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EXPLOITING PAYMENTS TO TRACK ITALIAN ECONOMIC ACTIVITY: THE EXPERIENCE AT BANCA D'ITALIA

by Valentina Aprigliano*, Guerino Ardizzi§, Alessia Cassetta°, Alessandro Cavallero^, Simone Emiliozzi*, Alessandro Gambini¤, Nazzareno Renzi° and Roberta Zizza*

Abstract

This paper provides an overview of how information on payments has been recently exploited by Banca d'Italia staff for the purposes of tracking economic activity and forecasting. In particular, the payment data used for this work are drawn from the payment systems managed by Banca d'Italia (BI-COMP and TARGET2) and from the Anti-Money Laundering Aggregate Reports submitted by banks and by Poste Italiane to the Banca d'Italia's Financial Intelligence Unit (Unità di Informazione Finanziaria, UIF). We show that indicators drawn from these sources can improve forecasting accuracy; in particular, those available at a higher frequency have proved crucial to properly assessing the state of the economy during the pandemic. Moreover, these indicators make it possible to assess changes in agents' behaviour, notably with reference to payment habits, and, thanks to their granularity, to delve deeper into the macroeconomic trends, exploring heterogeneity by sector and geography.

JEL Classification: C53, E17, E27, E32, E37, E42.
Keywords: short-term forecasting, high-frequency data, payment systems, TARGET2, money laundering, COVID-19.
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Contents

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1. Introduction[1]

Economic forecasters strive to improve the accuracy of their models in order to better inform the decision-making process. This task is particularly challenging when the forecast horizon is the current period or the very near term, as the timely information available is scant. Moreover, collecting information is often expensive and places a statistical burden on respondents. Finally, a particularly topical issue in relation with the outbreak of the COVID-19 pandemic – which has caused an abrupt recession worldwide and, in some circumstances, impaired the process of data production, making forecasting extremely difficult (Locarno and Zizza, 2020) – is having models that are flexible and rich enough to deal with these unprecedented challenges.

Therefore, in recent years, researchers in policy-making institutions have been prompted to search for innovative datasets – either collected for other purposes (e.g. administrative data recorded by government agencies or enterprise data) or built ad hoc by exploiting contents available on the Internet – that could be processed to derive plausible and timely signals of economic activity. In this respect, Banca d'Italia has a longstanding tradition in assessing the short-term outlook on the basis of this kind of "unconventional" data, starting from forecasting models based on the consumption of electricity (Bodo and Signorini, 1987; Marchetti and Parigi, 2000) and, more recently, on road and rail transport flows. Studies relying on data from the Internet include Google-based models, as in D'Amuri and Marcucci (2017); analyses of the real estate market grounded in a dataset of housing advertisements, as in Pangallo and Loberto (2018) and Loberto, Luciani and Pangallo (2018); and attempts at measuring inflation expectations using Twitter, as in Angelico *et al.* (2018). Finally, more traditional media – such as newspapers – have been exploited to build news-based sentiment and uncertainty indicators based on text-mining techniques (Aprigliano *et al.*, 2020).

In this paper we survey the empirical evidence obtained at Banca d'Italia on the value added of exploiting data drawn from payment systems (operated and overseen by Banca d'Italia) as well as those originating from anti-money-laundering activity (carried out by the Italian Financial Intelligence Unit, UIF) to track the short-term evolution of economic activity. These datasets belong to the first of the two categories referred to above, as the information is recorded and processed for the purpose of policy making, but their characteristics (timeliness, high frequency, absence of significant revisions) make them ideal candidates for broadening the information set available to

[1] We thank Libero Monteforte for launching this project when he was affiliated with Banca d'Italia. We also thank seminar participants at Banca d'Italia for useful comments. The views expressed in this paper are those of the authors and do not necessarily reflect the position of Banca d'Italia.

forecasters. As cashless means of payment become increasingly popular, these data flows are more and more promising for providing reliable signals of economic activity.

Using this sort of "big data" to replicate or anticipate the dynamics of macroeconomic aggregates, which are characterized by longer release times, does not mean moving into completely uncharted territory, as in the last decade several studies have successfully tackled this issue. At the same time, forecasters often already possess sophisticated models based on valuable "more conventional" information – e.g. disposable income and consumer confidence as determinants of household consumption – and it is far from clear whether the new models can outperform them. Moreover, processing this kind of information to make it usable for forecasting purposes is a challenge *per se*.

This paper is organized as follows. Section 2 reviews the characteristics of payment system and the empirical evidence obtained on payment systems data. Section 3 illustrates how information drawn from banks' aggregate transaction reporting for anti-money-laundering purposes can help to forecast economic aggregates both at the national and regional level. Section 4 concludes.

2. Exploiting payment system data

Payment system data can be thought of as the "best game in town" for forecasters: they capture a broad range of spending activities (households and businesses) as well as an increasing share of them, as cashless means of payment are becoming progressively more popular; they are available on a very timely basis and without backward revisions, do not entail extra-costs for their collection, and are virtually free of sampling errors as the electronic compilation and storage of transactions is the *raison d'être* of the functioning of the payments systems, which requires every transaction to be made observable and traceable.

2.1 Payment systems in a nutshell

The term "payment system" refers, at a general and broad level, to the complete set of instruments, intermediaries, rules, procedures, processes, interbank funds transfer systems which facilitate the settlement of a payment transaction and, as a result, the transfer of funds among economic agents.

In a narrower sense, "payment system" is used as a synonym for "interbank funds transfer system", which is a formal arrangement based on legislation or private contractual terms – with multiple membership, common rules and standardized procedures – for the transmission, clearing, netting and/or settlement of monetary obligations arising between its members. The use of payment systems is the most common way of settling payment transactions involving accounts held in different financial institutions. In practice, a payment system or interbank funds transfer system is an arrangement through which funds transfers are made between banks on their own account, either on their own behalf (including for refinancing operations) or on behalf of their customers (to discharge the obligations on the part of payers vis-à-vis payees)[2].

A payment system is classified as a "large-value" or "retail" payment system depending on the main type of transactions processed in the system. Large-value payment systems (LVPSs) are designed primarily to process wholesale payments, i.e. urgent or large-value payments exchanged between financial institutions in relation to financial markets' activity. Retail payment systems (RPSs) are instead designed to handle a high volume of relatively low-value non-time-critical payments between non-financial institutions (e.g. private households, non-financial corporations or government agencies). Those transactions are mostly related to the real economy and are considered the most promising for now- and forecasting macroeconomic aggregates, as they can proxy household and firm expenditure and, ultimately, economic activity. Sometimes, low-value retail payments requiring a timely and urgent settlement are also processed by LVPSs.

Banca d'Italia operationally manages: (i) the BI-COMP clearing system, which clears domestic retail payments on a multilateral net basis; (ii) the Italian component of TARGET2 (Trans-European Automated Real-Time Gross settlement Express Transfer system; hereafter referred to as T2-Banca d'Italia for the sake of brevity), which settles most domestic wholesale transfers, on a gross basis and in real-time, and whose retail branch (T2-retail, henceforth) is used by banks to settle urgent retail payments.

The retail non-cash payments settled through BI-COMP and T2-retail added up to 4.2 trillion euros in 2019 (about 45% of the total value of retail payments in Italy; 60% if we consider only electronic payments, excluding postal pre-printed and other paper-based credit transfers), an amount which is more than twice the nominal value of GDP. Figure 1 shows the monthly gross value of retail non-cash payments settled through BI-COMP and T2-retail, while Figure 2 illustrates the upward trend in the use of electronic payment instruments (especially credit transfers and debit cards) against the downward trend of paper-based payments (cheques).

The significant drop observed in 2014 for credit transfers and direct debits arises from the change in the clearing and settlement landscape following the migration to the Single Euro Payment Area (SEPA) in August 2014. In that moment, some BI-COMP participants decided to move to

[2] For more details, see ECB (2010).

STEP2-T, the SEPA-compliant pan-European automated clearing house, which is privately owned and managed by EBA CLEARING, for the clearing and settlement of SEPA Credit Transfers and SEPA Direct Debits. The activity of the retail branch of T2-Banca d'Italia was not affected by that decision since T2-retail meets retail customers' demand for timely and secure payments. Payment transactions by cheque 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 debit cards, the upward shift in July 2001 is linked to the inclusion of point of sale (POS) transactions.

Figure 3 shows the shares (in terms of number and value of the transactions[3]) of payment instruments out of the total gross flows settled in BI-COMP. Credit transfers represent the largest share in terms of value (around 55%), with direct debit and cheque both accounting for around 20%. Payment cards are used for low-value transactions (€50-€100 for POS; €100-€200 for ATM); they represent the most used payment instrument with a 70% share in terms of number of transactions, while they account for only 5% of the total value of non-cash payments. 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 since there is a strong correlation between the amount of cash withdrawn from ATMs and the cash used at the point of sale.

2.2 Payment system data and macro aggregates

Data on payment instruments (cheques, credit transfers, direct debits, payment cards) trace economic transactions and could in principle represent the ideal source of information for tracking the economic activity. This was already understood by Irving Fisher at the beginning of the last century, when he 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). The empirical evidence proves the strong relationship between the main macroeconomic aggregates (such as GDP, value added in the service sector, private consumption and gross fixed investments) and the payment flows as drawn from BI-COMP and T2-retail for the Italian economy (see Figure 4). As shown in Aprigliano *et al.* (2019), a more rigorous proof of the importance of the payment flows in improving the economic analysis comes out of a LASSO-based routine, which pins down the most important variables that shape the dynamics of

[3] The number of transactions processed by a payment system is the most relevant variable when we want to describe and measure the activity of an automated clearing house, while the aggregate value of payment transactions comes up as the most significant indicator when we want to proxy macroeconomic aggregates.

GDP among several short-term economic indicators. The T2-retail series stands out among the first 13 variables out of the 50 initially compiled.

Further evidence on the close link between payment flows and macroeconomic time series is displayed in Figure 5, which shows POS payments and total expenditure on non-durable consumption and services: the year-on-year growth rates display similar dynamics, resulting in a high unconditional correlation (around 0.6).[4] Similarly, and particularly topical in the context of the health emergency, indications of a sharp drop in consumption in March and April, when a national lockdown was in place, were also promptly suggested by trends in cash withdrawals via ATM and POS terminal payments (Figure 6).

2.3 Empirical analysis based on payment system data

The co-movements between payment system data and the main Italian macroeconomic aggregates observed in the previous section encouraged us to assess the usefulness of this dataset for the purposes of predicting economic activity in the short-term. In doing this, we relied on previous literature, which is not very vast but definitely insightful and quickly expanding, also prompted by the increasing capacity of processing large-scale datasets.

Carlsen and Storgaard (2010) examine whether electronic payments by card are able to nowcast retail sales in Denmark and show their ability to improve forecast accuracy. Esteves (2009) conducted research on the consumption of non-durable goods among Portuguese households by exploiting ATM/POS data, whose predictive power was tested against some competing indicators, such as retail trade sales, the consumer confidence indicator and consumption of electricity. That work showed that ATM/POS data performs significantly better than its competing indicators in the out-of-sample forecasting of the consumption of non-durables. Still for Portugal, Duarte *et al*. (2017) use Mixed Data Sampling (MIDAS) models *à la* Ghysels *et al.* (2004) to now- and forecast private consumption. While the target variable is at quarterly frequency, the authors test the predictive power of payment data at both monthly and daily frequencies, and conclude that the former are more informative. Verbaan *et al.* (2017) assess the value added of introducing electronic payment data for estimating private household consumption patterns for the Dutch economy. They plug debit card payment data into a variety of models – such as indicator models, modifications of the De Nederlandsche Bank macroeconomic model (DELFI) as well as MIDAS models – in order to improve

[4] POS data are adjusted for two important level shifts, due to some institutional changes that occurred in 2012 and 2013. The first shift was due the "SalvaItalia" decree (Law Decree 201/2011), which imposed limits to cash payments in Italy, including pension payments. The second shift was due to the entry of Poste Italiane into the debit card settlement procedure BI-COMP.

the forecast and nowcast accuracy of consumption. They find that a combination of models provides the most accurate forecast. Galbraith and Tkacz (2018) use a large set of electronic payment data to nowcast GDP and retail sales for Canada. Debit transaction data play the lion's share in reducing the nowcast error for both target variables, while cheques are of little or no value. Bodas *et al*. (2018) use retail transactions made by credit and debit card holders of a large bank to build an indicator accounting for the business evolution of the retail trade sector in Spain, which proves to track fairly well the official retail trade index.

As for Italy, Aprigliano *et al*. (2019) is the first attempt to assess the additional information content of retail payment data in order to forecast the short-term developments of our economy with respect to the indicators traditionally employed in the economic outlook analysis. Differently from the rest of the literature, they use a more comprehensive set of payment instruments, such as credit transfers, cheques, direct debits and debit cards. Dynamic factor models are used to handle efficiently large datasets. A mixed frequency structure is employed to predict the quarter-on-quarter growth of GDP and of its main components by using a large-scale monthly dataset. The contribution of payment system data to forecast accuracy turns out to be appreciable and promising, as shown in Table 1.

Still in the field of forecasting, the work by Aprigliano (2020) takes a step further. Kalman smoother estimates are used to express the forecasts as a weighted average of the observable regressors within the framework of the factor model. The weights of the T2-retail and BI-COMP payment flows are comparable to those of the Purchasing Managers' Index and higher than those of many standard soft indicators. T2-retail turns out to be particularly suitable for tracking services activity, gross fixed investments and general government consumption. The series of ATM and POS transactions considered jointly contribute mostly to the forecasts of household consumption (Figure 7). An intra-month simulation was conducted to evaluate how the root mean squared forecast error (RMSFE) evolves as soon as the news regarding the variables is released. Figure 8 shows that the payment series dampen the RMSFE for both the nowcasting and the forecasting of GDP quarter-on-quarter growth. The improvement in the accuracy of early estimates of quarterly value added and turnover indices for services in Italy, calculated on innovative datasets built on payment data, is confirmed by Ardizzi *et al.* (2020).

Ardizzi *et al.* (2019) focus on Italian household consumption. This paper first shows that the electronic transactions that go through the payments system are a reliable high-frequency proxy for household spending (i.e. expenditure for non-durable consumption and services as recorded in the national accounts; Figure 5). Exploiting unique daily data on debit card expenditures, the authors study the consumers' response to daily news relating to Economic Policy Uncertainty (EPU). Using big-data techniques, they construct daily EPU indices built from Bloomberg newswire articles and tweets from Twitter (Figure 9) and document a strong seasonal pattern in the data that must be removed before using payment system data for economic analysis. Their main finding is that both at the daily and the monthly level, shocks to EPU temporarily reduce debit card purchases, especially during the recent crises. Figure 10a shows the impulse responses calculated using local projections of POS payments following a positive innovation in uncertainty (Jordà, 2005). The main results are confirmed using monthly data, controlling for financial uncertainty and macroeconomic surprises. Finally, EPU affects the ratio of ATM withdrawals to POS debit card purchases, signalling an increase in households' preference for cash (Figure 10b).

In the context of the pandemic, policymakers needed a timely and accurate measure of the business cycle to assess promptly the severity of the ongoing recession. High-frequency macroeconomic variables that strongly responsive to abrupt developments affecting the real economy can be exploited to construct a synthetic and timely indicator of the business cycle. Delle Monache, Emiliozzi and Nobili (2020), borrowing from the methodology proposed by Lewis *et al.* (2020) for the US economy, developed the Italian Weekly Economic Index (ITWEI). The dataset includes variables both at weekly and monthly frequency. Weekly ones comprise the total consumption of electricity, gas consumption for industrial use, POS transactions with debit cards, and an index of searches on Google Trends of the term CIG (i.e. *Cassa integrazione guadagni*, the main Italian short-time work scheme). Monthly variables include information on traffic flows, manufacturing and service PMIs, consumption expenditure indicators, value added taxes on imports, and the actual value of CIG transfers.[5] The weekly indicator exhibits a clear cyclical pattern and a strong correlation with real GDP, and was able to timely anticipate its collapse in the first two quarters of 2020 and the strong rebound in the third one (Figure 11).

The epidemic has also induced a marked acceleration in online sales of food and essential goods and has in general led more households to resort to e-commerce, which had previously been less widespread in Italy compared with the rest of Europe (Banca d'Italia, 2020). This was also reflected in an acceleration in the adoption of electronic means of payments, another area in which Italy was lagging behind. Ardizzi *et al.* (2020) investigate the effects of the spread of COVID-19 on a number of high-frequency indicators of payment habits and cash demand in Italy. They rely on indicators of the spread of the epidemic based on Google as well as on the official series of new cases of infection to measure the intensity of the pandemic, and apply local projection methods to assess

[5] ITWEI is estimated as the first principal component of the dataset balanced with the EM algorithm (Dempster, Laird and Rubin, 1977) as in Stock and Watson (2002). Data on short-time work include the total amount of the three types of subsidies: "CIG ordinaria", "CIG straordinaria" and "CIG in deroga".

the effects on payment habits (measured by the ATM/POS ratio and the share of e-commerce and of contactless payments). The impulse responses calculated after the outbreak of the pandemic shock show a large and persistent substitution effect from cash to card-based transactions, especially using contactless and e-commerce options (Figure 12). The fear of infection has led to a new implicit cost associated with each payment instrument, thus affecting payment choices from the demand-side and boosting consumption carried out with non-cash transactions.

3. Exploiting aggregate anti-money-laundering reports

Italian anti-money-laundering legislation[6] requires that banks and other financial intermediaries report monthly to the UIF all transactions amounting to €15,000[7] or more, after aggregating them by, among other variables, branch, customer sector of economic activity and type of transaction. These reports are referred to as SARA reports. Being based on aggregate data, SARA reports are non-nominal, hence they contain no reference to the customers' personal data. For each aggregate transaction, SARA reports provide its *total amount and the number of individual transactions that make it up*, plus the *total amount and number of individual transactions* referring to the share carried out in cash, if applicable. In 2018, more than one hundred million records were reported, accounting for 330 million transactions, worth almost €30,000 billion euros.[8]

SARA data are mainly used for the UIF's strategic analysis, a strand of activity aimed at identifying and assessing money laundering-related phenomena, trends and system vulnerabilities, in connection with specific economic sectors, geographical areas or means of payment. Aggregate data are also analysed to identify individual anomalies that may be associated with money laundering or terrorist financing. The analyses deploy descriptive methods or more sophisticated quantitative techniques for the study of large amounts of data, such as statistical-econometric techniques.

Finally, aggregate anti-money-laundering reports can be deemed valid measures of the decrease in financial operations linked to the COVID pandemic, which affected almost all categories of households and businesses. In April, when a complete lockdown was in place in Italy, these reports show a particularly significant fall for cash, but also a significant one for the total amount of operations and wire transfers, widespread across all sectors though to a differing extent (Figure 13).

[6] Legislative Decree 231/2007, Article 33.

[7] Reports also include 'fractional' transactions, i.e. transactions of the same type featuring individual amounts below €15,000 that were carried out within 7 days and are considered to be mutually connected from a financial point of view (e.g., were carried out by the same customer with the clear intention of circumventing the threshold). All 'fractional' cash transactions whose cumulative worth still lays below the threshold are also reported.

[8] UIF (2018).

SARA data also show that the contraction in the total amount of operations was widespread, but its size was quite heterogeneous by region (Figure 14).

3.1 Aggregate anti-money-laundering reports in a nutshell

SARA data reporting began in January 1993. Over the years, amendments to the regulatory framework affected the reporting scheme, the domains of some classification variables and the applicable reporting threshold: in 2003 the threshold was raised from €10,329 (equivalent to 20 million Italian lire) to €12,500 and was further increased to €15,000 in 2008. The classification of the sector of economic activity has undergone various amendments over the years, reaching the current definition only in 2010. In 2012, reports started being filed through dedicated IT channels and thus more detailed information, namely on the client's residence and the bank branch where transactions are carried out, were added.

Data quality is monitored by automatic statistical controls: "systemic" (cross-section) checks compare the data of each reporting intermediary with the reports of the whole system in the same month; "non-systemic" (time-series) checks compare an intermediary's reports with those it sent in the previous twelve months. Anomalous data are referred back to the reporting entity, which is required to check whether the data are correct and originate from some clients' anomalous financial conduct.

3.2 Empirical analysis based on aggregate anti-money-laundering reports

The UIF widely uses SARA data in its studies on phenomena related to money laundering and terrorist financing.[9] One such topic is Italy's financial flows *vis-à-vis* jurisdictions which are considered more at risk from a money laundering standpoint. The model built by Cassetta *et al.* (2014) and based on SARA data aims at identifying anomalous funds from each Italian province to any foreign country; such anomalies were found *ex-post* to be correlated with exogenous indicators of money laundering (suspicious transaction reports) and criminal reports.

Another key issue is cash, which is unanimously considered criminals' favourite means of payment because of the anonymity it guarantees and which represents a distinctive vulnerability of the Italian economic system.[10] Using information on cash deposits from SARA reports, Ardizzi *et al.*

[9] In the same area, innovative techniques for exploiting data are under exploration. For a review of some of the UIF's applications of these methods on SARA data, see Coelho *et al.* (2019).
[10] See, in this regard, the National Assessment of Money Laundering Risk (http://www.dt.tesoro.it/export/sites/sitodt/modules/documenti_en/prevenzione_reati_finanziari/prevenzione_reati_finan

(2018) and Giammatteo (2019) estimate an econometric model to identify cash transactions and obtain risk indicators that may help authorities and intermediaries to calibrate their action on the basis of a robust risk-based approach.

SARA data are also used for oversight purposes. In cooperation with the Banca d'Italia Directorate General for Financial Supervision and Regulation, the UIF developed a set of quantitative indicators of exposure to money laundering risks for each bank, to be deployed in planning off-site checks and on-site inspections; moreover, the same data are also used to assess Italian banks' level of compliance with anti-money-laundering regulation, as in Gara and Pauselli (2015).

In the same context, Gara *et al.* (2019) show that inspections by Italy's anti-money-laundering supervisory authorities (Banca d'Italia and UIF), notably when followed by some type of intervention by the latter, induce, *ceteris paribus*, an increase in suspicious transaction reports filed by banks, with no impact on the information content of the reports themselves.

SARA data turn out to be suitable for macroeconomic forecasting as well. After some preliminary adjustments and treatment of these series to remove exceptional spikes and anomalies, the signal retrieved matches up well with the short-run evolution of the economic activity (see Figure 15). Despite SARA data not being timely, their information contribution to forecasting economic activity is not negligible. Similarly to the empirical analysis introduced in Section 2.3, Figure 16 shows the information contribution of SARA to shaping the growth projections of GDP and its main component (Aprigliano, 2020). In the second and third month of each quarter, the weight of SARA reports is comparable to those of many popular short-term indicators such as qualitative surveys, export/import flows and industrial production. Credit transfers represent the most relevant information for forecasting purposes. In particular, credit transfers for wholesale trade perform best in predicting imports, while credit transfers operated by households and by the industrial and agricultural sectors does best in predicting households' consumption. National credit transfers for retail sales are particularly relevant for tracking the evolution of general government consumption and of service sector activity.

Since SARA reports provide a breakdown by bank branch, it is possible to identify in which region that particular flow was originated; hence, SARA data can be exploited to analyse regional business cycles. Indeed, in Italy the analysis of economic activity at regional level is difficult owing to the scarcity of timely data; official statistics on regional GDP (and its main components) are

ziari/NRA_Synthesis_11_01_2017.pdf). An Italian-only updated version is available at http://www.dt.tesoro.it/export/sites/sitodt/modules/documenti_it/prevenzione_reati_finanziari/prevenzione_reati_finanziari/Analisi_dei_rischi_di_riciclaggio_e_di_finanziamento_del_terrorismo_2018_-_Sintesi.pdf.

released by the Italian National Institute of Statistics (Istat) with a delay of roughly one year. On the contrary, SARA reports are available with a delay of 62 days of their collection, a significantly shorter time interval; moreover, given that SARA data are available on a monthly basis, they could also be exploited to construct indicators of regional economic activity with a frequency of less than one year. For these purposes, Cavallero and Renzi (2020) carry out a correlation analysis in order to gauge the linkages between SARA data and local economic activity in Italy for four macro areas (North-West, North-East, Centre and South) and for each Italian region. For each regional disaggregation, the following series are available: total flows, domestic bank transfers, foreign bank transfers, cash and cheques. Each series is divided into two flows based on their accounting sign, i.e. debit and credit. The former represents flows out of a given Italian region to the Italian territory (or abroad for foreign bank transfers); the latter represents flows in a given Italian region coming from the Italian territory (or from abroad, in the case of foreign bank transfers). The data refer to the transactions carried out by households and firms and have been preliminarily deflated and seasonally adjusted. Since SARA data display significant outliers when disaggregated at regional level, some preliminary adjustments and treatment are necessary to remove exceptional spikes and anomalies.

The correlation analysis confirms that it is possible to find at least one SARA series that is highly correlated with the annual rate of growth of GDP[11] for each macro area (see Table 2). In particular, domestic bank transfers, cash and cheques are found to be highly and significantly correlated with GDP for all macro areas; (credit)foreign bank transfers (which can be considered a proxy of exports) are correlated with GDP in all macro areas but the North-West. At regional level, cheques are significantly correlated with GDP in 18 out of 20 regions, followed by domestic bank transfers and cash. Among regions, in Veneto, Marche, Campania and Calabria all SARA variables prove to be significantly correlated with GDP; in Liguria, Trentino Alto Adige and Sicily the number of SARA series significantly correlated with GDP is equal to or less than 3.

In order to extract a synthetic indicator of SARA series capable of capturing the dynamics of the real GDP growth rate, a Principal Component Analysis (PCA) was carried out for each macro area. PCA is a variable reduction procedure that is useful when there is redundancy among the observed variables (i.e. they are correlated with each other), often because they are measuring the same phenomenon, as in the case of SARA series. For each macro area, the first three components account for roughly 90 per cent of overall variation. After extracting components, a correlation

[11] Cavallero and Renzi (2020) carry out also a correlation analysis between SARA data and other macroeconomic variables such as the value added of different economic sector (which may turn out to be relevant for a specific Italian region), gross fixed investments and final consumption, as well as with a quarterly indicator of regional economic activity (Di Giacinto *et al.*, 2019).

analysis was carried out between them and the rate of growth of real GDP. In each macro area those factors associated with “traditional” means of payment (such as cash and cheques) and to domestic bank transfers, respectively, prove to be highly correlated with GDP (Figure 17 and Table 3).

4. Conclusions

Policymakers need timely and reliable information to track developments in the economy and to produce accurate forecasts. In this respect, data on payment instruments (cheques, credit transfers, direct debits, payment cards) are a unique source of information for the short-term forecasting of macroeconomic variables such as GDP and consumption. Their importance grows over time, as the payment ecosystem is changing rapidly thanks to digital innovations, app-based and contactless transactions, e-money wallets and new payment initiation services, such that an increasing share of financial transactions is made via these modern payment systems.

This paper provides an overview of how information on payments has been recently exploited by Banca d’Italia staff. In particular, the payment data used for this work are drawn from the payment systems managed by Banca d’Italia (BI-COMP and TARGET2) and from the Anti-Money Laundering Aggregate Reports submitted by banks and by Poste Italiane to the Banca d’Italia’s Financial Intelligence Unit (UIF).

Results from several empirical exercises confirm that indicators drawn from these sources can indeed improve forecasting accuracy; in particular, those available at a higher frequency (weekly) proved crucial to properly assessing the state of the economy during the most acute phase of the epidemic. Moreover, these indicators allow to assess changes in agents’ behaviour, notably with reference to payments habits, and, thanks to their granularity, to delve deeper into the macroeconomic trends, exploring the heterogeneity by sector and geographical area which is, as is well known, a significant issue for our country.

Appendix

Figure 1: Value of total payments settled through BI-COMP and T2-retail

(billions of euros)

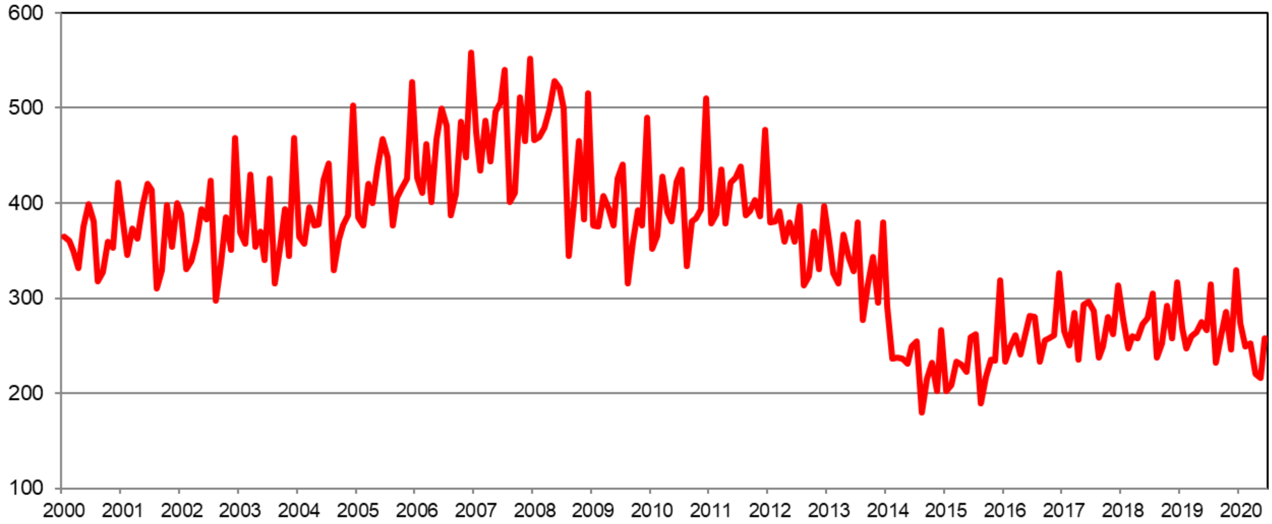


Figure 2: Value of payments settled through BI-COMP, by payment instrument

(billions of euros)

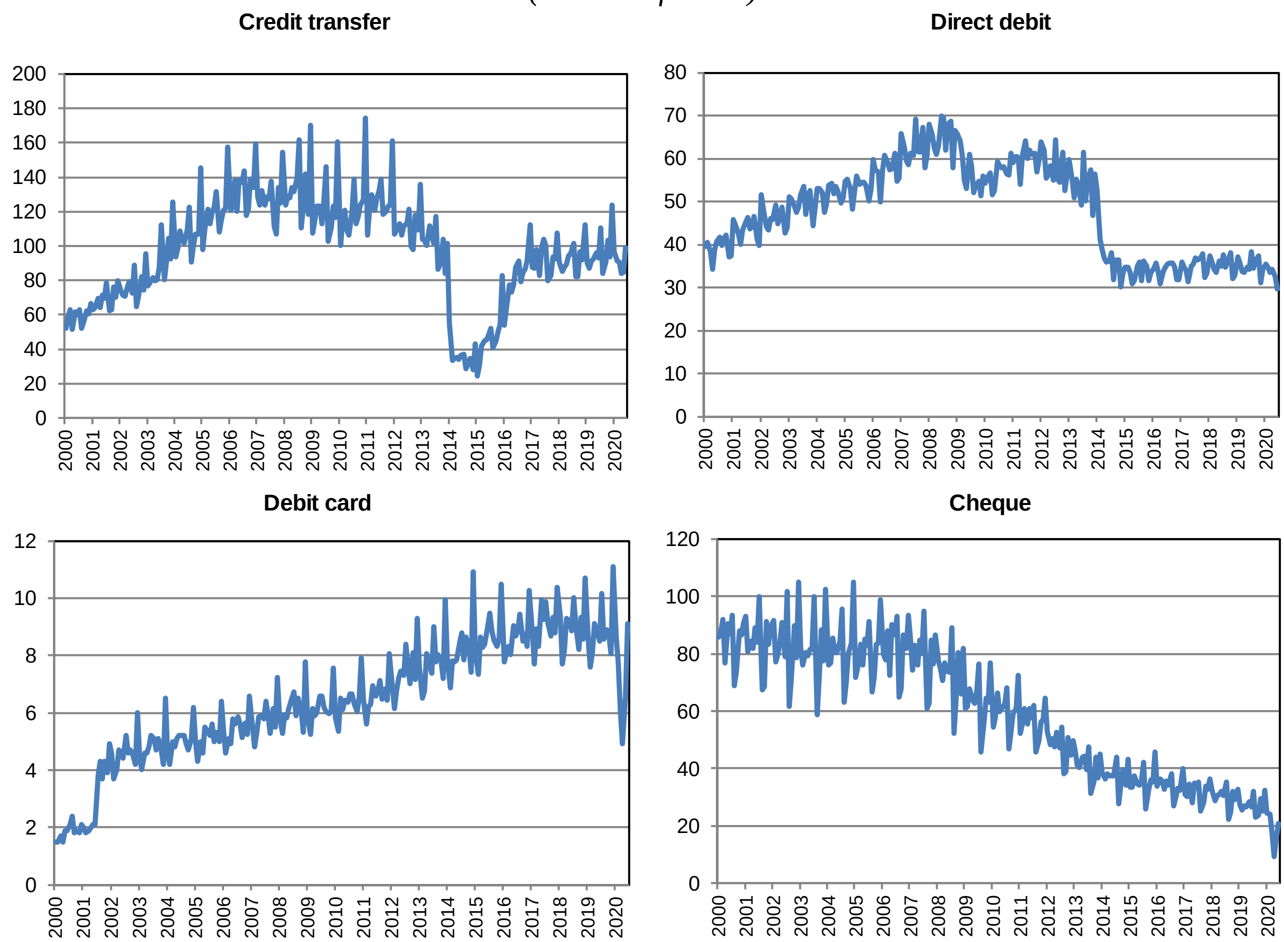


Figure 3: Payments settled through BI-COMP, by payment instrument

(share, in percentage points)

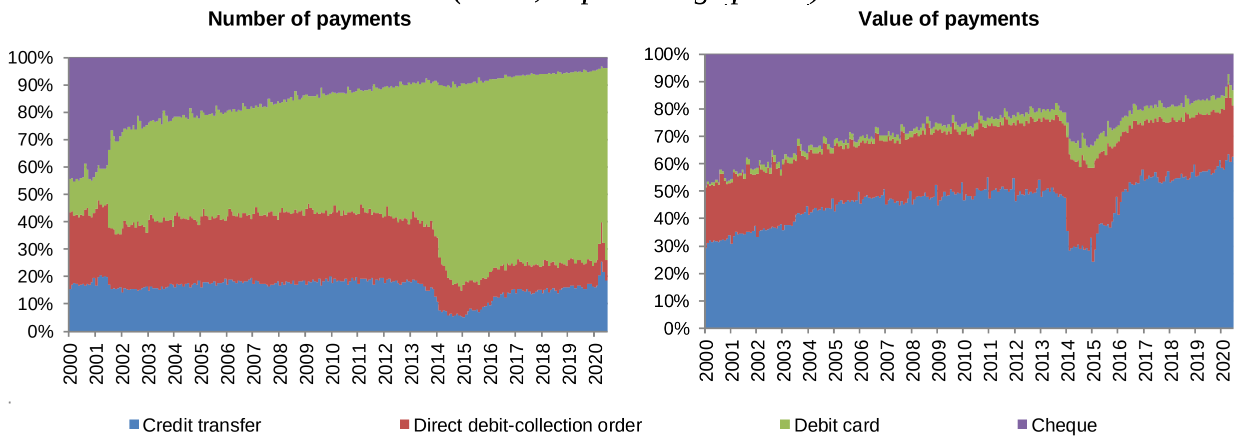


Figure 4: BI-COMP (dashed red line) and T2-retail (bold red line) flows compared with macro-economic aggregates (blue line)

(year-on-year percentage changes)

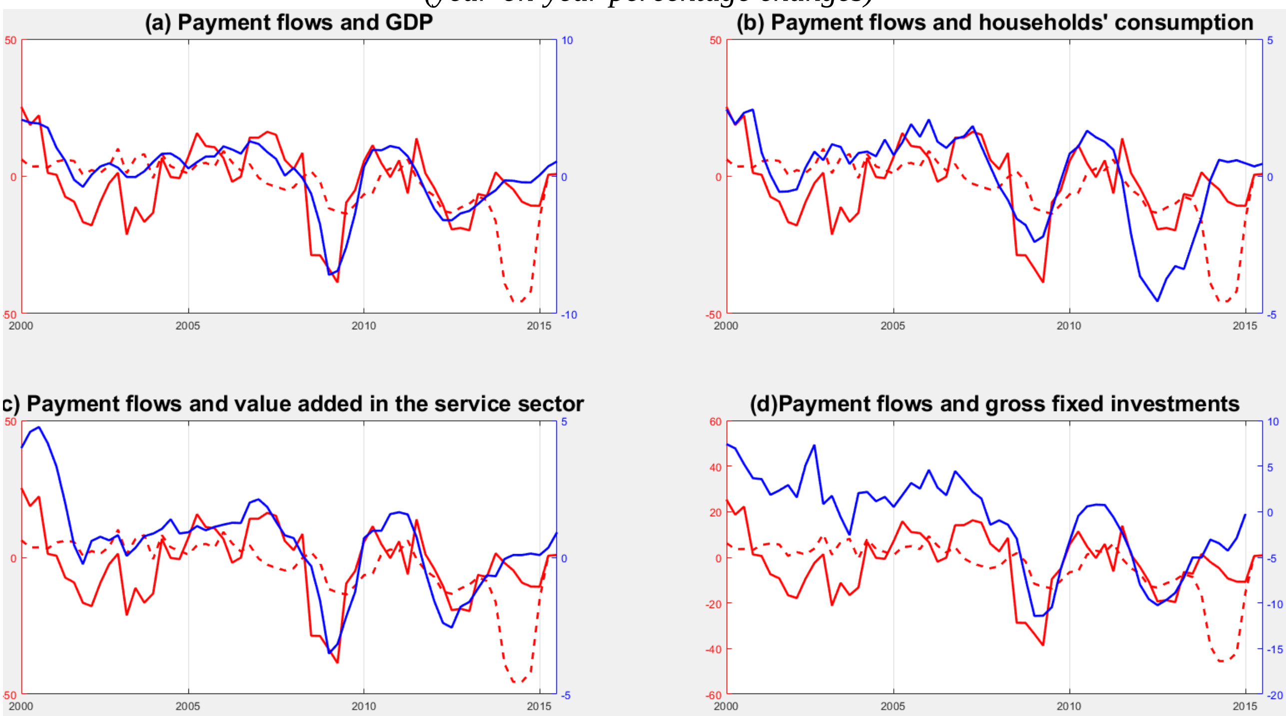


Figure 5: POS purchases settled through BI-COMP and consumption of services and non-durable goods

(4-terms moving averages and year-on-year growth rates)

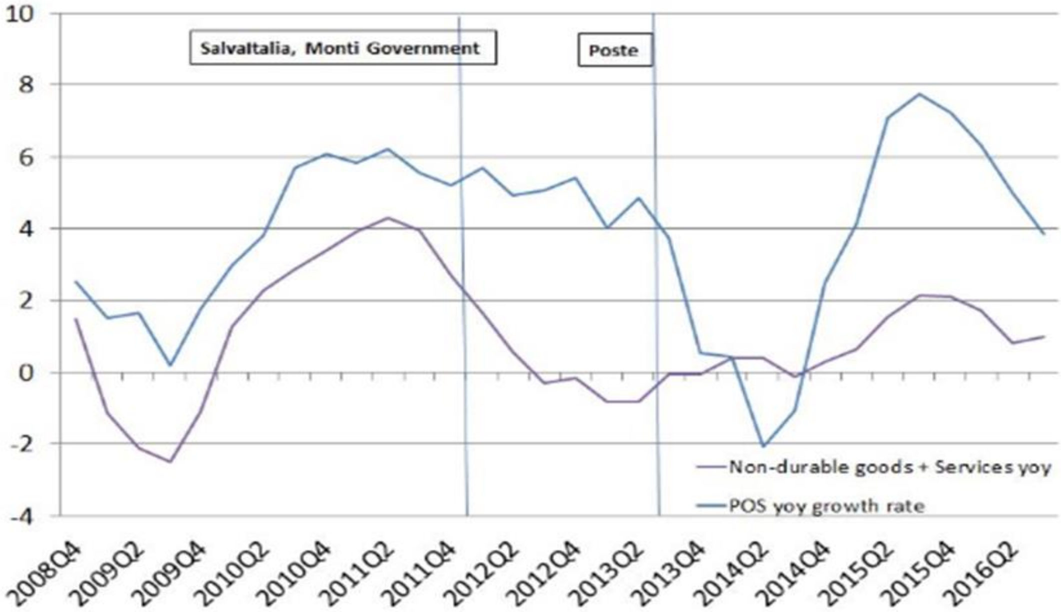
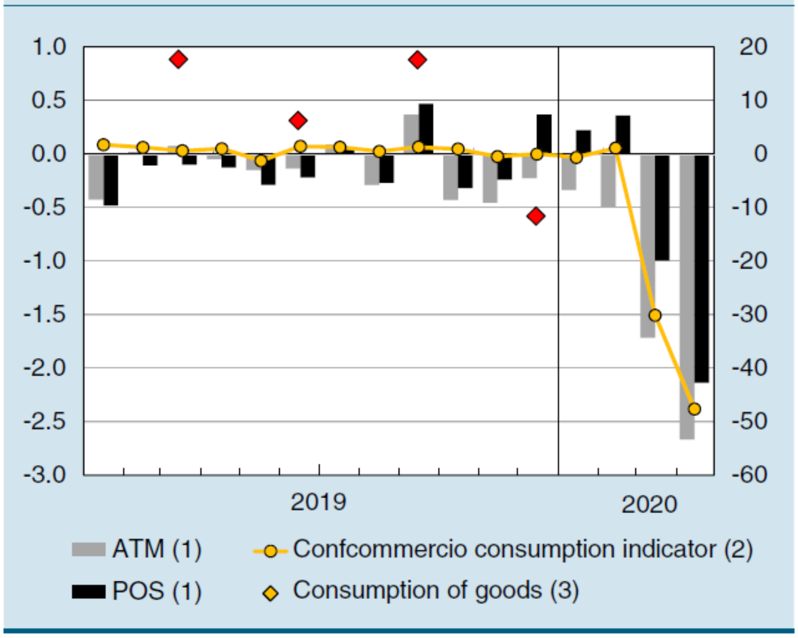


Figure 6: ATM withdrawal and POS payment amounts and consumption expenditure

(annual growth rates)

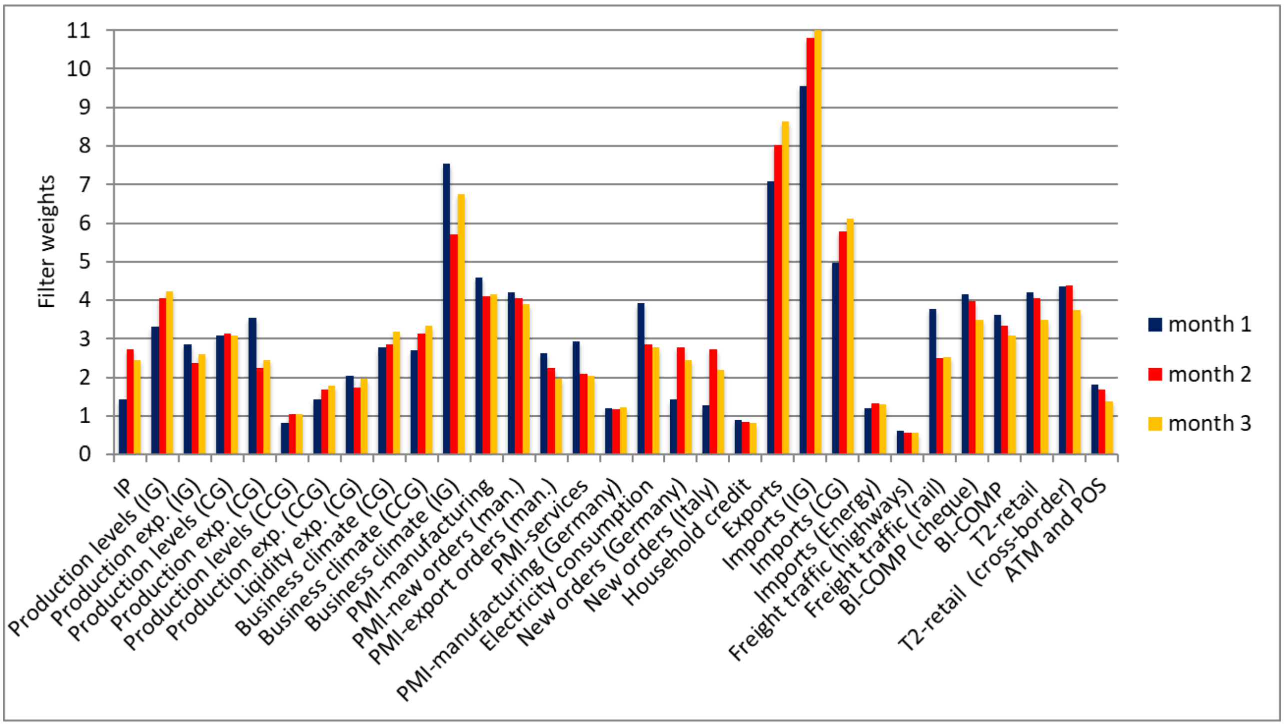


Sources: Based on data from the Bank of Italy, Istat and Confcommercio. (1) Data obtained from the BI-COMP multilateral clearing system; right-hand scale. For more details, see the Bank of Italy's website, 'BI-COMP and CABI: retail payments systems'. – (2) Right-hand scale. – (3) Final consumption expenditure of resident and non-resident households on the economic territory; current prices; the series are calendar adjusted.

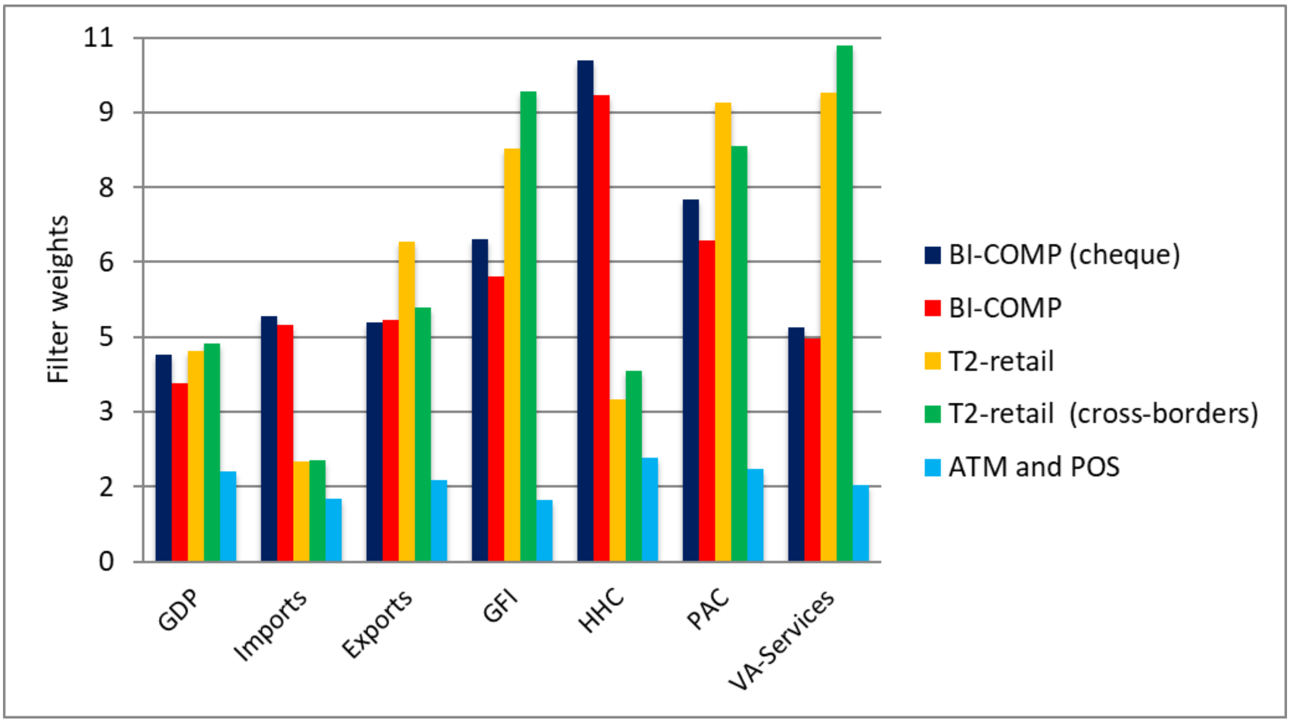
Figure 7: Filtering weights: payment series

(percentage values)

(a) Nowcast of GDP in each month of the quarter



(b) Nowcast of the national accounts in the first month of the quarter



Notes: IP = industrial production, IG = intermediate goods, CG = capital goods, CCG = consumer goods, HH = households, GFI = gross fixed investments, HHC = household consumption, PAC = public administration consumption.

Figure 8: Intra-month dynamics of the RMSFE

(a) Nowcasting GDP: payment system (b) Forecasting GDP: payment system

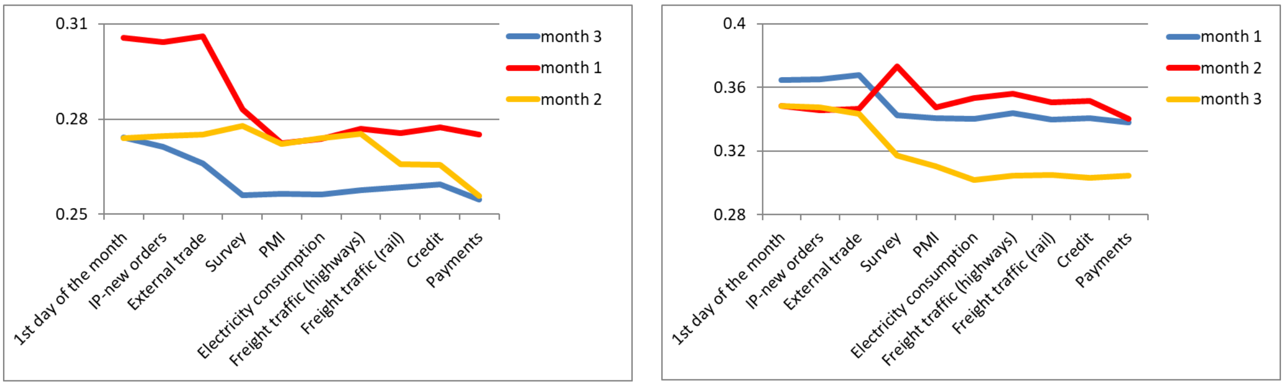
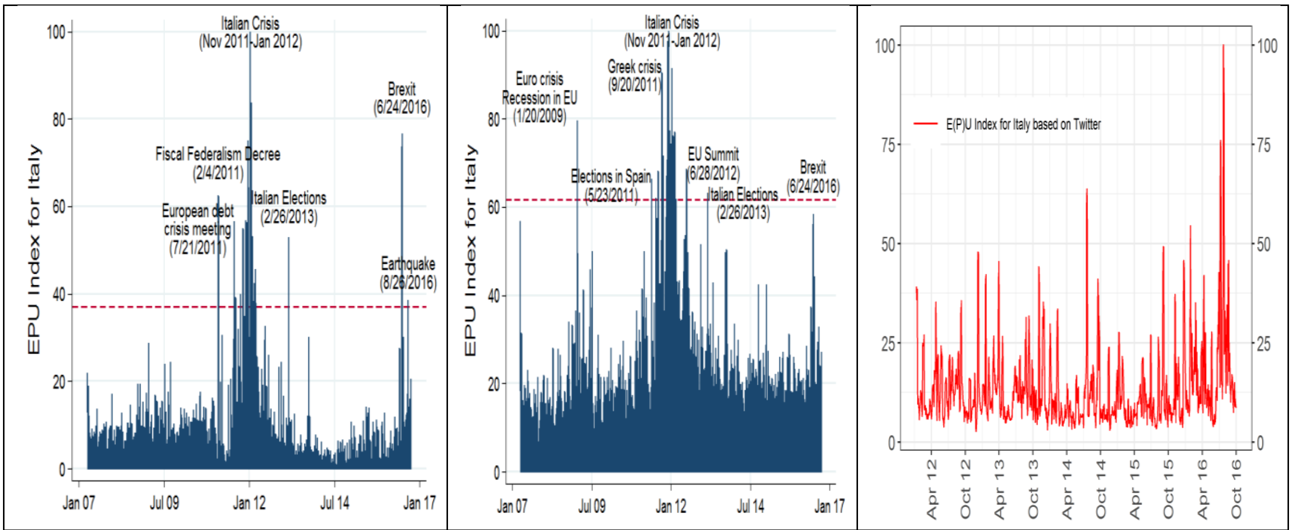


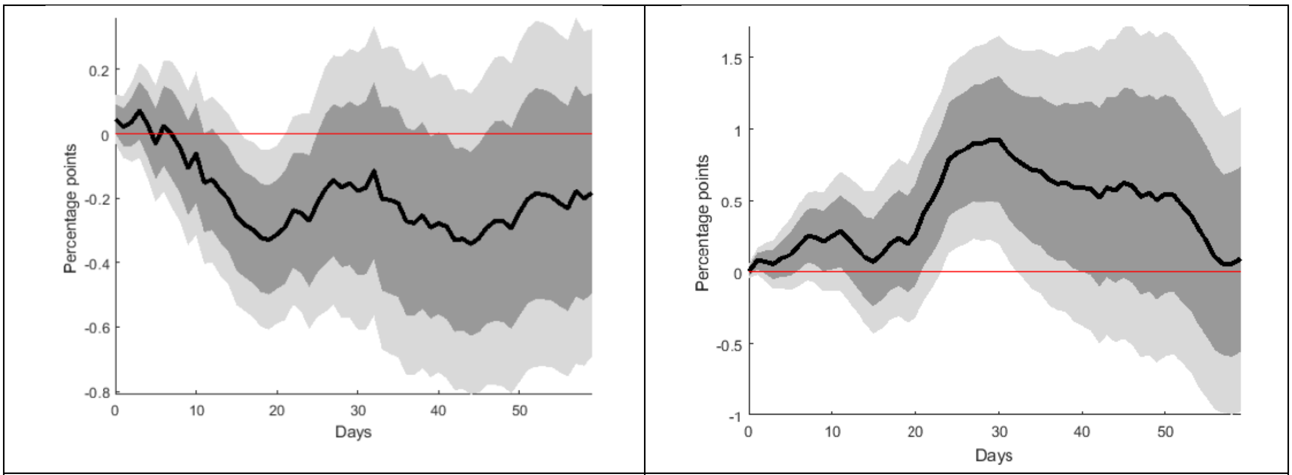
Figure 9: EPU and E(P)U indices computed with Bloomberg newswire and Twitter data



(a) EPU from Bloomberg (b) EU from Bloomberg (c) EU from Twitter

Notes: The two indices are obtained from keywords in English with the additional filter "AND ITAL*". The EPU index refers to news that contains at least one keyword from the "Economic", (Policy) and "Uncertainty" category. The E(P)U indicator is an "economic uncertainty" indicator and does not contain terms from the "Policy" category. Only the events inducing changes above the 99th percentile (displayed in red) are described.

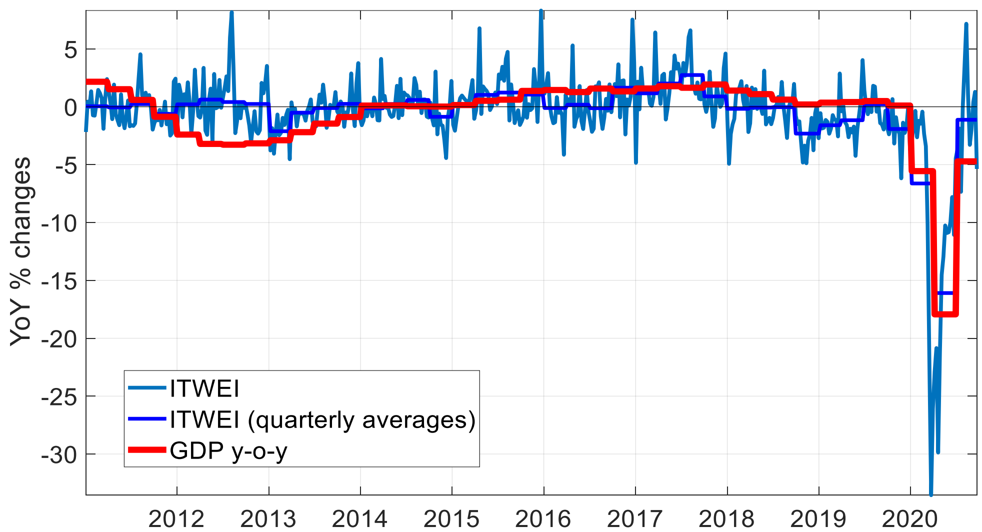
Figure 10: Response of POS payments and ATM withdrawals to a one-standard-deviation increase in the EPU index



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

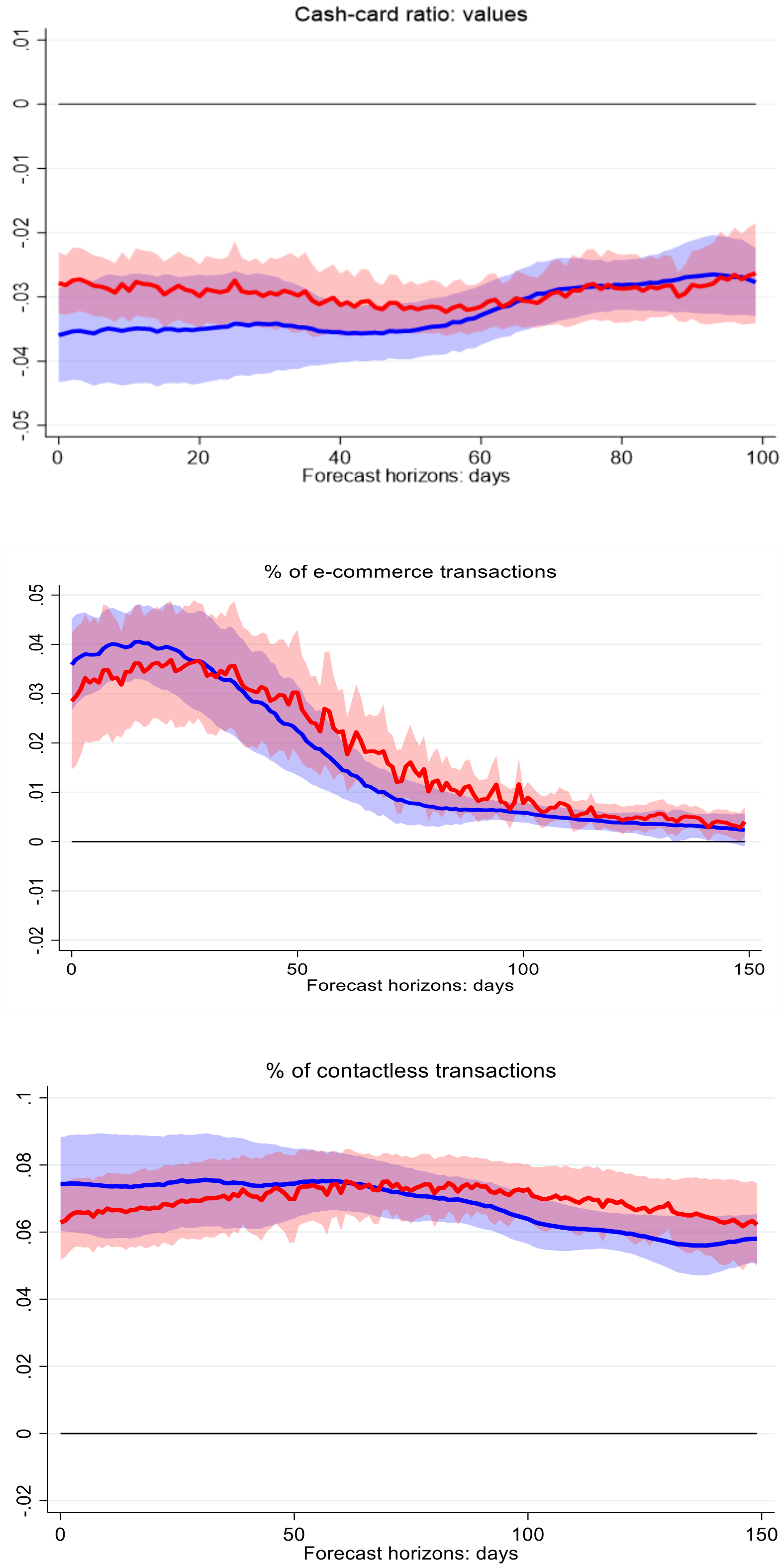
Figure 11: Italian Weekly Economic Indicator (ITWEI)

(weekly data; year-on-year changes)



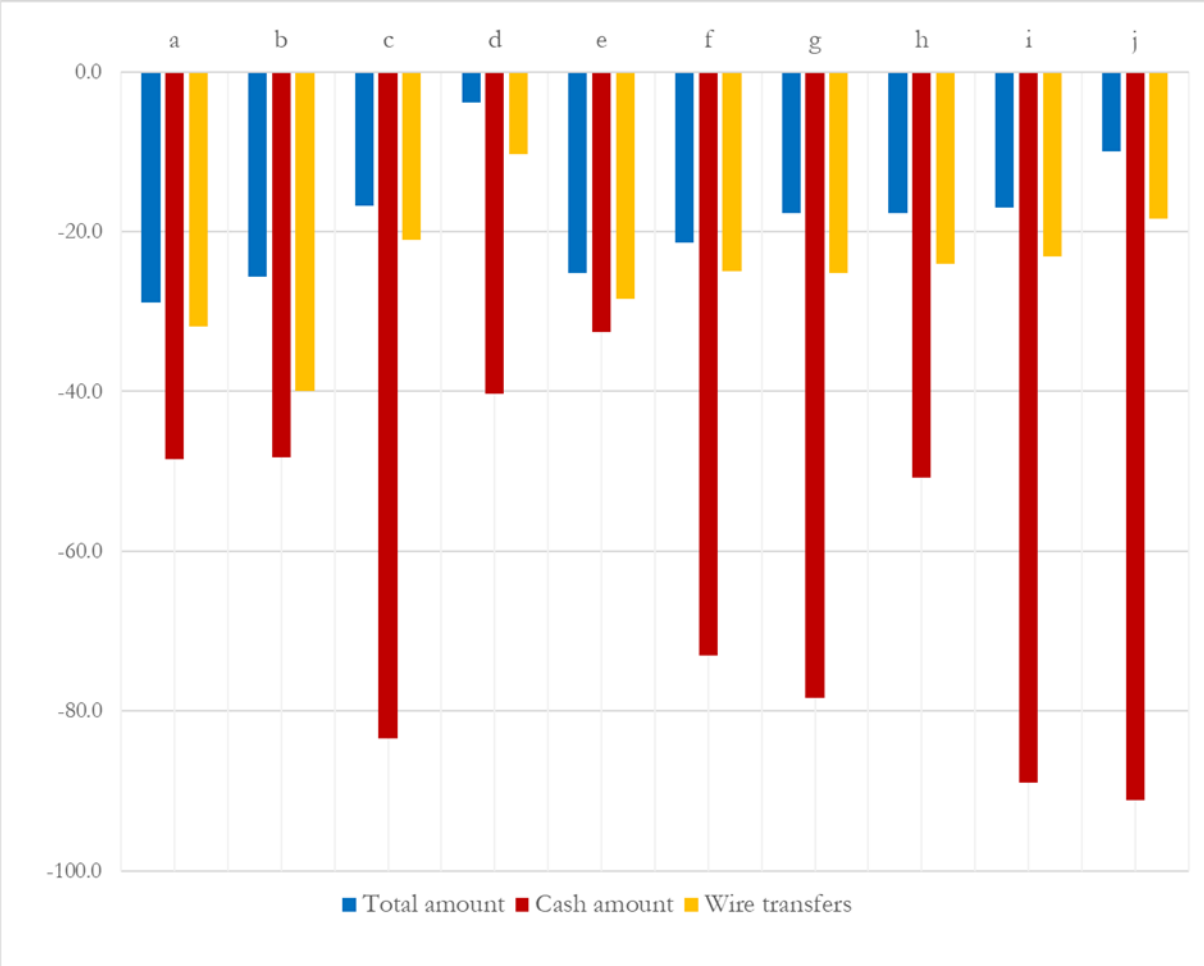
Notes: ITWEI is estimated using data from January 2010 to September 2020 (light blue). The dark blue line is the quarterly average of the weekly ITWEI. The red line is the quarterly year-on-year GDP growth rate (weekly disaggregation using constant values).

Figure 12: Effects of the pandemic on payment habits



Notes: The red line refers to impulse response functions to a pandemic shock, as captured by a Google Trends indicator; the blue line refers to impulse response functions to a pandemic shock, as captured by official new COVID-19 cases. See Ardizzi *et al*. (2020).

Figure 13: SARA – Total amount of operations by sector
(percentage change in April 2020 compared with April 2019)



Notes: a=Trade, b=Households, c=Manufacture of machinery and equipment, d=Food industry and agriculture, e=Other industrial products, f=Building, g=Mining, energy, petrochemical and steel industry, h=Transportation services, i=Other services, j=Other marketable services.

Figure 14: SARA – Total amount of operations by region

(percentage change in April 2020 compared with April 2019)

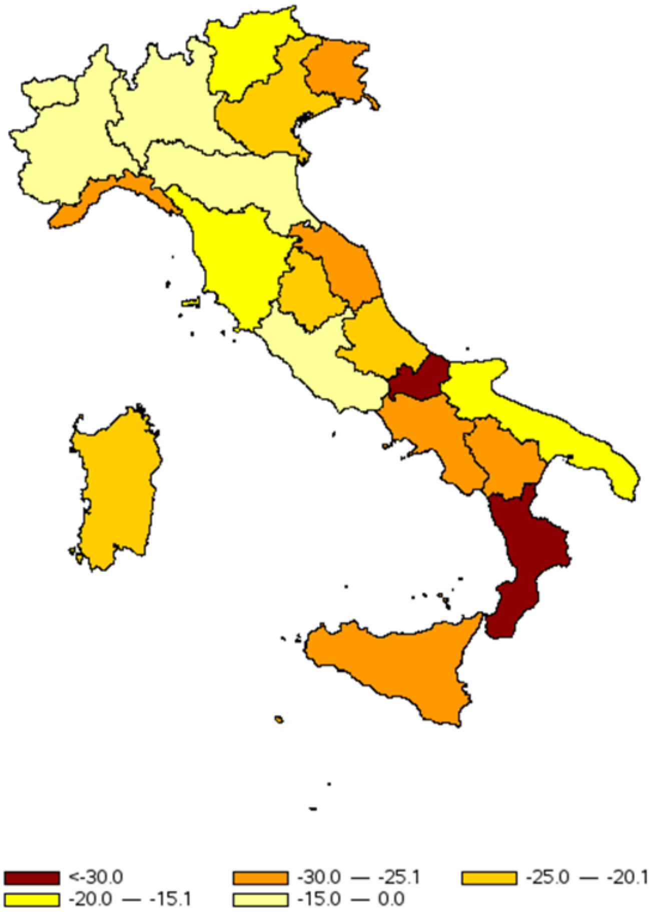
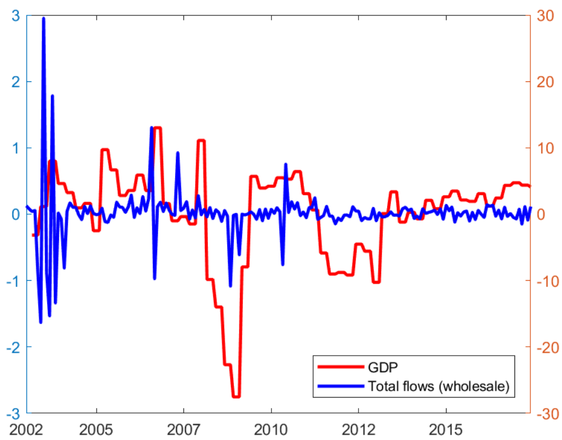


Figure 15: SARA total flows (wholesale) and GDP

(quarterly percentage growth)

(a) Unadjusted series



(b) Adjusted series

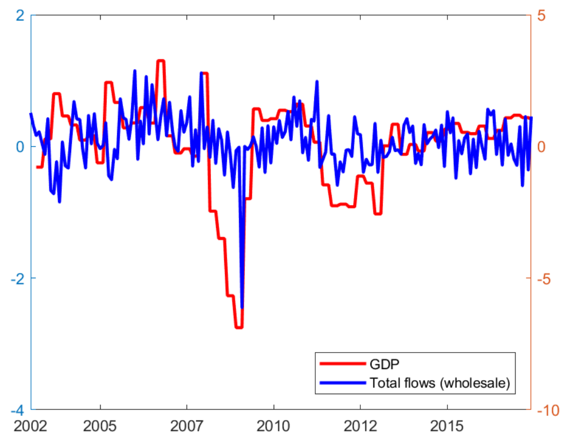
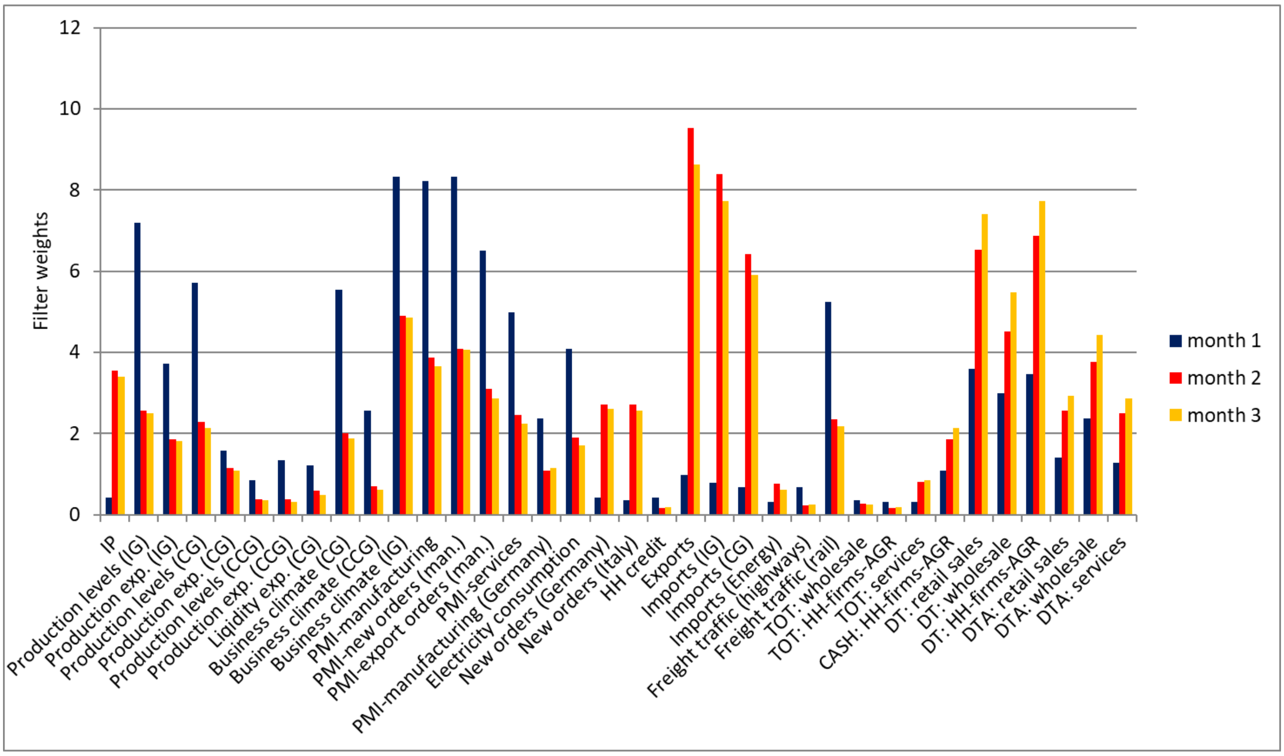


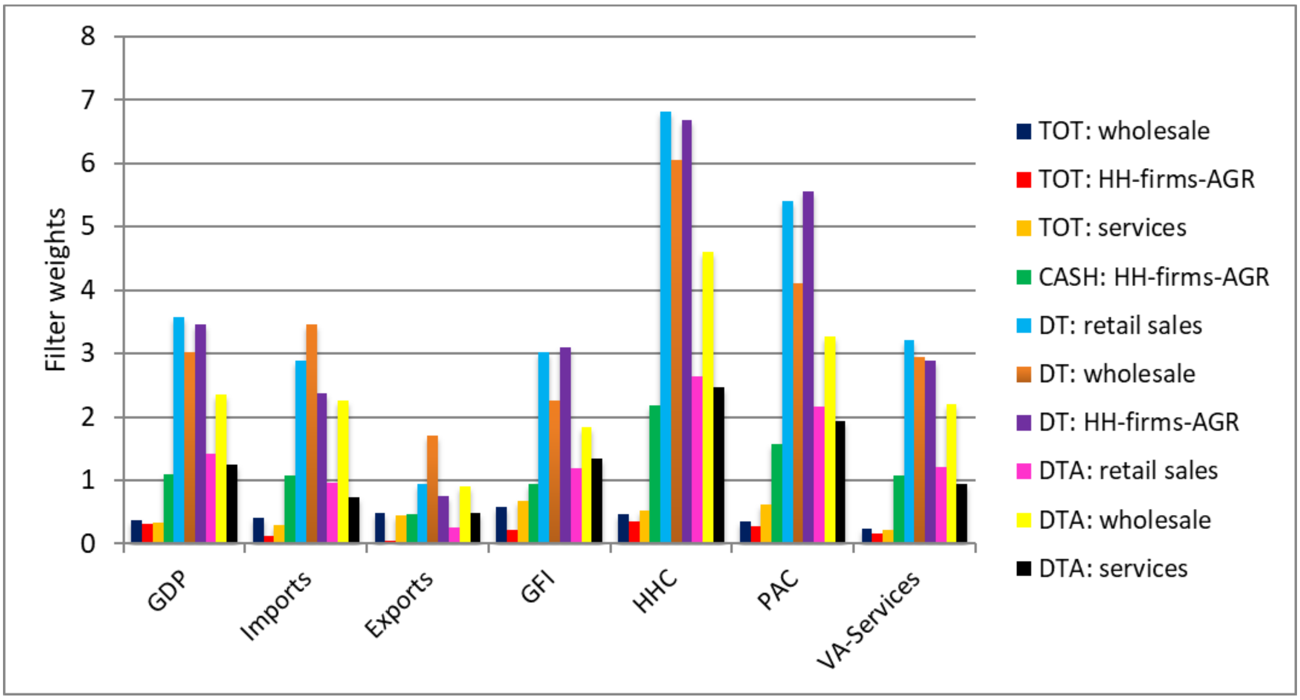
Figure 16: Filtering weights: SARA data

(percentage values)

(a) Nowcast of GDP in each month of the quarter

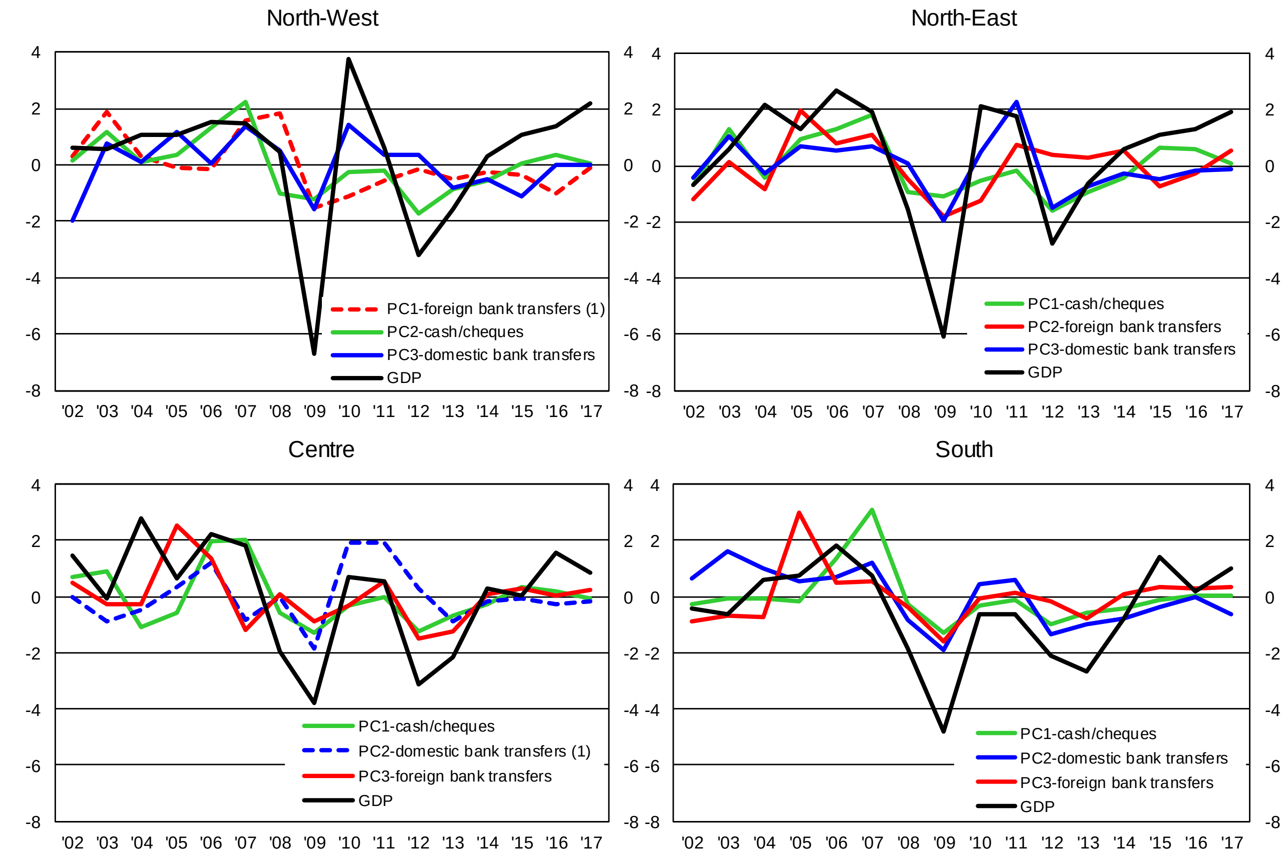


(b) Nowcast of the national accounts in the first month of the quarter



Notes: IP = Industrial production, IG = Intermediate goods, CG = Capital goods, CCG = Consumer goods, HH = Households, TOT = Total amount of SARA operations, DT = SARA direct transfers, DTA = SARA direct transfers abroad, GFI = Gross fixed investments, HHC = Households consumption, PAC = Public administration (general government) consumption.

Figure 17: SARA - Extracted principal components and annual rate of growth of real GDP



(1) Dashed lines indicate components not-significantly correlated to GDP.

Table 1: Relative RMSFE of $\hat{I}_{T2}$ vis–à-vis $\hat{I}_{PS}$

		Backcast	Nowcast	Forecast 1-step	Forecast 2-steps
HC	2008.Q2 - 2015.Q2	1.10[a]	1.14	1.15	1.14
	2011.Q3 - 2015.Q2	0.97	0.98	1.04	1.06
GFI	2008.Q2 - 2015.Q2	1.00	0.93	1.06	1.07
	2011.Q3 - 2015.Q2	0.80	0.82	1.17	1.12
VAS	2008.Q2 - 2015.Q2	1.00	1.08	1.11	1.12
	2011.Q3 - 2015.Q2	1.01	1.03	0.99	0.98
GDP	2008.Q2 - 2015.Q2	0.74	0.86	1.04	1.11
	2011.Q3 - 2015.Q2	1.28	1.10	0.91	0.94

[a] The figure is the ratio between the RMSFE of $\hat{I}_{-PS}$ and $\hat{I}_{T2}$. In this case, $\hat{I}_{T2}$ is 10% more accurate than $\hat{I}_{-PS}$.

Table 2: Correlations between SARA data and the rate of growth of real GDP

macro area/region		SARA data (*)									
		total flows		cash		domestic bank transfers		foreign bank transfers		cheques	
		Debit	Credit	Debit	Credit	Debit	Credit	Debit	Credit	Debit	Credit
NORTH-WEST	coeff.	0.39	0.44	0.30	0.46	0.46	0.50	0.16	0.16	0.63	0.67
	p-value	*0.138*	*0.090*	*0.259*	*0.075*	*0.071*	*0.050*	*0.555*	*0.556*	*0.009*	*0.005*
VALLE D'AOSTA	coeff.	0.42	0.47	0.32	0.37	0.48	0.47	0.10	0.60	0.50	0.39
	p-value	*0.103*	*0.069*	*0.222*	*0.156*	*0.059*	*0.067*	*0.713*	*0.013*	*0.049*	*0.141*
PIEDMONT	coeff.	0.42	0.47	0.44	0.51	0.26	0.23	0.44	0.57	0.65	0.59
	p-value	*0.109*	*0.065*	*0.085*	*0.044*	*0.329*	*0.388*	*0.090*	*0.022*	*0.006*	*0.016*
LIGURIA	coeff.	0.39	0.37	0.37	0.39	0.31	0.22	0.05	0.78	0.60	0.54
	p-value	*0.141*	*0.161*	*0.160*	*0.139*	*0.243*	*0.423*	*0.851*	*0.000*	*0.013*	*0.031*
LOMBARDY	coeff.	0.31	0.36	0.06	0.40	0.43	0.53	0.03	0.06	0.54	0.63
	p-value	*0.243*	*0.177*	*0.823*	*0.129*	*0.092*	*0.035*	*0.920*	*0.828*	*0.031*	*0.009*
NORTH-EAST	coeff.	0.50	0.54	0.58	0.49	0.67	0.69	0.32	0.75	0.71	0.66
	p-value	*0.048*	*0.031*	*0.019*	*0.057*	*0.004*	*0.003*	*0.233*	*0.001*	*0.002*	*0.005*
VENETO	coeff.	0.54	0.55	0.53	0.59	0.64	0.68	0.62	0.89	0.61	0.59
	p-value	*0.030*	*0.026*	*0.033*	*0.017*	*0.008*	*0.004*	*0.010*	*0.000*	*0.012*	*0.015*
TRENTINO ALTO ADIGE	coeff.	0.36	0.41	0.31	0.18	0.48	0.48	0.03	0.31	0.41	0.47
	p-value	*0.171*	*0.110*	*0.243*	*0.494*	*0.059*	*0.061*	*0.908*	*0.245*	*0.115*	*0.069*
FRIULI VENEZIA GIULIA	coeff.	0.35	0.37	0.57	0.30	0.20	0.05	0.49	0.46	0.57	0.65
	p-value	*0.178*	*0.155*	*0.023*	*0.263*	*0.451*	*0.851*	*0.053*	*0.074*	*0.021*	*0.007*
EMILIA ROMAGNA	coeff.	0.33	0.38	0.52	0.35	0.60	0.62	0.01	0.21	0.74	0.66
	p-value	*0.205*	*0.141*	*0.039*	*0.185*	*0.014*	*0.010*	*0.968*	*0.424*	*0.001*	*0.005*
CENTRE	coeff.	0.55	0.41	0.43	0.58	0.33	0.28	0.38	0.51	0.61	0.63
	p-value	*0.027*	*0.113*	*0.095*	*0.019*	*0.209*	*0.290*	*0.144*	*0.041*	*0.013*	*0.009*
LAZIO	coeff.	0.36	0.24	0.36	0.43	0.22	0.17	0.30	0.43	0.65	0.72
	p-value	*0.167*	*0.362*	*0.171*	*0.094*	*0.422*	*0.529*	*0.260*	*0.098*	*0.006*	*0.002*
TUSCANY	coeff.	0.49	0.35	0.35	0.48	0.52	0.49	0.33	0.44	0.45	0.44
	p-value	*0.056*	*0.179*	*0.187*	*0.063*	*0.038*	*0.054*	*0.216*	*0.090*	*0.080*	*0.091*
UMBRIA	coeff.	0.58	0.55	0.25	0.53	0.55	0.53	0.31	0.46	0.67	0.61
	p-value	*0.018*	*0.026*	*0.360*	*0.036*	*0.026*	*0.034*	*0.246*	*0.075*	*0.005*	*0.012*
MARCHE	coeff.	0.58	0.66	0.56	0.56	0.43	0.59	0.51	0.65	0.72	0.68
	p-value	*0.018*	*0.006*	*0.025*	*0.024*	*0.096*	*0.016*	*0.043*	*0.007*	*0.002*	*0.004*
SOUTH	coeff.	0.61	0.65	0.55	0.54	0.62	0.68	0.49	0.70	0.64	0.62
	p-value	*0.012*	*0.007*	*0.026*	*0.030*	*0.010*	*0.004*	*0.056*	*0.002*	*0.007*	*0.011*
CAMPANIA	coeff.	0.51	0.58	0.55	0.59	0.55	0.59	0.44	0.51	0.58	0.63
	p-value	*0.044*	*0.018*	*0.028*	*0.017*	*0.027*	*0.017*	*0.085*	*0.045*	*0.020*	*0.010*
PUGLIA	coeff.	0.50	0.49	0.48	0.33	0.56	0.59	0.57	0.64	0.58	0.51
	p-value	*0.049*	*0.055*	*0.060*	*0.216*	*0.024*	*0.017*	*0.021*	*0.008*	*0.018*	*0.045*
ABRUZZO	coeff.	0.54	0.60	0.44	0.33	0.44	0.58	0.44	0.32	0.61	0.44
	p-value	*0.029*	*0.014*	*0.092*	*0.213*	*0.091*	*0.017*	*0.089*	*0.226*	*0.011*	*0.086*
MOLISE	coeff.	0.37	0.41	0.56	0.51	0.52	0.49	0.26	0.32	0.50	0.59
	p-value	*0.163*	*0.115*	*0.024*	*0.042*	*0.038*	*0.054*	*0.339*	*0.232*	*0.046*	*0.016*
BASILICATA	coeff.	0.50	0.43	0.43	0.20	0.31	-0.03	0.39	-0.26	0.49	0.55
	p-value	*0.046*	*0.101*	*0.093*	*0.452*	*0.237*	*0.906*	*0.140*	*0.328*	*0.054*	*0.027*
CALABRIA	coeff.	0.71	0.74	0.49	0.61	0.63	0.65	0.77	0.58	0.60	0.64
	p-value	*0.002*	*0.001*	*0.054*	*0.012*	*0.008*	*0.006*	*0.000*	*0.019*	*0.015*	*0.008*
SICILY	coeff.	0.37	0.39	0.27	0.43	0.41	0.61	0.41	0.34	0.34	0.35
	p-value	*0.155*	*0.140*	*0.313*	*0.098*	*0.110*	*0.013*	*0.120*	*0.200*	*0.194*	*0.178*
SARDINIA	coeff.	0.81	0.65	0.41	0.61	0.74	0.46	0.24	0.27	0.54	0.58
	p-value	*0.000*	*0.006*	*0.113*	*0.012*	*0.001*	*0.073*	*0.378*	*0.304*	*0.030*	*0.019*

(*) Variables with a p-value equal or lower than 0.1 are marked in green.

Table 3: Correlations between principal components from SARA data and the rate of growth of real GDP

macro area		principal components		
		PC1	PC2	PC3
NORTH-WEST	coeff.	0.26	0.57	0.49
	p-value	*0.330*	*0.022*	*0.051*
	explained variance	57%	18%	15%
	identification	foreign bank transfers	cash and cheques	domestic bank transfers
NORTH-EAST	coeff.	0.63	0.45	0.71
	p-value	*0.009*	*0.084*	*0.002*
	explained variance	68%	13%	10%
	identification	cash and cheques	foreign bank transfers	domestic bank transfers
CENTRE	coeff.	0.58	0.35	0.46
	p-value	*0.018*	*0.188*	*0.071*
	explained variance	51%	32%	8%
	identification	cash and cheques	domestic bank transfers	foreign bank transfers
SOUTH	coeff.	0.61	0.65	0.60
	p-value	*0.013*	*0.006*	*0.015*
	explained variance	69%	32%	9%
	identification	cash and cheques	domestic bank transfers	foreign bank transfers

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