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Measuring political instability at a high frequency

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Measuring Political Instability at a High Frequency*

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Abstract

This study introduces the World Index of Political Instability (WIPI), a novel high-frequency measure that covers four dimensions of political instability in 182 countries, available from 1960 until 2022. Our measure is extracted from the curated texts of the Economist Intelligence Unit's Country Reports using text mining techniques, allowing us to track political instability on a high frequency while matching various established low-frequency proxies. We show that political instability has significant and negative short-run effects on the economy similar to a demand-side shock. In contrast to uncertainty shocks, the observed effects are not immediate but take up to one year until they materialize. The measured effects are stronger in low-income economies than in high-income economies and during recessionary periods.

Keywords: Political Instability; Business Cycle Fluctuation; Panel Local Projection; Text Mining

JEL Classification: C23, C55, O43, Z18,

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1 Introduction

What are the short-run effects of political instability on the economy? During a plenary session of the World Economic Forum Annual Meeting 2020, António Guterres, Secretary-General of the United Nations, described the current state of the world with two words: uncertainty and instability. While these terms are often used interchangeably, they capture distinct phenomena. Uncertainty refers to the unpredictability of future outcomes — particularly in economic or policy-related decisions. Political instability, by contrast, reflects the fragility or dysfunction of political institutions. Therefore, political instability can be a source of uncertainty, but not all uncertainty stems from political instability. The economic consequences of policy uncertainty — following the influential work of Baker et al. (2016) — have been extensively studied in recent years (see Castelnuovo (2023) and Cascaldi-Garcia et al. (2023) for a comprehensive review). However, the distinct effects of political instability have received comparatively less empirical attention in the past decade.

The limited academic attention stands in sharp contrast to the growing visibility of political instability worldwide, affecting both developing countries and advanced economies with long-standing democratic traditions. The United States, often seen as a bastion of stable democracy, for example, faced unprecedented political instability following the 2020 presidential election and President Trump's refusal to concede defeat following the end of his first term culminating in the January 6, 2021, Capitol riot. France's presidency of Emmanuel Macron faced various political challenges over its two terms such as the 2018-2020 yellow vest protest movement and the 2024 snap elections, while Italy experienced 69 cabinets over the past 70 years. In Asia, South Korea experienced significant political unrest following the declaration of martial law by former president Yoon Suk Yeol in December 2024, and an even more violent form was experienced in Myanmar in 2021 where the army led a coup to overthrow the democratically elected government.

So far, the existing literature has predominantly focused on the adverse long-run economic consequences of political instability. It is associated with reduced macroeconomic efficiency (Aisen and Veiga, 2013), weakened tax systems, and, in less-developed economies, greater reliance on seigniorage (Cukierman et al., 1992) and diminished central bank independence (Aisen and Veiga, 2006). Despite mixed evidence in some

studies (Campos and Nugent, 2002), most empirical analyses find that political instability significantly reduces economic growth (Alesina and Perotti, 1996; Uddin et al., 2017; Blum and Gründler, 2020; Dirks and Schmidt, 2024).

In contrast to the long-run consequences of political instability, relatively little is known about the short-run effects. Yet there are strong theoretical reasons to expect political instability to exert short-run macroeconomic effects, especially through the expectation channel. Political instability alters beliefs about future policy, security, and institutional continuity, which can immediately depress economic confidence among firms, households, and financial investors. Forward-looking firms may postpone investment or hiring due to heightened perceived risks to profitability or contract enforcement, while consumers may revise expectations about income security and reduce spending on durable goods.

The gap in the literature is due in part to the shortcomings of existing measures of political instability. Measuring political instability poses inherent challenges, as it is not directly observable. One-dimensional measures — such as counts of wars, coups, strikes, or regime changes (see (Parvin, 1973; Chen and Feng, 1996; Asteriou and Price, 2001; Aisen and Veiga, 2006; Dupas and Robinson, 2012; Gassebner et al., 2016; Blum and Gründler, 2020))— are appealing for their precision but capture only narrow aspects of instability. Multidimensional indices like the World Governance Indicators (Kaufmann et al., 2010) offer broader coverage but are typically available only at an annual frequency. In the need of high-frequency measures, researchers may turn to the broader uncertainty literature. However, commonly used indices — such as the EPU (Baker et al., 2016), WUI (Ahir et al., 2022), and GPR (Caldara and Iacoviello, 2022) — do not measure political instability directly, which may blur empirical interpretation.

To address this gap we propose a new multidimensional index available at a high frequency: the **World Index of Political Instability (WIPI)**. The WIPI is available on a monthly frequency for 92 countries since 1996 and on a quarterly frequency for 182 since 1960. The index is constructed from Country Reports published by *The Economist Intelligence Unit* (EIU). It is constructed along four dimensions derived from the literature on political instability reflecting internal and external sources of political pressure and various degrees of political unrest, namely 1) *instability within the political regime*, 2) *mass civil protests*, 3) *political violence*, and 4) *instability of the political regime*. The objective of this approach is to offer a more granular view of political instability within

a country, enhancing our understanding of its root causes and potential transmission channels. The dimensions are generated through a dictionary-based analysis of the EIU Country Reports. These reports assess the current and future state of a country's economy and political landscape, analyzing key political events, elections, government stability, and other relevant factors. To construct the dictionaries in a transparent manner and alleviate potential researcher bias we adopt a procedure that is transparent and objective. We begin with a set of keywords derived from the political instability literature, namely, the political events used by Jong-A-Pin (2009). Using these keywords as a basis, we expand the dictionary utilizing the help of a large language model *Gemini* by a simple prompt asking for synonyms in the context of political instability. This method ensures a reproducible and objective index, resistant to subjective alterations.

Furthermore, using the WIPI we document global trends in political instability. Our measure shows that political instability has risen in both developing and developed economies since the 1960s. We report major global episodes of instability — including the Anti war movement, the collapse of the Soviet Union, the war on terror, the Arab Spring, and the COVID-19 pandemic — and uncover systematic differences in the types of instability observed in developing versus advanced economies. To validate the WIPI, we compare it to established annual indicators such as the World Governance Indicators (WGI). We find strong correlations at both global and country levels, while also demonstrating that WIPI better captures short-term fluctuations, particularly during periods of crisis. We also show distinct differences with respect to measures of political uncertainty.

Leveraging the high-frequency availability of the WIPI we are, finally, able to examine the short-run effects of political instability on the economy. Analyzing a monthly panel of OECD and BRICS countries since 2000, accounting for almost 85% of global GDP, we find that an increase in political instability leads to a deterioration in economic expectations, accompanied by measurable declines in real activity and prices. One year after the shock, industrial production is about 0.5% lower, and consumer prices fall by roughly 0.3%, with both effects persisting over the subsequent year. In that respect political instability shocks resemble demand shocks. In contrast to uncertainty shocks, which tend to materialize very quickly, a shock in the WIPI takes considerable more time to propagate through the economy. For example, it takes more than 12 months for production and expectations to decline.

Decomposing the WIPI into its four dimensions reveals the drivers of this observation. Shocks to *political violence*, which plausibly generate immediate uncertainty and deterioration in confidence, produce an immediate and strongly contractionary response in both expectations and industrial production. Shocks related to *Instability within the political system* also exert a contractionary influence, though their effects materialize with a longer delay. By contrast, disturbances in *protest* and *instability of the political regime* are less contractive, contributing to more gradual overall responses. We conclude that political instability has short-run effects on the business cycle, especially through severe and violent events of political instability. Heterogeneity analyses reveals further that the estimated effects are more contractive in low income countries and during recessions compared to expansionary periods. While the former finding is well established in the literature, the latter business cycle effects of political instability are reported for the first time.

The structure of the paper is as follows: Section 2 outlines the methodology used to construct the index. In Section 3.1, we introduce the WIPI and provide an overview of the global and country-specific trends in political instability since 1960. Section 3.2 compares the WIPI with other commonly used political instability indices to validate its construction. Furthermore, we compare WIPI with the Economic Policy Uncertainty (EPU) index in Section 3.3 to highlight the distinctions between political instability and economic policy uncertainty. In Section 4.1 and Section 4.2, we present the estimation strategy and the baseline results showing the effect of political instability on four business cycle indicators — prices, interest rates, economic expectations, and industrial production — at a monthly frequency. In Section 4.4 and Section 4.5 we explore heterogeneities across dimensions of instability and income levels, while Section 4.3 presents a battery of robustness checks for the baseline results. The key findings are summarized in Section 5.

2 Measuring Political Instability

To create a multidimensional index of political instability at a high frequency, we rely on text-mining techniques that have been frequently used to quantify political developments (Gentzkow et al., 2019). Baker et al. (2016) have created an index on Economic Policy Uncertainty using newspaper articles. Since then, several text-mining based in-

dices have emerged to capture events in the political sphere that may affect the economy such as uncertainty (Ahir et al., 2022), Climate Policy Uncertainty (Gavriilidis, 2021) or Geopolitical Risk (Caldara and Iacoviello, 2022).

To measure political instability, we extract information from the Country Reports published by the Economist Intelligence Unit (EIU)¹ using text mining techniques. The Economist Intelligence Unit's Country Reports are comprehensive, regularly updated assessments of a country's political and economic environment. Each report synthesizes high-quality information on political developments, institutional stability, policy changes, and macroeconomic conditions. Beyond their extensive global coverage and frequent updates, the EIU reports are particularly well-suited for Natural Language Processing (NLP) applications measuring political instability for four reasons: First, given that the reports are intended for professionals, market participants, decision-makers, and scientists, the information value and relevance are of utmost importance. The texts are content-rich and employ mostly neutral language, making them well-suited for automated NLP analysis. Second, the reports are divided into three sections (*Economic forecast*, *Political outlook*, and *Economic policy outlook*), which are further subdivided into chapters, allowing targeted examination of specific content without resorting to topic modeling. Thus, the analysis of each country report should capture the full extent of political instability for the corresponding period. Third, the EIU reports have a low publication lag, making them suitable for analyzing instability at the current edge and for nowcasting applications. Finally, EIU Country Reports are updated versions of previous country reports. Thus, information occurs repeatedly in EIU Country Reports as long as it is relevant, in contrast to newspaper articles, where novelty often takes precedence over relevance.

However, the data do have limitations. Unlike traditional newspaper articles, which can draw on multiple sources to mitigate biases, EIU Country Reports rely on a single source, potentially introducing a form of home bias. While newspaper data allows for the inclusion of various perspectives from different outlets and countries, this diversification is not possible with EIU reports. Moreover, the comparability of the reports across countries is limited for several reasons: different authors are responsible for different countries; the reports are produced by a British publisher and potentially written from

¹EIU Country Reports have been already used as a text source to measure uncertainty, see Ahir et al. (2022).

a Western perspective, which may introduce ideological as well as attentional biases, and the restricted length of the reports means that less severe events are less likely to be mentioned if they coincide with more severe ones – a pattern that, however, also applies to newspaper data.

For the vast majority of countries (182 countries), reports have been issued since the 1960s. For 92 major economies we even have monthly data since the 2000 representing 95% of World GDP and 85% of the global population in 2024. For 27 countries the EIU has stopped publishing monthly reports and turned back to a quarterly frequency in 2012. For an additional 22 countries, it turned back to a quarterly frequency in 2021. Table A.1 and Table A.2 give a detailed overview of the coverage and frequencies available. We source EIU Country Reports from two different providers. For the period from 1960 to 1996, we obtained EIU data from ProQuest. From 1996 to 2022, we used EIU reports available through the ZBW – Leibniz Information Centre for Economics.

We employ a dictionary-based text-mining analysis to extract the relevant information from the EIU Country Reports. Political instability has many dimensions (Jong-A-Pin, 2009). To account for each dimension, we create a dictionary for each dimension of political instability identified by Jong-A-Pin (2009): 1) *Instability within the political regime*, 2) *mass civil protests*, 3) *political violence*, and 4) *instability of the political regime*. The first dimension involves changes that occur within the legal boundaries of the political system, such as both regular and irregular cabinet changes, reflecting shifts in leadership that, while sometimes disruptive, remain formally within the constitutional order. The second dimension encompasses events associated with social unrest, including strikes, demonstrations, and riots, where collective action challenges political authority from outside established institutions and expresses wider dissatisfaction with social or economic conditions. The third dimension deals with the use of violence to enforce political positions, ranging from guerrilla warfare and ethnic clashes to revolutions, purges, and campaigns of terror, where organized force rather than negotiation becomes the tool for political contestation. Finally, the fourth dimension targets changes beyond the legal limitations, such as coups or revolutionary overthrows, in which power is seized or regimes are dismantled outside the recognized constitutional framework.

To construct dictionaries associated with each dimension, we begin with the 20 events of political instability identified by Jong-A-Pin (2009) and use them as our *root words*, depicted in Table 1. We have performed a minimum of discretionary changes

- altered "number of elections" to "snap election" to emphasize the significance of irregular elections concerning political instability and including "terror attack" to capture topics related to terrorism, which, especially in Europe, have divided politics over the past decade. Next, we use Gemini, a large language model (LLM) developed by Google, to enrich the list of *root words* with synonyms. Specifically, we prompt Gemini with: *Please find 5 synonym nouns for **word** in the context of political instability, where **word** refers to one of the 20 events identified by Jong-A-Pin (2009).*

Table 1: List of Root Words sorted into its Dimension of Political Instability

| Instability of the political regime | Mass civil protest | Political Violence | Instability within the political system |
|-------------------------------------|--------------------|-----------------------|---|
| Revolution | Riot | Guerilla warfare | Fractionization |
| Coups d'etat | Demonstration | Assassination | Polarization |
| Major constitutional change | Strike | Ethnic tension | Years of largest party in office |
| Political regime change | | Medium civil conflict | Snap elections |
| Major government crisis | | | Changes in the chief executive |
| | | | Cabinet Change |
| | | | Veto player who drops from office |
| | | | Government stability |

Notes: The sorting follows Jong-A-Pin (2009)

The responses from Gemini are not fixed as each request generates a unique response with a potentially different selection of synonyms. To find the most relevant synonyms for each *root word*, we therefore make a thousand requests to Gemini, resulting in 20 lists of synonyms — one for each *root word*. Including the *root word* itself, this yields a total of 2253 unique *keywords*. Naturally, some synonyms occur more frequently than others. We use the distribution of the synonyms to assign them to the correct dimension of instability. If a synonym appears in multiple dimensions, it is assigned to the one where it occurs most frequently across the queries. This minimizes overlap between dimensions and reduces discretionary judgment. Finally, we kept all *keywords* found in more than 50 requests, our baseline threshold, leaving 240 *keywords* across the four dimensions of political instability. A visualization of the list of words contained in each dictionary is presented in Figure 1, where the color represents the dimension of the *keyword* and the size reflects the empirical frequency of the word in the EIU Country Reports. A complete list is found in Table A.3 and Table A.4 in the Appendix.

As shown in Panel a) of Figure A.1, our index proves robust to the choice of different thresholds: In addition to our baseline, we also report variations with thresholds of 25

(yielding 294 *keywords*) and 100 (yielding 189 *keywords*), which yield no substantial differences. In addition, Panel b) of Figure A.1 illustrates a leave-one-out exercise, where the gray band indicates the maximum deviation of the baseline index (with a threshold equal to 50) when any of the 240 *keywords* is excluded. The narrowness of this band shows that no single *keyword* exerts a dominant influence, underscoring the robustness of the index construction.

Figure 1: Word Cloud of Keywords in Economist Intelligence Unit Country Reports (1960–2022)



Notes: The figure shows the most frequently occurring keywords by dimension: *instability of the political regime* (purple), *mass civil protest* (green), *political violence* (red), and *instability within the political system* (blue). Larger words indicate a higher frequency.

To calculate the WIPI, we tokenize the texts of the EIU Country Reports and count how often the *keywords* occur for each of the $d = 4$ dimensions of political instability. Tokenization is the process of breaking up a stream of text into smaller, meaningful units, e.g., words, symbols, or other meaningful elements. If the keyword is a multigram, it is taken into account if all parts occur in the window of five tokens. Additionally, we perform lemmatization, a process that transforms various inflections of a word to its root, thus improving accuracy and efficiency of the dictionary. As a robustness check, Panel c) of Figure A.1 shows the index calculated without lemmatization. The overall trajectory remains broadly similar, but between 2008 and 2020 several *keywords* could not be identified in the non-lemmatized texts, leading to lower measured levels of political instability in this period.

The indicator of dimension Dim at period t for country i is then calculated as the ratio of found *keywords* and the number of tokens in the corresponding documents. By doing so, we control for different length of EIU Country Reports. Our composite indicator, the WIPI, is then calculated from the sum of the *Keywords* four indices for each dimension per 5,000 tokens:

$$WIPI_{i,t} = \sum_{Dim}^4 WIPI_{i,t}^{Dim}, \text{ where } WIPI_{i,t}^{Dim} = \frac{\#Keywords_{i,t}^{Dim}}{\#Tokens_{i,t}} \times 5000$$

Therefore, the index reflects the proportion of tokens — out of 5,000 — in EIU Country Reports that are associated with political instability. As the average EIU Country Reports has approximately 5,000 words, the index approximately gives the number of words associated with political instability by an average country report.

An additional source of bias could be that some of the selected keywords – despite our systematic checks – also occur in contexts unrelated to political events, or might primarily refer to a different country. To address this, we applied Llama 3.1 to all paragraphs in which a *keyword* was detected, using the following prompt: *Does the following text contain information about politics or political events in **country**? (Start your answer with Yes or No) : **paragraph***. The index calculated only in the paragraphs, where the prompt was affirmed (82.7% of the total paragraphs), is displayed in Panel d) of Figure A.1 for the period from 1996 onward.² Here, we find at most minor deviations from our baseline. While it would in principle be possible to use this LLM-based measure as the primary index, we consider our dictionary-based approach more transparent, replicable, and thus preferable as the baseline.

3 The World Index of Political Instability

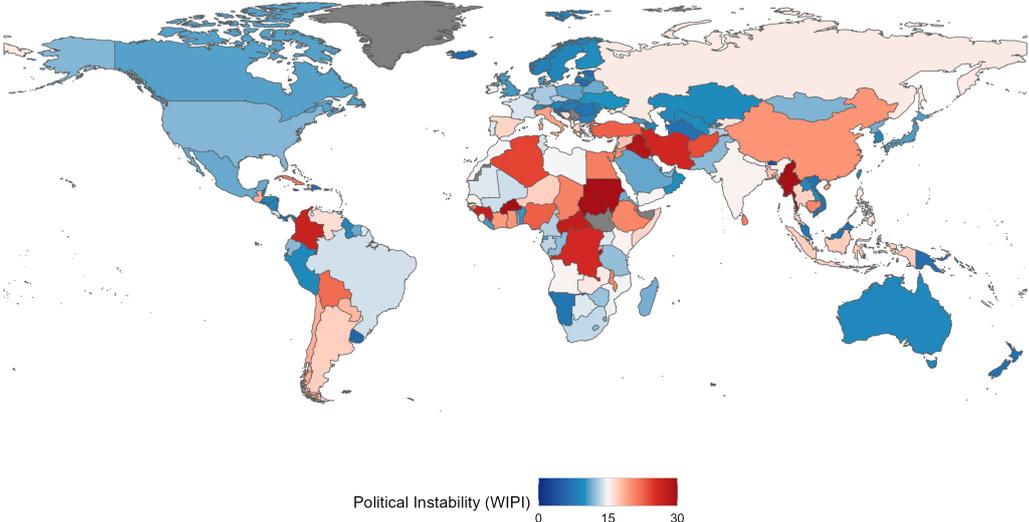
In this section, we present the WIPI and how political instability has evolved globally and across major economies from 1960 to 2022. By visualizing WIPI’s historical trajectory and geographical distribution, we highlight major global events, regional patterns, and the varying forms of instability across development levels. Finally, we validate the WIPI with existing indices of political instability and distinguish it from frequently used measures of uncertainty.

²EIU Country Reports published before 1996 are only available in PDF format, for which the extraction of single paragraphs is not feasible, in contrast to the HTML format of later reports.

3.1 Political Instability from 1960 to 2022

Regions such as North America, Northern Europe, Japan, South Korea, New Zealand and Australia exhibit the lowest levels of political instability as Figure 2 illustrates. Moderate levels of instability can be observed, for instance, across parts of Southern Europe, explained by a high frequency of government change in Italy for instance. In contrast, we observe consistently high levels of political instability in parts of Africa, the Middle East, South America and Southeast Asia, particularly in Afghanistan, Algeria, the Central African Republic, Sudan, Iraq, Iran, Kongo, Somalia, Myanmar, and Venezuela.

Figure 2: Global Distribution of Political Instability



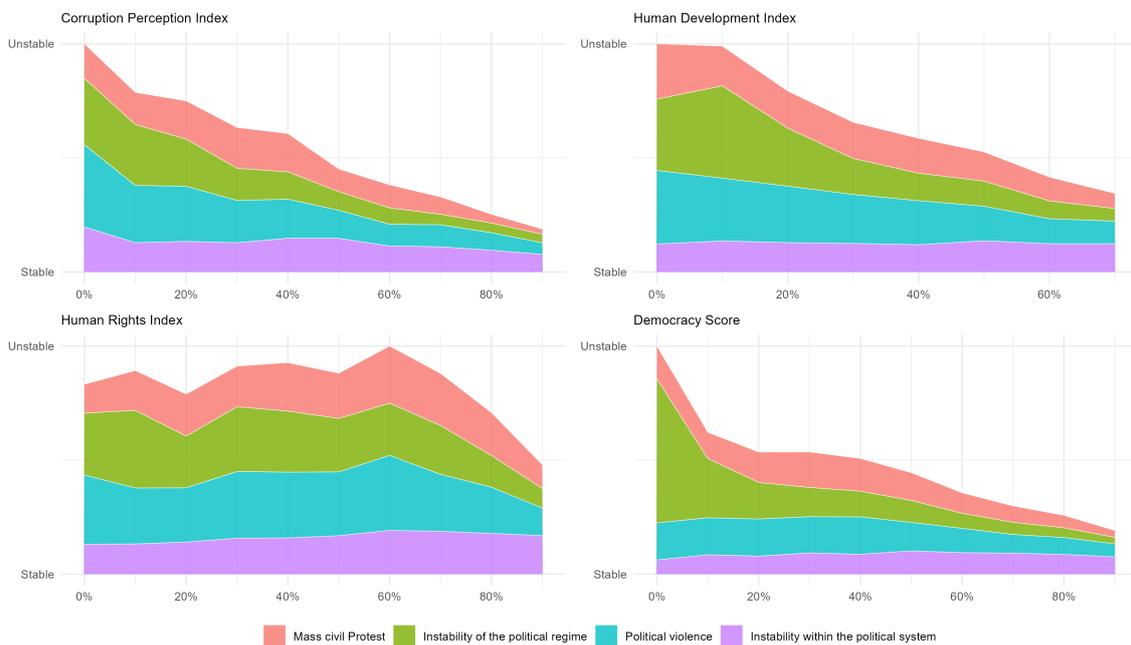
Notes: The figure shows the average WIPI from 1960 to 2022 by country. Higher levels of instability correspond to warmer colors.

Overall, the map highlights significant regional disparities in political stability, with clear clustering of stable regions with a high level of human development in the Global North and more instability concentrated in conflict-prone or developing regions with a lower level of human development. To emphasize the relationship with the level of human development, we plot a cross-section of WIPI and its dimensions versus different measures of human and political development, namely the Human Development Index, the Democracy Score obtained from POLITY5, the Human Rights Index and the Corruption Perception Index from the World Governance Indicators. To generate the graphs,

we group the annual values of each development index into 10% intervals and then calculate the average scores of the corresponding WIPI dimensions. Figure 3 depicts the WIPI on the vertical axis, while the different indices are plotted in each subplot on the horizontal axes. We find an inverse relationship in all four cases - countries with low human development index, low democracy score or high corruption tend to be on average more politically unstable and conversely countries with a higher degree of human development are associated with a lower degree of political instability. The figure also shows that depending on the level of human development specific dimensions of instability are more prevalent. In countries with a low level of human development the dimensions of *instability of the political regime* and *political violence* are much more prevalent, while in advanced economies the dimension *instability within the political system* is the most common form of political instability. This is unsurprising given that coups, forced regime changes, and revolutions have barely happened in the most advanced economies since the 1960s, while they often experience new elections, parliament reshuffles, and removed officials.

How has political instability developed over time? We agree with António Guterres, that instability has become a global issue of increasing relevance as the global WIPI has doubled from 1960 to 2022. Figure 4 plots the four dimensions of the WIPI for the World in the top left corner (GDP weighted) from 1960 to 2022: *mass civil protest*, *instability of the political regime*, *political violence*, and *instability within the political system*. The highest peaks for the *instability of the political regime* dimension occur during the 1960s and 1970s, coinciding with major global events such as decolonization in Africa, the anti-war movements, and numerous coups in Latin America and Africa. Another surge appeared in the early 1990s, which can be linked to the collapse of the Soviet Union and the political turmoil that followed in Eastern Europe and Russia. Similarly, the spike around 2020 corresponds with the COVID-19 pandemic, which caused widespread disruptions to political systems and governance worldwide. The *mass civil protest* dimension also shows significant activity in the 1960s and 1970s, reflecting global civil rights movements, anti-war protests, and uprisings. Peaks in the early 2010s align with events such as the Arab Spring, which saw mass protests across the Middle East and North Africa. A more recent spike around 2020 is related to global protests triggered by the pandemic. The *political violence* dimension index sees its most significant surges during the 1970s, reflecting the height of Cold War proxy conflicts in

Figure 3: WIPI Composition across Different Levels of Human and Political Development

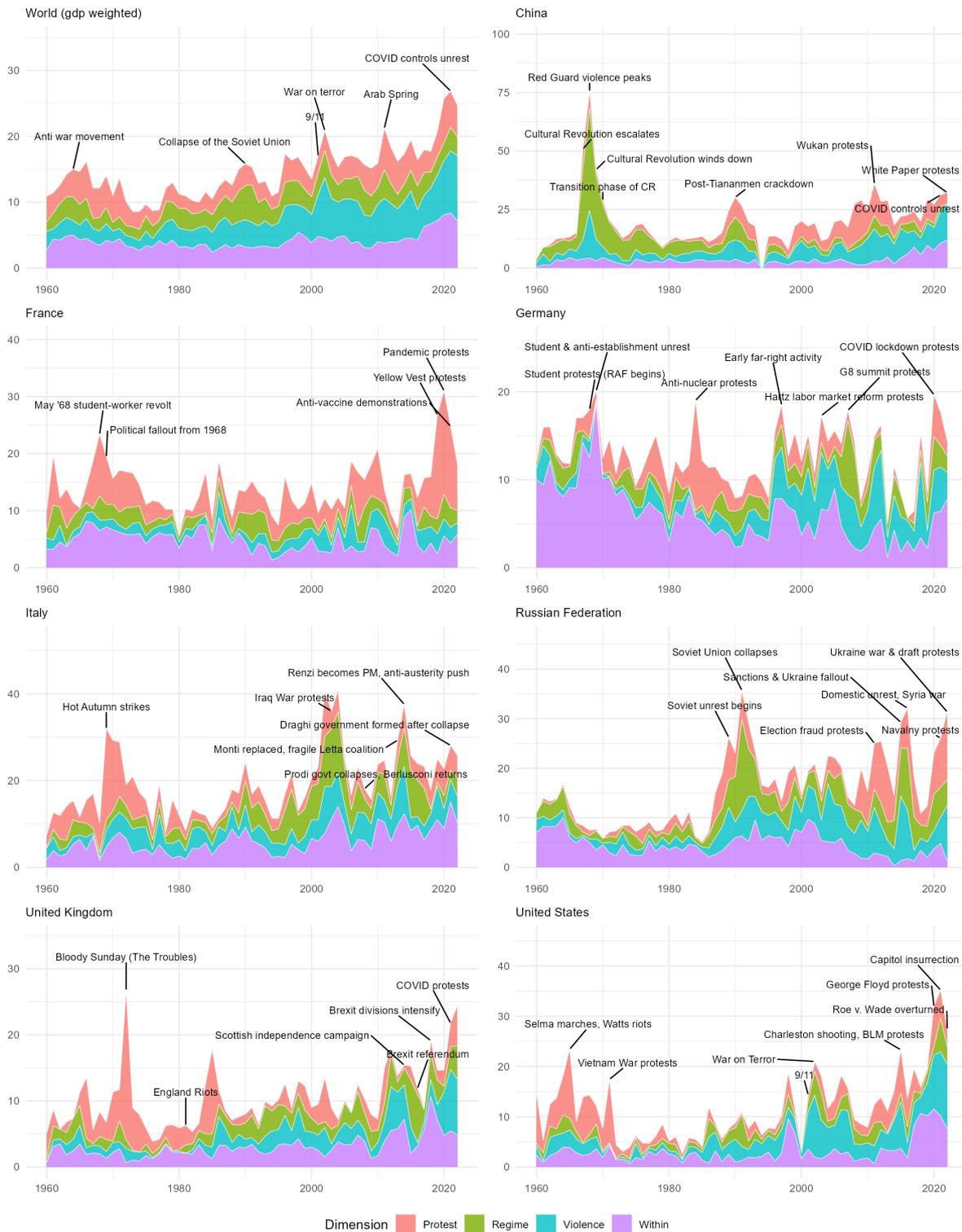


Notes: The figure shows the WIPI composition across the Human Development Index, the Democracy Score, the Human Rights Index, and the Corruption Perception Index. As indicated on the x-axis, we grouped all annual country-level values of each development indicator into 10% intervals. For each bin, we then computed and plotted the mean values of the corresponding WIPI dimensions on the y-axis.

Latin America, Africa, and Southeast Asia. The rise in the 2000s corresponds to the the 9/11 terror attacks, the post-9/11 era and the wars in Iraq and Afghanistan. Lastly, the dimension of *instability within the political system* remains relatively stable compared to the other indices but shows similar trends, with spikes during the 1960s-70s, the early 1990s, and the early 2020s, suggesting that internal governance crises are correlated with the broader trends of political unrest and violence. Overall, the figure highlights major historical periods of political instability, with notable surges linked to decolonization, Cold War conflicts, the collapse of the Soviet Union, the Arab Spring, and the global impact of the COVID-19 pandemic.

The remaining subplots of Figure 4 display how political instability has evolved over time in eight major economies, i.e., China, France, Germany, Italy, the Russian Federation, the United Kingdom and the United States from 1960 to 2022 where multiple notable peaks are observed. China exhibits a pronounced peak during the Cultural Revolution (1966-1976) and another around the Tiananmen Square protests in 1989,

Figure 4: Development and Composition of Political Instability by Country



Notes: The figure shows the WIPI by dimension: *mass civil protest, instability of the political regime, political violence, and instability within the political system*, across a global aggregate (GDP weighted), China, France, Germany, Italy, the Russian Federation, the United Kingdom, the United States from 1960 to 2022. At the global level, GDP-weighted aggregation has been applied. Higher values indicate greater levels of political instability.

reflecting periods of intense political violence and regime instability. Further, it shows that political instability was low in the early 2000s but has increased since then. The COVID-19 pandemic and the violent reaction to the Hong Kong Protests of 2019–2020 are especially visible by the increase in the dimension of *political violence*. In France we can observe that the most dominant dimensions of political instability are *political instability within the political system* and *mass civil protest*. Noticeable peaks occurred during the May 1968 protests, the yellow-vest movement, and the COVID-19 pandemic. Germany is a highly politically stable country as the WIPI illustrates. Most of the instability is sourced in government changes, constitutional debates or other political events inside the legal boundaries of the constitution. Heightened instability can be observed in the 1990s, i.e., the period of reunification. Relatively higher rates can be observed in Italy with its numerous government collapses and new elections highlighted by peaks in the dimensions of *instability of the political regime* and *political instability within the political system*. Especially, during the "Years of Lead" in the 1970s, during political corruption scandals in the early 1990s and in 2002. The Russian Federation, i.e., the UDSSR until 1991, demonstrates a significant rise following the dissolution of the Soviet Union, followed by periodic instability related to internal conflicts, such as the Chechen wars. Since the 2000s, many peaks can be attributed to Russia's authoritarian turn and the associated waves of protest. The United Kingdom shows political unrest during the 1980s, related to the miners' strikes and Thatcherite reforms, with another surge in instability following the COVID-19 pandemic. Notably, the Brexit referendum is not as pronounced as it is in indices such as the EPU or WUI, highlighting how political instability can be detached from uncertainty. The referendum was then marked by high uncertainty regarding the foreign and domestic policy. On political level, the referendum brought an unstable government with several cabinet changes, which is captured by the widening of the *instability of the political regime* dimension. The United States displays heightened instability in the 1960s and 1970s during the Civil Rights Movement and anti-Vietnam War protests, followed by significant peaks in the early 2000s post-9/11 and since the first Trump presidency in 2017, which culminated in the storming of the capitol and election-related unrest. These latest events become visible as a pronounced increase in the *instability within the political regime* dimension. The dominance of the dimension of "political violence" in the 21st century is due to terror attacks and school shootings that have plagued the country over the past 20 years.

3.2 Validation

In the following, we validate the WIPI by comparing it to several established measures used in the empirical literature. We begin with the WGI designed to explicitly capture political instability, before turning to other available indices. This comparison allows us to assess the coherence of our index with existing benchmarks.

The *World Governance Indicator* (WGI) by Kaufmann et al. (2010) is one of the most prominent indices of political instability frequently used in the corresponding literature (see e.g. Grechyna, 2018; Vu, 2021, 2022; Dirks and Schmidt, 2024). It provides valuable information about the state of political instability and the absence of violence in countries around the world. The WGI combines several perception-based indices, e.g., the *Economist Intelligence Unit Riskwire & Democracy Index*, the *Cingranelli Richards Human Rights Database and Political Terror Scale*, the *Political Risk Services International Country Risk Guide*, and the *Global Insight Business Conditions and Risk Indicators* that are built on the assessments of a variety of stakeholders, including firms, individuals, public officials, and commercial risk-rating agencies. This information is collected through a large number of surveys and cross-country assessments to provide a comprehensive picture of governance around the world. However, the WGI has some limitations which are debated in the literature such as bias or lack of comparability and the question of construct validity (Thomas, 2010). Furthermore, the WGI is aggregated on an annual basis prohibiting the analysis of short-term effects of political instability.

Figure 5 plots the WIPI (aggregated on an annual frequency) and the WGI from 1960 until 2022 for a global aggregate (GDP weighted), China, France, Germany, Italy, the Russian Federation, the United Kingdom and the United States. We plot the WGI with a negative sign, as it is defined as a measure for political stability and not instability. The figure highlights that our index has a high correlation with the WGI of 0.5, indicating that these indices often move in tandem at the global level. Yet the plots also highlight periods of divergence obscured by simple correlations. The WGI spikes in many Western countries around 2003–2005, most prominently in the UK and the US, likely reflecting the war on terror. While terror attacks and anti-war demonstrations are indeed dimensions of political instability, the military engagement in foreign wars is not. Consequently, the WIPI only spikes in 2001 and 2002, when EIU Country Reports extensively reported about the 9/11 attacks. Furthermore, a notable divergence emerges in the post-pandemic era. In 2020 and 2021, the WIPI peaks sharply, reflecting

widespread *mass civil protest* in many countries, while the WGI registers only a moderate increase. We argue that the protests, demonstrations, and strikes that occurred around the world against responses to the COVID-19 pandemic certainly have raised the degree of political instability and therefore should be covered by a reliable index.

Nonetheless, we find a strong correlation in countries like the United States (0.56) and China (0.38), suggesting that for these regions, the two indices generally track political instability in a comparable manner. Important differences can be found, for instance, in the US in 2021, the year of the Capitol riot, in which the WIPI peaks while the WGI shows a decline in political instability. We can also find moderate correlations between the indices for France, and Italy, while the for Germany, the Russian Federation and the United Kingdom the dynamics tend to diverge. In Germany, the WIPI suggests a relatively stable level of political instability, while the WGI shows a steady increase since 2005. In the Russian Federation, both indices tend to spike in the same quarters and reveal elevated political instability since 2018. However, while the WGI indicates a decreasing trend of instability, the WIPI shows the opposite trend, resulting in a low overall correlation of 0.12.

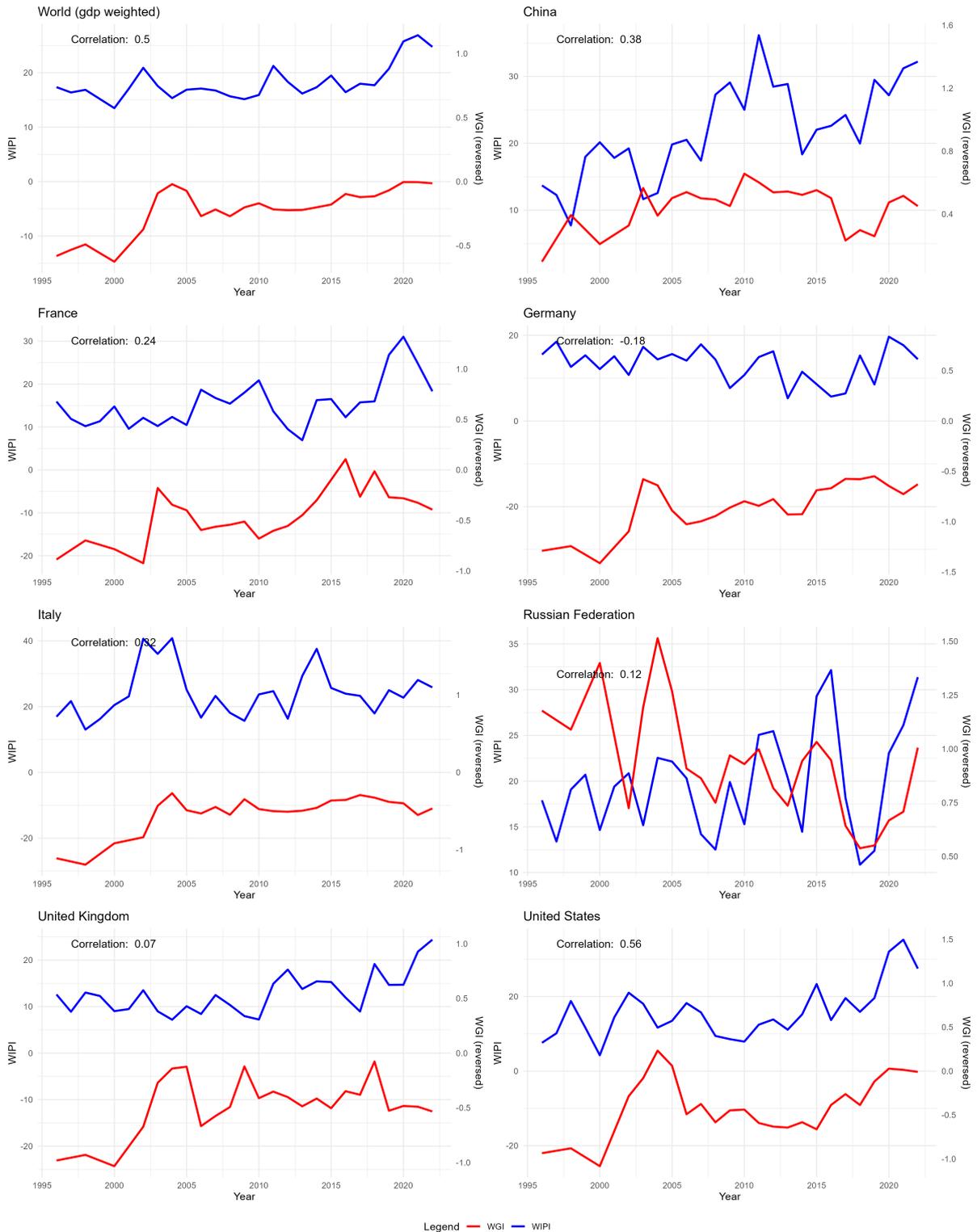
Table 2 shows the correlation between the WIPI, the WGI, and several political instability indices from various sources, namely the *Economist Intelligence Unit Riskwire*

Table 2: Cross-Correlation Table

| Variables | WIPI | WGI | EIU | HUM | PRS | WMO |
|-----------|------|------|------|------|------|-----|
| WIPI | | | | | | |
| WGI | 0.58 | | | | | |
| EIU | 0.42 | 0.54 | | | | |
| HUM | 0.36 | 0.67 | 0.41 | | | |
| PRS | 0.15 | 0.18 | 0.45 | 0.19 | | |
| WMO | 0.49 | 0.89 | 0.53 | 0.54 | 0.21 | |

Notes: This table shows the correlation between the the *World Index of Political Instability* (WIPI), the *WGI of Political Stability and the Absence of Violence* (WGI), the *Economist Intelligence Unit Riskwire & Democracy Index* (EIU), the *Cingranelli Richards Human Rights Database and Political Terror Scale* (HUM), the *Political Risk Services International Country Risk Guide* (PRS), and the *Global Insight Business Conditions and Risk Indicators* (WMO).

Figure 5: WIPI and WGI between 1996 and 2022



Notes: The figure shows yearly averages of the *World Index of Political Instability* compared with the *World Governance Indicator of Political Stability and Absence of Violence* (WGI)(Kaufmann et al. (2010)) between 1996 and 2022 for 182 countries. To aggregate global indices, GDP weights are employed. The WGI is inverted since it does not measure instability but stability.

& Democracy Index, the Cingranelli Richards Human Rights Database and Political Terror Scale, the Political Risk Services International Country Risk Guide, and the Global Insight Business Conditions and Risk Indicators. Note that in contrast to Figure 5, where the world WIPI and WGI are weighted by GDP, we show here the mean of the country correlations (i.e., simple average). Compared to Figure 5 the overall correlation depicted in Table 2 between the WIPI and the WGI is 0.58 and, thus, slightly larger than the correlation between the GDP weighted global averages. This indicates that the correlation between both measures is even stronger for countries with a relatively small GDP, i.e., the vast majority of countries. Not surprisingly, our index also has a strong correlation with the *Riskwire & Democracy Index* from the Economist Intelligence Unit. However, we also find moderate correlations with the *Global Insight Business Conditions and Risk Indicators (WMO)* and the *Cingranelli Richards Human Rights Database and Political Terror Scale (HUM)*. The strong correlations found between several indices and the WIPI, although all indices are constructed using different methods, make us confident that we are properly measuring political instability.

3.3 Instability and Uncertainty

Although economic policy uncertainty is interconnected with political instability, it represents a distinct phenomenon with unique implications for governance and economic performance. Economic policy uncertainty pertains to the uncertainty surrounding a country's future economic policies, including taxes, regulations, and government interventions. This uncertainty often arises from ambiguous or shifting political measures, disagreements on economic policies, or ongoing debates over economic issues. In contrast, political instability, reflects the fragility or dysfunction of political institutions and the degree to which the distribution of political power is contested by internal and external factors (Dirks and Schmidt, 2024). It commonly manifests through government changes, political upheavals, social unrest or protests, and conflicts among various political factions.

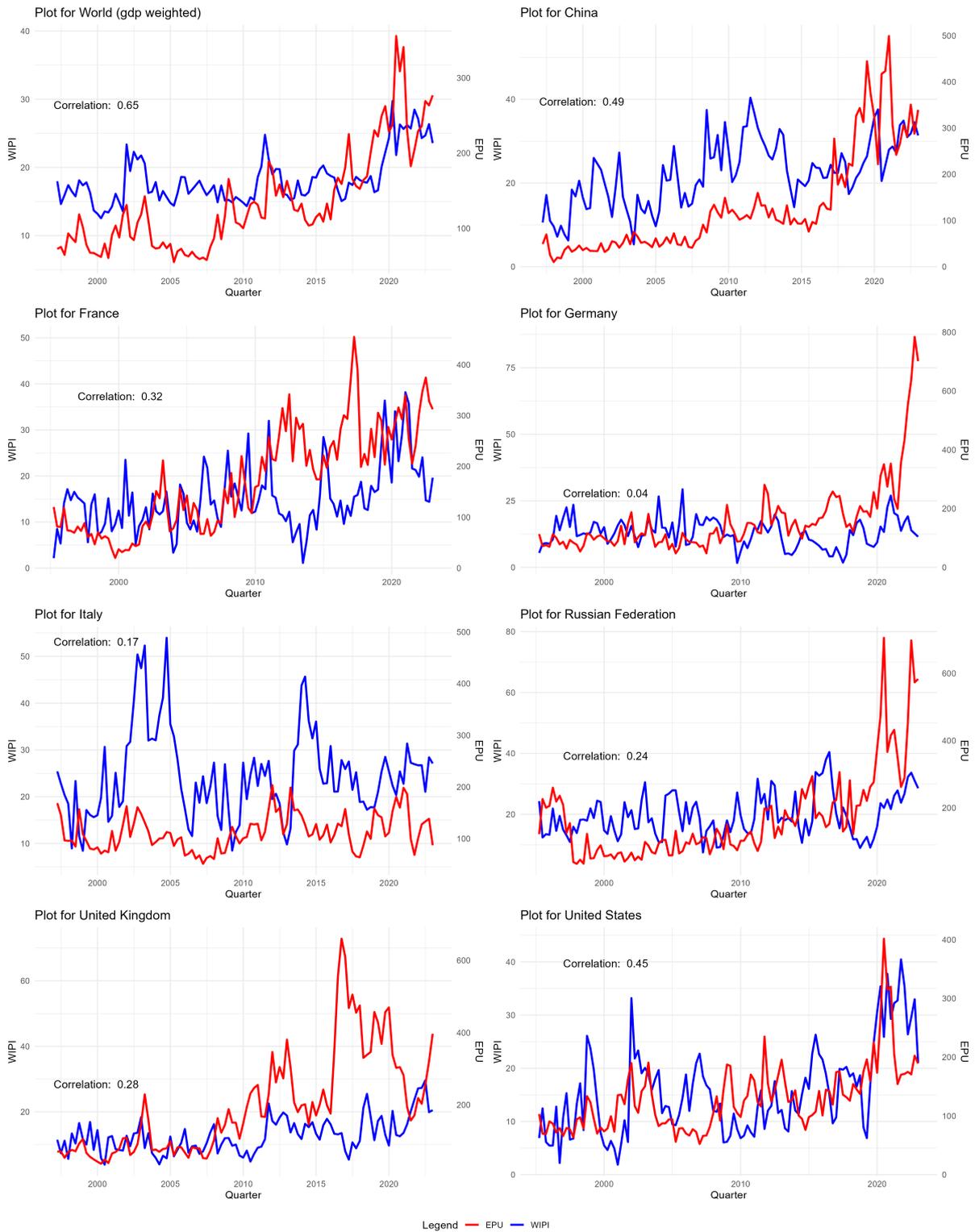
To explore the relationship between both phenomena, we assess how the WIPI compares to the Economic Policy Uncertainty (EPU) Index developed by Baker et al. (2016). We continue to focus on China, France, Germany, Italy, Russia, the UK and the US and a global aggregate as shown in Figure 6. The comparison spans the period from 1996 to

2022. We find relatively strong correlations between the two indices — around 0.65 for the world aggregate and up to 0.45 for individual countries such as the United States and China. Interestingly, our dictionary does not include any terms directly related to 'uncertainty' or 'economic policy'. At the global level, the observed correlation appears to be driven largely by major events, such as the 9/11 terrorist attacks and the COVID-19 pandemic, both of which contributed to spikes in both economic uncertainty and political instability.

Despite these similarities, key differences emerge. For instance, the WIPI does not exhibit the persistent upward trend seen in the EPU, a pattern that also holds at the country level. Events that generated considerable uncertainty in the EPU - such as the invasion of Ukraine or the Brexit referendum — do not manifest prominently in the WIPI for Russia and the United Kingdom, respectively. Other examples where peaks in both time series don't align and, in some cases, even move in opposite directions are France after 2010 or Italy during the early 2000s. These discrepancies underscore the conceptual distinction between political instability and economic policy uncertainty.

Political instability can thus generate economic policy uncertainty, as an unstable political environment often introduces uncertainty about economic policies and decisions, exacerbating economic policy uncertainty. Likewise, an economic uncertain environment with a shaking economy may lead to political instability. Running a Panel Granger Causality analysis on a sample of 15 major economies for which EPU and WIPI data is available since 2000 using monthly data confirms a one-directional causation from political instability to economic policy uncertainty. Specifically, the Dumitrescu and Hurlin (2012) panel Granger test estimated using monthly data and 12 lags indicates that the WIPI Granger-causes the EPU significantly with a \tilde{Z} statistic of -2.088 and a p -value = 0.0368 , while the reverse relationship is not statistically significant ($\tilde{Z} = -0.9554$, $p = 0.3394$). This result is robust to a different number of lags.

Figure 6: WIPI and the EPU between 1996 and 2022



Notes: The figure shows quarterly averages of the *World Index of Political Instability* compared with the *Economic Policy Uncertainty Index* by Baker et al. (2016) between 1996 and 2022 for a selection of countries. To aggregate global indices, GDP weights are employed.

4 The Business Cycle Effects of Political Instability

To examine the dynamic effect of political instability on the business cycle, we estimate a set of local projections in a panel framework using monthly data. We are interested in four macroeconomic variables closely linked to the business cycle: industrial production as a monthly proxy for economic output, prices, interest rates, and economic expectations.

4.1 Methodology

Our empirical strategy follows the standard local-projections framework of Jordà (2005), which allows us to trace the dynamic response of macroeconomic variables to changes in political instability without imposing a full-system parametric structure as in vector autoregressions. Plagborg-Møller and Wolf (2021) show that when local projections include sufficiently many lags, they recover the same population impulse responses as unrestricted VARs, while remaining robust to model misspecification.

Following these insights, we include 12 lags of economic activity, prices, interest rates, expectations, and political instability in all regressions. This lag length captures slow-moving macroeconomic adjustments and aligns with common practice in the related literature applied to monthly macroeconomic data. Further, we control for country-fixed effects to tackle time-invariant factors such as different political systems. Thus, we estimate the following baseline model:

$$Y_{i,t+h} - Y_{i,t-1} = \sum_{l=1}^{12} \beta_{h,l} Y_{i,t-l} + \sum_{l=1}^{12} \gamma_{h,l} WIP I_{i,t-l} + \mu_{i,h} + \varepsilon_{i,t+h} \quad (1)$$

where $Y_{i,t}$ is one of the four business cycle variables: industrial production, prices, economic expectations, and interest rates and $WIP I_{i,t}$ is the country-specific *World Index of Political Instability* standardized by the World WIPI. The parameter h denotes the projection horizon. $\gamma_{h,l}$ and $\beta_{h,l}$ are the projection coefficients and $\varepsilon_{i,t+h}$ is the projection error term. Country fixed effects are denoted by $\mu_{i,h}$. We note that the Nickell bias should not affect our results since our time dimension is long (Judson and Owen, 1999).

The coefficient $\gamma_{h,1}$ gives the cumulative impulse responses of an increase in one-month-lagged political instability by one standard deviation corresponding to approximately 10.8 index points, or 64% of the sample mean. This represents a shift from the median to roughly the 85th percentile of the WIPI distribution. Importantly, a political

instability shock does not necessarily correspond to a single discrete event. Rather, it reflects an unexpected deterioration in the political environment within a given month — whether triggered by a specific incident such as a terrorist attack or coup attempt, or by a sudden intensification of broader political tensions such as mass protests, constitutional crises, or coalition breakdowns. Nevertheless, to illustrate the magnitude of such a shock, we identify several episodes in which the WIPI increases by approximately one standard deviation. For the United States, such jumps occur during the political turmoil surrounding the early stages of the COVID-19 pandemic; for Spain during the 2004 Madrid bombings and the 2017 Catalan independence crisis; for France during the 2005 riots and the 2018–2019 Yellow Vest movement; for Italy during the 2011 sovereign debt crisis; for Brazil during the 2002 pre-election instability and the 2014–2018 protest and impeachment cycle; for Japan following the 2011 Fukushima disaster; for South Korea during the 2008 candlelight protests; and for Germany during the 2003 Hartz IV reform unrest and the onset of the 2008 financial crisis.

The sample consists of 36 OECD and BRICS countries since 2000 encompassing almost 80% of global GDP, for which monthly data was available for a sufficient duration.³ Industrial production data, sourced from the World Bank, is expressed in logarithmic form. Prices are measured using the Consumer Price Index in logarithmic form, too. Economic expectations are primarily gauged through the Purchasing Manager Index (PMI); when unavailable, the Manufacturing Confidence Indicator from the OECD or the Economic Sentiment Indicator from the European Commission is used. Data on expectations is standardized by country. Furthermore, we use policy rates as a measure for interest rates. For Eurozone member states, shadow rates are used in place of the ECB policy rate. In total, the dataset comprises nearly 9,000 observations.

4.2 Results

Figure 7 plots the estimated impulse response functions derived from local projections. Specifically, we show the estimated coefficients γ_h , which capture the effect of a one standard deviation shock to the WIPI on each business cycle variable at horizon h .

³These countries include Austria, Belgium, Brazil, Canada, China, Colombia, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Italy, Japan, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Russia, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

On average, political instability propagates through the economy with a notable delay. In the first 10 to 12 months following a shock to political instability, neither economic expectations nor industrial production and prices show significant responses. We also observe no effect on interest rates. This suggests that economic agents do not immediately react to the sudden onset of political instability. However, once expectations begin to adjust — typically after about a year — we observe a pronounced and prolonged negative response in expectations. In line, industrial production declines by roughly 0.5 percentage points on average and remains decreased for more than a year. Prices also decline, by about 0.3 percentage points, although the response emerges more gradually. These dynamics are consistent with a demand-side contraction. At longer horizons, the impulse responses of expectations and industrial production gradually return toward zero and become statistically insignificant, whereas the decline in prices persists.

How do our findings compare to the existing literature along the estimated signs, dynamics, and effect magnitudes? We note that the estimated effects of political instability on industrial production and economic expectations align with established empirical evidence: the economy tends to contract following a shock to political instability, a pattern consistently documented in prior research (Alesina and Perotti, 1996; Perotti, 1996; Uddin et al., 2017; Aisen and Veiga, 2013; Dirks and Schmidt, 2024). In contrast to Aisen and Veiga (2006), who find a positive effect of political instability on prices, our results indicate a short-run decline in prices. However, given that their analysis focuses on long-term effects while ours captures short-term dynamics, the findings are not directly comparable. Taken together, our results suggest that shocks to political instability propagate through the economy in a manner similar to demand-side shocks — characterized by delayed but persistent effects on output and expectations. This pattern is well known from the uncertainty literature but represents a novel contribution to the literature on political instability. In terms of magnitudes, Dirks and Schmidt (2024) find that a one-standard deviation shock to the WGI of political instability is estimated to reduce GDP growth by 0.7 percentage points in the first year and by 1.3 percentage points over three years. Within the related literature, this estimated effect lies at the lower bound of reported values (see Dirks and Schmidt (2024) for a discussion). In our monthly setting, the impulse response functions imply that industrial production declines by about 0.5 percentage points one year after a shock of the WIPI

by one standard-deviation and remains at roughly that lower level for another year. Therefore, the estimated magnitude is smaller than the growth-rate effects reported by Dirks and Schmidt (2024). However, comparing effect sizes across studies is challenging, as existing research relies on different measures of political instability, focuses on long-term growth rather than business cycle dynamics, and uses lower-frequency data. Moreover, a one-standard-deviation movement in WGI and WIPI is comparable only in a relative sense. Each reflects a shock of similar size within its own distribution, but the underlying political phenomena and transmission mechanisms may differ.

These findings contribute to the literature by demonstrating that political instability has short-run macroeconomic consequences that go beyond long-run effects. By using a high-frequency measure of instability and focusing on monthly business cycle indicators, we provide the first systematic evidence that political instability can act as a short-run demand-side shock, offering a more nuanced understanding of how political instability influences macroeconomic outcomes.

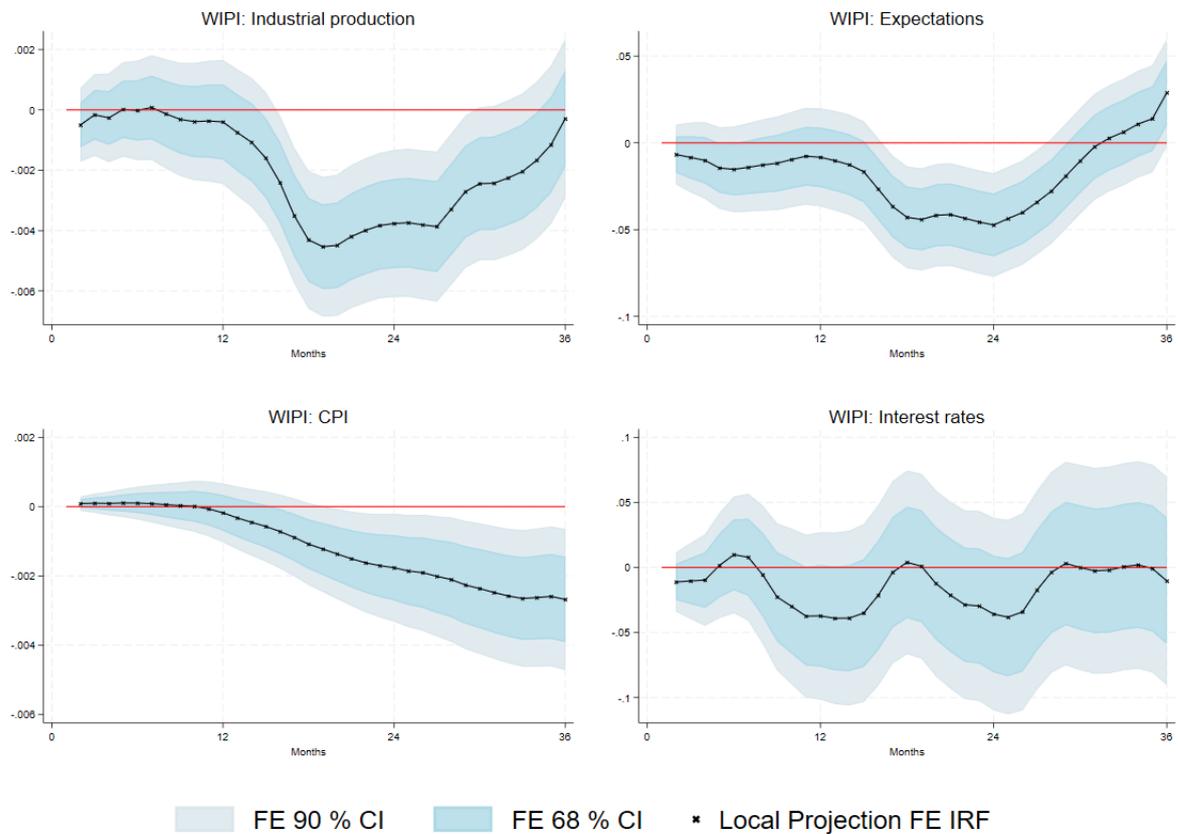
4.3 Robustness

To reinforce the robustness of our findings, we assess the sensitivity of our results to model specification by estimating a battery of alternative specifications. This allows us to verify whether our baseline results hold under different assumptions and functional forms.

We start by including the Economic Policy Uncertainty index by Baker et al. (2016) in the regression estimated in Equation 1. Controlling for economic policy uncertainty allows us to isolate the variation in the WIPI that is not already explained by the economic policy uncertainty proxy. The results in Figure 8 show the response of the four macroeconomic variables included in Equation 1 if 12 lags of economic policy uncertainty are included as additional controls. The figures show that controlling for Economic Policy Uncertainty does not affect the estimated coefficients of a shock of political instability. This underscores that political instability and economic policy uncertainty are two different political phenomena with different effects on the economy.

Second, during the COVID-19 pandemic industrial production and economic expectations have dropped dramatically. This may shift model coefficients dramatically. To ensure that our results are not driven by quarantine measures adopted to limit the

Figure 7: Fixed Effects Local Projection Estimates

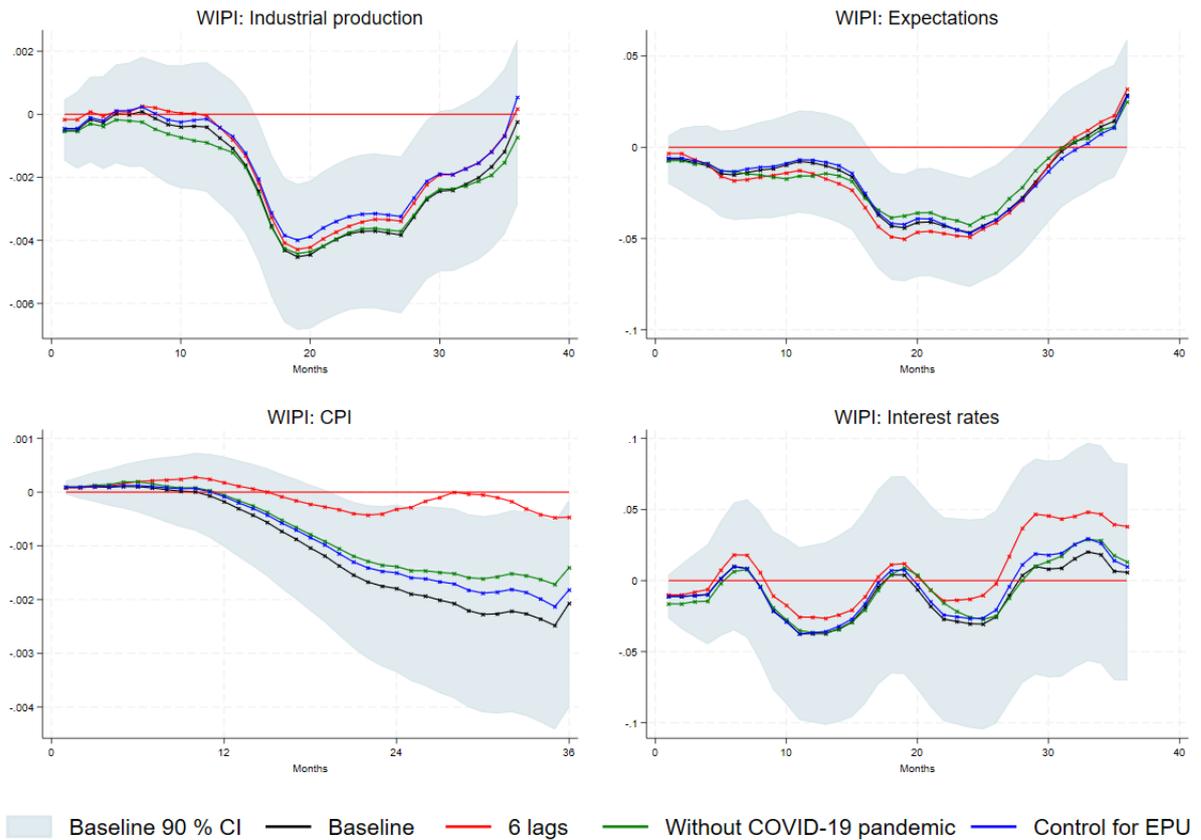


Notes: The figure shows the effect of political instability on consumer price index, interest rates, economic expectations, and industrial production employing monthly data. Monthly IRFs are smoothed using a 3-Month moving average representation, except at the end points. The IRFs show the responses to a shock of the WIPI by one standard deviation on impact and for the subsequent 36 months, i.e., 3 years. Blue areas present 68% and and light blue present 90% confidence bands.

spread of the virus and other events during the pandemic, we exclude the years most affected by the pandemic (i.e., the years 2020 and 2021) following Schorfheide and Song (2022). The results depicted in Figure 8 show the estimated coefficients are just slightly shifted and not significantly different from the baseline results. We conclude that our findings are not driven by the pandemic years.

In a third specification, we have reduced the number of lags included in the model from 12 to 6. In general, the IRFs do not drastically change compared to the baseline result. However, we can observe an important shift with respect to the estimated effects of political instability on prices: When the number of lags is reduced, the decrease in

Figure 8: Fixed Effects Local Projections for the Baseline Model and Three Different Specifications



Notes: The figure shows the effect of political instability on inflation, interest rates, economic expectations, and industrial production for the baseline model and three different specifications. Monthly IRFs are smoothed using a 3-Month moving average representation, except at the end points. The IRFs show the responses to a shock of the WIPI by one standard deviation on impact and for the subsequent 36 months, i.e., 3 years.

prices becomes much smaller. The reason for this is likely that prices respond more slowly to political instability than other business cycle variables, such as expectations or industrial production. By shortening the lag structure, the model captures fewer of the delayed transmission channels through which instability affects inflation. As a result, the estimated price response becomes attenuated, reflecting the model’s reduced ability to account for more persistent and lagged effects.

4.4 Heterogeneities across Dimensions

Although the negative effects on industrial production and prices are similar to uncertainty shocks, the observed dynamic is different. Studies analyzing the effects on uncertainty on business cycle variables tend to document a faster reaction, often within the first few quarters (e.g. Bloom, 2009; Baker et al., 2016; Caldara and Iacoviello, 2022). We note that the WIPI aggregates events of four different dimensions of political instability that may affect the economy through different transmission channel.

To analyze the contribution of each dimension to the baseline effects, we therefore decompose the WIPI into its four subindices: *political violence*, *protest*, *instability within the political system* and *instability of the political regime*. We estimate:

$$Y_{i,t+h} - Y_{i,t-1} = \sum_{l=1}^{12} \beta_{h,l} Y_{i,t-l} + \sum_{l=1}^{12} \gamma_{h,l} WIPIDim_{i,t-l} + \mu_{i,h} + \varepsilon_{i,t+h} \quad (2)$$

where $WIPIDim$ is a vector of the four subindices of the WIPI representing one of four dimension of political instability.

The results, presented in Figure 9, reveal notable variation across dimensions. We find that the baseline results are primarily driven by shocks related to *political violence* and *instability within the political system*, as these have the strongest effects, especially on industrial production and prices. However, the dynamic responses to these shocks differ strongly. Shocks in *political violence*, which likely generate immediate uncertainty and a sharp deterioration in confidence, trigger rapid declines in industrial production and expectations. In contrast, shocks related to *instability within the political system* result in a more gradual adjustment, with economic effects materializing only after a delay.

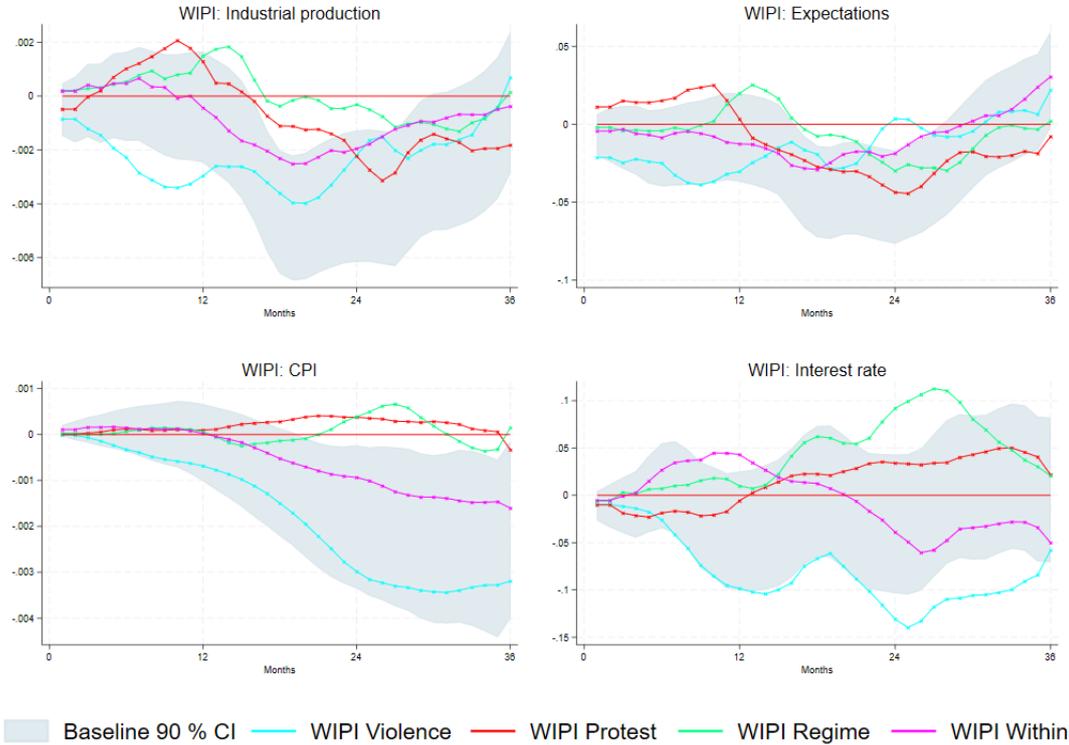
The estimated coefficients following a shock in *protest* are even smaller, while a shock in the *instability of the political regime* appears to have no effect. This is not unexpected: protests and strikes typically represent milder forms of instability. Meanwhile, revolutions and rebellions — the most extreme expressions of regime instability — are rare occurrences in the countries included in our sample, which explains their limited influence.

While most impulse responses exhibit broadly similar dynamics with different intensities, the responses of interest rates show considerable variation across different types of shocks. Specifically, a shock in *political violence* tends to reduce interest rates,

consistent with its pronounced negative impact on industrial production and prices. In contrast, a shock in the *instability of the political regime* dimension leads to an increase in interest rates. This heterogeneity in the responses helps explain the insignificant overall effect observed in the baseline estimate.

The analysis indicates that the delayed economic response to a WIPI shock is primarily driven by the dimension of *instability within the political system*, whereas shocks to *political violence* trigger a faster adjustment.

Figure 9: Fixed Effects Local Projections by Dimension of Political Instability



Notes: The figure shows the effect of each dimension of political instability on consumer price index, interest rates, economic expectations, and industrial production employing monthly data. Monthly IRFs are smoothed using a 3-Month moving average representation, except at the end points. The IRFs show the responses to a shock of the WIPI by one standard deviation on impact and for the subsequent 36 months, i.e., 3 years. Blue areas present 68% and light blue present 90% confidence bands.

4.5 Heterogeneities across Income Levels

The sample includes a diverse set of countries, ranging from developing economies such as Brazil, Colombia, India, and South Africa to advanced economies like the G7 nations, as well as Norway, Luxembourg, and Switzerland. Given the variation our sample, a uniform analysis may obscure important country-specific dynamics. Conducting a heterogeneity analysis allows us to uncover whether and how the effects of the WIPI differ systematically across income levels.

We examine heterogeneities in the estimated impulse responses depending on different country income levels. We estimate:

$$Y_{i,t+h} - Y_{i,t-1} = \sum_{l=1}^{12} \beta_{h,l} Y_{i,t-l} + \sum_{l=1}^{12} \gamma_{h,l} WIPI_{i,t-l} + \sum_{l=1}^{12} \delta_{h,l} WIPI_{i,t-l} \times D_i^{Low} + \mu_{i,h} + \varepsilon_{i,t+h} \quad (3)$$

We include the interaction term $WIPI_{i,t-l} \times D_i^{Low}$, where D_i^{Low} is a low-income dummy and δ is the associated interaction coefficient. The low-income dummy is equal to one if a country's GDP per capita is below the samples median. Since D_i^{Low} is time-invariant, its individual effect is absorbed by the country fixed effects $\mu_{i,h}$ and therefore not separately identified in the regression equation.

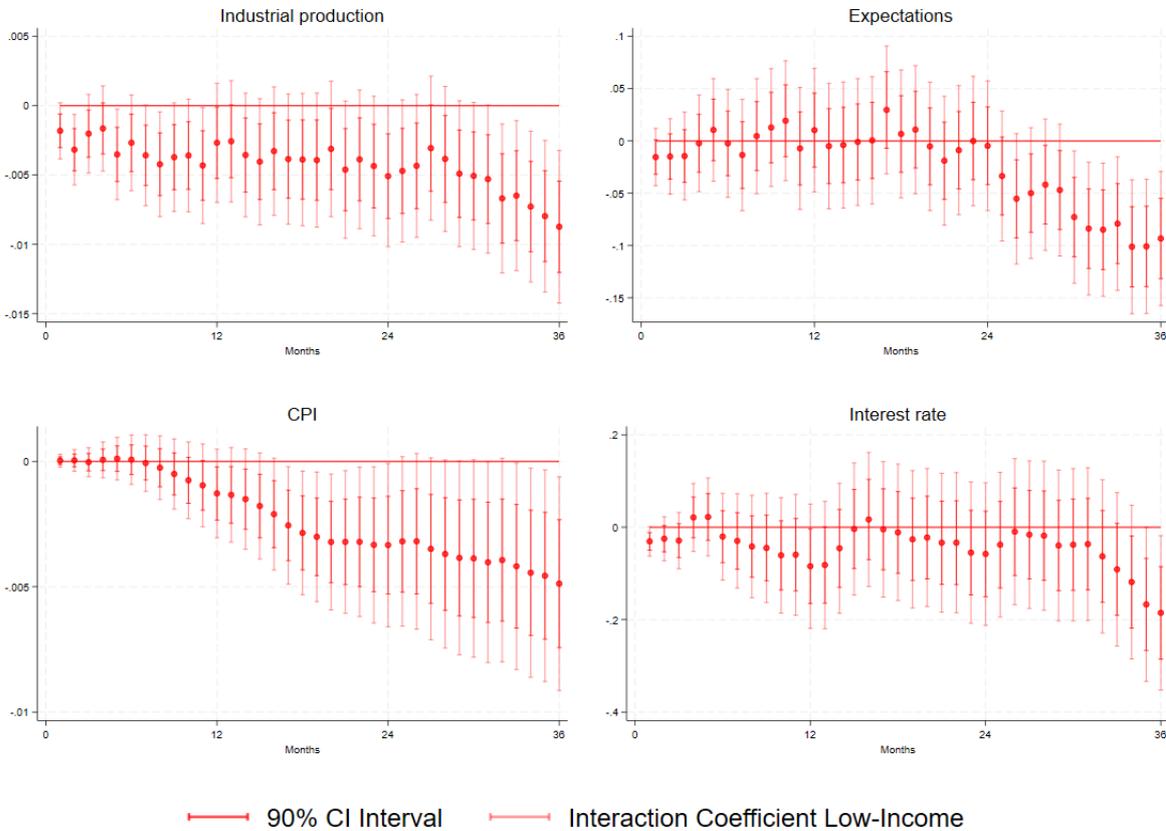
The interaction coefficient captures the difference in the WIPI responses between the low-income and high-income country groups. Figure 10 presents the estimated interaction coefficients for the four macroeconomic business cycle variables under investigation. Overall, most of the interaction coefficients are statistically insignificant. This suggests that our main results are not solely driven by countries at either end of the GDP per capita distribution. However, for industrial production and the consumer price index the interaction coefficients are predominantly negative. Several of these coefficients are statistically significant.

We therefore conclude that, although the majority of interaction coefficients are not statistically significant, the consistently negative signs — particularly for industrial production and CPI — offer suggestive evidence: Countries with below-median GDP per capita experience stronger negative responses of industrial production and prices to a shock of political instability. While these findings should be interpreted with caution, they suggest a potential pattern worth exploring in future research.

4.6 Heterogeneities across Phases of the Business Cycle

Next, we analyze whether the impact of political instability on key macroeconomic variables varies across different phases of the business cycle. The literature on uncertainty shocks suggests that their macroeconomic effects are amplified during recessions. Caggiano et al. (2014) show that uncertainty shocks are substantially more contractionary in downturns, as firms and households become more risk-averse, financial fric-

Figure 10: Heterogeneous Effects between High and Low-Income Countries



Notes: The figure shows the difference of the effect of a one-standard deviation shock to political instability on the consumer price index, interest rates, economic expectations, and industrial production between low-income and high-income countries, using monthly data over a 36-month horizon. Results are based on interaction coefficients of the WIPI and a high-income dummy estimated within a panel local projection framework. High-income countries serve as the reference group; thus, the plotted coefficients capture the additional response in low-income countries relative to high-income countries. We employ a median-split by GDP-per-capita for country grouping. Shaded areas indicate 90% confidence intervals.

tions intensify, and the policy space to offset adverse shocks is limited. Since political instability represents an important source of uncertainty, we expect a similar pattern: the negative effects of political instability should be stronger when the economy is already in recession, thereby amplifying contractions in demand, production, and expectations.

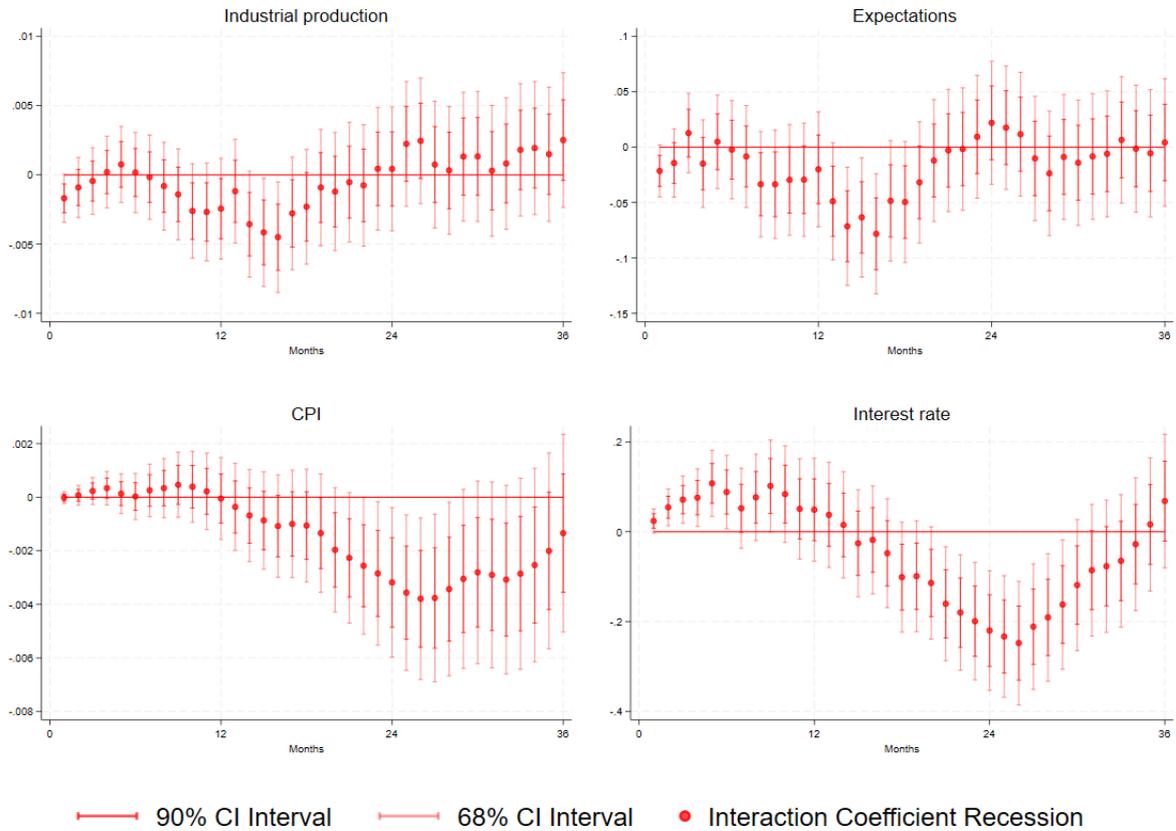
To assess this, we augment our baseline specification by interacting the WIPI with a recession dummy, $D_{i,t}^{Recession}$. The coefficient ρ of this interaction term captures the additional effect of a political instability shock when a country is in a recession compared to periods of expansion. We estimate:

$$Y_{i,t+h} - Y_{i,t-1} = \sum_{l=1}^{12} \beta_{h,l} Y_{i,t-l} + \sum_{l=1}^{12} \gamma_{h,l} WIPI_{i,t-l} + \sum_{l=1}^{12} \rho_{h,l} WIPI_{i,t-l} \times D_{i,t}^{Recession} + \mu_{i,h} + \varepsilon_{i,t+h} \quad (4)$$

The empirical literature proposes several ways to disentangle recessions from expansions and define $D_{i,t}^{Recession}$. For the United States, the National Bureau of Economic Research provides a well-used chronology of business cycle. However, comparable dating is not available for other countries of the sample. A common data-driven approach, the so-called *newspaper* definition, defines a recession period as two consecutive quarters of negative GDP growth. While easy to implement, the rule has been widely criticized for its mechanical nature, since it classifies recessions solely on short-term GDP movements without considering their severity, persistence, or scope across the economy (Hamilton et al., 2003). Alternatively, some studies use the unemployment rate as an indicator of times of slack (Ramey and Zubairy, 2018), but consistent monthly unemployment data are unavailable for several of the countries in our sample over the whole period. We, therefore, employ the Bry–Boschan approach as it is well-known and accepted in the literature and easily applicable for our sample.

The Bry–Boschan approach provides a rule-based method to divide a time series into an expansion and recession phase, characterized by sustained increases or decreases in economic activity (Bry and Boschan, 1971). These phases are connected by peaks and troughs: a peak marks the end of an expansion and the start of a contraction, while a trough indicates the opposite. Following Harding and Pagan (2002), we define a local peak (trough) as an observation that exceeds (falls below) its surrounding values within a symmetric time window, five months on either side. To ensure economic relevance, Harding and Pagan (2002) suggest that each phase must last at least six months and that

Figure 11: Heterogeneous Effects in Periods of Recession



Notes: The figure shows the difference in the response to a one-standard deviation shock to political instability across four macroeconomic indicators – consumer prices, interest rates, economic expectations, and industrial production – during recessionary periods, over a 36-month horizon using monthly data. Results are based on interaction coefficients of the WIPI and a recession dummy estimated within a panel local projection framework. The coefficients represent the additional effect of instability when a country is in recession. Recessions are identified using the Bry–Boschan (BBQ) algorithm applied to industrial production.

a complete cycle has a minimum duration of fifteen months. As monthly GDP data is not available, we identify peaks and troughs in the time series of industrial production.

The estimated coefficients, $\rho_{h,l}$, of the interacted terms are reported in Figure 11 over a 36-months horizon. Overall, the results indicate that shocks to political instability are more contractionary during recessions than during expansions. In particular, following a political instability shock in a recession, interest rates rise significantly within the first six months. The observed tightening of monetary conditions in response to political instability is unlikely to reflect a deliberate policy reaction. Rather, it appears to stem

from heightened perceived risk and uncertainty, which increase borrowing costs and risk premia, thereby tightening financial conditions endogenously. As higher interest rates depress aggregate demand, expectations deteriorate more strongly than after a similar shock in an expansion, leading to an additional decline in industrial production of nearly 0.5 percent one year after the shock. Eventually, weaker demand results in lower price pressures. The results are robust when the *newspaper* definition of recessions is employed.

5 Conclusion

This study contributes to the literature on political instability by providing the first multidimensional and high-frequency index of political instability, the *World Index of Political Instability*, available since 1960. Using text mining techniques we exploit information on political instability from EIU Country Reports to cover four dimensions of political instability: *political violence*, *mass civil protests*, *instability within the political regime*, and *instability of the political regime*. We propose an index for each of the four dimensions of political instability and a composite index for 182 countries.

Our index provides valuable insights into the development of political instability over time and highlights differences between countries and regions. First, we note that more developed nations are associated with a lower degree of political instability. Second, global surges in political instability have occurred during the civil rights movements in the 1960s, during the collapse of the Soviet Union, after 9/11, the Arab Spring and since the pandemic years. Third, some dimensions of political instability are more prevalent in certain countries. While the occurrence of *political instability within the political regime* and *mass civil protest* are the most prevalent dimensions in advanced economies, *political violence* and *instability of the political regime* are much more important in developing countries. To assess the validity of our index, we show a strong correlation between our index and existing frequently applied indices of political instability, such as the *World Governance Indicator of Political Stability and the Absence of Violence*. We further show, that political instability and political uncertainty are related but distinct political phenomena.

The WIPI enables the first analysis of the short-term business cycle effects of political instability using monthly data. Employing local projection methods, we find that

shocks to political instability propagate with a notable delay but ultimately resemble demand-side shocks in their impact. Economic expectations deteriorate immediately, and industrial production falls by about 0.5 percent one year after the shock, remaining at roughly that lower level over the subsequent year. Prices also exhibit a downward response of around 0.3 percent, though this effect materializes more gradually. The observed contraction of the economy aligns with the related empirical literature. The demand-side shock pattern is well known from the uncertainty literature. However, the observed dynamics differ from those, as uncertainty shock typically produces faster responses. Low-income countries and shocks in *political violence* appear to be the main driver of the identified effects. Furthermore, we show that a shock in political instability is more contractionary during recessions than during expansion periods. Finally, the results prove robust across various specifications.

The WIPI offers a new empirical tool for analyzing political instability at high frequency, opening the door to research questions that were previously out of reach. Its ability to capture short-term fluctuations in instability enables scholars to investigate transmission mechanisms, policy interactions, and country heterogeneity with greater precision. Moreover, by allowing for real-time tracking of political risks, the WIPI can support more responsive and forward-looking economic and political decision-making in periods of heightened instability.

References

- Ahir, H., N. Bloom, and D. Furceri (2022). The World Uncertainty Index. Technical Report w29763, National Bureau of Economic Research, Cambridge, MA.
- Aisen, A. and F. J. Veiga (2006). Does Political Instability Lead to Higher Inflation? A Panel Data Analysis. *Journal of Money, Credit, and Banking* 38(5), 1379–1389.
- Aisen, A. and F. J. Veiga (2013). How does Political Instability affect Economic Growth? *European Journal of Political Economy* 29, 151–167.
- Alesina, A. and R. Perotti (1996). Income Distribution, Political Instability, and Investment. *European Economic Review* 40(6), 1203–1228.
- Asteriou, D. and S. Price (2001). Political Instability and Economic Growth: UK Time Series Evidence. *Scottish Journal of Political Economy* 48(4), 383–399.
- Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics* 131(4), 1593–1636.
- Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica* 77(3), 623–685.
- Blum, J. and K. Gründler (2020). Political Stability and Economic Prosperity: Are Coups Bad for Growth? CESifo Working Paper 8317.
- Bry, G. and C. Boschan (1971). Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. In *Cyclical analysis of time series: Selected procedures and computer programs*. National Bureau of Economic Research.
- Caggiano, G., E. Castelnuovo, and N. Groshenny (2014). Uncertainty Shocks and Unemployment Dynamics in US Recessions. *Journal of Monetary Economics* 67, 78–92.
- Caldara, D. and M. Iacoviello (2022). Measuring Geopolitical Risk. *American Economic Review* 112(4), 1194–1225.
- Campos, N. F. and J. B. Nugent (2002). Who is Afraid of Political Instability? *Journal of Development Economics* 67(1), 157–172.
- Cascaldi-Garcia, D., C. Sarisoy, J. M. Londono, B. Sun, D. D. Datta, T. Ferreira, O. Grishchenko, M. R. Jahan-Parvar, F. Loria, S. Ma, M. Rodriguez, I. Zer, and J. Rogers (2023, June). What is certain about uncertainty? *Journal of Economic Literature* 61(2), 624–54.
- Castelnuovo, E. (2023). Uncertainty Before and During COVID-19: A Survey. *Journal of Economic Surveys* 37(3), 821–864.
- Chen, B. and Y. Feng (1996). Some Political Determinants of Economic Growth: Theory and Empirical Implications. *European Journal of Political Economy* 12(4), 609–627.

- Cukierman, A., S. Edwards, and G. Tabellini (1992). Seigniorage and Political Instability. *The American Economic Review* 82(3), 537–555.
- Dirks, M. W. and T. Schmidt (2024). Political Instability and Economic Growth: Causation and Transmission. *European Journal of Political Economy* 85.
- Dumitrescu, E. I. and C. Hurlin (2012). Testing for Granger-Non-Causality in Heterogeneous Panels. *Economic Modelling* 29(4), 1450–1460.
- Dupas, P. and J. Robinson (2012). The (Hidden) Costs of Political Instability: Evidence from Kenya’s 2007 Election Crisis. *Journal of Development Economics* 99(2), 314–329.
- Gassebner, M., J. Gutmann, and S. Voigt (2016). When to Expect a Coup d’état? An Extreme Bounds Analysis of Coup Determinants. *Public Choice* 169(3-4), 293–313.
- Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. *SSRN Electronic Journal*.
- Gentzkow, M., B. Kelly, and M. Taddy (2019). Text as Data. *Journal of Economic Literature* 57(3), 535–574.
- Grechyna, D. (2018). Shall We Riot Too? The Geographical Neighbor Impact on Political Instability: Shall We Riot Too? *Kyklos* 71(4), 581–612.
- Hamilton, J. D. et al. (2003). Comment on “A comparison of Two Business Cycle Dating Methods”. *Journal of Economic Dynamics and Control* 27(9), 1691–1693.
- Harding, D. and A. Pagan (2002). Dissecting the Cycle: a Methodological Investigation. *Journal of monetary economics* 49(2), 365–381.
- Jong-A-Pin, R. (2009). On the Measurement of Political Instability and its Impact on Economic Growth. *European Journal of Political Economy* 25(1), 15–29.
- Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review* 95(1), 161–182.
- Judson, R. A. and A. L. Owen (1999). Estimating Dynamic Panel Data Models: A Guide for Macroeconomists. *Economics Letters*, 7.
- Kaufmann, D., A. Kraay, and M. Mastruzzi (2010). The Worldwide Governance Indicators: Methodology and Analytical Issues. *World Bank Policy Research Working Paper* (5430).
- Parvin, M. (1973). Economic Determinants of Political Unrest: An Econometric Approach. *Journal of Conflict Resolution* 17(2), 271–296.
- Perotti, R. (1996). Growth, Income Distribution and Democracy: What the Data say. *Journal of Economic Growth* 1(2), 149–187.

- Plagborg-Møller, M. and C. K. Wolf (2021). Local Projections and VARs Estimate the Same Impulse Responses. *Econometrica* 89(2), 955–980.
- Ramey, V. A. and S. Zubairy (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of political economy* 126(2), 850–901.
- Schorfheide, F. and D. Song (2022). Real-Time Forecasting with a Standard Mixed-Frequency VAR During a Pandemic. *International Journal of Central Banking* 20(4), 275–320.
- Thomas, M. A. (2010). What Do the Worldwide Governance Indicators Measure? *The European Journal of Development Research* 22(1), 31–54.
- Uddin, M. A., M. H. Ali, and M. Masih (2017). Political Stability and Growth: An Application of Dynamic GMM and Quantile Regression. *Economic Modelling* 64, 610–625.
- Vu, T. V. (2021). Are Genetic Traits Associated with Riots? The Political Legacy of Prehistorically Determined Genetic Diversity. *Kyklos* 74(4), 567–595.
- Vu, T. V. (2022). Unbundling the Effect of Political Instability on Income Redistribution. *European Journal of Political Economy*, 102189.

A Appendix

Table A.1: Coverage and Frequency of EIU Country Reports I

1960 - 1999 Quarterly, Since 2000 Monthly

(72 countries, 95.4% of 2024 world GDP and 85.3% of 2024 world population)

United States, China, Japan, Germany, United Kingdom, India, France, Italy, Brazil, Canada, South Korea, Australia, Russian Federation, Spain, Mexico, Turkiye, Indonesia, Netherlands, Switzerland, Saudi Arabia (*since 1968*), Taiwan, Poland, Argentina, Sweden, Nigeria, Belgium, Ireland, Iran, Egypt, Thailand, United Arab Emirates (*since 1968*), Austria (*since 1964*), Philippines, Israel, Malaysia, Singapore, Pakistan, South Africa, Vietnam, Colombia, Hong Kong, Bangladesh (*since 1972*), Chile, Romania, Peru, Kazakhstan (*since 1993*), Czechia, Greece, Iraq, Algeria, Qatar (*since 1968*), Hungary, Morocco, Ecuador, Dominican Republic, Kenya, Venezuela, Oman (*since 1968*), Angola, Guatemala, Ukraine, Costa Rica, Ghana, Panama, Tanzania, Azerbaijan (*since 1993*), Tunisia, Uganda, Bolivia, Lebanon, Nicaragua, Mozambique (*monthly since 2006*)

1960 - 1999 Quarterly, 2000 - 2020 Monthly, Since 2021 Quarterly

(22 countries, 2.7% of 2024 world GDP and 3.5% of 2024 world population)

Norway (*since 1963*), Denmark, Finland, Portugal, New Zealand, Kuwait, Slovak Republic, Sri Lanka, Cuba, Sudan, Myanmar, Croatia, Bulgaria, Syrian Arab Republic, Libya, Jordan, Bahrain (*since 1968*), Zambia (*since 1964*), Papua New Guinea (*since 1970*), Cambodia (*since 1968, monthly 2006 - 2020*), Bosnia and Herzegovina (*monthly 2006 - 2020*), Jamaica (*since 1964*)

1960 - 1999 Quarterly, 2000 - Mid 2012 Monthly, Since Mid 2012 Quarterly

(27 countries, 1.1% of 2024 world GDP and 4.5% of 2024 world population)

Uzbekistan (*since 1993*), Ethiopia (*monthly 2006 - mid 2012*), Luxembourg, Cote d'Ivoire, Uruguay, Slovenia, Lithuania (*since 1993*), Paraguay, Cameroon, Latvia (*since 1993*), Estonia (*since 1993*), El Salvador, Cyprus (*since 1968*), Honduras, Senegal, Yemen (*since 1968*), Trinidad and Tobago (*since 1964*), Iceland, Zimbabwe, Botswana (*since 1966*), Gabon, Mauritius (*since 1974*), North Macedonia, Malawi (*since 1961*), Namibia, Equatorial Guinea (*since 1981, monthly 2006 - mid 2012*), Moldova (*since 1993*)

Table A.2: Coverage and Frequency of EIU Country Reports II

Since 1960 Quarterly

(65 countries, 0.8% of 2024 world GDP and 6.6% of 2024 world population)

Turkmenistan (*since 1993*), Puerto Rico (*since 1996*), Belarus (*since 1993*), Dem. Rep. Congo,, North Korea, Nepal (*since 1966*), Macao (*since 1984*), Georgia (*since 1993*), Laos, Afghanistan, Mali, Benin, Burkina Faso, Malta (*since 1968*), West Bank and Gaza (*since 1993*), Haiti, Mongolia (*since 1993*), Albania, Niger, Armenia (*since 1993*), Guyana (*since 1964*), Guinea, Tajikistan (*since 1993*), Madagascar, Brunei Darussalam (*since 1962*), Rwanda (*since 1963*), Bahamas (*since 1964*), Chad, New Caledonia (*since 1987*), Rep. Congo (*since 1996*), Kyrgyz Republic (*since 1993*), Togo (*since 1961*), Mauritania, Somalia, Bermuda (*since 1964*), Eritrea (*since 1993*), Maldives (*since 2019*), Sierra Leone, Cayman Islands (*since 1994*), Eswatini (*since 1966*), Fiji (*since 1971*), Barbados (*since 1964*), Suriname (*since 1976*), Liberia, Burundi (*since 1963*), Djibouti (*since 1976*), Aruba (*since 1993*), Belize (*since 1964*), Curacao (*since 2010*), Bhutan (*since 2001*), Timor-Leste (*since 2002*), Lesotho (*since 1966*), Cabo Verde (*since 1978*), Central African Republic, Gambia, Seychelles (*since 1978*), Solomon Islands (*since 1985*), Guinea-Bissau (*since 1978*), Comoros (*since 1978*), Turks and Caicos Islands (*since 1996*), Vanuatu (*since 1985*), Samoa (*since 1985*), British Virgin Islands (*since 1964*), Tonga (*since 1985*), Sao Tome and Principe (*since 1978*)

Historical States

(2 countries)

Soviet Union (*1960 - 1991*), Yugoslavia (*1960 - 1995*)

Table A.3: Dictionaries by Dimension of Political Instability I

Instability within the political system (91 words)

abdicated, abrupt election, administration shift, alienation, alignment, amendment, ascendancy, cabinet change, changes in the chief executive, disaggregation, disintegration, dismissed, divergence, durability, dynasty, early election, emergency election, estrangement, extraordinary election, flash election, fluctuation, flux, fractionalization, fragmentation, government stability, hasty election, impeach, impeached, impeachment, impromptu election, incumbency, intolerance, ministerial reshuffle, ouster, polarization, political pressure, political realignment, political re-alignment, political tension, political volatility, power struggle, preeminence, prejudice, premature election, realignment, rearrangement, reconfiguration, remodel, removed executive, removed politician, reorganization, replacement, reshuffle, resurgence, revolving door, rotation, sectionalism, segmentation, segregation, shakeup, shake-up, shuffle, snap election, social tension, solidity, splintering, stability under strain, steadfastness, steadiness, sudden election, surprise election, tenure, transfer of power, turnover, unforeseen election, unplanned election, unscheduled election, unseated, veto player who drops from office, years of largest party in office, alteration, antagonism, dissension, disunity, factionalism, modification, overhaul, partisanship, schism, sectarianism

Instability of the political regime (73 words)

anarchy, balkanization, calamity, cataclysm, catastrophe, churn, cleavage, constitutional reform, constitutional restructuring, constitutional revision, debacle, deposed, destabilization, destabilisation, divisiveness, dogmatism, executive paralysis, fanaticism, fascism, government collapse, government shakeup, government shake-up, institutional resilience, insurgency, intrigue, junta, maelstrom, major constitutional change, major government crisis, meltdown, nationalism, overthrow, political regime change, power vacuum, predicament, putsch, quagmire, racism, rebel, reformation, regime change, regime collapse, regime shakeup, regime shift, revolutionary, secession, separatism, state of emergency, succession, toppled, totalitarianism, tribalism, usurpation, voter fraud, xenophobia, zealotry, coup, coup d'etat, division, extremism, insurgency, mutiny, partition, radicalization, rebellion, revamp, revolt, revolution, sedition, transformation, turmoil, upheaval

Notes: The table shows the four dictionaries and the included *keywords* used to construct the WIPI.

Table A.4: Dictionaries by Dimension of Political Instability II

Political violence (63 words)

act of violence, animosity, assassination, bloodshed, brawl, clash, cleanse, cleansing, communalism, cull, discrimination, displacement, eliminate, elimination, enmity, eradication, ethnic tension, execution, expel, expulsion, expunge, extermination, genocide, guerrilla, guerrilla warfare, hostility, irregular warfare, liquidate, liquidation, maquis, massacre, medium civil conflict, melee, minor civil conflict, occupation, oppression, outbreak of violence, outrage, paramilitary, persecution, political violence, purging, purify, rivalry, sabotage, scuffle, security risks, seizure, suppression, supremacy, surveillance, tension, terror, terror attack, terrorism, unconventional warfare, violence, war crimes, warlord, insurrection, purge, skirmish, strife

Mass civil protest (13 words)

demonstration, disobedience, fray, protest, rally, sitin, strike, disorder, disturbance, riot, tumult, unrest, uprising

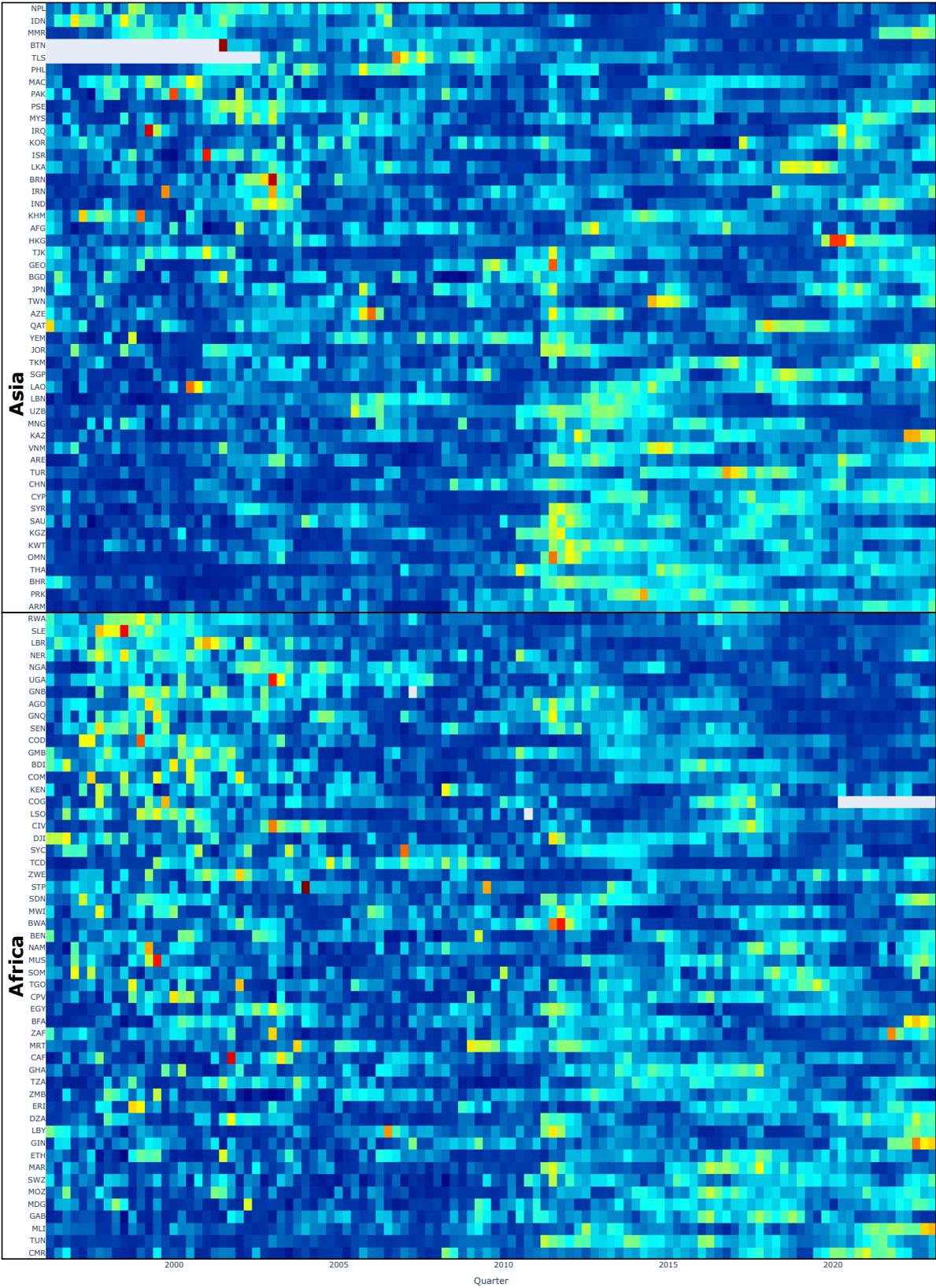
Notes: The table shows the four dictionaries and the included *keywords* used to construct the WIPI.

Figure A.1: WIPI Robustness Analysis



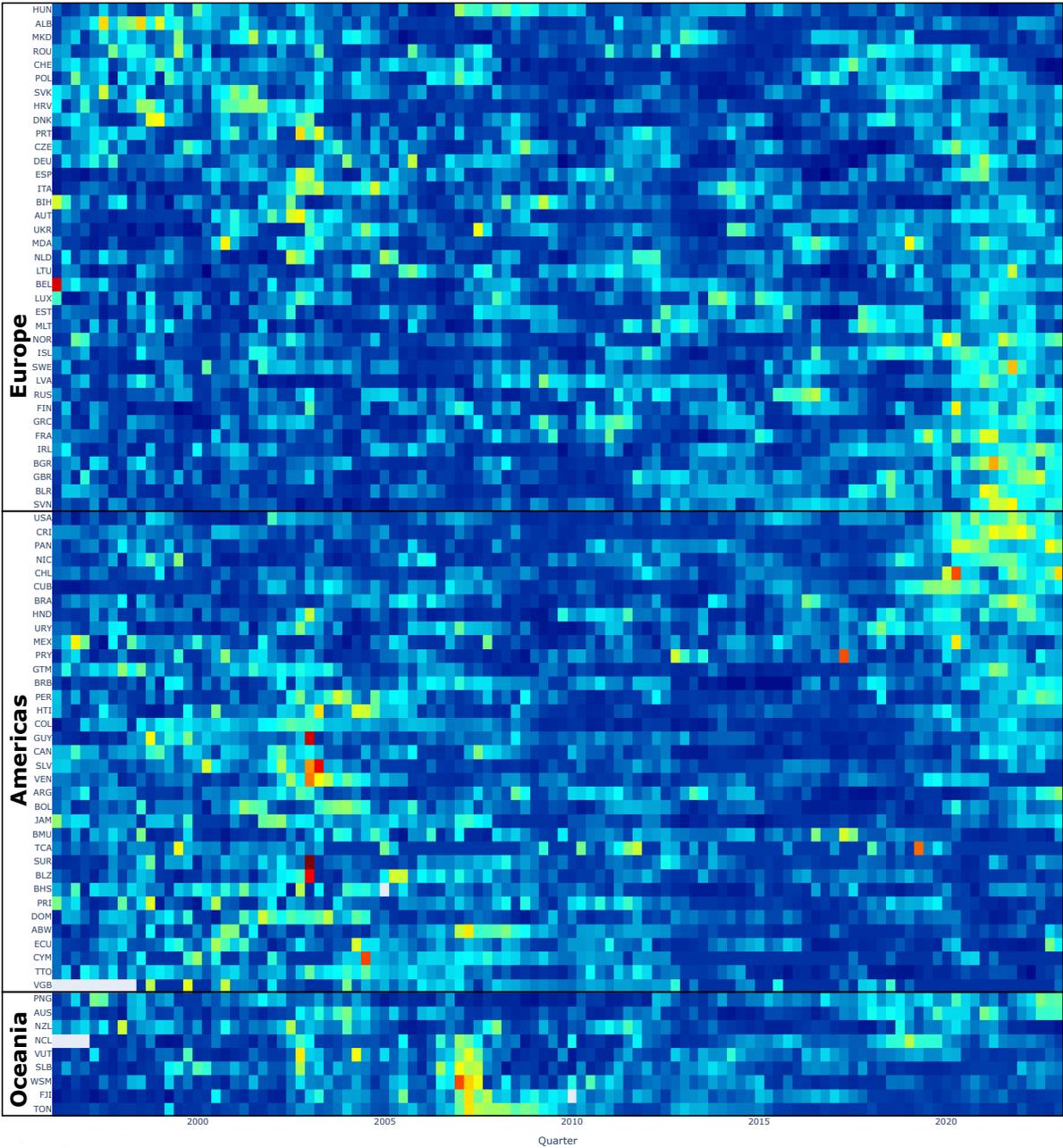
Notes: The figure displays the World WIPI (GDP-weighted) based on different construction specifications from 1960 to 2022. Panel a) shows the WIPI-25, WIPI-50, and WIPI-100 constructed using *keywords* that appeared in at least 25, 50, and 100 Gemini requests, respectively. In Panel b) we have employed a leave-one-out approach, dropping one *keywords* at a time, to report the importance of single *keywords* for our overall index. Panel c) shows the WIPI if we don't use lemmatization, while in Panel d) we applied Llama 3.1 to improve the precision of the index generation. To ensure comparability, all index variations are normalized to the variance and mean of the baseline index.

Figure A.2: Political Instability Measured by the WIPI by Country between 1996 and 2022 in Asia and Africa



Notes: The figure shows the level of political instability measured by the WIPI by country between 1996 and 2022 in Asia and Africa. Warmer colors correspond to higher WIPI scores, i.e., a higher level of political instability. WIPI scores are standardized by country.

Figure A.3: Political Instability Measured by the WIPI by Country between 1996 and 2022 in Europe, Oceania and the Americas



Notes: The figure shows the level of political instability measured by the WIPI by country between 1996 and 2022 in Europe, Oceania and the Americas. Warmer colors correspond to higher WIPI scores, i.e., a higher level of political instability. WIPI scores are standardized by country.