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Global Uncertainty and Economic Growth – Evidence from Pandemic Periods

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ABSTRACT

This paper investigates whether global uncertainty predicts economic growth rates using a global sample of 136 countries. We use the panel regression model and find strong evidence that global uncertainty negatively predicts the economic growth rate. Further, the negative impact of global uncertainty on economic growth rates is amplified during pandemic periods versus non-pandemic periods. Our main findings hold after a range of robustness tests.

KEYWORDS

Panel data; predictive regression model; COVID-19; GDP; global uncertainty

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1. Introduction

The objective of this study is to examine whether global uncertainty predicts the economic growth rate and whether this effect is enhanced during pandemic periods versus the non-pandemic periods. Since the global financial crisis, there have been a lot of concerns about uncertainty globally. This is further exacerbated by the recent COVID-19 crisis. For instance, the 2017 IMF reports for South Africa, the UK, and the US suggest that uncertainty has been a key factor of weaker economic performance in many economies. Also, the recent COVID-19 crisis has led to a large drop in economic growth rates globally. In 2020, the GDP of Indonesia fell by 2.07%, the largest fall since the Asian financial crisis. The real GDP of OECD area fell by 9.8% in the second quarter of 2020. This is the largest drop in growth rate ever recorded for the OECD area. It is therefore important to understand how global uncertainty can affect the macroeconomy and whether this impact is enhanced during the pandemic periods.

Our study is motivated by the theoretical work which points out that uncertainty affects growth and investment (see, Bernanke 1983; Bloom, Bond, and Van Reenen 2007; Baker et al. 2016). Bloom, Bond, and Van Reenen (2007) prove that under irreversible investments, global uncertainty reduces a firm's investment. Uncertainty also leads to a decrease in household spending as people become uncertain about their future income and start taking precautions (Caballero 1990). Several studies have examined the impact of uncertainties on macroeconomic variables, firm-specific variables, and asset prices. For instance, Wang et al. (2014) and Shi et al. (2020) examined the impact of uncertainties on corporate investment while Zhang et al. (2015) analyzed the effect of uncertainty on corporate governance. Scheffel (2016), Chen et al. (2019), and Caggiano et al. (2017), among others evaluated the importance of uncertainty for economic development, oil price, and unemployment, respectively. There are a plethora of studies that have looked at the impact of uncertainty on stock returns (see, for example, Ajmi et al. 2015; Hammoudeh et al. 2016; Kang and Ratti 2013; Golab et al. 2022).

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This literature is attractive and growing. A number of studies have used various measures of uncertainty such as policy uncertainty (Baker et al. 2016), financial uncertainty (Choi 2018), uncertainty associated with specific countries (Bhattarai, Chatterjee, and Park 2020; Hassan et al. 2020) and have examined their impact on macroeconomic variables. The bulk of this literature focuses on developed economies. There are a few studies on emerging economies. For instance, Carriere-Swallow and Cespedes (2013) examine the impact of uncertainty shocks on macroeconomic variables in emerging economies. They use a vector autoregression framework and find that uncertainty shocks lead to a significant fall in the economic activity of emerging economies relative to the US and other developed economies. Despite these studies, not much is known about the impact of global uncertainty on emerging and low-income economies particularly during pandemic periods. To fill this gap, we use a large sample of 136 countries out of which 29 are advanced economies, 58 are emerging economies and 49 are low-income economies. The countries included in the sample can be classified into five regions – Africa, Asia and the Pacific, Europe, Middle East and Central Asia, and Western Hemisphere. We use the world uncertainty index developed by Ahir, Bloom, and Furceri (2018) as the proxy for global uncertainty. This captures several uncertainties globally such as the terrorist attack, pandemics, financial crisis, debt crisis, Brexit and political crisis, among others. The data we use is annual from 1990 to 2020 and includes a maximum of 31 observations for each country. This poses a limitation for us as we are not able to use time-series predictive regression models. Therefore, we use the panel regression model proposed by Westerlund, Karabiyik, and Narayan (2017). It is not uncommon in literature to fit the predictive regression model to economic growth (see, for instance, Narayan and Ahmed 2014; Hamilton 2011, among others). We form nine panels – a global panel of all countries, five regional panels, and three panels based on income classification. We also test whether the predictability by global uncertainty is higher during pandemic versus non-pandemic periods.

Briefly foreshadowing the results, we find that global uncertainty negatively predicts GDP growth rate for six panels (Global, Asia and the Pacific, Europe, Western Hemisphere, Advanced economies and Emerging economies) at a 1-year forecast horizon. At the 2-year horizon, the predictability is evident for five panels. The magnitude of predictability is higher at the 1-year horizon relative to the predictability at the 2-year horizon. Further, the negative impact of uncertainty on the GDP growth rate is amplified during pandemic periods. We find that the magnitude of global uncertainty during pandemic periods is at least four times higher than the uncertainty coefficient during non-pandemic periods. To establish the robustness of our findings, we control for the oil price in the panel regression model. Our main results for the full sample period and pandemic periods hold even after controlling for the lagged oil price in the model.

Our findings contribute to the literature in multiple ways. First, this study contributes to the growing literature on the relationship between global uncertainty and macroeconomic variables. This literature has mainly focused on developed economies and a few on emerging economies (see, Carriere-Swallow and Cespedes 2013). We contribute to this literature by using a global sample of 136 countries. Second, we contribute to the evolving literature on COVID-19. This literature has examined how the COVID-19 shock was amplified by the news media, lockdowns and travel constraints and its subsequent effects on the dynamic nature of global equity markets (Baig et al. 2020; Gil-Alana and Claudio-Quiroga 2020; Haroon and Rizvi 2020b; Narayan, Devpura, and Wang 2020; Narayan, Phan, and Liu 2020; Salisu and Sikiru 2020; Yan and Qian 2020; Yuan et al. 2021), the international capital flows, liquidity and the exchange rate market (Aslam et al. 2020; Beirne et al. 2020; Chen, Chand, and Singh 2020; Haroon and Rizvi 2020a; Narayan 2020b; Zhang, Gao, and Li 2021), the potential safe haven status and diversification attributes of commodities such as gold and cryptocurrencies such as bitcoin during the uncertainties of a global pandemic (Ali, Alam, and Rizvi 2020; Conlon, Corbet, and McGee 2020; Corbet et al. 2020; Mnif, Jarboui, and Mouakhar 2020), corporate governance of companies and the integrated nature of global trade networks and value chains (Verbeke 2020; Xiao et al. 2020), the statistical traits of market and sector volatility during times of financial turmoil (Baek, Mohanty, and Glambosky 2020; Corbet et al. 2020; Narayan, Gong, and Aliahmed 2021; Zaremba et al. 2020), the disruptions in the energy market and the influence on investors preference for renewable and sustainable energy stocks to combat climate change (Barbier and Burgess 2020; Chang, McAleer, and Wang 2020; Devpura and Narayan 2020; Fu and Shen 2020; Huang and Zheng 2020; Kartal 2021; Liu, Wang, and Lee 2020; Narayan 2020c; Prabheesh, Padhan, and Garg 2020; Qin, Zhang, and Su 2020; Salisu and Adediran 2020). Our finding that the negative impact of global uncertainty is amplified during pandemic periods contributes to this growing literature on the impact of COVID-19 on the macroeconomy.

The rest of the paper is organized as follows. Section II discusses the data and methodology. Section III presents the empirical results. The robustness tests are presented in Section IV. The last section concludes the paper and provides policy implication.

2. Data and Methodology

2.1. Data and Preliminary Analysis

This paper is based on an annual dataset that includes 136 countries. Out of 136 countries, 29 are advanced economies, 58 are emerging economies and 49 are low-income economies. The sample period is from 1990 to 2020. This is dictated by data availability. The GDP growth rate data is obtained from World Development Indicators. The number of observations of GDP growth rate for each country is listed in Table 1. For 79% of countries, The GDP growth rate data is available from 1990 to 2020 for 79% of countries in our sample.

We use the world uncertainty index developed by Ahir, Bloom, and Furceri (2018) as the proxy for global uncertainty. This data is quarterly and is available from Federal Reserve Economic Data. In our analysis, we compute annual world uncertainty index as the average of the quarterly world uncertainty index. This index captures different types of global uncertainties such as the 9/11 terrorist attack, SARS outbreak, Gulf War II, Eurozone debt crisis, Brexit, US presidential elections, and COVID-19 crisis, among others. A plot of the world uncertainty index is provided in Figure 1. Some of the major peaks in the uncertainty data include the 2002 to 2004 SARS pandemic, the 2012 Eurozone debt crisis, and the COVID-19 pandemic. This enables us to examine whether the effect of uncertainty on growth rate is enhanced during pandemic periods versus other crisis periods. We follow Phan, Sharma, and Tran (2018), Bannigidadmath and Narayan (2021), Golab et al. (2022), among others and compute change in the world uncertainty index for our analysis.

Table 2 provides the list of countries used in the analysis along with the regional classification and the income-based classification. A total of 136 countries are used in the analysis. The regional classification is represented as Africa (AFR), Asia and the Pacific (APD), Europe (EUR), Middle East and Central Asia (MCD), and Western Hemisphere (WHD). The income-based classification of each country as per the IMF is reported in square brackets where 1 represents the advanced economy, 2 represents the emerging economy and 3 represents the low-income economy.

The preliminary analysis of our data is presented in Table 3. A total of nine panels are formed that include one global panel of all countries, five regional panels (Africa, Asia and the Pacific, Europe, Middle East and Central Asia, and Western Hemisphere) and the remaining three panels are based on the income classification (advanced, emerging and low-income economies). The number of countries in each panel is reported in the first column of Table 3. The descriptive statistics of the data are presented in Panel A. Specifically, we report the mean and standard deviation of GDP growth rate. The mean GDP growth rate varies from 2.23% for the panel of European countries to 4.92% for the panel of Asia Pacific countries. The standard deviation of GDP growth rate is highest for the Middle East and Central Asia Panel followed by the panel of emerging economies.

We next examine the statistical features of our data to test whether the data is characterized by persistent and endogenous predictors. In Panel B of Table 3, we report the endogeneity test results. When global uncertainty is used to predict the GDP growth rate, we find the predictor variable is endogenous for six out of nine panels. The persistency of the predictor (global uncertainty) is reported in Panel C. The mean and standard deviation of world uncertainty index is reported in Panel D. The mean world uncertainty index across our sample period is 17,356.74. As expected, the standard

Table 1. Macroeconomic data availability for each country.

Country	GDP	Country	GDP	Country	GDP
Afghanistan	18	Greece	31	Nicaragua	31
Albania	31	Guatemala	31	Niger	31
Algeria	31	Guinea	31	Nigeria	31
Angola	31	Guinea-Bissau	31	Norway	31
Armenia	30	Haiti	31	Oman	30
Australia	31	Honduras	31	Pakistan	31
Austria	31	Hong Kong	31	Panama	31
Azerbaijan	30	Hungary	29	Papua New Guinea	31
Bangladesh	31	India	31	Paraguay	31
Belarus	30	Indonesia	31	Peru	31
Belgium	31	Iran	31	Philippines	31
Benin	31	Iraq	31	Poland	30
Bolivia	31	Ireland	31	Portugal	31
Bosnia and Herzegovina	26	Israel	25	Qatar	20
Botswana	31	Italy	31	Romania	30
Brazil	31	Jamaica	31	Russia	31
Bulgaria	31	Japan	30	Rwanda	31
Burkina Faso	31	Jordan	31	Saudi Arabia	31
Burundi	31	Kazakhstan	30	Senegal	31
Cambodia	27	Kenya	31	Sierra Leone	31
Cameroon	31	Korea	31	Singapore	31
Canada	23	Kuwait	27	Slovak Republic	28
Central African Republic	31	Kyrgyz Republic	31	Slovenia	25
Chad	31	Lao P.D.R.	31	South Africa	31
Chile	31	Latvia	25	Spain	31
China	31	Lebanon	31	Sri Lanka	31
Colombia	31	Lesotho	31	Sudan	31
Congo	31	Liberia	20	Sweden	31
Congo Republic	31	Libya	21	Switzerland	31
Costa Rica	31	Lithuania	25	Tajikistan	31
Côte d'Ivoire	31	FYR Macedonia	30	Tanzania	31
Croatia	25	Madagascar	31	Thailand	31
Czech Republic	30	Malawi	31	Togo	31
Denmark	31	Malaysia	31	Tunisia	31
Dominican Republic	31	Mali	31	Turkey	31
Ecuador	31	Mauritania	31	Uganda	31
Egypt	31	Mexico	31	Ukraine	31
El Salvador	31	Moldova	25	UAE	30
Ethiopia	31	Mongolia	31	UK	31
Finland	31	Morocco	31	United States	31
France	31	Mozambique	31	Uruguay	31
Gabon	31	Myanmar	31	Vietnam	31
The Gambia	31	Namibia	31	Yemen	28
Georgia	31	Nepal	31	Zambia	31
Germany	31	Netherlands	31		
Ghana	31	New Zealand	31		

This table reports the specific number of observations of GDP growth rate data used in our analysis. The data is annual and starts from as far as 1990 to 2020.

deviation is higher indicating period of low uncertainty are followed by periods of high uncertainty. This is evident from Figure 1 that shows the plot of world uncertainty index.

The key findings from our preliminary analysis reveal that endogeneity of predictor is an issue when global uncertainty is used to predict GDP growth rate.

2.2. Methodology

Our study employs a panel predictive regression model proposed by Westerlund, Karabiyik, and Narayan (2017). This model has a number of advantages over the time-series predictive regression model commonly used in literature. First, the panel data model increases the total number of observations, reduces the noise coming from individual time-series regressions, and increases the power of the test. This is important

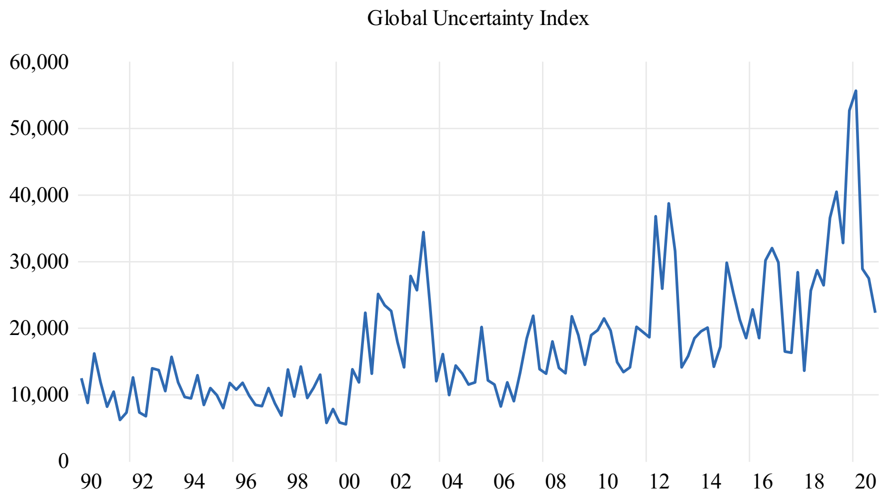

Figure 1. Plot of global uncertainty index. This figure shows a plot of the quarterly world uncertainty index. The data covers the sample period from 1990 to 2020. This data is developed by Ahir, Bloom, and Furceri (2018) and is obtained from the Federal Reserve Economic Data. In our analysis, we use annual data obtained by taking average of quarterly data.

particularly when the availability of data is annual and limited as in the case of a majority of developing and low-income economies. In our case, the sample period for around 38% of countries has less than 31 observations making it insufficient for fitting the time-series regression model. Second, the novel feature of this model is that the predictor variable $x_{i,t}$ can be treated as a black box, in the sense that a predictor can be stationary, non-stationary, and can contain a unit root. In addition, the predictors are not restricted to be homoskedastic but can be heteroscedastic. The panel predictive regression test proposed by Westerlund, Karabiyik, and Narayan (2017) is bias-free and robust to the predictor persistency and endogeneity relevant in our dataset. From our preliminary analysis, while persistency is not a major concern, endogeneity is and has to be dealt with in our model. Therefore, the recently developed Westerlund, Karabiyik, and Narayan (2017) panel predictive regression model is adopted. It is not uncommon in literature to fit the predictive regression model to economic growth (see, for instance, Narayan and Ahmed 2014; Hamilton, 2011, among others). The panel predictive regression model takes the form:

$$MI_{i,t} = \alpha_0 + \beta GU_{i,t-1} + u_{i,t} \tag{1}$$

where, $MI_{i,t}$represents the macroeconomic indicator, the GDP growth rate for country i, and $GU_{i,t}$ represents the global uncertainty. The error term in Equation (1) is represented by $u_{i,t}$.

$$u_{i,t} = \lambda_i f_t + \varepsilon_{i,t} \tag{2}$$

Westerlund, Karabiyik, and Narayan (2017) follow Pesaran (2006) and estimate the common factor f_t as the cross-sectional average of $r^*_{i,t}$; λ_i represents the associated factor loading and the idiosyncratic error term is represented by $\varepsilon_{i,t}$.

$$\hat{f}_t = \bar{r}^*_t \tag{3}$$

The estimator of β is given by:

$$\hat{\beta} = \left(\sum_{i=1}^{N} \left(x^*_{i,-1} \right)' M_{\hat{f}} x^{**}_{i,-1} \right)^{-1} \sum_{i=1}^{N} \left(x^{**}_{i,-1} \right)' M_{\hat{f}} r^*_i \tag{4}$$

Here $x^*_{i,-1} = \left(x^*_{i,1}, \ldots, x^*_{i,T-1} \right)'$ and $x^{**}_{i,-1} = \left(x^{**}_{i,1}, \ldots, x^{**}_{i,T-1} \right)'$ are $(T-1) \times m$; $r^*_i = \left(r^*_{i,2}, \ldots, r^*_{i,T} \right)'$ and $\hat{f} = \left(\hat{f}_2, \ldots, \hat{f}_T \right)'$ are $(T-1) \times 1$. x^*_i and x^{**}_i are forwards and backwards recursively demeaned

Table 2. List of countries including the regional and income-based classification.

Country	Region [Classification]	Country	Region [Classification]	Country	Region [Classification]
Afghanistan	MCD [3]	Greece	EUR [1]	Nicaragua	WHD [3]
Albania	EUR [2]	Guatemala	WHD [2]	Niger	AFR [3]
Algeria	MCD [2]	Guinea	AFR [3]	Nigeria	AFR [3]
Angola	AFR [2]	Guinea-Bissau	AFR [3]	Norway	EUR [1]
Armenia	MCD [2]	Haiti	WHD [3]	Oman	MCD [2]
Australia	APD [1]	Honduras	WHD [3]	Pakistan	MCD [2]
Austria	EUR [1]	Hong Kong	APD [1]	Panama	WHD [2]
Azerbaijan	MCD [2]	Hungary	EUR [2]	Papua New Guinea	APD [3]
Bangladesh	APD [3]	India	APD [2]	Paraguay	WHD [2]
Belarus	EUR [2]	Indonesia	APD [2]	Peru	WHD [2]
Belgium	EUR [1]	Iran	MCD [2]	Philippines	APD [2]
Benin	AFR [3]	Iraq	MCD [2]	Poland	EUR [2]
Bolivia	WHD [3]	Ireland	EUR [1]	Portugal	EUR [1]
Bosnia and Herzegovina	EUR [2]	Israel	EUR [1]	Qatar	MCD [2]
Botswana	AFR [2]	Italy	EUR [1]	Romania	EUR [2]
Brazil	WHD [2]	Jamaica	WHD [2]	Russia	EUR [2]
Bulgaria	EUR [2]	Japan	APD [1]	Rwanda	AFR [3]
Burkina Faso	AFR [3]	Jordan	MCD [2]	Saudi Arabia	MCD [2]
Burundi	AFR [3]	Kazakhstan	MCD [2]	Senegal	AFR [3]
Cambodia	APD [3]	Kenya	AFR [3]	Sierra Leone	AFR [3]
Cameroon	AFR [3]	Korea	APD [1]	Singapore	APD [1]
Canada	WHD [1]	Kuwait	MCD [2]	Slovak Republic	EUR [1]
Central African Republic	AFR [3]	Kyrgyz Republic	MCD [3]	Slovenia	EUR [1]
Chad	AFR [3]	Lao P.D.R.	APD [3]	South Africa	AFR [2]
Chile	WHD [2]	Latvia	EUR [1]	Spain	EUR [1]
China	APD [2]	Lebanon	MCD [2]	Sri Lanka	APD [2]
Colombia	WHD [2]	Lesotho	AFR [3]	Sudan	MCD [3]
Congo	AFR [3]	Liberia	AFR [3]	Sweden	EUR [1]
Congo Republic	AFR [3]	Libya	MCD [2]	Switzerland	EUR [1]
Costa Rica	WHD [2]	Lithuania	EUR [2]	Tajikistan	MCD [3]
Côte d'Ivoire	AFR [3]	FYR Macedonia	EUR [2]	Tanzania	AFR [3]
Croatia	EUR [2]	Madagascar	AFR [3]	Thailand	APD [2]
Czech Republic	EUR [1]	Malawi	AFR [3]	Togo	AFR [3]
Denmark	EUR [1]	Malaysia	APD [2]	Tunisia	MCD [2]
Dominican Republic	WHD [2]	Mali	AFR [3]	Turkey	EUR [2]
Ecuador	WHD [2]	Mauritania	MCD [3]	Uganda	AFR [3]
Egypt	MCD [2]	Mexico	WHD [2]	Ukraine	EUR [2]
El Salvador	WHD [2]	Moldova	EUR [3]	UAE	MCD [2]
Ethiopia	AFR [3]	Mongolia	APD [3]	UK	EUR [1]
Finland	EUR [1]	Morocco	MCD [2]	United States	WHD [1]
France	EUR [1]	Mozambique	AFR [3]	Uruguay	WHD [2]
Gabon	AFR [2]	Myanmar	APD [3]	Vietnam	APD [3]
The Gambia	AFR [3]	Namibia	AFR [2]	Yemen	MCD [3]
Georgia	MCD [2]	Nepal	APD [3]	Zambia	AFR [3]
Germany	EUR [1]	Netherlands	EUR [1]		
Ghana	AFR [3]	New Zealand	APD [1]		

This table reports the list of 136 countries used in our analysis. The second, fourth, and sixth columns of the table report the respective regional classification of the country. AFR represents the region "Africa," APD represents "Asia and the Pacific," EUR represents "Europe region, MCD represents the "Middle East and Central Asia" and lastly WHD represents the "Western Hemisphere." The income-based classification is reported in square brackets. "Advanced Economies" are denoted by 1 in square brackets. 2 and 3 represent "Emerging Economies" and "Low-Income Economies," respectively.

versions. For a generic variable a_t, $a_t^* = a_t - (T-t+1)^{-1}\sum_{n=t}^{T} a_n$, $a_t^{**} = a_t - t^{-1}\sum_{n=1}^{t} a_n$, and $M_A = I_{T-1} - A(A'A)^{-1}A'$ for any matrix A with $(T-1)$ rows. Similar to Hjalmarsson (2010), the variables $x_{i,-1}$ and r_i are projected on $\bar{x}_{-1} = N^{-1}\sum_{i=1}^{N} x_{i,-1}$. It is important to note that Westerlund, Karabiyik, and Narayan (2017) used both forwards and backwards recursively demeaned versions to avoid the "Stambaugh bias" that affects the inference.

To test whether the predictability is higher during pandemic versus the non-pandemic periods, we use a two-state predictive regression model:

Table 3. Descriptive statistics and preliminary analysis.

Country Panels	Mean	Std. dev
Panel A: Descriptive Statistics of GDP growth rate		
Global [136]	3.4223	6.0906
Africa [35]	3.6893	5.3346
Asia and the Pacific [21]	4.9265	4.1553
Europe [35]	2.2309	5.1998
Middle East and Central Asia [25]	3.7377	9.9389
Western Hemisphere [20]	3.0032	3.4248
Advanced Economies [29]	2.3352	3.2272
Emerging Economies [58]	3.5592	7.4738
Low-Income Economies [49]	3.8979	5.4523
Country Panels	*coefficient*	*p-value*
Panel B: Endogeneity Test		
Global [136]	−0.0066**	.0153
Africa [35]	−0.0009	.8465
Asia and the Pacific [21]	−0.0116**	.0156
Europe [35]	−0.0116**	.0119
Middle East and Central Asia [25]	0.0023	.8160
Western Hemisphere [20]	−0.0130***	.0013
Advanced Economies [29]	−0.0137***	.0000
Emerging Economies [58]	−0.0083*	.0941
Low-Income Economies [49]	−0.0002	.9695
	AR(1) coefficient	*p-value*
Panel C: Persistency Test		
Global Uncertainty	−0.2909	.1290
	Mean	Std. dev
Panel D: Descriptive statistics of world uncertainty index		
World uncertainty index	17356.74	7812.171

This table reports four sets of results – the descriptive statistics of GDP growth rates in Panel A, the endogeneity tests in Panel B, and the persistency test of the predictor in Panel C and the descriptive statistics of world uncertainty index in Panel D. We consider a total of nine panels for our analysis – a global panel of all countries, five regional panels, and three panels based on IMF income classification. The number of countries in each of the nine panels is reported in square brackets in the first column of the table. The mean and standard deviation of GDP growth rate for all the nine panels are reported in Panel A. The endogeneity tests results reported in Panel B are obtained by regressing the errors from the predictive regression model against the errors from an AR(1) model of the predictor variable – global uncertainty shocks. The coefficient and *p*-value are reported. In Panel C, we report the persistency of predictor measured using an AR (1) model of global uncertainty shock. ***, ** and * denotes significance at 1%, 5% and 10% significance levels, respectively.

$$MI_{i,t} = \alpha_0 + \beta_1 GU_{i,t-1} * HealthCrisis_{i,t} + \beta_2 GU_{i,t-1} * (1 - HealthCrisis_{i,t}) + u_{i,t} \tag{5}$$

Here, $HealthCrisis_{i,t}$ is a dummy variable constructed based on the World Pandemic Uncertainty Index data available from the Federal Reserve Economic Data. The $HealthCrisis_{i,t}$ dummy variable takes a value of 1 when the World Pandemic Uncertainty Index is greater than zero and a value of 0 otherwise. We consider the SARS, Avian flu, Swine flu, Ebola, Middle East respiratory syndrome and the COVID-19 pandemic periods. Specifically, the $HealthCrisis_{i,t}$ dummy variable takes a value of 1 during 2003 to capture SARS; a value of 1 during the years 2004, 2005, 2007 and 2009 to capture Avian flue; a value of 1 for 2010 to capture Swine flu; a value of 1 from 2014 to 2017 to represent the Bird flu and Ebola; a value of 1 during 2019 and 2020 to capture the COVID pandemic period. This specification enables us to test whether the impact of global uncertainty is higher during pandemic periods versus non-pandemic periods.

Table 4. Predictability tests during the full sample period and pandemic periods.

	h = 1		h = 2	
	coefficient	p-value	coefficient	p-value
Panel A: Full sample predictability test results				
Global	−0.0214***	.0000	−0.0068***	.0083
Africa	−0.0063	.4240	−0.0037	.4338
Asia and the Pacific	−0.0299***	.0001	−0.0022	.6479
Europe	−0.0280***	.0002	−0.0115**	.0107
Middle East and Central Asia	−0.0133	.4195	−0.0082	.3755
Western Hemisphere	−0.0366***	.0000	−0.0075*	.0612
Advanced Economies	−0.0340***	.0000	−0.0096***	.0023
Emerging Economies	−0.0263***	.0012	−0.0103**	.0291
Low-Income Economies	−0.0079	.2490	−0.0011	.7793
	Pandemic periods		Non-pandemic periods	
	coefficient	*p-value*	*coefficient*	*p-value*
Panel B: Predictability during pandemic periods				
Global	−0.0669***	.0000	−0.0047	.3456
Africa	−0.0414***	.0029	0.0064	.4765
Asia and the Pacific	−0.0713***	.0000	−0.0153*	.0812
Europe	−0.0632***	.0000	−0.0149*	.0810
Middle East and Central Asia	−0.0855***	.0032	0.0136	.4679
Western Hemisphere	−0.0900***	.0000	−0.0171**	.0162
Advanced Economies	−0.0633***	.0000	−0.0233***	.0000
Emerging Economies	−0.0867***	.0000	−0.0042	.6488
Low-Income Economies	−0.0455***	.0002	0.0059	.4517

The Panel A of the table reports the predictability test results for the full sample period using the panel predictive regression model proposed by Westerlund, Karabiyik, and Narayan (2017). The panel regression model takes the form: $MI_{i,t} = \alpha_0 + \beta GU_{i,t-1} + u_{i,t}$ where $MI_{i,t}$ represents the macroeconomic indicator, the GDP growth rate for country *i*, and $GU_{i,t}$ represents the global uncertainty computed as a change in the world uncertainty index. The coefficient and *p-value* are reported for a forecast horizon of 1-year and 2-years. Panel B of the table reports the results from a two-state panel predictive regression model that takes the form: $MI_{i,t} = \alpha_0 + \beta_1 GU_{i,t-1} * HealthCrisis_{i,t} + \beta_2 GU_{i,t-1} * \left(1 - HealthCrisis_{i,t}\right) + u_{i,t}$. Here, $HealthCrisis_{i,t}$ is a dummy variable constructed based on the World Pandemic Uncertainty Index available from the Federal Reserve Economic Data. The$HealthCrisis_{i,t}$ dummy variable takes a value of 1 when the World Pandemic Uncertainty Index is greater than zero and a value of 0 otherwise. The coefficient and *p-value* are reported. *, **, and *** denotes the significance level of 10%, 5%, and 1%, respectively.

3. Empirical Results

The predictability results with global uncertainty as a predictor variable are reported in Table 4. Panel A of Table 4 reports the results for the full sample period. We use a horizon of 1 year and 2 years for in-sample forecasting. At the 1-year horizon, we find global uncertainty negatively predicts the GDP growth rate for six panels – the global panel, three regional panels (Asia and the Pacific, Europe and Western Hemisphere), and two income-based panels (advanced economies and emerging economies). There is no evidence of predictability for the panel of low-income economies and two regional panels – Africa, Middle East and Central Asia. At the 2-year horizon, GDP growth rate predictability is evident for five out of nine panels. Across all the five panels that are predictable at both the horizons, the magnitude of coefficients is higher with *h = 1* than *h = 2*. This evidence is consistent with other studies that report the negative effect of uncertainty on the GDP growth rate (see, Carriere-Swallow and Cespedes, 2013; Choi, 2018).

We next examine whether the impact of global uncertainty on GDP growth rate is different during the pandemic periods versus the non-pandemic periods that may include financial or political crises. The results of the two-state predictive regression model are reported in Panel B of Table 4. There are two key findings. First, we find strong evidence that global uncertainty negatively predicts the GDP growth rate during pandemic periods. The coefficient of global uncertainty during pandemic periods is negative and statistically significant at a 1% significance level for all nine panels. During non-pandemic periods, we find evidence of GDP growth rate predictability for four panels – three regional (Asia and the Pacific, Europe, Western Hemisphere, Advanced Economies) and the advanced economies panel. Second, for four panels where predictability is evident during both pandemic and non-pandemic periods, the magnitude of global uncertainty during the pandemic period is at least four times the magnitude of global uncertainty during the non-pandemic period.

Overall, there are two key implications of our analysis. First, we find strong evidence of predictability of GDP growth rate by global uncertainty. Second, we find that global uncertainty has a large impact on the GDP growth rate during pandemic periods versus the other crisis periods.

4. Robustness Tests

We undertake a range of robustness tests to affirm our main findings. First, we use a different proxy of uncertainty. Specifically, we use regional uncertainty measures instead of global uncertainty to forecast the GDP growth rate. The regional uncertainty measures are obtained from Ahir, Bloom, and Furceri (2018). The full sample predictability test results are reported in Panel A of Table 5. We find that regional uncertainty predicts the GDP growth rate for five panels – Asia and the Pacific, Europe, Western Hemisphere, Advanced Economies, and Low-Income Economies. Comparing this with the forecasts from the global uncertainty (see Panel A of Table 4), we notice three key points. First, we find the magnitude of predictability is higher with the global uncertainty relative to regional uncertainty for three out of five panels (Asia and the Pacific, Western Hemisphere, and Advanced Economies), the exception being Europe. Second, global uncertainty does not predict the GDP growth rate of low-income economies while regional uncertainty predicts the GDP growth rate of low-income economies. Third, there is no evidence of predictability for two regional panels – Africa and the Middle East and Central Asia. This is consistent with results obtained when global uncertainty is used as a predictor of GDP growth rate. We now analyze the results from the two-state panel regression model reported in Panel B of Table 5. We

Table 5. Predictability test results using regional uncertainty.

	coefficient	p-value
Panel A: Predictability during the full sample period		
Africa	−0.0024	.7784
Asia and the Pacific	−0.0234***	.0036
Europe	−0.0358***	.0000
Middle East and Central Asia	0.0404	.0747
Western Hemisphere	−0.0120***	.0009
Advanced Economies	−0.0259***	.0000
Emerging Economies	−0.0128	.3358
Low-Income Economies	−0.0191**	.0102

	Pandemic periods		Non-pandemic periods	
	coefficient	*p-value*	*coefficient*	*p-value*
Panel B: Predictability during pandemic periods				
Africa	−0.0006	.9644	−0.0035	.7278
Asia and the Pacific	−0.0562***	.0000	0.0079	.4224
Europe	−0.0838***	.0000	−0.0164**	.0458
Middle East and Central Asia	−0.0896**	.0479	0.0883***	.0010
Western Hemisphere	−0.0302***	.0001	−0.0093**	.0133
Advanced Economies	−0.0496***	.0000	−0.0178***	.0000
Emerging Economies	−0.0272	.2204	−0.0046	.7772
Low-Income Economies	−0.0253**	.0330	−0.0219**	.0363

This table reports the predictability test results with region-specific uncertainty measures obtained from Ahir, Bloom, and Furceri (2018). Panel A of the table reports the predictability test results for the full sample period and Panel B reports the results for the pandemic and non-pandemic periods. The coefficient and *p-value* are reported. *, **, and *** denotes the significance level of 10%, 5%, and 1%, respectively.

find significant evidence of predictability during pandemic periods relative to non-pandemic periods. During pandemic periods, regional uncertainty predicts GDP growth rate for six panels while the predictability during non-pandemic periods is limited to five panels. In panels where predictability is evident across both pandemic and non-pandemic periods, the magnitude of predictability is higher during pandemic periods. This is consistent with our main findings obtained using global uncertainty.

Our second robustness test involves controlling for the oil price in the panel regression model. The relationship between oil price and economic growth is well established in the literature (see, for instance, Narayan and Ahmed 2014; Kilian 2008; Hamilton 2011). The main finding of this literature is that oil price usually has a negative effect on the GDP growth rate. We, therefore, control for the oil price in our model and test if the main findings hold. Table 6 reports the results after controlling for the lagged oil price in the panel regression model. Panel A of Table 6 reports the results for the full sample period. We find evidence of predictability for six panels – four regional panels (Global, Asia and the Pacific, Europe and Western Hemisphere) and two income-based panels (Advanced Economies and Emerging Economies). This is consistent with the earlier results obtained without controlling for the oil price in the regression model. Panel B of Table 6 reports the predictability test results for pandemic and non-pandemic periods. We find significant evidence of predictability during pandemic periods relative to non-pandemic periods even after controlling for the oil price. During pandemic periods, global uncertainty predicts the GDP growth rate of all the panels while during non-pandemic periods, the predictability is evident in five panels. Following an advise by the referee, we undertake additional roubustness test by including a first order autoregressive coefficient in Equation (1), see for instance, Junttila and Vataja (2018). This is following the seminal contribution by Stock and Watson (2003) that many macroeconomic variables are strongly history-dependent. Our results remain unchanged. The implication of this is that our main findings hold after a range of robustness tests.

Table 6. Predictability test results after controlling for oil price.

	coefficient	p-value
Panel A: Predictability during the full sample period		
Global	−0.0202***	.0000
Africa	−0.0047	.5519
Asia and the Pacific	−0.0299***	.0001
Europe	−0.0270***	.0003
Middle East and Central Asia	−0.0099	.5450
Western Hemisphere	−0.0366***	.0000
Advanced Economies	−0.0344***	.0000
Emerging Economies	−0.0248***	.0022
Low-Income Economies	−0.0061	.3763

	Pandemic periods		Non-pandemic periods	
	coefficient	*p-value*	*coefficient*	*p-value*
Panel B: Predictability during pandemic periods				
Global	−0.0775***	.0000	−0.0097*	.0529
Africa	−0.0431***	.0035	0.0012	.8969
Asia and the Pacific	−0.0901***	.0000	−0.0177**	.0432
Europe	−0.0790***	.0000	−0.0209**	.0137
Middle East and Central Asia	−0.0820***	.0083	0.0066	.7266
Western Hemisphere	−0.1140***	.0000	−0.0205***	.0029
Advanced Economies	−0.0858***	.0000	−0.0261***	.0000
Emerging Economies	−0.0987***	.0000	−0.0101	.2734
Low-Income Economies	−0.0473***	.0002	0.0006	.9403

This table reports the predictability test results after controlling for the oil price in the regression model. Panel A of the table reports the predictability test results for the full sample period and Panel B reports the results for pandemic and non-pandemic periods. The coefficient and *p-value* are reported. *, **, and *** denotes the significance level of 10%, 5%, and 1%, respectively.

5. Conclusion

This paper investigates whether global uncertainty predicts GDP growth rate and whether this effect heightens during the pandemic periods. We use an annual dataset that includes 136 countries. The sample period for each country varies and is from 1990 to 2020. A total of nine panels are formed that include one global panel of all countries, five regional panels (Africa, Asia and the Pacific, Europe, Middle East and Central Asia, and Western Hemisphere) and the remaining three panels are based on the income classification (advanced, emerging and low-income economies). Using a panel predictive regression model proposed by Westerlund, Karabiyik, and Narayan (2017), we find that global uncertainty negatively predicts the GDP growth rate for six panels – the global panel, three regional panels (Asia and the Pacific, Europe and Western Hemisphere), and two income-based panels (advanced economies and emerging economies).

We also test whether the impact of global uncertainty is higher during the pandemic periods versus the non-pandemic periods. We find strong evidence that global uncertainty negatively predicts the GDP growth rate for all nine panels during the pandemic periods. During non-pandemic periods, we find evidence of GDP growth rate predictability for four panels. Further, the magnitude of global uncertainty during the pandemic period is at least four times the magnitude of global uncertainty shock during the non-pandemic period. Our findings contribute to the evolving literature on COVID-19 impacts on the macroeconomy.

The main policy implication from our econometric model is that the central banks and the policy regulators have to incorporate global uncertainty as part of their forecasting models to predict the GDP growth rate. Our results indicate that global uncertainty predicts GDP growth rate during both pandemic and non-pandemic periods for the Asia Pacific, Europe, Western Hemisphere destinations, and advanced economies. Further, the magnitude of the effect of global uncertainty on the GDP growth rate is at least four times higher during pandemic periods than during non-pandemic periods. Therefore, ignoring global uncertainty shocks is risky and might distort the forecasts of GDP growth rate.

The focus of this study has been on global uncertainty. The uncertainty shocks that we have used do not capture well the trade-related uncertainty. International trade has seen a huge growth in the last decade leading to an increase in global imports and exports. Therefore, future research may investigate how trade-related uncertainty affects macroeconomic indicators and the degree to which this has amplified during the pandemic periods.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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