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The Use of payment transaction data for economic forecasts

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Abstract

Computation of the main components for Gross Domestic Product (GDP) and other relevant macroeconomic figures have been so far based on surveys among household and firms. These surveys are necessarily limited in sample size for obvious economic reasons. Aside from these reasons, natural phenomena like the recent Covid-19 pandemics, could completely wipe out the possibility to run this sort of surveys. On the other hand a huge amount of transaction data are regularly generated and digitally recorded from the different payment systems. These transaction data are very seldom used for building official statistics. In this work we consider billions of transactions from debit/credit card and data from the TARGET2 Gross settlement payment system as an alternative source of information for measuring variables such as consumption and tourism flows. Harnessing data arising from payment systems require special pre-processing and reconciliation operations, but once these steps are overcome they allow good improvements in pinning down the phase of the economic cycle, in squeezing the model forecasting variance and substantially shrinking the reporting times.

Even if card spending growth shows a substantial volatility compared with non-durable consumption growth, we find that normalized spending correlates quite closely with official consumption measures published by the National Statistical Office.

JEL classification: C32, C55, C81.
Keywords: Payment systems, technological platform, transaction data.

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1 Introduction and motivation

Doctrina bona dabit gratiam; in itinere contemptorum vorago.

Economic activity is based on monetary exchanges. Payment systems and infrastructures, which track the main commercial transactions in a timely and reliable manner, can therefore represent an important source of information for economic analysis and forecasting. Furthermore, the growing digitization of the economy favors the production of ever greater volumes of information based on digital technologies, capable of increasing analytical skills even in conditions of high macro-economic uncertainty. Statistical authorities and central banks are therefore gradually equipping themselves with tools aimed at allowing the use of this information, to build accurate and timely indicators to support economic policy decisions, as well as statistical measurement. However, although the link between economic activity and payment flows is based on a simple, intuitive consideration (think of the equivalence of Fisher exchanges), the use of payment data as an unconventional source of information for economic analysis could not be straightforward. In fact, payment systems and technological infrastructures were not developed by economists, but by specialists dedicated (rightly) to safeguarding the integrity, timeliness, cyber security of operations and, obviously, the business, with operating standards different from those that characterize economic statistics. The dynamics of monetary flows generally follows a cash criterion, not an accrual criterion; trends are usually erratic or highly seasonal, especially with reference to high-frequency flows, which do not always coincide, therefore, with those of the economic phenomena to be analysed.

The complexity in the use of payment data for economic-statistical analysis purposes is also linked to a series of reconciliation problems that need to be addressed ex ante. For example, if you want to analyze the purchases of retail goods and services, i.e. the transactions that payment experts define as person-to-business, the best thing would be to select transactions with payment cards; while, in the case of commercial exchanges between companies, the flows from bank transfer operations will be more representative. Nor is the point of observation irrelevant, which can be on the side of the originator of the payment (e.g. the consumer) or on the side of the recipient of the collection (e.g. the seller company), to be identified on the basis of the macroeconomic aggregate to be measured (e.g. household consumption or business added value).

The selection of the economic activity sector and the geolocation (territorial, national, to or from abroad) of the payment flow can also play an important role in directing the analysis. Granular information must also be extrapolated from complex payment messages processed by exchange and processing system managers or intermediaries. Often this information is not available from a single reporting agent, because it is dispersed among different players participating in the payment process (banks, processing companies, clearing and settlement systems) and it can be onerous as well as complicated to obtain and integrate the data in possession of each actor; in these cases it is therefore necessary to resort to proxies or assumptions based on the information available. For example, although you don't have specific data on wire orders ordered for retail purchases (P2B), the aggregate data on the flow of credit transfers exchanged by the interbank systems can in any case be correlated with the trend in consumption and provide useful signals for macroeconomic forecasts.

The paper shows some results in harnessing electronic payment transactions data for official statistical production purposes and in macroeconomic forecasts. The work is arranged in the following way. After this introduction section 2 illustrates the payment systems from which the relevant information is extracted for the construction of the payment indicators. In section 3 several case studies are presented in which it is shown that the introduction of transaction data improves the performance of the models of the Bank of Italy for short-term forecasts or for quick estimates, as well as Official statistics nowcasting and forecasting activities.

Finally section 4 provides some concluding remarks and suggestions for future research.

2 Payment systems and information bases for economic analysis

Every year the economic transactions are carried out with retail payment instruments for a value of more than 3 times the Italian GDP. Retail payments are those made by end customers (households, businesses, public administration) for the purchase of goods and services (P2B), for the payment of salaries and pension payments (B2P), in commercial exchanges between businesses (B2B) and in transfers between private individuals (so-called P2P).

Customer payment instruments (or services) concern all the methods and monetary means used for the settlement of "retail" economic transactions. They therefore include both legal (circulating) money and *alternative* instruments issued by banking and non-banking intermediaries (for example, credit card issuers) and by Poste Italiane and traditionally classified into four categories:

1. cheques;
2. wire transfers;
3. collection instructions;
4. payment cards.

The compositional relationship between fiat money and other instruments and, within the latter, between the various means of exchange (for example, cards, checks, etc.) is affected by cultural and institutional factors, linked to the degree of financial sophistication of a country. Furthermore, the evolution of the digital ecosystem and the application of information and communication technologies to the payment system determine continuous innovations of services and payment instruments that direct customer preferences regarding the use of the different instruments. These innovations concerned both the exchange processes and the interbank procedures for the electronic transmission of information (for example, electronic wire transfers, check truncation, use of cards via the Internet, etc.), and the physical media (for example, mobile applications , contact-less card, microcircuit, etc.). They have favored over time the progressive replacement of traditional paper-based payment instruments (and procedures) (cash, checks, etc.) with electronic ones (for example, payment cards, wire transfers, pre-authorized debits).

2.1 Payment transaction data source

Few years ago Bank of Italy set up a joint group with the National Institute for Statistics aiming to produce payment transaction data indicators and test their adoption in nowcasting or forecasting macroeconomic aggregates. The outcome of this activity has been the release of monthly and daily time series extracted from two clearance and settlement systems BI-COMP and TARGET2 retail. Albeit their timeliness and high frequency, these time series do not allow any commercial breakdown because they come at a high level of aggregation. Therefore using payment transaction data microdata coming from both BI-COMP (card data) and data from a major private card operator, after a phase of data munging and cleaning, derived a more granular set of monthly and daily time series. New series refer to the shares of the transaction by 10 Merchant category code groups (e.g., clothing, hotels and restaurants, home, work, retail, services, telecom, web and dm, travels and transport, cash advance, not defined) and the e-commerce transaction (from the acquirer side, namely, the expenditure of Italians on Italian firms).

Therefore, in our analysis we could apply the following four types of payment transaction data time series:

1. monthly time series of BI-COMP/T2 total transaction and by payment instruments (e.g., credit transfer, direct debit, payments cards - both Atm and Pos -, cheques, other); series are available since the

year 2000 (both in volume and amount);

2. monthly time series of BI-COMP e-commerce transaction in terms of indices (2014=100), available since 2014;
3. daily time series of BI-COMP/T2 total transaction and by payment instruments (POS, ATM), available since the year 2006 (both in volume and amount);
4. daily time series of BI-COMP domestic debit card transaction (considering only the proximity channel) by 10 MCC groups in terms of indices (2014=100), available since 2014.

3 Empirical application

3.1 Short-term GDP forecasts during the pandemic

Improving the accuracy of short-term forecasting models with new variables is a complex task given the scarcity of timely information available. In recent years there has been a strong push in institutions to use innovative data from unconventional sources (for example, data from payment systems, data collected on the Internet, data from social networks such as Twitter, and other textual data) to obtain timely and accurate signals on economic activity: see for example [7, 13, 1, 2, 3]. New challenges for modeling short-term forecasts have emerged following the outbreak of the Covid-19 pandemic, which caused a sharp recession and sometimes compromised the data production process, making forecasting extremely difficult (see [14] for example). Payment systems data are characterized by timeliness, high frequency and absence of relevant revisions. These characteristics make them ideal candidates for expanding the information available to forecasters. Furthermore, as electronic means of payment become more widespread, these data streams hold ever more promise for providing reliable signals of economic activity. In the last decade several studies have shown the importance of these data in anticipating the dynamics of macroeconomic aggregates, characterized by longer release times (see [3] and [4] for a review).

A broad debate has ignited in the literature on the most effective econometric strategies for predicting the strong fluctuations in macroeconomic variables observed during the pandemic in a robust manner and in real time (for a review, see Aprigliano, et al. 2021). An initial solution was to resort to models based on high-frequency data, including data from payment systems, which proved to be of fundamental importance in the construction of synthetic and timely indicators of the economic cycle (for the United States see Aruoba et al. 2009 [5] and Lewis et al., 2021; for Germany, see Eraslan and Gotz, 2021 [10]). For Italy, Delle Monache et al. 2021 [8] have developed a weekly indicator to measure economic activity (Italian Weekly Economic Index, ITWEI), estimated starting from a dataset including both weekly (the amount of debit card transactions at POS and withdrawals from ATMs, an index of expenditure made using credit cards, the total consumption of electricity, that of gas used, for industrial purposes, a search index on Google Trends of the term 'CIG' or 'Cassa Integrazione Guadagni', net job openings) and monthly (freight traffic flows, Purchasing Managers' Index - PMI of manufacturing and services, indicators from Confcommercio sources on expenditure for consumption of goods and services, cash flows generated by the collection of value added tax on imports, the effective value of transfers for the CIG). Payment data contributes substantially to the ITWEI estimate, assuming a very significant weight in the estimate of the main component on which the index is based [1]. ITWEI shows a clear cyclical pattern and a strong correlation with real GDP in the estimation sample from July 2010 to September 2021. During the pandemic period it was able to timely anticipate the collapse of economic activity in the first two quarters of the 2020, following the lockdown implemented in Italy to counter Covid-19, and the strong rebound in the third when many of the restrictions were lifted (see 3.1). 3.2 shows how the indicator provided highly accurate out-of-sample forecasts of Italian economic activity both in 2020 and 2021.

[1] ITWEI is estimated has the first principal component in the balanced del dataset with the Expectation-Maximization (EM) method proposed by Dempster et al. 1997 [9]

Figure 3.1: Economic activity weekly indicator (ITWEI) and GDP short term growth rate in the period January 2020 to September 2021.

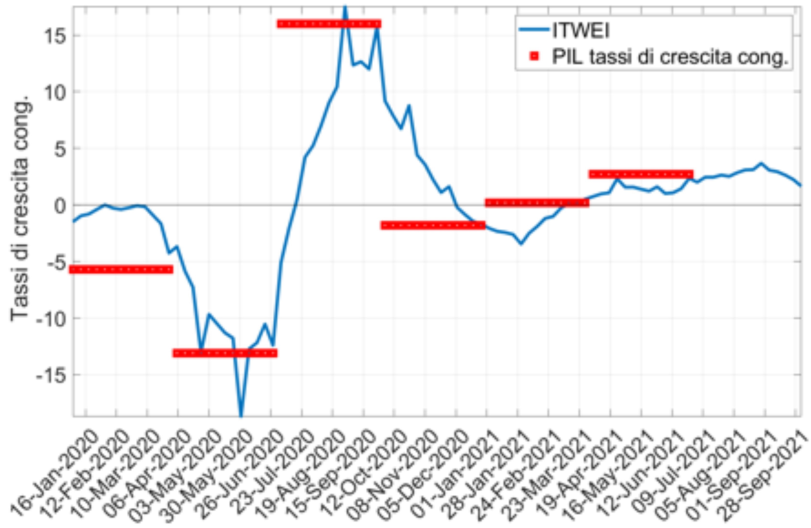
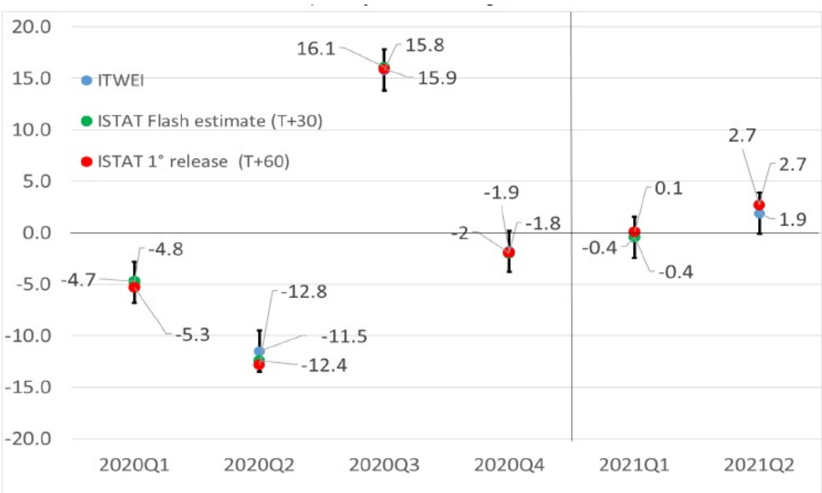


Figure 3.2: ITWEI out of sample performance during COVID-19 pandemics.



A second approach to generate robust short-term forecasts of economic activity during the pandemic resulted from the influential contribution of Ng (2021), applied by Aprigliano, Borin, Conteduca, Emiliozzi, Flaccadoro, Marchetti and Villa (2021) to the case of Italian GDP. The methodology is based on a mixed-frequency large factor model that combines macroeconomic variables, data from payment systems, epidemiological indicators and the degree of restriction of containment policies (see for example [6] and [11]). Also in this approach, the variables taken from payment systems provide an important contribution in tracing the short-term dynamics of the Italian economy. The econometric strategy used makes it possible to ”purify” the purely economic factors of the anomalous trends induced by the pandemic, making the forecasts of the model robust and more stable in the current and following quarters. The work also exploits the synergies between the econometric forecasting framework of the factor model and a sophisticated epidemic Susceptible-Infectious-Recovered (SIR) model with endogenous policy responses (see for example [15]). Despite the uncertainty induced by the numerous factors that may influence the future evolution of the pandemic, the epidemiological model is able to take into account many of the determinants of the epidemiological trends and the consequent responses in terms of containment policies.

3.2 Monthly Retail trade index and e-commerce sales index

In the context of quarterly National accounts flash estimation, retail trade indicators represent a crucial variable for estimating trade margins. The retail trade index is available monthly and it is released with a delay of around 43-50 days from the end of the month. Therefore, its information is partial for the GDP flash, which is released by ISTAT at $t + 30$ days and it requires to be supplemented by some prediction for last month. Retail trade is tracked by ISTAT through a monthly 2015=100 index detailed by type of product, employment size, and type of sales. The e-commerce index is a sub-component of total retail trade. Total retail trade is available over the period January 2000-March 2020, whereas e-commerce over a shorter period (January 2015-March 2020). We aim at verifying the size of one-step-ahead forecast errors resulting from modeling monthly retail trade index by two sets of predictors, the former provided by traditional Business surveys for firms operating in trade and the latter, more innovative, relative to payment transaction data series. Business surveys make available several statistics (monthly climate indexes, frequencies, and balances). However, after a preliminary analysis, the focus was limited to climates only. The set of electronic payment transaction data series concerns the BI-COMP/TARGET2 set of monthly series by main payment instrument (in terms of volume of transaction and in terms of value, in euro); and the BI-COMP/T2 retail components consisting of the monthly POS (BI-COMP) series in euro by nine MCC groups. Concerning the pre-treatment of BI-COMP/TARGET2 data by type of payment instrument, we removed all the outliers from the original data. Figure 1 shows these sets before (red line) and after (blue line) the outlier removal. Payment transaction data series by retail components have been backcasting to 2000 to make them homogeneous to the rest of the predictors. Finally, we computed the other two couples of series resulting from the extraction of the first two factors by principal component analysis applied respectively to the set of BI-COMP/TARGET2 by type of payment instrument and by retail component.

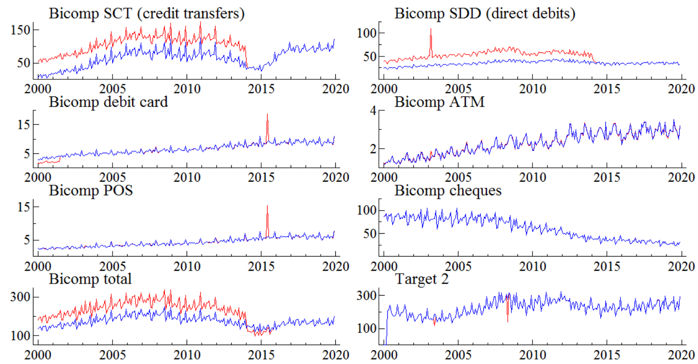


Figure 3.3: BI-COMP and TARGET2 series before (red line) and after (blue line) outlier correction.

Seasonal unadjusted data of the two retail trade indicators are shown by red lines in the two left-hand-side panels of Figure 3.4, the total on the top and the e-commerce component on the bottom. In the two right-hand-side panels, always in red, are shown the corresponding data in terms of annual growth rates. In each panel, retail trade data are accompanied by blue lines of the synthetic index of payments by retail component relative to the first-factor component, in levels for panels on the left and annual growth rates for those on the right.

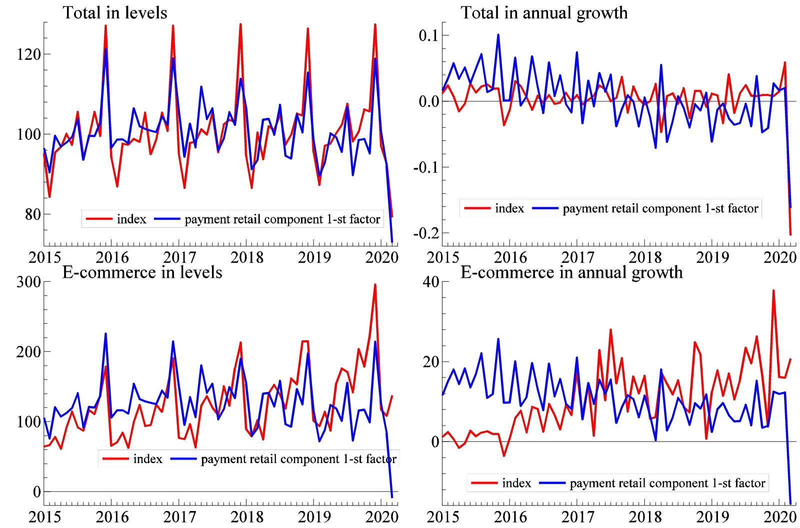


Figure 3.4: Retail trade data and synthetic index of payments by retail component

The analysis of Figure 3.4 shows that:
the first factor of payments by retail component presents higher volatility than retail trade indices, which emerge in particular over data in differences. The same evidence is even emphasized for single components of payments data (not shown here for brevity);

1. the first factor of payments by retail component fits generally better to total retail trade than the e-commerce component. This could be due to differences in the e-commerce sale boundary definition. For the construction of the Istat e-commerce index, only pure e-commerce activities are considered

2. and we only referred to the sales of goods and not services; moreover, Italian firms can sell not only to Italians but also to foreigners (even in a small share). In our payment transaction data series, we consider all the Italian firms selling only to the Italians both goods and services through a not pure e-commerce channel;

3. For both retail trade variables, the fit of same payment factor worsens moving from the comparison of data in levels (left-hand-side panels) to annual growth, with particular evidence for the e-commerce index. This could be due to both the dominance of seasonal factors in both series under comparison which is deleted out from the transformation and a higher order of the trend in the e-commerce component.

Concerning model strategy, after difficulties encountered within the multivariate Seemingly Unrelated Time Series Equation (SUTSE) system, we went for the univariate class of autoregressive distributed lag (ADL) models. This strategy has been followed both for variable selection and the setting of the final equation from which computing the forecasts. We adopted the general-to-specific (GETS) algorithm, developed into Autometrics, which is an algorithm for automatic model selection within the general-to-specific framework developed by D. Hendry (see [12]). A no-seasonal adjustment has been applied to the entire dataset, with the idea to mimic as much as possible the strategy applied in the statistical production process for which seasonal adjustment operates in a second step. The estimation sample has been set to January 2000-December 2017, whereas one-step-ahead forecasts have been computed over 27 months, from January 2018 to March 2020.

The strategy followed for the definition of the (general) unrestricted ADL model has been to start from models where the 3 sets of predictors (e.g., Business survey data; payment transaction data by type of payment instrument and by MCC groups) were all represented. In this way, we can measure the relative contribution of each set of data to the forecasting performance. For the payment transaction data series we conducted several experiments to understand if it is more favourable either the use of single components (alone, in couple, sets of three, altogether) or of the extracted factors. Other settings of the unrestricted ADL model concerned the choice of lag order of predictors (limited to 0 and 1 only), the inclusion of trading days effects (one regressor for the number of working days, Easter and leap year effect), seasonal dummies, constant and linear trend. The presence of the lagged dependent variable among predictors has been also limited to 1. Furthermore, both models of data in levels and annual growth are tested.

The estimations are carried out by ordinary least squares (OLS).

Table 1 presents the results of estimation for the model identified by the GETS Autometrics search for total retail trade and Figure 3(a) the fitted values versus the true ones. The specification is for data in annual growth rates and turns out to be particularly parsimonious since any regressor of the payment by trade component set resulted significant, neither taken individually nor through their synthetic indices. Both lagged dependent and predictors are strongly significant. Even if trading day effects are not statistically significant we did not remove them from the final specification because they help in increasing the forecasting performance.

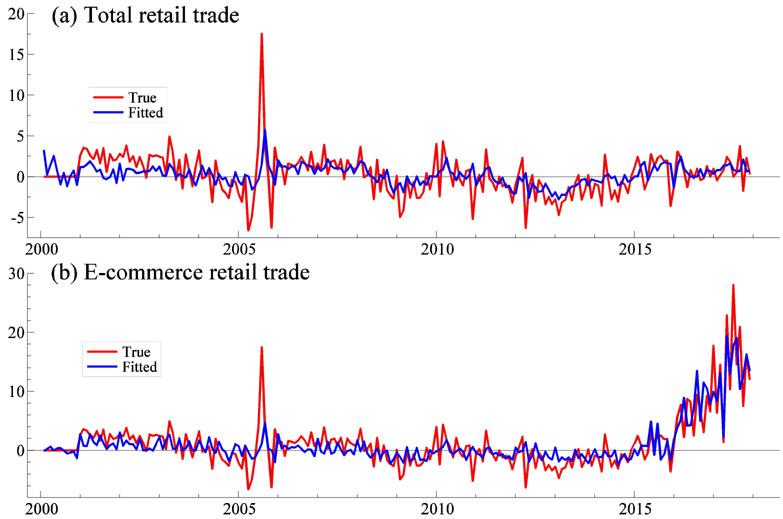


Figure 3.5: Fitted versus true values for specified ADL models

Even if the fit of the model to retail trade data is particularly effective, three negative elements emerge from Table 1: 1) the lack of payment transaction data by MCC groups within predictors, 2) the small impact of predictors measured by low values of the regression coefficient, 3) the absence of the common factor regressor for payment transaction data by type of payment instrument at lag 0 and of a negative sign at lag 1, the most promising at the beginning of the exercise. A possible explanation of this drawback is the high volatility of payments data which distorts the relationship with the dependent variable.

Table 1: ADL model for total retail trade in annual growth rates. OLS estimation results.

Predictor	Lag	Coefficient	t-students
Total retail trade	1	0.2618	3.93
BS climate index	0	0.0487	3.92
Payments by type of instrument 1-st factor	1	-0.046	-3.84
Easter effect	0	1.0157	1.74
Leap year	0	1.4961	1.27
Trading day	0	0.0984	1.78

Note: Estimation period February 2001 - December 2017.

Forecast errors in mean absolute (MAE) and mean squared (RMSE) terms are shown in Table 2, where they are computed over the annual growth rates of original data. Their values, a MAE around one for months of 2018-19, are not distant from values relative to analogous experiments conducted recently over other monthly Italian indicators (industrial production, labour force, etc.). The gains in terms of reduction of the relative statistics once payments data are removed from the specification of Table 1 are shown in parenthesis. The gain is 12.1% in terms of MAE and 3% in terms of RMSE.

Table 2: Onestep-ahead forecasting performance of ADL model for total retail trade over the period January 2018-March 2020.

Test period	**MAE**	**RMSE**
2018:2020(1)	1.1813 (12.1%)	1.6529 (3.0%)
2018:2020(2)	1.3031 (11.7%)	1.8315 (4.5%)
2018:2020(3)	1.9582 (7.9%)	4.0727 (1.2%)

Note: In parentheses gain from the specification without payment data

As foreseeable, the forecasting performance of ADL model of Table 1 worsens when the test period extends to February and March 2020, the beginning of the Covid-19 crisis period in Italy, as provided in Table 2. Notice, in particular, the explosion of RMSE to 4.0727 when the test period spans 27 months until March 2020, the month of the lockdown of the economic activities. Results of the ADL model fitted over the monthly e-commerce sales index are in Table 3, whereas fitted versus true values are shown in Figure 3(b). The fit concerns annual growth rates over the estimation sample on the period February 2001-December 2017. As for total retail trade, Table 3 presents the best performing model obtained by the GETS Autometrics procedure.

Table 3: ADL model for the e-commerce sales index in annual growth rates. OLS estimation results.

Predictor	Lag	Coefficient	t-students
e-commerce sales index	1	0.2471	4.48
Hotels and restaurants	0	-0.16	-2.3
Hotels and restaurants	1	0.6636	8.38
Home	1	1.0157	-5.47
Service	0	1.4961	5.57
Telecommunications	0	-0.307	-4.41
Telecommunications	1	-0.1128	-2.41
Transports	1	-0.1178	-2.98
Trend	0	-0.0074	-2.69
Seasonal dummy	0	1.6089	2.23
Seasonal dummy	6	1.2383	1.77
Easter	0	1.8724	2.49
Trading day	0	0.1439	2.03

Note: Estimation period February 2001 - December 2017.

The main pieces of evidence are as follows:

1. Business survey data are not significant and therefore disappear from the final specification;
2. same evidence for payment transaction data series by type of payment instrument;
3. payment transaction data by MCC groups are here largely represented and they appear by single components instead of their synthetic factor indexes;
4. the sign of payment indicators is counter-intuitive for payment data relative to hotels and restaurant and telecommunication (lag 0). This is because of the strong volatility encountered in this set of data;
5. the presence of significant deterministic effects among selected regressors, including a linear trend, which explains the accelerating behavior of e-commerce with respect to payments. Notice also the presence of some significant seasonal components, able to explain residual seasonality and trading effects.

Moving now to the one-step-ahead forecast performance in Table 4, we see that for all sample periods considered in the experiment, both MAE and RMSE are higher than the case of total retail trade shown in Table 2 . This occurs because the experiment runs over a component of detail for the total considered before which, furthermore, features an explosive evolution in recent periods. By contrast, the gain due to the inclusion of payment transaction data by MCC groups is remarkable in this case, larger than 50% in almost all cases.

Table 4: Onestep-ahead forecasting performance of ADL model for the e-commerce sales index over the period January 2018- March 2020.

Test period	MAE	RMSE
2018:2020(1)	6.8772 (66.9%)	8.8650 (57.2%)
2018:2020(2)	6.6367 (73.6%)	8.6937 (59.8%)
2018:2020(3)	7.6178 (54.2%)	10.6501 (31.9%)

Note: In parentheses gain from the specification without payment data

3.3 Final Consumption expenditure

In this third trial, the considered target variable is the National Account (NA) aggregate referring to the quarterly final consumption expenditure (chain-linked 2015=100 and working-day adjusted). As a first exercise, an Unrestricted MIxed DAta Sampling (U-MIDAS) regression has been estimated for the time span from the 3rd quarter of 2014 to the 4th of 2019, namely before the Covid-19 Crisis. payment transaction data series by nine Merchant category code groups (for the period starting from July 2014 to December 2019) have been considered as an independent variable in the regression to evaluate the forecast performance. Because the payment transaction data variables are calculated as index number (May 2014 = 100), in the pre-treatment phase, the final consumption expenditure has been calculated as well as an index number with base 2nd quarter 2014=100. As the second step, payment transaction data and final consumption have been adjusted estimating and removing a linear or quadratic deterministic trend without removing the seasonal component.

The graphical analysis of the combination of the quarterly series of final consumption and the monthly payment transaction data series exhibited a clear correlation between them. As an example, in Figure 3.6 a plot of final consumption and the payment transaction data series referring to clothing sales and hotels (two of the best performer) is presented: the series in dots indicate the quarterly NA final consumption growth rates and the line are the growth rates for the monthly payment transaction data series for clothing sales.

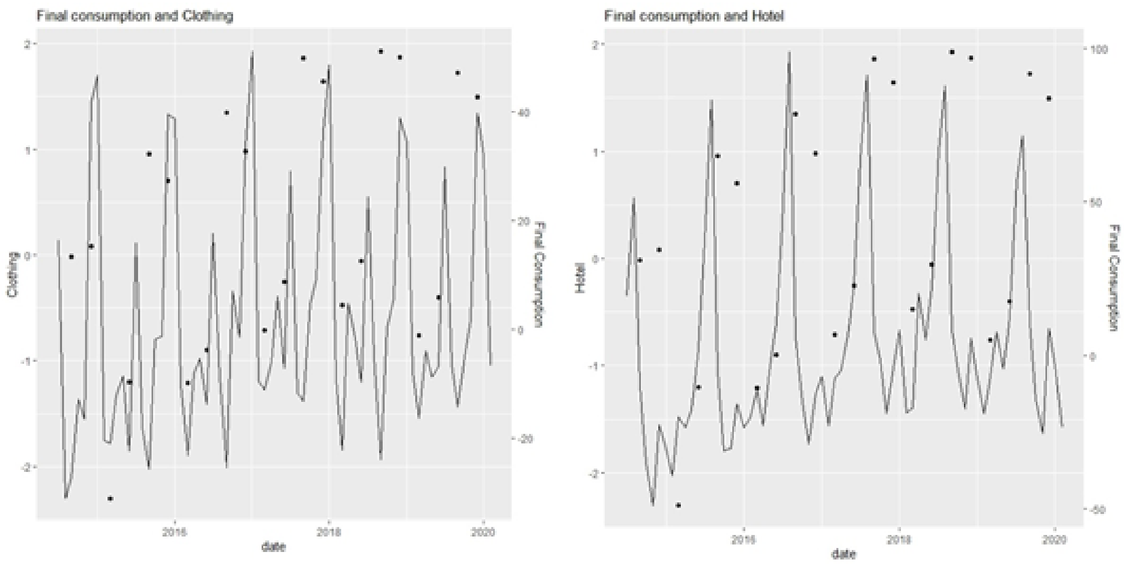


Figure 3.6: Quarterly series of final consumption and monthly payment transaction data series.

An unrestricted MIDAS model, as the one shown in formula 1, has been estimated for the period 3rd quarter 2014 to 4th 2018 :

$$y_t = \beta_0 + \beta_1 \cdot y_{t-1} + \beta_2 \cdot y_{t-2} + \beta_3 \cdot y_{t-3} + \theta_1 \cdot x_{1t} + \theta_2 \cdot x_{2t} + \theta_3 \cdot x_{3t} + \varepsilon_t \tag{1}$$

The forecasts have been evaluated out-of-sample on the period 1st quarter 2019 to 4th 2019 using a recursive and rolling window and the RMSE and the MAPE as to accuracy measures. In Table 5 the accuracy measures of our model are compared to the ones obtained estimating an auto-regressive model of order 3 as the benchmark. For values lower than one in Table 5 the predictor variable shows a better forecast performance than an AR(3) model without any predictor. Thus, results show that hotel, clothing and work series gives the best increases in forecasting performance.

	Rolling windows		**Recursive regression**	
	RMSE	**MAPE**	**RMSE**	**MAPE**
Clothing	0.99	0.87	0.91	0.84
Hotel	0.85	1.02	0.79	1.00
Food	1.57	1.06	1.77	1.15
Home	1.22	1.15	1.10	0.94
Work	0.87	0.78	0.82	0.78
Retail	1.02	0.91	1.04	0.94
Services	1.19	1.00	1.29	0.97
Communication	1.78	1.30	1.72	1.11
Transport	1.00	1.02	0.84	0.89

Table 5: Accuracy measures resulting from the MIDAS model used to forecast the Quarterly final Consumption expenditure model in the period 2019 (Q1)2019 (Q4).

The exercise has been repeated including the Covid-19 Crisis phase in the forecasting period; thus, we used the 1st quarter of 2020 for consumption and monthly data from January to March 2020 for payment transaction data series (Table 6). The same approach has been used to evaluate the forecast performance considering a recursive and rolling window and the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) as to accuracy measures. The hotel and clothing series show a better forecast performance compared to the previous exercise, particularly the improvement of 47% of the hotel series. The reason for this could be partly the autoregressive model of the benchmark, which is less able to predict the strong negative growth rates in nth1 quarter of 2020. Overall, the payment transaction data variables show an improvement thanks to their timeliness and monthly frequency that is more able to capture the strong decrease following the Covid-19 lockdown and the first signals of the consumption crisis due to the unpredictable exogenous factors.

	Rolling windows		**Recursive regression**	
	RMSE	**MAPE**	**RMSE**	**MAPE**
Clothing	0.85	0.89	0.81	0.86
Hotel	0.53	0.94	0.43	0.91
Food	1.04	1.05	1.13	1.12
Home	1.01	1.11	0.95	0.95
Work	1.01	0.85	1.00	0.85
Retail	0.95	0.93	0.92	0.95
Services	1.18	1.03	1.06	0.99
Communication	1.00	1.22	0.97	1.07
Transport	0.97	1.01	0.96	0.92

Table 6: Accuracy measures resulting from the MIDAS model used to forecast the Quarterly final Consumption expenditure model in the period 2019 (Q1) 2020 (Q1).

As a final exercise, we calculated a forecast combination of the nine payment transaction data series using as weights the in-sample root mean square error (RMSE) for the period from the 3rd quarter of 2014 to the 4th quarter of 2018. The combination led to a reduction in terms of RMSE of the forecast for the period 1st quarter 2019 to the 1st 2020 equal to 20% compared to the benchmark model (Autoregressive model of order 3).

4 Concluding Remarks

The empirical analyses carried out in this work show the relevance of payment transaction data in short-term macroeconomic forecasts and the production of official statistics. The series of electronic transactions (for business reasons, travel and transport, hotels and restaurants) recorded during the pandemic period have reduced the forecast error of expenditure for quarterly final consumption by more than 50% in some product sectors and have decreased the nowcasting forecast error of the total retail sales index by about 6% and that of the e-commerce index by about 10 percentage points.

The main advantages of using such sources of information certainly lie in their timeliness, coverage and level of detail they provide. However, some key challenges have to be overcome in order to achieve a systematic use of this information in official statistics. These challenges are essentially linked to the difficulty of accessing data, both at individual intermediaries and at private infrastructure managers, as well as the complexity and lack of standards in the IT protocols employed by the different technological platforms.

Furthermore, the preliminary phases of selection and treatment of the variables are also crucial, which have been accounted for in some contributions of this work. In our experiments, we could use only some aggregated payment transaction data series to assess how much payments-system data can contribute to the production of more accurate nowcasts/forecast of macroeconomic aggregates in Official statistics. Preliminary results look promising - although the time series are quite short for an accurate forecast -, we keep on investigating and improving the payment transaction data time series to employ this information into Istat forecasting models. In our first trial, the automatic General To Specific Selection Procedure for the selection of the best performer series in the ADL model makes new payment transaction data series work in both models and we observed a good fit especially for the period before the Covid-19 Crisis. The gains in terms of reduction of the relative statistics are 12.1% for the MAE in the case of the retail trade index, and 67-73% for the e-commerce. Considering also the Covid-19 period of the lockdown of economic activities (March 2020), the payment transaction data series still guarantees gains in the forecasting performance of the model that is still larger than 50% in terms of MAE in the case of e-commerce sales. In our second trial on the forecasting of the quarterly final consumption expenditure, an unrestricted MIDAS model has been estimated from the 3rd quarter 2014 to 4th 2018 and evaluated both for the period 1st quarter 2019 to 4th 2019 and the period 1st quarter 2019 to 1st 2020. We compared the accuracy measures of our model to the ones obtained estimating an auto-regressive model of order 3 as the benchmark. In the case of the forecasting out of sample before the Covid-19 period, results show that hotel and work reduce the forecast RMSE of the AR3 respectively 15% and 13%. When including the Covid-19 Crisis phase in the forecasting period (1st quarter 2020), the hotel and clothing series show a further improvement in the forecasting performance (47% of reduction in term of RMSE), being the timeliness of payment transaction data series able to capture the determined strong decrease in consumption. The retail and transport series also produced an improvement, although less relevant (less than 5%). Even using a weighted combination of the nine payment transaction data series in the model, the reduction in terms of RMSE is equal to 20% compared to the benchmark model. Considering these positive results, we will continue to investigate the relevance of payments-system data and the way to employ this information into nowcasting and forecasting models. These are still largely experimental activities, which will require further analytical investigations and cooperation with other experts from the institutions and the academy. Finally it is important to stress the need for an extended and well designed experimentation before we will be able to provide a full fledged contribution to the production of official statistics.

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Payment Microdata for Macroeconomic Forecasts

Guerino Ardizzi[1], Giuseppe Bruno[2], Roberto Iannaccone[3], Juri Marcucci[2], Filippo Moauro[3], Alessandra Righi[3], Davide Zurlo[3]

[1]Money circulation Directorate; [2]Economics and statistics Directorate, Bank of Italy;
[3]National Statistical Office, ISTAT.

Granular data: new horizons and challenges for central banks.
BoC-IFC Satellite seminar.
Bank of Canada, Ottawa, July 15th

The views expressed here are the authors' only and do not imply those of the Bank of Italy.

Outline

Statistical value of payment data

Computing the main components for Gross Domestic Product (GDP) and other relevant macroeconomic figures is traditionally based on surveys among household and firms.

- surveys are necessarily limited in sample size;
- they are usually very expensive;
- natural phenomena like the Covid-19 pandemics could wipe out the possibility to run these surveys;

Statistical value of payment data

Albeit the close relationship between payment flows and economic activity, the employment of payment data for the macroeconomic analysis is not straightforward.

Payment systems and technological infrastructures have been developed with the goal of protecting the integrity, the speed and the security of the involved computing platforms.

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The payment instruments in Italy

The Bank of Italy promotes the reliability and efficiency of payment instruments in order to preserve confidence in money and non-cash alternatives.

Every year the economic transactions are carried out with retail payment instruments for a value of more than 3 times the Italian GDP.

1. cheques;
2. wire transfers;
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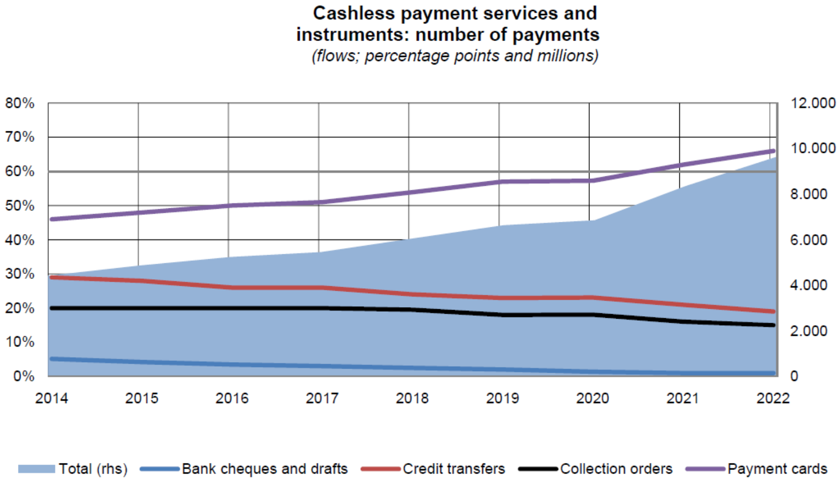
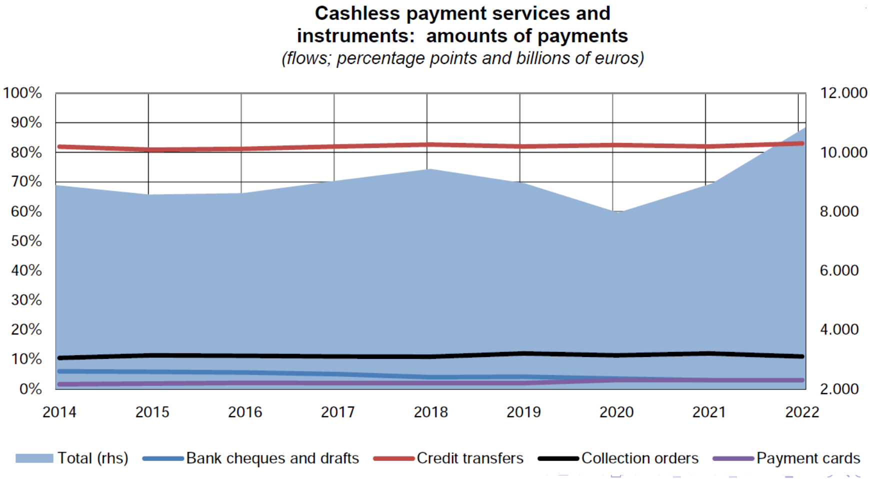
The distribution among the instruments: Volumes

The evolution of the volumes of payment instruments in Italy



The distribution among the instruments:Values

The evolution of the values of payment instruments in Italy



Banks vs digital platforms

Bank of Italy manages and oversees the national retail payment system BI-COMP and cooperates along with Bundesbank and Banque de France in the management and oversight of TARGET2, the Eurosystem Large-Value Payment Systems (LVPS).

The information collected from these two systems has played an essential role in building the databases employed for our macroeconomic analysis. These data are available at high frequency and very timely, but . . . .

They are not granular in the commodity dimension.

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Banks vs digital platforms

We do have two possible data sources:

- agreements with the banks;
- agreements with payment technological platform.

We followed the easiest avenue: the technological platform

nexi

Nexi is present in Europe with around 170 m cards and 2.2 m merchants.
In Italy Nexi has around 41 m cards and 890 K merchants.

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data exchange agreements

We have made an informal agreement with Nexi

- agreements on avoiding release of any confidential information;
- data granularity in order to prevent any privacy breach;
- data frequency;
- updating policy;

There is the need of internal agreements for making data available to different department

- a light dbms in postgreSQL;
- data authorization in a centralised fashion;
- user driven data analytics with open source back-ends;
- Big Data paradigms for data storing (**parquet**) and data processing (**Spark**).

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Outline

Payment data for GDP forecast

Improving the accuracy of GDP short-term forecasting models is of the utmost relevance in high volatility times. Introducing new variables is a complex task given the scarcity of timely information available.

In recent years there has been a strong push in institutions to use innovative data from unconventional sources (for example, data from payment systems, data collected on the Internet, data from social networks such as Twitter, and other textual data)

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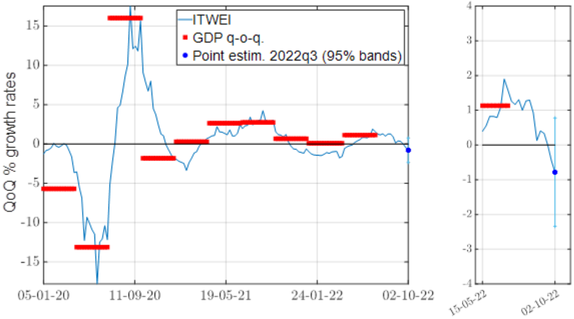
Italian GDP forecast

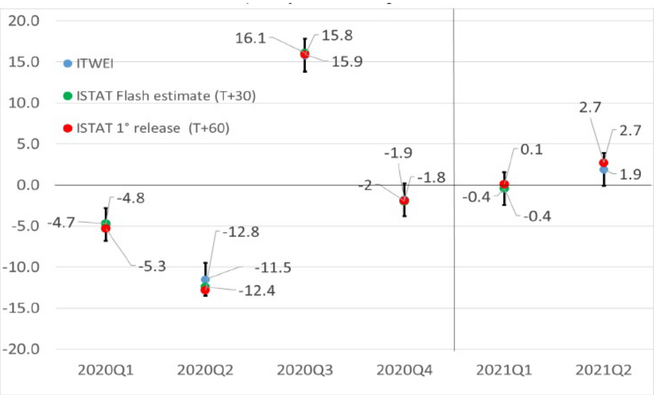
The evolution of the payment instruments in the last years in Italy



Italian weekly economic activity indicator and GDP growth rate from January 2020 to October 2022

GDP forecast

During the pandemics, ITWEI allowed us to anticipate the collapse of economic activity in 2020 Q1 and Q2, following the lockdown implemented in Italy to counter Covid-19, and the strong rebound in Q3 when many of the restrictions were lifted.

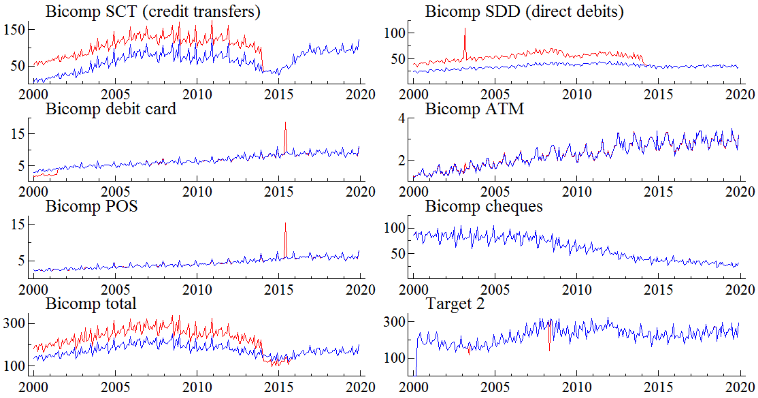


ITWEI out of sample performance in GDP forecast during COVID-19 pandemics

Outline

Monthly retail trade index

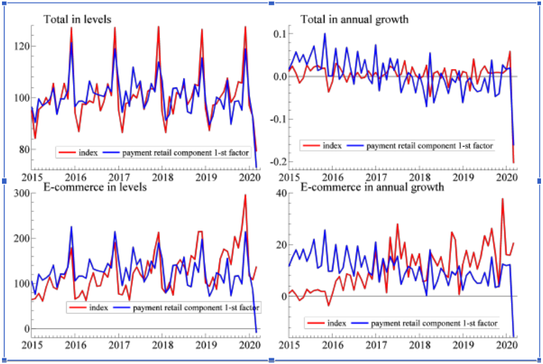
In the context of quarterly National accounts flash estimation, retail trade indicators represent a crucial variable for estimating trade margins.



BI-COMP and TARGET2 series before (red line) and after (blue line) outlier correction

Monthly retail trade index

Comparison between retail trade index series total and e-commerce and POS payments, 2014-2021 (levels and yearly variational trend).



Retail trade data total and e-commerce

Outline

1. Motivation
2. Payment systems and Economic analysis
   - Short-term GDP forecasts during the pandemic
   - Monthly Retail trade index and e-commerce sales index
   - Final Consumption expenditure
3. Concluding Remarks

The distributed lag model

Here the considered target variable is the National Account aggregate of the quarterly final consumption expenditure.

We estimated an Unrestricted MIxed DAta Sampling (U–MIDAS) regression from 2014 the 3rd to the 4th quarter of 2018:

$$y_0 = \beta_0 + \beta_1 \cdot y_{t-1} + \beta_2 \cdot y_{t-2} + \beta_3 \cdot y_{t-3} + \theta_1 \cdot x_{1t} + \theta_2 \cdot x_{2t} + \theta_3 \cdot x_{2t} + \varepsilon_t$$

The forecasts have been evaluated on the period 1st to 4th of 2019 using both a recursive and rolling window and the RMSE and the MAPE as to accuracy measures

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The forecasts have been evaluated on the period 1st to 4th of 2019 using both a recursive and rolling window and the RMSE and the MAPE as to accuracy measures

The statistical value of the expenditures

We compare the total RMSE and MAPE of the previous model with a simple 3–period distributed lag of the final consumption

	Rolling windows		Recursive regression	
	RMSE	**MAPE**	**RMSE**	**MAPE**
Clothing	0.99	0.87	0.91	0.84
Hotel	0.85	1.02	0.79	1.00
Food	1.57	1.06	1.77	1.15
Home	1.22	1.15	1.10	0.94
Work	0.87	0.78	0.82	0.78
Retail	1.02	0.91	1.04	0.94
Services	1.19	1.00	1.29	0.97
Communication	1.78	1.30	1.72	1.11
Transport	1.00	1.02	0.84	0.89

Accuracy measures resulting from the MIDAS model used to forecast the Quarterly final Consumption expenditure model in the period 2019 (Q1) 2019 (Q4).

The forecast error for total retail index

We compare the total RMSE and MAPE of the one step-ahead forecast error

Testing range	Mean Absolute Error (MAE)	Root Mean Square Error
2020(1) - 2020(6)	10.1414 (-5.5%)	14.0314 (-5.2%)
2020(1) - 2020(12)	6.7623 (-5.9%)	10.3337 (-5.6%)
2020(1) - 2021(6)	9.1654 (-1.7%)	12.9199 (-0.1%)
2020(1) - 2021(9)	8.4064 (-1.0%)	12.0768 (0.0%)

One step ahead forecast error for the total index of retail sale. In parentheses the percentage loss without payment data.

The forecast error for e-commerce index

We compare the total RMSE and MAPE of the one step-ahead forecast error

Testing range	Mean Absolute Error (MAE)	Root Mean Square Error
2020(1) - 2020(6)	16.7898 (-6.6%)	21.1267 (-9.4%)
2020(1) - 2020(12)	20.6482 (-10.2%)	24.9794 (-9.8%)
2020(1) - 2021(6)	20.9022 (-8.3%)	24.3784 (-9.0%)
2020(1) - 2021(9)	18.8256 (-9.2%)	22.7444 (-9.3%)

One step ahead forecast error for the e-commerce index. In parentheses the percentage loss without payment data.

Concluding remarks, part 1

The empirical analyses carried out in this work show the relevance of payment transaction data in short-term macroeconomic forecasts and the production of official statistics. Main advantages in employing payment data:

- timely availability;
- wide geographic coverage;
- highly detailed information on merchant category code

There are disadvantages to deal with as well:

- selecting a good set of metadata to prevent privacy breach;
- presence of different seasonal components;
- susceptibility to the market share variability of the payment platform.

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Discussion

Thank you very much for your Questions

Merci beaucoup pour vos Questions