News and consumer card payments

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Abstract

We exploit a unique daily data set on debit cards' expenditures to study the reaction of consumption to news related to economic policy uncertainty (EPU) or to payment system security. Adopting big data techniques, we construct indexes of EPU and payment security using either articles from Bloomberg newswire or tweets from Twitter social network. Quarterly payments with cards are a proxy of consumption but at daily frequency should be treated in order to remove strong seasonal components. Using local projections we find that daily positive innovations in EPU reduce purchases, mainly during periods of crisis. In the meantime, news on the debit cards' security has a negative impact on expenditure and seems to increase the preference for cash.

JEL: C11, C32, C43, C52, C55, E52, E58

Keywords: Consumption, Payment System, Policy Uncertainty, CyberSecurity, Bigdata, Daily Seasonality.

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1 Introduction

The great financial crisis of 2007-08 and the ensuing Great Recession broke the long calm of the Great Moderation. The world economy is now recovering in a more uncertain environment fostered by growing geopolitical risks related not only to institutional factors, such as Brexit, but also to other aspects, such as terrorism or climate change (Caldara and Iacoviello, 2017). Furthermore, the ever increasing digitalization of this decade is raising not only productivity but also the cyber-security costs incurred by firms and households (Biancotti, 2017; Kopp et al., 2017).

Following these recent developments there is a strong interest from both private agents and central bankers in finding ways to measure the macroeconomic impact of several risks, either related to policy uncertainty (Visco, 2017) or to the security of digital technologies (Draghi, 2017). Our paper investigates how the choice to consume (or save) and to use cash reacts to news about these risks: those concerning economic policy uncertainty (EPU henceforth) as in Baker et al. (2016) and those related to frauds and cyber attacks to the payment system (Arango and Taylor, 2009; Kahn and Liñares-Zegarra, 2016; Kosse, 2013). We tackle this issue using a novel data set for Italy on card payments settled on the clearing systems of the Bank of Italy. Payment system data are an extremely timely and reliable source of information for tracking the business cycle (Aprigliano et al., 2017) and may be used to construct a proxy of retail purchases. Transactions are observed in real time and time series may be extracted at very high frequencies. To the best of our knowledge, our paper is the first one to provide a quantitative assessment of the effects of either economic policy uncertainty or cybersecurity news on consumption at 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 time series.

The first contribution of our paper is the construction of a variety of indexes based either on news from Bloomberg newswire or from social networks such as Twitter. The indexes on EPU are computer generated according to the methodology put forward in Baker et al. (2016), those on cyber-security and frauds follow Kosse (2013). Both indexes are built from prominent sources, both for professionals and non experts, such as Bloomberg and Twitter. The second contribution refers to the peculiar seasonality of our daily time series analysis of the debit card flows. In fact, we apply a variety of seasonal adjustment methods finding strong seasonal patterns (within week, month and year) and calendar effects. Third, we show how consumption measured with card payments and consumers' preference for cash vary with respect to our news-based indexes of EPU and cyber security using impulse response functions (IRFs) based on the local projections approach by Jordà (2005) .

This paper sits at the intersection of two strands of literature. The first one relates to the effects of economic policy uncertainty (EPU) on economic activity, following the seminal work of Baker et al. (2016). However, while they identify 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. Second, while they investigate the impact of the supply, measured by industrial production and employment, we focus on the reaction of the demand for consumption as measured by card payments. Our work is also related to the literature on the impact of news on frauds and cyber-security on consumer card payments, similarly to Kosse (2013), but with computer-based textual search in our case.

The rest of the paper is organized as follows. Section 2 describes the data, the debit card series and the indexes based on news and social networks. Section 3 describes the analysis of the daily seasonal and calendar effects. Section 4 and Section 5 assess the macroeconomic effects of the news on EPU and cyber-security, respectively. Section 6 presents some robustness check, while Section 7 concludes.

2 Data

2.1 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. 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 the economic activity. The New Monetarist Economics literature (Williamson and Wright, 2010; Schneider and Piazzesi, 2015) has recently highlighted the importance of payments, jointly with banking and asset markets, in order to understand the functioning of a monetary economy.

Moreover payment data have been recently exploited for macroeconomic purposes: for example they have been used to either predict the GDP (Aprigliano et al., 2017) or consumption (Duarte et al., 2017). Given the increasing digitalization of the retail payment ecosystem, with new emphasis on 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.

Payment data are free of observation errors, as they are collected through the clearing and payment systems, which include a set of 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, that 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).[1]

We concentrate our analysis on debit card payment data, as they are the main payment tool for the average Italian consumer. According to the Survey of Household Income and Wealth (SHIW) of the Bank of Italy, 75% of the households in Italy hold a "*bancomat*" (i.e. a debit card), versus 28% for credit cards and 20 for prepaid cards. The banking statistics report about 55 million 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). Our data are a good indicator of the whole Italian market, because about two third of the operations with debit cards at POS in Italy are settled through the Bank of Italy's BI-COMP system.[2]

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) which imply an additional fee for the consumer. More in general, the "ATM cash withdrawals to POS card transactions" ratio (cash-card ratio) represents a good proxy of the preference for cash against electronic payments. Indeed, a strong positive correlation between the cash-card ratio and the share of expenditures with cash of Italian households was found with survey data (Ardizzi et al., 2014). In other words, if the ATM transactions grow more than the POS ones this is an index of an increasing preference for cash, while the opposite happens when there is a preference for electronic money.

Figure 1 shows the daily data on debit card payments. As expected there is a strong seasonal patterns of both POS and ATM flows, with peaks and troughs associated with

[1]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).

[2]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 (postal prepaid cards).

calendar effects, especially during Christmas or summer holidays.

Figure 2 depicts the correlation with macroeconomic series, at a lower frequency. Figure 2a 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 [3].

Figure 2b 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 that is consistent with the literature on cash demand (Stix, 2004; Schneider, 2010; Schiff et al., 2005). The higher the standard of living, the lower the relative use of cash and the greater the demand for alternative payment instruments.

2.2 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:

[3]The correction is based on the dynamics of an alternative payment system (the 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 entrance of the postal operator "*PT*" as a new participant in the debit card settlement procedure in BI-COMP.

- 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*'.

Since for our purposes we need a daily EPU index for Italy but we did not have access to the newspapers articles in Factiva, we decide to adopt two different sources of news.

We construct a first EPU index with exactly the same keywords as in Baker et al. (2016) but using as a news source Bloomberg newswire.[4]

The Bloomberg platform allows the user to compute the counts of news articles appeared on the Bloomberg newswire that contain specific keywords. Since 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*').

The second EPU index was constructed using a similar strategy applied to the Twitter feeds written in the Italian language. Twitter is a microblogging platform where users share some content which is publicly available. 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 few months ago 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 an alternative E(P)U index where we considered only those tweets with at least a keyword from both category (E) and category (U). Therefore, our E(P)U index is a sort of '*economic uncertainty index*', slightly more general than the EPU index.

In the end we built three indexes in total: an EPU and an E(P)U index in English from Bloomberg and an E(P)U index in Italian from Twitter.

Our indexes of EPU and E(P)U are built in a way similar to those of Google Trends. For those obtained from Bloomberg, for each day, we compute the proportion of news

[4]The Bloomberg newswire contains various sources of news. 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. Therefore, Bloomberg newswire is not only limited to business news, but it contains many other sources.

with respect to all the news counts in that day and then we normalize to 100 the index in the day in which such proportion of counts for E(P)U news is maximum. In the case of Twitter data, since we do not have the total number of tweets or any other series of tweets to normalize the series, we just set to 100 the index for the day in which we have the maximum number of tweets.

Figure 3 depicts both EPU and E(P)U indexes obtained from Bloomberg. As the reader can notice, the indexes seem to capture some episodes of high uncertainty in Italy, especially during the sovereign debt crisis at the end of 2011. Figure 4 shows the E(P)U index obtained from Twitter with tweets 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 ones computed by Baker et al. (2016) we aggregated our index to the monthly frequency (see figure 5) and we computed the correlations with the original EPU for Italy, downloaded from FRED. Our indexes computed from Bloomberg newswire show an 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).

2.3 News related to card frauds and cybersecurity

We compute several indexes of cycbersecurity and frauds related to ATM ans POS using news counts from Bloomberg, with keywords based on Kosse (2013). The keywords are selected both in Italian and English because most news in Bloomberg newswire are in English even for facts happening in Italy. For the empirical analysis we use three types of indexes for news on card frauds. The first one refers to frauds about POS payments, the second one to frauds on ATM while the third one is related to cybersecurity and payments.

1. Fraud index for POS: '*FRAUD*' AND '*PAYMENT*' AND '*POS*' AND '*ITAL**'
2. Fraud index for ATM: '*FRAUD*' AND '*ATM*' AND '*ITAL**'
3. Fraud index for Cybersecurity: '*CYBER**' AND '*FRAUD*' AND '*PAYMENT*' AND '*ITAL**'

For the keywords listed above we computed the fraud-related news indexes exactly as we did for the E(P)U indexes in Section 2.2.

Figure 6 depicts the three Fraud indexes. We can notice that there are some isolated peaks in the news on card frauds, as also found in Kosse (2013). This is because this kind of news is particularly intense around the day in which the fraud was discovered and then the frequency of news dies out very quickly.

3 Seasonal adjustment of daily payments

Since daily payment system data exhibit strong and regular seasonal components, for our purposes is crucial to separate the daily signal contained in the series from the predictable component due to seasonality. In fact the shocks faced by agents should have an impact only on components of daily payment series that are orthogonal to seasonal variation.

The predictable component is the result of two patterns: on the one hand there are the cycles associated with the day of the week, the day of the month and the day of the year; on top of these patterns, payment series display strong calendar effects connected with fixed (e.g. Christmas and the days around) and moving holidays (e.g. Easter).

In the scant literature dealing with payments at daily frequency the seasonal and calendar components are usually treated with a dummy approach (Rodrigues et al., 2010; Kosse, 2013). Since there is no benchmark method for seasonal adjustment at daily frequency, and the dummy approach is not parsimonious, we considered two alternative methodologies based on unobserved components, recently proposed in the literature.

The first approach, is the state-space framework for complex seasonal time series proposed by De Livera et al. (2011) called *TBATS*.[5] The second one, called *Prophet*, 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: the first one is a trend component modeled with a linear trend with random change points; the second one is the seasonal components (e.g., weekly, monthly and annual seasonality) and the third one is the calendar effect (either fixed or moving holidays).

Given the importance of the seasonal adjustment in our analysis we considered three different approaches. At the beginning we tried to use seasonal and calendar dummies, but this approach requires the estimation of too many parameters. We therefore preferred to apply the more parsimonious approaches based on unobserved component models, *TBATS* and *Prophet* (see Appendix A and Appendix B for an overview of these methodologies).

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

[5]The acronym TBATS stands for Trigonometric, Box-Cox transform, ARMA errors, Trend and Seasonal components.

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.

3.1 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.[6] In a second step we control for calendar effects using dummies for the Italian calendar holidays (see Table 1 for further details).

Figure 7a depicts the POS raw series and the fitted series using TBATS (in red): the estimated model fits the raw data pretty well and captures the volatility of the deterministic seasonal components. Figure 7b displays the weekly seasonality of the series: the biggest amount of POS payments is done during the weekend, when households have more time to purchase goods and services.[7]

Figure 7c shows the monthly seasonal component: the biggest amounts of POS payments happen around the first and the third week of each month. This pattern is consistent with rents being paid at the beginning of the month and salaries paid during the third week. This behavior found in monthly debit card payments goes against the prediction of economic theory given that the arrival of predictable streams of income should have little or not effect at all on spending patterns. 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 7d) POS payments are particularly high at the beginning and at the end of each year. 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 on average from September reaching a minimum in November. Basically, within the year, there are strong increases associated with holidays and, in particular, for Christmas.

Figure 8a shows the seasonal adjustment of the ATM series with TBATS (in red).

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

[7] 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 1) 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.

As for the POS, the model performs quite well in eliminating the cyclical components. Figure 8b depicts the weekly component showing that withdrawals reach a minimum on Tuesdays and increase during the central days of the week reaching 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. This pattern is consistent with the fact 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 (see Figure 3 in (Stix, 2004)). Their evidence shows similar usage frequencies of the POS payments and ATM withdrawals during the week or the month . The monthly seasonal pattern in Figure 8c has a shape similar to the one of POS, but again with a phase shift in anticipation. This confirms the already mentioned tendency of ATM withdrawals to lead consumption by a few days. 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.

3.2 Prophet

To check the estimated daily seasonally adjusted series using TBATS we employ an alternative methodology called *Prophet*. 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 9 and 10, 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*[8] (see Appendix B for more details), while the second is the quantification of the calendar effects.

The top panel of Figure 9 depicts the estimated long-run POS component: through the sample considered the trend is continuously growing. This evidence is consistent with the increasing share of electronic transactions, as mentioned in the previous section.

The long-run component of ATM payments (in Figure 10) instead displays several breaks that are likely related to changes in the laws regulating the use of cash in transactions. 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

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

countercyclical preference for cash, already mentioned in the previous section.

The second panels of Figures 9 and 10 depict the deterministic effects related to holidays for both POS and ATM, respectively. Payments increase strongly before Christmas and then register a strong decrease. During Easter we observe the same pattern but the oscillations are lower in magnitude. 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 confirming the robustness of our results. 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 approach we will adopt in the next section.

4 Econometric framework

To assess the impact of news on economic political uncertainty and on the security of the payments system we use the local projection methodology proposed by Jordà (2005) and recently adopted in several macroeconomic applications (Auerbach and Gorodnichenko, 2016; Owyang et al., 2013). We build impulse responses (IRFs) running regressions with the following specification

$$y_{t+h} - y_t = \alpha_h Index_t^v + \sum_{i=0}^{I} \beta_i y_{t-i} + \sum_{j=1}^{J} \gamma_i Index_{t-j} + \dots \tag{1}$$
$$\dots + det_t + \varepsilon_t, \quad h = 1, \dots, H, \quad v = \{EPU, Frauds\}.$$

where y_t is the logarithm of the daily trend 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 either EPU or Fraud index respectively ($Index_t^v$); det_t is a vector containing the deterministic components of the regression and H is the maximum horizon for the local projection.[9] Since the error term ε_t in equation (1) is serially correlated for $h > 1$, we use Newey-West consistent estimators to compute the standard errors as in Owyang et al. (2013).

[9]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.

The flexibility of this methodology has several advantages for our application that to the best of our knowledge is unique in the use of macroeconomic daily variables. The daily frequency is fundamental in order to rule out problems of endogeneity, but it also increases the volatility and the complexity of the autocorrelation structure of the data. Therefore model misspecification becomes a serious concern. Local projections are the right tool to tackle this issue, since they do not impose the restrictions implicit in (Vector Autoregressions) VARs (Jordà, 2005).[10] Furthermore, as the IRFs from an autoregressive model are obtained by recursively iterating the estimated one-period-ahead forecasting model, in VARs the misspecification errors are increasingly compounded with the forecast horizon. This is a peculiar concern in our context because using daily data we compute IRFs up to a large number of periods ahead.

Our identifying assumption is a timing restriction: since cards are a proxy for consumption, we assume that they are a slow moving variable and hence do not respond contemporaneously to jumps in either daily economic uncertainty or fraud-related news. When tracing the response of cards to daily news about policy uncertainty or payment security, the contemporaneous variation in $Index_t^v$ is purified by lags of y_t and $Index_t^v$ itself. In the baseline specifications we use 20 lags (almost one month in terms of working days) for the dependent variable y_t, and 10 lags for the daily shocks from news.[11]

5 Impulse responses of the news

In this section we report the empirical results on the IRFs split according to the nature of the news shock. Section 5.1 shows the effects of positive innovations in the series of daily news regarding economic policy uncertainty. Section 5.2 instead documents the effects of a burst in news about frauds on POS payments and ATM withdrawals.

In the baseline analysis we estimate equation (1) on the full sample of ten years of daily working days for the sample from the April 2, 2007 to September 30, 2016, for about 2400 observations.

5.1 Effects of Economic Policy Uncertainty shocks

The baseline results on the effects of policy uncertainty on consumption with POS are shown in Figure 11. The IRFs are computed for horizons from one to 60 working days ahead (i.e. around three months). The shaded bands represent the 95% confidence

[10] In a preliminary investigation, we used ARDL models with Almon polynomials to trace IRFs that increase in the news index and we have found qualitatively similar results.

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

interval. In Figure 11a the innovations refer to news on economic policy uncertainty in the news collected by Bloomberg, computed using the same keywords proposed by Baker et al. (2016). In Figure 11b the news-based EPU indicator excludes the keywords referring to policy, therefore relates to a more general concept of economic uncertainty. Figure 11c depicts the IRFs using as shock the same economic uncertainty index computed from the popular social network Twitter. Independently of the measure adopted for the indicator of economic (policy) uncertainty, there is a clear negative and statistically significant impact on purchases. The effects tend to be temporary and are reabsorbed in about one quarter, although the IRF based on Twitter seems more persistent.

Since our data span almost ten years at the daily frequency we could check if our findings were driven by specific episodes in our sample, splitting our sample in subsamples. This is particularly relevant for the Italian economy. In fact, within our sample Italy was hit by the strongest (double dip) recession since its unity in 1861, excluding the two world wars.[12]

Figure 12 displays the IRFs with respect to EPU (Figure 12a) and EU (Figure 12b) for the first half of the sample, from the beginning of 2007 to the end of 2012, therefore covering the worst phase of the recession. The negative impact is recorded both for the economic policy indicator and for the more general index of economic uncertainty.[13]

On the contrary, when computing the IRFs for the second half of the sample (Figure 13) the impact on purchases looks unstable and statistically not significant.

5.2 Effects of the shocks on the security of the payment

As explained in Section 2 we also extracted computer-generated indicators of news on the security of card payments. We have one index targeted on POS purchases, a second indicator more focused on the risks associated with the ATM withdrawals, and a third on cybersecurity and payments by and large.

We show that the IRFs computed using these three sources of risk on, respectively, POS (Figure 14), ATM (Figure 15), and the ratio ATM/POS (Figure 16). In each of these figures, panel (a) refers to the news related to frauds and risks on POS, panel (b) on ATM, and panel (c) on cybersecurity by and large.

As expected, the diffusion of news related to risks on POS determines a contraction in purchases with debit cards and an increase in the ratio ATM/POS, thus implying a shift toward cash. Therefore it seems that when card holders feel risks on electronic money,

[12]Between the first quarter of 2008 and the first quarter of 2013 the Italian GDP dropped cumulatively by around 9 percentage points.

[13]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).

they prefer paying with cash, perceived as the safe mean of payment, even though it implies a fee.[14]

Alternatively, when news is more focused on ATM, POS expenditures are basically unaffected, while ATM withdrawals are severely hit.

Based on these results it seems that a careful choice of the keywords is crucial to generate the news-related indicators to then identify macroeconomic effects. In particular, the news on frauds and attacks on debit cards have effects only if the texts are focused on the specific payment instrument.

Given the increasing relevance in public discussions and news about "cybersecurity", we also tried to select news related to this word, jointly with "payments" and "frauds". We find that this indicator (in panel (c) of Figures 14, 15 and 16) has sizable effects on the use of debit cards for purchases and it also increases the preference for cash.

6 Robustness checks

We claim that our identification strategy is best suited for daily data, as the fine granularity across the time dimension of the observations is such that it rules out problems of endogeneity and it is appropriate to identify effects within the quarter (in fact, official data on consumption and economic activity are only quarterly). To check the empirical relevance of this argument, we estimate the same model adopted in the previous section (see equation 1) using monthly data, constructed from the daily observations as sample average. In Figure 17 the IRF of POS-based purchases is reported, with respect to various measures of news on economic (policy) uncertainty. Independently of the news-related index and the horizon, there is no clear effect on purchases with monthly variables. This result confirms the relevance of using the daily frequency in this kind of analysis.

7 Conclusion

We use a unique data set for Italy on daily purchases with debit cards to study the effects of the news related to the economic policy uncertainty (EPU) or to the security of the payment system. The news-based indicators are generated from newspapers, news wires or the social network Twitter.

We study the daily seasonality of the purchases with POS and ATM withdrawals, finding strong evidence of seasonal patterns and calendar effects.

[14] As explained in Section (2.1) in our data set the ATM series refers to the "not-on-us" operations, therefore on third banks' cash machines, that usually require a fee for money withdrawals.

Using local projections we find that increases in EPU have negative effects on purchases, mainly concentrated in the sample covering the recent double dip crisis of the Italian economy. The news on cards security has an impact on expenditure and it also increases agents' preferences for cash.

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A TBATS model proposed by 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 [15] is particularly promising for the series at hands:[16] (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:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega} & \omega \neq 0, \\ logy_t, & \omega = 0, \end{cases} \tag{2a}$$

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{k=1}^{N} s_{t-m_i}^{(i)} + d_t, \tag{2b}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t, \tag{2c}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \alpha d_t, \tag{2d}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} + \gamma_i d_t, \tag{2e}$$

$$d_t = \sum_{i=1}^{p} \phi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{2f}$$

where the first equation contains the Box-Cox transform;[17] $m_1, \ldots, m_T$ 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, β, and γ_i for

[15] 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.

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

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

$i = 1, \ldots, T$.

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

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} \tag{3a}$$

$$s_{j,t}^{(*i)} = -s_{j,t-1}^{(i)} \sin \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos \lambda_j^{(i)} \tag{3b}$$

where $\lambda_j^{(i)} = \frac{2\pi j}{m_i}$. The stochastic *level* of the ith seasonal component is $s_{j,t}^{(i)}$ 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 $s_{j,t}^{*(i)}$. 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 following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t. \tag{4}$$

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 $j = 1, \ldots, S$.

$\delta \in \mathbb{R}^S$ 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

$$a_j(t) = \begin{cases} 1, if t \geq s_j, \\ 0, otherwise. \end{cases} \tag{5}$$

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:[18]

$$g(t) = (k + \mathbf{a}_t^{'}\boldsymbol{\delta})t + (k + \mathbf{a}_\mathbf{t}^{'}\boldsymbol{\gamma}) \tag{6}$$

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).[19]

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 (Harvey and Shephard, 1993) 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

$$s(t) = \sum_{n=1}^{N} (a_n \cos(\frac{2\pi nt}{P}) + b_n \sin(\frac{2\pi nt}{P})). \tag{7}$$

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

[19] 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.

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

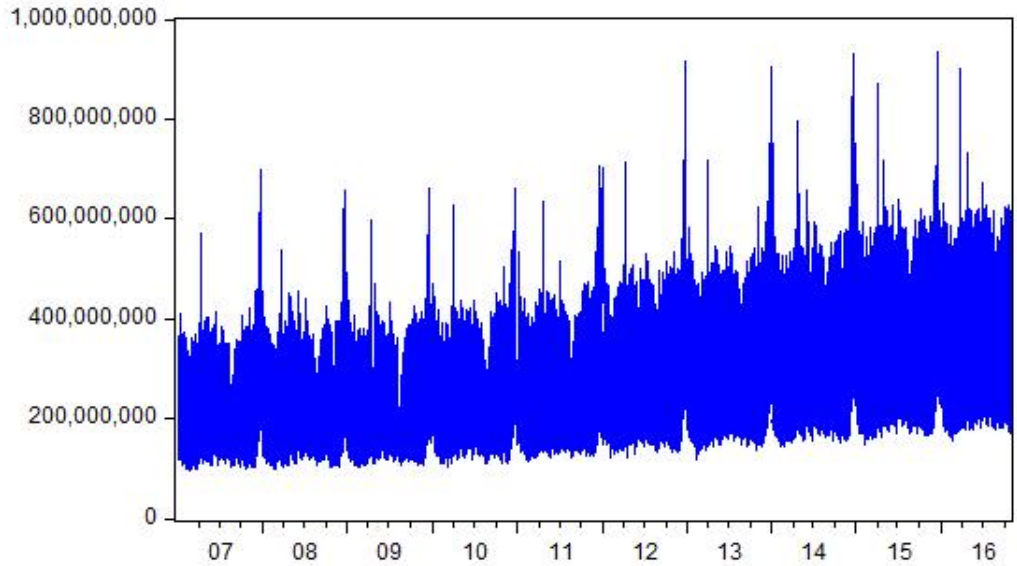
Table 1: Calendar of Italian Holidays

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

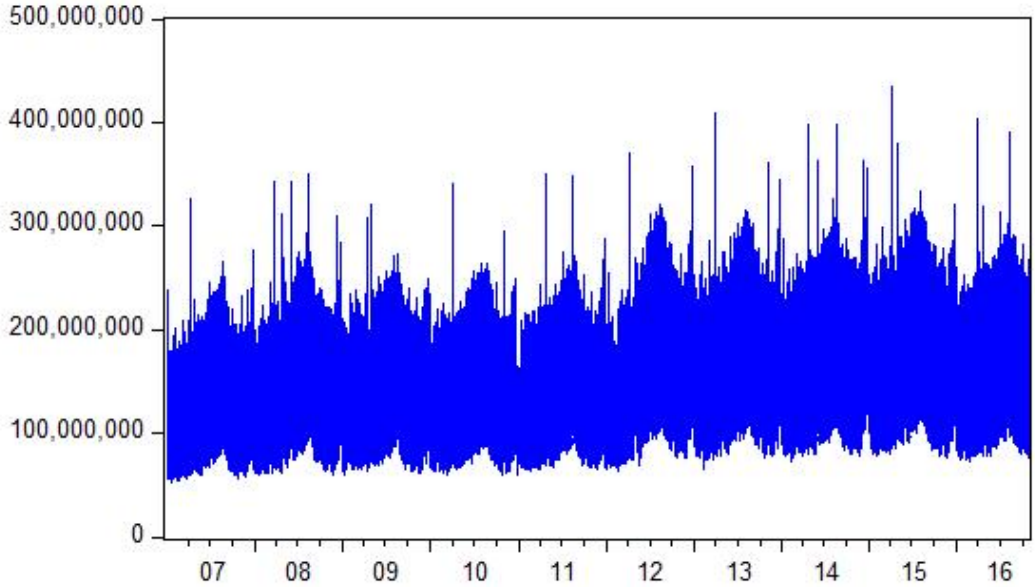
Notes: The windows represent the dummies used for days that are close to major holidays events.

C Tables and Figures

Figure 1: Payment series at daily frequency.



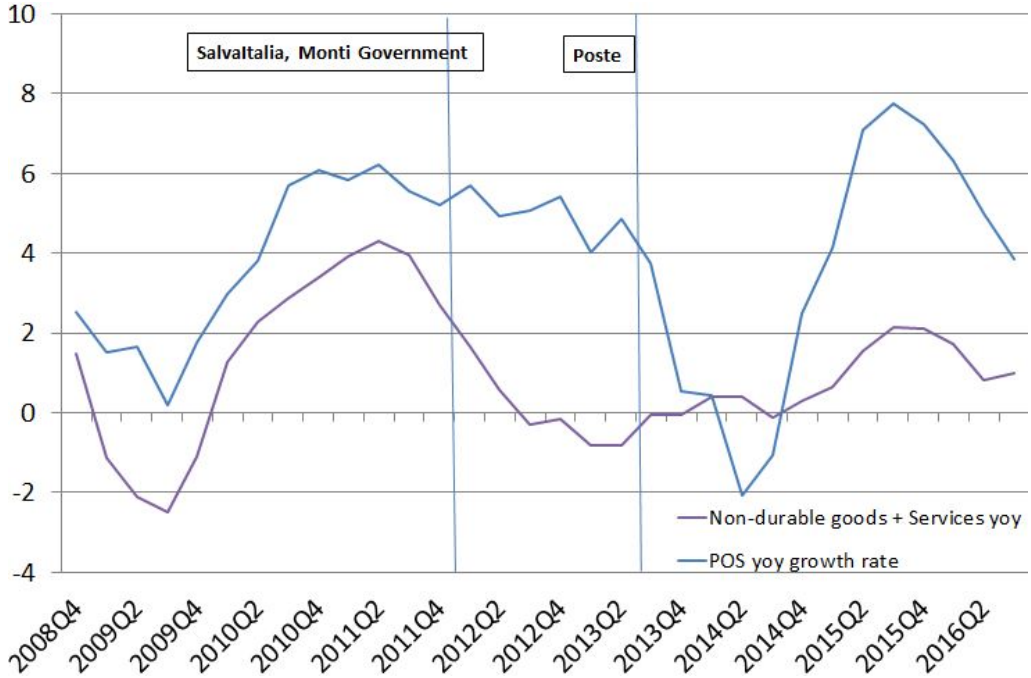
(a) POS, raw daily series.



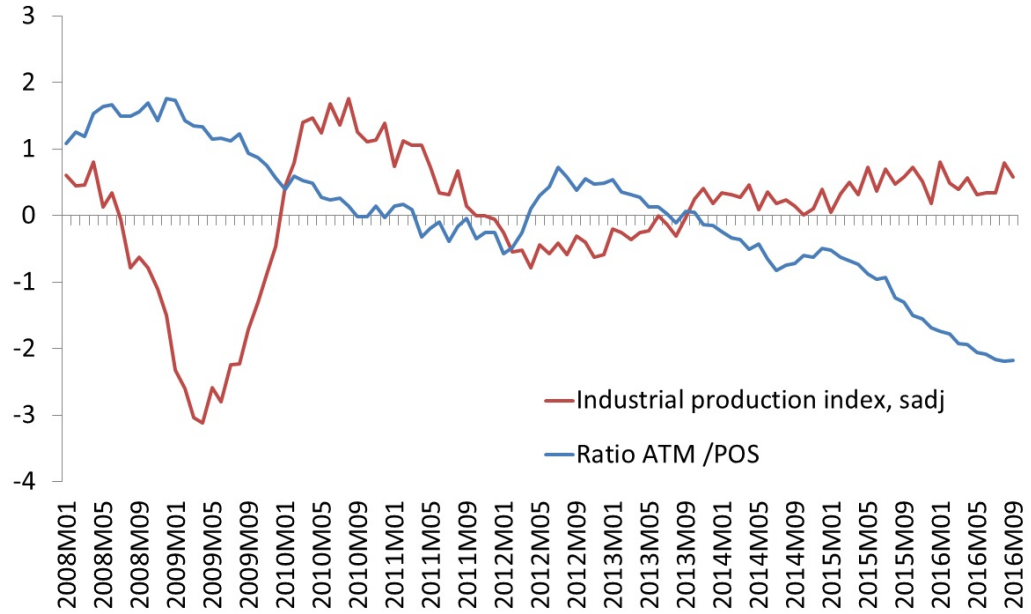
(b) ATM, raw daily series.

Notes: Data taken from the Retail section of the BI-COMP payment system managed by the bank of Italy. Data refer to 5 working days.

Figure 2: Payment series and macroeconomic variables.



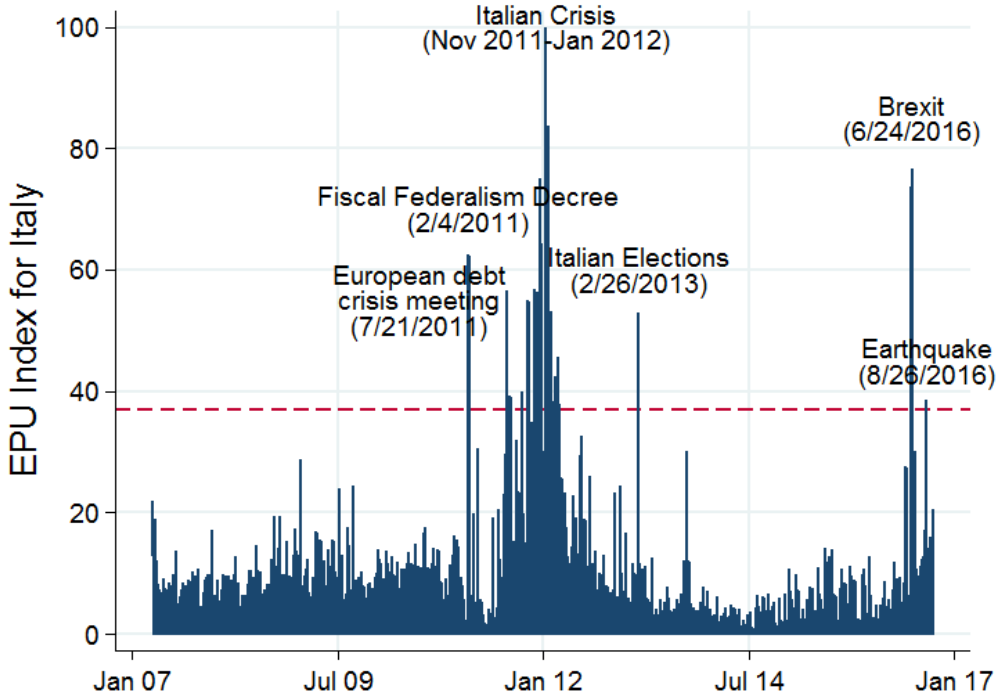
(a) POS purchases compared with the expenditure for services and non-durable consumption (2008Q4 - 2016Q3).



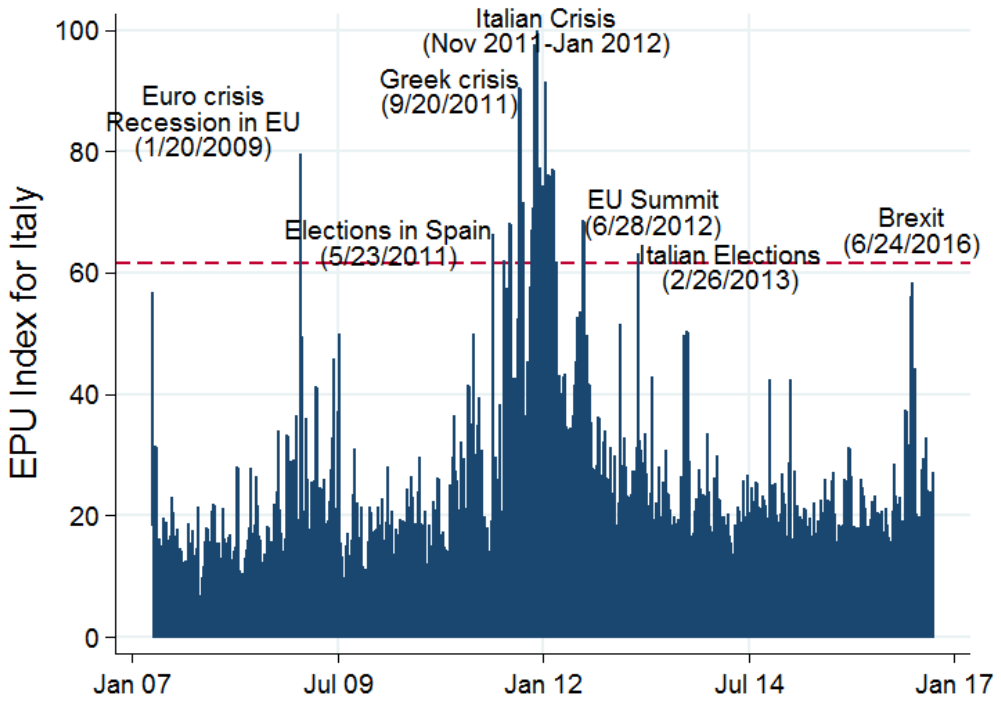
(b) ATM/POS ratio (seas. adj. at the monthly frequency) and the annual growth rate of industrial production (seas. adj.).

Notes: Panel (2a) 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 (2b) shows the ATM/POS ratio is countercyclical and it is negatively correlated (-0.48) with the annual growth rate of industrial production.

Figure 3: Econonic (Policy) Uncertainty – E(P)U – Indexes at daily frequency (Bloomberg).



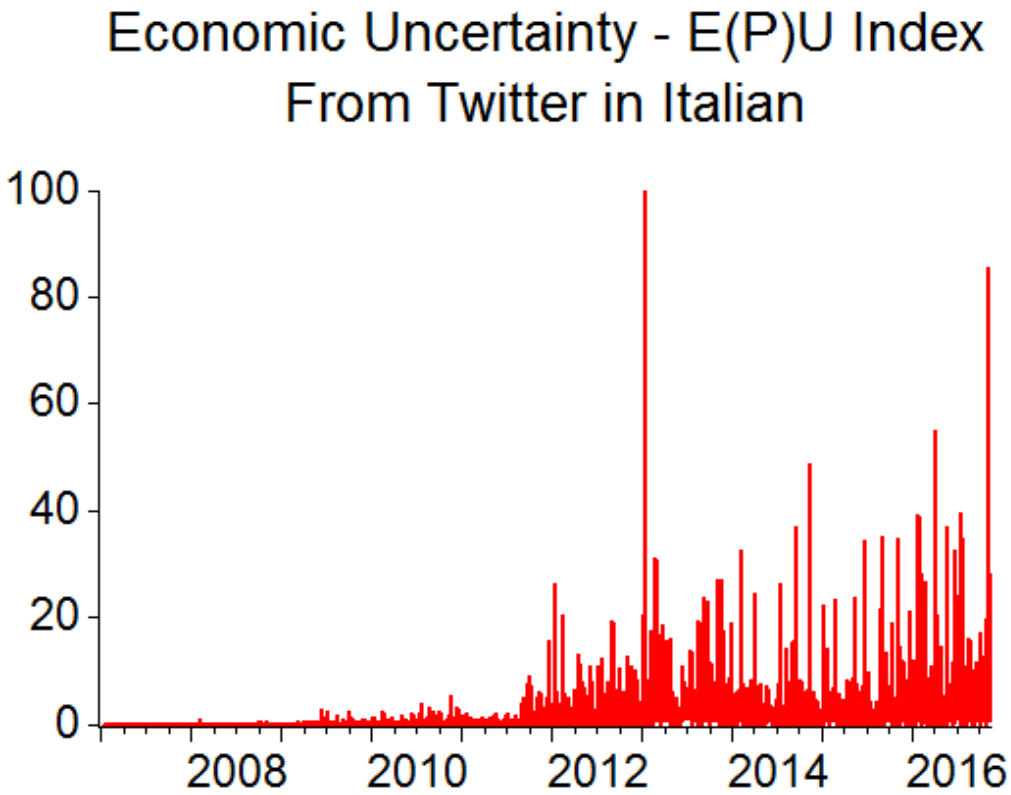
(a) EPU index calculated from Bloomberg newswire.



(b) E(P)U index calculated from Bloomberg newswire.

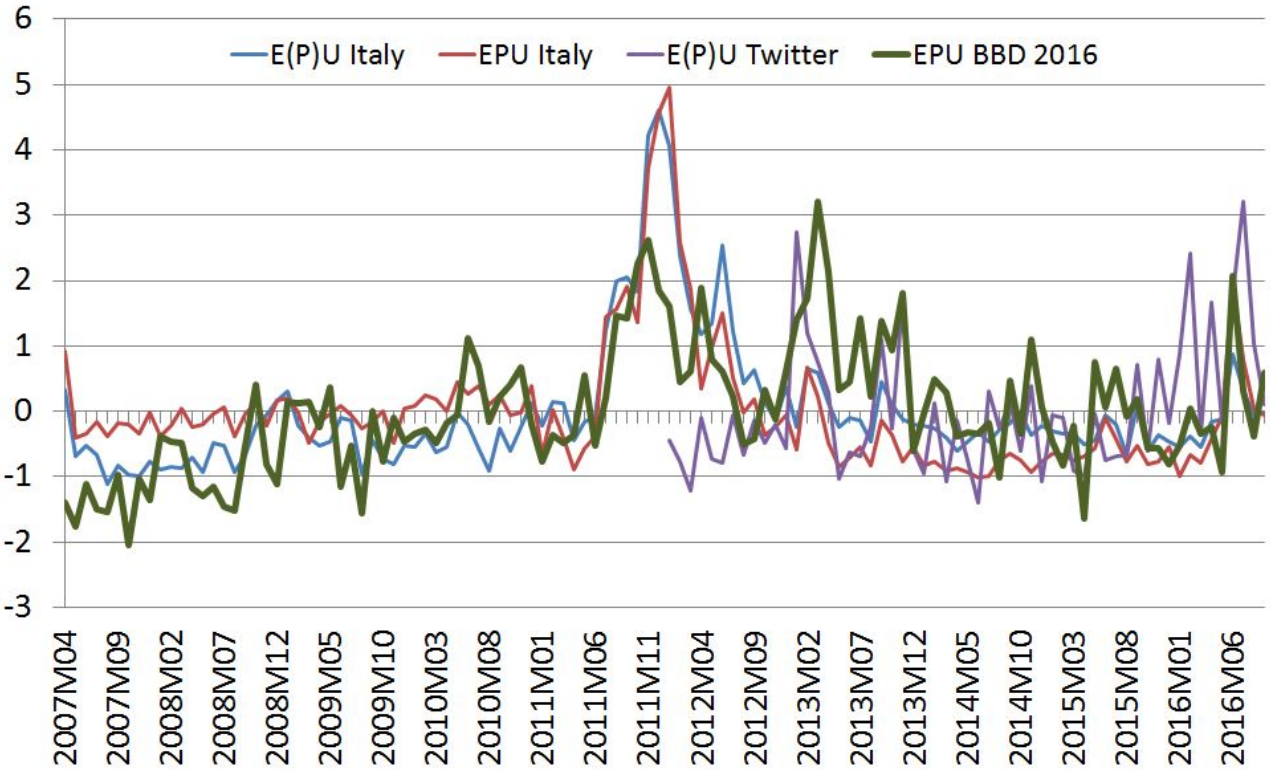
Notes: EPU and EU indexes computed with Bloomberg newswire. The two indexes are those obtained from keywords in English with the additional filter 'AND *ITAL**'. The events reported are those above the 99th percentile (displayed in red).

Figure 4: Econonic (Policy) Uncertainty – E(P)U – Indexes at daily frequency (Twitter).



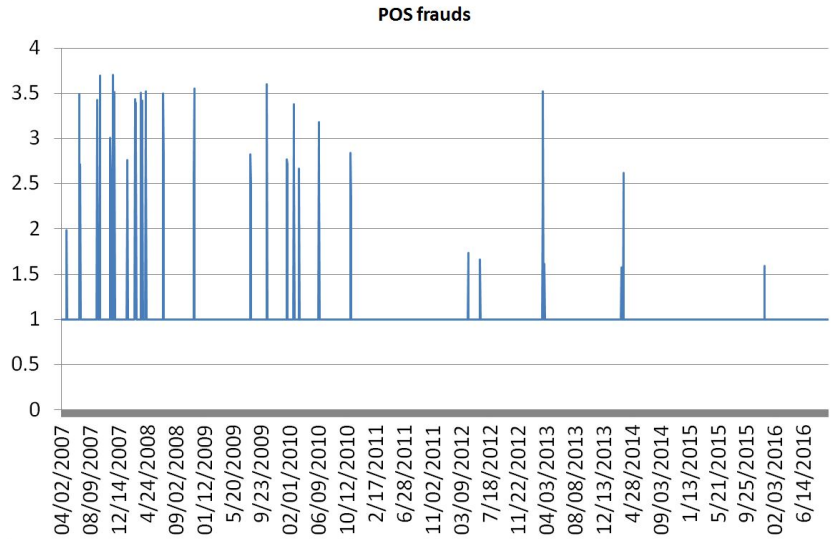
Notes: E(P)U index is computed counting the tweets in Italian that contain at least a keyword of the category (E) and (U).

Figure 5: Comparison between the EPU index of Baker et al. (2016) (EPU BBD 2016), our two EPU indexes from Bloomberg newswire (E(P)U and EPU Italy) and finally the E(P)U index calculated from *Twitter*. Our daily indicators are aggregated at the monthly frequency.

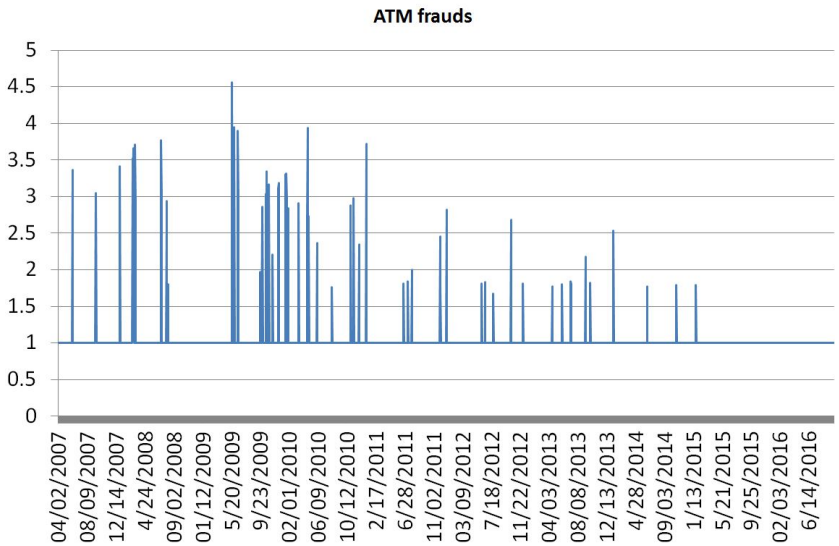


Notes: The Twitter E(P)U index is computed counting the tweets in Italian that contain at least a keyword of the category (E) and (U).

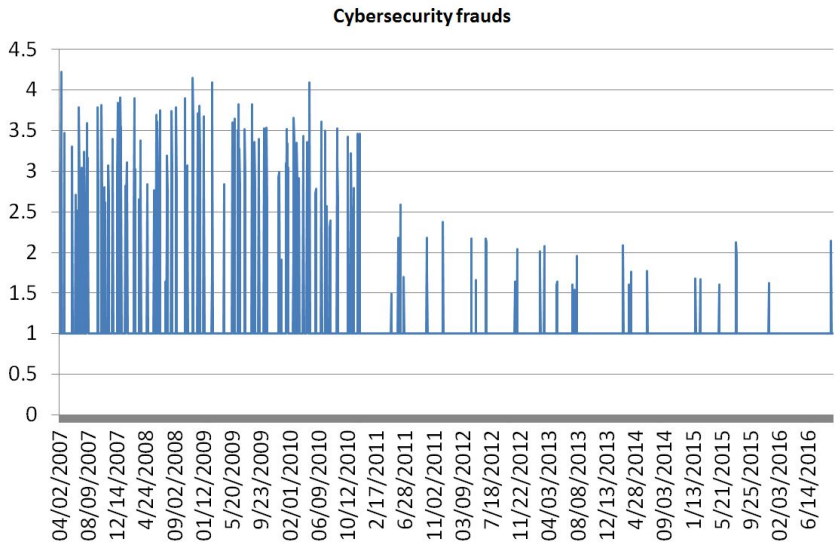
Figure 6: Indexes of Fraud at daily frequency (Bloomberg).



(a) POS fraud index - daily frequency.



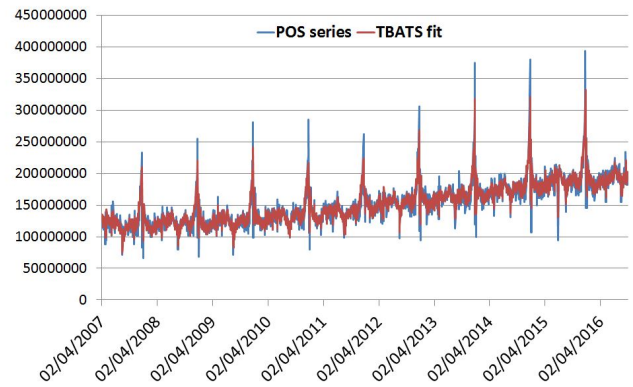
(b) ATM fraud index - daily frequency.



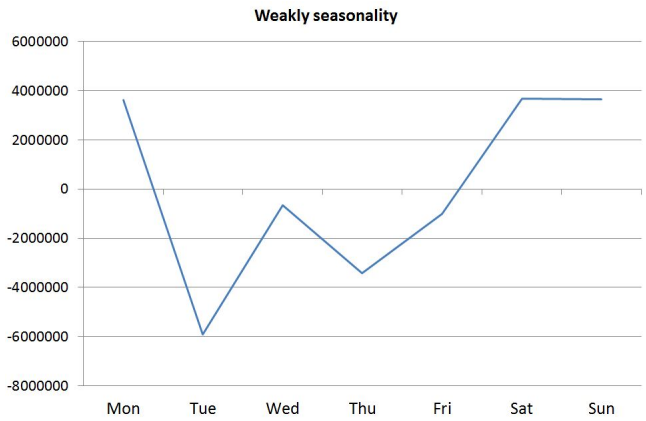
(c) Cybersecurity index - daily frequency.

Notes: Indexes of fraud obtained from Bloomberg newswire and normalized to 100 in the day in which the count of news on fraud is the maximum.

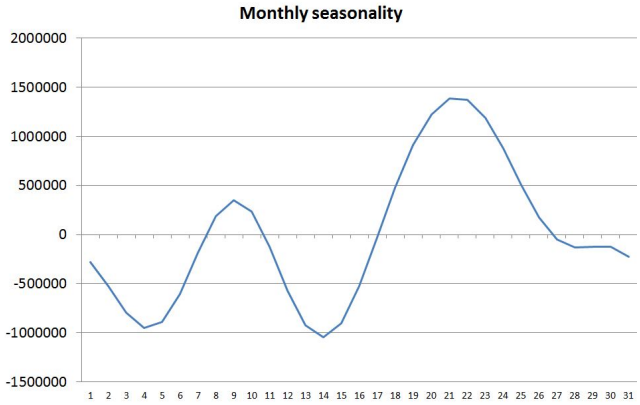
Figure 7: POS, daily series, fitted model with TBATS and seasonal components.



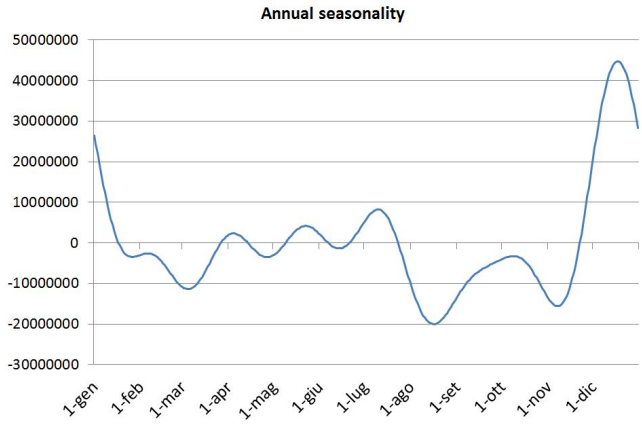
(a) POS daily series fitted with *TBATS*



(b) POS daily series - weekly seasonality

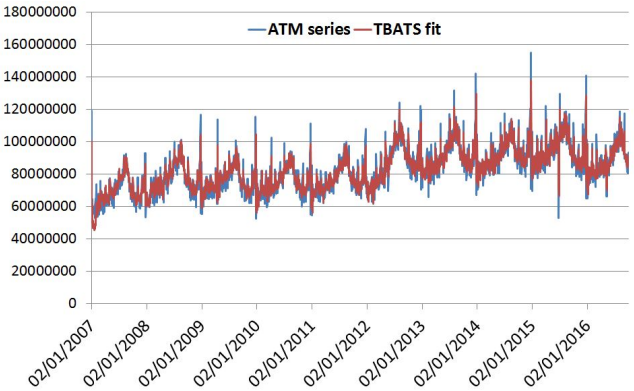


(c) POS daily series - monthly seasonality

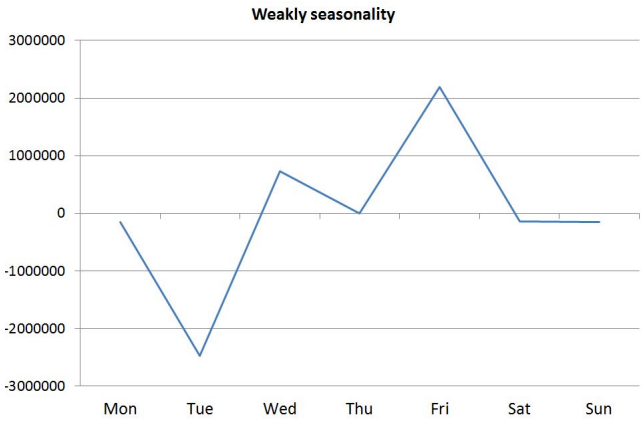


(d) POS daily series - annual seasonality

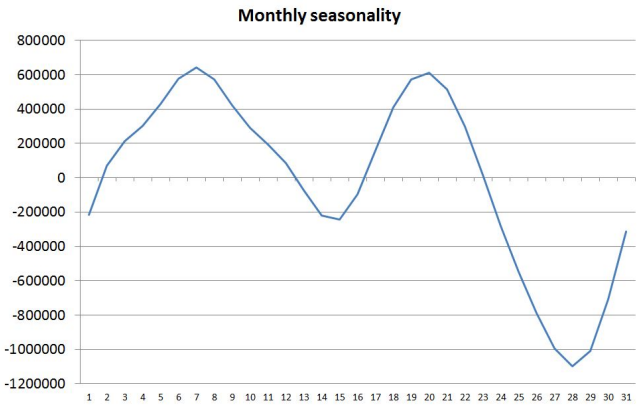
Figure 8: ATM, daily series, fitted model with TBATS and seasonal components.



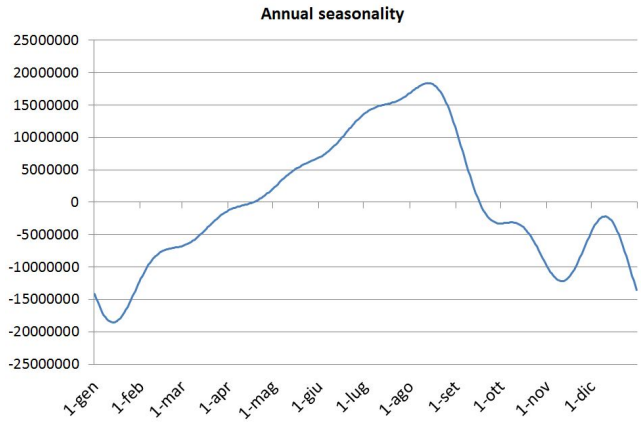
(a) ATM daily series fitted with *TBATS*



(b) ATM daily series - weekly seasonality



(c) ATM daily series - monthly seasonality



(d) ATM daily series - annual seasonality

Figure 9: POS daily series fitted with *Prophet*.

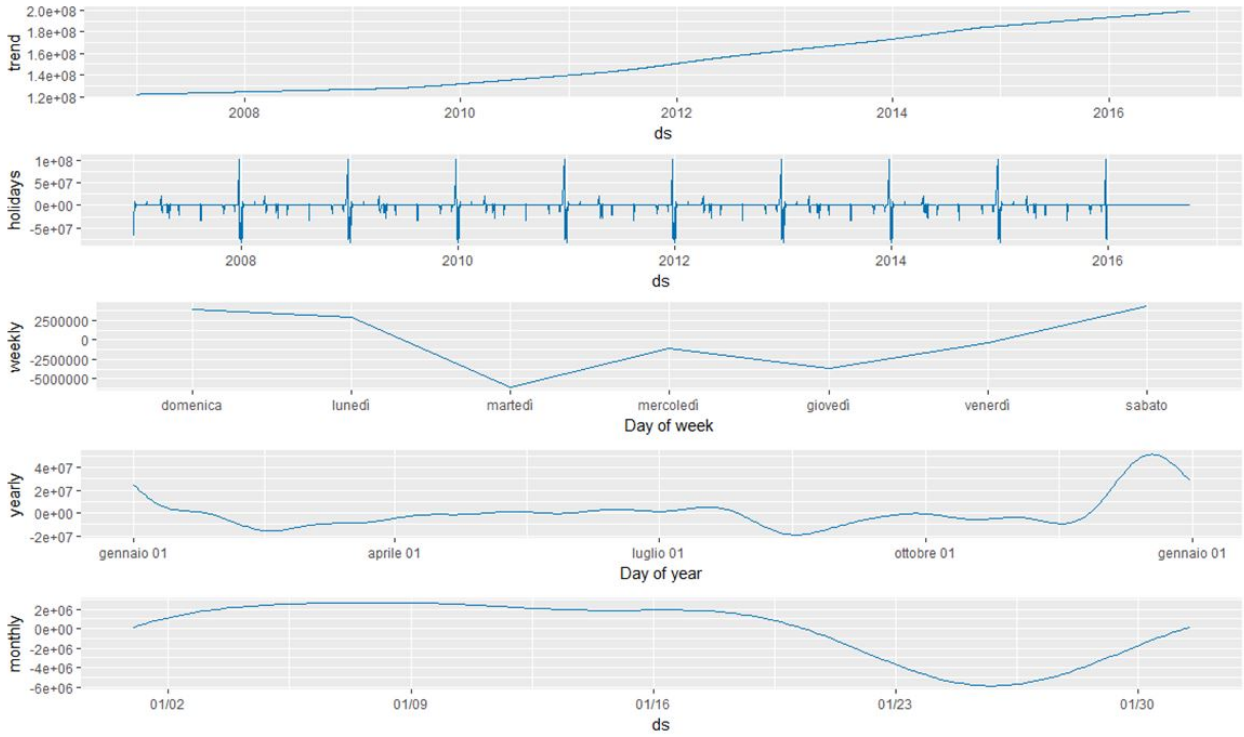


Figure 10: ATM daily series fitted with *Prophet*.

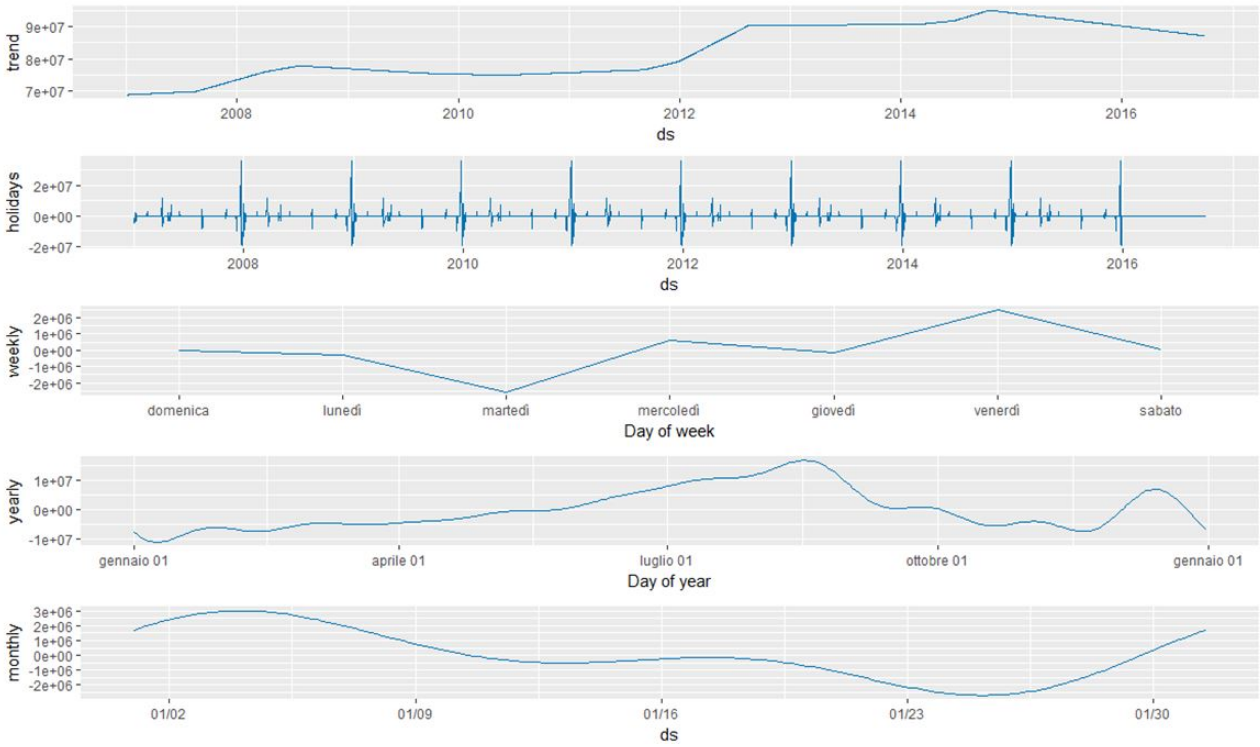
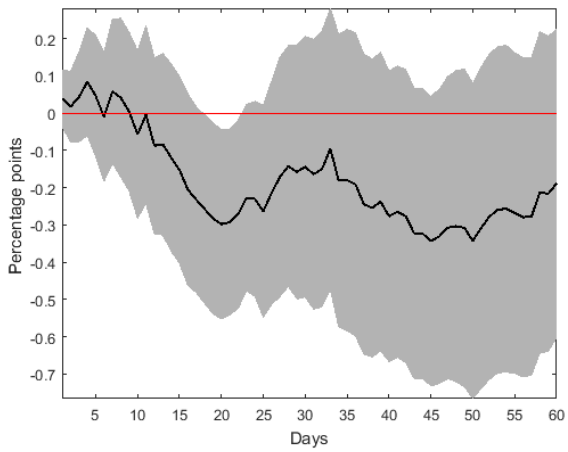
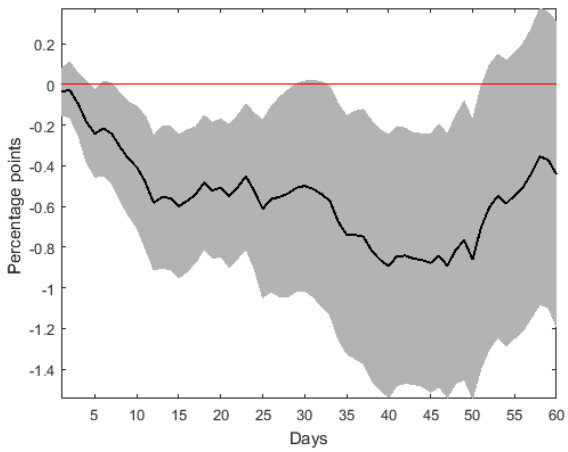


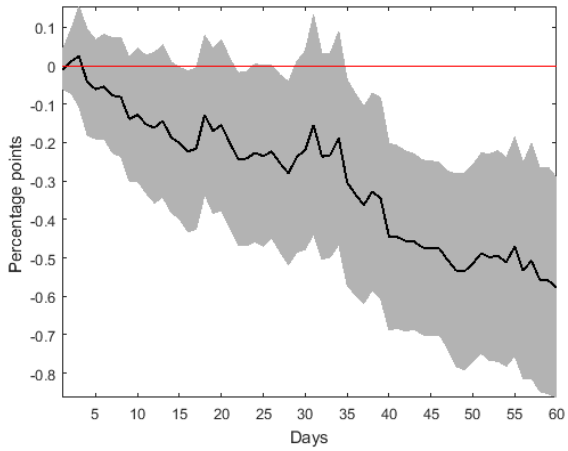
Figure 11: Impulse response of POS payments to an increase in the EPU index (whole sample April 2007- September 2016).



(a) Impulse of payments to a shock in uncertainty (EPU with words in English).



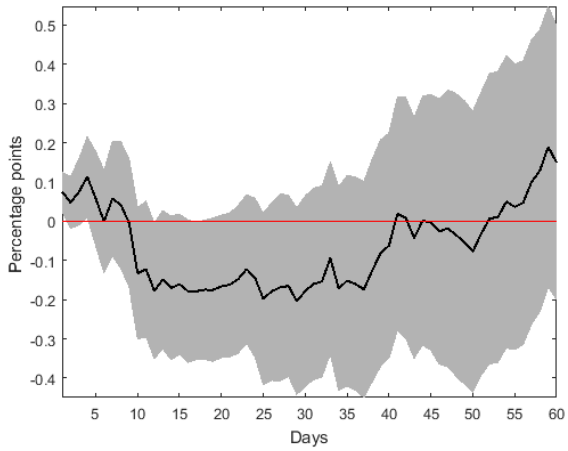
(b) Impulse of payments to a shock in uncertainty (EU with words in English).



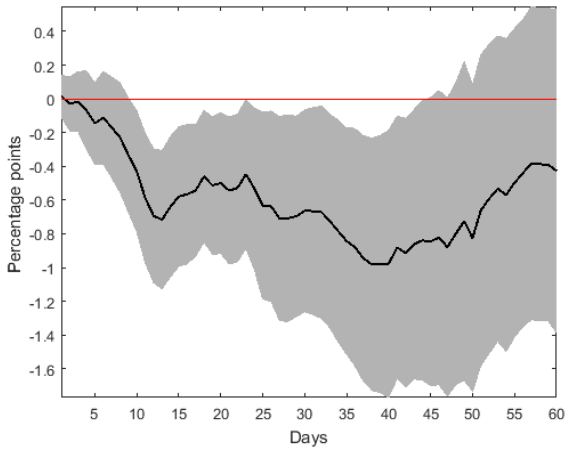
(c) Impulse of payments to a shock in uncertainty (Twitter). Sample January 2012- September 2016.

Notes: Shaded area represents 95% confidence level bands.

Figure 12: Impulse response of POS payments to an increase in the EPU index (subsample April 2007- November 2012).



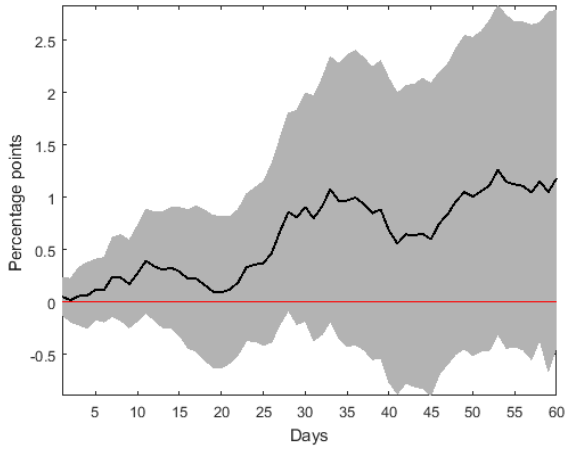
(a) Impulse of payments to a shock in uncertainty (EPU with words in English).



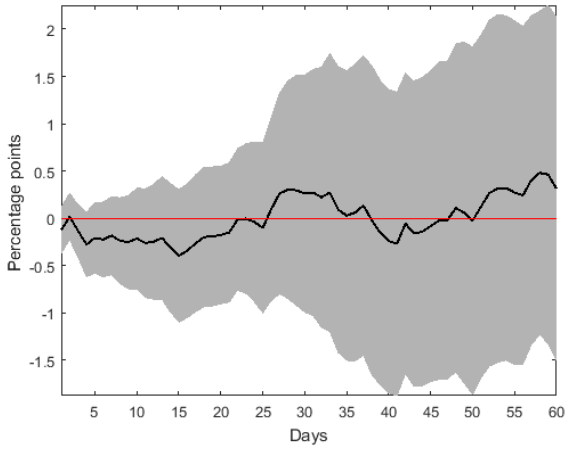
(b) Impulse of payments to a shock in uncertainty (EU with words in English).

Notes: Shaded area represents 95% confidence level bands. For the subsample April 2007- November 2012 Twitter results are not available because of its scarce diffusion in Italy.

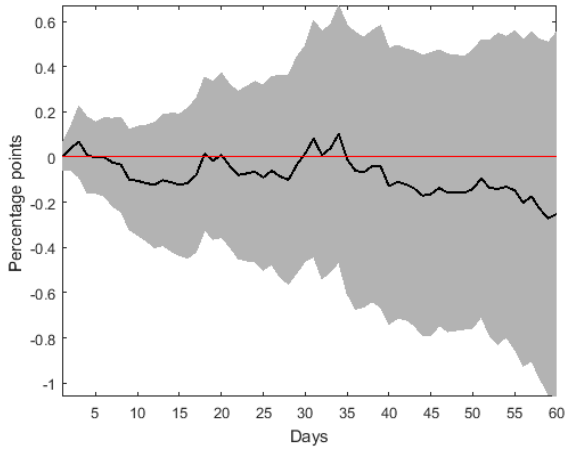
Figure 13: Impulse response of POS payments to an increase in the EPU index (subsample December 2012-September 2016).



(a) Impulse of payments to a shock in uncertainty (EPU with words in English).



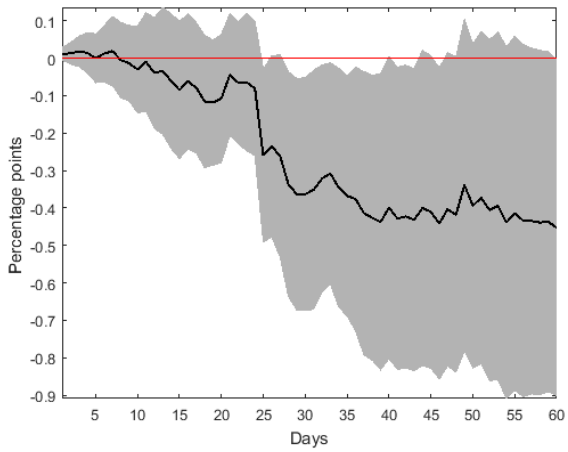
(b) Impulse of payments to a shock in uncertainty (EU with words in English).



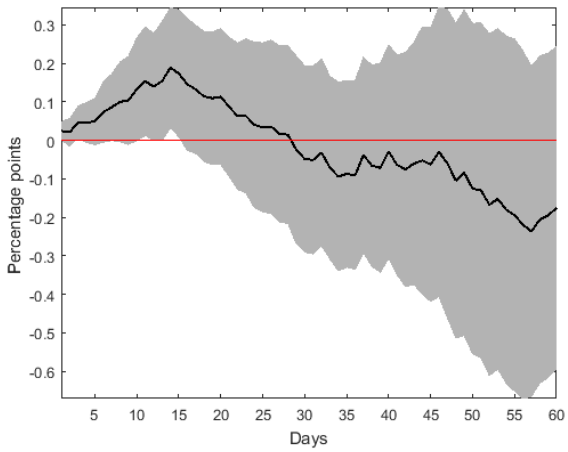
(c) Impulse of payments to a shock in uncertainty (Twitter).

Notes: Shaded area represents 95% confidence level bands. In the subsample December 2012- September 2016 we have results also using Twitter that becomes reliable in Italy after 2012.

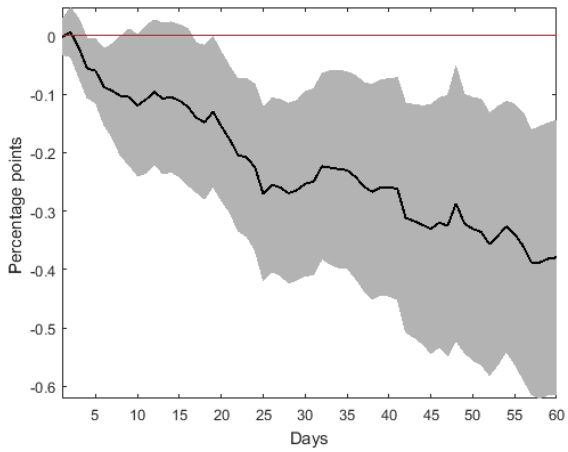
Figure 14: Impulse responses of the POS series (daily frequency and seasonally adjusted with TBATS) to a temporary increase in the various fraud indexes, whole sample April 2007-September 2016.



(a) POS response to increase in POS fraud index.



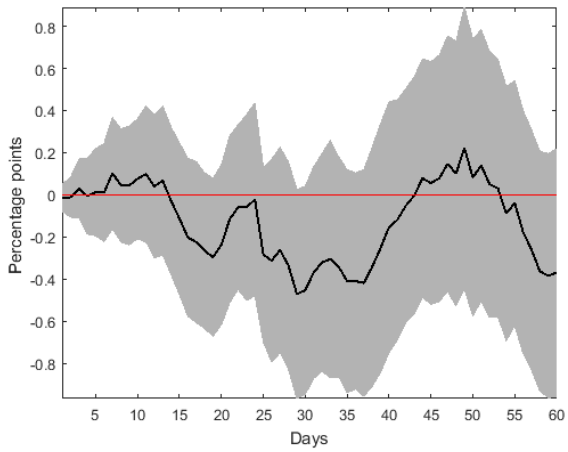
(b) POS response to a temporary increase in the ATM fraud index.



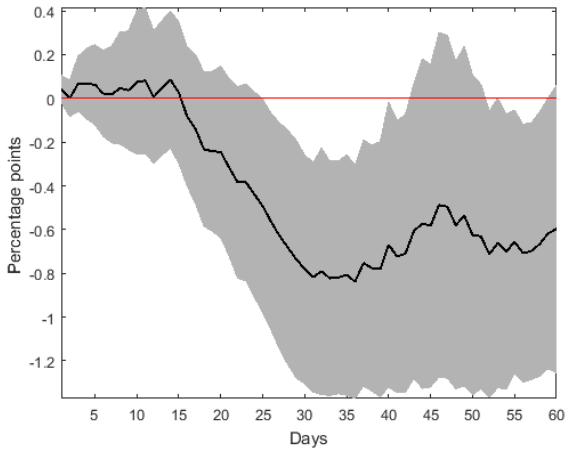
(c) POS response to a temporary increase in the Cyber-security fraud index.

Notes: Shaded area represents 95% confidence level bands.

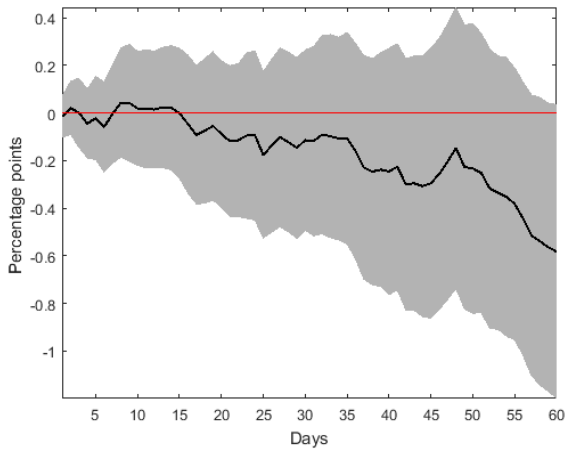
Figure 15: Impulse responses of the ATM series (daily frequency and seasonally adjusted with TBATS) to a temporary increase in the various fraud indexes (whole sample April 2007-September 2016).



(a) ATM response to increase in POS fraud index.



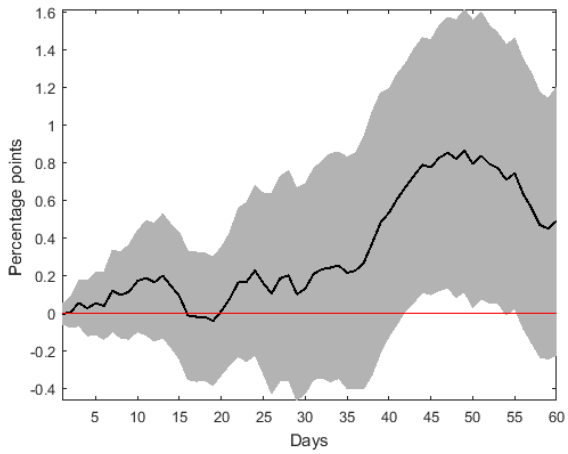
(b) ATM response to a temporary increase in the ATM fraud index.



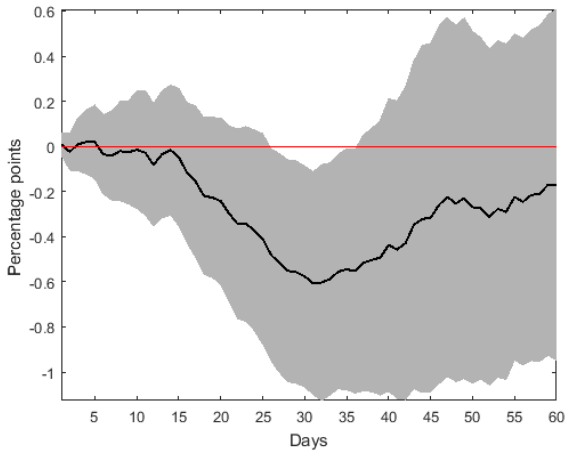
(c) ATM response to a temporary increase in the Cyber-security fraud index.

Notes: Shaded area represents 95% confidence level bands.

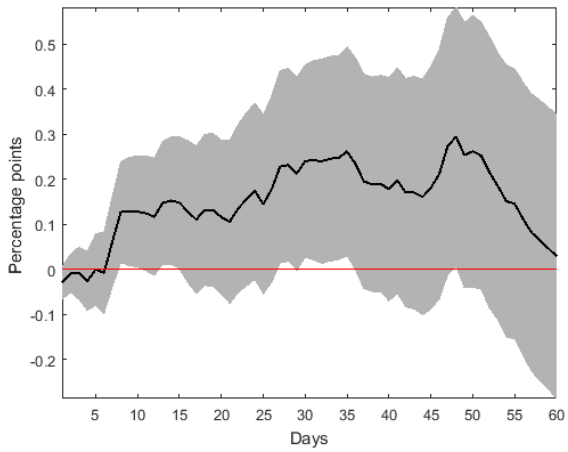
Figure 16: Impulse responses of the ATM/POS ratio (daily frequency and seasonally adjusted with TBATS) to a temporary increase in the various fraud indexes (whole sample April 2007-September 2016).



(a) ATM/POS ratio response to increase in POS fraud index.



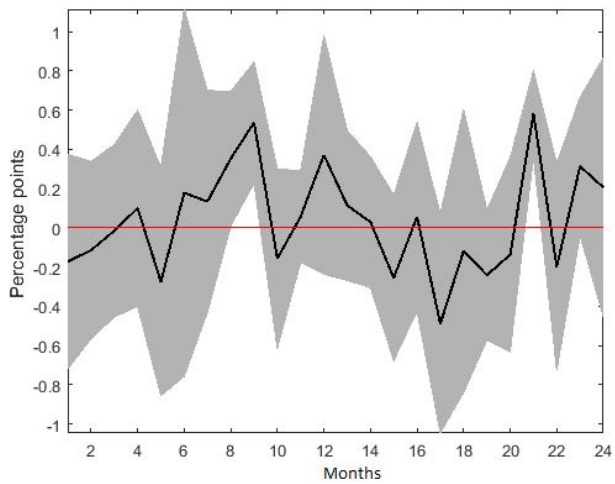
(b) ATM/POS ratio response to a temporary increase in the ATM fraud index.



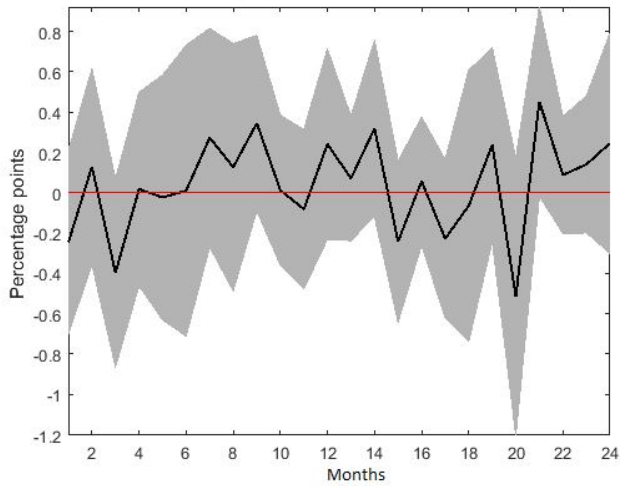
(c) ATM/POS ratio response to a temporary increase in the Cybersecurity fraud index.

Notes: Shaded area represents 95% confidence level bands.

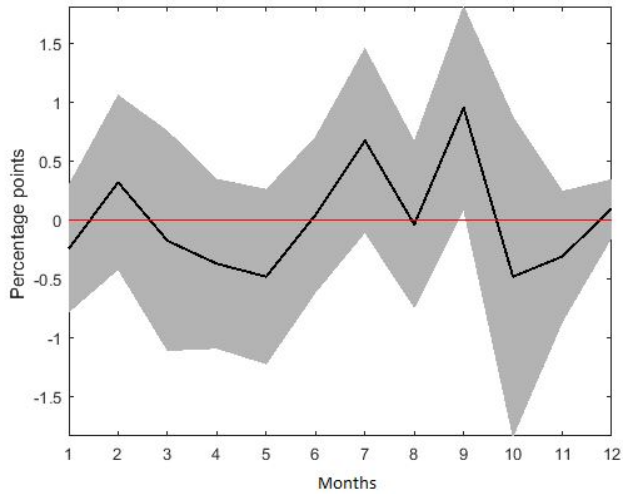
Figure 17: Impulse response of POS payments to an increase in the EPU index on monthly data (whole sample April 2007-September 2016).



(a) Impulse of payments to a shock in uncertainty (EPU with words in English).



(b) Impulse of payments to a shock in uncertainty (EU with words in English) - monthly frequency.



(c) Impulse of payments to a shock in uncertainty (Twitter) - monthly frequency. Sample January 2012- September 2016.

Notes: Shaded area represents 95% confidence level bands.