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NOWCASTING HOUSEHOLD CONSUMPTION IN AZERBAIJAN

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Nowcasting Household Consumption in Azerbaijan [1]

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Abstract

The paper investigates the performance of various combinations of the single predictor MIDAS models and DFM model to nowcast household consumption in Azerbaijan. We evaluate the out-of-sample forecasting performance at horizons of up to four quarters ahead. All models use the information on monthly indicators released ahead of quarterly household consumption. The results show that both DFM model and single predictor MIDAS models with high-frequency regressors of retail trade turnover and Google Trends (arts & entertainment, sports, travel, hobbies & leisure) outperform the univariate benchmark model for one quarter ahead forecast. However, in comparison with MIDAS models, DFM shows better forecast performance.

Keywords: nowcasting, household consumption, MIDAS, DFM

JEL classification: C32, C38, C52, C53, E21, E27

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Introduction

To make effective monetary and macroeconomic policy decisions, central bankers, policymakers, and economic agents require adequate and timely information about the current standing of the economy. However, it is challenging to make proper decisions due to considerable delays in the official release of the economic activity data. Macroeconomic indicators tend to be released with substantial delays, and this is especially true for the gross domestic product (GDP) and its components. To address this problem, policymakers have generally relied on simple forecasting models and judgment to estimate the current state of the economy, as well as that of the recent past. This process is now commonly referred to as nowcasting. Nowcasting is defined as the prediction of the present, the very near future for which no official data is yet available (Banbura et al., 2013). The term is a combination of the words "now" and "forecasting" and has been used for a long-time in meteorology and recently also in economics. The basic principle of nowcasting is the exploitation of the information, which is released early and possibly at higher frequencies than the target variable of interest to obtain an 'early estimate' before the official figure becomes available.

Nowcasting becomes important, especially in times of COVID-19 pandemic as immediate projections of main macroeconomic variables provide a valuable overview of the current economic situation. Since the pandemic of 2020 posed a challenge to traditional tools used by monetary authorities and policymakers, using big datasets of high-frequency indicators gained popularity among central banks.

Since private consumption accounts for approximately 60% of Azerbaijan's GDP, timely information on private household spending is important for assessing and predicting overall economic activity. Data on private household consumption for Azerbaijan are released quarterly and with a lag of approximately three months. There is numerous alternative, relevant, and timely information, which become available much sooner and usually at a higher frequency that can be used to nowcast household consumption. Given the importance of timely and reliable nowcasts, this paper aims to assess the usefulness of alternative sources of information and a mixed-frequency modeling approach in nowcasting the quarterly household consumption in Azerbaijan.

The paper introduces a new indicator for private consumption that is constructed using data on internet search behavior provided by Google Trends. Due to the increasing popularity of the internet, it is certain that a substantial number of people also use web search engines to collect information on goods and services they intend to buy. Data on search queries could be more related to the spending decisions of private households. While macroeconomic variables indicate consumers' ability and willingness to spend (Wilcox, 2007), the Google indicator intends to provide a measure for consumers' preparatory steps to spend by employing the volume of consumption-related search queries. Additionally, the paper makes use of payment data and other monthly macroeconomic indicators that are correlated with private consumption and evaluates whether the information content of such series improves the performance of nowcasting models.

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

Literature Review

The literature on nowcasting, particularly for GDP is quite vast, and the majority of papers employ two well-known models: Mixed Data Sampling (MIDAS) regressions and Dynamic Factor Models (DFM). The relatively new literature on nowcasting GDP growth in real-time is based on the study of Giannone, Reichlin, and Small (2008). They adopt a GDP forecast model incorporating factors from a large set of high-frequency predictors. The authors employ a DFM using approximately 200 macroeconomic indicators of the US economy over the period 1982-2005. The results indicate that compared with the benchmark model (Survey of Professional Forecasters relative to a naive constant growth model for GDP), the dynamic factor model has a higher forecasting accuracy and the use of monthly indicators is critical to enhancing the quality of forecasting. Furthermore, most survey indicators and labor market indicators are found to be essential for improving forecasting accuracy.

Given the focus of this paper, the following literature review highlights only studies on nowcasting household consumption. Compared with the literature on GDP nowcasting, the empirical studies on nowcasting household consumption are limited. A few empirical studies, undertaken predominantly by central banks, determine the usefulness of payment data for nowcasting purposes of economic activity statistics. Thus, Aastveit et al. (2020) nowcast quarterly Norwegian household consumption using debit card transactions data. The data provide an early indicator of household spending and are available at a weekly frequency, without delays and sampling errors. It comes from BankAxept, the national payment system of Norway, which records all domestic debit card transactions in physical terminals by Norwegian bank account holders. Both point and density forecasting performance over the period 2011Q4-2020Q1 were evaluated using Mixed Data Sampling (MIDAS) regressions. The results show that MIDAS regressions with debit card transaction data improve both point and density forecast accuracy over competitive standard benchmark models (AR and DFM).

Duarte, Rodrigues, and Rua (2016) incorporate high-frequency data collected from ATM and POS terminals to nowcast Portuguese private consumption growth. MIDAS regressions were used to take advantage of the high-frequency nature of such data. The ATM/POS data, which includes all ATM cash withdrawals and POS payments by residents, and are made available by the Bank of Portugal, comprises 5235 daily and 172 monthly observations over the period from September 2000 to December 2014. Retail sales and consumers' confidence are also included in the model for tracking private consumption. The results show 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.

Caka (2020), in his paper, aims to evaluate the usefulness of payment data for nowcasting the quarterly growth rate of Slovene private consumption and GDP. For this purpose, ATM cash withdrawals, POS payments, and TARGET2 system data are taken from BankArt, the money transfer management company. For estimation, MIDAS/UMIDAS and bridge equations are employed to tackle different frequency problems. The results show that, in conjunction with other traditional indicators, payment data are a valuable source of information for nowcasting Slovene's private consumption and GDP. Moreover, relative to baseline models and bridge equations, MIDAS/UMIDAS regressions increase the accuracy of nowcasting models for both the quarterly growth rate of GDP and that of private consumption.

Frale, Marcellino, Mazzi, and Proietti (2011), in their paper construct EUROMIND, a monthly indicator of the euro area economic conditions, which is based on a monthly estimate of real gross domestic product. Since the indicator provides a monthly estimate of GDP components (final consumption, gross capital formation, and net exports) and value-added of economic sectors, the authors nowcast GDP using two models: one based on expenditures and the other one based on economic sector output. They employ Dynamic factor models using both monthly and quarterly data from the Eurostat Euro-IND database. Additionally, they apply univariate filtering and smoothing procedures to increase the efficiency of the estimation. The results show that unlike the model with the disaggregated expenditure components, the model with the sectoral data shows better performance because gross capital formation and net export components of GDP have high volatility.

Idham and Rakhman (2018) nowcast household consumption and investment using the DFM. The data for the reference variables were taken from BPS Statistics Indonesia and covered the period from 2003 to 2015. Frequencies of household consumption and investment are quarterly while other variables are monthly. The indicators used for nowcasting household consumption include motor vehicle sales, total deposits, the lending rate on consumer loans, M1, and the Rupiah Exchange Rate (NEER) while cement sales, motor vehicle production, electricity consumption, total credit, and M1 variables are used when nowcasting investment. The results of the estimation revealed that the forecast error of the nowcasting model for household consumption is small. Meanwhile, the forecast error of the investment nowcasting model is large but smaller than the benchmark model.

Nowadays, nowcasting with Google Trends (GT) gains popularity among researchers. Suhoy (2009) analyzes Israel's Google Trends data and finds out that it provides useful information about the current economic situation, especially the current unemployment rate. Vosen and Schmidt (2011) analyze whether Google Trends data could nowcast private consumption in the United States and their results suggest that Google search data are more accurate in explaining private consumption than the consumer confidence index and consumer sentiment index. The reason is that survey-based indicators are not able to capture the actual consumption. Later, Vosen and Schmidt (2012) extend Google Trends consumption research to Germany, where they find similar results. Likewise, Kholodilin, Podstawski, and Siliverstovs (2010) study the ability of Google Trends data to nowcast the United States' private consumption. In addition to the consumer sentiment index and consumer confidence index, they use financial market variables (interest rates and the S&P 500 stock market index). The results indicate that Google Trends data are a more accurate indicator of nowcasting private consumption in the United States. Gotz and Knetsch (2019) publish the first known study in which, they examined the ability of Google Trends to nowcast German GDP using a bridge equation. The results show that Google Trends variables provide accurate information for long and mid-term GDP forecasts.

The focus of the paper by Gil, Perez, Sanchez, and Urtasun (2018) is nowcasting and forecasting quarterly private consumption in Spain. The explanatory variables selected for this purpose are monthly indicators with a focus on standard (hard/soft indicators) and less-standard variables. They include traditional indicators (hard indicators: employees registered in the social security system, retail trade index, services sector activity; soft indicators: purchasing manager's index, and consumer confidence indicator), economic and policy uncertainty indicators, payment card transactions, and indicators based on consumption-related search queries retrieved by Google Trends application. They estimate mixed-frequency factor models and apply the Kalman filtering technique to the real-time database for the period from January 2001 to December 2017. The results point out that hard indicators and payment card data are the best performing indicators for nowcasting Spanish quarterly private consumption.

This paper extends the existing literature in several ways. First, this paper contributes to the scarce literature on household consumption nowcasting in developing and emerging economies as the majority of papers are devoted to developed countries. Second, the paper along with traditional macro variables uses other data sources such as payment and Google Trends data. The effective use of payment and Google Trends demonstrates the possibility for developing countries to nowcast consumption with little data collecting efforts. Additionally, the paper compares forecasting accuracy for several cases of single predictor MIDAS models and the DFM model, so the obtained evidence can help practitioners in choosing the suitable model.

Data Description

This section describes the data used in the nowcasting. The success of the nowcast depends heavily on the time series indicators used in the model. The indicators for household consumption need to meet several criteria. First of all, as in regular forecasting, the selected variables should be correlated with household consumption, in other words, they should have some predictive power on consumption. Second, nowcasting works better with indicators that are released frequently and timely. The prior focus was set on time series with the monthly frequency of availability/publication. Third, the selected time series should have enough data points to obtain reliable results. A final 'criterion' is the reliability of the continuation of the time series. For using the nowcasting model in practice, one does not want to rely on time series of private parties that might stop publishing them in the future.

Considering the above-mentioned points, we built datasets that consist of 30 monthly time series indicators that well describe household consumption in Azerbaijan. Two types of data were used in the paper: 1) non-standard data including Google Trends and payments and 2) hard data released with some delay.

i. Google Trends

Google Trends provides a time series index of the volume of search queries that users enter into Google in a given geographic area. The query index is based on query share: the total query volume for the search term in question within a particular geographic region divided by the total number of queries in that region during the period being examined. The maximum query share in the period specified is normalized to be 100, and the query share at the initial date being examined is normalized to be zero. Additionally, the application provides aggregated indexes of search queries, which are classified into categories and sub-categories using an automated classification engine. We select 12 consumption relevant categories that in our view are the best matches for the product categories of personal consumption expenditures of Azerbaijan, as described below:

- Arts & Entertainment
- Autos & Vehicles
- Internet & Telecom
- Shopping
- Sports
- Travel
- Hobbies & Leisure
- Health
- Games
- Food & Drink
- Books & Literature
- Beauty & Fitness

ii. Debit and credit card transaction data

Data collected from payment systems qualify as the new data sources considered to nowcast our target variables. Debit and credit card transactions cover all debit and credit card transactions in both national and foreign currencies. It includes both cash withdrawals and cashless payments. The frequency of this data provided by the Central Bank of Azerbaijan is monthly.

iii. Macroeconomic variables

Besides non-standard data, we also consider 17 macroeconomics variables which are available relatively later than the abovementioned indicators. They include retail trade turnover, paid services, the nominal income of the population, a nominal average monthly wage, industrial production, consumer price index (CPI), food CPI, non-food CPI, services CPI, the interest rate on the national currency for 9-12 month, total loans, mortgage loans, mortgage loans rate, M2 money aggregate, imports of goods and services, nominal effective exchange rate (NEER), and real effective exchange rate (REER). All variables are available at a monthly frequency and provided by the Central Bank and State Statistical Committee of the Republic of Azerbaijan.

Overall, the data set used in this paper was collected from January 2010 to June 2020. The indicators used in the empirical analysis and their respective units are listed in Table 1. In this model, there are one quarterly and 30 monthly variables that enter in the different units and therefore necessitate certain transformation. The indicators under consideration were pre-adjusted in the following way. The first step is a seasonal adjustment, which is followed by calculating the logarithm and differencing individual time series if necessary to make them stationary. Variables except percentage and index form have been taken in logarithms and found to be stationary at the first difference. All variables are seasonally adjusted by the X-13 ARIMA method.

Table 1. Description, units, and frequency of variables

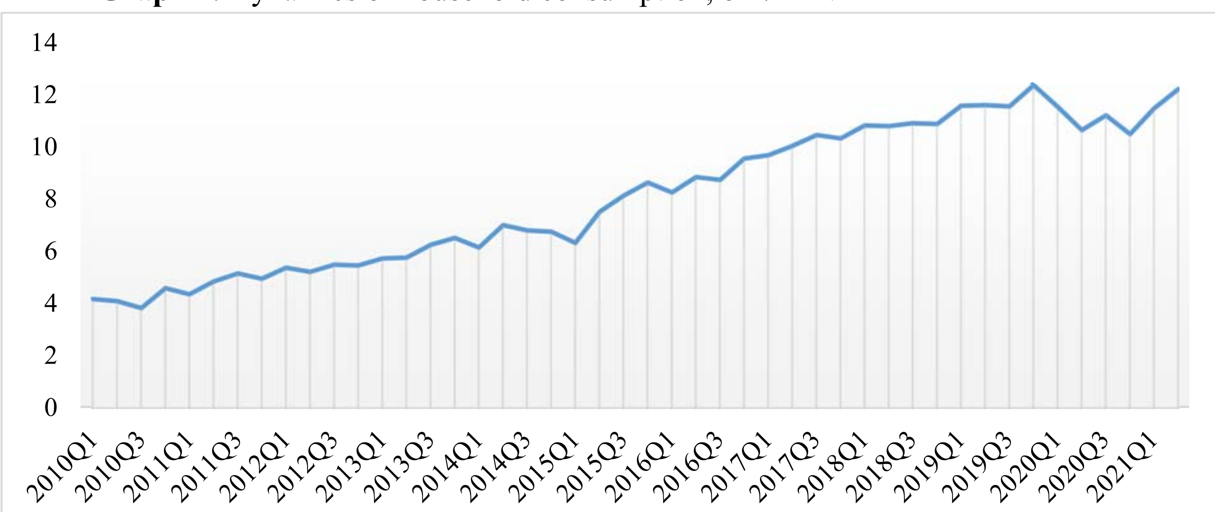
Variables	Variables description	Units	Frequency	Blocks		
				Payment	Hard	Google Trends
cons	Household consumption	QoQ%	Quarterly			
debit_credit	Transactions by debit and credit cards	MoM%	Monthly	1	0	0
trade_tur	Retail trade turnover	MoM%	Monthly	0	1	0
paid_serv	Paid services rendered to population	MoM%	Monthly	0	1	0
income	Nominal income of population	MoM%	Monthly	0	1	0
nom_wage	Average monthly nominal salary	MoM%	Monthly	0	1	0
ind_prod	Industrial production	MoM%	Monthly	0	1	0
cpi	CPI	Index	Monthly	0	1	0
cpi_food	CPI on food	Index	Monthly	0	1	0
cpi_nonfood	CPI on non-food	Index	Monthly	0	1	0
cpi_services	CPI on services	Index	Monthly	0	1	0
interest_rate	Interest rate on national currency, 9-12 months	%	Monthly	0	1	0
loans	Total loans	MoM%	Monthly	0	1	0
mortg_loans	Mortgage loans	MoM%	Monthly	0	1	0
mortg_rate	Mortgage rate	%	Monthly	0	1	0
m2	M2	MoM%	Monthly	0	1	0
import	Import of goods and services	MoM%	Monthly	0	1	0
neer	NEER	Index	Monthly	0	1	0
reer	REER	Index	Monthly	0	1	0
art	Google Trends: Arts & Entertainment	Index	Monthly	0	0	1
auto_vehicle	Google Trends: Autos & Vehicles	Index	Monthly	0	0	1
beauty_fitness	Google Trends: Beauty & Fitness	Index	Monthly	0	0	1
books	Google Trends: Books & Literature	Index	Monthly	0	0	1
food_drink	Google Trends: Food & Drink	Index	Monthly	0	0	1
games	Google Trends: Games	Index	Monthly	0	0	1
health	Google Trends: Health	Index	Monthly	0	0	1
internet	Google Trends: Internet & Telecom	Index	Monthly	0	0	1

leisure	Google Trends: Hobbies & Leisure	Index	Monthly	0	0	1
shopping	Google Trends: Shopping	Index	Monthly	0	0	1
sports	Google Trends: Sport	Index	Monthly	0	0	1
travel	Google Trends: Travel	Index	Monthly	0	0	1

In the DFM model used in the paper, 30 monthly variables are divided into three blocks to avoid identification problems. Blocks are the following: payment block (P) which includes variables related to the payment system of the economy, hard block (H) which consists of variables that are measurable and factual, and Google Trend (GT) block which includes variables based on the internet search query.

Regarding household consumption, we consider nominal quarterly household consumption from quarterly National Accounts released by State Statistical Committee. Graph 1 represents the dynamics of household consumption in Azerbaijan from 2010 to 2021. In times of crises and recently during the pandemic, consumption decreased unexpectedly despite the ongoing increase in the recent past, which makes short-term forecasting using timely available high-frequency variables essential. It is also important to mention that we consider final data, that is, the latest available vintage for all series.

Graph 1. Dynamics of household consumption, bln.AZN



Source: The State Statistical Committee of the Republic of Azerbaijan

Empirical Methodology

This section provides a brief overview of the modeling framework employed in the empirical exercise. The first modeling approach pertains to the MIDAS regression framework that allows for the exploitation of within-quarter information to nowcast quarterly aggregates. This method estimates a model for the low-frequency target variable by transforming the high-frequency variable into a low-frequency vector.

An alternative approach proposed in the literature is to summarize the information about economic predictors with a few common factors and exploit their dynamic structure to make predictions. Dynamic mixed-frequency factor models can be understood as 'large bridge equations' combining monthly and quarterly frequencies (Giannone et al., 2008). Although the projection on all variables is infeasible, common factors provide a good approximation for the infeasible and over-parametrized full model. This type of model is usually estimated using Kalman filtering in a state-space framework (Mariano & Murasawa, 2003).

1. *Single-predictor Mixed Data Sampling (MIDAS) regressions*

In this section, we provide a brief overview of the Mixed-Data Sampling (MIDAS) approaches that will be used in our nowcasting exercise. The general MIDAS regression was originally proposed by Ghysels et al (2004). The central idea of the MIDAS approach is to explain a low-frequency variable by variables measured at a higher frequency, without aggregation, and in a parsimonious way. It is the extension of the distributed lag model which allows working with a data set composed of indicators with different frequencies, such as monthly and quarterly. In such regressions, the observations of the low-frequency variable are directly related to lagged high-frequency observations of the indicators without time aggregation (Schumacher, 2016). 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 dependent low-frequency variable is modeled 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.

The standard MIDAS model can be written as follows:

$$Y_t^L = \sum_{i=1}^{q} \beta_i W_{t-i}^L + \lambda f(\gamma, X_{j,t}^H) + \varepsilon_t$$

where,
Y_t^L - is the dependent variable sampled at low frequency;
W_t^L- is the set of regressors sampled at the same (low) frequency as the regressand (possibly including lags of Y for autoregressive or ARDL form);

$X_{j,t}^H$ - is the set of regressors sampled at a higher frequency;

β_i, λ, γ – are the parameters to be estimated;

f (.) – is a function translating the higher frequency data into the low frequency.

MIDAS estimation offers several different weighting functions/schemes, which define a specific MIDAS regression model. In this paper, we will refer to Almon weighting and Step weighting parametrization.

1.1 ***Polynomial Distributed Lag or Almon Weighting parametrization***

The PDL or Almon Weighting is widely used to put restrictions on lag coefficients in the class of autoregressive models. This weighting scheme is considered a natural candidate for mixed frequency weighting. For each high-frequency lag up to j, the regression coefficients are modeled as a p dimensional lag polynomial in the MIDAS parameters. The number of the coefficients to be estimated depends on the polynomial order (p) and not on the number of lags (j) chosen. It uses the functional form with up to p coefficients of $\gamma_1, \gamma_2, \dots, \gamma_p$. Equation (8) can be updated to a MIDAS with PDL structure:

$$Y_t^L = \sum_{i=1}^{q} \beta_i W_{t-i}^L + \sum_{i=1}^{p} \gamma_i \sum_{j=0}^{k} j^{i-1} X_{t-j}^H + u_t$$

The term k is the chosen number of lags; p is the order of the polynomial.

1.2 Step Weighting Parametrization

MIDAS with step functions was introduced by Forsberg and Ghysels (2007). The step-function approximates the distributed lag pattern by a number of discrete steps (η). The more steps appear in the regressions, the less parsimonious the regression model is. The number of coefficients $\gamma_1, \gamma_2, \dots, \gamma_\eta$ to be estimated depends on the functional form up to (η) steps. Step weighting lowers the number of estimated coefficients since it restricts consecutive lags to have the same coefficient. For example, if *j*=12 and η=4, the first 4 lags have the same coefficient, the next four lags have the same coefficient, and so on, all the way up to *j*=12. MIDAS with step weighting is defined as follows:

$$Y_t^L = \sum_{i=1}^{q} \beta_i \, W_{t-i}^L + \sum_{j=0}^{k} \phi_{t-j} \, X_{t-j}^H + u_t$$

$$\phi_j = \gamma_k \,, k = 1, \dots, \eta$$

2. Dynamic factor models

The Mixed Frequency Dynamic Factor Model is another common nowcasting approach. The methodology was developed by Giannone, et al. (2008) for large-scale models. The nowcasting framework of Giannone et al. (2008) has become the workhorse model of short-term forecasters at many central banks and other institutions. The framework is based on a dynamic factor model cast in the state space representation and on the application of the Kalman filter to deal with mixed frequencies and unbalanced datasets. The framework can accommodate a potentially large number of variables by summarizing the information with a few common factors, thus overcoming the so-called curse of dimensionality (Stock and Watson, 2002; Bernanke and

Boivin, 2003). An additional advantage of the framework is that it allows forecasters not only to predict variables of interest in real-time but also to interpret and comment on the sources of the changes in the forecasts. This provides a story-telling dimension and a deeper understanding of the forecast that is almost as important to policymakers as the accuracy of the forecast itself. This feature is missing from most of the statistical models that are currently used for near-term projections.
The empirical model can be summarized in the following equation:

$$y_{i,t} = \lambda_{i,1} f_{1,t} + \cdots + \lambda_{i,r} f_{r,t} + e_{i,t}, \;\; for\; i = 1, \ldots, n \;\; (1)$$

where
$y_{1,t} \ldots y_{n,t}$ – observed variables;
$f_{1,t} \ldots f_{r,t}$ – common factors;
$\lambda_{i,1} \ldots \lambda_{i,r}$ – factor loadings;
$e_{i,t}$ – idiosyncratic component.

To conduct inference in DFMs using likelihood-based methods and Kalman filtering techniques, the common factors and the idiosyncratic components are modeled as Gaussian autoregressive processes, which account for their serial correlation and persistence.

$$f_{j,t} = a_j f_{j,t-1} + u_{j,t}, \;\; u_{j,t} \sim i.i.d.\; N\left(0,\, \sigma^2_{uj}\right) \;\; for\; j = 1, \ldots, r \;\; (2)$$
$$e_{i,t} = p_i e_{i,t-1} + \mathcal{E}_{i,t}, \;\; \mathcal{E}_{i,t} \sim i.i.d.\; N(0,\, \sigma^2_{\mathcal{E}i}) \;\; for\; i = 1, \ldots, n \;\; (3)$$

Equation 1 is known as the measurement equation. These equations are where the common factors and the idiosyncratic components are unobserved states. *"Idio"* means not to know; thus, these are the shocks of the economy. Equations 2 and 3 known as the transition equations describe the dynamics of the system. The first equation allows us to understand how dynamic factor models are used in the data. We assume that the idiosyncratic component of the variables follows an AR(1) process.

Design of the nowcast exercise

To assess the relative performance of the above-mentioned models and predictors to forecast private consumption, we conduct the following out-of-sample forecasting exercise.

The out-of-sample forecast evaluation period runs from the 3rd quarter of 2020 up to the 2nd quarter of 2021, which corresponds to one year. One should note that both the ongoing effects of the pandemic and the war make this period difficult for Azerbaijan. Hence, such an out-of-sample period constitutes a challenge putting to test the informational content of each predictor, as well as each model's ability in a context of major macroeconomic stress.

Given the type of predictors at hand, we focus on the nowcasting performance but for the sake of curiosity, we also assess the four-quarter ahead forecasting case. In both cases, we consider one possible information set for the predictors in which all months of the quarter are available.

As discussed in section 3, we consider two types of MIDAS regressions namely PDL weighting and STEP weighting and a DFM model. All in all, this means 25 cases for each forecasting horizon.

The out-of-sample forecasting performance is assessed through recursive Root Mean Squared Error (RMSE). It is based on the idea that the initial estimation period is fixed and additional observations are added to the estimation period one at a time. We take into account all information available in the current quarter. Since the available period for Azerbaijan is from 2010Q1 to 2020Q2, we have 42 observations for the estimation and 4 observations for the out-of-sample period. With the estimated coefficients for the models, first, we compute the value of household consumption for the 3rd quarter of 2020. Then we increase our sample by one observation and re-estimate the model in the same way. Continuing in this manner, we obtain four out-of-sample nowcasting for the Azerbaijan household consumption.

In particular, we present the relative RMSE for each single predictor MIDAS model and DFM model vis-a-vis the univariate benchmark which is AR(1) in this paper. A ratio lower than one denotes a forecasting gain by the MIDAS and DFM approach whereas a value higher than one means that the univariate model outperforms the alternative models.

Empirical results

To assess the relative performance of the above-mentioned models and predictors to forecast private consumption, we conduct the following out-of-sample forecasting exercise. As nowcasting is relevant for short-term forecasting, the out-of-sample forecast evaluation covers one year from 2020Q2 to 2021Q2.

We applied DFM and MIDAS models using various combinations of variables and examined whether some of the models tend to outperform our benchmark model (AR(1)). Based on the results of out-of-sample testing, the model with the smallest RMSE was selected.

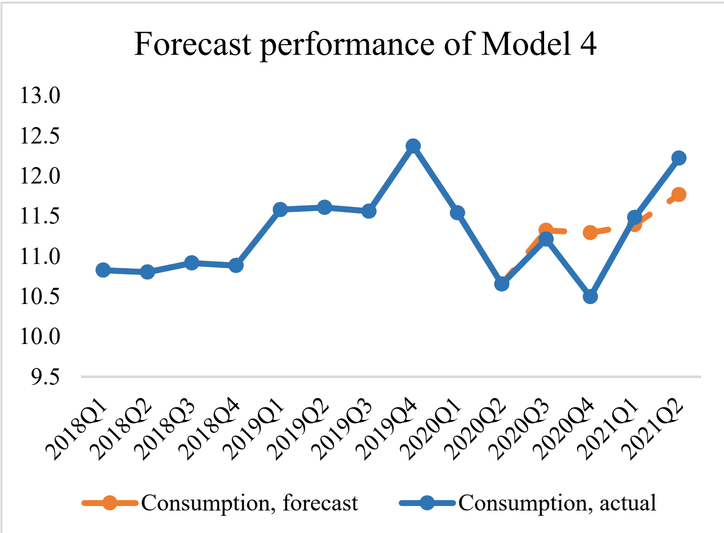
Table 2 presents the RMSE of individual nowcasting models respective to the AR(1) benchmark model. Several findings emerge from the analysis of Table 2. Firstly, in terms of predictors, most Google Trends data outperform the so-called hard data (retail trade turnover) and they are better compared with debit and credit card transaction data. Regarding models, DFM always delivers the best nowcasting and forecasting performance relative to any given MIDAS variant. Explicitly, both DFM and MIDAS models add value and outperform AR(1) in a majority of cases. Single predictor MIDAS model with variables retail trade turnover and Google Trends (arts&entertainment, sports, travel, hobbies&leisure, books&literature) outperform the benchmark model. However, the findings indicate that mixed frequency DFM with three blocks is better for nowcasting household consumption in Azerbaijan. Google Trends and payment system data together with key macroeconomic variables increase forecasting efficiency. Factors of payment systems have a more significant impact.

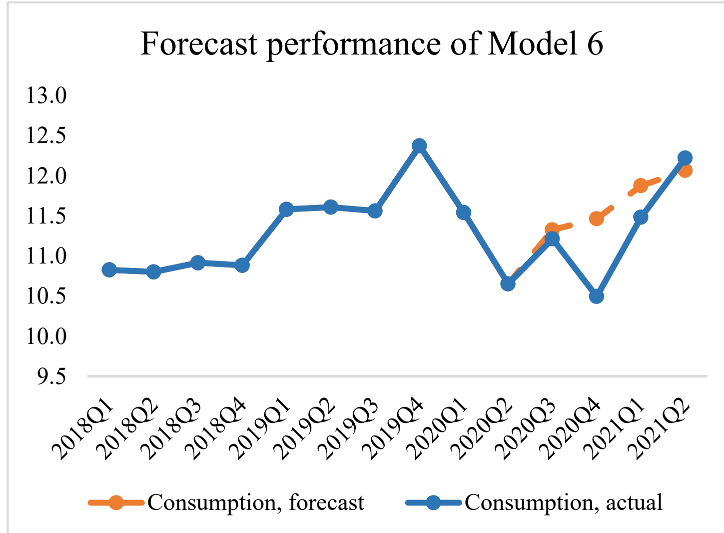
Table 2. Model Performance (RMSE)

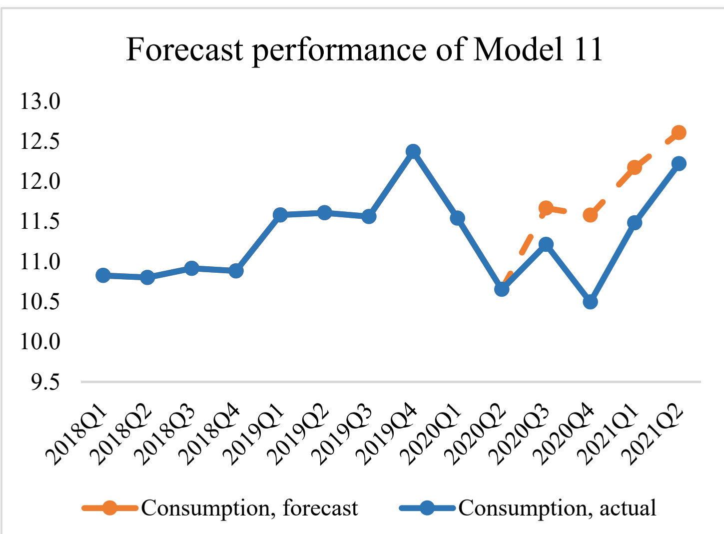
Model	Methodology	Explanatory variables	RMSE			
			nowcasting	+2Q	+3Q	+4Q
1	MIDAS (PDL)	Transactions with debit and credit cards	1.08	1.17	1.24	1.27
2	MIDAS (Step)		1.02	1.09	1.15	1.15
3	MIDAS (PDL)	Retail trade turnover	1.01	1.04	1.01	1.03
4	MIDAS (Step)		0.94	0.93	0.93	0.93
5	MIDAS (PDL)	GT: arts & entertainment	0.96	1.01	0.99	1.01
6	MIDAS (Step)		0.99	0.99	0.98	0.98
7	MIDAS (PDL)	GT: autos & vehicles	1.09	1.02	0.98	0.99
8	MIDAS (Step)		1.05	1.03	1.01	0.99
9	MIDAS (PDL)	GT: shopping	1.05	1.1	1.16	1.16
10	MIDAS (Step)		0.98	1.01	1.05	1.08
11	MIDAS (PDL)	GT: sports	0.94	0.95	0.94	0.96
12	MIDAS (Step)		0.95	0.97	0.95	0.96
13	MIDAS (PDL)	GT: travel	0.99	0.95	0.93	0.89
14	MIDAS (Step)		0.68	0.73	0.69	0.70
15	MIDAS (PDL)	GT: hobbies & leisure	0.85	0.85	0.83	0.86
16	MIDAS (Step)		0.93	0.90	0.92	0.95
17	MIDAS (PDL)	GT: health	1.49	1.62	1.58	1.78
18	MIDAS (Step)		1.21	1.23	1.20	1.24
19	MIDAS (PDL)	GT: food & drink	1.20	1.09	1.04	1.08
20	MIDAS (Step)		1.04	1.01	1.01	1.04
21	MIDAS (PDL)	GT: books & literature	0.95	0.98	0.94	0.89
22	MIDAS (Step)		0.98	1.02	1.04	1.03
23	MIDAS (PDL)	GT: beauty & fitness	1.18	1.16	1.20	1.17
24	MIDAS (Step)		1.20	1.14	1.16	1.15
25	DFM	Payment data, Hard data, Google Trends	0.34	0.26	0.20	0.20

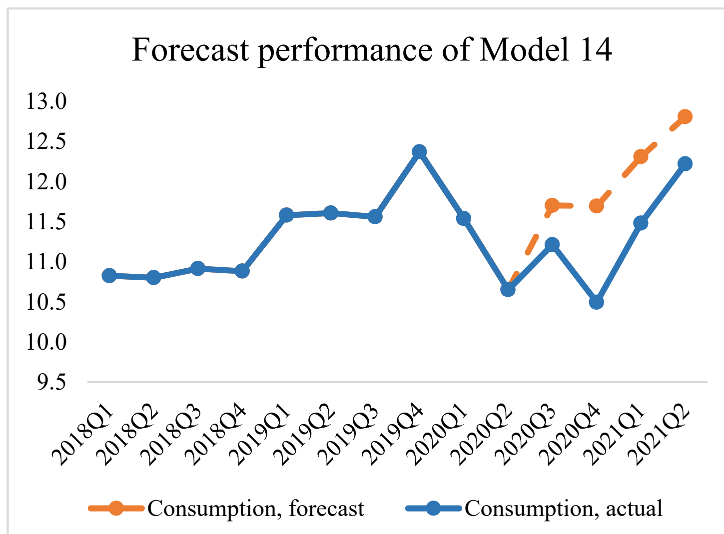
Figure 1 indicates the graphical representations of the models with higher predictability. As can be seen from the graphs, the forecast results of MIDAS models do not reflect the decline in the 4th quarter of 2020 well. During this period, both the ongoing effects of the pandemic and the war led to a decline in consumption. Only the DFM model can accurately predict the break in this period. Findings from other literature also pointed out that the DFM model is the best compared to other traditional models for short-term forecasting in times of crisis. On the other hand, while the DFM model gives a good forecast for the first two quarters, it does not reflect the reality so well in the forecast for the next quarters. This can be explained by the fact that nowcasting models are mainly a reliable tool for short-term forecasting.

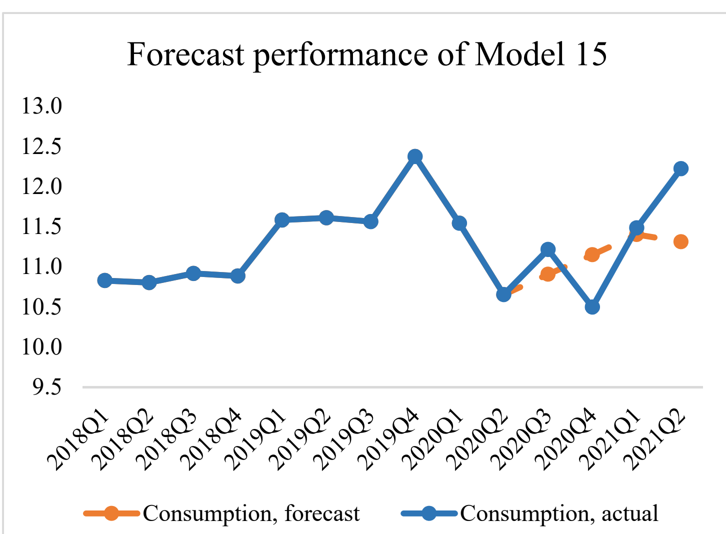
Figure 1. Examples of Model Performances

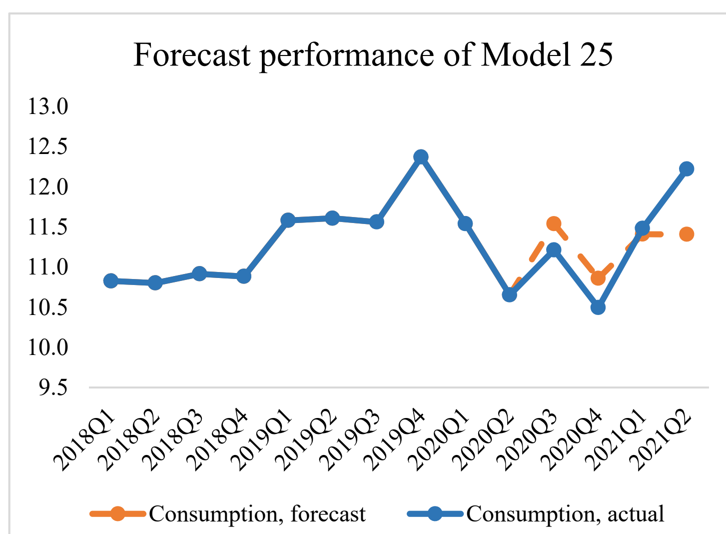












Conclusion

The publication lag of the official estimates of household consumption necessitates the use of alternative timely high frequency indicators for nowcasting. These nowcasts are important for policymakers as it can have an impact on short-term policy decisions.

In this paper, we evaluate the performance of MIDAS and DFM models in obtaining accurate nowcasts of household consumption for Azerbaijan. We estimate single predictor MIDAS models with different variables and three blocks DFM model over the period 2010-2020 using 30 high-frequency variables. We then compare the forecasts obtained from these models with the forecasting accuracy of an autoregressive benchmark model (AR). We find that the majority of the MIDAS models and DFM can produce more accurate forecasts than those of the AR. The results also suggest that three blocks DFM model is better for nowcasting compared with the MIDAS model. The use of payment and Google Trends data along with macroeconomic variables used in this paper increases nowcasting performance. Our results thus recommend the use of the DFM model as a useful addition to a forecaster's suite of household consumption nowcasting models.

Future research can go in many different areas. A potentially further development of this research would be the use of comprehensive and timely settlement data from the Real Time Gross Settlement System (AZIPS) managed by the Central Bank of the Republic of Azerbaijan. This kind of data can improve the policy decision-making process as it covers a wide range of financial activities across sectors.

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