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Global Economic Policy Uncertainty and Global Economic Leaders' Influence on Regional Economic Growth

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Abstract

This study aims to evaluate the regional economic growth of select American, European, and Asian countries amidst global economic uncertainty. The proposed methodology incorporates mixed frequencies in the data (VAR-MIDAS), facilitating the assessment of their reliance on lagged values, the impact of economic growth in other countries within the same region, and the influence of Global Economic Policy Uncertainty (GEPU). This sheds light on the effects of economic news from relevant newspapers on GDP growth. The primary hypothesis suggests a significant influence of other countries within the same region and the two major global economic powers on the Gross Domestic Product (GDP) growth of each studied region, namely the United States and China. This research also examines this hypothesis across 19 GEPU-included economies, categorizing them regionally by continent. The econometric results confirm the influence of the two leading economies on economic growth and identify causal relationships, with GEPU also exhibiting effects on GDP. Additionally, in-sample estimations reveal disparities in the influence of leaders on the economic growth of the examined economies.

JEL Classification: C3, C4, C5, F6, O4.

Keywords: GEPU, regional economic growth, VAR, Granger Causality.

La incertidumbre de la política económica mundial y la influencia de los líderes económicos mundiales en el crecimiento económico regional

Resumen

Este estudio tiene como objetivo evaluar el crecimiento económico regional de países seleccionados de América, Europa y Asia en medio de la incertidumbre económica global. La metodología propuesta incorpora frecuencias mixtas en los datos (VAR-MIDAS) facilitando la evaluación de su dependencia de valores rezagados y la medición del impacto y la influencia de de la incertidumbre de la Política Económica Global (GEPU) en el crecimiento económico en otros países dentro de la misma región. Lo anterior da luz sobre los efectos de las noticias económicas de los periódicos relevantes sobre el crecimiento del PIB. La hipótesis principal sugiere una influencia significativa de otros países dentro de la misma región y de las dos principales potencias económicas mundiales en el crecimiento del Producto Interno Bruto (PIB) de cada región estudiada, a saber, Estados Unidos y China. Esta investigación también examina esta hipótesis en 19 economías incluidas en GEPU, categorizándolas regionalmente por continente. Los resultados econométricos confirman la influencia de las dos economías líderes en el crecimiento económico e identifican relaciones causales, y el GEPU también muestra efectos sobre el PIB. Además, las estimaciones dentro de la muestra revelan disparidades en la influencia de los líderes en el crecimiento económico de las economías examinadas.

Clasificación JEL: C3, C4, C5, F6, O4.

Palabras clave: GEPU, crecimiento económico regional, VAR, Causalidad de Granger.

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1. Introduction

Regional economic integration and globalization processes have long been recognized as drivers of economic growth. Various trade agreements among countries within specific regions typically contribute to economic development and foster cultural, educational, financial, scientific, and social integration. A prime example of this phenomenon is the Euro Zone where monetary, commercial, migratory, and educational aspects have been standardized and extended to neighboring countries not formally part of the European Union. Moreover, other trade agreements worldwide, such as the United States-Mexico-Canada Agreement (USMCA), the trade agreement within the Association of Southeast Asian Nations (ASEAN-FTA), and the Southern Common Market (MERCOSUR), have similarly bolstered economic cooperation and integration. Even in the absence of specific agreements between two countries, shared borders and geographical proximity facilitate the diffusion of economic effects and sentiments across borders. These sentiments can be gauged through various indicators and often manifest in the real economy and its key variables due to the influence of media and increased access to social media, digital newspapers, and real-time news streaming on mobile devices. One such measure used to capture uncertainty is the Economic Policy Uncertainty (EPU), which monitors newspaper articles covering topics such as the economy, legislation, monetary policy, money markets, and central bank actions, among others, as well as the opinion of experts. The Global Economic Policy Uncertainty Index (GEPU) aggregates the weighted average of these indicators from 21 countries, reflecting each country's contribution to the index based on the proportion of newspaper articles covering relevant topics.[2] This globalized index serves as a tool to capture uncertainty worldwide and its potential impact on Gross Domestic Product (GDP) growth.

The influence of news on key economic variables has been previously examined through models incorporating mixed-frequency data, first introduced by Ghysels et al. (2004). This approach enables the aggregation of higher frequency data and its reduction to a lower frequency for regression model estimation. Such models are particularly appropriate since commonly used economic variables, as GDP, are typically measured quarterly, while other variables with predictive utility may be observed at higher frequencies. This research makes a dual contribution: firstly, it demonstrates the significant influence of certain countries within the same region on the GDP growth of each studied region; secondly, it evaluates the impact of economic news from newspapers on GDP, as represented by GEPU. We employ a Vector Autoregressive (VAR) model with Mixed Data Sampling (MIDAS), resulting in a VAR-MIDAS framework. This methodology is advantageous as it allows for the incorporation of information sampled at a higher frequency into a dependent variable, a capability lacking in traditional VAR models. Additionally, we conduct Granger Causality analysis to assess causal effects among regional economies and GEPU. Understanding causality is vital for comprehending the channels through which uncertainty is transmitted, as emphasized by Baker et al. (2014). This methodology is well-suited for evaluating uncertainty's impact, given that the dependent variable (GDP) and the independent variable (GEPU) are sampled at different frequencies—quarterly and monthly, respectively. By including leading economies, we can ascertain

[2] The Global Economic Policy Uncertainty Index (GEPU) is a GDP-weighted average of national Economic Policy Uncertainty (EPU) indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.

causal relationships between economies and gauge the level of interconnectedness and their influence on economic growth. This study contributes to understanding how uncertainty affects economic agents' decision-making in uncertain circumstances, potentially delaying or halting investment intentions. Recognizing these effects can guide policymakers and governments in adjusting fiscal and monetary policies to counteract high levels of uncertainty and stabilize the economy. Furthermore, exploring the interconnectedness of economies and the dominant role of major economies sheds light on how economic and commercial globalization shapes GDP evolution.

This study shares similarities with that of Li et al. (2020), whom examined the U.S. EPU and its impact on the stock markets of China and India. However, our research extends this investigation by considering the GDP of a more extensive range of countries and analyzing the influence of both the U.S. and China on these countries, grouped by geographical regions. While Li et al. (2020) also employed Granger causality analysis, they utilized discrete wavelet transform. In contrast, our study focuses on the influence of leading economies on other economic groups, with China exhibiting a more pronounced influence than the U.S. on American and European countries, alongside the observed impact of GEPU. Moreover, we identify causal relationships between GEPU and GDP, and generally find that incorporating the influence of leading economies into our models enhances the fit.

The organization of our contribution is as follows: Section 2 presents a comprehensive literature review, Section 3 describes the data used for the study, including their frequencies and sources, Section 4 outlines the methodology employed in our investigation, Section 5 presents the most significant findings and observations, and Section 6 finally concludes.

2. A Short literature review

2.1 Uncertainty and GEPU

Economic uncertainty is quantified through the frequency of newspaper coverage, encompassing uncertainties surrounding policy decision-makers, anticipated economic policies, and their timing (Baker et al., 2016). This captures the ambiguity surrounding government policies and regulatory frameworks in the short term (Al-Taqueb and Algharabali, 2019). The GDP-weighted average index, incorporating the Economic Policy Uncertainty (EPU) of each country, is termed the Global Economic Policy Uncertainty (GEPU) index, developed by Davis (2016). This index encompasses significant non-economic events impacting the economy, such as 9/11, the Iraq invasion, the European Immigration crisis, and Brexit (Dai et al., 2021). Recent research has identified breakpoints in the relationship between the Geopolitical Risk Index (GPR) and GEPU due to events like the Russia-Ukraine conflict (Shen and Hong, 2023). The EPU for each country reflects the relative frequencies of newspaper articles mentioning economic, policy, and uncertainty topics, while the GEPU is a normalized version of each country's EPU, weighted by GDP to compute the index, encompassing each country's GDP. This index covers 20 countries, identical to those considered in weighing GDP to construct the index.

Uncertainty exerts notable effects on various aspects including consumer spending, financial markets, corporate behavior, and risk management (Al-Taqueb and Algharabali, 2019). In Latin

American countries, uncertainty has been observed to impact stock markets and macroeconomic variables (Coronado et al., 2020; Coronado et al., 2022). Additionally, in Latin American emerging markets, interest rates and inflation show positive responses to uncertainty in the long run (Aytaç and Saraç, 2022). The effects of uncertainty extend to a wide array of variables including bitcoin, grain prices, agricultural commodities, crude oil, energy assets, as well as travel and leisure companies (Khan et al., 2021; Long et al., 2023; Hamidu et al., 2022; Lyu et al., 2021; Chen et al., 2021; Ersan et al., 2018). Trade policies have been identified as a source of uncertainty affecting stock market stability (Davis, 2019). The uncertainty of leading regional countries has been examined by Keddad (2024), while Caporale et al. (2022) demonstrate cointegrated relationships between ASEAN (Association of Southeast Asian Nations) countries and the U.S. and China. Causal effects stemming from GEPU have been investigated by Wu et al. (2015) within the context of OECD countries. Pirgaip and Dinçergök (2020) explored policy uncertainty, energy consumption, and carbon emissions in G7 countries. Wu et al. (2019) identified a causal relationship between uncertainty and International Tourism Receipts (ITR), while Olanipekun et al. (2019) linked uncertainty to the exchange market in BRIC countries, considering Brazil, Russia, India, and China.

2.2. GEPU and economic growth

Damstra and Bourkes (2021) studied the impact of economic news on public perceptions of the economy in the Dutch context. They distinguished between positive and negative changes in coverage as well as people's judgments. Hollanders and Vliegenthart (2011) also examined the economic coverage of Dutch media, highlighting the relationship between negative news and decreasing consumer confidence, particularly after the onset of the credit crisis. Danisman et al. (2020) conducted a panel data analysis considering Economic Policy Uncertainty (EPU), a variable similar to GEPU, and found a negative impact of EPU on credit growth for private and listed banks in the United Kingdom, Germany, Spain, Italy, and France. Chen et al. (2019) used a VAR model and Granger causality test with GEPU and oil prices to analyze China's economic growth, finding that GEPU harms it, while oil prices, combined with GEPU, Granger cause economic growth in the industrial sector. Lunde and Torkar (2020) performed an analysis for China, concluding that the predictive power of news sentiment improves GDP forecasts. Wu et al. (2021) also identified a causal relationship between GEPU and tourism in Brazil, India, Indonesia, South Africa, and Turkey, noting that it changes over time. Hong et al. (2022) revealed a strong relationship between GDP and categorical economic policy uncertainty in the USA through a mixed frequency and Granger causality approach.

Ma et al. (2020) stated that GEPU contains predictive information about the gold futures markets, revealing that higher levels of GEPU lead to higher volatility. Adam et al. (2022) investigated the impact of uncertainty and volatility in ten Islamic countries and the predictive content of GEPU for forecasting and nowcasting GDP in emerging markets such as Brazil, Indonesia, Mexico, South Africa, and Turkey. They noted that including GEPU in benchmark and dynamic factor econometric models leads to superior GDP growth predictions and highlighted its capacity to reflect spillover effects in emerging markets. Luk et al. (2018) established that economic policy uncertainty shocks affect real economic activities in small open economies such as Hong Kong, remarking on the deteriorating financial conditions due to international spillovers of uncertainty from major economies. Özyeşil (2022) explored a combination of the Baltic Dry Index (BDI), Volatility Index (VIX), and GEPU for the USA, UK, Germany, Italy, France, and Canada, stating that these indexes have a statistically significant effect on stock markets. He also remarked that these indexes are useful tools for efficient timing in stock markets by monitoring BDI, VIX, and GEPU. Asafo-Adjei et al. (2021) examined the BRICS (Brazil, Russia, India, China, and South Africa) economies, noting a bidirectional and positive causality between the financial sector and economic growth in the presence of GEPU. They identified that South Africa's financial markets and GDP are particularly vulnerable to GEPU. Xu (2020) also identified GEPU as a transmission channel that increases firms' cost of capital.

Nowzohour and Stracca (2020) highlighted the potential of sentiment as a driver for business cycles and concluded that there is a global factor for international spillovers of sentiment. This reasoning justifies using GEPU, the global index for EPU, as a common variable affecting economies. Effects of US economic policy uncertainty shocks on India's economy were assessed by Nyawo and van Wyk (2018), who found that the contribution to Indian macroeconomic variables from US economic policy uncertainty is even larger than that from domestic Indian shocks. A similar conclusion was reached by Stockhammar and Österholm (2016) in their study on the effects of US policy uncertainty on Swedish GDP growth, using a Bayesian VAR model, which concluded that there is a negative effect from US policy uncertainty on the Swedish economy. Yalçinkaya and Daştan (2020) went further by combining GEPU with geopolitical uncertainties for the Turkish economy in a VAR analysis, finding negative effects on macroeconomic indicators such as inflation, interest rates, unemployment, exchange rates, account balances, and economic growth in both the short and long run. Other studies involving GEPU as a determinant variable include Korus and Celebi (2019), who found a relationship between Brexit and the depreciation of the British pound against the euro and the US dollar. The media's impact on the British hotel industry was assessed by Tajvidi and Karami (2021), who found a positive relationship between marketing and firm performance.

The present research document contributes to the understanding of the role of global economic uncertainty and their impact on the economic growth of several countries by accounting for the effects of economic news (e.g. newspapers) as a transmitter of relevant information, which influences expectations about economic growth. Through rigorous analysis and comprehensive data evaluation, our research not only corroborates existing findings but also seeks to identify new relationships and effects, thereby contributing to a more nuanced and detailed comprehension of economic policy uncertainty's role in shaping global economic dynamics.

3. Nature of data

The countries selected for this study are those with available Global Economic Policy Uncertainty (GEPU) information: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, South Korea, Spain, Sweden, the United Kingdom, and the United States. Colombia and Russia were excluded due to insufficient sample lengths comparable to the other countries. Consequently, the study focuses on 20 nations with both monthly GEPU and quarterly GDP data available for the same periods.[3] The studied period spans from January 1997 to January 2021, providing a total of 289 monthly GEPU observations and 97 quarterly GDP observations for each country. **Table 1** lists the studied countries and their abbreviations, while **Table 2** details the sources and frequencies of data for all countries. The GDP data, obtained without seasonal components, represents the percentage difference from the previous period and was tested to ensure the absence of unit root in each time series before inclusion in VAR models. The countries were grouped by continent: America, Europe, and Asia. Australia was included in the Asian group due to its geographical proximity, despite being the only country from Oceania.

Table 1. Countries and abbreviations.

Country	Abbreviation	Country	Abbrevaition
Australia	AEl	Ireland	IRL
Belgium	BEL	Italy	ITA
Brazil	BRA	Japan	JAP
Canada	CAN	Mexico	MEX
Chile	CHL	Netherlands	NLD
China	CHN	South Korea	KOR
France	FRA	Spain	SPN
Germany	GER	Sweden	SWE
Greece	GRE	United Kingdom	UK
India	IND	United States	US

Table 2. Sources, frequencies and sample.

Variable	Source	Frequency	Source
GDP	https://fred.stlouisfed.org/	Quarterly	1997Q1-2021Q1
GEPU	http://www.policyuncertainty.com/	Monthly	1997M1-2021M1

Source: Own elaboration

4. Methodology

A MIDAS (Mixed Data Sampling) model approach addresses the challenge of working with different data frequencies by specifying conditional expectations using distributed lags of regressors recorded at higher frequencies (Ghysels et al., 2004). This is a valuable tool for including variables sampled at different frequencies and can be combined with factor and VAR models. It is particularly useful for nowcasting and forecasting low-frequency variables, such as GDP, by leveraging valuable information from higher-frequency variables (Marcellino and Schumacher, 2010). The simplest linear regression model also accommodates multivariate and non-linear relationships (Ghysels et al., 2004), $\left(L^{1/m}\right)$ represents a polynomial with j^{max} as its length in the $L^{1/m}$ operator, which produces a value of x_t lagged by j/m periods, Y_t is a time series sampled at a fixed frequency, $\mathrm{X}^{(m)}$ is another time

[3] These countries were selected firstly considering that they are part of the GEPU Index and secondly, by its relevant GDP size compared with other similar countries. Source: Own elaboration

series sampled m times faster than Y_t, β_0 stands for the slope in the model, while ε_t represents the random component. The original VAR model has been considered a benchmark for capturing comovements in macroeconomic time series. Since this data is often sampled at different frequencies, combining both VAR and MIDAS models addresses this issue while maintaining understandable dynamics, resulting in more powerful models. The VAR-MIDAS model also incorporates techniques to study hidden periodic structures in time series and capture their seasonal components. For these reasons, a VAR-MIDAS model is an interesting approach for estimating GDP, a quarterly sampled variable, by using GEPU, a monthly sampled variable, as a regressor. Applications of the MIDAS models include studies on the relationships among monetary supply, interest and exchange rates, income, and the relationship between economic growth and energy (Xu and Liao, 2022).

$$Y_t = \beta_0 + \beta_1 B\left(L^{1/m}\right) X_{t-1}^{(m)} + \varepsilon_t^{(m)} \tag{1}$$

The main idea behind any MIDAS approach is to handle the different frequencies present in macroeconomic and financial data, which tend to be available in quarterly, monthly, or even daily frequencies. This involves the disaggregation of a quarterly variable, such as GDP, into a monthly variable. This concept follows the methodology of Mariano and Murasawa (2003, 2010) and Kuzin et al. (2011), as shown in (4.2), where $t_m = 3, 6,9, \ldots T_m^y$, because of the quarterly observation of GDP, which means that it is observed only each third month. Even when GDP is observable only each third month, there is a latent $y_{t_m}^*$ process that generates the observation together with its corresponding monthly observation x_{t_m}. The result is a VAR(*p)* process (Kuzin, 2011). In this model, GDP has a quarterly frequency, while GEPU is monthly, hence the U-MIDAS (unrestricted MIDAS) was performed because of the small difference in sampling frequencies (Ghysels et al 2020), which allows projecting quarterly onto monthly. It is considered a k-dimension process with $K_L < K$ elements belonging to the vector process $x_L(\tau_L)$, is observable only every m fixed periods, and represents the low frequency variables, while the process $x_H(\tau_L, k_H)$ has a higher frequency with k_H= 1,…,m being the high frequency periods observed during the period τ_L (Ghysels, 2016). The vector process represents the mixed frequency stacked skip-sampled processes, which are present at the end of the highest frequency series. The final representation of a finite order VAR considers a stacked vector as in **(3)** according to (Ghysels, 2016) which also represents a $K_L + m * K_H$ dimensional VAR with P lags. The U-MIDAS approach also allows for simplifying the data via a classical VAR and using least squares to estimate the slope.

$$y_{t_m} = \frac{1}{3}\, y_{t_m}^* + \frac{2}{3} y_{t_m-1}^* + y_{t_m-2}^* + \frac{2}{3} y_{t_m-3}^* + \frac{1}{3} y_{t_m-4}^* \tag{2}$$

$$\begin{bmatrix} x_H(\tau_L, 1) \\ . \\ . \\ . \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = \mathrm{A}_0 + \sum_{j=1}^{P} A_j \begin{bmatrix} x_H(\tau_L - j, 1) \\ . \\ . \\ . \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \underline{\varepsilon}(\tau_L) \tag{3}$$

A VAR-MIDAS model was developed for each continent, including only the countries within that continent. If the US or China does not belong to that continent, they were included as additional variables to account for their influence on economic growth, first separately and then jointly. This approach follows Keddad (2024) in assessing the influence of the US and China as leading countries. For example, Europe has four VAR-MIDAS models: one includes only the European countries, another includes China, a third includes the US, and the fourth includes both China and the US. For America and Asia, which include at least one of the leading countries, an extra model including the missing leader was created. This paper presents a total of eight VAR-MIDAS models to compare whether an external actor influences the economic growth of a continental region. The GDP for each country is presented in percentage differences without seasonal components, while the GEPU is presented as a raw series. The VAR-MIDAS model is estimated using EViews 12, which is also used to forecast GDP for countries in the model and to determine causal relationships. Including the GDP of leading economies allows us to quantify their influence on others, while including GEPU as an explanatory variable captures the comovements of news impacts on economic growth, representing common sentiments and general economic performance. Although other methodologies can capture the effects of uncertainty on economic growth and assess the influence of leading countries, they require transforming or weighting the data to ensure the samples have the same frequency. The methodology used in this document allows for the use of data without needing transformation or preprocessing, while still capturing the influence of leading countries and the impact of uncertainty on the economic growth of others.

5. Results

This section presents general and relevant results for all VAR-MIDAS models developed. The initial models include only countries from the same region, while subsequent models incorporate the influence of leading countries (the US and China) as exogenous variables. The most relevant results from the Granger causality tests are presented at the end of the corresponding section for each continent. The numbers following GEPU in the results tables indicate the number of lags included in each model. These tables display the statistics representing the accuracy of the model. Complete results, including coefficients, are available upon request.

5.1. Results for America

The first VAR-MIDAS model did not show a high *R*-squared for any of the involved countries. The highest *R*-squared is present for Brazil with 0.39, and 0.38 for Mexico, but for the rest of the countries, the *R*-squared is not higher than 0.33. The model was estimated with 2 lags **(Table 3)**. The second VAR-MIDAS was estimated with 2 lags and included China's GDP as an extra endogenous variable. The *R*-squared improved significantly with the influence of China with Mexico reaching a 0.75 and with the lowest value being 0.49 **(Table 4)**. Regarding the estimations for the American countries, the model that includes China replicates better the behavior of the series and we present Mexico as an example. It can be seen that the second model **(Figure 2)** follows better the ups and downs of economic downturns than the first model **(Figure 1)**. The influence of China in the American region improved the estimations and its presence is indicative of an important relationship and economic integration with the region. Regarding the causality test in both models, GEPU has a causal influence only on Brazil, but jointly with the rest of the countries, influences the GDP of the region. Some causal relationships that appeared in the first model are those from the US to Brazil, from Brazil, Chile, and Mexico to Canada, with the latter being bidirectional. Chile also influences Mexico and the US, while Canada has a causal relationship with the US. The second model showed causal relationships from Mexico, the US, and China to Brazil, from China to Canada, and the US, while Mexico causes Chile's GDP. China also has bidirectional relationships with Chile and Mexico.

The economics of causal GDP relationships between different countries involves understanding how economic activity in one country influences or is influenced by economic activity in another. This interconnectedness can be analyzed through various lenses, including trade, investment flows, financial linkages, policy decisions, and global economic conditions. Here are some key aspects:

A. Trade Linkages:
   i. Exports and Imports: Countries that are major trading partners can significantly impact each other's GDP. For instance, if Country Mexico exports a substantial amount of goods to Country the US, an economic downturn in Country in the US could reduce its demand for imports, thereby negatively affecting Country Mexico's GDP.
   ii. Supply Chains: Global supply chains mean that production processes are spread across countries. Disruptions in one part of the chain can impact GDP in all connected economies.
B. Investment Flows:
   i. Foreign Direct Investment (FDI): Investments by one country into business interests in another can drive economic growth. Positive economic developments in the investing country can increase FDI, boosting the recipient country's GDP.
   ii. Portfolio Investment: Financial markets are interconnected, and investment flows can transmit economic conditions across borders. Economic instability in one country can lead to capital flight, impacting the GDP of both the originating and receiving countries.
C. Financial Linkages:
   i. Banking and Credit: International banking connections mean that financial crises can have a ripple effect. The 2008 financial crisis, for instance, began in the US but quickly affected economies worldwide through interconnected financial systems.
   ii. Debt: Sovereign debt held by foreign entities means that a country's economic policies and health can impact its creditors' economies.
D. Policy Decisions:
   i. Monetary Policy: Central banks' decisions in major economies can affect global capital flows and exchange rates, impacting other countries' GDP. For example, US Federal Reserve policy changes often influence global interest rates and investment flows in many countries.
   ii. Fiscal Policy: Government spending and taxation policies can also have spillover effects, especially in closely linked economies.

E. Global Economic Conditions:
    i. Commodity Prices: Countries dependent on exporting commodities (like oil or minerals) are influenced by global price changes, which in turn affect their GDP. Global economic conditions that affect these prices can thus have widespread effects.
    ii. Economic Cycles: Business cycles can be synchronized to varying degrees across countries. A recession in a major economy can lead to reduced demand for exports from its trading partners, influencing their GDP.

F. Exchange Rates:
    i. Currency Valuation: Fluctuations in exchange rates can affect trade balances and, subsequently, GDP. A strong currency can make a country's exports more expensive and imports cheaper, affecting domestic economic growth.

G. Spillover Effects:
    i. Contagion: Economic crises can spread from one country to another through various channels, such as trade, financial markets, and investor sentiment. The Asian financial crisis of the late 1990s is an example where economic problems in one region affected multiple countries.

H. Global Integration:
    i. Multinational Corporations: These entities operate in multiple countries, and their performance can be influenced by economic conditions in any of these countries, affecting GDP in both the home and host countries.
    ii. International Organizations: Institutions like the IMF and World Bank provide financial assistance and policy advice that can influence economic conditions and GDP in recipient countries.

Understanding these relationships could require sophisticated econometric tools and models, such as the ones applied in the present research document. Again, these are VAR (Vector Autoregression), VAR-MIDAS, and Granger causality tests, to identify and quantify the directions and magnitudes of these influences. By analyzing how GDP in one country responds to changes in another, it is recommended that economists do understand the global economic environment and to closely follow inform policy decisions. About these recommendations we make a suggestion to do it for future research.

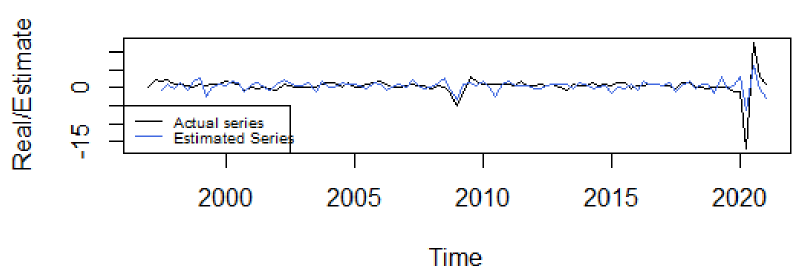

Figure 1. Estimation for Mexico (fisrt model)
Source: own elaboration using R computer language

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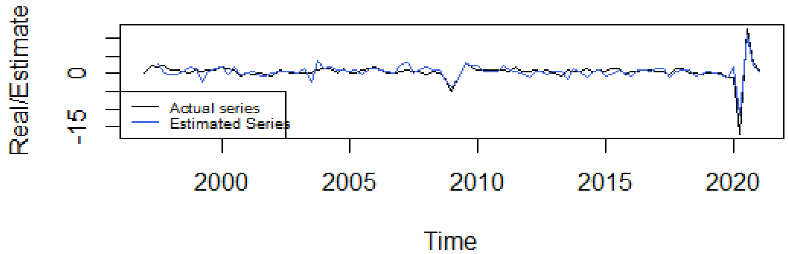

Figure 2. Estimation for Mexico (second model)
Source: own elaboration using R computer language

Table 3. First model for America.

	GEPU	BRA	CAN	CHL	MEX	US
R-squared	0.7701	0.3865	0.3316	0.2320	0.3845	0.2968
Adj. R Squared	0.7364	0.2967	0.2338	0.1196	0.2944	0.1939
Sum of sq. Resids.	93917.11	133.3694	295.9402	272.107	333.3548	122.3311
S.E. equation	33.8427	1.2753	1.8997	1.8216	2.0162	1.2214
R-statatistic	22.8934	4.3056	3.3908	2.0648	4.2691	2.8848
Log Likelihood	-462.373	-150.9133	-188.7725	-184.7843	-194.4274	-146.8097
Akaike AIC	10.0078	3.4508	4.2478	4.1638	4.3668	3.3644
Schwarz SC	10.3573	3.8002	4.5973	4.5133	4.7163	3.7138
Mean dependent	128.4609	0.4122	1.0715	0.8589	0.4978	0.5442
S.D. dependent	65.9273	1.5207	2.1703	1.9415	2.4003	1.3604

Source: own elaboration with estimations from EViews 12

Table 4. Second model for America, including China.

	GEPU	BRA	CAN	CHL	MEX	US	CHN
R-squared	0.7705	0.4921	0.6810	0.5943	0.7467	0.6027	0.4291
Adj. R Squared	0.7303	0.4032	0.6252	0.5233	0.7024	0.5332	0.3292
Sum of sq. Resids.	93761.56	110.4114	141.2275	143.735	137.1421	69.1077	186.0483
S.E. equation	34.2347	1.1747	1.3286	1.3404	1.3093	0.9294	1.5249
R-statatistic	19.1855	5.5373	12.2018	8.3723	16.8533	8.6712	4.2958
Log Likelihood	-462.2942	-141.9402	-153.6327	-154.4687	-152.2383	-119.684	-166.7253
Akaike AIC	10.0483	3.3040	3.5501	3.5677	3.5208	2.8354	3.8257
Schwarz SC	10.4515	3.7072	3.9534	3.9710	3.92405	3.2387	4.22904
Mean dependent	128.4609	0.4122	1.0715	0.8589	0.4978	0.5442	3.5512
S.D. dependent	65.9273	1.5207	2.1703	1.9415	2.4003	1.3604	1.8620

Source: own elaboration using estimations using EViews 12

5.2. Results for Europe

For the model including only European countries, the appropriate number of lags was one (considering information criterion). The countries with the highest *R*-squared values are France (0.97), Italy (0.96), and Belgium (0.95). The lowest *R*-squared values are for Spain (0.24) and Ireland (0.31), while the rest of the countries had values of at least 0.72. (Tables 5a and 5b). Regarding the estimations produced by the first model, it is notably accurate for France (Figure 3) and Italy (Figure 4), while the model including China did not represent a difference (Figure 5 and Figure 6).

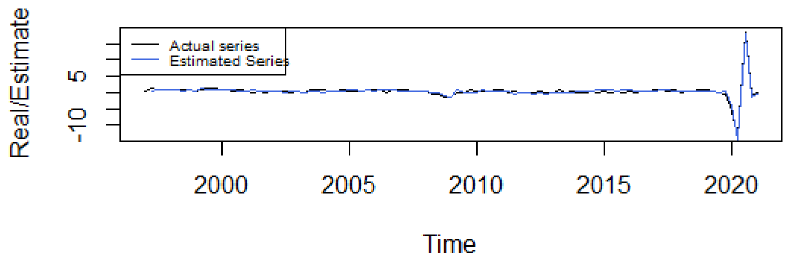

Figure 3. Estimation for France (first model)
Source: own elaboration using EViews 12

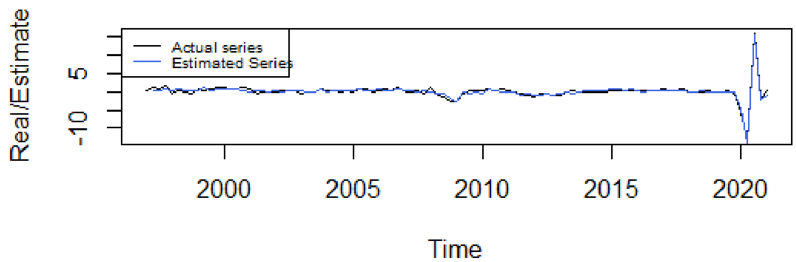

Figure 4. Estimation for Italy (first model)
Source: own elaboration using R computer language

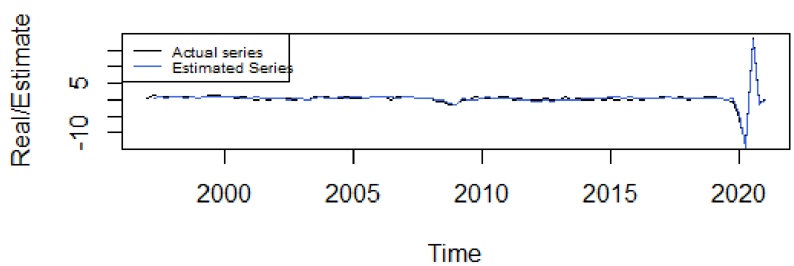

Figure 5. Estimation for France (second model)
Source: own elaboration using R computer language

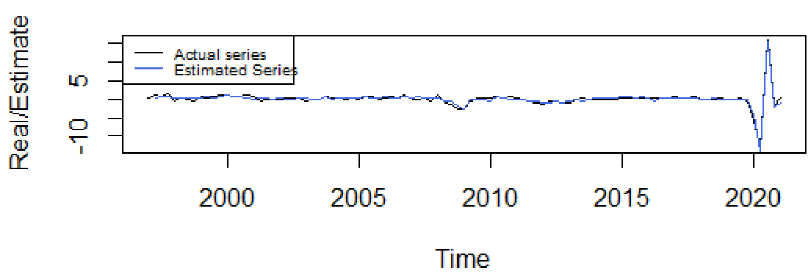

Figure 6. Estimation for Italy (second model)
Source: own elaboration using R computer language

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Table 5a. First model for Europe.

	GEPU	GEPU_2	GEPU_3	BEL	CRO	FRA	GER
R-squared	0.9190	0.8306	0.7808	0.9565	0.7689	0.9727	0.8581
Adj. R Squared	0.9049	0.8010	0.7424	0.9489	0.7285	0.9679	0.8333
Sum of sq. Resids.	31491.01	75370.75	95506.2	13.9213	100.7393	15.8396	35.7589
S.E. equation	19.8403	30.6942	34.5518	0.4171	1.1221	0.4449	0.6685
R-statatistic	64.9173	28.0327	20.3548	125.7056	19.022	203.8931	34.5636
Log Likelihood	-410.4692	-451.9233	-463.17	-43.5775	-137.5855	-49.7096	-88.3880
Akaike AIC	8.9572	9.8299	10.0667	1.2332	3.2123	1.3623	2.1765
Schwarz SC	9.3604	10.2332	10.4699	1.6364	3.6155	1.7655	2.5798
Mean dependent	126.3273	123.4576	131.7148	0.4031	0.4010	0.3713	0.32
S.D. dependent	64.3499	68.8136	68.0822	1.8455	2.1538	2.4861	1.6374

Source: own elaboration using estimations from EViews 12

Table 5b. First model for Europe (cont).

	GRE	IRL	ITA	NLD	SPN	SWE	UK
R-squared	0.7459	0.3456	0.9608	0.8813	0.2409	0.7755	0.8852
Adj. R Squared	0.7015	0.2311	0.9540	0.8605	0.1081	0.7362	0.8651
Sum of sq. Resids.	105.596	756.9698	19.8707	25.0960	521.0883	41.6164	48.4385
S.E. equation	1.1488	3.0760	0.4983	0.5600	2.5521	0.7212	0.7781
R-statatistic	16.7806	3.0188	140.3726	42.4375	1.8139	19.7470	44.0626
Log Likelihood	-139.822	-233.3829	-60.4792	-71.5686	-215.6462	-95.5935	-102.804
Akaike AIC	3.2594	5.2291	1.5890	1.8224	4.8557	2.3282	2.4800
Schwarz SC	3.6626	5.6323	1.9922	2.2257	5.2589	2.7315	2.8833
Mean dependent	0.0410	1.3515	0.0852	0.8915	0.4221	0.5863	0.9189
S.D. dependent	2.1029	3.5081	2.3247	1.4999	2.7024	1.4045	2.1186

Source: Own elaboration using estimations from EViews 12

The model including China did not show significant improvement but Spain and Ireland enhance their R-squared with 0.289 and 0.356 respectively (Tables 6a and 6b). The rest of the countries showed just marginal improvement. The third model for Europe (Tables 7a and 7b), which included European countries and the US showed significant improvement for Ireland but for the rest of the countries, there are similar results with the R-squared worsening notably for Italy with just 0.32.

Table 6a. Second model for Europe including China.

	GEPU_1	GEPU_2	GEPU_3	BEL	CRO	FRA	GER	GRE
R-squared	0.9191	0.8306	0.7812	0.9583	0.7836	0.9740	0.8659	0.7469
Adj. R Squared	0.9037	0.7985	0.7397	0.9503	0.7425	0.9691	0.8404	0.6989
Sum of sq. Resids.	31470.81	75366.12	95303.22	13.3496	94.3375	15.0603	33.7914	105.1803
S.E. equation	19.9590	30.8869	34.7328	0.4110	1.0927	0.4366	0.6540	1.1538
R-statatistic	59.8739	25.8387	18.8115	121.0454	19.0793	197.9185	34.0176	15.5480
Log Likelihood	-410.4388	-451.9204	-463.0689	-41.5858	-134.4668	-47.3131	-85.6999	-139.6346
Akaike AIC	8.9776	9.8509	10.0856	1.2123	3.1677	1.3329	2.1410	3.2765

Schwarz SC	9.4077	10.2810	10.5157	1.6424	3.5978	1.7630	2.5711	3.7066
Mean dependent	126.3273	123.4576	131.7148	0.4031	0.4010	0.3713	0.32	0.0410
S.D. dependent	64.3499	68.8136	68.0822	1.8455	2.1538	2.4861	1.6374	2.1029

Source: Own elaboration using estimations from EViews 12

Table 6b. Second model for Europe including China (cont).

	IRL	ITA	NLD	SPN	SWE	UK	CHN
R-squared	0.3846	0.9615	0.8864	0.2900	0.7756	0.8938	0.1856
Adj. R Squared	0.2678	0.9542	0.8648	0.1552	0.7330	0.8737	0.0310
Sum of sq. Resids.	711.8377	19.5428	24.0178	487.372	41.5956	44.7726	267.1465
S.E. equation	3.0017	0.4973	0.5513	2.4838	0.7256	0.7528	1.8389
R-statatistic	3.2927	131.6358	41.1055	2.1518	18.2120	44.3673	1.2006
Log Likelihood	-230.4629	-59.6889	-69.4828	-212.4688	-95.5697	-99.0658	-183.9104
Akaike AIC	5.1886	1.5934	1.7996	4.8098	2.3488	2.4224	4.2086
Schwarz SC	5.6188	2.0235	2.2297	5.2399	2.7789	2.8525	4.6387
Mean dependent	1.3515	0.0852	0.8915	0.4221	0.5863	0.9189	3.5719
S.D. dependent	3.5081	2.3247	1.4999	2.7024	1.4045	2.1186	1.8681

Source: Own elaboration using estimations from EViews 12

Table 7a. Third model for Europe including the US.

	GEPU_1	GEPU_2	GEPU_3	BEL	CRO	FRA	GER	GRE
R-squared	0.9193	0.8306	0.7826	0.9565	0.7693	0.972	0.8601	0.7460
Adj. R Squared	0.9040	0.7985	0.7413	0.9482	0.7255	0.9676	0.8335	0.6978
Sum of sq.	31402.4	75369.51	94717.52	13.9187	100.5724	15.8001	35.2563	105.5731
S.E. equation	19.9373	30.8876	34.6259	0.4197	1.1283	0.4472	0.6680	1.1560
R-statatistic	60.0158	25.8373	18.9604	115.8814	17.5700	188.4054	32.3853	15.4706
Log Likelihood	-410.3354	-451.9225	-462.7761	-43.5685	-137.5067	-49.59077	-87.7156	-139.8117
Akaike AIC	8.9754	9.851	10.0795	1.2540	3.2317	1.3808	2.1834	3.2802
Schwarz SC	9.4056	10.2811	10.5096	1.6842	3.6618	1.8109	2.6136	3.7103
Mean	126.3273	123.4576	131.7148	0.4031	0.4010	0.3713	0.32	0.0410
S.D. dependent	64.3499	68.8136	68.0822	1.8455	2.1538	2.4861	1.6374	2.1029

Source: Own elaboration using estimations from EViews 12

Table 7b. Third model for Europe including the US (cont.).

	ITA	IRL	NLD	SPN	SWE	UK	US
R-squared	0.9609	0.3545	0.8882	0.2410	0.7915	0.8875	0.8855
Adj. R Squared	0.9534	0.2319	0.8670	0.0968	0.7520	0.8662	0.8637
Sum of sq. Resids.	19.8548	746.7235	23.6224	521.0543	38.6477	47.4277	19.9486
S.E. equation	0.5013	3.0744	0.5468	2.5681	0.6994	0.7748	0.5025
R-statatistic	129.4843	2.8928	41.8816	1.6723	20.0028	41.5887	40.7364
Log Likelihood	-60.4413	-232.7355	-68.6944	-215.6431	-92.0782	-101.8024	-60.6650
Akaike AIC	1.6092	5.2365	1.7830	4.8766	2.2753	2.4800	1.6140
Schwarz SC	2.0394	5.6666	2.2131	5.3068	2.7054	2.9101	2.0441
Mean dependent	0.0852	1.3515	0.8915	0.4221	0.5863	0.9189	0.5455

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S.D. dependent	2.3247	3.5081	1.4999	2.7024	1.4045	2.1186	1.3615

Source: Own elaboration using estimations from EViews 12

The last model for Europe, which included both China and the US did not show better results in general (Tables 8a and 8b). The model including the US showed an acceptable fit to estimate Ireland (Figure 7) except for times with extreme perturbations, and reflecting the *R*-squared improvement described prior, but the same did not hold for the model including China and the US (Figure 8). Estimations for the rest of the countries look like the first model.

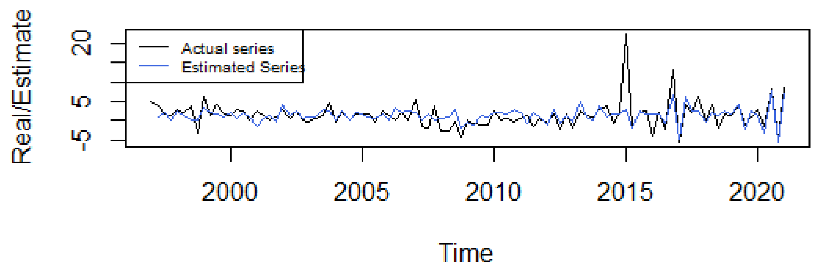

Figure 7. Estimation for Ireland (third model)
Source: own elaboration using R computer language.

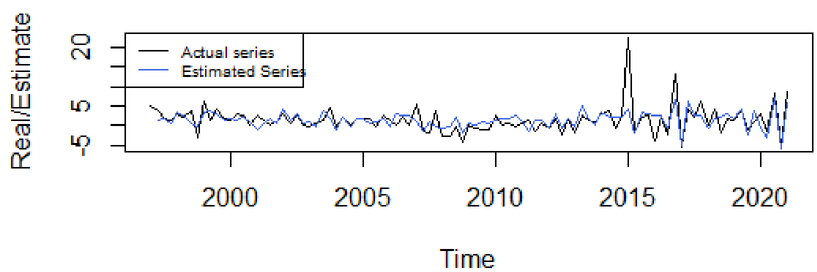

Figure 8. Estimation for Ireland (fourth model)
Source: own elaboration using R computer language.

Table 8a. Fourth model for Europe including China and the US.

	GEPU_1	GEPU_	GEPU_3	BEL	CRO	FRA	GER	GRE	IRL
R-squared	0.9193	0.8306	0.7833	0.9583	0.7836	0.9742	0.8692	0.7471	0.3892
Adj. R Squared	0.9028	0.7959	0.7389	0.9498	0.7393	0.9689	0.8424	0.6952	0.2639
Sum of sq. Resids.	31392.02	75365.4	94382.39	13.3249	94.3340	14.9552	32.9602	105.1214	706.5754
S.E. equation	20.0614	31.0841	34.7854	0.4133	1.0997	0.4378	0.6500	1.1609	3.0097
R-statatistic	55.5726	23.9174	17.6300	112.2606	17.6612	184.5212	32.4048	14.4026	3.1068
Log Likelihood	-410.3197	-451.92	-462.6077	-41.4977	-134.465	-46.9805	-84.5168	-139.608	-230.1104
Akaike AIC	8.9962	9.8719	10.097	1.2315	3.1887	1.3469	2.1371	3.2970	5.2023
Schwarz SC	9.4532	10.3290	10.5540	1.6885	3.6457	1.8039	2.5942	3.7540	5.6593
Mean dependent	126.3273	123.457	131.7148	0.4031	0.4010	0.3713	0.32	0.0410	1.3515
S.D. dependent	64.3499	68.8136	68.0822	1.8455	2.1538	2.4861	1.6374	2.1029	3.5081

Source: Own elaboration using estimation from EViews 12

Table 8b. Fourth model for Europe including China and the US (cont.).

	ITA	NLD	SPN	SWE	UK	CHN	US
R-squared	0.9615	0.8953	0.2915	0.7923	0.8977	0.1938	0.8856
Adj. R Squared	0.9536	0.8738	0.1461	0.7497	0.8768	0.0284	0.8622
Sum of sq. Resids.	19.5406	22.1391	486.378	38.4984	43.1279	264.4727	19.9207
S.E. equation	0.5005	0.5327	2.4971	0.7025	0.7435	1.8413	0.5053
R-statatistic	121.8609	41.6910	2.0058	18.6060	42.8200	1.1718	37.7665
Log Likelihood	-59.6835	-65.6139	-212.3719	-91.8943	-97.2881	-183.4326	-60.5987
Akaike AIC	1.6143	1.7392	4.8288	2.2925	2.4060	4.2196	1.6336
Schwarz SC	2.0714	2.1962	5.2858	2.7495	2.8630	4.6766	2.0906
Mean dependent	0.0852	0.8915	0.4221	0.5863	0.9189	3.5719	0.5455
S.D. dependent	2.3247	1.4999	2.7024	1.4045	2.1186	1.8681	1.3615

Source: Own elaboration using estimations from EViews 12

Regarding causal relationships in Europe, the first model showed a causal relationship from Spain to all countries in the model, but this relationship is bidirectional with Belgium. Spain is a special case in this model because it influences all other countries, but only Belgium influences it. All countries and GEPU jointly influence each country's GDP, except for Spain's. Bidirectional relationships are present between Germany and Belgium, France and Croatia, and Germany and the UK.

Results for the model that includes China showed a causal relationship from China to Croatia, France, Germany, Ireland, the Netherlands, Spain, and the UK. Again, Spain influences all countries' GDP, including China, in a bidirectional relationship. The difference with the first model is that in the second model, all countries and GEPU jointly influence Spain's GDP. Other bidirectional relationships are present between Spain and Belgium, Germany and Greece, the UK and France, the Netherlands and France, and Spain and the Netherlands.

The third model for Europe, which included the US, showed the same causal relationship from Spain to all countries, but Spain is no longer influenced by the rest of the countries and GEPU, except for the bidirectional relationship with Belgium, which remains. The US Granger-causes only the Netherlands and Sweden, while bidirectional relationships are present between Germany and France, and the Netherlands and Greece.

For the fourth model, which included both the US and China, findings indicate bidirectional relationships between Croatia and France, Germany and France, Germany and Greece, and China and Spain. The US and China influence only the Netherlands and the UK simultaneously, while Spain again influences all countries in the model but is influenced only by China. The joint influence of all countries and GEPU on a specific country's GDP is present for all economies except Spain.

Some insights about the casual and bidirectional relationships between uncertainty and economic growth can be, among others, exchange rate volatility. That is, uncertainty can lead to volatility in exchange rates, affecting competitiveness, trade balances, and ultimately GDP (Benavides, 2021). Countries with volatile exchange rates may experience economic instability, impacting their growth. Also, stock market fluctuations. Considering that uncertainty can lead to increased volatility in stock markets, affecting wealth and consumption patterns. Declines in stock markets can reduce household wealth and consumer spending, thus impacting GDP in several economies (Benavides, 2023).

5.3. Results for Asia

For the first VAR-MIDAS model only which only included Asian **countries (Table 9),** the country with the highest *R*-squared is India with 0.821 followed by Japan, with 0.68. The lowest *R*-squared value is China with 0.37. Regarding the forecast using this model, it was capable to capture the effects of the COVID-19 pandemic and generally for the rest of the sample. We present India **(Figure 9)** and Japan **(Figure 10)** as examples. This model was estimated with 5 lags. With the second model including influence from the US, the *R*-squared improved for all countries (Table 10) and also was estimated with 5 lags. The forecasts using the second model for Asia also showed better results, especially for China **(Figure 11)**.

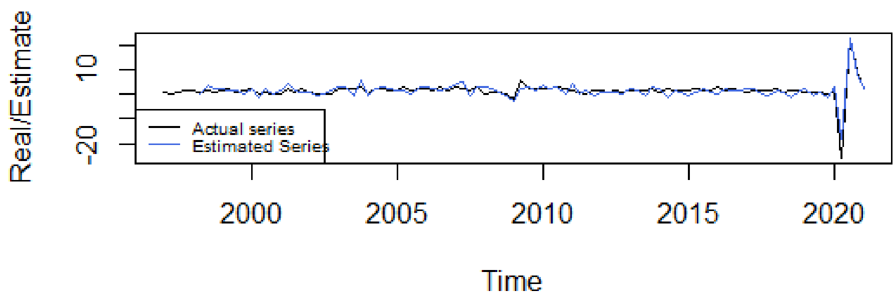

Figure 9. Estimation for India (first model)
Source: own elaboration using R computer language.

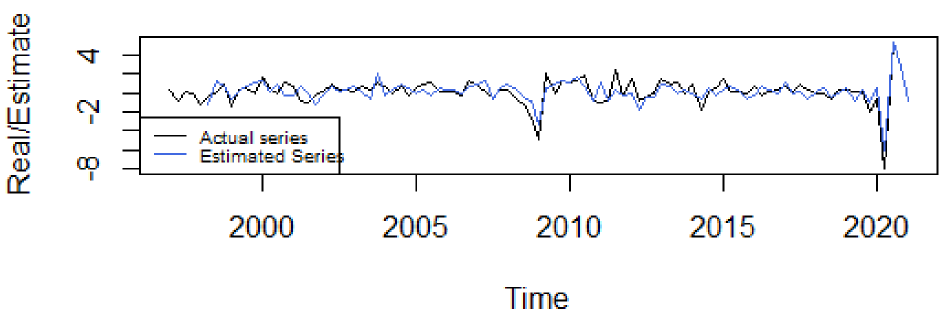

Figure 10. Estimation for Japan (first model)
Source: own elaboration using R computer language.

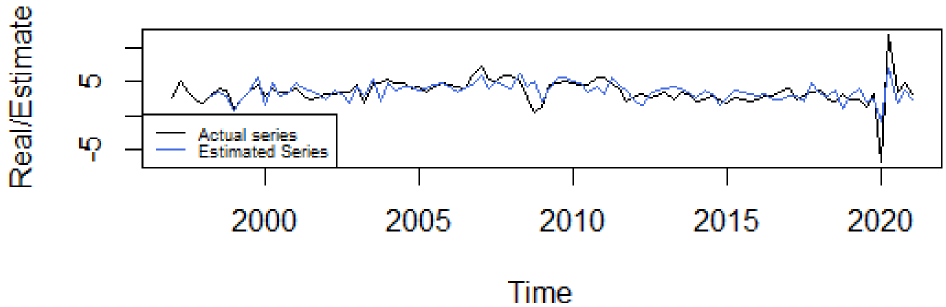

Figure 11. Estimation for China (second model)
Source: Own elaboration using R computer language.

Table 9. First model for Asia

	GEPU_1	AUS	CHN	IND	JAP	KOR
R-squared	0.8010	0.6098	0.3744	0.8211	0.6776	0.5647
Adj. R Squared	0.7031	0.4180	0.0668	0.7332	0.5191	0.3506
Sum of sq. Resids.	79794.5	36.3189	201.098	243.4471	59.8752	48.2117
S.E. equation	36.1677	0.7716	1.8156	1.9977	0.9907	0.8890
R-statatistic	8.1862	3.1787	1.2173	9.3378	4.2746	2.6379
Log Likelihood	-441.7517	-87.7877	-166.5145	-175.3054	-110.7841	-100.8178
Akaike AIC	10.2772	2.5823	4.2937	4.4849	3.0822	2.8656
Schwarz SC	11.1269	3.4320	5.1435	5.3346	3.9319	3.7153
Mean dependent	130.0034	0.7088	3.5818	1.6989	0.15	1.0315
S.D. dependent	66.3861	1.0114	1.8796	3.8679	1.4287	1.1032

Source: Own elaboration using estimations from EViews 12

Table 10. Second model for Asia Including the US

	GEPU_1	AUS	CHN	IND	JAP	KOR	US
R-squared	0.8088	0.6338	0.4601	0.8343	0.7127	0.5963	0.7036
Adj. R Squared	0.6893	0.4049	0.1226	0.7308	0.5331	0.3440	0.5183
Sum of sq. Resids.	76667.04	34.0908	173.5768	225.519	53.3645	44.7086	51.3163
S.E. equation	37.0007	0.7802	1.7605	2.0067	0.9761	0.8935	0.9572
R-statatistic	6.7696	2.7693	1.3635	8.0591	3.9692	2.3637	3.7986
Log Likelihood	-439.9125	-84.8753	-159.7446	-171.7867	-105.4888	-97.3477	-103.6885
Akaike AIC	10.3459	2.6277	4.2553	4.5171	3.0758	2.8988	3.0367
Schwarz SC	11.3327	3.6145	5.2421	5.5038	4.0626	3.8856	4.0234
Mean dependent	130.0034	0.7088	3.5818	1.6989	0.15	1.0315	0.5281
S.D. dependent	66.3861	1.0114	1.8796	3.8679	1.4287	1.1032	1.3793

Source: Own elaboration using estimations from EViews 12

Regarding the causal effects appreciated in the first model, China showed influence over all countries in the model, while GEPU influences South Korea. As in the models for America, there is a joint causal effect from the set of variables to the GDP, but it does not hold for China, with the same results for the second model including the US. The second model showed a causal effect from China to all countries individually, and from Japan to South Korea. These results confirm China is a strong economic leader in its region and also confirm this influence does not change in the presence of external factors. Possible reasons for these causal relationships could be, for example, credit conditions. Uncertainty can tighten credit conditions, making it harder for businesses and consumers to borrow and spend, leading to slower economic growth. Also, Global Economic Integration i.e. in a highly globalized world, economies are interconnected through various channels. A shock in one part of the world can quickly transmit to other parts, affecting GDP through trade, investment, and financial linkages.

6. Conclusions

This article aims to assess the influence of uncertainty on GDP growth and the relationships between countries within the same region and global leaders. The methodology employed allows for the inclusion of variables with different frequencies in a VAR model, capturing their effects on GDP. By constructing models that incorporate leading economies, it becomes possible to evaluate these countries' influence on the GDP growth of others and consider the transmission of uncertainty. An advantage of this methodology is its ability to use data directly without requiring transformation or preprocessing to align frequencies.

Additionally, it facilitates the assessment of the influence of entire country groups, as well as that of leading countries and uncertainty. The results revealed expected relationships driven by geographical proximity and trade agreements. Unexpectedly, Spain was found to influence all other European countries and China. While the inclusion of leading economies improved R-squared values and estimation accuracy, it did not uncover a significant number of causal relationships.

Regarding the influence of GEPU, it directly affects only a few countries, but its broader influence contributes to GDP causation across all analyzed country groups. Interestingly, China exhibited a stronger causal influence on European countries' GDP than the US, a trend similarly observed in American economies, where China's influence extended to more countries than that of the US.

These findings underscore the importance of globalization in reducing distances, fostering competition, and promoting economic growth. However, globalization also intensifies the spread of uncertainty and its adverse effects across borders and beyond geographical regions. Future research could expand to include additional countries, analyze comprehensive sets of countries within the same region, or focus on countries within specific trade agreements or economic zones.

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