World Uncertainty Indices, Financial Markets, and U.S. GDP Growth

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We investigate whether the world uncertainty indices (Ahir et al. 2022) derived from the Economist Intelligence Unit (EIU) country reports provide superior forecasting ability for U.S. GDP growth in comparison to stock and bond market indicators. Our hypothesis is that if there is a report of uncertainty in the press, equity and bond traders are likely to be aware of it, and the trading data for securities may reflect this uncertainty. We use different indicators, such as corporate bond credit spreads measured from unsecured corporate bond trading data, to forecast U.S. GDP growth. During the 1990-2022 sample period, we find that U.S. stock market returns predict U.S. GDP growth more accurately than the world uncertainty indices. Excluding the Covid-19 period, we find that U.S. corporate bond credit-spreads and stock market returns exhibit superior forecasting performance compared to the world uncertainty indices. These results underscore the significance of financial market indicators in comparison to EIU reports for assessing the future state of the U.S. economy.

Keywords: World Uncertainty Index, corporate bond credit-spreads, treasury term spread, oil prices, stock market returns, economic growth

INTRODUCTION

Forecasting national output, specifically the real Gross Domestic Product (GDP), is essential for both private and government forecasters as shown in the literature (e.g., Chauvet and Potter 2013). The accuracy of GDP forecasts is critical as they serve as a crucial input for decision-making by central banks, fiscal authorities, and private sector agents. To produce these forecasts, a range of approaches and indicators are used.

One key indicator of future GDP is the current level of uncertainty, and higher uncertainty can affect the real economy in various ways. For instance, uncertainty can impact both corporations and households (Bloom 2009). Uncertainty may prevent corporations from investing in new projects that have a positive net present value, while household consumption may also be affected. Therefore, both investment and consumption, and consequently real GDP, could be adversely affected by uncertainty. Various measures, such as volatility indices, are used as a proxy for uncertainty by forecasters because of its significance in predicting future GDP.

In a recent study, Ahir et al. (2022) propose a new measure of uncertainty by computing a series of world uncertainty indices, including the global world uncertainty index (WUI hereafter). The WUI indices are computed from the frequency of the word ‘uncertainty’ in the quarterly Economist Intelligence Unit (EIU) country reports. Importantly, they show that higher WUI leads to lower economic growth for a panel of 147 countries. Liu and Gao (2022) further show that the US_WUI, which is the WUI computed specifically for the U.S., best forecasts U.S. real GDP growth. However, the literature cited above does not investigate whether financial market indicators, which often co-move with uncertainty, can forecast economic growth. Thus, in this study, we investigate the forecasting ability of financial indicators relative to the WUI and US_WUI indices for U.S. real GDP growth. Our motivation for this study is as follows.

If the EIU country report writers believe in an uncertain future and write about it, traders must be aware about this uncertainty. As a direct consequence, market participants would trade stocks and bonds based on the perceived level of uncertainty, which may result in changing the dynamics of the stock and bond markets. Therefore, if the WUI indices contain information about future economic growth, then financial indicators should have leading information about it. Furthermore, the literature (e.g., Harvey 1989; Levine 1991; Stock and Watson 2003; Gilchrist and Zakrajšek 2012, among others) has investigated the importance of both stock and bond market variables as leading indicators of economic growth. Therefore, we focus on financial indicators from the U.S. Treasury bond, corporate bond, and stock markets in forecasting U.S. real GDP growth, and investigate their relative importance compared with world uncertainty indices.

Our findings for the 1990-2022 sample are as follows. Our in- and out-of-sample results show that U.S. stock market excess returns better forecast U.S. real GDP growth than the other variables. Since Covid-19 brought unprecedented uncertainty about future economic growth, both U.S. stock prices and GDP contracted sharply and then rebounded, which may bias the above results. To address this concern, we conducted robustness tests excluding the Covid-19 period, which show that both U.S. corporate bond credit-spreads and stock market excess returns have better performance than world uncertainty indices.

Additionally, as commodities such as crude oil may also trade based on uncertainty, and oil price shocks may affect the macroeconomy (e.g., Blanchard and Galí 2007), we further investigate whether oil prices predicts U.S. GDP growth. Our results suggest that oil prices are not a reliable leading indicator for forecasting U.S. GDP growth, possibly due to the decreasing trend of U.S. oil imports and the country's increased oil independence. Therefore, our findings align with the existing literature (e.g., Jiménez-Rodríguez and Sanchez 2004), which suggests that the relationship between economic growth and oil prices is nuanced, with oil prices having a negative impact on economic growth for most oil-importing countries. Our results contribute to different strands of literature.

First, we contribute to the literature on the financial accelerator mechanism. The financial accelerator/credit-cycle theories in the literature (e.g. Bernanke and Gertler 1989; Kiyotaki and Moore 1997; Bernanke, et al. 1999) shows the relationships between the quality of borrowers' balance sheet and their access to external finance. A weak balance sheet of borrowers leads to less borrowing, and hence less spending and lower economic activity, and vice versa. Motivated by the financial accelerator theory, empirical literature (e.g., Gilchrist et al. 2009; Gilchrist and Zakrajšek 2012; Faust et al. 2013) demonstrates that corporate credit spreads, as a proxy for the external finance premium, predict the real economy. We contribute to this strand of the literature by showing that corporate credit spreads perform better than other indicators in forecasting U.S. GDP growth for the sub-sample period of 1990-2019, which excludes the uncertainties during Covid-19. This result is not surprising because the financial accelerator mechanism primarily aims to explain business cycles from the perspective of borrowers' balance sheets and may not fully capture uncertainties caused by exogenous shocks like the Covid-19 pandemic.

Second, we contribute to the literature (e.g., Bencivenga and Smith 1991; Levine 1991) that argues for the importance of the stock market on economic development through the investment channel. We show that stock market returns provide robust leading information about U.S. real GDP growth, further supporting this argument. Third, we contribute to the macroeconomic forecasting literature (e.g., Stock and Watson 2003) by demonstrating that both stock and corporate bond market variables are reliable predictors of U.S. GDP growth. While Stock and Watson (2003) found that asset prices are unstable predictors, our sample does not exhibit such instability. Finally, our study adds to the existing literature on the role of uncertainty indices in forecasting economic growth (e.g., Ahir et al. 2022) by demonstrating that US_WUI remains a significant predictor of economic growth, even when financial market indicators are considered.

Our research could be pursued in various directions. While our primary focus has been on the information contained in the fluctuations of financial asset prices, future studies could explore whether other commodities besides oil and/or nonfinancial asset prices provide better leading information about the economy compared to WUI indices. Moreover, further investigation into whether our findings hold true in other countries and regions would be worthwhile.

The paper proceeds as follows: Section 2 describes the data sources and characteristics; Section 3 presents in- and out-of-sample real GDP forecasting results, while Section 4 concludes.

DATA SOURCE AND CHARACTERISTICS

Our sample is from the first quarter of 1990 to the third quarter of 2022, the period for which WUI data are available. Unless otherwise stated, our data source is the U.S. Federal Reserve Bank's database. We obtain world uncertainty indices data from the website worlduncertaintyindex.com. Furthermore, we collect stock market data from the Center for Research in Security Prices (CRSP). If we have monthly data, we compute quarterly variables by taking arithmetic averages of the monthly data over a three-month period starting from January of each year.

We use US_WUI index based on the "frequency" of the word "uncertain" or its variant, WUI is the average global world uncertainty index, the annualized real GDP percentage change over the previous quarter (ΔGDP hereafter). Liu and Gao (2022) show that among the different world uncertainty indices, WUI_US (frequency) performs best in predicting U.S. GDP growth. Thus, we use US_WUI as our benchmark world uncertainty index. However, we also use WUI to ensure robustness.

As for the bond market indicators, we use two corporate bond credit-spreads measures proposed in Gilchrist and Zakrajšek (2012): excess bond premium (EBP hereafter) and GZ Spread (GZS hereafter), respectively. Following the literature (e.g., Estrella and Mishkin 1998; Harvey 1989) we further use the Treasury term spread (TS hereafter), which is computed as the difference in the yields on the 3-month Treasury-bill and the 10-year Treasury bond index. As for stock market indicators, we use stock market excess returns (XMRET hereafter), stock market volatility (VOL hereafter), quoted bid-ask spreads (SPREAD hereafter) as a measure of stock market liquidity for virtually all U.S. stocks. Moreover, we use CBOE (Chicago Board Options Exchange) SP500 volatility index (VIX hereafter). Lastly, we use the West Texas Intermediate Oil Prices (OIL hereafter). Table 1 describes the U.S. GDP growth predictors.

TABLE 1
U.S. GDP GROWTH PREDICTORS

Predictors	Description
EBP	U.S. Unsecured Corporate Bonds Credit-Spreads
GZS	Alternative Measure of U.S. Unsecured Corporate Bond Credit-Spreads
WUI	WUI Global Index
US_WUI	U.S. World Uncertainty Index (frequency)
XMRET	U.S. stock market excess returns
VIX	Chicago Board Options Exchange (CBOE) SP500 volatility index
VOL	U.S. Stock Market Volatility
SPREAD	U.S. stock market Effective bid-ask Spreads
TS	U.S. Treasury Term Spread, the difference between 10 year and 3-month Treasury Yields
OIL	West Texas Intermediate Oil Prices

By conducting stationarity tests, such as both ADF (Dickey and Fuller 1979) unit-root and KPPS (Kwiatkowski et al. 1992) stationarity tests, we observe that all variables, except for OIL, are stationary. Therefore, in our analysis, we use the first difference of OIL, which is represented as ΔOIL. Panel A of Table 2 shows the summary statistics for all variables. Table 2 shows that the mean XMRET, which represents the quarterly arithmetic average of stock market excess returns, is 0.66 %. Unreported results show that the realized quarterly excess returns are 2.06 %, and their correlation with XMRET is 0.999. Thus, we prefer using XMRET to ensure consistency with the computation of other variables, such as EBP, which are also calculated using arithmetic averages of monthly data.

TABLE 2
DATA CHARACTERISTICS

Panel A: Summary Statistics		
	Mean	Std. dev.
ΔGDP	1.16	1.31
WUI*10^{-3}	17.65	9.05
US_WUI	0.17	0.16
EBP	0.03	0.61
GZS	2.08	0.97
XMRET	0.66	2.91
VIX	19.71	7.07
VOL	3.92	1.81
SPREAD (basis points)	3.52	2.46
TS	1.75	1.09
ΔOIL	0.54	9.17

Panel B: Correlation Matrix										
	ΔGDP	US_WUI	WUI	EBP	GZS	XMRET	VIX	SPREAD	VOL	ΔOIL
US_WUI	-0.23									
WUI	-0.15	0.88								
EBP	-0.39	0.15	-0.04							
GZS	-0.37	0.27	0.18	0.85						
XMRET	0.034	-0.08	-0.05	-0.36	-0.27					
VIX	-0.27	0.16	0.11	0.63	0.68	0.37				
SPREAD	-0.33	0.19	0.17	0.61	0.67	0.48	0.91			
VOL	-0.02	0.15	0.17	0.52	0.51	0.21	0.71	0.64		
ΔOIL	0.41	-0.09	-0.07	-0.38	-0.33	0.23	-0.27	-0.38	-0.12	
TS	-0.02	-0.13	-0.03	-0.44	0.07	-0.03	-0.26	-0.23	-0.30	0.12

Panel C: Pairwise Granger Causality Test Results	
	Probability
US_WUI does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause US_WUI	0.95
WUI does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause WUI	0.61
EBP does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause EBP	0.52
GZS does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause GZS	0.58
XMRET does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause XMRET	0.63
VIX does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause VIX	0.59
SPREAD does not Granger Cause ΔGDP	0.00***
ΔGDP does not Granger Cause SPREAD	0.51
VOL does not Granger Cause ΔGDP	0.98
ΔGDP does not Granger Cause VOL	0.06*
TS does not Granger Cause ΔGDP	0.12
ΔGDP does not Granger Cause TS	0.96
ΔOIL does not Granger Cause ΔGDP	0.02**
ΔGDP does not Granger Cause ΔOIL	0.41

This table shows the summary statistics of the variables used in this study. ΔGDP is the real U.S. GDP percentage change over previous quarter (annualized); ΔOIL is the first difference of OIL; other variables are described in Table 1. Panel A presents summary statistics; Panel B presents the pairwise correlation results; Panel C presents the pairwise Granger Causality test results, where an optimal lag of one-quarter is chosen based on AIC criteria in a standard vector-autoregression model. Sample 1990:Q1 to 2022:Q3.

Looking next at Table 2 Panel B, we find that except for XMRET and ΔOIL, all other variables are negatively correlated with ΔGDP. The results further show that very high correlation exists between the following pairs: 1) WUI and US_WUI, 2) EBP and GZS, and 3) VIX and SPREAD. That is, a forecaster will not gain much when using these pairs together to forecast ΔGDP since they contain similar information.

Nevertheless, contemporaneous correlation is not useful to forecast ΔGDP. Thus, we conduct pairwise Granger causality tests. For this test, we select an optimal lag of one-quarter based on both Swartz and Hannan-Quinn information criterion in a standard vector-autoregression setup. The corresponding Granger causality results are shown in Table 2 Panel C. The results show that except for VOL and TS, all other variables have future information about ΔGDP. Moreover, except for VOL, the reverse Granger causality is absent for all other variables. This is the first piece of evidence that most stock and corporate bond market variables, along with uncertainty indices, contain leading information about ΔGDP. While important, the Granger causality tests cannot determine which variables provide the most accurate forecasts. Therefore, we next formally test the variables that demonstrate the strongest predictive power for ΔGDP.

EMPIRICAL RESULTS

The forecasting literature (e.g., Inoue and Kilian 2004, among others) suggests that in-sample predictions must precede out-of-sample predictions. Thus, we conduct the analysis with the 1990Q1-2022Q3 full-sample, and Our baseline model is an AR one, which is as per Eq. (1). Next, using the unary model as per Eq. (2) we evaluate the forecast accuracy of predictor variables relative to the above AR model.

$$\Delta GDP_t = \alpha + \beta * DGDP_{t-1} + \varepsilon_t \tag{1}$$

$$\Delta GDP_t = \alpha + \beta * X_{t-1} + \varepsilon_t \tag{2}$$

where, α is the intercept term, ε_t is the error term; X represents one of the predictor variables such as US_WUI, EBP, XMRET, etc. Table 3 presents the in-sample coefficient estimates of Eq. (1) and (2).

TABLE 3
IN-SAMPLE RESULTS: PREDICTING U.S. GDP GROWTH

Model	α	β	Adj. R-Squared
AR	1.25^{***}	-0.09	0.00
EBP	1.17^{***}	-0.66^{***}	0.09
GZS	1.94^{***}	-0.38^{***}	0.08
WUI	1.85^{***}	$-4.01\text{x}10^{-5}$	0.08
US_WUI	1.58^{***}	-2.48^{*}	0.09
XMRET	1.02^{***}	0.19^{*}	0.19
VOL	1.08^{***}	0.02	0.00
VIX	1.85^{***}	-0.04	0.04
SPREAD	1.91^{***}	-11.22^{**}	0.09
TS	1.17^{***}	0.35^{**}	0.01
ΔOIL	1.13^{***}	0.02	0.01

This table shows the in-sample prediction results. The variables are described in earlier tables. ***, **, * represent the statistical significance at the 1% , 5% and 10% level of significances. Sample 1990:Q1 to 2022:Q3.

The results in Table 3 shows that except for AR, WUI, ΔOIL, and VIX, the "β" coefficients are statistically significant for other predictors at least at the 10% level of significance. We find that the highest adjusted-R-squared value of 19% is obtained if XMRET is the predictor. Next, we find that EBP has the same performance as US_WUI with the adjusted-R-squared values of 9%. The performance of other predictors is lower than the above three predictors. Overall, the in-sample results suggest that US_WUI, EBP, XMRET and SPREAD may have more information about future ΔGDP than other predictors. The results further show that VOL and TS do not predict ΔGDP since the adjusted-R-squared value is zero, and the result is in accordance with the Granger causality results. We also find that ΔOIL may not predict ΔGDP well. Overall, we find stock market returns have the best performance predicting ΔGDP. Since the in-sample results may not hold out-of-sample, which we conduct next.

Out-of-Sample Test Methodology and Evaluation Results

For this analysis, we omit ΔOIL and VOL since the above in-sample results show that these indicators do not predict ΔGDP. We use 1990Q1-1995Q4 for the model estimation and forecast ΔGDP from 1996Q1-2022Q3. Following the literature (e.g., Campbell and Thomson 2008), we compute out-of-sample R^2 (defined as R^2_{oos}) values and use it as a criterion for the out-of-sample predictive power of a model with an indicator relative to the baseline AR model.

$$R_{oos}^2 = 1 - \frac{\sum_{t=M+1}^{T} (y_t - \hat{y}_{t,F})^2}{\sum_{t=M+1}^{T} (y_t - \hat{y}_{t,B})^2} \tag{3}$$

where y_t is the actual ΔGDP value at time "t", T is the full sample size, M is the sample used for the model estimation, $\hat{y}_{t,B}$ is the forecast of ΔGDP by the baseline model at time "t", and $\hat{y}_{t,F}$ is the forecast of ΔGDP by a model with the forecasting variables at time "t". A positive R_{oos}^2 would indicate that a competing model produces better forecasts than those by the baseline model.

Since the models we compare are *not-nested*, we further compute modified Diebold-Mariano (MDM) test statistics to compare the out-of-sample forecast performance of different models. We base this comparison on their mean squared error (MSE) ratios and their corresponding MDM statistical significance.

By construction, MSE ratios are 1-R_{oos}^2, and a model is better than the other if the MSE ratio is less than "1". However, MDM tests allow for comparing the model accuracy based on the MDM-statistics. The MDM proposed by Harvey, et al. (1998) has greater power than the original DM (Diebold and Mariano 1995) test. The DM and MDM test statistics are computed as follows:

$$\bar{d} = \{(y_t - \hat{y}_{t,F})^2 - (y_t - \hat{y}_{t,B})^2\} * P^{-1} \tag{4}$$

$$DM = \bar{d}/(\sigma_{\bar{d}}^2/P)^{0.5} \tag{5}$$

$$MDM = DM * ((\mathrm{P} + 1 - 2\mathrm{h} + P^{-1}\mathrm{h}(\mathrm{h} - 1))/\mathrm{P})^{0.5} \tag{6}$$

where P is the number of out-of-sample forecasts, and "h" is the forecast horizon. Harvey, et al. (1998) recommend that the MDM statistic is compared with critical values from the Student's t-distribution with (P − 1) degrees of freedom. The out-of-sample results are presented in Table 4.

TABLE 4
OUT-OF-SAMPLE FORECASTS

Model	R_{oos}^2	MSEs	MSE Ratios
AR		2.04	
EBP	0.03	1.97	0.97^{*}
GZS	-0.61	3.29	1.61^{***}
WUI	0.05	1.93	0.95^{**}
US_WUI	0.07	1.90	0.93^{*}
XMRET	0.09	1.86	0.91^{*}
VIX	-0.01	2.05	1.01^{**}
TS	0.01	2.01	0.99^{*}
SPREAD	0.07	1.90	0.93^{**}

This table shows the out-of-sample forecasts evaluation results. The variables are described in earlier tables. An MDM-statistic (described in the text) with *, **, and *** denote a rejection of the null hypothesis of equal forecast accuracy at the 10%, 5% and 1% level. The model estimation period is 1990Q1-1995Q4 and the forecasts are from 1996:Q1 to 2022:Q3.

Looking at table 4 from the top, we find that except for the models with GZS and VIX as predictors, all models have positive R_{oos}^2. EBP as a forecasting variable does well relative to the baseline model in predicting ΔGDP, and the corresponding model has the R_{oos}^2 value of 0.03. We further find that US_WUI is better than WUI in forecasting ΔGDP. Furthermore, we find that the R_{oos}^2 values of the models with

XMRET and SPREAD as predictors are 0.09 and 0.07, respectively, and those for the models with US_WUI and WUI are 0.07 and 0.05, respectively. The MSE ratios and their corresponding MDM test statistics confirm the conclusions we draw based on R^2_{oos}. Overall, the results indicate that, except for GZS and VIX, financial indicators and world uncertainty indices have predictive information about ΔGDP, and XMRET performs better than US_WUI. These results are in accordance with the in-sample results.

Robustness: Analysis Excluding the Covid-19 Period

In this section, we investigate the relative performance of the models *without* the Covid-19 period. During the Covid-19 period both GDP and stock market fell sharply, and then, both recovered very rapidly in the subsequent quarters. To ascertain that our results are not driven by the 2020-2022 data, we conduct out-of-sample tests without the Covid-19 period. The out-of-sample forecast results for the 1996Q1-2019:Q4 period are presented in Table 5.

TABLE 5
ROBUSTNESS: OUT-OF-SAMPLE FORECASTS EXCLUDING COVID-19 EFFECTS

Model	R^2_{oos}	MSEs	MSE Ratios
AR		0.44	
EBP	0.15	0.38	0.85***
GZS	-3.07	1.80	4.07***
WUI	-0.12	0.50	1.12***
US_WUI	0.06	0.42	0.94***
XMRET	0.07	0.41	0.93***
VIX	0.00	0.44	1.00
TS	0.01	0.44	0.99
SPREAD	0.03	0.43	0.97***

This table shows the out-of-sample forecasts evaluation results excluding the Covid-19 period. The variables are described in earlier tables. An MDM-statistic with *, **, and *** denote a rejection of the null hypothesis of equal forecast accuracy at the 10%, 5% and 1% level. The model estimation period is 1990Q1-1995Q4 and the forecasts are from 1996:Q1 to 2019:Q4.

We find that EBP has the least forecast error with the R^2_{oos} value of 0.15. While US_WUI, XMRET, and SPREAD continue to perform better than WUI, VIX, TS, and GZS, the R^2_{oos} values are far lower than 0.15. However, these results are qualitatively similar to the results we obtain in Table 4. Nevertheless, these results highlight the importance of both the stock and bond market variables as leading indicators of ΔGDP: while XMRET is a better predictor with the Covid-19 period, EBP is a better predictor without it. These results further underline the importance of US_WUI as a U.S. GDP forecasting variable since the performance of the model with US_WUI as a leading indicator is robust to the exclusion of the Covid-19 period.

Further Robustness: Larger Models

As an additional robustness check, we investigate the relationship in a multivariate setup. First, we conduct in-sample analysis using Eq. (7), where [X] is a vector of predictor variables.

$$\Delta GDP_t = \alpha + \beta * [X]_{t-1} + \varepsilon_t \tag{7}$$

Table 6 shows the results for the in-sample analysis. We have omitted some predictors for the sake of parsimony since previous results show that these variables are less accurate in forecasting ΔGDP. Our analysis indicate that, in a multivariate setup, the primary predictors are US_WUI, XMRET, and EBP.

Although we have previously shown that SPREAD is a good predictor of ΔGDP when used alone, Table 6 shows that it does not have predictive power for ΔGDP in a multivariate setup. Thus, our main conclusion remains unchanged and are robust to alternative specifications.

TABLE 6
ROBUSTNESS: IN-SAMPLE PREDICTION OF U.S. GDP GROWTH FOR LARGER MODELS

Predicting ΔGDP Multivariate Models				
α	1.83***	1.62***	1.82***	1.51***
AR	-0.17*	-0.18**	-0.27***	-0.31***
US_WUI	-2.81***	-2.56***	-2.48***	-2.55***
XMRET		0.18***	0.14***	0.14***
EBP			-0.55***	-0.63***
SPREAD				-1.09
Adj. R-Squared	0.11	0.24	0.28	0.28

This table shows the in-sample prediction results in a multivariate setup. The variables are described in earlier tables. ***, **, * represent the statistical significance at the 1% , 5% and 10% level of significances. Sample 1990:Q1 to 2022:Q3.

To further ascertain robustness of our results, we next conduct out-of-sample analysis in a multivariate setup. While there are many models, we would like to contrast the forecast results of EBP and XMRET with that of US_WUI. Thus, we compare two models:1) AR+US_WUI and 2) AR+XMRET+EBP. We use the AR term to account for the variables that we do not consider. None of the two models above nest each other, and hence we use MDM test statistics to evaluate forecast accuracies. Table 7 Panels A shows the out-of-sample forecast results for the 1996-2022 period, while Table 7 Panels A shows the results for the 1996-2019 period.

TABLE 7
ROBUSTNESS: OUT-OF-SAMPLE FORECASTS FOR LARGER MODELS

Panel A: With Covid-19 Period			
Model	R^2_{oos}	MSEs	MSE Ratios
AR+ US_WUI		1.96	
AR+EBP+XMRET	0.12	1.73	0.88**

Panel B: Without Covid-19 Period			
Model	R^2_{oos}	MSEs	MSE Ratios
AR+US_WUI		0.40	
AR+EBP+XMRET	0.16	0.33	0.84**

This table shows the out-of-sample prediction results in a multivariate setup. The variables are described in earlier tables. An MDM statistic with *, **, and *** denote a rejection of the null hypothesis of equal forecast accuracy at the 10%, 5% and 1% level. The model estimation period is 1990Q1-1995Q4. Panel A forecasts are from 1996:Q1 to 2022:Q3; Panel B forecasts are from 1996:Q1 to 2019:Q4.

Table 7 Panel A results show that stock and bond market variables provide more information about ΔGDP than US_WUI, supporting the in-sample results. Table 7 Panel B results indicate that the model with XMRET and EBP as predictors remains more accurate than the model with US_WUI, further supporting our earlier conclusion that stock and bond market indicators are better predictors of real GDP growth than world uncertainty indices.

CONCLUSION

In a recent paper, Ahir et al. (2022) computed a series of world uncertainty indices using the Economist Intelligence Unit (EIU) country reports and showed that these indices contain leading information about economic growth. This paper argues that if EIU report writers believe in an uncertain future and write about it, financial market traders should also be aware of it and trade financial assets accordingly. As a direct consequence, financial assets should contain leading information about the real economy. Thus, we examine the relative importance of stock and bond market variables as predictors of U.S. GDP *vis-à-vis* the world uncertainty indices.

We find that while world uncertainty indices contain leading information about U.S. GDP growth, both bond and stock market indicators contain more information about it. Moreover, we find that world uncertainty indices perform better than oil or the Treasury bond prices. Future research may investigate whether our results hold in other countries. Furthermore, future research may investigate other indicators that may provide more information about the real economy than financial indicators.

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