Modeling the Determinants of Global Economic Uncertainty

Olha Kovalchuk[1], Kateryna Berezka[2], Oksana Tulai[3], Bohdan Ferens[4], Ludmila Babala[5] and Oleksandr Zapolskyi[3]

[1]*Theory of Law and Constitutionalism Department, West Ukrainian National University, Lvivska Str. 11, 46009 Ternopil, Ukraine*

[2]*Department of Applied Mathematics, West Ukrainian National University, Lvivska Str. 11, 46009 Ternopil, Ukraine*

[3]*Department of International Relations and Diplomacy, West Ukrainian National University, Lvivska Str. 11, 46009 Ternopil, Ukraine*

[4]*Committee on Integration of Ukraine into EU, Verkhovna Rada of Ukraine, Hrushevskogo Str. 5, 01008 Kyiv, Ukraine*

[5]*Department of Economic Cybernetics and Informatics, West Ukrainian National University, Lvivska Str. 11, 46009 Ternopil, Ukraine*

o.kovalchuk@wunu.edu.ua, k.berezka@wunu.edu.ua, o.tulai@wunu.edu.ua, ferens@rada.gov.ua, ludaduma7@gmail.com, zapolskyolexandr@gmail.com

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Abstract: Economic uncertainty poses a significant challenge for decision-makers across the public and private sectors. While uncertainty is an inherently nebulous concept, developing consistent quantitative measures allows for rigorous analysis of its impacts. The World Uncertainty Index (WUI) provides a standardized quarterly index of uncertainty levels for 143 countries dating back to 1952 based on language in Economist Intelligence Unit reports. This study applies correspondence analysis to examine the relationship between countries' WUI values and their levels of economic development classified by the IMF's income groups. The results reveal distinct associations - advanced, high-income economies exhibit relatively low uncertainty while emerging markets and developing economies face higher uncertainty levels. Low-income countries experience moderate uncertainty. These findings underscore how economic instability can impede development progress. By quantifying uncertainty through empirical measures and analyzing its linkages with other economic factors, researchers can derive valuable insights for policymakers aiming to cultivate confidence and stability.

1 INTRODUCTION

Several major events in recent years, such as the global financial and ecological crisis, the growth of cybercrime, increasing political polarization and trade tensions, the COVID-19 pandemic, and the war in Ukraine have heightened concerns about rising levels of economic uncertainty worldwide [1–3]. However, quantifying uncertainty in a consistent way that allows for comparisons across different periods and countries poses an intrinsic challenge. Uncertainty is an inherently nebulous concept, reflecting the state of uncertain minds among consumers, business leaders, and policymakers about future potential events and outcomes. It is also a broad concept, relating to macro-economic phenomena like GDP growth rates as well as micro-level aspects like the growth trajectories of individual firms. Moreover, uncertainty extends beyond just economic factors to encompass other major events and issues such as elections, wars, and climate change. Despite its nebulous and wide-ranging nature, developing robust measurements of uncertainty is crucial for research and analysis.

WUI is a panel index that measures uncertainty levels across 143 countries every quarter, going back to 1952. It provides uncertainty data for a wide range of developed and developing nations over an extensive period. The WUI is calculated by counting how frequently the word “uncertainty” and its variants (like “uncertain”) appear in the country reports published by the Economist Intelligence Unit. To enable cross-country comparability, these raw uncertainty word counts are scaled by the total word count of each report. In other words, the WUI reflects the number of “uncertainty” words expressed per thousand words in each report [4].

Having a standardized panel index of uncertainty covering many countries over multiple decades represents a major new resource. It allows researchers to analyze uncertainty trends over time and compare uncertainty levels between different nations and regions in a consistent quantitative manner [5–7].

The series of major disruptive events that have rocked the global economy in recent years, sometimes stemming from political rifts between nations, have ushered in a new era of heightened turbulence and volatility. These turbulent episodes have caused uncertainty levels to skyrocket to exceptionally high levels worldwide, according to the research. Elevated uncertainty, in turn, has acted as a drag on economic growth.

As depicted in the Chart of the World Uncertainty Index (Fig. 1), while the index fell slightly in December 2023, it has remained at elevated levels in recent times due to the compounding effects of successive shocks. Among the most recent shocks were Russia’s invasion of Ukraine and the associated cost-of-living crisis rippling across the world [4].

The WUI illustrates the rise in war-related uncertainty spanning the globe. While uncertainty initially peaked in European nations versus other regions, this geographic gap has narrowed over time, underscoring the war's widening economic spillover effects.

Despite the December 2023 dip, the index continues to reflect the new normal of higher uncertainty that has taken hold amid the tumultuous global conditions over the past few years. The turbulence from repeated economic, political, and geopolitical shocks has kept worldwide uncertainty readings much higher than historical levels.

Analyzing and quantifying uncertainty becomes particularly valuable in the context of the multitude of major shocks that have impacted the global economy over the past several years. Measuring uncertainty through indices like the World Uncertainty Index allows researchers to disentangle and examine the various potential sources and drivers contributing to heightened uncertainty levels during this tumultuous period.

With the global economy being repeatedly buffeted by disruptive events ranging from the financial crisis to trade conflicts, political upheaval, the pandemic, and geopolitical tensions, uncertainty analysis provides a lens to assess the relative impacts of each of these shocks. By dissecting how uncertainty levels responded to specific shocks, we can better understand which events or sources of turbulence were most destabilizing and detrimental to economic certainty worldwide.

Analyzing uncertainty through empirical measures is crucial for policymakers, businesses, and economists to comprehend the prevailing global economic climate. During periods of concurrent, compounding crises, uncertainty monitoring offers insights into disentangling the complex mix of factors fueling business and consumer uncertainty that weighs on economic growth and decision-making.

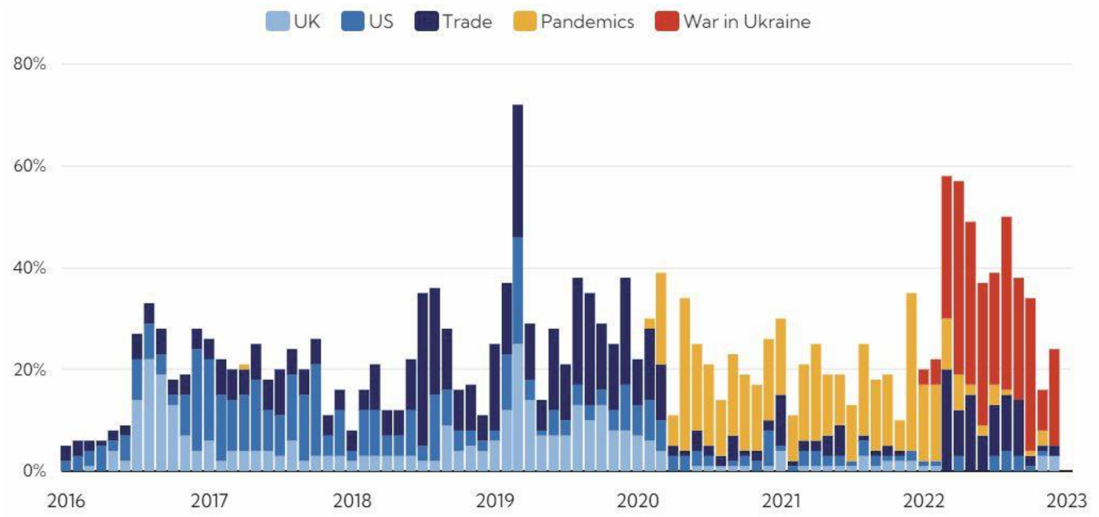

Figure 1: 3D plot of row and column coordinates [6].

2 RELATED WORKS

Recently, scholars and practitioners have been paying close attention to the study of serious challenges that create political and economic uncertainty on a global scale. The authors E. Bouri et al. analyzed the role of monetary policy uncertainty in predicting jumps in nine advanced equity markets [8]. Researchers H. Chen et al. studied the impact of economic policy uncertainty on capital investment by Australian firms [9]. H. Almustafa et al. examined the effect of economic policy uncertainty on firm-level investment and corporate financial leverage [10]. I. Khandokar and A. Serletis investigated the dynamic empirical relationship between modern risk/uncertainty indicators and leverage [11]. M. S. Kaviani et al. studied the relation between changes in policy uncertainty and changes in credit spreads. They found that macroeconomic conditions, including general uncertainty, do not explain this result, which also holds when they use instrumental variables to address endogeneity issues [12]. H. Ahir et al. introduced the WUI, which utilizes Economist Intelligence Unit reports [13]. However, reports on developed economies demonstrate a more detailed and technical presentation style with an emphasis on monetary policy and financial markets, while reports on developing countries often focus more on political risks and institutional changes [6]. The reports also vary in their depth of regional coverage: larger economies and key regional players receive comprehensive analysis with quarterly updates, while reports for smaller economies may be less detailed and updated less frequently [14]. S. R. Baker et al. developed the Economic Policy Uncertainty Index (EPU), which is based on the analysis of newspaper articles in developed countries [15]. While both the EPU and WUI measure uncertainty, the WUI demonstrates broader global coverage by capturing major international events like the 9/11 attacks, the SARS outbreak, and Brexit, whereas the EPU tends to focus more on domestic policy uncertainty. The WUI shows that uncertainty levels are generally lower in advanced economies compared to developing countries, with uncertainty spikes being more synchronized among advanced economies and those with stronger trade and financial connections. Despite the existence of several publications on this topic [16], further scientific research on economic uncertainty is needed due to the emergence of new risks and challenges that continue to shape the global economic landscape.

3 METHODOLOGY

Uncertainty is an important factor in making many decisions [17]. It negatively impacts economic development, while stability and confidence in the future foster growth. In this work, an attempt is made to identify non-obvious relationships between the level of uncertainty and the economic development of countries around the world.

The WUI quantifies the level of uncertainty mentioned in the Economist Intelligence Unit's country reports. It is calculated by finding the percentage of times the word "uncertain" (or its variants like "uncertainty") appears in the reports. This percentage is then scaled up by a factor of 1,000,000 to obtain the WUI value. A higher WUI number signals greater uncertainty expressed in the reports, while a lower value indicates less uncertainty being mentioned. For example, a WUI of 200 means the word "uncertain" accounted for 0.02% of all words used in the reports. Given that these reports average around 10,000 words, a WUI of 200 roughly corresponds to the word "uncertain" appearing twice per report on average. Therefore, the WUI provides a quantitative measure of the degree of uncertainty discussed and projected in these country reports from the Economist Intelligence Unit [18].

The WUI is computed as follows:

$$Q_1 = \frac{0.6 \cdot Q_4 + 0.3 \cdot Q_3 + 0.1 \cdot Q_2}{3},$$

where Q_1, Q_2, Q_3, Q_4 are the quarters of the World Uncertainty Index for 143 countries from the 1950s onwards. The 3-quarter weighted moving average of the index serves as the preferred measure when analyzing data at the country level [18].

The IMF classifies countries into three broad groups primarily based on their income levels and stages of economic development:

- Advanced Economies. These are high-income countries with well-developed economies and advanced economic structures. Examples include the United States, Japan, Germany, the United Kingdom, France, etc.
- Emerging Market and Developing Economies: This group includes both emerging market economies and other developing economies. Emerging markets tend to have rapid economic growth and increasing economic liberalization, like Ukraine, China, India, Brazil, etc. Other developing economies have lower incomes and are at earlier stages of development.
- Low-Income Developing Countries. These are the poorest countries in the world with low gross

national income per capita. Many are faced with severe economic, political, and social challenges. Examples include Afghanistan, Haiti, Yemen, South Sudan, etc.

To identify non-obvious interdependencies between WUI levels and the economic development of countries around the world, correspondence analysis was used [19]. It is an exploratory technique used to visualize and analyze the associations within high-dimensional contingency tables. Its computational objective is to represent the distances between rows and columns in a lower-dimensional space while preserving the relationships as accurately as possible.

The method utilizes the Pearson chi-squared statistic to evaluate how well a lower-dimensional representation captures the structure of the original high-dimensional table. Essentially, correspondence analysis performs factor analysis on categorical data, acting as a dimensionality reduction technique.

The rows and columns of the initial table are mapped to points in space, with the chi-squared distance calculated between them. The goal is to find a low-dimensional (typically 2D) space that minimizes the distortion of these distances, thereby reproducing the structure of the original table faithfully.

Correspondence analysis operates on frequency tables, consisting of rows representing one set of categorical variables and columns representing another set. The following terminology is associated with this technique:

- Mass. The observations in the table are normalized by calculating relative frequencies. The sum of all elements in the table becomes equal to 1 (each element is divided by the total number of observations). This resulting standardized table shows how the mass is distributed across the cells or points in space. The row and column sums in the matrix of relative frequencies are referred to as the row mass and column mass, respectively.
- Quality: In correspondence analysis, quality refers to how well a row or column point is represented in the coordinate system defined by the selected number of dimensions. The quality of a point is defined as the ratio of the squared distance from the point to the origin in the chosen dimensionality, divided by the maximum squared distance in the full-dimensional space. A low quality indicates that the selected dimensionality inadequately represents the corresponding row or column.
- Relative Inertia. Inertia is defined as Pearson's chi-squared statistic for a 2x2 table, divided by the total number of observations. Relative inertia represents the dimensionality's contribution. A partial solution may represent a point reasonably well (high quality), but that point may contribute little to the overall inertia.
- Row & Column Profiles. If the rows and columns of the table are completely independent, then the elements can be represented using the row and column sums or, in correspondence analysis terminology, using the row and column profiles.
- Relative Dim n. This column displays the relative contribution of the corresponding row or column point to the inertia accounted for by dimension n. This value is provided for each point (row or column) across all dimensions.
- Cosine^2 – Quality. This column contains the quality of representation for each point in the corresponding dimension. The cosine squared can be interpreted as the "correlation" between the point and that dimension. It is the square of the cosine of the angle formed by the point and the dimension's axis.
- Metric Coordinate System. In correspondence analysis, the term "distance" refers to the differences between the rows and columns of the relative frequency matrix, represented in a lower-dimensional space. The coordinates in this reduced space represent these distances. However, unlike standard Euclidean distances calculated directly from the frequencies, these distances are weighted.

Graphical analysis is the most crucial part of correspondence analysis. Typically, the horizontal axis represents the dimension accounting for maximum inertia. The plot shows the percentage of total inertia explained by each eigenvalue. The smaller the distance between points of the same type (rows or columns), the stronger their association.

To assess the relationship between points of different types, one must consider the angles they form with the vertex at the centroid (0,0) coordinates.

The general rules for visually assessing the degree of dependence are:

- Draw line segments from two points of different types to the centroid.
- If the angle formed is acute, the row and column are positively correlated.
- If the angle is obtuse, the correlation between the variables is inverse/negative.
- If the angle is straight (90 degrees), there is no correlation.

- The angles between row and column points relative to the centroid reveal the nature and strength of their associations in the low-dimensional representation.

4 RESULTS AND DISCUSSION

We applied correspondence analysis [19] to identify non-obvious relationships between IMF income (advanced economies, emerging economies, low-income economies) [20] and the WUI for 143 countries [18].

For 143 countries, the values of the World Uncertainty Index were determined in the range from 0 to 0.31. One-third of the countries (31) have a WUI value less than 0.025, one-third (31 countries) – have a WUI value in the range from 0.025 to 0.057, and one-third – a WUI value greater than 0.057 [14]. We ranked the WUI for the 143 analyzed countries into the following levels (Table 1) [8].

Frequency tables were constructed for the distribution of the analyzed countries into groups by levels of economic development (advanced economies, emerging economies, and low-income economies) and levels of WUI (low, medium, high) (Table 2).

Among the 143 analyzed countries, the following groups were identified:

- 12 countries with advanced economies and low WUI;
- 7 countries with advanced economies and medium WUI;
- 11 countries with advanced economies and high WUI;
- 19 countries with emerging economies and low WUI;
- 15 countries with emerging economies and medium WUI;
- 27 countries with emerging economies and high WUI;
- 12 countries with low-income economies and low WUI;
- 18 countries with low-income economies and medium WUI;
- 24 countries with low-income economies and high WUI.

Table 1: Grouping of countries worldwide based on their values.

Ranking	Range
low	<0.025
medium	between 0.025 and 0.057
high	> 0.057

Table 2: Frequency table for IMF income and WUI.

	Observed Table (Frequencies) Row variables: IMF_income (3) Column variables: WUI_Rank (3)			
Edvanced Economies	12	11	7	30
Emerging Economies	19	27	15	61
Low-Income Economies	10	24	18	52
Total	41	62	40	143

Correspondence analysis is fundamentally a component decomposition of the chi-squared (χ^2) statistic. Its primary objective is to identify the lowest dimensional space that can adequately represent the deviations from the expected values. Table 3 presents the calculated eigenvalues, which indicate the minimum number of dimensions required to qualitatively capture the information contained in the data tables for each pair of analyzed variables.

For a qualitative representation of the contingency table between the IMF income and WUI, two dimensions are sufficient. First dimension accounts for 56% of the total inertia, while the second accounts for the remaining 44%. Pearson's chi-squared (χ^2) statistic objectively assesses how close the empirical distributions are to the theoretical ones. The obtained level of 0.001 indicates statistical significance. With 9 degrees of freedom (df = 9), the calculated χ^2 value is 26139.8, which exceeds the critical value of 28.88 at the 0.001 level. Therefore, it can be stated that the predicted values closely match the observed ones.

Special statistics are employed to assess the quality of the solution obtained from correspondence analysis. Ideally, all or most of the points should be accurately represented – the distances between them should not be significantly distorted as a result of applying the dimensionality reduction procedure. Table 4-5 presents the calculation results of these statistics based on the row and column coordinates.

Table 3: Eigenvalues and inertia for all dimensions.

	Total Inertia = 1.00				
Number of Dims.	Singular Values	Eigen-Values	Pers. of Inertia	Cumulative Percent	χ^2
1	0.7487	0.5605	56.0521	56.0521	14784.78
2	0.6629	0.4395	43.9479	100.0000	11592.09

Table 4: Row coordinates and contributions to inertia.

Row Name	Row Coordinates and Contributions to Inertia Input Table (Rows × Columns): 3×3 Standardization: Row and column profiles									
	Row Num.	Coordin. Dim. 1	Coordin. Dim. 2	Mass	Quality	Relative Inertia	Inertia Dim. 1	Cosine^2 Dim. 1	Inertia Dim. 2	Cosine^2 Dim. 2
advanced economies	1	-0.2444	0.0550	0.2098	1	0.3919	0.3916	0.9518	0.3986	0.0481
emerging economies	2	-0.0671	-0.0438	0.4266	1	0.0815	0.0560	0.7016	0.5134	0.2984
low-income economies	3	0.2197	0.0196	0.3636	1	0.5266	0.5484	0.992	0.0879	0.,0079

Table 5: Column coordinates and contributions to inertia.

Row Name	Column Coordinates and Contributions to Inertia Input Table (Rows × Columns): 3×3 Standardization: Row and column profiles									
	Column Number	Coordin . Dim. 1	Coordin. Dim. 2	Mass	Quality	Relative Inertia	Inertia Dim. 1	Cosine^2 Dim. 1	Inertia Dim. 2	Cosine^2 Dim. 2
advanced economies	1	-0.2741	0.01500	0.2867	1	0.6430	0.6729	0.9970	0.0404	0.0030
emerging economies	2	0.0697	-0.0429	0.4336	1	0.0864	0.0658	0.7256	0.5006	0.2744
low-income economies	3	0,17293 2	0.0511	0,2797	1	0.2707	0.2607	0.9197	0.4590	0,0803

For the two-dimensional solution obtained from correspondence analysis of the IMF income and the World Uncertainty Index, a high-quality value of 1 was achieved for all groups of convicts. This indicates that the selected two dimensions adequately represent all the rows and columns of the original data table.

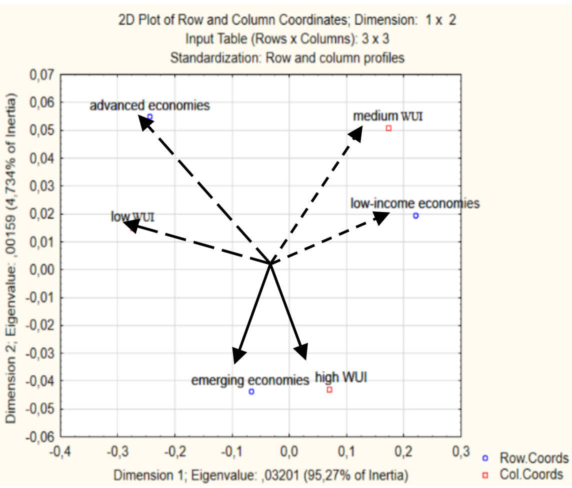

Figure 2: 3D plot of row and column coordinates.

A graphical analysis was conducted to examine the relationship between IMF income and the WUI used in this analysis. The analysis of 2-dimensional plots depicting the row and column coordinates for the corresponding pairs of variables provides the basis for the following conclusions (Fig. 2):

- most high-income countries have a low World Uncertainty Index;
- emerging market and developing economies are characterized by a high World Uncertainty Index;
- low-income developing countries have a medium World Uncertainty Index.

The analysis revealed distinct associations between countries' levels of economic development based on IMF income classifications and their degrees of economic uncertainty captured by the WUI. The results indicate that advanced, high-income economies tend to exhibit relatively low levels of uncertainty while emerging markets and developing economies are more prone to higher uncertainty. Low-income developing countries fall somewhere in between, with moderate uncertainty levels. These findings underscore how economic uncertainty can act as a headwind to development, with more economically advanced nations better positioned to cultivate stability and confidence. By quantifying uncertainty through empirical indices like the WUI and employing analytical techniques like correspondence analysis, we can gain deeper insights into the complex interplay between economic turbulence and a country's stage of development. Such analysis can help policymakers and economists better understand and address the factors fueling economic uncertainty across the global landscape.

5 CONCLUSIONS

This study applied correspondence analysis to investigate the relationship between countries' economic development levels, as classified by the IMF's income groups, and their degrees of economic uncertainty measured by the WUI. The results revealed clear associations, with advanced, high-income economies exhibiting relatively low uncertainty levels, emerging and developing economies facing higher uncertainty, and low-income countries experiencing moderate uncertainty. These findings underscore the importance of economic stability and confidence in fostering growth and development. Nations with more established, robust economies appear better able to mitigate uncertainty and its detrimental impacts. Conversely, emerging markets and less-developed countries grapple with greater volatility, which can hinder investment, spending, and overall economic progress.

Quantifying uncertainty through empirical measures like the WUI and rigorously analyzing its relationships with other economic indicators represents a valuable contribution. It provides empirical insights into the complex dynamics between uncertainty, instability, and a nation's economic standing on the global stage. Future research could focus on investigating the relationship between prolonged periods of high uncertainty and key economic indicators, as well as evaluating the effectiveness of various policy measures aimed at reducing economic instability and bolstering confidence during turbulent periods.

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