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Using National Payment System Data to Nowcast Economic Activity in Azerbaijan

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Abstract

This study examines whether payment system data can be useful for tracking economic activity in Azerbaijan. We utilise the transactional payment system data at the sectoral level and employ a Dynamic Factor Model (DFM) and Machine Learning (ML) techniques to nowcast quarter-over-quarter and year-over-year nominal gross domestic product. We compared the nowcasting performance of these models against the benchmark model in terms of the out-of-sample root mean square error at three different horizons during the quarter. The results suggest that ML and DFM models have higher predictability than the benchmark model and can significantly lower nowcast errors. Although our payment time series is still too short to obtain statistically robust results, the findings indicate that variables at a higher frequency in such data can be helpful in assessing the current state of the economy and have the potential to provide a faster estimate of the economic activity.

Keywords: payment data, nowcasting, ML, DFM

JEL: C32, C38, C52, C53, E42

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The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Central Bank of the Republic of Azerbaijan.

1 Introduction

Considerable delays in the official release of gross domestic product (GDP) data lead, among others, to uncertainty about the ongoing state of the economy, which may hamper policy decisions. In the current context of growing economic uncertainty in the global economy, including the impact of the coronavirus disease 2019 pandemic, the need for timely monitoring of economic activity has become even more important. In Azerbaijan, the official GDP is released quarterly, with a lag of approximately three months, and undergoes multiple revisions that necessitate the use of alternative methods for the current state assessment and short-term forecasting. These forecasts need to be as accurate as possible because real-time decisions depend on them. Therefore, policymakers and forecasters are interested in alternative indicators that can reduce forecast errors. In this case, there is a clear demand for more timely information, such as payment system data.

Payment systems data provides a unique source of information about the current state of the economy and specific sectors, as economic activity is based on the exchange of goods and services, either with cashless payment instruments or banknotes. Although cash payments constitute a significant share of total payments in Azerbaijan, no transactional data are available for measuring economic activity.[1] However, payment systems data are timely and available at high frequency, are precise (carry no sampling or measurement error), and comprehensive, as they cover a broad range of financial activities across sectors. Thus, payment transactions are a unique information source that can improve the policy decision-making process.

In this study, we combined Azerbaijani payment system data with a dynamic factor model and machine learning (ML) techniques to obtain a rough estimate of whether this method has the potential to yield faster estimates of domestic economic activity than at a quarterly frequency. First, we used comprehensive and timely settlement data from the real-time gross settlement system (AZIPS) managed by the Central Bank of the Republic of Azerbaijan. The AZIPS typically involves large value interbank transactions and is one of the main components of the national payment system, where each transaction is recorded along with its unique taxpayer identification number (TIN) for both the sender and recipient sides of the transaction. The highly disaggregated data structure enables us to identify the sectoral classification of each transaction. Over time, and with sufficiently long time-series (which are not yet available today), it has become possible to nowcast GDP and track economic activity for each sector of the domestic economy throughout the quarter in real time.

We used the dynamic factor model (DFM) and the following two ML models: LASSO and random forest. The DFM can effectively handle a large number of predictors by capturing the common dynamics of a set of predictors in a relatively small number of latent factors. ML models are useful for handling multicollinearity in the data, as there is a high correlation between sectoral payment flow data (Chapman and Desai, 2021) and for capturing sudden shifts and nonlinear effects of changes in economic activity during periods of high uncertainty, such as pandemics.

[1] As the end of 2021, approximately 63 percent of all transactions are settled in cash in Azerbaijan.

Although our payment time series is still too short to obtain statistically robust results with the chosen analytical methods, we proceed as if they were sufficiently long. We target both quarter-over-quarter (QoQ) and year-over-year (YoY) nominal GDP growth rates and use sectoral payment data weighted by GDP as predictors. We produce a nowcast three times per quarter as new information is available for each month. This approach allows us to estimate the current quarter GDP from the beginning of the second month of the quarter and to evaluate the marginal impact of each new data release throughout the quarter on the nowcast and its accuracy.[2]

Although the time series is short and hence, gives statistically inconclusive results, we aim to contribute to the literature in the following ways. To our knowledge, this is the first attempt to nowcast GDP by using disaggregated sectoral payment flow data. Most studies have examined the predictive content of payment flows either on an aggregated basis or by combining different payment streams (i.e. debit or credit card transactions and POS payments). Because the highly detailed structure of the AZIPS data allows us to identify the sectoral classification of each transaction (through TIN), we can utilise the informational content of each sectoral payment record and their corresponding contribution to nowcasting GDP. Additionally, considering the high nowcasting potential of payment flow data, this study is the first attempt to assess the ability of payment data to make accurate short-term forecasts by focusing on Azerbaijan.

The remainder of this paper is organised as follows. Section 2 reviews existing literature on this topic. Section 3 describes the payment system data and presents the data preparation for macroeconomic predictions. Section 4 provides a brief overview of various methods employed for nowcasting, and Section 5 discusses the results. Finally, Section 6 concludes the paper.

2 Literature Review

Aprigliano, Ardizzi, and Monteforte (2019) predict economic activity using high-frequency payment data in Italy. Different aggregates of payment data jointly with other macroeconomic indicators (industrial production and business surveys) were selected using LASSO, and the results showed that the contribution of payment system flows improves the forecasting accuracy. Moreover, the mixed-frequency factor model with retail payment flows outperforms the benchmark model, which only uses standard short-term indicators in terms of forecasting accuracy.

Maehashi and Shintani (2020) discussed various factor models and machine learning methods based on the data on monthly observations of a large set of Japanese macroeconomic time series from 1973 to 2018 to nowcast several target variables, including industrial production, unemployment rate, and real household consumption expenditure. Their results suggest that factor and machine learning models perform better than the conventional AR models in many cases; in particular, machine learning methods provide more precise predictions for a longer time- horizons.

[2] Transactional payment data for each month is available within the 3 days of the following month.

Richardson et al. (2020) assessed the accuracy of nowcasts of real GDP growth for New Zealand using common machine learning methods in real-time. Using numerous vintages of historical GDP data and approximately 600 domestic and international variables, they estimated the number of ML models from 2009–2019. They found that the ML models produced more accurate forecasts as compared to a dynamic factor model, a naive AR benchmark, and the official Reserve Bank of New Zealand projections.

Chapman and Desai (2021) combined ML models with timely payment system data for macroeconomic nowcasting. They applied a Shapley value-based technique for model interpretability and a slightly altered version of the cross-validation strategy to avoid overfitting the nowcasting model. They found that ML models and data from the payment system can dramatically reduce the number of nowcast errors compared with the linear benchmark models. There is a Root Mean Square error (RMSE) reduction of up to 40 % compared to the linear benchmark for nowcasting GDP, retail and wholesale trade sales.

3 Payments Data

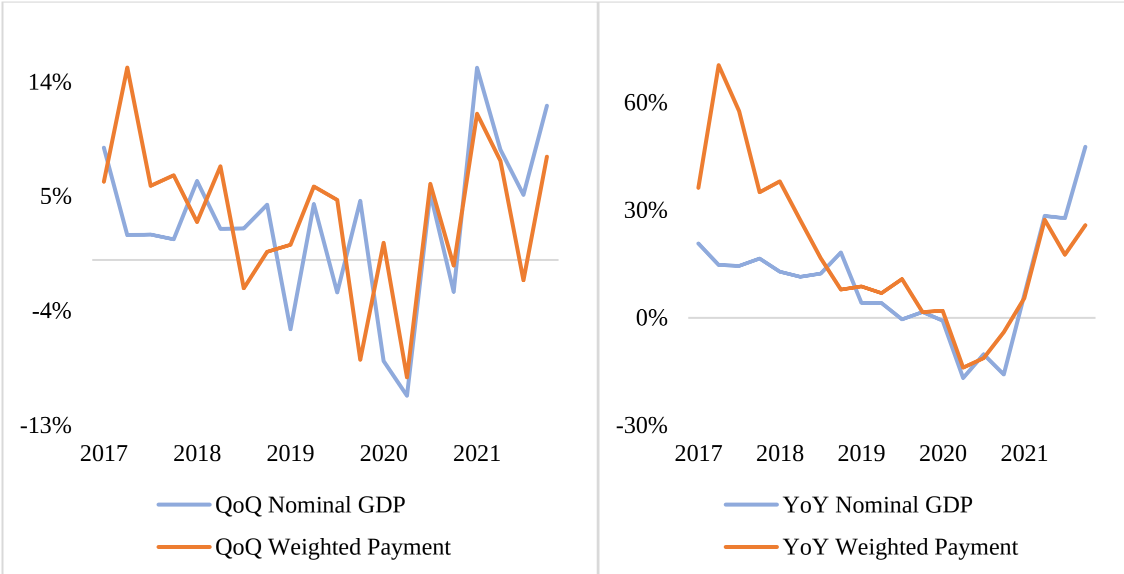
In Azerbaijan, AZIPS and the Low-Value Payments Clearing and Settlement System (LVPCSS) managed by the central bank are used to settle the transactions. The AZIPS typically involves large-value interbank transactions, whereas the LVPCSS is a clearing system for small-scale non-instant payments. In this study, we use the AZIPS payments dataset because data from the LVPCSS are only available from 2018 onwards. In 2021, it recorded an average of 4,308 transactions per business day, with an average value of 480 million manats (over 280 million USD). The aggregate nominal value of these transactions in 2021 is 115.7 billion manats, equivalent to 135 % of the national GDP. The dataset includes information on the value, date, and currency of the transaction as well as the TIN for both the sender and the recipient.

We include individual-to-firm (or legal person) and firm-to-firm (or legal person) transactions in constructing the dataset. Once the information is extracted, the corresponding economic classification (ISIC Rev. 4) is identified using the TIN of each transaction record. To replicate the sectoral decomposition of GDP, we weigh each sectoral payment flow data point with its corresponding time-varying share in the system of national accounts GDP data. The daily payment flows aggregated at the sectoral level were corrected for outliers.[3]

The following figures (Figure 1) illustrate the relationship between quarterly GDP and total weighted payment flows.[4]

[3] Outliers are corrected to reduce the distortionary impact of very large payments (extreme, unusual, one-off payments). For each sector, the smallest (lower than the 5 % quantile of the series) and the largest values (higher than 95 % quantile) are detected and then replaced by their less extreme values, 5th percentile and 95th percentile, respectively.
[4] Both data series are seasonally adjusted. Share of value-added in GDP by type of economic activity is used in calculating the weighted sum of sectoral payment flows.

Figure 1. The correlation between GDP growth rate and growth rate of payments data



While we observed a weak correlation for the initial years, the correlation between the two-time series became stronger for the later observations. More precisely, the correlation between the year-over-year (YoY) growth rate of nominal GDP and weighted payment flows increases from 0.55 to 0.88 for years before and after 2019, respectively. Particularly, in times of stress or uncertainty, such as the lockdown periods during pandemics, recovery, and subsequent normalisation since the beginning of 2021, payment inflows seem promising in capturing the dynamics of the economy.

Table 1 compares the sectoral payment inflows against the sectoral decomposition of GDP provided by the State Statistics Committee of the Republic of Azerbaijan. While a few sectors such as agriculture, mining, and quarrying and real estate activities are underrepresented by payment inflows, overall, the total amount of transactions provided by payment inflows in 2021 are comparable and informative in terms of explaining sectoral GDP.

Table 1. GDP and Payment inflows by sector in 2021 (in million AZN): AZIPS vs State Statistics Committee of the Republic of Azerbaijan (SSCRA)

Sector	Sector Name	Payment inflows	Sectoral allocation of GDP (SSCRA)	Payment inflows as a share of sectoral GDP
A	Agriculture; forestry and fishing	499.0	5,456.8	9.1%
B	Mining and quarrying	5,992.6	31,931.1	18.8%
C	Manufacturing	5,722.4	6,337.1	90.3%
D	Electricity; gas, steam and air conditioning supply	2,173.3	1,018.1	213.5%
E	Water supply; sewerage, waste management	497.8	211.3	235.6%
F	Construction	7,958.6	5,470.9	145.5%
G	Wholesale and retail trade; repair of motor vehicles	8,264.4	9,422.2	87.7%
H	Transportation and storage	1,888.8	6,397.1	29.5%
I	Accommodation and food service activities	263.4	1,164.0	22.6%
J	Information and communication	1,649.4	1,632.5	101.0%
K	Financial and insurance activities	51,977.4	1,639.0	3171.3%
L	Real estate activities	596.4	4,196.0	14.2%
O	Public administration and defence; social security	21,332.1	3,197.1	667.2%
P	Education	620.8	2,970.5	20.9%
Q	Human health and social work activities	1,046.5	2,101.3	49.8%
	Other activities	5,243.2	2,220.2	236.2%
	Total	**115,726.2**	**85,365.2**	**135%**

For nowcasting exercises, we use both YoY and QoQ nominal GDP growth rates at the latest available vintages as target variables. Because QoQ GDP and payment system data have a strong seasonal component, we adjust these series for seasonality using the Tramo-Seats tool.[5] Both the YoY and seasonally adjusted QoQ payment series are used to predict YoY and the similarly adjusted QoQ GDP growth rate.

Sectoral payment data are represented by the 19 value-added sectors of the economy along with the cash-to-card variable. Table 2 provides a short description of the variables used in the model. The sectoral payment data are weighted by GDP for a better representation of sectoral GDP.[6] The cash-to-card variable is the ratio of all cash transactions to transactions made with debits and credit cards. Cash transactions are the sum of cash withdrawals via ATM and POS, while debit and credit card transactions are the total non-cash payments made through POS, ATM,

[5] Tramo-Seats implements the ARIMA model-based seasonal adjustment method developed by Gomez and Maravall (1996).
[6] Weights are derived from the State Statistical Committee of the Azerbaijan Republic. See appendix (Table 6) for time-varying share of sectoral GDP.

and e-commerce. Both variables are derived from the monthly payment indicator dataset of the CBAR.[7] The reason for including cash-to-card variables in the dataset is to control for sudden changes in the payment behaviour (i.e., a shift from cash payments to cashless payments), as the number and volume of transaction records may rise or fall for various reasons other than overall economic activity.

Table 2. List of variables included in the nowcasting model

Variables	Short description	Delay (days)
A	Payment in agriculture, forestry and fishing sector	3
B	Payment in mining and quarrying sector	3
C	Payment in manufacturing sector	3
D	Payment in production, distribution and supply of electricity, gas and steam	3
E	Payment in water supply, waste management and manufacturing	3
F	Payment in construction sector	3
G	Payment in trade sector	3
H	Payment in transportation and storage sector	3
I	Payment in accommodation of tourists and public catering sector	3
J	Payment in information and communication sector	3
K	Payment in financial sector	3
L	Payment in real estate transactions	3
M	Payment in professional, scientific and technical activities	3
N	Payment in provision of administrative and support services	3
O	Payment in state management and protection, social security	3
P	Payment to education sector	3
Q	Payment in provision of health and social services to the population	3
R	Payment in activities in the field of leisure, entertainment and art	3
S	Payment in other	3
Cashtocard	The ratio of total cash payments to total card transactions	3

4 Methodology

This section describes the model specifications and cross-validation techniques employed. We also discuss the dynamic factor model (DFM) followed by a brief description of the machine learning (ML) models.

[7] https://www.cbar.az/page-45/payment-system-indicators

4.1 Model Specifications

We perform nowcasting at three monthly time horizons extending from the start of the first month of the quarter until the end of the third month of the quarter. First, the cumulative average of the daily payment inflows was calculated for each month of the quarter. For example, for the first month of the quarter, we calculate the average daily payment inflows for that month, and for the second month of the quarter, the average daily payment inflows are calculated for the first two months of the quarter. The empirical specification takes the following form for each monthly GDP nowcast during the quarter:

Month 1: $\Delta GDP_{Q_t} = \alpha + \sum_{j=1}^{19} B_j \Delta S_{j,Q_{t_1}} + \Theta_1 \Delta cashtocard_{Q_{t_1}} + \varepsilon_{Q_{t_1}}$

Month 2: $\Delta GDP_{Q_t} = \alpha + \sum_{j=1}^{19} B_j \Delta S_{j,Q_{(t_1,t_2)}} + \Theta_2 \Delta cashtocard_{Q_{(t_1,t_2)}} + \varepsilon_{Q_{(t_1,t_2)}}$

Month 3: $\Delta GDP_{Q_t} = \alpha + \sum_{j=1}^{19} B_j \Delta S_{j,Q_{(t_1,t_2,t_3)}} + \Theta_3 \Delta cashtocard_{Q_{(t_1,t_2,t_3)}} + \varepsilon_{Q_{(t_1,t_2,t_3)}}$

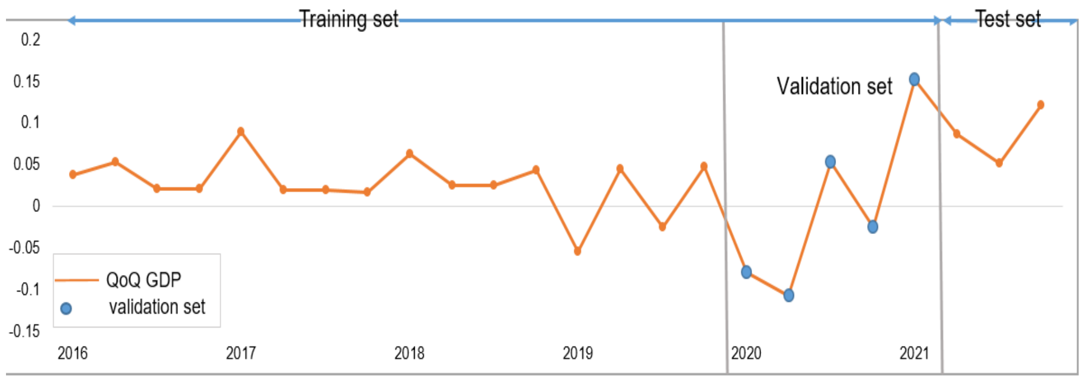
Here, ΔGDP_{Q_t} is the growth rate of nominal GDP at quarter t. t_1, t_2 and t_3 indicating the first, second, and third month of the quarter; $\Delta S_{j,Q_{t_1}}, \Delta S_{j,Q_{(t_1,t_2)}}, \Delta S_{j,Q_{(t_1,t_2,t_3)}}$ is the growth rate of average payment inflows in sector j at the first, second, and third month of the quarter, respectively; $\Delta cashtocard$ is the growth rate of cash to card ratio, α, B, Θ are the vector of unknown parameters to be estimated; and ε is the error term.

4.2 Cross-Validation Technique

The main task of predictive modelling is related to the process of using the available data to minimise the loss (out-of-sample error) that a model will incur on the unseen data. One of the most commonly encountered problems in these models is overfitting which is a model that fits well against its training set but results in poor performance on the unseen data. Cross-validation (CV) is one of the most common techniques used for solving overfitting problems. The standard approach is to randomly split the sample into k-folds, where k-1 folds are utilised for in-sample training, and the k^{th} fold is used for out-of-sample testing for each iteration. Thus, each sample is used in the hold-out sample once and used to train the model k-1 times. This approach is the most suitable for independent and identically distributed (i.i.d) observations. However, serial correlation and non-stationarity in the time-series data make the use of CV problematic. Additionally, future information should not be used to predict the past.

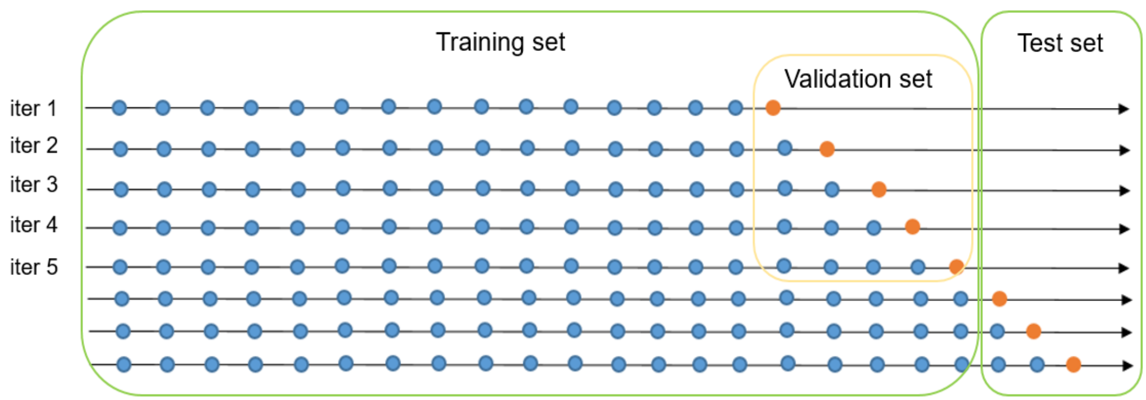
An alternative method that we employ is the expanding window approach. In this approach, the end part of the training set was kept aside for the validation set for model tuning and cross-validation, whereas the test set was used for the evaluation of the model performance. Figure 2 illustrates the expanding window approach for cross-validation in time series where the data from the second quarter of 2016 to 2019 were used for training, and observations from 2020 to the first quarter of 2021 were utilised for parameter tuning and cross-validation. For each iteration of the expanding window, the training sample was increased by one period, and the model prediction was performed in the next period from the validation sets (Figure 3). In this way, we can deal with the temporal correlation between the consecutive values of the time series and account for the dependency among the observations.

Figure 2. Expanding window approach for cross-validation.



At the end of this step, when iterating over the validation set, a few selected hyperparameters for each model were tuned using cross-validation. In the second step, the tuned models were used for prediction by reutilising the expanding window approach over the training and testing sets.

Figure 3. Schematic of five-fold expanding window approach for training, cross-validation, and out-of-sample prediction[8]



The payment data used for the nowcasting exercises ranged from January, 2017 to December, 2021 for YoY nowcasting, and from April, 2016 to December, 2021 for QoQ nowcasting. The in-sample training period was January, 2017 to March, 2021 (n = 17) for YoY nowcasting and April 2016 to March 2021 (n = 20) for QoQ nowcasting. The out-of-sample testing period for both YoY and QoQ nowcasting was from April, 2021 to December, 2021 (n = 3). Our

[8] The available dataset is divided into a training set, validation set, and testing set. In each fold, the blue dot represents the training set and the orange dot represents the next period prediction.

training set includes the COVID-19 crisis period which allows us to examine the model performance during crisis periods.

The AR and DFM models were directly trained on the training set and used to evaluate the test set. The ML models, which required extensive hyperparameter tuning and cross-validation, were trained using the following procedure:

1. We split the dataset into training and test sets (Figure 2). The training set was from April, 2016 to March, 2021, and the test set was from April, 2021 to December, 2021.
2. The last five quarters of the training set were set aside from the validation set (highlighted in blue in Figure 2). To include the pandemic period, we chose the dates between January, 2020 and March, 2021.
3. Using the trained model, we predicted selected sample points in the validation subset. Each time, we expanded the training set by one period.
4. After finishing iterating the chosen validation subset, we compute the validation RMSE.
5. We select the parameters for which the average validation RMSE is the smallest.
6. The tuned model was used to obtain the RMSE for the testing set, as illustrated in Figure 3.

4.3 Dynamic Factor Model

DFMs are based on the fundamental idea that many economic variables that exhibit similar trends over time can be described by a small number of common factors. This can act as a dimension reduction technique by estimating a small set of dynamic factors from a large set of observed variables. DFM assumes that many observed variables are driven by a few unobserved dynamic factors.

We implement the approach proposed by Giannone et al. (2008) together with the maximum likelihood estimation methodology of Banbura and Modugno (2014). This approach can handle arbitrary patterns of missing data. The key idea is to write the likelihood as if the data were complete and to fill in the missing data in the expectation step. In the second step, using the parameters estimated in the first step, an updated estimate of the common factors was obtained using the Kalman smoother. Considering the uncertainty that the factors have been estimated in each round, the maximum likelihood estimate was obtained by iterating the two steps until the convergence. An additional advantage of the maximum likelihood approach is that it allows us to easily impose restrictions on the parameters. We use a block factor structure similar to that developed by Banbura et al. (2010). The basic representation of the model is as follows:

$$X_t = \Lambda f_t + \varepsilon_t$$

$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p} + \mathrm{u_t}, u_t \sim i.i.d. N(0, \delta^2)$$

$$\varepsilon_{i,t} = \alpha_i \varepsilon_{i,t-1} + e_{i,t}, e_{i,t} \sim i.i.d. N(0, \delta_i^2)$$

where X_t is the set of predictors at time t; f_t is the unobserved factor; Λ is the vector of factor loadings; ε_t is the idiosyncratic disturbance; A_i is the matrix of autoregression coefficients; and $\mathrm{u_t}$ is the factor disturbance at time t.

We estimate the model with three block factors and two lags (p = 2) in the vector autoregression (VAR), driving the dynamics of those factors and allowing the idiosyncratic components to follow an AR (1) process. The choice of the number of lags is based on a comparison of the out-of-sample forecasting performance of the alternative specifications, and the number of factors depends on the block structure.

Table 5 (Appendix) demonstrates the distribution of the blocks used in the DFM implementation. The blocks are the oil sector, tradable sector, and non-tradable sector blocks. The oil sector block includes payments to the economy's oil sector. The tradable sector blocks span payments in the agriculture, oil, manufacturing, electricity, and water supply sectors. Payments in the remaining sectors are included in non-tradable sector blocks. The cash-to-card variable is included in the non-tradable sector block because of its high correlation with the sectoral payment inflows involved in this block.

4.4 ML Models

We used two popular parametric and non-parametric ML models: elastic net (LASSO) and random forest.

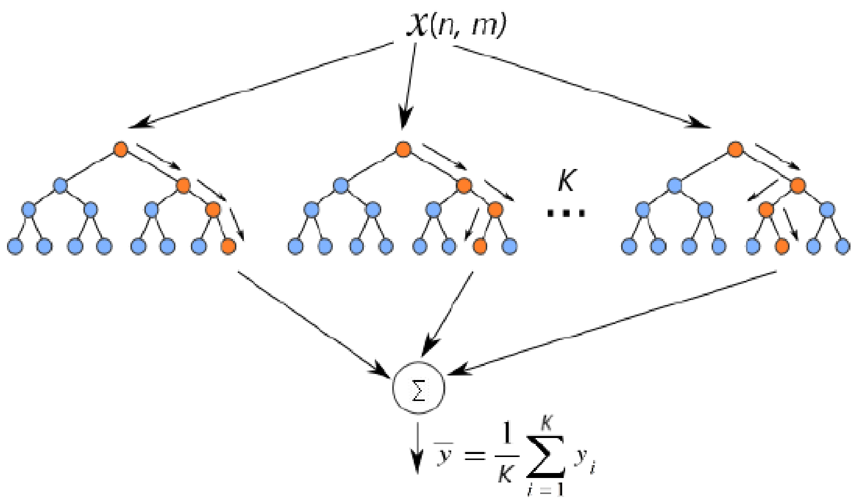
The elastic net is a regularised linear regression model, which is similar to the ordinary least squares (OLS) regression along with the addition of L_1 and L_2 penalties. In this study, we focus on a regression model that uses only L_1 penalty. This is called Least Absolute Shrinkage and Selection Operator (LASSO) regression. The fundamental idea of this methodology is to produce models in which the parameters of irrelevant variables are projected to be exactly zero, leading to a variable selection setting. This is particularly suitable for our case because of the small sample size and the relatively large number of variables. The minimisation problem of LASSO can be expressed as follows:

$$\beta^{LASSO} = argmin\{(y - X\beta)'(y - X\beta) + \lambda \sum_{j=1}^{K} |\beta_j|\}$$

where y is the dependent variable; X is the vector of explanatory variables; β is the vector of unknown coefficients, and λ is the shrinkage penalty.

Another method that we employ is random forest regression (RF). RF is based on bootstrap aggregation or bagging decision trees. In RF, we first obtain B bootstrapped training sets from the original data, and then fit a decision tree to each bootstrapped training set. Each tree was built independently from a subset of the training dataset. This is performed to reduce the variance while improving the prediction performance of the decision trees. Only a random sample of variables is considered in each split so that the fitted trees are dissociated from each other. The final prediction was performed by averaging the predictions of all the regression trees (Breiman, 2001; Liaw and Wiener, 2002).

Figure 5. Random forest with K trees using n samples and m features for each tree



Source: Chapman and Desai, 2021

The procedure is illustrated in Figure 5. A random subset of the sample and features are incorporated to build decision trees that can help reduce the variance in the predictions. RF can help deal with the non-linear interactions between multiple predictors and a target variable.

5 Empirical results

This section presents the results of nowcasting for the cases specified above. Each prediction was computed on the day following the end of each month, and we produced three predictions per quarter. As a benchmark, we used AR (1) as an autoregressive model. We then use the DFM to assess the marginal contribution of the payments data and test for the usefulness of the two ML models (LASSO and RF). Subsequently, we compared the performance of the ML models with the benchmark case and DFM. We used the RMSE as the key performance indicator for the out-of-sample model evaluation.

Tables 3 and 4 present the nowcasting performance in terms of out-of-sample RMSEs for the ML and DF models relative to the benchmark AR model at the first, second, and third months of the quarter, respectively.

Overall, the results show a reduction in RMSEs over the three months of the nowcasting horizons of the YoY and QoQ GDP growth rates. All the models indicate the lowest RMSE in the third month of the quarter once we have complete information on the current quarter. The results of QoQ nowcasting suggest that LASSO has the highest prediction accuracy at the third nowcast (month 3), whereas DFM performs better at the shorter end (months 1 and 2). Specifically, we observed approximately a 40.6 % reduction in the RMSE over the benchmark case in nowcasting QoQ GDP growth rate with the LASSO model in the third month (Table 3).

Next, we compared the ML models with the DFM. DFM contributes up to 31.3 % and 8.5 % reductions, respectively in the first and second months over LASSO. Conversely, we observed a 23.7 % reduction in RMSE over the DFM model in the third nowcast (month 3). The RF results showed highly volatile RMSEs compared to DFM and LASSO (Table 3).

Table 3. Out-of-sample RMSE for seasonally adjusted QoQ GDP growth rate relative to benchmark model (AR)[9]

Models	Month 1	Month 2	Month 3
DFM	0.90	0.99	0.78
ML:			
LASSO	1.31	1.08	**0.59**
Random Forest	0.98	1.04	0.8

Table 4 shows the out-of-sample RMSE of the DFM and ML models for the YoY GDP growth rate relative to the benchmark model. Similar to QoQ nowcasting, both DFM and LASSO performed better than the benchmark model when the information for three months of the quarter is available. In this case, DFM reduces nowcasting errors over the LASSO by 4.3 % and over the benchmark model by 30.3 % in month 3.

Table 4. Out-of-sample RMSE for YoY GDP growth rate relative to the benchmark model (AR)

Models	Month 1	Month 2	Month 3
DFM	1.17	1.5	**0.70**
ML:			
LASSO	1.06	0.97	0.73
Random Forest	1.17	1.14	1.13

Comparisons of in-sample and out-of-sample predictions of both QoQ and YoY GDP growth rates are shown in Figures 6 and 7, respectively. In both cases, nowcasting with payment data provides downturn and recovery indications with higher accuracy than the benchmark model in both in- and out-of-sample periods.

[9] A ratio of less than 1 indicates that the model has higher predictability than AR model.

Figure 6. Comparison of nowcasting models for QoQ GDP growth rate at month 1, month 2, and month 3

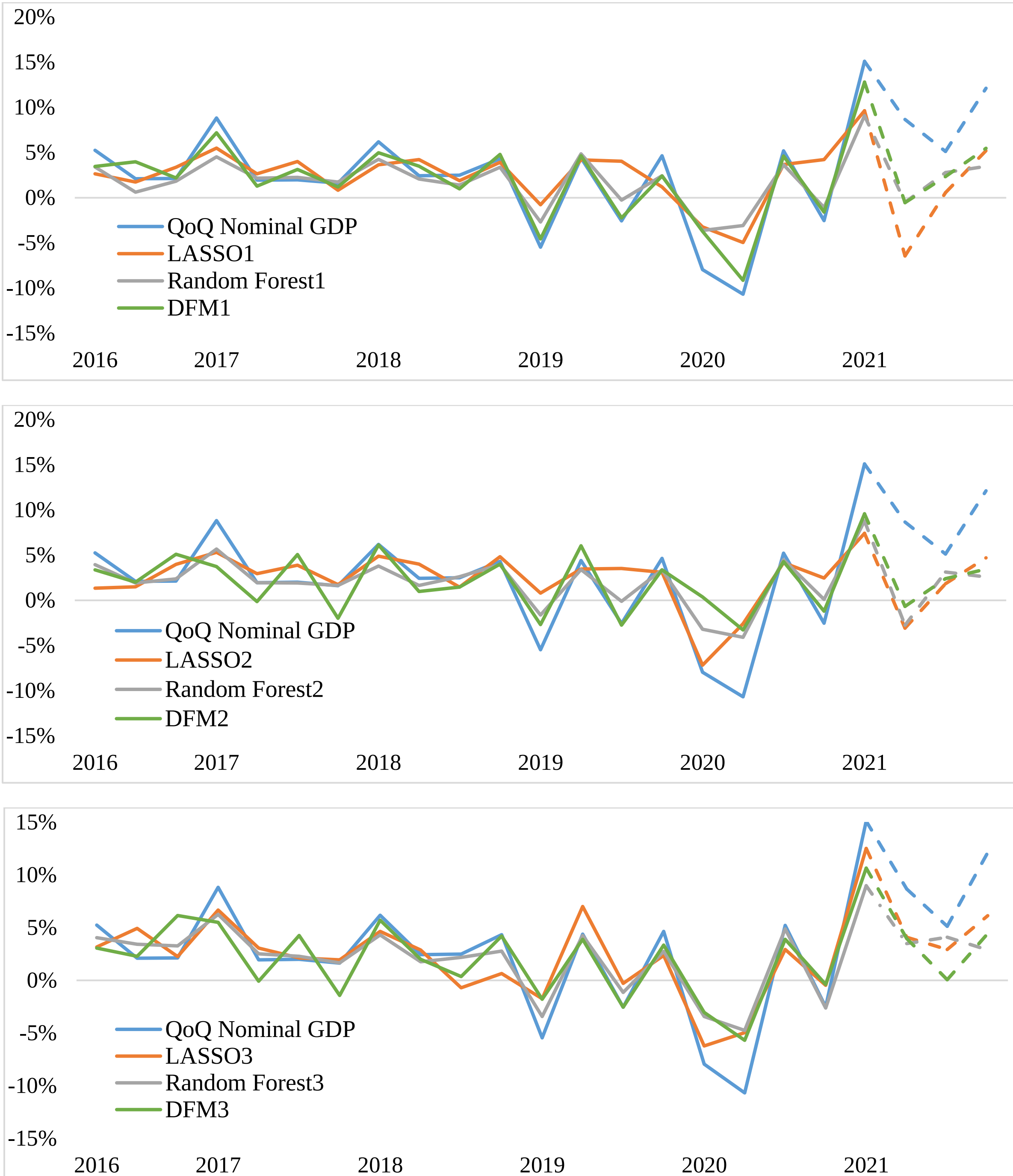
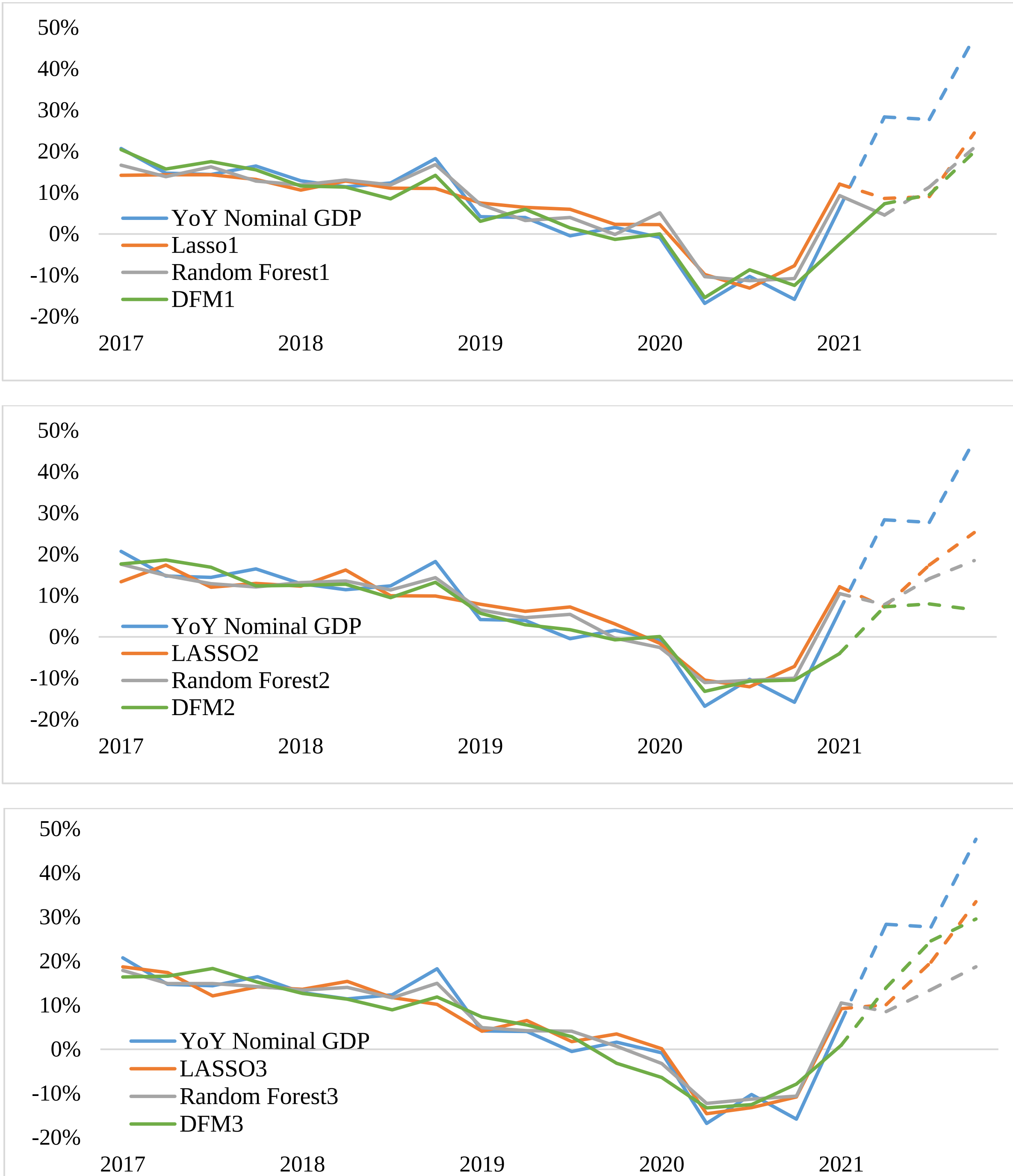


Figure 7. Comparison of nowcasting models for YoY GDP growth rate at month 1, month 2, and month 3



6 Conclusion

Tracking the current state of economic activity is crucial to policy and other decision-makers, as it can affect, for example, the implementation of countercyclical policies or short-term policy decisions. In this sense, the use of payment system data and the information they can convey concerning the economic outlook is gaining wide interest.

The purpose of this study was to assess whether payment flow data and, in particular, sectoral payment inflows, can help predict economic growth. Previous studies that have examined the predictive content of payment flow data have employed broad-based aggregated indices. However, we believe that some sectors are more closely linked to the business cycle than others.

In this study, we utilised timely sectoral national payment system data with DFM and ML models to nowcast economic activity in Azerbaijan. We contribute to the literature by showing first impressions of the potential forecasting power of sectoral payment flow data.

Although our sample spans only from 2016 to 2021 and thus, is too short for a robust evaluation, we examine the ‘forecast power’ with the out-of-sample nowcasts obtained recursively over the period 2021Q2-2021Q4. In this sense, we also employed a cross-validation technique with an expanding window approach to reduce overfitting and improve the prediction accuracy in the ML models.

Our results imply that using sectoral payment data might help increase the accuracy of nowcasting. All models show improvement in nowcast accuracy through the nowcasting horizons of months 1 to 3. We observed reductions in RMSE for the nowcasting QoQ GDP growth rate over the benchmark model when using LASSO and DFM. Additionally, LASSO appears to be the best alternative model for QoQ nowcasting in month 3 when informational content is improved. However, for YoY nowcasting in month 3, DFM shows the highest prediction accuracy as it reduces the nowcasting error over LASSO and the benchmark model. Nevertheless, the results should be taken with caution as the payment data are available only from 2016, and the estimations are based on a small number of quarterly GDP measurements to make a statistically conclusive statement.

Overall, the results suggest that sectoral payment data have the potential to help assess economic activity at a higher frequency, even during times of high uncertainty such as pandemics. Official quarterly GDP is released with a three-month delay in Azerbaijan, and timely available payment data make it possible to gain insights about the current state of the economy starting from the beginning of the quarter and provide a more accurate nowcast of GDP in the subsequent months towards the end of the quarter. Such timely nowcasting of economic activity provides a useful tool for policymakers to overcome the challenges associated with the uncertainty of the ongoing state of the economy and to help in decision-making in a fast-changing environment. Against this background, it makes sense for our work to be resumed in a few years and then with a longer data series. However, today, we must inevitably leave this task for future research.

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Appendix

Table 5. The distribution of Blocks

Data series	Short description	Blocks		
		Oil	Tradable	Non-tradable
Nominal GDP growth	Nominal GDP growth	1	1	1
A	Agriculture, forestry and fishing	0	1	0
B	Mining and quarrying	1	0	0
C	Manufacturing	0	1	0
D	Production, distribution and supply of electricity, gas and steam	0	1	0
E	Water supply, waste management and manufacturing	0	1	0
F	Construction	0	0	1
G	Trade	0	0	1
H	Transportation and storage	0	0	1
I	Accommodation of tourists and public catering	0	0	1
J	Information and communication	0	0	1
K	Financial sector	0	0	1
L	Real estate transactions	0	0	1
M	Professional, scientific and technical activities	0	0	1
N	Provision of administrative and support services	0	0	1
O	State management and protection, social security	0	0	1
P	Education	0	0	1
Q	Provision of health and social services to the population	0	0	1
R	Activities in the field of leisure, entertainment and art	0	0	1
S	Other	0	0	1
cash to card	The ratio of cash to card data	0	0	1

Table 6. Production share of GDP by sector (%)

Sectors	Description	2016	2017	2018	2019	2020	2021
A	Agriculture, forestry and fishing	5.6	5.6	5.2	5.7	6.9	5.9
B	Mining and quarrying	30.7	34.2	38.8	35.2	26.7	33.6
C	Manufacturing	4.9	4.7	4.6	5	5.8	5.1
D	Production, distribution and supply of electricity, gas and steam	1.2	1	1	1	1.1	1.0
E	Water supply, waste management and manufacturing	0.2	0.2	0.2	0.2	0.2	0.2
F	Construction	10.5	9.6	7.7	7.5	7.7	7.6
G	Trade	10.3	10.4	9.6	10	11.5	10.4
H	Transportation and storage	6.7	6.7	6.1	5.9	7.1	6.4
I	Accommodation of tourists and public catering	2.4	2.4	2.3	2.4	1.1	1.9
J	Information and communication	1.8	1.6	1.6	1.8	2	1.8
K	Financial sector	2.6	2.2	1.7	1.8	2.3	1.9
L	Real estate transactions	3.1	3	2.7	2.9	3.4	3.0
M	Professional, scientific and technical activities	1.4	1.5	1.4	1.6	1.8	1.6
N	Provision of administrative and support services	0.6	0.6	0.5	0.6	0.7	0.6
O	State management and protection, social security	2.9	2.9	2.7	3	4	3.2
P	Education	3.1	2.8	2.8	2.9	3.5	3.1
Q	Provision of health and social services to the population	1.8	1.6	1.6	1.7	2.5	1.9
R	Activities in the field of leisure, entertainment and art	0.9	0.9	0.7	0.7	0.8	0.7
S	Other	1.1	1.1	1	1.1	1.2	1.1