International Business Research; Vol. 16, No. 8; 2023
ISSN 1913-9004 E-ISSN 1913-9012
Published by Canadian Center of Science and Education

Economic Policy Uncertainty, World Uncertainty, and Economic Growth: Evidence from a Bayesian Vector Autoregression Analysis

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Received: June 21, 2023 Accepted: July 21, 2023 Online Published: July 25, 2023

doi:10.5539/ibr.v16n8p28 URL: https://doi.org/10.5539/ibr.v16n8p28

Abstract

This paper examines the relationship between the information content of newspaper-based Economic Policy Uncertainty (EPU) and the Economist Intelligence Unit (EIU) country report-based World Uncertainty (WUI) indices in relation to U.S. economic growth. Using data from 1990 to 2022 and incorporating a number of variables known to predict economic growth, our findings demonstrate the following: i) Based on different measures of WUI, whether U.S.-specific or global, and under various model specifications, we find that WUI is an important measure of uncertainty that negatively impacts real GDP growth. ii) EPU consistently exhibits a counterintuitive positive relationship with economic growth. iii) Variables such as corporate credit spreads and oil prices show a robust negative relationship with real GDP growth, while stock market returns are positively and robustly related to economic growth, underlying the importance of prices of financial assets and commodities for gauging the health of the economy.

Keywords: economic policy uncertainty, world uncertainty index, corporate bond credit-spreads, oil prices, stock market returns, economic growth

JEL: E37, G17, G12

1. Introduction

Uncertainty, a crucial predictor of future GDP, has a substantial influence on the real economy. Its impact extends to both corporations and households, impeding corporate investments in profitable ventures and influencing household consumption patterns. Consequently, uncertainty can have adverse effects on both investment and consumption, thereby exerting a significant influence on real GDP. Given its importance for businesses, policymakers, and corporate managers, forecasters commonly employ measures such as volatility indices as proxies for uncertainty due to their substantial predictive power regarding future GDP.

Ahir et al. (2022) propose a novel measure of uncertainty called the world uncertainty index (WUI). The WUI is computed based on the frequency of the word 'uncertainty' in quarterly Economist Intelligence Unit (EIU) country reports. The authors demonstrate within a vector autoregression (VAR) framework that higher WUI is associated with lower economic growth across a panel of countries. Building upon this research, Liu and Gao (2022) further establish, in a univariate setup, that the U.S.-specific WUI (US_WUI) provides the best forecast for U.S. real GDP growth. In this study, our objective is to investigate the relationship between US real GDP growth and the US_WUI index within a Bayesian VAR (BVAR) framework, motivated by several factors.

Firstly, we depart from the cross-country analysis conducted by Ahir et al. (2022) and instead focus on investigating the U.S.-specific WUI index and its relationship with U.S. GDP growth. While Liu and Gao (2022) utilize the US_WUI for forecasting U.S. GDP, they do not consider any other variables except WUI indices to forecast real GDP growth. Importantly, they do not consider the endogenous relationship between GDP growth and US_WUI. However, Ahir et al. (2022) argue that the WUI is likely to endogenously evolve with economic growth and have a relationship with other indicators of economic growth such as stock market returns. Therefore, our aim is to incorporate this endogenous relationship within the BVAR framework.

Secondly, the aforementioned studies that investigate the WUI do not examine the marginal impact of the WUI relative to Economic Policy Uncertainty (EPU). EPU is an index based on the frequency of articles in leading U.S. newspapers that contain words such as "uncertainty" and "economic" (Baker et al., 2016). Within a VAR framework, EPU has been found to have a negative impact on the macroeconomy. Although Ahir et al. (2022) establish a correlation between the WUI and EPU, they do not delve into the comparative effects of these two uncertainty indices on economic growth. As a result, the relative influence and marginal impact of the WUI, specifically in relation to EPU, remain unexplored in the existing literature. Hence, our study aims to concurrently investigate the effects of both the WUI and EPU on real GDP to better understand their respective contributions.

Third, the literature (e.g., Gilchrist and Zakrajšek, 2012; Faust et al., 2013; Gilchrist and Zakrajšek, 2009, among others) argues that credit market conditions or monetary policy play a crucial role in determining economic growth. Additionally, commodities such as oil prices are leading indicators of future uncertainty and economic growth (Jiménez et al., 2004). However, the aforementioned studies have not incorporated credit market conditions or oil prices. Moreover, literature (e.g., Levine 1991; Bencivenga and Smith 1991, among others) argue that the stock market plays an important role in economic development. Therefore, our aim is to include these indicators in our analysis to better comprehend the marginal information content of WUI or EPU.

Finally, unlike Ahir et al. (2022), we employ a BVAR approach due to its suitability for VAR models with a larger number of variables, which addresses the overparameterization concerns associated with a standard VAR model when there are a large number of endogenous variables (see, e.g., Koop and Korobilis, 2010). In essence, our study aims to investigate the endogenous relationship between U.S. GDP growth and the US_WUI index within a BVAR framework in a multivariate setup that includes variables such as oil price and corporate credit spreads.

We investigate the 1990-2022 full sample and the 1990-2019 subsample. During the Covid-19 period, there was a significant decline in U.S. GDP accompanied by a rapid increase in the US_WUI index. Subsequently, both indicators experienced a rapid recovery in the following quarters. Thus, we extend our analysis with the 1990-2019 subsample by excluding the Covid-19 period to reduce any potential bias of our results. Our primary findings for the 1990-2022 sample and the 1990-2019 subsample are as follows.

Firstly, considering the full sample, we find while most variables including US_WUI Granger causes real GDP growth, EPU does not Granger cause real GDP growth. Next, the forecast error variance decomposition analysis upon convergence show that approximately 3% of the forecast error variance of real GDP growth could be attributed to EPU and US_WUI, respectively. In contrast, approximately 7% and 4% of the forecast error variance of real GDP growth could be attributed to monetary policy, captured in the effective Federal funds rate, and stock market returns, respectively. Since the forecast error variance decomposition cannot indicate the direction of the impact of shocks to those variables on real GDP growth, we investigate the impulse responses of real GDP growth.

We find that for a one standard deviation orthogonalized positive shock to US_WUI leads to an accumulated response of approximately -0.45 percentage points in U.S. real GDP growth after ten quarters, and this result is consistent with Ahir et al. (2002) findings. In contrast, EPU exhibits a nonintuitive positive effect of approximately 1.1 percentage points on real GDP growth. This finding aligns with the argument made in Baker et al. (2016) that drawing causal inferences based on EPU using VARs is extremely challenging due to the potential for policy and policy uncertainty to respond to current and anticipated future states of the economy. However, similar shocks to corporate bond credit spreads and stock market returns impact real GDP growth by about -5.0 and 7.0 percentage points, respectively.

Second, for the 1990-2019 sub-sample, which excludes the 2020-2022 Covid-19 pandemic period, shocks to EPU yields positive effects on real GDP growth, while US_WUI yields a slightly negative -0.03% percentage points impact. In contrast, the results for corporate bond credit spreads, oil prices, and stock market returns remain robust. These results are also robust across alternative BVAR specifications, the definition of shocks to endogenous variables, and an alternative definition of uncertainty index. The contribution of our findings are as follows.

Our study contributes to the existing literature (e.g., Bloom 2009; Liu and Gao 2022; Ahir et al. 2022) on the relationship between uncertainty and economic growth by incorporating the endogenous relationship between uncertainty and economic growth within a BVAR framework. Moreover, our findings highlight that the US_WUI or WUI may not offer valuable information about U.S. real GDP growth if we exclude the Covid-19 pandemic period. We also contribute to the literature (e.g., Baker et al., 2016; Chowdhury and Ahmed 2023) that investigates the effect of EPU on micro- and macro-economic activities by demonstrating that no Granger causality exists between EPU and real GDP growth.

We further contribute to the literature (e.g., Stock and Watson 2003; Gilchrist and Zakrajšek 2012, among others) on the predictive relationship between asset prices and economic growth by demonstrating that, regardless of the sample period, variables such as corporate credit spreads or oil prices have a far greater impact on GDP growth compared to US_WUI or WUI. This underscores the significance of exploring the prices of financial assets and commodities, not only to effectively capture uncertainty but also to forecast economic growth.

The paper proceeds as follows: Section 2 describes the data sources and characteristics; Section 3 presents the empirical results including robustness tests, while Section 4 concludes.

2. Data Source and Characteristics

Our sample spans from the first quarter of 1990 to the third quarter of 2022. The data for the World Uncertainty Index (WUI) is obtained from the U.S. Federal Reserve Bank's database, which is also the primary source for other data, such as real GDP, unless specified otherwise. We utilize two WUI indices based on worldwide EIC country reports containing the word "uncertain" or its variants: i) the US_WUI index, an uncertainty index specifically for the U.S.; ii) the WUI, the average global world uncertainty index. As for the U.S. economic policy uncertainty (EPU) index, we collect EPU data for the U.S. from the website www.policyuncertainty.com. We compute the real GDP percentage change over the previous quarter and is represented as ΔGDP. The above four are our primary variables of interest.

Regarding stock market indicators, we consider stock market excess returns (XMRET) and the CBOE (Chicago Board Options Exchange) SP500 volatility index (VIX), which are commonly used in the literature. We collect stock market data from the Center for Research in Security Prices (CRSP). We include the change in the Federal funds rate (FFR) is employed as a measure of the monetary policy stance. These variables are included following the related literature (e.g., Estrella and Mishkin, 1998; Harvey, 1989). We further incorporate corporate bond credit-spread measures proposed in Gilchrist and Zakrajšek (2012), specifically the excess bond premium (EBP), which is shown to contain robust leading information about GDP. Additionally, we include changes in West Texas Intermediate Oil Prices (OIL) as another indicator of uncertainty, as economic uncertainty can often be reflected in the performance of important commodities such as crude oil (e.g., Blanchard and Galí 2007). Since GDP data is reported quarterly, any monthly data is converted into quarterly variables by calculating the arithmetic averages over three-month periods, starting from January of each year.

By conducting stationarity tests, such as the Augmented Dickey-Fuller (ADF) unit-root test (Dickey and Fuller, 1979) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test (Kwiatkowski et al., 1992), we observe that all variables exhibit stationarity. Panel A of Table 1 shows the summary statistics for all variables.

Table 1. Data Characteristics

Table 1 Panel A: Summary Statistics

	FFR	ΔGDP	EPU	US_WUI	EBP	XMRET	OIL	VIX
Mean	-0.05	0.59	125.98	0.17	0.03	0.62	0.55	19.72
Median	0.00	0.64	117.97	0.12	-0.12	1.04	0.69	17.80
Maximum	1.42	7.85	401.72	0.79	3.31	7.23	25.92	51.72
Minimum	-1.43	-8.48	52.09	0.00	-0.79	-9.36	-59.61	10.12
Std. Dev.	0.44	1.19	53.87	0.16	0.60	2.92	9.17	7.10
Skewness	-0.90	-1.82	1.92	1.44	2.59	-0.82	-2.31	1.41
Kurtosis	5.58	37.51	8.95	5.36	12.39	4.15	16.68	5.98

Table 1 Panel B: Pairwise Correlations

	FFR	ΔGDP	US_WUI	EPU	EBP	XMRET	OIL	VIX
ΔGDP	0.38							
US_WUI	-0.09	-0.25						
EPU	-0.32	-0.42	0.57					
EBP	-0.49	-0.63	0.14	0.40				
XMRET	0.10	0.35	-0.03	-0.17	-0.44			
OIL	0.21	0.38	-0.03	-0.25	-0.37	0.27		
VIX	-0.40	-0.39	0.11	0.37	0.71	-0.41	-0.32	
WUI	-0.07	-0.18	0.89	0.63	0.05	0.05	-0.06	-0.02

Note: This table shows the summary statistics of the variables used in this study. FFR is the change in the effective Federal Funds rate; ΔGDP is the real U.S. GDP percentage change over previous quarter; EPU is the economic policy uncertainty index for the U.S.; US_WUI is the world uncertainty index for the U.S.; WUI is the world uncertainty index; EBP is corporate bond credit spreads; XMRET is U.S. stock market excess returns; OIL is the first difference of west Texas oil prices; VIX is the CBOE volatility index. 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.

Next, moving on to Panel B of Table 1, we find that, except for FFR, XMRET, and OIL, all other variables are negatively correlated with ΔGDP. It is worth noting that WUI and US_WUI are highly correlated. Therefore, for the majority of our analysis, we use US_WUI since we are specifically investigating U.S. GDP. Next, we conduct pairwise Granger causality tests. For this test, we find that the optimal lag is one quarter based on both the Schwarz (SIC) and Hannan-Quinn (HQ) information criteria within a standard vector autoregression (VAR) framework. The corresponding Granger causality results are presented in Panel C of Table 1, where ≢> implies does not Granger cause. Due to space limitations, we do not show all the results.

Table 1 Panel C: Pairwise Granger Causality

Null Hypothesis:	Prob.
US_WUI ≢>ΔGDP	0.00***
ΔGDP ≢>US_WUI	0.94
ΔGDP ≢>EPU	0.84
ΔGDP ≢> EBP	0.91
XMRET ≢> ΔGDP	0.00***
ΔGDP ≢> XMRET	0.71
US_WUI ≢> EPU	0.00***
EPU ≢> US_WUI	0.16
EBP ≢> EPU	0.49
EPU ≢> EBP	0.04*
XMRET ≢> EPU	0.00***
EPU ≢> XMRET	0.02***
XMRET ≢> EBP	0.00***
EBP ≢> XMRET	0.17

The Granger causality results indicate that US_WUI, EBP, and XMRET Granger cause ΔGDP, while there are no reverse Granger causalities. Interestingly, we do not find any Granger causality between EPU and ΔGDP. Additionally, we find that while US_WUI Granger causes EPU, there is no causality running in the other direction. Furthermore, we find that EPU and XMRET Granger cause each other. In summary, we observe complex causality relationships, highlighting the importance of conducting a VAR analysis, which we proceed to do next.

3. World Uncertainty, Economic Uncertainty, and Real GDP growth

We utilize a Bayesian VAR (BVAR) methodology for our analysis, specifically focusing on the effects of US_WUI and EPU shocks on ΔGDP. The Bayesian approach is particularly well-suited for situations like ours where the number of endogenous variables in the VAR model is relatively large compared to the length of the dataset, which is often the case in macroeconomic research (Koop and Korobilis, 2010). To contrast the endogenous VAR variables in Ahir et al.'s (2022) study with ours, they consider four variables, whereas we consider eight variables for a dataset that spans 131 quarters. In essence, some of our VAR specifications, where we use 4 lags of each endogenous variable, have 8*4 = 32 variables, as opposed to their 4*4 = 16. Thus, the BVAR approach seems to be a better choice. In our study, we employ the "Minnesota Prior," which is a widely used prior specification in BVAR literature (e.g., Litterman 1986).

The ordering of VAR variables is important. However, there are varying perspectives on the ordering of endogenous variables. Christiano et al. (1996) suggest that monetary policy should have the ability to respond contemporaneously to macroeconomic shocks, while the effects of monetary policy shocks on macro variables may exhibit a time lag. Consequently, they advocate for policy variables to be ordered first in the VAR model. In line with this, we order the BVAR endogenous variables as follows: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX.

Based on both the Schwarz information criterion (SIC) and the Akaike information criterion (AIC), we find an optimal lag length of "one" quarter. To assess the BVAR(1) results, we analyze both the forecast error variance decomposition (FEVD) and the accumulated impulse response functions (IRFs) of the variables of interest over a period of ten quarters. We do not report the BVAR(1) coefficient estimates for the sake of parsimony. We further do not report the impulse response functions of ΔGDP to all shocks or FEVDs of all variables, but these results are available on request.

Table 2. Forecast Error Variance Decomposition of GDP growth

Table 2 Panel A: FEVD of ΔGDP, **EPU ordered before US_WUI**									
Period	S.E.	FFR	ΔGDP	EPU	US_WUI	EBP	XMRET	OIL	VIX
1	0.31	8.43	91.57	0.00	0.00	0.00	0.00	0.00	0.00
2	0.39	7.26	87.99	0.01	1.54	0.58	2.32	0.28	0.01
3	0.44	7.20	84.92	0.25	2.66	1.00	3.42	0.52	0.01
4	0.47	7.20	83.33	0.76	3.12	1.24	3.69	0.63	0.04
5	0.49	7.17	82.46	1.34	3.23	1.37	3.70	0.66	0.08
6	0.50	7.12	81.88	1.86	3.22	1.46	3.67	0.66	0.12
7	0.51	7.09	81.45	2.28	3.20	1.52	3.66	0.66	0.15
8	0.52	7.06	81.12	2.59	3.20	1.56	3.65	0.66	0.17
9	0.53	7.03	80.87	2.83	3.21	1.58	3.64	0.66	0.18
10	0.53	7.02	80.67	3.00	3.24	1.60	3.64	0.66	0.18

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: FFR ΔGDP EPU US_WUI EBP XMRET OIL VIX

Note: This table shows the forecast error variance decomposition (FEVD) of ΔGDP for the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX. Variables are explained in the previous table. The FEVD of ΔGDP is shown for 10 quarters is shown in %; the FEVDs for other variables are not shown for parsimony. Panels A and B shows different orderings of the endogenous variables. Quarterly sample 1990:Q1-2022:Q3.

Table 2 Panel A presents the forecast error variance decomposition (FEVD) of ΔGDP. We observe that at a one-quarter forecast horizon, the forecast variance is entirely attributed to FFR (8.43%) and ΔGDP (91.57%). However, after ten quarters, ΔGDP accounts for approximately 80% of the forecast variance, while FFR, EPU, US_WUI, and XMRET contribute around 7.02%, 3.00%, 3.24%, and 3.64% respectively. On the other hand, the contributions of other variables, such as OIL or VIX, are lower compared to US_WUI after ten quarters.

Given that there is no economic reason to place EPU before US_WUI in the BVAR ordering, we explore an alternative ordering. Table 2, Panel B presents the FEVD results of ΔGDP with an alternative ordering, placing US_WUI before EPU. However, this alternative ordering does not qualitatively alter the previous findings. Both EPU and US_WUI continue to be significant contributors to the FEVD of ΔGDP.

Table 2 Panel B: FEVD of ΔGDP, **EPU ordered after US_WUI**									
Period	S.E.	FFR	ΔGDP	US_WUI	EPU	EBP	XMRET	OIL	VIX
1	0.31	8.43	91.57	0.00	0.00	0.00	0.00	0.00	0.00
2	0.39	7.26	87.99	1.45	0.10	0.58	2.32	0.28	0.01
3	0.44	7.20	84.92	2.36	0.56	1.00	3.42	0.52	0.01
4	0.47	7.20	83.33	2.64	1.23	1.24	3.69	0.63	0.04
5	0.49	7.17	82.46	2.67	1.89	1.37	3.70	0.66	0.08
6	0.50	7.12	81.88	2.65	2.43	1.46	3.67	0.66	0.12
7	0.51	7.09	81.45	2.65	2.83	1.52	3.66	0.66	0.15
8	0.52	7.06	81.12	2.68	3.12	1.56	3.65	0.66	0.17
9	0.53	7.03	80.87	2.73	3.32	1.58	3.64	0.66	0.18
10	0.53	7.02	80.67	2.78	3.46	1.60	3.64	0.66	0.18

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: FFR ΔGDP US_WUI EPU EBP XMRET OIL VIX

To complement the FEVD analysis, we further investigate the IRFs of ΔGDP in response to various shocks. Figure 1 displays the IRFs of ΔGDP for a one standard deviation positive Cholesky shocks to selected variables. As depicted in Figure 1, an unanticipated positive shock to US_WUI leads to an accumulated response of approximately -0.45 percentage points in ΔGDP after 10 quarters. Similarly, shocks to XMRET result in an accumulated response of approximately 0.6 percentage points in ΔGDP. Notably, EBP exerts a negative effect on ΔGDP consistent with the results in Gilchrist and Zakrajšek (2012), while EPU demonstrates a positive effect. These findings provide some evidence that US_WUI, as a measure of uncertainty, has a negative impact on economic growth, consistent with the results found in Ahir et al. (2022).

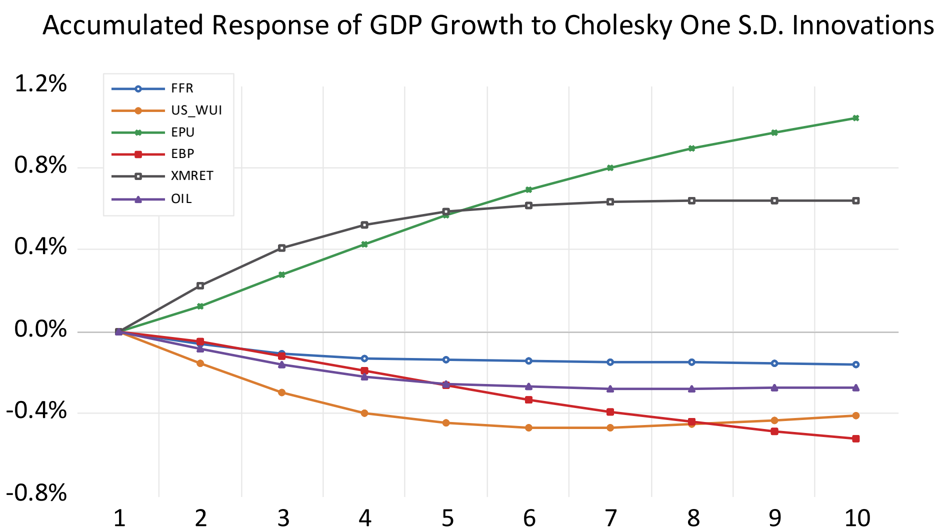

Figure 1. Impulse Response Functions of GDP growth with Cholesky Shocks

Note: This figure shows accumulated impulse responses of different variables to positive one standard deviation Cholesky shocks for the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX. Variables are explained in previous tables. Response functions are plotted for 10 quarters in % points. Other response functions are not shown for parsimony. "S.E." bands for the IRFs are not shown for visual clarity. Quarterly sample 1990:Q1-2022:Q3.

However, Figure 1 clearly demonstrates that EPU, as another measure of uncertainty related to economic policy, has a positive effect on economic growth even after accounting for other variables. Therefore, this result is inconsistent with the findings in Baker et al. (2016). It is important to note that the study by Baker et al. (2016) did not specifically examine variables such as US_WUI, OIL, and EBP, which may contribute to the disparity in our results. Additionally, our findings align with the argument presented in Baker et al. (2016) that drawing causal inferences based on EPU using VARs is extremely challenging due to the potential for policy and policy uncertainty to respond to current and anticipated future states of the economy.

To ensure the robustness of the above results, we proceed to investigate alternative definitions of shocks to different endogenous variables. It has been suggested by studies such as Thorbecke (1997) and others that ordering the endogenous VAR variables should begin with the macro variables. Additionally, when it comes to uncertainty indices like EPU or US_WUI, there are no established economic guidelines regarding their ordering. In order to address this issue, we adopt a generalized impulse definition. Pesaran and Shin (1998) shows that generalized impulse definition do not require a specific ordering of the VAR variables. It is important to note that the endogenous BVAR variables we include in our analysis remain the same throughout.

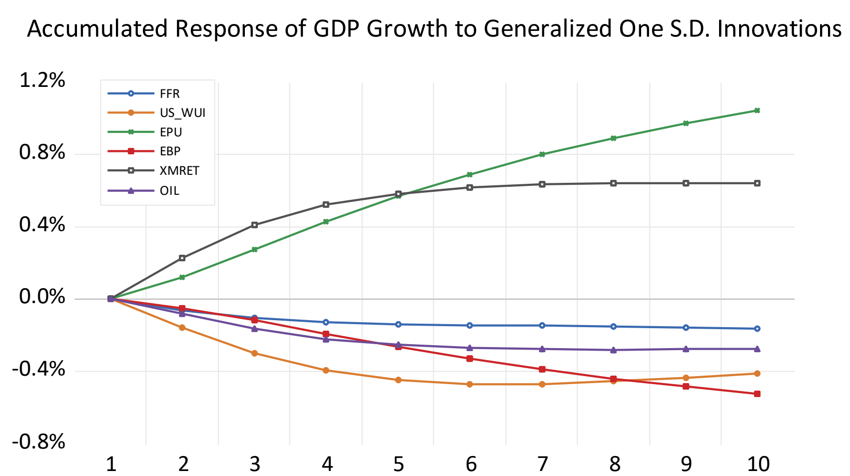

Figure 2. Impulse Response Functions of GDP growth with Generalized Shocks

Note: This figure shows accumulated impulse responses of different variables to positive one standard deviation

Generalized shocks for the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX. Variables are explained in previous tables. Response functions are plotted for 10 quarters in % points. Other response functions are not shown for parsimony. "S.E." bands for the IRFs are not shown for visual clarity. Quarterly sample 1990:Q1-2022:Q3.

In Figure 2, we present the accumulated IRFs of ΔGDP for a one standard deviation positive generalized shocks to selected variables, considering this alternative definition. Remarkably, we find that the alternative shock definition does not have any qualitative impact on the results obtained previously. Overall, the above analysis shows that US_WUI contains economically important information about U.S. real GDP, while the information content of EPU about U.S. economic growth is counterintuitive after we account for other known economic growth predictors.

3.1 Sub-sample Analysis excluding the Covid-19 Period

In this section, our focus is to assess the informational advantage of US_WUI by excluding the Covid-19 period. Unreported data reveals that during this period, there was a significant decline in GDP along with a rapid increase in the US_WUI index. Subsequently, both indicators experienced a rapid recovery in the following quarters. To ensure that our results are not influenced by the data from 2020-2022, we conduct a BVAR analysis for the 1990-2019 subsample. We employ the same BVAR model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX.

First, we examine the FEVD of ΔGDP over a ten-quarter period. Subsequently, we investigate the accumulated IRFs of ΔGDP to different shocks using the Generalized impulse definition so that the ordering of the endogenous variables are unimportant. The FEVD of ΔGDP in Table 3 indicates that after ten quarters, US_WUI and EPU account for approximately 0.85% and 0.59% of the forecast error variance of ΔGDP, respectively. Comparing the FEVD results of Tables 2 and 3, we find the contribution of both US_WUI and EPU are far lower for this subsample. These findings suggest that when we exclude the Covid-19 period, both uncertainty measures, US_WUI and EPU, have relatively less significance in explaining the forecast error variance of ΔGDP.

Table 3. Forecast Error Variance Decomposition of GDP growth Excluding Covid-19

FEVD of ΔGDP Excluding Covid-19									
Period	S.E.	FFR	ΔGDP	US_WUI	EPU	EBP	XMRET	OIL	VIX
1	0.29	4.56	95.44	0.00	0.00	0.00	0.00	0.00	0.00
2	0.37	3.84	95.53	0.04	0.06	0.11	0.00	0.36	0.05
3	0.41	3.47	94.90	0.13	0.14	0.39	0.00	0.82	0.16
4	0.44	3.29	93.97	0.24	0.22	0.78	0.00	1.21	0.29
5	0.45	3.20	92.99	0.37	0.30	1.23	0.00	1.49	0.43
6	0.47	3.15	92.08	0.49	0.37	1.67	0.00	1.68	0.57
7	0.47	3.11	91.30	0.60	0.43	2.07	0.00	1.79	0.70
8	0.48	3.08	90.65	0.70	0.49	2.40	0.00	1.86	0.81
9	0.48	3.06	90.12	0.78	0.54	2.67	0.00	1.90	0.92
10	0.49	3.05	89.71	0.85	0.59	2.87	0.00	1.93	1.01

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: FFR ΔGDP US_WUI EPU EBP XMRET OIL VIX

Note: This table shows the forecast error variance decomposition (FEVD) of ΔGDP for the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, US_WUI, EPU, EBP, XMRET, OIL, and VIX. Variables are explained in the previous table. The FEVD of ΔGDP is shown for 10 quarters is shown in %; the FEVDs for other variables are not shown for parsimony. Quarterly sample 1990:Q1-2019:Q4.

Next, in Figure 3 we present the IRFs of ΔGDP to different generalized shocks to ensure that the ordering of the endogenous VAR variables is unimportant. Upon examining the IRFs of ΔGDP in Figure 3, we observe that shocks to US_WUI and EPU have approximately a 1.5 and 1.0 percentage point impact on ΔGDP, respectively. These results are inconsistent with the findings in Ahir et al. (2022) and Baker et al. (2016) since US_WUI and EPU, as measures of uncertainty, should have a negative impact on ΔGDP. In contrast, other variables such as EBP and XMRET exhibit qualitatively similar relationships to those obtained for the full sample. Specifically, an expansion in EBP leads to a reduction in ΔGDP, while an increase in XMRET is associated with an increase in ΔGDP.

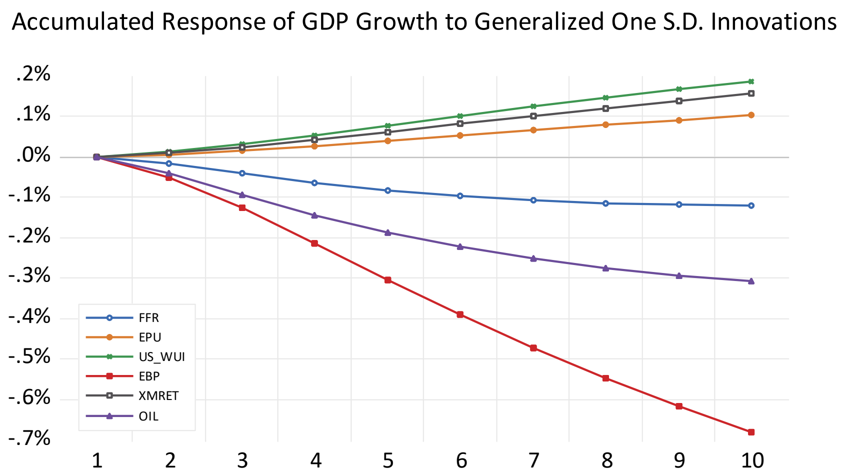

Figure 3. Impulse Response Functions of GDP growth Excluding Covid-19 using BVAR(1) model

Note: This figure shows accumulated impulse responses of different variables to positive one standard deviation Generalized shocks for the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX. Variables are explained in previous tables. Response functions are plotted for 10 quarters in *% points*. Other response functions are not shown for parsimony. “S.E.” bands for the IRFs are not shown for visual clarity. Quarterly sample 1990:Q1-2019:Q4.

Next, we ensure the robustness of the above results by modifying the BVAR specification. Although the lag-length criteria suggest a BVAR (1) model, we employ a BVAR (4) model, incorporating four lags of each endogenous variable, as suggested by Ahir et al. (2022).

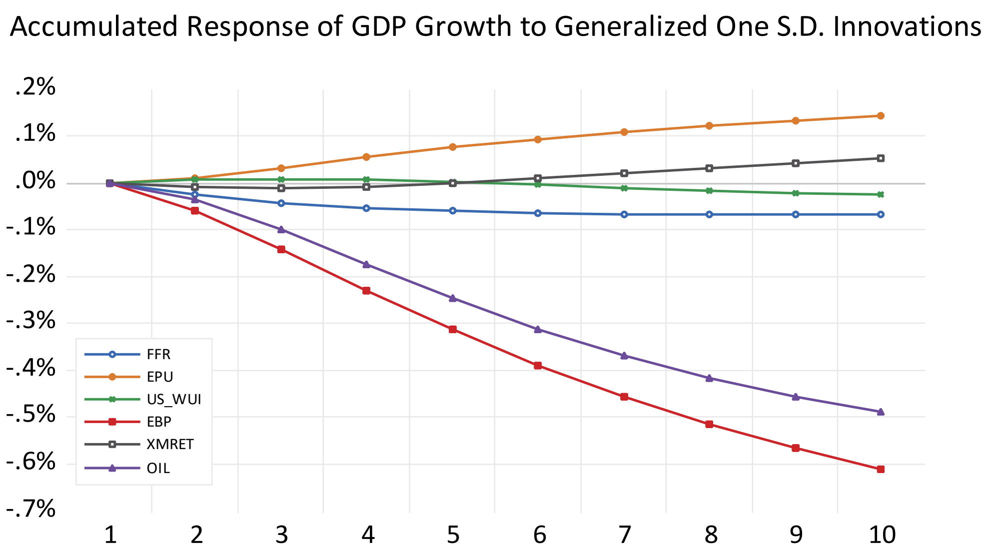

Figure 4. Impulse Response Functions of GDP growth Excluding Covid-19 using BVAR(4) model

Note: This figure shows accumulated impulse responses of different variables to positive one standard deviation Generalized shocks for the BVAR(4) model with the following endogenous variables: FFR, ΔGDP, EPU, US_WUI, EBP, XMRET, OIL, and VIX. Variables are explained in previous tables. Response functions are plotted for 10 quarters in *% points*. Other response functions are not shown for parsimony. "S.E." bands for the IRFs are not shown for visual clarity. Quarterly sample 1990:Q1-2019:Q4.

Figure 4 presents the IRFs of ΔGDP using the BVAR(4) model. Upon examining the IRFs of ΔGDP in Figure 4, we observe that US_WUI exhibits a slightly negative impact of -0.03 percentage points after 10 quarters, while EPU continues to positively impact real GDP growth. In contrast, shocks to variables such as XMRET, OIL and EBP continue to exhibit a robust expected impact on ΔGDP under the BVAR(4) model specification. In summary, these results show that US_WUI may have a negative impact on U.S. economic growth, although not as significant as other indicators if we consider four lags of the endogenous variables in the BVAR model. This underscores the importance of US_WUI in evaluating future U.S. economic growth.

Since we find that EPU is positively associated with GDP growth irrespective of the lag choices of the endogenous variables in the BVAR model, which is economically challenging to explain if EPU represents uncertainty, we ensure the robustness of our findings as follows. We exclude US_WUI from our analysis and examine whether EPU exhibits a negative relationship with GDP growth in the absence of the other uncertainty index. Specifically, we investigate the BVAR(1) model with the following endogenous variables: FFR, ΔGDP, EPU, EBP, XMRET, OIL, and VIX. Unreported results show that that EPU continues to be positively related to GDP growth even when US_WUI is omitted from the model. If we use a BVAR(4) model instead of a BVAR(1) model, the results remain the same for EPU, and these results are available upon request.

3.2 Robustness: Alternative World Uncertainty Measure

To ensure the robustness of our findings, we now explore whether WUI index, a measure of uncertainty for the entire world, alters our conclusions, where we use the 1990-2019 sub-sample. Given the high correlation between WUI and US_WUI, we solely incorporate WUI. Furthermore, we use 4 lags of the endogenous variables as in Ahir et al. (2022) to be consistent. Thus, we have the following endogenous variables in the BVAR(4) model: FFR, ΔGDP, EPU, WUI, EBP, XMRET, OIL, and VIX. For parsimony, we do not report the FEVD of ΔGDP. In Figure 5, we examine the IRFs of ΔGDP to different generalized shocks to ensure that the ordering of the endogenous VAR variables is not an issue.

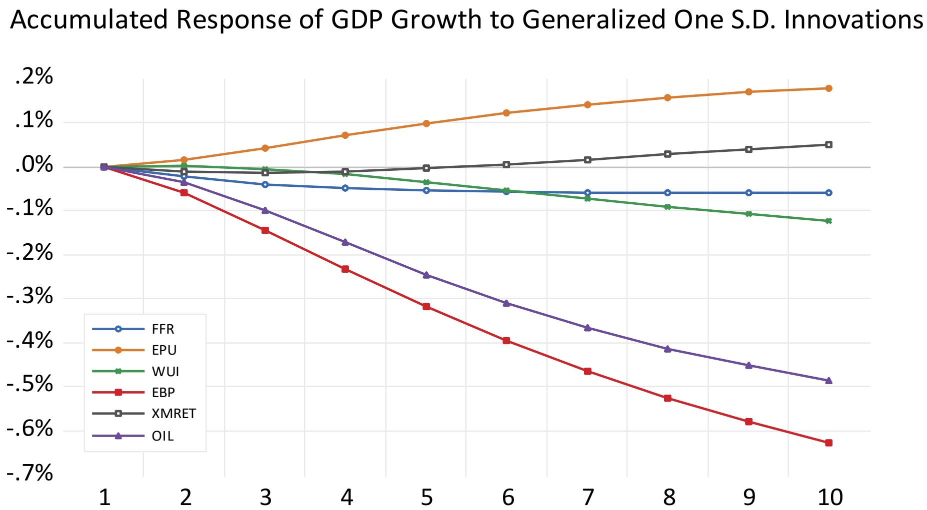

Figure 5. Response Functions of GDP growth excluding Covid-19 period with Alternative World Uncertainty Measure using BVAR(4) model

Note: This figure shows accumulated impulse responses of different variables to positive one standard deviation Generalized shocks for the BVAR(4) model with the following endogenous variables: FFR, ΔGDP, EPU, WUI, EBP, XMRET, OIL, and VIX. Variables are explained in previous tables. Response functions are plotted for 10 quarters in *% points*. Other response functions are not shown for parsimony. "S.E." bands for the IRFs are not shown for visual clarity. Quarterly sample 1990:Q1-2019:Q4.

The IRFs demonstrate that although the WUI has a negative impact on ΔGDP, the magnitude of this effect is significantly smaller compared to the effects of shocks to variables such as OIL or EBP. However and importantly, the relationship between EPU and real GDP remains positive. These findings align with our earlier results, reinforcing the consistency of our findings.

Overall, based on different measures of WUI, whether U.S.-specific or global, and under different specifications of the VAR model, we find that WUI is an important measure of uncertainty that has a negative impact on real GDP growth. However, EPU exhibits a consistently and counterintuitively positive relationship with economic growth. In contrast, variables such as corporate credit spreads, stock prices, and oil prices show a robust and expected relationship with real GDP growth.

4. Conclusions

A recent study introduces the world uncertainty index (WUI), which is derived from the frequency of the word 'uncertainty' in Economist Intelligence Unit (EIU) country reports. They show that higher WUI is associated with lower economic growth for a panel of countries using a vector autoregression (VAR) framework. In this study, we build upon the stated research and investigate the relationship between the U.S.-specific WUI, represented by the US_WUI index, and U.S. GDP growth. To analyze this relationship, we employ a Bayesian VAR framework. We do so by including other potential measures of uncertainty such as oil prices and corporate credit spreads and the Economic Policy Uncertainty (EPU) index for the U.S.

Our findings indicate that the US_WUI index is informative regarding U.S. GDP, but this relationship appears to be largely influenced by the uncertainties experienced during the Covid-19 period. However, when we exclude the Covid-19 period from our analysis, other indicators such as corporate credit spreads and crude oil prices demonstrate greater informational value and exhibit more robust relationships with U.S. GDP. Therefore, these alternative indicators appear to offer more reliable insights into the dynamics of U.S. economic growth, even when we do not consider the impact of the Covid-19 period.

Our research opens up avenues for further exploration. Our study focuses specifically on the U.S. To enhance the breadth and applicability of our findings, it would be valuable for future research to extend the obtained results to other countries and regions. This would allow for a more comprehensive understanding of the relationship between uncertainty and economic growth on a global scale.

Funding: Open access funding provided by Università degli Studi di Trento.

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