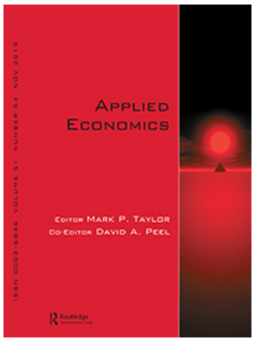

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Forecasting GDP all over the world using leading indicators based on comprehensive survey data

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ABSTRACT
Comprehensive and international comparable leading indicators across countries and continents are rare. In this paper, we use a free and instantaneous available source of leading indicators, the ifo World Economic Survey (WES), to forecast growth of Gross Domestic Product (GDP) in 44 countries and three country aggregates separately. We come up with three major results. First, for more than three-fourths of the countries or country-aggregates in our sample, a model containing one of the major WES indicators produces on average lower forecast errors compared to a benchmark model. Second, the most important WES indicators are either the economic climate or the expectations on future economic development for the next six months. And third, adding the WES indicators of the main trading partners leads to a further increase in forecast accuracy in more than 50% of the countries. It seems therefore reasonable to incorporate economic signals from the domestic economy's main trading partners.

KEYWORDS
World economic survey; Economic Climate; Forecasting GDP

JEL CLASSIFICATION
E17; E27; E37

I. Introduction

Macroeconomic projections based on leading indicators is a widely accepted approach when it comes to practical forecasting or by looking at the corresponding scientific literature. Especially survey indicators have often been proved to be very good predictors for the real economy (see, among others, Girardi, Gayer, and Reuter 2016). Leading indicators, however, crucially differ between countries, which makes a general statement on the usefulness of a specific group of leading indicators between countries nearly impossible. One freely available source of comparable qualitative indicators is the ifo World Economic Survey (WES). In this paper, we use the main indicators from this survey among economic experts to evaluate their forecasting performance for gross domestic product (GDP) growth in 44 countries and three aggregates (EU-27, the Eurozone and a World aggregate).

There are only a few surveys with questionnaires that are comparable across countries. Three examples are the Purchasing Manager Index (PMI) provided by Markit, indicators from the European Commission's Joint Harmonised EU Programme of Business and Consumer Surveys (BCS) and the Composite Leading Indicator (CLI) of the OECD. Whereas the first two are solely business or consumer surveys, the CLIs of the OECD are also based on several hard indicators. The PMI covers more than 30 advanced and emerging economies using an identical questionnaire. The BCS ensures harmonized questions across business and consumer surveys among almost all European countries. Unfortunately, PMIs are not freely accessible for almost all countries and the CLIs have a publication lag of two months. The WES, in contrast, is freely available to researchers[1] and covers more than 100 countries. Furthermore, the WES employs comparable questionnaires which allow us to formulate a statement on the WES forecasting performance across a large set of countries.

Up to date, a vast literature on country-specific GDP forecasts exists that either focuses on methodological or data issues.[2] A recent study for global GDP growth is the one by Ferrara and Marsilli (2019).

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[1]Non-researchers, however, have to pay a small fee to access the data.
[2]See, for example, China: Zhou, Wang, and Tong (2013), France: Barhoumi, Darné, and Ferrara (2010), Germany: Drechsel and Scheufele (2012), Greece: Kiriakidis and Kargas (2013b), Spain: Pons-Novell (2006), Sweden: Österholm (2014), UK: Barnett, Mumtaz, and Theodoridis (2014), US: Banerjee and Marcellino (2006).

However, a comprehensive study for many countries using identical survey data to forecast national economic activity is missing. One exception is Fichtner, Rüffer, and Schnatz (2011) who investigate the forecasting properties of the OECD leading indicators for 11 countries. Lehmann (2015) and Lehmann and Weyh (2016) use data from the BCS to forecast export growth or employment growth for various European countries.

Despite the instantaneous and free availability, the WES survey data have only been used by a small number of studies. Henzel and Wollmershäuser (2005) develop a new methodology to elicit inflation expectations from the WES. For 43 countries and two country aggregates, the paper by Kudymowa, Plenk, and Wohlrabe (2013) assesses the in-sample performance of the WES economic climate as a business cycle indicator. They find strong cross-correlations between the WES indicators and country-specific year-on-year growth rates in real GDP. Thus, the climate indicator can be used to assess the state of the economy or even upcoming future economic development. The relevant literature for our purpose, namely the studies that focus on forecasting issues, is also very scarce. For Euro Area real GDP, Hülsewig, Mayr, and Wollmershäuser (2008) use three business cycle indicators and ask whether the optimal pooling of nationwide information of these indicators help to increase forecast accuracy of the European aggregate. They find an improvement in their approach over alternative techniques. One of the applied nationwide indicator is the WES economic climate because of its comparability between different countries. Hutson, Joutz, and Stekler (2014) apply the Carlson-Parkin framework and the Pesaran-Timmermann Predictive Failure statistic to several WES indicators for the US economy. As a result, the WES experts provide statistical significant superior directional forecasts for total GDP and sub-components.

Our paper has two major contributions to the literature. First, as there is no comprehensive out-of-sample forecasting study for a large set of countries, this paper evaluates the performance of WES indicators for 44 countries and three country aggregates to forecast national GDP. We use the three major indicators from the WES (the assessment of the current economic situation, the expectations on future economic development for the next six months, and the economic climate) and ask whether models containing one of these indicators have a higher forecast accuracy compared to an autoregressive benchmark. Our second contribution deals with the question whether national GDP forecasts can be improved by additionally using the WES survey results from the country-specific most important trading partners. Since business cycle synchronization between countries rises the higher their trading intensity is (Inklaar, Jong-A-Pin, and de Haan 2008; Duval et al. 2016), one can suggest that country-specific forecast accuracy of GDP can be increased by adding WES indicators from economically important countries.[3] Our results indicate that the WES indicators have a higher forecast accuracy compared to the benchmark model in more than three-fourths of countries or country-aggregates and forecast horizons; concerning the nowcast situation, the WES indicators are better in 45 of our 47 countries or aggregates. Only for Switzerland and Indonesia the WES indicators cannot improve GDP forecasts over the benchmark. Adding the WES indicators from a country's main trading partners further increases the forecast accuracy in more than 50% of countries and forecast horizons; the largest improvement – with more than 70% of the countries in the sample – can again be observed by forecasting the current quarter. Thus, relying on economic signals from economic important countries to the home country leads to a higher forecast accuracy in most of the cases.

The remainder of the paper is organized as follows: Section 2 briefly describes the data set and the WES. The forecasting approach is introduced in Section 3. In Section 4, we present the results. We end by offering some conclusions in Section 5.

II. Data

Countries and target series to forecast

Forecasting gross domestic product (GDP) all over the world requires a large sample of countries. We build our exercise on 44 single countries and three additional aggregates (the EU-27, the Eurozone

[3]The idea of including indicators from other geographic areas to forecast GDP of the domestic economy has also been put forward – in a regional context – by Lehmann and Wohlrabe (2015).

and the World[4]). This sample comprises emerging countries such as Argentina or Brazil as well as highly developed countries such as Norway or the United States. The country selection is driven by both the availability of a long quarterly GDP series and a sufficient number of respondents in the WES. Table A1 in the Appendix lists all countries and aggregates in our sample.

As the target variable, we use GDP as the main indicator to measure economic activity. We can rely on seasonally adjusted GDP in real terms for all countries. All GDP series are transformed into quarter-on-quarter growth rates. Since official statistics have developed differently in various countries, the length of the GDP series differ between the countries in our sample. The earliest starting point in our sample is Q1-1990 (for example, Canada).[5] For the Russian Federation, we observe the shortest GDP series (first quarterly growth rate for Q1-2003). Unfortunately, we cannot rely on real-time GDP data. To the best of our knowledge, a real-time database for such a large number of countries is not available. We therefore decided to be consistent over the whole set of countries by using the latest available GDP figures, thus, we can compare the forecasting performance of the indicators in a similar setup for each country. Even if we apply real-time data for a small subset of countries, we would not be able to draw meaningful conclusions for the forecasting performance of the other countries. We therefore decided to be consistent over the set of 44 countries and use the latest vintage each, which is in line with our research question of evaluating the WES forecast performance across countries. Table A1 in the Appendix also shows the starting points for all country GDP figures, along with the source from which we obtained the data.

ifo World economic survey

The ifo World Economic Survey (WES) is one of the standard surveys provided by the ifo Institute in Munich (Becker and Wohlrabe 2008). Its aim is to detect worldwide economic trends. To this end, the ifo Institute currently polls over 1,000 economists worldwide from international and national organizations on current economic developments in their respective countries (see Stangl 2007b; Boumans and Garnitz 2017). Unlike quantitative information from official statistics, the WES focuses on qualitative information by asking economists to assess main economic indicators for the present and the near-term future. This allows for a rapid, up-to-date assessment of the economic situation around the world, and particularly in developing and transition economies that often lack a number of official statistics. The uniform questionnaire, methodology and data processing guarantee comparability across countries and over time as well as the aggregation of country results in various country groups. At present, the survey covers almost 120 countries. The WES was launched via two trial runs in 1981 and conducted three times a year from 1983 to 1988 (Stangl 2007a). Since 1989 the WES is a quarterly survey conducted in January, April, July, and October. We start our analysis in 1990 at the earliest possible, because the number of respondents for many countries in the WES survey are sufficiently enough from that point in time, as the indicators are much smoother compared to the first quarters in which the survey was conducted.

The WES is a survey among experts that applies a top-down approach, i.e., the surveyed experts assess the present and future economic situation in their country by taking into account all of the aspects that they regard as important. The panel includes representatives of multinational enterprises, academic institutions, foundations, economic research institutes, national and international chambers of industry and trade. Although the panel members are heterogeneous with respect to their professional affiliation, all of the respondents are highly qualified, either being in a leading position or occupied with economic research within their institution. The participation in the survey is absolutely voluntary. As it is

[4]In this article, world GDP is the weighted average of advanced countries (Canada, the EU-28, Hong Kong, Japan, Norway, Singapore, South Korea, Switzerland, Taiwan, and the USA) and emerging countries (Argentina, Brazil, Chile, China, Colombia, India, Indonesia, Malaysia, Mexico, the Philippines, Russia, Thailand, Turkey, and Venezuela).

[5]We have to mention that longer GDP series are available. However, our quarterly survey indicator first starts in 1990 with a sufficient number of respondents for some countries.

common in panel surveys, some economists have left or joined the panel over time and not all participants respond to every survey, thus, the composition of the panel varies with each wave. At present, about 1,100 responses are received each quarter, which leads to a return rate of about 70% of filled questionnaires. Table A1 in the Appendix shows the average number of respondents for the 44 countries and three aggregates for the years 1990 to 2017.

In the past 20 years, the number of respondents varies strongly from at least 3 up to 50 experts per country. Generally, the higher a country's economic importance – according to the country's share in world GDP – the more WES experts participate. For our analysis, we only consider countries with at least four WES respondents on average as well as a sufficient number of observations.

All tendency questions contained in the WES have, in general, three possible and qualitative answers each: '*good, better, higher*' for a positive assessment or an improvement $(+)$, '*satisfactory, about the same, no change*' for a neutral assessment $(=)$, and '*bad, worse, lower*' for a negative assessment or a deterioration $(-)$. For each quarterly survey, the percentage shares of each tendency category $(+)$, $(=)$ and $(-)$ are calculated from the individual replies. Therefore, no specific weighting of the individual answers per country exist, thus, a simple arithmetic mean is applied. As common in the majority of well-known surveys (for example, the business and consumer survey of the European Commission), a balance statistic is calculated from the percentage shares of positive and negative responses.[6] This results in a statistic ranging from -100 to $+100$ balance points. If positive and negative shares equal each other, the balance statistic has a value of zero. The GDPs measured in purchasing power parities serve as weights to calculate results for country groups or regions.

For our forecasting exercise, we use the three main indicators which catch the most attention by the public: the assessment of the present economic situation (SIT), expectations for the economic situation in the next six months (EXP), and the resulting indicator of both questions, the economic climate (CLI). The underlying assessment for the three indicators is as follows: '*This country's general situation regarding the overall economy is:*'. For the judgment of the present economic situation, the respondents can choose either '*good*', '*satisfactory*' or '*bad*'. For the expected situation by the end of the next six months, the answers are '*better*', '*about the same*', and '*worse*'. The economic climate is the geometric mean of the balance statistics for the present situation and the expectation indicator according to the following formula:

$$CLI = \sqrt{(SIT + 200)(EXP + 200)} - 200 \quad .$$

This is the usual way of the ifo Institute to calculate its composite indicators such as the most important leading indicator for the German economy, the ifo Business Climate for Industry and Trade (Seiler and Wohlrabe 2013). Long time series for the ifo World Economic Climate or the ifo Economic Climate for the Euro Area are available free of charge at the ifo homepage.[7] The survey results for other countries are published in the journal *ifo World Economic Survey* or are available upon request. Compared to other indicators that are available for a majority of countries and for which the user regularly has to pay for (see, for example, the Purchasing Managers Index by Markit), the WES results are free of charge and can be accessed by anyone that is interested in these indicators.

III. Forecasting approach

Univariate one-indicator models

As a starting point for our pseudo-out-of-sample forecasting approach, we consider the following forecasting model

$$y^j_{i,t+h} = c^j_i + \alpha^j_{1,i} y_{i,t-1} + \beta^j_{1,i} WES^j_{i,t} + \varepsilon^j_{i,t} \quad , \qquad (1)$$

where $y_{i,t}$ is the quarter-on-quarter growth rate of GDP for a specific country i and a given point in time t; $y_{i,t-1}$ denotes the first lag of quarterly GDP

[6]We are aware of the fact that the usage of balance statistics is not free of criticism in the existing literature as this form of calculation neglects the information of the 'neutral' category. In order to be comparable to the majority of forecasting papers, we stick to their approach and also apply a balance as the usual form of transformation.

[7]http://www.cesifo-group.de/ifoHome/facts/Survey-Results/World-Economic-Survey.html. http://www.ifo.de/en/umfragen/time-series

growth. One of the three possible WES indicators (present economic situation, *SIT*, expectations for the next six months, *EXP*, or the economic climate, *CLI*) is denoted by $WES^j_{i,t}$. Each h-step ahead direct forecast is calculated by shifting the specific indicator back in time in the estimation equation. The forecast horizon h is defined in the range of $h \in \{0, 1, 2\}$ quarters, whereas $h = 0$ defines the nowcast and $h = 2$ the maximum forecast of a half year. We assume that the forecast is produced at the end of each quarter t, thus, the GDP growth rate of $t - 1$ as well as the contemporaneous WES indicator are known to the forecaster. We also experimented with additional lags for both the target series as well as the survey indicators. The results remained qualitatively the same.[8] As the benchmark model, we apply an AR (1), which proved to be a quite good competitor in the forecasting literature. However, we also present the results of the following models that might serve as additional benchmarks: an AR(2) and an AR(p).

We calculate the forecasts as follows. For each country, we have a different number of observations (T_i). As this difference prevents us from applying a fix starting point for all countries to forecast GDP, we decided to use the first $T_i/3$ observations as the initial estimation period. First, the model parameters (c^j_i, $\alpha^j_{1,i}$ and $\beta^j_{1,i}$) are estimated via ordinary least squares (OLS). Second, based on these estimates, we calculate the forecasts for all three horizons. And last, the estimation window is expanded by one quarter. After this expansion, the model is re-estimated and new forecasts are calculated. This iterative procedure is continued until the end of our observation period.

Univariate multi-indicator models

In times of a globalized world, we may gain some forecasting improvements for national GDP by adding survey indicators of the most important trading partners. The literature on international linkages has found that a higher trade intensity between countries leads to a more intensive business cycle synchronization across those (see, among others, Inklaar, Jong-A-Pin, and de Haan 2008; Duval et al. 2016). Based on survey forecasts, Lahiri and Zhao (2019) also find that especially business cycles across industrialized countries converge to each other. Another of their finding is that international news shocks are incorporated in domestic survey forecasts after six months at latest. We thus sequentially add the WES results of the three most important trading partners to Equation (1), ending up in the following multi-indicator models

$$y^j_{i,t+h} = c^j_i + \alpha^j_{1,i} y_{i,t-1} + \beta^j_{1,i} WES^j_{i,t} + \gamma^j_{1,i} WES^j_{TP1,t} + \varepsilon^j_{i,t}\ , \tag{2}$$

$$= c^j_i + \alpha^j_{1,i} y_{i,t-1} + \beta^j_{1,i} WES^j_{i,t} + \gamma^j_{1,i} WES^j_{TP1,t} + \gamma^j_{2,i} WES^j_{TP2,t} + \varepsilon^j_{i,t}\ , \tag{3}$$

$$= c^j_i + \alpha^j_{1,i} y_{i,t-1} + \beta^j_{1,i} WES^j_{i,t} + \gamma^j_{1,i} WES^j_{TP1,t} + \gamma^j_{2,i} WES^j_{TP2,t} + \gamma^j_{3,i} WES^j_{TP3,t} + \varepsilon^j_{i,t}\ . \tag{4}$$

First, we add the same WES indicator j from the most important trading partner (TP1) and repeat the forecasting experiment from the previous section. Second, we also add indicator j from the second most important trading partner (TP2) of country i. Finally, the largest model comprises the survey indicators of all three most important trading partners (TP3). Taking Germany as an example, its three most important trading partners are the US, France, and China. If we set up a model with the WES economic climate for Germany, we sequentially add the WES economic climate of (i) the US, (ii) France, and (iii) China. We refrain from allowing a mix of indicators, thus, we have 12 forecasting models per country (3 one-indicator and 9 multi-indicator models). All other steps of the forecasting exercise are equal to the univariate one-indicator approach. The choice of the most important trading partners is also limited to the availability of WES information. In cases where we do not have survey indicators from the

[8] Automatic model selections either by the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) suggested very parsimonious models in the majority of cases. Such simple indicator models have been proved to do a good job in forecasting Euro Area GDP growth (see Girardi, Gayer, and Reuter 2016).

WES for a main trading partner, we replace it with information from the next most important trading partner. The last three columns of Table A1 in the Appendix list the three main trading partners per country.

Forecast evaluation

We apply the standard root mean squared forecast error (RMSFE) as the measure of forecast accuracy. Let $FE^j_{i,t+h} = y_{i,t+h} - \hat{y}^j_{i,t+h}$ denote the h-step ahead forecast error resulting from one of the univariate one- or multi-indicator models j, then the $RMSFE^j_{i,h}$ is defined as

$$RMSFE^j_{i,h} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(FE^{j,n}_{i,t+h}\right)^2} \quad ,$$

with N as the total number of forecasts that were calculated. The respective RMSFE for the autoregressive benchmark model of order one is: $RMSFE^{AR(1)}_{i,h}$. In order to decide whether the WES indicator model delivers smaller forecast errors on average, we calculate the relative root mean squared forecast error (rRMSFE):

$$rRMSFE^j_{i,h} = \frac{RMSFE^j_{i,h}}{RMSFE^{AR(1)}_{i,h}} \quad .$$

A ratio smaller of one means that the specific indicator model j has, on average, a higher forecast accuracy compared to the autoregressive benchmark. The opposite is indicated by ratios larger than one.

The standard way to discriminate between the forecasting performances of two competing models in a statistical way is to apply a forecast accuracy test such as the one proposed by Diebold and Mariano (1995) (DM test). This pairwise test evaluates whether the average loss differential between the two models is statistically different from zero. Under the null hypothesis,

$$H_0 : E\left[d^j_{i,t+h}\right] = E\left[\mathcal{L}^{AR(1)}_{i,t+h} - \mathcal{L}^j_{i,t+h}\right] = 0 \quad ,$$

the DM test examines in a statistical sense whether two models produce equal quadratic losses. In our case, $\mathcal{L}^j_{i,t+h}$ is the quadratic loss from one specific indicator model and $\mathcal{L}^{AR(1)}_{i,t+h}$ the quadratic loss of the benchmark.

Expressed in other words, the null hypothesis of the DM test states that – in our case – the AR(1) process is the data generating process. As our univariate one- and multi-indicator models all include one lag of the target series, the typical problem of nested models arises. Thus, these larger models introduce an estimation bias as the parameters of the survey-indicators are zero in the population. Our AR(1)-benchmark therefore nests the indicator-models by setting the parameters to zero. According to Clark and West (2007), the problem of nested models cause the mean squared forecast error of the larger model to increase because of the estimation of redundant parameters. The result is that standard tests such as the DM test loose their power in testing performance differentials in a statistical sense. By following the literature (see, among others, Weber and Zika 2015; Lehmann and Weyh 2016), we apply the adjusted test statistic by Clark and West (2007)

$$\mathrm{CW}_h = \sqrt{\frac{1}{\hat{V}(a^j_{i,t+h})N}} \sum_{n=1}^{N}\left(\underbrace{MSFE^{AR(1)}_{i,h} - \left[MSFE^j_{i,h} - \left(\hat{y}^j_{i,t+h} - \hat{y}^{AR(1)}_{i,t+h}\right)^2\right]}_{a^j_{i,t+h}}\right) ,$$

with $\widehat{V}(a^j_{i,t+h})$ as the variance of $a^j_{i,t+h}$ and $\left(\widehat{y}^j_{i,t+h} - \widehat{y}^{AR(1)}_{i,t+h}\right)^2$ as the adjustment term of Clark and West (2007). The adjustment than allows to use standard critical values from the Student's t-distribution with $N-1$ degrees of freedom to decide whether the forecasts errors are different from each other in a statistical sense.

IV. Results

Baseline performance: one-indicator models

Table 1 presents the forecasting performance of the one-indicator models and thus the performance of the three WES indicators (the current economic situation, *SIT*, the expectations for the next half year, *EXP*, or the economic climate, *CLI*). For each country, the table shows the relative root mean squared forecast

Table 1. Best WES indicators across countries and forecast horizons.

	$h = 0$		$h = 1$		$h = 2$	
Country	rRMSFE	Indicator	rRMSFE	Indicator	rRMSFE	Indicator
Argentina	0.996	CLI	1.009	SIT	1.001	SIT
Australia	**0.974**	EXP	0.997	EXP	1.008	EXP
Austria	**0.974**	CLI	0.984	EXP	**0.944**	EXP
Belgium	**0.961**	CLI	1.004	EXP	0.990	EXP
Brazil	**0.881**	CLI	**0.946**	CLI	**0.953**	CLI
Bulgaria	**0.927**	CLI	**0.962**	CLI	1.024	CLI
Canada	**0.959**	EXP	0.993	CLI	**0.967**	EXP
Chile	**0.971**	CLI	**0.931**	CLI	**0.857**	CLI
China	0.985	CLI	0.998	SIT	0.987	SIT
Czech Republic	**0.968**	EXP	1.002	EXP	0.983	EXP
Denmark	0.988	CLI	1.016	CLI	1.005	CLI
Estonia	**0.858**	CLI	**0.937**	EXP	1.014	EXP
Finland	**0.905**	EXP	**0.877**	EXP	**0.908**	EXP
France	**0.944**	CLI	**0.986**	EXP	0.974	EXP
Germany	**0.948**	CLI	**0.960**	EXP	0.978	EXP
Hong Kong	**0.938**	EXP	**0.994**	EXP	0.991	SIT
Hungary	0.995	CLI	0.992	CLI	**0.960**	SIT
India	0.997	CLI	1.001	EXP	1.001	CLI
Indonesia	1.115	EXP	1.045	SIT	1.030	CLI
Ireland	**0.925**	EXP	**0.976**	EXP	0.984	EXP
Italy	**0.966**	CLI	**0.942**	EXP	**0.920**	EXP
Japan	**0.953**	EXP	0.978	EXP	0.999	EXP
Latvia	**0.847**	CLI	**0.822**	CLI	**0.782**	EXP
Mexico	**0.970**	EXP	0.983	EXP	**0.967**	SIT
Netherlands	0.925	CLI	0.971	CLI	0.996	EXP
New Zealand	**0.975**	SIT	**0.986**	SIT	1.002	SIT
Norway	**0.941**	EXP	0.983	EXP	0.991	EXP
Philippines	**0.946**	EXP	0.986	EXP	0.986	SIT
Poland	**0.976**	CLI	0.994	CLI	**0.985**	CLI
Portugal	**0.857**	CLI	0.909	CLI	0.998	SIT
Russia	**0.966**	EXP	**0.998**	SIT	0.795	SIT
Slovakia	**0.920**	CLI	**0.985**	CLI	1.011	EXP
Slovenia	**0.933**	CLI	0.996	CLI	0.980	SIT
South Africa	**0.963**	CLI	**0.971**	CLI	**0.931**	CLI
South Korea	0.989	EXP	1.017	CLI	0.998	EXP
Spain	**0.698**	CLI	**0.688**	CLI	**0.913**	CLI
Sweden	**0.895**	EXP	**0.942**	EXP	**0.971**	EXP
Switzerland	1.011	CLI	1.019	EXP	1.010	CLI
Taiwan	0.999	CLI	1.002	EXP	0.991	CLI
Thailand	0.944	EXP	1.028	EXP	1.017	SIT
Turkey	**0.911**	CLI	**0.964**	CLI	0.994	EXP
United Kingdom	**0.975**	CLI	**0.978**	EXP	0.975	EXP
United States	**0.951**	CLI	**0.976**	CLI	1.002	SIT
Uruguay	**0.841**	CLI	**0.909**	CLI	0.978	SIT
EU-27	0.911	EXP	0.959	EXP	0.829	EXP
Eurozone	**0.886**	CLI	0.957	EXP	**0.898**	EXP
World	**0.880**	EXP	**0.982**	EXP	0.900	EXP

For each forecast horizon and country or aggregate, the table reports the smallest relative root mean squared forecast error (rRMSFE) of the three possible univariate one-indicator models; the columns 'Indicator' show these best indicators. The indicators are abbreviated as: *SIT* . . . WES present economic situation, *EXP* . . . WES expectations for the next six months and *CLI* . . . WES economic climate. The benchmark is always the AR(1). A rRMSFE hold in bold face indicates a significant improvement in forecast accuracy due to the Clark-West test at least to the 10% confidence level.

errors (rRMSFE) of the best WES indicator compared to the autoregressive benchmark of order one.[9] The results for the country aggregates are shown at the bottom of the table. A rRMSFE hold in bold face indicates that the corresponding WES-indicator model performs – according to the Clark-West-test – statistically better on average at least to the 10% confidence level.

Sticking to the nowcasting situation, one out of the three WES indicators provides forecast errors that are, on average, lower compared to the benchmark for 45 countries or aggregates in our sample. No WES indicator does improve upon the AR(1) benchmark model in case of two countries, namely Indonesia and Switzerland. For $h = 1$ the WES indicators can beat the benchmark model for

[9] The results for the other two benchmark models, AR(2) and AR(p), can be found in Appendix B. In the minority of cases, the other two benchmarks produce, on average, lower forecast errors than the AR(1) process. For these cases, however, our qualitative results remain unchanged as the best WES indicator models still produce rRMSFEs that are smaller than one. Thus, sticking to the autoregressive process of order one as benchmark seems reasonable.

37 countries, which equals a quota of 78.7% in our sample. Also for two quarter-ahead predictions, the best WES indicator beats the autoregressive model in 35 countries (quota: 74.5%).

Concerning the best indicator, we find differences across the three forecasting horizons. For the prediction of the current quarter ($h = 0$), the WES economic climate, *CLI*, is the best performing indicator in 28 countries (for example, Estonia), followed by the WES expectations for the next six months, *EXP*, as the best indicator in 16 countries (for example, Sweden). The WES economic situation is only superior in one case (New Zealand). By taking a closer look at one quarter-ahead predictions ($h = 1$), we find that the WES economic climate and the WES expectations are more or less astride in serving as the best indicator: 16 countries with *CLI* as the best indicator, *EXP* in 18 countries. The WES economic situation, *SIT*, is again less frequently the best predictor (3 countries). For $h = 2$, *EXP* clearly dominates the other two WES indicators, which might not be surprising at all as *EXP* is the most forward-looking indicator out of the three applied in our sample. Compared to 6 (*CLI*) or 9 countries (*SIT*), the WES economic expectations, *EXP*, is the best indicator in 20 countries of the sample. Across all forecast horizons and countries, the WES economic expectations is the best predictor (54 cases), followed by the WES economic climate (50 cases); the WES economic situation does only serve as the best indicator in 13 cases.

In the following, we take a closer look at the performance of the indicators across the countries in the sample. The largest relative improvement in the nowcast situation can be found for Spain ($rRMSFE_{h=0} = 0.689$), followed by Uruguay ($rRMSFE_{h=0} = 0.841$) and Latvia ($rRMSFE_{h=0} = 0.847$). For $h = 1$, the top 3 improvements are observable for Spain, Latvia, and Finland ($rRMSFE_{h=1} = 0.688, 0.822,$ and 0.877). Turning to the longest forecast horizon, we again find Latvia with the highest relative improvement ($rRMSFE_{h=2} = 0.782$), in addition to the Russian Federation ($rRMSFE_{h=2} = 0.795$) and the EU-27 ($rRMSFE_{h=2} = 0.829$). We, however, also have to mention that the WES indicators do not improve the forecasting performance of the benchmark model for a small minority of countries. As previously stated: no WES indicator is able to beat the autoregressive model for all three forecast horizons in Indonesia and Switzerland. In the cases of Argentina, Denmark, India and Thailand, the best WES indicator is only able to beat the AR(1) process for one out of the three forecast horizons.

By grouping the countries into advanced and emerging economies, the correlation between being an emerging economy and the rRMSFE is negative (≈ -0.2), thus, the relative forecast errors are on average smaller for advanced economies. This holds true for $h = 0$ and $h = 1$; for the longest forecast horizon, the correlation is virtually zero. This finding for advanced and emerging economies raises the question whether the performance of the WES indicators depends on the number of interviewed experts. There seems to be a slight linear relationship between the relative forecast errors and the number of experts for the specific country. Furthermore, this correlation is negative, indicating that the rRMSFEs are on average smaller the more experts are interviewed. A composition effect of the pool of experts on the relative forecast performance is also imaginable. However, the corresponding affiliation of the expert is only captured in the data set since 2015. For all countries together, approximately 50% of the experts are either affiliated with a research institution (institute or university) or a financial institution (central bank, commercial bank or other financial organization). The composition of experts may deliver more insights into the heterogeneity of forecast accuracy between countries. We, however, have to leave such a question for future research activities.

Performance by adding main trading partners

In the previous section, we examined the forecasting power of the single WES indicators. This section answers the question whether adding the WES indicators of the most important trading partners for each country improves the performance of the one-indicator models.[10] Table 2 compares the relative root mean squared forecast errors (rRMSFE) of the best model from the baseline (column 'Base')

Table 2. Forecast performance after adding the main trading partners.

	$h=0$			$h=1$			$h=2$		
	rRMSFE			rRMSFE			rRMSFE		
Country	Base	MTP	Model	Base	MTP	Model	Base	MTP	Model
Argentina	0.996	**0.966**	CLI–3	1.009	1.015	SIT–1	1.001	1.008	SIT–1
Australia	**0.974**	**0.951**	EXP–1	0.997	0.996	EXP–1	1.008	**0.982**	SIT–1
Austria	**0.974**	**0.955**	CLI–3	0.984	0.980	EXP–1	**0.944**	**0.939**	EXP–1
Belgium	**0.961**	0.845	CLI–1	1.004	0.899	CLI–1	0.990	0.930	CLI–1
Brazil	**0.881**	**0.860**	CLI–1	**0.946**	**0.958**	CLI–1	**0.953**	**0.970**	EXP–1
Bulgaria	**0.927**	**0.912**	CLI–2	**0.962**	**0.947**	CLI–3	1.024	**0.987**	EXP–3
Canada	**0.959**	**0.962**	EXP–1	0.993	0.995	EXP–1	**0.967**	**0.963**	EXP–1
Chile	**0.971**	**0.956**	CLI–1	**0.931**	**0.932**	CLI–1	**0.857**	**0.868**	CLI–1
China	0.985	0.997	CLI–1	0.998	1.049	SIT–1	0.987	1.030	CLI–1
Czech Republic	**0.968**	0.991	EXP–2	1.002	1.033	EXP–3	0.983	**0.949**	EXP–3
Denmark	0.988	**0.932**	EXP–2	1.016	**0.905**	EXP–1	1.005	0.996	SIT–1
Estonia	**0.858**	**0.841**	CLI–3	**0.937**	**0.895**	EXP–3	1.014	1.034	SIT–3
Finland	**0.905**	**0.905**	CLI–3	**0.877**	**0.858**	EXP–3	**0.908**	**0.874**	SIT–3
France	**0.944**	**0.934**	CLI–2	**0.986**	**0.966**	EXP–1	0.974	**0.932**	SIT–1
Germany	**0.948**	**0.968**	EXP–3	**0.960**	**0.972**	EXP–3	0.978	**0.951**	SIT–3
Hong Kong	**0.938**	**0.935**	EXP–2	**0.994**	**0.990**	EXP–1	0.991	1.004	SIT–1
Hungary	0.995	**0.927**	EXP–3	0.992	**0.931**	EXP–1	**0.960**	0.941	EXP–1
India	0.997	0.993	EXP–1	1.001	1.007	EXP–1	1.001	1.027	CLI–1
Indonesia	1.115	1.104	EXP–1	1.045	1.090	EXP–1	1.030	1.040	EXP–2
Ireland	**0.925**	**0.917**	CLI–1	**0.976**	**0.960**	SIT–1	0.984	0.990	EXP–1
Italy	**0.966**	**0.946**	EXP–1	**0.942**	**0.921**	EXP–1	**0.920**	**0.886**	EXP–1
Japan	**0.953**	**0.893**	EXP–3	0.978	**0.961**	EXP–2	0.999	0.994	EXP–1
Latvia	**0.847**	**0.801**	CLI–2	**0.822**	**0.781**	CLI–2	**0.782**	**0.776**	EXP–2
Mexico	**0.970**	**0.958**	EXP–3	0.983	0.992	EXP–1	**0.967**	**0.969**	SIT–3
Netherlands	0.925	**0.898**	CLI–3	0.971	**0.944**	CLI–1	0.996	**0.972**	EXP–1
New Zealand	**0.975**	**0.984**	SIT–2	**0.986**	**0.974**	SIT–2	1.002	**0.961**	SIT–2
Norway	**0.941**	**0.939**	EXP–1	0.983	**0.970**	SIT–1	0.991	1.015	SIT–1
Philippines	**0.946**	0.937	EXP–2	0.986	0.983	EXP–2	0.986	**0.998**	SIT–3
Poland	**0.976**	**0.981**	CLI–1	0.994	1.003	CLI–1	**0.985**	**0.994**	CLI–1
Portugal	**0.857**	**0.804**	EXP–1	0.909	**0.836**	EXP–1	0.998	**0.936**	EXP–1
Russia	**0.966**	**0.938**	EXP–1	**0.998**	1.025	SIT–1	0.795	0.812	SIT–1
Slovakia	**0.920**	**0.939**	CLI–1	**0.985**	0.987	EXP–1	1.011	1.026	SIT–2
Slovenia	**0.933**	**0.942**	CLI–3	0.996	0.947	CLI–3	0.980	**0.935**	EXP–1
South Africa	**0.963**	**0.945**	CLI–2	**0.971**	0.992	SIT–1	**0.931**	**0.966**	SIT–3
South Korea	0.989	0.990	EXP–2	1.017	1.025	CLI–1	0.998	0.993	EXP–1
Spain	**0.698**	**0.701**	CLI–1	**0.688**	**0.713**	CLI–1	**0.913**	**0.896**	CLI–1
Sweden	**0.895**	**0.856**	EXP–2	**0.942**	**0.910**	EXP–1	**0.971**	**0.934**	EXP–1
Switzerland	1.011	0.994	CLI–3	1.019	1.011	EXP–1	1.010	1.010	SIT–1
Taiwan	0.999	**0.975**	EXP–2	1.002	1.000	EXP–2	0.991	0.996	EXP–1
Thailand	0.944	**0.927**	EXP–1	1.028	1.033	EXP–1	1.017	1.017	SIT–1
Turkey	**0.911**	**0.935**	CLI–1	**0.964**	1.024	CLI–1	0.994	**0.933**	EXP–3
United Kingdom	**0.975**	**0.965**	EXP–2	**0.978**	**0.985**	EXP–2	0.975	**0.973**	CLI–2
United States	**0.951**	**0.941**	EXP–1	**0.976**	**0.947**	EXP–1	1.002	**0.942**	SIT–2
Uruguay	**0.841**	**0.858**	CLI–1	**0.909**	**0.939**	CLI–1	0.978	1.030	EXP–1
EU-27	0.911	**0.896**	CLI–3	0.959	0.975	EXP–1	0.829	0.773	SIT–3
Eurozone	**0.886**	**0.839**	CLI–2	0.957	**0.957**	SIT–1	**0.898**	**0.887**	EXP–1
World	**0.880**	0.871	EXP–1	**0.982**	0.986	SIT–1	0.900	0.871	SIT–3

For each forecast horizon and country or aggregate, the table compares the relative root mean squared forecast error (rRMSFE) of the baseline (column 'Base') with the smallest rRMSFE of the 9 possible multi-indicator models based on sequentially adding the main trading partners (column 'MTP'); the columns 'Model' show the abbreviation of this best multi-indicator model. An underline indicates which of the two competitors, baseline model or a model based on main trading partners, produces the smaller rRMSFE. The indicators are abbreviated as: *SIT* ... WES present economic situation, *EXP* ... WES expectations for the next six months and *CLI* ... WES economic climate. Numbers in the model's name indicate whether a multi-indicator model includes the WES indicators of one (–1), two (–2) or three (–3) main trading partners. The benchmark is always the AR(1). A rRMSFE hold in bold face indicates a significant improvement in forecast accuracy due to the Clark-West test at least to the 10% confidence level.

with the rRMSFE of the best multi-indicator model including the WES indicators of the main trading partners (column 'MTP') for each forecast horizon. The model's rRMSFE that is lower compared to the one of its competitors is underlined. The best multi-indicator model (column 'Model') is always abbreviated as a combination of the specific indicator and the number of additional survey results from the main trading partners. For

[10] We also experimented by replacing the most important trading partners of each country by the survey results for the US, the Eurozone and the World aggregate. The corresponding results can be found in Appendix B. For approximately two-fifths of all countries, adding the indicators for the US, the Eurozone and the World aggregate to the univariate indicator-models further increases the forecasting performance upon the benchmark model. Thus, for some countries, it might be recommendable to add those three aggregates instead of the three main trading partners.

example, EXP–1 for Australia is a model with WES economic expectations for the next six months of Australia and China. Another example is the Netherlands: the best multi-indicator model is CLI–3, thus, it is a model that includes the WES economic climates of the Netherlands plus the ones of its three main trading partners Germany, Belgium, and the United Kingdom each. A rRMSFE set in bold again indicates that the specific model produces significant lower forecast errors compared to the AR(1) benchmark according to the Clark-West-test.

For the nowcast situation ($h = 0$) it turns out that adding the WES indicators from the main trading partners improves the already good performance of the baseline model in 34 cases, which are 72.3% of the countries in our sample. For one and two quarter-ahead forecasts adding the indicators for the main trading partners improves the performance of more than half of the countries: 24 countries for $h = 1$ (51.1%) and 27 countries for $h = 2$ (57.4%).

The most important indicator in the countries for which an improvement is reached through adding the trading partners' indicators are the WES economic expectations, *EXP*. For $h = 0$, 19 out of the former described 34 models include the WES economic expectations; for 15 countries the WES economic climate is the most important indicator and the WES economic situation does not play a role. This picture becomes even more pronounced by turning to one and two quarter-ahead predictions: *EXP* is the most important indicator in 16 out of 24 countries for $h = 1$ and 15 out of 27 countries for $h = 2$. These results clearly underpin the role of the WES economic expectations for GDP forecasting found in the previous baseline section.

Next, we ask how much trading partners should be added to improve the forecasts. In the nowcast situation, the number of added trading partners' indicators are rather equally distributed: in 14 cases, the best multi-indicator model includes one trading partner (for example, Ireland), followed by two trading partners in 11 cases (for example, Hong Kong) and three trading partner in 9 countries (for example, Italy). This picture changes tremendously by looking at the two longer forecast horizons. For both horizons, adding one trading partner's indicators dominates the best multi-indicator models (15 countries for $h = 1$ and 16 countries for $h = 2$). Taking care of the developments of a country's main trading partners can thus improve the GDP forecast of the domestic economy.

At last, we stick to the countries for which the performance of the WES indicators in the baseline was not that overwhelming. For Indonesia, also the adding of the trading partners' indicators does not help at all to beat the benchmark model; for Argentina, India and Thailand the qualitative results from the baseline also hold after adding trading partners. We find the opposite for Switzerland. At least for the nowcast, the multi-indicator models now produce lower forecast errors compared to the autoregressive benchmark. We additionally find a strong improvement for Denmark. Compared to the baseline, the multi-indicator models now produce rRMSFEs smaller than one across all forecast horizons.

V. Conclusion

A comprehensive international study on forecasting GDP in which the accuracy for countries is comparable, requires the same set of indicators. Since official data vary between countries, such a comparability is hard to reach. In this paper, we use instantaneous and free available indicators that are, on top, international comparable: the survey results from the ifo World Economic Survey (WES). By applying the three main indicators from the WES (the assessment of the current economic situation, the expectations on future economic development for the next six months, and the economic climate), our paper studies the forecasting performance of these indicators for 44 countries and three country aggregates separately. Additionally, we investigate whether the national-specific forecast accuracy for GDP can be improved by adding WES indicators of the three main trading partners by country. For, on average, more than three-fourths of the countries in the sample, as well as the three country aggregates, a model containing WES information produces lower forecast errors than an autoregressive benchmark up to two quarters ahead. Only for two countries (namely Switzerland and

Indonesia), the indicator models cannot beat the benchmark at all. We also find that the root mean squared forecast errors relative to the benchmark model are on average smaller for advanced economies compared to emerging economies. The most important indicators are the economic climate and the expectations on future economic development for the next six months. The assessment of the current economic situation plays only a minor role in forecasting GDP. Sticking to our second contribution, adding the WES indicators of the main trading partners leads to a further increase of forecast accuracy in more than 50% of the countries. Thus, using survey information for economic important partners to the specific country improves national GDP forecasts.

There are several conclusions that can be drawn from our study. As the WES results are instantaneously and freely available, it makes the WES a powerful tool for business cycle analysis and economic forecasting. However, follow-up studies may also investigate the performance of the WES indicators compared to other leading indicators such as the Purchasing Manager Index or the Composite Leading Indicator of the OECD. Another possibility is to test the forecasting performance of the WES indicators in a real-time setup for a small number of countries (as, for example, suggested by Croushore 2006). Furthermore, the WES questionnaire also captures experts' expectations on other economic aggregates such as the inflation rate or export volumes. Future research activities on economic forecasting might take these indicators into account.

Further promising indicators the WES offers are quantitative, current year forecasts for the inflation rate (quarterly frequency) and GDP (annual frequency). Researchers might use these quantitative information and evaluate the experts' forecasts in follow-up studies with those produced by either large institutions (for example, IMF) or other surveys (for example, Consensus Economics or the Survey of Professional Forecasters). This can also be done with the rather mechanical forecasts of our approach. The WES further contains medium-term forecasts (up to five years) for inflation and GDP. Thus, future research activities can immediately build upon the article by Aromí (2019), who evaluates whether the IMF expert's medium-term projections outperform simple models. Such an analysis can easily be transferred to the WES sample that incorporates experts from a large set of economic institutions.

The characteristics of the experts (for example, the institution) might also be used in order to ask whether the forecast performance of the leading indicators that we have applied in this paper or the quantitative forecasts are affected thereby. The composition of the pool of experts and thus the cross-section variance may explain country differences in relative forecasting performance.

Lastly, the WES survey might help to find new or additional insights on the discussion of information rigidities and expectations formation (see Coibion and Gorodnichenko 2012, 2015) as the pool of experts offers some heterogeneity. We leave such considerations for future research activities.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A. Data set description

Table A1. Countries, data sources and main trading partners 2017.

Country	GDP	Source	Start	WES	Main Trading Partners: First	Second	Third	Source
Argentina	R, SA	OECD	Q1-1993	9	Brazil	US	China	World Bank
Australia	R, SA	OECD	Q1-1990	11	China	Japan	South Korea	World Bank
Austria	R, SA	Eurostat	Q1-1990	13	Germany	US	Italy	Eurostat
Belgium	R, SA	Eurostat	Q1-1990	15	Germany	France	Netherlands	Eurostat
Brazil	R, SA	OECD	Q1-1996	21	China	US	Argentina	World Bank
Bulgaria	R, SA	Eurostat	Q1-2000	14	Germany	Italy	Turkey	Eurostat
Canada	R, SA	OECD	Q1-1990	11	US	China	UK	World Bank
Chile	R, SA	OECD	Q1-1996	9	China	US	Japan	World Bank
China	R, SA	National	Q1-1992	43	US	Hong Kong	Japan	World Bank
Czech Republic	R, SA	Eurostat	Q1-1996	10	Germany	Slovakia	Poland	Eurostat
Denmark	R, SA	Eurostat	Q1-1991	7	Germany	Sweden	UK	Eurostat
Estonia	R, SA	Eurostat	Q1-1997	20	Finland	Sweden	Latvia	Eurostat
Finland	R, SA	Eurostat	Q1-1990	17	Germany	Sweden	US	Eurostat
France	R, SA	Eurostat	Q1-1990	17	Germany	Spain	Italy	Eurostat
Germany	R, SA	Eurostat	Q1-1990	48	US	France	China	Eurostat
Hong Kong	R, SA	National	Q1-1990	8	China	US	India	World Bank
Hungary	R, SA	Eurostat	Q1-1995	11	Germany	Italy	Austria	World Bank
India	R, SA	OECD	Q2-1996	13	US	Hong Kong	China	World Bank
Indonesia	R, SA	OECD	Q1-1990	7	China	US	Japan	World Bank
Ireland	R, SA	Eurostat	Q1-1990	7	US	UK	Belgium	Eurostat
Italy	R, SA	Eurostat	Q1-1990	21	Germany	France	US	Eurostat
Japan	R, SA	OECD	Q1-1990	29	US	China	South Korea	World Bank
Latvia	R, SA	Eurostat	Q1-1997	6	Russia	Estonia	Germany	Eurostat
Mexico	R, SA	OECD	Q1-1990	12	US	Canada	Germany	World Bank
Netherlands	R, SA	Eurostat	Q1-1990	15	Germany	Belgium	UK	Eurostat
New Zealand	R, SA	OECD	Q1-1992	10	China	Australia	US	World Bank
Norway	R, SA	Eurostat	Q1-1990	6	UK	Germany	Netherlands	World Bank
Philippines	R, SA	National	Q1-1998	6	Japan	US	Hong Kong	World Bank
Poland	R, SA	Eurostat	Q1-1996	16	Germany	Czech R.	UK	Eurostat
Portugal	R, SA	Eurostat	Q1-1990	11	Spain	France	Germany	Eurostat
Russia	R, SA	OECD	Q1-2003	19	China	Netherlands	Germany	World Bank
Slovakia	R, SA	Eurostat	Q1-1998	10	Germany	Czech R.	Poland	Eurostat
Slovenia	R, SA	Eurostat	Q1-1998	7	Germany	Italy	Austria	Eurostat
South Africa	R, SA	OECD	Q1-1990	20	China	US	Germany	World Bank
South Korea	R, SA	OECD	Q1-1990	9	China	US	Hong Kong	World Bank
Spain	R, SA	Eurostat	Q1-1990	24	France	Germany	Italy	Eurostat
Sweden	R, SA	Eurostat	Q1-1990	13	Germany	Finland	US	Eurostat
Switzerland	R, SA	Eurostat	Q1-1990	14	Germany	US	China	World Bank
Taiwan	R, SA	National	Q1-1990	10	China	Hong Kong	US	WTO
Thailand	R, SA	National	Q1-1993	8	US	China	Japan	World Bank
Turkey	R, SA	OECD	Q1-1998	11	Germany	UK	US	World Bank
United Kingdom	R, SA	Eurostat	Q1-1990	18	US	Germany	France	Eurostat
US	R, SA	OECD	Q1-1990	27	Canada	Mexico	China	World Bank
Uruguay	R, SA	National	Q1-1997	5	China	Brazil	US	World Bank
EU-27	R, SA	Eurostat	Q1-1995	292	US	China	Switzerland	Eurostat
Eurozone	R, SA	Eurostat	Q1-1995	252	US	China	Switzerland	Eurostat
World	R, SA	–	Q1-1994	807	US	China	Germany	World Bank

For each country or aggregate, the table reports the characteristics of the GDP series, its corresponding data source as well as starting point and the average sample size of the WES between 1990 and 2017. The last four columns show the three main trading partners of each country or aggregate and again the data source from which we obtained the trade data. *Abbreviations*: SA … seasonally adjusted, R … real terms.

Appendix B. Additional results

Table B1. Relative performance of other benchmark models.

	$h = 0$		$h = 1$		$h = 2$	
Country	AR(2)	AR(p)	AR(2)	AR(p)	AR(2)	AR(p)
Argentina	1.020	1.056	1.020	1.056	1.022	1.133
Australia	1.026	1.054	1.026	1.054	1.027	1.024
Austria	1.028	1.010	1.028	1.010	1.004	0.996
Belgium	0.981	0.978	0.981	0.978	1.078	1.208
Brazil	0.998	0.981	0.998	0.981	0.978	1.015
Bulgaria	1.028	1.219	1.028	1.219	1.081	1.011
Canada	1.022	1.042	1.022	1.042	1.100	1.153
Chile	1.014	1.050	1.014	1.050	1.058	1.055
China	0.994	0.989	0.994	0.989	0.993	1.014
Czech Republic	1.022	1.050	1.022	1.050	1.088	1.070
Denmark	0.990	1.013	0.990	1.013	1.031	1.053
Estonia	0.906	1.031	0.906	1.031	1.195	1.195
Finland	1.013	1.009	1.013	1.009	0.992	1.052
France	1.010	1.000	1.010	1.000	1.039	1.132
Germany	1.007	1.026	1.007	1.026	1.035	1.035
Hong Kong	0.996	1.006	0.996	1.006	1.053	1.112
Hungary	1.034	1.001	1.034	1.001	1.093	1.058
India	1.024	1.063	1.024	1.063	1.011	1.078
Indonesia	0.997	1.215	0.997	1.215	1.105	1.068
Ireland	1.013	1.076	1.013	1.076	0.990	1.052
Italy	1.006	1.000	1.006	1.000	1.025	1.029
Japan	1.016	1.063	1.016	1.063	1.036	1.050
Latvia	0.874	0.884	0.874	0.884	1.064	1.138
Mexico	0.979	0.984	0.979	0.984	1.105	1.123
Netherlands	0.991	1.007	0.991	1.007	1.038	1.032
New Zealand	1.006	1.048	1.006	1.048	1.003	1.036
Norway	1.008	1.023	1.008	1.023	1.043	1.115
Philippines	1.019	1.065	1.019	1.065	0.959	1.011
Poland	1.028	0.983	1.028	0.983	1.134	1.153
Portugal	0.931	0.936	0.931	0.936	1.037	1.087
Russland	0.971	1.017	0.971	1.017	0.724	0.807
Slovakia	1.011	1.054	1.011	1.054	1.030	1.066
Slovenia	1.023	1.035	1.023	1.035	1.132	1.072
South Africa	1.005	1.000	1.005	1.000	1.038	1.149
South Korea	0.999	1.184	0.999	1.184	0.992	1.027
Spain	0.691	0.632	0.691	0.632	1.159	1.292
Sweden	1.000	0.999	1.000	0.999	0.993	1.098
Switzerland	1.001	1.004	1.001	1.004	1.033	1.096
Taiwan	1.017	1.030	1.017	1.030	1.025	1.009
Thailand	1.011	1.054	1.011	1.054	0.997	1.074
Turkey	1.011	1.072	1.011	1.072	1.012	0.934
United Kingdom	1.013	1.004	1.013	1.004	0.998	1.134
United States	0.993	1.021	0.993	1.021	1.026	1.075
Uruguay	0.919	0.959	0.919	0.959	1.049	1.071
EU-27	1.020	1.000	1.020	1.000	0.961	0.980
Eurozone	1.018	1.000	1.018	1.000	1.000	1.030
World	1.022	1.051	1.022	1.051	1.057	1.076

For each forecast horizon and country or aggregate, the table reports the RMSFE of the two additional autoregressive models, AR(2) and AR(p), relative to our chosen AR(1) benchmark.

Table B2. Forecast performance by adding the US, the Eurozone and the World as main trading partners.

	$h=0$			$h=1$			$h=2$		
	rRMSFE			rRMSFE			rRMSFE		
Country	Base	MTP	UEW	Base	MTP	UEW	Base	MTP	UEW
Argentina	0.996	0.966	0.932	1.009	1.015	1.009	1.001	1.008	0.998
Australia	0.974	0.951	1.007	0.997	0.996	1.006	1.008	0.982	1.011
Austria	0.974	0.955	0.935	0.984	0.980	0.985	0.944	0.939	0.954
Belgium	0.961	0.845	0.918	1.004	0.899	0.982	0.990	0.930	0.947
Brazil	0.881	0.860	0.897	0.946	0.958	0.975	0.953	0.970	0.966
Bulgaria	0.927	0.912	0.846	0.962	0.947	0.887	1.024	0.987	0.957
Canada	0.959	0.962	0.962	0.993	0.995	0.995	0.967	0.963	0.963
Chile	0.971	0.956	0.945	0.931	0.932	0.897	0.857	0.868	0.862
China	0.985	0.997	0.997	0.998	1.049	1.049	0.987	1.030	1.030
Czech Republic	0.968	0.991	0.911	1.002	1.033	0.997	0.983	0.949	0.975
Denmark	0.988	0.932	0.858	1.016	0.905	0.888	1.005	0.996	0.949
Estonia	0.858	0.841	0.840	0.937	0.895	0.928	1.014	1.034	1.023
Finland	0.905	0.905	0.886	0.877	0.858	0.866	0.908	0.874	0.904
France	0.944	0.934	0.894	0.986	0.966	0.977	0.974	0.932	0.943
Germany	0.948	0.968	0.973	0.960	0.972	0.983	0.978	0.951	0.998
Hong Kong	0.938	0.935	0.887	0.994	0.990	1.001	0.991	1.004	1.023
Hungary	0.995	0.927	0.920	0.992	0.931	0.958	0.960	0.941	0.911
India	0.997	0.993	0.993	1.001	1.007	1.007	1.001	1.027	1.021
Indonesia	1.115	1.104	1.102	1.045	1.090	1.103	1.030	1.040	1.017
Ireland	0.925	0.917	0.917	0.976	0.960	0.960	0.984	0.990	0.984
Italy	0.966	0.946	0.834	0.942	0.921	0.911	0.920	0.886	0.889
Japan	0.953	0.893	0.905	0.978	0.961	0.986	0.999	0.994	0.994
Latvia	0.847	0.801	0.818	0.822	0.781	0.791	0.782	0.776	0.752
Mexico	0.970	0.958	0.954	0.983	0.992	0.992	0.967	0.969	0.983
Netherlands	0.925	0.898	0.853	0.971	0.944	0.915	0.996	0.972	0.937
New Zealand	0.975	0.984	0.988	0.986	0.974	0.993	1.002	0.961	1.015
Norway	0.941	0.939	0.938	0.983	0.970	0.951	0.991	1.015	0.997
Philippines	0.946	0.937	0.932	0.986	0.983	0.982	0.986	0.998	0.986
Poland	0.976	0.981	1.019	0.994	1.003	1.011	0.985	0.994	1.002
Portugal	0.857	0.804	0.793	0.909	0.836	0.809	0.998	0.936	0.886
Russia	0.966	0.938	0.891	0.998	1.025	1.000	0.795	0.812	0.780
Slovakia	0.920	0.939	0.968	0.985	0.987	0.991	1.011	1.026	1.024
Slovenia	0.933	0.942	0.890	0.996	0.947	0.945	0.980	0.935	0.922
South Africa	0.963	0.945	0.924	0.971	0.992	0.984	0.931	0.966	0.947
South Korea	0.989	0.990	0.998	1.017	1.025	1.036	0.998	0.993	1.019
Spain	0.698	0.701	0.735	0.688	0.713	0.681	0.913	0.896	0.816
Sweden	0.895	0.856	0.919	0.942	0.910	0.944	0.971	0.934	0.969
Switzerland	1.011	0.994	0.954	1.019	1.011	1.009	1.010	1.010	1.000
Taiwan	0.999	0.975	0.952	1.002	1.000	0.997	0.991	0.996	0.987
Thailand	0.944	0.927	0.927	1.028	1.033	1.033	1.017	1.017	1.017
Turkey	0.911	0.935	0.940	0.964	1.024	0.983	0.994	0.933	0.909
United Kingdom	0.975	0.965	0.961	0.978	0.985	0.990	0.975	0.973	0.983
United States	0.951	0.941	0.916	0.976	0.947	0.947	1.002	0.942	0.928
Uruguay	0.841	0.858	0.819	0.909	0.939	0.903	0.978	1.030	0.961
EU-27	0.911	0.896	0.862	0.959	0.975	0.969	0.829	0.773	0.776
Eurozone	0.886	0.839	0.854	0.957	0.957	0.957	0.898	0.887	0.874
World	0.880	0.871	0.868	0.982	0.986	0.984	0.900	0.871	0.867

For each forecast horizon and country or aggregate, the table compares the relative root mean squared forecast error (rRMSFE) of the baseline (column 'Base') with the smallest rRMSFE of the 9 possible multi-indicator models based on sequentially adding either the three main trading partners (column 'MTP') or the US, the Eurozone and the World (column 'UEW'). The benchmark is always the AR(1).