A Comparison of Monthly Global Indicators for Forecasting Growth*

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Abstract

This paper evaluates the predictive content of a set of alternative monthly indicators of global economic activity for nowcasting and forecasting quarterly world real GDP growth using mixed-frequency models. We find that a recently proposed indicator that covers multiple dimensions of the global economy consistently produces substantial improvements in forecast accuracy, while other monthly measures have more mixed success. Specifically, the best-performing model yields impressive gains with MSPE reductions of up to 34% at short horizons and up to 13% at long horizons relative to an autoregressive benchmark. The global economic conditions indicator contains valuable information also for assessing the current and future state of the economy for a set of individual countries and groups of countries. We use this indicator to track the evolution of the nowcasts for the US, the OECD area, and the world economy during the COVID-19 pandemic and quantify the main factors driving the nowcasts.

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1 Introduction

What is the current state of the business cycle and where is the economy headed? These are questions of first-order importance that guide the decision-making process of economic analysts, governments, central banks, and international organizations. One of the most closely followed and comprehensive measures to monitor macroeconomic developments is real GDP since it constitutes the primary indicator of the business cycle. An important drawback is that it becomes available only with considerable time delay which hampers an early assessment of the current and future economic situation. Therefore, policymaking institutions and the private sector channel substantial resources toward collecting more timely information to analyze short-term fluctuations in economic activity in real time. This is particularly useful in a fast-evolving economic environment that we experienced at the onset of the COVID-19 pandemic.

These efforts have been supported by a large academic literature that has developed nowcasting and forecasting approaches geared toward reliably gauging the underlying state of the economy before the release of official real GDP numbers based on high-frequency indicators. Popular approaches include factor models (e.g., Stock and Watson, 2002; Giannone, Reichlin, and Small, 2008; Schumacher and Breitung, 2008; Chernis and Sekkel, 2017), bridge equations (e.g., Baffigi, Golinelli, and Parigi, 2004; Foroni and Marcellino, 2014; Golinelli and Parigi, 2014), mixed-frequency models (e.g., Andreou, Ghysels, and Kourtellos, 2010; Berger, Morley, and Wong, 2020; Clements and Galvão, 2008, 2009; Kuzin, Marcellino, and Schumacher, 2011; Schorfheide and Song, 2020), and combinations thereof (e.g., Marcellino and Schumacher, 2010; Schumacher, 2016). This literature has concluded that exploiting the information content of high-frequency variables improves the accuracy of macroeconomic nowcasts and forecasts.

Most studies in this literature have focused on predicting the growth rate of real GDP in individual countries relying mainly on domestic variables. Much less attention has been devoted to assessing current and future growth developments beyond national borders. Only a few papers have applied these approaches for the purpose of nowcasting and forecasting world economic growth. For example, Golinelli and Parigi (2014) use several monthly business cycle indicators to generate individual-country forecasts for output growth which are combined into world forecasts by modeling country linkages via bridge equations. This type of bottom-up approach where forecasts for individual countries are aggregated to the global level are also widely used by international organizations like the IMF and the OECD. Ferrara and Marsilli (2019) focus on nowcasting annual global growth directly using a mixed data sampling approach where the predictor variable is the common component extracted from a large cross section of monthly real and financial variables for 37 countries. These studies are based on large datasets of economic indicators for advanced and emerging countries which are difficult to maintain for regular updates throughout the quarter. Another set of papers uses available global indicators directly to track quarterly world output growth. For example, Rossiter (2010) and Stratford (2013) examine the usefulness of the global Purchasing Managers Index, world goods trade, and the IFO World Economic Climate survey, among others, for nowcasting global growth based on bridge models. Ravazzolo and Vespignani (2020) propose a new indicator of world steel production whose reliability they evaluate based on a set of statistical criteria among which its out-of-sample forecast accuracy for world real GDP.[1]

Our paper contributes to the latter strand of this literature by investigating the promise of mixed-frequency models using five popular monthly indicators of global real activity for forecasting quarterly world output growth. We show that the global economic conditions (GECON) indicator recently proposed by Baumeister, Korobilis, and Lee (2020) consistently outperforms all other existing indicators considered here. This finding suggests that GECON is a useful indicator to gauge the timing and magnitude of fluctuations in the global business cycle at the monthly frequency also in other applications. Given that this indicator covers multiple dimensions of the global economy including measures of expectations and uncertainty, industrial activity, mobility and financial indicators, among others, it allows us to gauge how information from various sources affects our assessment of the current state of the world economy by analyzing the contribution of each data category to the nowcasts. These nowcasts and forecasts can be used as inputs for other models such as DSGE models that are used for scenario analysis at policy institutions such as central banks and international organizations.

Given the deep economic interdependence among countries created by decades of globalization, we also examine whether global economic indicators provide useful information for nowcasting and forecasting output growth in groups of countries and single countries that differ in their exposure to international economic developments. We find overwhelming evidence that GECON is by far the best indicator also for the purpose of forecasting changes in regional and domestic real output. The predictive power of GECON is strongest for the within-quarter updates across the entire set of countries, while the forecasting success at longer horizons is concentrated in the larger countries and economic blocs. Our analysis suggests that global economic conditions contain valuable information for assessing the current and expected state of national business cycles. We further show that these gains in forecast accuracy can be achieved in real time. Based on these encouraging results, we use our mixed-frequency model with GECON to track real GDP nowcasts as the COVID-19 pandemic unfolded and quantify how much of the variation in the nowcasts can be attributed to each category of data underlying the global economic conditions indicator.

The remainder of the paper is structured as follows. Section 2 evaluates the usefulness of a set of existing monthly indicators of global economic activity for nowcasting and forecasting quarterly world output growth using mixed-frequency models. We also investigate whether global indicators have predictive power for real GDP growth for regional blocks like the OECD area and the G7 economies as well as for a diverse set of individual countries. Section 3 extends this analysis to a real-time setting and tracks the evolution of the nowcasts for the US, the OECD area, and the

[1] Hamilton (2019) identifies the most useful monthly indicator of global economic activity based on the correlation with observed annual real GDP growth. Kilian and Zhou (2018) rely on anecdotal evidence and qualitative criteria to compare indicators of global real activity but do not investigate the statistical relationships between the various indicators and a target variable.

world economy during the COVID-19 pandemic based on the best performing model. Specifically, we determine what type of information has been driving the nowcasts in the first half of 2020. Section 4 offers some concluding remarks.

2 Nowcasting and Forecasting Real GDP Growth

2.1 Mixed-Frequency Models

A widely followed approach to forecasting a low-frequency variable of interest y_t with variables sampled at a higher frequency f denoted by $X_t^{(f)}$ is the MIDAS approach originally proposed by Ghysels, Sinko, and Valkanov (2007) and Andreou, Ghysels, and Kourtellos (2010). The standard MIDAS regression model relates the dependent variable to the higher-frequency explanatory variable in a parsimonious way by modeling the coefficients as a distributed lag function to keep the number of model parameters that need to be estimated small. We are interested in forecasting the cumulative growth rate of real GDP for $h = 1, 2, ..., 8$ quarters ahead, measured at an annual rate:

$$y_t^h = \frac{400}{h} \ln\left(\frac{Y_t}{Y_{t-h}}\right) \qquad \text{for } h = 1, 2, ..., 8. \tag{1}$$

We also explore nowcasts of the growth rate in quarter t obtained on the basis of monthly data from some of the months of quarter t, and defined as:

$$y_t^h = 400 \ln\left(\frac{Y_t}{Y_{t-1}}\right) \qquad \text{for } h = 0, \frac{1}{3}, \frac{2}{3} \tag{2}$$

where $h = 0$ denotes a nowcast when all of the months of quarter t are available but real GDP has not yet been reported, $h = \frac{1}{3}$ when the first of two months of quarter t are available but not the third, and $h = \frac{2}{3}$ when only the first month is available. We will be basing forecasts and nowcasts on monthly series of a candidate global indicator whose three values for quarter t are denoted $X_t^{(3)}$. Following the notation in Ghysels, Sinko, and Valkanov (2007), we will interpret the fractional lag operator $L^{2/3}X_t^{(3)}$ as picking up the first month of quarter t, $L^{1/3}X_t^{(3)}$ as the second month of quarter t, and $L^{0/3}X_t^{(3)}$ as the final month of quarter t. Allowing for autoregressive dynamics as in Andreou, Ghysels, and Kourtellos (2013) results in the following model specification:

$$y_t^h = \beta_0^h + \beta_1^h \; B(L^{\frac{1}{3}}; \theta^h) \; X_{t-h}^{(3)} + \rho^h y_{t-d}^h + \varepsilon_t^h \tag{3}$$

where $d = 1$ for $h = 0, \frac{1}{3}, \frac{2}{3}$, and $d = h$ otherwise, and the MIDAS lag polynomial $B(L^{\frac{1}{3}}; \theta^h)$ is an exponential Almon lag weight function of the form:

$$B(L^{\frac{1}{3}}; \theta^h) \equiv \sum_{k=0}^{2} b(k; \theta^h) L^{k/3} = \sum_{k=0}^{2} \frac{\exp(\theta_1(k+1) + \theta_2(k+1)^2)}{\sum_{k=0}^{2} \exp(\theta_1(k+1) + \theta_2(k+1)^2)} \; L^{k/3} \tag{4}$$

with shape parameters $\theta^h = \{\theta_1, \theta_2\}$. The weights $b(k; \theta^h)$ sum to one by construction. The horizon-specific parameters $\beta_0^h, \beta_1^h, \theta^h$, and ρ^h are estimated by the method of nonlinear least squares and updated recursively. Using the estimated coefficients and the most recent observations for the global economic indicator and output growth based on the definitions in equations (1) and (2), we generate the nowcasts and h-step-ahead forecasts for $\widehat{y}_{t+d}^h$ as follows:

$$\widehat{y}_{t+d}^h = \widehat{\beta}_0^h + \widehat{\beta}_1^h \ B(L^{\frac{1}{3}}; \widehat{\theta}^h) \ X_{t+m}^{(3)} + \widehat{\rho}^h y_t^h \tag{5}$$

where $m = (1 - h)$ for $h = 0, \frac{1}{3}, \frac{2}{3}$, and $m = 0$ otherwise. One advantage of this direct forecasting approach is that there is no need to forecast the monthly global indicators. At the same time, the MIDAS approach allows us to include monthly information available within the current quarter. We deal with the ragged-edge problem at the end of the sample by applying simple nowcasting techniques which have been shown to work well in other contexts (see, e.g., Baumeister, Korobilis, and Lee, 2020). Details on the nowcasting rules for each global indicator are provided in the next section.

A more flexible alternative that relaxes the constraints incorporated in the functional lag polynomial in the traditional MIDAS model has been developed by Foroni, Marcellino, and Schumacher (2015). They show that unrestricted MIDAS (or U-MIDAS) models perform particularly well when mixing variables of quarterly and monthly frequency. We consider the following U-MIDAS model:

$$y_t^h = \alpha_0^h + \textstyle\sum_{q=0}^{2} \alpha_q^h \ X_{t-h-q/3}^{(3)} + \rho^h y_{t-d}^h + \varepsilon_t^h \tag{6}$$

which is linear in the parameters and thus can be estimated recursively by ordinary least squares.

While all of our monthly indicators of global activity are available from the 1960s and 1970s onward, our sample starts in 1980Q1 since this is the earliest date for which data on world real GDP, the broadest measure we want to forecast, can be obtained at the quarterly frequency. *Oxford Economics* provides data on quarterly world GDP at constant prices constructed on the basis of market exchange rates in its Global Macroeconomic Databank. One advantage of this series is that it is reported in levels which allows for the horizon-specific transformation in equation (1). Data for world real GDP are released with a delay of one quarter which means that the first forecast is actually a nowcast.

We conduct a pseudo real-time forecasting evaluation where data vintages are constructed by adding the latest available data point taking the real-time data flow and thus publication lags into account. We mimic as closely as possible the real-time forecasting environment that a forecaster would have encountered at the time the out-of-sample forecast was generated. The first estimation sample runs from 1980Q2 to 1989Q4 to obtain reliable parameter estimates. We then condition on the information contained in the most recent monthly global indicators as they become available throughout the first quarter of 1990 to nowcast real GDP growth in January 1990 for $h = \frac{2}{3}$, in February 1990 for $h = \frac{1}{3}$, and in March 1990 for $h = 0$. Forecasts for real GDP growth use the information for the monthly predictors available in the quarter at the end of which the forecast is generated; that is, we condition on the information until December 1989 for the monthly predictors when forecasting 1990Q1 output growth for $h = 1$, 1990Q2 output growth for $h = 2$, 1990Q3 output growth for $h = 3$, and so on. Since MIDAS models use the direct method to calculate the forecasts, the models are separately estimated for each forecast horizon. We then re-estimate the horizon-specific parameters using data through 1990Q1 to nowcast 1990Q2 growth for each month of the second quarter of 1990 and to forecast 1990Q2 for $h = 1$, 1990Q3 for $h = 2$, up to 1992Q1 for $h = 8$. We continue to expand our estimation sample by one quarter until we reach the end of the sample.

We evaluate the forecast accuracy in terms of the mean-squared prediction error (MSPE) of output growth. All forecasting results are presented relative to the direct forecasts obtained with an AR(1) model which we use as the benchmark for evaluating the forecasting ability of competing models as is done in Clements and Galvão (2009) for U.S. real GDP growth and in Ravazzolo and Vespignani (2020) for world real GDP growth.[2] An MSPE ratio below 1 indicates that a given model outperforms the AR(1) benchmark. To get a sense of the statistical significance of differences in forecasting performance, we use the Diebold-Mariano (1995) test of equal predictive ability. The forecast evaluation period ends in 2018Q4. The use of such a long evaluation period reduces the risk of spurious forecast successes.

2.2 The Predictive Content of Monthly Global Economic Indicators for World Output Growth

In this section we evaluate the predictive power of the most prominent global economic indicators at the monthly frequency that have been proposed in the literature for the purpose of forecasting world real GDP growth out of sample.[3] Details on the different global measures can be found in Table 1.

2.2.1 World Industrial Production

The first economic indicator measures the level of real output in the manufacturing sector, mining, as well as the electric and gas industries worldwide. Up until 2011.10 the OECD published a monthly index of industrial production covering OECD countries and six major emerging markets (Brazil, China, India, Indonesia, the Russian Federation and South Africa) in its Main Economic Indicator (MEI) database going all the way back to 1958.1. Baumeister and Hamilton (2019) constructed an updated version of this index by applying the same methodology as the OECD.[4] The index is shown in growth rates in the upper left panel of Figure 1.

Since the world industrial production index (WIP) is subject to data revisions, we use the real-time vintages compiled by Baumeister, Korobilis, and Lee (2020) to account for the prelim-

[2] Table 3A in the online appendix reports results for world real GDP when a no-change forecast is used as the benchmark model.

[3] While there are other popular indicators like the J.P. Morgan global manufacturing PMI, world goods trade, and international air freight tonne kilometers (see Stratford (2013) and Kilian and Zhou (2018) for additional discussion), none of them extend far enough back in time and thus are less suitable for our purpose of forecasting global real GDP growth over a long enough evaluation period.

[4] This series is regularly updated and available at https://sites.google.com/site/cjsbaumeister/research.

inary nature of the most recent observations. Specifically, they extend the real-time dataset of Baumeister and Kilian (2014) that contains vintages for the monthly, seasonally-adjusted index of OECD+6 industrial production up to the end of 2011 with real-time vintages of production-weighted, seasonally-adjusted world industrial production provided by the CPB Netherlands Bureau for Economic Policy Analysis from March 2012 onward.[5] The March 2012 vintage contains data from 1991.1 to 2012.1 which they backcast to 1973.1 using the OECD+6 series. For each vintage the most recent two observations are not yet available which we nowcast at the average growth rate of the earlier data.

Table 2 presents the recursive MSPE ratios for the MIDAS and U-MIDAS models. The forecast accuracy of WIP for global growth is mixed. Columns 1 and 2 show that the unrestricted MIDAS model does better than the MIDAS model at most forecasting horizons but only outperforms the AR(1) benchmark in the second month of the current quarter and at the three- and four-quarter-ahead horizons, while being about as accurate as the AR(1) forecast at most other horizons. The largest MSPE reduction of 8% is observed for $h = \frac{1}{3}$ with more modest gains at horizons 3 and 4.

2.2.2 Global Steel Production Factor

Ravazzolo and Vespignani (2020) propose monthly world steel production as an indicator of global real economic activity based on the insight that steel is a key input for many industries including construction, transportation, and manufacturing, and that it is traded freely worldwide. Instead of using their aggregate measure of the level of steel produced worldwide which is only available since 1994, we follow Baumeister, Korobilis, and Lee (2020) and extract the common component from an unbalanced panel of monthly growth rates of crude steel production for individual countries and groups of countries using the EM algorithm.[6] The advantage of this approach is that the resulting measure of global activity is equally broad in coverage but goes further back in time, while circumventing the problem of structural breaks that result from aggregating steel in physical units. The global steel production factor is displayed in the middle left panel of Figure 1.

The World Steel Association publishes information on the amount of steel produced reported by member countries with a one-month lag. We nowcast the missing observations for the current month using the average growth rate of each production series over the available sample. While there are some small data revisions, we rely on the currently available time series since the factor approach would likely filter them out as idiosyncratic noise (see Giannone, Reichlin, and Small, 2008).

[5] For a quantitative analysis of the nature of data revisions, the reader is referred to Section A of the online appendix.

[6] Crude steel production data for the United States, Japan, the European Union and other reporting countries start in 1968.1. Data for China, Eastern Europe, and the Middle East become available in 1990.1 and for Russia and Ukraine in 1992.1. This results in an unbalanced panel of seven time series for monthly production of crude steel measured in thousands of tons. Among these seven time series, only steel production for China and for the EU and other reporting countries display a seasonal component. They are seasonally adjusted using the X13-ARIMA procedure.

The forecasting performance of the global steel production factor is comparable to WIP and it makes little difference whether we use the MIDAS or the U-MIDAS model. Columns 3 and 4 of Table 2 reveal that the MIDAS models with the steel index lead to some improvements in forecast accuracy in the nowcasting period with MSPE reductions between 5% and 7% and some smaller improvements at horizons 3 and 4. These results are consistent with Ravazzolo and Vespignani (2020) who use an aggregate measure of world steel production and a shorter evaluation period.

2.2.3 Kilian Index

The next indicator of global real economic activity is an index based on international shipping costs developed by Kilian (2009). The reasoning underlying this measure is that raw industrial materials need to be shipped before they can be used in production. An upswing in the global economy will lead to an increase in the demand for industrial commodities and thus shipping services which raises the cost of shipping given that the supply of ships is fixed in the short run. To identify the cyclical component of global economic activity, Kilian (2009) proposed to remove a linear time trend from the shipping cost index after deflating it with the U.S. consumer price index (CPI). Kilian (2009) makes the case that the resulting index which is plotted in the bottom left panel of Figure 1 is proportionate to the overall level of global real economic activity. Based on a qualitative analysis, Kilian and Zhou (2018) reinforce this idea by concluding that the Kilian index is better suited than other measures for capturing the timing and amplitude of fluctuations in the global business cycle. Given this interpretation, the Kilian index should be a useful measure for predicting global growth.

Hamilton (2019) provides in-sample evidence that the Kilian index has no statistically significant correlation with annual world real GDP growth rates, while our focus is on out-of-sample forecasts of quarterly world real GDP growth rates. For this purpose, we use the new definition of the Kilian index now recommended by Kilian (2019) which corrects a coding error in the calculation of his original index uncovered by Hamilton (2019). Since our goal is to mimic as closely as possible a real-time setting, the Kilian index available on Lutz Kilian's webpage is not suitable given that it is already transformed using the entire sample period.[7] Instead, we use the series of the log nominal shipping index provided on Jim Hamilton's webpage.[8] This allows us to account for the one-month lag in the release of U.S. CPI which we nowcast based on past average inflation and to linearly detrend the deflated index only using data available to the forecaster at the time the forecast is made.[9]

Columns 5 and 6 of Table 2 show that neither model using the Kilian index beats the AR(1) benchmark except for one horizon. While the U-MIDAS model reduces the MSPE by 4% at the

[7]Note that Ravazzolo and Vespignani (2020) used this full-sample version of the Kilian index which implies that their forecasting results are subject to a look-ahead bias.

[8]See http://econweb.ucsd.edu/~jhamilto/shipping_costs.xlsx

[9]Note that data revisions in the U.S. CPI tend to be small so that they can be safely ignored. Section B of the online appendix documents the implications of linear detrending for the real-time properties and economic interpretation of the Kilian index.

one-quarter horizon, all other MSPE ratios are above 1, and the forecasting performance of the models with the Kilian index deteriorates considerably as the horizon lenghtens.[10] These results are inconsistent with the notion that the Kilian index is a useful measure of global business cycle fluctuations.

2.2.4 Real Commodity Price Factor

Another measure of global economic activity suggested by Alquist, Bhattarai, and Coibion (2020), Delle Chiaie, Ferrara, and Giannone (2017), and West and Wong (2014) relies on the common variation in a large cross-section of real commodity prices. The idea is that a factor extracted from this dataset captures demand-driven global fluctuations which make all prices comove, while commodity-specific developments affect prices in idiosyncratic ways. We use the same 23 basic industrial and agricultural commodities selected by Baumeister, Korobilis, and Lee (2020) and summarized in Table 1 since they feed directly into the production of final goods and are thus related to real output. The upper right panel of Figure 1 shows the real commodity price factor constructed from the first principal component of the balanced panel of percent changes of real commodity prices. While nominal commodity prices are available in real time and are not subsequently revised, U.S. CPI is released with a delay of one month. As before, we use the past average inflation rate to nowcast the current-month CPI to deflate the commodity prices before extracting the real commodity price factor in real time.

The models with the real commodity factor perform consistently well at short horizons. Columns 7 and 8 of Table 2 show that both MIDAS models using the real commodity price factor dominate the AR(1) forecast for horizons up to 1 year with considerable gains in predictive accuracy of up to 14% during the nowcasting quarter and up to 4% one quarter ahead. The MSPE reductions are at most 2% at longer horizons.

2.2.5 Global Economic Conditions Indicator

Baumeister, Korobilis, and Lee (2020) recently developed a global indicator based on a diverse dataset that covers multiple dimensions of the world economy relevant for measuring aggregate fluctuations. Specifically, they put together a panel of 16 variables including broad measures of real economic activity, commodity prices, financial indicators, uncertainty measures, weather-related variables, indicators of transportation demand, expectations measures, and energy-related indicators.[11] For example, leading economic indices as well as expectations and uncertainty measures provide an assessement of households' and businesses' outlook for future spending and growth;

[10] Hamilton (2019) and Funishima (2020) show that one problem with the Kilian index is the assumption of a linear time trend. While alternative transformations of shipping costs, as recommended by Hamilton and Funishima, might be more useful, Kilian and Zhou (2018) insist that "the Kilian index [...] is constructed as a business cycle index and, hence, must not be differenced or otherwise transformed" (p.57).

[11] For the full list of variables, see Table 1. All data series have been seasonally adjusted at the source.

world industrial production, energy consumption, and mobility measures capture the current intensity of real economic activity; stock returns, foreign exchange fluctuations and real copper prices contain forward-looking information of trade and financial flows. The first principal component extracted from this rich cross-section of variables which is plotted in the middle right panel of Figure 1 provides a summary measure of current and future global economic conditions that affect macroeconomic performance worldwide.

The 16 variables that enter the construction of the global economic conditions (GECON) indicator are released with varying publication lags as detailed in Table 1. We fill the data gaps at the end of the sample using the same nowcasting techniques as Baumeister et al. (2020). Most of the series underlying GECON are subject to either small or no revisions which is why we use the currently available time series except for WIP where we use the real-time vintages described earlier.

The MIDAS models with the GECON indicator are the most successful for purposes of nowcasting and forecasting global growth. Columns 9 and 10 of Table 2 show a dramatic improvement in forecast accuracy across all horizons. Both the MIDAS model and the U-MIDAS model using GECON outperform the AR(1) forecast by a wide margin with the MIDAS model yielding the best overall results. The nowcasts achieve statistically significant reductions in MSPE ratios of 12% for the first month, 24% for the second month, and 34% for the last month of the current quarter. This indicates that as more information becomes available throughout the quarter, the forecasting performance improves substantially. Similarly impressive gains are obtained for forecast horizons one-to-eight quarters ahead with average MSPE reductions of 10%.

2.2.6 Tracking the Forecasting Performance of Indicators over Time

The results reported in Table 2 summarize the average forecast accuracy. The most accurate model by far is the MIDAS model using the GECON indicator, while the MIDAS model with the Kilian index displays the weakest overall performance. The models with the real commodity price factor come in second producing gains mainly at shorter horizons. There is no systematic pattern for the models relying on WIP and the steel factor which only occasionally improve upon the AR(1) forecast.

To get a better sense of where the differences across global indicators come from, we take a look at the evolution of the cumulative mean-squared prediction errors over time. For this purpose, we compare the forecasting performance of the MIDAS and the U-MIDAS models relative to the AR(1) benchmark for three different horizons: the nowcast when only one monthly observation of the global indicator is available, the nowcast at the end of the current quarter, and the one-year-ahead forecast. Figure 2 illustrates that the forecasts obtained with the MIDAS models using the GECON index consistently outperform the AR(1) forecasts over the entire evaluation period and across horizons. Some of the superior forecast accuracy of the GECON models derives from the period following the 2008/09 financial crisis. The markedly more accurate nowcasts of the models with the real commodity factor are exclusively due to the post-2010 period. This is consistent with evidence provided in Bjørnland, Ravazzolo, and Thorsrud (2017) who show that gains in the short-run forecast accuracy of domestic real GDP growth for a large panel of countries are mainly realized in the aftermath of the Great Recession for models that include a common international business cycle factor. The opposite is true for the models using the Kilian index where the post-2010 period is detrimental to the forecasting performance. This is in line with the problem highlighted by Hamilton (2019) that since 2010 the Kilian index has exhibited increased volatility and periods of sharp contractions that are incompatible with any other available measure of recent fluctuations in world economic activity. At the one-year horizon, the models with WIP, the steel index, and the commodity factor are essentially on par with the AR(1) forecast. The figure also confirms that in most cases there is little to choose between the MIDAS and U-MIDAS models given their similar performance across indicators and time.

2.2.7 Excluding the Great Recession

The previous analysis suggests that the Great Recession is a key episode for some monthly global indicators to outperform the AR(1) benchmark. This begs the question of what happens to the forecasting performance of our mixed-frequency models if we exclude the period of the Great Recession. To assess the predictive content of our global activity variables for world real GDP growth in the absence of the Great Recession, we consider two cases: first, we end the evaluation period in 2007Q3 just before the start of the Great Recession, and second, we omit the observations from 2007Q4 to 2009Q2 from estimation and evaluate the models under the assumption that the Great Recession never happened.

Table 3 presents the recursive MSPE ratios for the MIDAS models across all five indicators.[12] Panel (a) shows that for the shorter evaluation period from 1990Q1 to 2007Q3 the model with the GECON index is the only model that beats the AR(1) benchmark across all forecasting horizons. Compared to the full evaluation period, the MSPE reductions at short horizons are somewhat less impressive but still sizeable. For example, the nowcast for the last month of the current quarter reduces the MSPE ratio by 13% and is statistically significant. At the intermediate horizons of 1 to 4 quarters ahead the accuracy gains are about half of those for the longer evaluation period. At the two-year horizon, the GECON model evaluated over the shorter out-of-sample forecasting period further improves upon the AR(1) benchmark with an additional reduction in MSPE of 3 percentage points relative to the full sample. The other model that yields a better performance at longer horizons is the one with the real commodity price factor. While this model does not dominate the AR(1) forecast when evaluated over the entire period, it produces somewhat more accurate forecasts at horizons 6 and 8 over the shorter evaluation period. Panel (b) that displays the results for the 1990Q1 to 2018Q4 evaluation period but without the observations pertaining to the Great Recession largely confirms this pattern. Extending the evaluation period by the decade

[12] The corresponding results for the U-MIDAS models are reported in Table 4A in the online appendix.

following the Great Recession changes the MSPE ratios only slightly and does not alter the ranking of the models.

While the experience of the Great Recession is informative for the accuracy of our mixed-frequency models, it is not critical to the success of the MIDAS model with the GECON indicator which comes out as the clear winner of this forecasting race even in the absence of the financial crisis period. This finding attests to the robustness of the GECON model for forecasting global growth.

2.2.8 Can Pooling Improve the Forecast Accuracy Further?

Another way to deal with unusual episodes and structural change is to combine forecasts. It is well known that pooling forecasts not only can lead to superior forecasting performance but can also guard against varying accuracy of individual forecasting models over time (see, e.g., Timmermann, 2006). To explore the benefits of forecast combinations, we consider aggregating the individual forecasts using both inverse MSPE weights and equal weights.

Table 4 reports the results for pooling global growth forecasts across indicators and across all models. While the forecast combinations obtained with inverse MSPE weights beat the AR(1) benchmark across all horizons, none of them matches the excellent performance of the models with the GECON indicator. For example, during the nowcasting period statistically significant reductions in MSPE ratios of 14% for the first month, 19% for the second month, and 21% for the last month of the current quarter are achieved with pooling compared to 15%, 24%, and 34% for the GECON models. At longer forecast horizons, the differences are even starker with an average loss in accuracy of more than 8 percentage points one to two years ahead. The forecasts aggregated with inverse MSPE weights dominate the equal-weighted ones. The U-MIDAS combinations tend to perform slightly better than the MIDAS combinations but the difference in MSPE ratios is modest with an average of 2 percentage points. The MSPE reductions obtained by combining all the model forecasts fall in between those of the pooled MIDAS and U-MIDAS forecasts.

In sum, nothing beats the mixed-frequency models with the global economic conditions indicator for the purpose of forecasting world real GDP growth.

2.3 The Role of Global Indicators for Regional and Domestic Growth Forecasts

Over the past decades the world economies have become more and more integrated and the evolution of national business cycles is increasingly influenced by global economic conditions as a result of globalization. For example, Ductor and Leiva-León (2016) document a marked increase in business cycle interdependence across the globe in the early 2000s. This begs the question whether and to what extent worldwide economic conditions contain valuable information for forecasting the path of output growth in different countries and groups of countries.[13] For this purpose, we evaluate the information content of the same set of monthly indicators of global activity for growth forecasts for the OECD area, the G7 economies, and a diverse set of individual countries. While for some countries data for real GDP are available further back in time, we keep 1980Q1 as the common start date, mainly for purposes of comparability with the forecasting results for global growth. Another consideration is that economic integration played a more prominent role since the 1980s and that many advanced economies have undergone important transformations beforehand.

2.3.1 Groups of Countries

We investigate the usefulness of global economic indicators for two country blocs that differ in their size and composition: the OECD area which consists of 37 member countries and the Group of Seven (G7) which includes the seven major advanced economies in the world.[14] We obtain data on quarterly real GDP for the OECD area from the November 2019 OECD *Economic Outlook* database and for the G7 countries from *Haver Analytics*.[15]

Table 5, panel (a) shows that the MIDAS model using the GECON indicator which consists of the most diversified set of variables has the highest predictive value for nowcasting and forecasting growth in the OECD economies among the five global indicators. This model yields the largest MSPE reductions relative to the AR(1) benchmark across all horizons, most of which are statistically significant. The second-best model for nowcasts and long-horizon forecasts is the MIDAS model based on the global steel index but the MSPE reductions do not measure up to those achieved with GECON. For example, the MIDAS model with GECON yields gains in forecast accuracy of 17% for the first month, 26% for the second month, and 39% for the last month of the current quarter, while the corresponding gains for the MIDAS model with the steel index are only 7%, 2%, and 14%. Equally impressive are the MSPE reductions of the GECON model at longer horizons with improvements of about 20% over the benchmark. At horizons 1, 2, and 3-quarters-ahead, the U-MIDAS model with the Kilian index has some success but it never performs better than GECON. The models using WIP and the real commodity price factor are not useful for the purpose of forecasting growth for the OECD area.

A similar picture emerges for the G7 growth forecasts. Panel (b) of Table 5 highlights that the MIDAS model using GECON is again the winner by a large margin with substantial improvements

[13] Using a dynamic factor model, Bjørnland et al. (2017) show that a quarterly common international business cycle factor adds marginal predictive power to forecasting domestic real GDP growth at short horizons for the period after the Great Recession.

[14] Current OECD member countries are Australia, Austria, Belgium, Canada, Chile,Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. The G7 is composed of Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

[15] Both aggregates are constructed using market exchange rates and are released with a delay of one quarter. Real GDP for the G7 countries (S005NGCD@G10) is only available from 1981Q1 onward.

in forecast accuracy that are highly statistically significant. MSPE reductions range between 36% for the nowcast, 23% at the 1-year horizon, and 22% at the 2-year horizon. The usefulness of the other indicators is a bit more mixed compared to the OECD area and dependent on the forecast horizon. During the nowcast period, the information conveyed by WIP and the steel index seems useful in the first month of the quarter, while WIP and the commodity price factor are more important in the second month, and the global steel index performs best among those three at the end of the current quarter. At intermediate horizons the MIDAS and U-MIDAS models with WIP and the Kilian index deliver some modest gains relative to the AR(1) benchmark but never larger than 5%.

2.3.2 A Diverse Set of Individual Countries

We now focus on several individual countries that differ in their exposure to international developments and a number of other distinctive characteristics which should help shed light on the usefulness of global economic indicators for domestic growth. In particular, we distinguish between large economies and small open economies, some of which are net commodity importers, while others are net commodity exporters.

Large Economies. The common perception is that large economies are more closed since foreign trade contributes a relatively small share to GDP and that they are therefore less susceptible to economic fluctuations in the rest of the world. We examine to what extent indicators of global activity have predictive content for quarterly growth rates in the Euro area and the United States.

Euro area. While the Euro area could be considered as a group of countries, it has stronger economic ties than the OECD and the G7 which is why we treat it as a single, country-like entity. This is supported by the fact that institutions like the European Central Bank (ECB) are mandated to take only area-wide economic developments into account when conducting monetary policy, for example. It is thus of direct policy interest to understand whether worldwide economic conditions matter for the purpose of forecasting area-wide growth. The broadest aggregate for Euro-area real GDP comprising all 19 countries is available from Eurostat starting in 1995Q1. We use the growth rate of real GDP from the ECB's Area Wide Model (AWM) database to extend this series back to 1980Q1.

Table 6, panel (a) shows that WIP is the most useful predictor in the first month of the current quarter, while the MIDAS model using the GECON indicator performs best across all other horizons with statistically significant MSPE reductions of 24% for the full-quarter nowcast and of 15% at the 2-year horizon. The MIDAS models with the global steel production factor are also more accurate than the AR(1) forecast with sizeable MSPE reductions of up to 14% at short horizons. This forecasting success is not entirely surprising given the important role of the steel industry for the European economy. Among the other global indicators, the Kilian index again displays the worst overall performance.

United States. U.S. real GDP growth is probably one of the most often forecast variables. A lot of effort has been put into finding suitable predictor variables for this key measure of macroeconomic performance. We obtain data for quarterly U.S. real GDP from the FRED database.

Panel (b) of Table 6 shows that using current-quarter global information embodied in GECON leads to staggering gains in forecast accuracy when forecasting U.S. growth rates. MSPE reductions are as large as 19% in the first month, 28% in the second month, and 37% in the last month of the nowcasting quarter for both the MIDAS model and the U-MIDAS model. The gains for horizons 1- to 8-quarters ahead range between 10% and 18%. None of the other indicators of world activity have additional predictive power relative to the AR(1) forecast. In particular, the MSPE ratios for the models with the Kilian index and the real commodity price factor are all above 1.

Small Open Economies. It is well known that economic activity in small open economies tends to be heavily influenced by foreign economic developments given their strong trade linkages with the rest of the world. It is particularly important for policy institutions to find ways to incorporate global developments into their forecasting models for the domestic economy (see, e.g., Rossiter, 2010; Stratford, 2013). External forces are typically taken into account by a large share of international predictor variables in a data-rich environment (see, e.g., Chernis and Sekkel, 2017). Here we focus directly on the value of existing global indicators for growth forecasts in small open economies. We consider four representative countries that mainly differ in their dependence on commodities: Canada, Norway, the United Kingdom, and Japan.[16]

Net Commodity Exporters. Canada and Norway are both resource-rich economies which export a large share of their natural resources, mainly crude oil and petroleum products. Thus, we would expect global indicators tied to the demand for energy and commodities more broadly to be useful for forecasting domestic output growth.

The results for Canada reported in Table 7, panel (a), show that once again the MIDAS models with the GECON indicator produce the lowest MSPE ratios for all horizons with an average improvement of 15% relative to the AR(1) benchmark. The MIDAS model using the real commodity price factor also achieves gains of up to 7% for forecast horizons up to one year. What is surprising is that the Kilian index that is supposed to track the demand in industrial commodity markets is not able to beat the AR(1) forecast at any horizon despite Canada's role as net exporter of a range of commodities. Also WIP and the steel index have barely any predictive power for Canadian real GDP growth.

Table 7, panel (b) presents the results for Norway which turn out not to be as strong as those for Canada. GECON is the only global economic indicator that achieves any reductions in MSPEs, but does not dominate the AR(1) forecast at all horizons. The MIDAS model delivers

[16] The data for real GDP for each country were obtained from *Haver Analytics* and they become available with a one-quarter lag. The mnemonics are as follows: S156NGPC@G10 for Canada; S142NGPC@G10 for Norway; S112NGPC@G10 for the U.K.; and S158NGPC@G10 for Japan.

statistically significant gains of around 5% for the within-quarter nowcasts and the one-quarter-ahead forecasts.[17]

Baumeister et al. (2020) show that the indicator of global economic conditions is particularly useful for forecasting the real price of Brent crude oil, so it is not entirely unexpected that models using GECON also perform well for forecasting output growth in oil-exporting countries. What about countries whose primary resource endowments imply different trading patterns?

Net Commodity Importers. The United Kingdom is a hybrid case since it switched from being an oil exporter to being an oil importer during our evaluation period, while Japan's resource scarcity makes it heavily dependent on imported energy, raw materials, and food commodities.

Table 8, panel (a) shows that for the UK the MIDAS model with GECON outperforms all other global activity indicators and beats the AR(1) forecast across all horizons. The MSPE reduction is largest for the full-quarter nowcast with 14%, while for the other horizons the improvements are on average around 5%. The only model that is competitive at the intermediate horizons of 3- and 4-quarters ahead is the MIDAS model using the world industrial production index, while the MIDAS model using the steel index shows some promise for the within-quarter nowcasts. Neither the Kilian index nor the commodity factor have any predictive content for output growth in the UK.

The picture for Japan is a bit more mixed. Panel (b) of Table 8 indicates that WIP delivers the first useful piece of information for the nowcast in the first month of the quarter which yields an MSPE reduction of 12% for the U-MIDAS model. Adding the information contained in the other variables underlying GECON increases the forecast accuracy by 13% also in the second and third months of the current quarter relative to the AR(1) benchmark. While GECON is also the best predictor at longer forecasting horizons, 1-quarter to 1-year-ahead forecasts obtained with the models using WIP and the global steel production factor perform better. The U-MIDAS model with the real commodity factor also displays a solid performance beating the AR(1) forecast for most horizons but by smaller margins than the other three indicators. The Kilian index again ranks last.

3 Assessing the Real-Time Forecasting Performance

The evidence presented thus far clearly suggests that, among the monthly global indicators considered here, the global economic conditions indicator of Baumeister et al. (2020) is the most relevant predictor for output growth not just at the global level but also for economic blocs and individual countries. Up to this point we have abstracted from the fact that real GDP data get

[17] Norway also has the concept of 'Mainland GDP' which excludes activities that stem from the exploration of crude oil and natural gas as well as related services like transportation. We find qualitatively similar results for this definition of GDP; in fact, the forecasting performance of the MIDAS model with GECON for mainland GDP is even somewhat better at short horizons.

revised over time. A possible concern is that not accounting for data revisions may result in an overly optimistic assessment of the forecast ability of our best-performing model (see, e.g., Golinelli and Parigi, 2014). While no real-time vintages of data on real GDP exist for the world and the country aggregates, we are able to track data revisions for all individual countries. This allows us to conduct a proper real-time exercise. In Section 3.1, we evaluate to what extent the use of preliminary data affects the forecast accuracy of the GECON model, and in Section 3.2, we use this model to nowcast output growth in real time during the first two quarters of the COVID-19 pandemic.

3.1 The Importance of Real-Time Data Vintages

We collect seasonally-adjusted vintages for quarterly U.S. real GDP from the Federal Reserve Bank of Philadelphia's *Real-Time Dataset for Macroeconomists* (see Croushore and Stark, 2001). The first vintage corresponds to 1990Q1 which contains information available to the public in the middle month of the previous quarter in line with the forecast origin for our evaluation period that starts in 1990Q1. As before, we only use data from 1980Q1 onward. Keeping this starting point fixed, we re-estimate the model at the end of each quarter, now using the vintage consistent with the information a forecaster had in real time. For Canada, Norway, the UK, and Japan, we obtain real-time vintages of quarterly, seasonally-adjusted real GDP from the *Original Release Data and Revisions Database* for the OECD Main Economic Indicators. A consistent set of vintages that contains data going back to 1980Q1 starts in December 1999 for all four countries.[18] Thus, the ability to fully account for data revisions comes at the cost of having to shorten the evaluation period by a decade. At the same time, this provides a useful check to verify that the forecasting success of the GECON model is robust to the specific choice of the evaluation sample complementing our earlier analysis for world real GDP summarized in Table 3. To separate the influence of the shorter evaluation period from the aspect of data revisions, Table 9, panel (b) reports the MSPE ratios for forecasts obtained with both the most recent vintage of data and the real-time vintages for the evaluation period 2000Q1 to 2018Q4. For completeness, panel (a) provides results for the full forecast evaluation period but only for the US. The forecasts are evaluated against the same realized values for output growth as before.

We focus on the MIDAS model since the results for the U-MIDAS model turn out to be very similar. Panel (a) reveals that for the longer evaluation period, the forecasts for U.S. output growth generated with real-time data generally outperform those generated with the most recent vintage with additional gains of up to 7%. While this might seem surprising, it is important to keep in mind that the preliminary nature of the data not only affects the forecasts of the MIDAS models but also

[18] Publication lags for real GDP series vary across economies and over time within economies. We use the GDP release from the middle month of the quarter containing information for GDP of the previous quarter, or the first release of data on the level of output when GDP is released with a publication lag longer than two months (assuming that it is actually available in the middle month of the quarter). For a detailed analysis of the quantitative importance of data revisions to real GDP across countries, the reader is referred to Section A of the online appendix.

the AR(1) benchmark. For the shorter evaluation period the results are a bit more mixed. Panel (b) shows that the nowcasts and short-horizon forecasts obtained with the real-time and revised data are mostly tied, but from horizon 3 onward the MSPE ratios of the MIDAS model based on the real-time vintages are on average 8% higher compared to those using the final vintage of data. The improvements in forecast accuracy relative to the benchmark model remain sizeable however, with MSPE reductions between 4% and 12%.

For Canada the forecasting performance of the MIDAS models based on real-time vintages and revised data is more comparable. Rows 5 and 6 of Table 9 show that no model dominates across all horizons and that differences in MSPE reductions amount to at most 3% with both models achieving sizeable gains in forecast accuracy of 18% on average up to 6 quarters ahead. Rows 7 and 8 indicate that the accuracy of the nowcasts and 1-quarter-ahead forecast for Norwegian output growth suffers slightly when real-time data vintages are used, registering an average loss of 2% in MSPE reductions. At horizons 3 and 4 instead real-time vintages yield additional gains of 3% and 7% respectively relative to the revised data. Using real-time data improves the forecast performance for U.K. real GDP growth across all horizons with additional MSPE reductions of up to 9% (see rows 9 and 10). In contrast, for Japan, rows 11 and 12 show that the preliminary nature of the data leads to a loss in forecast accuracy of 6% on average at short horizons but the MIDAS model using GECON still improves the nowcasts and the 1-quarter-ahead forecast relative to the AR(1) benchmark.

Taken together, the use of real-time data vintages for real GDP does not have a large impact on the performance of the MIDAS forecasts using GECON across all countries. This means that these gains in forecast accuracy are achievable in real time. Figure 3 shows the evolution of the recursive MSPE ratios for selected horizons for the final and real-time vintages and the two evaluation periods which allows for a direct comparison along these two dimensions as well as across countries. The figure confirms that in most cases it makes little difference whether we use revised or real-time data for real GDP at each point of the evaluation period. It also reveals that the shorter evaluation period yields slightly more favorable results at shorter horizons. The MIDAS models get a lot of milage out of the 2008/09 financial crisis episode which is in line with the evidence presented in Figure 2 for world real GDP growth and the findings of Bjørnland et al. (2017) for output growth in individual countries. However, on average the gains in MSPE reductions for the shorter evaluation period are only around 5% for horizons up to 1 year. For most countries, the differences at longer horizons are even smaller except for Canada and Japan where the longer evaluation period yields larger improvements in forecast accuracy at horizons 6 and 8. Overall, the pattern of forecasting performance is robust across evaluation periods.

3.2 Nowcasting Growth during the COVID-19 Pandemic

The COVID-19 pandemic was an event of global scale with unprecedented economic consequences. As the health crisis unfolded, one of the most pressing tasks for policymakers around the world was to gauge the evolution of the state of the economy in a timely fashion. There are a number of recent studies that provide nowcasts and forecasts of real GDP growth for the U.S. economy (see, e.g., Berger, Morley, and Wong, 2020; Diebold, 2020; Schorfheide and Song, 2020) and the G7 countries (see, e.g., Foroni, Marcellino, and Stevanović, 2020) for 2020. Existing growth assessments for a particular country tend to rely on domestic variables only. It stands to reason that a measure of global economic conditions that captures key aspects of the current crisis could be especially useful for monitoring economic developments during the pandemic. In particular, the most recent episode is characterized by worldwide disruptions of industrial activity and trade flows, a sharp drop in global mobility, plummeting consumer confidence, and rampant uncertainty – all variables that figure prominently in GECON. While domestic variables are undoubtedly important, global economic conditions might also have a role to play. This consideration is even more important once we try to track the decline in economic activity that transcends national boundaries.

Using a model that allows to incorporate new information about the global economy every month is key to picking up the latest developments in economic conditions and gauging the slowdown as it unfolds. This feature was particularly important in the first quarter of 2020 where the bulk of events was concentrated in the last month of the quarter. Based on our MIDAS model, we generate real-time nowcasts of real GDP growth for the US, the OECD area, and the global economy for the first half of this year using vintages of GECON as they were assembled in real time at the end of each month over the period January to June 2020.

Crisis-Specific Considerations. As pointed out by Foroni et al. (2020), in unusual times it makes sense to deviate from established practices to accurately capture special circumstances in an effort to obtain informative nowcasts. We consider two adjustments along those lines. First, while simple nowcasting rules based on the time series properties of the variables underlying GECON work well during normal times, rapid changes in a crisis environment like the pandemic warrant a more careful treatment. For example, the collapse of transportation demand as a result of the lockdown measures and travel restrictions cannot be captured by the average historical behavior of U.S. vehicle miles traveled. Therefore, we nowcast the two missing observations at the end of March 2020 by the no-change forecast; in April, traffic data firm INRIX[19] reported an average drop of nationwide traffic volume of 30% for the second half of March 2020. Based on this information, we assume a reduction in mobility of 15% to nowcast the March value and a 30% reduction to nowcast the April value; in May, we used the most recent change to nowcast the April and May values and in June we switched back to the average growth rate. Another important variable for transportation are OECD passenger car registrations, the data for which are released with an 8-month lag. To obtain more timely information, we collect data on vehicle registrations for the US, EU28, Canada, Japan, and Australia in units of thousands of cars from the OECD MEI database which are published with a delay of only one month, sum them up, and apply the growth

[19] https://inrix.com/blog/2020/03/covid19-us-traffic-volume-synopsis/

rate of this aggregated series to the OECD index.[20] Similarly, there was no doubt that world industrial production would be hit hard which made nowcasting based on the past average growth rate implausible. To ensure that the nowcasts in the April 2020 vintage reflect this expectation, we extrapolate the two missing observations for March and April based on the average growth rates of manufacturing PMI for the US, Canada, the Euro area, the UK, Australia, Russia, China, and India where the selection of countries was determined by data availability for both months. Consumer confidence was also shattered as a result of the pandemic and extended lockdowns and even though this variable becomes available with a delay of just one month, assuming no change to nowcast the value in April was unrealistic. Instead, we use the average of growth rates of consumer confidence for the US, Canada, France, Spain, Italy, and Australia to obtain a more reasonable nowcast for April 2020.[21] All other variables are nowcast as summarized in Table 1.

Second, exceptionally large deviations from the historical behavior of the economy raise concerns about the stability of forecasting relationships and the ability of the model to perform well. This is relevant when deciding whether to update the estimates of the model parameters by including the most recent observations or whether to fix the parameters at pre-crisis estimates. Schorfheide and Song (2020) note that if the pandemic shock was a one-time aberration that did not change the structure of the economy, then it is best to omit the crisis observations from estimation since they might distort the parameter estimates; but, if the pandemic did affect how economic variables interact, then parameter estimates should be updated using the latest information. We examine the role of the estimation sample by comparing the nowcasts for 2020Q2 derived from a model with updated estimates and estimates kept at their 2019Q4 values.

A last modification pertains to the model for world GDP growth. Since we no longer have access to the *Oxford Economics* database, we estimate the GECON model without an autoregressive term to produce nowcasts for global growth as in the basic MIDAS approach of Ghysels et al. (2007).[22] These results, while informative, should be viewed as an approximation and thus be taken with a grain of salt.[23]

Nowcasting Evidence. Figure 4 displays the monthly nowcasts of real GDP growth for the US, the OECD area, and the global economy during the first and second quarters of 2020. Output nowcasts in the first quarter are too optimistic across all three economies. While the new information that arrives in March lowers the nowcasts considerably pointing to a deceleration of growth, they are far from the realized values of negative growth that were released about a month later and range from -5% for the US to -7% for the OECD. This is a common feature across alternative real-time

[20] The correlation between the growth rate of this aggregated series and the OECD index is 0.93 for the overlapping period from January 1994 to December 2018.

[21] The data for the manufacturing PMIs and consumer confidence indices were obtained from tradingeconomics.com.

[22] The last available data point for world real GDP is 2019Q2.

[23] We also investigated the impact of omitting the autoregressive dynamics for the nowcasts for the US and the OECD area. We do not find major differences in the nowcasting performance across the two types of models which we find reassuring.

nowcasting attempts in 2020Q1. For illustration purposes, we include the nowcasts for U.S. real GDP growth produced by the Federal Reserve Bank of New York.[24] In contrast to our nowcasts, the New York Fed nowcasts were over one percentage point lower in January and February but 0.6 percentage points higher in March when our model points to a sharp downward correction.

We can not only track the evolution of the nowcasts over time but we can also determine which categories of data underlying the GECON indicator drive the nowcasts. The major forces pulling down the nowcast in March 2020 were a drastic reduction in real activity and in traffic volumes and to some extent rising uncertainty. Financial indicators on the other hand remained strong and were stemming the slowdown by making a positive contribution to the nowcasts. A similar pattern emerges for the OECD area and the world economy.

For the second quarter of 2020, we report nowcasts for US and OECD growth using the MIDAS model once with coefficients updated during the crisis and once with coefficients fixed at their pre-crisis estimates as well as the respective decompositions. The nowcasts obtained with both models are broadly similar with the most recent estimates indicating a somewhat more pronounced decline. While both nowcasts pick up the substantial deterioration of economic activity in the US and the OECD, they cannot match the sheer magnitude of this extreme event. What is interesting is that in May 2020 the NY Fed nowcast reaches a low of -35%, while the GECON model signals some improvement relative to April; yet, both nowcasts are pretty close in June 2020 with our model indicating a drop of 10% and the New York Fed model a drop of 16%. The realized values were a staggering -31.7% for the US and -33.8% for the OECD. The nowcasts for global growth monotonically decline as the second quarter progresses but the predicted size of the downturn is smaller. However, as the decomposition shows, this is not due to the information content of GECON whose components explain a similar amount of the decline as for the US and the OECD; rather, it must be the case that the constant term which captures past average growth prevents the nowcasts from falling further. While all data categories make a negative contribution to the nowcasts in the second quarter, plummeting economic activity and transportation demand account for the lion's share of the severe contraction in line with the travel bans and widespread lockdown measures. Other important sources of slack are increasing uncertainty, pessimistic expectations, and weakening financial indicators. The breakdown is again similar across economies.

4 Conclusions

Monthly global economic conditions have the potential to provide useful information about current and future output growth at the global and regional levels as well as for individual countries in a timely manner. In this paper we evaluated the usefulness of several existing monthly measures

[24] The New York Fed updates its nowcasts throughout the quarter as new data are released (https://www.newyorkfed.org/research/policy/nowcast). We use their nowcasts that correspond to the end of each month to match them with the timing of our nowcast updates.

of global economic activity in terms of their out-of-sample forecasting performance for quarterly real GDP growth using mixed-frequency models. We showed that the most accurate model uses a global economic conditions indicator based on a set of 16 variables recently proposed by Baumeister, Korobilis, and Lee (2020) that covers multiple dimensions of the world economy. The nowcasts and forecasts for global growth generated by this model present a valuable complement to the economic outlook obtained from a bottom-up approach used by international organizations like the OECD and the IMF.

Global developments captured by this indicator turned out to be helpful also for forecasting output growth for country groups and a heterogeneous set of individual countries and gains in forecast accuracy can be achieved in a real-time setting. This is not to say that domestic economic conditions do not matter but rather that there is additional valuable information in global economic conditions that should not be disregarded. While this has been recognized before, previous studies relied on large datasets that are tedious to update frequently. This paper offers an alternative in the form of the global economic conditions indicator that is based on just 16 variables that can be easily updated in real time. Thus, an interesting question for future research is to what extent the forecasting performance of national real GDP growth can be improved by augmenting standard forecasting models with this global predictor variable.

References

Alquist, Ron, Saroj Bhattarai, and Olivier Coibion (2020). "Commodity-Price Comovement and Global Economic Activity," *Journal of Monetary Economics* 112: 41-56.

Andreou, Elena, Eric Ghysels, and Andros Kourtellos (2010). "Regression Models with Mixed Sampling Frequencies," *Journal of Econometrics* 158(2): 246-261.

Andreou, Elena, Eric Ghysels, and Andros Kourtellos (2013). "Should Macroeconomic Forecasters Use Daily Financial Data and How?" *Journal of Business and Economic Statistics* 31(2): 240-251.

Baffigi, Alberto, Golinelli, Roberto, and Giuseppe Parigi (2004). "Bridge Models to Forecast the Euro Area GDP," *International Journal of Forecasting* 20: 447-460.

Baumeister, Christiane, and James D. Hamilton (2019). "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks," *American Economic Review* 109(5): 1873-1910.

Baumeister, Christiane, and Lutz Kilian (2014). "What Central Bankers Need to Know About Forecasting Oil Prices," *International Economic Review* 55(3): 869-889.

Baumeister, Christiane, Dimitris Korobilis, and Thomas K. Lee (2020). "Energy Markets and Global Economic Conditions," *Review of Economics and Statistics*, forthcoming.

Berger, Tino, James Morley, and Benjamin Wong (2020). "Nowcasting the Output Gap," *Journal of Econometrics*, in press.

Bjørnland, Hilde C., Francesco Ravazzolo, and Leif Anders Thorsrud (2017). "Forecasting GDP with Global Components: This Time is Different," *International Journal of Forecasting* 33(1): 153-173.

Caldara, Dario, and Matteo Iacoviello (2018). "Measuring Geopolitical Risk," Federal Reserve Board of Governors, mimeo.

Chernis, Tony, and Rodrigo Sekkel (2017). "A Dynamic Factor Model for Nowcasting Canadian GDP Growth," *Empirical Economics* 53: 217–234.

Clements, Michael P. and Ana Beatriz Galvão (2008). "Macroeconomic Forecasting with Mixed-Frequency Data: Forecasting US Output Growth," *Journal of Business and Economic Statistics* 26: 546-554.

Clements, Michael P. and Ana Beatriz Galvão (2009). "Forecasting US Output Growth Using Leading Indicators: An Appraisal using MIDAS Models," *Journal of Applied Econometrics* 24(7): 1187– 1206.

Croushore, Dean, and Tom Stark (2001). "A Real-Time Data Set for Macroeconomists," *Journal of Econometrics* 105(1): 111-130.

Delle Chiaie, Simona, Laurent Ferrara, and Domenico Giannone (2017). "Common Factors of Commodity Prices," Federal Reserve Bank of New York, mimeo.

Diebold, Francis X. (2020). "Real-Time Real Economic Activity: Exiting the Great Recession and Entering the Pandemic Recession," University of Pennsylvania, mimeo.

Diebold, Francis X., and Roberto S. Mariano (1995). "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics* 13(3): 253-263.

Ductor, Lorenzo, and Danilo Leiva-León (2016). "Dynamics of Global Business Cycle Interdependence," *Journal of International Economics* 102: 110-127.

Ferrara, Laurent, and Clément Marsilli (2019). "Nowcasting Global Economic Growth: A Factor-Augmented Mixed-Frequency Approach," *World Economy* 42(3): 846-875.

Foroni, Claudia, and Massimiliano Marcellino (2014). "A Comparison of Mixed Frequency Approaches for Nowcasting Euro Area Macroeconomic Aggregates," *International Journal of Forecasting* 30(3): 554-568.

Foroni, Claudia, Massimiliano Marcellino, and Christian Schumacher (2015). "U-MIDAS: MIDAS Regressions with Unrestricted Lag Polynomials," *Journal of the Royal Statistical Society – Series A* 178(1): 57-82.

Foroni, Claudia, Massimiliano Marcellino, and Dalibor Stevanović (2020). "Forecasting the Covid-19 Recession and Recovery: Lessons from the Financial Crisis," CEPR Discussion Paper 15114.

Funishima, Yoshito (2020). "Global Economic Activity Indexes Revisited," *Economics Letters* 193: 1-3.

Ghysels, Eric, Arthur Sinko, and Rossen Valkanov (2007). "MIDAS Regressions: Further Results and New Directions," *Econometric Reviews* 26: 53-90.

Giannone, Domenico, Lucrezia Reichlin, and David Small (2008). "Nowcasting: The Real-Time Informational Content of Macroeconomic Data," *Journal of Monetary Economics* 55(4): 665-676.

Golinelli, Roberto, and Giuseppe Parigi (2014). "Tracking World Trade and GDP in Real Time," *International Journal of Forecasting* 30: 847-862.

Hamilton, James D. (2019). "Measuring Global Economic Activity," *Journal of Applied Econometrics*, forthcoming.

Kilian, Lutz (2009). "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review* 99(3): 1053-1069.

Kilian, Lutz (2019). "Measuring Global Economic Activity: Do Recent Critiques Hold Up to Scrutiny?" *Economics Letters* 178: 106-110.

Kilian, Lutz, and Xiaoqing Zhou (2018). "Modeling Fluctuations in the Global Demand for Commodities," *Journal of International Money and Finance* 88: 54-78.

Kuzin, Vladimir, Massimiliano Marcellino, and Christian Schumacher (2011). "Midas vs. Mixed-Frequency VAR: Nowcasting GDP in the Euro Area," *International Journal of Forecasting* 27: 529-542.

Marcellino, Massimiliano, and Christian Schumacher (2010). "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP," *Oxford Bulletin of Economics and Statistics* 72(4): 518-550.

Ravazzolo, Francesco, and Joaquin Vespignani (2020). "World Steel Production: A New Monthly Indicator of Global Real Economic Activity," *Canadian Journal of Economics* 53(2): 743-766.

Rossiter, James (2010). "Nowcasting the Global Economy," Bank of Canada Discussion Paper 2010-12.

Schorfheide, Frank, and Dongho Song (2020). "Real-Time Forecasting with a (Standard) Mixed-Frequency VAR during a Pandemic," University of Pennsylvania, mimeo.

Schumacher, Christian (2016). "A Comparison of MIDAS and Bridge Equations," *International Journal of Forecasting* 32: 257-270.

Schumacher, Christian, and Jörg Breitung (2008). "Real-time Forecasting of German GDP Based on a Large Factor Model with Monthly and Quarterly Data," *International Journal of Forecasting* 24(3): 386-398.

Stock, James H., and Mark W. Watson (2002). "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business and Economic Statistics* 20(2): 147-162.

Stratford, Kate (2013). "Nowcasting World GDP and Trade Using Global Indicators," *Bank of England Quarterly Bulletin* 53(3): 233-242.

Timmermann, Allan (2006). "Forecast Combinations," in: Graham Elliott, Clive W.J. Granger, and Allan Timmermann (eds.), *Handbook of Economic Forecasting*, Volume 1, Amsterdam: North-Holland, 135-196.

West, Kenneth D., and Ka-Fu Wong (2014). "A Factor Model for Co-movements of Commodity Prices," *Journal of International Money and Finance* 42: 289-309.

Table 1. Monthly Indicators of Global Real Economic Activity and Underlying Disaggregated Data

Global Economic Activity Indicator	Components	Transformation	Data delay	Nowcast rule	Data source	Start date
World industrial production index (WIP)	Industrial production of OECD, Brazil, China, India, Indonesia, the Russian Federation and South Africa aggregated as described in Baumeister and Hamilton (2019)	First log difference	2	AG	BH	1958.1
Global steel production factor	Crude steel production, US	Growth rates computed as first log differences and missing observations filled with EM algorithm	1	AG	WSA	1968.1
	Crude steel production, Japan		1	AG	WSA	1968.1
	Crude steel production, EU and other reporting countries (29 in total) (SA)		1	AG	WSA	1968.1
	Crude steel production, China (SA)		1	AG	WSA	1990.1
	Crude steel production, Eastern Europe		1	AG	WSA	1990.1
	Crude steel production, Middle East		1	AG	WSA	1990.1
	Crude Steel production, Russia and Ukraine		1	AG	WSA	1992.1
Kilian index (REA)	Log of the nominal shipping cost index calculated as described in Hamilton (2019)	Deflated with U.S. CPI and linearly detrended (recursively)	1	AG	JDH, FRED	1968.1
Real commodity price factor	Aluminum	Nominal dollar prices deflated with U.S. CPI and growth rates computed as first log differences	1	AG	WB, FRED	1972.5
	Barley		1	AG	WB, FRED	1960.1
	Beef		1	AG	WB, FRED	1960.1
	Coffee, Arabica		1	AG	WB, FRED	1973.1
	Coffee, Robusta		1	AG	WB, FRED	1973.1
	Copper		1	AG	WB, FRED	1964.1
	Cotton, A Index		1	AG	WB, FRED	1971.1
	Lead		1	AG	WB, FRED	1960.1
	Logs, Malaysian		1	AG	WB, FRED	1971.5

	Maize		1	AG	WB, FRED	1972.1
	Nickel		1	AG	WB, FRED	1973.1
	Palm Oil		1	AG	WB, FRED	1964.1
	Rice, Thai 5%		1	AG	WB, FRED	1960.1
	Rubber, SGP/MYS		1	AG	WB, FRED	1960.1
	Sawnwood, Malaysian		1	AG	WB, FRED	1971.5
	Soybeans		1	AG	WB, FRED	1973.1
	Soybean meal		1	AG	WB, FRED	1973.1
	Soybean oil		1	AG	WB, FRED	1971.1
	Sugar, US		1	AG	WB, FRED	1973.1
	Sugar, world		1	AG	WB, FRED	1973.1
	Tin		1	AG	WB, FRED	1960.1
	Wheat, US HRW		1	AG	WB, FRED	1973.1
	Zinc		1	AG	WB, FRED	1973.1
Global economic conditions indicator	World industrial production index	First log difference	2	AG	BH	1958.1
	Conference Board Leading Economic Index	First log difference	1	AG	DS	1973.1
	Consumer Confidence Index	First log difference	1	RW	OECD MEI	1974.1
	Real copper price	First log difference	1	AG	WB, FRED	1964.1
	Real trade-weighted U.S. Dollar index: broad	First log difference	0		FRED	1973.1
	MSCI World Stock Price Index	Year-on-year growth rates	0		GFD	1972.1
	Excess returns on Fama-French portfolio: transportation	Year-on-year growth rates	2	RW	FF	1973.1
	Passenger car registrations	First log difference	8	AG	OECD MEI	1973.1
	Total vehicle miles traveled	First log difference	2	AG	FRED	1973.1
	Geopolitical Risk Index	First log difference	0		CI	1973.1
	Long-run oil price uncertainty	Level	0		B	1989.4
	University of Michigan Index of Consumer Expectations	First log difference	0		UMS	1978.1

Spread between long-run and short-run oil price expectations	Level	0		B	1988.11
Oceanic Niño Index	Level	2	RC	NOAA	1973.1
Residential Energy Demand Temperature Index	Level	1	RW	NOAA	1973.1
Energy production and electricity distribution	First log difference	3	AG	FRED, CEIC	1991.1

NOTES: SA indicates that the series has been seasonally adjusted using the X13-ARIMA procedure; all other series are either available in seasonally-adjusted form or do not contain a seasonal component. The delay in data release is expressed in months. Nowcasts are based on the average growth rate (AG), the most recent change (RC), or the assumption of no change (RW). The codes for the data sources are as follows: B – Bloomberg, BH – Baumeister and Hamilton (2019) update of the discontinued OECD+6 series (https://sites.google.com/site/cjsbaumeister/OECD_plus6_industrial_production.xlsx?attredirects=0&d=1), CEIC (ceicdata.com), CI – Caldara and Iacoviello (2018) (https://www.matteoiacoviello.com/gpr.htm), DS – Datastream, FF – Fama-French 17 Industry Portfolios (average value-weighted returns) (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), FRED – Federal Reserve Bank of St. Louis Economic Database, GFD – Global Financial Database, JDH – Hamilton (2019) (http://econweb.ucsd.edu/~jhamilto/shipping_costs.xlsx), NOAA – U.S. National Oceanic and Atmospheric Administration, National Climatic Data Center (https://www.noaa.gov/), OECD – OECD Main Economic Indicators Database, UMS – Survey of Consumers, University of Michigan (http://www.sca.isr.umich.edu/), WB – World Bank Commodity Price Data, The Pink Sheet (http://pubdocs.worldbank.org/en/561011486076393416/CMO-Historical-Data-Monthly.xlsx), WSA – World Steel Association, Steel Statistical Yearbook (https://www.worldsteel.org/). The groupings for the crude steel production data comprise the following countries: EU and other reporting countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom, former Yugoslavia (now consisting of Bosnia-Herzegovina, Croatia, Macedonia, Serbia, and Slovenia), Canada, Argentina, Brazil, Chile, Mexico, Venezuela, Australia, India, Republic of Korea, South Africa, and Taiwan; Eastern Europe includes the Czech Republic, Hungary, Poland, and the Slovak Republic; Middle East includes Egypt, Iran, and Saudi Arabia. Oil price uncertainty is defined as realized volatility and is calculated as follows: $vol_p^m = 100 * \sqrt{\frac{252}{n} * (\sum_{d=1}^{n} (\Delta f_d^m)^2)}$ where Δf_d^m is the daily return for the oil futures contract on day d in month m computed as the log difference between the futures price on day d and $d-1$, and n is the number of trading days in a given month. Oil price expectations are proxied by log futures prices. Long-run refers to futures with 12-month maturity and short-run to futures with 3-month maturity. The start date indicates the earliest available observation. If data are available at a frequency higher than monthly, we obtain monthly data by averaging.

Table 2. Recursive MSPE Ratios Relative to AR(1) Forecast of Quarterly World Real GDP Growth
Evaluation Period: 1990Q1-2018Q4

Quarterly horizon	**World IP index (WIP)**		**Global steel production factor**		**Kilian index (REA)**		**Real commodity price factor**		**Global economic conditions (GECON)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.105	1.014	**0.956**	**0.929**	1.023	1.180	**0.925**	**0.925**	**0.661****	**0.668***
1/3	**0.927**	**0.922**	1.010	1.010	1.040	1.172	**0.860**	**0.888**	**0.758***	**0.775***
2/3	1.010	1.010	**0.951**	**0.951**	1.055	1.114	**0.959**	**0.960**	**0.877***	**0.847***
1	1.120	1.127	1.004	1.014	1.036	**0.960**	**0.958**	**0.975**	**0.885***	**0.911**
2	1.016	1.012	1.010	1.010	1.084	1.025	**0.999**	**0.999**	**0.905**	**0.927**
3	1.004	**0.982**	**0.974**	**0.974**	1.185	1.142	**0.977**	**0.978**	**0.901**	**0.920**
4	1.020	**0.993**	**0.978**	**0.978**	1.308	1.290	**0.993**	**0.992**	**0.893**	**0.901**
6	1.037	1.036	1.007	1.007	1.477	1.475	1.051	1.051	**0.869**	**0.874**
8	1.045	1.053	**0.993**	1.004	1.575	1.612	1.079	1.079	**0.905**	**0.912**

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among all global indicators and blue indicates whether the MIDAS or the U-MIDAS model performs better.

Table 3. The Role of the Great Recession for the Forecasting Performance of the MIDAS Models for Quarterly World Real GDP Growth

		Quarterly horizon								
		0	1/3	2/3	1	2	3	4	6	8
		(a) Evaluation period: 1990Q1-2007Q3								
(1)	World IP index (WIP)	1.163	1.056	1.241	1.101	1.109	1.095	1.082	1.057	1.038
(2)	Global steel production factor	1.208	1.177	1.168	1.158	1.185	1.077	1.029	1.023	**0.984**
(3)	Kilian index (REA)	1.023	1.026	1.024	1.025	1.046	1.105	1.215	1.478	1.671
(4)	Real commodity price factor	**0.991**	**0.954**	1.002	1.011	1.085	1.048	**0.991**	**0.966**	**0.986**
(5)	Global economic conditions (GECON)	**0.871***	**0.916**	**0.946**	**0.946**	**0.963**	**0.955**	**0.943**	**0.864**	**0.875**
		(b) Evaluation period: 1990Q1-2018Q4 excluding observations from 2007Q4-2009Q2								
(6)	World IP index (WIP)	1.144	1.057	1.228	1.095	1.089	1.070	1.067	1.052	1.033
(7)	Global steel production factor	1.184	1.142	1.130	1.137	1.158	1.053	1.023	1.019	**0.988**
(8)	Kilian index (REA)	1.006	1.011	1.011	1.008	1.029	1.071	1.157	1.362	1.535
(9)	Real commodity price factor	1.022	**0.977**	1.018	1.046	1.137	1.086	1.017	**0.967**	**0.976**
(10)	Global economic conditions (GECON)	**0.864****	**0.911**	**0.943**	**0.955**	**0.962**	**0.955**	**0.946**	**0.885**	**0.897**

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test.

Table 4. The Role of Pooling for the Accuracy of Recursive Forecasts of Quarterly World Real GDP Growth
Evaluation Period: 1990Q1-2018Q4

	Pooling Across Indicators				Pooling Across All Models	
Quarterly horizon	Inverse MSPE weights		Equal weights		Inverse MSPE weights	Equal weights
	MIDAS	U-MIDAS	MIDAS	U-MIDAS		
0	**0.790****	**0.788****	**0.838****	**0.836****	**0.788****	**0.836****
1/3	**0.808****	**0.825****	**0.844****	**0.865****	**0.816****	**0.854****
2/3	**0.873***	**0.863***	**0.897**	**0.893***	**0.867***	**0.894***
1	**0.916***	**0.877**	**0.940**	**0.907**	**0.892***	**0.921**
2	**0.918***	**0.905***	**0.935**	**0.921**	**0.911***	**0.927**
3	**0.931***	**0.910***	**0.950**	**0.927**	**0.919***	**0.938**
4	**0.952**	**0.930***	**0.973**	**0.949**	**0.940***	**0.960**
6	**0.978**	**0.968**	1.009	**0.999**	**0.972**	1.004
8	**0.989**	**0.980**	1.027	1.028	**0.984**	1.027

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test.

Table 5. Recursive MSPE Ratios Relative to AR(1) Forecasts of Quarterly Real GDP Growth in Country Blocs
Evaluation Period: 1990Q1-2018Q4

Quarterly horizon	**World IP index (WIP)**		**Global steel production factor**		**Kilian index (REA)**		**Real commodity price factor**		**Global economic conditions (GECON)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) OECD economies									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.121	1.134	**0.856**	**0.859**	1.025	1.210	**0.988**	**0.996**	**0.614****	**0.636***
1/3	1.107	**0.973**	**0.978**	**0.978**	1.026	1.158	**0.939**	**0.954**	**0.738***	**0.747***
2/3	1.113	1.113	**0.930**	**0.930**	1.031	1.116	1.024	1.025	**0.830****	**0.828***
1	1.108	1.122	1.021	1.040	**0.972**	**0.890**	**0.984**	1.031	**0.881**	**0.910**
2	**0.970**	**0.972**	1.043	1.044	**0.954**	**0.908**	1.003	1.058	**0.819****	**0.845****
3	**0.998**	1.021	1.003	1.008	1.012	**0.988**	1.000	1.020	**0.797***	**0.822***
4	1.052	1.052	**0.980**	**0.994**	1.073	1.090	1.002	1.015	**0.797***	**0.811***
6	1.065	1.062	**0.994**	**0.995**	1.139	1.142	1.024	1.033	**0.816***	**0.819***
8	1.046	1.040	**0.995**	1.001	1.133	1.135	1.040	1.046	**0.829***	**0.835***
	(b) G7 countries									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.107	1.053	**0.918**	**0.938**	1.022	1.160	**0.982**	**0.997**	**0.644****	**0.672****
1/3	**0.978**	**0.913**	1.012	1.016	1.017	1.136	**0.950**	**0.968**	**0.740****	**0.772***
2/3	**0.947**	**0.972**	**0.944**	**0.945**	1.025	1.103	1.024	1.031	**0.874**	**0.864**
1	1.027	1.008	1.015	1.028	**0.996**	**0.957**	1.005	1.064	**0.880**	**0.896**
2	**0.959**	**0.965**	1.047	1.044	**0.948**	**0.952**	1.038	1.066	**0.822****	**0.840****
3	**0.965**	**0.966**	**0.974**	**0.972**	**0.986**	**0.959**	**0.999**	1.011	**0.773****	**0.787****
4	**0.976**	**0.977**	**0.930***	**0.931***	1.046	**0.999**	**0.996**	**0.989**	**0.769****	**0.780****
6	1.014	1.020	**0.940****	**0.940****	1.092	1.037	1.013	1.019	**0.761****	**0.770***
8	1.044	1.045	1.003	**0.990**	1.083	1.052	1.036	1.040	**0.780****	**0.793****

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among all global indicators and blue indicates whether the MIDAS or the U-MIDAS model performs better.

Table 6. Recursive MSPE Ratios Relative to AR(1) Forecasts of Quarterly Real GDP Growth in Large Economies
Evaluation Period: 1990Q1-2018Q4

Quarterly horizon	**World IP index (WIP)**		**Global steel production factor**		**Kilian index (REA)**		**Real commodity price factor**		**Global economic conditions (GECON)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) Euro Area									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.028	1.028	**0.930**	**0.935**	1.040	1.293	1.012	1.036	**0.763***	**0.763***
1/3	**0.857**	**0.853**	**0.861***	**0.858***	1.046	1.258	**0.965**	1.009	**0.841**	**0.876**
2/3	**0.872**	**0.875**	**0.956**	**0.966**	1.043	1.111	1.039	1.057	**0.928**	**0.940**
1	1.072	1.126	**0.972**	**0.966**	1.035	**0.994**	**0.946**	**0.979**	**0.899**	**0.923**
2	1.094	1.104	**0.909***	**0.911***	1.052	**0.992**	**0.978**	**0.990**	**0.910**	**0.959**
3	**0.982**	1.020	**0.932**	**0.937**	1.063	1.005	1.016	1.023	**0.932**	**0.990**
4	**0.985**	1.003	**0.960**	**0.984**	1.106	1.069	1.006	1.016	**0.937**	**0.963**
6	1.005	1.015	**0.969***	**0.975**	1.178	1.159	1.031	1.034	**0.901**	**0.914**
8	1.018	1.023	**0.993**	1.004	1.144	1.138	1.018	1.024	**0.851****	**0.865****
	(b) United States									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	**0.972**	**0.995**	**0.933**	**0.933**	1.044	1.089	1.062	1.110	**0.626****	**0.629****
1/3	1.073	1.076	1.015	1.015	1.015	1.015	1.037	1.081	**0.721***	**0.726***
2/3	1.086	1.097	**0.980**	**0.986**	1.008	1.015	1.076	1.092	**0.817****	**0.808****
1	1.015	1.034	1.023	1.023	1.010	1.090	1.015	1.022	**0.848****	**0.849****
2	**0.995**	1.018	1.033	1.052	1.016	1.051	1.069	1.075	**0.892**	**0.899**
3	**0.997**	1.023	1.046	1.055	1.029	1.049	1.053	1.066	**0.844***	**0.843***
4	1.055	1.047	1.040	1.041	1.105	1.132	1.037	1.043	**0.817***	**0.820***
6	1.053	1.060	1.024	1.034	1.155	1.161	1.060	1.031	**0.833***	**0.834***
8	1.014	1.024	1.022	1.016	1.147	1.163	1.064	1.039	**0.868***	**0.870**

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among all global indicators and blue indicates whether the MIDAS or the U-MIDAS model performs better.

Table 7. Recursive MSPE Ratios Relative to AR(1) Forecasts of Quarterly Real GDP Growth in Small Open Economies
Evaluation Period: 1990Q1-2018Q4

Quarterly horizon	**World IP index (WIP)**		**Global steel production factor**		**Kilian index (REA)**		**Real commodity price factor**		**Global economic conditions (GECON)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) Canada									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.012	1.013	1.072	1.072	1.038	1.250	1.098	1.083	**0.840**	**0.819**
1/3	1.098	1.091	**0.987**	1.011	1.071	1.237	1.049	1.102	**0.883**	**0.904**
2/3	1.050	1.053	**0.982**	**0.987**	1.069	1.249	**0.929**	1.012	**0.840**	**0.840**
1	**0.951**	**0.969**	1.001	1.047	1.054	1.189	**0.925**	**0.987**	**0.851**	**0.851**
2	1.001	1.014	1.040	1.041	1.123	1.191	**0.927**	**0.980**	**0.859**	**0.865**
3	1.025	1.015	1.065	1.059	1.165	1.246	**0.941**	**0.983**	**0.853**	**0.856**
4	1.057	1.113	1.059	1.045	1.236	1.284	**0.991**	**0.990**	**0.834**	**0.834**
6	1.078	1.142	1.058	1.064	1.339	1.340	1.033	1.016	**0.817***	**0.813***
8	1.035	1.072	1.036	1.007	1.413	1.402	1.053	1.023	**0.906**	**0.908**
	(b) Norway									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.043	1.045	1.004	**0.999**	1.080	1.104	1.065	1.061	**0.960**	**0.979**
1/3	1.010	1.030	1.030	1.010	1.088	1.125	1.053	1.052	**0.950***	**0.965**
2/3	**0.998**	**0.995**	1.014	1.044	1.075	1.123	1.045	1.053	**0.936****	**0.946***
1	1.021	1.025	1.056	1.042	1.078	1.131	1.126	1.142	**0.939***	**0.962**
2	1.023	1.020	1.051	1.005	1.104	1.134	1.078	1.071	**0.978**	1.014
3	1.042	1.048	1.037	1.037	1.110	1.089	1.080	1.089	**0.982**	**0.992**
4	1.018	1.024	1.006	1.012	1.183	1.188	1.095	1.115	**0.980**	**0.992**
6	1.007	1.004	1.033	1.025	1.342	1.381	1.036	1.078	1.003	1.010
8	1.017	1.011	1.001	1.042	1.528	1.531	1.050	1.113	1.024	1.059

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among all global indicators and blue indicates whether the MIDAS or the U-MIDAS model performs better.

Table 8. Recursive MSPE Ratios Relative to AR(1) Forecasts of Quarterly Real GDP Growth in Small Open Economies
Evaluation Period: 1990Q1-2018Q4

Quarterly horizon	**World IP index (WIP)**		**Global steel production factor**		**Kilian index (REA)**		**Real commodity price factor**		**Global economic conditions (GECON)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) United Kingdom									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	1.060	1.068	**0.998**	1.020	1.025	1.264	1.023	1.061	**0.860**	**0.891**
1/3	**0.985**	**0.983**	**0.929**	**0.919**	1.018	1.173	1.027	1.046	**0.915**	**0.946**
2/3	1.008	1.012	**0.987**	1.016	1.026	1.079	1.112	1.126	**0.957**	**0.964**
1	1.035	1.035	1.064	1.073	1.000	1.031	1.060	1.129	**0.978**	1.019
2	**0.977**	1.003	1.100	1.118	1.002	1.034	1.091	1.115	**0.965**	1.007
3	**0.949**	**0.958**	1.098	1.117	1.026	1.018	1.110	1.063	**0.932**	**0.939**
4	**0.960**	**0.984**	1.098	1.103	1.056	1.063	1.079	1.066	**0.933**	**0.947**
6	1.087	1.058	1.064	1.077	1.166	1.165	1.008	1.028	**0.906**	**0.895**
8	1.093	1.068	1.020	1.017	1.277	1.288	1.038	1.023	**0.994**	**0.990**
	(b) Japan									
	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS	MIDAS	U-MIDAS
0	**0.994**	1.068	**0.975**	**0.987**	1.042	1.163	**0.999**	**0.987**	**0.874***	**0.874***
1/3	1.005	**0.897**	1.016	1.018	1.044	1.189	1.006	1.018	**0.874***	**0.886***
2/3	**0.895**	**0.882**	**0.973**	**0.975**	1.042	1.086	1.021	**0.975**	**0.913**	**0.922**
1	**0.989**	1.018	**0.941**	**0.950**	1.015	**0.952**	**0.995**	**0.950**	**0.949**	**0.975**
2	**0.972**	1.035	1.015	1.019	1.016	1.029	1.054	1.019	**0.979**	**0.992**
3	**0.974**	**0.971**	**0.976**	**0.987**	1.021	1.021	1.016	**0.987**	1.015	1.008
4	1.012	**0.994**	**0.970**	**0.980**	1.020	1.007	1.042	**0.980**	1.013	**0.999**
6	1.037	1.033	**0.991**	1.004	1.041	1.017	1.078	1.004	**0.970**	**0.973**
8	1.039	1.054	**0.969****	**0.984**	1.086	1.093	1.057	**0.984**	**0.946**	**0.958**

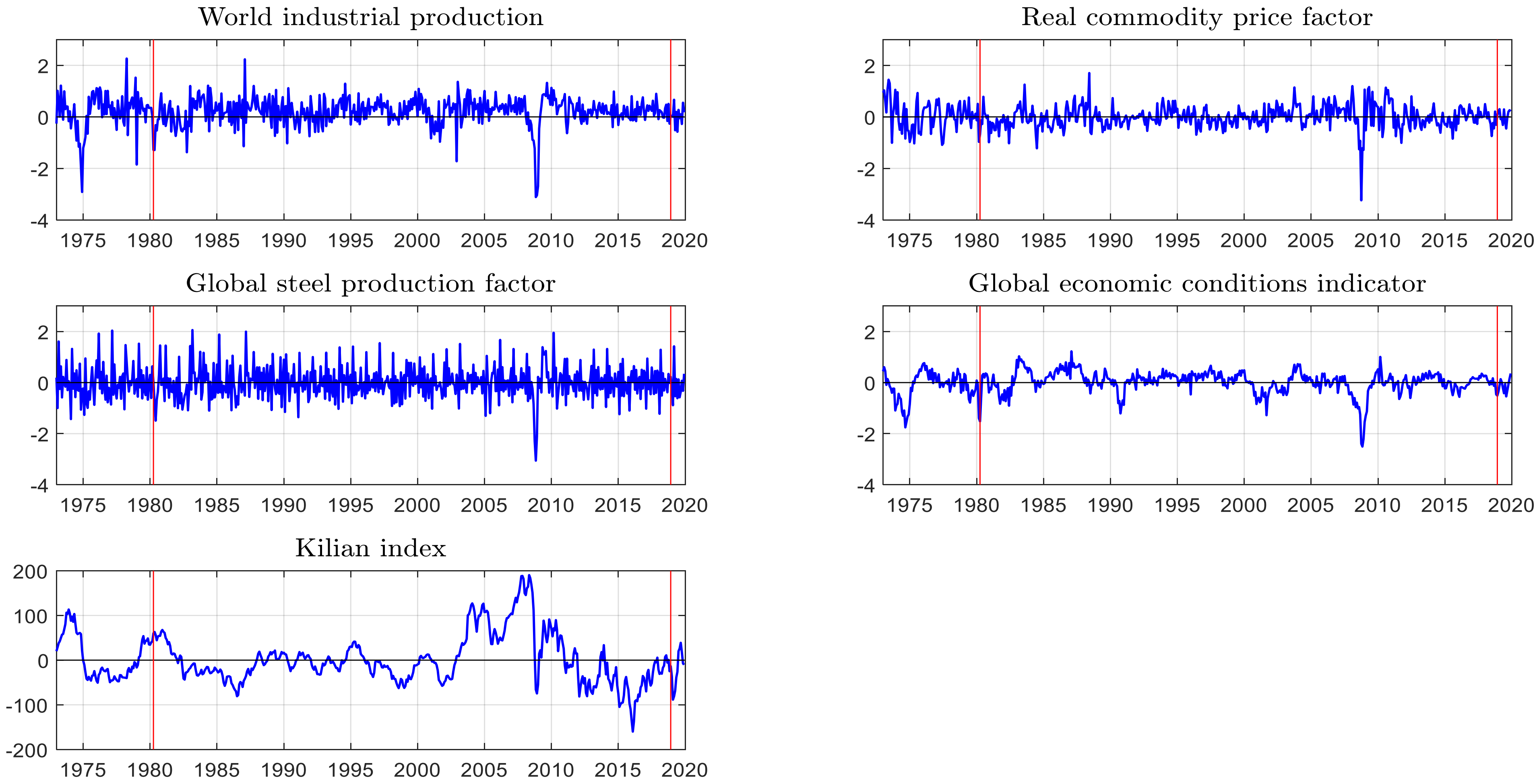
NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among all global indicators and blue indicates whether the MIDAS or the U-MIDAS model performs better.

Table 9. The Role of Real-Time Vintages for the Forecasting Performance of the MIDAS Model with the GECON Indicator

		Quarterly horizon								
		0	1/3	2/3	1	2	3	4	6	8
	United States	(a) Evaluation period: 1990Q1-2018Q4								
(1)	Final vintage	**0.626****	**0.721***	**0.817****	**0.848****	**0.892**	**0.844***	**0.817***	**0.833***	**0.868***
(2)	Real-time vintages	**0.617****	**0.724***	**0.788***	**0.826***	**0.824***	**0.812**	**0.789***	**0.819***	**0.863***
		(b) Evaluation period: 2000Q1-2018Q4								
(3)	Final vintage	**0.594***	**0.694***	**0.816***	**0.864***	**0.902**	**0.828**	**0.788**	**0.814**	**0.839**
(4)	Real-time vintages	**0.588***	**0.707***	**0.858***	**0.866**	**0.896**	**0.889**	**0.876**	**0.880**	**0.960**
	Canada									
(5)	Final vintage	**0.802**	**0.842**	**0.813**	**0.818**	**0.793**	**0.775**	**0.771**	**0.882**	1.002
(6)	Real-time vintages	**0.830**	**0.858**	**0.788**	**0.791**	**0.803**	**0.798**	**0.797**	**0.879**	**0.994**
	Norway									
(7)	Final vintage	**0.903****	**0.888****	**0.862****	**0.868****	**0.956**	**0.973**	**0.984**	1.033	1.024
(8)	Real-time vintages	**0.912****	**0.915****	**0.881****	**0.889****	**0.954**	**0.935**	**0.905***	1.031	1.009
	United Kingdom									
(9)	Final vintage	**0.783***	**0.852***	**0.913**	**0.948**	**0.950**	**0.906**	**0.899**	**0.911**	**0.962**
(10)	Real-time vintages	**0.743***	**0.775****	**0.847***	**0.883***	**0.855***	**0.853**	**0.856**	**0.883**	**0.967**
	Japan									
(11)	Final vintage	**0.814***	**0.823***	**0.863**	**0.909**	**0.977**	1.043	1.072	1.083	1.118
(12)	Real-time vintages	**0.878**	**0.878**	**0.923**	**0.966**	1.030	1.103	1.125	1.114	1.111

NOTES: Boldface indicates improvements relative to AR(1) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test.

Figure 1. Alternative Monthly Indicators of Global Real Economic Activity, 1973.1-2019.12



NOTES: The vertical red lines indicate the estimation and evaluation periods used in the main analysis (1980M4-2018M12). World industrial production is shown in month-on-month growth rates. The real commodity price factor is extracted from a balanced panel of monthly growth rates of industrial and agricultural commodity prices deflated by the U.S. CPI. The global steel production factor is extracted from a cross-section of monthly growth rates of crude steel production data for individual and groups of countries. The global economic conditions indicator is the first principal component extracted from the 16 variables listed in Table 1. The Kilian index refers to the linearly detrended real shipping cost index.

Figure 2. Cumulative Out-of-Sample Mean-Squared Prediction Errors for Global Growth Forecasts Across Global Indicators
Evaluation Period: 1990Q1-2018Q4

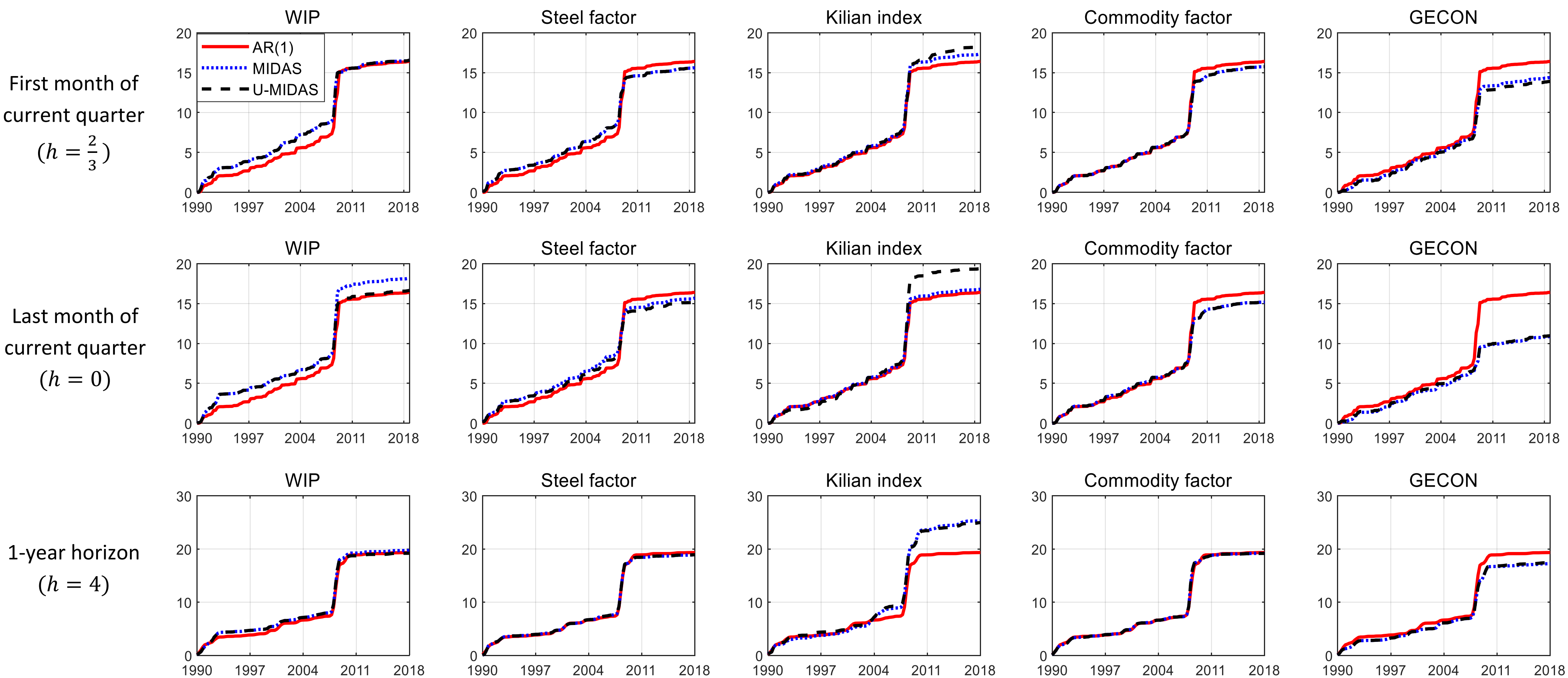
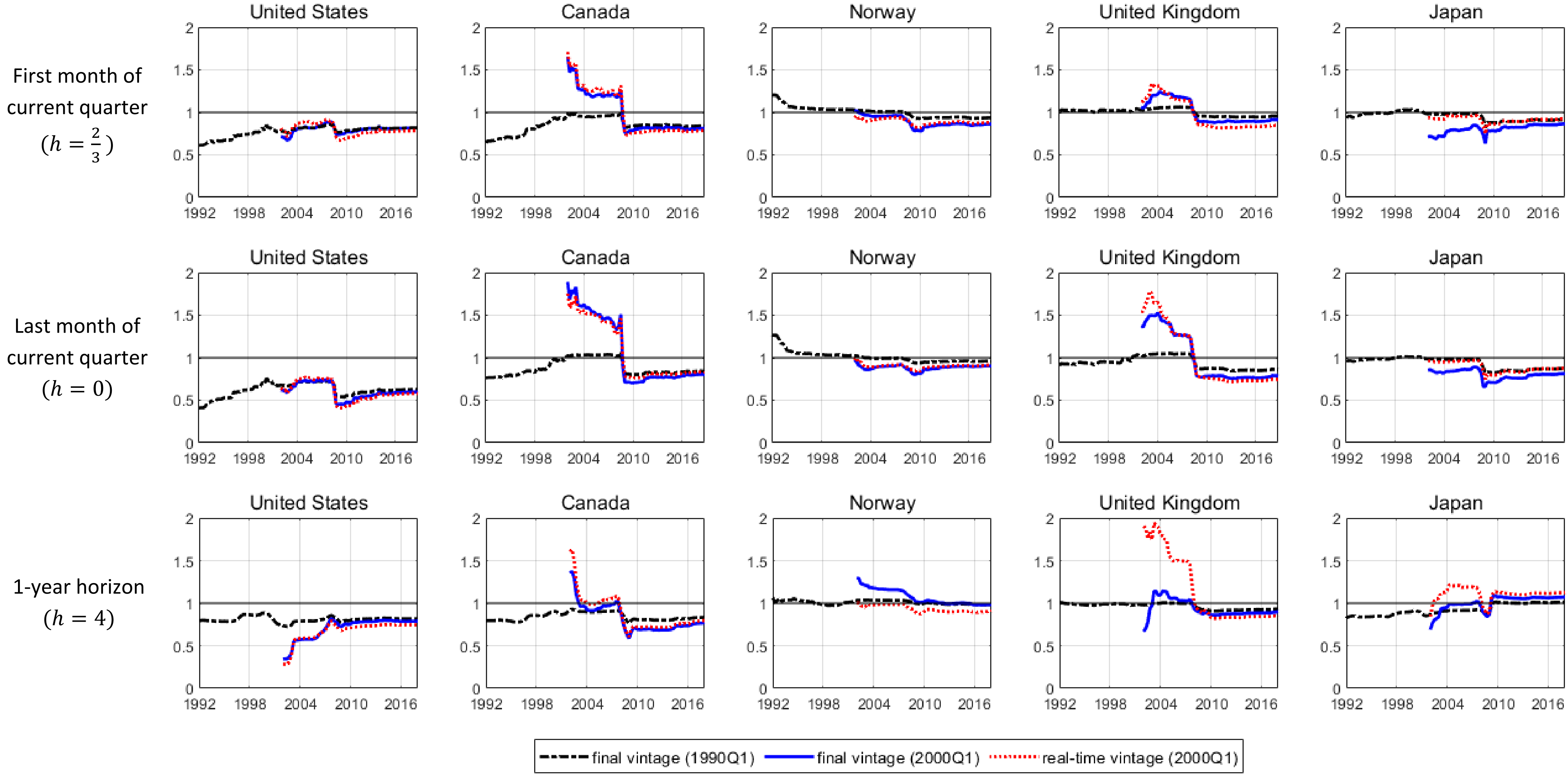


Figure 3. Real-Time vs. Revised Recursive MSPE Ratios for Growth Forecasts Across Countries for the MIDAS Model with the Global Economic Conditions Indicator



NOTES: A ratio below 1 indicates an improvement relative to the AR(1) forecast. The plots show the evolution of the recursive MSPE ratios over time from 1992Q1 onward for the evaluation period 1990Q1-2018Q4 and from 2002Q1 onward for the evaluation period 2000Q1-2018Q4 to allow the MSPE ratio to stabilize.

Figure 4. The Evolution of Monthly Nowcasts during the COVID-19 Pandemic and their Decomposition