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Regime-dependent nowcasting of the Austrian economy

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Abstract

We nowcast and forecast Austrian economic activity, namely real gross domestic product (GDP), consumption and investment, which are available at a quarterly frequency. While nowcasting uses data up to (and including) the quarter to be predicted, forecasting uses only data up to the previous quarter. We use a large number of monthly indicators to construct early estimates of the target variables. For this purpose we use different mixed-frequency models, namely the mixed-frequency vector autoregressive model according to Ghysels (2016) and mixed data sampling approaches, and compare their forecast and nowcast accuracies in terms of the root mean squared error. We also consider traditional benchmark models which rely only on quarterly data. We are particularly interested in whether explicitly considering different regimes improves the nowcast. Thus we examine regime-dependent models, taking into account business cycle regimes (recession/non-recession) or financial/economic uncertainty regimes (high/low uncertainty) driven by global and Austrian economic and financial uncertainty indicators. We find that taking explicit account of regimes clearly improves nowcasting, and different regimes are important for GDP, consumption and investment. While the recession/non-recession regimes seem to be important to nowcast GDP and consumption, high/low global financial uncertainty regimes are important to nowcast investment. Also, some variables seem to be important only in certain regimes, like tourist arrivals in the non-recession

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regime when nowcasting consumption, while other variables are important in both regimes, like order books in the high and low global financial uncertainty regimes when nowcasting investment. In addition, nowcasting indeed provides a value added to forecasting, and the new information available in the first month seems to be most important. However, sometimes also the forecast performs quite well, and then it mostly comes from a mixed-frequency model. So monthly information seems to be helpful also in forecasting, not only in nowcasting. Finally, we do not find a clear winner among the different mixed-frequency models.

Keywords: nowcasting, mixed-frequency VAR models, mixed data sampling regressions, macroeconomic forecasting, GDP nowcast, consumption nowcast, investment nowcast, regimes

JEL codes: C10, C22, C32, C53, E17

1 Introduction

Economists have imperfect knowledge of the present state of the economy, as many key statistics, for example GDP growth, are released with a long delay. Policy makers, on the other hand, would like to know as much as possible about the current state of the economy. As a consequence, there is a strong need for "forecasting the present", also called nowcasting. Nowcasting is particularly important for those key economic variables which are collected at low frequency, typically at a quarterly basis, and released with a substantial time lag. To obtain early estimates of such key economic indicators, economists use the information from data which are related to the target variables but are collected at a higher frequency, typically monthly, and released in a more timely manner. These include, for example, data on industrial production and the labour market, survey indicators and financial data. The latter are often even available at a daily frequency, see, e.g., Anthonisz (2021) or Baumeister et al. (2015).

For a long time economists have analysed the co-movement of variables sampled at different frequencies in such a way that they only considered the joint process sampled at the common low frequency. A typical example, following the work of Sims (1980), is a vector autoregressive (VAR) model[1] with both real and financial variables sampled quarterly, even though financial variables are available at a higher frequency. In the mid of 2000 a vast literature has emerged providing models that explicitly exploit the information in mixed-frequency datasets and avoid pre-filtering and temporal aggregation. There is clear empirical evidence that taking into account the information inherent in high-frequency data in order to nowcast/forecast low-frequency data provides better nowcasts/forecasts in the short run, i.e., typically up to one or two quarters ahead.

Baffigi et al. (2004), among others, is one of the early approaches to deal with mixed-frequency data that focuses on forecasting and relies on bridge equations which, due to their simple estimation method and transparency, have been widely used in policy organizations. Additional applications in the literature, including comparisons with other mixed-frequency approaches, are Angelini et al. (2011), Diron (2008), Bulligan et al. (2010), Bulligan et al. (2015), Foroni and Marcellino (2014a), Golinelli and Parigi (2007), Hahn and Skudelny (2008), and Rünstler et al. (2009), among others.

A more recent approach is the mixed data sampling (MIDAS) method originally proposed by Ghysels et al. (2004), see also Ghysels et al. (2007). MIDAS can be regarded as a time-series regression approach that allows the regressand and regressors to be sampled at

[1] See Stock and Watson (2001) for the advantages and limitations of VAR models.

different frequencies and where distributed lag polynomials are used to ensure parsimonious specifications. While MIDAS models were initially introduced in financial applications (see, e.g., Ghysels et al., 2006), this method has also been widely employed in macroeconomic forecasting, where typically a quarterly series like GDP growth is forecasted by monthly indicators (see, e.g., Clements and Galvão, 2008, 2009). Foroni et al. (2015) propose an unrestricted version of the MIDAS model without imposing any lag distribution restrictions, as are typical for traditional MIDAS. They show that when the mismatch between the two frequencies is low, like for quarterly and monthly data, then the unrestricted version improves the nowcasting performance. Additional contributions related to the MIDAS approach include Andreou et al. (2013), Duarte (2014), Drechsel and Scheufele (2012), Ferrara et al. (2014), Foroni et al. (2015), Kuzin et al. (2011), and Schumacher (2016).

Another recent approach are mixed-frequency (dynamic) factor models. These models may be used to extract an unobserved state of the economy and create a new coincident indicator, or to forecast and nowcast a low-frequency variable. Contributions in this field include Aastveit and Trovik (2012), Bańbura and Rünstler (2011), Bragoli and Fosten (2018), Chernis and Sekkel (2017), Giannone et al. (2008), Girardi et al. (2017), Mariano and Murasawa (2003, 2010), Nunes (2005), and den Reijer and Johansson (2019). Marcellino and Schumacher (2010) propose to merge factor models with the MIDAS approach, where the explanatory variables in the MIDAS regression are estimated factors.

Finally, there is the mixed-frequency vector autoregressive approach (MF-VAR). One way of specifying a VAR model for data observed at lower and at higher frequencies involves latent shocks, because not all shocks are observed at the higher frequency. The model is set up in the state-space form, where low-frequency variables are considered high-frequency variables with missing observations. The Kalman filter is then applied to estimate the missing observations and to generate forecasts. Examples of this approach include Zadrozny (1988), Mariano and Murasawa (2010), Eraker et al. (2015), Kuzin et al. (2011), Schorfheide and Song (2015), Foroni and Marcellino (2014a, 2014b), and Cimadomo et al. (2022). On the other hand, Ghysels (2016) proposed an alternative MF-VAR specification which does not rely on latent processes and in this sense is fundamentally different from the previous models. This MF-VAR model is observation-driven as it is formulated exclusively in terms of observable data, it does not involve latent processes, and thus avoids the need to formulate measurement equations, filtering, etc. As a consequence it also allows to directly measure the impact of high-frequency data on low-frequency data and vice versa. Ghysels (2014, 2016) also proposes various parsimonious parameterizations, in part inspired by MIDAS regressions. In addition, Fosten and Greenaway-McGrevy (2022) propose a mixed-frequency panel vector autoregressive model (MF-PVAR) by extending the MF-VAR approach of Ghysels (2016) to the case when there is panel data with observations measured across time and individual units and when also limited cross-sectional heterogeneity through fixed effects are accommodated. Their approach can be used when the objective is to simultaneously nowcast a low-frequency variable across many regions or sectors.[2]

Rather recently, practitioners use large sets of alternative data, such as Google data, scanner data or satellite data, when nowcasting GDP, see Ferrara and Simoni (2023) and Goetz and Knetsch (2019), among many others. Their empirical findings support the idea that Google search data tend to increase nowcasting accuracy. In addition, Ferrara and Simoni (2023) analyze different periods and observe that the gain differs between periods of recessions and of macroeconomic stability. We explicitly consider regime-dependent models, including recession-based regimes, and find that this helps to increase nowcast accuracy.

In the current paper we apply a mixed-frequency VAR model along the lines of Ghysels (2016) in order to nowcast (and forecast) Austrian economic activity and compare it with univariate MIDAS approaches as well as with some other benchmark forecast models. More precisely we nowcast and forecast the growth of real GDP, real consumption and real investment for Austria. GDP for Austria is available at a quarterly frequency, like in all other European countries,[3] and its first estimate is released 30 days after the close of the quarter. This means that in March 2023, for instance, we only have information up to the last quarter of 2022 and we need to wait until the beginning of May to obtain a first estimate of the first quarter of 2023. However, there are several variables, available at monthly frequency and published with shorter delay, which can be used to construct earlier estimates of GDP. For example, towards the end of March comes a release of Austrian industrial production for January. This series measures directly certain components of GDP and is considered to contain a strong signal on its short-term developments.

Additional timely information is provided by various surveys. They measure expectations of economic activity and are typically available around the end of the month or shortly after the end of the month to which they refer. Beyond industrial production and surveys, many other data (such as exports, imports, retail sales, employment, vacancies and consumer/producer prices) may be informative: usually their releases are closely watched

[2] Fosten and Greenaway-McGrevy (2022) apply their methodology (MF-PVAR) to nowcast quarterly US state-level GDP growth.

[3] In July 2018, the United Kingdom became one of the first developed economies in the world to publish economic growth figures on a monthly basis.

by financial markets which react whenever there are surprises about the value of the new data. Finally, financial variables themselves, which are available at very high frequency and carry information on expectations of future economic developments, may be useful in nowcasting economic activity.[4] We are particularly interested in whether explicitly considering different regimes may improve the nowcast/forecast accuracy. So we look at models taking account of business cycle regimes (recession/expansion) or high/low uncertainty regimes driven by global or Austrian economic or financial uncertainty. We thus contribute to the nowcasting literature by explicitly considering such kind of regime-dependent models. We also nowcast investment and consumption, in addition to GDP which is usually examined in the literature.

The remainder of this paper is organized as follows. Section 2 revises the methodology we use to perform nowcasting and forecasting. Section 3 describes the data. Section 4 presents the nowcasting/forecasting results for Austrian GDP, consumption and investment with a special focus on regime-dependent models. Section 5 summarizes and concludes.

2 Methodology

In this paper we consider three mixed-frequency methods: the mixed-frequency vector autoregressive model (MF-VAR), the unrestricted mixed data sampling regression (MIDAS-u) and the mixed data sampling regression with Almon polynomial distributed lags (MIDAS-pdl).

We use the MF-VAR model as introduced in Ghysels (2016), where techniques used in the seasonal time series literature (with hidden periodic structure) are adopted. These models allow to measure the impact of high-frequency data on low-frequency data and vice versa. Such an MF-VAR model with p lags can be written as the following $(3k +$

[4] In an earlier version of this study we also investigated the use of financial and economic uncertainty indicators as monthly variables and considered indicators like truck toll mileage, rail freight and electricity consumption, which started to be used more widely during the Covid-19 crisis but which are only available for a very short period and we did not want to use such a short data sample in our main analysis. We do not use the financial and economic uncertainty indicators in our current analysis due to the unsatisfactory nowcast accuracy found in the preliminary analysis.

1)−dimensional VAR(p) model for one low-frequency and k high-frequency variables[5]

$$x(t) \equiv \begin{bmatrix} x_H(t,1) \\ x_H(t,2) \\ x_H(t,3) \\ x_L(t) \end{bmatrix} = c\,\mathbf{D}_t + \sum_{j=1}^{p} A_j \begin{bmatrix} x_H(t-j,1) \\ x_H(t-j,2) \\ x_H(t-j,3) \\ x_L(t-j) \end{bmatrix} + \varepsilon(t) \tag{1}$$

where the low-frequency variable, $x_L(t)$, is a value of the quarterly variable x_L at quarter t, $x_H(t,1)$, $x_H(t,2)$, $x_H(t,3)$ are $k-$dimensional vectors of monthly variables x_H for all three months of quarter t, A_j $j = 1, \ldots, p$ are $(3k+1) \times (3k+1)$ matrices, and $\mathbf{D}_t \in \mathbb{R}^q$ collects the deterministic terms (such as an intercept) and strictly exogenous variables with corresponding parameters $c \in \mathbb{R}^{3k+1 \times q}$. Finally, $\varepsilon(t)$ is a $(3k+1)-$dimensional white noise process with zero mean and constant covariance matrix, and all variables under consideration are stationary.

If we assume that the quarterly GDP is the low-frequency variable and the monthly industrial production index (IPM) is the only, i.e., $k = 1$, high-frequency variable and, in addition, t represents the last quarter of year 2022, i.e., $t = 2022Q4$, then $x_L(t)$ denotes the GDP for the last quarter of 2022 and $x_H(t,1)$, $x_H(t,2)$ and $x_H(t,3)$ represent the IPM for the months of October, November and December of year 2022. In this example the focus is on nowcasting (forecasting) a low-frequency variable (GDP) by means of a high-frequency variable (IPM). Thus, the core equation in (1) is the last equation.

For nowcasting the structure of the stacked $(3k+1)-$dimensional vector $x(t)$, see (1), is crucial and allows making use of the following representation of the variance-covariance matrix of the MF-VAR model

$$\mathbb{E}[\varepsilon(t)\varepsilon(t)'] = P\Omega P'$$

where P is an $(3k+1) \times (3k+1)$ dimensional lower triangular matrix with ones on its diagonal and Ω is a diagonal matrix of the same dimension. Let $N_{[3]} = P^{-1}$ and let $N_{[i]}$, $i = 1, 2, 3$, be a partial triangular decomposition orthogonalizing only the first i shocks,

[5] To simplify the notation we assume one low-frequency variable, x_L, which we also employ in this study. The model can be generalized to more low-frequency variables and also to different frequency combinations, like quarterly/daily.

namely

$$N_{[1]} = \begin{bmatrix} I & 0 & 0 & 0 \\ N_{[1]}^{2,1} & I & 0 & 0 \\ N_{[1]}^{3,1} & 0 & I & 0 \\ N_{[1]}^{4,1} & 0 & 0 & 1 \end{bmatrix}, \; N_{[2]} = \begin{bmatrix} I & 0 & 0 & 0 \\ N_{[2]}^{2,1} & I & 0 & 0 \\ N_{[2]}^{3,1} & N_{[2]}^{3,2} & I & 0 \\ N_{[2]}^{4,1} & N_{[2]}^{4,2} & 0 & 1 \end{bmatrix}, \; N_{[3]} = \begin{bmatrix} I & 0 & 0 & 0 \\ N_{[3]}^{2,1} & I & 0 & 0 \\ N_{[3]}^{3,1} & N_{[3]}^{3,2} & I & 0 \\ N_{[3]}^{4,1} & N_{[3]}^{4,2} & N_{[3]}^{4,3} & 1 \end{bmatrix} \quad (2)$$

where I is the $k \times k$ identity matrix and all $N_{[\cdot]}^{a,b}$ matrices with $a < 4$ are of dimension $k \times k$ while $N_{[\cdot]}^{4,b}$ are of dimension $1 \times k$. The following structural VAR, when equation (1) is pre-multiplied by $N_{[i]}$, will thus facilitate the use of real higher-frequency information already available

$$N_{[i]}x(t) = B_{[i]0} + \sum_{j=1}^{p} B_{[i]j}x(t-j) + e_{[i]}(t) \quad (3)$$

for $i = 1, 2, 3$, where $B_{[i]0} = N_{[i]}c\,\mathbf{D}_t$, $B_{[i]j} = N_{[i]}A_j$, $j = 1, \ldots, p$ and $e_{[i]}(t) = N_{[i]}\varepsilon(t)$. Thus, if in our example we would like to nowcast the GDP for $t = 2023Q1$, i.e, $x_L(t)$, using information of the monthly IPM for $2023M1$ and $2023M2$, i.e., $x_H(t,1)$ and $x_H(t,2)$, and all available data for the past time points, then the last equation of (3) implies

$$\begin{aligned} \hat{x}_L(t) &= B_{[2]0}^{4} - N_{[2]}^{4,1}x_H(t,1) - N_{[2]}^{4,2}x_H(t,2) \\ &+ \sum_{j=1}^{p} \Big[B_{[2]j}^{4,1}x_H(t-j,1) + B_{[2]j}^{4,2}x_H(t-j,2) + B_{[2]j}^{4,3}x_H(t-j,3) + B_{[2]j}^{4,4}x_L(t-j) \Big] \end{aligned}$$

where $\hat{x}_L(t)$ denotes the forecasted/nowcasted value of $x_L(t)$. Thus, the available information in the first two months updates the forecasts, while information in the third month is ignored as it is not yet observed.

MF-VAR models can be viewed as the multivariate extension of the univariate mixed data sampling (MIDAS) regressions that help to keep the parameter space low-dimensional, as the issue of parameter proliferation is likely to be even more acute in MV-VAR models than in VAR models.

In this paper we use also the unrestricted MIDAS (MIDAS-u) approach (see Foroni et al., 2015), namely we estimate

$$x_L(t) = (\mu_0)'\mathbf{D}_t + \mu_1 x_L(t-1) + \sum_{\tau=0}^{p_x-1} (\mu_\tau)' x_{H,t-1-\frac{\tau}{3}} + u(t) \quad (4)$$

where $\mu_0 \in \mathbb{R}^q$ are coefficients corresponding to the deterministic term $\mathbf{D}_t \in \mathbb{R}^q$, $\mu_1 \in \mathbb{R}$, p_x is the number of lags, μ_τ is a $k-$dimensional vector of parameters, $\tau = 0, \ldots, p_x$, $x_{H,t-\frac{\tau}{3}}$ is the $k-$dimensional vector of high-frequency (monthly) variables at month $t - \frac{\tau}{3}$, i.e., τ months prior to quarter t, and $u(t)$ is the error term which is assumed to be normally distributed with zero mean and standard deviation σ.[6]

Finally, we consider also the MIDAS regression with Almon polynomial distributed lag weighting (MIDAS-pdl), which is widely used to place restrictions on lag coefficients in the autoregressive model

$$x_L(t) \;=\; (\mu_0)'\mathbf{D}_t + \mu_1 x_L(t-1) + \sum_{\tau=0}^{p_x-1}\left(\sum_{j=1}^{P}\tau^j\theta_j\right)' x_{H,t-1-\frac{\tau}{3}} + u(t) \tag{5}$$

where P is the Almon polynomial order such that $P < p_x$ and θ_j are $k-$dimensional vectors of parameters, $j = 1, \ldots, P$.[7]

As pointed out by Kuzin et al. (2011), there are differences between the MF-VAR and MIDAS approaches which both exploit higher frequency observations. Namely, unlike MIDAS, MF-VAR is a multivariate approach that explains both low-frequency and high-frequency variables and thus a misspecification in one equation can affect the estimation and thus forecast accuracy of the other equations. On the other hand, forecasts of higher-frequency variables can also be of interest by themselves. In addition the MIDAS approach has the advantage of sparse parameterization, whereas MF-VAR suffers from the curse of dimensionality. For instance, adding one monthly variable to the predictors in MIDAS-pdl requires only P more coefficients to be estimated, while adding one monthly variable in the MF-VAR model increases the number of the estimated coefficients by $9p$.[8] On the other hand, the restrictions in MIDAS-pdl might be invalid, whereas coefficients of the MF-VAR (as well as of MIDAS-u) are not restricted. The relative advantages of MF-VAR and MIDAS approaches will be evaluated empirically in Section 4.

3 Data

We forecast and nowcast three quarterly (low-frequency) variables, real GDP, real consumption (consumption of private households) and real investment (gross fixed capital for-

[6] Note that for $p_x = 3$, the estimated coefficients in (4) coincide with the estimated coefficients in the last equation of (1) when $p = 1$.

[7] For $p_x = 3$ the estimated coefficients in (5) coincide with the estimated coefficients in (4).

[8] Not counting the coefficients corresponding to the deterministic part of the system.

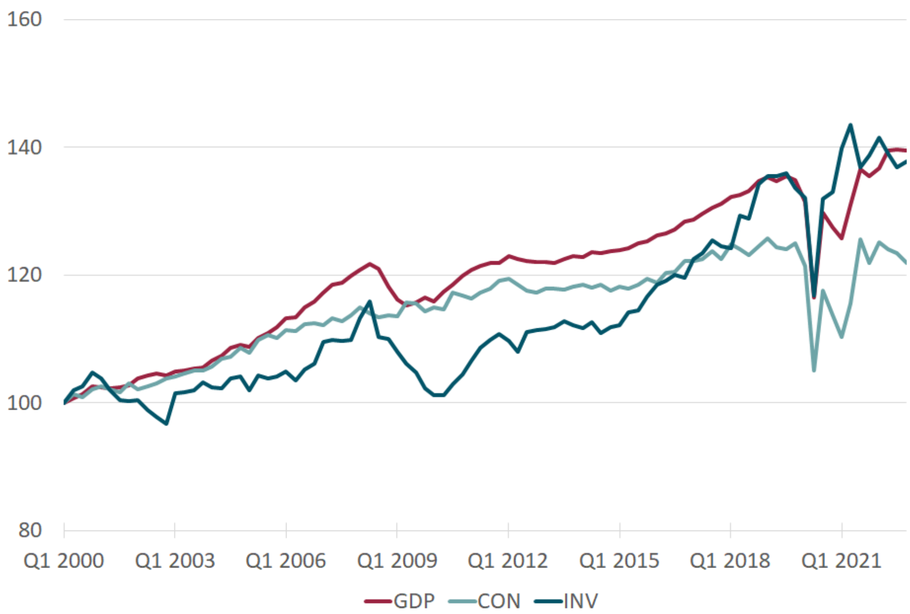
mation), using monthly (high-frequency) data. The monthly data include 54 series for the main analysis. We group the variables into the following classes: (i) production and trade indicators (Prod) including, e.g., industrial production, exports and imports, (ii) consumption indicators (Con) including, e.g., retail sales and car registrations, (iii) labour market variables (Lab) including, e.g., employment, unemployment and vacancies, (iv) price indicators (Pri) such as consumer prices and wholesale prices, (v) variables related to money and credit (Mon) such as loans to households and real effective exchange rates, (vi) financial and uncertainty indicators (Fin) including, e.g., interest rates and the Austrian stock market (ATX, ATX volatility), and finally (vii) purchasing managers indices and other survey and sentiment indicators (Sur) such as UniCredit Bank Austria purchasing managers' indices and WIFO survey indicators.[9] Table A.2 in the appendix lists all variables with codes, sources and transformations. The transformations are performed to ensure stationarity. All data are standardized. In addition, we consider principal components of the described variables. More precisely, we consider the first principal component of all variables and the first principal components of the seven sub-groups (production and trade, consumption, labour market, prices, money and credit, financial markets and uncertainty, surveys and sentiment), respectively. We call them f, f1, f2, . . ., f7.

The data are not real-time and do not include vintages of data, so that we cannot assess the influence of revisions on the nowcast/forecast accuracy. Among the quarterly variables considered investment is typically most heavily revised. A revision of two to three percentage points in the yearly growth rates is not unusual, and sometimes revisions may be even larger. However, some empirical findings, e.g., in Bernanke and Boivin (2003) and Schumacher and Breitung (2008) suggest that data revisions do not considerably affect the forecast accuracy. We do take into account the different availability of variables due to different publication lags and adjust (by shifting) individual variables to mimic the availability of information in real time.

Figure 1 shows the developments of the quarterly data we forecast and nowcast. For GDP, consumption and investment, we forecast/nowcast quarter over quarter (QoQ) growth rates, i.e., growh rates of a given quarter with respect to the previous quarter, and year over year (YoY) growth rates, i.e., growth rates of a given quarter with respect to the same quarter of the previous year. Statistical offices mostly report both QoQ and YoY rates (for quarterly GDP). Most nowcasting studies seem to look at QoQ growth rates; however, some also use YoY growth rates (see Anthonisz, 2021; Dahlhaus et al., 2017; Bragoli and

[9] WIFO, the Austrian Institute of Economic Research, is a well known economic research institute in Austria.

Figure 1: GDP, consumption and investment



The graph shows real GDP, real consumption (CON) and real investment (INV) for Austria, indexed at 100 in 2000Q1.

Fosten, 2018; Fosten and Greenaway-McGrevy, 2022). Our results generally differ between those based on QoQ and those based on YoY growth rates. Table A.1 in the appendix presents descriptive statistics of QoQ and YoY growth rates, for GDP, consumption and investment. The larger standard deviations of investment, when compared with GDP, may be an indication of poorer predictability. In fact this is what we observe in our empirical results. In general the forecasting/nowcasting accuracy in terms of the root mean squared error (RMSE) for investment is much worse than for GDP, see, e.g., Table 1.

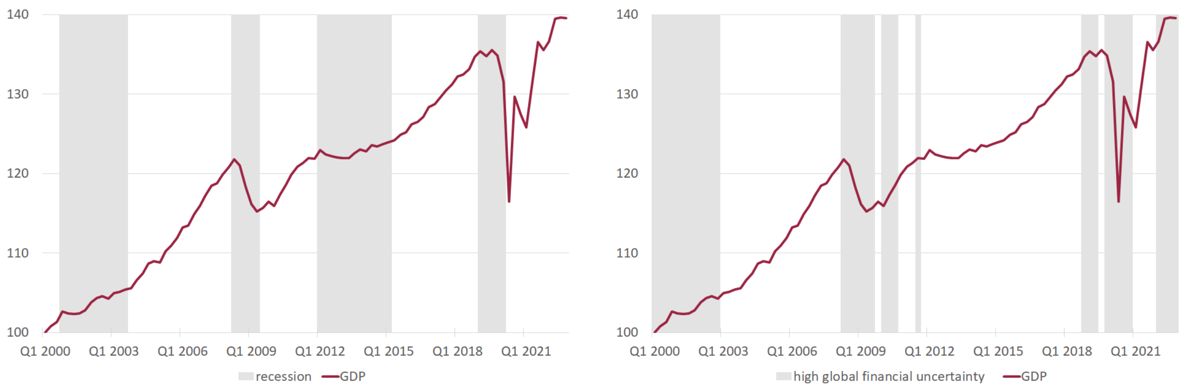
In our regime-dependent models we consider five dummy variables defining the regimes, (i) the OECD recession indicator for Austria, (ii) indicators defining high/low financial and economic global uncertainty,[10] and (iii) indicators defining high/low financial and economic uncertainty in Austria. The recession indicator is the OECD recession indicator from the peak to the trough, where a value of one signals recession. It is available at a monthly frequency and we take end-of-quarter values when transforming the monthly to the quarterly series.[11] For the dummy variables defining high/low global financial and economic uncer-

[10] Both financial and economic global uncertainties, proxied by financial and economic uncertainty in the US, have been found to show a strong impact on economic variables in Austria, in fact stronger than local (Austrian) financial and economic uncertainties, see Fortin et al. (2023).

[11] The OECD recession indicator can be retrieved, e.g., from the Federal Reserve Bank of St. Louis

tainties we use the indicators computed by Jurado et al. (2015), for the respective dummies for Austria we use the financial and economic uncertainty indices for Austria, as computed in Fortin et al. (2023).[12] For the global and the Austrian dummies we define periods of high uncertainty (where the dummy is equal to one) when the uncertainty indicator is larger than the median, and periods of low uncertainty when the indicator is smaller than (or equal to) the median. We transform monthly to quarterly series by taking end-of-quarter values. Figure 2 shows the periods of recession and the periods of high global financial uncertainty, together with GDP. These are the regimes turning out to be most important in nowcasting.

Figure 2: GDP and different regimes



The graphs show the development of GDP (indexed at 100 in 2000Q1) and periods of recession shaded grey (left), and GDP and periods of high global financial uncertainty shaded grey (right).

4 Empirical analysis

Our primary goals are to find out which variables and methods forecast and nowcast GDP, consumption and investment best and whether explicitly considering different regimes can improve the forecast/nowcast. Regarding forecasts, state-of-the art research suggests that building large models with parameter shrinkage ensures best forecast accuracy. However, when it comes to nowcasting this approach is often impractical. It requires constant management of large datasets and takes significant computational time. In large models gen-

database (FRED), at the following link: `https://fred.stlouisfed.org/series/AUTRECM`

[12] We use the one-month ahead (total) financial and economic uncertainty indices for the US, see `https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes` and we consider the period January 1995 until December 2022 to define periods of high/low uncertainty. Similarly, we use the one-month ahead financial and economic uncertainty indices for Austria, see Fortin et al. (2023).

erating nowcasts and updating them every instance a new release comes in is not only demanding but sometimes infeasible. We thus suggest a practical approach towards variable selection, which is based on measuring the out-of-sample performance of mixed-frequency models including one,[13] two and three monthly (high-frequency) variables. In particular we examine whether explicitly considering regimes improves the nowcast performance. To this end we look at regimes implied by a recession indicator for Austria, and regimes implied by (local and global) financial and economic uncertainty indicators. Each regime (recession/expansion or high/low financial/economic uncertainty) considers one variable and thus we can examine the importance of variables in certain regimes. In terms of forecast/nowcast performance we use the traditional root mean squared error (RMSE), namely

$$RMSE^{fore} = \sqrt{\frac{1}{T}\sum_{j=1}^{T}\left(\hat{y}_{t+j|t+j-1} - y_{t+j}\right)^2} \qquad RMSE^{ni} = \sqrt{\frac{1}{T}\sum_{j=1}^{T}\left(\hat{y}_{t+j|t+j|i} - y_{t+j}\right)^2} \quad (6)$$

for $i = 1, 2, 3$, where y is the QoQ or YoY growth rate of GDP, consumption or investment, $\hat{y}_{t+j|t+j-1}$ is the forecast of y for quarter $t + j$ conditional on the information available in the previous quarter $t + j - 1$, $\hat{y}_{t+j|t+j|i}$ is nowcast i of y for quarter $t + j$ conditional on the information available in the $i-$th month of quarter $t + j$, and T is the total number of quarters in the out-of-sample evaluation period. Thus, $RMSE^{fore}$ denotes the RMSE of the forecast and $RMSE^{ni}$ denotes the RMSE of nowcast i.

Preliminary results from Blagov (2022) show that for Germany, France, Italy, and Spain out of around 80 prominent indicators considered, only a handful are useful for nowcasting GDP. These findings support our approach considering small models with only a few variables, which appears convenient and efficient in practice. Also, the historical performance of additional indicators can be easily tested, and thus new indicators simply added. In addition to the monthly economic indicators described above we use factors extracted from these economic indicators. Benchmark (forecast) models are traditional quarterly (low-frequency) VAR models. For using quarterly VAR forecasts with monthly variables we transform monthly to quarterly series by taking quarterly averages. Table A.3 lists the names of the monthly indicators, sorted alphabetically according to their abbreviations, so that the variables can be easily identified in the following discussions.

To analyse the potential effect of regimes we look at five different indicators defining regimes. We explore the regime effect in the intercept and in the monthly (high-frequency)

[13] Also Kuzin et al. (2011), Schumacher (2016) and Foroni et al. (2013), among others, use only one high-frequency variable.

variable. In more detail, the regime effect in the intercept is expressed such that $\mathbf{D}_t$ in (1), (4) and (5) is defined such that $\mathbf{D}_t = (D_t, 1 - D_t)'$, where D_t is the (quarterly) dummy variable representing periods of recession (or high uncertainty, respectively) if $D_t = 1$ and periods of expansion (or low uncertainty periods, respectively) if $D_t = 0$. Note that D_t is expressed in quarterly frequency. Finally, the regime effect in the monthly variable, when one – not necessarily the same – monthly variable is included in each regime, is taken into account such that $x_H(t,i) = (D(t,i)z_1(t,i), (1 - D(t,i))z_2(t,i))'$, for $i = 1, 2, 3$, in (1), where $z_1(t,i)$ and $z_2(t,i)$ are monthly variables, not necessarily the same, and $D(t,i)$ is the corresponding monthly dummy variable at quarter t and month i of quarter t.[14] A more detailed description of the recession indicator and the financial and economic uncertainty indicators can be found in Section 3.

We also examine the question of what is the value added of nowcasting over forecasting, and the question whether nowcasting with more information, i.e., nowcasting later in a given quarter, outperforms nowcasting with less information, i.e., nowcasting earlier in a given quarter. In general we have three nowcasts for a given quarter. "Nowcast 1" is the nowcast estimated based on monthly variables available until the first month in a given quarter, "nowcast 2" is the nowcast estimated based on data until the second month in a given quarter, and "nowcast 3" is the nowcast estimated based on data available for all three months. The forecast, however, uses only information up to the previous quarter and thus, in the case of mixed-frequency models, the information of all three months in the previous quarter.

We use 54 monthly (high-frequency) variables to nowcast GDP, consumption and investment.[15] With respect to the mixed-frequency models we consider eleven models, including two models following Ghysels and nine univariate MIDAS models, of which six unrestricted MIDAS models and three MIDAS models with functional distributed lags. More precisely, we use the following model parameters: the number of lags in MF-VAR models is $p = 1, 2$, the number of lags in unrestricted MIDAS models is $p_x = 1, \ldots, 6$, and the Almon polynomial order is $P = 3$ in MIDAS-pdl, where $p_x = 4, 5, 6$ (see Section 2).[16] When using

[14] In terms of the notation used in MIDAS regressions for high-frequency variables, see (4) and (5), the monthly variable $x_{H,t-\frac{\tau}{3}}$ becomes a two-dimensional vector such that $x_{H,t-\frac{\tau}{3}} = \left(D_{t-\frac{\tau}{3}} z_{1,t-\frac{\tau}{3}}, (1 - D_{t-\frac{\tau}{3}}) z_{2,t-\frac{\tau}{3}}\right)'$, $\tau = 0, 1, \ldots$.

[15] In a preliminary analysis we used many more (over 100) variables and then discarded some based on the nowcast performance in one-variable models and correlations.

[16] For three-variable models we do not employ MF-VAR models and for regime-dependent and two-variable models we set $p = 1$. Note that the number of estimated coefficients in MF-VAR models with three monthly variables would be 100, not taking into account intercepts, wich are too many to get reliable estimates.

two-variable, three-variable and regime-dependent models, we reduce the original number of variables to approximately 20 variables including principal components based on the forecast performance in one-variable models and correlations, see Tables A.4 and A.5 in the appendix. We use potentially different variables in the short lists for GDP, consumption and investment, and for QoQ and YoY growth rates. In total we consider 49,316 models, thereof 30,900 regime-dependent and 18,416 non regime-dependent, to nowcast and forecast GDP. The mixed-frequency models we consider include roughly 10% mixed-frequency VAR models and 90% MIDAS models. Similarly for consumption and investment.

In our main analysis we exclude the financial crisis and the Covid-19 period from the evaluation period. In general different crisis periods are distinct, being driven by different dynamics, and also potential future crises will most probably be different again. However, we would like to perform a forecast analysis for "normal times", not for times in which variables follow particular dynamics being characteristic for these times only. This means that the out-of-sample evaluation period ranges from 2012Q3 to 2019Q4, and we use recursive windows starting with a minimum of 50 quarters, thus providing 30 quarters for comparison. For each of these quarters we compute nowcasts and forecasts. For example, for the first quarter in the evaluation period, 2012Q3, we compute a forecast using quarterly and monthly data up to 2012Q2, and we generate nowcasts using quarterly data up to 2012Q2 and monthly data up to 2012Q3. Nowcast 1 uses data until July, nowcast 2 uses data up to August, and nowcast 3 uses data until September.[17]

In a robustness check we include the Covid-19 period (2020 and 2021) in the out-of-sample evaluation period. As expected all forecast and nowcast models perform extremely badly during this period, see Figure B.1 in the appendix.

4.1 Importance of new information

Looking at all the (mixed-frequency) models considered we can conclude that nowcasting does indeed provide a value added to forecasting. In the large majority of cases (roughly 80%) at least one of the three nowcasts improves the forecast (in terms of the RMSE), see Figure 3. However, in only about half the cases are all nowcasts better than the forecast. Also, the forecast performs quite well sometimes, in approximately 20% of the cases the forecast is more accurate than any of the nowcasts. Note that when this is true the forecast

[17] As discussed above we use monthly data according to their availability not according to the month they relate to.

mostly comes from a mixed-frequency model.[18] So monthly information also seems to be beneficial in forecasting, not only in nowcasting, quarterly variables. Indeed, mixed-frequency models are also used for forecasting, see, e.g., Brave et al. (2019), Baumeister et al. (2015) and Foroni et al. (2018).

It is rarely the case, however, that all three nowcasts improve the previous nowcast or forecast with new incoming information, as one might ideally expect. This is only true in about 5% of all cases, see Figure 4. In general, the first available monthly information in a given quarter seems to be the most beneficial, while the additional data in the second and third months do not seem to provide as much value added. See again Figure 4.[19] Considering GDP (both QoQ and YoY growth rates) and the top 1% models (with respect to the RMSE) the first nowcast is indeed the best, showing a better forecast performance than the nowcasts created later (nowcast 2 and nowcast 3), see Figure 5.

Considering consumption QoQ growth rates and investment YoY growth rates and the top 1% models (with respect to the RMSE) the forecast is on average, rather surprisingly, better than any of the nowcasts, see Figure 5. However, looking at only the best models for GDP, consumption and investment, the forecast performs worst (except of GDP, QoQ) and nowcast 2 or nowcast 3 is the best, as one would expect.

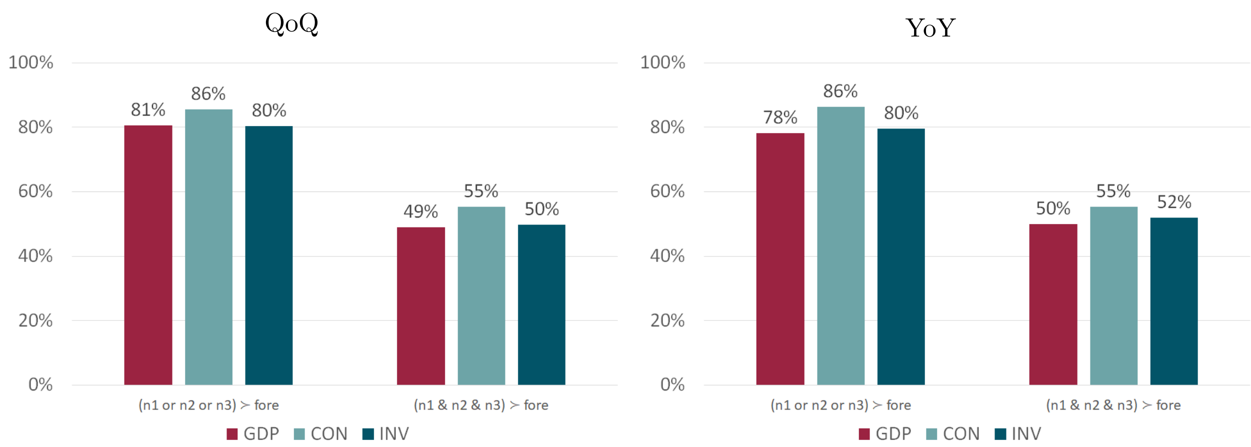
Figure 6 presents a dynamic version of the results presented in the second panel of Figure 5. Instead of the RMSE calculated over the total out-of-sample period (2012Q3 – 2019Q4) it presents the time-changing RMSE over rolling windows of eight quarters (for GDP, consumption and investment) for the forecast, nowcast 1, nowcast 2 and nowcast 3, so that one can see the proportions of times when a certain nowcast or the forecast performs the best. These values provide complementary information to the static (aggregate) values shown in Figure 5 and, except for the results implied by the best models forecasting/nowcasting consumption (YoY growth rates), are in line with those results.[20]

[18] This is also supported by Figure 11 in Section 4.4 when forecasting GDP and consumption. In these cases the mixed-frequency models seem to forecast better than VAR models when looking at the top 1% models with respect to forecast accuracy.

[19] In about 70% of all cases nowcast 1 improves the forecast, while in only approximately 30% of all cases nowcast 2 improves nowcast 1, or nowcast 3 improves nowcast 2. Note that we have 49,300 models for forecasting and 34,900 models for nowcasting GDP, and similar numbers for forecasting/nowcasting consumption and investment.

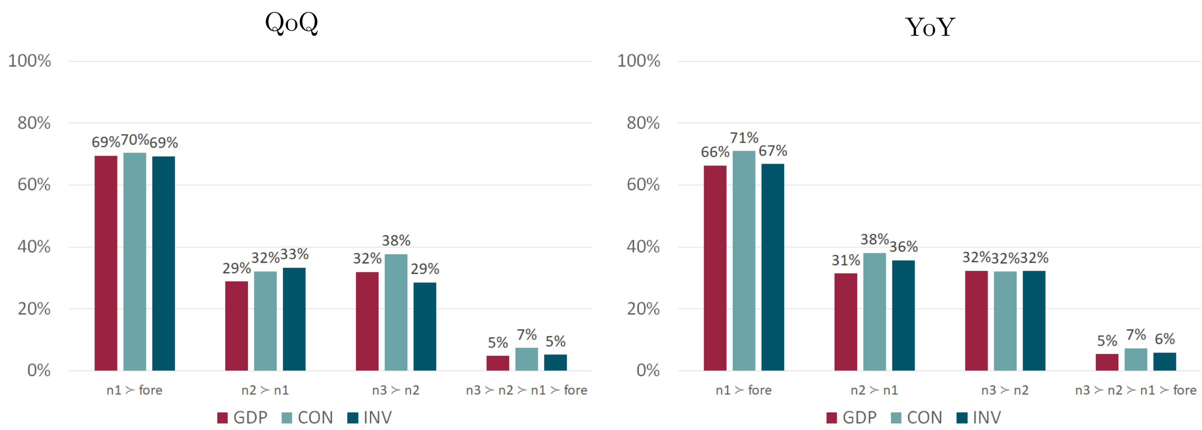
[20] Considering time-changing RMSE, the forecast of consumption (YoY) seems to be the best, as it outperforms the nowcasts more often (39%) than any nowcast outperforms the other nowcasts/forecast, see Figure 6. However, based on aggregate RMSE the forecast is worse than any of the nowcasts, see Figure 5. Also, the best nowcast based on aggregate RMSE is nowcast 3, while looking at time-changing RMSE nowcast 1 seems to be the best. This is caused by the very good performance of nowcast 3 prior to 2014Q2. In any case, one should not undervalue forecasts when evaluating nowcasts.

Figure 3: Improvement of nowcasts over the forecast



The graphs present the percentages of cases when at least one of the three nowcasts improves the forecast, (n1 or n2 or n3) $\succ$ fore, and when all of the three nowcasts improve the forecast, (n1 & n2 & n3) $\succ$ fore, considering all models, all variables, and the RMSE, for QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4.

Figure 4: Improvement of nowcasts over the quarter



The graphs present the percentages of cases when nowcast 1 improves the forecast (n1 $\succ$ fore), when nowcast 2 improves nowcast 1 (n2 $\succ$ n1), when nowcast 3 improves nowcast 2 (n3 $\succ$ n2), and when nowcast 3 improves nowcast 2 which improves nowcast 1 which improves the forecast (n3 $\succ$ n2 $\succ$ n1 $\succ$ fore), considering all models, all variables, and the RMSE, for QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4.

Figure 5: Forecasting and nowcasting

top 1% models

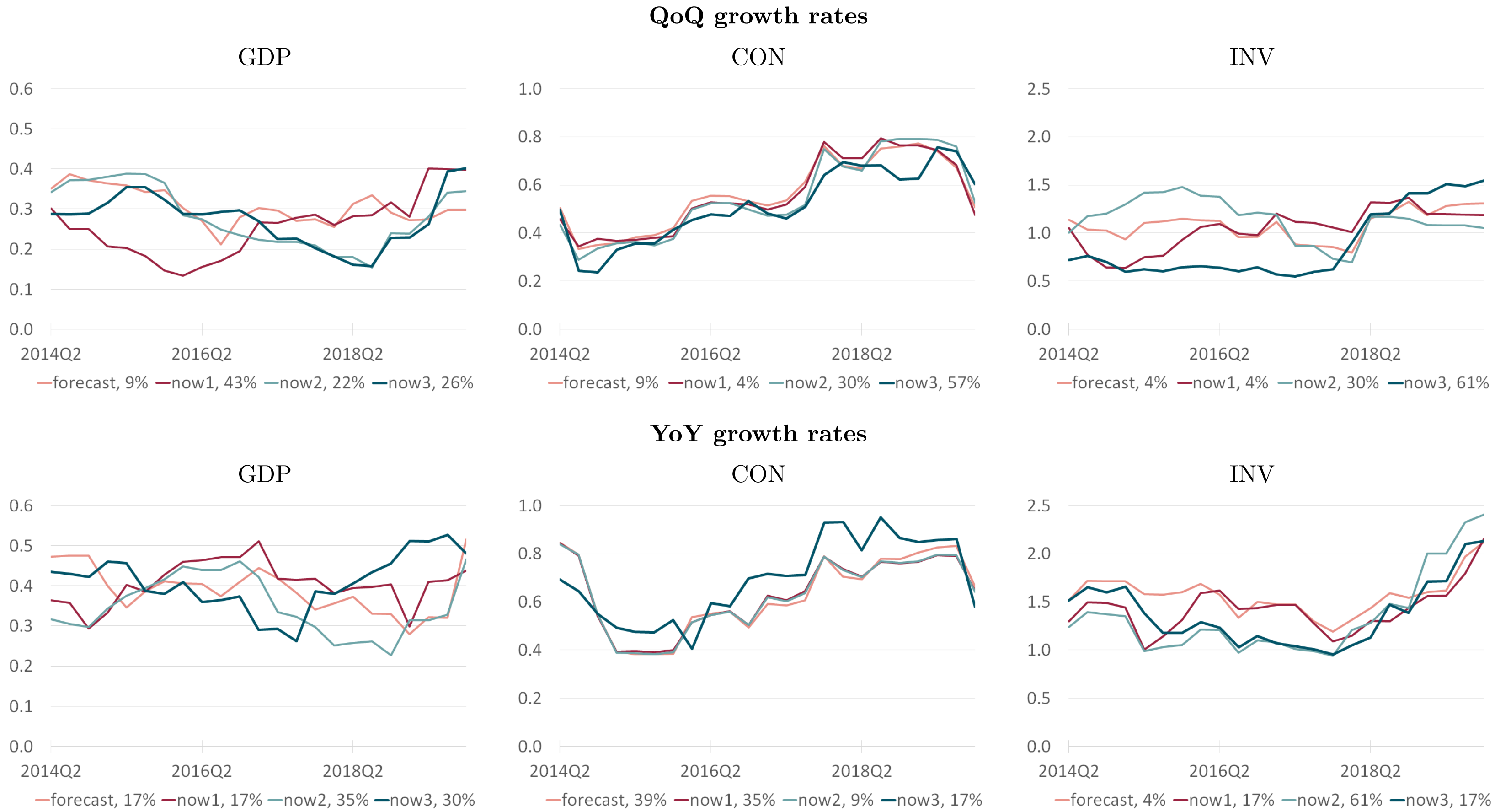
	QoQ GDP	QoQ CON	QoQ INV	YoY GDP	YoY CON	YoY INV
Forecast	0.346	0.623	1.237	0.492	0.864	1.761
Nowcast 1	0.333	0.632	1.227	0.478	0.873	1.781
Nowcast 2	0.341	0.628	1.221	0.481	0.854	1.767
Nowcast 3	0.341	0.626	1.258	0.492	0.851	1.810

best model

	QoQ GDP	QoQ CON	QoQ INV	YoY GDP	YoY CON	YoY INV
Forecast	0.300	0.573	1.129	0.452	0.707	1.630
Nowcast 1	0.298	0.556	1.091	0.426	0.703	1.569
Nowcast 2	0.300	0.550	1.090	0.388	0.701	1.570
Nowcast 3	0.302	0.557	0.984	0.421	0.698	1.534

The figure shows the average RMSE of the top 1% models (left) and the RMSE of the best model (right) when forecasting/nowcasting GDP, consumption and investment, for QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4.

Figure 6: Best forecasts and nowcasts of GPD, consumption and investment



The graphs show time-changing RMSE over rolling windows of eight quarters of best models for GDP, consumption and investment, considering QoQ and YoY growth rates. The percentage shown in labels indicates the proportion of cases when the given forecast/nowcast is better than the others shown, considering time-changing RMSE. The variables included and the methods used in the best nowcast/forecast models can be found in Tables B.1, B.2 and B.3. Note that in all cases but one (CON QoQ, nowcast 3) the best models are regime-dependent models.

4.2 Regime-dependent versus non regime-dependent models

Our results suggest that regime-dependent models clearly outperform non regime-dependent models, and that different regimes are important for GDP, consumption and investment. For nowcasting GDP and consumption it seems to be important to explicitly consider recession-driven regimes while for nowcasting investment the regimes based on global financial uncertainty should primarily be taken into account. See Table 1 which presents the RMSE of the 20 best models for forecasting and nowcasting GDP, consumption and investment, for both QoQ and YoY growth rates, respectively. The colour coding, where different colours indicate different regimes, clearly identifies the superiority of regime-dependent models and the importance of different regimes for GDP, consumption and investment. Note that only in one single case[21] the best model is a non regime-dependent model, namely a three-variable model, for nowcast 3 of consumption with respect to QoQ growth rates.[22] In addition, global financial and economic uncertainties seem to be important when producing forecasts and early nowcasts (nowcast 1) for GDP QoQ growth rates, AT financial uncertainty seems to play a role when forecasting consumption QoQ growth rates, and recession-driven regimes are important when doing late nowcasts (nowcast 3) for investment QoQ growth rates.

Even if in the majority of cases regime-dependent models outperform non regime-dependent models there are also periods when the situation is reverse and non regime-dependent models seem to perform better. We present time-changing RMSE over rolling windows of eight quarters of *best* regime-dependent models and *best* non regime-dependent models for the forecast and all three nowcasts for consumption (YoY growth rates), see Figure 7, and for investment (QoQ growth rates), see Figure 8.[23]

Considering nowcast 1 of consumption YoY growth rates (see Figure 7), for example, the regime-dependent model outperforms the non regime-dependent model in 100% of all cases. Considering nowcast 2 and nowcast 3, however, the regime-dependent model[24] is

[21] All together there are 24 cases: 3 variables, 2 growth rates, 4 forecasts/nowcasts.

[22] Tables B.1, B.2 and B.3 in the appendix provide detailed information on the corresponding best 20 models including methods and variables, for GDP, consumption and investment.

[23] The corresponding graphs for GDP (QoQ, YoY), consumption (QoQ) and investment (YoY) can be obtained from the authors upon request.

[24] The best regime-dependent models include the nominal effective exchange rate (RR1) in recession times and tourists arrivals (TOU) in non-recession times for the forecast, nowcast 1 and nowcast 2, while for nowcast 3 the best model is driven by global financial uncertainty with the first principal component over all variables in the high financial uncertainty regime and PMI for new orders (BA3) in the low financial uncertainty regime. See Table B.2 in the appendix.

better than the non regime-dependent model[25] in only 74% and 57%, respectively. In particular, towards the end of the evaluation period, when growth rates of consumption are mostly positive but rather volatile, the regime-dependent models show a better forecast performance than non regime-dependent models. The regimes in these regime-dependent models are driven by recession for the forecast, nowcast 1 and nowcast 2, and by global financial uncertainty for nowcast 3. Turning to investment QoQ growth rates (see Figure 8), the best regime-dependent model for nowcast 3 outperforms the best non regime-dependent model in 83% of all cases,[26] while the best regime-dependent models for the forecast, nowcast 1 and nowcast 2 outperform the best non regime-dependent models only in less than half the cases (43%, 35%, 48%).[27]

Finally, we perform the Diebold–Mariano test of equal forecast accuracy of the best regime-based model against the best non regime-based models (see Diebold and Mariano, 1995). A significant outperformance of regime-dependent models occurs in two cases: (i) when nowcasting consumption (YoY) in the first month of a quarter (nowcast 1), where the (best) model is driven by the recession regime including the nominal effective exchange rate (RR1) in recession times and tourists arrivals (TOU) in non-recession times, and it significantly outperforms (at the 5% significance level) the best non regime-dependent model including imports (IMP), labour force (LAB) and the real effective exchange rate (RR2); and (ii) when nowcasting investment (QoQ) in the third month of a quarter (nowcast 3), where the (best) model is driven by the recession regime including male unemployed (UNM) in recession times and the economic expectations index (WEE) in non-recession times, and it significantly outperforms the best non regime-dependent model including employment (EMP), the assessment of order books (ISO) and the first principal component over all variables (f).[28]

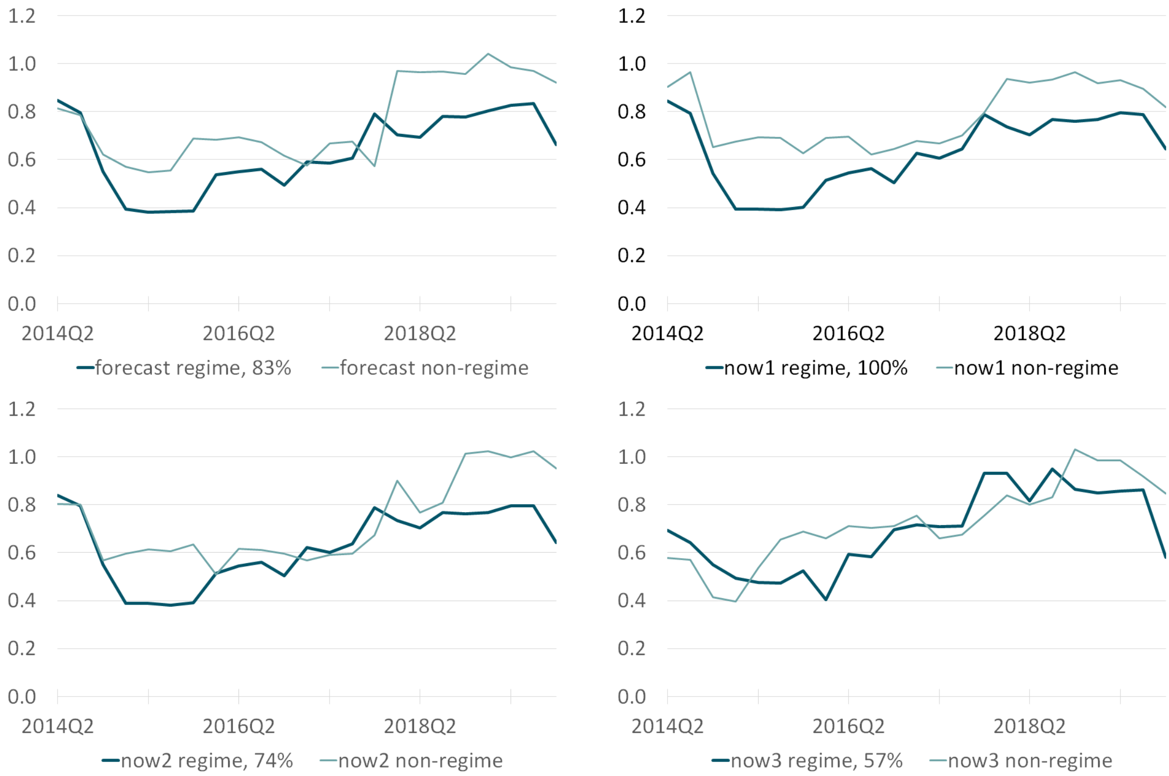
[25] The best non regime-dependent models for consumption are defined by the following variables: AT2-RR2-WBE (forecast), IMP-LAB-RR2 (nowcast 1), AT2-LOH-f2 (nowcast 2) and IMP-CAR-LOH (nowcast 3). See Table A.3 for the abbreviations of the variables.

[26] The best regime-dependent models when forecasting/nowcasting investment (QoQ) include in the high global financial uncertainty regime the PMI related to suppliers' delivery times (BA5) for the forecast, the assessment of order books (ISO) for nowcast 1, and exports (EXX) for nowcast 2, while in the low global financial uncertainty regime they include the assessment of order books (ISO) for the forecast and nowcast 1, and the economic sentiment indicator (SEN) for nowcast 2. In the case of nowcast 3 the regime is driven by recessions, and in recession time the best model includes male unemployed (UNM) and in non-recession times it includes the economic expectations index (WEE). See Table B.3 in the appendix.

[27] The best non regime-dependent models for investment (QoQ) include the following variables: EMP-ISO-f (forecast), EXX-LAB-ISO (nowcast 1), EMP-ISO-f (nowcast 2 and nowcast 3). See Table A.3 for the abbreviations of the variables.

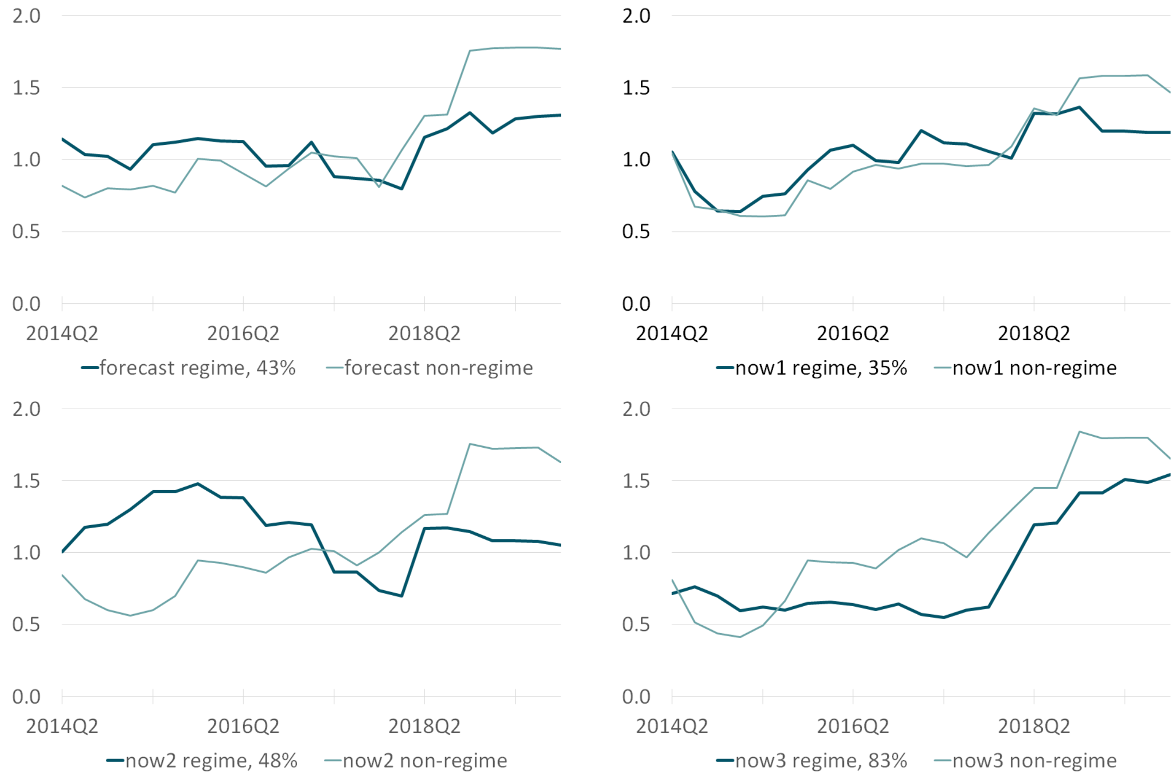
[28] Note that the best regime-dependent model for nowcasting consumption (YoY) in the first month of a quarter (nowcast 1) is MF-VAR while for the best non regime-dependent model it is MIDAS-u. The best

Figure 7: Best regime-dependent versus best non regime-dependent models when nowcasting consumption (YoY growth rates)



The graphs show time-changing RMSE over rolling windows of eight quarters of best regime-dependent and best non regime-dependent models for the forecast and the three nowcasts for consumption, considering YoY growth rates. The percentage shown in labels indicates the percentage of cases when the regime-dependent model is better than the non regime-dependent model, considering time-changing RMSE. The best regime-based models are driven by the recession indicator for forecast, nowcast 1 and nowcast 2, and by global financial uncertainty for nowcast 3.

Figure 8: Best regime-dependent versus best non regime-dependent models when nowcasting investment (QoQ growth rates)



The graphs show time-changing RMSE over rolling windows of eight quarters of best regime-dependent and best non regime-dependent models for the forecast and the three nowcasts for investment, considering QoQ growth rates. The percentage shown in labels indicates the percentage of cases when the regime-dependent model is better than the non regime-dependent model, considering time-changing RMSE. The best regime-based models are driven by global financial uncertainty for forecast, nowcast 1 and nowcast 2, and by the recession indicator for nowcast 3.

Table 1: 20 best nowcasting models for GDP, consumption and investment

GDP

	GDP QoQ fore	GDP QoQ now 1	GDP QoQ now 2	GDP QoQ now 3	GDP YoY fore	GDP YoY now 1	GDP YoY now 2	GDP YoY now 3
1	0.2997	0.2982	0.2998	0.3023	0.4520	0.4262	0.3883	0.4210
2	0.3108	0.2991	0.3024	0.3063	0.4631	0.4267	0.4134	0.4407
3	0.3122	0.2993	0.3034	0.3069	0.4645	0.4279	0.4218	0.4411
4	0.3149	0.2993	0.3109	0.3081	0.4648	0.4280	0.4224	0.4456
5	0.3160	0.3007	0.3110	0.3091	0.4652	0.4281	0.4226	0.4487
6	0.3161	0.3023	0.3115	0.3124	0.4657	0.4286	0.4282	0.4493
7	0.3198	0.3038	0.3116	0.3132	0.4657	0.4317	0.4287	0.4504
8	0.3201	0.3047	0.3119	0.3133	0.4658	0.4323	0.4307	0.4552
9	0.3203	0.3061	0.3123	0.3138	0.4671	0.4330	0.4332	0.4559
10	0.3203	0.3068	0.3133	0.3142	0.4671	0.4342	0.4335	0.4564
11	0.3210	0.3072	0.3133	0.3154	0.4683	0.4349	0.4374	0.4564
12	0.3212	0.3073	0.3138	0.3155	0.4684	0.4361	0.4375	0.4576
13	0.3244	0.3074	0.3145	0.3160	0.4686	0.4365	0.4385	0.4581
14	0.3246	0.3078	0.3162	0.3162	0.4687	0.4368	0.4402	0.4581
15	0.3249	0.3078	0.3163	0.3164	0.4692	0.4375	0.4423	0.4618
16	0.3250	0.3080	0.3163	0.3164	0.4708	0.4379	0.4436	0.4626
17	0.3250	0.3086	0.3164	0.3166	0.4710	0.4382	0.4450	0.4633
18	0.3252	0.3089	0.3166	0.3167	0.4712	0.4385	0.4450	0.4635
19	0.3255	0.3098	0.3167	0.3172	0.4714	0.4387	0.4456	0.4636
20	0.3256	0.3112	0.3176	0.3173	0.4715	0.4388	0.4464	0.4645

CON

	CON QoQ fore	CON QoQ now 1	CON QoQ now 2	CON QoQ now 3	CON YoY fore	CON YoY now 1	CON YoY now 2	CON YoY now 3
1	0.5727	0.5564	0.5503	0.5569	0.7073	0.7031	0.7013	0.6981
2	0.5728	0.5592	0.5552	0.5627	0.7318	0.7351	0.7351	0.7143
3	0.5728	0.5594	0.5615	0.5647	0.7324	0.7361	0.7427	0.7278
4	0.5733	0.5661	0.5655	0.5663	0.7343	0.7409	0.7458	0.7374
5	0.5744	0.5669	0.5659	0.5674	0.7534	0.7433	0.7527	0.7482
6	0.5745	0.5680	0.5676	0.5714	0.7567	0.7538	0.7557	0.7496
7	0.5746	0.5686	0.5709	0.5731	0.7600	0.7592	0.7565	0.7572
8	0.5753	0.5688	0.5723	0.5737	0.7613	0.7826	0.7575	0.7600
9	0.5759	0.5689	0.5729	0.5748	0.7670	0.7837	0.7612	0.7648
10	0.5767	0.5736	0.5778	0.5749	0.7794	0.7843	0.7669	0.7810
11	0.5772	0.5757	0.5792	0.5758	0.7810	0.7847	0.7683	0.7836
12	0.5778	0.5767	0.5795	0.5796	0.7821	0.7895	0.7694	0.7884
13	0.5802	0.5770	0.5852	0.5801	0.7851	0.7910	0.7710	0.7899
14	0.5806	0.5796	0.5867	0.5806	0.7874	0.7928	0.7825	0.7900
15	0.5814	0.5816	0.5870	0.5811	0.7885	0.7932	0.7833	0.7910
16	0.5826	0.5826	0.5872	0.5819	0.7887	0.7953	0.7857	0.7941
17	0.5831	0.5831	0.5876	0.5820	0.7889	0.7953	0.7859	0.7956
18	0.5834	0.5832	0.5877	0.5848	0.7893	0.7998	0.7860	0.7969
19	0.5841	0.5835	0.5881	0.5854	0.7906	0.8006	0.7860	0.7977
20	0.5842	0.5859	0.5893	0.5855	0.7913	0.8026	0.7874	0.8000

INV

	INV QoQ fore	INV QoQ now 1	INV QoQ now 2	INV QoQ now 3	INV YoY fore	INV YoY now 1	INV YoY now 2	INV YoY now 3
1	1.1295	1.0907	1.0899	0.9837	1.6295	1.5695	1.5698	1.5343
2	1.1447	1.1016	1.0965	1.0918	1.6295	1.5837	1.6048	1.5388
3	1.1478	1.1088	1.1032	1.0924	1.6311	1.6106	1.6097	1.5714
4	1.1492	1.1137	1.1089	1.1146	1.6417	1.6235	1.6187	1.5983
5	1.1493	1.1217	1.1131	1.1173	1.6428	1.6254	1.6236	1.6148
6	1.1537	1.1246	1.1249	1.1185	1.6428	1.6266	1.6269	1.6156
7	1.1543	1.1250	1.1272	1.1269	1.6439	1.6300	1.6282	1.6279
8	1.1554	1.1256	1.1272	1.1280	1.6439	1.6338	1.6289	1.6307
9	1.1578	1.1297	1.1292	1.1293	1.6480	1.6457	1.6294	1.6370
10	1.1610	1.1322	1.1356	1.1381	1.6485	1.6498	1.6339	1.6540
11	1.1631	1.1333	1.1377	1.1382	1.6498	1.6498	1.6376	1.6541
12	1.1645	1.1345	1.1379	1.1411	1.6525	1.6499	1.6379	1.6552
13	1.1671	1.1363	1.1411	1.1412	1.6539	1.6547	1.6381	1.6609
14	1.1672	1.1366	1.1445	1.1444	1.6545	1.6572	1.6388	1.6618
15	1.1691	1.1395	1.1451	1.1452	1.6578	1.6593	1.6417	1.6629
16	1.1715	1.1411	1.1454	1.1475	1.6598	1.6606	1.6450	1.6645
17	1.1716	1.1411	1.1495	1.1478	1.6606	1.6607	1.6469	1.6658
18	1.1721	1.1450	1.1508	1.1491	1.6622	1.6702	1.6488	1.6669
19	1.1723	1.1474	1.1513	1.1592	1.6625	1.6707	1.6504	1.6681
20	1.1735	1.1476	1.1517	1.1598	1.6641	1.6742	1.6526	1.6687

The table shows the RMSE of the 20 best models, when nowcasting GDP, consumption and investment, considering QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. Coloured RMSE indicate that the underlying model is a regime-dependent model. For details with respect to the variables and methods of the 20 best models for GDP, consumption and investment see Tables B.1, B.2 and B.3 in the appendix.

AT recession | global financial uncertainty | global economic uncertainty | AT financial uncertainty | AT economic uncertainty | no regime

4.3 Regime-dependent models

Regarding the importance of variables in different regimes we present the average RMSE of the top 1% regime-dependent models including a certain variable. We look at recession-based models for GDP and consumption (Figure 9) and at models based on global financial uncertainty for investment (Figure 10). These are the regime-dependent models performing best for GDP, consumption and investment, respectively.[29] Results are presented for each quarterly variable, for both growth rates (QoQ and YoY), and for both regimes, such that all models including a specific variable are taken into consideration. For instance, the column under variable IPM (industrial production) in Figure 9 in regime 1, which corresponds to recession, is the average RMSE (for the forecasts and all three nowcasts) of the top 1% recession-based models including IPM in regime 1. The same applies in regime 2, which corresponds to non-recession. Overall we find that sometimes a certain variable seems to be important in only one of the two regimes, while some other times it seems to be important in both regimes.

The most important variables for forecasting/nowcasting GDP are survey data and in-

regime-dependent model for nowcasting investment (QoQ) in the third month of a quarter (nowcast 3) is MIDAS-u and for the best non regime-dependent model it is MIDAS-pdl.

[29] A summary of the results for each regime (i.e., the regimes based on recession, global financial uncertainty, global economic uncertainty, AT financial uncertainty, and AT economic uncertainty) and each quarterly variable can be obtained from the authors upon request.

dustrial production.[30] While some Purchasing Managers' Indices (PMI), namely the ones related to the overall index, to output, to new orders and to employment (BA1 to BA4),[31] are clearly more important in recession than in non-recession periods, the industrial confidence indicator (ISC) and the assessment of the current level of order books (ISO) seem to be important in both regimes, and production expectations (ISP), the consumers' unemployment expectations (CSU) and employed persons (EMP, YoY growth rates) are more important in non-recession times. In addition, industrial production (IPM) is important in both regimes for YoY growth rates, however, for QoQ growth rates it is more important in non-recession periods. Finally, the short-term interest rate (VIB, YoY growth rates) is an important variable in both recession and non-recession periods.

The most valuable variables for nowcasting consumption in recession periods are female unemployed (UNF), young unemployed (UNY, QoQ growth rates), the nominal effective exchange rate (RR1), as well as expectations about retail trade (WTE) and about buildings (WBE, YoY growth rates). However, in non-recession times tourist arrivals (TOU), overnight stays in Vienna (STV, QoQ growth rates) and retail sales (SAL, YoY growth rates) seem to be most important.

In nowcasting investment the main variables in the regime reflecting high global financial uncertainty are the PMIs (BA1–BA4), among which the most important one seems to be the PMI related to employment (BA4). The assessment of order books (ISO) is important in both high and low global financial uncertainty regimes. Note that the regime-dependent model with ISO in both regimes outperforms the (non regime-dependent) one-variable model including ISO.[32] This finding supports the importance of regime-based models, even if the same variable is included in both regimes. In times of low global financial uncertainty the economic sentiment indicator (SEN), the consumer confidence indicator (CCO, YoY growth rates), and labour market variables such as employment (EMP) and young unemployed (UNY, YoY growth rates) are most essential for nowcasting.

Note that overall the variables identified in regime-dependent models as being important in either one of the two regimes or in both regimes are also found to be important in one-variable models, see Figure B.2 in the appendix. The presentation there is particularly useful in comparing across GDP, consumption and investment and across QoQ and YoY

[30] When not mentioned otherwise, then the results apply to both QoQ and YoY growth rates.

[31] See Table A.3 for a list of the abbreviations of monthly variables.

[32] The Wald test suggests that the coefficients in different regimes are not the same. Also the Diebold-Mariano test on equal forecast accuracy suggests that the regime-dependent model based on global financial uncertainty including ISO in both regimes significantly outperforms the (non regime-dependent) one-variable model including ISO.

growth rates, as we show the total list of 54 variables for all growth rates.

4.4 Comparison of different methods

We consider both the multivariate mixed-frequency VAR model following Ghysels (MF-VAR) and univariate mixed-frequency models: unrestricted MIDAS models (MIDAS-u) and MIDAS regressions with Almon polynomial distributed lag weighting (MIDAS-pdl). In forecasting, we additionally consider vector autoregressive (VAR) models based solely on quarterly data.[33] Our empirical findings do not suggest a clear winner among the different methods for nowcasting. Sometimes the MF-VAR approach performs better, sometimes the MIDAS models are superior. See Figure 11, which shows the average RMSE for the forecasts and the three nowcasts for different methods, which are included in the top 1% methods, respectively (note that a smaller RMSE implies higher forecast accuracy). Figure 12 is complementary to Figure 11 and shows the proportions of different nowcasting methods in the top 1% models, along with the corresponding proportions in all models. The **X** in the field of a certain method denotes that this method is the best (with respect to average RMSE) in the top 1% models, and this method is also the one with the smallest column in Figure 11, for a given nowcast. The first column (out of the four) in the graphs shown in Figure 12 represents the proportions of all nowcasting methods in the sample of total models (34,892). Looking at the other three columns one can see how these proportions change in the top 1% models (when compared to the sample of all models). For instance, when comparing the change of the methods' proportions from the whole sample to the top 1% sample for GDP (QoQ), then the proportion of MF-VAR models decreases from 7% (in the whole sample) to 3% (in the top 1% models), MIDAS-u models decrease from 62% to 47%, and MIDAS-pdl models increase from 31% to 50%. The obvious observation from Figure 12 is that the vast majority of models in the top 1% models are univariate MIDAS models.

Our observations based on Figures 11 and 12 suggest that for nowcasting GDP (both QoQ and YoY) and investment (QoQ) MIDAS models seem to perform best. However, for consumption (both QoQ and YoY) and investment (YoY) MF-VAR models seem to be the winners.[34] Note that even if MF-VAR models are the clear minority of models in the top

[33] Among all forecasting models there are 5% MF-VAR, 44% MIDAS-u, 22% MIDAS-pdl, and 29% VAR models. Among all nowcasting models there are 93% MIDAS models (namely, 62% MIDAS-u and 31% MIDAS-pdl) and 7% are MF-VAR models.

[34] See also Table B.2, which reports the top 20 models with respect to RMSE when forecasting/nowcasting consumption.

1% models (and actually in all models), they are the nowcasting winners for consumption and investment (YoY). Regarding forecasts, Figure 11 shows that for investment quarterly VAR models forecast the best,[35] while for GDP and consumption mixed-frequency models forecast the best.[36] These results are in line with the aggregate results presented in Figure 5, which shows the average RMSE of the top 1% models. In general, the differences between RMSE for different methods in the top 1% models are rather small and may sometimes not be significant.

[35] Note that for investment (YoY) the forecast implied by the VAR models provides the smallest RMSE over all forecast and nowcasts.
[36] Namely, MIDAS models when forecasting GDP (YoY) and consumption (QoQ), and MF-VAR models when forecasting GDP (QoQ) and consumption (YoY).

Figure 9: Important variables in nowcasting GDP and consumption: recession-based models

GDP, QoQ

regime 1 = recession

	IPM	EXX	UR	SEN	ISC	ISO	ISP	CSE	CSU	BA1	BA2	BA3	BA4	BA5	WME	WBE	WSE	WEE	f	f4	f7
Fore	0.38	0.35	0.46	0.35	0.35	0.36	0.35	0.38	0.37	0.35	0.36	0.34	0.34	0.36	0.34	0.41	0.35	0.36	0.33	0.36	0.33
Now1	0.38	0.35	0.42	0.37	0.32	0.32	0.34	0.38	0.37	0.35	0.37	0.36	0.34	0.37	0.32	0.38	0.37	0.37	0.35	0.45	0.31
Now2	0.36	0.33	0.38	0.38	0.33	0.32	0.38	0.36	0.39	0.32	0.33	0.35	0.34	0.36	0.35	0.39	0.35	0.37	0.34	0.42	0.32
Now3	0.38	0.34	0.38	0.37	0.32	0.34	0.35	0.36	0.39	0.32	0.32	0.36	0.38	0.39	0.37	0.39	0.36	0.38	0.32	0.43	0.33

regime 2 = non-recession

	IPM	EXX	UR	SEN	ISC	ISO	ISP	CSE	CSU	BA1	BA2	BA3	BA4	BA5	WME	WBE	WSE	WEE	f	f4	f7
Fore	0.35	0.35	0.37	0.35	0.34	0.33	0.34	0.35	0.34	0.36	0.35	0.36	0.36	0.36	0.35	0.35	0.35	0.35	0.35	0.34	0.35
Now1	0.33	0.33	0.35	0.33	0.33	0.33	0.32	0.35	0.32	0.35	0.33	0.35	0.33	0.36	0.34	0.32	0.32	0.34	0.34	0.35	0.32
Now2	0.31	0.34	0.35	0.34	0.33	0.33	0.34	0.34	0.33	0.36	0.34	0.36	0.35	0.36	0.36	0.36	0.34	0.35	0.35	0.36	0.34
Now3	0.31	0.37	0.34	0.34	0.34	0.34	0.34	0.35	0.34	0.36	0.34	0.35	0.37	0.35	0.35	0.35	0.34	0.35	0.35	0.36	0.34

GDP, YoY

regime 1 = recession

	IPM	EMP	UNM	UNY	WPI	VIB	SEN	ISC	ISO	ISP	CSU	BA1	BA2	BA3	BA4	WME	WSE	WEE	f	f4	f7
Fore	0.49	0.53	0.49	0.48	0.56	0.48	0.55	0.50	0.51	0.49	0.55	0.48	0.51	0.49	0.47	0.49	0.53	0.51	0.49	0.58	0.50
Now1	0.51	0.56	0.52	0.49	0.63	0.49	0.59	0.47	0.43	0.55	0.60	0.47	0.53	0.51	0.44	0.48	0.61	0.58	0.50	0.62	0.45
Now2	0.47	0.59	0.54	0.52	0.66	0.49	0.59	0.50	0.49	0.56	0.64	0.45	0.46	0.47	0.47	0.52	0.56	0.59	0.50	0.62	0.43
Now3	0.50	0.55	0.58	0.57	0.68	0.51	0.57	0.50	0.50	0.53	0.66	0.46	0.47	0.48	0.53	0.53	0.59	0.59	0.51	0.62	0.46

regime 2 = non-recession

	IPM	EMP	UNM	UNY	WPI	VIB	SEN	ISC	ISO	ISP	CSU	BA1	BA2	BA3	BA4	WME	WSE	WEE	f	f4	f7
Fore	0.49	0.49	0.50	0.50	0.48	0.48	0.50	0.49	0.49	0.47	0.49	0.51	0.50	0.51	0.51	0.51	0.50	0.51	0.50	0.48	0.48
Now1	0.45	0.45	0.46	0.46	0.47	0.45	0.50	0.48	0.48	0.44	0.46	0.50	0.47	0.49	0.49	0.50	0.48	0.50	0.47	0.49	0.45
Now2	0.43	0.48	0.48	0.48	0.51	0.46	0.51	0.49	0.48	0.45	0.46	0.52	0.49	0.50	0.53	0.55	0.48	0.53	0.50	0.57	0.46
Now3	0.47	0.48	0.48	0.49	0.50	0.46	0.52	0.49	0.48	0.47	0.47	0.55	0.50	0.52	0.55	0.55	0.49	0.53	0.52	0.53	0.48

CON, QoQ

regime 1 = recession

	IPM	CAR	SAL	TOU	STV	UNE	LAB	UNF	UNY	CPI	CIX	AT1	AT2	RR1	RR2	LOH	ISP	WTE	f2	f4	f5
Fore	0.64	0.68	0.69	0.66	0.65	0.60	0.70	0.60	0.59	0.69	0.70	0.62	0.62	0.59	0.63	0.65	0.64	0.61	0.68	0.67	0.64
Now1	0.62	0.71	0.68	0.68	0.67	0.62	0.66	0.59	0.59	0.68	0.68	0.62	0.62	0.60	0.63	0.66	0.64	0.62	0.71	0.66	0.67
Now2	0.63	0.71	0.68	0.70	0.71	0.61	0.67	0.58	0.59	0.66	0.68	0.63	0.63	0.60	0.62	0.66	0.65	0.61	0.72	0.67	0.66
Now3	0.64	0.61	0.68	0.68	0.71	0.64	0.68	0.60	0.61	0.69	0.65	0.66	0.65	0.64	0.64	0.67	0.68	0.63	0.62	0.71	0.68

regime 2 = non-recession

	IPM	CAR	SAL	TOU	STV	UNE	LAB	UNF	UNY	CPI	CIX	AT1	AT2	RR1	RR2	LOH	ISP	WTE	f2	f4	f5
Fore	0.68	0.68	0.67	0.58	0.59	0.62	0.64	0.64	0.63	0.62	0.65	0.66	0.66	0.65	0.60	0.66	0.67	0.66	0.68	0.63	0.66
Now1	0.63	0.69	0.68	0.57	0.59	0.65	0.65	0.64	0.64	0.62	0.64	0.64	0.64	0.67	0.62	0.65	0.67	0.67	0.70	0.63	0.65
Now2	0.62	0.76	0.60	0.58	0.59	0.64	0.62	0.62	0.64	0.60	0.65	0.65	0.65	0.67	0.62	0.64	0.65	0.66	0.74	0.61	0.63
Now3	0.63	0.65	0.61	0.61	0.60	0.66	0.64	0.63	0.65	0.62	0.65	0.66	0.66	0.67	0.64	0.63	0.66	0.66	0.66	0.65	0.63

CON, YoY

regime 1 = recession

	SAL	TOU	UNE	LAB	UNF	AT2	RR1	RR2	LOH	ATX	ISP	BA2	BA3	WBE	WTE	f	f1	f2	f4	f5
Fore	0.95	0.87	0.88	0.88	0.86	0.82	0.77	0.91	0.85	0.88	0.88	0.88	0.90	0.81	0.81	0.87	0.88	0.94	0.86	0.93
Now1	0.93	0.88	0.89	0.89	0.86	0.82	0.78	0.91	0.89	0.88	0.90	0.87	0.93	0.87	0.82	0.89	0.90	0.94	0.87	0.98
Now2	0.88	0.84	0.88	0.84	0.84	0.80	0.77	0.87	0.83	0.86	0.88	0.90	0.91	0.85	0.84	0.88	0.87	0.90	0.86	0.90
Now3	0.91	0.88	0.96	0.88	0.90	0.84	0.79	0.91	0.86	0.91	0.94	0.92	0.93	0.83	0.84	0.96	0.89	0.90	0.92	0.97

regime 2 = non-recession

	SAL	TOU	UNE	LAB	UNF	AT2	RR1	RR2	LOH	ATX	ISP	BA2	BA3	WBE	WTE	f	f1	f2	f4	f5
Fore	0.87	0.75	0.89	0.88	0.89	0.86	0.85	0.87	0.88	0.89	0.90	0.88	0.87	0.89	0.88	0.90	0.88	0.88	0.87	0.87
Now1	0.89	0.76	0.90	0.89	0.91	0.89	0.88	0.89	0.90	0.90	0.91	0.90	0.89	0.91	0.92	0.91	0.90	0.89	0.87	0.89
Now2	0.78	0.76	0.89	0.88	0.90	0.90	0.89	0.89	0.89	0.91	0.91	0.89	0.86	0.93	0.91	0.90	0.89	0.86	0.89	0.88
Now3	0.82	0.77	0.92	0.88	0.91	0.92	0.90	0.91	0.89	0.90	0.91	0.90	0.88	0.93	0.91	0.90	0.92	0.86	0.91	0.89

The shown numbers are average RMSE of the top 1% recession-based models including the given variable, differentiating between regimes, where regime 1 = recession and regime 2 = non-recession. We present the RMSE for QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. We use the following colour coding. The minimum value (best measure) is dark green, the maximum value (worst measure) is dark red, the median is yellow, and percentiles are mixtures between yellow and green/red.

Figure 10: Important variables in nowcasting investment: models based on global financial uncertainty

INV, QoQ

regime 1 = high global financial uncertainty

	EXX	IMP	EMP	UNE	UNM	UNY	VIB	SEN	ISC	ISO	ISP	BA1	BA2	BA3	BA4	BA5	WME	WSE	WEE	f
Fore	1.24	1.28	1.30	1.24	1.22	1.25	1.27	1.22	1.25	1.25	1.24	1.17	1.19	1.20	1.18	1.18	1.20	1.23	1.21	1.20
Now1	1.20	1.23	1.34	1.27	1.26	1.29	1.29	1.24	1.20	1.17	1.24	1.20	1.23	1.23	1.17	1.20	1.19	1.26	1.22	1.20
Now2	1.13	1.18	1.40	1.28	1.26	1.31	1.27	1.21	1.19	1.20	1.23	1.20	1.24	1.22	1.16	1.18	1.23	1.24	1.20	1.18
Now3	1.19	1.26	1.38	1.33	1.31	1.34	1.33	1.24	1.23	1.18	1.28	1.24	1.32	1.29	1.19	1.22	1.27	1.29	1.25	1.26

regime 2 = low global financial uncertainty

	EXX	IMP	EMP	UNE	UNM	UNY	VIB	SEN	ISC	ISO	ISP	BA1	BA2	BA3	BA4	BA5	WME	WSE	WEE	f
Fore	1.26	1.27	1.23	1.25	1.26	1.29	1.31	1.24	1.25	1.17	1.28	1.31	1.34	1.36	1.34	1.37	1.24	1.21	1.16	1.27
Now1	1.25	1.25	1.20	1.22	1.24	1.25	1.29	1.22	1.25	1.12	1.27	1.33	1.32	1.33	1.32	1.36	1.25	1.27	1.19	1.27
Now2	1.25	1.26	1.17	1.21	1.21	1.27	1.30	1.14	1.15	1.17	1.27	1.35	1.35	1.37	1.34	1.37	1.30	1.26	1.19	1.26
Now3	1.31	1.30	1.17	1.27	1.27	1.26	1.29	1.18	1.20	1.29	1.32	1.36	1.36	1.41	1.40	1.41	1.31	1.27	1.24	1.31

INV, YoY

regime 1 = high global financial uncertainty

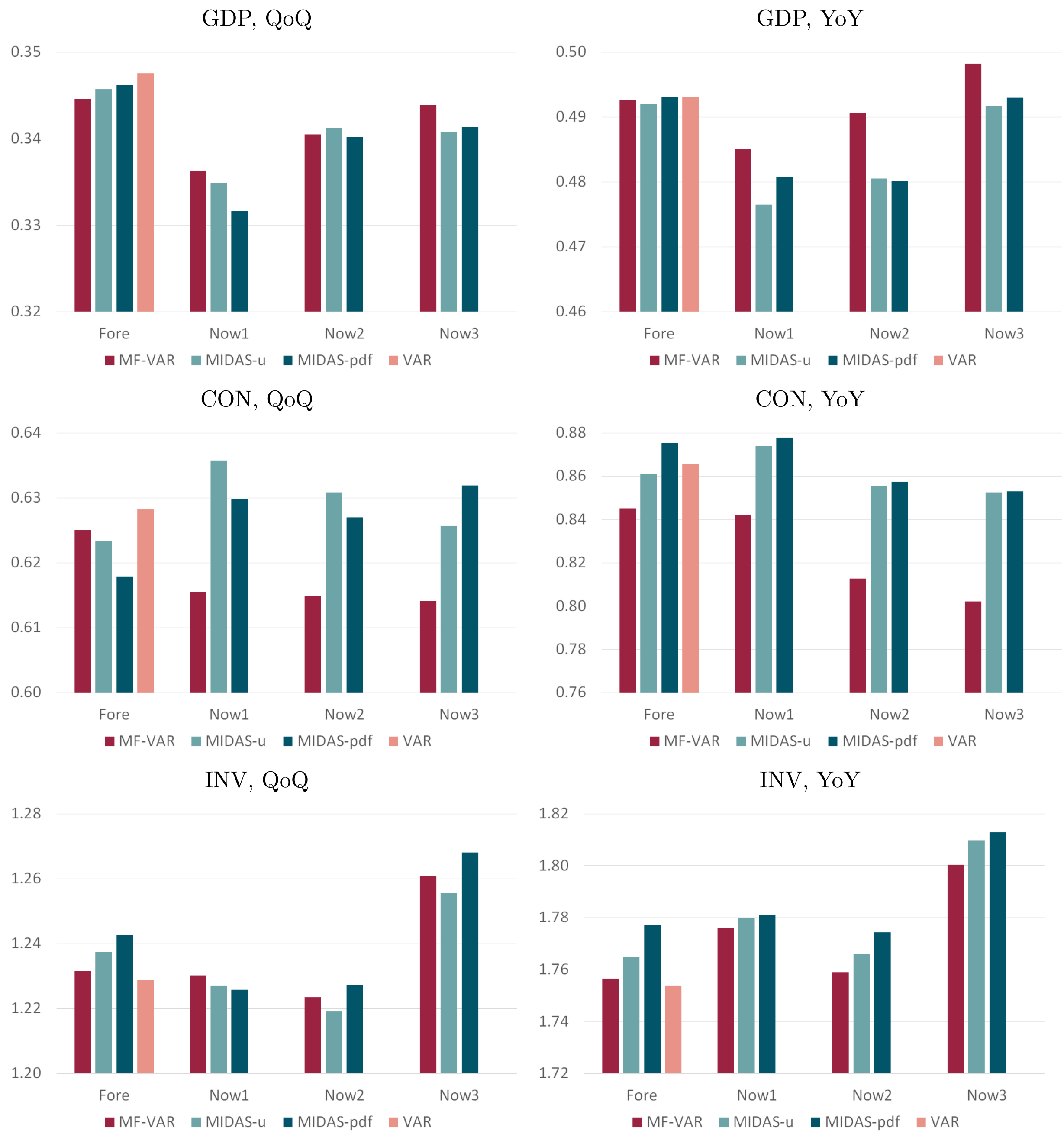
	IPM	EXX	IMP	EMP	UNY	VAC	VIB	SEN	CCO	ISC	ISO	BA1	BA2	BA3	BA4	WME	WSE	WEE	f	f4
Fore	1.94	1.85	1.88	1.74	1.80	1.79	1.92	1.75	1.93	1.75	1.75	1.73	1.76	1.80	1.66	1.70	1.78	1.73	1.78	1.74
Now1	2.00	1.96	1.95	1.79	1.91	1.83	1.99	1.79	1.97	1.78	1.63	1.71	1.79	1.81	1.67	1.70	1.84	1.75	1.82	1.77
Now2	1.81	1.95	1.90	1.70	1.89	1.81	1.96	1.77	1.96	1.77	1.63	1.69	1.81	1.79	1.65	1.74	1.82	1.75	1.80	1.78
Now3	1.86	1.97	1.80	1.76	1.93	1.91	2.02	1.83	2.04	1.83	1.61	1.73	1.89	1.79	1.69	1.79	1.87	1.78	1.88	1.90

regime 2 = low global financial uncertainty

	IPM	EXX	IMP	EMP	UNY	VAC	VIB	SEN	CCO	ISC	ISO	BA1	BA2	BA3	BA4	WME	WSE	WEE	f	f4
Fore	1.78	1.85	1.81	1.68	1.68	1.80	1.75	1.70	1.68	1.78	1.67	1.87	1.83	1.83	1.93	1.80	1.78	1.77	1.83	1.78
Now1	1.78	1.80	1.80	1.71	1.65	1.74	1.72	1.71	1.70	1.74	1.68	1.85	1.79	1.80	1.91	1.83	1.89	1.81	1.83	1.82
Now2	1.81	1.82	1.81	1.65	1.65	1.72	1.77	1.68	1.78	1.67	1.74	1.92	1.86	1.87	1.98	1.86	1.90	1.82	1.84	1.87
Now3	1.84	1.96	1.87	1.67	1.67	1.80	1.76	1.71	1.76	1.69	1.76	1.95	1.88	1.89	1.97	1.87	1.90	1.86	1.84	1.87

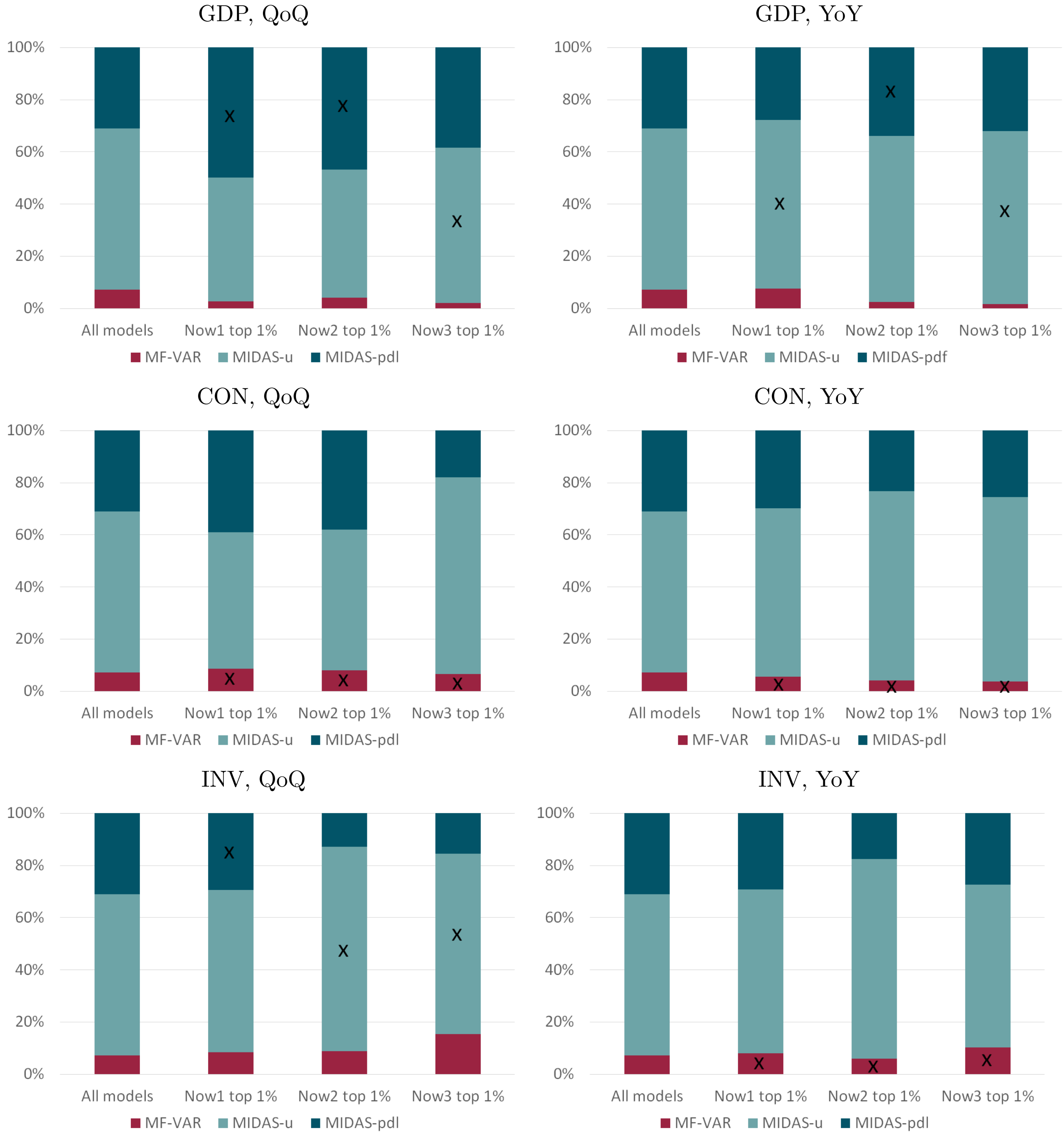
The shown numbers are average RMSE of the top 1% models based on global financial uncertainty including the given variable, differentiating between regimes, where regime 1 = high global financial uncertainty and regime 2 = low global financial uncertainty. We present the RMSE for QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. We use the following colour coding. The minimum value (best measure) is dark green, the maximum value (worst measure) is dark red, the median is yellow, and percentiles are mixtures between yellow and green/red.

Figure 11: Prediction accuracy of different methods in the top 1% models



The graphs present the average RMSE for a given method included in the top 1% models, when nowcasting GDP, consumption and investment, for QoQ and YoY growth rates. A smaller RMSE implies a better forecast. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4.

Figure 12: Proportions of different methods in the top 1% models



The graphs present proportions of different methods in the top 1% models, when nowcasting GDP, consumption and investment, for QoQ and YoY growth rates. The **X** with a certain method signifies that this method performs the best on average in the top 1% models. The first column, labelled "All models", presents the proportions of certain methods (MF-VAR, MIDAS-u, MIDAS-pdl) among all models, namely 7% MF-VAR, 62% MIDAS-u and 31% MIDAS-pdl models. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4.

5 Conclusion

Our goal is to nowcast and forecast Austrian economic activity, namely real GDP, consumption and investment, which are available at a quarterly frequency. We use a large number of monthly indicators to construct early estimates of the target variables. For this purpose we use different mixed-frequency models, namely the mixed-frequency vector autoregressive (MF-VAR) model according to Ghysels (2016) and mixed data sampling (MIDAS) approaches, and compare their forecast and nowcast accuracies in terms of the root mean squared error. We also consider traditional benchmark models which rely only on quarterly data, namely vector autoregressive (VAR) models, i.e., they do not take into account timelier and finer information. We estimate the models and evaluate the forecasts and nowcasts both in terms of quarterly (QoQ) and yearly (YoY) growth rates. Above all we are interested in whether explicitly considering regimes improves the nowcast. Thus we examine five different regime-dependent models, taking into account business cycle regimes (recession/non-recession) or financial/economic uncertainty regimes (high/low uncertainty) driven by global and Austrian financial and economic uncertainty indicators.

In total we consider 54 monthly variables which are related to: (i) production and trade indicators including, e.g., industrial production, exports and imports, (ii) consumption indicators containing, e.g., retail sales and car registrations, (iii) labour market variables including, e.g., employment, unemployment and vacancies, (iv) price indicators like consumer prices and wholesale prices, (v) variables related to money and credit like loans to households and real effective exchange rates, (vi) financial and uncertainty indicators, and finally (vii) survey and sentiment indicators. Our empirical findings are as follows.

First, our results suggest that there is indeed a value added of nowcasting over forecasting. In about 80% of the cases at least one of the nowcasts improves the forecast.[37] Also, the new information in the first month seems to be most important, while additional information in the second and third months does not seem to provide as much value added. However, sometimes also the forecast performs very well, providing better prediction accuracy than any of the nowcasts.

Second, we find that regime-dependent models clearly outperform non regime-dependent models and that different regimes are important for GDP, consumption and investment. While the recession-based regimes seem to be important to nowcast GDP and consumption, the regimes based on global financial uncertainty are important to nowcast investment.

[37] In total, we consider 49,316 models including all methods (MF-VAR, MIDAS, VAR), all combinations of variables and all lags to nowcast and forecast GDP (similarly for consumption and investment).

Third, we find that only a handful of variables are important to forecast and nowcast GDP, consumption and investment, respectively, and that sometimes the variables nowcasting best in regime 1 and regime 2 are different and in other times they are the same. When nowcasting GDP the most important variables are survey data (such as the industrial confidence indicator and the assessment of order books) and industrial production. In times of recession the key data are the purchasing managers' indices (PMI) related to the overall index, to output, to new orders and to employment, while in times of non-recession the key data are production expectations and consumers' unemployment expectations. Industrial production seems to be important in both recession and non-recession periods. When nowcasting consumption, the key variables in recession times are female unemployed, the effective exchange rate and retail trade expectations while the outstanding variable in non-recession periods is tourists arrivals. Finally, for nowcasting investment, an important variable in times of high global financial uncertainty is the PMI related to employment, while the economic sentiment indicator and employment related data (YoY growth rates) seem to be essential in times of low global financial uncertainty. A key variable in both times of high and low global financial uncertainty is the assessment of order books.

Finally, our empirical results suggest that there is no clear winner among the different types of mixed-frequency models. Univariate MIDAS models seem to outperform the MF-VAR models when nowcasting GDP (for both QoQ and YoY growth rates) and investment (QoQ growth rates), while MF-VAR models perform better than MIDAS models when nowcasting consumption (for both QoQ and YoY growth rates) and investment (YoY growth rates). However, sometimes also the forecast performs quite well, and then it mostly comes from a mixed-frequency model. Hence, finer information also seems to be important for forecasting, not only for nowcasting.

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A Appendix: Data

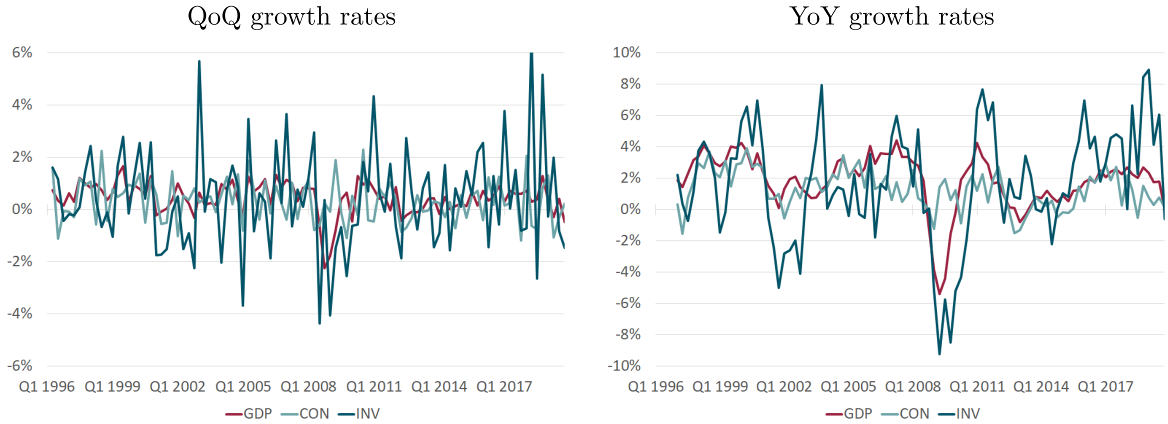
For the monthly (high-frequency) variables we take the variables contained in the key indicators of Refinitiv Datastream, available at monthly frequency, as a starting point. The code M#OEKEY, where OE is the country code for Austria, provides a list of these indicators for Austria. Then we delete the variables which we think are not suitable (e.g., monthly government deficit/surplus, agreed minimum wages) and add others which we think could also be useful (e.g., tourist arrivals, overnight stays, etc.). In addition we consider survey data from the industrial and consumption surveys of the European Commission (DG ECFIN), survey data from the business cycle survey of WIFO,[38] data from the UniCredit Bank Austria purchasing managers' indices of S&P Global, and some financial data like the stock market index (returns, volatility) and interest rates. WIFO calculates three different types of indices for all economic (sub-) groups: an index reflecting the current situation, an index describing expectations and one combined index. In general, the three indices are very highly correlated, so we only use one of them, the expectations index. All survey indicators are seasonally adjusted. See Table A.2 for the complete list of monthly (high-frequency) variables we consider.

If we want to use growth rates relating to month over previous month, or month over three months ago, we have to consider seasonally adjusted data. So we seasonally adjust all variables related to output, which are not already seasonally adjusted, using the Census X-12 seasonal adjustment procedure; we use either the multiplicative or the additive method, depending on whether the data contain only positive values (multiplicative) or whether they also contain negative values (additive). We also adjust price indices, as we find seasonality to be present in nearly all of the series (Census X-12 seasonal adjustment). However, we do not seasonally adjust foreign exchange rates, interest rates and money supply.

With respect to data transformations we use growth rates of price indices and other increasing variables like industrial production, employment, loans, tourist arrivals, etc. We also transform exchange rates and interest rates. Survey/sentiment indices are not transformed. In the analysis we use two different types of growth rates, quarterly and yearly growth rates. These rates refer to the growth of a quarter with respect to the previous quarter (QoQ) and to the growth of a quarter with respect to the previous year's

[38] The WIFO business cycle survey (WIFO-Konjunkturtest) is a monthly survey of Austrian companies on their economic situation and its development in the coming months. The results of the WIFO business cycle survey help to reliably assess the economic development in Austria at an early stage. The WIFO business cycle has been conducted since 1954 and has been part of the "Joint Harmonised EU Programme of Business and Consumer Surveys" since 1996.

Figure A.1: Growth rates of GDP, consumption and investment



quarter (YoY). Figure A.1 shows QoQ and YoY growth rates of GDP, consumption and investment over the sample period 1996Q1 to 2021Q4. Table A.1 presents the descriptive statistics of the quarterly and yearly growth rates for GDP, consumption and investment. We use the root mean squared error (RMSE) as the forecast performance measure. In an earlier version of this study we also considered the mean absolute error and the hit rate but we now concentrate on the RMSE to streamline the results. The estimation is always performed such that the growth rates of monthly and quarterly variables “fit together”, i.e., we use QoQ growth rates, or YoY growth rates, for both monthly and quarterly variables. The QoQ growth rate of monthly variable corresponds to the growth rate of a given month with respect the month three periods before. For example the growth rate in December is calculated with respect to October. We hence perform the estimations and out-of-sample evaluations twice, once with QoQ growth rates and once with YoY growth rates. Alternatively, we used month over previous month growth rates in a preliminary analysis and and the results were very similar. We use discrete (rather than continuous) growth rates. We also did some preliminary analysis using continuous rates and the results were very similar.

For data which are available at a daily frequency we take the monthly average for a given month (rather than the value observed at the end of the month). For the monthly volatility of the stock index we consider daily stock index returns and compute the volatility over a rolling window of one month (or, alternatively, three months) and report the value of this series observed at the end of a given month.

Table A.1: Descriptive statistics of GDP, consumption and investment

	QoQ growth rates			YoY growth rates		
	GDP	CON	INV	GDP	CON	INV
Mean	0.37	0.27	0.35	1.54	1.10	1.51
Std	0.64	0.78	1.64	1.77	1.11	3.58
Skew	-1.47	0.30	0.22	-1.64	-0.13	-0.49
Kurt	6.99	2.53	3.97	7.22	2.66	3.16

The table shows mean, standard deviation (Std), skewness (Skew) and kurtosis (Kurt) for quarter-over-quarter (QoQ) and year-over-year (YoY) growth rates of GDP, consumption and investment, for Austria. The sample period is 2000Q1 until 2019Q4. Growth rates are given in percent.

Table A.2: Variables for Austria

	Abb	Type	Code	Name	Source	Base date	Seas	Trans	Lag
1	IPM	Prod	OEES493KG	OE volume index of production: manufacturing (2015=100) VOLA	Eurostat	31.01.96	n	1	1
2	EXX	Prod	OEEXPGDSA	OE exports (FOB) CURN	StatA	31.01.53	y	1	2
3	IMP	Prod	OEIMPGDSA	OE imports (CIF) CURN	StatA	31.01.53	y	1	2
4	REA	Prod	IGREA	Index of global real economic activity	FRED	31.01.68	n	0	1
5	CAR	Con	OECAR...P	OE new registrations of vehicles VOLN	StatA	31.07.87	y	1	0
6	SAL	Con	OEES7JYMG	OE deflated turnover: retail trade excl. motorvehicles, motorcycles & fuel (2015=100) SA	Eurostat	31.01.99	n	1	1
7	TOU	Con	OETOURISP	OE tourist arrivals VOLN	StatA	31.01.99	y	1	1
8	STV	Con	OEOVNLIEP	OE overnight stays, by land: Vienna VOLN	StatA	31.01.99	y	1	1
9	EMP	Lab	gen_absegm	OE employed	DVSV	01.01.50	y	1	0
10	UNE	Lab	gen_aalogm	OE unemployed (registered) NA	AMS	01.01.50	y	1	0
11	LAB	Lab	gen_aunsgm	OE labour force NA	WIFO	01.01.50	y	1	0
12	UNF	Lab	gen_aalowm	OE unemployed, females NA	AMS	01.01.50	y	1	0
13	UNM	Lab	gen_aalomm	OE unemployed, males NA	AMS	01.01.50	y	1	0
14	UNY	Lab	gen_u08_aaljuggm	OE unemployed, 15–24 years NA	AMS	01.01.90	y	1	0
15	UR	Lab	gen_aalrg3	OE unemployment rate (national) SA	WIFO	01.01.88	n	0	0
16	VAC	Lab	gen_aostgm	OE job vacancies NA	AMS	01.01.60	y	1	0
17	CPI	Pri	OECPALLRF	OE CPI (2020=100) NA	StatA/Refinitiv	31.07.48	y	1	0
18	CIX	Pri	OECONPRCF	OE CPI excluding seasonal items NA	StatA	31.01.57	y	1	1
19	WPI	Pri	OEWPI...F	OE WPI (2020=100) NA	StatA	31.01.96	y	1	0
20	AT1	Mon	OEXRUSD.	OE Austrian Schillings to US dollar (monthly average) NA	BoE	31.01.57	n	1	0
21	AT2	Mon	OEXRUSE.	OE US dollar to Euro (Austrian Schilling derived history prior 1999) NA	BoE	31.01.57	n	1	0
22	RR1	Mon	EMECBEYBR	EMU nominal effective exchange rate: broad group (41 partner) NA	ECB	31.01.93	n	1	0
23	RR2	Mon	OEBISRXNR	OE real effective exchange rate: narrow index NA	BIS	31.10.63	n	1	1
24	M1	Mon	OEM1....A	OE money supply M1 CURN	OeNB	30.09.97	n	1	1
25	M2	Mon	OEM2....A	OE money supply M2 CURN	OeNB	30.09.97	n	1	1
26	M3	Mon	OEM3....A	OE money supply M3 CURN	OeNB	30.09.97	n	1	1
27	LOH	Mon	OECRDCONA	OE bank loans to households CURN	OeNB	31.12.98	y	1	1
28	LOP	Mon	OEBANKLPA	OE bank lending to private sector CURN	OeNB	30.09.97	y	1	1
29	ATX	Fin	ATXINDX	Austrian Traded Index (ATX)	VSE	07.01.86	n	1	0
30	YIE	Fin	TROE10T	RF Austrian government bond benchmark bid yield (10y)	Refinitiv	02.01.85	n	1	0
31	VIB	Fin	ASVIB3M	OE 3m VIBOR/3m EURIBOR	Refinitiv	10.06.91	n	1	0
32	SPR	Fin		OE government bond yields (10y) minus OE/EUR interest rates (3m)	Refinitiv, own	10.06.91	n	0	0
33	SPD	Fin		OE minus German government bond yields (10y)	Refinitiv, own	02.01.85	n	0	0
34	VO1	Fin		ATX volatility, 1m	VSE, own	31.01.86	n	0	0
35	VO2	Fin		ATX volatility, 3m	VSE, own	31.03.86	n	0	0
36	EPU	Fin	EUEPUINDXM	Economic policy uncertainty index for Europe	BBD (FRED)	31.01.87	n	0	1
37	SEN	Sur	OECNFBUSG	OE economic sentiment indicator SA	DG ECFIN	31.01.85	n	0	0
38	CCO	Sur	OECNFCONQ	OE Fessel GFK consumer confidence indicator SA	OeNB	31.10.95	n	0	0
39	ISC	Sur	OETTA99BQ	OE industry: overall – industrial confidence indicator SA	DG ECFIN	31.01.85	n	0	0

	Abb.	Type	Code	Name	Source	Base date	Seas	Trans	Lag
40	ISO	Sur	OETTA2BSQ	OE industry: overall – order books SA	DG ECFIN	31.01.85	n	0	0
41	ISP	Sur	OETTA5BSQ	OE industry: overall – production expectations SA	DG ECFIN	31.01.85	n	0	0
42	CSE	Sur	OETOT4BSQ	OE consumer: all respondents – economic situation next 12m SA	DG ECFIN	31.10.95	n	0	0
43	CSU	Sur	OETOT7BSQ	OE consumer: all respondents – unemployment next 12m SA	DG ECFIN	31.10.95	n	0	0
44	BA1	Sur		OE PMI overall index SA	S&P Global	31.10.98	n	0	0
45	BA2	Sur		OE PMI output SA	S&P Global	31.10.98	n	0	0
46	BA3	Sur		OE PMI new orders SA	S&P Global	31.10.98	n	0	0
47	BA4	Sur		OE PMI employment SA	S&P Global	31.10.98	n	0	0
48	BA5	Sur		OE PMI suppliers' delivery times SA	S&P Global	31.10.98	n	0	0
49	BA6	Sur		OE PMI stocks of purchases SA	S&P Global	31.10.98	n	0	0
50	WME	Sur		OE manufacturing, expectations SA	WIFO	31.01.96	n	0	0
51	WBE	Sur		OE buildings, expectations SA	WIFO	31.01.96	n	0	0
52	WSE	Sur		OE services, expectations SA	WIFO	31.01.97	n	0	0
53	WTE	Sur		OE retail trade, expectations SA	WIFO	31.01.96	n	0	0
54	WEE	Sur		OE economic expectations SA	WIFO	31.01.97	n	0	0
55	f	PC		first principal component of all variables	own				
56	f1	PC		first principal component of the variables in Prod	own				
57	f2	PC		first principal component of the variables in Con	own				
58	f3	PC		first principal component of the variables in Lab	own				
59	f4	PC		first principal component of the variables in Pri	own				
60	f5	PC		first principal component of the variables in Mon	own				
61	f6	PC		first principal component of the variables in Fin	own				
62	f7	PC		first principal component of the variables in Sur	own				

The table shows the monthly variables used for nowcasting Austrian GDP, consumption and investment. We classify the variables into the following groups: production (Prod), consumption (Con), labour market (Lab), prices (Pri), money and credit (Mon), financial and uncertainty indicators (Fin), survey and sentiment indicators (Sur), and we additionally consider principal components (PC). In the column titled Seas (seasonal adjustment) "n" indicates that the variable is not seasonally adjusted because it is already seasonally adjusted or because we do not think that adjustment is needed and "y" indicates that the variable is seasonally adjusted; in the column titled Trans (transformation) "1" means that the variable is transformed to (QoQ or YoY) growth rates and "0" signifies no transformation; in the column titled Lag "0", "1", and "2" indicate a lag of 0, 1, and 2 months in data availability. For data retrieved from Refinitiv Datastream, FRED and WIFO we list the corresponding codes. Abb = Abbreviation, AMS = Arbeitsmarktservice Austria (Austrian Public Employment Service), BBD = Baker, Bloom & Davis (FRED), BoE = Bank of England, BIS = Bank for International Settlements, CURN = current prices, not seasonally adjusted, DG ECFIN = Directorate General for Economic and Financial Affairs, DVSV = Dachverband der Sozialversicherungsträger (umbrella organisation of social insurance institutions in Austria), ECB = European Central Bank, FRED = Federal Reserve Bank of Dallas, MEI = Main Economic Indicators, NA = not seasonally adjusted, OE = Österreich (Austria), OeNB = Oesterreichische Nationalbank (Austrian National Bank), own = own calculations, SA = seasonally adjusted, StatA = Statistics Austria, VOLA = volumes, seasonally adjusted, VOLN = volumes, not seasonally adjusted, VSE = Vienna Stock Exchange, WIFO = Austrian Institute of Economic Research.

Table A.3: Variables for Austria (alphabetical list)

Abb	Group	Name
AT1	Mon	OE Austrian Schillings to US dollar (monthly average)
AT2	Mon	OE US dollar to Euro (Austrian Schilling derived history prior to 1999)
ATX	Fin	Austrian Traded Index (ATX)
BA1	Sur	OE PMI overall index
BA2	Sur	OE PMI output
BA3	Sur	OE PMI new orders
BA4	Sur	OE PMI employment
BA5	Sur	OE PMI suppliers' delivery times
BA6	Sur	OE PMI stocks of purchases
CAR	Con	OE new registrations of vehicles
CCO	Sur	OE FESSEL GFK consumer confidence indicator
CIX	Pri	OE CPI excl. seasonal items
CPI	Pri	OE CPI (2020=100)
CSE	Sur	OE consumer: all respondents – economic situations next 12m
CSU	Sur	OE consumer: all respondents – unemployment next 12m
EMP	Lab	OE employed
EPU	Fin	Economic policy uncertainty index for Europe
EXX	Prod	OE exports (FOB)
IMP	Prod	OE imports (CIF)
IPM	Prod	OE volume index of production: manufacturing (2015=100)
ISC	Sur	OE industry: overall – industrial confidence indicator
ISO	Sur	OE industry: overall – order books
ISP	Sur	OE industry: overall – production expectations
LAB	Lab	OE labour force
LOH	Mon	OE bank loans to households
LOP	Mon	OE bank lending to private sector
M1	Mon	OE money supply M1
M2	Mon	OE money supply M2
M3	Mon	OE money supply M3
REA	Prod	Index of global real economic activity
RR1	Mon	EMU nominal effective exchange rate: broad group (41 partners)
RR2	Mon	OE real effective exchange rate: narrow index
SAL	Con	OE deflated turnover: retail trade excl. mototvehicles, motorcycles & fuel (2015=100)
SEN	Sur	OE economic sentiment indicator
SPD	Fin	OE minus German government bond yields (10y)
SPR	Fin	OE government bond yields (10y) minus OE/EUR interest rates (3m)
STV	Con	OE overnight stays: by land – Vienna
TOU	Con	OE tourist arrivals
UNE	Lab	OE unemployed (registered)
UNF	Lab	OE unemployed, females
UNM	Lab	OE unemployed, males
UNY	Lab	OE unemployed, 15-24 years
UR	Lab	OE unemployment rate (national)
VAC	Lab	OE job vacancies
VIB	Fin	OE 3M VIBOR/3M EURIBOR
VO1	Fin	ATX volatility, 1m
VO2	Fin	ATX volatility, 3m
WBE	Sur	OE buildings expectations
WEE	Sur	OE economic expectations
WME	Sur	OE manufacturing expectations
WPI	Pri	OE WPI (2020=100)
WSE	Sur	OE services expectations
WTE	Sur	OE retail trade expectations
YIE	Fin	RF Austrian government bond benchmark bid yield (10y)

Table A.4: Short list of variables for two- and three-variable models

	Variables						Groups					
	GDP		CON		INV		GDP		CON		INV	
	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY
1	IPM	IPM	IMP	IMP	IPM	IPM	Prod	Prod	Prod	Prod	Prod	Prod
2	EXX	EXX	REA	REA	EXX	EXX	Prod	Prod	Prod	Prod	Prod	Prod
3	TOU	SAL	CAR	CAR	EMP	CAR	Con	Con	Con	Con	Lab	Con
4	EMP	EMP	SAL	SAL	LAB	EMP	Lab	Lab	Con	Con	Lab	Lab
5	LAB	LAB	TOU	TOU	UNY	UNY	Lab	Lab	Con	Con	Lab	Lab
6	UNY	UNY	LAB	LAB	UR	VAC	Lab	Lab	Lab	Lab	Lab	Lab
7	UR	UR	UNF	UNF	CIX	WPI	Lab	Lab	Lab	Lab	Pri	Pri
8	WPI	WPI	UR	UR	AT1	RR2	Pri	Pri	Lab	Lab	Mon	Mon
9	M1	M1	CIX	CIX	RR1	M1	Mon	Mon	Pri	Pri	Mon	Mon
10	LOH	LOH	AT2	AT2	LOH	LOH	Mon	Mon	Mon	Mon	cv Mon	Mon
11	ATX	ATX	RR2	RR2	ATX	VIB	Fin	Fin	Mon	Mon	Fin	Fin
12	VIB	VIB	LOH	LOH	VIB	SPD	Fin	Fin	Mon	Mon	Fin	Fin
13	SEN	SEN	VIB	ATX	CCO	VO1	Sur	Sur	Fin	Fin	Sur	Fin
14	BA1	BA1	CCO	CCO	ISO	CCO	Sur	Sur	Sur	Sur	Sur	Sur
15	BA2	BA2	ISP	ISP	CSU	ISO	Sur	Sur	Sur	Sur	Sur	Sur
16	WBE	WBE	WBE	WBE	BA4	CSU	Sur	Sur	Sur	Sur	Sur	Sur
17	WEE	WEE	WTE	WTE	WME	BA4	Sur	Sur	Sur	Sur	Sur	Sur
18	f	f	f2	f1	f	WME	PC	PC	Con	Prod	PC	Sur
19	f4	f4	f4	f2	f3	f	Sur	Sur	Sur	Con	Lab	PC
20	f7	f7	f5	f4	f6	f4	Fin	Fin	Pri	Sur	Mon	Sur

The table shows the short lists of monthly variables used for nowcasting GDP, consumption and investment, for QoQ and YoY growth rates. The variables in the short lists are chosen based on the ranking in one-variable models and correlations such that 20 variables, including principal components, are included. f indicates the first principal component (PC) of all variables, f1, f2, . . . , f7 are the first principal components of the groups Prod, Con, . . . , Sur. Prod = production and trade, Con = consumption, Lab = labour market, Pri = prices, Mon = money and credit, Fin = financial and uncertainty indicators, Sur = survey and sentiment indicators.

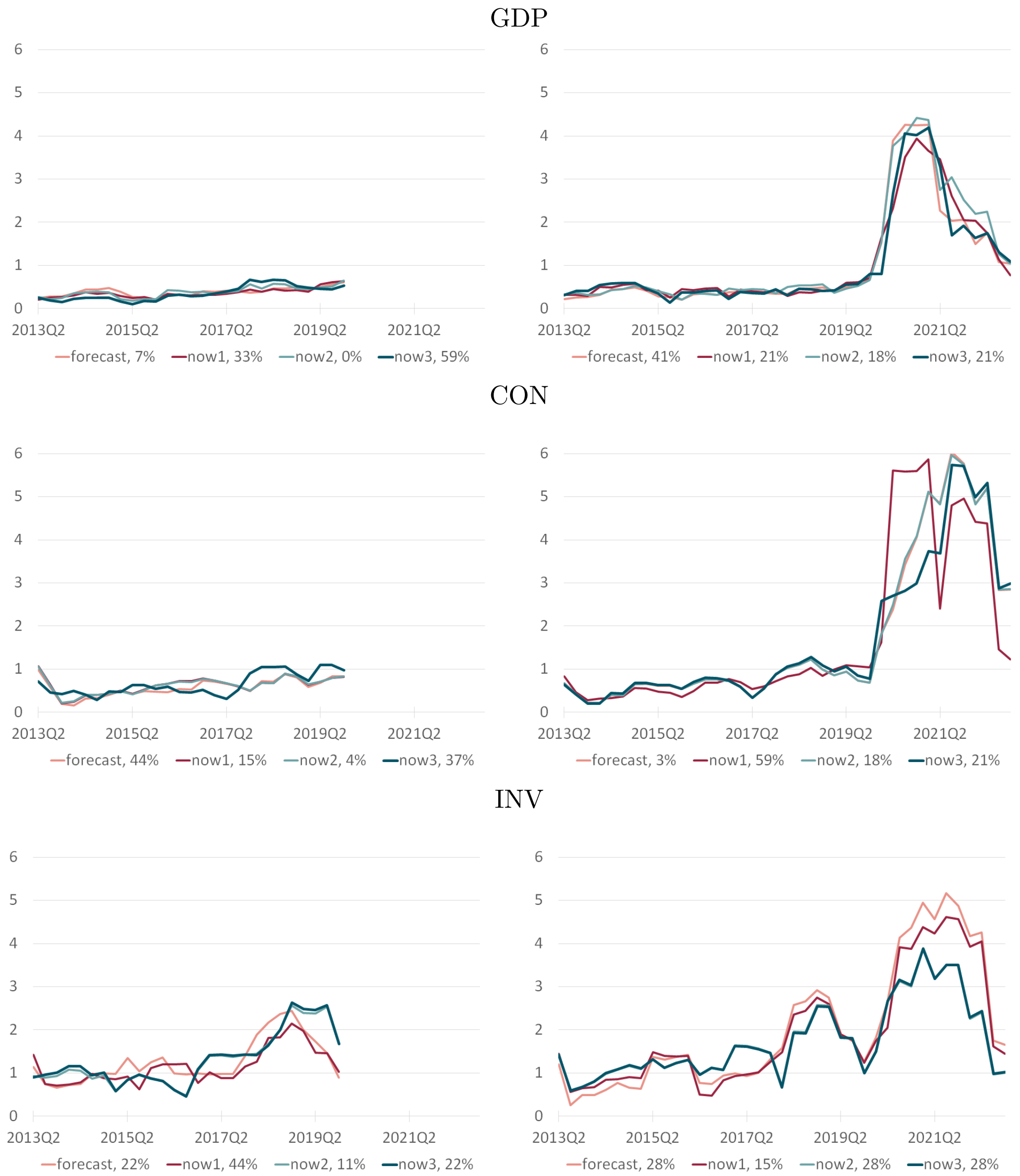
Table A.5: Short list of variables for regime-dependent models

	Variables						Groups					
	GDP		CON		INV		GDP		CON		INV	
	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY	QoQ	YoY
1	f	f	RR2	f1	ISO	EMP	PC	PC	Mon	Prod	Sur	Lab
2	BA3	BA2	TOU	f2	BA4	ISC	Sur	Sur	Con	Con	Sur	Sur
3	ISP	WEE	f2	RR2	ISC	ISO	Sur	Sur	Con	Mon	Sur	Sur
4	ISC	WME	CAR	SAL	EMP	BA4	Sur	Sur	Con	Con	Lab	Sur
5	BA2	BA1	UNF	LOH	SEN	IPM	Sur	Sur	Lab	Mon	Sur	Prod
6	BA1	BA3	UNE	ATX	BA1	f	Sur	Sur	Lab	Fin	Sur	PC
7	WEE	WSE	CIX	RR1	VIB	SEN	Sur	Sur	Pri	Mon	Fin	Sur
8	WME	ISP	AT2	BA2	ISP	VAC	Sur	Sur	Mon	Sur	Sur	Lab
9	WSE	ISC	AT1	UNF	WME	WME	Sur	Sur	Mon	Lab	Sur	Sur
10	SEN	f7	LOH	f4	BA5	BA1	Sur	Sur	Mon	Pri	Sur	Sur
11	ISO	BA4	UNY	BA3	WEE	EXX	Sur	Sur	Lab	Sur	Sur	Prod
12	CSU	ISO	LAB	TOU	BA2	CCO	Sur	Sur	Lab	Con	Sur	Sur
13	IPM	EMP	CPI	ISP	f	WEE	Prod	Lab	Pri	Sur	PC	Sur
14	BA4	SEN	IPM	WTE	WSE	IMP	Sur	Sur	Prod	Sur	Sur	Prod
15	CSE	IPM	STV	UNE	UNM	f4	Sur	Prod	Con	Lab	Lab	Pri
16	BA5	VIB	RR1	f5	UNE	UNY	Sur	Fin	Mon	Mon	Lab	Lab
17	f4	UNY	f5	WBE	EXX	BA2	Pri	Lab	Mon	Sur	Prod	Sur
18	UR	UNM	WTE	LAB	IMP	BA3	Lab	Lab	Sur	Lab	Prod	Sur
19	EXX	CSU	SAL	AT2	UNY	WSE	Prod	Sur	Con	Mon	Lab	Sur
20	WBE	WPI	ISP	f	BA3	VIB	Sur	Pri	Sur	PC	Sur	Fin
21	f7	f4	f4			f4	Sur	Pri	Pri			Pri

The table shows the short lists of monthly variables used for nowcasting GDP, consumption and investment, for QoQ and YoY growth rates. The variables in the short lists are chosen based on aggregate RMSE such that the best 20 variables are included, and in addition principal components are added if they rank among the top 25 variables. f indicates the first principal component (PC) of all variables, f1, f2, ..., f7 are the first principal components of the groups Prod, Con, ..., Sur. Prod = production and trade, Con = consumption, Lab = labour market, Pri = prices, Mon = money and credit, Fin = financial and uncertainty indicators, Sur = survey and sentiment indicators.

B Appendix: Empirical results

Figure B.1: Best forecasts and nowcasts of GPD, consumption and investment – Covid-19



The graphs show the RMSE over rolling windows of four quarters, for the out-of-sample evaluation period 2012Q3 to 2019Q4 (left) and for the out-of-sample evaluation period 2012Q3 to 2022Q4 including the Covid-19 period (right) of best one-variable models for GDP, consumption and investment, considering QoQ growth rates.

Table B.1: Best 20 models to nowcast GPD

GDP, QoQ

	forecast	nowcast 1	nowcast 2	nowcast 3
1	reg glo fin, BA5_1r, f_2r, midas_u(6)	reg glo eco, BA1_1r, SEN_2r, midas_pdl(4)	reg rec, BA1_1r, IPM_2r, midas_pdl(5)	reg rec, BA2_1r, IPM_2r, midas_u(3)
2	reg glo eco, BA1_1r, SEN_2r, midas_pdl(5)	reg rec, WME_1r, WBE_2r, midas_pdl(6)	reg rec, BA1_1r, IPM_2r, midas_u(1)	reg rec, BA2_1r, IPM_2r, midas_u(2)
3	reg glo eco, BA4_1r, SEN_2r, midas_pdl(5)	reg rec, f7_1r, CSU_2r, midas_pdl(5)	reg rec, BA1_1r, IPM_2r, midas_pdl(6)	reg rec, BA2_1r, IPM_2r, midas_pdl(6)
4	reg glo eco, f_1r, SEN_2r, midas_pdl(5)	reg rec, f7_1r, WSE_2r, midas_pdl(5)	reg rec, BA1_1r, IPM_2r, midas_u(2)	3 var, IPM, VIB, BA2, midas_u(2)
5	reg glo fin, BA5_1r, ISP_2r, midas_u(6)	reg glo eco, BA1_1r, SEN_2r, midas_u(4)	**reg glo fin, BA1_1r, f_2r, mfvar(1)**	reg rec, BA2_1r, IPM_2r, midas_pdl(5)
6	reg glo eco, BA1_1r, SEN_2r, midas_pdl(4)	reg glo eco, BA3_1r, SEN_2r, midas_pdl(4)	reg rec, f7_1r, IPM_2r, midas_u(4)	reg rec, BA1_1r, IPM_2r, midas_pdl(6)
7	reg glo eco, f_1r, SEN_2r, midas_pdl(4)	reg glo eco, BA2_1r, SEN_2r, midas_pdl(4)	reg rec, BA2_1r, IPM_2r, midas_pdl(5)	reg rec, BA2_1r, IPM_2r, midas_pdl(4)
8	reg glo eco, BA1_1r, SEN_2r, midas_u(4)	reg rec, f7_1r, WSE_2r, midas_pdl(4)	reg rec, ISC_1r, IPM_2r, midas_pdl(6)	reg rec, ISC_1r, IPM_2r, midas_u(4)
9	reg glo fin, BA5_1r, ISC_2r, midas_u(6)	reg glo eco, ISC_1r, SEN_2r, midas_pdl(4)	reg glo eco, BA3_1r, SEN_2r, midas_pdl(5)	reg rec, BA2_1r, IPM_2r, midas_u(4)
10	reg rec, f_1r, ISO_2r, midas_u(3)	reg rec, ISO_1r, SEN_2r, midas_u(4)	reg rec, f7_1r, WSE_2r, midas_u(5)	reg rec, ISC_1r, IPM_2r, midas_u(3)
11	reg glo eco, BA1_1r, SEN_2r, midas_u(3)	reg glo fin, ISO_1r, SEN_2r, midas_pdl(6)	reg rec, ISO_1r, IPM_2r, midas_u(3)	reg rec, BA2_1r, ISC_2r, midas_pdl(6)
12	reg glo eco, BA1_1r, SEN_2r, midas_u(5)	reg glo eco, BA2_1r, SEN_2r, midas_u(4)	reg rec, BA2_1r, IPM_2r, midas_u(1)	reg rec, f_1r, IPM_2r, midas_pdl(4)
13	reg glo eco, BA5_1r, SEN_2r, midas_u(4)	reg rec, WME_1r, CSU_2r, midas_pdl(6)	reg rec, f7_1r, CSU_2r, midas_u(4)	reg rec, ISC_1r, IPM_2r, midas_pdl(5)
14	reg rec, f_1r, ISO_2r, midas_u(4)	reg rec, f7_1r, WBE_2r, midas_pdl(5)	reg rec, EXX_1r, IPM_2r, midas_pdl(6)	reg at eco, BA1_1r, f_2r, midas_u(3)
15	**reg rec, f_1r, ISO_2r, mfvar(1)**	reg glo eco, BA3_1r, SEN_2r, midas_u(4)	reg rec, ISO_1r, SEN_2r, midas_pdl(5)	reg rec, f_1r, IPM_2r, midas_u(4)
16	reg glo eco, f_1r, SEN_2r, midas_u(4)	reg rec, f7_1r, CSU_2r, midas_pdl(4)	reg rec, BA1_1r, IPM_2r, midas_u(3)	reg rec, ISC_1r, IPM_2r, midas_u(2)
17	reg glo eco, BA5_1r, SEN_2r, midas_u(3)	reg glo fin, ISO_1r, SEN_2r, midas_pdl(5)	reg rec, ISO_1r, IPM_2r, midas_u(6)	reg rec, f7_1r, IPM_2r, midas_pdl(5)
18	*reg rec, f7_1r, f4_2r, var(2)*	reg glo eco, BA4_1r, SEN_2r, midas_pdl(4)	reg rec, BA2_1r, IPM_2r, midas_u(2)	reg rec, BA1_1r, IPM_2r, midas_u(3)
19	**reg rec, f7_1r, ISP_2r, mfvar(1)**	reg rec, WME_1r, WBE_2r, midas_pdl(5)	reg rec, ISC_1r, IPM_2r, midas_pdl(5)	reg glo eco, BA2_1r, BA2_2r, midas_pdl(6)
20	**reg rec, BA4_1r, ISC_2r, mfvar(1)**	reg glo eco, BA1_1r, SEN_2r, midas_u(5)	reg rec, EXX_1r, IPM_2r, midas_pdl(5)	reg rec, ISC_1r, IPM_2r, midas_pdl(6)

GDP, YoY

	forecast	nowcast 1	nowcast 2	nowcast 3
1	reg at eco, ISP_1r, BA4_2r, midas_u(2)	reg rec, ISO_1r, IPM_2r, midas_u(2)	reg rec, f7_1r, IPM_2r, midas_u(4)	reg rec, f7_1r, CSU_2r, midas_u(5)
2	*reg rec, BA1_1r, f4_2r, var(1)*	reg rec, ISO_1r, VIB_2r, midas_u(3)	3 var, IPM, SAL, f7, midas_pdl(5)	reg rec, BA1_1r, VIB_2r, midas_u(4)
3	reg rec, BA4_1r, WPI_2r, midas_u(1)	reg rec, ISO_1r, ISP_2r, midas_u(3)	reg rec, f7_1r, ISP_2r, midas_u(4)	reg rec, BA1_1r, VIB_2r, midas_u(5)
4	reg rec, VIB_1r, ISP_2r, midas_u(3)	reg rec, ISO_1r, ISP_2r, midas_u(2)	reg rec, f7_1r, IPM_2r, midas_pdl(4)	reg rec, BA1_1r, VIB_2r, midas_u(2)
5	**reg rec, VIB_1r, ISP_2r, mfvar(1)**	reg rec, ISO_1r, VIB_2r, midas_u(2)	reg rec, f7_1r, IPM_2r, midas_u(5)	reg rec, f7_1r, CSU_2r, midas_u(6)
6	*reg rec, ISP_1r, f4_2r, var(1)*	reg rec, ISO_1r, EMP_2r, midas_u(3)	reg rec, BA1_1r, IPM_2r, midas_pdl(5)	reg rec, f7_1r, ISP_2r, midas_u(6)
7	reg rec, BA4_1r, f7_2r, midas_u(2)	reg rec, ISO_1r, EMP_2r, midas_u(4)	reg rec, f7_1r, ISP_2r, midas_u(5)	reg rec, BA1_1r, ISP_2r, midas_u(6)
8	*reg rec, UNY_1r, IPM_2r, var(4)*	reg rec, ISO_1r, IPM_2r, midas_u(3)	reg rec, f7_1r, ISP_2r, midas_u(6)	reg rec, BA1_1r, ISP_2r, midas_u(5)
9	**reg at eco, f7_1r, EMP_2r, mfvar(1)**	reg rec, ISO_1r, UNM_2r, midas_u(2)	3 var, IPM, SAL, f7, midas_pdl(6)	reg rec, BA3_1r, VIB_2r, midas_u(5)
10	reg at eco, f7_1r, EMP_2r, midas_u(3)	reg rec, ISO_1r, WPI_2r, midas_u(2)	reg rec, f7_1r, IPM_2r, midas_u(6)	reg rec, BA1_1r, IPM_2r, midas_pdl(5)
11	reg rec, VIB_1r, ISP_2r, midas_u(2)	reg rec, BA4_1r, f7_2r, midas_u(3)	reg rec, f7_1r, IPM_2r, midas_pdl(5)	reg rec, BA1_1r, VIB_2r, midas_u(3)
12	reg glo eco, BA2_1r, VIB_2r, midas_u(6)	reg rec, f7_1r, ISP_2r, midas_pdl(5)	reg rec, BA2_1r, IPM_2r, midas_pdl(5)	reg rec, BA2_1r, IPM_2r, midas_pdl(6)
13	reg rec, VIB_1r, ISP_2r, midas_u(4)	reg rec, f7_1r, ISP_2r, midas_u(5)	reg rec, BA2_1r, IPM_2r, midas_u(5)	3 var, VIB, BA2, f4, midas_u(1)
14	reg rec, BA4_1r, ISP_2r, midas_pdl(5)	reg rec, ISO_1r, CSU_2r, midas_u(2)	reg rec, BA1_1r, IPM_2r, midas_pdl(6)	reg rec, BA1_1r, ISP_2r, midas_u(4)
15	reg glo eco, BA2_1r, VIB_2r, midas_u(5)	reg rec, ISO_1r, f7_2r, midas_u(3)	reg rec, f7_1r, CSU_2r, midas_u(4)	reg rec, BA2_1r, VIB_2r, midas_pdl(6)
16	*reg rec, BA1_1r, WPI_2r, var(1)*	reg rec, BA4_1r, EMP_2r, midas_pdl(4)	reg rec, f7_1r, IPM_2r, midas_u(3)	reg rec, BA3_1r, VIB_2r, midas_u(2)
17	*3 var, IPM, WBE, WEE, var(4)*	reg rec, BA4_1r, IPM_2r, midas_u(1)	reg rec, f7_1r, UNY_2r, midas_u(5)	reg rec, f7_1r, UNM_2r, midas_pdl(6)
18	reg rec, BA4_1r, ISP_2r, midas_u(1)	reg rec, f7_1r, ISP_2r, midas_u(3)	reg at eco, BA1_1r, IPM_2r, midas_u(3)	reg rec, f7_1r, ISP_2r, midas_u(5)
19	reg glo eco, BA1_1r, VIB_2r, midas_u(6)	reg rec, BA4_1r, WPI_2r, midas_u(1)	2 var, IPM, f7, midas_pdl(5)	reg rec, BA2_1r, EMP_2r, midas_pdl(6)
20	reg rec, BA4_1r, EMP_2r, midas_u(2)	reg rec, BA4_1r, EMP_2r, midas_u(3)	reg at eco, BA1_1r, IPM_2r, midas_u(4)	reg rec, BA1_1r, VIB_2r, midas_u(6)

The table shows the 20 best models when nowcasting GDP, considering QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. Different colours highlight different regimes. Boldface text indicates Ghysels' mixed-frequency model, italic text indicates a VAR model. The first regime (_1r) is the recession-based regime or the regime of high (global or AT) financial/economic uncertainty, the second regime (_2r) is non recession-based regime or the regime of low (global or AT) financial/economic uncertainty.

AT recession | global financial uncertainty | global economic uncertainty | AT financial uncertainty | AT economic uncertainty | no regime

Table B.2: Best 20 models to nowcast consumption

CON, QoQ

	forecast	nowcast 1	nowcast 2	nowcast 3
1	reg rec, UNY_1r, TOU_2r, midas_u(3)	reg rec, UNY_1r, TOU_2r, midas_pdl(5)	reg rec, UNY_1r, TOU_2r, midas_pdl(5)	3 var, CAR, UNF, LOH, midas_u(1)
2	reg at fin, f4_1r, WTE_2r, midas_pdl(4)	**reg rec, UNE_1r, TOU_2r, mfvar(1)**	reg rec, UNF_1r, TOU_2r, midas_pdl(5)	**reg rec, UNE_1r, TOU_2r, mfvar(1)**
3	reg rec, UNY_1r, TOU_2r, midas_u(4)	reg rec, UNF_1r, TOU_2r, midas_pdl(4)	**reg rec, UNE_1r, TOU_2r, mfvar(1)**	**reg rec, UNE_1r, STV_2r, mfvar(1)**
4	reg at fin, WTE_1r, WTE_2r, midas_pdl(4)	**reg rec, UNE_1r, STV_2r, mfvar(1)**	**reg rec, UNE_1r, STV_2r, mfvar(1)**	**reg rec, UNF_1r, STV_2r, mfvar(1)**
5	reg rec, RR1_1r, RR2_2r, midas_u(4)	**reg rec, UNY_1r, STV_2r, mfvar(1)**	reg rec, UNE_1r, TOU_2r, midas_pdl(5)	**reg rec, UNY_1r, STV_2r, mfvar(1)**
6	**reg rec, UNY_1r, TOU_2r, mfvar(1)**	**reg rec, UNY_1r, TOU_2r, mfvar(1)**	**reg rec, UNY_1r, STV_2r, mfvar(1)**	reg rec, UNF_1r, SAL_2r, midas_u(4)
7	reg rec, UNE_1r, TOU_2r, midas_u(3)	reg rec, RR1_1r, TOU_2r, midas_pdl(4)	**reg rec, UNF_1r, STV_2r, mfvar(1)**	**reg rec, UNY_1r, TOU_2r, mfvar(1)**
8	reg at fin, WTE_1r, WTE_2r, midas_u(4)	**reg rec, UNF_1r, STV_2r, mfvar(1)**	**reg rec, UNY_1r, TOU_2r, mfvar(1)**	3 var, CAR, UNF, CIX, midas_u(1)
9	**reg rec, UNE_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_pdl(5)	reg rec, RR1_1r, TOU_2r, midas_pdl(5)	3 var, UNF, LOH, f2, midas_u(1)
10	*reg rec, UNY_1r, STV_2r, var(1)*	reg glo eco, LAB_1r, LAB_2r, midas_pdl(5)	reg rec, UNF_1r, SAL_2r, midas_u(3)	3 var, CAR, UNF, f5, midas_u(1)
11	reg rec, UNY_1r, TOU_2r, midas_pdl(4)	reg rec, UNE_1r, TOU_2r, midas_pdl(5)	reg rec, UNF_1r, RR2_2r, midas_u(6)	3 var, CAR, UNF, WBE, midas_u(1)
12	reg at fin, CPI_1r, WTE_2r, midas_pdl(4)	reg rec, UNF_1r, TOU_2r, midas_pdl(5)	reg rec, UNY_1r, TOU_2r, midas_pdl(6)	3 var, CAR, AT2, LOH, midas_u(1)
13	reg at fin, CAR_1r, WTE_2r, midas_pdl(4)	reg rec, UNY_1r, TOU_2r, midas_pdl(4)	reg rec, UNY_1r, f4_2r, midas_pdl(6)	reg rec, UNF_1r, SAL_2r, midas_u(5)
14	reg at fin, LAB_1r, WTE_2r, midas_pdl(4)	3 var, TOU, UR, LOH, midas_u(5)	reg rec, RR1_1r, CPI_2r, midas_pdl(4)	3 var, CAR, LOH, ISP, midas_u(1)
15	reg rec, RR1_1r, TOU_2r, midas_u(3)	**reg rec, WTE_1r, STV_2r, mfvar(1)**	reg rec, WTE_1r, f4_2r, midas_pdl(6)	**reg rec, UNF_1r, TOU_2r, mfvar(1)**
16	reg at fin, f2_1r, WTE_2r, midas_pdl(4)	reg glo eco, TOU_1r, LAB_2r, midas_pdl(5)	reg rec, UNY_1r, SAL_2r, midas_u(3)	3 var, CAR, LAB, UNF, midas_u(1)
17	reg at fin, UNF_1r, WTE_2r, midas_pdl(4)	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	**reg rec, WTE_1r, STV_2r, mfvar(1)**	reg rec, CAR_1r, CAR_2r, midas_u(1)
18	reg rec, RR1_1r, RR2_2r, midas_u(5)	**reg rec, AT2_1r, STV_2r, mfvar(1)**	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	reg rec, CAR_1r, SAL_2r, midas_u(2)
19	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	reg rec, IPM_1r, TOU_2r, midas_pdl(4)	reg rec, UNF_1r, TOU_2r, midas_pdl(6)	3 var, CAR, LOH, f5, midas_u(1)
20	reg at fin, LOH_1r, WTE_2r, midas_pdl(4)	**reg rec, AT1_1r, STV_2r, mfvar(1)**	**reg rec, f5_1r, STV_2r, mfvar(1)**	3 var, CAR, UNF, ISP, midas_u(1)

CON, YoY

	forecast	nowcast 1	nowcast 2	nowcast 3
1	**reg rec, RR1_1r, TOU_2r, mfvar(1)**	**reg rec, RR1_1r, TOU_2r, mfvar(1)**	**reg rec, RR1_1r, TOU_2r, mfvar(1)**	**reg glo fin, f_1r, BA3_2r, mfvar(1)**
2	reg rec, RR1_1r, TOU_2r, midas_u(3)	reg rec, RR1_1r, TOU_2r, midas_u(4)	**reg rec, WTE_1r, TOU_2r, mfvar(1)**	**reg rec, RR1_1r, TOU_2r, mfvar(1)**
3	**reg rec, WTE_1r, TOU_2r, mfvar(1)**	reg rec, WTE_1r, TOU_2r, midas_u(4)	**reg rec, WBE_1r, TOU_2r, mfvar(1)**	3 var, IMP, CAR, LOH, midas_pdl(5)
4	reg rec, RR1_1r, TOU_2r, midas_u(4)	**reg rec, WBE_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_u(5)	**reg rec, WTE_1r, TOU_2r, mfvar(1)**
5	reg rec, WTE_1r, TOU_2r, midas_u(3)	reg rec, RR1_1r, TOU_2r, midas_u(5)	reg rec, RR1_1r, SAL_2r, midas_u(4)	**reg glo fin, f_1r, BA2_2r, mfvar(1)**
6	**reg rec, WBE_1r, TOU_2r, mfvar(1)**	**reg rec, AT2_1r, TOU_2r, mfvar(1)**	3 var, AT2, LOH, f2, midas_u(6)	reg rec, RR1_1r, TOU_2r, midas_u(6)
7	**reg rec, AT2_1r, TOU_2r, mfvar(1)**	**reg rec, WTE_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_u(6)	**reg rec, WBE_1r, TOU_2r, mfvar(1)**
8	reg rec, RR1_1r, AT2_2r, midas_u(6)	reg rec, RR1_1r, TOU_2r, midas_pdl(4)	**reg glo fin, f_1r, BA2_2r, mfvar(1)**	**reg rec, AT2_1r, TOU_2r, mfvar(1)**
9	*reg rec, RR1_1r, TOU_2r, var(2)*	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	**reg rec, AT2_1r, TOU_2r, mfvar(1)**	3 var, IMP, SAL, AT2, midas_u(6)
10	*reg rec, RR1_1r, TOU_2r, var(1)*	reg rec, AT2_1r, TOU_2r, midas_u(4)	reg rec, LAB_1r, SAL_2r, midas_u(2)	reg rec, RR1_1r, SAL_2r, midas_u(5)
11	reg rec, WBE_1r, TOU_2r, midas_u(2)	reg rec, RR1_1r, TOU_2r, midas_u(2)	reg rec, RR1_1r, SAL_2r, midas_u(2)	**reg rec, UNF_1r, TOU_2r, mfvar(1)**
12	3 var, AT2, RR2, WBE, midas_u(6)	reg rec, RR1_1r, TOU_2r, midas_u(3)	3 var, IMP, SAL, AT2, midas_u(6)	reg rec, RR1_1r, SAL_2r, midas_u(6)
13	reg rec, AT2_1r, TOU_2r, midas_u(3)	reg rec, WTE_1r, TOU_2r, midas_pdl(4)	3 var, IMP, SAL, AT2, midas_u(5)	3 var, CAR, LAB, LOH, midas_pdl(5)
14	reg rec, RR1_1r, TOU_2r, midas_u(5)	reg rec, AT2_1r, TOU_2r, midas_u(5)	reg rec, RR1_1r, SAL_2r, midas_u(3)	3 var, IMP, SAL, AT2, midas_u(5)
15	reg rec, WBE_1r, TOU_2r, midas_u(4)	reg rec, RR1_1r, TOU_2r, midas_u(6)	reg rec, RR1_1r, SAL_2r, midas_pdl(5)	3 var, CAR, UNF, LOH, midas_u(1)
16	reg rec, RR1_1r, TOU_2r, midas_u(1)	reg rec, RR1_1r, TOU_2r, midas_pdl(5)	reg rec, AT2_1r, TOU_2r, midas_u(5)	reg glo fin, WBE_1r, f2_2r, midas_pdl(5)
17	reg rec, WBE_1r, TOU_2r, midas_u(3)	reg rec, WTE_1r, TOU_2r, midas_u(2)	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_pdl(6)
18	**reg rec, UNF_1r, TOU_2r, mfvar(1)**	**reg rec, LOH_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_pdl(5)	**reg rec, f4_1r, TOU_2r, mfvar(1)**
19	reg rec, RR1_1r, RR1_2r, midas_u(6)	**reg rec, f4_1r, TOU_2r, mfvar(1)**	reg rec, RR1_1r, TOU_2r, midas_u(3)	3 var, IMP, CAR, LOH, midas_u(5)
20	reg rec, AT2_1r, AT2_2r, midas_u(6)	reg rec, RR1_1r, TOU_2r, midas_pdl(6)	reg rec, AT2_1r, SAL_2r, midas_u(4)	reg rec, WBE_1r, TOU_2r, midas_pdl(4)

The table shows the 20 best models when nowcasting consumption, considering QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. Different colours highlight different regimes. Boldface text indicates Ghysels' mixed-frequency model, italic text indicates a VAR model. The first regime (_1r) is the recession-based regime or the regime of high (global or AT) financial/economic uncertainty, the second regime (_2r) is non recession-based regime or the regime of low (global or AT) financial/economic uncertainty.

AT recession | global financial uncertainty | global economic uncertainty | AT financial uncertainty | AT economic uncertainty | no regime

Table B.3: Best 20 models to nowcast investment

INV, QoQ

	forecast	nowcast 1	nowcast 2	nowcast 3
1	*reg glo fin, BA5_1r, ISO_2r, var(3)*	reg glo fin, ISO_1r, ISO_2r, midas_pdl(6)	reg glo fin, EXX_1r, SEN_2r, midas_u(4)	reg rec, UNM_1r, WEE_2r, midas_u(6)
2	reg glo fin, BA1_1r, WEE_2r, midas_u(3)	reg glo fin, ISO_1r, ISO_2r, midas_pdl(5)	reg glo fin, EXX_1r, ISC_2r, midas_u(6)	reg rec, UNM_1r, WSE_2r, midas_u(6)
3	**reg glo fin, BA1_1r, WEE_2r, mfvar(1)**	reg glo fin, WME_1r, ISO_2r, midas_u(6)	reg glo fin, EXX_1r, ISO_2r, midas_u(6)	reg rec, UNM_1r, WEE_2r, midas_u(5)
4	**reg rec, UNM_1r, SEN_2r, mfvar(1)**	reg at fin, IMP_1r, ISO_2r, midas_u(6)	reg glo fin, EXX_1r, SEN_2r, midas_u(5)	reg rec, f_1r, SEN_2r, midas_u(5)
5	reg glo fin, BA2_1r, ISO_2r, midas_pdl(5)	reg glo fin, WME_1r, ISO_2r, midas_u(5)	reg glo fin, EXX_1r, ISC_2r, midas_u(5)	reg glo fin, EXX_1r, SEN_2r, midas_u(5)
6	reg glo fin, BA4_1r, WEE_2r, midas_u(3)	reg glo fin, BA4_1r, ISO_2r, midas_pdl(5)	**reg glo fin, BA4_1r, WEE_2r, mfvar(1)**	reg rec, UNE_1r, WEE_2r, midas_u(6)
7	reg glo fin, BA5_1r, WEE_2r, midas_u(3)	reg glo fin, ISC_1r, ISO_2r, midas_pdl(6)	**reg glo fin, BA4_1r, WSE_2r, mfvar(1)**	reg rec, UNM_1r, WEE_2r, midas_u(4)
8	reg glo fin, BA1_1r, WEE_2r, midas_u(2)	3 var, EXX, LAB, ISO, midas_u(6)	reg glo fin, IMP_1r, SEN_2r, midas_u(4)	reg glo fin, ISO_1r, EMP_2r, midas_u(5)
9	reg glo fin, BA1_1r, ISO_2r, midas_pdl(5)	reg glo fin, ISC_1r, ISO_2r, midas_u(6)	reg glo fin, IMP_1r, SEN_2r, midas_u(5)	reg glo fin, EXX_1r, EMP_2r, midas_u(6)
10	*reg glo fin, BA2_1r, ISO_2r, var(2)*	reg glo fin, BA4_1r, ISO_2r, midas_u(5)	reg glo fin, BA4_1r, SEN_2r, midas_u(4)	**reg glo fin, BA4_1r, WEE_2r, mfvar(1)**
11	reg glo fin, BA1_1r, WEE_2r, midas_u(4)	reg glo fin, BA4_1r, ISO_2r, midas_u(6)	reg glo fin, BA4_1r, SEN_2r, midas_u(5)	reg glo fin, EXX_1r, SEN_2r, midas_u(6)
12	reg glo fin, BA2_1r, WEE_2r, midas_u(2)	reg glo fin, WME_1r, ISO_2r, midas_pdl(5)	reg glo fin, EXX_1r, SEN_2r, midas_u(6)	reg glo fin, EXX_1r, ISC_2r, midas_u(6)
13	**reg glo fin, BA4_1r, WEE_2r, mfvar(1)**	reg glo fin, ISC_1r, ISO_2r, midas_pdl(5)	reg glo fin, EXX_1r, ISC_2r, midas_u(4)	reg rec, f_1r, WEE_2r, midas_u(6)
14	*reg glo fin, BA1_1r, ISO_2r, var(2)*	reg at fin, IMP_1r, ISO_2r, midas_u(5)	reg glo fin, WEE_1r, ISC_2r, midas_u(6)	reg rec, UNM_1r, WSE_2r, midas_u(5)
15	*reg glo fin, BA4_1r, ISO_2r, var(3)*	reg glo fin, BA5_1r, ISO_2r, midas_u(5)	reg glo fin, ISO_1r, EMP_2r, midas_pdl(4)	**reg glo fin, BA4_1r, WSE_2r, mfvar(1)**
16	reg glo fin, UNM_1r, WEE_2r, midas_u(2)	reg glo fin, BA5_1r, ISO_2r, midas_u(6)	reg glo fin, EXX_1r, EMP_2r, midas_u(5)	reg rec, f_1r, SEN_2r, midas_u(6)
17	reg glo fin, BA4_1r, WEE_2r, midas_u(4)	**reg glo fin, BA4_1r, WEE_2r, mfvar(1)**	reg glo fin, ISO_1r, EMP_2r, midas_pdl(5)	reg glo fin, ISO_1r, UNY_2r, midas_pdl(5)
18	reg glo fin, WME_1r, WEE_2r, midas_u(3)	reg glo fin, WEE_1r, ISO_2r, midas_pdl(5)	reg glo fin, BA5_1r, ISO_2r, midas_u(6)	reg glo fin, ISO_1r, EMP_2r, midas_pdl(6)
19	reg glo fin, UNM_1r, WEE_2r, midas_u(3)	reg glo fin, SEN_1r, ISO_2r, midas_pdl(5)	reg glo fin, BA1_1r, SEN_2r, midas_u(4)	reg glo fin, ISO_1r, UNY_2r, midas_pdl(6)
20	reg rec, UNM_1r, SEN_2r, midas_u(3)	reg glo fin, WEE_1r, ISO_2r, midas_u(6)	reg rec, UNM_1r, WEE_2r, midas_u(6)	reg rec, UNE_1r, WEE_2r, midas_u(4)

INV, YoY

	forecast	nowcast 1	nowcast 2	nowcast 3
1	reg glo fin, f4_1r, CCO_2r, midas_u(5)	reg glo fin, ISO_1r, ISO_2r, midas_pdl(6)	reg glo fin, ISO_1r, EMP_2r, midas_u(4)	reg glo fin, ISO_1r, EMP_2r, midas_u(5)
2	reg glo fin, f4_1r, CCO_2r, midas_u(5)	reg glo fin, ISO_1r, ISO_2r, midas_pdl(5)	reg glo fin, ISO_1r, ISC_2r, midas_u(3)	reg glo fin, ISO_1r, EMP_2r, midas_u(4)
3	*reg glo fin, ISO_1r, EMP_2r, var(4)*	reg glo fin, ISO_1r, VAC_2r, midas_u(1)	reg glo fin, ISO_1r, VAC_2r, midas_u(2)	reg glo fin, ISO_1r, ISC_2r, midas_u(4)
4	*reg glo fin, EMP_1r, EMP_2r, var(4)*	reg glo fin, ISO_1r, UNY_2r, midas_u(4)	reg glo fin, ISO_1r, UNY_2r, midas_u(5)	reg glo fin, ISO_1r, EMP_2r, midas_u(6)
5	**reg glo fin, BA4_1r, UNY_2r, mfvar(1)**	reg glo fin, ISO_1r, UNY_2r, midas_u(3)	reg glo fin, BA4_1r, UNY_2r, midas_u(5)	reg glo fin, ISO_1r, EMP_2r, midas_pdl(4)
6	*reg glo fin, SEN_1r, ISO_2r, var(3)*	reg glo fin, ISO_1r, VAC_2r, midas_u(2)	reg glo fin, ISO_1r, EMP_2r, midas_u(2)	reg glo fin, ISO_1r, UNY_2r, midas_u(6)
7	reg glo fin, BA4_1r, EMP_2r, midas_u(2)	reg glo fin, ISO_1r, UNY_2r, midas_pdl(4)	reg glo fin, BA1_1r, SEN_2r, midas_u(4)	reg glo fin, ISO_1r, UNY_2r, midas_pdl(5)
8	reg glo fin, BA4_1r, CCO_2r, midas_u(2)	reg glo fin, ISO_1r, EMP_2r, midas_u(3)	reg glo fin, ISO_1r, UNY_2r, midas_u(4)	reg glo fin, ISO_1r, UNY_2r, midas_pdl(4)
9	reg glo fin, BA4_1r, CCO_2r, midas_u(5)	reg glo fin, BA4_1r, UNY_2r, midas_u(4)	reg glo fin, ISO_1r, EMP_2r, midas_u(3)	reg glo fin, ISO_1r, ISC_2r, midas_u(5)
10	*3 var, EXX, EMP, WPI, var(4)*	reg glo fin, f4_1r, CCO_2r, midas_u(6)	reg glo fin, ISO_1r, EMP_2r, midas_u(5)	reg glo fin, ISO_1r, UNY_2r, midas_u(5)
11	reg glo fin, BA2_1r, CCO_2r, midas_u(5)	reg glo fin, f4_1r, CCO_2r, midas_u(6)	reg glo fin, BA4_1r, UNY_2r, midas_pdl(4)	**reg glo fin, BA4_1r, UNY_2r, mfvar(1)**
12	reg glo fin, BA4_1r, UNY_2r, midas_u(3)	reg glo fin, BA4_1r, UNY_2r, midas_u(3)	reg glo fin, BA4_1r, UNY_2r, midas_u(4)	reg glo fin, BA4_1r, UNY_2r, midas_pdl(5)
13	reg glo fin, BA4_1r, UNY_2r, midas_u(2)	reg glo fin, WME_1r, UNY_2r, midas_u(4)	reg glo fin, BA4_1r, EMP_2r, midas_pdl(4)	**reg glo fin, BA4_1r, EMP_2r, mfvar(1)**
14	*reg glo fin, BA4_1r, ISO_2r, var(3)*	reg glo fin, ISO_1r, UNY_2r, midas_u(2)	reg glo fin, BA4_1r, UNY_2r, midas_u(6)	**reg glo fin, BA4_1r, SEN_2r, mfvar(1)**
15	*reg glo fin, VAC_1r, ISO_2r, var(4)*	**reg glo fin, BA4_1r, UNY_2r, mfvar(1)**	reg glo fin, BA1_1r, UNY_2r, midas_u(6)	reg glo fin, ISO_1r, ISO_2r, midas_pdl(5)
16	reg glo fin, WME_1r, UNY_2r, midas_u(3)	**reg glo fin, BA4_1r, SEN_2r, mfvar(1)**	reg glo fin, ISO_1r, VAC_2r, midas_u(3)	reg glo fin, BA1_1r, SEN_2r, midas_u(5)
17	reg glo fin, BA4_1r, CCO_2r, midas_u(6)	reg glo fin, BA4_1r, UNY_2r, midas_u(5)	reg glo fin, BA4_1r, SEN_2r, midas_u(4)	reg glo fin, ISO_1r, EMP_2r, midas_pdl(5)
18	*reg glo fin, BA4_1r, EMP_2r, var(4)*	**reg glo fin, BA4_1r, EMP_2r, mfvar(1)**	reg glo fin, BA1_1r, SEN_2r, midas_u(5)	reg glo fin, EMP_1r, ISC_2r, midas_u(3)
19	reg glo fin, BA4_1r, UNY_2r, midas_u(4)	reg glo fin, BA4_1r, ISO_2r, midas_pdl(5)	3 var, IPM, EMP, LOH, midas_pdl(4)	reg glo fin, BA1_1r, UNY_2r, midas_u(5)
20	*3 var, EMP, RR2, VO1, var(4)*	reg glo fin, BA4_1r, ISO_2r, midas_pdl(6)	**reg glo fin, BA4_1r, SEN_2r, mfvar(1)**	reg glo fin, ISO_1r, UNY_2r, midas_u(4)

The table shows the 20 best models when nowcasting investment, considering QoQ and YoY growth rates. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. Different colours highlight different regimes. Boldface text indicates Ghysels' mixed-frequency model, italic text indicates a VAR model. The first regime (_1r) is the recession-based regime or the regime of high (global or AT) financial/economic uncertainty, the second regime (_2r) is non recession-based regime or the regime of low (global or AT) financial/economic uncertainty.

AT recession | global financial uncertainty | global economic uncertainty | AT financial uncertainty | AT economic uncertainty | no regime

Figure B.2: Important variables in nowcasting GDP, consumption and investment

GDP, QoQ

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	0.40	0.41	0.42	0.43	0.41	0.40	0.45	0.43	0.44	0.42	0.42	0.43	0.41	0.44	0.47	0.45	0.40	0.41	0.39	0.42	0.42	0.43	0.40	0.40	0.42	0.42	0.41	0.42	0.41	0.42	0.41	0.43	0.40	0.43	0.43	0.42	0.39	0.46	0.38	0.39	0.39	0.43	0.42	0.39	0.39	0.39	0.38	0.40	0.41	0.40	0.42	0.41	0.40	0.41	0.39	0.42	0.40	0.43	0.37	0.42	0.43	0.40
Now1	0.42	0.38	0.40	0.43	0.42	0.40	0.47	0.44	0.42	0.43	0.40	0.43	0.41	0.45	0.46	0.44	0.41	0.42	0.46	0.42	0.42	0.44	0.40	0.43	0.42	0.42	0.41	0.44	0.45	0.41	0.41	0.43	0.41	0.46	0.45	0.44	0.40	0.49	0.36	0.35	0.37	0.45	0.41	0.40	0.38	0.41	0.38	0.39	0.41	0.37	0.41	0.42	0.39	0.42	0.38	0.43	0.42	0.43	0.45	0.42	0.42	0.40
Now2	0.37	0.39	0.41	0.42	0.43	0.39	0.49	0.46	0.46	0.43	0.42	0.43	0.42	0.45	0.45	0.44	0.40	0.42	0.50	0.42	0.41	0.43	0.39	0.43	0.42	0.42	0.41	0.43	0.45	0.41	0.41	0.43	0.41	0.46	0.47	0.46	0.42	0.49	0.38	0.38	0.40	0.44	0.42	0.40	0.37	0.39	0.39	0.40	0.39	0.44	0.41	0.41	0.40	0.45	0.41	0.39	0.40	0.43	0.48	0.42	0.42	0.40
Now3	0.38	0.42	0.41	0.42	0.42	0.41	0.45	0.45	0.45	0.43	0.43	0.43	0.43	0.45	0.44	0.42	0.41	0.43	0.47	0.42	0.42	0.44	0.41	0.43	0.44	0.43	0.42	0.43	0.45	0.41	0.42	0.43	0.40	0.45	0.46	0.45	0.43	0.48	0.39	0.37	0.39	0.43	0.41	0.41	0.36	0.40	0.45	0.41	0.37	0.46	0.41	0.41	0.40	0.48	0.41	0.40	0.43	0.42	0.44	0.44	0.43	0.40

GDP, YoY

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	0.53	0.56	0.56	0.57	0.49	0.55	0.54	0.59	0.54	0.56	0.57	0.57	0.55	0.55	0.68	0.61	0.58	0.59	0.57	0.54	0.54	0.59	0.53	0.54	0.54	0.56	0.55	0.56	0.56	0.55	0.55	0.59	0.53	0.63	0.61	0.55	0.59	0.62	0.55	0.55	0.56	0.59	0.56	0.55	0.53	0.54	0.54	0.61	0.53	0.54	0.53	0.56	0.52	0.54	0.54	0.58	0.49	0.54	0.52	0.56	0.59	0.52
Now1	0.54	0.53	0.53	0.56	0.49	0.60	0.54	0.62	0.54	0.55	0.55	0.57	0.54	0.55	0.68	0.62	0.58	0.58	0.57	0.56	0.56	0.60	0.57	0.58	0.54	0.55	0.55	0.56	0.60	0.54	0.56	0.58	0.53	0.65	0.65	0.57	0.63	0.69	0.54	0.52	0.59	0.71	0.60	0.62	0.55	0.59	0.55	0.66	0.57	0.58	0.54	0.56	0.58	0.63	0.56	0.57	0.53	0.52	0.62	0.56	0.59	0.52
Now2	0.51	0.51	0.53	0.57	0.51	0.53	0.54	0.56	0.55	0.58	0.55	0.58	0.57	0.57	0.62	0.64	0.57	0.58	0.65	0.55	0.55	0.59	0.57	0.57	0.54	0.55	0.56	0.56	0.60	0.54	0.56	0.58	0.56	0.66	0.66	0.63	0.63	0.69	0.57	0.57	0.62	0.70	0.61	0.63	0.54	0.56	0.60	0.68	0.55	0.62	0.54	0.58	0.57	0.65	0.58	0.58	0.52	0.53	0.71	0.56	0.59	0.52
Now3	0.54	0.61	0.57	0.57	0.56	0.55	0.54	0.59	0.53	0.60	0.59	0.62	0.60	0.57	0.59	0.63	0.55	0.57	0.63	0.54	0.54	0.60	0.58	0.57	0.57	0.58	0.56	0.55	0.61	0.53	0.56	0.57	0.54	0.65	0.67	0.60	0.63	0.69	0.57	0.58	0.58	0.70	0.59	0.63	0.53	0.57	0.66	0.69	0.56	0.65	0.55	0.60	0.56	0.67	0.58	0.57	0.59	0.56	0.63	0.53	0.54	0.52

CON, QoQ

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	0.75	0.72	0.72	0.74	0.75	0.76	0.66	0.69	0.71	0.71	0.74	0.69	0.75	0.71	0.77	0.75	0.74	0.74	0.74	0.75	0.75	0.75	0.68	0.74	0.75	0.76	0.72	0.75	0.75	0.74	0.74	0.75	0.69	0.74	0.74	0.73	0.74	0.77	0.73	0.75	0.74	0.75	0.75	0.70	0.71	0.72	0.72	0.71	0.74	0.75	0.74	0.75	0.74	0.76	0.74	0.71	0.76	0.75	0.73	0.75	0.75	0.72
Now1	0.69	0.74	0.75	0.75	0.77	0.76	0.67	0.70	0.73	0.73	0.72	0.71	0.74	0.73	0.73	0.75	0.74	0.72	0.76	0.74	0.73	0.75	0.69	0.76	0.74	0.75	0.71	0.74	0.76	0.72	0.75	0.75	0.71	0.74	0.74	0.75	0.75	0.76	0.74	0.74	0.74	0.75	0.75	0.71	0.71	0.71	0.73	0.70	0.75	0.75	0.75	0.75	0.75	0.76	0.74	0.74	0.78	0.72	0.74	0.72	0.75	0.72
Now2	0.69	0.73	0.74	0.73	0.76	0.73	0.67	0.70	0.71	0.70	0.75	0.65	0.73	0.69	0.73	0.75	0.73	0.74	0.76	0.74	0.73	0.74	0.69	0.76	0.74	0.75	0.71	0.74	0.75	0.75	0.75	0.75	0.71	0.75	0.74	0.76	0.75	0.77	0.74	0.73	0.74	0.75	0.76	0.68	0.69	0.69	0.74	0.71	0.74	0.74	0.74	0.75	0.73	0.76	0.75	0.74	0.79	0.76	0.73	0.73	0.74	0.72
Now3	0.69	0.73	0.74	0.74	0.64	0.73	0.67	0.70	0.72	0.66	0.75	0.66	0.71	0.66	0.74	0.73	0.73	0.73	0.75	0.76	0.75	0.75	0.70	0.76	0.74	0.75	0.72	0.74	0.76	0.74	0.74	0.73	0.71	0.75	0.74	0.77	0.75	0.77	0.74	0.74	0.74	0.74	0.76	0.71	0.70	0.70	0.75	0.69	0.74	0.73	0.74	0.75	0.73	0.76	0.74	0.74	0.66	0.75	0.74	0.74	0.74	0.74

CON, YoY

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	0.95	0.96	0.96	1.01	1.00	1.04	0.97	0.98	0.98	0.95	0.98	0.96	0.96	0.95	1.07	1.01	0.96	0.99	0.98	0.99	0.97	0.98	0.95	0.97	0.99	1.00	0.96	1.00	0.97	0.98	0.98	1.02	0.88	0.97	0.99	0.98	0.97	1.03	0.97	1.01	0.96	1.03	0.98	0.93	0.94	0.93	0.98	1.00	0.95	0.98	0.97	0.98	0.96	0.99	0.98	0.97	1.00	1.03	0.93	0.99	0.99	0.92
Now1	0.99	0.95	0.94	1.02	1.05	1.04	0.98	0.99	1.03	0.97	0.98	0.97	1.01	1.03	1.02	1.04	0.98	0.99	1.03	1.01	1.00	0.99	0.98	0.98	1.02	1.00	0.99	1.01	1.02	0.97	1.01	1.03	0.97	1.03	1.06	1.04	1.02	1.03	1.00	1.00	1.00	1.03	1.02	0.94	0.95	0.94	1.00	1.00	1.03	1.00	0.97	1.05	1.00	1.04	1.01	0.96	1.03	1.00	0.89	1.01	0.99	0.92
Now2	0.99	0.96	0.95	1.03	1.07	0.87	0.98	1.03	1.05	0.97	1.01	0.96	1.02	1.03	1.03	1.04	0.99	0.98	1.02	1.01	1.00	0.98	1.00	0.96	1.01	1.01	0.97	1.00	1.04	0.98	1.01	1.03	0.99	1.01	1.04	1.04	1.05	1.02	0.99	0.98	1.01	1.03	1.03	0.95	0.94	0.95	0.99	0.96	1.03	1.00	0.97	1.03	1.01	1.03	1.01	0.94	0.92	1.03	0.94	1.01	0.99	0.92
Now3	0.98	0.97	0.96	1.04	0.93	0.89	0.99	1.01	1.05	0.90	1.00	0.96	0.97	1.02	1.00	1.03	0.99	1.00	1.01	1.02	1.00	0.98	1.01	0.95	1.03	1.01	0.98	1.01	1.04	0.96	1.01	1.04	0.97	0.99	1.03	1.04	1.07	1.00	0.99	0.99	1.02	1.02	1.05	0.93	0.91	0.97	1.00	0.95	1.02	0.99	0.97	1.03	1.00	1.03	1.03	0.96	0.88	1.02	0.92	1.00	0.98	0.95

INV, QoQ

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	1.41	1.43	1.40	1.48	1.45	1.49	1.64	1.51	1.28	1.44	1.43	1.45	1.40	1.42	1.41	1.37	1.49	1.48	1.46	1.47	1.47	1.48	1.49	1.38	1.42	1.44	1.49	1.52	1.46	1.43	1.45	1.47	1.51	1.45	1.44	1.50	1.39	1.45	1.39	1.36	1.40	1.52	1.49	1.41	1.45	1.45	1.35	1.35	1.42	1.38	1.39	1.44	1.43	1.38	1.42	1.46	1.47	1.37	1.43	1.41	1.44	1.51
Now1	1.42	1.41	1.41	1.47	1.48	1.52	1.59	1.58	1.39	1.44	1.43	1.44	1.43	1.43	1.42	1.34	1.49	1.49	1.50	1.48	1.48	1.48	1.49	1.37	1.43	1.44	1.48	1.49	1.46	1.46	1.46	1.47	1.50	1.45	1.44	1.48	1.37	1.44	1.34	1.27	1.39	1.51	1.49	1.40	1.44	1.44	1.34	1.37	1.42	1.39	1.40	1.46	1.44	1.43	1.42	1.43	1.50	1.39	1.48	1.44	1.44	1.49
Now2	1.44	1.41	1.47	1.48	1.52	1.47	1.74	1.60	1.34	1.40	1.47	1.47	1.38	1.43	1.45	1.34	1.45	1.48	1.45	1.48	1.48	1.48	1.49	1.39	1.46	1.47	1.47	1.50	1.45	1.45	1.46	1.47	1.49	1.44	1.43	1.48	1.37	1.44	1.31	1.27	1.40	1.51	1.49	1.39	1.44	1.45	1.35	1.35	1.42	1.38	1.42	1.47	1.44	1.43	1.41	1.47	1.54	1.46	1.46	1.46	1.43	1.47
Now3	1.42	1.50	1.41	1.46	1.50	1.52	1.56	1.57	1.34	1.41	1.46	1.46	1.39	1.42	1.48	1.35	1.46	1.47	1.47	1.48	1.47	1.49	1.47	1.39	1.45	1.45	1.48	1.49	1.47	1.45	1.46	1.47	1.49	1.47	1.46	1.48	1.37	1.45	1.34	1.35	1.42	1.50	1.48	1.39	1.44	1.44	1.35	1.36	1.37	1.38	1.42	1.46	1.44	1.44	1.43	1.42	1.54	1.45	1.49	1.45	1.44	1.42

INV, YoY

	Prod IPM	Prod EXX	Prod IMP	Prod REA	Con CAR	Con SAL	Con TOU	Con STV	Lab EMP	Lab UNE	Lab LAB	Lab UNF	Lab UNM	Lab UNY	Lab UR	Lab VAC	Pri CPI	Pri CIX	Pri WPI	Mon AT1	Mon AT2	Mon RR1	Mon RR2	Mon M1	Mon M2	Mon M3	Mon LOH	Mon LOP	Fin ATX	Fin YIE	Fin VIB	Fin SPR	Fin SPD	Fin VO1	Fin VO2	Fin EPU	Sur SEN	Sur CCO	Sur ISC	Sur ISO	Sur ISP	Sur CSE	Sur CSU	Sur BA1	Sur BA2	Sur BA3	Sur BA4	Sur BA5	Sur BA6	Sur WME	Sur WBE	Sur WSE	Sur WTE	Sur WEE	PC f	PC f1	PC f2	PC f3	PC f4	PC f5	PC f6	PC f7
Fore	2.13	2.06	2.02	2.06	1.89	2.09	2.12	2.05	1.75	2.12	1.96	2.08	2.09	1.96	1.97	2.01	2.06	2.07	2.06	2.05	2.06	2.04	1.94	2.00	2.01	2.00	2.02	2.05	2.04	2.04	2.05	2.04	2.07	1.98	1.97	2.03	1.97	2.04	2.01	2.01	1.99	2.22	2.08	2.09	2.12	2.13	1.98	2.01	2.12	1.99	1.95	2.02	2.03	2.00	2.10	2.02	2.00	1.91	2.13	2.01	1.98	2.13
Now1	2.16	2.15	2.12	2.07	1.91	2.14	2.17	2.05	1.89	2.10	1.93	2.08	2.09	1.97	2.08	1.98	2.08	2.06	2.14	2.07	2.07	2.04	1.97	2.03	2.01	2.00	2.01	2.06	2.04	2.04	2.05	2.02	2.08	2.00	1.98	1.99	2.02	2.09	1.95	1.91	2.04	2.21	2.11	2.09	2.10	2.12	2.01	1.96	2.13	2.00	1.98	2.04	2.06	2.03	2.12	2.01	2.00	1.91	2.11	2.01	1.94	2.09
Now2	2.01	2.13	2.12	2.06	1.98	2.03	2.11	2.07	1.82	2.07	1.88	2.09	2.01	1.97	2.04	1.98	2.05	2.06	2.08	2.07	2.08	2.04	2.03	2.04	2.01	2.02	2.06	2.05	2.05	2.06	2.05	2.01	2.07	2.00	1.97	2.04	2.01	2.09	1.91	1.94	2.04	2.15	2.11	2.09	2.09	2.14	2.03	2.02	2.14	2.06	2.01	2.01	2.07	2.01	2.10	2.03	2.04	1.91	2.10	2.01	1.93	2.05
Now3	1.99	2.10	1.95	1.96	1.97	2.08	2.02	1.97	1.88	2.07	1.90	2.07	2.02	1.96	2.04	1.98	2.07	2.06	2.13	2.08	2.08	2.02	2.03	2.09	2.07	2.06	2.07	2.05	2.07	2.05	2.04	2.01	2.07	1.96	1.95	2.09	2.03	2.07	1.95	1.94	2.06	2.17	2.10	2.10	2.10	2.15	2.03	2.02	1.99	2.06	2.00	2.02	2.07	2.02	2.10	1.88	2.03	1.91	2.14	2.05	1.93	2.00

The table presents RMSE for QoQ and YoY growth rates, when nowcasting GDP, consumption and investment. The shown numbers are minimum values over all one-variable models including the given variable. The out-of-sample evaluation period ranges from 2012Q3 to 2019Q4. We use the following colour coding. The minimum value (best measure) is dark green, the maximum value (worst measure) is dark red, the median is yellow, and percentiles are mixtures between yellow and green/red.