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Regime-Dependent Nowcasting of the Austrian Economy

Jaroslava Hlouskova[1,2] | Ines Fortin[1]

[1]Institute for Advanced Studies, Vienna, Austria | [2]Department of Economics, Faculty of Economics and Finance, University of Economics in Bratislava, Bratislava, Slovakia

Correspondence: Ines Fortin (fortin@ihs.ac.at)

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ABSTRACT

We nowcast and forecast economic activity in Austria, namely, real gross domestic product (GDP), consumption, and investment, which are available at a quarterly frequency, using a preselected number of monthly indicators based on a combination of statistical procedures. We consider regime-dependent and non–regime-dependent mixed data sampling approaches and compare their forecast and nowcast accuracies in terms of the root mean square error and the mean absolute error. We are particularly interested in whether explicitly considering different regimes improves the nowcast. We examine business cycle-related regimes (good/bad economic times) and financial uncertainty regimes (high/low uncertainty) and compare regime-dependent and non–regime-dependent models applying, among others, forecast combination methods. We find strong evidence that taking explicit account of regimes improves nowcasting and that only a handful of variables are important for nowcasting. In addition, different variables are important in different regimes. We observe, for example, that for GDP, in bad times, real industrial production matters more than its survey counterpart, namely, production expectations, and the other way around. The most important predictor for consumption in both regimes is bank loans to households, while for investment labor market indicators are most relevant. For all target variables, industrial production is more important in bad times than in good times.

1 | Introduction

Economists have imperfect knowledge of the present state of the economy, as many key statistics, for example, gross domestic product (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 labor market, survey indicators, and financial data. The latter are often even available at a daily frequency (see, e.g., Anthonisz (2023) or Baumeister et al. (2015)).

For a long time, economists have analyzed the comovement 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 the vector autoregressive model 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 prefiltering 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, that is, 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 focus 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 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. 2007), 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), Kuzin et al. (2011), and Schumacher (2016).

Another recent approaches 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 is formulated exclusively in terms of observable data. Ghysels (2014, 2016) also proposes various parsimonious parameterizations, in part inspired by MIDAS regressions.

In a lot of different fields of forecasting, regime-dependent models have been found to be useful. See, for example, Guidolin and Timmermann (2005, 2009) for stock and bond returns and interest rates, Li et al. (2022) for stock price volatility, Guidolin (2006) for asset prices and macroeconomic variables, Goulet Coulombe et al. (2022) for macroeconomic variables, and Guidolin and Pedio (2021) and Crespo Cuaresma et al. (2024) for commodity prices. In the current paper we examine whether taking explicit account of regimes may improve nowcasting. In doing so, we explicity do not target the Covid-19 period but want to see the gains of regime-dependent models in non-Covid-19 times, i.e., in "normal" times not characterized by exceptional dynamics. We thereby contribute to the nonlinear nowcasting literature, which is still rather small. Guérin and Marcellino (2013), for example, propose the Markov-switching MIDAS models and find that nonlinear MIDAS models usually outperform linear MIDAS models, when forecasting/nowcasting US GDP growth. Ferrara and Simoni (2023) do not explicitly consider regime-dependent models but analyze different periods and observe that the gains in nowcast accuracy differ between periods of recessions and of macroeconomic stability. We investigate regimes defining good and bad economic times, regimes subject to high and low inflation, and regimes describing low and high financial uncertainty.

More precisely, we apply MIDAS models, both regime-dependent and non–regime-dependent, to nowcast and forecast the growth of real GDP, real consumption, and real investment in Austria. GDP for Austria is available at a quarterly frequency, 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, industrial production. 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 by financial markets which react whenever there are surprises about the value of 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.[1]

Alternative approaches to nowcasting Austrian GDP are mostly based on dynamic factor models (see, e.g., Sellner (2023) and Glocker and Kaniovski (2022). Modifications were implemented especially for the Covid-19 period; however, they are not used anymore due to their poor performance in "normal" times.[2] Currently used models for nowcasting economic activity in

Austria do not consider regime-dependent dynamics, as suggested in our approach.

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

2 | Methodology and Data

We forecast and nowcast three quarterly (low-frequency) variables, real GDP, real consumption (consumption of private households), and real investment (gross fixed capital formation), using monthly (high-frequency) data. In this paper, we consider two mixed-frequency methods: the unrestricted mixed data sampling regression (MIDAS-u) and the MIDAS regression with Almon polynomial distributed lags (MIDAS-pdl). The unrestricted MIDAS approach (see Foroni et al. 2015) estimates

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

where the low-frequency variable, $x_L(t)$, is a value of the quarterly variable x_L (e.g., GDP) at quarter t, $x_{H,t-\frac{\tau}{3}}$ is the $k-$dimensional vector of high-frequency (monthly) variables at month $t-\frac{\tau}{3}$, that is, τ months prior to quarter t, $\mu_0 \in \mathbb{R}^q$ 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, $\tau = 0, \ldots, p_x$, and $u(t)$ is the error term which is assumed to be normally distributed with zero mean and standard deviation σ. In more detail, $x_{H,t-\frac{\tau}{3}}$ are values of high-frequency variables at the third month of quarter t when $\tau = 0$, the second month of quarter t when $\tau = 1$, the first month of quarter t when $\tau = 2$, and the third month of quarter $t-1$ when $\tau = 3$.

In addition, we consider also the MIDAS regression with Almon polynomial distributed lag weighting, which is widely used to place restrictions on lag coefficients in the autoregressive model

$$x_L(t) = (\mu_0)'\mathbf{D}_t + \mu_1 x_L(t-1) + \sum_{\tau=0}^{p_x-1} \left(\sum_{j=1}^{P} \tau^j \theta_j \right)' x_{H,t-1-\frac{\tau}{3}} + u(t) \quad (2)$$

where P is the Almon polynomial order such that $P < p_x$ and θ_j are k-dimensional vectors of parameters, $j = 1, \ldots, P$.[3]

As the focus of this study is on analyzing the value added (if any) of the regime-based models against models where the regimes are not considered, the following notation applies. If no regime is considered, then $q = 1$ and $\mathbf{D}_t = 1$. If regimes are considered, then $q = 2$ (we consider two regimes) and $\mathbf{D}_t = (D_t, 1-D_t)'$ where D_t is the (quarterly) dummy variable presenting Regime 1 (such as recession, high financial uncertainty) if $D_t = 1$ and Regime 2 (expansion, low financial uncertainty) if $D_t = 0$. 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 $x_{H,t-\frac{\tau}{3}} = \left(D_{t-\frac{\tau}{3}} z_{1,t-\frac{\tau}{3}}, 1 - D_{t-\frac{\tau}{3}} z_{2,t-\frac{\tau}{3}} \right)'$ for $\tau = 0, 1, 2, 3$ where $z_{1,t-\frac{\tau}{3}}$ and $z_{2,t-\frac{\tau}{3}}$ are monthly variables, not necessarily the same, and $D_{t-\frac{\tau}{3}}$ is the corresponding monthly dummy variable. See Section 3 on more detailed definition of regimes under consideration.

We group the monthly variables into the following seven classes: (i) production and trade indicators (Prod), (ii) consumption indicators (Con), (iii) labor market variables (Lab), (iv) price indicators (Pri), (v) variables related to money and credit (Mon), (vi) financial and uncertainty indicators (Fin), and (vii) purchasing managers' indices and other survey and sentiment indicators (Sur). The main advantage of sentiment indicators is that they are promptly available. Table B2 in Appendix B lists all variables with codes, sources, and transformations. The transformations are performed to ensure stationarity. All data are standardized.

We work with pseudo-real-time data that do not include vintages of data, so 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, for example, in Bernanke and Boivin (2003) and Schumacher and Breitung (2008), suggest that data revisions do not considerably affect the forecast accuracy. We take into account different publication delays of the economic indicators (the ragged edge) by using the approach used in Altissimo et al. (2010) and Marcellino and Schumacher (2010) and apply a realignment of each time series to obtain a balanced dataset. This guarantees that at a certain time, we only use information which is actually available to the researcher at a given point in time. Note that information regarding the regimes is also adjusted to this realignment, that is, if a monthly indicator has the publication delay of 1 month, then also the regime dummy is lagged in 1 month. The information regarding the publication delay for each monthly variable is presented in the last column of Table B2 in our manuscript.[4] The lags and corresponding realignments concern mainly the case when forecasting/nowcasting consumption as in the case of forecasting/nowcasting GDP and investment, there is only one variable (namely, IPM, the index of industrial production for manufacturing) that has a publication delay of 1 month.

For GDP, consumption, and investment, we forecast/nowcast quarter over quarter (QoQ) growth rates, that is, growth rates of a given quarter with respect to the previous quarter.[5] Most nowcasting studies seem to look at QoQ growth rates; however, some also use year-over-year growth rates.[6] Table B1 in the appendix presents descriptive statistics of QoQ 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 both the root mean square error (RMSE) and mean absolute error (MAE) for investment is much worse than for GDP; see, for example, Tables 2 and A3.

In our regime-dependent models, we consider five dummy variables defining the regimes, based on the following indicators: (i) the WIFO economic climate index for Austria,[7] (ii) the economic sentiment indicator for Austria (ESI), (iii) inflation for Austria, (iv) the volatility of the ATX (Austrian traded index), and (v) the volatility of the S&P 500.[8] The WIFO index and the ESI represent business cycle indicators, while ATX and S&P volatilities reflect local and global financial uncertainties. All indicators are available around the end of a given month and can be used in real time. The business cycle indicators show periods of recession (bad economic times) and nonrecession (good economic times), where we use the natural cutoff values to define periods of good and bad times.[9] For inflation, we use the flash estimate, which is published around the end of the month, and define periods of high and low inflation using a cutoff value of 2%. The volatilities are calculated as standard deviations of daily returns over a given month, annualized, and we define periods of high and low volatilities using the mean. Figure B2 in Appendix B shows, for example, the periods of recession and nonrecession based on the ESI, together with GDP.

3 | Empirical Analysis

Our primary goal is to find out whether explicitly considering different regimes can improve the forecast/nowcast of GDP, consumption, and investment. If this is the case, then what indicators contribute most? 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. With large models, generating nowcasts and updating them every instance a new release comes in is not only demanding but also sometimes infeasible. We thus suggest a practical approach towards preselecting a limited number of variables, which is based on a combination of statistical procedures described in more detail below. Also, Camacho and Perez-Quiros (2010) suggest that including more (noisy) indicators does not necessarily improve the forecasting accuracy and that it may be sufficient to focus on a small number of key variables. Other studies use only a few monthly indicators for nowcasting GDP (see, e.g., Kuzin et al. (2011) and Schumacher (2016).

Our main focus is to look at the potential value added of explicitly considering regimes to improve the nowcast performance. We consider good and bad economic times (defined by two different economic survey indicators), times of high and low inflation, and times of low and high (local and global) financial uncertainty. Each regime (expansion/recession, high/low inflation, or low/high financial uncertainty) considers one variable, and thus, we can examine the importance of certain variables in certain regimes. In terms of forecast/nowcast performance, we use the traditional RMSE and the MAE

$$\begin{aligned}
RMSE^{f} &= \sqrt{\frac{1}{T}\sum_{j=1}^{T}\left(\hat{y}_{t+j|t+j-1}-y_{t+j}\right)^2}\\
RMSE^{ni} &= \sqrt{\frac{1}{T}\sum_{j=1}^{T}\left(\hat{y}_{t+j|t+j|i}-y_{t+j}\right)^2}\\
MAE^{f} &= \frac{1}{T}\sum_{j=1}^{T}\left|\hat{y}_{t+j|t+j-1}-y_{t+j}\right|\\
MAE^{ni} &= \frac{1}{T}\sum_{j=1}^{T}\left|\hat{y}_{t+j|t+j|i}-y_{t+j}\right|
\end{aligned} \tag{3}$$

for $i = 1, 2, 3$, where y is the 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, exponent f denotes the performance measure (RMSE or MAE) of the forecast, and exponent ni denotes the performance measure of nowcast i. "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 3 months. The forecast uses only information up to the previous quarter.

To assess the potential value of regime-based models against non–regime-based models, we calculate the forecast/nowcast combination, where the weights are based on the discounted mean square forecast error (MSE), following Stock and Watson (2004), as follows:

$$\hat{y}^{MSE}_{t+1|t} = \sum_{m=1}^{M} w^{f,MSE}_{mt}\hat{y}^{(m)}_{t+1|t} \quad \text{and} \quad \hat{y}^{MSE}_{t+1|t+1|i} = \sum_{m=1}^{M} w^{ni,MSE}_{mt}\hat{y}^{(m)}_{t+1|t+1|i} \tag{4}$$

where M is the number of individual forecasts/nowcasts and the weights in (4) depend inversely on the historical performance (in terms of MSE) of individual models. Namely,

$$\begin{aligned}
w^{f,MSE}_{mt} &= \frac{W^{f,MSE}_{mt}}{\sum_{l=1}^{M} W^{f,MSE}_{lt}} \quad \text{with}\\
W^{f,MSE}_{mt} &= \sum_{\tilde{t}=T_1}^{t} \theta^{T-1-\tilde{t}}\left(y_t-\hat{y}^{(m)}_{\tilde{t}\,|\,\tilde{t}-1}\right)^2 \quad \text{and}
\end{aligned} \tag{5}$$

$$\begin{aligned}
w^{ni,MSE}_{mt} &= \frac{W^{ni,MSE}_{mt}}{\sum_{l=1}^{M} W^{ni,MSE}_{lt}} \quad \text{with}\\
W^{ni,MSE}_{mt} &= \sum_{\tilde{t}=T_1}^{t} \theta^{T-1-\tilde{t}}\left(y_t-\hat{y}^{(m)}_{\tilde{t}\,|\,\tilde{t}|\,i}\right)^2
\end{aligned} \tag{6}$$

where θ is a discount factor and in our empirical application, we use $\theta = 0.95$. In a similar manner, we calculate the forecast/nowcast combination based on discounted MAE, where values $W^{f,MSE}_{mt}$ and $W^{ni,MSE}_{mt}$ in (5) and (6), are replaced by $W^{f,MAE}_{mt} = \sum_{\tilde{t}=T_1}^{t} \theta^{T-1-\tilde{t}}\left|y_t-\hat{y}^{(m)}_{\tilde{t}\,|\,\tilde{t}-1}\right|$ and $W^{ni,MAE}_{mt} = \sum_{\tilde{t}=T_1}^{t} \theta^{T-1-\tilde{t}}\left|y_t-\hat{y}^{(m)}_{\tilde{t}\,|\,\tilde{t}|\,i}\right|$.

In order to reduce the number of predictors, we perform a preselection of the monthly variables. Namely, for a given target variable (GDP, consumption, investment), we first collect a large number of potential predictors and then narrow them down to variables with the highest predictive power. To tackle collinearity, we first remove variables from the dataset that are highly correlated with other variables (larger than 0.85). Then we combine the following three methods. First, the sure independence screening of Fan and Lv (2008) ranks predictors based on their (absolute) correlation with the target variable.[10] This method is used for nowcasting in Ferrara and Simoni (2023), Proietti and Giovannelli (2021), or Linzenich and Meunier (2024). Second, the Lasso variable selection method with the penalty parameter is being determined by cross-validation method K-fold with a mean square error objective. And finally, third, the Bayesian model averaging (BMA) where regression models (i.e., the target variable regressed on groups of variables chosen from the pool of 37 predetermined variables) are averaged making use of posterior model probabilities as weights.[11] After performing BMA, we consider those indicators with the largest PIP. For a general description of the method, see Steel (2020). Lasso and BMA confirmed that the indicators selected by the SIS approach were most of the time among the set of indicators selected by LASSO and/or BMA. In this way, we identify 10 variables with the highest predictive power for each target variable. The variables preselected in this way are presented in Table A1.[12]

To circumvent the problem of overfitting the data, we first evaluate our models in a cross-validation period (2011Q1–2014Q4); that is, we choose the top 1% best models (in terms of RMSE and MAE) from each class of regime-based models (we assume five classes of regimes driven by the threshold variables WIFO indicator, ESI, inflation, ATX and S&P) and from two non–regime-based models (when all combinations of three-variable and two-variable models are considered). We consider all possible combinations of variables in both regime-based and non–regime-based models. The top 1% rule roughly yields a number of 10 models per class, so we consider the top 10 models chosen in each class (i.e., 10 times 7=70) in the cross-validation period in the further analysis. In order to achieve a high degree of diversification among model classes, we chose the top 10 best models from each model category. This model selection step ensures that we have representatives of different specifications and thus models aimed at capturing the diverse characteristics of the dynamics of our variable of interest.

To assess the value added of regime-based models over non–regime-based models, we evaluate the 1% top best models from the cross-validation period in the final out-of-sample period (2015Q1–2019Q4) and report their performance (RMSE and MAE) in Tables 2, A2, and A3. In addition, we calculate weights for the forecast combination based on previous forecast accuracy, namely, discounted mean square errors following Stock and Watson (2004), as well as discounted MAE (depending on which forecast performance we use, RMSE or MAE); see (4–6). These weights suggest that, for nowcasting/forecasting GDP, the largest average weights are nearly always assigned to the regime-based models, as will be detailed below.

Our total sample ranges from 1999Q3 to 2019Q4, and we use recursive windows starting with a minimum 46 quarters and thus obtain 16 quarters (2011Q1–2014Q4) for comparison in cross-validation period and 20 quarters for comparison in the final out-of-sample period. For each of these quarters, we compute nowcasts and forecasts.

Finally, we compare the performance of the forecast combination based on all regime-dependent models chosen in the cross-validation period with the forecast combination based on non–regime-dependent models and find that for all target variables, the forecast combination based on all regime-dependent models outperforms the forecast combination based on non–regime-dependent models in the forecast validation period.

With respect to the mixed-frequency models, we consider nine univariate MIDAS models, of which six are unrestricted MIDAS models and three are MIDAS models with polynomial distributed lags. More precisely, we use the following model parameters: 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). In total, we consider 5985 models in the cross-validation period, thereof 4500 regime-dependent and 1485 non–regime-dependent, from which we choose the top 10 models from each category with respect to forecast performance. Thus, in the last out-of-sample period, we have 70 models.

In our main analysis, we explicitly exclude the financial crisis and the Covid-19 period from the evaluation period. In general, different crisis periods are distinct, 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 which are characteristic for these times only.[13]

3.1 | Regime-Dependent Versus Non–Regime-Dependent Models

To compare regime-dependent models with non–regime-dependent models in terms of forecast performance, we calculate the forecast combination based on the best regime-based models and the forecast combination based on the best non–regime-based models. We employ forecast combinations with weights that are based on the discounted mean square errors and the discounted MAEs as described above. We apply the forecast combination on the top 10 best models from each of the five classes of regime-based models obtained as winners in the cross-validation period. This corresponds to approximately the top 1% best models from each class of regime-based models driven by WIFO index, ESI, inflation, ATX, and S&P. Thus, the forecast combination driven by regime-based models is assessed by the weighted average of 50 forecasts/nowcasts. Then we apply a forecast combination on the top 10 best models from two classes of non–regime-based models[14] obtained as winners in the cross-validation period, and thus, the forecast combination driven by non–regime-based models is assessed by the weighted average of 20 forecasts/nowcasts. The performance of the forecast combinations from both regime-dependent and non–regime-dependent models for GDP, consumption, and investment is presented in Table 1. Our results strongly suggest that regime-dependent models outperform non–regime-dependent models. This holds for all nowcasts when the forecast performance is measured with respect to both the MAE and the RMSE. Only for very few selected forecasts, the non–regime-based models outperform the regime-based models.[15]

In addition, we apply the forecast combination on *all* best, namely, 70, models from the cross-validation period; that is, the weights are calculated for the forecasts implied by both the regime-based and non–regime-based models. These weights suggest that in the case of nowcasting/forecasting GDP, the largest average weights are always assigned to regime-based models.[16] Note that the forecasts implied by this forecast combination (see rows marked by *both* in Table 1) are still, in the vast majority of cases, outperformed by the forecast combination from regime-based models (see rows marked by *reg* in Table 1).[17] Usually, the performance is the best for forecast combinations based on regime-based models, followed by forecast combinations for all models (both regime- and non–regime-based) and the worst for non–regime-based models.

The importance of certain models can also be assessed by visual inspection of Table 2 for GDP, where the models are ranked with respect to the performance measure (MAE, RMSE),[18] for the time of the quarter when the forecast/nowcasting was performed (forecast, Nowcast 1, Nowcast 2, Nowcast 3). These results suggest again that regime-dependent models outperform non–regime-dependent models and that business cycle-related regimes (WIFO, ESI, inflation) are mostly important for GDP, especially for Nowcast 2. This is actually the nowcast mostly used in macroeconomic forecasting, which is usually done in the third month of the quarter when the information for the second month, and so Nowcast 2, is available. Tables A2 and A3 present the forecast performance of the best models for consumption and investment, respectively. Note that in case of consumption, see Table A2, the regimes driven by the economic climate index (WIFO) seems to be relevant in Nowcast 2, while for investment, see Table A3, the regimes driven by financial uncertainties are getting more important (in addition to the business cycle related regimes).

Our results are in line with other recent studies, which find that regime-dependent (or nonlinear) models prove useful in forecasting, at least over intermediate horizons.[19]

Finally, the comparison of the best regime-based model to the best non–regime-based model, over the period composed of the cross-validation period and the consequent evaluation period (2011Q1–2019Q4), is presented in the last row in Table 3 for GDP and MAE, Table A4 for GDP and RMSE, Table A5 for consumption and MAE, Table A6 for consumption and RMSE, Table A7 for investment and MAE, and Table A8 for investment and RMSE.

3.2 | Assessment of the Contribution of Monthly Indicators

To address the source of gains of forecasts/nowcasts implied by regime-based models, we look at the relative performance of the best performing regime-based models against: (i) the corresponding non–regime-based (linear) model, namely, the model with the same variables and same method when no regimes are taken into account; (ii) the regime-based model with the same variable in both regimes, where the variable is the variable in the first regime of the best model; (iii) the regime-based model with the same variable in both regimes, where the variable is

TABLE 1 | Performance (MAE and RMSE) of forecast combinations of regime-based models and non–regime-based models for GDP, consumption, and investment.

	MAE				RMSE			
	fore	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**
GDP								
reg	0.320	0.308	0.307	0.319	0.462	0.403	0.410	0.397
noreg	0.377	0.357	0.363	0.391	0.448	0.404	0.459	0.455
both	0.343	0.313	0.321	0.334	0.459	**0.396**	0.413	0.407
consumption								
reg	0.624	0.653	0.634	0.638	0.774	0.794	0.767	0.762
noreg	0.712	0.710	0.700	0.701	0.830	0.815	0.807	0.815
both	0.638	0.662	0.640	0.645	0.779	**0.789**	0.767	0.767
investment								
reg	1.317	1.292	1.185	1.210	1.614	1.610	1.551	1.528
noreg	1.303	1.315	1.290	1.258	1.670	1.686	1.687	1.612
both	1.315	1.305	1.229	1.234	1.634	1.641	1.600	1.561

Note: Colored values of MAE and RMSE indicate whether the forecast combination of regime-based models (reg) performs better or the forecast combination of non–regime-based models (noreg) performs better. The boldface values of MAE or RMSE indicate when the forecast combination based on all models, that is, both regime-based models and non–regime-based models, perform the best.

TABLE 2 | Ten best nowcasting models for GDP.

	MAE		
Forecast	Nowcast 1	Nowcast 2	Nowcast 3
	RMSE		

Note: The table shows the MAE and the RMSE of the 10 best models, when nowcasting GDP. The out-of-sample evaluation period ranges from 2015Q1 to 2019Q4. Colors indicate that the underlying model is a regime-dependent model. For the abbreviations of the variables, see Table B2.

WIFO	ESI	Inflation	ATX	S&P

the variable in the second regime of the best model. Performing these comparisons, we can assess which factors have the largest contribution, that is, whether the contribution is driven by the possibility of allowing for regime-dependent behavior, whether the variable in the first regime is important, or whether the variable in the second regime is important. In order to perform this exercise, we carry out the Diebold–Mariano (DM) test of equal forecast accuracy (Diebold and Mariano (1995)); see Tables 3 and A4 for GDP, Tables A5 and A6 for consumption, and Tables A7 and A8 for investment.[20] In addition, we create boxplots of the distribution of relative forecast accuracy (differences between one of the three alternative models and the forecast accuracy of the best regime-dependent model); see Figure 1. In more detail, Figure 1 presents boxplots of the differences between absolute forecast errors of nowcasts two for the nonregime model that corresponds to the best regime-based model and the best regime-based model (first boxplot); for the regime-based model with the variable in the first regime of the best regime-based model being in both regimes and the best regime-based model (second boxplot); and the regime-based model with the variable in the second regime of the best regime-model being in both regimes and the best regime-based model (third boxplot).[21,22] We observe that for GDP, the survey variable industrial production expectation (ISP) in the low inflation regime (second regime) significantly[23] contributes to the good performance (in terms of absolute forecast errors) of the best regime-based model which consists of industrial production (IPM) in the high inflation regime and industrial production expectation (ISP) in the low inflation regime. See also Table 3 (in the column marked by "n2") for more details. In case of consumption (the middle graph in Figure 1), the bank loans to households (LOH) in the high global financial uncertainty regime significantly contribute to the good performance of the best regime-based model which consists of loans to households (LOH) in the high global financial uncertainty regime and of CPI in the low global financial uncertainty regime. See Table A5 for more details. Finally, for investment (the last graph in Figure 1), both the regime-based model as well as the consumer confidence indicator (CCO) in the high inflation regime significantly contribute to the good performance of the best regime-based model which consists of the consumer confidence indicator (CCO) in the high inflation regime and of suppliers' delivery times (BA5) in the low inflation regime. See Table A7 for more details.

We also address the importance of variables in different regimes by calculating average weights (driven by forecast combination based on the discounted MAE) as the sum of all weights assigned to models with a certain variable in a certain regime. Figure 2 presents these average weights for GDP, consumption, and investment for Nowcast 2 for both regimes, namely, Regime 1 in the first column and Regime 2 in the second column. The main observation for GDP (the first row) is that in Regime 1 (bad economic times or times with larger financial uncertainty),[24] the most important variable is industrial production (IPM), followed by the overall purchasing managers' index—PMI (BA1) and the PMI of suppliers' delivery times (BA5). These indices are, however, not important in Regime 2 (good economic times or times with smaller financial uncertainty) where the major role is plaid by industrial production expectations (ISP) followed by the consumers' assessment of the economic situation in the next 12 months (CSE). Thus, in bad times, the real (hard) variable IPM plays an important role, while in good times, it does not seem to have a big impact. However, its expectation, namely, the survey variable ISP, is relevant in good times but not in bad

TABLE 3 | Performance (MAE) of best regime-dependent models against different alternatives, when nowcasting GDP.

	MAE				Regime				Model specification: Variables and method			
	fore	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**
reg best	0.284	0.268	0.298	0.254	ATX	ATX	inf	ATX	WTE, BA1 midas-pdl(4)	BA5, ISP midas-u(2)	IPM, ISP midas-pdl(5)	BA5, BA3 midas-pdl(6)
non-reg	0.389	0.359	0.325	0.334					WTE, BA1 midas-pdl(4)	BA5, ISP midas-u(2)	IPM, ISP midas-pdl(5)	BA5, BA3 midas-pdl(6)
reg best	0.284	0.268	0.298	0.254	ATX	ATX	inf	ATX	WTE, BA1 midas-pdl(4)	BA5, ISP midas-u(2)	IPM, ISP midas-pdl(5)	BA5, BA3 midas-pdl(6)
reg var1	0.327	0.324	0.349	0.301	ATX	ATX	inf	ATX	WTE, WTE midas-pdl(4)	BA5, BA5 midas-u(2)	IPM, IPM midas-pdl(5)	BA5, BA5 midas-pdl(6)
reg best	0.284	0.268	0.298	0.254	ATX	ATX	inf	ATX	WTE, BA1 midas-pdl(4)	BA5, ISP midas-u(2)	IPM, ISP midas-pdl(5)	BA5, BA3 midas-pdl(6)
reg var2	0.376	0.308	0.318	0.316	ATX	ATX	inf	ATX	BA1, BA1 midas-pdl(4)	ISP, ISP midas-u(2)	ISP, ISP midas-pdl(5)	BA3, BA3 midas-pdl(6)
reg best	0.284	0.268	0.298	0.254	ATX	ATX	inf	ATX	WTE, BA1 midas-pdl(4)	BA5, ISP midas-u(2)	IPM, ISP midas-pdl(5)	BA5, BA3 midas-pdl(6)
non-reg best	0.309	0.302	0.283	0.298					IPM, ISP midas-u(1)	IPM, ISP midas-u(1)	ISP, VIB, WTE midas-u(1)	BA1, ISP midas-u(1)

Note: The table shows the MAE, the regimes, and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-based model with the same variables and method (non-reg), the regime-dependent model with the variable in the first regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the second regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. ATX = Austrian traded index, inf = inflation. Colored MAE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored MAE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models, the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by "fore," "n1," "n2," and "n3"). Regime 1 refers to high inflation (inf), high financial uncertainty in Austria (ATX). See Table B2 for a list of abbreviations of the monthly variables.

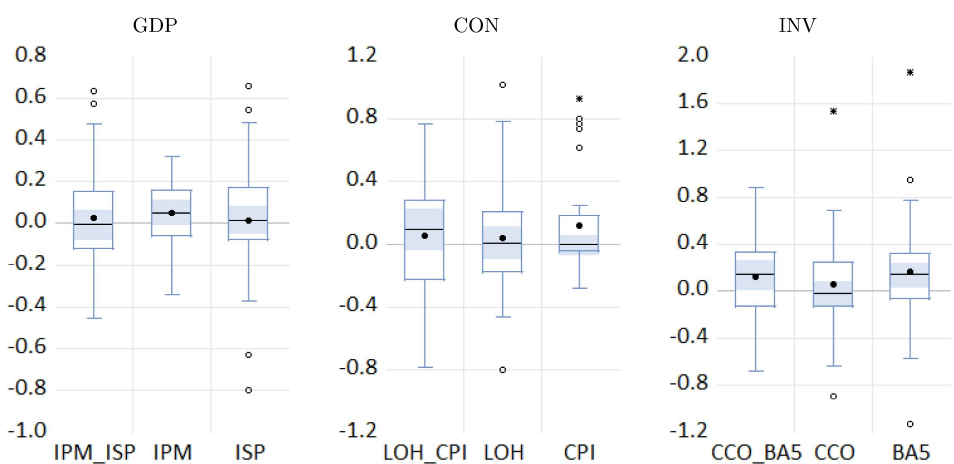

FIGURE 1 | Boxplots of GPD, consumption and investment. The boxplots show the difference between absolute errors for (i) non–regime-based model that corresponds to the best regime-based model and the best regime-based model (first boxplot), (ii) regime-based model with variable in the first regime of the best regime-model being in both regimes and the best regime-based model (second boxplot), (iii) regime-based model with variable in the second regime of the best regime-based model being in both regimes and the best regime-based model (third boxplot). Note that the differences are taken such that a higher mass in the positive region indicates a better performance of the best regime-based model.

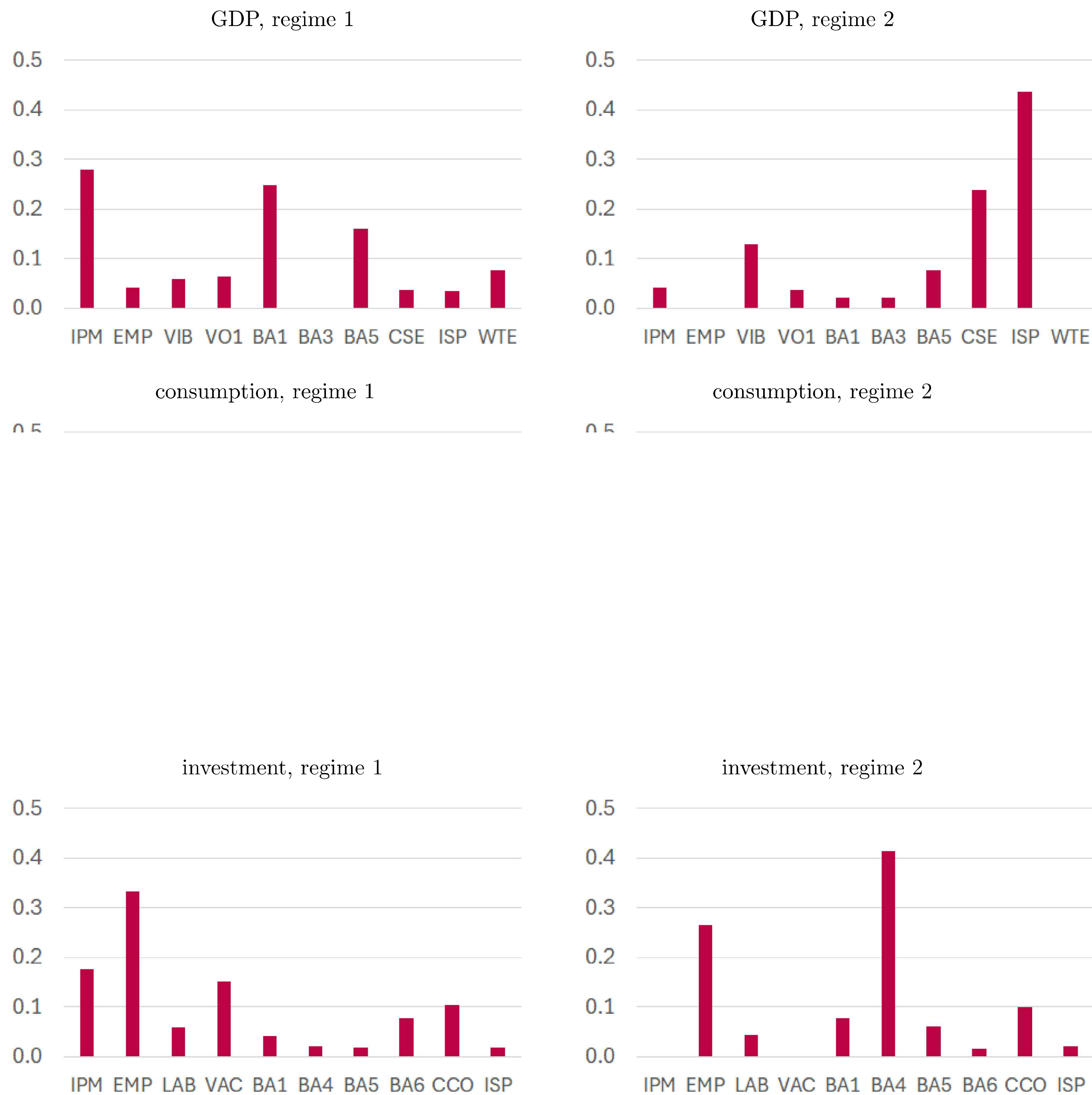

FIGURE 2 | Average forecast combination weights of regime-based models, based on MAE, of variables in the top best 50 models for GDP, consumption, and investment, when nowcasts are performed in the second month of a quarter (nowcast 2). The left figures correspond to the average sum of weights of regime-based models where monthly indicators occur in Regime 1 (bad times)—first column. The right figures correspond to the average sum of weights of regime-based models where monthly indicators occur in Regime 2 (good times)—second column. The first row corresponds to GDP, the second row corresponds to consumption, and the third row corresponds to investment. See Table B2 for a list of abbreviations of the monthly variables.

times. Similar findings apply to Nowcast 1 of GDP; see Table 4 and Figure A1.[25] Figure 3 presents the average sum of weights of the models, where a given monthly indicator occurs, for all forecast and nowcasts of GDP. We again observe that real industrial production (IPM) is more dominant in bad times than in good times and its expectation (ISP) is, on the other hand, more dominant in good times than in bad times. For the forecast and Nowcast 3, the most prominent indicator in good times is the consumers' assessment of the economic situation in the next 12 months (CSE) which is not that relevant in bad times.

The contribution of the variables when nowcasting consumption, through the average sum of (forecast combination) weights of the models where these variables appear, is presented in the middle row of Figure 2 for Nowcast 2 and in Figure A2 where the average weights implied by forecasts/

TABLE 4 | Average forecast combination weights of regime-based models, based on MAE, of variables in the top best models for GDP.

	fore	n1	n2	n3
IPM-1r	0.068	0.279	0.279	0.076
IPM-2r	0.035	0.076	0.040	0.018
EMP-1r	0.153	0.042	0.042	0.206
EMP-2r	0.019	0.038	0.000	0.080
VIB-1r	0.233	0.165	0.059	0.039
VIB-2r	0.094	0.057	0.129	0.000
VO1-1r	0.048	0.019	0.063	0.040
VO1-2r	0.087	0.036	0.037	0.057
BA1-1r	0.079	0.038	0.248	0.266
BA1-2r	0.024	0.039	0.020	0.080
BA3-1r	0.041	0.039	0.000	0.019
BA3-2r	0.000	0.099	0.021	0.024
BA5-1r	0.023	0.174	0.159	0.184
BA5-2r	0.017	0.000	0.076	0.058
CSE-1r	0.000	0.019	0.037	0.018
CSE-2r	0.355	0.140	0.240	0.446
ISP-1r	0.288	0.200	0.034	0.152
ISP-2r	0.350	0.514	0.437	0.237
WTE-1r	0.066	0.024	0.078	0.000
WTE-2r	0.019	0.000	0.000	0.000

Note: The table shows the average sum of weights of regime-based models where monthly indicators occur. Darker color indicates the variable with the largest value for Regime 1, and lighter color indicates the variable with the largest value for Regime 2. See Table B2 for a list of abbreviations of the monthly variables.

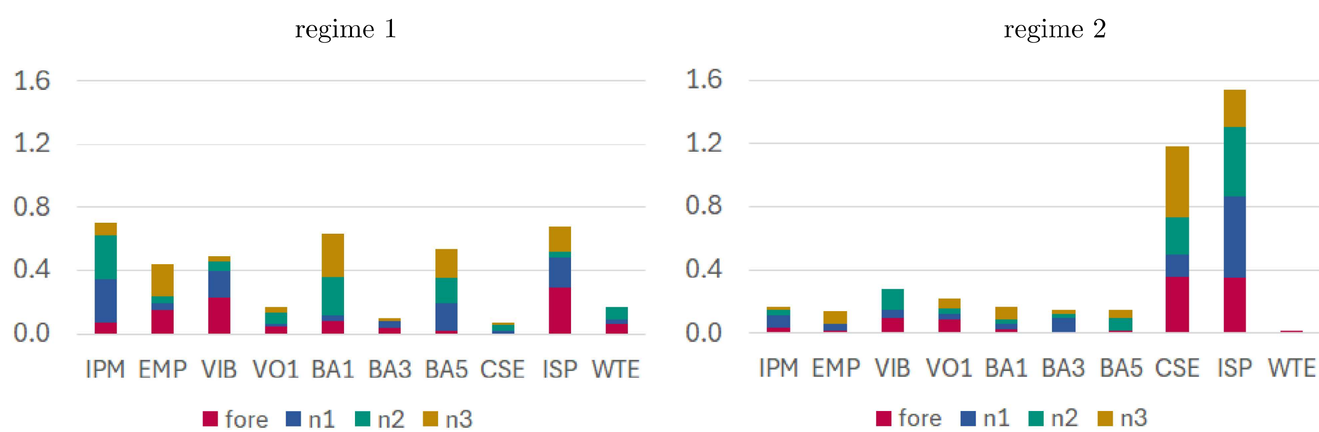

FIGURE 3 | Average forecast combination weights of regime-based models, based on MAE, of variables in the top best models for GDP. The left figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 1 (bad times). The right figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 2 (good times). See Table B2 for a list of abbreviations of the monthly variables.

nowcasts are presented. The most relevant variable for consumption is bank loans to households (LOH), which seems to be more important in good times for Nowcasts 2 and 3 and in bad times for forecast and Nowcast 1, that is, LOH is an essential indicator when nowcasting consumption in both regimes. Industrial production (IPM) has the larger weight in bad times than in good times and is one of the key variables that contributes to nowcast consumption. Finally, labor force (LAB) seems to be important in good times while it seems to have a minor effect in bad times.

The most important contribution when nowcasting investment, see the last row in Figures 2 and A3, comes from employment (EMP) in both regimes (for Nowcasts 2 and 3). Industrial production (IPM) contributes mainly in bad times, while in good times, the PMI for employment (BA4) becomes relevant. Thus, real employment is more essential than its survey counterpart (BA4) in bad times, while BA4 becomes more relevant than employment in good times. This is similar to what we observe when nowcasting GDP, namely, that a real indicator (IPM) is more relevant in bad times, while its survey counterpart (ISP) is more relevant in good times. Finally, Figure A3 suggests that also the consumer confidence indicator (CCO) has a notable impact when nowcasting investment (especially for forecast and Nowcast 1).

4 | Conclusion

Our goal is to nowcast and forecast economic activity in Austria, namely, real GDP, consumption, and investment, which are available at a quarterly frequency. We first reduce the total universe of monthly variables to ten predictors per target variable, applying a combination of preselection procedures. Then we proceed with actual nowcasting; that is, we choose a certain number of best models in the cross-validation period which are used to produce the final nowcasts. Our main goal is to examine whether explicitly considering different regimes in MIDAS methods improves the nowcasting accuracy of the target variables when compared to nonregime-based (linear) models. We explicitly exclude the Covid-19 period, as this is characterized by its own specific dynamics, and our results should be valid for “normal” times. In order to compare regime-dependent and non–regime-dependent models, we apply, among others, forecast combinations based on the discounted mean square/absolute forecast error of all (best) regime-based and all (best) non–regime-based models and compare their forecast accuracies. The regimes we consider are driven by economic climate and sentiment indices for Austria (to capture different stages of the business cycle), Austrian inflation, and proxies of the local and global financial uncertainties given by the volatilities of the Austrian traded index (ATX) and S&P 500 that are available in real time.

We find strong evidence that allowing for regime-dependent dynamics leads to improvements in the nowcasting accuracy of Austrian GDP, consumption, and investment. For example, this is supported by comparing the forecast combination of regime-based models to the forecast combination of non–regime-based models and also to the forecast combination of all models (i.e., regime-based and non–regime-based models). Regarding regimes, business cycle and inflation related regimes are important when nowcasting GDP and consumption, while when nowcasting investment, also regimes driven by financial uncertainty become relevant.

We also observe that only a handful of the ten preselected variables are important to forecast and nowcast GDP, consumption, and investment, respectively, and that different variables are important in different regimes. For GDP, the most relevant indicator in bad times is *real* industrial production which is not relevant in good times, while in good times, the most important indicator is its expectation which is not relevant in bad times. This observation suggests that in bad times, real indicators seem to matter more than their survey counterparts. The key indicator for consumption in both regimes are bank loans to households, while for investment, the most important variables seem to be labor market-related variables, where the survey variable PMI for employment is relevant only in good times. We observe that for all target variables (GDP, consumption and investment), the industrial production index is more important in bad times than in good times.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] In an earlier version of this study, we considered MIDAS models as well as MF-VAR models according to Ghysels (2016) and used slightly different indicators defining regimes which were replaced with others being readily available.

[2] These modifications include the use of higher frequency data, namely, weekly data; see Fenz and Stix (2021), and Markov-switching dynamic factor models, see Glocker and Wegmueller (2020).

[3] For $p_x = 3$, the estimated coefficients in (2) coincide with the estimated coefficients in (1).

[4] This information is taken from the sources of the different variables, respectively. See column *Source* in Table B2.

[5] Statistical offices mostly report both QoQ and year over year (YoY) rates.

[6] See Anthonisz (2023), Dahlhaus et al. (2017), Bragoli and Fosten (2018), Fosten and Greenaway-McGrevy (2022).

[7] The WIFO (Austrian Institute of Economic Research) conducts business cycle surveys for Austria at a regular basis, comparable to those carried out by ifo for Germany.

[8] A more detailed description of these indicators can be found in Table B2.

[9] In the strict sense, the dummies report periods of bad times and good times not periods of recession and nonrecession, as we do not use the definition of recession but use the natural cut-off values to create the dummies. In the case of the WIFO indicator periods of recession are identified by negative values and periods of nonrecession are identified by positive values. In the case of the ESI the cutoff value is 100, and periods of recession are identified by values smaller than 100 and periods or nonrecession by values greater than 100.

[10] Fan and Lv (2008). provide theoretical ground for their approach by demonstrating that it has the sure screening property that "all important variables survive after applying a variable screening procedure with probability tending to 1".

[11] We chose the prior model size being ten and the prior inclusion probability being equal (i.e., to 10/37). We used other prior models sizes and the posterior inclusion probabilities (PIPs) and results were not very sensitive on these.

[12] As the target variables are in quarterly frequency while predictor indicators are in monthly frequency, we adjusted monthly variables to quarterly variables (in the preselection phase) by (i) averaging over the quarter, (ii) considering the first month of a quarter, (iii) considering the second month of a quarter, and (iv) considering the third month of a quarter (for robustness checks). In all these cases, we have obtained similar results.

[13] 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.

[14] Classes of non–regime-based models comprise all combinations of 2-variable and 3-variable models.

[15] The only exception is the forecast for GDP with respect to the RMSE and the forecast for investment with respect to the MAE.

[16] The material for these findings can be obtained from the authors upon request.

[17] Exceptions are nowcasts performed in the first month of the quarter (Nowcast 1) when forecast combination applied on all models has the best performance measured by the RMSE for GDP and consumption.

[18] RMSE and MAE were calculated over the last evaluation period 2015Q1–2019Q4.

[19] See, for example, Guidolin and Timmermann (2005, 2009) for stock and bond returns and interest rates, Guidolin (2006) for asset prices and macroeconomic variables, Goulet Coulombe et al. (2022) for macroeconomic variables, and Guidolin and Pedio (2021), and Crespo Cuaresma et al. (2024) for commodity prices.

[20] Tables 3, A5, and A7 present results with respect to the MAE and Tables A4, A6, and A8 present results with respect to the RMSE.

[21] Note that the differences in Figure 1 are taken such that a higher mass in the positive region indicates a better performance of the best regime-based model.

[22] Similar findings apply also for the case when the forecast performance is measured by squared errors.

[23] In terms of the DM test.

[24] For the sake of brevity, we refer to bad economic times indicated by inflation, WIFO, or ESI index, or times with larger financial uncertainty as the *bad times* and to good economic times or times with smaller financial uncertainty as *good times*.

[25] However, also in forecast and Nowcast 3 is the IPM more pronounced in Regime 1 than in Regime 2 and IPS is more pronounced in Regime 2 than in Regime 1.

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Appendix A

Empirical Results

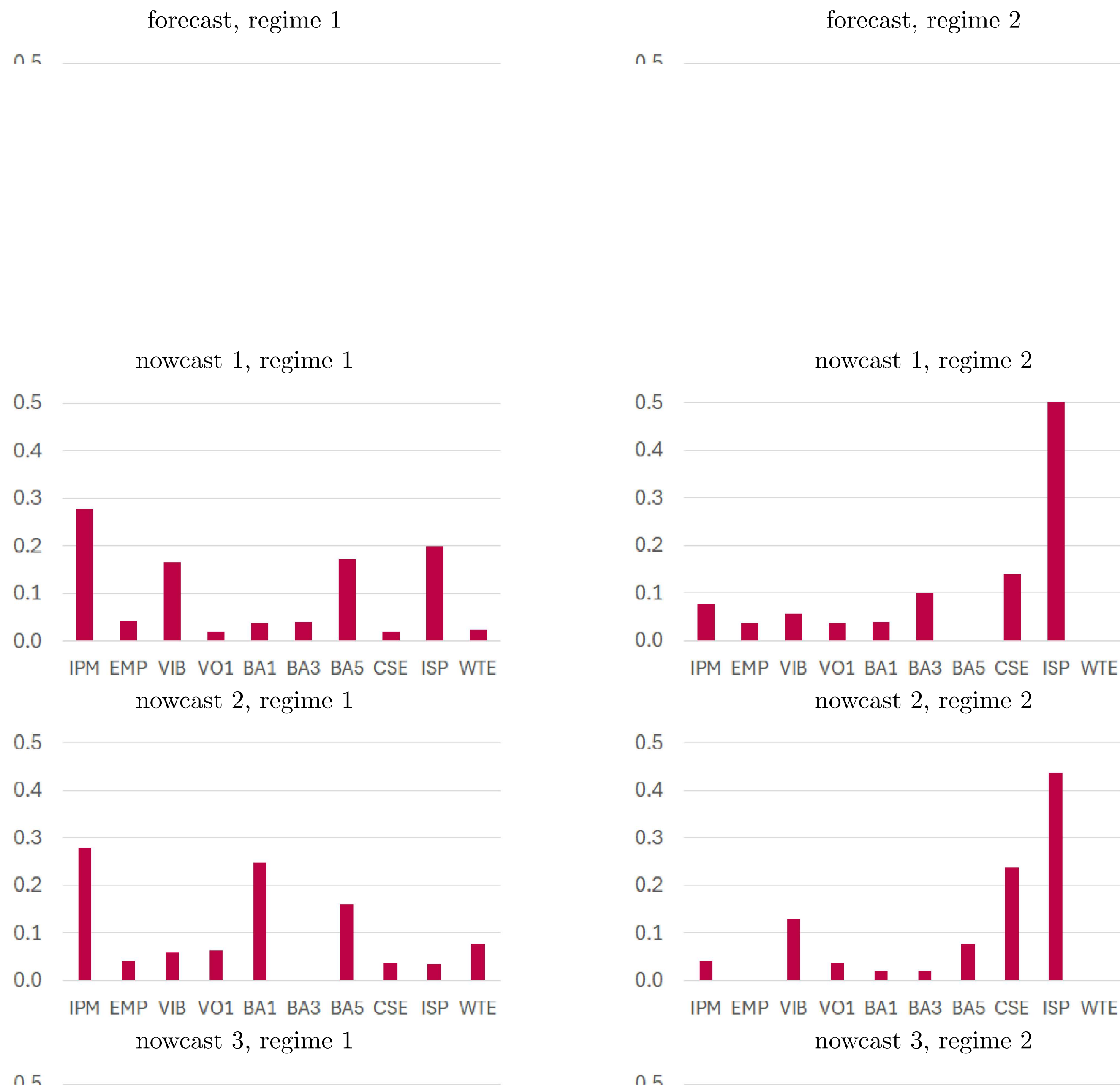

FIGURE A1 | Average forecast combination weights of regime-based models, based on MAE, of variables in the top best 50 models for GDP and forecasts (first row), nowcasts 1 (second row), nowcasts 2 (third row) and nowcasts 3 (last row). The left figures correspond to the average sum of weights of regime-based models where monthly indicators occur in Regime 1 (i.e., bad economic times and/or times of higher financial uncertainty)—first column. The right figures correspond to the average sum of weights of regime-based models where monthly indicators occur in Regime 2 (i.e., better economic times and/or times of lower financial uncertainty)—second column. See Table B2 for a list of abbreviations of the monthly variables.

FIGURE A2 | Average forecast combination weights of regime-based models, based on AE, of variables in the top best models for consumption. The left figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 1 (bad times). The right figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 2 (good times). See Table B2 for a list of abbreviations of the monthly variables.

FIGURE A3 | Average forecast combination weights of regime-based models, based on MAE, of variables in the top best models for investment. The left figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 1 (bad times). The right figure corresponds to the average sum of weights of regime-based models where a given monthly indicator occurs in Regime 2 (good times). See Table B2 for a list of abbreviations of the monthly variables.

TABLE A1 | Ten monthly variables chosen in the preselection phase.

GDP		**Consumption**		**Investment**	
IPM	Prod	EXX	Prod	IPM	Prod
EMP	Lab	IPM	Prod	EMP	Lab
VIB	Fin	CAR	Con	LAB	Lab
VO1	Fin	SAL	Con	VAC	Lab
BA1	Sur	STV	Con	BA1	Sur
BA3	Sur	LAB	Lab	BA4	Sur
BA5	Sur	CPI	Pri	BA5	Sur
CSE	Sur	AT2	Mon	BA6	Sur
ISP	Sur	LOH	Mon	CCO	Sur
WTE	Sur	ISP	Sur	ISP	Sur

Note: The preselection of variables is based on a combination of sure independence screening (SIS), Lasso, and Bayesian model averaging (BMA). Variable abbreviations are presented in Table B2. The second, fourth and the last column present the groups the variables belong to: production (Prod), consumption (Con), labour market (Lab), prices (Pri), money and credit (Mon), financial and uncertainty indicators (Fin), and survey and sentiment indicators (Sur).

TABLE A2 | Ten best nowcasting models for consumption.

MAE

Forecast		Nowcast 1		Nowcast 2		Nowcast 3	

RMSE

Note: The table shows the MAE and the RMSE of the 10 best models, when nowcasting consumption. The out-of-sample evaluation period ranges from 2015Q1 to 2019Q4. Colors indicate that the underlying model is a regime-dependent model. For the abbreviations of the variables see Table B2.

WIFO	ESI	Inflation	ATX	S&P

TABLE A3 | Ten best nowcasting models for investment.

MAE

Forecast		Nowcast 1		Nowcast 2		Nowcast 3	
EMP_1r, BA4_2r, atx, midas_u(3)	1.138	BA4_1r, BA4_2r, atx, midas_u(3)	1.157	CCO_1r, BA5_2r, inf, midas_pdl(5)	1.114	EMP_1r, EMP_2r, wif, midas_u(1)	1.147
EMP_1r, BA4_2r, atx, midas_u(4)	1.139	BA4_1r, BA5_2r, wif, midas_u(2)	1.162	BA1_1r, BA4_2r, atx, midas_u(5)	1.121	IPM_1r, EMP_2r, inf, midas_pdl(5)	1.161
BA4_1r, BA4_2r, atx, midas_u(2)	1.151	EMP, BA4, BA6, midas_pdl(6)	1.174	EMP_1r, ISP_2r, esi, midas_u(5)	1.131	LAB_1r, EMP_2r, atx, midas_u(1)	1.164
CCO_1r, BA4_2r, atx, var(1)	1.160	VAC_1r, BA4_2r, snp, midas_u(4)	1.179	BA1_1r, BA4_2r, atx, midas_u(4)	1.143	EMP_1r, VAC_2r, inf, midas_pdl(4)	1.171
EMP_1r, BA4_2r, atx, midas_u(2)	1.164	VAC_1r, CCO_2r, snp, midas_pdl(4)	1.182	BA4_1r, BA4_2r, atx, midas_u(4)	1.152	EMP_1r, BA4_2r, snp, midas_u(6)	1.178
BA5_1r, BA6_2r, snp, midas_pdl(4)	1.181	EMP_1r, BA4_2r, atx, midas_u(4)	1.190	EMP, BA1, midas_pdl(4)	1.153	IPM_1r, VAC_2r, inf, midas_u(4)	1.180
IPM_1r, BA5_2r, atx, midas_pdl(4)	1.194	ISP_1r, BA5_2r, wif, midas_u(2)	1.193	EMP, BA6, midas_pdl(4)	1.159	EMP_1r, VAC_2r, inf, midas_u(2)	1.182
CCO_1r, IPM_2r, inf, midas_u(4)	1.208	IPM_1r, CCO_2r, esi, midas_u(5)	1.227	CCO_1r, BA4_2r, inf, midas_pdl(5)	1.172	IPM_1r, VAC_2r, inf, midas_pdl(4)	1.183
EMP, BA4, BA6, var(1)	1.209	CCO_1r, IPM_2r, inf, midas_u(5)	1.229	EMP_1r, EMP_2r, wif, midas_pdl(4)	1.182	EMP, BA4, midas_pdl(5)	1.190
BA4_1r, BA5_2r, atx, midas_u(3)	1.218	IPM_1r, IPM_2r, inf, midas_pdl(5)	1.238	EMP_1r, BA4_2r, snp, midas_u(5)	1.184	LAB_1r, EMP_2r, atx, midas_pdl(6)	1.196

RMSE

Forecast		Nowcast 1		Nowcast 2		Nowcast 3	
EMP_1r, BA4_2r, atx, midas_u(4)	1.419	VAC_1r, BA4_2r, snp, midas_u(4)	1.409	EMP_1r, BA4_2r, atx, midas_u(6)	1.472	IPM_1r, EMP_2r, inf, midas_pdl(5)	1.444
EMP_1r, BA4_2r, atx, midas_u(3)	1.420	EMP_1r, BA4_2r, atx, midas_u(5)	1.446	EMP_1r, EMP_2r, wif, midas_pdl(4)	1.479	EMP_1r, BA1_2r, esi, midas_u(6)	1.445
BA4_1r, BA4_2r, atx, midas_u(2)	1.454	EMP_1r, BA4_2r, atx, midas_u(4)	1.454	EMP_1r, EMP_2r, wif, midas_u(4)	1.485	IPM_1r, EMP_2r, inf, midas_pdl(6)	1.471
EMP_1r, BA4_2r, atx, midas_u(2)	1.455	VAC_1r, BA4_2r, snp, midas_u(5)	1.504	EMP_1r, BA4_2r, atx, midas_u(5)	1.495	EMP_1r, EMP_2r, atx, midas_pdl(5)	1.473
BA6_1r, BA4_2r, snp, midas_u(4)	1.508	IPM_1r, CCO_2r, esi, midas_pdl(4)	1.508	EMP_1r, BA4_2r, atx, midas_u(4)	1.512	LAB_1r, LAB_2r, snp, midas_u(6)	1.488
BA4_1r, CCO_2r, esi, midas_pdl(5)	1.518	EMP_1r, BA4_2r, atx, midas_u(3)	1.510	IPM_1r, BA1_2r, esi, midas_pdl(5)	1.555	EMP_1r, EMP_2r, wif, midas_pdl(5)	1.506
BA4, BA6, var(1)	1.533	BA5_1r, BA4_2r, snp, midas_pdl(6)	1.513	IPM_1r, BA1_2r, esi, midas_u(5)	1.558	LAB_1r, EMP_2r, atx, midas_pdl(6)	1.513
BA6_1r, BA4_2r, snp, midas_pdl(4)	1.534	VAC_1r, BA4_2r, snp, midas_pdl(4)	1.517	EMP_1r, EMP_2r, wif, midas_u(5)	1.560	IPM_1r, BA4_2r, inf, midas_pdl(6)	1.515
BA4_1r, BA5_2r, esi, midas_pdl(5)	1.542	IPM_1r, BA1_2r, esi, midas_u(4)	1.543	EMP_1r, BA1_2r, esi, midas_u(5)	1.564	IPM_1r, EMP_2r, inf, midas_u(5)	1.515
BA4_1r, BA5_2r, esi, midas_pdl(4)	1.559	IPM_1r, BA4_2r, snp, midas_pdl(5)	1.564	IPM_1r, EMP_2r, atx, midas_pdl(5)	1.570	EMP_1r, EMP_2r, snp, midas_u(5)	1.528

Note: The table shows the MAE and the RMSE of the 10 best models, when nowcasting investment. The out-of-sample evaluation period ranges from 2015Q1 to 2019Q4. Colors indicate that the underlying model is a regime-dependent model. For the abbreviations of the variables see Table B2.

WIFO	ESI	Inflation	ATX	S&P

TABLE A4 | Performance (RMSE) of best regime-dependent models against different alternatives, when nowcasting GDP.

	RMSE				regime				model specification: variables and method			
	fore	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**
reg best	0.390	0.355	0.365	0.317	ATX	inf	WIFO	ATX	VIB, BA1	ISP, ISP	VO1, ISP	EMP, ISP
									midas-u(1)	midas-u(1)	midas-u(2)	midas-u(1)
non-reg	0.428	0.369	0.425	0.376					VIB, BA1	ISP	VO1, ISP	EMP, ISP
									midas-u(1)	midas-u(1)	midas-u(2)	midas-u(1)
reg best	0.390		0.365	0.317	ATX	inf	WIFO	ATX	VIB, BA1		VO1, ISP	EMP, ISP
									midas-u(1)		midas-u(2)	midas-u(1)
reg var1	0.407		0.441	0.401	ATX	inf	WIFO	ATX	VIB, VIB		VO1, VO1	EMP, EMP
									midas-u(1)		midas-u(2)	midas-u(1)
reg best	0.390		0.365	0.317	ATX	inf	WIFO	ATX	VIB, BA1		VO1, ISP	EMP, ISP
									midas-u(1)		midas-u(2)	midas-u(1)
reg var2	0.406		0.423	0.388	ATX	inf	WIFO	ATX	BA1, BA1		ISP, ISP	ISP, ISP
									midas-u(1)		midas-u(2)	midas-u(1)
reg best	0.390	0.355	0.365	0.317	ATX	inf	WIFO	ATX	VIB, BA1	ISP, ISP	VO1, ISP	EMP, ISP
									midas-u(1)	midas-u(1)	midas-u(2)	midas-u(1)
non-reg best	0.405	0.372	0.385	0.371					ISP, BA1	ISP, BA3	VIB, BA5, IPM	BA1, IPM
									midas-u(2)	midas-u(1)	midas-u(1)	midas-pdl(6)

Note: The table shows the RMSE, the regimes and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-based model with the same variables and method (non-reg), the regime-dependent model with the variable in the 1st regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the 2nd regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. ATX = Austrian traded index, WIFO = business cycle surveys for Austria conducted by Austrian Institute for Economic Research (WIFO), inf = inflation. Colored RMSE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored RMSE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by "fore," "n1," "n2," and "n3"). Regime 1 refers to recession (WIFO), high inflation (inf), high financial uncertainty in Austria (ATX). See Table B2 for a list of abbreviations of the monthly variables.

TABLE A5 | Performance (MAE) of best regime-dependent models against different alternatives, when nowcasting consumption.

	MAE				regime				model specification: variables and method			
	fore	n1	n2	n3	fore	n1	n2	n3	fore	n1	n2	n3
reg best	0.539	0.508	0.521	0.499	S&P	S&P	S&P	WIFO	STV, IPM	STV, CPI	LOH, CPI	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
non-reg	0.589	0.618	0.584	0.497					STV, IPM	STV, CPI	LOH, CPI	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
reg best	0.539	0.508	0.521	0.499	S&P	S&P	S&P	WIFO	STV, IPM	STV, CPI	LOH, CPI	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
reg var1	0.570	0.594	0.594	0.605	S&P	S&P	S&P	WIFO	STV, STV	STV, STV	LOH, LOH	IPM, IPM
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
reg best	0.539	0.508	0.521	0.499	S&P	S&P	S&P	WIFO	STV, IPM	STV, CPI	LOH, CPI	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
reg var2	0.584	0.648	0.643	0.509	S&P	S&P	S&P	WIFO	IPM, IPM	CPI, CPI	CPI, CPI	CAR, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
reg best	0.539	0.508	0.521	0.499	S&P	S&P	S&P	WIFO	STV, IPM	STV, CPI	LOH, CPI	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)
non-reg best	0.530	0.558	0.575	0.497					STV, LOH	LAB, EXX	LOH, EXX	IPM, CAR
									var(2)	midas-pdl(5)	midas-pdl(6)	midas-u(1)

Note: The table shows the MAE, the regimes and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-dependent model with the same variables and method (non-reg), the regime-dependent model with the variable in the 1st regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the 2nd regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. S&P = S&P 500, WIFO = business cycle surveys for Austria conducted by Austrian Institute for Economic Research (WIFO). Colored MAE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored MAE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by “fore,” “n1,” “n2,” and “n3”). Regime 1 refers to recession (WIFO), high global financial uncertainty (S&P). See Table B2 for a list of abbreviations of the monthly variables.

TABLE A6 | Performance (RMSE) of best regime-dependent models against different alternatives, when nowcasting consumption.

	RMSE				regime				model specification: variables and method			
	fore	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**
reg best	0.672	0.645	0.646	0.640	ATX	S&P	WIFO	WIFO	LOH, LAB	STV, EXX	ISP, IPM	STV, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
non-reg	0.715	0.824	0.709	0.666					LOH, LAB	STV, EXX	ISP, IPM	STV, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
reg best	0.672	0.645	0.646	0.640	ATX	S&P	WIFO	WIFO	LOH, LAB	STV, EXX	ISP, IPM	STV, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
reg var1	0.732	0.780	0.742	0.766	ATX	S&P	WIFO	WIFO	LOH, LOH	STV, STV	ISP, ISP	STV, STV
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
reg best	0.672	0.645	0.646	0.640	ATX	S&P	WIFO	WIFO	LOH, LAB	STV, EXX	ISP, IPM	STV, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
reg var2	0.816	0.725	0.654	0.646	ATX	S&P	WIFO	WIFO	LAB, LAB	EXX, EXX	IPM, IPM	CAR, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
reg best	0.672	0.645	0.646	0.640	ATX	S&P	WIFO	WIFO	LOH, LAB	STV, EXX	ISP, IPM	STV, CAR
									midas-pdl(4)	midas-pdl(5)	midas-u(2)	midas-u(1)
non-reg best	0.716	0.712	0.681	0.635					LOH, IPM	CPI, LOH	LOH, IPM	CAR, ISP
									var(2)	midas-pdl(6)	midas-u(4)	midas-u(1)

Note: The table shows the RMSE, the regimes and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-dependent model with the same variables and method (non-reg), the regime-dependent model with the variable in the 1st regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the 2nd regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. ATX = Austrian traded index, S&P=S&P 500, WIFO = business cycle surveys for Austria conducted by Austrian Institute for Economic Research (WIFO). Colored RMSE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored RMSE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by “fore,” “n1,” “n2,” and “n3”). Regime 1 refers to recession (WIFO), high financial uncertainty in Austria (ATX), high global financial uncertainty (S&P). See Table B2 for a list of abbreviations of the monthly variables.

TABLE A7 | Performance (MAE) of best regime-dependent models against different alternatives, when nowcasting investment.

	MAE				regime				model specification: variables and method			
	fore	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**	**fore**	**n1**	**n2**	**n3**
reg best	0.972	0.991	0.987	1.027	ATX	ATX	inf	WIFO	EMP, BA4	BA4, BA4	CCO, BA5	EMP, EMP
									midas-u(3)	midas-u(3)	midas-pdl(5)	midas-u(1)
non-reg	1.084	1.063	1.115	1.038					EMP, BA4	BA4	CCO, BA5	EMP
									midas-u(3)	midas-u(3)	midas-pdl(5)	midas-u(1)
reg best	0.972		0.987		ATX	ATX	inf	WIFO	EMP, BA4		CCO, BA5	
									midas-u(3)		midas-pdl(5)	
reg var1	0.972		1.046		ATX	ATX	inf	WIFO	EMP, EMP		CCO, CCO	
									midas-u(3)		midas-pdl(5)	
reg best	0.972		0.987		ATX	ATX	inf	WIFO	EMP, BA4		CCO, BA5	
									midas-u(3)		midas-pdl(5)	
reg var2	0.997		1.151		ATX	ATX	inf	WIFO	BA4, BA4		BA5, BA5	
									midas-u(3)		midas-pdl(5)	
reg best	0.972	0.991	0.987	1.027	ATX	ATX	inf	WIFO	EMP, BA4	BA4, BA4	CCO, BA5	EMP, EMP
									midas-u(3)	midas-u(3)	midas-pdl(5)	midas-u(1)
non-reg best	0.996	0.987	0.994	0.989					BA4, BA6	BA4, BA6	BA4, BA6	EMP, BA4
									var(1)	midas-pdl(6)	midas-pdl(4)	midas-pdl(5)

Note: The table shows the MAE, the regimes and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-dependent model with the same variables and method (non-reg), the regime-dependent model with the variable in the 1st regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the 2nd regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. ATX = Austrian traded index, WIFO = business cycle surveys for Austria conducted by Austrian Institute for Economic Research (WIFO), inf = inflation. Colored MAE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored MAE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by "fore," "n1," "n2," and "n3"). Regime 1 refers to recession (WIFO), high inflation (inf), high financial uncertainty in Austria (ATX). See Table B2 for a list of abbreviations of the monthly variables.

TABLE A8 | Performance (RMSE) of best regime-dependent models against different alternatives, when nowcasting investment.

	RMSE				regime				model specification: variables and method			
	fore	n1	n2	n3	fore	n1	n2	n3	fore	n1	n2	n3
reg best	1.243	1.250	1.293	1.242	ATX	S&P	ATX	inf	EMP, BA4	VAC, BA4	EMP, BA4	IPM, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
non-reg	1.422	1.405	1.407	1.334					EMP, BA4	VAC, BA4	EMP, BA4	IPM, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
reg best	1.243	1.250	1.293	1.242	ATX	S&P	ATX	inf	EMP, BA4	VAC, BA4	EMP, BA4	IPM, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
reg var1	1.292	1.390	1.387	1.395	ATX	S&P	ATX	inf	EMP, EMP	VAC, VAC	EMP, EMP	IPM, IPM
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
reg best	1.243	1.250	1.293	1.242	ATX	S&P	ATX	inf	EMP, BA4	VAC, BA4	EMP, BA4	IPM, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
reg var2	1.211	1.226	1.324	1.482	ATX	S&P	ATX	inf	BA4, BA4	BA4, BA4	BA4, BA4	EMP, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
reg best	1.243	1.250	1.293	1.242	ATX	S&P	ATX	inf	EMP, BA4	VAC, BA4	EMP, BA4	IPM, EMP
									midas-u(4)	midas-u(4)	midas-u(6)	midas-pdl(5)
non-reg best	1.318	1.373	1.369	1.339					BA4, BA6	LAB, CCO	CCO, IPM	EMP, BA4
									var(1)	midas-u(4)	midas-pdl(5)	midas-pdl(6)

Note: The table shows the RMSE, the regimes and the model specifications of the best regime-dependent model (reg best), the corresponding non–regime-dependent model with the same variables and method (non-reg), the regime-dependent model with the variable in the 1st regime of the best regime-dependent model being in both regimes (reg var1), the regime-dependent model with the variable in the 2nd regime of the best regime-dependent model being in both regimes (reg var2), and the best non–regime-dependent (non-reg best) models. The out-of-sample evaluation period ranges from 2011Q1 to 2019Q4. ATX = Austrian traded index, S&P = S&P 500, inf = inflation. Colored RMSE indicates that the best regime-dependent model outperforms the corresponding alternative. Dark colored RMSE indicates rejection of the null hypothesis of equal forecast accuracy between the best regime-dependent model and its alternative at the 10% significance level. In regime-based models the first variable is the one included in Regime 1, the second variable is the one included in Regime 2 (see columns marked by "fore," "n1," "n2," and "n3"). Regime 1 refers to high inflation (inf), high financial uncertainty in Austria (ATX), high global financial uncertainty (S&P). See Table B2 for a list of abbreviations of the monthly variables.

Appendix B

Data

The analysis is done for QoQ growth rates of GDP, consumption, and investment. The source of GDP, consumption, and investment, which are available at a quarterly frequency, is Statistics Austria with the following LSEG Datastream codes: OEGDP...D (GDP), OECNPER.D (CON), and OEESXBGZD (INV). The QoQ growth rate of monthly variables corresponds to the growth rate of a given month with respect to the month three periods earlier. For both monthly and quarterly data, we use discrete growth rates. Figure B1 shows QoQ growth rates of GDP, consumption, and investment over the period 1996Q1 to 2021Q4. Figure B2 shows the periods of good and bad economic times, together with GDP. Table B1 presents the descriptive statistics of the quarterly and yearly growth rates for GDP, consumption, and investment.

Table B2 provides a detailed description of the monthly variables considered, including sources, transformations, seasonal adjustments, and publication lags. For data which are available at a daily frequency, we take the monthly average. For the monthly volatility of the stock index, we consider daily stock index returns and compute the standard deviation of returns 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.

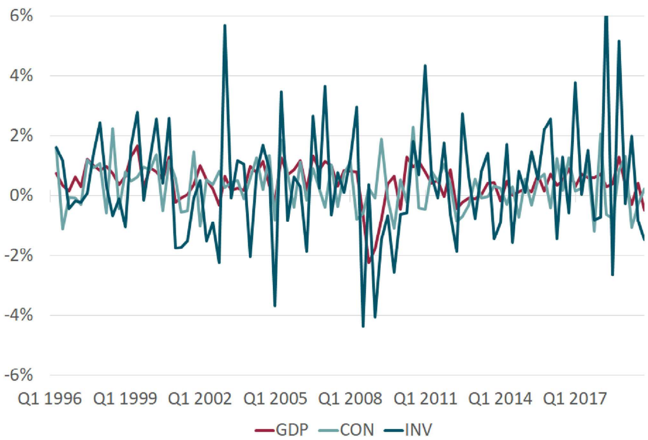

FIGURE B1 | Growth rates of GDP, consumption, and investment.

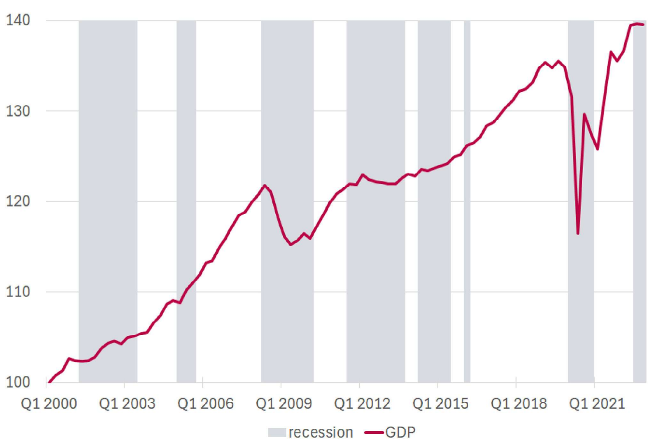

FIGURE B2 | GDP and recession-based regimes. The graph shows the development of GDP (indexed at 100 in 2000Q1) and periods of bad economic times based on the ESI indicator shaded gray.

TABLE B1 | Descriptive statistics of GDP, consumption, and investment.

	GDP	CON	INV
Mean	0.37	0.27	0.35
Std	0.64	0.78	1.64
Skew	−1.47	0.30	0.22
Kurt	6.99	2.53	3.97

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

TABLE B2 | 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 labor 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 3 m VIBOR/3 m 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

(Continues)

TABLE B2 | (Continued)

	Abb	Type	Code	Name	Source	Base date	Seas	Trans	Lag
34	VO1	Fin		ATX volatility, 1 m	VSE, own	31.01.86	n	0	0
35	VO2	Fin		ATX volatility, 3 m	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
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 12 m SA	DG ECFIN	31.10.95	n	0	0
43	CSU	Sur	OETOT7BSQ	OE consumer: All respondents—unemployment next 12 m 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
Indicators defining regimes									
1	WIFO index			WIFO economic climate index	WIFO	31.01.97	n	0	0
2	ESI		OECNFBUSG	OE economic sentiment indicator SA	DG ECFIN	31.01.85	n	0	0
3	inflation			OE inflation, flash estimate	StatA	31.01.99	n	0	0
4	ATX		ATXINDX	ATX volatility, 1 m	VSE, own	07.01.86	n	1	0
5	S&P		S&PCOMP	S&P 500 volatility, 1 m	S&P, own	31.12.63	n	1	0

Note: The table shows the monthly variables used for nowcasting Austrian GDP, consumption and investment and the variables defining regimes. We classify the variables into the following groups: production (Prod), consumption (Con), labor market (Lab), prices (Pri), money and credit (Mon), financial and uncertainty indicators (Fin), and survey and sentiment indicators (Sur). In the column named 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, using Census X-12 seasonal adjustment; in the column named Trans (transformation) "1" means that the variable is transformed to (QoQ) growth rates and "0" signifies no transformation; in the column named Lag "0", "1", and "2" indicate a lag of 0, 1, and 2 months in data availability. For data retrieved from LSEG Datastream, FRED and WIFO we list the corresponding codes.
Abbreviations: 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 organization 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, Ã–sterreich (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.