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Abstract

We present evidence that global vectorautoregressive (GVAR) models produce significantly more accurate recession forecasts than country-specific time-series models in a Bayesian framework. This result holds for most countries and forecast horizons as well as for several country groups.

JEL classification: C53, E17, E37, F41, F47
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1 Introduction

Forecasting economic turning points is essential for optimally designing stabilization policy because of the lagged economic impact that fiscal and monetary policy stimuli. Consequently, the issue has been addressed in numerous studies (see, e. g., Zellner et al., 1991; Canova and Ciccarelli, 2004). In a globalized world, recessions are often triggered by external events. An example is given by the financial crisis of 2008/09 that pushed many economies into a recession but originated, as many belief, from the burst of the U. S. housing market. This leaves room for global models to outperform country-specific models in forecasting turning points.

Global vectorautoregressive (GVAR) models (Pesaran et al., 2004) are designed to capture the dynamics of a large part of the world economy by linking country-specific VAR models to each other using trade weights. Though GVAR models are linear,

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they offer a fair degree of flexibility in modeling business-cycle dynamics of the world economy. Recent studies show that they have merits of providing good forecasts for a range of macroeconomic variables (Pesaran et al., 2009; Crespo Cuaresma et al., 2014; Dovern et al., 2015). Yet, if they also provide accuracy gains (relative to country-specific models) in terms of forecasting the business-cycle regime remains an open question. Though Greenwood-Nimmo et al. (2012) address the issue, their study provides only limited evidence both in terms of country coverage and length of the evaluation period; it also presents no formal assessment of the accuracy of recession probability forecasts.

In this paper, we present broad-based evidence that GVAR models can be used to generate probability forecasts for the occurrence of recessions that are more accurate in terms of the quadratic probability score (QPS) than country-specific benchmark models.

The paper is organized as follows. The next section presents the econometric framework. Section 3 discusses how we evaluate and compare the forecast performance of the models. Sections 4 and 5 describe the data set and empirical results, respectively. Finally, Section 5 concludes the paper.

2 The Model Framework

2.1 The GVAR Model

The model consists of $N+1$ country-specific models that are combined to form the global model. Let $x_{i,t}$ be the $k_i \times 1$ vector of domestic variables for country $i = 0, \ldots, N$ and time $t = 1, \ldots, T$, in which the first element is equal to the (log) level of gross domestic product (GDP) $y_{i,t}$. For each country, we consider a VAR model which is augmented with a set of foreign variables (VARX*). Each model is specified as follows:

$$\Phi_i(L)x_{i,t} = \Lambda_i(L)x^*_{i,t} + \varepsilon_{i,t}. \tag{2.1}$$

Here, $\Phi_i(L) = 1 - \Phi_{i1}L - \ldots - \Phi_{ip}L^p$ and $\Lambda_i(L) = \Lambda_{i0} + \Lambda_{i1}L + \ldots + \Lambda_{iq}L^q$ are properly sized matrix lag polynomials measuring the impact of lagged domestic variables and foreign variables, respectively.[1] In the empirical application we set $p = q = 3$. The foreign variables are calculated as a weighted average of the domestic variables of all other countries based on trade weights, $x^*_{i,t} = \sum_{j=0}^{N} w_{ij}x_{j,t}$, under the restriction that

[1]For notational simplicity, we ignore any deterministic terms.

$w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1$. We assume that the $\varepsilon_{i,t}$s are uncorrelated across time and normally distributed with a covariance matrix Σ_i.

Pesaran et al. (2004) show how the $N+1$ country models can be combined to form the GVAR model. The reduced-form of this GVAR, which is all we need to form conditional forecasts, is given by

$$F(L)x_t = e_t, \tag{2.2}$$

where all endogenous variables of the model are collected in the $k \times 1$ vector $x_t = (x'_{0,t}, x'_{1,t}, \ldots, x'_{N,t})$ with $k = \sum_{i=0}^{N} k_i$. $F(L) = 1 - F_1 L - \ldots - F_{\tilde{p}} L^{\tilde{p}}$, $\tilde{p} = \max\{p, q\}$, and the covariance matrix of e_t, say Σ_e, are functions of the estimated parameters of the country-specific models and the bilateral trade weights that are used to link these models.

Because traditional GVARs can suffer from overfitting issues which normally translate into a weak out-of-sample forecasting performance, we take a Bayesian stance to estimation and inference. More specifically, we use the prior setup stipulated in Sims and Zha (1998) and implemented for GVAR models in Crespo Cuaresma et al. (2014), who emphasize the strong forecasting performance of this specification. The prior selects several important aspects of the specification (e. g. the lag order or whether the model is estimated in levels or first differences) in a data-driven fashion which are otherwise chosen subjectively by the forecaster. For a detailed description of the model, we refer the reader to Crespo Cuaresma et al. (2014).

2.2 Benchmark Models

With a view to assessing the potential superiority of GVAR models over country-specific models, we select a set of country-specific Bayesian VAR (BVAR) models and Bayesian univariate autoregressions (AR) as benchmarks to produce alternative probability forecasts. We obtain these benchmark by ‘shutting down’ the interaction between variables from different countries or between all variables, respectively. More formally, the BVAR models are given by a restricted version of (2.1), $\Phi_i(L)x_{i,t} = \varepsilon_{i,t}$, and the AR models are given by $\phi_i(L)y_{i,t} = \varepsilon^{y}_{i,t}$.[2]

[2]As for the GVAR model, we assume a lag order of 3 in each case.

3 Forecast Setup and Evaluation

We use a quasi real-time out-of-sample analysis to investigate the ability of the models to produce accurate probability forecasts for the occurrence of recessions at a particular point in time. Beginning in $\tau = t_0$, we re-estimate the GVAR model (and the benchmarks) and simulate the predictive densities $p^m(x_{\tau+h}|\mathcal{D}_\tau)$ for $h = 1, \dots, 5$ and $m = \{\text{GVAR}, \text{BVAR}, \text{AR}\}$. This procedure is repeated until $\tau = T - h$ is reached. This yields a sequence of predictive densities for the verification period. Our initial estimation period ranges from 1979q2 to τ_0=2003q4. The verification period consists of 40 observations, covering the time span between 2004q1 and T=2013q4.

We define a recession as a decline of the level of GDP in two consecutive quarters, i. e., country i is in recession in period t if either $y_{i,t} < y_{i,t-1}$ and $y_{i,t+1} < y_{i,t}$ or if $y_{i,t-1} < y_{i,t-2}$ and $y_{i,t} < y_{i,t-1}$.[3] It is straightforward to use this definition to construct a binary indicator $\chi_{i,t}$ for each country, which equals one if country i is in a recession in period t, and zero otherwise.

Probability forecasts for the occurrence of a recession can be constructed based on $p^m(x_{\tau+h}|\mathcal{D}_\tau)$, or more precise on $p^m(y_{i,\tau+h}|\mathcal{D}_\tau)$ which refers to the predictive marginal density for GDP in country i after integrating out all other variables of the GVAR model.[4] Using our definition of a recession, the conditional recession probabilities $f^m_{\tau+h|\tau}$ are given by

$$\begin{aligned} f^m_{i,\tau+h|\tau} =& P(y_{i,\tau+h-1} < y_{i,\tau+h-2}; y_{i,\tau+h} < y_{i,\tau+h-1}|D_\tau) \\ &+ P(y_{i,\tau+h-1} \geq y_{i,\tau+h-2}; y_{i,\tau+h} < y_{i,\tau+h-1}; y_{i,\tau+h+1} < y_{i,\tau+h}|D_\tau). \end{aligned} \tag{3.1}$$

The first term refers to the possibility that period $t + h$ constitutes the first quarter of a new recession while the second term refers to the probability that a recession began already earlier and continues in period $t + h$. The probabilities in equation (3.1) can be approximated from the predictive densities using numerical methods.

A natural measure to assess the accuracy of probability forecasts is the QPS, which corresponds to the mean squared error in a non-binary forecast setup. It is given by

$$\text{QPS}^m_{i,h} = 1/(T - h - \tau_0 + 1) \sum_{t=\tau_0}^{T-h} (f^m_{i,t+h|t} - \chi_{i,t})^2, \tag{3.2}$$

[3] While this simple approach is clearly imperfect, its results are very similar to quasi-official business-cycle datings and it is highly transparent and easy to implement.

[4] Here, $\mathcal{D}_\tau$ refers to any information available at time τ.

The statistic ranges from 0 to 1 and lower values indicate a better forecast accuracy.[5]

4 Data

We use an extended version of the data set from Dées et al. (2007a) and Dées et al. (2007b), which has been used already in a companion paper (Dovern et al., 2015). It contains quarterly data for 36 countries spanning the period from 1979q2 to 2013q4.[6] We include the following variables in $x_{i,t}$: real gross domestic product (GDP), the change of the consumer price level, real equity prices, the real exchange rate, and short- and long-term interest rates. For further details on the data set and the special treatment of the U.S. economy we refer the reader to Dovern et al. (2015).

5 Empirical Results

Table 1 summarizes the most important results of our analysis. It contains information about the performance in terms of QPS for the different models corresponding to the major economies and several country groups.[7] We use Diebold-Mariano tests to check the significance of differences in forecast performance (Diebold and Mariano, 1995). To test for performance differences with respect to groups of countries, we apply the panel version of the test proposed in Pesaran et al. (2009).

Regarding individual countries, the GVAR model outperforms both benchmarks for a little more than half of the major economies—especially at short forecast horizons. To take an example: The one-step-ahead QPS of the GVAR model for the US is 0.104, which is 0.005 (or roughly 5 %) lower than the corresponding QPS of the BVAR model. We observe similar and statistically significant performance gains for Italy, Canada, the UK, and Brazil. The GVAR model performs (marginally) worse than one or both of the benchmarks only for Japan and India.[8]

[5] See Lahiri and Wang (2013) for an excellent overview about alternative and complementary performance statistics for probability forecasts. An application of these is, however, beyond the scope of this short paper.

[6] The countries are: Austria, Belgium, Germany, Spain, Finland, France, Greece, Italy, the Netherlands, Portugal, Denmark, Great Britain, Switzerland, Norway, Sweden, Australia, Canada, Japan, New Zealand, United States, China, India, Indonesia, Malaysia, Korea, Philippines, Singapore, Thailand, Argentina, Brazil, Chile, Mexico, Peru, Turkey, Saudi Arabia, and South Africa.

[7] Results for other countries of our sample are available upon request from the authors.

[8] India and China constitute special cases since no recession occurred during the verification period for these countries. For India, the GVAR model predicts a recession one occasion while the benchmark models do not predict any recession over the entire verification period. For China, all models do not forecast any recession.

Table 1: Forecast Performance of Alternative Models

	GVAR (QPS)				AR (ΔQPS)				BVAR (ΔQPS)			
	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
DE	0.157	0.110	0.091	0.091	−0.002	0.020	0.020	0.019	−0.002	0.004	0.008	0.012
FR	0.170	0.136	0.125	0.134	0.032**	0.049*	0.046*	0.040*	0.013	0.009	0.007	0.006
IT	0.218	0.294	0.262	0.271	0.029**	0.051**	0.048**	0.041**	0.010*	0.017*	0.018*	0.012**
JP	0.269	0.233	0.195	0.190	−0.009	−0.002	−0.007	−0.004	0.001	0.001	−0.003	−0.000
CA	0.088	0.062	0.054	0.064	0.015*	0.014	0.015	0.005	0.016*	0.015	0.008	−0.001
GB	0.157	0.151	0.136	0.153	0.028**	0.035**	0.039*	0.022	0.011**	0.009*	0.010	0.011
US	0.104	0.123	0.108	0.113	0.027**	0.022**	0.027	0.022	0.005**	0.006	0.010	0.008
G7	0.166	0.158	0.139	0.145	0.017**	0.027**	0.027**	0.021**	0.008**	0.009**	0.008**	0.007**
IN	0.001	0.001	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
BR	0.124	0.104	0.087	0.087	0.009**	0.007*	0.002	0.003*	0.004*	0.003*	0.003	0.006*
CN	0.000	0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
B(R)IC	0.042	0.035	0.029	0.029	0.003**	0.002**	0.001*	0.001*	0.001*	0.001*	0.001*	0.002*
AE	0.172	0.165	0.145	0.152	0.014**	0.026**	0.030**	0.023**	0.004**	0.007**	0.008**	0.007**
EE	0.069	0.062	0.055	0.056	0.003**	0.005**	0.003**	0.002*	−0.000	−0.000	−0.000	0.000
Total	0.127	0.120	0.105	0.109	0.012**	0.019**	0.019**	0.015**	0.005**	0.006**	0.006**	0.005**

Notes: The numbers for the GVAR models refer to the estimated QPS. Numbers for the AR and BVAR models denote deviations of the QPS to those for the corresponding GVAR model. Positive numbers indicate that the GVAR model outperforms the respective benchmark model.
* indicates significance at the 10% level.
** indicates significance at the 5% level.

For many combinations of countries and forecast horizons the differences between the GVAR-QPS and those of the benchmarks are not statistically significant. One factor behind this is the relatively short verification period that contains not many recessions for each individual country and leads to low power of the DM tests. The test results for country groups show, however, that the performance gains of the GVAR model are indeed real. We look at the following country groups: the G7, the 'BIC' (formed by Brazil, India, and China), all advanced economies (AE), all emerging economies (EE), and all countries of the sample. The GVAR outperforms both benchmark models for all of these groups except for the emerging economies, for which the BVAR model is marginally better than the GVAR model. Relative to the AR model the performance gains reach from 3 % (BIC, $h = 3, 4$) to 17 % (AE, $h = 3$). Relative to the BVAR model the gains are smaller and reach from 2 % (AE, $h = 1$) to 6.5 % (AE, $h = 4$). Overall, i. e. based on all countries of the sample, the QPS of the GVAR model is 3.8 % to 5.4 % lower than the QPS of the BVAR model and 8.6 % to 15.3 % lower than that of the AR model.

6 Conclusion

Using a large international panel of macroeconomic data, we have shown that GVAR models produce more accurate forecasts of recession probabilities than country-specific BVARs or univariate models. This result holds for most individual countries and forecast horizons as well as for several country groups. Thus, in a globalized world it might pay off to take information from other economies into account to improve the ability to forecast the future business-cycle regime. We anticipate that performance gains are even higher in the case of event forecasts when the event definition involves variables from more than one country (e. g. a recession in six of the G7 countries).

Since the focus of this paper is to study the gains from moving from country-specific models to a global model, we concentrate on relatively tractable linear benchmark models. At the same time, we acknowledge that other classes of non-linear models such as Markov-switching models can be superior tools to forecast business-cycle turning points (e. g., Kim and Nelson, 1998). Thus, it would be an interesting extension of our research to see whether taking the international dimension into account pays off also when comparing country-specific Markov-switching models with a Markov-switching GVAR model (as, e. g., in Binder and Gross, 2013).

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