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USING THE PAYMENT SYSTEM DATA TO FORECAST THE ITALIAN GDP

by Valentina Aprigliano*, Guerino Ardizzi** and Libero Monteforte*

Abstract

Payment systems track economic transactions and therefore could be considered important indicators of economic activity. This paper describes the available monthly data on the retail settlement system for Italy and selects some of them for short-term forecasting. Using a mixed frequency factor model to predict Italian GDP, we find that payment system flows stand out when compared to other standard business cycle indicators.

JEL Classification: C53, E17, E27, E32, E37, E42.
Keywords: short term forecasting, LASSO, mixed frequency models, Kalman smoothing, payment systems, TARGET2.

Contents

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1 Introduction[*]

Following the global recession the interest for new macroeconomic forecasting tools, especially those based on monetary and financial information, has been increasing. On the back of the developments of computational tools for storing and elaborating large-scale datasets, the analysts are focusing on the search for new timely and reliable information in order to improve the forecasting ability in real time.

Data on payment instruments (cheques, credit transfers, direct debits, payment cards) could represent a unique source of information for short-term forecasting of the economic activity, as they trace economic transactions. This link was already clear at the beginning of the last century, when Irving Fisher described the seminal equations of the quantitative theory of money writing: "such elementary equations mean that the money paid in any transaction is the equivalent of the goods bought at the price of sale" (Fisher, 1912). Moreover the importance of payments, jointly with banking and asset markets, to understand the functioning of a monetary economics has recently received a new attention following the body of research called New Monetarist Economics (see Williamson and Wright 2010 and Schneider and Piazzesi 2015). Nevertheless, the use of payment data for forecasting purposes has been exploited only recently. Studies for Canada (Galbraith and Tkacz, 2007), (Galbraith and Tkacz, 2009), Portugal (Esteves, 2009) and Denmark (Carlsen and Storgaard, 2010) find that payment transactions can help with nowcasting and forecasting private consumption (and thereby also GDP) on a short-term basis. It is worth noting that this literature concentrates on payment cards (i.e. ATM/POS transactions as in Esteves 2009 and Carlsen and Storgaard 2010) or on cheques (Galbraith and Tkacz 2007), thus offering only a partial view of the economic activity: payments with cards can be related to private consumption but they represent a small share of the value of payments, especially in Italy.

To the best of our knowledge this paper is the first attempt to assess the ability of retail payment data to forecast the short-term development of the Italian economic activity. Differently from the previous literature for other countries, we use a comprehensive set of payment instruments, such as credit transfers, cheques, direct debits and debit cards. This extension allows us to conduct a more robust forecasting exercise compared to similar studies referred to other countries, which mainly consider a subset of payment instruments (debit cards or cheques). Such data are recorded electronically through clearing and settlement circuits managed by the Bank of Italy (for retail transactions, BI-COMP; for wholesale payments including customer transactions, BI-REL up to May 2008 and TARGET2-Bank of Italy subsequently) and they are not revised because they are recorded without errors by construction.[1] Another appreciable feature of these data is their timeliness. Indeed, the payment data are available on a daily basis with a short delay.

We show that there is a close correlation between the retail payment series (PS, onward) and the main macroeconomic aggregates, such as GDP and its main components. In the empirical

[*]This paper represents the authors personal opinions and does not reflect the view of the Bank of Italy. Preliminary draft, please do not quote or circulate.
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[1]Our data are extracted by the payment system infrastructures, while in some structural analysis data are collected by means of surveys or diaries (see Bagnall et al. 2016).

application, we develop a mixed frequency dynamic factor model to predict the quarter-on-quarter growth of the GDP by using a large-scale monthly dataset, which includes standard business cycle indicators; we perform out of sample forecasting simulations, including and excluding the PS. The contribution of the PS to the forecasts turns out to be appreciable and promising.

The rest of the paper is organized as follows. Section 2 gives an overview of the payment systems in Italy. Section 3 introduces the data, providing some descriptive evidence on the relationship between PS and the main macroeconomic aggregates (3.1) and showing that the *Least Absolute Shrinkage Selector Operator* (LASSO, onward) picks the PS amongst the first 13 predictors (out of the 50 indicators we compiled) to be included in the model (3.2). In Section 4 we describe the mixed frequency dynamic factor model and in section 5 we look at the forecasting contribution of the PS. Section 6 draws the conclusions.

2 Overview of the payment system for the Italian economy

A payment system is the set of instruments, rules, procedures and technologies used to settle money transfers among economic agents.

We can distinguish between *wholesale payments* and *retail payments*. The former typically involve the banking system handling large-value payments (interbank transactions), more connected with financial markets flows and refinancing operations with national central banks; the latter refer to transactions within the circuit of individuals and firms and mostly related to the economic activity (speech by Padoa Schioppa, Seoul May 2004).[2]

Before the launch of the euro in 1999, the payment system in Europe was highly fragmented. The Monetary Union posed the problem of harmonizing the infrastructure to transfer money among economic operators to foster the financial and commercial integration. The broad-based reorganization of the payment system has been mostly effective for wholesale payments, operated by two area-wide systems: TARGET2 (Trans-European Automated Real-Time Gross Settlement Express Transfer System; T2 onward), provided by the Eurosystem, and EURO1, privately owned. The Bank of Italy, along with Deutsche Bundesbank and Banque de France, contributed to develop T2, which settles the most part of the wholesale transfers, on a gross-basis in real-time.

As for the retail payments,[3] the system is not fully integrated yet. However, since 2014 the *Single Euro Payments Area* (SEPA, onward) has strongly fostered the standardization and interoperability among different national clearing and settlement retail systems. The Bank of Italy manages the BI-Comp clearing system, which works in compliance with the rules of SEPA. BI-Comp clears the domestic payments on a multilateral net basis. These payments can be settled both in BI-Comp and in TARGET2. In fact, due to urgency and security reasons, banks may prefer to settle customers' payments in TARGET2. This retail branch of TARGET2 is named TARGET2-retail from here onward (T2-retail for the sake of brevity).

The retail non-cash payments settled through BI-Comp and T2-retail add up to 5 trillion € on a yearly basis (about 60% of the total value of retail payments in Italy; 80% if we consider only electronic payments, excluding postal pre-printed processed and other paper-based credit transfers), about three times higher than the nominal value of the GDP.[4] Although in Italy cash payment is still the most frequently used instrument of retail payments (about 80% of the *number* of retail payments), new information and communication technologies fostered non-cash payments, mainly those processed through electronic devices, allowing more flexibility and customization. If

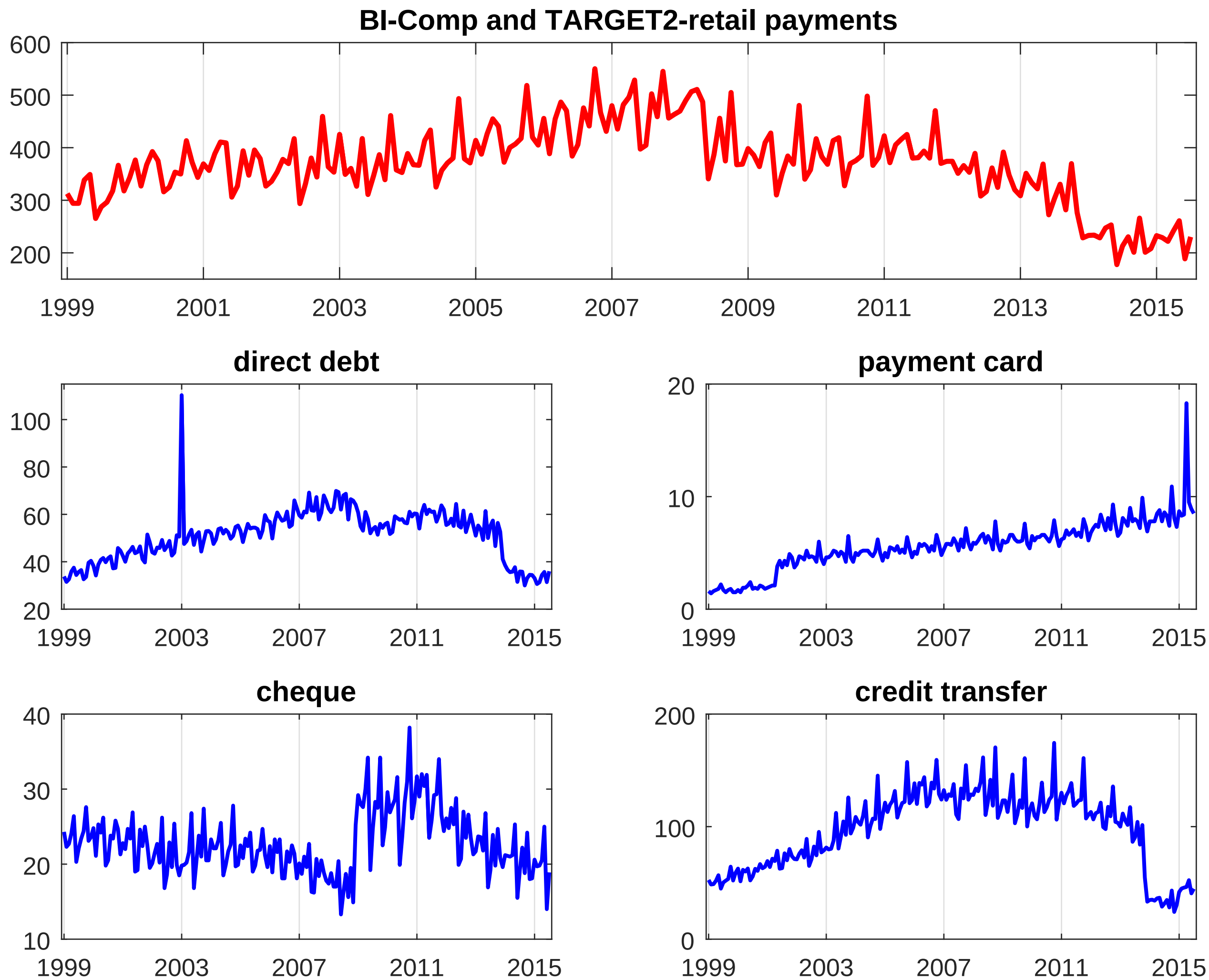
[2] See https://www.ecb.europa.eu/press/key/date/2004/html/sp040513_1.en.html

[3] The retail payments system generally uses the Clearing and Settlement mechanism (CSM), in which one or more operators perform clearing (i.e. transmission, matching, confirmation of payments and calculation of a settlement position) and settlement (completion of the payment).

[4] Unlike cash payments, which are immediate vis-a-vis transfers of value between the payer and the payee through banknotes and coins, non-cash payments are exchanges of funds through accounts. Therefore, the relationship between the payer and the payee is mediated by authorized institutions (such as banks, postal offices), which actually process the payment before settling the transaction. It follows a crucial distinction depending on the party submitting the payment order: the *credit-based* instruments (i.e. credit transfers, card payments), submitted by the payer, and the *debit-based* instruments (i.e. direct debits, cheques), submitted by the payee. Credit transfers are the most common credit-based instrument, while debit-based instruments include direct-debits, card payments and cheques. For a detailed description of payment instruments see http://www.bancaditalia.it/compiti/sispaga-mercati/strumenti-pagamento/index.html and *Payments, securities and derivatives, and the role of the Eurosystem*, by ECB.

we consider the *value* of the transactions, on annual average,[5] the share of the cash payments shrinks to about 45% of the consumer-to-business transactions (for instance, point of sales purchases) and to less than 10% of all transactions, including business-to-business payments. Figure 1 shows the monthly gross flow of retail non-cash payments settled through BI-Comp and T2-retail in Italy and it also depicts the upward trend in the use of electronic payment instruments (credit transfer, direct debit, debit cards) against the downtrend of the cheques.

Figure 1: Total payments settled in BI-Comp and TARGET2-retail (values)



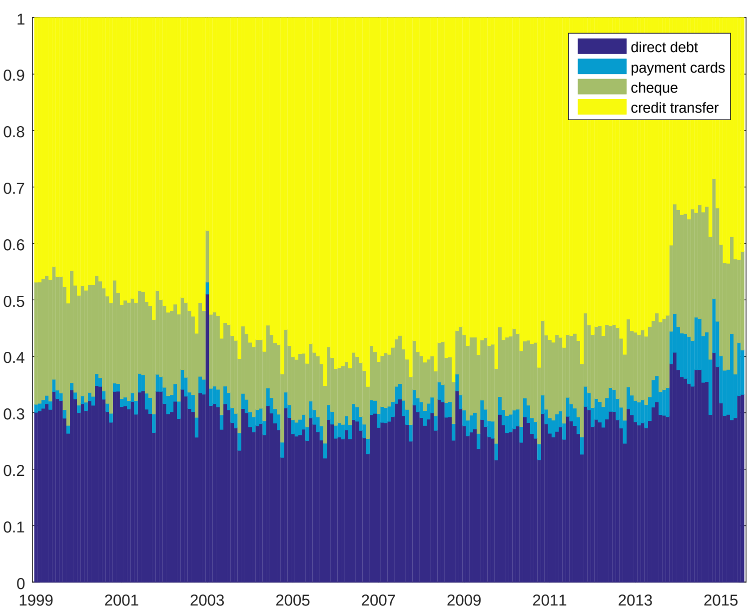
The strong decrease observed in 2014 for credit transfers and for direct debit payments stems from the changes in the customer payment landscape following the migration to SEPA. Some participants reconsidered the routing policies for their customer payments and they ultimately chose in favour of SEPA-compliant automated clearing houses other than BI-Comp and T2. However, T2-retail has been less affected, because it meets some specific customers's demands concerning urgency and assurance of the payments. The peak reached by direct debits in 2003 is due to interbank procedural changes and routing policies after the launch of the new domestic real-time

[5]These data refer to 2014.

gross settlement system (the so called "New Birel"). As regards cheques payments, the strong increase in 2009 is due to changes to the interbank procedures and to truncation limits for low-value cheques. More generally, transactions by cheques have been declining over the years because of the increasing use of electronic payments and the adoption of anti-money laundering restrictions, which have strongly limited their negotiability between private operators. As regards transactions by payment cards, the upward jump on July 2001 was caused by the inclusion of point of sale payments (POS); the peak in 2015 is due to more recent regulatory changes in the card market and to the inclusion of postal debit card and automated teller machine (ATM) transactions in the BI-Comp system.

Figure 2 depicts the share of transactions enabled by different payment instruments on the total gross flows settled in BI-Comp. Credit transfers represent the largest share (almost 55%);[6] also direct debits have a sizeable weight (29%) since they provide a very handy solution to manage recurrent payments (e.g. utility bills, mortgage payments). Payment cards are far less used, accounting for only 3% of the total non-cash payments; the agents use payment cards for low-value transactions (50-100 € for POS; 100 - 200 € for ATM).

Figure 2: Total payments settled in BI-COMP



However, a large share of credit card payments are recorded as direct debits, since credit card statements are often charged on the payer's bank current account. Italy is lagging behind for non-cash payment instruments compared to the other euro area major countries. Although retail cash transactions are not recorded in the clearing and settlement systems, ATM operations settled through the interbank procedures in BI-COMP may be a useful proxy of the demand for cash because there is a strong correlation between the amount of cash acquired at the ATM and the cash used at the point of sale.

[6]For business purposes credit transfers are the most popular and suitable payment instrument indeed (they account for 80% of the total value of the business-to-business transactions; direct debits add up to 10% as well as cheques).

3 Data

3.1 Payments data and macroeconomic aggregates

In this section we glance at some descriptive statistics which prove the tight relationship between the main macroeconomic aggregates (such as GDP, value added in service sector, private consumption and gross fixed investments) and the payment flows. In our analysis, we focus on retail payment instruments since they are used to settle commercial transactions as consumer-to-business and business-to-business payments. We find a strong empirical evidence underpinning the role of payment time series in tracking the economic activity.

We rely on the systems BI-Comp and T2-retail to collect timely and high-frequency data. Data are collected by the central bank for the individual transactions of the payment systems. These systems close each day, therefore the observation error is basically nil. We do not use the individual payments (that could be eventually relevant for a big data analysis) but the monthly time series stored in the Banca d'Italia's database, publicly available.[7] The monthly observations are simply the sum of the nominal value of the individual payments recorded in the month.

Some preliminary adjustments of the time series are needed. Firstly, we take the year-on-year (y-o-y, onward) growth rate to remove the seasonal pattern characterizing the payment flows[8] as well as the macroeconomic variables and the high-frequency volatility. The breaks observed in Figure 1 are smoothed out when we consider the aggregated flow of payments. Finally, we divide the nominal values by the gdp national account deflator in order to obtain a measure of the volume of transactions.

The annual growth of GDP and of its main components comove closely with the annual growth of payment flows settled through BI-Comp and T2-retail (see Figure 3). The big drop at the end of the sample proves that BI-Comp was more affected than T2-retail by the launch of SEPA as of October 2014.[9] Some interesting results come out of the correlation matrix (see Table 1).[10] The correlation between the PS and the target variables is valuable and similar to the one shown by other activity indicators such as industrial production and business confidence, usually adopted in short-term forecasting. Results in Table 1 are consistent with the picture of the payment instruments composition in Italy. Credit transfers and direct debits are the most widespread payment tools; they are also more correlated with target variables than payment cards and cheques.

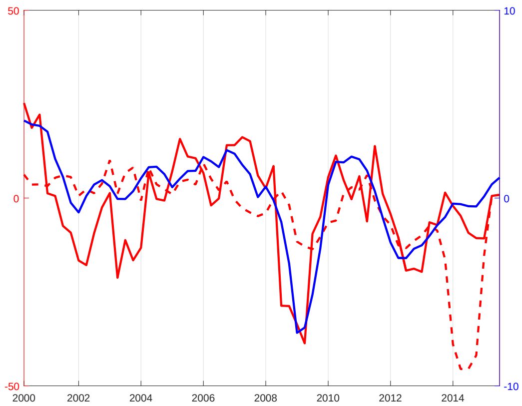
[7]Data are issued on Supplements to the Statistical Bulletin for Payment System, https://www.bancaditalia.it/pubblicazioni/sistema-pagamenti/index.html.

[8]Money transfers typically peak during Christmas and summer holidays.

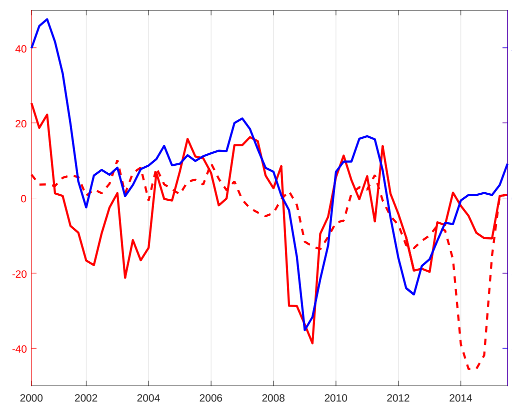
[9]The launch of SEPA has entailed the switching of all domestic credit transfers and direct debits from BI-COMP into STEP2, which is the pan-European infrastructure managed by a private body (SIA-Società Interbancaria per l'Automazione). Information on payment flows in STEP2 are not publicly available.

[10]We consider the contemporaneous correlation.

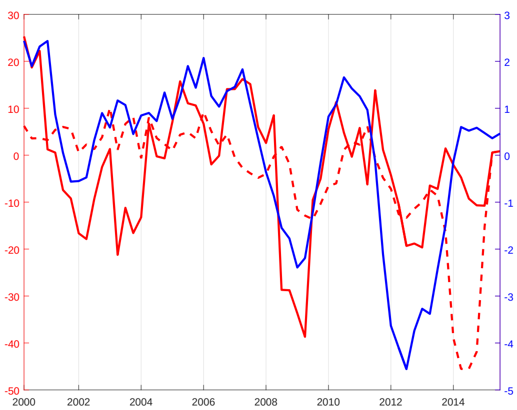
Figure 3: BI-Comp (dashed red line) and T2-retail (bold red line) flows compared with macroeconomic aggregates (blue line); y-o-y percentage changes



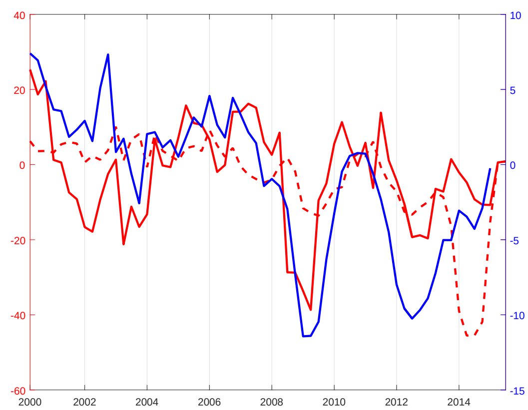
(a) Payment flows and GDP



(b) Payment flows and households' consumption



(c) Payment flows and value added in service sector



(d) Payment flows and gross fixed investment

3.2 Selection of the targeted predictors

In this section, we use the Least Absolute Shrinkage and Selection Operator (LASSO) to make a first screening of the variables depending on their ability to anticipate the quarterly GDP growth (for a review of Lasso estimator see Tibshirani 1996 and Hastie et al. 2009; Bai and Ng 2008 and Bulligan et al. 2012 for the selection of targeted predictors to make forecasts).

We compiled $N = 50$ variables providing a quite complete picture of the economic activity. This large sample (N-sample, onward) included indicators of the industrial and service activity (industrial production, electricity consumption, freight truck, business confidence), of the households' consumption (retail sales of goods and services, consumers' confidence), financial indexes, credit flows to firms other than time series from the payment systems T2-retail and BI-Comp.

The monthly indicators are transformed in quarterly variables and then LASSO regression is

Table 1: Correlation between payment flows and macroeconomic indicators; y-o-y percentage changes

Payment flows[a]	GDP	Private Consumption	Gross Fixed Investment	Value added service sector
Cheques	-44.4	-2.1	-37.2	-35.6
Cards[b]	1.4	-12.3	16.4	4.0
Credit Transfer	59.1	61	65.3	59.5
Direct Debts	52.1	39.4	48.7	54.4
BI-Comp	71.8	70.5	74.3	68.4
T2-retail	79.4	67.7	64	74.3
BI-Comp + T2-retail	90.7	82.5	82.3	85.9
Other indicators				
M2	-38.1	-11.5	-20.4	-45.6
Industrial production	92.8	68.7	74.3	79.8
Business Confidence[c]	68.5	74.9	67.3	64.3
Consumer Confidence[d]	9.9	40.0	14.3	19.7

[a] Correlations are computed on the sample 2000.Q1 - 2012.Q4 in order to exclude the break caused by the new standard SEPA.
[b] Debit card.
[c] Economic Sentiment Indicator (ESI) provided by Istat.
[d] Consumer confidence survey by Istat.

performed. LASSO selects the regressors by solving the minimization problem

$$min\Big(\sum_{T}^{t=1}(y_t - \sum_{j=1}^{N}\beta_j X_{jt})^2\Big) \quad s.t. \sum_{j=1}^{N}|\beta_j| \leq t \tag{1}$$

where t is the tuning parameter.

LASSO selects n_L targeted variables, among all N collected:

$$\hat{L}_{n_L} = \{j \in \{1, 2, \dots, N\} : |\hat{\beta}_{Lj}| > 0\} \tag{2}$$

including T2-retail along with other business cycle indicators, such as industrial production, electricity consumption, freight truck, retail sales and many business and consumers confidence indicators (mainly referred to the evolution of the economic situation, saving opportunities and expected new orders).

The final model $\hat{I}_n \supseteq \hat{L}_{n_L}$ includes some additional indicators earlier discarded by Lasso, which contribute to improve forecast accuracy.[11] They account for concerns of households about labor market, firms' assessment of liquidity constraints and of the current level of production and orders, in particular for the sectors producing intermediate and investment goods.

We implement a large-scale dynamic factor model on $\hat{I}_n$, which is more suitable when the cross-section size of the dataset, n, is valuable in respect of the number of observations, T. Working with large datasets proves convenient to detect whether PS contribute to improve the accuracy

[11] The additional indicators were selected by minimizing the RMSFE in an out-of-sample forecasting exercise.

in the estimation of the economic growth. Their role in forecasting stands out when compared to many other indicators, often used to track the short-term dynamics of the economy.

Table (2) shows a detailed description of the N-sample (first column), as well as of the source and treatment of the data (second and third column, respectively). The fourth and the last columns indicate the variables $\hat{L}_{n_L}$ picked by Lasso and finally included in our information set, $\hat{I}_n$.

Table 2: The N-sample compared to the one selected by LASSO and to the final one

Indicators	Source	Treatment	Lasso selected	Added to Lasso selection
Total electricity consumption	Italian Electrical Net Society	(1-L)logSA	yes	yes
Industrial production	Istat	(1-L)log	yes	yes
Business Climate	Istat	SA	no	no
CCS[a] - Future General Economic sit.	Istat	SA	no	no
CCS - Future Personal Economic sit.	Istat	SA	no	no
CCS - Unemployment exp.	Istat	SA	no	no
CCS - Saving opportunities, next 12 mth	Istat	SA	yes	yes
CCS - Households balance sheet	Istat	(1-L)	yes	yes
CCS - Current saving opportunities	Istat	SA	no	yes
BCS - Current level of orders (intermediate goods)	Istat	SA	no	yes
BCS - Current level of production (int. goods)	Istat	SA	no	yes
BCS - Exp. level of production (int. goods)	Istat	SA	no	yes
BCS - Exp. level of orders (int. goods)	Istat	SA	yes	yes
BCS - Future general economic sit. (int. goods)	Istat	SA	no	yes
BCS - Exp. level of liquidity (int. goods)	Istat	SA	no	yes
BCS - Current level of liquidity (int. goods)	Istat	SA	no	yes
BCS - Current level of orders (investment goods)	Istat	SA	no	yes
BCS - Current level of production (inv. goods)	Istat	SA	no	no
BCS - Current level of liquidity (inv. goods)	Istat	SA	no	no
BCS - Exp. level of orders (inv. goods)	Istat	SA	no	no
BCS - Exp. level of production (inv. goods)	Istat	SA	yes	yes
BCS - Future General Economic sit. (inv. goods)	Istat	SA	no	no
BCS - Exp. level of liquidity (inv. goods)	Istat	SA	no	no
BCS - Current level of orders (consumer goods)	Istat	SA	no	no
BCS - Current level of production (cons. goods)	Istat	SA	no	no
BCS - Exp. level of orders (cons. goods)	Istat	SA	yes	yes
BCS - Exp. level of production (cons. goods)	Istat	SA	no	no
BCS - Future General Economic sit. (cons. goods)	Istat	SA	yes	yes
BCS - Exp. level of liquidity (cons. goods)	Istat	SA	no	no
BCS - Current level of liquidity (cons. goods)	Istat	SA	no	no
Current accounts deposits (stock)	Bank of Italy	(1-L)logSA	no	no
Credit flows to firms[b]	Bank of Italy	(1-L)logSA	no	no
HICP	Istat	(1-L)logSA	no	yes
FTSE Italy (Banks)	Datastream	(1-L)log	no	no
FTSE Italy (Insurance)	Datastream	(1-L)log	no	no
FTSE Italy (Transport)	Datastream	(1-L)log	no	no
PMI Services - Business activity	Markit	SA	no	no
PMI Services - New business	Markit	SA	yes	yes
PMI Manufacturing - Output	Markit	SA	yes	yes
PMI Manufacturing - New orders	Markit	SA	yes	yes
PMI Manufacturing - Employment	Markit	SA	no	no
PMI Manufacturing - New export orders	Markit	SA	no	no
Freight truck	ASPI[c]	(1-L)logSA	no	yes
Retail trade - goods	Confcommercio[d]	SA	yes	yes
Retail trade - services	Confcommercio	SA	no	no
BI-COMP	Bank of Italy	(1-L)logSA	no	no
TARGET RETAIL	Bank of Italy	(1-L)logSA	yes	yes
Payment system-total[e]	Bank of Italy	(1-L)logSA	no	no

[a] CCS: consumer survey; BCS: business survey.
[b] Up to 1 mln €; 1-5 years maturity.
[c] Italian concessionaire for the construction and management of toll highways.
[d] Italian General Confederation of Enterprises, Professions and Self-Employment.
[e] The sum of BI-COMP and T2-retail.

4 The model

Let $\mathbf{X}_t$ be the n-vector of observable monthly variables earlier selected. They are assumed to be driven by q common factors, $\mathbf{f}_t = [f_{1t}, \ldots, f_{qt}]'$, and by an idiosyncratic component, ξ_t. The $n \times q$ matrices Λ_i, for $i = 1 \ldots s$, are the common-factor loadings. The dynamic factor model

$$\begin{aligned} \mathbf{X}_t &= \Lambda_s(L)\mathbf{f}_t + \xi_t \\ &= \Lambda_0\mathbf{f}_t + \Lambda_1\mathbf{f}_{t-1} + \Lambda_2\mathbf{f}_{t-2} + \cdots + \Lambda_s\mathbf{f}_{t-s} + \xi_t \end{aligned} \tag{3}$$

can be mapped to the static model

$$\mathbf{X}_t = \mathbf{D}\mathbf{F}_t + \xi_t \tag{4}$$

where $\mathbf{F}_t = [\mathbf{f}_t', \mathbf{f}_{t-1}', \ldots \mathbf{f}_{t-s}']'$ has dimension $r = q(s+1)$ and can be represented as a VAR(l) process[12]

$$\mathbf{F}_t = \mu + \Psi_1\mathbf{F}_{t-1} + \cdots + \Psi_l\mathbf{F}_{t-l} + \mathbf{u}_t \tag{5}$$

As stated in Bai and Ng (2007), $\mathbf{F}_t$ is driven by $q < r$ common shocks if $\mathbf{u}_t = \mathbf{R}\epsilon_t$, where ϵ_t is a q-vector of mutually orthogonal shocks and the $q \times r$-matrix $\mathbf{R}$ has rank q, then $E(\mathbf{u}_t'\mathbf{u}_t) = \Sigma_u = \mathbf{R}\Sigma_\epsilon\mathbf{R}$ has reduced rank q. We estimate $\mathbf{R}$ as in Marcellino and Schumacher (2010). Given the OLS estimate $\hat{\Sigma}_u$ and its eigenvalue decomposition $\mathbf{MPM}'$, let $\mathbf{M}_*$ be the $r \times q$-matrix of the first q eigenvectors and $\mathbf{P}_*$ the diagonal matrix of the corresponding eigenvalues, then $\hat{\mathbf{R}} = \mathbf{M}_*\mathbf{P}_*^{-1/2}$. We follow Bai and Ng (2002) and Bai and Ng (2007) to set the number of static ($r = 4$) and of dynamic factors ($q = 1$) and then we estimate the factors' space $\mathcal{G}(F_t) = \overline{\text{span}}(F_{1t}, \ldots, F_{rt})$ by principal components extracted from the balanced monthly dataset.
The quarterly growth rate of the real GDP, y_{t_q} with t_q labeled by a multiple of the last month of each quarter (i.e. $t_q = 3, 6, \ldots, 3\lceil T/3 \rceil$), is projected by an unrestricted MIDAS model on the monthly information (see Ghysels et al. 2004 for an extensive treatment of MIDAS model; we also refer to Foroni et al. 2015 for the unrestricted MIDAS model). For each quarter t_q we have $m = 3$ values of the monthly regressors, therefore we apply the $L^{j/m}$ operator to obtain regressors lagged by j months with respect to the quarter. Put formally:

$$\begin{aligned} y_{t_q} &= c + \beta_0\mathbf{F}_{t_q} + \beta_1\mathbf{F}_{t_q-1/m} + \cdots + \beta_p\mathbf{F}_{t_q-p/m} + \epsilon_{t_q} \\ &= c + \beta(L^{1/m})\mathbf{F}_{t_q} + \epsilon_{t_q} \end{aligned} \tag{6}$$

where the loadings β_j, for $j = 1, \ldots, p$ have dimension $1 \times r$. Equations from (4) to (6) are cast in a state-space form. The state equation is

$$\mathbf{X}_t = \begin{bmatrix} \mathbf{D} & 0_{n \times rl+1} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{F}_t^* \\ \\ y_t \end{bmatrix} + \xi_t \tag{7}$$

where

$$\mathbf{F}_t^* = \begin{cases} [\mathbf{F}_t', \mathbf{F}_{t-1}', \ldots \mathbf{F}_{t-l+1}']' & \text{if } l \geq p \\ [\mathbf{F}_t', \mathbf{F}_{t-1}', \ldots \mathbf{F}_{t-p+1}']' & \text{otherwise} \end{cases} \tag{8}$$

[12] According to Akaike information criteria, we set the order l of the VAR equal to 4.

and $\xi_t \sim N(0_{n\times 1}, \Sigma_\xi)$. To include the quarterly GDP growth into the state-space framework we constructed a monthly series y_t where $y_t \equiv y_{t_q}$ when $t \equiv t_q$ and missing otherwise.
If $l \geq p$ the transition equation is

$$\begin{bmatrix} \mathbf{I}_{rl} & 0_{rl\times 1} & \\ & & \\ -\beta_0 & 0_{1\times r(l-1)} & 1 \end{bmatrix} \cdot \begin{bmatrix} \mathbf{F}_t^* \\ \\ y_t \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} \mathbf{Psi} \\ \mathbf{I}^* \end{bmatrix} & 0_{rl\times 1} \\ & \\ \begin{bmatrix} \beta_1 \cdots \beta_p \end{bmatrix} & 0_{1\times r(l-p)+1} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{F}_{t-1}^* \\ \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \mu \\ 0_{r(l-1)\times 1} \\ c \end{bmatrix} + \begin{bmatrix} \mathbf{u}_t \\ 0_{r(l-1)\times 1} \\ \epsilon_t \end{bmatrix} \tag{9}$$

where

$$\begin{bmatrix} \mathbf{Psi} \\ \mathbf{I}^* \end{bmatrix} = \begin{bmatrix} \Psi_1 & \Psi_2 & \cdots & \Psi_l \\ \mathbf{I}_r & & 0_{r\times r(l-1)} & \\ \vdots & & & \\ 0_{r\times r(l-2)} & & \mathbf{I}_r & 0_{r\times r} \end{bmatrix}$$

while if $l < p$

$$\begin{bmatrix} \mathbf{I}_{rp} & 0_{rp\times 1} & \\ & & \\ \beta_0 & 0_{1\times r(p-1)} & 1 \end{bmatrix} \cdot \begin{bmatrix} \mathbf{F}_t^* \\ \\ y_t \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} \mathbf{Psi} \\ \mathbf{I}^* \end{bmatrix} & 0_{rl\times r(p-l)+1} \\ & \\ 0_{r(p-l)\times rp+1} & \\ & \\ \begin{bmatrix} \beta_1 \cdots \beta_p \end{bmatrix} & 0 \end{bmatrix} \cdot \begin{bmatrix} \mathbf{F}_{t-1}^* \\ \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \mu \\ 0_{rp\times 1} \\ c \end{bmatrix} + \begin{bmatrix} \mathbf{u}_t \\ 0_{rp\times 1} \\ \epsilon_t \end{bmatrix} \tag{10}$$

We implement the Kalman recursions (Kim and Nelson, 1999) to extract the smoothed state variable $\mathbf{FF}_t = [\mathbf{F}_t^{*'} \quad y_t]'$. Let T_ν be the vintage of the monthly series and h the forecasting horizon in terms of quarters, then the smoothed state variable is the estimate at time t, for $t = 1, 2, \ldots, T_\nu + 3h$, based on information up to $T = T_\nu + 3h + 1$, i.e. $\mathbf{FF}_{t|T}$. This is very appreciable because we use the latest information to make inference on the dynamics of the state variable. In fact, when $t = T_\nu + 1, ..., T_\nu + 3h$ all observations are missing and they are given no weight by the Kalman filter, which basically forecasts the factors as elaborated in Giannone et al. (2008). In particular, we are interested in the forecast of the GDP at time $T_{q_\nu} + h$, where T_{q_ν} is the quarter corresponding to the month T_ν:

$$y_{T_{q_\nu}+h} = c + \beta(L^{1/m})\mathbf{F}_{T_{q_\nu}+h|T} + \epsilon_{T_{q_\nu}+h} \tag{11}$$

One of the most common remarks to factor models concerns the possibility to disentangle the contribution of the observable variables to the forecasts. The variance of y_{t_q} is explained by the common factors, as shown in (6), which are not definitely given an economic meaning. As showed in Koopman and Harvey (2003), the output of the Kalman recursions can be used to size the weights attached to the observable variables in $\mathbf{X}_j$ when forecasting y_{t_q}, for $j = 1, \ldots, T_\nu + 3h + 1$. The smoothed state vector can be expressed as the weighted sum:

$$\mathbf{FF}_{t|T} = \sum_{j=1}^{T} w_j(\mathbf{FF}_{t|T})\mathbf{X}_j \tag{12}$$

where the weights $w_j(\cdot)$ are function of the state vector. Each month t, the weights are computed by the backward recursions (for $j = t-1, t-2, \ldots, 1$) and the forward recursions (for $j = t, t+1, \ldots, T$) introduced in Koopman and Harvey (2003).[13]

[13]For a detailed description of the algorithms refer to Koopman and Harvey (2003), p. 1322.

5 Forecasting application

The latest available vintage for the empirical application ranges from January 2000 to November 2015. Because of the asynchronous release of the indicators, the dataset has a typical *ragged-edge* structure and it is balanced on August 2015.

LASSO selected T2-retail among the first 13 most informative variables to fit the quarterly GDP growth, over the 50 indicators early collected. This result is a first evidence of the importance of the PS series to track the economic activity.

In Table 3 we assess how the forecasting performance of our model changes depending on whether we include or exclude the PS from the set of regressors. More precisely, we compare the benchmark model ($\hat{I}$), including all the variables listed in the fourth column of Table 2, with the model excluding the PS ($\hat{I}_{-PS}$) and with the model replacing PS with the first variable discarded by LASSO ($\hat{I}_{-PS,CLIMATE}$), i.e. Consumer survey – future economic climate (CLIMATE). We simulated the out-of-sample forecasts and we calculated the root mean squared forecast errors (RMSFE, onward) on two samples: the first one from 2008.Q2 until 2015.Q2; the second one from the bout of the sovereign-debt crisis in 2011.Q3 to 2015.Q2. The simulation was run in *pseudo* real-time, since we use the latest available vintage of data and we cut it period by period being careful to replicate the missing values' pattern at the end of the sample. The size of the estimation sample is fixed and it includes 78 months. The forecasting horizon is $h = -1, 0, 1$, depending on which month of the quarter is taken as the *pseudo* vintage. For instance, in the first month of the quarter t_q, we backcast ($h = -1$) GDP of the previous quarter not yet released by the national statistical office (Istat),[14] other than nowcasting ($h = 0$) and forecasting 1 quarter ahead ($h = 1$).

Table 3: RMSFE of the models $\hat{I}$ and $\hat{I}_{-PS}$

RMSFE			
	Sample [2008.Q2 - 2015.Q2]		
	Backcast	Nowcast	Forecast 1-step
$\hat{I}$	0.910	0.985	0.991
$\hat{I}_{-PS}$	0.911	1.028	1.038
$\hat{I}_{-PS,CLIMATE}$	0.923	1.062	1.053
	Sample [2011.Q3 - 2015.Q2]		
$\hat{I}$	0.517	0.529	0.544
$\hat{I}_{-PS}$	0.528	0.543	0.572
$\hat{I}_{-PS,CLIMATE}$	0.646	0.635	0.584

The PS improve the forecasting accuracy broadly. If we throw out only T2-retail the RMSFE rises throughout the forecasting horizons in both samples and in both competing models, $\hat{I}_{-PS}$ and $\hat{I}_{-PS,CLIMATE}$. This is a first rough proof of the relevance of the PS to make forecast. This result is even more remarkable if we consider that within a factor-model framework the marginal

[14] The preliminary estimate of the Italian GDP is available 45 days later than the reference quarter.

contribution of the single indicator to the covariance of the common components typically fades as the cross-section dimension of the dataset becomes sizeable.

In order to disentangle the predictive contribution of the single indicator, we estimate the weights in (12), which are implicitly assigned to the observations when estimating the smoothed vector $\mathbf{FF}_{t|T}$. Figures from 4 to 6 show the weights attached to T2-retail (red bars) and to some other indicators (blue bars), which track very well the short-term evolution of the economic activity (as electricity consumption, industrial production index, freight truck, manufacturing PMI - output component, expectations about liquidity of the manufacturing firms producing intermediate goods). Let us assume that the current month is October 2015. Therefore, we need to anticipate the GDP growth on 2015.Q3 (backcast; Figure 4), 2015.Q4 (nowcast; Figure 5) and 2016.Q1 (one-step-ahead forecast; Figure 6).

Let us consider the case of nowcasting (2015.Q4). In general, we observe that past observations contribute less to the forecasts, as expected; since November 2015 onward the weights are exactly zero because no observation is available yet. The weights of the PS are comparable to those of electricity consumption and liquidity expectations throughout the forecasting horizons considered. PS have sizeable weights compared to those of the manufacturing PMI (output component). This means that past information on PS contributes more than that on the PMI to anticipate the GDP growth. When forecasting 1-step ahead, the latest available data on PS weight as much as those on the freight traffic and they contribute to make up for the missing information on industrial production at the end of the sample.

Figure 4: Weights for backcasting (PS red bar; other variable blue bar)

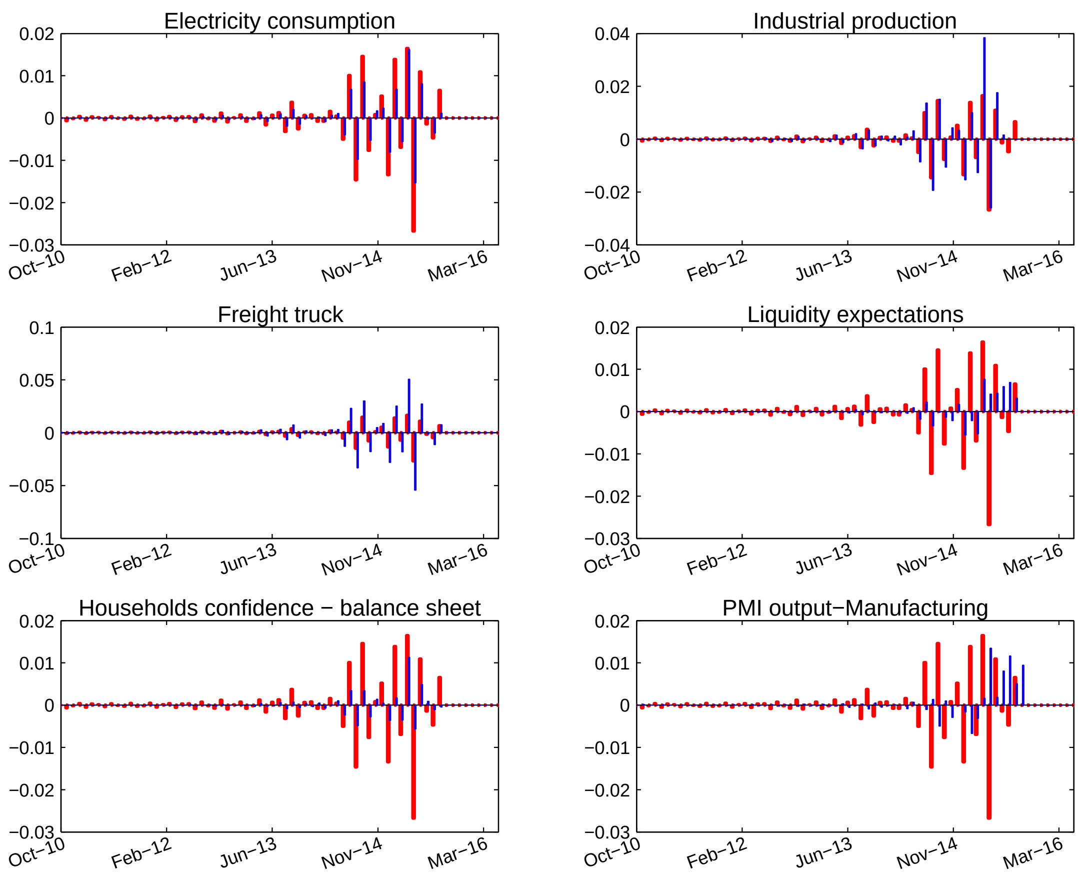


Figure 5: Weights for nowcasting (PS red bar; other variable blue bar)

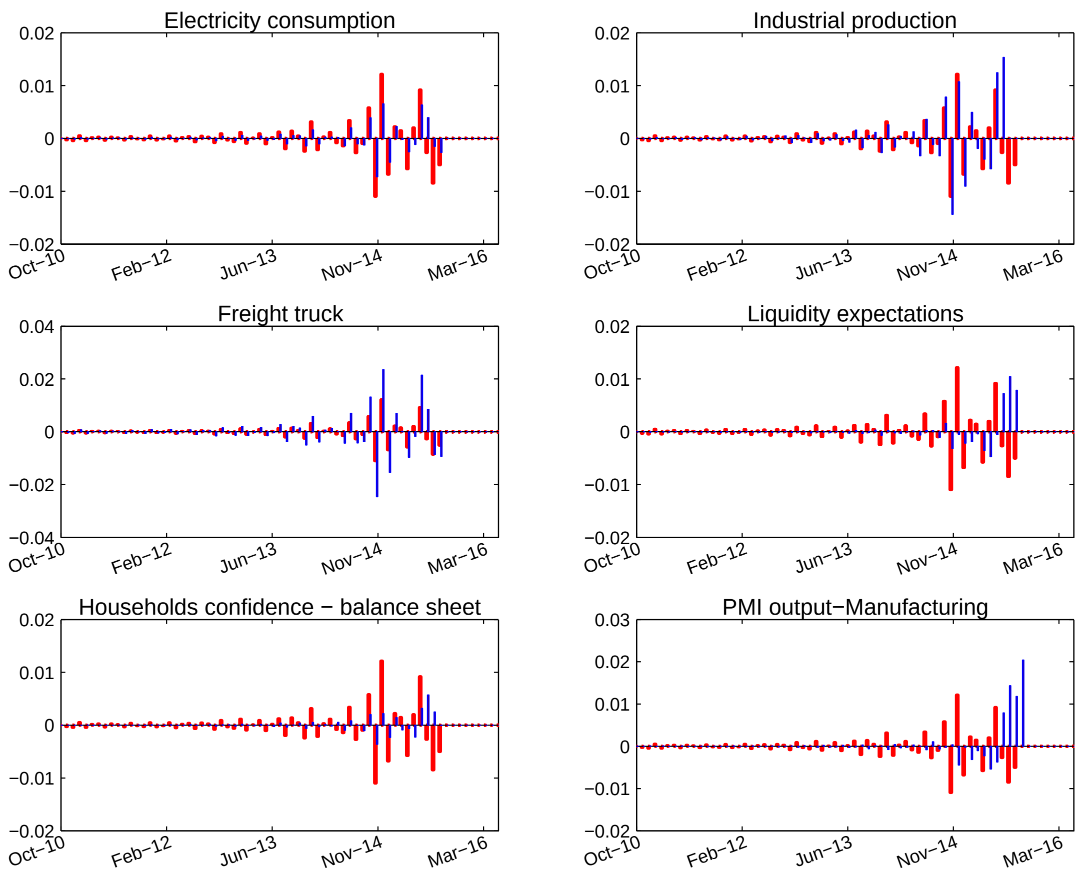


Figure 6: Weights for 1-step ahead forecasting (PS red bar; other variable blue bar)

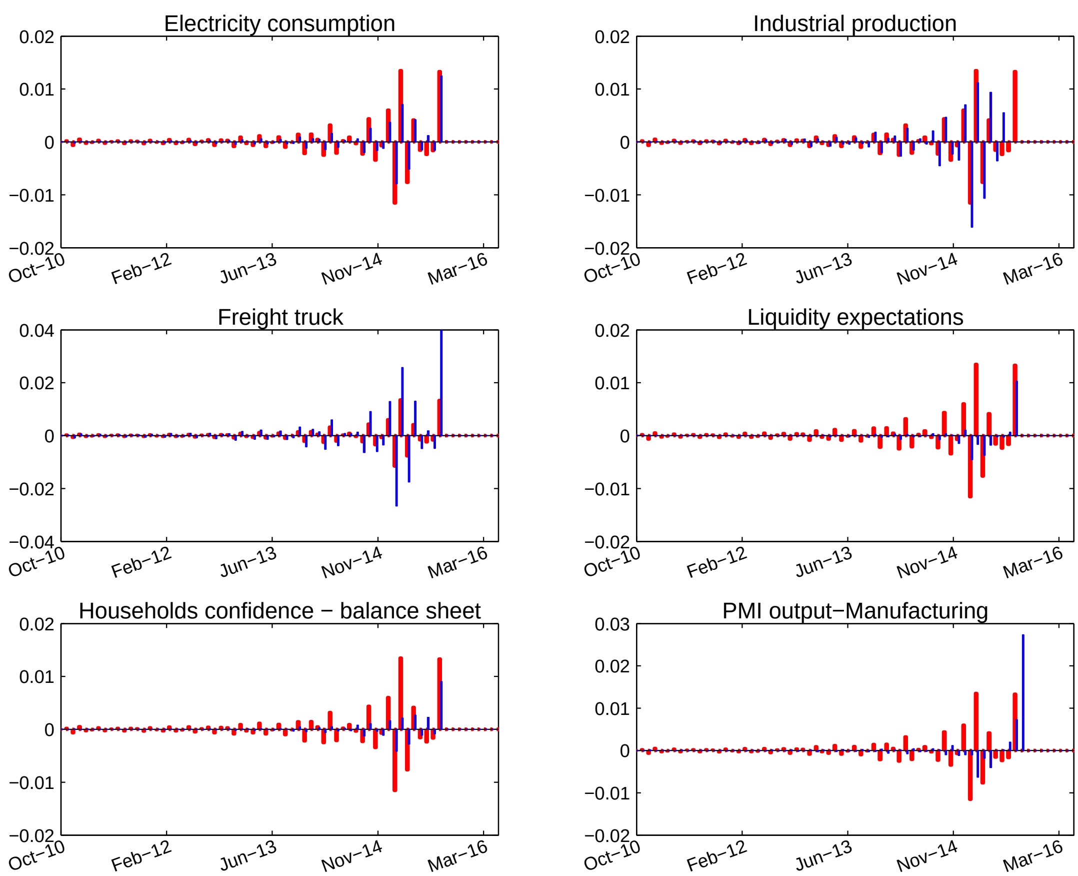
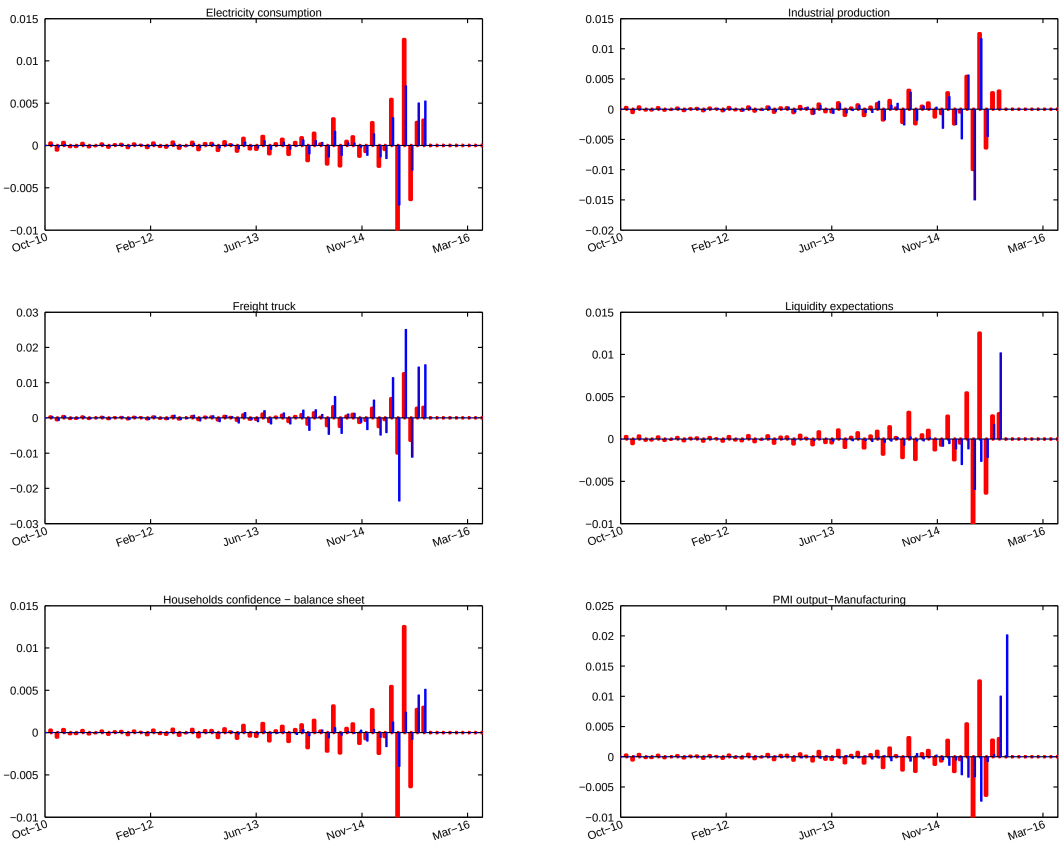


Figure 7: Weights for 2-steps ahead forecasting (PS red bar; other variable blue bar)



6 Conclusions

Our findings show that payment data help with tracking the economic activity in Italy. We look at different aggregates of payment system flows in Italy, jointly with other indicators usually adopted in GDP forecasting, and we see that they maintain some additional information content. We start from a large database of short term monthly indicators and Lasso selects a series of retail payment, jointly with other standard business cycle indicators such as industrial production and business surveys. Moreover, an out of sample forecasting application using a mixed frequencies MIDAS model shows that the model including retail payments flows outperforms the one based on standard short-term indicators only, in terms of forecasting accuracy. In order to disentangle the contribution of the observable variables to the forecasts of GDP, we estimate the weights proposed in Koopman and Harvey (2003) and we find that the weights attached to PS are comparable to those of some of the most important short-term indicators generally used to track the economic activity.

Our analysis is based on pseudo real-time data, but given that payment system data are available with a short delay and are not affected by revisions this result looks relevant also for real time forecasting.

The payment data indicator used in this model is the aggregate of a huge number of transactions. The forecasting ability of this indicator paves the way for a future work exploring the big data base of the individual transactions.

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