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Measuring Macroeconomic Uncertainty Using Internet Search Data: The Case of Poland

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Abstract

Motivation: Despite extensive discussion, measuring uncertainty – especially macroeconomic uncertainty – remains an open issue. While valuable, traditional data sources may be temporally or spatially limited and may not accurately capture public sentiment or the uncertainty perceived by diverse social groups such as households, especially considering the recent transition from traditional media to electronic.
Aim: A new Macroeconomic Uncertainty Index (MUI) for Poland, covering the period from 2004 to 2024 is presented and evaluated. This index utilizes the behavior of economic agents expressed through online search patterns, providing a real-time tool for assessing economic uncertainty.
Results: The MUI captures uncertainty perceived by diverse social groups, particularly considering the recent transition from traditional media to electronic channels of information flow. Comparative analysis revealed the unique characteristics of the MUI compared to other uncertainty indicators, such as survey-based and text-based measures, emphasizing the need

for multiple metrics to fully capture the multifaceted nature of macroeconomic uncertainty. The MUI provides an alternative to traditional measures, making it especially valuable for studies on public responses to macroeconomic changes.

Keywords: uncertainty, perception of uncertainty, Google Trends
JEL: E65, E71

1. Introduction

Uncertainty and its significance for macroeconomic processes have recently been among the most discussed topics (DeMartino et al., 2024). However, despite extensive discussion, measuring uncertainty – especially macroeconomic uncertainty – remains an open issue.

As is common in the social sciences, defining economic uncertainty to measure it requires addressing the challenges posed by the term's varied, ambiguous, and context-dependent interpretations. Uncertainty arises in various fields, including psychology, sociology, measurement, and forecasting. In economics, uncertainty is typically defined in the spirit of F. Knight's (1921) proposal: the inability to determine an event's probability or even the event's nature. The most discussed types of uncertainty are often interpreted as a lack of information. As Rowe (1994) states, '*Uncertainty is essentially the absence of information, information that may or may not be obtainable.*' However, it is important to note that this is not the only possible interpretation of the uncertainty. However, a similar view is standard in economics (DeMartino et al., 2024) and psychology (Alquist & Baumeister, 2023; Bar-Anan et al., 2009). From this perspective, uncertainty can be broadly described as a state of nature in which economic agents lack the information necessary to assess the current situation with sufficient confidence or to predict future outcomes. Economic agents – both businesses and consumers – find it difficult to estimate current and future economic conditions. Similarly, macroeconomic uncertainty is understood as uncertainty regarding agents' challenges in assessing the current or future states of macroeconomic processes, such as the behavior of macroeconomic variables and the relationships between them.

Initially, uncertainty was considered an unobservable variable. However, contemporary macroeconomics is heavily empirical, and thus, creating reliable tools for measuring uncertainty is a prerequisite for systematically incorporating uncertainty into macroeconomic research. Recently, numerous methods for indirect measuring uncertainty have been proposed (Cascaldi-Garcia et al., 2023). One prominent research approach involves utilizing text data, exemplified by the Economic Policy Uncertainty (EPU) index, which relies partially on text data from press articles (Baker et al., 2016). While valuable, traditional data sources may not accurately capture the uncertainty perceived by diverse social groups, especially considering the recent transition from traditional media to electronic channels of information flow. Consequently, alternative sources of information for economic research emerged, such as Google Trends (GT).

This article proposes a new macroeconomic uncertainty index (MUI) that uses data from GT (2024). While the use of GT to assess economic and political uncertainty is not new (Bontempi et al., 2021), our proposed index introduces some novel features. First, it focuses on macroeconomics, whereas previous measures have typically covered a broad range of economic and political issues. MUI is more suitable for interpretation and application in macroeconomic research. Second, we address methodological issues related to constructing the index and using GT data, as Cebrián and Domenech (2023) outlined. Third, we take a different approach than Bontempi et al. (2021), using GT topics (i.e., aggregated queries from a specific area grouped into broader thematic categories) and not keywords (i.e. individual search terms). More generally, our primary motivation is to propose an alternative approach to measure uncertainty because uncertainty measurement is a relatively new area of research, and it is still necessary to propose alternative concepts.

The article's main aim is to present the methodology for calculating the indicator and its evaluation, including verifying its characteristics in relation to other existing uncertainty measures. To test the characteristics of the new indicator, we use data for Poland. The data cover the period from January 2004 to September 2024, aggregated on a monthly basis. It constitutes an additional added value of the article since, in the case of Poland, no indicator based on text data has been calculated so far (to the best of the authors' knowledge), with the exception of the proposal by Hołda (2019).

The remainder of the article is structured as follows. We begin with a literature review on the principles of uncertainty measurement. We then address methodological issues related to using GT to measure uncertainty, present the methodology for constructing the MUI, and examine its characteristics.

2. Literature review

In the past several years, uncertainty has become one of the key issues in macroeconomics, prompting the development of various methodologies for calculating uncertainty indicators. Cascaldi-Garcia et al. (2023) summarize the current state of research and propose a classification of four types of measurement – news-, survey- econometric- and market-based uncertainty and risk measures. The authors analyze the advantages of individual indicators and show their different interpretative values. For example, they show that survey-based measures allow precision concerning the sector in which the uncertainty is located and the horizon over which the uncertainty prevails; these measures tend to be available at lower frequency and hence possibly be constantly relative to news-based or market-based measures.

An extensive review of all uncertainty measurement methods is beyond the scope of this article. Indicators using GT data can be interpreted as one of the approaches in constructing news-based measures, which is why we focus below on the discussion of literature concerning the approach to measuring uncertainty using text data and show the origins of the idea of using GT data to measure uncertainty.

Typically, these indicators are created by searching text databases, usually containing articles from daily newspapers, and focusing on the frequency of keywords related to uncertainty. In its simplest form, the searched text phrases often include the word uncertainty (in contexts related to the economy). This methodology was developed by Baker et al. (2016) when constructing the EPU index. This indicator is currently one of the most well-known approaches to measuring uncertainty and is calculated for several economies (Economic Uncertainty, 2024). Similar indicators use other text data sources. For example, the World Uncertainty Index (WUI), developed by the International Monetary Fund, uses Economist Intelligence Unit reports as its text data source (Ahir et al., 2022; IMF, 2024).

Uncertainty indicators that use data from GT are, to a large extent, an extension of the newspaper-based text data indicators. However, in this case, the data come not from newspaper articles but from queries entered into an internet search engine (usually Google, given its dominant market share). In other words, these indicators are based on the observed behavior of economic entities on the Internet, rather than on journalists' interpretations of economic uncertainty. This approach more accurately reflects contemporary channels of information dissemination among various social groups, including households, compared to traditional newspaper articles.

One of the key studies in the development of uncertainty indicators based on GT is the work of Castelnuovo and Tran (2017), who created an uncertainty indicator for the United States and Australia. Bontempi et al. (2021) proposed the Economic Uncertainty Related Queries (EURQ) index, which measures economic, political, and normative uncertainty, calculated for the USA and Italy.

In recent years, the use of GT data has expanded across various contexts. Eichenauer et al. (2022) developed a method for constructing consistent high-frequency time series using GT data, enabling the creation of real-time uncertainty indicators for German-speaking countries. Kupfer and Zorn (2020) constructed a Google economic policy uncertainty index for nine Eastern European countries, combining data related to the economy and politics. Bouri and Gupta (2021) compared the predictive power of uncertainty measures based on internet searches versus those derived from newspaper analysis in the context of Bitcoin returns. They found that the indicator based on internet queries had stronger predictive power than the newspaper-based measure. In a series of recent articles, GT data have been used to analyze uncertainty in financial markets (Szczygielski et al., 2023, 2024). Pratap and Priyaranjan (2023) propose a high-frequency indicator to measure economic policy uncertainty in the context of India. Additionally, GT data have been used to construct uncertainty or risk indicators outside the field of economics, such as the geopolitical risk (GPR) index (Caldara & Iacoviello, 2022; Iacoviello et al., 2024) and grassroots socio-political risk (Puhr & Müllner, 2024). Donadelli and Gerotto (2019) studied uncertainty related to health, environmental, security, and political issues.

3. GT as a Data Source

GT is a service provided by Google that offers insights into the popularity of specific search terms within its search engine. It allows researchers to analyze search trends and gain valuable information about internet users' behavior. Reports, which include time-series data, are available for any user-selected period from 2004 to the present day and can be further refined to focus on searches conducted in a specific language or from a particular location.

One of the main advantages of using GT data is that they reflect the spontaneous behavior of a wide range of agents. The information comes from a large group of internet users who freely express their interests and concerns while searching for information. This distinguishes GT data from other data sources used in uncertainty indicators, which are often based on more limited datasets, such as text data from press materials, surveys, or analysts' assessments. Another benefit is the high frequency of available data. GT provides the ability to analyze daily, weekly, and monthly data, which is particularly useful for studying dynamic phenomena, such as changes in uncertainty. Additionally, GT data are freely available, facilitating research replication and increasing transparency.

However, despite its many advantages, GT also has limitations. One notable limitation is the lack of transparency regarding data collection and processing methods. Google does not provide complete documentation on the methodology used to generate and aggregate results, which may hinder data interpretation and limit independent researchers' ability to fully verify the results. That said, it is important to note that this issue is common across many types of data used in economic research. For instance, microdata, which underpin most aggregated economic variables, often lack detailed methodological transparency or are difficult to access (this is also the case with most public statistics).

Another issue that arises with GT data is the potential for misinterpretation. Increased interest in specific search terms may be driven by factors unrelated to actual economic processes. For example, a spike in searches for the keyword 'inflation' could be caused by rising inflation or increased media coverage on the topic. While this could limit the applicability of GT data in certain studies, it does not pose a significant obstacle to constructing uncertainty indicators, particularly when the focus is on public perception rather than strictly rational economic behavior. Narratives, public discourse, and emotions related to macroeconomic phenomena contribute to uncertainty as much as actual economic processes do. From the perspective of economic agents, the source of uncertainty is less important than its existence.

It is also important to note that GT data are based on sampling. Cebrián & Domenech (2023), who conducted a systematic analysis of the main quality dimensions of GT data and generally rated them positively, pointed out that Google does not report statistical errors associated with the data. Eichenauer et al. (2022) showed that this lack of error reporting could lead to variability in results, especially when analyzing high-frequency data (e.g., daily series) over long periods. However, they proposed a method to address this issue.

Despite these limitations, GT data have found wide application in various fields, particularly in marketing research, sentiment analysis, and even macroeconomic studies. For example, the OECD's GDP Tracker uses GT data to estimate trends in the real economy based on searches related to economic activity (Woloszko, 2020). Additionally, GT data have been shown to be useful for forecasting macroeconomic processes, such as private consumption (Woo & Owen, 2019), unemployment (Mulero & Garcia-Hiernaux, 2023), financial markets (Huang et al., 2020; Petropoulos et al., 2022), inflation (Bleher & Dimpfl, 2022), and subjective quality of life (Murtin & Salomon-Ermel, 2024).

4. Methodology

Measuring uncertainty using data from online information searches relies on the assumption that economic agents, represented by internet users, seek online information when they are uncertain. This assumption implies that the frequency of searches for terms related to uncertain future events increases when the level of uncertainty is high. This assumption is commonly adopted in all proposed uncertainty indicators of this type (Bontempi et al., 2021; Castelnuovo & Tran, 2017; Dzielinski, 2012).

Surprisingly, this assumption, which is crucial for constructing such indicators, has not been discussed extensively. As mentioned earlier, the information gap, or lack of information, plays a central role in understanding uncertainty. Uncertainty arises when knowledge or information is lacking, either about future events or current situations. This absence of information leads to feelings of unpredictability and ambiguity, which, in turn, can influence decision-making, emotional responses, and behavioral strategies.

Numerous studies on responses to uncertainty have been conducted in psychology. Some studies suggest that information-seeking is a key strategy for coping with uncertainty (Alquist & Baumeister, 2023; Bar-Anan et al., 2009). People, aware of their lack of knowledge, often seek additional information – even if it may be unpleasant or useless – driven by a desire to reduce the discomfort associated with ignorance. While information-seeking is a dominant strategy, individuals can also exhibit other reactions, particularly under conditions of high uncertainty. For example, people may take more risks in uncertain situations. Not all responses to uncertainty are purely rational. In addition to information-seeking, individuals may rely on non-rational or in-between strategies, such as intuition, trust, hope, and faith (Schulz & Zinn, 2023; Zinn, 2016).

Thus, following the previous studies, we assume that when uncertainty arises economic entities (e.g., households, businesses) recognize their limited knowledge about current macroeconomic conditions and the potential outcomes of future events. In this sense, uncertainty can be understood as a state in which entities believe they cannot accurately define the key variables of their environment, such as estimating risks stemming from extraordinary events. In such situations, entities may show an increased interest in acquiring new information to restore a state in which they can accurately define key states of the world and thus make more informed predictions. This heightened search for information typically occurs for a limited period after a shock.

Of course, this understanding of uncertainty requires moving away from the rational choice assumptions that economic agents always have access to public, free information and can it easily process (such as households immediately adjusting their expectations according to an economic model with all available information). Instead, the information search is costly and time consuming. Information sought and found will include not only verified data but also narratives, interpretations, and opinions (Claus & Dedewanou, 2024; Dräger & Lamla, 2024; Johnson et al., 2023).

It is important to note that the methodology used to create uncertainty indicators does not distinguish between 'positive' and 'negative' events for two main reasons. First, both types of events–regardless of their definitions–can alter previous assessments of the state of the world, which may lead to incorrect evaluations of prior probabilities and, consequently, increase uncertainty. Second, determining what qualifies as a positive or negative event can be challenging, as it often depends on the observer's perspective and the criteria used for evaluation. For instance, when analyzing an inflation shock, it is crucial to differentiate between the notion that rising inflation complicates our understanding of the economic situation (which signals uncertainty) and whether inflation is viewed as a positive or negative phenomenon by any specific individual and in any specific economic condition.

Authors constructing indicators using GT data have approached the selection of keywords (i.e., search terms in the search engine) differently. Dzielinski (2012) and Donadelli and Gerotto (2019) analyze the search volume of a single keyword, while Szczygielski et al. (2024) use a few terms. On the other hand, Castelnuovo and Tran (2017) select a broad range of search terms. Bontempi et al. (2021) selected 184 policy-relevant search terms closely related to keywords in the U.S. Economic Policy Uncertainty Index developed by Baker, Bloom, and Davis (2016).

An obvious argument for using a large set of keywords is the more precise coverage of various economic areas and processes. However, this approach also has significant weaknesses. With a large set of keywords, the risk of correlation between terms increases (i.e., duplicating the same information). A large set of keywords naturally includes terms of lesser significance (e.g., *'tax rate – calculator'*) or terms referring to specific events (e.g., *'quantitative easing'*).

When constructing an index based on search data, one of the key issues is selecting keywords that are unrelated to specific events and have a general, rather than temporal or localized, nature. However, they must remain relevant within the local context (i.e., a specific country and language). In creating the initial list of keywords for the MUI, the principle of excluding terms related to single events (e.g., 'global financial crisis') was adopted. Universal terms referring to macroeconomic phenomena (e.g., gross domestic product, inflation, unemployment, etc.) were considered.

GT (2024) provides search data in two formats. Primarily, it distinguishes between search terms (i.e., actual queries) and topics (i.e., aggregated queries from a specific area grouped into broader thematic categories). Previously, using GT to construct an uncertainty indicator was mainly done with search terms (e.g. Castelnuovo & Tran, 2017; Bontempi et al., 2018; Donadelli & Gerotto, 2019). However, some newer studies have started using topics (Kupfer & Zorn, 2020; Puhr & Müllner, 2024).

We used topics to build the MUI. This approach offers several advantages over the search terms used in most previous uncertainty indicators. Because topics aggregate various search terms from a specific area, it is possible to bypass the problem of users entering similar but not identical search terms, issues related to Polish grammar (such as inflectional endings), and potential spelling errors or typos. An additional benefit is that topics also include terms entered in other languages (but from within Poland). This allows the MUI to include searches from Poland that were made in English (e.g., to access content unavailable in Polish or content considered more reliable).

The list of thematic areas and keywords was created in several steps. The starting point was the database of terms proposed in Baker et al. (2016) and Bontempi et al. (2021). This database was adjusted (shorted) because the point of interest is macroeconomic uncertainty. Next, this list was tailored for Polish specifics. In the following step, the list was discussed with a group of macroeconomic experts to minimize potential bias arising from reliance on existing uncertainty indicator literature. This process resulted in the initial list of keywords. It should be emphasized that the index is very robust to adding or removing individual topics, as demonstrated in the section on the sensitivity study.

The raw set of keywords was then validated against the topics as defined in GT, and the relative popularity of these topics. In this step, a significant aggregation of terms was performed, considering the characteristics of the content of topics offered by GT. For example, for terms related to the situation on financial markets (e.g., stocks, stock indices), taking into account Polish specifics (e.g., WIG – the Polish stock exchange index), the aggregated topic with the highest number of searches was 'stock index.' Viewing this topic solely through the lens of the query (keyword) 'stock index' would be inadequate, because it would omit other key potential queries in this area. However, within GT, the aggregate encompassing various related queries is named 'stock index.'

It is essential to note that the list of topics used in constructing the MUI (Table 1) is not a list of individual keywords or search queries. Instead, it should be viewed as a collection of thematic aggregates that encompass many different queries within a specific area (i.e., a large number of keywords), as defined by GT. The names of topics and their associated keywords result from Google's algorithms. For example, the topic 'social security' should not be viewed as referring to users entering the query 'social security' into the search engine, but rather as a general category encompassing numerous terms related to various types of social benefits and other forms of social assistance.

The raw data for individual topics showed strong seasonality. For most topics, the number of queries decreased during the summer months, with the lowest point occurring in August. To address this, the data were seasonally adjusted using the X-13ARIMA-SEATS monthly seasonal adjustment method (Census, 2024), implemented in the statistical package EViews.

In the next step, the results for individual topics were aggregated using equal weights. This process yielded an aggregated indicator, which we refer to as the MUI. The MUI takes values from 0 to 100, with higher values indicating a higher level of aggregated macroeconomic uncertainty.

5. Results and discussion

5.1. Macroeconomic uncertainty in Poland as shown by MUI

To show the properties of the indicator we will now discuss the level of uncertainty in Poland as indicated by the MUI. The MUI (Fig. 1) identified several periods of heightened uncertainty, particularly in 2004, 2008–2012, 2020, and 2022. The lowest levels of macroeconomic uncertainty were observed short before 2008 and between 2014 and 2019. These periods of high and low uncertainty were primarily correlated with global events (with one notable exception) rather than local events in Poland.

The MUI identified the following periods of heightened uncertainty.

1. The beginning of the analyzed period (notably 2004): This period was characterized by relatively high macroeconomic uncertainty in Poland, which can be attributed to preparations for the country's accession to the European Union. This represented a significant economic and political shift. The uncertainty may have resulted from concerns about aligning Polish laws with EU standards, adapting the economy to the common market, and the potential effects of opening up European markets (particularly regarding the competitiveness of the Polish economy). This outcome is consistent with findings from other Central and Eastern European countries (Kupfer & Zorn, 2020) but differs from results observed in other regions (Bontempi et al., 2021).
2. The financial crisis (2008–2009): In 2008, the MUI experienced a sharp increase, which is understandable given the global financial crisis that severely impacted world economies. Although the direct consequences of the crisis for Poland (especially in the financial sector) were minimal – there was no banking crisis or recession in the real sector – the immediate effects included significant depreciation of the Polish zloty, some tensions in the labor market, and a deterioration in public finances. The global context and related narratives likely played a key role in the uncertainty observed in Poland, because this was the first major external shock following the opening of the Polish economy.
3. The eurozone debt crisis (2011–2012): During the eurozone crisis, the Polish economy was notably affected, which may explain the persistently high uncertainty during these years, although it was less pronounced than during the 2007+ financial crisis.
4. The COVID-19 pandemic (2020): A significant increase in the MUI occurred at the beginning of 2020, directly linked to the initial response to the COVID-19 pandemic. Lockdowns, changes in international trade, and a global recession contributed to heightened macroeconomic uncertainty. However, the effect, as shown by the MUI, was relatively short-lived and, interestingly, weaker than during the 2007+ crisis. This outcome may be surprising but can be explained by the concept of the index. First, the MUI measures macroeconomic uncertainty, which remained relatively lower during the pandemic, despite prolonged uncertainty surrounding health and daily life. This was due to public authorities in Poland (as in many other countries) easing macroeconomic policies to support the labor market. Furthermore, inflationary pressures resulting from these policies had not yet fully materialized. Sec-

ond, the index measures the perception of uncertainty across a broad group of agents, not just professional analysts or entrepreneurs.

5. The war in Ukraine (2022): The outbreak of the war in Ukraine in February 2022 led to an increase in the MUI in Poland. This reflected, primarily, the impact of geopolitical uncertainty and potential disruptions in supply chains. However, this period was also marked by high inflation and rising interest rates, which added further sources of macroeconomic uncertainty.

The MUI demonstrates a strong alignment with historical data, including periods typically associated with heightened uncertainty.

5.2. Sensitivity analysis

Aggregation Methods

Typically, data are aggregated using equal weights, a solution that is acceptable and often recommended when establishing a natural, problem-driven weighting system is challenging (OECD, 2008). However, it is worth conducting sensitivity analyses with different aggregation methods.

Two alternative indices were constructed to compare with our baseline MUI, which uses equal weights. In the first approach, thematic grouping was used for preliminary aggregation. Four areas of macroeconomic data were identified: the real economy, the labor market and social security, the monetary economy, and finance and investment. Topic values within each area were aggregated using equal weights, followed by aggregation across areas (MUI_sub).

In the second approach, factor analysis was used to reduce the number of variables and focus subsequent analyses on the resulting, mutually independent factors. Principal component analysis and varimax rotation were applied during the factor analysis. Five factors were identified using the Kaiser criterion. The values of the new variables obtained through factor analysis were then used for aggregation (MUI_fa).

The alternative MUIs calculated showed a strong correlation with our baseline MUI. MUI_sub, had a correlation of 0.99 with the baseline MUI, whereas MUI_fa had a correlation of 0.88. In the latter case, the indicator suggests a slightly stronger increase in uncertainty during the 2007+ crisis and the pandemic. Despite this difference, the periods of heightened and reduced uncertainty were generally consistent. Therefore, we can conclude that the choice of aggregation method does not significantly affect the results of the baseline MUI.

Sampling

A potential weakness of using GT is its reliance on sampling. Cebrián & Domenech (2023) noted that this can lead to discrepancies in outcomes depending on the day the data are retrieved, limiting accuracy and reliability.

To illustrate the effects of sampling, Cebrián & Domenech (2023) conducted an experiment by repeating the same search query for four Austrian cities on different days. They found that the obtained results were not identical, indicating a lack of result stability. Further analysis showed that Pearson correlation coefficients between individual time series ranged from 0.79 to 0.94. Although these results were highly correlated, they were not identical, highlighting the impact of sampling on the accuracy of GT data.

A similar procedure was conducted to examine the potential consequences of this issue for the MUI. In addition to the data used to construct the MUI, additional data on the same topics were collected three times between October 16 and October 28, 2024. Our procedure focused on five topics: gross domestic product, inflation, unemployment, international trade, and exchange rates. Pearson linear correlation coefficients were then calculated for pairs of the same topic across the four sampling waves: during the MUI data collection and the three waves in the experiment.

Very high correlations were observed between all the data collection waves (in all cases, exceeding 0.99). Therefore, we can conclude that there are no significant threats to data stability related to the timing of data collection.

Choice of topics

An analysis was conducted to determine how the method of selecting topics for constructing the MUI impacts its overall value. We created indicators using different sets of topics and compared these indicators with the MUI. Specifically, a series of indicators was developed by omitting individual topics. Following this, we calculated the correlation between the new indicators and the MUI. The results showed that all these indicators are highly correlated with the MUI, usually around 0.99. This indicates that omitting or adding individual topics does not significantly affect their value. In other words, the MUI is robust to slight changes in the topics selected for its construction.

5.3. Characteristics of MUI compared to other uncertainty indicators

A comparative analysis was conducted to assess the characteristics of the MUI relative to existing uncertainty indicators. Only a few uncertainty indicators have been calculated for Poland so far. The EPU index is not publicly available for Poland at the time of writing this article (Economic Uncertainty, 2024). Although Hołda (2019) calculated a text-based index using Gazeta Wyborcza newspaper articles, this data is publicly unavailable. Therefore, only the available data were used for comparison. These include indicators prepared by the International Monetary Fund (IMF, 2024) and survey-based indicators calculated by the European Commission (2024). The WUI time series began in 2008. The European Commission's aggregate indicator for

Poland (EC_a) is available starting from January 2021, and a slightly longer series is available for consumer surveys (from May 2020), denoted as EC_c. Additionally, we used the GPR index, which measures the occurrence of threats and escalations of geopolitical events related to wars, terrorism, and international tensions (Caldara & Iacoviello, 2022).

For comparison purposes, an index based on data from the Polish Statistical Office (GUS) was also calculated, following the approach proposed by Bachmann et al. (2013). The indices calculated for Poland for this publication were sourced from the economic condition survey conducted by GUS (Statistics Poland, 2024). The survey included the question: '*What changes do you expect in the general economic situation of the country over the next 12 months?*' The index (denoted as GUS_c) was calculated using the metric proposed by Bachmann et al. (2013). Monthly data from 2018 through September 2024 were used. An aggregate index (denoted as GUS_a) was also constructed using other questions from the GUS survey, specifically those related to the household's personal situation, unemployment, and inflation (Statistics Poland, 2024). Each of these four questions was used to construct a separate series, which was then aggregated using equal weights to form the overall index. A summary of the indicators and data sources used in the study is provided in Table 2.

To assess how similar the various uncertainty indicators are in signaling uncertainty levels in Poland, linear (Pearson) correlations were calculated between individual uncertainty measures for the period when data were available for all indicators (i.e., January 2021 to September 2024) (Table 3).

The results indicate that the informational value of individual indicators differs, which is consistent with the literature (Cascaldi-Garcia et al., 2023). These indicators reflect different areas of uncertainty and use different data sources. The results should not be interpreted as weaknesses of individual research approaches but rather as indicating that different measures capture a partial picture of the multifaceted and often ambiguous phenomenon of uncertainty.

As expected, relatively high correlations exist between indicators calculated using similar methodologies and based on the same data. The MUI shows the highest correlation with the GPR, but only during periods of significant geopolitical shocks (2021–2024). The correlation is lower over a longer period without geopolitical shocks (for the entire period of MUI data availability, i.e., from 2004), at 0.40 (Figure 2).

The MUI also has a high correlation with indicators constructed using survey data. This is particularly true for indicators based on GUS data, which tend to show stronger uncertainty inertia. Among the studied indicators, the IMF's WUI exhibits distinctly different characteristics. This difference may be because the source of text data for the WUI is IMF documents, and the uncertainty assessments by IMF analysts may differ significantly from household perceptions of uncertainty.

Figures 2 and 3 compare the month-over-previous-month percentage change of individual indexes and provide a closer examination of the differences among the indicators. The WUI, which generates signals for Poland that are significantly different from those of other indicators, is the least correlated with the MUI. The WUI can be challenging to interpret and often shows surprising and delayed responses. For example, it indicated extremely high levels of uncertainty in the second quarter of 2015 and the fourth quarter of 2016. In contrast, it showed average uncertainty in the first quarter of 2020 (at the onset of the pandemic) and a level of uncertainty well below average in the first half of 2022 (at the beginning of the war in Ukraine). For the remaining indicators, the relatively short time series make analysis challenging. However, the case of the war in Ukraine is particularly interesting. The start of the war in Ukraine is characterized by a sharp increase in the GPR, while survey-based uncertainty indicators (GUS) show only moderate changes. These findings align with intuition – Poland experienced a significant rise in geopolitical risk during this period, but this did not strongly translate into economic perceptions by agents. Nevertheless, when considering macroeconomic phenomena, the period was dominated by uncertainty arising from heightened inflation, which was well captured by the MUI.

Thus, MUI is a valuable alternative to existing uncertainty measures. Moreover, the features of this indicator, including the data source, make it very suitable for real-time tracking of uncertainty, especially in the perception of households, not analysts and researchers.

5. Conclusion

This study presents the construction and evaluation of the MUI. As case study we use Poland, covering the period from 2004 to 2024. The MUI, based on GT data, successfully captures periods of heightened economic uncertainty, including the financial crisis, the eurozone debt crisis, the COVID-19 pandemic, and the war in Ukraine. Our analysis demonstrates that the MUI provides valuable insights into macroeconomic uncertainty in Poland.

The MUI offers a new approach to measuring uncertainty by leveraging the behavior of economic agents as expressed through internet search patterns. Despite potential limitations, such as reliance on GT's sampling methodology, the MUI may provide a high-frequency, real-time perspective on macroeconomic uncertainty in the general public's perception, not analysts or researchers.

The comparative analysis highlights also the distinct characteristics of the MUI compared to other uncertainty indicators. While the MUI aligns closely with geopolitical risk measures during periods of significant global shocks, it also provides a unique perspective that complements survey-based and text-based measures of uncertainty. The differences among these indicators underscore the need for a diverse set of tools to fully capture the multifaceted nature of macroeconomic uncertainty.

In conclusion, the MUI represents a promising alternative to traditional uncertainty measures, particularly for capturing public sentiment in response to macroeconomic shocks. Future research could extend this methodology to other countries and regions, which is possible considering GT features.

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Appendix

Table 1. GT topics used for the calculation of MUI

Topics (in polish)	Topics (in English, for information purposes only)
bankomat, bezrobocie, ceny, ceny paliw, curriculum vitae, dług publiczny, gotówka, handel zagraniczny, indeks giełdowy, inflacja, kredyt, kryzys finansowy, kryzys gospodarczy, kurs walutowy, obligacja, odsetki, praca, produkt krajowy brutto, recesja gospodarcza, stopa procentowa, upadłość, urząd pracy, waluta, WIBOR, wzrost gospodarczy, zabezpieczenie społeczne, zwolnienia grupowe	ATM, unemployment, prices, fuel prices, curriculum vitae, public debt, cash, foreign trade, stock exchange index, inflation, credit, financial crisis, economic crisis, exchange rate, bond, interest, work, gross domestic product, economic recession, interest rate, bankruptcy, employment office, currency, WIBOR, economic growth, social security, collective layoffs

Source: Own preparation.

Table 2. Source of data

	Methodology	Source of data
WUI	News based indicator of uncertainty	IMF (2024)
GPR	Index of geopolitical risks (measures the occurrence of threats and escalations of geopolitical events related to wars, terrorism, and international tensions)	Iacoviello et al. (2024)
EC_a	Survey-based indicator of uncertainty; aggregated indicator	European Commission (2024)
EC_c	Survey-based indicator of uncertainty; consumers survey	European Commission (2024)
GUS_a	Survey-based indicator of uncertainty; aggregated	Statistics Poland (2024a); own calculation
GUS_c	Survey-based indicator of uncertainty	Statistics Poland (2024a); own calculation
MUI	Macroeconomics Uncertainty Indicator	Google Trends (2024); own calculation

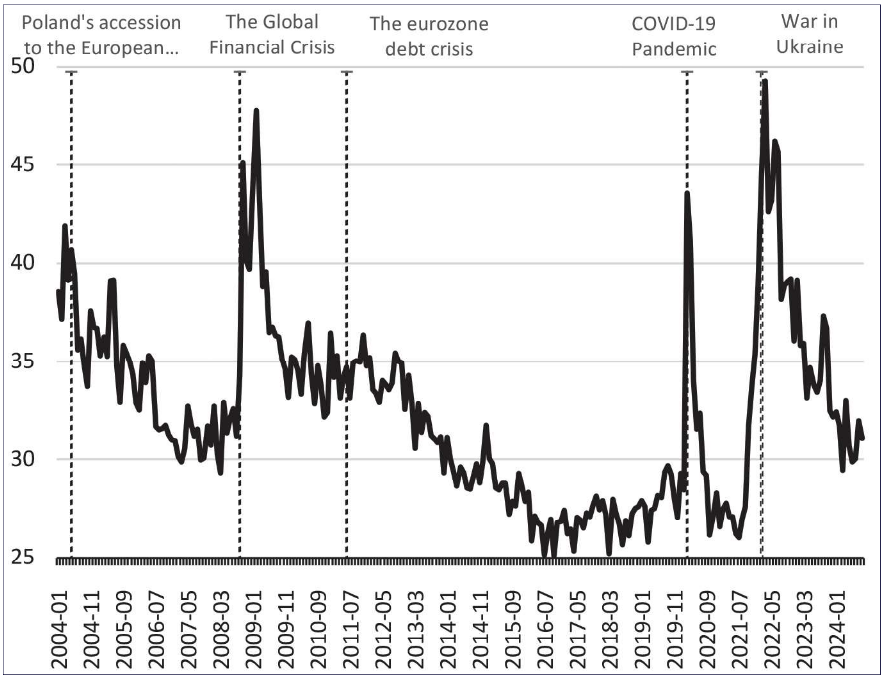
Source: Own preparation.

Table 3. Correlation matrix of uncertainty indicators

	WUI	GPR	EC_a	EC_c	GUS_c	GUS_a	MUI
WUI	1.00						
GPR	0.07	1.00					
EC_a	0.43	0.49	1.00				
EC_c	0.37	0.47	0.78	1.00			
GUS_c	0.32	0.60	0.83	0.72	1.00		
GUS_a	0.47	0.59	0.57	0.76	0.66	1.00	
MUI	0.17	0.80	0.50	0.66	0.66	0.78	1.00

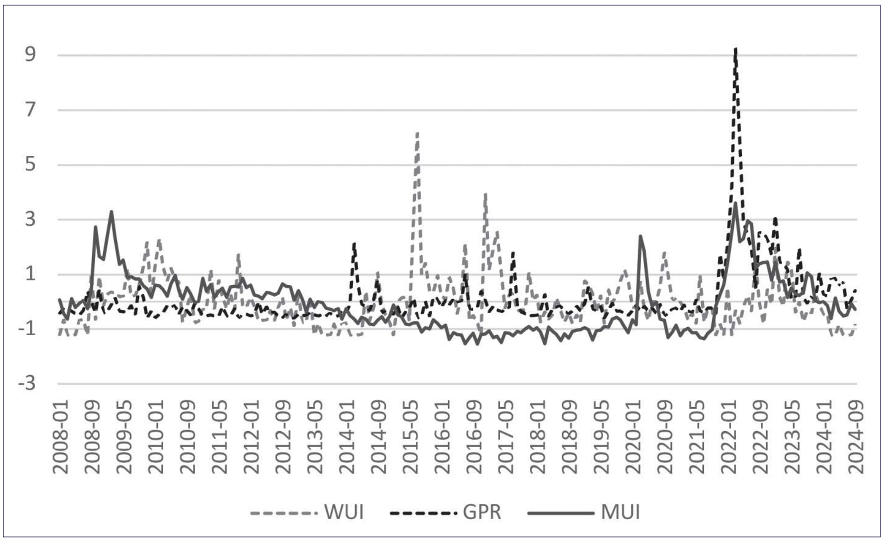
Source: Own calculations.

Figure 1. Macroeconomic Uncertainty Index (Poland)



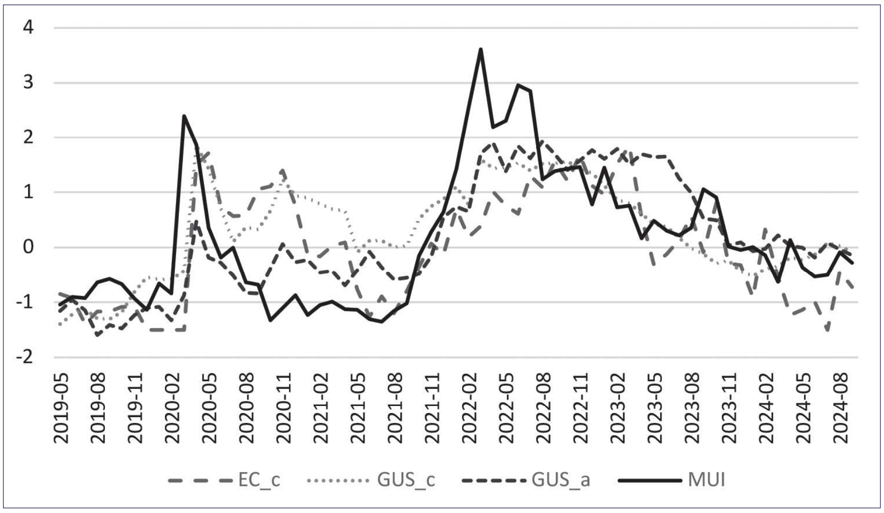
Source: Own calculations.

Figure 2. Comparative dynamics of uncertainty indicators: WUI, GPR, and MUI in Poland



% change m-o-m
All indicators have been standardized
Source: Own calculations; Iacoviello et al. (2024); IMF (2024).

Figure 3. Comparative dynamics of uncertainty indicators: EC, GUS, and MUI in Poland



% change m-o-m
All indicators have been standardized
Source: Own calculation; Statistics Poland (2024a); European Commission (2024).