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Forecasting U.S. Economic Growth in Downturns Using Cross-Country Data*

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Abstract

To examine whether including economic data on other countries could improve the forecast of U.S. GDP growth, we construct a large data set of 77 countries representing over 90 percent of global GDP. Our benchmark model is a dynamic factor model using U.S. data only, which we extend to include data from other countries. We show that using cross-country data produces more accurate forecasts during the global financial crisis period. Based on the vintage data on August 6, 2020, our benchmark model forecasts U.S. real GDP growth in 2020Q3 to be -6.9% (year-over-year rate) or 14.9% (quarter-over-quarter annualized rate), whereas the forecast is revised upward to -6.1% (yoy) or 19.1% (qoq) when cross-country data are used. These examples suggest that U.S. data may fail to capture the spillover effects of other countries in downturns. However, we show that foreign variables are much less useful in normal times.

Keywords: forecasting, dynamic factor model, GDP growth, cross-country data, global financial crisis, Covid-19

JEL codes: C32, C38, C53, C55, E32, E37

*The views in the paper are strictly those of the authors and do not necessarily reflect those of the New Zealand Treasury, the New Zealand Government, the Federal Reserve Bank of Kansas City or the Federal Reserve System. All remaining errors are ours. The authors have no conflict of interest to declare.

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1 Introduction

The Covid-19 pandemic has created tremendous downward pressure on economic activity and revived interest in forecasting economic growth during severe downturns. However, forecasting in downturns has been particularly difficult. One important reason is that the dynamics of the economy is different in good and bad times. We notice that most forecasting models use only domestic data; so we explore in this paper whether including data from other countries could improve forecasts of US growth in economic downturns.

The intuition why cross-country data may help is straightforward. The globalization process in the past decades has made countries more and more interdependent, meaning that economic fluctuations in one country can significantly spill over into the other countries through the trade channel or others. When one country is in a downturn, the other countries might be growing as usual, thus their demand of goods and services can provide the country in trouble with a buffer. Even though all countries are hit by a global shock, they may differ in the timing of being hit, the length of the recession, and the timing of recovering. As a result, when forecasting a country's growth, it is worth taking into account other countries' economic conditions.

We construct a large data set covering 77 countries that represent more than 90 percent of world GDP. The data set, which starts in 2000, includes a wide range of economic indicators that are commonly used to measure growth momentum. As the benchmark, we employ a popular dynamic factor model that uses US data only. Then we consider a few extensions using the cross-country data we collect. In these models, US GDP growth is assumed to depend on an unobserved global factor common to all variables. This factor is supposed to capture changes in economic fundamentals, including the spillover effects of foreign countries. Using cross-country data may deliver a better estimate of the factor by augmenting the information set. This is particularly important in downturns. First, economic conditions usually evolve very quickly in bad times, so additional information is more valuable than in normal times. Second, the spillover effects might be larger in bad times, and cross-country data can directly capture such effects. For example, it is well recognized that China's soaring demand during the global financial crisis (GFC) boosted economic growth across the world.

We apply the models considered in the present paper to forecast US economic growth in the GFC, the current recession generated by the Covid-19 pandemic, and the normal period from 2018-2019. During the GFC and the pandemic, some major economies recovered earlier than the US. As a result, any forecast based on US variables only may fail to capture the positive spillover effects of other countries, and thus overestimate the severity of the recessions. This conjecture is supported by our results. We show that our benchmark model overestimates the drop in economic activity in 2009Q2 and 2009Q3, and the forecast errors are partly corrected when cross-country data are used. However, our results show that using cross-country data does not significantly reduce forecast errors in 2018-2019.

Applying our model to forecast U.S. growth in the current quarter (2020Q3), we find that, based on data ending on August 6, 2020, a forecast incorporating cross-country data is about 4 percentage points stronger than a forecast using only US variables. This likely reflects the different recovery paces between the United States and other countries due to different Covid-19 developments. Our analysis emphasizes the value of incorporating economic data from other countries to forecast US GDP growth during volatile times.

Our contributions to the literature are three-fold. First, to the best of our knowledge, this paper is the first to use cross-country data in a dynamic factor model to forecast GDP growth. In recent years, dynamic factor models have been applied to forecast GDP in many countries in addition to the US, including Germany (Schumacher and Breitung, 2008), France (Barhoumi, Darné and Ferrara, 2010), the Netherlands (De Winter, 2011), Norway (Aastveit and Trovik, 2012), New Zealand (Matheson, 2010), Indonesia (Luciani et al., 2018), the Czech Republic (Arnoštová et al., 2011), Belgium (de Antonio Liedo, 2014), Turkey (Modugno, Soybilgen and Yazgan, 2016), and China (Yiu and Chow, 2010, Giannone, Agrippino and Modugno, 2013). For a survey, see Bańbura et al. (2013). However, these studies use only domestic data. Second, we show that using cross-country data leads to better forecasting performance than using domestic data during economic downturns, however, the gain in normal times tends to be very small. Third, we construct a large cross-country data set which can be updated at a daily frequency and used in other research.

The remainder of the paper is organized as follows. Section 2 describes our methodology. Section 3 describes our data sources. Section 4 reports results. Section 5 concludes.

2 Methodology

Our benchmark model basically follows the dynamic factor model (DFM) that the Federal Reserve Bank of New York uses to produce their nowcast of US real GDP growth. Suppose a few monthly macroeconomic variables $(y_{1,t}, \ldots, y_{n,t})$ that are standardized to mean 0 and unit variance are driven by some unobserved common factors $(f_{1,t}, \ldots, f_{r,t})$ but also have their idiosyncratic components, then the DFM has the following representation:

$$y_{i,t} = \lambda_{i,1} f_{1,t} + \cdots + \lambda_{i,r} f_{r,t} + e_{i,t}, \tag{2.1}$$

$$e_{i,t} = \rho_i e_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim i.i.d.N(0, \sigma^2_{\varepsilon_i}) \tag{2.2}$$

for $i = 1, \ldots, n$. $(\lambda_{i,1}, \ldots, \lambda_{i,r})$ are factor loadings for $y_{i,t}$. $e_{i,t}$ is the idiosyncratic error that is assumed to be uncorrelated with $(f_{1,t}, \ldots, f_{r,t})$ at all leads and lags, normally distributed and cross-sectionally uncorrelated, and follow an AR(1) process. To capture potential serial correlation, we model the dynamics of the factors as AR(1) processes as well:

$$f_{j,t} = \alpha_j f_{j,t-1} + u_{j,t}, \quad u_{j,t} \sim i.i.d.N(0, \sigma^2_{u_j}) \quad \text{for } j = 1, \ldots, r. \tag{2.3}$$

For variables that are not stationary, we transform them into year-on-year (yoy) growth rates. We do not transform variables into quarter-on-quarter (qoq) growth rates because some cross-country data are only available in yoy form. For quarterly variables $(x_{1,t}, \ldots, x_{k,t})$, including the real GDP growth, we assume that their unobserved monthly counterparts $(\tilde{x}_{1,t}, \ldots, \tilde{x}_{k,t})$ admit the same factor structure as the other monthly variables:

$$\tilde{x}_{l,t} = \lambda_{l,1} f_{1,t} + \cdots + \lambda_{l,r} f_{r,t} + e_{l,t}, \tag{2.4}$$

$$e_{l,t} = \rho_l e_{l,t-1} + \varepsilon_{l,t}, \quad \varepsilon_{l,t} \sim i.i.d.N(0, \sigma^2_{\varepsilon_l}) \tag{2.5}$$

for $l = 1, \ldots, k$. We assign quarterly values to the third month of each quarter, then using the following approximation:

$$x_{l,t} \approx \frac{1}{3}(\tilde{x}_{l,t} + \tilde{x}_{l,t-1} + \tilde{x}_{l,t-2}), \tag{2.6}$$

we can link the quarterly variable $x_{l,t}$ to factors through:

$$x_{l,t} = \frac{1}{3}[\Lambda_l, \Lambda_l, \Lambda_l][F_t, F_{t-1}, F_{t-2}]' + \frac{1}{3}(e_{l,t} + e_{l,t-1} + e_{l,t-2}) \tag{2.7}$$

where $\Lambda_l = [\lambda_{l,1}, \dots, \lambda_{l,r}]$ and $F_t = (f_{1,t}, \dots, f_{r,t})$. As a result, there are restrictions on factor loadings for quarterly variables.

In our benchmark model, we include the same US economic variables and specify the same block structure of factors as the New York Fed does. In addition to a global factor affecting all variables, there are also factors specific to subgroups of variables capturing local correlations. Specifically, there is a "soft" factor for survey data and two separate factors for real and labor variables. By nature, the real GDP growth is postulated to depend on both the global factor and the real factor. Figure 1 shows the variable names and the block structure of factors. Obviously, in the presence of factor blocks, we need to impose additional restrictions that some factor loadings are zero.

To explore the role of cross-country data in forecasting US economic growth, we extend our benchmark model by including economic variables of three country groups: China, emerging market economies excluding China (EME-excl-China), advanced economies excluding US (AE-excl-US). Different groups of countries are likely to have different growth paths. Each of these variables depends on the global factor in the benchmark model and a country group-specific factor. In particular, we consider five combinations of non-US variables that may help forecast US growth: (1) China, (2) China and EMEs excluding China, (3) AEs excluding US, (4) EMEs excluding China and AEs excluding US, and (5) EMEs (including China) and AEs excluding US. As a result, including the benchmark model, we have six competing models in total.

Factor models have been employed in macroeconomic forecasting for a long time; see Stock and Watson (2002), Marcellino, Stock and Watson (2003), Boivina and Ngb (2005), Forni et al. (2009) and D'Agostino and Giannone (2012) among others. The seminal work by Giannone, Reichlin and Small (2008) builds a framework based on dynamic factor models for nowcasting. They adapt the traditional large factor models to deal with the "ragged-edge" data problem due to nonsynchronous data releases. While Giannone, Reichlin and Small (2008) use a two-step procedure based on principal component analysis, Bańbura and Modugno (2014) develop a quasi-maximum likelihood estimation approach that has several advantages. First, it can deal with general pattern of missing data, including the non-synchronicity of data releases, mixed-frequency data sets, and data of different sample lengths. Second, it allows imposing restrictions on parameters. Last but not least, it is more efficient for small samples. As a result, we employ this approach for our estimation. We initialize the algorithm by estimating the factors based on principal components, then estimate parameters through OLS regressions. Given the estimated parameters, we use the Kalman smoother to update our estimates of the factors. Finally we iterate the previous steps until convergence.

3 Data

Our analysis uses two data sets: one for US data and the other for global data. The US data set is standard, including all monthly and quarterly series that the New York Fed uses in their DFM. The global data set covers 77 countries which together account for about 90 percent of world GDP in 2018. We retrieve the data from Haver Analytics, the European Commission, Now-Casting Economics, IHS Markit, Wolters Kluwer, countries' individual central banks and national statistical agencies. We include various types of variables: Blue Chip forecasts, business confidence, consumer confidence, employment, exports, industrial production, now-cast index, PMI, and private sector credit. In selecting the data, there are two main considerations. First, we want to cover as many countries as possible. Second, the variables included are able to capture growth momentum. All variables, except GDP and US unit labor cost, are monthly, which is a key feature of our data set.

Our sample starts in April 2000. Some variables have missing values at the beginning of the sample; however, our estimation strategy based on Kalman filtering enables us to handle such irregularity in the data. Appendix A.1 lists all countries in our data set and Appendix A.2 lists all types of data used in our analysis. Figures 5 through Figure 12 plot individual types of data for different countries. There are clear cross-country co-movements.

4 Results

In this section, we compare the forecasting performance of different models during the global financial crisis, a turbulent time before the pandemic-led recession, and during the most recent normal period (2018-2019). The comparison helps illustrate the contribution of cross-country data in forecasting US GDP growth in economic downturns and booms. We then use the various models to forecast GDP growth in 2020Q3 based on the latest vintage data.

4.1 Global Financial Crisis

First, we run the aforementioned six models to forecast US real GDP growth (yoy) in 2009Q2 based on the sample ending in March 2009 and forecast growth in 2009Q3 based on the sample ending in June 2009. Because the genuine vintage data are not available, we use historical data and assume for simplicity that we can observe the values of all variables in the ending months.

Table 1 shows the results and the top two charts in Figure 3 provide a visual view of the forecast errors. Although all models overestimate the decline in US GDP in the GFC around trough, the forecast errors from the benchmark model which uses US data only are significantly larger than the others, suggesting that cross-country data help forecast US economic growth in bad times. In particular, compared to the forecast errors from Model 6 that uses data from all country groups, the forecast error from the benchmark model is 0.4 percentage points (or about 70%) higher (in absolute value) for 2009Q2 and 1.1 percentage points (or about 150%) higher for 2009Q3.

Our results can be explained by the different recovery pace of different country groups. Figure 2 displays historical growth rates. During the GFC, while US growth reached its trough in 2009Q2, the other country groups reached trough in 2009Q1 and started recovering as of 2009Q2. As a result, the cross-country data capture the positive spillover effects on the US economy of other economies that were improving. This important information is largely missing in US data.

4.2 Normal Period

Next, we examine how helpful cross-country data are in normal times. As an illustration example, we show in Table 1 the forecasts of economic growth in 2019Q3 based on the historical sample ending in June 2019. The forecast errors for 2019Q3 are much smaller compared to those for 2009Q3, suggesting that the forecasts are relatively accurate in this normal period. In addition, we find that the models using cross-country data do not necessarily outperform the benchmark model, which means the additional information in cross-country data is not useful in normal times. To check the generality of this finding, we show in Figure 3 the forecast errors for the second and third quarters of the most recent three years, 2017, 2018, and 2019 (the second to fourth panels). Compared to the top panel, the following three panels show a general pattern that the forecast errors are small and similar across different models. In other words, the benefit of including global data in forecasting US GDP growth is much smaller in normal times than in downturns.

To provide a more complete view, we forecast US economic growth in all non-recession quarters during 2007-2020 and calculate the mean and the standard deviation of the forecast error based on alternative models. The results in Table 2 confirm that during normal times, all models produce very small forecast errors and including cross-county data is of little help.

4.3 Alternative Specification

So far, we have assumed that US GDP only depends on the global factor and the real factor following the specification adopted by the New York Fed. We therefore extend our models, allowing US GDP growth to directly depend on the country-group factors in addition to the global factor and the real factor. The results, shown in Table 3, turn out to be close to our baseline results in Table 1 and confirm that including cross-country data is useful in forecasting US GDP growth during a downturn.

This finding is supported by a variance decomposition result showing that the global factor and the real factor account for the majority of the variation in GDP. Specifically, we run a model allowing GDP to depend on the global factor, the real factor, the soft factor, the labor factor, and the three country-group factors based on the sample from April 2000 to the end of 2019. The results in Table 4 show that the global factor and the real factor explain 47.3% and 30.2% of the total variation in US GDP growth, respectively, while the other five factors explain less than 1% in total.

4.4 Forecasting Growth in 2020Q3

Finally, we apply our models to forecast US economic growth during the Covid-19 pandemic. In particular, we forecast the growth in 2020Q3 based on the latest vintage data ending on August 6, 2020 when this paper is completed. The pandemic is similar to the GFC in the sense that while the US is still struggling with containing the virus and the economy is weak, the other major economies, such as China and Europe, are already in recovery (see Figures 4 for a comparison of Covid-19 developments in the US, China, and major European countries).

As a consequence, the US economic variables may not contain enough information about the positive effects of foreign demand, thus overestimating the decline in economic conditions.

The conjecture is confirmed by our results in Table 5: almost all models using cross-country data are more optimistic about the economic outlook than the benchmark model using US data only. For example, the benchmark model forecasts the real GDP in 2020Q3 to be 6.9% down on the same quarter last year. However, when cross-country data are used, the forecast becomes stronger. In particular, when all countries' data are used (Model 6), the forecast for US year-over-year real GDP growth in 2020Q3 increases by 0.8 percentage points. If we translate these results into quarterly annualized growth rates, the current forecast based on Model 6 is 19.1%, compared to 14.9% based on the benchmark model.

5 Conclusions

Most models forecasting US economic growth in the literature use only US data. An influential example is the dynamic factor model developed by the Federal Reserve Bank of New York. We start with a similar model as the benchmark, then consider alternative models that use cross-country data. We show that including cross-country data produces more accurate forecasts of US real GDP growth during the global financial crisis period, but is not very useful during normal times. This is probably because foreign variables contain useful information about the spillover effects on the US economy, which are particularly important in downturns. Then we apply our models to the Covid-19 pandemic, which is similar to the global financial crisis in the sense that growth in different countries recovers at different paces. The particularly large number of Covid-19 cases and the slow recovery process in the

US suggest that the US is probably again the last to recover among major economies, which makes cross-country data useful for forecasting its growth. Our results based on the most recent vintage data show that including cross-country data revises the forecast of US GDP growth in 2020Q3 upward significantly.

Whereas we focus on the US economy in this paper, our idea of using cross-country data for forecasting domestic economic growth is probably more important for small open economies which are usually more dependent on external demand. We leave it for future research.

References

Aastveit, Knut Are and Tørres Trovik. 2012. "Nowcasting Norwegian GDP: The Role of Asset Prices in a Small Open Economy." *Empirical Economics* 42(1):95–119.

Arnoštová, Kateřina, David Havrlant, Luboš Ržička and Peter Tóth. 2011. "Short-term forecasting of Czech quarterly GDP using monthly indicators." *Finance a úvěr (Czech Journal of Economics and Finance)* 61(6):566–583.

Bańbura, Marta, Domenico Giannone, Michele Modugno and Lucrezia Reichlin. 2013. Now-Casting and the Real-Time Data Flow. In *Handbook of economic forecasting*. Vol. 2 Elsevier pp. 195–237.

Bańbura, Marta and Michele Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29(1):133–160.

Barhoumi, Karim, Olivier Darné and Laurent Ferrara. 2010. "Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP?" *Journal of Forecasting* 29(1-2):132–144.

Boivina, Jean and Serena Ngb. 2005. "Understanding and Comparing Factor-Based Forecasts." *International Journal of Central Banking* .

Bok, Brandyn, Daniele Caratelli, Domenico Giannone, Argia M Sbordone and Andrea Tambalotti. 2018. "Macroeconomic Nowcasting and Forecasting with Big Data." *Annual Review of Economics* 10:615–643.

de Antonio Liedo, David. 2014. "Nowcasting Belgium.". National Bank of Belgium Working Paper.

De Winter, Jasper. 2011. "Forecasting GDP Growth in Times of Crisis: Private Sector Forecasts versus Statistical Models." De Nederlandsche Bank Working Paper.

D'Agostino, Antonello and Domenico Giannone. 2012. "Comparing Alternative Predictors Based on Large-Panel Factor Models." *Oxford Bulletin of Economics and Statistics* 74(2):306–326.

Forni, Mario, Domenico Giannone, Marco Lippi and Lucrezia Reichlin. 2009. "Opening the Black Box: Structural Factor Models with Large Cross Sections." *Econometric Theory* 25(5):1319–1347.

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.

Giannone, Domenico, Silvia Miranda Agrippino and Michele Modugno. 2013. "Nowcasting China Real GDP." Working Paper.

Luciani, Matteo, Madhavi Pundit, Arief Ramayandi and Giovanni Veronese. 2018. "Nowcasting Indonesia." *Empirical Economics* 55(2):597–619.

Marcellino, Massimiliano, James H Stock and Mark W Watson. 2003. "Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information." *European Economic Review* 47(1):1–18.

Matheson, Troy D. 2010. "An Analysis of the Informational Content of New Zealand Data Releases: The Importance of Business Opinion Surveys." *Economic Modelling* 27(1):304–314.

Modugno, Michele, Barış Soybilgen and Ege Yazgan. 2016. "Nowcasting Turkish GDP and News Decomposition." *International Journal of Forecasting* 32(4):1369–1384.

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 & Economic Statistics* 20(2):147–162.

Yiu, Matthew S and Kenneth K Chow. 2010. "Nowcasting Chinese GDP: Information Content of Economic and Financial Data." *China Economic Journal* 3(3):223–240.

Appendix A Data Appendix

A.1 List of Countries by Country Group

- Advanced Economies (AEs): Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Macao SAR, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China, United Kingdom
- Emerging Market Economies (EMEs): Argentina, Armenia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Guatemala, Hungary, India, Indonesia, Iran, Kazakhstan, Kyrgyz Republic, Lebanon, Malaysia, Mexico, Pakistan, Paraguay, Peru, Philippines, Poland, Romania, Russia, Serbia, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, Uruguay, Venezuela

A.2 List of Countries by Data Category

- Employment: Austria, Australia, Canada, Germany, Finland, Hong Kong, Croatia, Japan, Korea, Luxembourg, Macao SAR, Russia, Sweden, Taiwan Province of China, Bulgaria, United Kingdom, Kyrgyz Republic, Norway, Romania
- Exports: Brazil, Iceland, Korea, Argentina, Armenia, Australia, Bosnia and Herzegovina, Switzerland, Chile, China, Colombia, Costa Rica, Hong Kong, Indonesia, India, Israel, Japan, Lebanon, Luxembourg, Mexico, Malaysia, Norway, New Zealand, Pak-

istan, Paraguay, Singapore, El Salvador, Sweden, Thailand Turkey, Taiwan Province of China, Uganda, Uruguay, Austria, Belgium, Bulgaria, Canada, Czech Republic, Germany, Denmark, Ecuador, Egypt, Spain, Estonia, Finland, France, United Kingdom, Croatia, Hungary, Ireland, Iran, Italy, Kazakhstan, Kyrgyz Republic, Lithuania, Latvia, Malta, Netherlands, Peru, Philippines, Poland, Portugal, Romania, Russia, Slovenia, Ukraine

- Industrial Production: China, Spain, Estonia, Croatia, Ireland, Japan, Kazakhstan, Korea, Lithuania, Latvia, Poland, Russia, Serbia, Sweden, Austria, Belgium, Bulgaria, Canada, Cyprus, Czech Republic, Germany, Denmark, Finland, France, United Kingdom, Greece, Hungary, India, Italy, Luxembourg, Malta, Malaysia, Netherlands, Norway, Romania, Slovak Republic, Slovenia, Tunisia, Turkey

- Private Sector Credit: Australia, Bulgaria, Bosnia and Herzegovina, Brazil, Canada, Switzerland, Denmark, Estonia, France, United Kingdom, Georgia, Greece, Guatemala, Hong Kong, Indonesia, Kazakhstan, Lithuania, Macedonia, Malaysia, Netherlands, Norway, New Zealand, Poland, Singapore, Taiwan Province of China, South Africa, India, Ireland, Italy, Korea

- Business Confidence: Belgium, Switzerland, Germany, Denmark, France, Hungary, Netherlands, Poland, Slovakia, Slovenia, Sweden, Thailand

- Consumer Confidence: Australia, Austria, Belgium, Switzerland, Czech Republic, Germany, DEV, Denmark, ERU, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Italy, Japan, Netherlands, Poland, Portugal, Russia, Slovakia, Slovenia, Sweden, Brazil, China, Luxembourg

- Blue Chip GDP Forecasts: Australia, Brazil, Canada, China, Germany, France, United Kingdom, Hong Kong, Japan, Korea, Mexico, Netherlands, Taiwan Province of China

- Now-cast Index: Brazil, China, United Kingdom, Mexico, South Africa

- PMI: Hungary, Netherlands, Singapore, Slovenia, Sweden, South Africa, Israel

Table 1: Forecasts of US real GDP growth (yoy %)

Model	Period	Forecast	Data	Forecast error
	2009Q2	-4.5	-3.9	-0.6
Benchmark	2009Q3	-4.8	-3.1	-1.8
	2019Q3	1.8	2.1	-0.3
	2009Q2	-4.4	-3.9	-0.5
Model 2	2009Q3	-4.7	-3.1	-1.7
	2019Q3	1.8	2.1	-0.3
	2009Q2	-4.1	-3.9	-0.2
Model 3	2009Q3	-4.2	-3.1	-1.2
	2019Q3	2.0	2.1	-0.1
	2009Q2	-4.3	-3.9	-0.4
Model 4	2009Q3	-3.7	-3.1	-0.6
	2019Q3	1.6	2.1	-0.4
	2009Q2	-4.1	-3.9	-0.2
Model 5	2009Q3	-3.7	-3.1	-0.7
	2019Q3	2.0	2.1	-0.1
	2009Q2	-4.1	-3.9	-0.2
Model 6	2009Q3	-3.7	-3.1	-0.7
	2019Q3	1.6	2.1	-0.4

Note: The benchmark model includes US variables only, while the other models use both US and non-US variables. Model 2 includes variables of China. Model 3 includes variables of China and other emerging market economies. Model 4 includes variables of advanced economies. Model 5 includes variables of emerging market economies (excluding China) and advanced economies. Model 6 includes variables of China, other emerging market economies, and advanced economies. The forecasts for 2009Q2, 2009Q3, and 2019Q3 are based on historical samples ending in March 2009, June 2009, and June 2019, respectively.

Table 2: Mean and standard deviation of forecast error in recent normal period

	Benchmark	Model 2	Model 3	Model 4	Model 5	Model 6
Avg of Forecast Error (%)	0.0	0.0	0.1	0.1	0.1	0.1
Std of Forecast Error (%)	0.6	0.6	0.6	0.6	0.6	0.6

Note: Based on each model, we forecast US economic growth in all non-recession quarters during 2007-2020 and calculate the mean and the standard deviation of the forecast error. The benchmark model includes US variables only, while the other models use both US and non-US variables. Model 2 includes variables of China. Model 3 includes variables of China and other emerging market economies. Model 4 includes variables of advanced economies. Model 5 includes variables of emerging market economies (excluding China) and advanced economies. Model 6 includes variables of China, other emerging market economies, and advanced economies.

Table 3: Forecasts of US real GDP growth (yoy %): alternative specification

Model	Period	Forecast	Data	Forecast error
Benchmark	2009Q2	-4.5	-3.9	-0.6
	2009Q3	-4.8	-3.1	-1.8
	2019Q3	1.8	2.1	-0.3
Model 2	2009Q2	-4.4	-3.9	-0.5
	2009Q3	-4.8	-3.1	-1.8
	2019Q3	1.8	2.1	-0.3
Model 3	2009Q2	-4.1	-3.9	-0.2
	2009Q3	-4.2	-3.1	-1.2
	2019Q3	2.0	2.1	-0.1
Model 4	2009Q2	-4.3	-3.9	-0.4
	2009Q3	-3.6	-3.1	-0.5
	2019Q3	1.7	2.1	-0.4
Model 5	2009Q2	-4.1	-3.9	-0.2
	2009Q3	-3.6	-3.1	-0.5
	2019Q3	2.0	2.1	-0.1
Model 6	2009Q2	-4.1	-3.9	-0.2
	2009Q3	-3.8	-3.1	-0.8
	2019Q3	2.0	2.1	-0.1

Note: In this alternative specification, US GDP growth directly depends on country-group factors. The benchmark model includes US variables only, while the other models use both US and non-US variables. Model 2 includes variables of China. Model 3 includes variables of China and other emerging market economies. Model 4 includes variables of advanced economies. Model 5 includes variables of emerging market economies (excluding China) and advanced economies. Model 6 includes variables of China, other emerging market economies, and advanced economies. The forecasts for 2009Q2, 2009Q3, and 2019Q3 are based on historical samples ending in March 2009, June 2009, and June 2019, respectively.

Table 4: Contribution of factors to GDP variation

Factor	Contribution (%)
Global	47.3
Soft	0.0
Real	30.2
Labor	0.3
China	0.0
EME (excl. China)	0.1
AE (excl. US)	0.4

Note: This table shows the contribution of different factors to the variation in US real GDP growth. The model allows GDP to directly depend on all the factors listed. We use the sample from April 2000 to the end of 2019.

Table 5: Forecasts of US real GDP growth in 2020Q3

	Benchmark	Model 2	Model 3	Model 4	Model 5	Model 6
2020Q3 (yoy%)	-6.9	-6.8	-6.6	-6.1	-6.1	-6.1
2020Q3 (qoq%)	14.9	15.5	16.4	19.0	19.1	19.1

Note: The benchmark model includes US variables only, while the other models use both US and non-US variables. Model 2 includes variables of China. Model 3 includes variables of China and other emerging market economies. Model 4 includes variables of advanced economies. Model 5 includes variables of emerging market economies (excluding China) and advanced economies. Model 6 includes variables of China, other emerging market economies, and advanced economies. The forecasts for 2020Q3 are based on the vintage data ending on August 6, 2020.

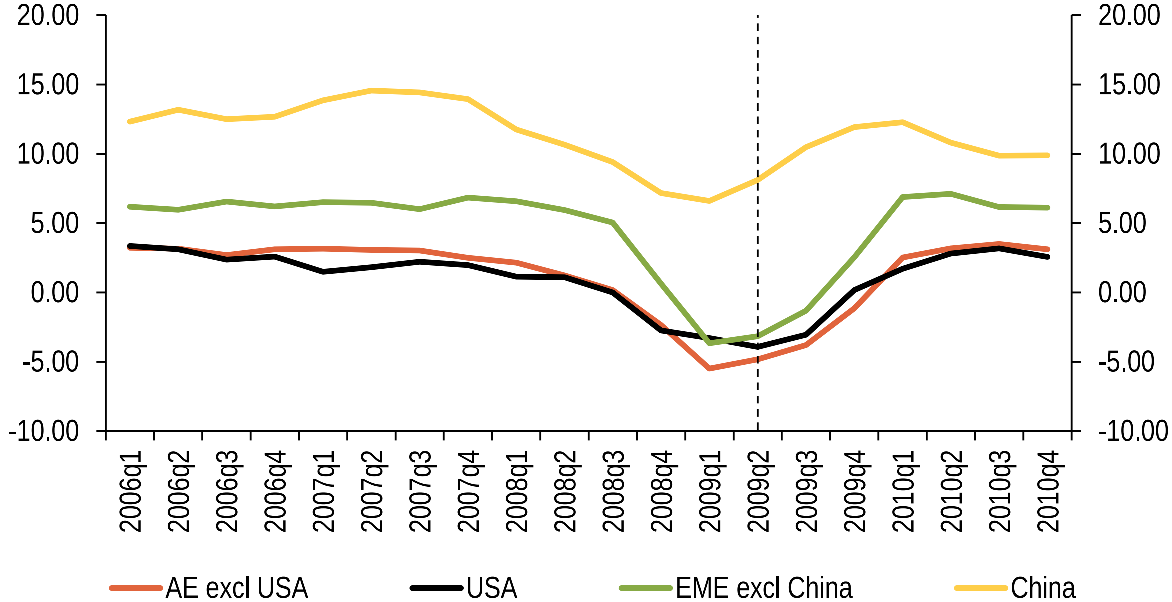
Figure 1: List of US variables

Data Series	G	S	R	L	Units
All employees: Total nonfarm	■	□	□	■	Level change (thousands)
Real gross domestic product	■	□	■	□	QoQ % change (annual rate)
ISM mfg.: PMI composite index	■	■	□	□	Index
CPI-U: All items	■	□	□	□	MoM % change
Manufacturers new orders: Durable goods	■	□	■	□	MoM % change
Retail sales and food services	■	□	■	□	MoM % change
New single family houses sold	■	□	■	□	MoM % change
Housing starts	■	□	■	□	MoM % change
Civilian unemployment rate	■	□	□	■	Ppt. change
Industrial production index	■	□	■	□	MoM % change
PPI: Final demand	■	□	□	□	MoM % change
ADP nonfarm private payroll employment	■	□	□	■	Level change (thousands)
Empire State Mfg. Survey: General business conditions	■	■	□	□	Index
Merchant wholesalers: Inventories: Total	■	□	■	□	MoM % change
Value of construction put in place	■	□	■	□	MoM % change
Philly Fed Mfg. business outlook: Current activity	■	■	□	□	Index
Import price index	■	□	□	□	MoM % change
ISM nonmanufacturing: NMI composite index	■	■	□	□	Index
ISM mfg.: Prices index	■	■	□	□	Index
Building permits	■	□	■	□	Level change (thousands)
Capacity utilization	■	□	■	□	Ppt. change
PCE less food and energy: Chain price index	■	□	□	□	MoM % change
CPI-U: All items less food and energy	■	□	□	□	MoM % change
Inventories: Total business	■	□	■	□	MoM % change
Nonfarm business sector: Unit labor cost	■	□	□	■	QoQ % change (annual rate)
JOLTS: Job openings: Total	■	□	□	■	Level change (thousands)
Real personal consumption expenditures	■	□	■	□	MoM % change
PCE: Chain price index	■	□	□	□	MoM % change
ISM mfg.: Employment index	■	■	□	□	Index
Export price index	■	□	□	□	MoM % change
Manufacturers shipments: Durable goods	■	□	■	□	MoM % change
Mfrs. unfilled orders: All manufacturing industries	■	□	■	□	MoM % change
Manufacturers inventories: Durable goods	■	□	■	□	MoM % change
Real gross domestic income	■	□	■	□	QoQ % change (annual rate)
Real disposable personal income	■	□	■	□	MoM % change
Exports: Goods and services	■	□	■	□	MoM % change
Imports: Goods and services	■	□	■	□	MoM % change

Housing and construction · Manufacturing · Surveys · Retail and consumption · Income · Labor · International trade · Others

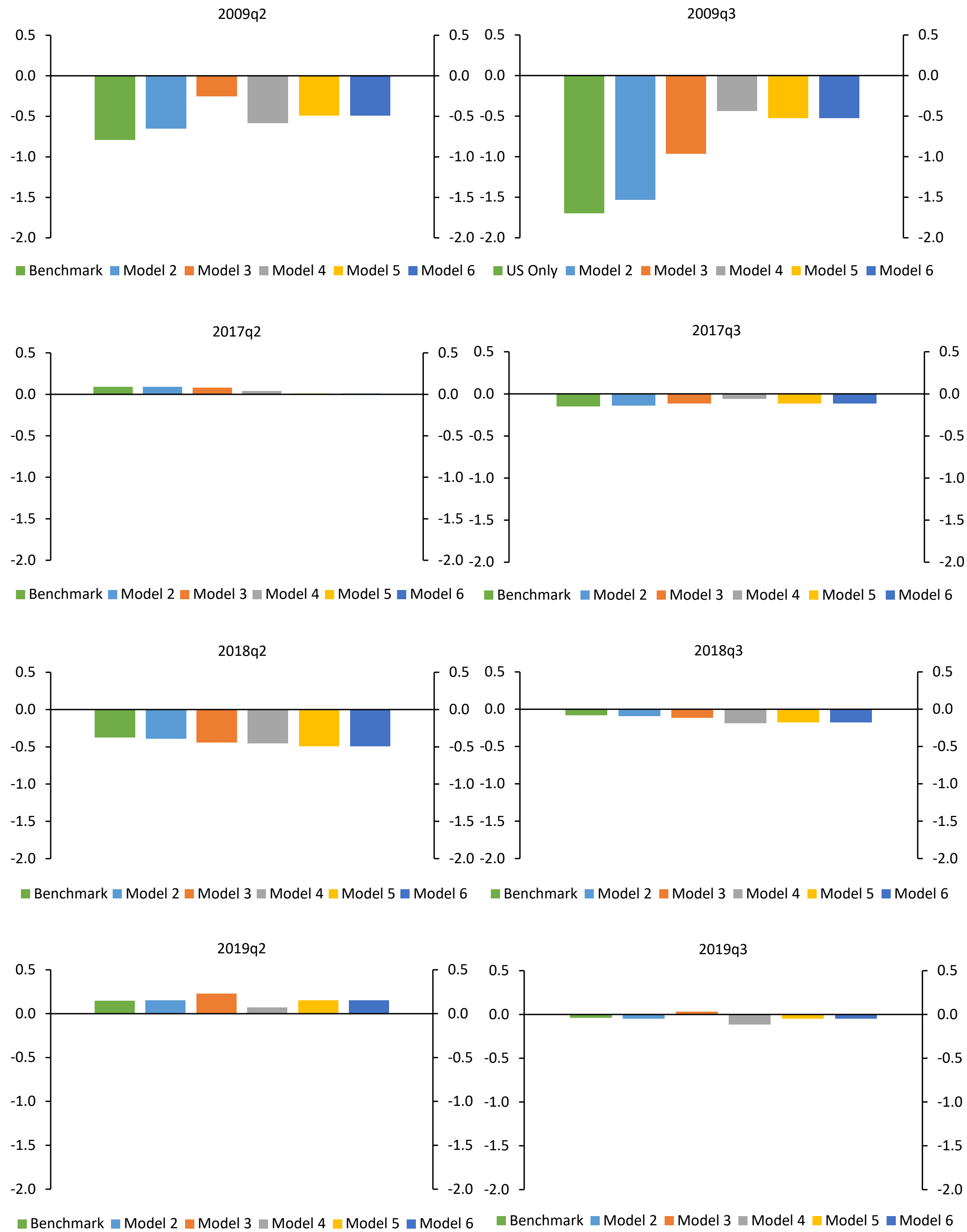
Note: G, S, R, and L indicate the global, soft, real, and labor factors, respectively. In our model, we take YoY % change rather than MoM % change or QoQ % change. Source: Bok et al. (2018).

Figure 2: Historical real GDP growth rates (yoy) for major country groups



Note: The dashed vertical line corresponds to 2009Q2.

Figure 3: Comparing forecast errors associated with different models



Note: Benchmark model includes US variables only, while the other models use both US and non-US variables. Model 2 includes variables of China. Model 3 includes variables of China and other emerging market economies. Model 4 includes variables of advanced economies. Model 5 includes variables of emerging market economies (excluding China) and advanced economies. Model 6 includes variables of China, other emerging market economies, and advanced economies.

Figure 4: Covid-19 developments in the US, China, and major European countries

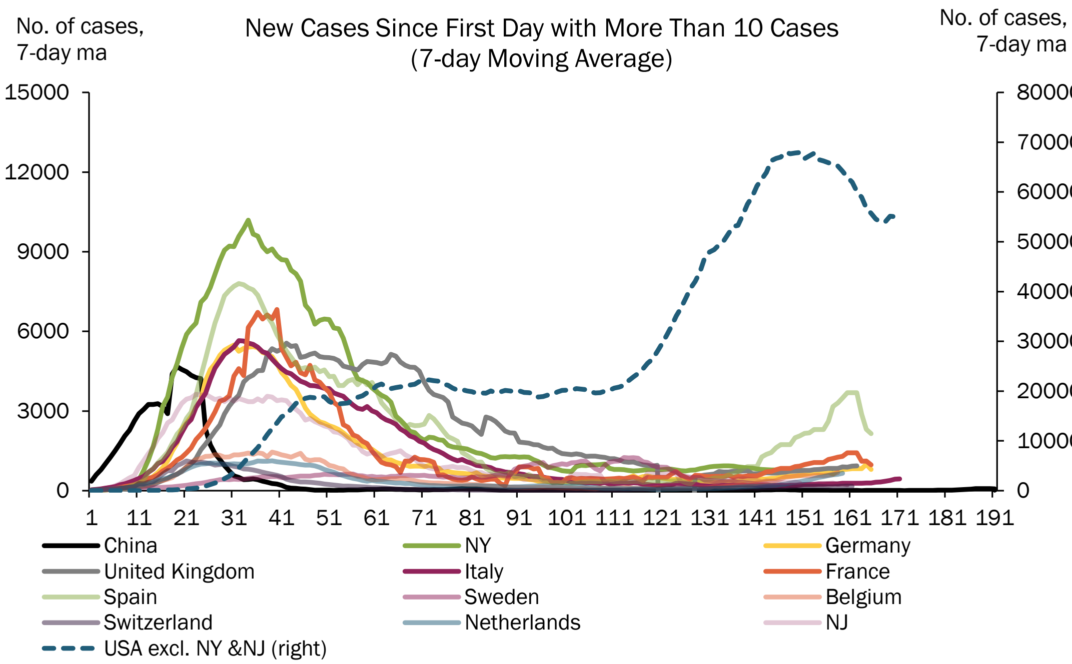


Figure 5: Employment

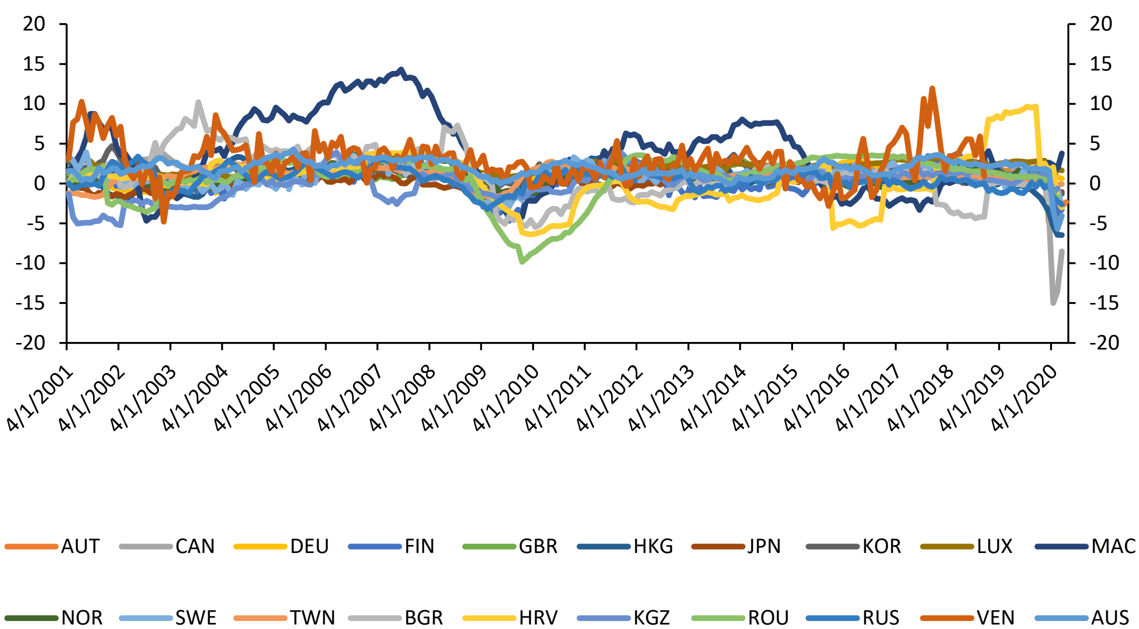


Figure 6: Industrial production

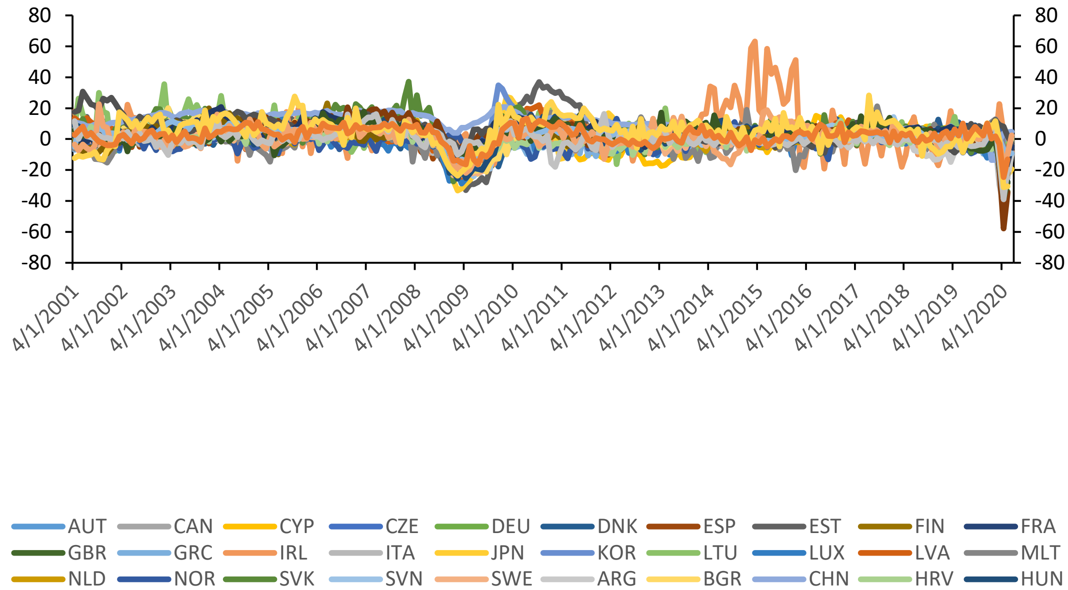


Figure 7: Credit

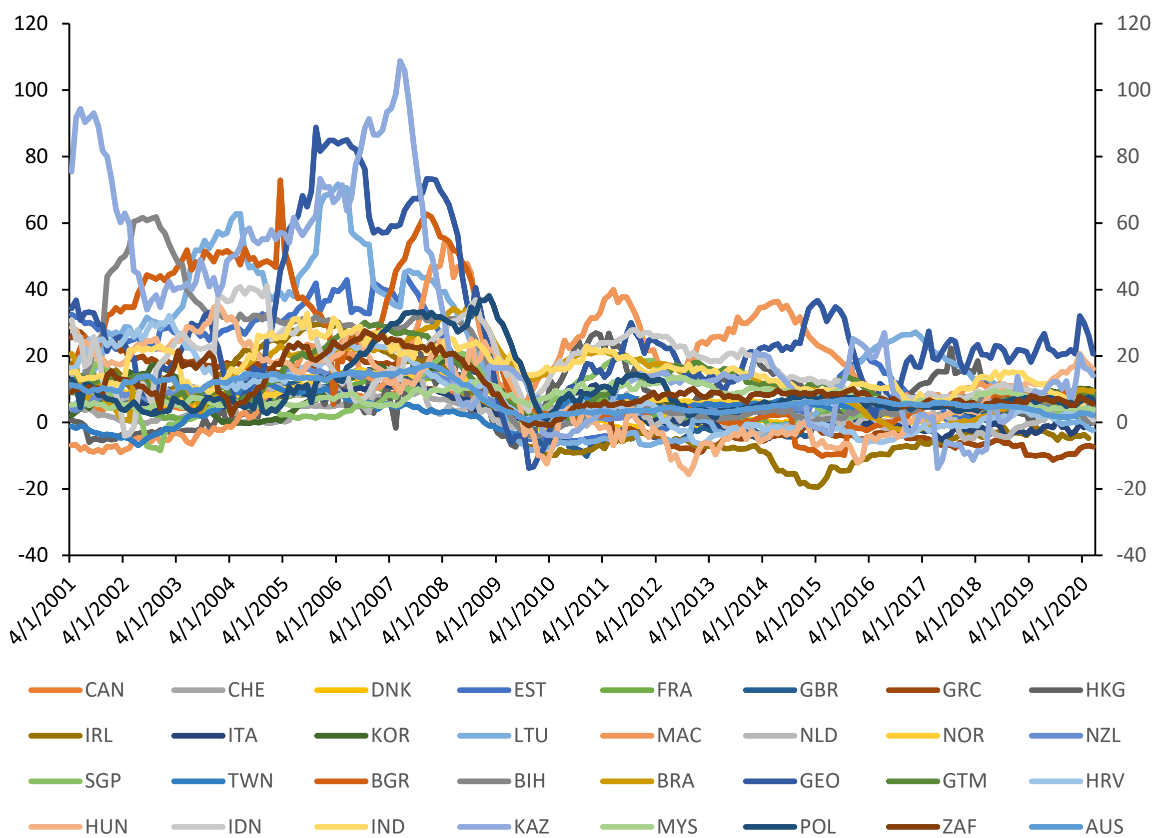


Figure 8: Business confidence

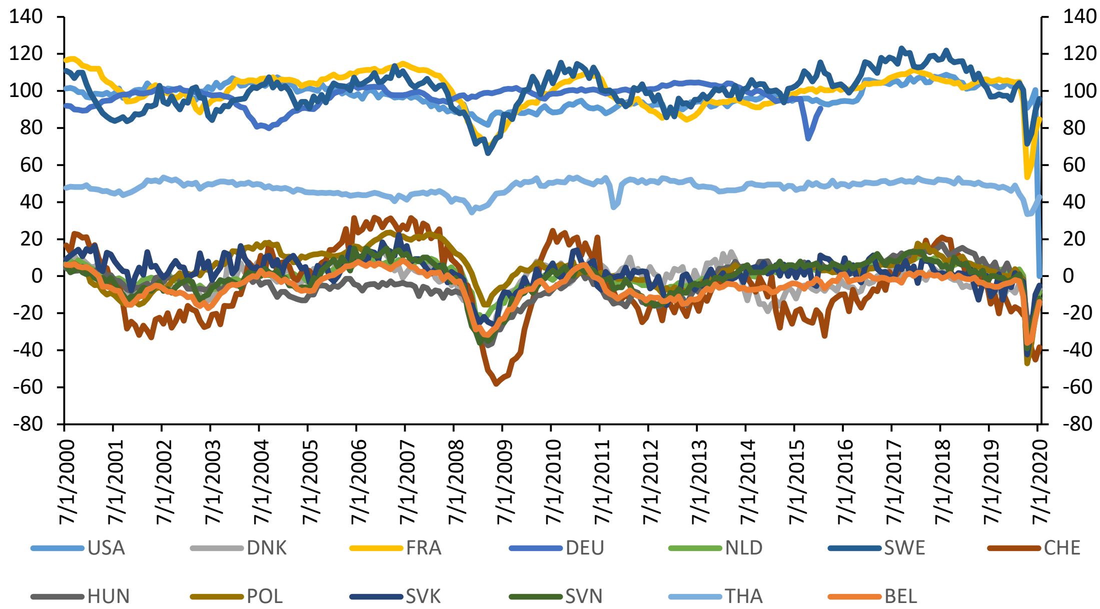


Figure 9: Consumer confidence

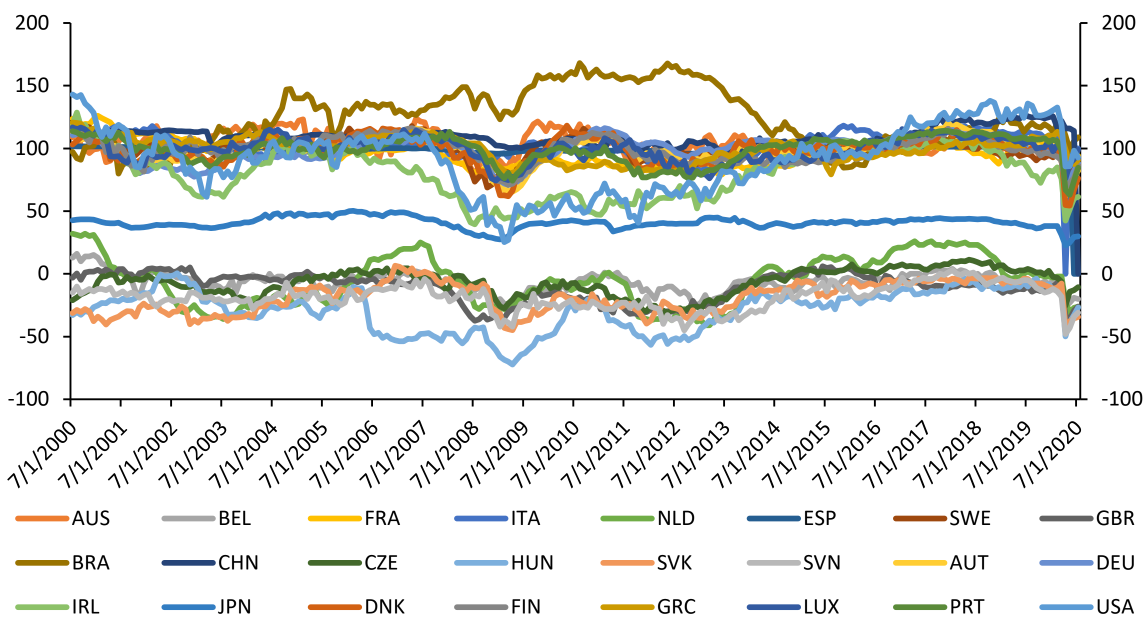


Figure 10: PMI

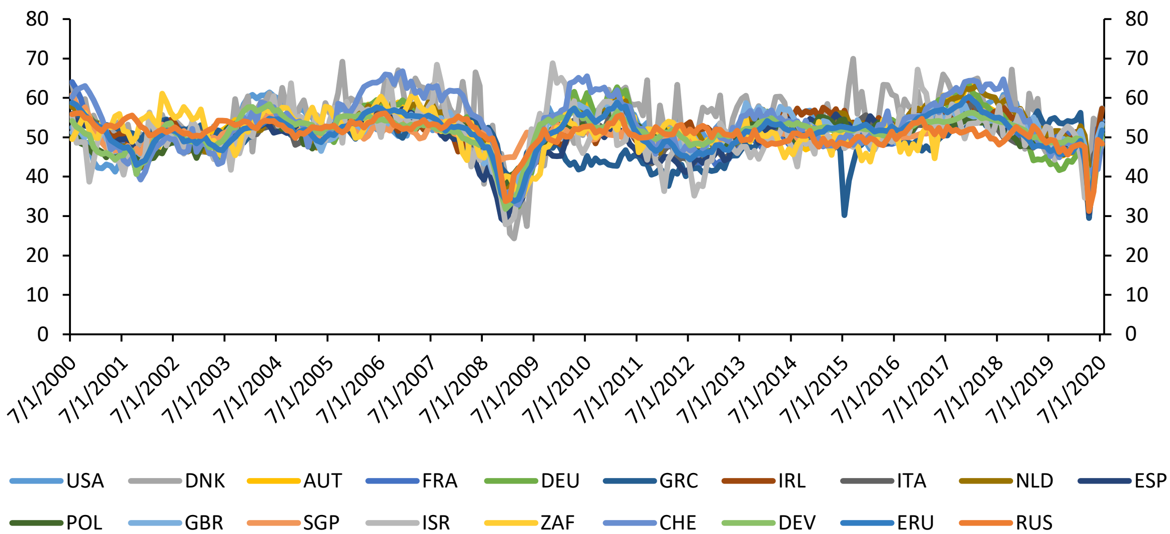


Figure 11: Blue Chip GDP Consensus Forecasts

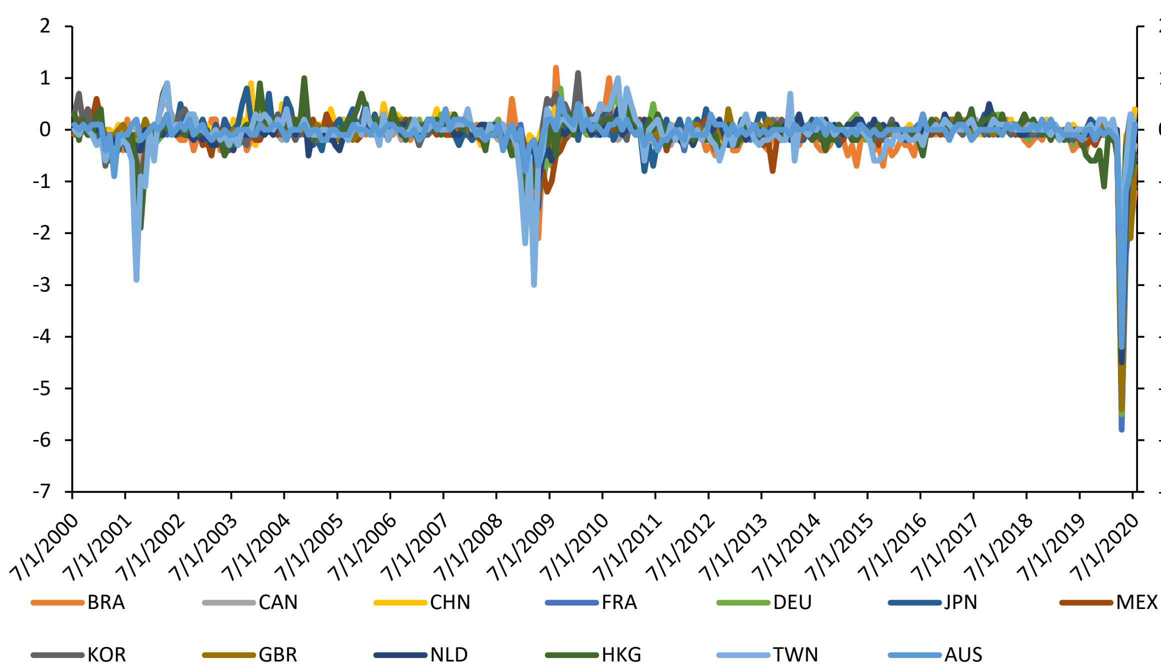


Figure 12: Now-Casting Index of Economic Activity