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Using payment data to nowcast Slovene GDP and private consumption: a mixed-frequency approach

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Abstract

This paper aims to assess the usefulness of payment data, collected through ATM cash withdrawals, POS payments and TARGET2 payment system, for nowcasting quarterly growth rate of Slovene private consumption and GDP. To tackle this, the exercise employs a mixed-frequency approach using MIDAS/UMIDAS regressions, which allow exploitation of the different frequencies across the series, and bridge equations, which qualify as the first set of models linking mixed-frequency data. Using a pseudo-real time nowcasting exercise, this study shows that, in conjunction with other traditional indicators, payment data are valuable sources of information for nowcasting Slovene GDP and private consumption. Moreover, as indicated by the performance of MIDAS/UMIDAS regressions relative to baseline autoregressive models and, for the most part, bridge equations, monthly variation of high-frequency indicators is important in increasing the accuracy of nowcasting models for both quarterly growth rate of GDP and that of private consumption, especially for nowcasts estimated at the end of the quarter. Nevertheless, given the setup set forth in the paper, both MIDAS/UMIDAS regressions and bridge equations remain useful tools for nowcasting purposes in the Slovene case.

JEL Classification Numbers: C53, E27

Keywords: nowcasting, payment data, MIDAS, UMIDAS, bridge equations.

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Povzetek

Članek preučuje pomen podatkov o plačilih za namene kratkoročnega napovedovanja četrtletnih stopenj rasti zasebne potrošnje in gospodarske aktivnosti, merjene z BDP, v Sloveniji. Podatki o plačilih združujejo podatke o dvigih gotovine na bankomatih in plačilih preko POS terminalov ter plačilnega sistema TARGET2. Analiza uporablja pristop mešanih frekvenc z uporabo regresij MIDAS/UMIDAS, ki omogočajo uporabo podatkov z različnimi frekvencami, in modeli premostitvenih enačb (angl. "bridge equations"), ki kot prvi povezujejo podatke mešanih frekvenc. Analiza kaže, da so podatki o plačilih – skupaj z drugimi tradicionalnimi kazalniki – pomemben vir informacij za pripravo kratkoročnih napovedi četrtletnih rasti BDP in zasebne potrošnje. Obenem analiza kaže, da se je – v primerjavi z osnovnimi avtoregresijskimi modeli – pri kratkoročnemu napovedovanju z uporabo regresij MIDAS/UMIDAS in v večini primerov napovedovanja z modeli premostitvenih enačb mesečno gibanje kazalnikov znotraj posameznega četrtletja izkazalo kot zelo pomembno. Slednje namreč pomembno izboljšuje napovedno moč teh modelov pri napovedovanju četrtletnih rasti gospodarske aktivnosti in privatne potrošnje, predvsem proti koncu četrtletja. Regresije MIDAS/UMIDAS in modeli premostitvenih enačb tako predstavljajo pomembno orodje za kratkoročno napovedovanje gospodarskih gibanj in zasebne potrovsnje v Sloveniji.

1 Introduction

Solid monetary and economic decisions, be it by central bankers, policy makers, investors or economic agents, require timely and adequate information about the current standing of the economy. This is even more prevalent during volatile and uncertain periods, such as the global financial crisis, which underline the importance of early signals as *harbingers* of adverse dynamics. Two of the most important estimates of economic activity pertain to Gross Domestic Product (GDP) and its largest component - private consumption. For Slovenia, private consumption accounts for more than 50 percent of nominal GDP, and since 1995, it has contributed an average of 1.2 p.p. to its year-on-year growth (averaging around 2.7 percent). Therefore, both statistics play a prominent role in reflecting the health of the economy. However, as part of the National Accounts (NA) computed by the official statistical entities across countries, these quarterly figures become available with a significant delay, ranging from six to eight weeks after the end of a given quarter (Jansen, Jin, & Winter, 2012). For Slovenia, these statistics, computed by the Statistical Office of Slovenia (SORS), are published with an eight-week delay. Given this gap, it becomes rather necessary to exploit other sources of information to assess economic activity dynamics in a timely manner. There are numerous alternative, relevant and timely information, which become available much sooner and usually at a higher frequency that can be used to nowcast GDP and private consumption. As defined by Bell et.al. (2014), nowcasts refer to estimates of official statistics for the current or most recent quarter for which no official data is yet available. Their importance is even more prevalent for Slovenia, which is one of the five countries in the euro-area with no flash estimates, i.e. early official estimates of a particular variable of interest over the most recent period (European Commission, 2018).

Given the importance of timely and reliable nowcasts, this paper aims to assess the usefulness of *alternative sources of information* and *a mixed-frequency modelling approach* in nowcasting the quarterly growth rate of Slovene GDP and private consumption. In terms of *alternative sources of information*, this paper makes use of payment data and evaluates whether the information content of such series improves the performance of nowcasting models that rely on traditional (hard and soft) indicators. Specifically, it incorporates Automated Teller Machines (ATM) withdrawals and Point-of-Sale (POS) payment data in nowcasting models of private consumption, and Trans Automated Real-Time Gross Settlement (TARGET2) payment system data in nowcasting models of GDP. To tackle this, the paper employs *a mixed-frequency modelling approach*. Since, for Slovenia, almost all indicators are available at a monthly frequency, with the exception of ATM/POS payment data and NA statistics which are available only at a quarterly frequency, this paper explores the potential advantages of mixed data sampling (MIDAS) regressions to nowcast the target variables of interest. As indicated by Foroni & Marcellino (2013), modelling of mixed frequency data can be convenient because a lot of potentially useful information might be lost when transforming high-frequency right-hand side variables to match the low-frequency left-hand side dependant variable. Apart from MIDAS regressions, the paper also includes bridge equations, which even though qualify as aggregated low-frequency models, they serve as the first set of models linking low- and high-frequency variables for nowcasting purposes and are widely used across central banks (Ghysels & Marcellino, 2018). Moreover, they serve as another reference point of comparison for MIDAS regressions apart from the baseline models. Such a comparison is possible as both bridge equations and MIDAS regressions belong to the family of distributed-lag models (Schumacher, 2016). Similar to other studies, the nowcasting exercise in this paper is a pseudo-real time analysis, as it does not account for the usual uncertainty surrounding data revisions.

Based on the results of the nowcasting exercise and similar with other country-specific studies, the information content provided by TARGET2 and ATM/POS payment data proves to be valuable for nowcasting quarterly growth rate of Slovene GDP and private consumption respectively. For GDP, the usefulness of TARGET2 data is primarily evident for nowcasts obtained at the end of the quarter when more information becomes available, while for private consumption the addition of ATM/POS payment data renders the results more accurate across all periods of the quarter. The increase in accuracy becomes even more evident across all models when the previous quarter's value of GDP and private consumption is observed. Moreover, the within-quarter dynamics of monthly predictors show to be an important source of information for the quarterly developments of the target variables. This is confirmed by the significantly better performance of MIDAS (and UMIDAS) regressions, which result in the lowest nowcast errors, as measured by Root Mean Squared Forecast Error (RMSFE), relative to the univariate baseline models and, towards the end of the quarter, also to bridge equations.

The paper is organized as follows: Section 2 presents a brief literature review of similar studies. Section 3 briefly describes the modelling framework used in the empirical exercise. Section 4 presents the data. Section 5 discusses the design of the nowcasting exercise. Section 6 presents the results. Finally, Section 7 concludes.

2 Literature review

The nowcasting literature, for GDP in particular, is quite vast. Numerous empirical studies have been undertaken as both country specific (or area-wide for the euro zone) and cross-country comparison nowcasting exercises making use of traditional (hard and soft) indicators (e.g. Giannone, Reichlin, & Small (2008), Clements & Galvao (2008), Kuzin, Marcellino, & Schumacher (2013), Anesti, Hayes, Moreira, & Tasker (2017), Bok, Caratelli, Giannone, Sbordone, & Tambalotti (2017), Heinisch & Scheufele (2018), Kindberg-Hanion & Sokol (2018)). While the modelling approach varies across the different studies, with some of the papers incorporating also MIDAS regressions and most forecasting also a few quarters ahead, the type of information pool used is widely similar. Given the focus of this paper, the following literature review highlights only studies that incorporate alternative sources of information, specifically payment data, in nowcasting models of either GDP or private consumption.

The pool of empirical studies using alternative sources of information, such as data from payment systems, to nowcast aggregates such as GDP and private consumption, is limited, even though it has been growing markedly in recent years. A few empirical studies, undertaken predominantly by staff of central banks, have set forth the usefulness of payment data for nowcasting purposes of economic activity statistics. In terms of ATM/POS payment data, Esteves (2009) accounts for one of the pilot papers to emphasize the potential usefulness of this data source for short-term forecasting of year-on-year growth rate of non-durable Portuguese private consumption. Following his work, Duarte, Rodrigues, & Rua (2017) incorporate both daily and monthly ATM/POS payment data to nowcast Portuguese private consumption growth. In doing this, they make use of bridge equations, MIDAS regressions and factor models. They find that the use of monthly ATM/POS payment data improves the nowcasting performance significantly and that MIDAS regressions result in the lowest nowcasting errors among the alternative models employed in the study. For Spain, Gil, Javier J. Perez, & Urtasun (2018) make use of an extended pool of indicators, including ATM/POS payment data to nowcast and forecast the quarterly growth rate of Spanish private consumption. In line with other studies, they find that such data are valuable indicators and that mixed-frequency models outweigh the performance of models employing a same-frequency approach. Verbaan, Bolt, & Cruijsen (2017) use debit card payments to nowcast Dutch household consumption. They incorporate payment data in models with traditional indicators and make use of a mixed-frequency approach to show that payment data are valuable additions and that MIDAS regressions outperform the other models.

Others have incorporated such data for nowcasting GDP also. For Canada, Galbraith & Tkacz (2015) use payment data to nowcast Canadian GDP and retail sales. They focus on transactions via debit cards, credit cards and cheques separately and show that inclusion of debit cards in particular improves the nowcast accuracy compared to their baseline model which uses lagged GDP growth, change in unemployment rate and price level. Different from others, their study highlights that the marginal contribution in nowcast accuracy through the inclusion of debit card information is no longer detectable once the previous quarter's GDP value is observed. In terms of TARGET2 data, Dias & Dias (2017) highlight the relevance of incorporating this data source in nowcasting models of Portuguese GDP. Aprigliano, Ardizzi, & Monteforte (2017) make use of an extended set of payment instruments and TARGET2 data to nowcast quarterly growth rate of Italian GDP and find that the nowcasting errors of models decrease significantly with the inclusion of this type of data. Different from the other papers, they incorporate mixed-frequency factor models in their estimation strategy.

In line with the presented literature, this paper serves as the first study for Slovenia to incorporate payment data from both ATM/POS and TARGET2 system to nowcast quarterly growth rate of private consumption and GDP respectively. Moreover, this is a first attempt of using MIDAS regressions to nowcast Slovene economic aggregates. In terms of data used, this paper is closest to Aprigliano, Ardizzi, & Monteforte (2017). In terms of general methodology, the paper is similar to the work of Duarte, Rodrigues & Rua (2017), but different from their approach, the current analysis focuses on pooled models, takes publication lags of indicators into account and aims to nowcast both GDP and private consumption.

The nowcasting exercise in this study entails also an assessment of MIDAS regressions relative to bridge equations. In the literature, the work of Schumacher (2016) is known to provide a comprehensive comparison of these two nowcasting approaches. Even though the empirical exercise employed in his study focuses on euro area GDP only, it suggests that while some specifications of MIDAS regressions outperformb bridge equations, the overall relative performance of the two models is largely similar. This is also observed in the results of Duarte, Rodrigues & Rua (2017) where, even though MIDAS regressions result in lower nowcast errors, the difference in performance between MIDAS and bridge equations for nowcasting private consumption is not substantially different.

3 Modelling framework

This section provides a brief overview of the modelling framework used in the empirical exercise. The first modelling approach pertains to bridge equations, which serve as the first type of models used for nowcasting economic aggregates, while the second one pertains to MIDAS regressions, a modelling framework allowing for the exploitation of within-quarter information to nowcast quarterly aggregates. The following subsections shortly summarize the generalized key features of these two modelling frameworks and highlight components relevant to this paper. For a detailed survey on the econometric properties and a thorough comparison of these models, see Foroni & Marcellino (2013) and Schumacher (2016).

3.1 Bridge equations

Bridge equations qualify as one of the early methods applied to nowcasting with mixed-frequency data (Foroni & Marcellino, 2013). They are widely used across central banks for nowcasting GDP (e.g. Bell, Co, Stone, & Wallis (2014) from Bank of England), primarily due to the simple estimation method and their transparency (Schumacher, 2016). The inclusion of indicators into bridge equations is based on the statistical fact that they contain timely and relevant information, rather than on casual relations, rendering these models different from standard macroeconomic models (Foroni & Marcellino, 2013). Even though bridge equations entail low-frequency variables on both sides of the equation, they qualify as dynamic regressions since the explanatory variables on the right-hand side of the equation are quarterly lags of the indicator. The right-hand side low-frequency indicators are obtained using a deterministic time-aggregation function of the high-frequency indicators, the specification of which depends on the flow-stock nature of the indicator itself [1]. Following Foroni & Marcellino (2013) and Schumacher (2016), a single-indicator bridge equation model can be specified as follows:

$$y_t^L = \beta_0 + \lambda y_{t-1}^L + \beta(L)x_t^L + \epsilon_t^L \tag{1}$$

where y_t^L is the low-frequency target variable in low-frequency period t; for example, quarterly growth rate of GDP or private consumption in quarter t. $\beta(L)$ is a low-frequency lag-polynomial and x_t^L is a low-frequency indicator aggregated over time from the high-frequency indicator x_t^H, and available for the same periods as the low-frequency target variable. Formally, the computation behind x_t^L entails the following specification:

$$x_t^L = \omega(L^{\frac{1}{m}})x_t^H \tag{2}$$

where $\omega(L^{\frac{1}{m}})$ is the deterministic time-aggregator function, mapping from the high-frequency indicator x_t^H to the aggregated low-frequency one x_t^L. The exact form of $\omega(L^{\frac{1}{m}})$, as indicated earlier, depends on the stock-flow nature of the indicator at hand. Since we are trying to nowcast quarterly target variables using indicators available at monthly frequency for that particular quarter, $m = 3$ in our case.

As depicted in (1), the bridge equation also contains a constant β_0 and an autoregressive term y_{t-1}^L. The general specification depicted in equation (1) is normally displayed without a lag of the dependant variables, i.e. an autoregressive term. However, in practice, bridge equations are usually augmented

[1] For detailed explanation of time-aggregation methods see Schumacher (2016) and Appendix A on data irregularities from Stock & Watson (2002).

with at least one lag of the dependant variable, and may further involve other quarterly regressors alongside the aggregated high-frequency indicator on the right-hand side of the equation (Ghysels & Marcellino, 2018). The main results presented in Section 5 entail both specifications, without and with an AR term. In empirical studies, augmenting models with an AR term of the dependant variable, as specified in (1), has shown to result in lower nowcast errors (Jansen, Jin, & Winter, 2012).

As implied by the general specification set forth in (1) and (2), bridge equations require for the whole set of high-frequency indicators to be known over the nowcasting period, allowing for an estimate only of the current period. Therefore, the estimation in bridge equations is undertaken in two steps. Initially, high-frequency time-series models are used to obtain forecasts of the unavailable observations of the high-frequency indicator over the nowcasting horizon. Formally, the high-frequency time series model may follow this structure:

$$x_t^H = \alpha_0 + \alpha(L^{\frac{1}{m}})x^H_{t-\frac{1}{m}} + \epsilon_t^H \tag{3}$$

where x_t^H refers to the high-frequency indicator at time t (i.e. high-frequency period t expressed in fraction of low-frequency such that $x_t^H = x^H_{t-0/m}$, $L^{\frac{1}{m}}$ is a lag operator spanning across the frequency of already available observations of x_t^H (in our case this is monthly). In forecasting high-frequency indicators, ARIMA specifications are usually used, even though in recent literature also VARs have been incorporated due to their superior forecasting performance (Ghysels & Marcellino, 2018). As the objective is to obtain forecasts of the not yet available observations of the high-frequency indicator in the remaining months of the quarter, this study incorporates autoregressive (AR) models, which are re-estimated with each additional month/observation of the particular indicator. In the second step, the forecast high-frequency estimates of the indicator from (3) (together with the already available observations - if any - of the high-frequency indicator for the particular low-frequency period) are then aggregated over time as in (2) to match the frequency of the dependant variable and serve as an input into the main bridge equation used to obtain the nowcast of the low-frequency variable as specified in (1).

To illustrate the bridge modelling approach, suppose that we are currently at the end of February 2019 and would like to obtain an estimate for the quarterly growth rate of private consumption for the first quarter, i.e. 2019Q1. For simplicity, suppose that we are using only retail sales as a predictor in our estimation. The information set by the end of February 2019 entails the quarterly growth rate of private consumption for 2018Q4 and retail sales for January 2019 only. Therefore, to obtain an initial nowcast, first retail sales are forecast for the remaining months of 2019Q1, i.e. February and March 2019 using a variation of the specification in (3). The realization of retail sales for January 2019 and the resulting forecasts for February and March 2019 are then aggregated using the appropriate deterministic time-aggregation function as in (2) and plugged into (1). Estimating (1) then provides the nowcast of quarterly growth rate of private consumption for 2019Q1 using information provided by its past dynamics and retail sales.

3.2 MIDAS regressions

The MIDAS regression was originally proposed by Ghysels, Santa-Clara, & Volkanov (2004) and used for financial analysis. Later, numerous studies applied the methodology to macroeconomic aggregates such as GDP. In such regressions, and different from bridge equations, the observations of the low-frequency variable are directly related to lagged high-frequency observations of the indicators without time aggregation (Schumacher, 2016). For example, in nowcasting quarterly target variables, while bridge equations initially forecast the monthly indicator for the remaining months within the quarter and then aggregate them to a quarterly frequency, MIDAS regresses the quarterly target variable on the already available monthly information for the quarter of interest. The response of the high-frequency indicators to the dependant low-frequency variable is modelled using highly parsimonious distributed lag polynomials to prevent the proliferation of parameters, in particular when the change between the high- and low-frequency is large (e.g. annual dependant variable and monthly indicators/predictors). Formally, the general (AR-augmented) MIDAS regression for a single explanatory variable, as specified by Ghysels and Marcellino (2018) and Schumacher (2016), is given by:

$$y_t^L = \beta_0 + \lambda y_{t-1}^L + \beta_1 C(L^{\frac{1}{m}}; \theta) x_t^H + \epsilon_t^L \tag{4}$$

where y_t^L refers to the low-frequency dependent variable in period t, x_t^H refers to the monthly predictors, and $C(L^{\frac{1}{m}}; \theta) = \sum_{k=0}^{K} c(k; \theta) L^{\frac{k}{m}}$ refers to the distributed lag polynomial. From the latter expression, $c(k; \theta)$ qualifies as the distinct feature of MIDAS. The most commonly used parametrization of the lagged coefficients of $c(k; \theta)$ is the "exponential Almon Lag", which is flexible and accommodates different shapes, such as increasing, decreasing or hump-shaped, while using only a few parameters (the most widely used number of parameters in the literature is two parameters). Other polynomial specifications, apart from the exponential Almon Lag, include also the Beta polynomial, Step Functions, and the traditional Almon lag polynomial. For the purpose of this study, the parametrization considered in the MIDAS regressions is the traditional Almon lag polynomial. Similar to bridge, also MIDAS allows for the addition of other regressors on the right-hand side, such as past information of the dependant variable (already specified in (4) as one AR-term) or other regressors in a quarterly frequency. Due to the structure of the MIDAS regression, the estimation is undertaken by non-linear least squares.

If the difference in the sampling frequencies between the explained low-frequency variable and high-frequency indicators is not too large (quarterly and monthly data for example), unrestricted linear polynomials have been considered in the literature as well, and they can be estimated by OLS. Unrestricted MIDAS, hereafter UMIDAS, is a variant of MIDAS, which does not incorporate functional distributed lag polynomials (Foroni, Marcellino, & Schumacher, 2011). Similar to the MIDAS, UMIDAS regressions are a nowcasting tool of low-frequency variables from high-frequency indicators. Instead of using functional distributed lag polynomials, the estimation is undertaken on the monthly observations directly in a general dynamics framework. The general indicator-specific UMIDAS model is given by:

$$y_t^L = \alpha_0 + \lambda y_{t-1}^L + \sum_{k=0}^{K} \gamma_k x_{t-\frac{k}{m}}^H + \epsilon_t^L \tag{5}$$

where $x_{t-k/m}^H$ for $k = 0, 1, \ldots, K$, in our case with maximum $K = 2$, refers to the information available for each of the months within a particular quarter. UMIDAS has all parameters unconstrained and therefore to avoid parameter proliferation it only works for small values of m (Ghysels & Marcellino, 2018). Monte Carlo experiments have shown that UMIDAS performs better than MIDAS when mixing quarterly and monthly data, in particular for nowcasting GDP (Foroni, Marcellino, & Schumacher, 2011).

To illustrate the general MIDAS modelling approach, suppose that similar as before, we are currently in the end of February 2019 and would like to obtain an estimate for the quarterly growth rate of private consumption for the first quarter, i.e. 2019Q1. Rather than forecasting retail sales for the remaining months of the quarter as in (1), MIDAS regressions obtain a nowcast for the quarterly growth rate of private consumption for 2019Q1 given the information set already available for the quarter, i.e. retail sales for January 2019, using the specification (4) or (5).

4 Data

Data collected from payment systems qualify as the new data sources considered to nowcast our target variables. According to the Bank of International Settlements (BIS), a payment system is "a set of instruments, procedures and rules for the transfer of funds between or among participants" which are "generally categorized as either a retail payment system or a large-value payment system" (2018). Data collected from these systems is usually available in a timely fashion and is free of measurement errors (see Gil, Javier J. Perez, & Urtasun (2018), Duarte, Rodrigues, & Rua (2017), Aprigliano, Ardizzi, & Monteforte (2017), Galbraith & Tkacz (2015)). In this analysis, the two types of payment system data pertain to ATM/POS data and TARGET2 data. While the former type of data belong to the retail payment system, usually appropriate for nowcasting purposes of private consumption, the latter type pertains to the large-value payment system, appropriate for nowcasting purposes of GDP (Dias & Dias, 2017).

4.1 TARGET2 payment system data

TARGET2 is a broad-based pan-European payment system that started operating in November 2007 and serves as a harmonizer of the payment infrastructure within the monetary union. As a whole, it is operated by the Eurosystem on a single common technology platform, while each central bank included in TARGET2 manages its national component. More than 1,900 participants are involved in TARGET2: the European Central Bank (ECB), national central banks, commercial banks, savings banks and other credit institutions providing payment services. Including all correspondents and affiliates of all the participants in the system, as many as 60,000 credit institutions can be reached through the TARGET2 system. All TARGET2 participants are subject to uniform standards for the distribution of settlement orders, uniform participation conditions and a uniform pricing policy. The TARGET2 system is primarily focused in settling large-value payments and time-critical payments in euros, both domestic (between participants within the country) and cross-border (among participants in countries included in TARGET2).[2] TARGET2-Slovenia is the system that operates on the common platform of TARGET2, while the legally formal system is under the control and management of the Bank of Slovenia.

In examining the correlation between the growth rates of GDP and the number and value of transactions executed in the TARGET2-Slovenia payment system, the recorded transactions have been filtered to exclude two types of transactions. Due to the specific nature of the operations of the Bank of Slovenia in the TARGET2 payment system, all its transactions and the transactions of its customers are excluded from this analysis. In addition, transactions with amounts less than EUR 50,000 were eliminated, since after 2008 (the gradual) implementation of the Single Euro Payments Area (SEPA) and, in parallel, the development of (other) payment systems took place, which was reflected in the migration of smaller-payment transactions from TARGET2 to more affordable payment systems. Both indicators have been seasonally adjusted while transaction value has also been converted in real terms using the HICP to obtain a measure of the volume of transactions.[3]

[2]For additional information on TARGET2 see the designated page on the website of ECB: https://www.ecb.europa.eu/paym/target/TARGET2/html/index.en.html

[3]Aprigliano, Ardizzi, & Monteforte (2017) use the GDP deflator to convert TARGET2 indicators to real terms. However, as we aim to use the indicators in their monthly frequency also, the other possibility remains the HICP which is available at a monthly frequency

Table 1: Correlation of GDP and TARGET2 payment data

Indicator	*Real GDP*
TARGET2 Number of Transactions	0.89
TARGET2 Volume of Transactions	0.79

***Source**: Bank of Slovenia, own calculations.*
***Note**: All series are seasonally adjusted and in real terms (except for number of transactions). Correlation coefficients of y-o-y growth rates computed over 2008Q1 – 2019Q1.*

Table 1 presents the Pearson correlation coefficients of real GDP growth with TARGET2 number and volume of transactions in year-on-year (*y-o-y*) growth terms over the period 2008 – 2019, which underlines the length of the TARGET2 series (also displayed in Figure A.1(a) in Appendix A). The correlation coefficients indicate a high degree of co-movement between both the volume and number of TARGET2 payment transactions with real GDP growth. In particular, *y-o-y* growth rate of number of transactions accounts for a correlation coefficient of almost 90 percent.[4] Apart from this high-degree of co-movement, TARGET2 indicators are timely, available on a monthly basis and, as indicated, free of measurement error. This highlights the advantage of these indicators for nowcasting purposes relative to other traditional indicators in terms of both timely availability and real-time accuracy. Given that growth of both indicators shows a high degree of correlation with real GDP growth, both will be incorporated in the nowcasting exercise.

4.2 ATM cash withdrawals and POS payment data

In Slovenia, ATM cash withdrawals and POS payments are cleared through the payment system operated by Bankart d.o.o.. The frequency of this data at the Bank of Slovenia is available on a quarterly basis only. Depending on the type of card used, data collected from ATM cash withdrawals and POS payments fall in the following four categories of payments undertaken via: debit cards, credit cards, deferred debit cards and pre-paid cards. Given the peculiarity of each card type [5], the data is aggregated to account for the following categories

whereas the GDP deflator is only available at a quarterly frequency. In quarterly terms, there are negligible differences in the series deflated by HICP and the one deflated by the GDP deflator.

[4] In quarter-on-quarter (*q-o-q*) growth terms, the correlations are 0.71 and 0.51 for number and volume of transaction respectively highlighting a high degree of co-movement also for quarterly dynamics.

[5] Debit cards allow the holder to execute payments whereby during each use the card issuer immediately debits his/her transaction account by the amount of the payments executed, while credit cards allow purchases or cash withdrawals up to a credit limit agreed in advance. There are revolving credit cards, where the cardholder settles the liabilities in part at the end of the accounting period, the issuer bank charging interest on the unsettled amount, and deferred debit cards, where the holder settles the liabilities in full at the end of the

underlying the types of payment instruments: debit payment instruments and credit payment instruments. The former include payments undertaken only via debit cards, while the latter include payments undertaken via both credit and deferred debit cards. Pre-paid cards are excluded from the analysis as despite being highly volatile and subject to significant outliers, they pertain to cards provided mainly by telecom companies, which could potentially be purchased by cash withdrawn from ATMs resulting in "double-counting" within the series. While the starting period of each type of card and payment instrument varies, the joint starting date for all series is 2002Q1. However, given the high volatility of the series in the initial three years, the series used in the analysis starts as of 2005Q1. Different from TARGET2, for this type of payment data only the value of transactions will be considered. The series have been seasonally adjusted and deflated by the HICP to obtain a measure of the volume of transactions.

Table (2) presents a snapshot of the correlation coefficients across payment data and two types of private consumption: aggregate private consumption and consumption of households on other goods and services excluding durables, which qualifies as nondurables consumption. The coefficients indicate, in y-o-y growth terms, that data collected through ATM cash-withdrawals co-moves more closely with consumption than data collected through POS payments. This may suggest that cash payments are still a dominant payment method in the Slovene market.

Table 2: Correlations of private consumption and ATM/POS payment data value

Indicator	*Total*	*Nondurable*
ATM (Debit)	0.40	0.48
ATM (Credit + Deferred Debit)	0.37	0.34
ATM (Debit + Credit + Deferred Debit)	0.58	0.64
POS (Debit)	0.54	0.58
POS (Credit + Deferred Debit)	0.35	0.44
POS (Debit + Credit + Deferred Debit)	0.50	0.57

Source*: Bank of Slovenia, own calculations.*
Note*: All series are seasonally adjusted and in real terms. Correlation coefficients of y-o-y growth rates computed over 2005Q1 – 2019Q1.*

Since we are interested in nowcasting aggregate figures, it seems feasible to consider aggregation of data collected through both, POS and ATM, to better account for the total expenditure of consumers. Moreover, as pointed out by Galbraith & Tkacz (2015), using all the modes together would "endogenise" the movement of consumers from one card type to another, which otherwise

accounting period (Bank of Slovenia, 2017).

could be reflected if the modes are used in isolation. That is, payments via separate card types may rise or fall for reasons other than an overall increase or decrease in spending; they also change as consumers choose to switch to a credit card from a debit card for particular purchases, which would result in a growth in credit card transactions and a fall in debit card transactions, but not in overall spending *per se*.

Table 3: Correlations of private consumption and ATM/POS payment data value

Indicator	*Total*	*Nondurable*
ATM&POS (Debit)	0.58	0.67
ATM&POS (Credit + Deferred Debit)	0.45	0.50
ATM&POS (Debit + Credit + Deferred Debit)	0.62	0.69

Source*: Bank of Slovenia, own calculations.*
Note*: All series are seasonally adjusted and in real terms. Correlation coefficients of y-o-y growth rates computed over 2005Q1 – 2019Q1.*

As observed in Table (3), aggregating information from cash withdrawals via ATM and payments via POS using both debit and credit payment instruments results in a higher correlation coefficient with total private consumption as opposed to using each payment and instrument type in isolation (also displayed in Figure A.1(b) in Appendix A). Considering these dynamics, the main payment data indicator to be included in the analysis pertains to ATM/POS data using both debit and credit payment instruments. It is worth mentioning that the co-movement of payment data is slightly more synchronized for consumption of goods and services excluding durable goods. This is expected, as consumption of durables, part of aggregate private consumption, is usually undertaken via loans and not ATM/POS payments (see Esteves (2009) and Duarte, Rodrigues, & Rua (2017)). For Slovenia, the share of durables consumption to total private consumption accounts for approximately 10 percent. Given this small share, and the fact that we will also incorporate car registrations as a separate indicator to account for consumption of durables in the nowcasting models, in this exercise, different from the empirical studies mentioned, aggregate rather than just private consumption of other goods and services will be considered.[6] The other reason underlines the fact that in the current exercise the goal is to assess the usefulness of ATM/POS payment data, which if rendered true for aggregate private consumption, it should, in

[6]We do estimate the results also using private consumption of other goods and services, while excluding car registrations. Whereas the performance of models entails lower nowcasting errors with consumption of other goods and services as dependent variable, the general conclusions of usefulness of ATM/POS payment data in improving nowcast accuracy, highlighted in Section 6 with aggregate private consumption as dependent variable, remain in tact.

principle, hold also for private consumption excluding durables.

4.3 Other data

Data on the target variables, GDP and private consumption, come from SORS. The rest of the data comprise two data pools used in the nowcasting exercise of each target variables. For GDP, the remaining pool of data incorporates traditional hard and soft indicators. Hard indicators entail monthly data on industrial production, retail trade, services trade, exports and imports, and unemployment. Soft indicators entail survey-based indicators from Business Tendency and Consumer Surveys, including the composite Economic Sentiment Indicator and composite and sub-indicators across components, i.e. industry, retail, services, construction and consumers. For private consumption, hard indicators entail monthly data on retail trade, services trade, car registrations, income and employment. Soft indicators entail survey-based indicators from Business Tendency and Consumer Surveys, including the composite Economic Sentiment Indicator, Consumer Confidence Indicator and its sub-indicators. The hard indicators come from SORS, while the soft indicators, i.e. the survey-based indicators, come from Eurostat.[7]

As the number of series pertaining each category is relatively large[8], for the purpose of this paper only one indicator per category is selected based on the highest correlation with the target variable. That is, for industrial production, the quarterly growth rate of industrial production for manufacturing and mining accounts for the highest correlation with the quarterly growth rate of GDP growth, hence it is the main indicator selected to account for the industry component in the data. Appendix B presents the list of main indicators selected across all categories and for both data pools. Following other similar studies, all the series used in the analysis are seasonally adjusted, in logarithms (except for soft indicators and unemployment) and in first differences.

5 Nowcasting exercise and estimation setup

This section illustrates and describes the nowcast design, the baseline models, the evaluation methods employed to assess nowcast performance of compet-

[7]Survey-based indicators are also provided by SORS, but the length of the seasonally adjusted series provided by Eurostat starts in 1995, while the one provided by SORS starts in 2005.

[8]For example, for Retail Confidence Indicators, there are six series available, including sub-indicators and the composite indicator. While numerous papers that employ the single-indicator modelling approach compute single-indicator nowcasts based on a large set of indicators separately and then pool them together to compute a single final nowcast (see Schumacher (2016)), in this paper, since the usefulness of one specific type of data is assessed, it suffices to incorporate one main indicator for each of the categories (see Duarte, Rodrigues, & Rua (2017) for an example pertaining main indicators used for nowcasting private consumption).

ing models and the weighting scheme used in pooling single-indicator model nowcasts.

5.1 Nowcast design

The nowcast design employs a pseudo-real time nowcasting exercise. As such, it aims to replicate the availability of data, i.e. publication lags, at the time of estimation in order to simulate the real-time flow of information as closely as possible. In real-time, initial releases of data, such as industrial production and NA statistics, are prone to future revisions the more information becomes available to the statistical entities. Regardless of this, and as is implied by the pseudo real-time designs, errors stemming from data revisions are not taken into account. Hence, the results provided in this exercise may overestimate the nowcasting accuracy of the presented models in real-time. However, as indicated by Jansen et al. (2012), the effects of data revisions tend to cancel out due to pooling of a significant number of single-indicator models. While the number of single-indicator models in our analysis is smaller, the potential data revision effects are expected to be small as the analysis considered here is based on relative performance of models.

Estimation of the parameters in each of the models is done recursively using *only* the information available at the time of the nowcast, which for this exercise corresponds to the end of each month within the quarter. This means that for a given quarter t, the first nowcast is estimated in the first month of quarter t, denoted $m1_t$, conditional on the data available as of the last day of $m1_t$; the second nowcast is estimated in $m2_t$ conditional on the data available as of the last day of $m2_t$; and the third nowcast is similarly estimated in $m3_t$, conditional on the data available as of the last day of $m3_t$.[9] As a result, for a given quarter, three nowcasts are available, enabling the comparison of early nowcasts to end-of-quarter nowcasts (for the period considered in this paper). However, in real-time, this is not the case for specifications augmented with an AR-term of the dependent target variable (specified in Section 3), as in the first month of a given quarter t, the quarterly target variables are not yet available for the previous quarter $t-1$ (they only become available by the end of $m2_t$). While the nowcast of the previous quarter can be considered, with the setting set forth in this paper, for the AR-augmented specifications, only nowcasts estimated in $m2_t$ and $m3_t$ are displayed as they rely on actual realizations. In genera, the presented approach provides an easy way to assess the impact of monthly incremental expansion of the available information set on nowcast accuracy for a given quarter, especially as (also) the most recent data on quarterly target variables become available.

While the general design of the nowcasting exercise remains the same for

[9]For a depiction of available information sets considered across indicators at each month of the quarter please see Appendix C.

both GDP and aggregate private consumption, the different available frequency of ATM/POS payment data and TARGET2 data necessitates distinct modelling approaches for each of the two target variables. For GDP, all indicators, including TARGET2 payment data, are available on a monthly frequency. To illustrate the usefulness of TARGET2 data in improving nowcasting accuracy of quarterly growth rate of GDP, we initially obtain single-indicator nowcasts based on all traditional indicators and TARGET2 indicators separately. Next, pooling of single-indicator nowcasts is undertaken initially for nowcasts derived from traditional indicators only and then for nowcasts derived from both traditional indicators and TARGET2 indicators. This allows for the accuracy of the nowcasts stemming from traditional indicators only to be compared to the nowcasting performance of pooled single-indicator models including also the models based on TARGET2 data. The estimation period across all nowcasting models for GDP starts in 2008, while the nowcasting exercise is undertaken for the period 2017Q1 – 2019Q1. This means that from the sample available, constrained by the availability of TARGET2 data to start in 2008, the first 80 percent of the data is used for estimation, while the remaining 20 percent is used for testing. For Slovenia, the period allocated for testing, i.e. 2017Q1 – 2019Q1, is characterized by a relatively stable economic growth (see Figure A.2(c) in Appendix A). As observed across empirical studies, in periods of stability as opposed to distressed period (i.e. the financial crisis), baseline models (such as AR models) tend to perform relatively well, if not best (Bell, Co, Stone, & Wallis, 2014). Hence, we expect the different models to outperform baseline models to a lower extent than they would in periods of economic uncertainty and turmoil.

For private consumption, while all traditional indicators are available at a monthly frequency, ATM/POS payment data are only available at a quarterly frequency. To illustrate the potential usefulness of ATM/POS data in improving the accuracy of private consumption nowcasting models, the performance of the pooled single-indicator models based on traditional indicators is compared to the performance of the pooled single-indicator models augmented with the quarterly indicator of ATM/POS data. While this approach is not ideal, it does not hinder the objective of the exercise nor diminish the resulting conclusions. As indicated in Section 3 of the paper, the modelling framework of both bridge equations and MIDAS allows the inclusion of additional variables in the regressions. For MIDAS in particular, the framework is flexible to the inclusion of other right-hand side variables that are in the same frequency as the dependant left-hand side variable. In terms of conclusions, if ATM/POS payment increase performance accuracy in a quarterly format, then this suggests that such data have valuable information in nowcasting private consumption dynamics and that availability of the series in the monthly frequency could potentially be an even better candidate. The estimation period across all nowcasting models for private consumption starts in 2005, while the out-of-sample nowcasting exercise is undertaken for the period 2016Q3 –

2019Q1. The choice of samples allocated for estimation and testing follows the same rule applied to GDP, i.e. 80 percent of data used for estimation and the remaining 20 percent of data used for testing. For Slovenia, similar to GDP, the testing period, i.e. 2016Q3 – 2019Q1 pertains to a relatively stable growth of private consumption, albeit more volatile than that of real GDP (see Figure A.2(d) in Appendix A).

5.2 Baseline models, weighting scheme and performance evaluation methods

Since we are aiming to assess the information power of specific indicators vis-a-vis a set of traditional indicators, the modelling approach is based on pooled single-indicator models. The pooling of single-indicator nowcasts is undertaken using a weighted average of single-indicator nowcasts with weights calculated from the inverse nowcast errors of models, i.e. RMSFE, over the out-of-sample exercise period (similar to Kuzin et al. (2013)). Although this violates the spirit of a pseudo-real time exercise, the *relatively* short sample considered in the analysis, makes it necessary to express the weights from the full-sample.

The performance of the models is evaluated based on the Root Mean Squared Error (RMSE) relative to the performance of baseline models. The choice for RMSE as a measure of performance reflects its wide usage in similar studies and the fact that it "penalizes larger errors compared to other common metrics such as average absolute error" (Verbaan, Bolt, & Cruijsen, 2017). The baseline models for both GDP and private consumption pertain to univariate autoregressive AR models, with number of lags determined using the Akaike-Information criterion (AIC).[10] In illustrating whether monthly variation is important in nowcasting the quarterly growth rates of the target variables, the performance of MIDAS regressions is evaluated also against bridge equations. To assess whether the relative accuracy (to baseline AR models or bridge equations for MIDAS) of nowcasting models is statistically significant, the paper makes use of Diebold-Mariano tests (DM) (Diebold & Mariano, 1995). However, the author recognizes that the DM test has a low power in samples of similar size to the one considered in this analysis (Clark, 1999), which renders it less likely to reject the null of no difference in forecast errors.

6 Empirical results

This section presents the results of the nowcasting exercise. Given the highlighted differences across the two sets of data pools as well as the modelling approach, the results of GDP and private consumption are presented separately in the following two subsections.

[10]The baseline autoregressive models for GDP and private consumption based on the AIC are $AR(1)$.

6.1 GDP

Table 4 presents the relative RMSFEs of nowcasting models for the quarterly growth rate of GDP against the baseline autoregressive model. The relative RMSFEs are reported for each month of the quarter across the three models: pooled bridge, pooled UMIDAS, and pooled MIDAS. Following the exercise design, the nowcast errors pertaining each month of the quarter are derived from pooled models that take into account partial information sets, which mirror as closely as possible the real-time availability of information. To evaluate the performance under complete information sets, the last column reports the relative RMSFEs stemming from models that assume data on all indicators is available for the whole quarter.[11]

Across each model type, three specifications are evaluated: pooled model of single-indicator nowcasts based on traditional indicators only (hereafter with suffix $-TI$), pooled model incorporating also the single-indicator nowcast from TARGET2 number of transactions (hereafter with suffix $-T2N$) and pooled model incorporating the single-indicator nowcast from TARGET2 volume of transactions (hereafter with suffix $-T2V$). For each of the specifications, two sets of results are presented: results stemming from models without an AR term of the dependant variable and results stemming from models augmented with an AR term of the dependent variable (hereafter augmented with suffix AR). As set forth in Section 5.1, since data on GDP for a particular quarter t becomes available only at the end of the second month $m2$ of quarter $t+1$, only the nowcasts obtained in the second and third month, i.e. $m2$ and $m3$, are presented for specifications augmented with an AR term of the dependant variable.

At a first glance and in line with expectations, the accuracy of nowcasts across models increases the more information becomes available. This is indicated by the lowest RMSFEs for the nowcasts estimated in the third month. The nowcasts become even more precise when the complete information set is accounted for, as shown in the last column. As already highlighted in Section 3, augmenting equations across the different models with an AR tem of the dependent variable does not only result in lower nowcast errors, but also renders most results statistically significant vis-à-vis the baseline model. Given this, for the second month and third month of the quarter, the discussion will largely focus on the AR-augmented specifications. Nevertheless, across both specifications, with and without an AR term, while pooling of traditional single-indicator nowcasts outperforms the baseline model for nowcasts

[11] In Duarte, Rodrigues, & Rua (2017), the relative nowcast errors are derived from models that assume availability of full information sets for each month, without considering publication lags. The complete set of results following their approach is reported in Appendix D. Whereas the quantitative implications from full information sets are evident, the qualitative conclusions of the usefulness of payment data indicators remain largely similar to the ones discussed here.

estimated in the second and third month of the quarter, the accuracy increases further by the inclusion of TARGET2 indicators in all three models by the end of the quarter. among the two TARGET2 indicators, specifications incorporating $T2N$ result in the lowest nowcast errors, especially towards the end of the quarter. This is to be expected given the statistics presented in Section 4.1, in which $T2N$ has a higher correlation with GDP growth compared to $T2V$.

Table 4: Relative RMSFEs of nowcasting models against baseline models

Models	Included	$m1$	$m2$	$m3$	$fullquarter$
Pooled Bridge					
BRIDGE-TI	TI	**1.015**	0.924	0.880	*0.752**
BRIDGE-$T2N$	TI, T2N	1.028	0.940	0.809	*0.710**
BRIDGE-$T2V$	TI, T2V	1.037	0.946	0.898	*0.769**
BRIDGEAR-TI	TI, AR		**0.875***	0.831*	*0.728***
BRIDGEAR-$T2N$	TI, T2N, AR		0.885*	0.777*	*0.695***
BRIDGEAR-$T2V$	TI, T2V, AR		0.886*	0.840*	*0.740***
Pooled UMIDAS					
UMIDAS-TI	TI	1.033	0.900	0.769	*0.756**
UMIDAS-$T2N$	TI, T2N	1.041	0.907	0.715*	*0.710**
UMIDAS-$T2V$	TI, T2V	1.057	0.918	0.787	*0.770*
UMIDASAR-TI	TI, AR		0.879*	0.756*	*0.661***
UMIDASAR-$T2N$	TI, T2N, AR		0.884*	**0.714***	***0.636*****
UMIDASAR-$T2V$	TI, T2V, AR		0.886*	0.763*	*0.669***
Pooled MIDAS					
MIDAS-TI	TI	1.057	0.936	0.788	*0.788*
MIDAS-$T2N$	TI, T2N	1.052	0.942	0.735*	*0.705**
MIDAS-$T2V$	TI, T2V	1.081	0.956	0.803	*0.797*
MIDASAR-TI	TI, AR		0.883*	0.789*	*0.715**
MIDASAR-$T2N$	TI, T2N, AR		0.888	0.726*	*0.669***
MIDASAR-$T2V$	TI, T2V, AR		0.885*	0.790*	*0.717**

***Source**: Own calculations.*
***Note**: TI- traditional indicators, AR-autoregressive term, T2N – number of TARGET2 transactions, T2V – volume of TARGET2 transactions. 1^{st}, 2^{nd} and 3^{rd} month columns pertain to relative RMFSE of models based on information sets available up to the last day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively. Best performing models highlighted in bold.*

Focusing on nowcasts obtained in the first month, even though all insignificant, no model outperforms the baseline model for nowcasting GDP.[12] In

[12] It is important to note that the baseline model estimated for nowcasts obtained in the first month of the quarter assumes data availability of the quarterly target variable (GDP in this case) in the last quarter, $t-1$. In real-time, as explained in Section 5, this is not

general, given the testing sample period considered in this exercise, which as indicated entails a relatively stable growth of GDP, the good performance of the baseline model, especially at the beginning of the quarter when less information is available, is not surprising. Nevertheless, as we move forward into the quarter, which translates into a richer information set, the baseline model underperforms all three models. For nowcasts computed in the second month of the quarter, almost all specifications based on traditional indicator models across pooled bridge, pooled UMIDAS and pooled MIDAS become significant with the inclusion of the AR-term. For this period, BridgeAR-TI outperforms the rest of the models and specifications, and results in a significant gain in accuracy of 13 percent. An almost identical performance is observed for UMIDASAR-TI. While inclusion of TARGET2 indicators into BridgeAR, UMIDASAR and MIDASAR (the latter, at least for $T2V$) results in significantly more accurate nowcasts than the baseline autoregressive model, their performance is slightly worse than that of their counterparts relying solely on traditional indicators. These results suggest that, at least for periods of stable growth, baseline autoregressive models and traditional indicators remain important and sufficient sources of information for nowcasting purposes, especially at the beginning of the quarter.

When moving to the third month of the quarter, which entails a richer set of information available, the performance of models changes compared to the performance observed earlier in the quarter. First, pooled UMIDAS outperforms the rest of the models across all specifications. For specifications relying on traditional indicators only, the relative gain in accuracy across BridgeAR-TI and MIDASAR-TI accounts for 17 percent and 21 percent respectively, while for UMIDASAR-TI the gain surpasses 24 percent. While the inclusion of $T2V$ in the model slightly worsens their performance, albeit more accurate than the baseline autoregressive model, the inclusion of $T2N$ renders the GDP nowcasts of all three models more accurate. As observed, BridgeAR-$T2N$, UMIDASAR-$T2N$ and MIDASAR-$T2N$ largely outperform their traditional indicator counterparts. In terms of overall performance, UMIDASAR-$T2N$ performs the best and accounts for a significant increase in accuracy relative to the baseline autoregressive model of 29 percent. This is amplified further when the full information set is accounted for.

As depicted in the last column, UMIDASAR-$T2N$ retains its top position by delivering the lowest relative RMSFE when all data is available, resulting in a statistically significant accuracy gain of 36 percent. The superior

the case, as the last quarter's observation for the target variable becomes available only at the end of the second month of the current quarter, t. While the second lag or a forecast of the target variable could have been used in the baseline model for nowcasts obtained in the first month of quarter t, the author chooses to maintain the same baseline model (with the already explained assumption) across all specifications considered in this paper for consistency and simplicity purposes.

performance of UMIDAS is in line with other empirical studies and Monte Carlo simulations (Foroni, Marcellino, & Schumacher, 2011), which find that for nowcasting GDP, considering methods which entail mixing quarterly and monthly frequencies of variables, UMIDAS regressions outperform other specifications such as MIDAS, regardless of the choice of functional form. In general, the results suggests that, at least for the period considered in this paper, the information content of TARGET2 indicators is a valuable addition to the traditional pool of indicators used to nowcast the quarterly growth rate of real GDP, but only when more information becomes available. In particular, at the end of the quarter, models including $T2N$ are more accurate compared to the other specifications and result in lowest nowcast errors, even if comparison is restricted within each specific pooled model.

Table 5: Relative RMSFEs of UMIDAS and MIDAS against corresponding bridge equations

Models	Included	$m1$	$m2$	$m3$	$fullquarter$
Pooled UMIDAS					
UMIDASAR-TI	TI, AR		1.005	0.910*	*0.908**
UMIDASAR-$T2N$	TI, T2N, AR		0.999	0.918*	*0.915**
UMIDASAR-$T2V$	TI, T2V, AR		1.000	0.908*	*0.905**
Pooled MIDAS					
MIDASAR-TI	TI, AR		1.009	0.949	*0.983*
MIDASAR-$T2N$	TI, T2N, AR		1.003	0.935*	*0.962*
MIDASAR-$T2V$	TI, T2V, AR		0.998	0.940	*0.970*

***Source**: Own calculations.*
***Note**: TI- traditional indicators, AR-autoregressive term, T2N – number of TARGET2 transactions, T2V – volume of TARGET2 transactions. 1^{st}, 2^{nd} and 3^{rd} month columns pertain to relative RMFSE of models based on information sets available up to the last day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively.*

The relative performance across pooled MIDAS and UMIDAS models in the second and third month of the quarter against the baseline model implies that the monthly variation across indicators does provide valuable information for the quarterly growth dynamics of real GDP. However, pooled bridge specifications also perform well, especially in the second month of the quarter. To assess the relative performance of pooled MIDAS and UMIDAS against pooled bridge, Table 5 reports the relative RMSFEs of the AR-augmented UMIDAS and MIDAS specifications against the corresponding bridge specifications (e.g. UMIDASAR-IT relative to BridgeAR-IT). As observed, in the second month of the quarter, the difference in accuracy among UMIDAS, MIDAS, and bridge is insignificant, albeit bridge specifications are largely more accurate. This suggests that, for the nowcasting period under evaluation (i.e. 2017Q1-2019Q1), the nowcasting performance across the models is largely similar. In the third month of the quarter, all UMIDAS specifications significantly outperform bridge, while for MIDAS only MIDAS$AR\text{-}T2N$ renders the difference in accuracy statistically significant. Similar to the case vis-à-vis the baseline autoregressive models, UMIDAS$AR\text{-}T2N$ accounts for the lowest RMSFE in the third month, and this becomes even more accurate under full information sets.

This suggests that when more information is available, mixed frequency data sampling methods tend to better exploit the richness of the traditional monthly indicators as opposed to time-aggregation techniques applied in bridge equations. Nevertheless, despite the differences, bridge equations remain a useful tool for nowcasting purposes of GDP in the Slovene case, especially for nowcasts computed in the second month of the quarter. This is also in line with the observations of Schumacher (2016), who finds that compared to different specifications of mixed-frequency sampling methods, bridge equations tend to perform well in several instances for nowcasting euro area GDP.

6.2 Private consumption

Similar to GDP, Table (6) presents the relative RMSFEs of nowcasting models for the quarterly growth rate of private consumption against the baseline autoregressive model. While the general structure remains the same, the ATM/POS (hereafter AP) indicator enters each specification in its quarterly frequency. Different from GDP, albeit still insignificant, nowcasts obtained in the first month of the quarter entail lower nowcast errors relative to the baseline autoregressive model. This may be reasonable given that, as depicted in Appendix D, the growth dynamics of private consumption for the Slovene case are much more volatile than what is observed for GDP, especially for the testing sample period considered in this paper. Nevertheless, similar to what was observed for GDP, the accuracy of nowcasts largely increases the more information becomes available, as suggested by the lowest RMSFEs in the third month of the quarter. In addition, and in line with expectations, augmenting models with an AR-term improves accuracy, albeit to a lesser extent than in the case of GDP. As before, availability of the full information set increases the accuracy even further across all models and specifications. In terms of indicators considered, augmenting models with AP improves the accuracy of nowcasts significantly, suggesting that the information content of payment data is valuable for nowcasting the quarterly growth rate of private consumption.

Turning to the first month and focusing on models relying on traditional indicators only, the relative RMSFE of UMIDAS-TI outperforms the others models, albeit neither model is significant. Whereas the latter persist, inclusion of AP increases the accuracy across all three models.

Table 6: Relative RMSFE of nowcasting models against baseline models

Models	Included	$m1$	$m2$	$m3$	$fullquarter$
Pooled Bridge					
BRIDGE-TI	TI	0.967	0.964	0.955	*0.865**
BRIDGE-AP	TI, AP	0.916	0.911	0.907	*0.835**
BRIDGEAR-TI	TI, AR		0.960	0.950	*0.846**
BRIDGEAR-AP	TI, AP, AR		0.910	0.905*	*0.822***
Pooled UMIDAS					
UMIDAS-TI	TI	0.965	0.904*	0.880*	*0.856**
UMIDAS-AP	TI, AP	0.902	0.849*	0.821**	*0.820***
UMIDASAR-TI	TI, AR		0.896*	0.963**	*0.831***
UMIDASAR-AP	TI, AP, AR		**0.843***	**0.813****	*0.799***
Pooled MIDAS					
MIDAS-TI	TI	0.992	0.947	0.915*	*0.837***
MIDAS-AP	TI, AP	**0.889**	0.877*	0.857*	*0.797***
MIDASAR-TI	TI, AR		0.931	0.904*	*0.819***
MIDASAR-AP	TI, AP, AR		0.870*	0.856*	***0.794*****

Source: *Own calculations.*
Note: *TI- traditional indicators, AR-autoregressive term, AP – ATM/POS volume of transactions.* 1^{st}, 2^{nd} *and* 3^{rd} *month columns pertain to relative RMFSE of models based on information sets available up to the 30th day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively. Best performing models highlighted in bold.*

Different to the ordering based on traditional indicators only, now MIDAS-AP outperforms the other models and results in an increase in accuracy of 11 percent, albeit still insignificant. The performance of Bridge-AP and UMIDAS-AP is slightly similar, yet neither is significant as before. In the second month, as more information becomes available, all models entail more accurate nowcasts, with UMIDAS-TI, UMIDAS-AP and MIDAS-AP now also significantly better than the baseline model. However, different from the first month, UMIDAS-AP performs better than MIDAS-AP. The relative increase in accuracy in the second month provided by UMIDAS-AP accounts for approximately 15 percent. As with GDP, AR-augmented specifications, render models more accurate, and their performance improves further with the inclusion of AP. MIDASAR-AP and UMIDASAR-AP perform better than Bridge-AP, and as with the non-AR augmented specifications, UMIDASAR-AP results in the lowest RMSFE. At the end of the quarter, UMIDASAR-AP retains its superior performance, resulting in a statistically significant increase in accuracy of approximately 19 percent. While BridgeAR-AP and MIDASAR-AP significantly outperform the baseline model, they remain behind UMIDASAR-AP. Under complete information sets, the increase in accuracy across most models becomes highly statistically significant. MIDAS*AR-AP* outperforms the rest, but it is very close to the performance displayed by UMIDAS*AR-AP*. In the case of complete information set, the gain in accuracy by the best performing model vis-à-vis the baseline model accounts for 21 percent.

While MIDAS and UMIDAS result in lower relative RMSFEs vis-à-vis the baseline autoregressive models, the performance of bridge equations is not substantially different. For example, in the third month, conditional on partial information sets, the relative gain in accuracy from Bridge*AR-AP* is almost 10 percent. To better assess the relative performance of both UMIDAS and MIDAS compared to that of bridge, similar to GDP, Table 7 presents the relative RMSFEs of pooled UMIDAS and MIDAS regressions to the corresponding pooled bridge equation specifications. The results displayed focus only on the *AR*-augmented specification, as in the first month, the non-*AR* augmented specification does not display a significantly better performance vis-à-vis the baseline model. The results depicted in Table 7 indicate that in the second month of the quarter, albeit insignificant, Bridge*AR-TI* underperforms relative to UMIDAS*AR-TI* but not relative to MIDAS*AR-TI*.

Table 7: Relative RMSFEs of UMIDAS and MIDAS against corresponding bridge equations

Models	Included	$m1$	$m2$	$m3$	$fullquarter$
Pooled UMIDAS					
UMIDAS*AR-TI*	TI, AR		0.985	0.953*	*1.011*
UMIDAS*AR-AP*	TI, AP, AR		0.926	0.898*	*0.972**
Pooled MIDAS					
MIDAS*AR-TI*	TI, AR		1.023	0.999*	*0.997**
MIDAS*AR-AP*	TI, AP, AR		0.957	0.945*	*0.966**

Source: *Own calculations.*
Note: *TI- traditional indicators, AR-autoregressive term, AP – ATM/POS volume of transactions.* 1^{st}, 2^{nd} *and* 3^{rd} *month columns pertain to RMFSE of models based on information sets available up to the 30th day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively.*

Even though this changes with the inclusion of *AP*, the lower relative RMSFEs for UMIDAS*AR-AP* and MIDAS*AR-AP* remain statistically insignificant. In the third month, both UMIDAS*AR-AP* and MIDAS*AR-AP* supersede the performance of Bridge*AR-AP*. The significant increase in accuracy of the UMIDAS*AR-AP* is more emphasized, resulting in a relative gain in accuracy of 10 percent. When considering the full information set, the performance of bridge equations is superseded by both MIDAS and UMIDAS for the specifications that include also *AP*. Under this setting, the gain in accuracy, relative to Bridge*AR-AP*, provided by both UMIDAS*AR-AP* and MIDAS*AR-AP* oscillates at around 3 percent. Overall, the significant gain in accuracy provided by MIDAS and UMIDAS vis-à-vis bridge equations ranges from 3 percent to 10 percent, and prevails at the end of the quarter. This suggests that, similar to the exercise with GDP, bridge equations do remain useful nowcasting tools also for the case of private consumption earlier in the quarter, if not only for comparison purposes.

7 Conclusions

The publication lag of key measures of economic activity, such as GDP and private consumption, necessitates the use of alternative timely information to nowcast the two quarterly figures. These nowcasts are important inputs to economic and policy decisions, especially in absence of official estimates. Given their importance, obtaining nowcasts of the current (or most recent) dynamics of GDP and private consumption with the lowest errors possible remains a priority and a challenge at the same time. Payment data collected through ATM cash withdrawals, POS payments and TARGET2 system are a useful alternative source of information, in particular due to their timeliness and free-of-measurement-error nature. In evaluating the information content of these alternative sources of information for nowcasting Slovene GDP and private consumption, this paper designs a pseudo-real time nowcasting exercise using a mixed-frequency modelling approach. As with other similar studies, the inclusion of these alternative data sources in the traditional pool of indicators, results in reductions of relative RMSFEs across the nowcasting models of quarterly growth rate of Slovene private consumption and GDP respectively, especially towards the end of the quarter, when more information becomes available. Moreover, the gain in accuracy increases further when the previous quarter's value of the target variables is observed. Nevertheless, other traditional indicators remain important sources of information for the dynamics of target variables. Moreover, the results show that the monthly variation of the high-frequency indicators proves to be important for the quarterly growth dynamics of our low-frequency variables, as shown by the relative performance of UMIDAS and MIDAS regressions, especially as more information becomes available. While bridge equations perform significantly worse than MIDAS and UMIDAS for nowcasts estimated at the end of the quarter, their performance remains useful for nowcasts undertaken earlier in the quarter, especially for GDP. As such, they do remain valuable modelling tools for nowcasting purposes of GDP as well as private consumption in the Slovene case.

References

1. Anesti, N., Hayes, S., Moreira, A., & Tasker, J. (2017). Peering into the present: the Bank's approach to GDP nowcasting. *Quarterly Bulletin* 2018Q3.

2. Aprigliano, V., Ardizzi, G., & Monteforte, L. (2017, February). Using the payment system data to forecast the Italian GDP. *Banca D'Italia Working Papers*, Number 1098.

3. Bank of International Settlements. (2018, July). Committee on Payments and Market Infrastructure. Retrieved from BIS: https://www.bis.org.

4. Bank of Slovenia. (2017). Payment instruments and payment orders. Retrieved from Banka Slovenije Evrosistem: https://www.bsi.si.

5. Bell, V., Co, L. W., Stone, S., & Wallis, G. (2014). Nowcasting UK GDP Growth. *Bank of England Quarterly Bulletin 2014 Q1*, pp. 58-68.

6. Bok, B., Caratelli, D., Giannone, D., Sbordone, A., & Tambalotti, A. (2017). Macroeconomic Nowcasting and Forecasting with Big Data. *Federal Reserve Bank of New York Staff Reports*, No. 830.

7. Clark, T. E. (1999). Finite-sample properties of tests for equal forecast accuracy. *Journal of Forecasting, 18*(7), 489-504.

8. Clements, M., & Galvao, A. B. (2008). Macroeconomic Forecasting with Mixed-Frequency Data: Forecasting Output Growth in the United States. *Journal of Business and Economic Statistics*, 546-554.

9. Dias, L. T., & Dias, A. C. (2017). Money talks - Nowcasting real economic activity with payment systems data. International Statistical Institute - Regional Statistics Conference.

10. Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics, 13*(3), 253-263.

11. Duarte, C., Rodrigues, P. M., & Rua, A. (2017). A mixed frequency approach to the forecasting of private consumption with ATM/POS data. *International Journal of Forecasting*, 61-75.

12. Esteves, P. S. (2009). Are ATM/POS data relevant when nowcasting private consumption? *Banco de Portugal Working Papers*, No 25.

13. European Commission. (2018, August 21). Eurostat. Retrieved from Eurostat Glossary: https://ec.europa.eu/eurostat.

14. Foroni, C., & Marcellino, M. (2013, February). A Survey of Econometric Methods for Mixed-Frequency Data. *European University Institute - Working Papers.*

15. Foroni, C., Marcellino, M., & Schumacher, C. (2011). UMIDAS: MIDAS regressions with unrestricted lag polynomials. *Deutsche Bundesbank Discussion Papers*, No 35.

16. Galbraith, J. W., & Tkacz, G. (2015). Nowcasting GDP with electronics payment data. *ECB Statistics Paper Series*, No 10.

17. Ghysels, E., & Marcellino, M. (2018). *Applied Economic Forecasting Using Time Series Methods*. New York: Oxford University Press.

18. Ghysels, E., Santa-Clara, P., & Volkanov, R. (2004, May). The MIDAS Touch: Mixed Data Sampling Regression Models. *CIRANO Scientific Series*.

19. Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 665-676.

20. Gil, M., Javier J. Perez, A. J., & Urtasun, A. (2018). Nowcasting Private Consumption: Traditional Indicators, Uncertainty Measures, Credit Cards and some Internet Data. *Banco de Espana Working Paper*, No. 1842.

21. Heinisch, K., & Scheufele, R. (2018). Bottom-up or direct? Forecasting German GDP win a data-rich environment. *Empirical Economics*, 705-745.

22. Jansen, J., Jin, X., & Winter, J. d. (2012, December). Forecasting and nowcasting real GDP: Comparing statistical models and subjective forecasts. *De Nederlandsche Bank Working Paper*, No. 365.

23. Kindberg-Hanion, G., & Sokol, A. (2018). Gauging the globe: the Banks's approach to nowcasting world GDP. *Quarterly Bulletin* 2017Q2.

24. Kuzin, V., Marcellino, M., & Schumacher, C. (2013). Pooling versus model selection for nowcasting GDP with many predictors: empirical evidence from six industrialized countries. *Journal of Applied Econometrics*, 392-411.

25. Schumacher, C. (2016). A comparison of MIDAS and bridge equations. *International Journal of Forecasting*, 257-270.

26. Stock, J. H., & Watson, M. W. (2002). Macroeconomic Forecasting using Diffusion Indexes. *Journal of Business and Economic Statistics, 20*(2), 147-162.

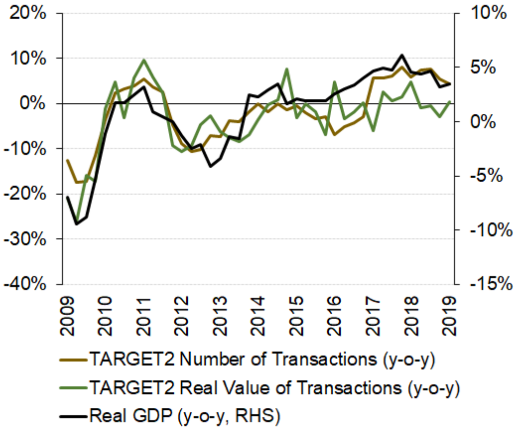
27. Verbaan, R., Bolt, W., & Cruijsen, C. v. (2017). Using debit card payments data for nowcasting Dutch household consumption.

Appendices

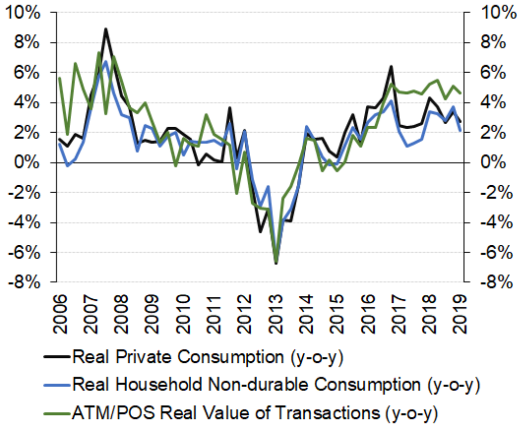
A Growth dynamics of payment data and target variables and testing sample period

Figure A.1: Growth rates (y-o-y) of payment data and target variables

(a) GDP and TARGET2 payment data



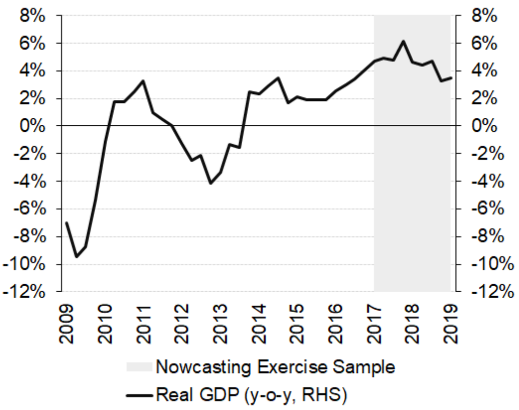
(b) Private Consumption and ATM-POS payment data



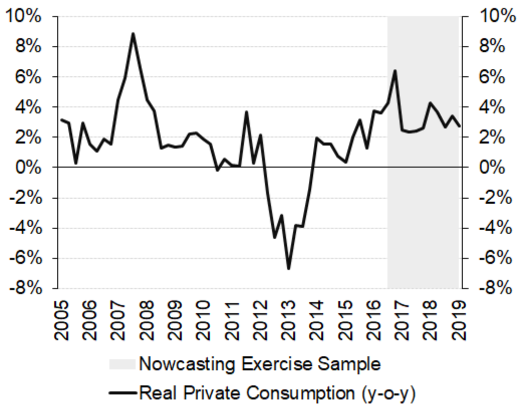
Source: *Bank of Slovenia, SORS.*

Figure A.2: Growth rates (y-o-y) of target variables and testing sample periods

(c) GDP (y-o-y)



(d) Private Consumption (y-o-y)



Source: *Bank of Slovenia, SORS.*

B Datasets

Table B.1: Indicators used for nowcasting GDP

nr	category	description	source	transf.
1	Production	Industrial Production - Total	SORS	2
2	Sales	Retail Trade Turnover	SORS	2
3	Sales	Services Trade Turnover	SORS	2
4	Survey	Economic Sentiment Indicator	EUROSTAT	1
5	Survey	Industry-Composite	EUROSTAT	1
6	Survey	Retail-Expected business situation	EUROSTAT	1
7	Survey	Services-Composite	EUROSTAT	1
8	Survey	Construction-Composite	EUROSTAT	1
9	Survey	Consumers-General economic situation	EUROSTAT	1
10	Labour	Registered Unemployment Rate	SORS	1
11	Trade	Imports-All countries of the world	SORS	2
12	Trade	Exports-Extra EA	SORS	2
13	Payment	TARGET2 Transaction Number	Bank of Slovenia	2
14	Payment	TARGET2 Transaction Volume	Bank of Slovenia	2

***Note**: Transformation:* 0 = *no change,* 1=*first difference,* 2 = *first log difference.*

Table B.2: Indicators used for nowcasting Private Consumption

nr	category	description	source	transf.
1	Sales	Retail Trade Turnover	SORS	2
2	Sales	Services Trade Turnover	SORS	2
3	Survey	Economic Sentiment Indicator	EUROSTAT	1
4	Survey	Consumers-General economic situation	EUROSTAT	1
5	Labour	Persons in paid employment	SORS	2
6	Labour	Average monthly income	SORS	2
7	Other	Car registrations	SORS	2
8	Payment	ATM/POS Transaction Value	Bank of Slovenia	2

***Note**: Transformation:* 0 = *no change,* 1=*first difference,* 2 = *first log difference.*

C Informations sets

Table C.1: Information sets available for nowcasting GDP

q_t	Production	Sales	Survey	Labour	Trade	Payment	GDP
$m1_t$	$m2_{t-1}$	$m3_{t-1}$	$m1_t$	$m2_{t-1}$	2_{t-1}	$m1_t$	q_{t-2}
$m2_t$	$m3_{t-1}$	$m1_t$	$m2_t$	$m3_{t-1}$	$m3_{t-1}$	$m2_t$	q_{t-1}
$m3_t$	$m1_t$	$m2_t$	$m3_t$	$m1_t$	$m1_t$	$m3_t$	q_{t-1}

Note: *Information sets pertain to information available at the last day of a particular month m for a given quarter q.*

Table C.2: Information sets available for nowcasting private consumption

q_t	Sales	Survey	Labour	Other	Payment	PCR
$m1_t$	$m3_{t-1}$	$m1_t$	$m2_{t-1}$	$m3_{t-1}$	q_{t-1}	q_{t-2}
$m2_t$	$m1_t$	$m2_t$	$m3_{t-1}$	$m1_t$	q_{t-1}	q_{t-1}
$m3_t$	$m2_t$	$m3_t$	$m1_t$	$m2_t$	q_{t-1}	q_{t-1}

Note: *Information sets pertain to information available at the last day of a particular month m for a given quarter q.*

D Empirical results based on complete information sets

Table D.1: GDP - Relative RMSFEs of nowcasting models against baseline models

Models	Included	$m1$	$m2$	$m3$
Pooled Bridge				
BRIDGE-TI	TI	*0.960*	*0.832*	*0.752**
BRIDGE-$T2N$	TI, T2N	*0.975*	*0.846*	*0.710**
BRIDGE-$T2V$	TI, T2V	*0.983*	*0.852*	*0.769**
BRIDGEAR-TI	TI, AR	*0.881*	*0.784**	*0.728***
BRIDGEAR-$T2N$	TI, T2N, AR	*0.891*	*0.795**	*0.695***
BRIDGEAR-$T2V$	TI, T2V, AR	*0.894*	*0.797**	*0.740***
Pooled UMIDAS				
UMIDAS-TI	TI	*0.936*	*0.828*	*0.756**
UMIDAS-$T2N$	TI, T2N	*0.946*	*0.832*	*0.710**
UMIDAS-$T2V$	TI, T2V	*0.958*	*0.844*	*0.770*
UMIDASAR-TI	TI, AR	*0.879**	***0.719*****	*0.661***
UMIDASAR-$T2N$	TI, T2N, AR	*0.887**	*0.728***	***0.636*****
UMIDASAR-$T2V$	TI, T2V, AR	*0.883**	*0.730***	*0.669***
Pooled MIDAS				
MIDAS-TI	TI	*0.907*	*0.782*	*0.788*
MIDAS-$T2N$	TI, T2N	*0.906*	*0.790*	*0.705**
MIDAS-$T2V$	TI, T2V	*0.928*	*0.801*	*0.797*
MIDASAR-TI	TI, AR	***0.864****	*0.740***	*0.715***
MIDASAR-$T2N$	TI, T2N, AR	*0.871**	*0.750***	*0.669***
MIDASAR-$T2V$	TI, T2V, AR	*0.871**	*0.750***	*0.717**

Source*: Own calculations.*
Note*: TI- traditional indicators, AR-autoregressive term, T2N – number of TARGET2 transactions, T2V – volume of TARGET2 transactions.* 1^{st}, 2^{nd} *and* 3^{rd} *month columns pertain to relative RMFSE of models based on information sets available up to the last day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively. Best performing models highlighted in bold.*

Table D.2: Private consumption - Relative RMSFE of nowcasting models against baseline models

Models	Included	$m1$	$m2$	$m3$
Pooled Bridge				
BRIDGE-TI	TI	*0.965*	*0.955*	*0.865**
BRIDGE-AP	TI, AP	*0.911*	*0.906*	*0.835**
BRIDGEAR-TI	TI, AR	*0.960*	*0.950*	*0.846**
BRIDGEAR-AP	TI, AP, AR	*0.910*	*0.905*	*0.822***
Pooled UMIDAS				
UMIDAS-TI	TI	*0.906**	*0.877**	*0.856**
UMIDAS-AP	TI, AP	*0.850**	*0.817***	*0.820***
UMIDASAR-TI	TI, AR	*0.899**	*0.860***	*0.831***
UMIDASAR-AP	TI, AP, AR	***0.848****	***0.809*****	*0.799***
Pooled MIDAS				
MIDAS-TI	TI	*0.949*	*0.918**	*0.837***
MIDAS-AP	TI, AP	*0.872**	*0.864**	*0.797***
MIDASAR-TI	TI, AR	*0.930*	*0.912**	*0.819***
MIDASAR-AP	TI, AP, AR	*0.865**	*0.863**	***0.794*****

Source*: Own calculations.*

Note*: TI- traditional indicators, AR-autoregressive term, AP – ATM/POS volume of transactions.* 1^{st}, 2^{nd} *and* 3^{rd} *month columns pertain to relative RMFSE of models based on information sets available up to the 30th day of the respective month. Full quarter assumes availability of all information for all three months. *. **, *** indicate statistical significance at 1, 5 and 10 percent respectively. Best performing models highlighted in bold.*