdrawals with respect to the electronic payments (ATM/POS ratio) is considered a proxy of the preference for cash. Indeed, a strong positive correlation between the ATM/POS ratio and the share of expenditures with cash of Italian households was found in survey data (Ardizzi et al., 2014). In other words, if the ATM transactions grow faster than POS ones, this is an indication of an increasing preference for cash, while the opposite happens when there is a preference for electronic money.

Figure 2 shows the daily data on debit card payments. As expected there are strong seasonal patterns in both POS and ATM flows, with peaks and troughs associated with calendar effects, especially during Christmas, Easter and summer holidays.

The correlation with macroeconomic series is clear, starting from a visual inspection; Figure 3a displays quarterly POS payments and total expenditure on non-durable consumption and services; the year-on-year growth rates have a similar dynamics resulting in a high unconditional correlation (around 60%). POS data are adjusted for two important level shifts, due to some institutional changes occurred in 2012 and 2013.[6]

Figure 3b illustrates at monthly frequency the ratio ATM/POS against the dynamics of industrial production, the most important observable indicator of the business cycle at monthly frequency. There is a clear negative correlation (about 50%) suggesting a countercyclical pattern in cash transactions consistent with the literature on cash demand

[5] Furthermore, debit card data are timely and directly available from the clearing and settlement system managed by the Bank of Italy, while credit or prepaid card data are either recorded through different procedures with a settlement lag (credit card transactions) or mainly channeled through other settlement systems (e.g. postal prepaid cards or other international debit cards).

[6] The correction is based on the dynamics of an alternative payment system (the Italian retail component of TARGET2) that was not affected by these changes. Regarding the first shift, an important law called '*SalvaItalia*' decree (Law Decree 201/2011) did impose limits to cash payments in Italy, including pension payments. These limits led to a re-composition of cash balances by operators, especially during the period between the end of 2011 and the first months of 2012 (period of entry into force of the Decree). Such re-composition strongly affected debit card usage. For instance, more money available on bank account balances increased the usage of debit cards at ATM and POS. Regarding the second shift in the series, this is due to the entry of the postal operator "*PT*" as a new participant in the debit card settlement procedure in BI-COMP.

(Stix, 2004; Schneider, 2010). The higher the standard of living, the lower the relative use of cash and the greater the demand for alternative payment instruments.

3.2 News on Italian Economic (Policy) Uncertainty - E(P)U

Baker et al. (2016) suggest an innovative index of economic policy uncertainty (EPU). The EPU index is based on newspaper frequency of three groups of keywords: i) a group related to economic (E) keywords with "economy" and "economic"; ii) one related to uncertainty (U) keywords with "uncertain", "uncertainty"; and iii) the last one related to policy (P) keywords, where for the US Baker et al. (2016) use "Congress", "deficit", "Federal Reserve", "legislation", "regulation", or "White House" including variants like "uncertainties", "regulatory", or "the Fed". In a nutshell, in order to be counted as relevant to compute the EPU index a newspaper article has to contain a word from each of the three categories, i.e. (E), (P), and (U).

Baker et al. (2016) compute the EPU index not only for the US but also for the G10 countries, including Italy. The EPU index is usually computed monthly for all the G10 countries such as Italy except for the US and the UK where it is also calculated on a daily basis. For Italy Baker et al. (2016) construct a monthly EPU index searching articles in two major Italian newspapers: the '*Corriere Della Sera*' and '*La Repubblica*' using Dow Jones Factiva. The three categories of the Italian keywords are the following:

- for (E): '*economia*' OR '*economico*' OR '*economica*' OR '*economici*' OR '*economiche*';
- for (P): '*tassa*' OR '*tasse*' OR '*politica*' OR '*regolamento*' OR '*regolamenti*' OR '*spesa*' OR '*spese*' OR '*spesa*' OR '*deficit*' OR "'*Banca Centrale*" OR "'*Banca d'Italia*" OR '*budget*' OR '*bilancio*';
- for (U): '*incerto*' OR '*incerta*' OR '*incerti*' OR '*incerte*' OR '*incertezza*'.

We construct a first EPU index with exactly the same keywords as in Baker et al. (2016) but using as a news source, instead of Factiva, Bloomberg and Twitter.

Bloomberg news-wire is not only limited to business news, but it contains many other sources. Among them there are almost all the newspapers (for example for Italy, 'Il Sole 24 Ore', 'La Repubblica', 'Il Corriere della Sera', etc.). For some newspapers Bloomberg adopts web scraping techniques to gather the articles. In addition to that, there are many other news sources like Ansa, Bloomberg news, etc. Since in Bloomberg news-wire most articles are in English we construct an EPU index using the keywords in English with an additional feature 'AND *ITAL**' in order to select all the news relating to EPU which contain all the words with root '*ital*' (e.g. '*Italy*' or '*Italian*'). [7]

An alternative EPU index was constructed, with a similar strategy, using as source the social network Twitter, focusing on the feeds written in the Italian language. To construct our daily EPU index for the Italian economy we counted all tweets containing the same keywords for (E), (P) and (U). Unfortunately, one significant limitation of Twitter until the 7th November 2017 was that each tweet was limited to a maximum of 140 characters. With such an upper limit, and with many hashtags, urls or emojis, the number of words in a tweet is never greater than 12/14. Using the same strategy as Baker et al. (2016) we noticed that we ended up selecting a very limited number of tweets. In fact, while there were many tweets talking about (E) and (U), the number of tweets talking about (P) were limited to one or two each day. To overcome such a limitation, we constructed two E(P)U indexes, based either on Bloomberg or Twitter, where we considered only the keywords from categories (E) and (U); therefore, our E(P)U series are a sort of general '*economic uncertainty index*', less focused than the EPU.

In the end we built three indexes: an EPU and an E(P)U index from English texts in Bloomberg, which can be considered an 'external' index (i.e. how foreign journalists perceive Italian EPU) and an E(P)U from Twitter in Italian which represent an 'internal' index of EPU. Given our interest on policy uncertainty the most relevant indicator for this paper is the EPU index, but we also present results for the other two E(P)U indexes, for additional evidence.

Our indexes of EPU are built similarly to those of Google Trends. For those based on Bloomberg, for each day we compute the share of the selected news with respect to all the news counts of the day; then we scale the time series, with respect to the value of 100 on the day of the historical maximum. In the case of Twitter data we do not have the total number of tweets, or similar information to normalize the series, therefore we just set to 100 the index for the day recording the maximum number of selected tweets.

Figure 4 depicts both EPU and E(P)U indexes obtained from Bloomberg. The indexes seem to capture some episodes of high uncertainty in Italy, especially during the sovereign debt crisis at the end of 2011. Figure 5 shows the E(P)U index obtained from Twitter with texts in Italian containing keywords in the categories (E) and (U). We use the E(P)U index calculated from Twitter starting from January 2012 since before Twitter had a limited diffusion in Italy. Here the variability is more pronounced, but again one clear peak in economic uncertainty is at the end of 2011.

To check the robustness of our daily EPU or E(P)U indexes with respect to the original ones proposed by Baker et al. (2016) we aggregated our index to the monthly frequency

[7] This can be thought as an 'external' EPU index, because it represents the uncertainty as perceived by foreign journalists.

(see Figure 7) and we computed the correlations with the original EPU for Italy. Our indexes computed from Bloomberg news-wire show a high unconditional correlation with the original series, respectively of 0.60 for EPU and 0.43 for E(P)U. The correlation with the Twitter-based index would be 0.50, but since there are many zeros before June 2009 we consider more reliable the correlation over the sample January 2012-September 2016 (at 0.31).

4 Seasonal adjustment of daily payments

While EPU indexes do not show seasonal components, the daily data on payments are strongly affected by regular calendar components, as showed in Figure 2.[8] Our empirical application therefore needs a preliminary analysis on seasonality, as for our purposes it is crucial to separate the daily signal contained in the series from the predictable component generated by strong seasonal factors. In fact the shocks faced by agents should have an impact only on components of daily payment series that are orthogonal to the usual seasonal variation.

The predictable component of payments is connected with two main deterministic sources of variability: on the one hand there are the cycles associated with expenditures in the day of the week, the day of the month and the day of the year; on the other hand payment series display strong calendar effects connected with fixed (e.g. Christmas and the days around) and moving holidays (e.g. Easter).

A full description of the seasonal components of the spending process is beyond the scope of this paper, but given the uniqueness of our daily dataset we think it may be useful to briefly describe the seasonal patterns at high frequency.[9] In fact, knowing the daily seasonality of payment data may be of interest per se on top of the econometric application of the following Sections.

In the scant literature dealing with daily time series of payments the seasonal and calendar components are usually treated with a dummy approach (Rodrigues and Esteves, 2010; Kosse, 2013). We initially tried with seasonal and calendar dummies, but this approach requires the estimation of too many parameters. We therefore ended up with two recent methodologies, based on unobserved component models, that are much more parsimonious.

The first approach is the state-space framework for complex seasonal time series proposed by De Livera et al. (2011) called *TBATS* (see Appendix A for an overview).[10] The

[8]The results of the preliminary analysis on seasonality on EPU series are available upon request.

[9]Official data on retail sales are monthly and national accounts on consumption are quarterly, therefore with those data only monthly (and quarterly) seasonal components may be extracted.

[10]The acronym TBATS stands for Trigonometric, Box-Cox transform, ARMA errors, Trend and Sea-

second one, called *Prophet* (see Appendix B for more details), is a methodology proposed in Taylor and Letham (2017) from Facebook Research and it is based on a flexible Bayesian model that decomposes the time series with complex seasonal patterns in three main parts: (i) a trend component modeled with a linear trend with random change points; (ii) the seasonal components (e.g., weekly, monthly and annual seasonality); and (iii) the calendar effect (either fixed or moving holidays).

The two approaches are similar, but there are non negligible differences. With *TBATS* we first remove seasonality and then control for calendar effects using dummies for major Italian holidays such as Christmas, Easter, the 1th of May (see Table 1 for a list of Italian holidays and the amplitude of the dummy windows for related days); when using *Prophet* instead it is possible to control jointly for both seasonal components and calendar effects. Moreover, while for *TBATS* maximum likelihood estimates are proposed, *Prophet* is based on a bayesian estimator.

4.1 Results with TBATS

We have tried several model specifications in TBATS and we ended up with one that includes three cycles: i) within the week, ii) within the month, and iii) within the year.[11] In a second step we control for calendar effects using dummies for the Italian calendar holidays (see Table 1 for further details).

Figure 8a depicts the POS, raw and fitted series with TBATS: the estimated model captures the deterministic seasonal components very well. According to the weekly seasonality (Figure 8b) most of the POS payments are done during the weekend, when households have more time to purchase goods and services.[12]

The seasonality within the month is shown in Figure 8c: the largest amounts of POS payments are concentrated around the first and the third week of each month. This pattern is consistent with the pensions paid at the beginning of the month and salaries paid in the third week; this simultaneity of revenue inflows with expenditures seems to

sonal components.

[11] We fit several specifications and we consider those that maximize the log-likelihood of the TBATS model.

[12] The original data extracted from BI-COMP are available only for working days (5 days a week). Transactions made during weekends and holidays are recorded in BI-COMP usually on Mondays or on the first working day of the week, generating large spikes in the data at the beginning of the week (see Figure 2) that are difficult to capture using TBATS, *Prophet*, and dummies. To reduce the volatility of the original series over the weekends, we take the daily data recorded on Monday and we split them with equal weights over Saturday, Sunday and Monday. In this way we impute a value also for Saturdays and Sundays. This procedure is also used to treat payment data spikes following holidays such as Christmas and Easter. In these latter cases the first working day of the week following the holiday is usually a Tuesday and we then split with equal weights the data on Tuesday over Saturday, Sunday and Monday. We experimented changing the equal weight assumption and results from the seasonal procedures remain substantially robust.

go against the standard rational expectation theory, according to which the predictable incomes should have little contemporaneous effects on spending. Instead, consistently with the findings in Gelman et al. (2014), people do seem to spend after getting their wages or pensions. At the yearly frequency (Figure 8d) POS payments are on average high at the beginning and at the end of each year, in connection with Christmas Holidays and the thirteenth monthly salary. They decrease in February and go up again during Easter time (between the end of March and April). They tend to slightly increase again during summer holidays (June and July) and then they start to decrease from September, reaching a minimum in November.

A similar analysis was performed for the ATM series (Figure 9a). As for the POS, the model performs quite well in eliminating the cyclical components. Figure 9b depicts the weekly component, showing that withdrawals reach a minimum on Tuesdays and increase during the central days of the week with a maximum on Fridays. The weekly seasonality for Mondays and weekends is close to zero. This is in contrast with the POS series, for which the days with the highest values of payments are either at the end of the week or on Mondays. These patterns seem to suggest that ATM withdrawals lead the purchases of the following days and this anticipation is more evident during weekends. This is in line with the evidence provided by the literature on the usage of debit cards in the US (Stix, 2004), showing similar frequencies in the POS and ATM operations during the week or the month. The monthly seasonal pattern in Figure 9c has a shape similar to POS, but with an anticipated phase shift; this confirms the tendency of ATM withdrawals to lead shortly consumption expenditure, as already mentioned for the pattern within the week. Looking at the pattern within the year, the peak is in summer, again signaling the relevance of the precautionary withdrawals of money when agents go on holiday.

4.2 Results with Prophet

We also employ an alternative methodology, called *Prophet*, in order to check the seasonality found with TBATS. Similar results emerge in terms of fit, as the estimated weekly, monthly and annual components are remarkably similar, across the two approaches, for both POS and ATM series (see Figures 10 and 11, respectively). Here we want to focus on two peculiar elements provided by *Prophet*: the first is the possibility of estimating a long-run component of the payment series alternative to *TBATS*[13] (see Appendix B for more details), while the second is the quantification of the calendar effects.

The top panel of Figure 10 depicts the estimated long-run POS component: through the sample considered the trend is continuously growing. This evidence is consistent with

[13] The estimated long-run component provided by *Prophet* is piecewise linear and displays several breaks.

the increasing share of electronic transactions, as mentioned in the previous Section.

The long-run component of ATM payments (in Figure 11) instead displays several breaks, that are likely related to institutional changes in the regulation of the use of cash. The trend component of ATM started to increase during the Great Financial Crisis in 2008 and 2009 and recorded a second jump with the burst of the sovereign debt crisis in 2011. It is difficult to disentangle the impact of the business cycle on payments from the effects of the several laws regulating the use of cash for transactions passed by the Italian Parliament in the last decade. Nevertheless, it seems that this result again confirms the countercyclical preference for cash, already mentioned in the previous Section.

The second panels of Figures 10 and 11 depict the deterministic effects related to holidays for both POS and ATM, respectively. Payments increase strongly before Christmas and then register a strong decrease; at Easter time we observe the same pattern but with a smaller variability. To conclude, for both POS and ATM series, the changes associated to holidays are of utmost importance. Therefore not taking into account such variation in the estimates could severely bias the results.

Even though substantially different, the two methodologies deliver similar estimates of the seasonal components. In the econometric analysis that follows we use as dependent variable the daily trend component estimated with TBATS, for both POS and ATM. The preference of TBATS over *Prophet* is just technical: TBATS generates a smooth daily trend while that one produced by *Prophet* is piecewise linear and it cannot be used for the estimation of IRF through the local projections method explained in the next Section.

5 Econometric framework

We study the impact of our EPU indexes on daily expenditures with POS and on ATM withdrawals. The estimates are based on the local projection methodology, proposed by Jordà (2005) and recently adopted in several macroeconomic applications (Owyang et al., 2013; Auerbach and Gorodnichenko, 2016; Stock and Watson, 2018). Local projections represent a rather flexible framework; they differentiate from vector autoregressions (VARs) because the conditional dynamic path of the variable of interest is estimated directly, without imposing any implicit dynamic restrictions on the shape of the impulse response.

We build impulse responses (IRFs) running regressions with the following specification

$$
\begin{aligned}
\ln Y_{t+h} - \ln Y_{t-1} = \alpha_h \ln \left(Index_t^{EPU}\right) + \sum_{i=0}^{I} \beta_i \ln Y_{t-i} + \ldots \\
+ \sum_{j=1}^{J} \gamma_i \ln \left(Index_{t-j}^{EPU}\right) + det_t + \varepsilon_{t+h}, \quad h = 1, \ldots, H.
\end{aligned} \tag{3}
$$

where $\ln Y_t$ is the logarithm of the daily seasonally adjusted component of the payment series data estimated using TBATS; $\{\alpha_h\}_{h=0}^{H}$ is the impulse response function of the target variable to a shock to the EPU index ($Index_t^{EPU}$); det_t is a vector containing the deterministic components of the regression and H is the maximum horizon for the local projection.[14] Since the error term ε_t in Equation (3) is serially correlated for $h > 1$, we use Newey-West consistent estimators to compute the standard errors as in Owyang et al. (2013).

When tracing the response of card payments to daily news about policy uncertainty, we focus on the contemporaneous variation in $Index_t^{EPU}$, controlling for the lags of y_t and $Index_t^{EPU}$ itself following the specification suggested in Auerbach and Gorodnichenko (2016). In the baseline specifications we use 20 lags (almost one month in terms of working days) for both the dependent variable y_t and the daily EPU shocks.[15]

The daily frequency is key to rule out problems of endogeneity, due to the fact that economic uncertainty usually increases during bad times (Gazzani and Vicondoa, 2019). In our application this circularity is not an issue; when there is a big jump in uncertainty, due to a bad exogenous news, consumers may cut consumption expenditure in the same day, but it is reasonable to assume that the negative feedback on EPU does not have the time to occur in the same day. Moreover, the use of daily data considerably reduces the issue of the temporal aggregation bias, that is usually present when time series are aggregated to lower frequency (Marcellino, 1999; Swanson and Granger, 1997).

The daily frequency has also shortcomings, as series are characterized by complex autocorrelation structures, raising the risks of model misspecification. Local projections are the right tool to tackle this issue, since they do not impose the restrictions implicit in VARs (Jordà, 2005). This is especially relevant in our application, as the daily frequency requires to compute IRFs up to a large number of periods ahead (60). With VARs the IRFs would be obtained by recursively iterating the estimated one-period-ahead forecasting model, therefore the misspecification errors would be increasingly compounded with the forecast horizon.

[14]Local projections are based on data on working days, otherwise they would be specified differently. Generically IRFs are traced for 60 working days that correspond approximately to three months.

[15]We fitted several alternative specifications and the results – available from the authors upon request – are qualitatively similar.

6 Impulse responses of Economic Policy Uncertainty shocks

This Section shows the responses of daily POS and ATM payments to positive shocks in the EPU indexes. In the baseline analysis we estimate Equation (3) on the full sample of ten years of daily working days from April 2, 2007 to September 30, 2016, for a total of about 2400 observations.

The baseline results of the effects of policy uncertainty shocks on consumption paid with POS are shown in Figure 12; the IRFs are computed for an horizon going from one to 60 working days ahead (i.e. approximately three months) and shaded bands of confidence intervals are also reported. The North-West panel (Figure 12a) refers to the baseline results, as the innovations are based on news focused on policy uncertainty (EPU, computed as in Baker et al. (2016)). Results for the other two indicators are also shown, for additional evidence; since they exclude the keywords on "policy" they are related to a more general concept of economic uncertainty (as explained in Section 3.2).

Whatever the measure adopted for the economic (policy) uncertainty shock, there is a clear negative, hump-shaped and statistically significant impact on POS purchases. Contemporaneous effects are negligible, implying that consumers do not cut immediately POS expenditures after bad news that increase uncertainty. The responses tend to be temporary and are reabsorbed in about one quarter (the IRF based on Twitter seems more persistent, but refer to a shorter sample, because of data availability). This result therefore qualifies the EPU news as a transitory shock in the variance of the future consumption path of the consumers, as in the simple model sketched in Section (2).

The transitory contraction of private consumption in response to an EPU shock is qualitatively in line with previous empirical analyses (Giavazzi and McMahon, 2012; Baker and Yannelis, 2017; Gelman et al., 2018) and theoretical predictions (Basu and Bundick, 2017; Bayer et al., 2018; Bloom et al., 2018; Fernández-Villaverde et al., 2015; Challe et al., 2017). Our findings are consistent with the theoretical mechanisms highlighted in Fernández-Villaverde et al. (2015) where an unexpected and temporary fiscal policy uncertainty shocks, increase the volatility of future income stream of the representative agents that cuts non-durable consumption for a precautionary saving reason; this process slow down economic activity. Interpreting our results using an heterogeneous agents framework, unexpected E(P)U jumps can be considered a source of uninsurable risk faced by individuals that induces greater volatility on future income. This generate a time-varying precautionary motive and hence fluctuations in consumption (McKay, 2017; Challe et al., 2017; Bayer et al., 2018).

We also investigate the impact of policy uncertainty on the use of cash. A first set of results is about the response of ATM withdrawals to innovations in EPU (Figure 13). After a temporary shock in uncertainty, consumers tend to increase withdrawals, with a peak response 25 working days after the shock. This surge is temporary and the statistical significance is borderline.[16]

The money taken at the ATM machine may be used either to spend or to increment cash balances. In order to disentangle these different needs we rely on a focused measure of preference for cash (as described in Section 3), which is the ATM/POS ratio. Results in Figure 14 are in line with expectations: when EPU indicators obtained from Bloomberg are used, the ATM/POS ratio is boosted between 20 and 35 working days following the shock, as a result of the decline in POS payments and the expansion in ATM withdrawals. As previously mentioned, positive jumps in the Twitter E(P)U indicator are not associated with an increase in money withdrawals from ATM machines.

These findings of an increase in cash holdings following uncertainty shocks look consistent with the literature on the cash demand for precautionary motives. For instance, Frenkel and Jovanovic (1980) develop a stochastic framework for determining transactions and precautionary demand for money. They show that optimal money holdings are an increasing function of volatility in payments. Alvarez and Lippi (2009) extend the static Baumol-Tobin cash inventory model to a dynamic environment with uncertainty introducing a precautionary motive for holding cash. Finally Bayer et al. (2018) develop a novel and tractable framework that combines nominal rigidities and incomplete markets in which households choose portfolios of liquid paper and illiquid physical assets. Higher uncertainty about income triggers a slowdown in economic activity combined with a flight to liquidity since liquid assets have superior value in uncertain times for consumption smoothing reasons. In our empirical application the policy uncertainty may affect the cash balances also for fiscal reasons, of taxation of financial asset, or for financial stability concerns related to the banking account.

To summarize the results of this Section we find that positive innovations in uncertainty generate both a contraction in expenditures and an increase in the preference for cash.

6.1 Subsample analysis

Our daily data span almost ten years, with more than two thousands observations, largely enough to split the sample. We are interested in checking if our findings were driven by specific episodes, which are relevant for the Italian economy, as in the last decade it was

[16]Using the Twitter based indicator the results are even not statistically significant but, as already stated for POS, the most relevant results are those of the North-West panel (referring to the fully fledged EPU indicator).

hit by an unprecedented (double dip) recession.[17] Figure 15 displays the IRFs with respect to EPU (Figure 15a) and E(P)U (Figure 15b) for the first half of the sample, from the beginning of 2007 to the end of 2013, therefore covering the worst phase of the recession. The negative impact is recorded, both for the proper policy uncertainty indicator (EPU) and for the more general index of economic uncertainty.[18] On the contrary, when computing the IRFs for the second half of the sample characterized by few and less persistent policy uncertainty episodes, the impact on purchases looks unstable and statistically not significant (Figure 16).

7 Policy uncertainty, financial uncertainty and macroeconomic surprises

In this Section we present robustness checks on the EPU shock used in our identification strategy; more specifically we investigate the empirical relevance of EPU shocks in affecting household's spending, when alternative sources of uncertainty are also taken into account. We consider two candidates that can influence the payment flows: a) financial uncertainty, and b) macroeconomic surprises, potentially affecting the sentiment on the Italian economy.

7.1 Policy and financial uncertainty

Financial uncertainty can be considered a major driver of the business cycle, similarly to policy uncertainty. Consumer payments can respond to financial rather than policy uncertainty (Jurado et al., 2015; Caldara et al., 2016; Ludvigson et al., 2019; Alessandri and Mumtaz, 2019; Angelini et al., 2019; Berger et al., 2019) and the two are also clearly linked, especially in bad times. In order to assess the empirical relevance of these two sources of uncertainty we expand our baseline LP regression in equation (3) adding as controls the following three financial variables, with ten lags:

- the ten-year spread between Italian and German government bond yields;[19]
- the daily realized volatility for the Italian stock market index FTSE MIB;

[17]Between the first quarter of 2008 and the first quarter of 2013 the Italian GDP dropped cumulatively by around ten percentage points; according to time series since the unification (1861) this was the sharpest drop, excluding the two world wars.

[18]The IRFs for Twitter are not available for this first subsample because in Italy the social network became popular with some lag with respect to US (in 2010/2011). We consider Twitter reliable for Italy starting in 2012.

[19]In the regression we use the first difference of the spread. Results remain robust to the inclusion of the 5 years Italian CDS spread.

- the daily returns of the Italian stock market index FTSE MIB.

The first row in Figure 17 shows the estimated response of POS payments to shocks in the policy uncertainty index in each column, controlling for all the three financial indicators. IRFs are provided for the three EPU measures discussed in Section 3.2. As already stated in the previous Section the most relevant indicator is EPU (IRFs are shown in panel 17a); results are also provided for the two additional measures of uncertainty, i.e. E(P)U based on Bloomberg (panel 17b), and on Twitter (panel 17c).

The main finding of the previous Section are barely affected by the inclusion of financial variables. Either the timing or the size of the estimated impact of EPU on POS payments are basically unchanged with respect to the case in which financial factors are not included in the regression (see Figure 12).

Regarding the financial shocks, the three panels in the second row of Figure 17 display the reaction of POS payments to a one-standard-deviation shock to the ten-year spread between the Italian and the German government bond yields for each the EPU indicator. Following an increase in the spread there is a contraction in the POS expenditures, even larger than that associated with the policy uncertainty innovation, but with a smaller statistical significance. The IRFs of the most focused indicator (EPU, in the first column of Figure 17) and those ones related to the spreads have similar shape and magnitude, since the two shocks are correlated; still, the daily unconditional correlation is low (about 0.4) as not all relevant policy uncertainty episodes are associated with increases in the spread (as in the case of the 2016 earthquake). Moreover, the direct exposition of households to the Government bond market in Italy is not high; financial investments are mainly intermediated by banks and financial institutions, therefore consumers do not feel directly affected by fluctuations in the fixed income market.

The results for the two additional stock market variables are weaker than those obtained with the spreads. An increase in the stock market realized volatility generates a slowdown in POS expenditures only for a few days, as effects tend to revert back to baseline in an extremely short time horizon (third row of Figure 17). This result is only qualitatively in line with findings in Berger et al. (2019), where realized volatility shocks induce a contraction in economic activity. In Italy realized volatility bursts seem to play a minor role when compared to the US, possibly because of the lower stock market participation of households.

Finally, a positive innovation in the stock market returns have negligible effects on POS flows (fourth row in Figure 17). A plausible explanation for the limited impact of financial variables on consumers' expenditures is due to the low stock market holdings by the Italian households.

To conclude, the results of this Section indicate that Italian households' expenditures are indeed affected by news about policy uncertainty, on top of the impact due to sovereign spreads. Announcements of future tax or pension reforms have a straightforward link with the volatility of future income path, and therefore they are clearly affecting - although temporarily - precautionary savings. On the contrary, the link with financial market indicators of risk is less direct in households' balance sheet and the estimates are less significant.

7.2 EPU vs Daily macroeconomic surprises

Our EPU indexes are measured using newspaper articles and Twitter and thus they may be affected by news (on the same day) about the release of some macroeconomic variables, such as GDP, the unemployment rate and the consumer confidence . Hence the effects of EPU on POS payments could be potentially overestimated because the EPU index can capture "surprises" on business cycle indicators that are relevant for households expenditure decisions.

In order to disentangle the impact on POS of policy uncertainty innovations from those of news on the general economic conditions we expand the baseline regression (equation 3) adding daily macroeconomic surprises (Scotti, 2016; Altavilla et al., 2017; Hachula et al., 2019). Surprises are computed as the difference between the first-released data and the expected values corresponding to the median estimate of a panel of experts surveyed by Bloomberg. We consider the surprises to three macroeconomic variables which are a priori relevant for household consumption decision:

- The Italian GDP;
- the Italian Unemployment rate;
- the Italian consumer confidence index.

These macroeconomic surprises contain good/bad news on economic activity, so they can be interpreted like first moment shocks that can potentially influence consumption expenditure.

The baseline results of Section 6 are confirmed, as the IRF on POS payments, in the first row on Figure 18 are in line with those of Figure 12. The effect of daily EPU shocks on payments are therefore robust to the inclusion of all the three macroeconomic surprises.

The remaining rows of Figure 18 display the estimated impact of each of the three macroeconomic surprises for the various EPU indexes presented in the paper. A positive surprise (a good news) on the Italian GDP generates an increase in purchases (second row in Figure 18); results are clear for the most relevant indicator of EPU (in the first column of the Figure), but they are also confirmed for the additional two indexes of E(P)U (second and third column).

The third row displays the effects of an unemployment release where the official data provided by the Italian national statistical Institute (Istat) is higher than expected by the Bloomberg median forecaster (bad news). In this case POS payments temporarily decrease following the shock and then overshoot reverting quickly to the baseline.

Finally the last row in the Figure shows the effects of a positive surprise (good news) on consumer confidence index computed by Istat: when controlling for EPU (and the other two macroeconomic surprises), confidence news seem not to have a strong relevance in shaping payment flows.

To conclude, we find evidence that EPU shocks are able to generate per se a slowdown in economic activity, even after controlling for alternative drivers that induce sizeable declines in payments, such as negative macroeconomic news for GDP and unemployment.

8 Estimates with monthly data

This Section deals with estimates of EPU shocks on POS purchases at the monthly frequency. As shown in the literature changing the periodicity of the data can lead to a bias in the impulse response function, if the relevant shock is not properly identified (Marcellino, 1999).

In order to investigate the relationship between EPU shocks and POS expenditure response at lower frequency we follow the methodology put forward by Gazzani and Vicondoa (2019), that is explicitly aimed to control for the endogeneity between uncertainty and the business cycle. The approach hinges on the identification of the shocks at high frequency, so to minimize risks of endogeneity, as the day is a time period shorter enough to consider second order feed-back with economic activity negligible. Shocks are computed at the daily level, regressing the EPU indicators on their past (40 lags), lags of POS payments (40 lags), macro surprises and financial indicators presented in the previous Section; these daily shocks are then aggregated at the monthly frequency (see Figure 19 with major uncertainty events for Italy) and included in the following local projection equation:

$$\begin{aligned}\ln Y_{t+h} - \ln Y_{t-1} = \alpha_h \ln\left(Index_t^{EPU}\right) + \sum_{i=0}^{I} \beta_i \ln Y_{t-i} + \dots \\ + \sum_{j=1}^{J} \gamma_i \ln\left(Index_{t-j}^{EPU}\right) + controls_t + det_t + \varepsilon_{t+h}, \quad h = 1, \dots, H.\end{aligned} \tag{4}$$

For the monthly local projections we use as controls two relevant conjunctural monthly series: the industrial production and the consumer confidence index.[20] Industrial production is one of the most timely indicators of the business cycle and is included in the baseline estimation since payments can be partly driven by the general economic conditions; the consumer confidence is important since consumers can modify their spending following their mood (Angeletos et al., 2018).

In Figure 20 the IRF's of the POS purchases are reported. The monthly IRFs are in line with those estimated with daily data, although with some difference. The three monthly IRFs display a negative, hump-shaped and statistically significant impact on POS purchases, as for the daily ones. The contemporaneous effect is not statistically significant for the most relevant indicator (EPU, as always in the Nort-West panel of the Figure); coherently with the daily analysis, consumers do not cut immediately POS expenditures after news on policy uncertainty. The three IRFs display a trough after three or four months, with payments being lower by 0.3/0.4 percentage points. The timing of the trough is slightly anticipated with respect to the one obtained with the daily estimates (at around 40 working days, equivalent to two months); this marginal difference may be due to the aggregation of the series at a lower frequency, that by construction tend to increase the autocorrelation of the time series (Marcellino, 1999).

The proper identification of the shocks is crucial for the previous results. Performing the same monthly local projections as before, but without the identification of the shocks at the daily level, would let the researcher to conclude that there is no relation between EPU shocks on POS payments (see Figure 21). We therefore conclude that the identification of shock at the daily frequency is key to assess the impact of policy uncertainty with lower frequency observations.

Monthly estimates are also useful in order to shed light on the economic impact of EPU shocks on POS expenditures. This is especially of interest for the two major historical events of policy uncertainty in Italy, such as the the Italian sovereign debt crisis and the Italian general elections on February 2013. In fact during these two episodes, non durable consumption slowed down significantly, and the question is on how much of this drop was the result of policy uncertainty. According to our time series indicators these two events are associated with a jump in the order of three standard deviations. Using as a metric the previously mentioned monthly IRFs peak response, a three standard deviation shock would imply a contraction of POS payments of about 1 to 1.2 percentage points (the cumulated loss after three months is of about 200 millions of euros). This implies that following a temporary increase in policy uncertainty of this magnitude, it is as if Italian consumers decided to completely stop POS payment for an entire day, out of 60

[20] For industrial production and the Istat consumer confidence indicator we include two lags

working days.

9 Conclusion

We use a unique data set on daily POS and ATM transactions with debit cards in Italy, to study the effects of policy uncertainty on consumption and payment habits. Investigating how consumers react to news that make them more uncertain about future policies may be relevant for shaping policy actions and the communication of Governments and other institutions.

Using big data techniques we extract daily EPU indicators from newspapers (Bloomberg news wires) or *tweets* from Twitter that closely track the index proposed by Baker et al. (2016).

Given the unconventional frequency of our data-set, the empirical application required a thorough analysis of the seasonality of the daily series on payments. We find strong evidence of seasonal patterns, including those within the week and within the month, that may only be estimated with daily data-sets.

Using local projections we find that daily increases in EPU have short-lived but statistically significant negative effects on purchases, mainly concentrated during the double dip crisis. The adverse effect of the policy uncertainty is confirmed when using monthly data and controlling for financial uncertainty and macroeconomic surprises. We also study the impact of EPU on the use of electronic money vs cash, finding that uncertainty tends to increase the preference for cash.

Given the fast evolution of the payment systems and the increasing diffusion of electronic money and cryptocurrencies (such as Bitcoin or Ethereum), it is reasonable to expect that in the near future new data will be available, opening the box for a variety of other economic studies.

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A TBATS model De Livera et al. (2011)

Several common and widely used time series models are able to detect simple seasonal patterns for monthly or quarterly data. These approaches fail when the time series at hand displays multiple non-integer seasonality both at low and high frequency as payment system data. Several papers in the literature have already tried to model complex seasonal patterns (De Livera et al., 2011) but TBATS [21] is particularly promising for the series at hands:[22] (i) it handles typical nonlinear features that are often seen in real time series; (ii) it allows for any autocorrelation in the residuals to be detected automatically; (iii) it involves a simpler but very efficient estimation procedure; (iv) it is more parsimonious and v) it performs better than other alternative methods based on exponential smoothing techniques since seasonality is modeled through trigonometric representations based on Fourier series functions (Harvey, 1990; Harvey et al., 1997; West, 1996).

The model can be cast in state-space form as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega} & \omega \neq 0, \\ log y_t, & \omega = 0, \end{cases} \tag{5a}$$

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{k=1}^{N} s_{t-m_i}^{(i)} + d_t, \tag{5b}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t, \tag{5c}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \alpha d_t, \tag{5d}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} + \gamma_i d_t, \tag{5e}$$

$$d_t = \sum_{i=1}^{p} \phi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{5f}$$

where the first equation contains the Box-Cox transform;[23] $m_1, \dots, m_T$ denote the various overlapping seasonal frequencies, l_t is the local level in period t, b is the long-run trend, b_t is the short-run trend in period t, $s_t^{(i)}$ represents the ith seasonal component at time t, d_t denotes an $ARMA(p,q)$ process, and ε_t is a Gaussian white-noise process with zero mean and constant variance σ^2. The smoothing parameters are given by α, ϕ, and γ_i for

[21] The acronym TBATS stands for Trigonometric, Box-Cox transform, ARMA errors, Trend and Seasonal components. Trigonometric because it uses trigonometric functions to model multiple seasonal component in a parsimonious way. Box-Cox transformation because the model is able to handle non linearities. $ARMA(p,q)$ because the residuals of the model are cleaned using this methodology. Trend and seasonal components.

[22] TBATS has been used by Auerbach and Gorodnichenko (2016) in order to purge daily government spending data from multiple seasonal patterns.

[23] In our application the Box-Cox transform is of course never used.

$i = 1, \dots, T$.

Each seasonal component $s^{(i)}_{j,t}$ is modeled as

$$s^{(i)}_{j,t} = s^{(i)}_{j,t-1} \cos \lambda^{(i)}_j + s^{*(i)}_{j,t-1} \sin \lambda^{(i)}_j \tag{6a}$$

$$s^{(*i)}_{j,t} = -s^{(i)}_{j,t-1} \sin \lambda^{(i)}_j + s^{*(i)}_{j,t-1} \cos \lambda^{(i)}_j \tag{6b}$$

where $\lambda^{(i)}_j = \frac{2\pi j}{m_i}$. The stochastic *level* of the ith seasonal component is $s^{(i)}_{j,t}$ while the stochastic *growth* in the level of the ith seasonal component that describes the change in the seasonal component over time is indicated by $s^{*(i)}_{j,t}$. The number of harmonics required for the ith seasonal component is denoted by k_i.

B Prophet by Taylor and Letham (2017)

The *Prophet* proposed by Taylor and Letham (2017) of Facebook Research is a state-of-the-art forecasting model designed to handle complex seasonality problems and calendar effects that are a common features of daily time series (e.g., piecewise trends, multiple seasonality, moving holidays). Following Harvey and Peters (1990) they propose a decomposable time series model with three main components: trend, seasonality and holidays that are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t. \tag{7}$$

The first term $g(t)$ is the trend function that models non-periodic changes in the value of the time series, $s(t)$ represent seasonal changes (e.g. intra-daily, weekly, monthly and annual seasonality), the $h(t)$ component estimates the calendar effect associated with fixed and moving holidays which occur on irregular schedules over one or more days. Finally the error terms ε_t represents any idiosyncratic changes which are not accommodated by the model and it is assumed to be normally distributed.

This specification is similar to a generalized additive model (GAM) (Hastie and Tibshirani, 1987). Therefore it has the advantage that it easily decomposes and accommodates new components as necessary, for instance when a new source of seasonality is identified and can be rapidly estimated.

B.1 Trend specification with multiple change points

The model incorporates trend changes explicitly defining change points where the growth rate is allowed to change. Suppose there are S change points at times s_j with $j = 1, \dots, S$.

$\delta \in \mathbb{R}^S$ is a vector of rate adjustments where δ_j is the change in rate of growth occurring at time s_j. At any time t the rate is then the base rate k, plus all of the adjustments up to that point. It is possible to define a vector $a(t) \in 0,1^S$ such that

$$a_j(t) = \begin{cases} 1, ift \geq s_j, \\ 0, otherwise. \end{cases} \tag{8}$$

The rate at time t is then $k + a(t)'\delta$. When the rate k is adjusted, the offset parameter m must be adjusted as well to connect the endpoints of the segments. In our application to daily payment system data the trend $g(t)$ is estimated as a piece-wise constant rate of growth as follows:[24]

$$g(t) = (k + \mathbf{a}_t^{'}\boldsymbol{\delta})t + (k + \mathbf{a_t}^{'}\boldsymbol{\gamma}) \tag{9}$$

where k is the growth rate, $\boldsymbol{\delta}$ is the rate adjustments, m is the offset parameter and λ_j is set to $-s_j\delta_j$ in order to make the function continuous. Change points can be specified by the analyst (e.g., for payment data growth-altering events could be the passage of a law that drives the substitution between POS usage and cash).[25]

In our empirical application we opted for an automatic selection using a sparse prior on $\boldsymbol{\delta}$: the default is one change in the trend growth in each month using a prior for $\delta_j \sim Laplace(0, \tau)$. The τ parameter controls for the flexibility of the model in altering its rate and for τ going to zero, the trend becomes a standard (not-piecewise) linear growth trend. Further the prior assumption on $\boldsymbol{\delta}$ does not alter the estimation of the primary growth rate k.

B.2 Seasonality and calendar effects in Prophet

Since the payment series have a multi-period seasonality, Prophet relies on Fourier series to provide a flexible and parsimonious model of periodic effects. Suppose P is the regular period we expect the time series to have (e.g. $P = 365.25$ for yearly data or $P = 7$ for weekly data, when we scale our time variable in days). An approximate arbitrary smooth seasonal effect can be captured using a standard Fourier series

$$s(t) = \sum_{n=1}^{N} (a_n \cos(\frac{2\pi nt}{P}) + b_n \sin(\frac{2\pi nt}{P})). \tag{10}$$

Fitting a seasonal component with N harmonics requires the estimation of the $2N$

[24] In the equation that follows, $'$ is the transpose operator.

[25] In recent years in Italy there have been numerous laws that changed the threshold for the use of cash and hence of ATM withdrawals versus POS.

parameters $\boldsymbol{\beta} = [a_1, b_1, \ldots, a_N, b_N]'$. The way to choose the parameter N for each seasonal component is done fitting several models to our time series and choosing those with the lowest AIC.

Fixed and moving calendar holidays and similar events generate predictable shocks to our payment series and generically they do not follow exactly a periodic pattern. For example Easter holidays can be concentrated in March or April depending on the year and the moon calendar. Holidays and other calendar effects are estimated using dummies D_i for the various i holidays considered in the sample. For some holidays such as Christmas or Easter we include a window of dummies since payments increase abruptly during these periods of the year.

The following table shows the holidays and the windows used:

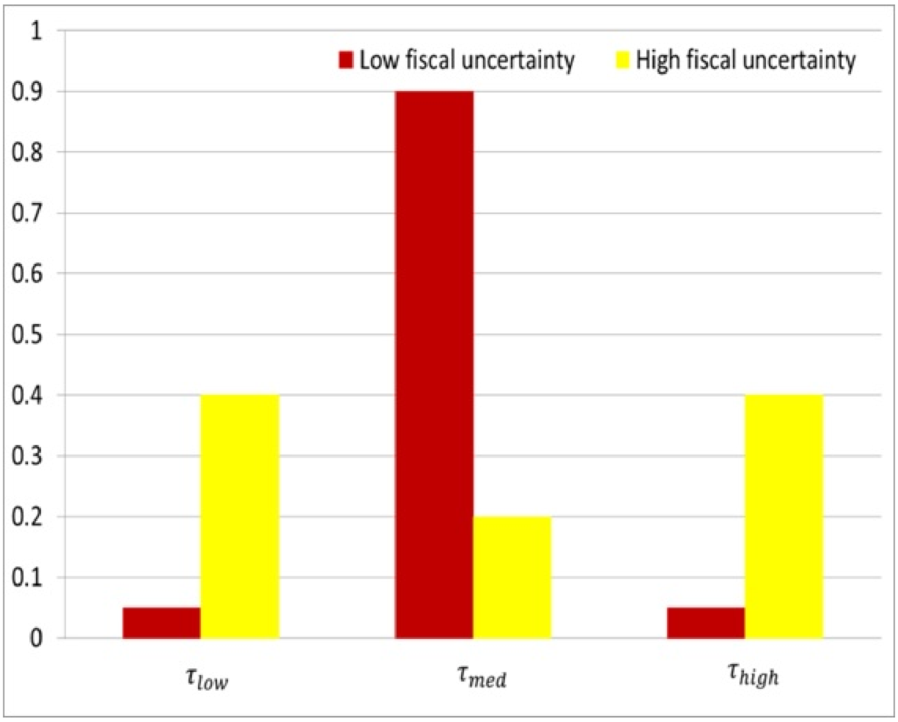
Table 1: Calendar of Italian Holidays

Holiday	Date	**windows**
Easter Day	First Sunday after first Full Moon on or after the March equinox	t-7 - t+2
Christmas Day	December 25	t-6 - t+2
San Valentine Day	February 14	no window
Republic Day	June 2	t-1 - t+1
Liberation Day	April 25	t-1 - t+1
New Year's Day	January 1	t-4 - t+7
All Saints' Day	November 1	t-2 - t+2
Labor Day	May 1	t+2
Assumption Day	August 15	t-1 - t+1
Immaculate Conception Day	December 8	t-1 - t+1

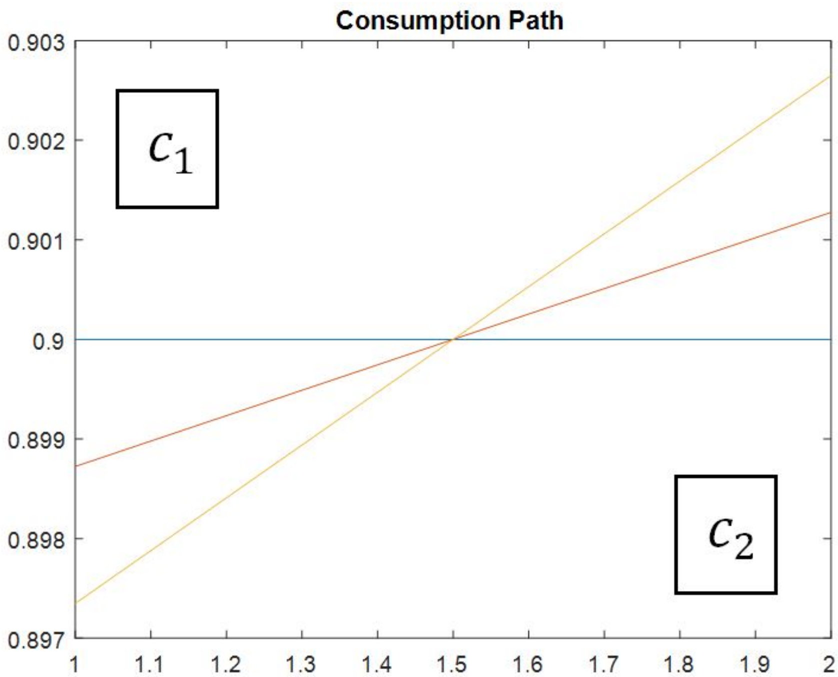
Notes: The windows represent the dummies used for days that are close to major holidays events.

C Tables and Figures

Figure 1: Consumption path to an economic policy uncertainty shock in the toy model.



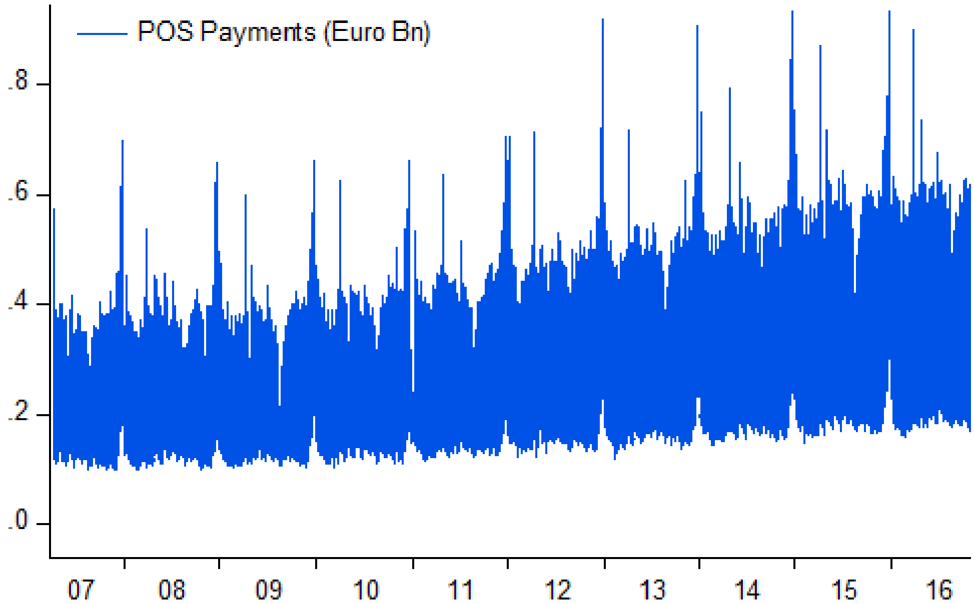
(a) high (yellow) and low (red) uncertainty scenarios for the stochastic tax rate τ.



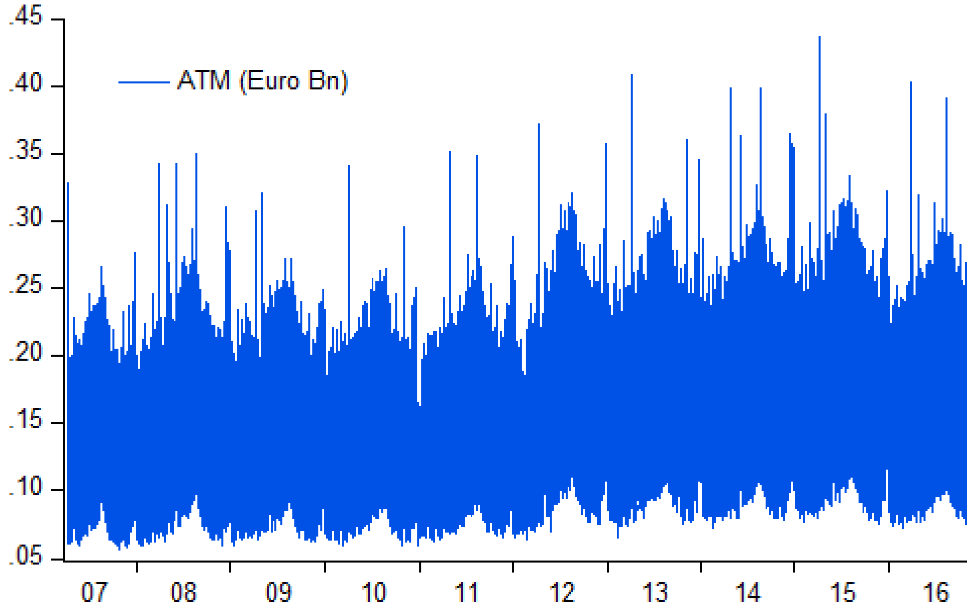
(b) Consumption path after an EPU shock.

Notes: Panel 1a displays an economic policy uncertainty shock as a a mean preserving spread in the tax rate distribution from a low uncertain environment (red bars) to a high uncertain one (yellow bars). Panel 1b displays the consumption path in the two periods, under no uncertainty (blue line), low uncertainty (red line) and high uncertainty (yellow line).

Figure 2: Payment series at daily frequency.



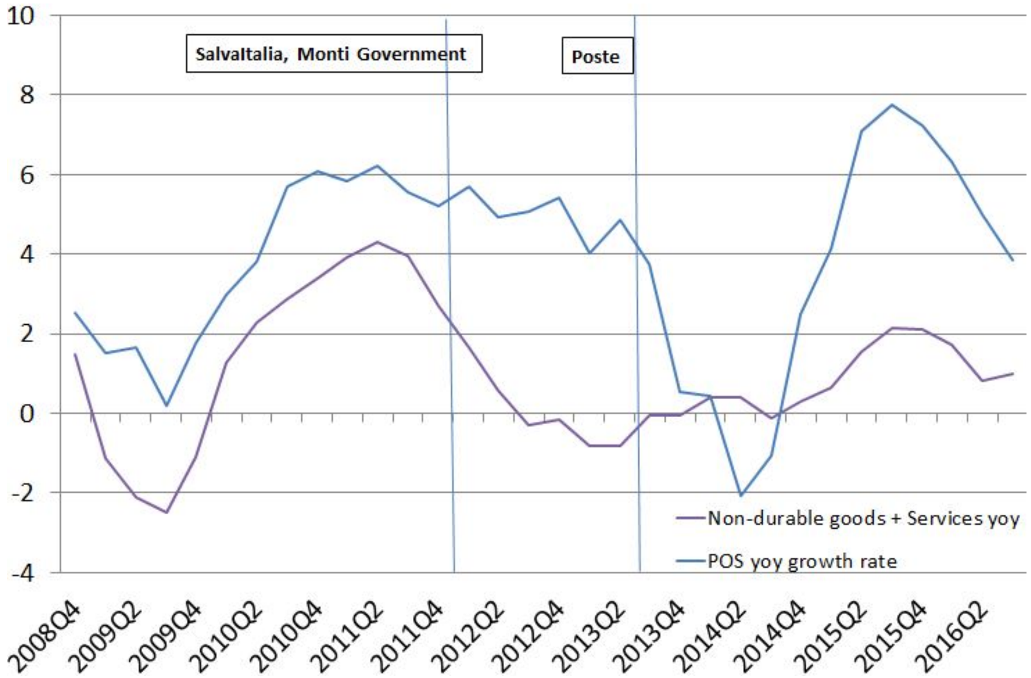
(a) POS debit card payments, raw daily series (in euro billions).



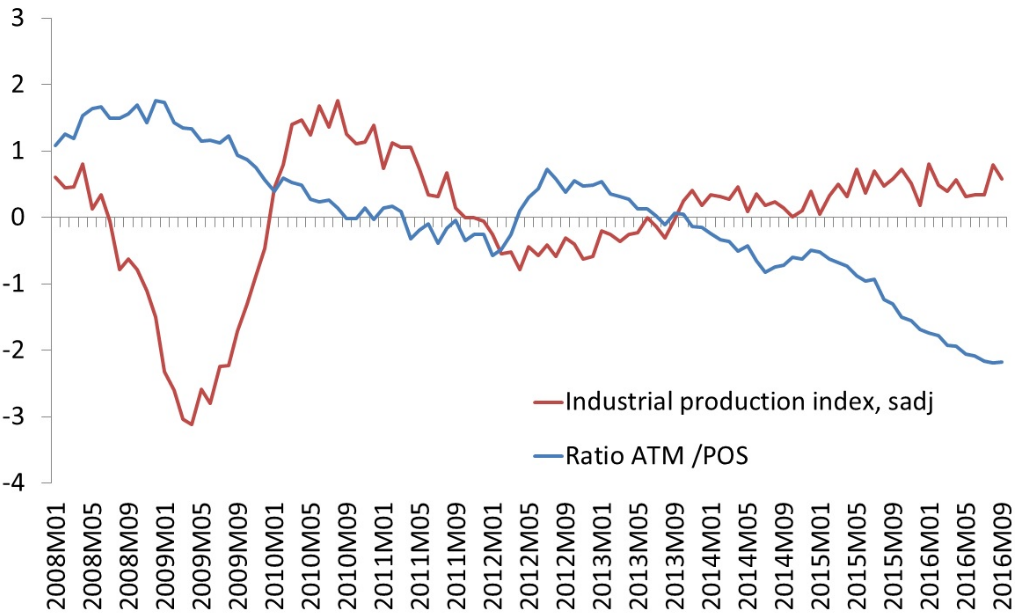
(b) ATM withdrawals, raw daily series (in euro billions).

Notes: Data taken from the retail component of the BI-COMP payment system, managed by the Bank of Italy. Data are recorded on a 5-working-day basis.

Figure 3: Payment series and macroeconomic variables.



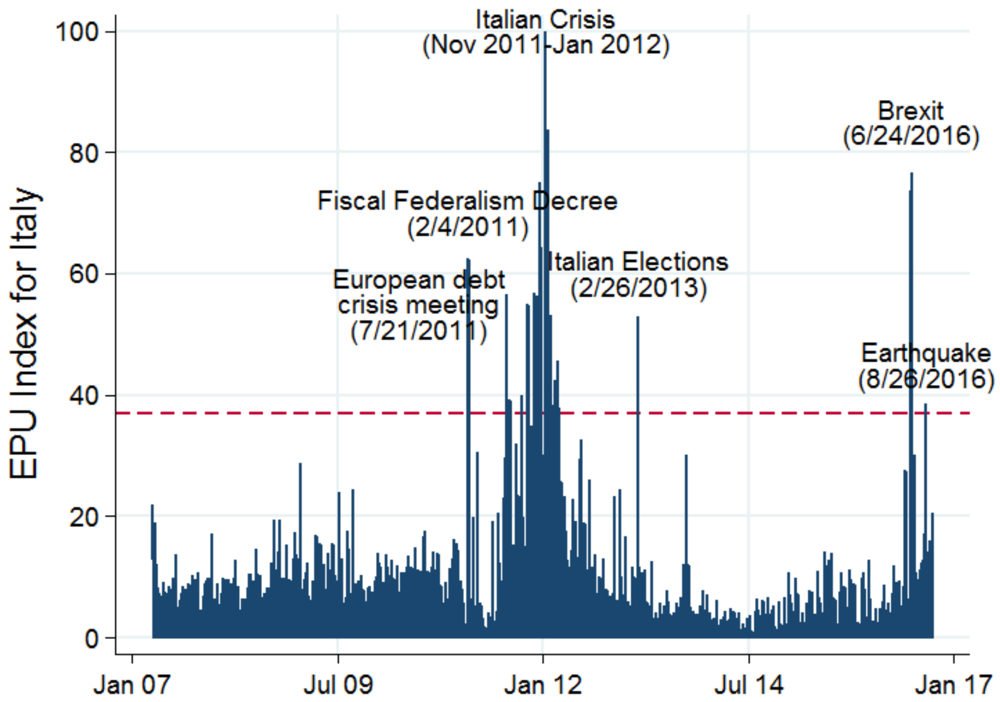
(a) POS purchases and national accounts consumption for services and non-durable goods (2008Q4 - 2016Q3).



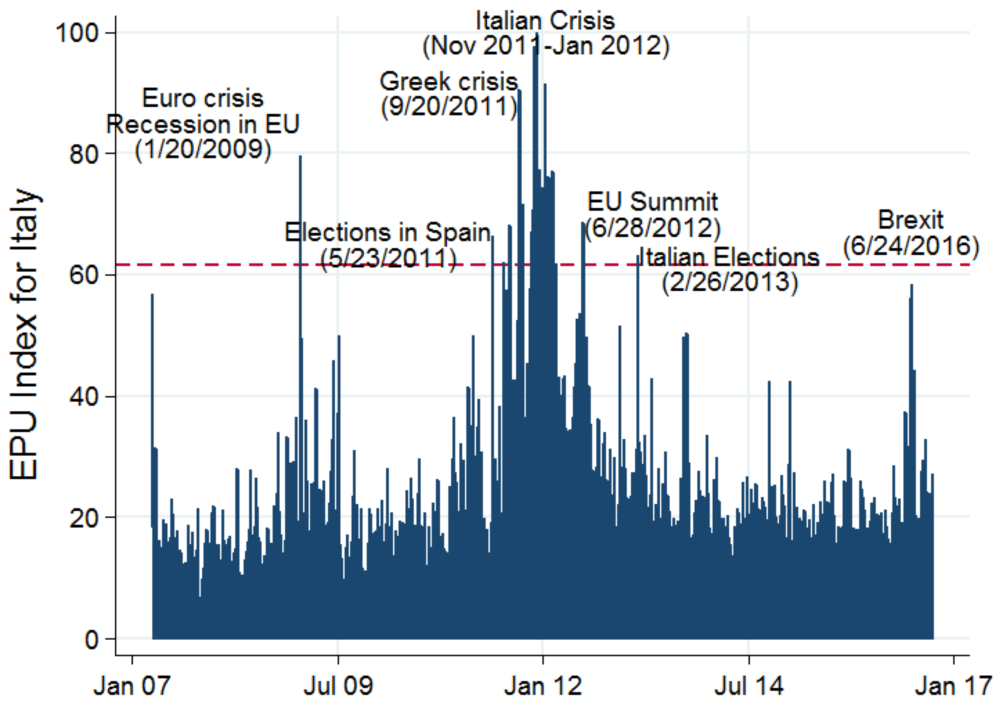
(b) ATM/POS ratio (seas. adj. at the monthly frequency) and the annual growth rate of industrial production (seas. adj.).

Notes: Panel (3a) shows the y-o-y growth rate of the nominal value of POS smoothed using a moving average of 4 terms together with the y-o-y growth rate of the nominal, raw values of the sum of expenditure in services plus non-durable consumption (Source: Italian National Accounts). Panel (3b) shows the ATM/POS ratio and with the annual growth rate of industrial production (they are negatively correlated, by -0.48).

Figure 4: Econonic (Policy) Uncertainty – Indexes at daily frequency (Bloomberg).



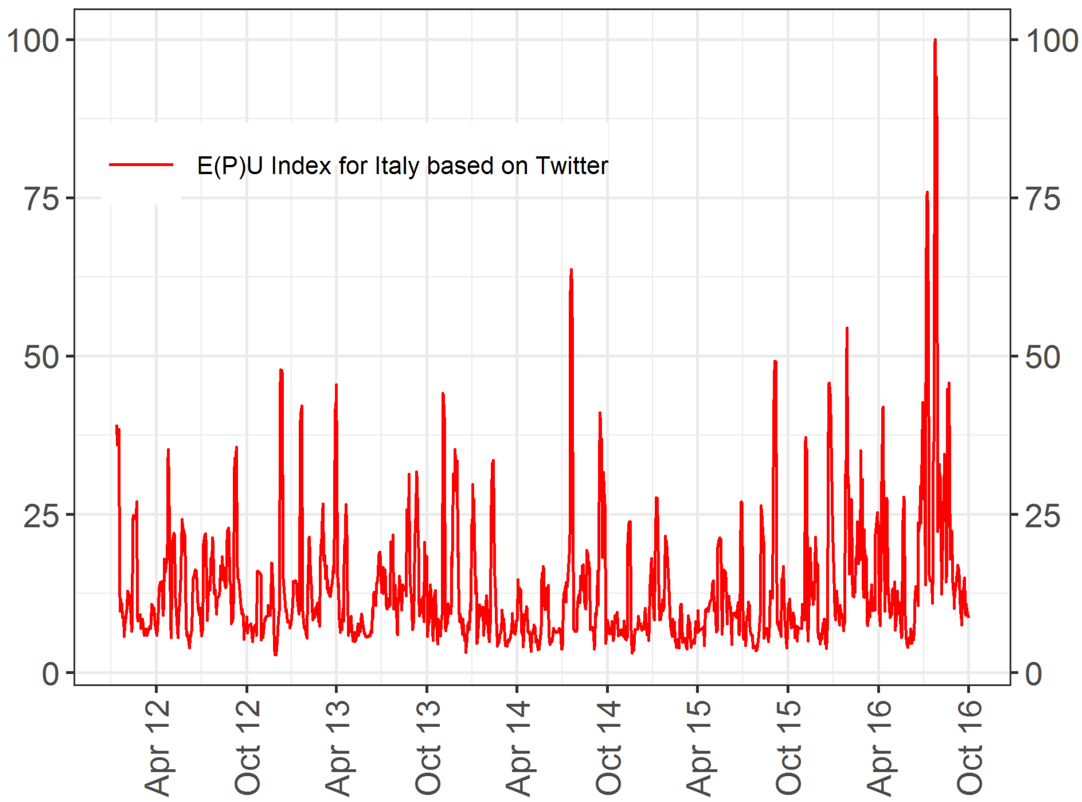
(a) EPU index calculated from Bloomberg news-wire.



(b) E(P)U index calculated from Bloomberg news-wire.

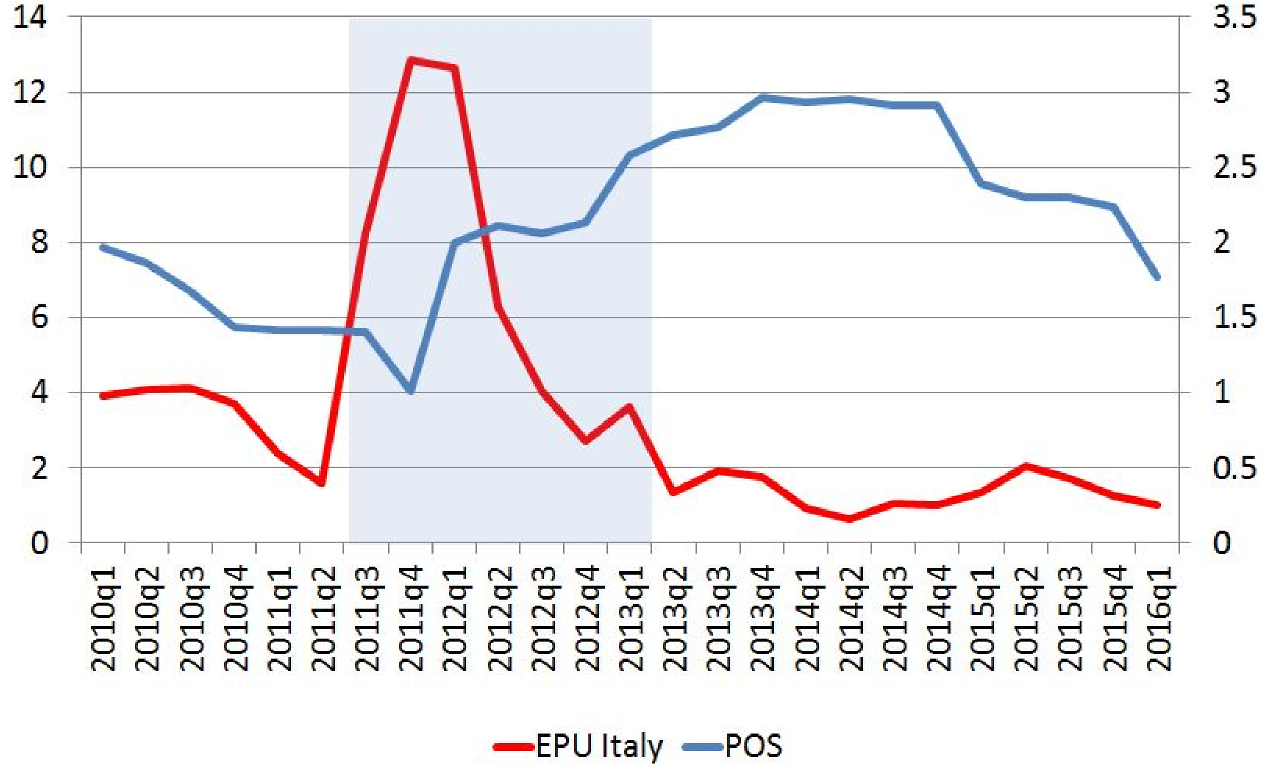
Notes: EPU and E(P)U indexes computed with Bloomberg news-wire. The two indexes are those obtained from keywords in English with the additional filter 'AND *ITAL**'. The EPU index refers to news that contain at least a keyword of the category (E) (P) and (U), while for the E(P)U they contain at least a keyword of (E) and (U). The events inducing changes above the 99th percentile (displayed in red) are described.

Figure 5: Econonic (Policy) Uncertainty – Index at daily frequency (Twitter).

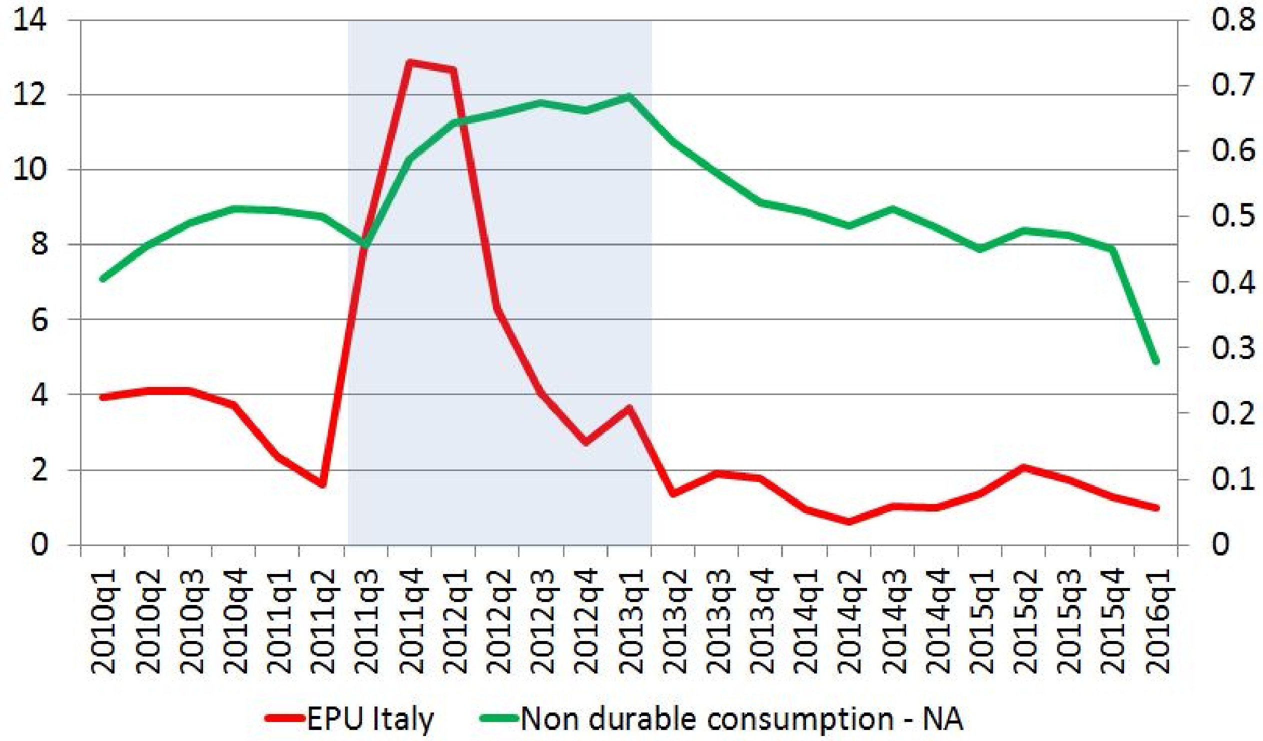


Notes: E(P)U index is computed counting the tweets in Italian that contain at least a keyword of the category (E) and (U). Then a 5-day moving average is adopted to smooth the index which is then set to a 100 on the day of the maximum over the sample.

Figure 6: EPU index and rolling standard deviation (3-years window) the growth rate of POS payments and Non durable consumption.



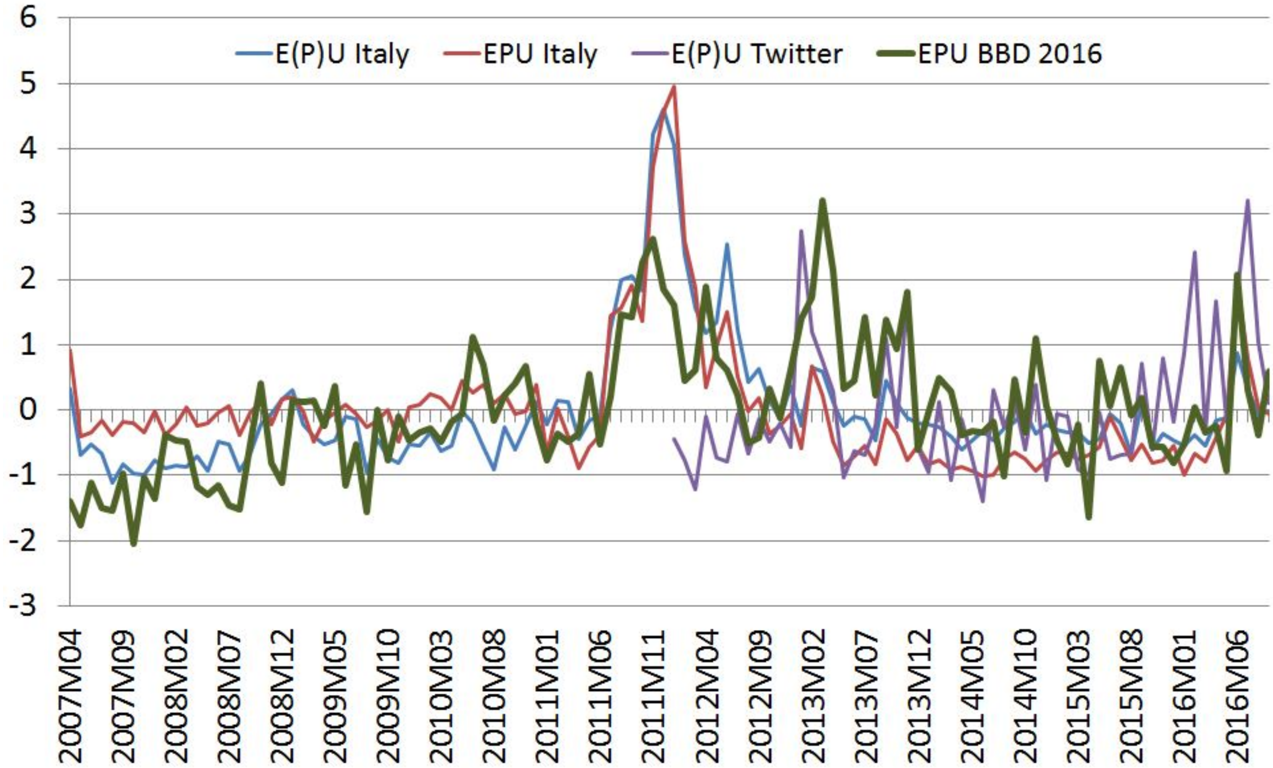
(a) EPU index from Bloomberg and rolling standard deviation in quarterly growth rate of POS payments.



(b) EPU index from Bloomberg and rolling standard deviation in quarterly growth rate of Non durable consumption (National accounts, seasonally adjusted data).

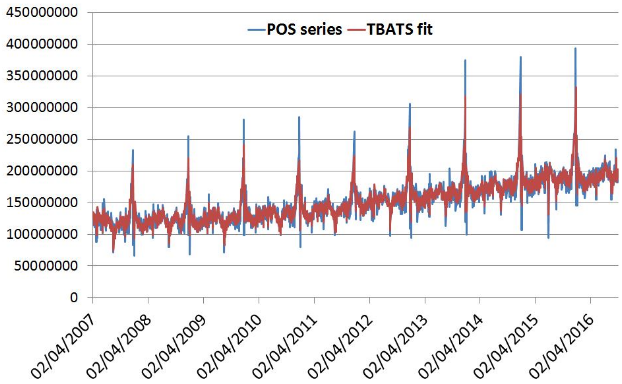
Notes: The Bloomberg based EPU quarterly index is computed as the average of the daily values. POS payments are first aggregated to the quarterly frequency and then seasonally adjusted using TRAMO. The sample of the rolling standard deviations goes from 2010Q1 till 2016Q1. The shaded area indicates the recession.

Figure 7: Comparison between our EPU indexes with the one of Baker et al. (2016) (EPU BBD 2016)

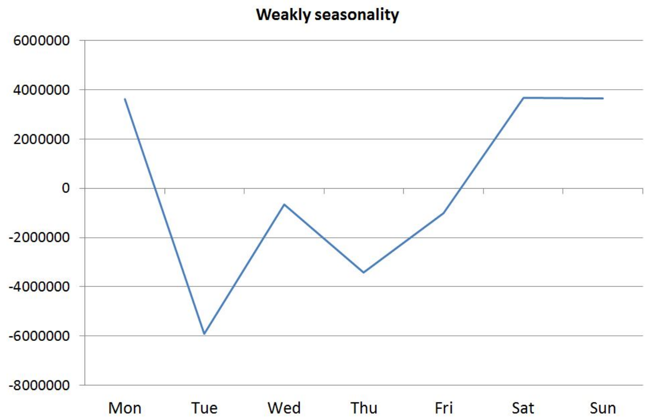


Notes: Our EPU indexes are described in Section 3.2

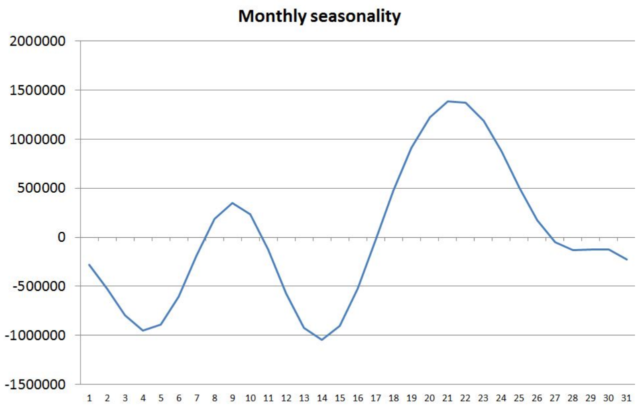
Figure 8: POS, daily raw series and seasonal components estimated with TBATS.



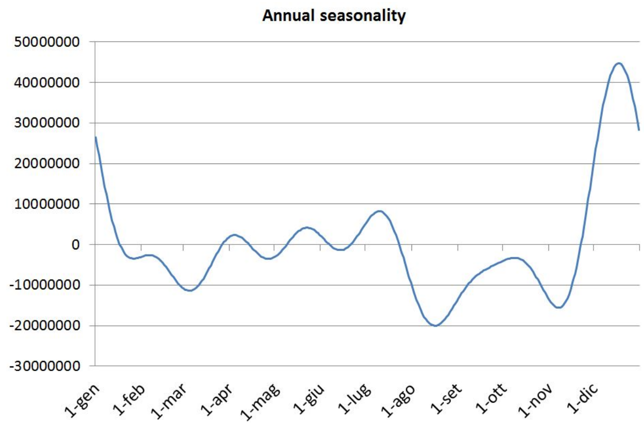
(a) POS daily series fitted with *TBATS*



(b) POS daily series - weekly seasonality

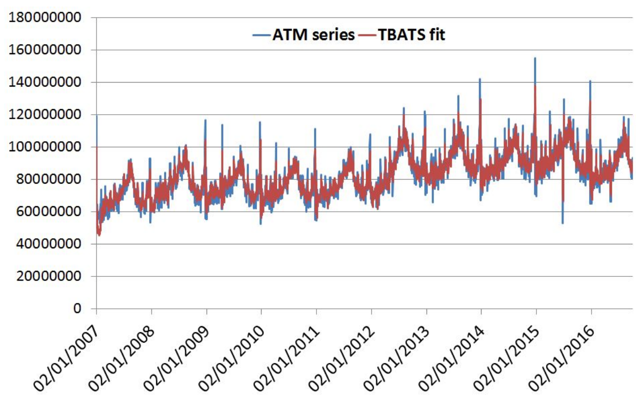


(c) POS daily series - monthly seasonality

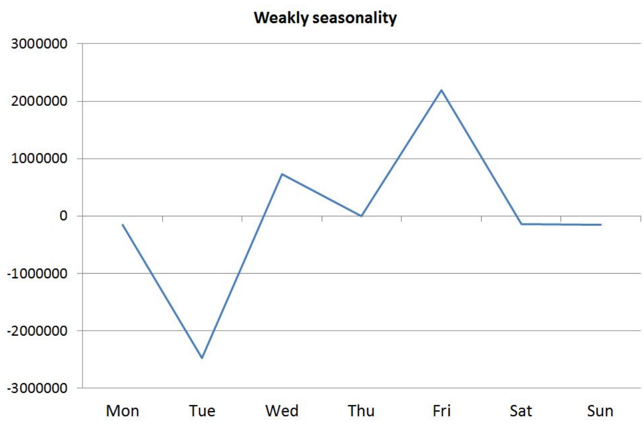


(d) POS daily series - annual seasonality

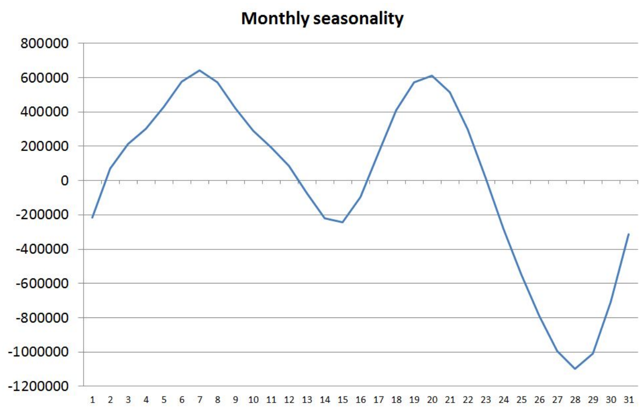
Figure 9: ATM, daily raw series and seasonal components estimated with TBATS.



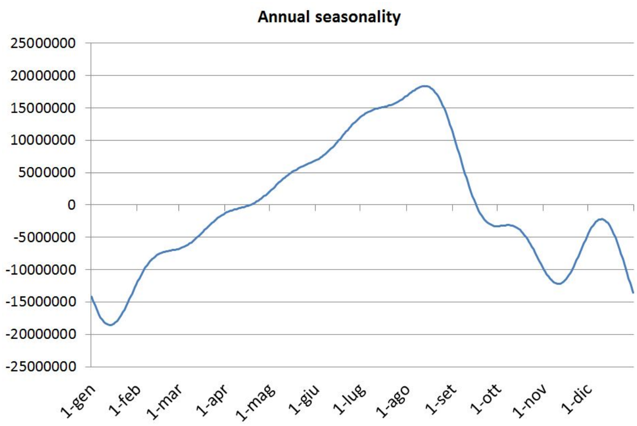
(a) ATM daily series fitted with *TBATS*



(b) ATM daily series - weekly seasonality



(c) ATM daily series - monthly seasonality



(d) ATM daily series - annual seasonality

Figure 10: POS daily series fitted with *Prophet*.

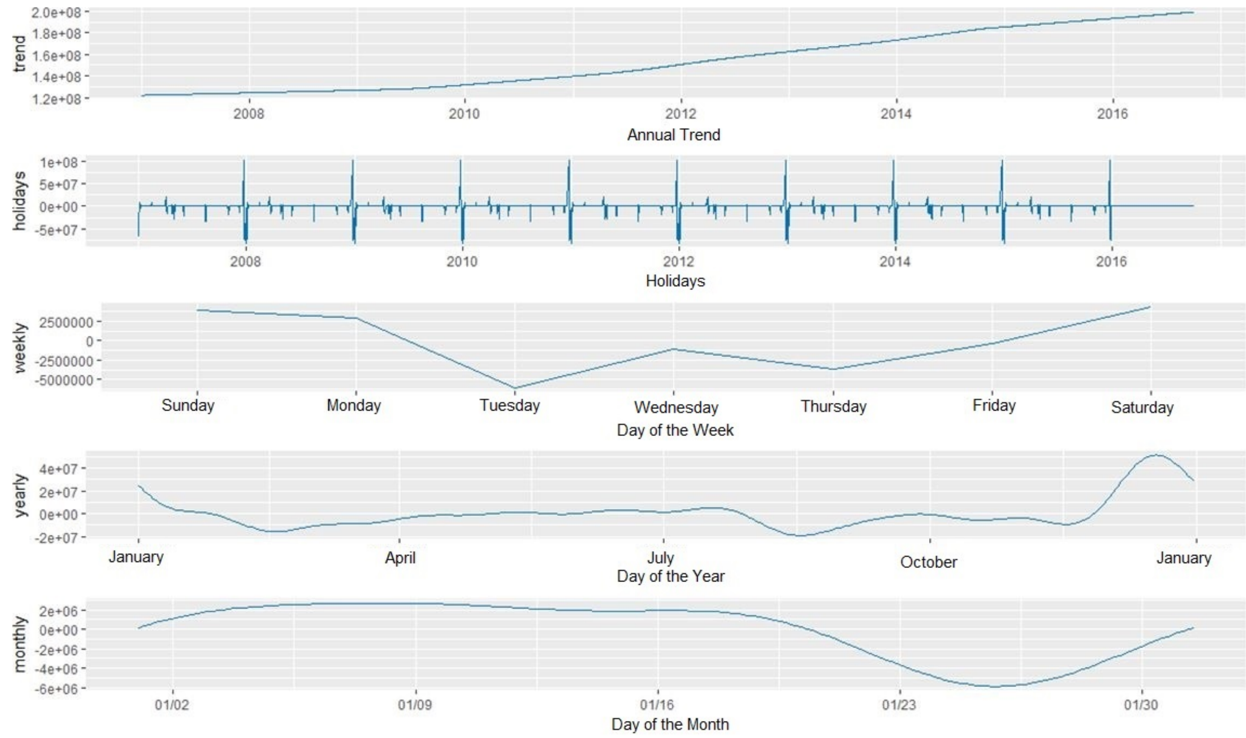
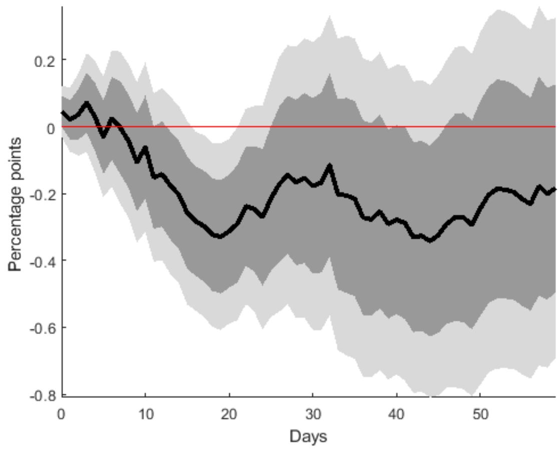
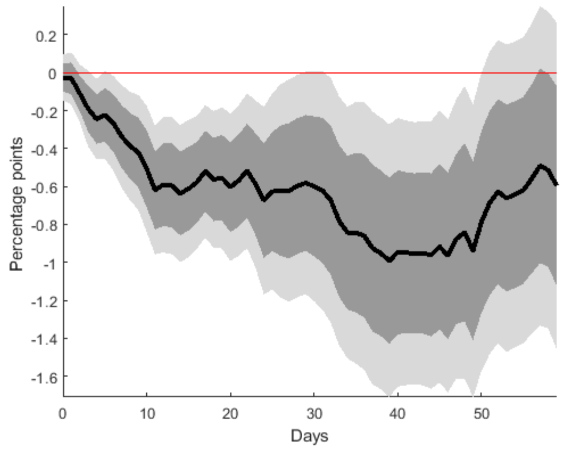


Figure 11: ATM daily series fitted with *Prophet*.

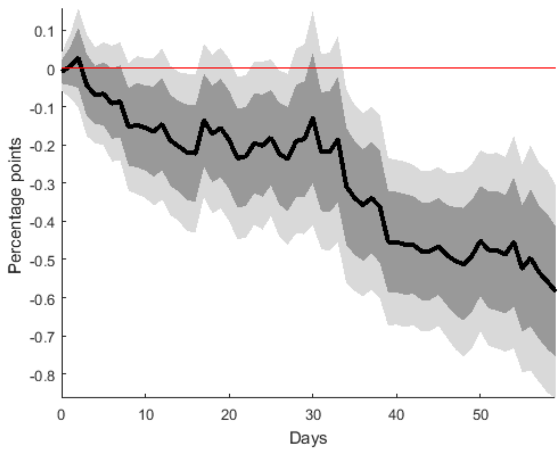
Figure 12: Response of POS payments to a one-standard-deviation increase in the EPU index (whole sample April 2007- September 2016).



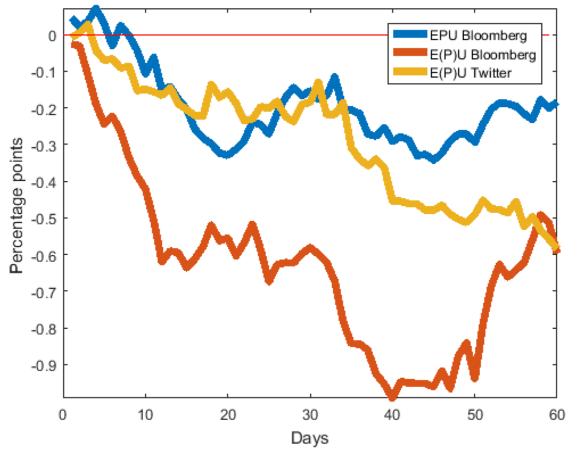
(a) POS response to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) POS response to a one-standard-deviation shock in uncertainty (E(P)U with words in English).



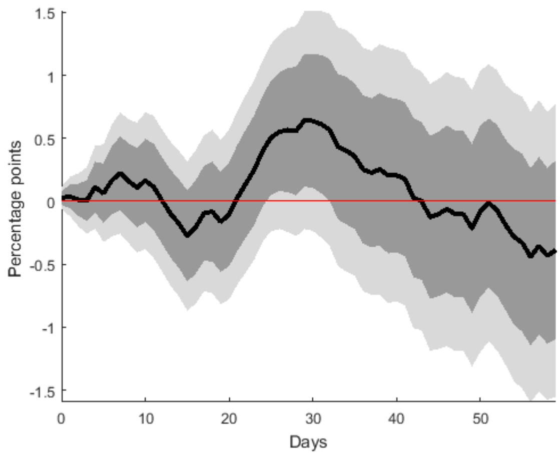
(c) POS response to a one-standard-deviation shock in uncertainty (Twitter). Sample January 2012- September 2016.



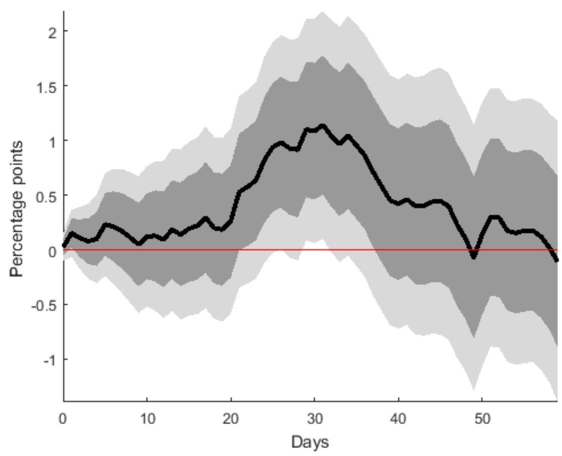
(d) POS response to a one-standard-deviation shock in E(P)U, median responses.

Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

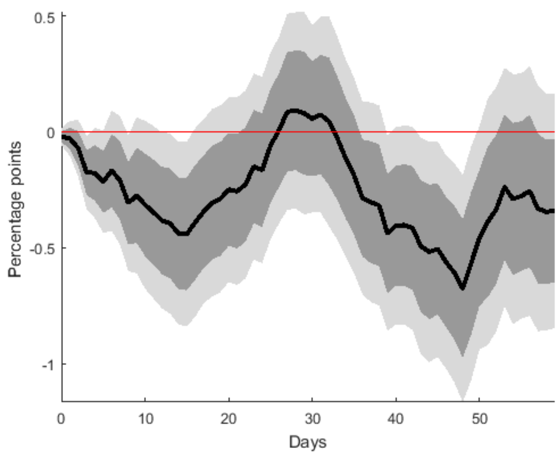
Figure 13: Response of ATM payments to a one-standard-deviation increase in the EPU index (whole sample April 2007- September 2016).



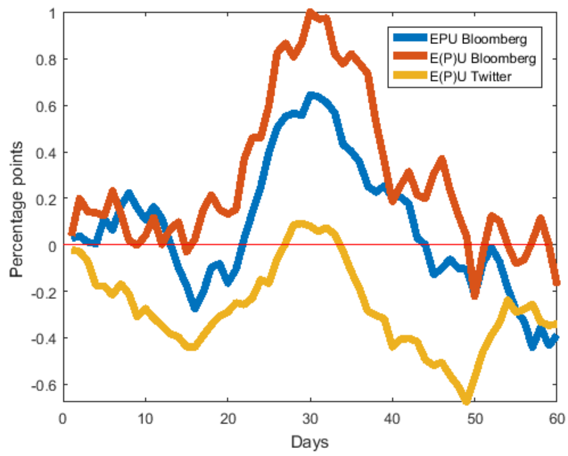
(a) ATM response to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) ATM response to a one-standard-deviation shock in uncertainty (E(P)U with words in English).



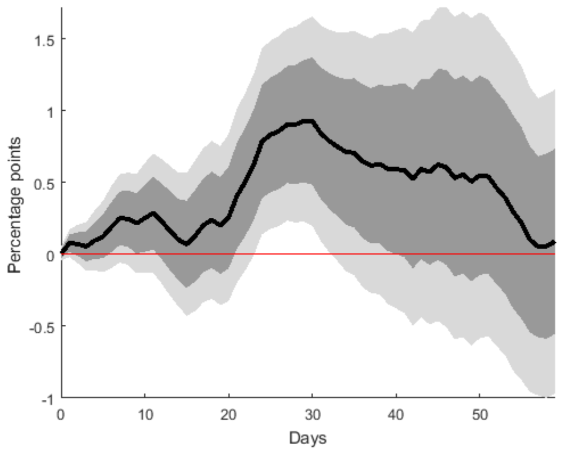
(c) ATM response to a one-standard-deviation shock in uncertainty (Twitter). Sample January 2012- September 2016.



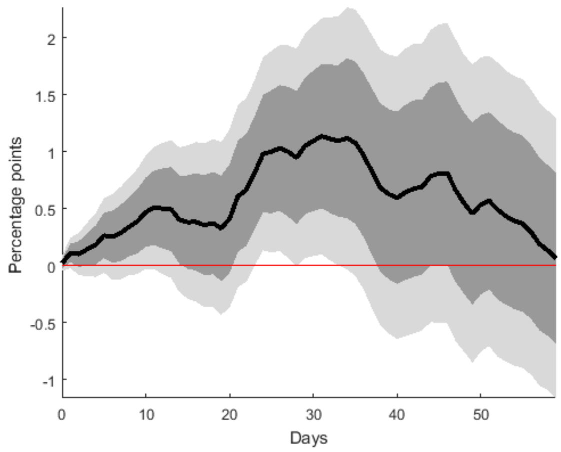
(d) ATM response to a one-standard-deviation shock in E(P)U, medians responses.

Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

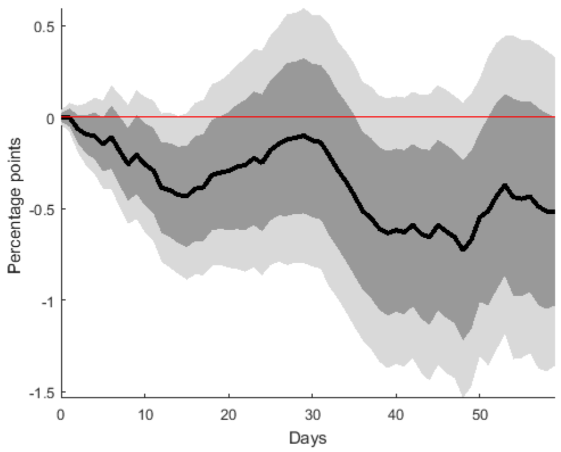
Figure 14: Response of ATM/POS ratio to a one-standard-deviation increase in the EPU index (whole sample April 2007- September 2016).



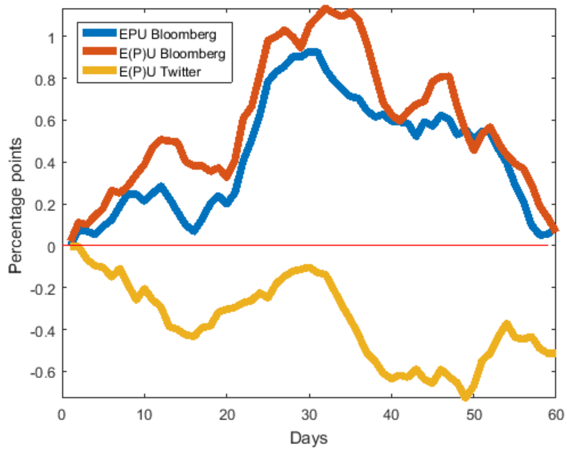
(a) ATM/POS ratio response to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) ATM/POS ratio response to a one-standard-deviation shock in uncertainty (E(P)U with words in English).



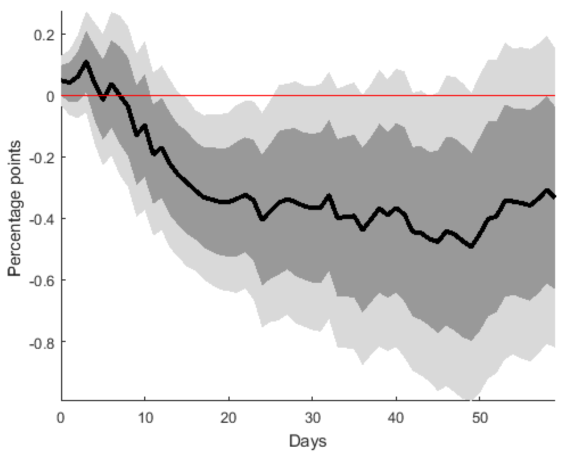
(c) ATM/POS ratio to a one-standard-deviation shock in uncertainty (Twitter). Sample January 2012- September 2016.



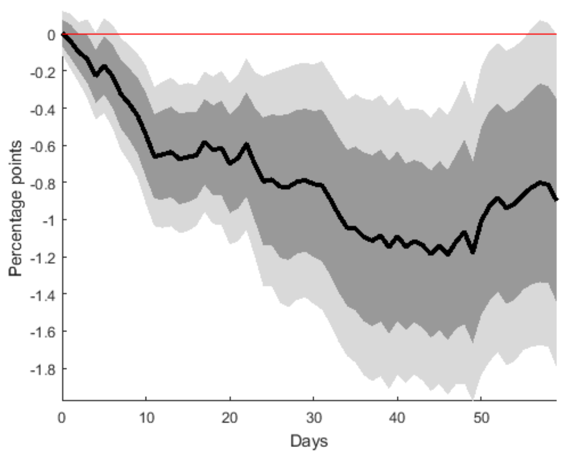
(d) ATM/POS ratio response to a one-standard-deviation shock in E(P)U, medians responses.

Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

Figure 15: Impulse response of POS payments to a one-standard-deviation increase in the EPU index (subsample April 2007- December 2013).



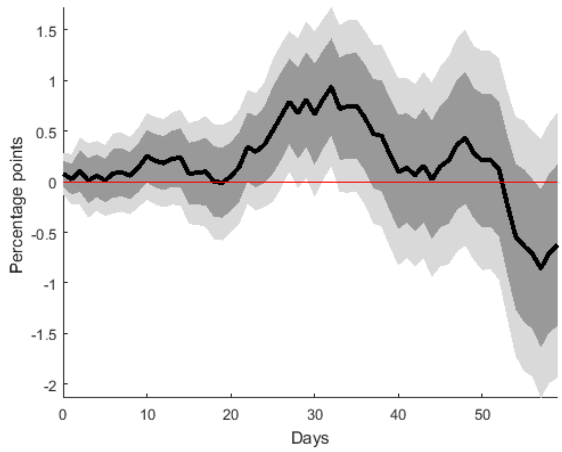
(a) POS response to a one-standard-deviation shock in uncertainty (EPU with words in English).



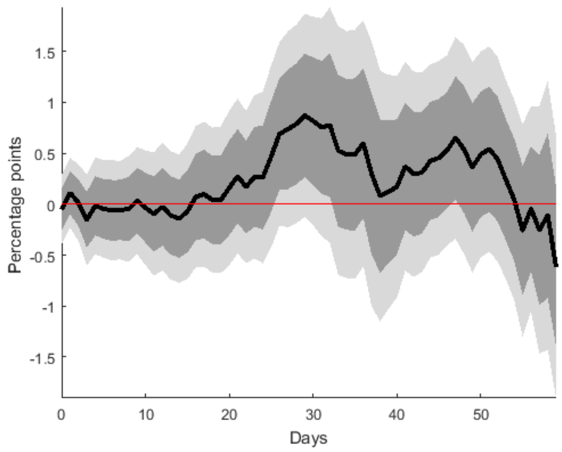
(b) POS response to a one-standard-deviation shock in uncertainty (E(P)U with words in English).

Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area). For the subsample April 2007- December 2013 Twitter results are not available because of its scarce diffusion in Italy.

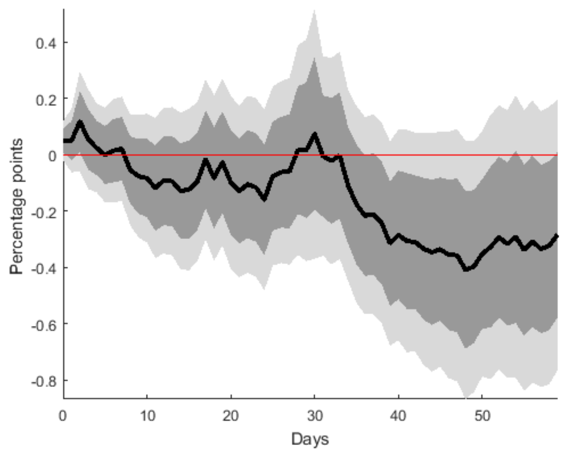
Figure 16: Impulse response of POS payments to a one-standard-deviation increase in the EPU index (subsample January 2014 - September 2016).



(a) POS response to a to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) POS response to a one-standard-deviation shock in uncertainty (E(P)U with words in English).

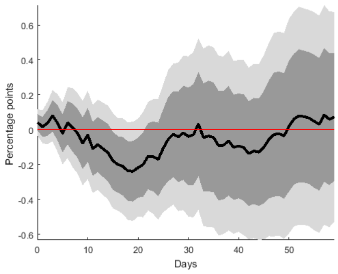


(c) POS response to a one-standard-deviation shock in uncertainty (Twitter).

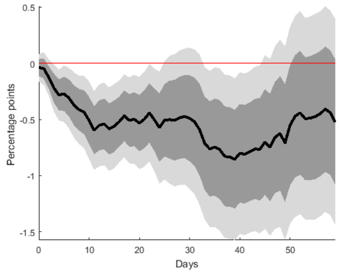
Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area). In the subsample January 2014 - September 2016 we have results also using Twitter that becomes reliable in Italy after 2012.

Figure 17: Impulse response of POS payments to a one-standard-deviation shock in the EPU index controlling for the daily Italian 10-year spread with respect to the German Bund, the daily returns and the daily realized volatility of the FTSE MIB index.

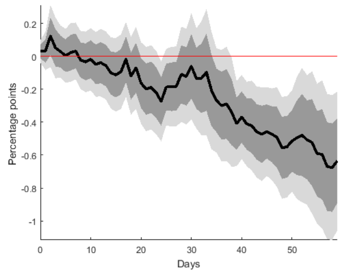
EPU	$\mathbf{E(P)U^1}$	$\mathbf{E(P)U^2}$



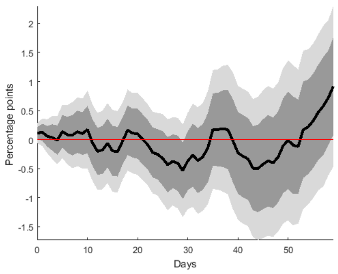
(a) POS response to a one-standard-deviation shock to EPU conditional on the inclusion of the three financial variables.



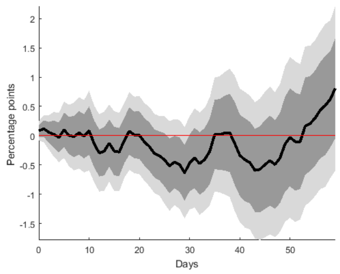
(b) POS response to a one-standard-deviation shock to $E(P)U^1$ conditional on the inclusion of the three financial variables.



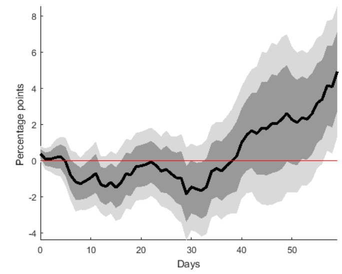
(c) POS response to a one-standard-deviation shock to $E(P)U^2$ conditional on the inclusion of the three financial variables.



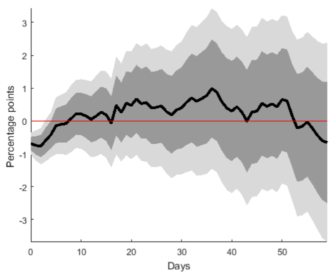
(d) POS response to a one-standard-deviation shock of the 10-year sovereign spread conditional on EPU.



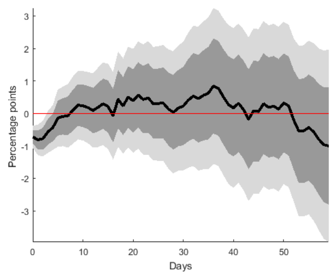
(e) POS response to a one-standard-deviation shock of the 10-year sovereign spread conditional on $E(P)U^1$



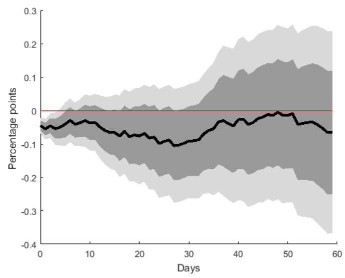
(f) POS response to a one-standard-deviation shock of the 10-year sovereign spread conditional on $E(P)U^2$.



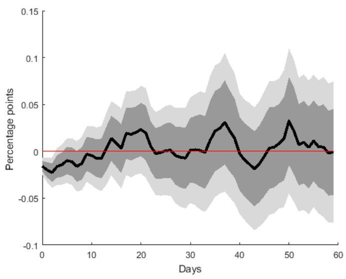
(g) POS response to a one-standard-deviation shock of the realized volatility conditional on EPU.



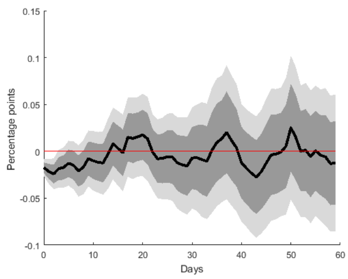
(h) POS response to a one-standard-deviation shock of the realized volatility conditional on $E(P)U^1$.



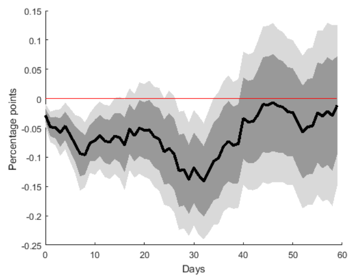
(i) POS response to a one-standard-deviation shock of the realized volatility conditional on $E(P)U^2$.



(j) POS response to a one-standard-deviation shock of the FTSE MIB return conditional on EPU



(k) POS response to a one-standard-deviation shock of the FTSE MIB return conditional on $E(P)U^1$

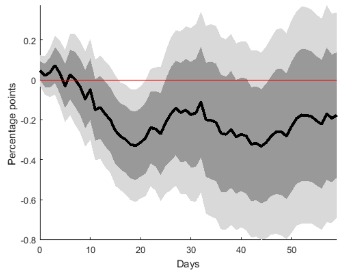


(l) POS response to a one-standard-deviation shock of the FTSE MIB return conditional on $E(P)U^2$

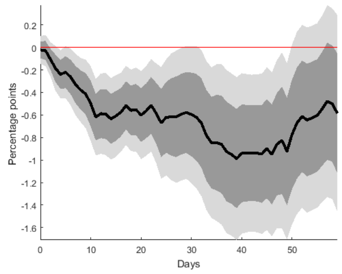
Notes: EPU is computed from Bloomberg with words in English. $E(P)U^1$ is computed from Bloomberg with words in English and without the policy words. $E(P)U^2$ is computed from Twitter with words in Italian and without the policy words. Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

Figure 18: Impulse response of POS payments to a shock in the EPU index controlling for macroeconomic surprises for the releases of the Italian GDP, the unemployment rate and the consumer confidence indicator.

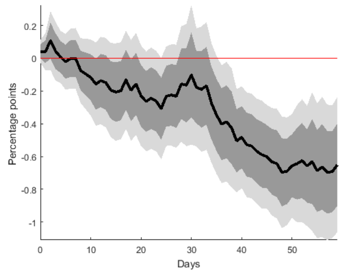
EPU	**E(P)U^1**	**E(P)U^2**



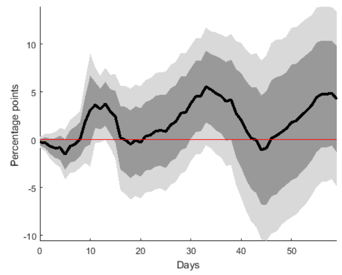
(a) POS response to a one-standard-deviation EPU shock, conditional on the three macroeconomic surprises.



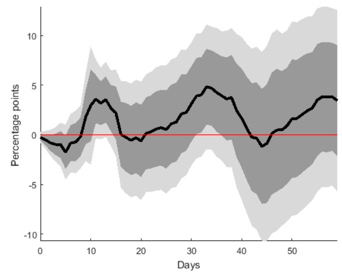
(b) POS response to a one-standard-deviation E(P)U^1 shock conditional on the three macroeconomic surprises.



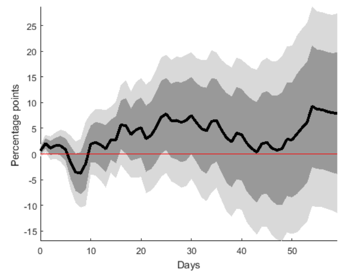
(c) POS response to a one-standard-deviation E(P)U^2 shock conditional on the three macroeconomic surprises.



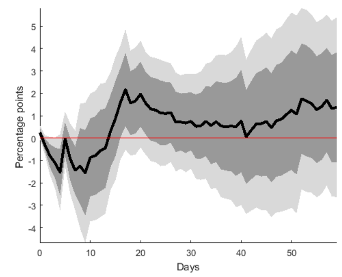
(d) POS response to a one-standard-deviation positive surprise in GDP using EPU.



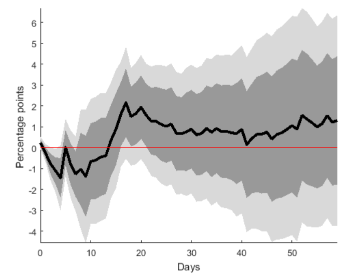
(e) POS response to a one-standard-deviation positive surprise in GDP using E(P)U^1.



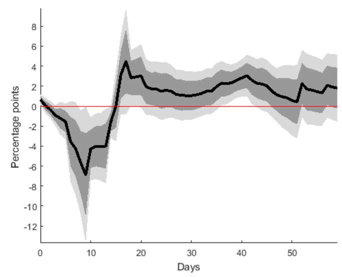
(f) POS response to a one-standard-deviation positive surprise in GDP using E(P)U^2.



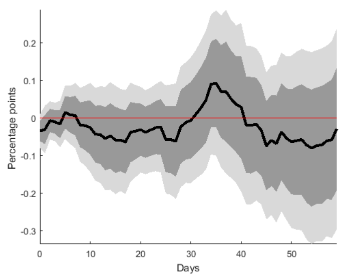
(g) POS response to a one-standard-deviation negative surprise in unemployment using EPU.



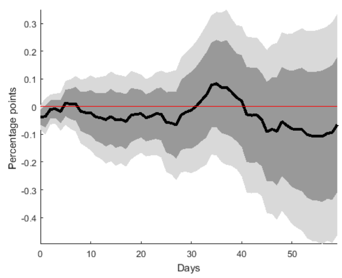
(h) POS response to a one-standard-deviation negative surprise in unemployment using E(P)U^1.



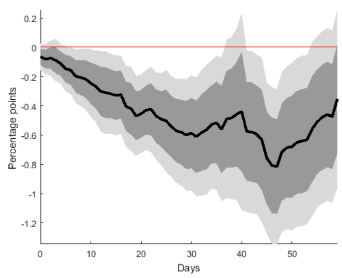
(i) POS response to a one-standard-deviation negative surprise in unemployment using E(P)U^2



(j) POS response to a one-standard-deviation positive surprise in consumer confidence using EPU.



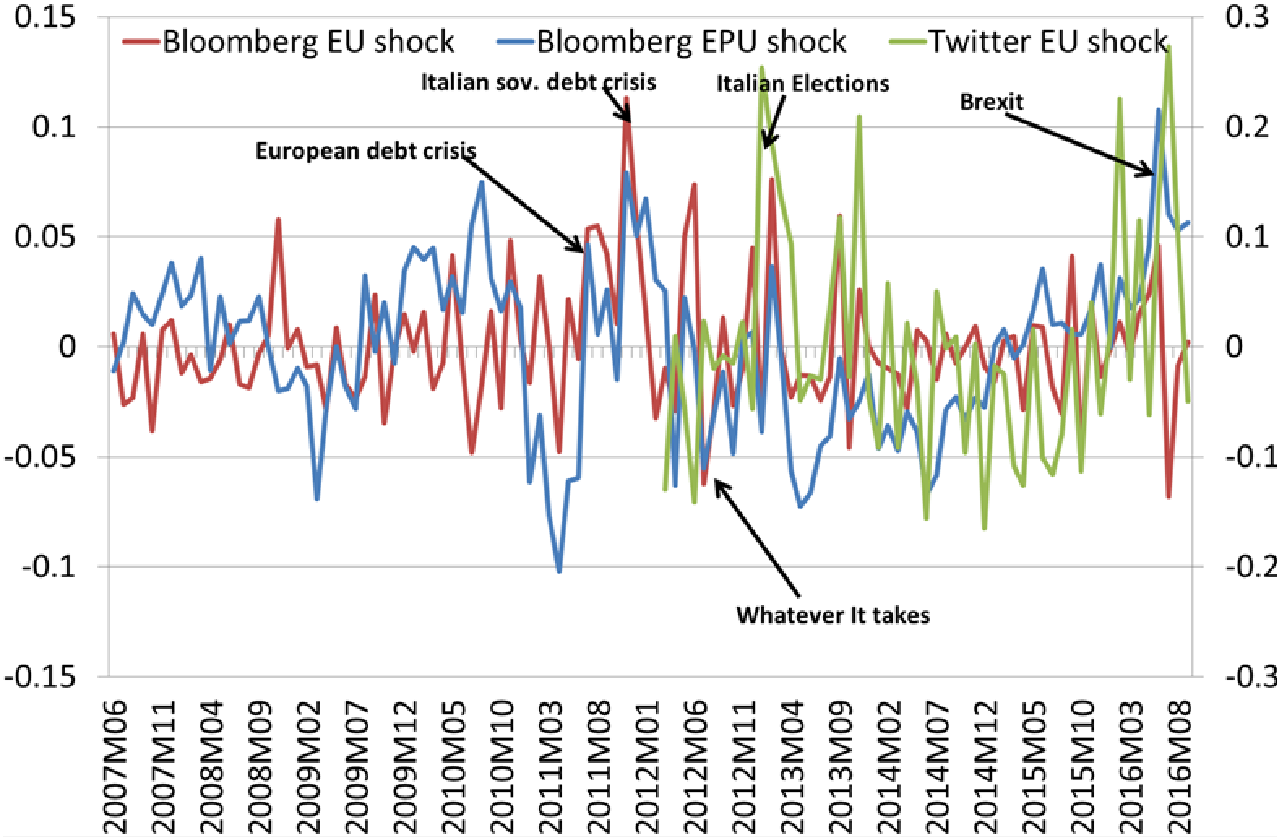
(k) POS response to a one-standard-deviation positive surprise in consumer confidence using E(P)U^1.



(l) POS response to a one-standard-deviation positive surprise in consumer confidence using E(P)U^2.

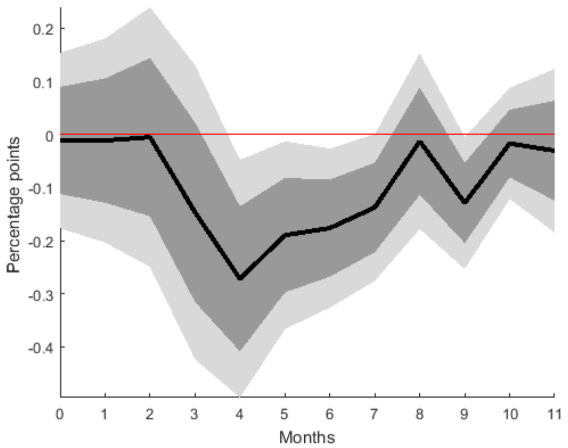
Notes: EPU is computed from Bloomberg with words in English. E(P)U^1 is computed from Bloomberg with words in English and without the policy words. E(P)U^2 is computed from Twitter with words in Italian and without the policy words. Surprises are calculated as the difference between the release of the indicator and the forecast provided by the Bloomberg median analysts. Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

Figure 19: Monthly EPU series computed from the daily shocks.

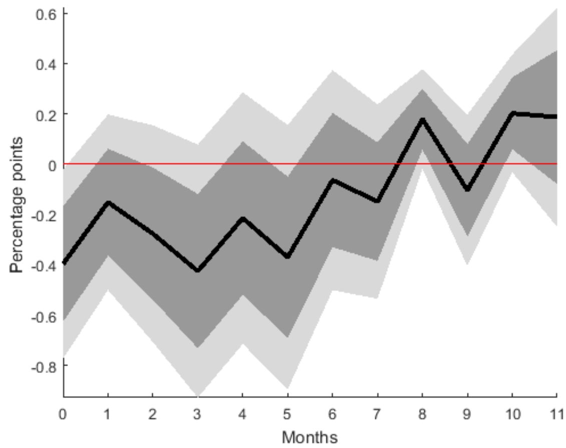


Notes: Monthly EPU shocks obtained aggregating the daily shocks estimated as described in Section 8. The major uncertainty events are dated.

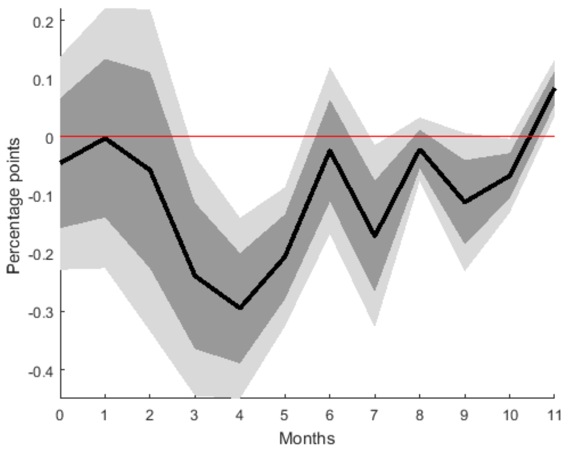
Figure 20: Impulse response of POS payments to a temporary one-standard-deviation increase in the EPU index on monthly data (shocks identified at the **daily frequency**).



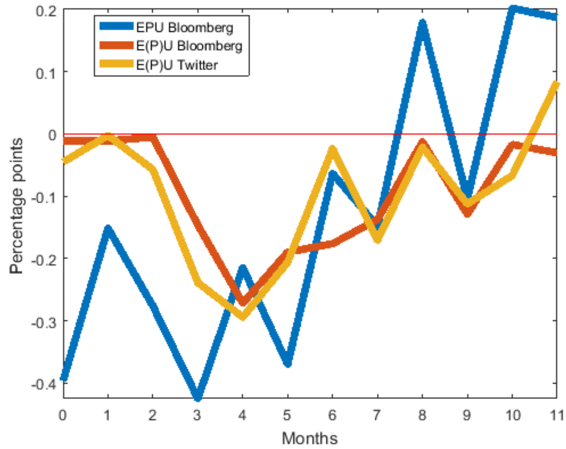
(a) POS response to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) POS response to a one-standard-deviation shock in uncertainty (E(P)U with words in English) - monthly frequency.



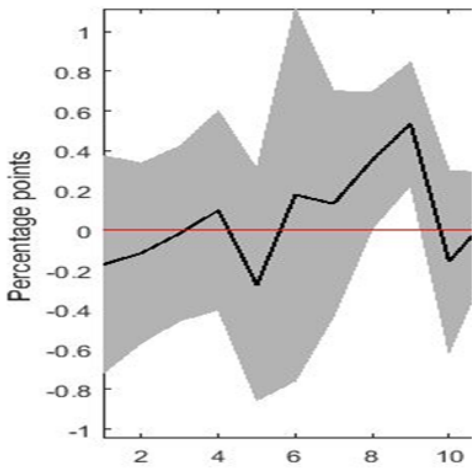
(c) POS response to a one-standard-deviation shock in uncertainty (Twitter) - monthly frequency. Sample January 2012- September 2016.



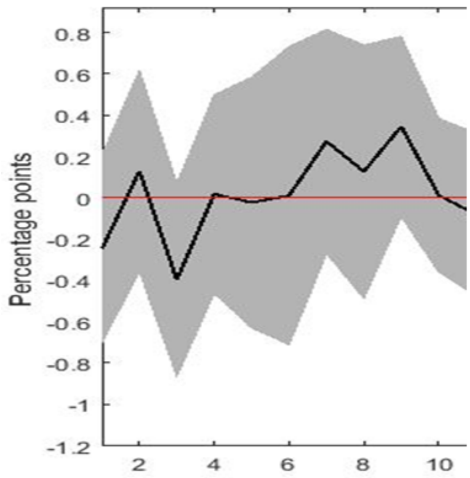
(d) POS response to a one-standard-deviation shock in E(P)U, median responses.

Notes: Dark grey shaded area represents 68% confidence level bands (95% for the light grey area).

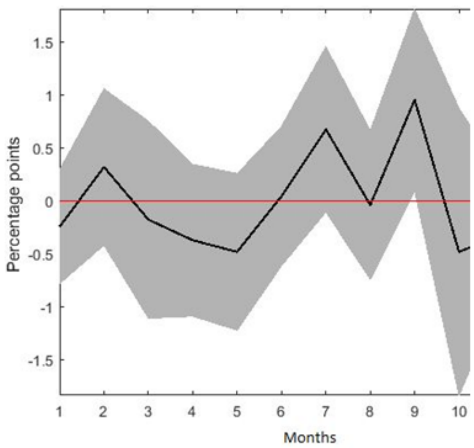
Figure 21: Impulse response of POS payments to a temporary one-standard-deviation increase in the EPU index on monthly data (shocks identified at the **monthly frequency**).



(a) POS response POS response to a one-standard-deviation shock in uncertainty (EPU with words in English).



(b) POS response to a one-standard-deviation shock in uncertainty (E(P)U with words in English) - monthly frequency.



(c) POS response to a one-standard-deviation shock in uncertainty (Twitter) - monthly frequency. Sample January 2012- September 2016.

Notes: Shaded area represents 95% confidence level bands.

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