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The world uncertainty index

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Abstract

We construct the World Uncertainty Index (WUI) for an unbalanced panel of 143 individual countries on a quarterly basis from 1952. This is the frequency of the word “uncertainty” in the quarterly Economist Intelligence Unit country reports. Globally, the Index spikes around major events like the Gulf War, the Euro debt crisis, the Brexit vote and the COVID pandemic. The level of uncertainty is higher in developing countries but is more synchronized across advanced economies with their tighter trade and financial linkages. In a panel vector autoregressive setting we find that innovations in the WUI foreshadow significant declines in output. This effect is larger and more persistent in countries with lower institutional quality, and in sectors with greater financial constraints.

JEL: E0

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I. INTRODUCTION

Several events in recent years, including the global financial crisis, political polarization and trade conflicts, and the pandemic have raised concerns over rising economic uncertainty. Indeed, even before the COVID pandemic Kristalina Georgieva, the Managing Director of the IMF, noted on January 24th, 2020 *“If I had to identify a theme at the outset of the new decade it would be increasing uncertainty.”*

Yet, measuring uncertainty is intrinsically difficult, particularly across time and countries in a way that enables researchers to compare levels and growth rates. Uncertainty is a nebulous concept, reflecting uncertainty in the minds of consumers, managers, and policymakers about future events (that may or may not happen). It is also a broad concept since it relates to macro phenomena like GDP growth and micro phenomena like the growth rate of firms—as well as other events like elections, wars, and climate change.

Given all these challenges, it is not surprising that researchers have relied on different methods to measure uncertainty. One approach is based on the volatility of key economic and financial variables (Leahy and Whited 1996; Bloom 2009; Fernandez-Villaverde (2011), Jurado, Ludvigson and Ng (2013), and Ludvigson, Ma, and Ng, 2021). Another method is based on text-searching newspaper archives, for example, the Baker, Bloom and Davis (2016) Economic and Policy Uncertainty index, the Geopolitical Risk Index of Caldara and Iacoviello (2021), the Twitter measure of Baker et al. (2021) and the Search measure of Bontempi et al. (2021). Other researchers have tried to capture uncertainty that business executives have about the sales outlooks of their own firms (e.g., Altig et al. 2021), about disagreement or surprise indices (e.g., Bachman and Bayer 2013; Scotti 2013). However, these approaches, while all useful, share an important limitation: they are typically limited to

a set of mostly advanced economies, and for many of these countries the data are available only after the early 1990s.

To fill this gap, we constructed a new index of uncertainty—the World Uncertainty Index (WUI)—for an unbalanced panel of 143 individual countries on a quarterly basis from 1952. To the best of our knowledge, this is the first effort to construct a panel index of uncertainty for a large set of developed and developing countries. The index reflects the frequencies of the word “uncertainty” (and its variants) in the EIU country reports. To make the WUI comparable across countries, we scale the raw counts by the total number of words in each report—that is, the number of “uncertainty” words per thousand words.

We also develop category-specific measures of uncertainty, such as uncertainty spillovers stemming from economic and political events in key systemic economies (G7 economies plus China), trade uncertainty, and pandemic uncertainty.

In contrast to existing measures of economic policy uncertainty, two factors help improve the comparability of the WUI across countries. First, the index is based on a single source that has specific topic coverage—economic and political developments. Second, the reports follow a standardized process and structure, making these values reasonably comparable across time and countries. In addition, the process through which EIU country reports are produced helps to mitigate concerns about the accuracy, ideological bias and consistency of the WUI. On the downside, we only have one EIU report per country per quarter, leading to potentially quite large sampling noise.

To address potential concerns regarding accuracy, reliability and consistency of our dataset, we evaluate the WUI in several ways. First, we examine the narrative associated with the largest global spikes. Second, we show that the index is associated with greater

economic policy uncertainty (EPU), stock market volatility, and forecaster disagreement, and lower GDP growth, and tends to rise close to political elections. Finally, our index has a market use validation: commercial data providers that include Bloomberg, FRED, Haver, and Reuters carry our index to meet demands from banks, hedge funds, corporations, and policy makers.

We use the WUI to provide new stylized facts about uncertainty. Globally, in the last three decades, WUI spikes have occurred near the 9/11 attacks, the Gulf War II, the failure of Lehman Brothers, the Euro debt crisis, the UK's referendum vote in favor of Brexit, the 2016 US presidential elections, the US-China trade tensions, and the COVID-19 pandemic. Looking at the evolution of the index, we observe that global uncertainty has increased since 2012 (with the occurrence of the European debt crisis) and it reached its historical peak in the second quarter of 2020, around the beginning of the COVID-19 pandemic. This increase in global uncertainty while reflecting rising uncertainty in systematically large economies, also reflects significant uncertainty spillovers from the United States (related to US 2016 elections and trade policies) and the United Kingdom (related to Brexit) to the rest of the World. Uncertainty spikes tend to be more synchronized within advanced economies and between economies with tighter trade and financial linkages. Cross-country comparisons reveal that the level of uncertainty significantly varies across countries and is, on average, smaller in advanced economies than in the rest of world. In addition, we find that there is an inverted U-shaped relationship between uncertainty and democracy—that is, uncertainty increases as countries move from a regime of autocracy and anocracy towards democracy, it then decreases from middle to high levels of democracy.

Next, we use the index to examine the effect of uncertainty on economic activity for a large set of advanced and developing economies. Establishing casual inference is challenging because uncertainty responds to changes in economic activity. To make progress, we follow macro and micro approaches. At the macro level, we first use a vector autoregression (VAR) model to an international panel data and we show that innovations in the WUI foreshadow significant declines in output, with uncertainty innovations explaining about 3 percent of variation in GDP growth after 8 quarters. This effect is robust to several alternative specifications. We also apply a SVAR-IV approach (Plagborg-Moller and Wolf, 2021) in which we instrument the WUI with exogenous national election dates. The results of this exercise confirm that innovations in the WUI foreshadow significant declines in output.

We exploit the large country coverage of the dataset to examine whether the effect of uncertainty on economic activity varies across countries. In particular, we use the WUI to investigate whether institutional quality facilitates or mitigates the transmission of economic and political uncertainty. The results strongly suggest that the effects of uncertainty on output depend on the level of institutional quality. While the effect of uncertainty is large and persistent in countries with relatively low institutional quality, it is smaller and short-lived in countries with relatively high institutional quality. Importantly, this result holds when controlling for the level of development and its interactions with uncertainty.

Finally, we use sector-level data and a differences-in-differences strategy, to exploit sectoral differences in the exposure to uncertainty. Consistent with the theoretical work of Aghion et al. (2010) we find that uncertainty has larger effect in sectors with higher external financial dependence. These sector-level results are suggestive of a casual impact of uncertainty on output and productivity in sectors that are financially-constrained.

This paper contributes to three main strands of the literature. The first, and main motivation of the paper, is research on the measurement of uncertainty. As discussed before, we contribute to this literature by providing a new measure which is comparable for a large set of advanced and developing economies. Second, we contribute to the literature on text search methods—using newspaper archives, in particular—to measure a variety of outcomes. Examples include Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh et al. (2013), Alexopoulos and Cohen (2015) and the stream of the literature which has followed the approach of Baker et al. (2016) to measure uncertainty. The main difference in our approach is the use of on a single source that has specific topic coverage—economic and political developments—and is subject to a standardized process and structure. Third, we contribute to the voluminous research on the impact of economic and policy uncertainty on growth (see, Cascaldi-Garcia et al. 2020, for a recent review of the literature). Our main contribution to this literature is to analyze how the effect of uncertainty shocks varies across a large set of countries.

The rest of the paper is organized as follows. Section II describe the source and the methodology used to construct our uncertainty indexes. Section III presents key stylized facts of uncertainty around the world. Section IV discusses the category-specific measures of uncertainty. Section IV provides reliability test. Section VI presents analyses on the effect of uncertainty on economic activity at the country and sectoral level. Section VII concludes.

II. MEASURING UNCERTAINTY

We build a new country uncertainty index for 143 countries using the Economist Intelligence Unit (EIU) country reports. This uncertainty index is provided in full, and updated quarterly,

on the website <https://worlduncertaintyindex.com/>. To the best of our knowledge, this is the first effort to construct a panel index of uncertainty for a large set of developed and developing countries. The index captures uncertainty related to economic and political developments, regarding both near-term (e.g. uncertainty associated with elections) and long-term concerns (e.g. uncertainty engendered by the impending withdrawal of international forces in Afghanistan, or tensions between North and South Korea). This section will first briefly describe the EIU country reports, then turn to the construction of our quarterly indices.

A. Economist Intelligence Unit (EIU) country reports

The EIU—a leading company in the field of country intelligence—provides country reports on a regular basis for 189 countries. The country report typically covers politics, economic policy, the domestic economy, foreign and trade payments events, and on their overall impact on the country risk. In short, these reports examine and discuss the main economic, financial, and political trends in a country.

To put together the country reports, the EIU relies on a comprehensive network of experts that are based in the field, and country experts that are based at the headquarter. Country experts based at the headquarter have at least 5-7 years of experience. Each of the analysts is in charge of two to three countries, and visits them regularly, ensuring up-to-date and focused expertise (Musacchio 2004).

When putting together the country reports, the EIU follows a five-step process: writing the report, editing, second check, sub-editing, and production. In the writing the report step, field experts prepare a draft and send it to country experts based at headquarters.

In the editing step, country experts at headquarters integrate the draft with their own inputs, and make sure the structure of the report is consistent and standardized. They also check that the report is consistent with the EIU's global and regional views. In the second check step, a senior staff at headquarters does a thorough check of the draft. In the sub-editing step, sub-editors do a check to make sure that the report is well drafted, consistent, accurate, and do fact checking. In the production step, the report is checked to make sure that the report is properly coded and styled adequately.

B. Constructing the index

We construct the uncertainty index for the set 143 countries with a population of at least 2 million. To construct the indexes, we compiled the EIU country reports which are available in online and pdf copies from 1996Q1 onward and in digitally scanned copies from 1952—for the latter we used Optical Character Recognition (OCR) to make the files text searchable.

When compiling the reports for each country until 1999 we used the quarterly report. In 2000 for larger countries the EIU switched to producing a “Main” report each quarter and monthly “Updaters”, and we used the “Main” report. From 2008 onwards the EIU switched to monthly reporting frequency for larger countries and we used the March, June, September and December monthly reports, and from 2020Q4 we averaged across all three monthly reports in each quarter.

The approach to construct the WUI is to count the number of times uncertainty is mentioned in the EIU country reports. Specifically, for each country and quarter, we search through the EIU country reports for the words “uncertain”, “uncertainty”, and “uncertainties”.

An obvious difficulty with these raw counts is that the overall length of country reports varies across time, and across countries. Thus, to make the WUI comparable across countries, we scale the raw counts by the total number of words in each report.¹ In particular, the scale of the WUI is the number of uncertain (and its variants) per thousand of words. While the number of pages (words) is on average larger in advanced economies than in emerging and low-income countries, we do not observe systematic differences across income groups. For example, country reports for countries such as Nigeria or Egypt have a larger number of pages (words) than many advanced economies. Similarly, while the number of pages (words) increases, on average, over time we do not find systematic differences in the increase in the number of pages (words) across countries.

Two factors help improve the comparability of the WUI across countries. First, the index is based on a single source that has specific topic coverage—economic and political developments. Second, the reports follow a standardized process and structure. In addition, the five-step process described earlier helps to mitigate concerns about the accuracy, ideological bias and consistency of the WUI.

Table 1 shows the country coverage for our index, and the starting date for which the index is available for each country. It covers 37 countries in Africa, 22 in Asia and the Pacific, 35 in Europe, 27 in Middle East and Central Asia, and 22 in Western Hemisphere. This set of countries constitute 99 percent of the world' GDP in 2018.

While we collect data from the early 50s, we present the stylized facts and reliability check using data for the 90s. The reason to do this is threefold: first, this period allows to

¹ We also produce an index obtained by scaling the raw counts by the total number of pages in each report. This looks extremely similar to the index scaled by the number of words, since across the EIU reports words/page have little variation – reflecting in part the consistent editorial style across the reports.

include more countries in the sample; second, our discussion with Staff of EIU reports suggests that the accuracy and consistency of the report has increased around this time; and third, there are no other measures of uncertainty that go sufficiently back in time and cover several countries that we can use to cross-check and validate our measure.

C. The Global WUI

We display the evolution of the global GDP-weighted WUI in Figure 1 from the first quarter of 1996 to the fourth quarter of 2020. We use US\$ GDP as weights, which are calculated as 5-year centered moving average. The index spikes near the 9/11 attacks, the SARS outbreak, the Gulf War II, the failure of Lehman Brothers, the Euro debt crisis, El Niño, Europe border-control crisis, the UK's referendum vote in favor of Brexit, the 2016 US presidential elections, the US-China trade tensions and the COVID-19 pandemic.

In Figure A1 in Appendix A, we show the global WUI index based on unweighted averages. The pattern is similar to the one show in Figure 1A, with the notable exception of the absence of spike near the failure of Lehman Brothers, which was more important in developed countries. Similar evidence emerges also when using the geometric mean and the arithmetic mean on winsorized data (see Figure A1 in Appendix A).

A similar pattern also emerges when scaling the raw counts by the number of pages (see Figure A2 in Appendix A). Given the similarity of the two series, in what follows we will focus on the WUI scaled by the number of words, while all results apply also to the WUI scaled by the total number of pages.

As robustness check, we constructed two alternative versions of the WUI using different keywords: (i) neutral keywords such as ambiguous, ambivalent, dubious, erratic,

hazy, hesitant, unclear, undecided, undetermined, unpredictable, unreliable, unsettled, unsure, vague, questionable, insecure, plus uncertain (or the variant); (ii) negative synonyms count the following keywords: risk, risks, risky, precarious, unresolved, plus uncertain (or the variant). While these two versions of the index are highly correlated with the baseline WUI—the correlation is 0.91 for the neutral synonyms-version and 0.81 for the negative synonyms-version—there are also some remarkable differences (Figure 2).² First, the index based on negative synonyms shows a stronger upward trend than the baseline and the neutral synonyms index, with “negative” words being almost five times more frequent than neutral words in EIU reports. Second, the two indexes behave a bit differently around major uncertainty spikes. Most notably, Brexit has been given a negative connotation and has been characterized more as a risk than as a neutral uncertain event. Overall, we prefer our baseline version as simpler than the “neutral” alternative version and capturing less first moment shocks (or perceptions) than the “negative” version.

III. STYLIZED FACTS

In this section, we present five stylized facts based on the uncertainty index:

Fact 1: Global uncertainty has increased significantly since 2012. Figure 1 shows that global uncertainty has increased since 2012 (with the occurrence of the European debt crisis) and it reached its historical peak in the second quarter of 2020, around the beginning of the COVID-19 pandemic. As we will discuss in the next section, this increase in global uncertainty while reflecting rising domestic uncertainty in systematically large economies, also reflects significant uncertainty spillovers from the United States (related to US 2016

² See Figure A3 in Appendix A for a chart using non-normalized indexes.

elections and trade policies) and the United Kingdom (related to Brexit) to the rest of the World. Figure 3 shows this rising trend in the Baker, Bloom and Davis (2016) Economic Policy Uncertainty index to which the WUI is correlated at about 0.7).³

Fact 2: Uncertainty is higher in emerging and low-income economies than in advanced economies (Figure 4).⁴ One potential reason for this is that developing countries appear to have more domestic political shocks like coups, revolutions, and wars; are more susceptible to natural disasters like floods; and their economies are more volatile as they are more regularly hit by external shocks with less capacity to manage these shocks. At the same time, as evidenced by the high standard deviation within each income group, there is significant heterogeneity. For example, the WUI for the United Kingdom is higher than those of many emerging market and low-income countries because of the impact of the Brexit vote.

Fact 3: There is an inverted U-shaped relationship between uncertainty and democracy (Figure 5). Uncertainty is typically low in fully autocratic regimes, where the prospects of a regime change are exiguous. But as countries move from a regime of autocracy and anocracy towards democracy, uncertainty increases. Finally, we do observe that as countries move from some degree of democracy to full democracy, uncertainty slightly declines.

³ In contrast, we do not find a strong significant relation with US VIX (correlation about 0.1)—a similar low correlation is observed between the EPU and the VIX. This highlights an interesting fact that text-based measures of uncertainty have been rising since the early 2000s but financial market measures after rising until about 2010 have fallen back to low levels. As argued by Pastor and Veronesi (2016), a reason behind the disconnect between text-based uncertainty stock market volatility in recent years is that political news has been more unreliable and difficult for financial investors to interpret. Another factor is that VIX is influenced by monetary policy actions and that the expansionary US monetary policy in the post GFC period may have contributed to reduce the VIX (Bekaert et al. 2013).

⁴ The income groups classification follows the IMF WEO. Figure A4 in Appendix A provides results by regions.

Fact 4: Uncertainty spikes are more synchronized in advanced economies than in emerging and low-income countries. Following the approach of Kalemli-Ozcan, Papaioannou and Peydro (2013) to compute business cycle synchronization, we measure synchronization in uncertainty between country i and j at time t as:

$$\varphi_{i,j,t} = -|U_{i,t} - U_{j,t}| \quad (1)$$

where U denotes the WUI. Table 2 (column I) reports the average synchronization of the uncertainty index for the various income groups. It shows that uncertainty is significantly more synchronized in advanced economies than in emerging markets and low-income countries. In addition, within advanced economies, uncertainty synchronization is higher in the euro area countries. Similar findings are obtained when looking at the average pairwise correlation of the WUI (column II) and the common variance explained by the first component identified through a principal component analysis (column III). This explains why in Figure 6 uncertainty in emerging and low-income economies mostly follow the global average (because individual country shocks are not synchronized, so get averaged away). In contrast, uncertainty in advanced economies spike sharply because these countries tend to move together.

Next, we check whether the degree of synchronization between countries is associated with the strength of their trade and financial linkages. For this purpose, we estimate the following equation:

$$\varphi_{i,j,t} = \alpha_{i,j} + \gamma_t + \beta_1 TR_{i,j,t} + \beta_2 FI_{i,j,t} + \delta O_{i,j,t} + \varepsilon_{i,j,t} \quad (2)$$

where $TR_{i,j}$ denotes trade linkages—defined as bilateral trade between country i and j , normalized by the sum of total trade of country i and j ; $FI_{i,j}$ denotes financial linkages—defined as bilateral assets and liabilities between country i and j , normalized by the sum of total assets and liabilities of country i and j . $O_{i,j}$ denotes output synchronization—defined as minus the absolute value GDP growth difference between country i and j , normalized by the sum of GDP growth of country i and j . The results suggest that that trade and financial linkages are positively associated with uncertainty synchronization, even when controlling for business cycle synchronization (Table 3).

Fact 5: Uncertainty is counter-cyclical. Across advanced and developing economies, average uncertainty is larger during recessions years—defined as years of negative growth—than during non-recession years (Table 4).

IV. CATEGORIES OF UNCERTAINTY

We created indexes of uncertainty for specific categories that have significant contributed to the increase in the global WUI in recent years: (i) spillovers of uncertainty from the United States and other systemic economies; (ii) trade uncertainty; and (iii) uncertainty associated to pandemic events.

A. Uncertainty Spillovers

Economic growth in key systemic economies, like those of the United States, European Union or China is typically found to be a key driver of economic activity in the rest of the world (IMF 2017 and reference therein). Similarly, financial conditions in the United States

are identified as key drivers of the global financial cycle (e.g., Agrippino and Rey 2020). Is this also true when it comes to global uncertainty? For example, given the higher interconnectedness across countries, should we expect that uncertainty from the U.S. election, Brexit, or China-U.S. trade tensions spill over and affect uncertainty in other countries?

To answer this question, we construct an index that measures the extent of “uncertainty spillovers” from key systemic economies—the Group of 7 (G7) countries plus China—to the rest of the world. In particular, we search the country reports for the word uncertain (and its variants) appearing near words related to each country. The country-specific words include country’s name, name of presidents, name of the central bank, name of central bank governors, and selected country’s major events (such as Brexit). As for the main index, we express the counts in terms of thousand words.

This exercise reveals two key facts. First: yes, uncertainty in systemic economies matters for uncertainty around the world. Second: only the United States and the United Kingdom have had significant uncertainty spillover effects, while the other systemic economies played a little role, on average.

Starting with the United States, Figure 7.1 displays the global (excluding the United States) GDP-weighted average of the ratio of uncertainty related to the United States to overall uncertainty. It shows that uncertainty related to the United States—specially that associated with the US 2016 elections and US trade policy under President Trump—has been a key source of uncertainty around the world since the past few years. For instance, during the 2001–2003 period, U.S.-related uncertainty accounted for about 8 percent of the uncertainty in other countries—about 23 percent of the increase in global uncertainty from

the historical mean. In the last 4 years, U.S.-related uncertainty accounted for about 13 percent of uncertainty in other countries—with peaks of about 30 percent—and approximately 20 percent of the increase in global uncertainty from historical mean.

Uncertainty related to the UK-EU Brexit negotiations has also had significant global spillovers in the last 4 years, with a peak of more than 30 percent and accounting for about 11 percent in the rise in global uncertainty during this period (Figure 7.2).

Finally, the ratio of uncertainty related to the other systemic countries to overall uncertainty shows Canada, China, France, Germany, Italy, and Japan combined have little uncertainty spillover effects on the rest of the world (Figure 7.3). An exception is China in the recent years, but most of the China-related uncertainty is due to trade tensions with the United States. That said, while other systemic economies have limited global uncertainty spillovers, they have important regional uncertainty effects—such as for example, Germany for the other European economies and China and Japan for several Asian economies.

Overall, these spillover measures could be useful to quantify the economic impact of uncertainty spillovers, and potentially be used as instruments for domestic uncertainty in empirical analyses.

While, to the best of our knowledge, we are not aware of other spillover uncertainty measures, other researchers have constructed measures of US-China trade tensions and Brexit. On US-China trade tensions, Rogers et al. (2021) study text data in leading U.S. newspapers, and quantify media coverage on high or rising US-China hostility. They show that increases in US-China trade tensions lead to protracted output declines and reduced bilateral trade. Exploiting firm-level data, they find that elevated US-China hostility has persistent negative effects on investment, R&D, and hiring.

The literature on uncertainty related to Brexit has increased significantly in the past few years. For example, Bloom et al. (2018) uses survey responses from around 3,000 businesses to evaluate the level and impact of this uncertainty. It finds that Brexit uncertainty has already reduced growth in investment by 6 percentage points and employment by 1.5 percentage points, and is likely to reduce future UK productivity by half of a percentage point. Hassan et al. (2021) estimates the impact of Brexit-related uncertainty and find widespread reverberations on listed firms in 81 countries. International firms most exposed to Brexit uncertainty not only significantly lost market value but also reduced hiring and investment. Graziano et al. (2021) find that increases in the probability of Britain's exit from the European Union (Brexit) reduce bilateral export values and trade participation. These effects are increasing in trade policy risk across products. They estimate that at the average disagreement tariff of 4.5% the increase in the probability of Brexit after the referendum lowered EU–UK bilateral export values between 11–20%. Neither the EU nor UK exporters believed a trade war was likely.

B. Trade Uncertainty

We constructed a measure of trade uncertainty—the World Trade Uncertainty Index (WTUI)—by counting the number of times uncertainty (and its variants) is mentioned, in proximity to a word related to trade, in the EIU country report. Specifically, we looked at the following words: protectionism, North American Free Trade Agreement (NAFTA), tariff, trade, United Nations Conference on Trade and Development (UNCTAD) and World Trade Organization (WTO). Example of texts referring to trade uncertainty include: “uncertainty over the renegotiation of the North American Free Trade Agreement”, and “market

uncertainty over future trade policy will weigh on investor sentiment”. As for the main index, we scale the index per thousand of words.

Figure 8 reports the evolution of the global GDP-weighted average of the WTU. After having been stable at low levels for about 20 years, the index started increasing around the third quarter of 2018, coinciding with a series of tariff increases by the US and China (the US tariffs on \$34 billion of Chinese imports, and the China’s tariffs on \$34 billion of US imports). It then declined in the fourth quarter of 2018 as US and Chinese officials announced a deal to halt the escalating of tariffs at the G20 meeting in Buenos Aires in December. It significantly spiked again in the first quarter of 2019 following the tariff increase on \$200 billion of imports from China, which was scheduled to go into effect on 1 March.

Trade uncertainty increased not only in the United States and China—the economies at the center of recent trade tensions—but also in many countries around the world. Data also reveals that high levels of trade uncertainty have been recorded in key US trading partners including Canada and Mexico, Japan and large European economies, and in many other countries geographically close to the US and China. In addition, the increase in trade uncertainty, however, varied significantly both across regions and income groups. Across regions, the rise in the WTU index has been felt the most in the Western Hemisphere, followed by Asia and the Pacific and Europe. In contrast, trade uncertainty remained moderately low countries with lower trade ties with the United States and China, such as those in the Middle East and Central Asia and in Africa.

Other researchers have constructed measures of trade uncertainty focusing either on the United States (the trade component of Economic Policy Uncertainty index by Scott

Baker, Nicholas Bloom, and Steven Davis; Caldara et al. 2020) or for the whole global economy (the index of BlackRock), or for a set of 44 countries (Hlatshwayo 2021). Caldara et al. (2020) construct a firm-level measure of Trade Policy Uncertainty (TPU) and link it to firm-level investment data. They show that firms that experience larger increases in TPU accumulate less capital after one year. At the macroeconomic level, they find that a shock similar to the rise in trade policy uncertainty in 2018 induces a decline in aggregate investment of between 1 and 2%.

C. Pandemic Uncertainty

As the coronavirus continues to spread, the fear of contagion and income losses remains an important source uncertainty around the world. To quantify uncertainty related to the coronavirus crisis, we developed the World Pandemic Uncertainty Index (WPUI). To construct the index, we tally the number of times “uncertainty” is mentioned near a word related to pandemics or epidemics in the Economist Intelligence Unit (EIU) country reports. We make the WPUI index comparable across countries, by scaling the raw counts by thousands of words in each report.

Figure 9 reports the evolution of the global (GDP-weighted) average of the WPUI, and it compares the level of uncertainty during COVID-19 with that associated with other recent pandemics (SARS in 2002-03; Avian Flu 2003-09; Swine Flu 2009-10; Bird Flu 2013-17; Ebola 2014-16; MERS 2014-20). As Figure 9 shows, the level of global uncertainty related to the COVID-19 is unprecedented. Interesting, this does not reflect the fact that the COVID-19 has influenced more larger economies than previous pandemics, as it also holds when looking at the simple average (Figure A5). Looking at the simple average figure it

shows that as of the first quarter of 2020, uncertainty associated with the COVID-19 reached five times the size of the uncertainty associated with the 2002-03 severe acute respiratory syndrome (SARS) epidemic and about twenty times the size with the Ebola outbreak.

While, to the best of our knowledge, we are not aware of other measures of uncertainty related to pandemic more broadly, other researchers have looked at the increase in uncertainty associated with COVID-19. For example, Altig et al. (2021) examined several high-frequency economic uncertainty indicators for the US and UK before and after COVID-19: implied stock market volatility, newspaper-based policy uncertainty, Twitter chatter about economic uncertainty, subjective uncertainty about business growth, forecaster disagreement about future GDP growth, and a model-based measure of macro uncertainty. All these measures point to record high-levels of uncertainty at the onset of the pandemic.

V. RELIABILITY TESTS

We evaluate the WUI in several ways. First, we examine the narrative associated with the major spikes in the index to make sure that the word uncertain (or its invariant) indeed refers to economic, economic policy and political developments, either domestic or foreign, that are relevant for the short- and/or medium-term outlook of the country discussed in the EIU report. We do so for the 34 largest global economies and for the entire period from 1952Q1 up to now (see Figure A7 in Appendix A for the evolution of the WUI in these countries).⁵

⁵ The 34 countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Ireland, Israel, Italy, Japan, Korea, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Russia, South Africa, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

Reassuringly, this exercise confirms that all the spikes identified are indeed associated with “uncertain” economic and political developments.

Second, we test the relationship between our measures of uncertainty and other measures of economic uncertainty based on (i): text-searching approaches, such as the EPU index developed by Baker, Bloom and Davis (2016); and (ii) on the volatility of key economic and financial variables. Third, we check whether the WUI tends to spike during uncertain events such as political elections in democratic countries.

A. Uncertainty index versus EPU

The WUI differs from the EPU along three key dimensions: source, frequency and country-coverage. First, the sources used to construct the indexes are different. While the EPU relies on a large set of newspapers, the WUI is constructed using country reports from the same EIU source tailored to national economic and political developments. As discussed earlier this has pros and cons. On the positive side, the narrower focus of the EIU reports compared to newspapers significantly reduces the risk that the word captured by text-search does not refer to economic uncertainty. It also mitigates concerns about the ideological bias and consistency of the WUI. In addition, it can be more easily compared in levels across countries. This makes the index particularly useful to researchers that are interested in examining how cross-country variations in the level of uncertainty affect economic outcomes (for example, whether foreign investor invest more in countries with lower level of uncertainty). On the downside, we only have one EIU report per country per quarter, so a far smaller body of text than the EPU index, so the sampling noise is likely to be substantial

higher. Moreover, we are reliant on the accuracy of the EIU reports, which to our knowledge are high quality, but it still raises potential concerns over reliance on one underlying source.

Second, while the EPU is available at monthly frequency, the WUI is constructed at the quarterly frequency. Third, while the EPU is typically limited to a set of mostly advanced economies, the WUI covers a large sample of advanced and emerging markets and developing economies.

We start comparing the WUI and EPU index by plotting the average evolution of these two indicators, for the countries for which the EPU is available, in Figure 3. The global WUI shows a remarkably high correlation (0.667) with the global EPU index.⁶ A strong statistically significant relationship is also found when regressing EPU on the WUI in a panel framework and purging for country and time fixed effects (Table 5, Columns I). When looking at individual countries (see Figure A6 in the Appendix A) we similarly see a reasonably strong relationship for many of them. In six countries (Chile, China, Ireland, Spain, the United Kingdom and the United States) the correlation is above 0.4, in other six countries (Australia, Brazil, Canada, France, Germany, Greece) it is above 0.3, and for the remaining countries it is 0.2 or less.

Given the differences in the focus in the sources used to construct the WUI and the EPU (the WUI being based on country-specific reports focusing on economic and political developments, while the EPU is based on newspapers covering also global news) a possible explanation of the differences in correlations is that the EPU index tends to give more weights to global events than the WUI—that is, that EPU is more global in nature.⁷ As a

⁶ The countries included are Brazil, Canada, Chile, China, France, Germany, India, Ireland, Italy, Japan, Korea, Mexico, the Netherlands, Russia, Singapore, Spain, Sweden, the United Kingdom, and the United States.

⁷ Another explanation is that the WUI has more idiosyncratic noise.

simple test of this conjecture, we regressed the EPU and the WUI against time (quarters) fixed effects. We found results consistent with this in that while 37 percent of variation in the EPU index is explained by time fixed effects, the variance explained for the WUI by common time dummies is 22 percent (for the same set of countries and period which the EPU index is available).

Similar evidence also emerges when we look at country-specific cases. Chile is a remarkable example, despite the relatively high correlation between the two measures (0.549). EPU spikes for Chile are mostly related to global events (Asian Crisis, Sub-prime crisis, Euro zone crisis and China's slowdown) and only one spike is related to labor and tax reform (Cerda et al. 2016). In contrast, most of the WUI spikes are related to domestic uncertainty episodes (e.g., 1998Q1 uncertainty related to monetary policy decisions; 2001Q2 uncertainty related to December electoral outcomes; 2003Q3 regulatory uncertainty related to legislation for the electricity sector; 2004Q4 uncertainty regarding mining royalty; 2010Q3 uncertainty related to the earthquake; 2013Q1 uncertainty related to the electoral reform, the tax reform, and general economic conditions; 2017Q1 uncertainty regarding the presidential and legislative elections).

B. The WUI versus Volatility and Risks

We also check the correlation between the WUI and existing measures of volatility such as stock market price, exchange rate and cross-sectional volatility (all from Baker, Bloom and Terry 2022). Figure 10 reports the scatterplot between the average level of each of these measures against the average WUI for each country. It shows that the cross-country correlation between the WUI and the measures of volatility is positive, statistically

significant: 0.195 for stock market rate price volatility, 0.538 for exchange rate volatility and 0.320 for cross-sectional volatility. Similarly, the spearman's rank correlations are also positive and statistically significant: 0.208 for stock market rate price volatility, 0.505 for exchange rate volatility and 0.247 for cross-sectional volatility.

As for the EPU, we also run panel regressions between the stock market volatility and the WUI, allowing also for country and time fixed effects. The results reported in Table 5 (Columns II) suggest that the two series are statistically significantly correlated also when purging for country and time fixed effects.⁸

Given that uncertainty and risk are intrinsically related, we also check whether the WUI is positively correlated with measures of risks. For this purpose, we rely on the risk assessment provided by EIU Risk Analysis, which scores countries in terms of “economic, financial and political risk”.⁹ The results reported in Figure 11, suggest that the average level of uncertainty in each country is positively and statistically significantly correlated with these measures of risk. The correlations are very similar across different type of risk measures, suggesting that the WUI captures different aspects of economic and political uncertainty. Interestingly, the correlation is lower than with other measures of volatility, confirming that uncertainty and risk are two related but conceptually distinct concepts.

Finally, we run panel regressions between the GDP growth forecast disagreement—a common measure of macroeconomic uncertainty—and the WUI, allowing also for country

⁸ Comparable results are obtained using the EPU index instead of the WUI.

⁹ The EIU's economic risk indicator is derived from a series of macroeconomic variables of a structural rather than a cyclical nature. Consequently, the rating for economic structure risk will tend to be relatively stable, evolving in line with structural changes in the economy. The financial risk indicator assesses the risk of a systemic crisis whereby bank(s) holding 10 percent or more of total bank assets become insolvent and unable to discharge their obligations to depositors and/or creditors. The political risk indicator evaluates a range of political factors relating to political stability and effectiveness that could affect a country's ability and/or commitment to service its debt obligations and/or cause turbulence in the foreign-exchange market.

and time fixed effects. The results reported in Table 5 (Columns III) suggest that the two series are statistically significantly correlated.

C. The WUI near Elections

There is evidence from the financial literature that uncertainty tends to increase around elections. Bialkowski, Gottschalk and Wisniewski (2008) and Boutchkova, Doshi, Durnev and Molchanov (2010) examine the stock market volatility around national elections and find that volatility is significantly higher than normal during the election period. Boutchkova et al. (2010) find that the return volatility is higher around elections for firms operating in politically sensitive industries, suggesting that the increased volatility reflects a higher political risk. Bernhard and Leblang (2006) document changes in bond yields, exchange rates, and equity volatility around elections and other political changes and show that these changes are larger during elections with less predictable outcomes. Thus, a valuable check is whether the WUI is higher than normal during elections.

To test for this, we collect data on national elections in 72 countries from 1996q1 to 2019q1. The detailed election information is obtained from a variety of sources. Our main source is the official record published by each country's election authority. Among other sources we most commonly used were Bormann and Golder (2013), Adam Carr's Electoral Archive *Psephos*; Roberto Ortiz de Zárate's *World Political Leaders*; PARLINE database on national parliaments by the Inter-Parliamentary Union; *European Election Database* by Norwegian Centre for Research Data; and the "Elections in [...]" series by Dieter Nohlen and coauthors.

The resulting dataset comprises 377 elections, among which 162 are exogenously specified by electoral law and cannot be dissolved before the expiry of the government full term.

Table 6 presents bivariate regressions between the WUI index and lags and leads of elections dates, purging for country and time fixed effects. It shows that the WUI tends to increase in the quarter preceding the election date and stays above its average up to one-to-two quarters after the election. The increase in uncertainty tends to be higher in the case of exogenous elections.

VI. EMPIRICAL ANALYSIS

A. VAR Analysis

We explore the relationship between uncertainty and economic activity using VAR analysis. In particular, we fit a VAR to a quarterly unbalanced panel of 49 countries from 1970Q1 to 2020Q1. To recover orthogonal shocks, we use a Cholesky decomposition with the following order: the log of average stock return, the WUI and GDP growth. Our baseline VAR specification includes four lags of all variables. Country and time fixed effects are included. Of course, these results have no implications for causality—future slowdowns in economic activity could increase current perceptions of uncertainty—but do provide results on whether rising uncertainty predicts future growth.

Figure 12 reports the model-implied impulse response of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—and the associated 90 percent confidence bands. The figure shows that the response of output is statistically significant through the entire estimation horizon and picks at about

1.1 percent after 10 quarters of the shock. These responses are also moderate in sizes, with uncertainty innovations explaining about 3 percent of variation in GDP growth after 8 quarters.¹⁰

Figure 13 shows that the impulse response function is robust to several alternative specifications: including 7 lags instead of 4 in the VAR; placing the WUI last in the ordering, including the implied stock market volatility before the WUI, and limiting the sample to before the Global Financial Crisis (2008Q1); repeating the analysis using data before and after 1990; as well as excluding the first quarter of 2020Q1 which may be affected by uncertainty related to COVID-19. While we refrain from giving a causal interpretation to these results, they show that the innovations to the uncertainty index robustly foreshadow weaker economic performance.

Instrumenting WUI with Exogenous Elections

As discussed earlier, establishing causal inference is challenging. To make progress on this, we rely on an instrumental variable approach in which innovations in WUI are instrumented by exogenous election dates. As discussed by Julio and Yook (2012), exogenous elections provide a natural experiment framework for studying the economic implications of political uncertainty and allow to disentangle some of the endogeneity between economic growth and uncertainty.

The approach we follow is the SVAR-IV proposed by Plagborg-Møller and Wolf (2021). It consists in ordering the instrument (election dates) first in the VAR and compute

¹⁰ As a term of comparison, innovations in the average stock return explain about 13 percent of variation in GDP growth after 8 quarters.

the IV impulse response function as the ratio between the impulse response function of output to innovations in the instrument and the initial response of the endogenous variable (the WUI) to innovation in the instrument. As discussed by Plagborg-Moller and Wolf (2021), the relative impulse responses obtained from this approach are (nonparametrically) identical to those obtained from the Local Projection-IV procedure of Jordà et al. (2020), Stock and Watson (2018) and Ramey and Zubairy (2018).

Figure 14 reports the model-implied impulse response of GDP to an exogenous one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—and the associated 90 percent confidence bands. The figure shows that the response of output remains statistically significant through the entire estimation horizon and the effect is similar to, albeit slightly larger than, the baseline in Figure 12 (it peaks about 1.3 percent after 8 quarters of the shock).

While the instrument is strong (Table 6 and Figure 14), a possible concern with its validity is that political uncertainty is not the only mechanism through which elections can affect economic activity. Indeed, according to the political business cycle hypothesis (Nordhaus 1975), incumbents may have an incentive to manipulate fiscal and monetary policy to stimulate economic activity prior to an election in order to maximize the probability of re-election. This, however, would likely attenuate the negative effect of uncertainty on economic activity because WUI is counter-cyclical and fiscal and monetary policies implemented close to elections are aimed at stimulating economic activity. To further address this issue, we re-run the SVAR-IV to include change in the government budget balance and

short-term rates.¹¹ In particular, we use a shock decomposition with the following order: exogenous elections, the log of average stock return, changes in short-term rates, changes in the budget balance, the WUI and GDP growth. As for the baseline, we include four lags of all variables and country and time fixed effects are included.

The results of this exercise (Figure B1 of Appendix B) are similar to, and not statistically different from, the baseline SVAR-IV.¹² In all, the results corroborate previous evidence on the negative effects of political uncertainty and instability on economic activity (Barro 1991; Alesina and Perotti 1996, Julio and Yook 2012).

B. WUI and the Role of Institutional Quality

The economic literature has long established that the quality of institutions is an important driver of economic development and long-run growth (Acemoglu et al. 2001, and references therein). This section tests whether a channel through which institutional quality affects economic activity is by amplifying the economic effect of uncertainty shocks.

Daude and Stein (2007) argue that corruption may increase uncertainty, pointing to interactions between institutional quality and uncertainty. Julio and Yook (2012) find the investment cycles are much less pronounced in countries with relatively stable political systems, higher control of corruption and more checks and balances on executive authority. They also find that institutional quality is an important channel through which political uncertainty affects capital flows. FDI cycles around elections are large for countries with

¹¹ We use short-term rates instead of monetary policy rates as they are available for a larger set of countries over an extensive period. Similar results are obtained using the monetary policy rates or the long-term interest rates.

¹² The results are robust to different orderings.

lower institutional quality. Countries with well-functioning institutions quality experience mild-to-insignificant cycles in FDI around elections.

In this section, we use the WUI to investigate whether institutional quality facilitates or mitigates the transmission of economic and political uncertainty. For this purpose, we follow the local projection method proposed by Jordà (2005) to estimate impulse-response functions. This approach has been advocated by Auerbach and Gorodnichenko (2013) and Romer and Romer (2015), among others, as a flexible alternative to vector autoregression (or autoregressive distributed lags) specifications since it does not impose dynamic restrictions. It is better suited to estimating nonlinearities in the dynamic response—such as, in our context, interactions between uncertainty shocks and institutional quality. We proceed in two steps. First, we estimate the unconditional effect of uncertainty on output, using the following specification:

$$y_{t+k,i} - y_{t-1,i} = \alpha_i + \gamma_t + \beta_k WUI_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (3)$$

in which y is the log of GDP; β_k denotes the (cumulative) response of log GDP in each k year after a shock to WUI; α_i are country fixed effects, included to take account of differences in countries' average growth rates; γ_t are time fixed effects, included to take account of global shocks; and X_{it} is a set of control variables including two lags of WUI, as well as lags of GDP growth.

Equation (3) is estimated using OLS for a balanced sample of 122 countries over the period 1991-2020. Impulse response functions (IRFs) are obtained by plotting the estimated

β_k for $k=0,1,\dots,4$, with 90 percent confidence bands computed using the standard deviations associated with the estimated coefficients β_k —based on clustered robust standard errors.

Figure 15 reports the impulse response functions of output to a one standard deviation increase in the WUI. The figure shows that the response of output is statistically significant for up to 3 years following and picks at about 0.8 percent after 2 years of the shock.

Interestingly, and reassuringly, the magnitude of the effect is similar to that obtained using quarterly data. The results are robust when extending the analysis to the entire (unbalanced) sample of 143 countries from 1952 (Figure B2 Annex B), as well as to VAR estimates (Figure B3 and B4). Annex Figure B4 (using local projections) and B5 (using VAR) shows that also investment declines following an increase in the WUI, with the effect—as expected and found in the previous literature—being typically larger than that for output.

Second, we extend the previous specification to allow the response of output to vary with the level on institutional quality as follows:

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta^l D_i WUI_{i,t} + \beta^h (1 - D_i) WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t} \quad (4)$$

where D is a dummy variable which takes value 1 for countries with a score in the indicator of rule of law (our baseline indicator of quality of institutions).¹³

The results obtained examining equation (4) are reported in Figure 16. They show the average effect of uncertainty in output depicted in Figure 15 masks important differences across countries depending on the level of institutional quality. While the effect of

¹³ The results, available upon requests, are qualitatively similar to those obtained with other governance indicators such as control for corruption and regulatory quality.

uncertainty is large and persistent in countries with relatively low institutional quality, it is smaller and short-lived in countries with relatively high institutional quality. This result is robust to alternative estimation frameworks to examine how the effect of uncertainty vary with the level of institutional quality, such as: (i) using a linear interaction of WUI with the level of institutional quality; (ii) replacing the dummy in equation (2) with a smooth transition function of institutional quality; and (iii) adopting a semi-parametric approach in which we interact the WUI with quartiles (“bins”) of institutional quality.

Institutional quality is likely to be related to other countries structural features linked to the level of development. To check the robustness of our findings we use we augment equation (1) to include the interaction between the level of GDP per capita and the WUI. The results reported in Figure B7 of Annex B are similar to, and not statistically different, from the baseline results.

We also perform additional robustness checks that are available upon request. First, we modify the dummy variable to take value 1 for rule of law reforms (defined as those observation where the rule of law indicator increases by more than the 75th percentile of the distribution of the change in the indicator). This specification allows to test whether the effect of uncertainty in a given country is smaller (larger) after the country improved its institutional quality. Second, we estimate equation (2) by instrumenting the institutional quality dummy with European settler’s mortality rates, in the same spirit of Acemoglu et al. (2001). The results obtained with these specifications are consistent with the baseline results, further confirming that institutional quality is an important factor mediating the impact of uncertainty on the economy.

C. Sector-level analysis

In this section we extend the analysis in Choi et al. (2018) to examine the impact of uncertainty on productivity by testing a specific channel through which uncertainty can affect productivity growth: during periods of high uncertainty, firms that are credit constrained may switch the composition of investment by reducing productivity-enhancing investment—such as on information and communication technology (ICT) capital—which is more subject to liquidity risks (Aghion et al., 2010).

For this purpose, we use industry-country to estimate the following specification:

$$\Delta y_{jit} = \alpha_{ij} + \gamma_{it} + \delta_{jt} + \sum_{k=0}^3 \beta_k WUI_{i,t-k} EFD_j + \varepsilon_{jit} \quad (3)$$

where y is the log of sectoral output; α_{ij} are sector-country fixed effects; γ_{it} are country-time fixed effects; δ_{jt} are sector-time fixed effects; EFD is the Rajan and Zingales's (1998) measure of the degree of dependence on external finance in each industry—measured as the median across all U.S. firms, in each industry, of the ratio of total capital expenditures minus the current cash flow to total capital expenditures.

Industry-level dependent variables are taken from the United Nations Industrial Development Organization (UNIDO) database. We measure industry output by value-added.¹⁴ Nominal output is deflated by the Consumer Price Index taken from the World Economic Outlook database. All these variables are reported for 22 manufacturing industries

¹⁴ Similar results are obtained using gross output instead.

based on the INDSTAT2 2016, ISIC Revision 3, and are available for 55 advanced and developing economies from 1970 to 2014.¹⁵

The advantage of having a three-dimensional (j industries, i countries, and t periods) panel dataset is twofold. First, it allows controlling for various unobserved factors by including country-time (i, t), industry-country (j, i), and industry-time (j, t) fixed effects. The inclusion of country-time fixed effect is particularly important, as it allows controlling for any unobserved cross-country heterogeneity in the macroeconomic shocks that affect industry growth. In a pure cross-country analysis, this control would not be possible, leaving open the possibility that the impact attributed to uncertainty would be due to other unobserved macro shocks. Second, it mitigates concerns about reverse causality. While it is typically difficult to identify causal effects using aggregate data, it is much more likely that uncertainty affects industry-level outcomes than the other way around. This is because when one controls for country-time fixed effect—and, therefore, aggregate growth, reverse causality implies that differences in growth across sectors influence uncertainty at the aggregate level. Moreover, our main independent variable is the interaction between uncertainty and industry-specific technological characteristics obtained from the U.S. firm-level data, which makes it less plausible that causality runs from industry-level growth to this composite variable.

Figure 17 reports the differential output effects to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—of an industry with high external financial dependence (at the 75th percentile distribution of the indicator)

¹⁵ While the original INDSTAT2 database includes 23 manufacturing industries, we exclude the “manufacture of recycling” industry due to insufficient observations. See Table B1 for the list countries covered in the analysis.

compared to an industry with low external financial dependence (at the 25th percentile distribution of the indicator). The figures show that the response of output becomes statistically significant after one year of the uncertainty shocks. The effects are also moderate in size. In particular, a one-standard deviation increase in the WUI reduces output of an industry with high external financial dependence compared to an industry with low external financial dependence by about 2½ percent three years after the uncertainty shock. Similar results are obtained when looking at labor productivity (Figure B8 of Annex B).

VII. CONCLUSIONS

We construct a new index of uncertainty—the World Uncertainty Index (WUI)—for an unbalanced panel of 143 individual countries on a quarterly basis from 1952, using the Economist Intelligence Unit country reports.

We believe that this dataset can be extremely valuable to researchers for many applications. First, the fact that innovations to WUI foreshadows output declines suggest that the WUI could be used as alternative measures of economic activity when these are not available (such as quarterly GDP for many countries). Second, the dataset can be used to examine the impact of differences in the level of uncertainty across countries on key macroeconomic outcomes.

We use the WUI to investigate the relationship of uncertainty to output, investment and productivity. Our findings are broadly consistent with theories and previous empirical studies highlighting negative economic effects of uncertainty shocks. The results suggest that the high world level of uncertainty may harm global economic activity.

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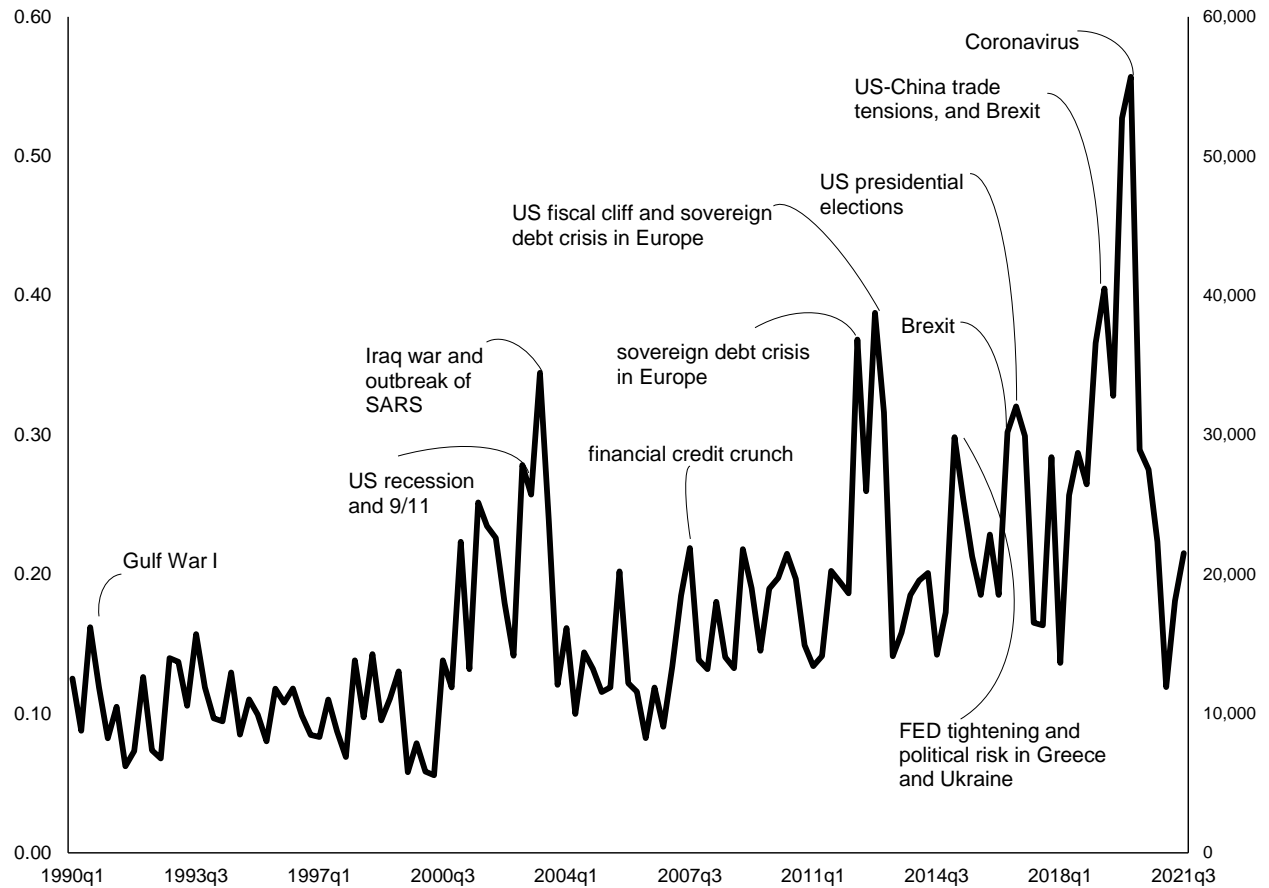
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FIGURES

Figure 1. World Uncertainty Index (WUI) over time

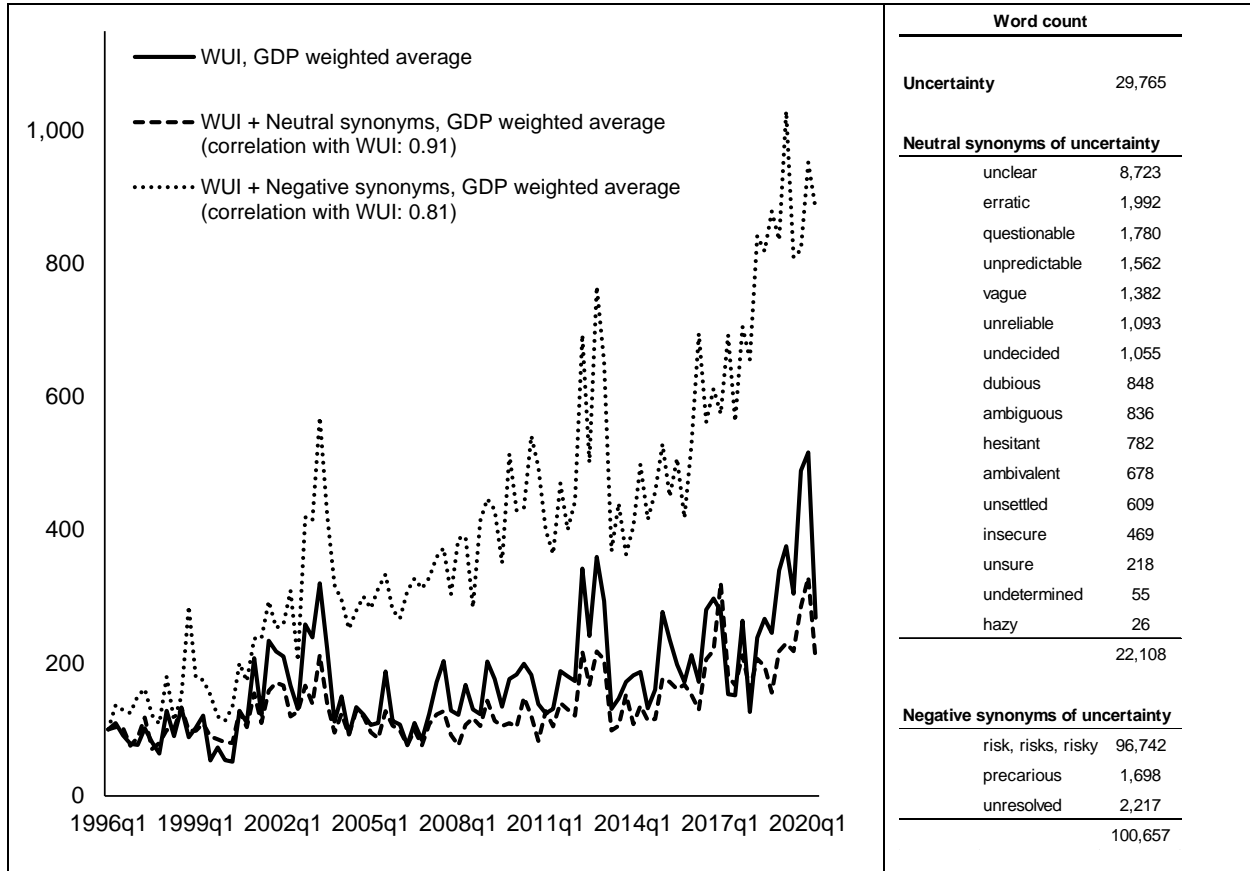
(GDP weighted average)



Note. Left scale: number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. Right scale: number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words multiplied by 100,000. A higher number means higher uncertainty and vice versa. For the list of countries included in the index, see Table 1. The data plotted in the figure above is from 1990Q1 to 2021Q3.

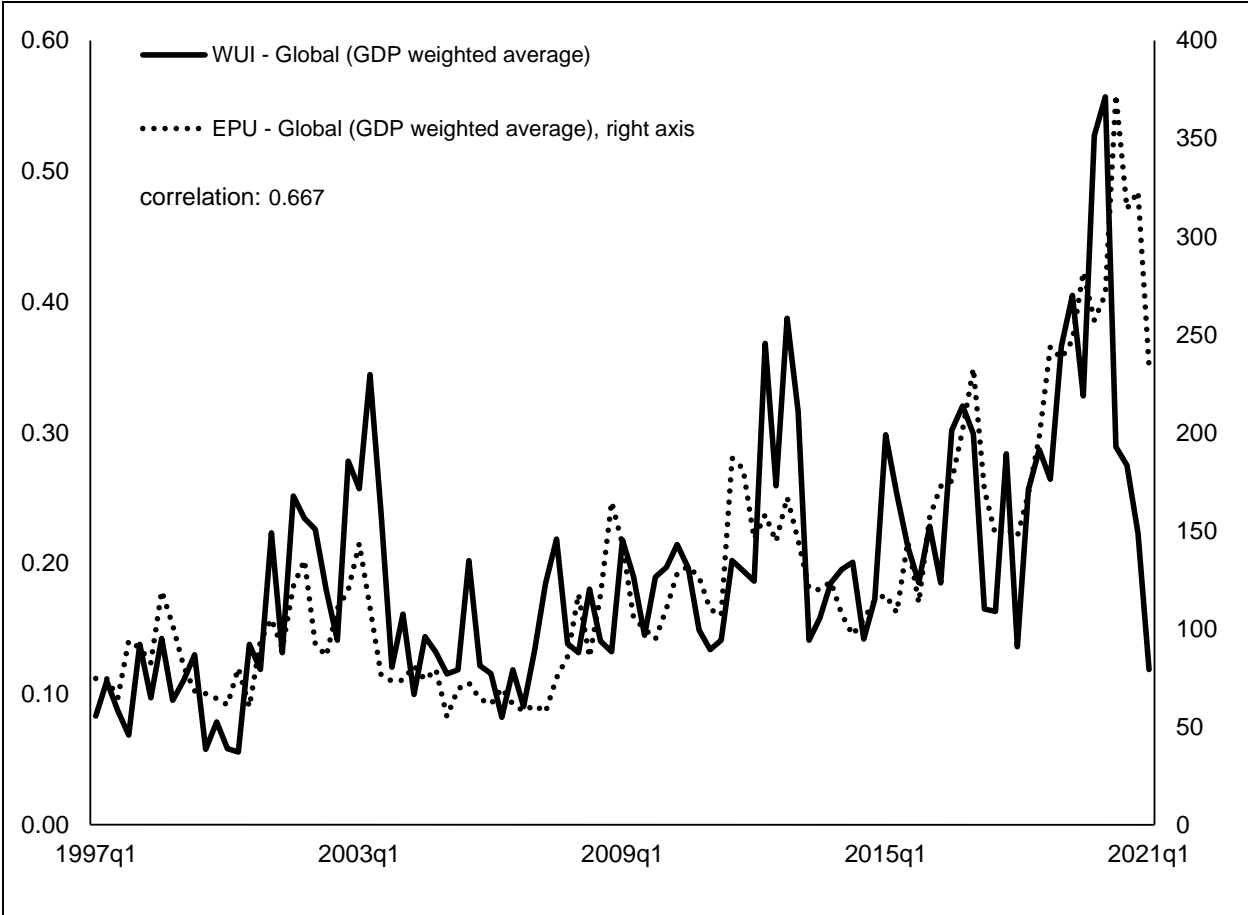
Figure 2. World Uncertainty Index vs. synonyms of uncertainty

(GDP weighted average, 1996Q1 = 100)



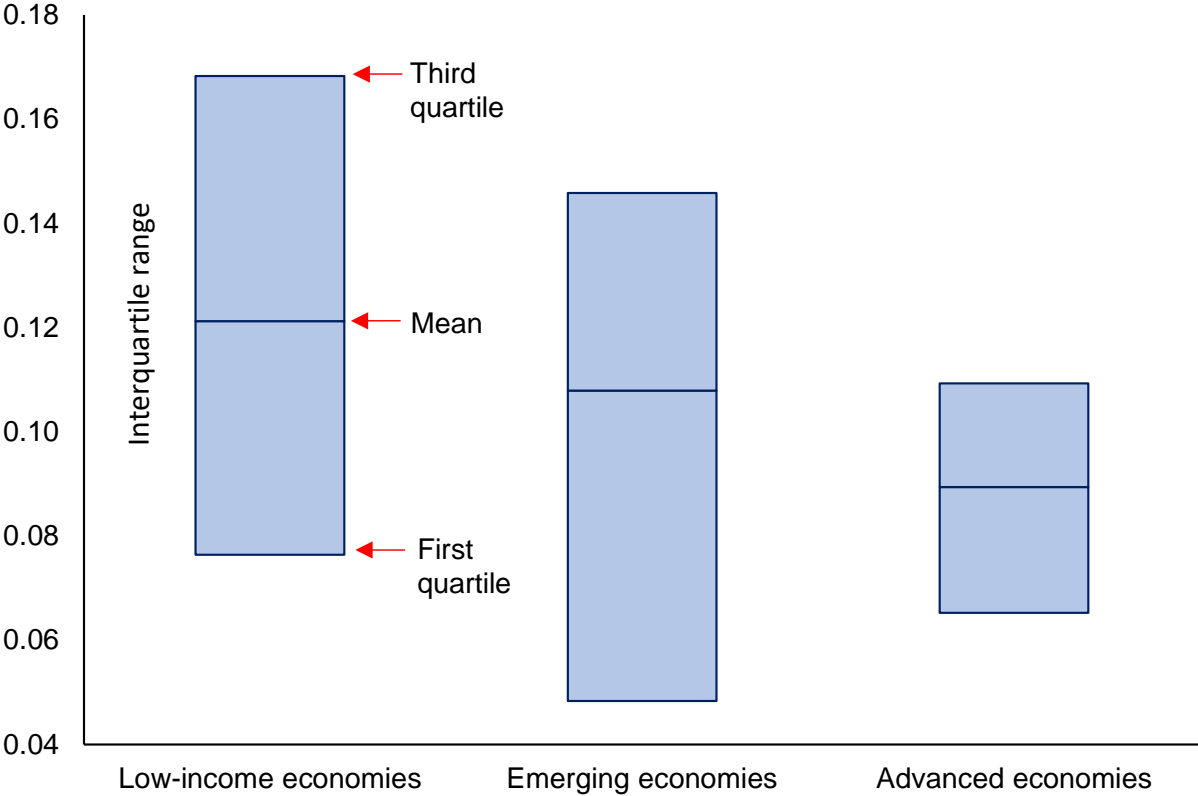
Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. WUI + neutral synonyms count the following keywords: ambiguous, ambivalent, dubious, erratic, hazy, hesitant, unclear, undecided, undetermined, unpredictable, unreliable, unsettled, unsure, vague, questionable, insecure, plus uncertain (or the variant). Negative synonyms count the following keywords: risk, risks, risky, precarious, unresolved, plus uncertain (or the variant). The three indexes are then normalized by total number of words, rescaled by multiplying by 1,000. A higher number means higher uncertainty and vice versa. For the list of countries included, see Table 1. The data plotted in the figure above is from 1996Q1 to 2020Q2.

Figure 3. World Uncertainty Index (WUI) vs. EPU Indexes



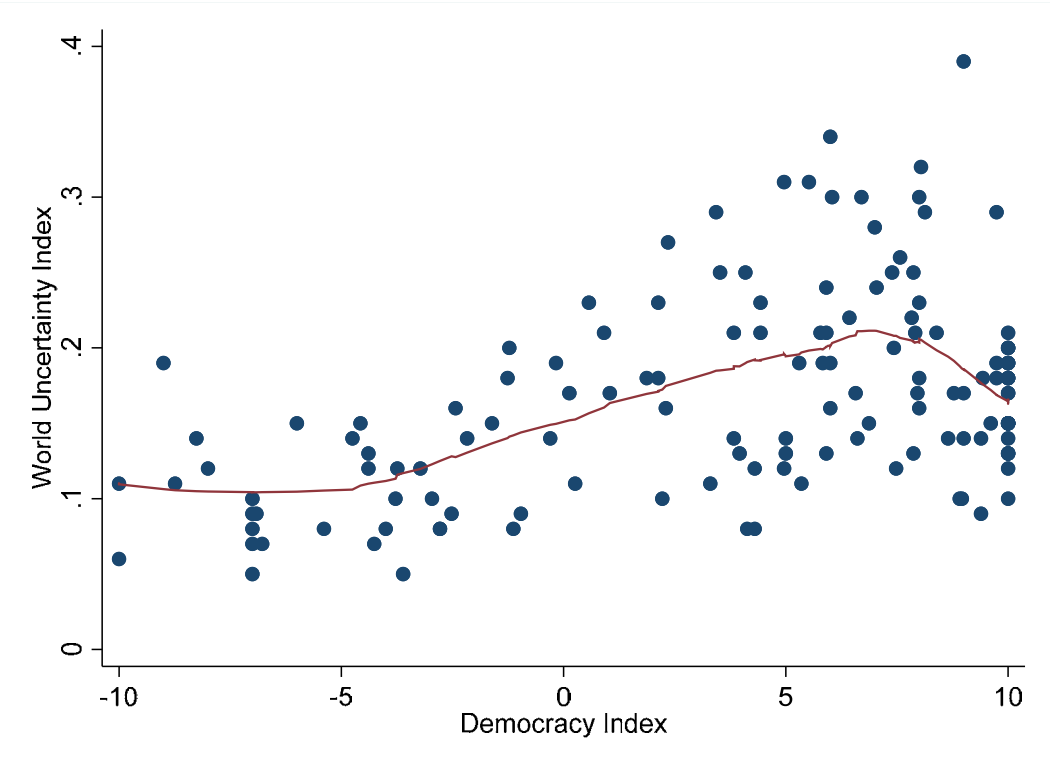
Note. Left Scale: WUI—number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. Right scale: EPU from Baker, Bloom and Davis (2016). The data plotted in the figure above is from 1997Q1 to 2021Q1.

Figure 4. Average World Uncertainty Index (WUI) by income group



Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. For the list of countries in each income group, see Table 1. The figure above is based on data from 1996Q1 to 2019Q4.

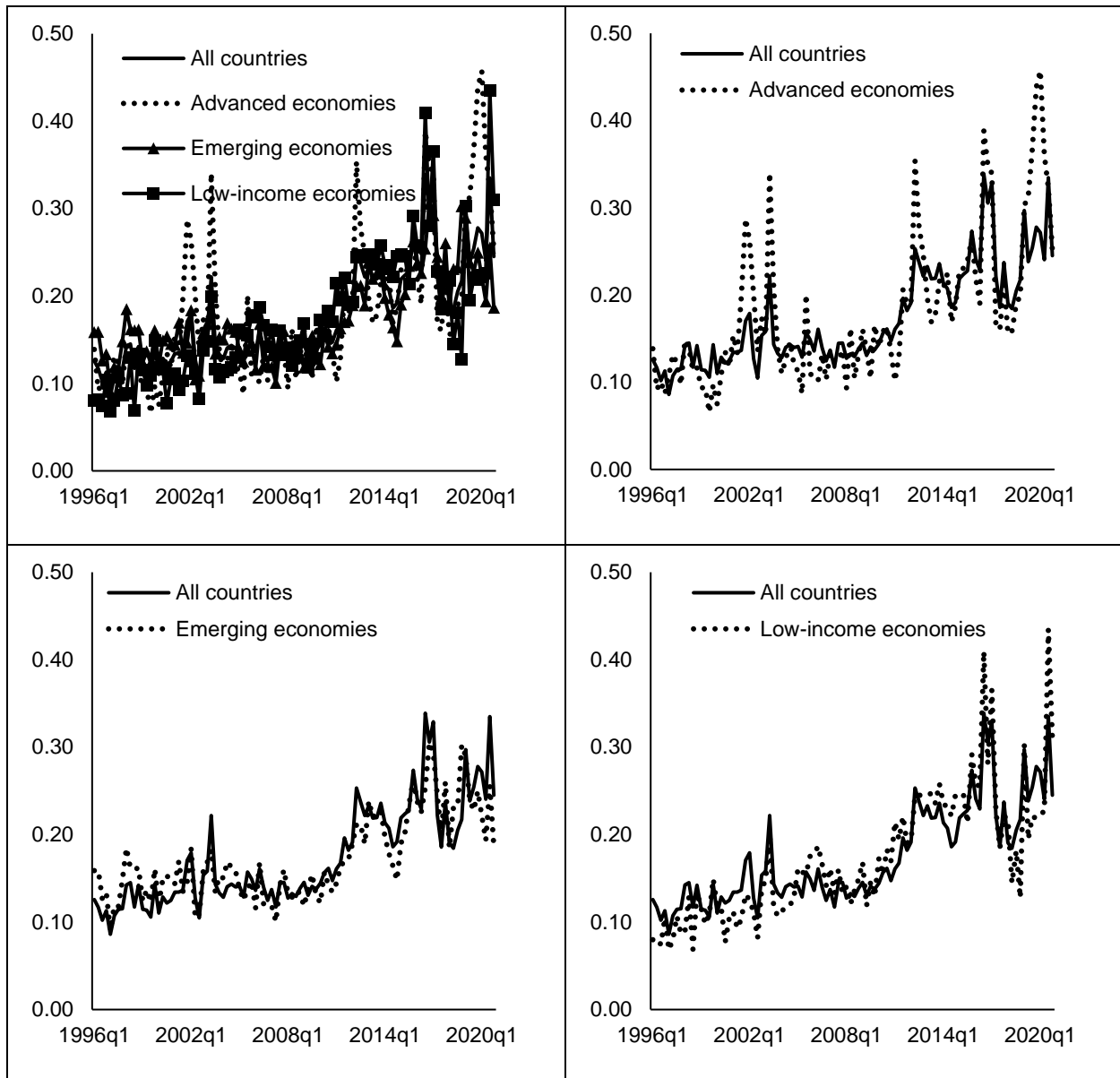
Figure 5. Relationship between uncertainty and political regimes



Note: X-axis reports the democracy index comes from the Center for Systemic Peace, which classifies the country regimes as 10: full democracy, 6-9: democracy, 1-5: open anocracy, -5-0: open anocracy, and -10 to -6: autocracy. The Y-axis reports the WUI. The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. The figure above uses Lowess smoothing with a bandwidth=0.4 and is based on data from 1996 to 2018.

Figure 6. World Uncertainty Index (WUI) by income group over time

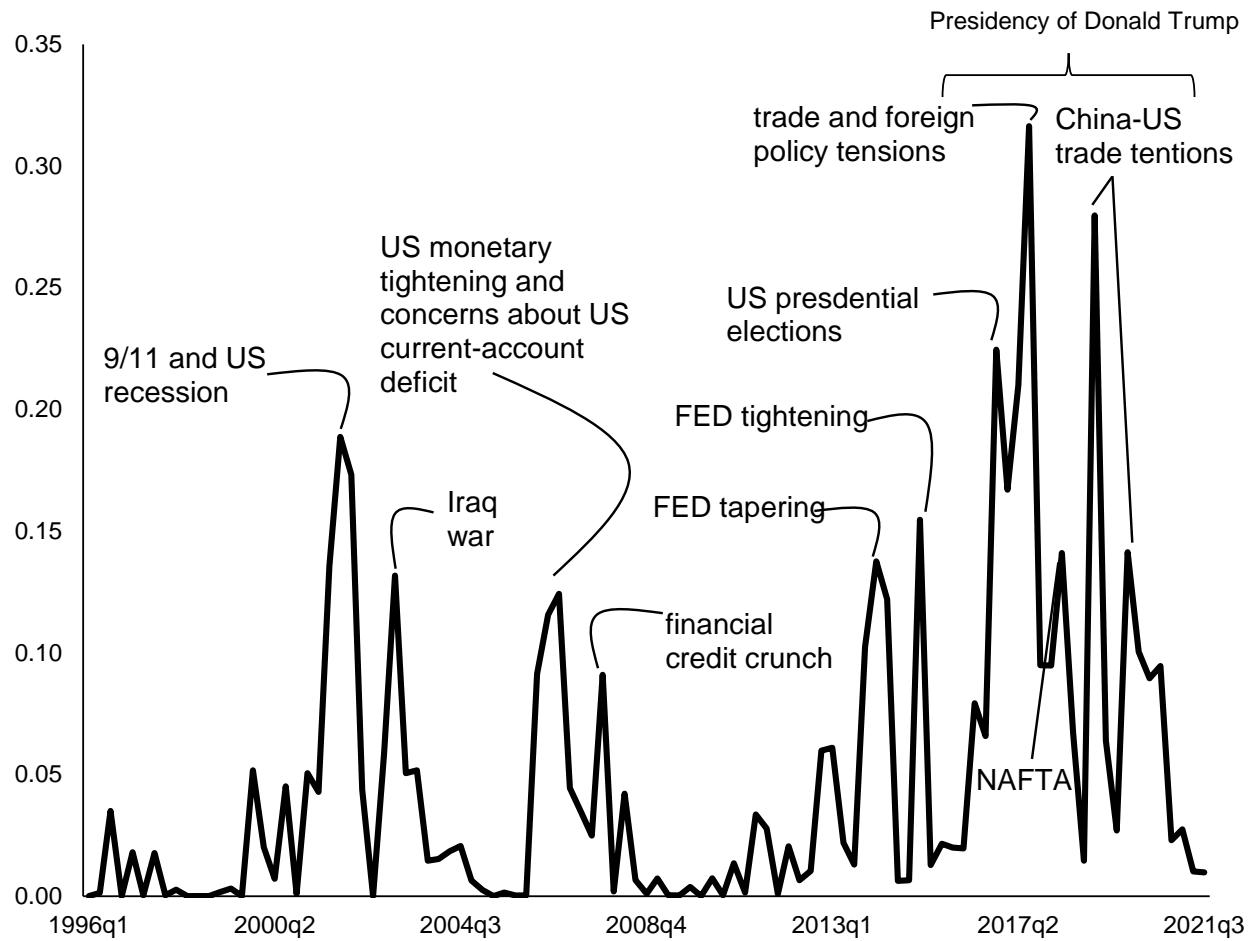
(simple average)



Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. For the list of countries included in each income group, see Table 1. Simple average is shown for each income group. Time period covered is 1996Q1 to 2020Q4.

Figure 7.1. World Uncertainty Spillover Index (WUSI): US Spillovers

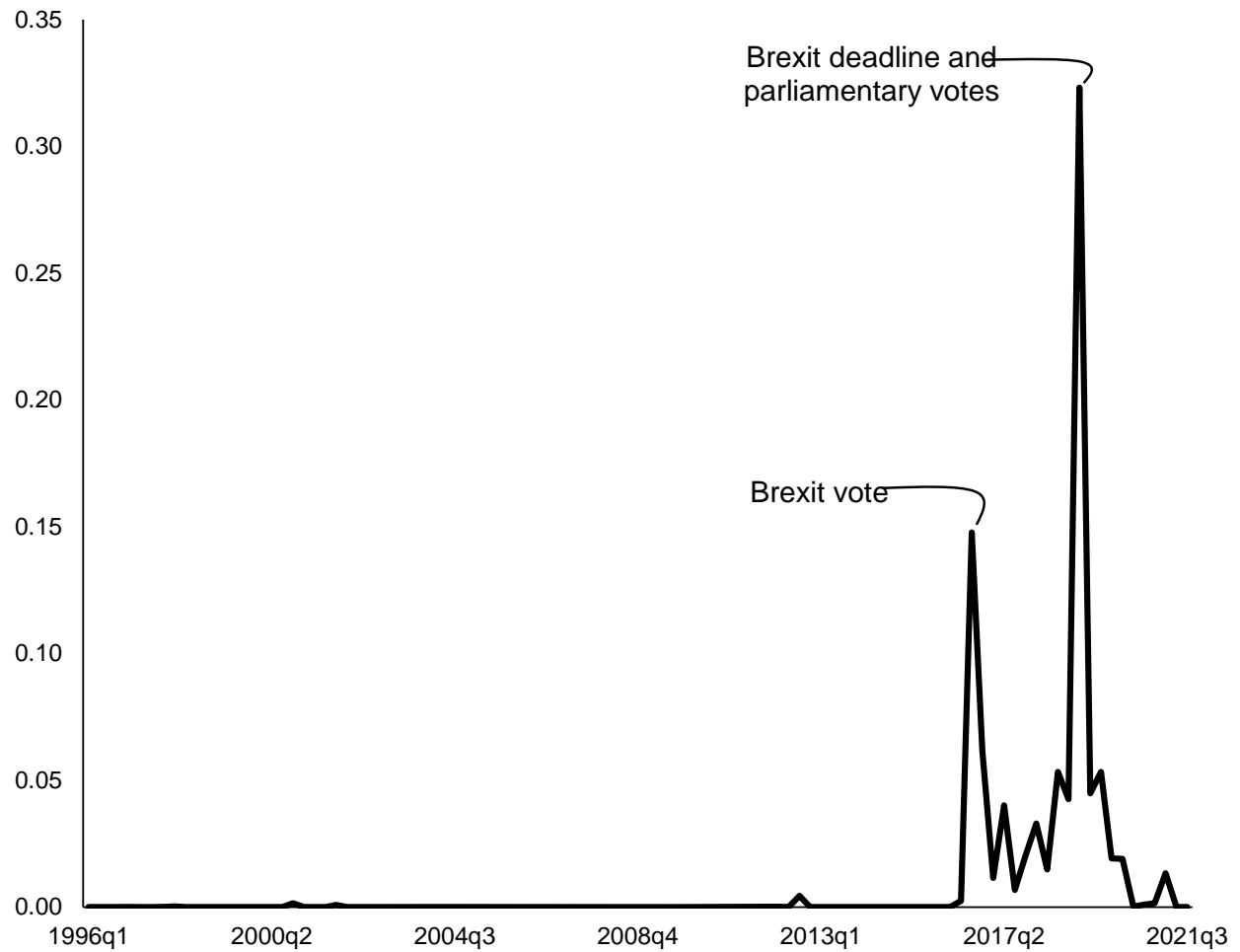
(as a ratio of overall uncertainty)



Note: The WUSI index for the United States is computed by counting the number of times uncertain (or the variant) is near words related to the United States: Alan Greenspan, America, Barack Obama, Ben Bernanke, Joe Biden, Bill Clinton, Donald Trump, Federal Reserve, George H. W. Bush, George W. Bush, Janet Yellen, Jerome Powell, NAFTA, North America, and the United States. The WUSI is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. Period covered is 1996Q1 to 2021Q3.

Figure 7.2. World Uncertainty Spillover Index (WUSI): UK Spillovers

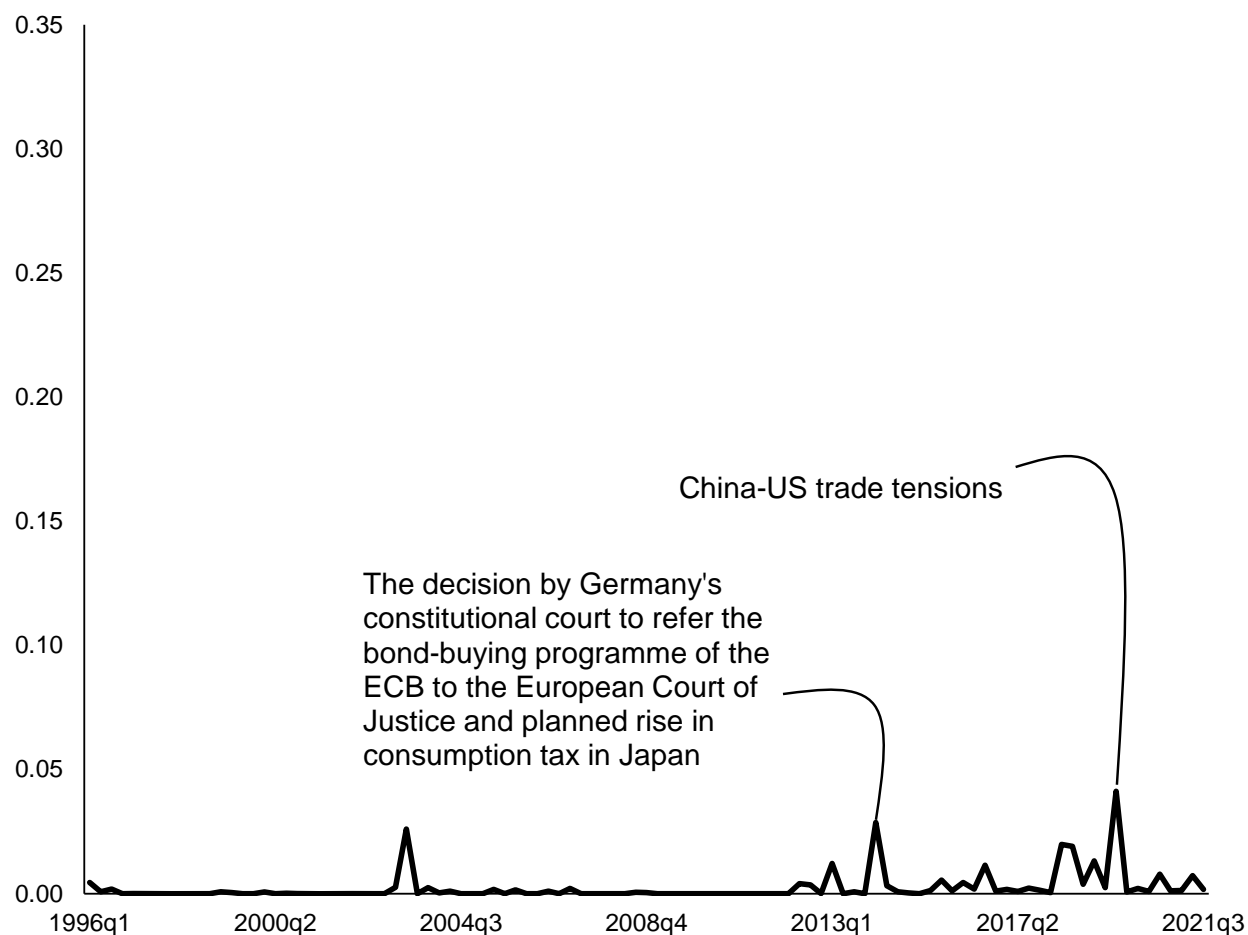
(as a ratio of overall uncertainty)



Note: The WUSI index for the United Kingdom is computed by counting number of times uncertain (or the variant) is near words related to the United Kingdom: Andrew Bailey, Bank of England, Boris Johnson, Brexit, Britain, David Cameron, Edward George, Gordon Brown, John Major, Mark Carney, Mervin King, Theresa May, Tony Blair, and the United Kingdom. The WUSI is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. Period covered is 1996Q1 to 2021Q3.

Figure 7.3. World Uncertainty Spillover Index (WUSI): Spillovers from G5 + China

(as a ratio of overall uncertainty)



Note: The WUSI index for the G5 + China is computed by counting number of times uncertain (or the variant) is near words related to the respective systemic-economy country (Canada, France, Germany, Italy, Japan, and China). The country-specific words include country's name, name of presidents, name of the central bank, name of central bank governors, and selected country's major events. The WUSI for the G5 + China is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. Period covered is 1996Q1 to 2021Q3.

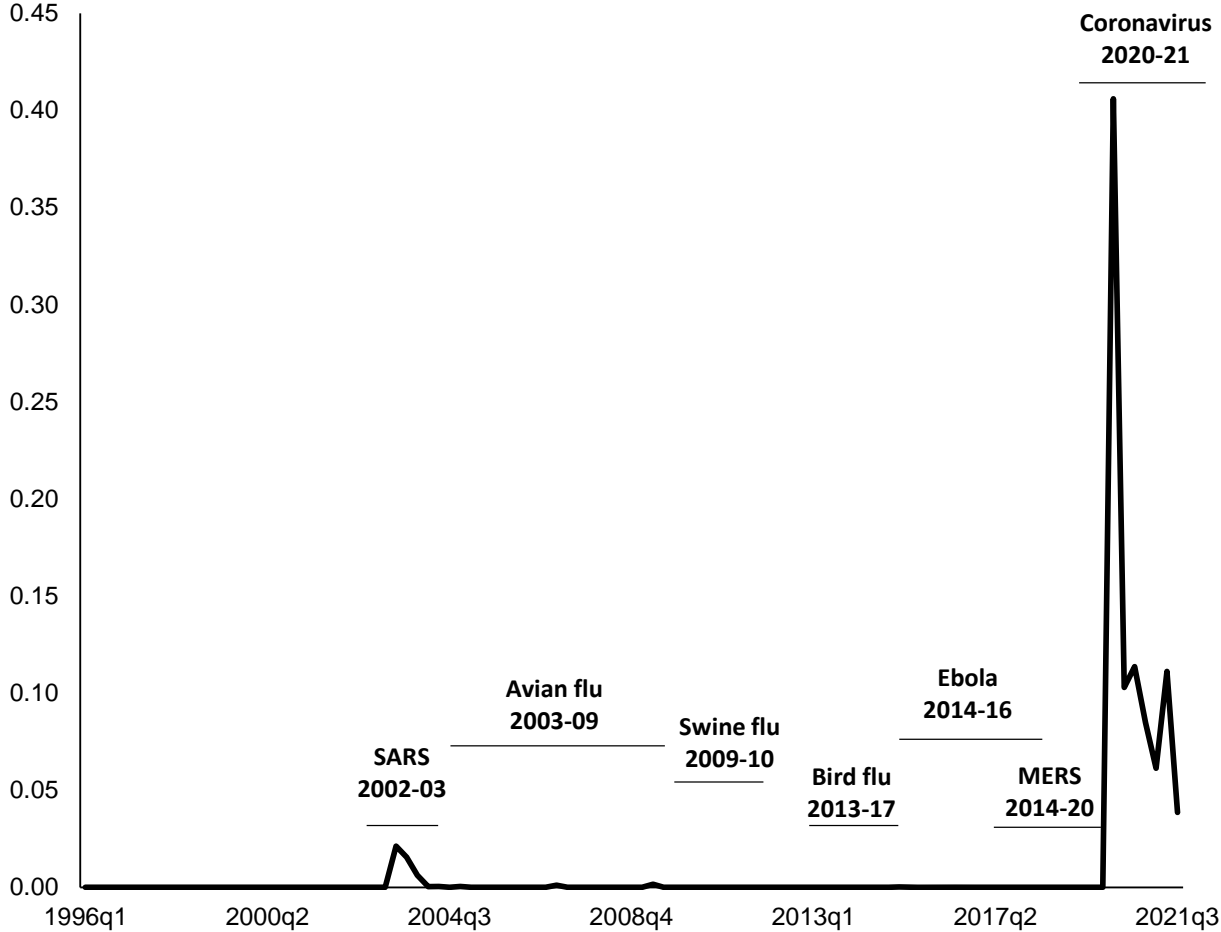
Figure 8. World Trade Uncertainty Index (WTUI) over time

(GDP weighted average)



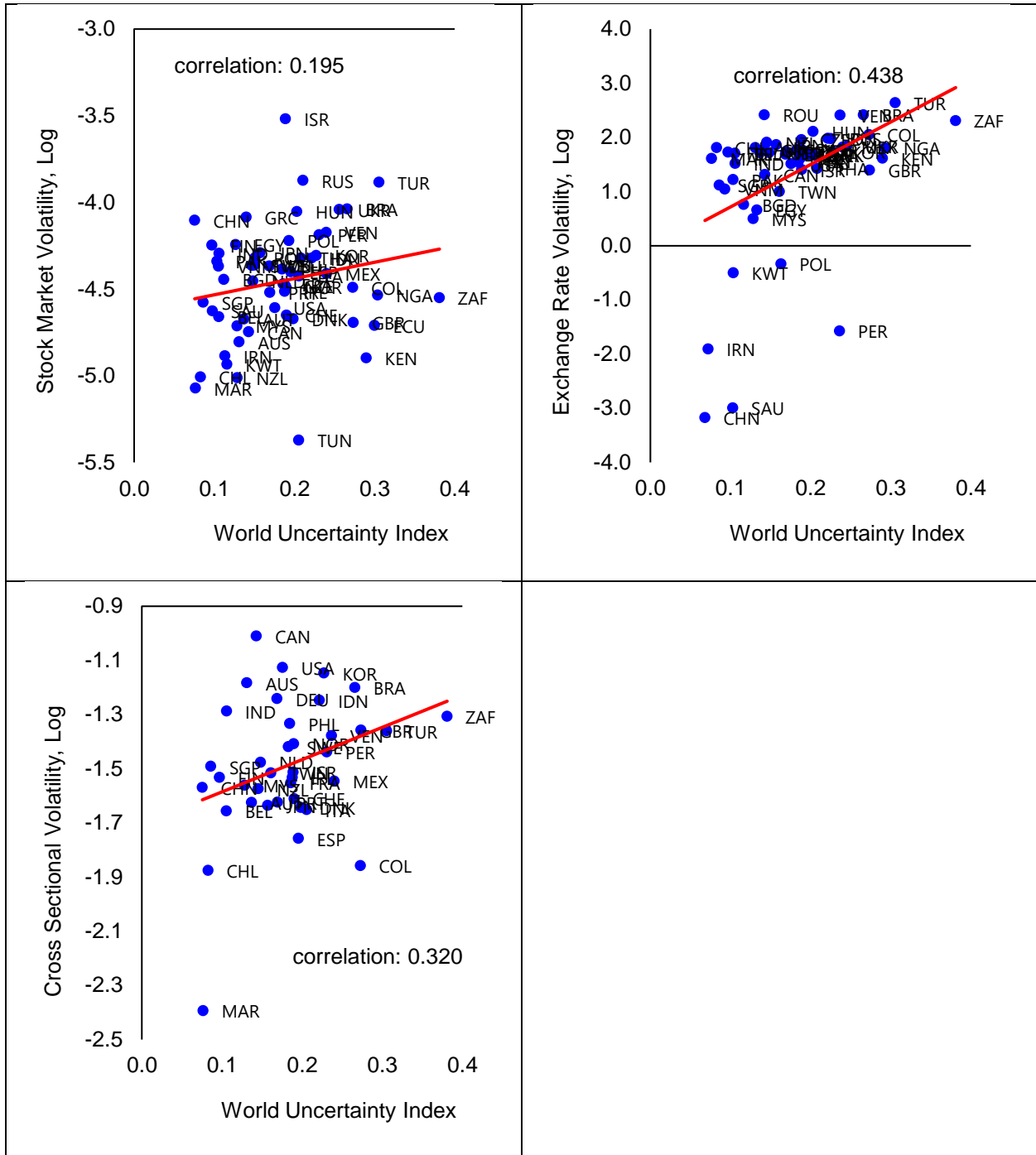
Note: The WTUI index is computed by counting the number of times uncertain (or the variant) is near the following words: protectionism, North American Free Trade Agreement (NAFTA), tariff, trade, United Nations Conference on Trade and Development (UNCTAD) and World Trade Organization (WTO) in EIU country reports. The WTUI is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. Period covered is 1996Q1 to 2021Q3.

Figure 9. World Pandemic Uncertainty Index (WPUI) over time
(GDP weighted average)



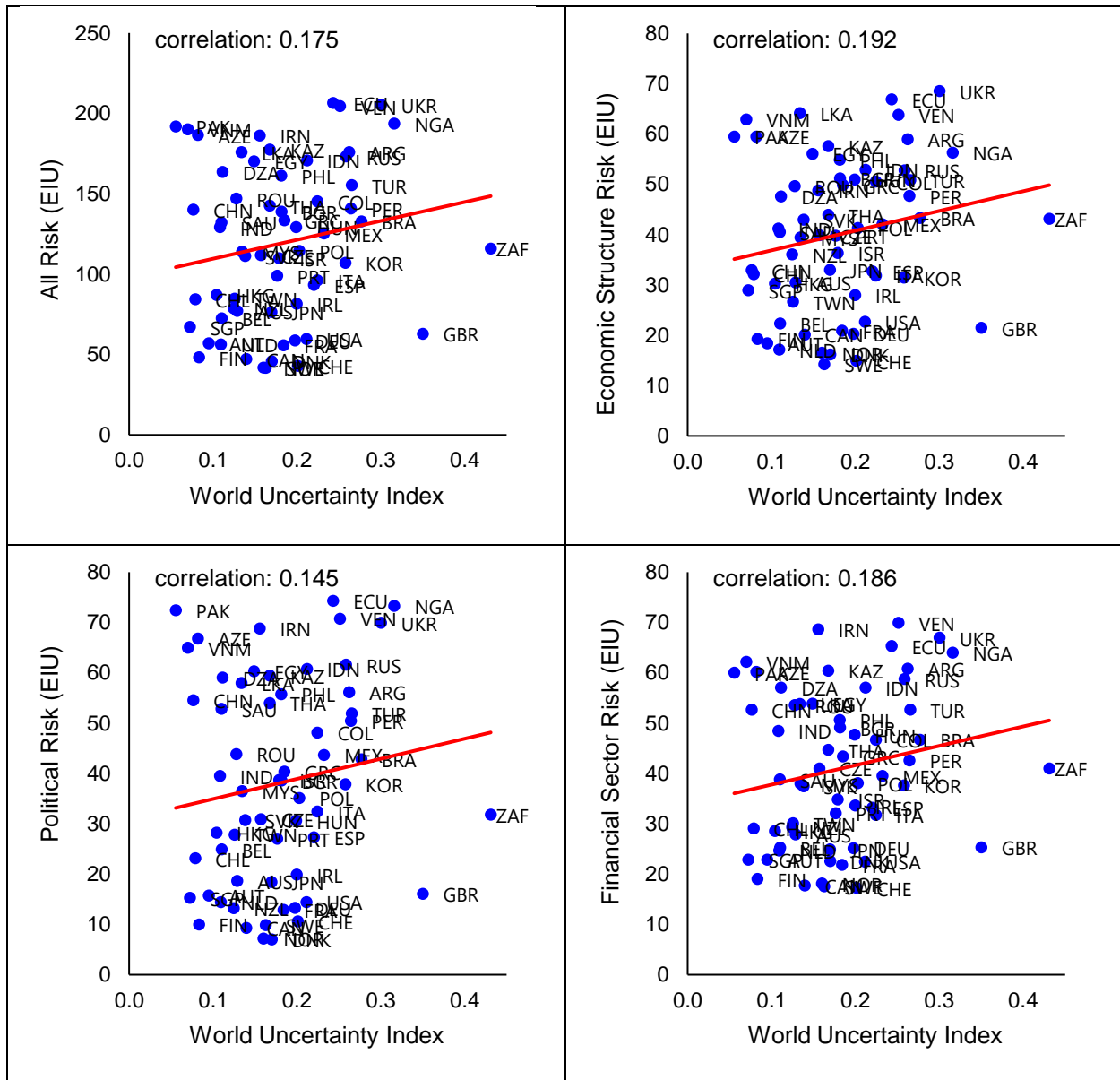
Note: The WPUI index is computed by counting the number of times uncertain (or the variant) is near the following words: Severe Acute Respiratory Syndrome (SARS), Avian flu, H5N1, Swine flu, H1N1, Middle East respiratory syndrome (MERS), Bird fu, Ebola, Coronavirus, Covid-19, Influenza, H1V1, and World Health Organisation (WHO) in EIU country reports. The WPUI is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. Period covered is 1996Q1 to 2021Q3.

Figure 10. World Uncertainty Index (WUI) vs. Market Volatility



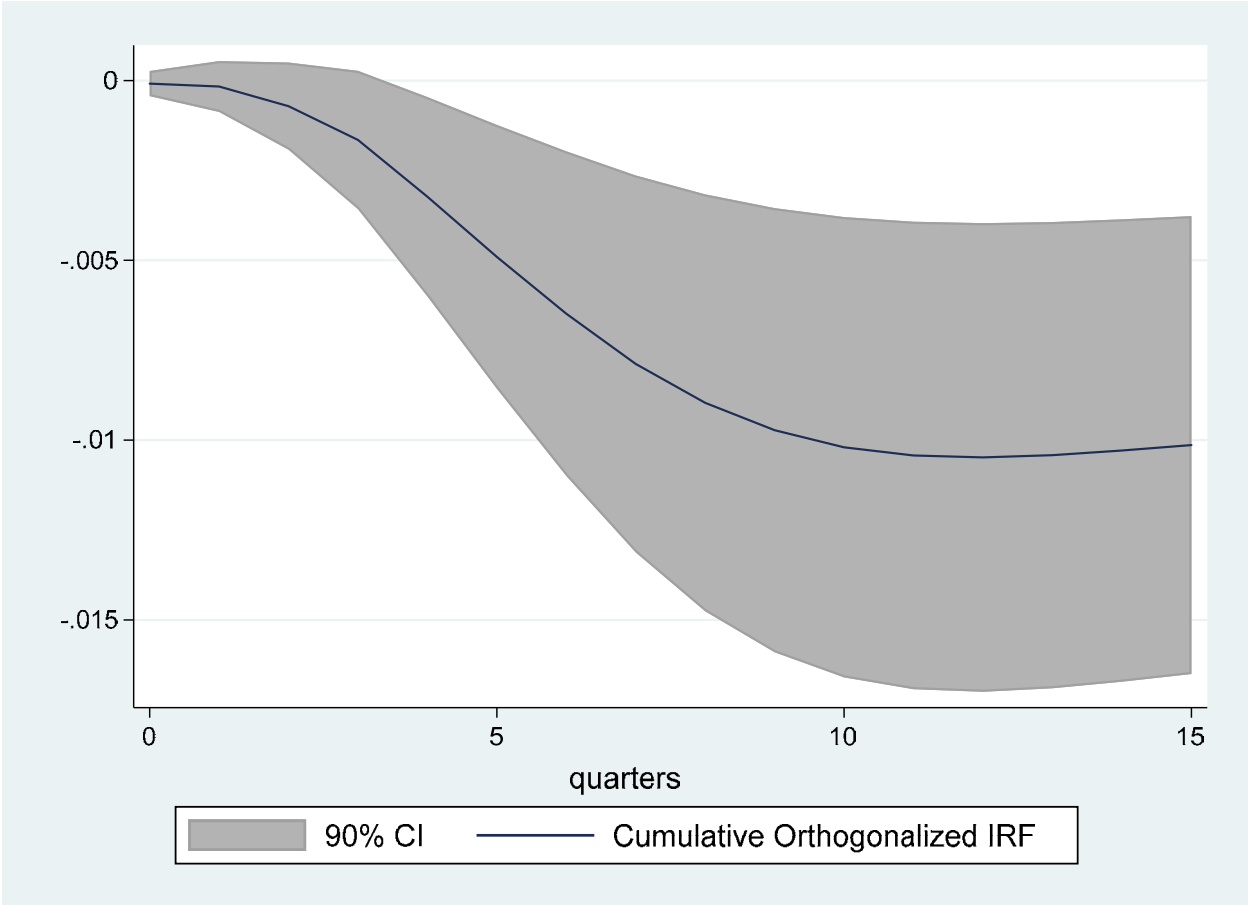
Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. The data plotted in the figures above is the average from 1996Q1 to 2017Q4.

Figure 11. World Uncertainty Index (WUI) vs. Risks



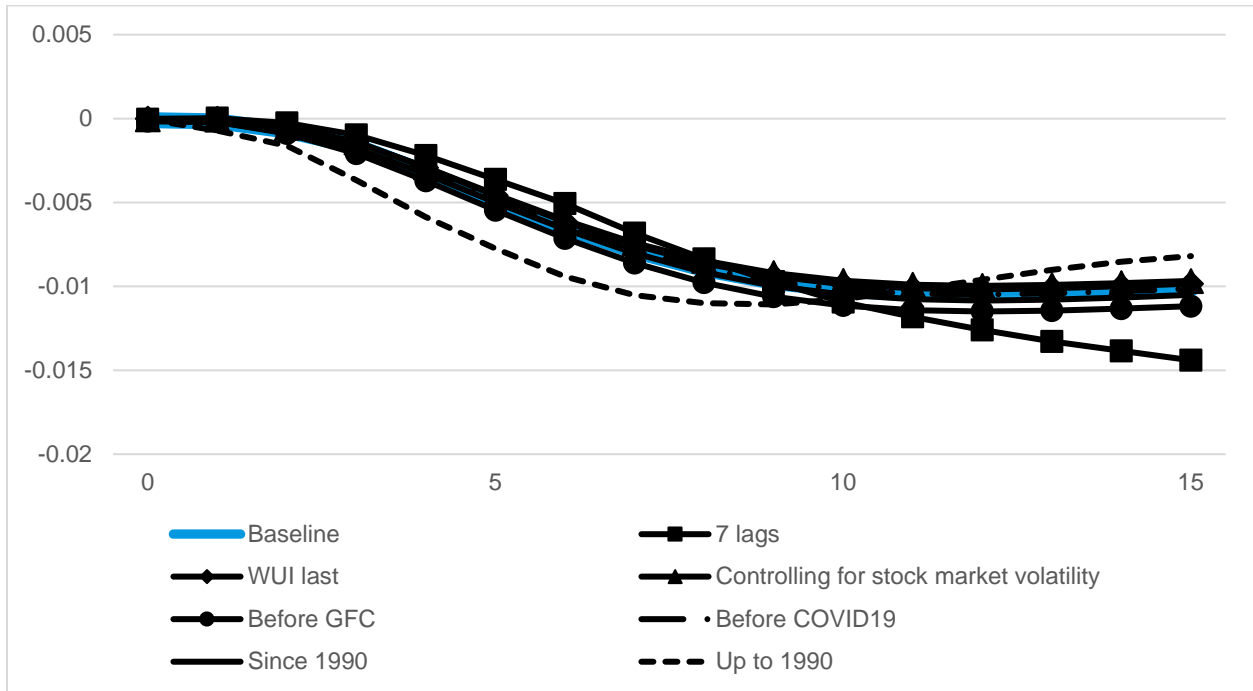
Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. The EIU's economic risk indicator is derived from a series of macroeconomic variables of a structural rather than a cyclical nature. Consequently, the rating for economic structure risk will tend to be relatively stable, evolving in line with structural changes in the economy. The financial risk indicator assesses the risk of a systemic crisis whereby bank(s) holding 10 percent or more of total bank assets become insolvent and unable to discharge their obligations to depositors and/or creditors. The political risk indicator evaluates a range of political factors relating to political stability and effectiveness that could affect a country's ability and/or commitment to service its debt obligations and/or cause turbulence in the foreign-exchange market. The All-risk indicator is the sum of the three indicators. The data plotted in the figures above is the average from 1997 to 2019.

Figure 12. GDP response to WUI innovations



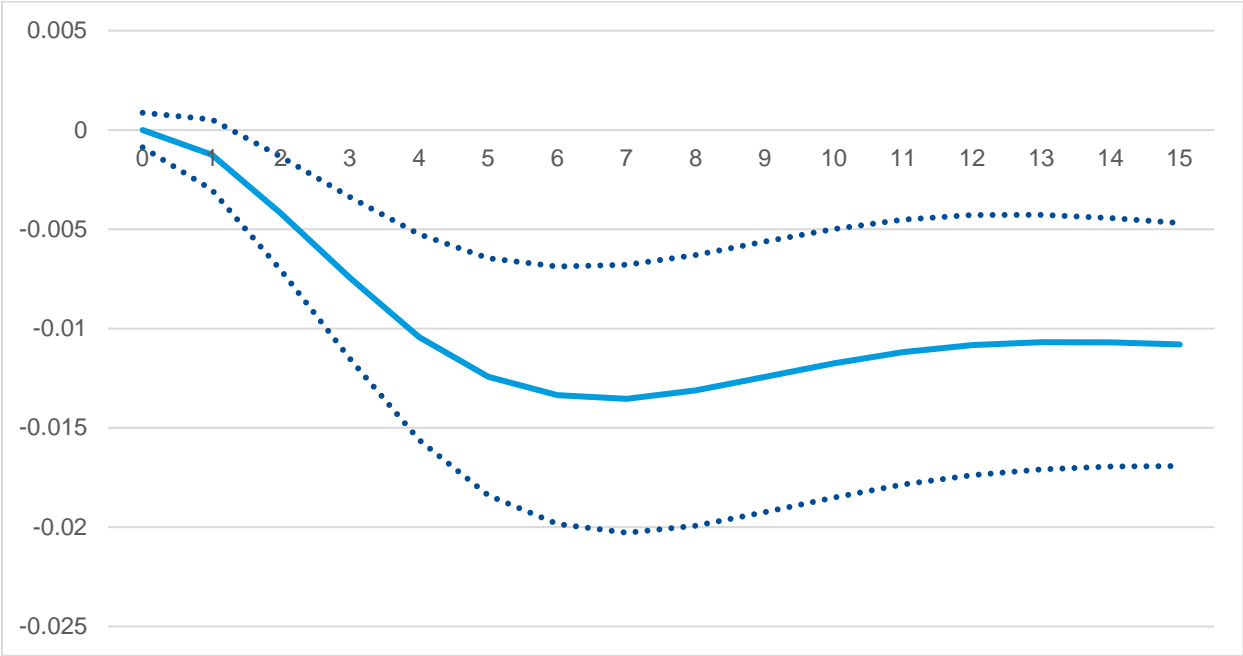
Note: VAR fit to quarterly data for an unbalanced panel of 49 countries from 1970q1 to 2020q1. Impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—based on a Cholesky decomposition with the following order: the average stock return, the WUI and GDP growth. The specification includes four lags of all variables. Country and time fixed effects are included.

Figure 13. GDP response to WUI innovations—robustness checks



Note: VAR fit to quarterly data for an unbalanced panel of 49 countries from 1970q1 to 2020q4. Impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—based on a Cholesky decomposition with the following order: the average stock return, the WUI and GDP growth. The specification includes four lags of all variables. Country and time fixed effects are included.

Figure 14. GDP response to WUI innovations—IV exogenous elections



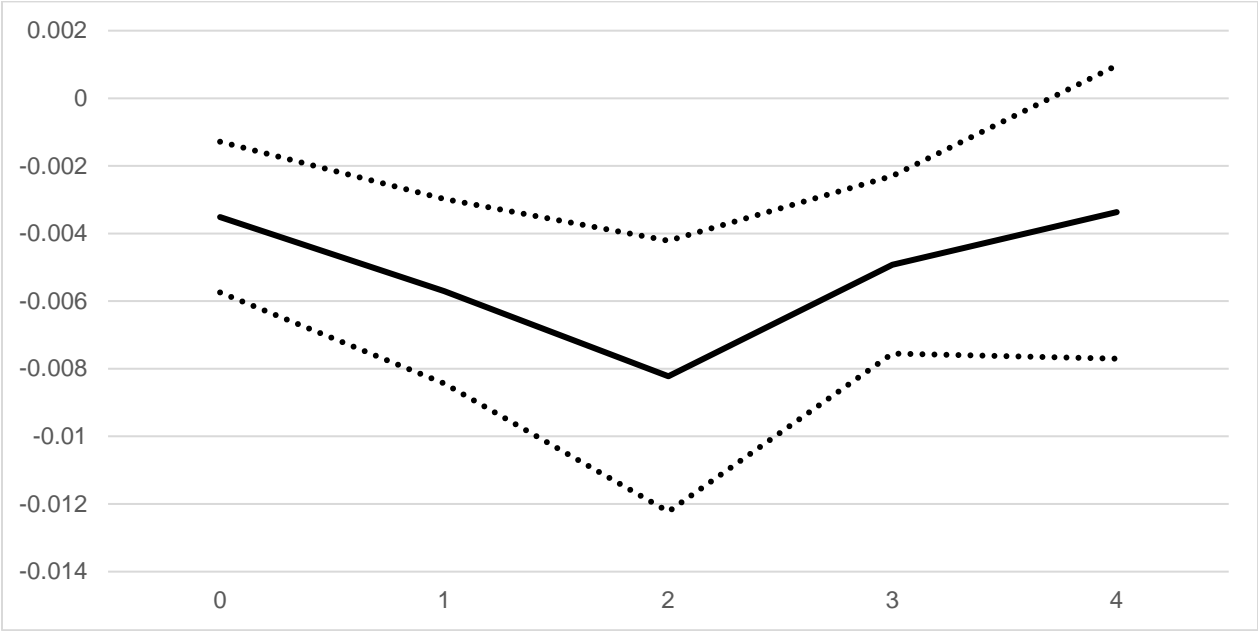
Note: VAR fit to quarterly data for an unbalanced panel of 49 countries from 1970q1 to 2020q4. Impulse responses of GDP to a one-standard deviation increase in WUI—equal to the change in average value in the index from 2014 to 2016—using as instrument exogenous elections and based on a Cholesky decomposition with the following order: exogenous elections, the log of average stock return, the WUI and GDP growth. The specification includes four lags of all variables. Country and time fixed effects are included. First stage:

$$WUI_{i,t} = 0.185 + 0.099Exogenous\ elections$$

(6.09)

t-statistics in parenthesis.

Figure 15. GDP response to WUI innovations-annual data — Local Projection

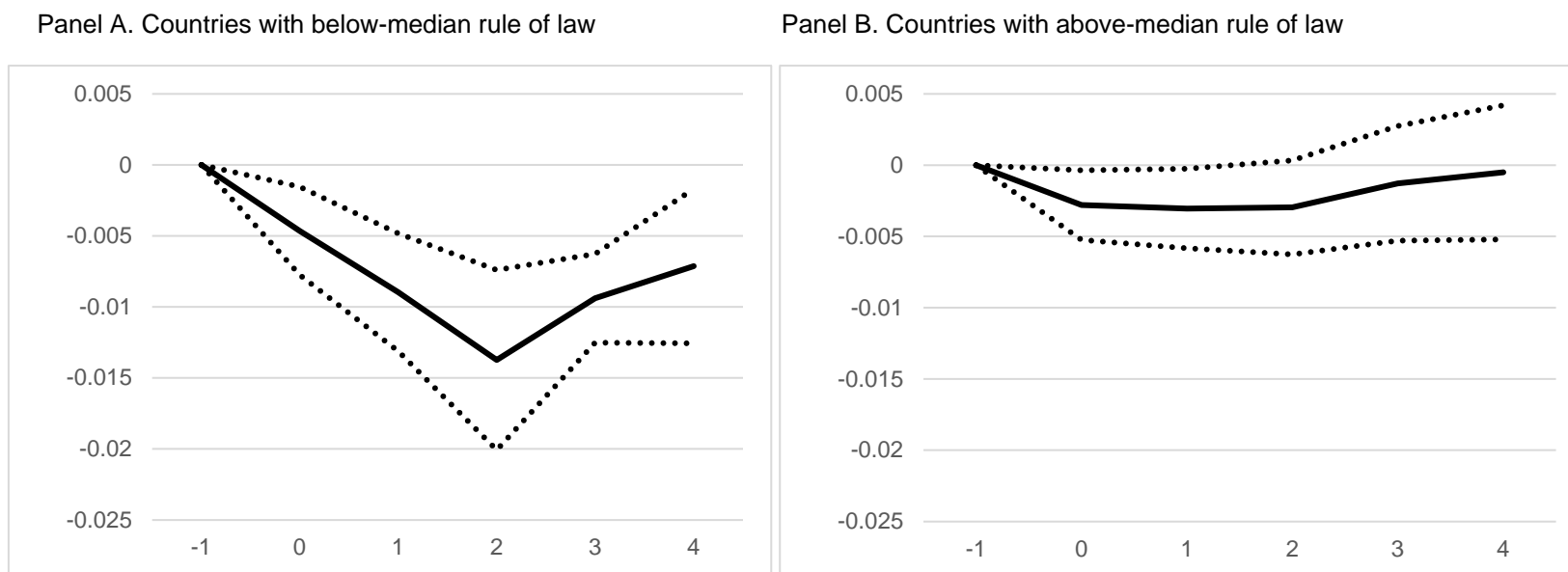


Note: Response estimated using the local projection method (Jorda 2005):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t}$$

where y is the log of output; α_i are country-fixed effects; γ_t are time-fixed effects; X is a set of controls including lags of the growth rate of output and of the WUI index. Estimates based on annual data for a panel of 122 countries from 1991 to 2020. Solid line denoted the impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016. Dotted lines denote 90 percent confidence bands.

Figure 16. GDP response to WUI innovations—annual data—Local Projection, the role of institutions.

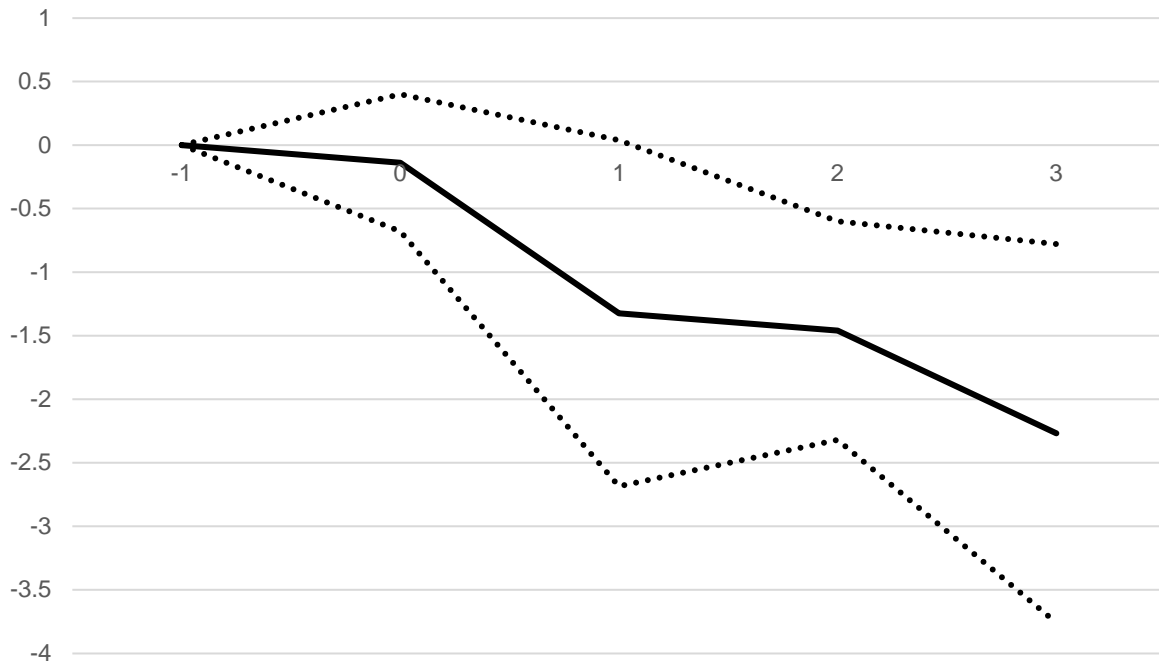


Note: Response estimated using the local projection method (Jorda 2005):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta^l D_i WUI_{i,t} + \beta^h (1 - D_i) WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t}$$

where y is the log of output; α_i are country-fixed effects; γ_t are time-fixed effects; D is a dummy variable which takes value 1 for countries with a score in the indicator of rule of law below median; X is a set of controls including lags of the growth rate of output and of the WUI index. Estimates based on annual data for a panel of 122 countries from 1991 to 2020. Solid line denoted the impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016. Dotted lines denote 90 percent confidence bands.

Figure 17. Sectoral output response to WUI innovations—role of financial constraints (%)



Note: Response estimated using the following specification:

$$\Delta y_{jit} = \alpha_{ij} + \gamma_{it} + \delta_{jt} + \sum_{k=0}^3 \beta_k WUI_{i,t-k} EFD_j + \varepsilon_{jit}$$

where y is the log of sectoral output; α_{ij} are sector-country fixed effects; γ_{it} are country-time fixed effects; δ_{jt} are sector-time fixed effects; EFD is the Rajan and Zingales's (1998) measure of the degree of dependence on external finance in each industry—measured as the median across all U.S. firms, in each industry, of the ratio of total capital expenditures minus the current cash flow to total capital expenditures. Estimates based on annual data for a panel of 22 industries, 56 countries from 1995 to 2017 (the size of the estimation sample is 25,618 observations). Solid line denotes the differential output effect to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—of an industry with high external financial dependence (at the 75th percentile distribution of the indicator) compared to an industry with low external financial dependence (at the 25th percentile distribution of the indicator). Dotted lines denote 90 percent confidence bands.

TABLES

Table 1. Country coverage

Country	Group 1	Group 2	Start date	Country	Group 1	Group 2	Start date	Country	Group 1	Group 2	Start date
Afghanistan	MCD	3	1956Q1	Guatemala	WHD	2	1954Q2	Oman	MCD	2	1971Q1
Albania	EUR	2	1956Q1	Guinea	AFR	3	1960Q1	Pakistan	MCD	2	1952Q1
Algeria	MCD	2	1960Q1	Guinea-Bissau	AFR	3	1978Q2	Panama	WHD	2	1954Q2
Angola	AFR	2	1974Q1	Haiti	WHD	3	1956Q1	Papua New Guinea	APD	3	1970Q1
Argentina	WHD	2	1952Q1	Honduras	WHD	3	1954Q2	Paraguay	WHD	2	1955Q1
Armenia	MCD	2	1993Q1	Hong Kong SAR	APD	1	1953Q1	Peru	WHD	2	1954Q1
Australia	APD	1	1952Q1	Hungary	EUR	2	1953Q1	Philippines	APD	2	1952Q2
Austria	EUR	1	1963Q4	India	APD	2	1952Q1	Poland	EUR	2	1971Q1
Azerbaijan	MCD	2	1993Q1	Indonesia	APD	2	1952Q2	Portugal	EUR	1	1952Q1
Bangladesh	APD	3	1972Q1	Iraq	MCD	2	1953Q3	Qatar	MCD	2	1971Q1
Belarus	EUR	2	1992Q2	Ireland	EUR	1	1953Q1	Republic of Congo	AFR	3	1963Q1
Belgium	EUR	1	1952Q1	Islamic Republic of Iran	MCD	2	1953Q3	Romania	EUR	2	1956Q1
Benin	AFR	3	1962Q1	Israel	EUR	1	1952Q3	Russia	EUR	2	1953Q1
Bolivia	WHD	3	1954Q1	Italy	EUR	1	1952Q1	Rwanda	AFR	3	1965Q1
Bosnia and Herzegovina	EUR	2	1993Q1	Jamaica	WHD	2	1963Q4	Saudi Arabia	MCD	2	1968Q1
Botsswana	AFR	2	1966Q4	Japan	APD	1	1952Q3	Senegal	AFR	3	1963Q1
Brazil	WHD	2	1952Q1	Jordan	MCD	2	1956Q1	Sierra Leone	AFR	3	1957Q1
Bulgaria	EUR	2	1956Q1	Kazakhstan	MCD	2	1993Q1	Singapore	APD	1	1957Q3
Burkina Faso	AFR	3	1962Q3	Kenya	AFR	3	1966Q4	Slovak Republic	EUR	1	1993Q2
Burundi	AFR	3	1965Q1	Korea	APD	1	1956Q1	Slovenia	EUR	1	1993Q1
Cambodia	APD	3	1956Q1	Kuwait	MCD	2	1968Q1	South Africa	AFR	2	1961Q3
Cameroon	AFR	3	1962Q1	Kyrgyz Republic	MCD	3	1993Q1	Spain	EUR	1	1952Q1
Canada	WHD	1	1952Q1	Lao P.D.R.	APD	3	1956Q1	Sri Lanka	APD	2	1953Q1
Central African Republic	AFR	3	1963Q1	Latvia	EUR	1	1993Q1	Sudan	MCD	3	1954Q1
Chad	AFR	3	1963Q1	Lebanon	MCD	2	1956Q1	Sweden	EUR	1	1952Q1
Chile	WHD	2	1954Q2	Lesotho	AFR	3	1966Q4	Switzerland	EUR	1	1952Q2
China	APD	2	1953Q1	Liberia	AFR	3	1956Q3	Taiwan Province of China	APD	1	1956Q1
Colombia	WHD	2	1953Q3	Libya	MCD	2	1956Q1	Tajikistan	MCD	3	1993Q1
Costa Rica	WHD	2	1954Q2	Lithuania	EUR	2	1993Q1	Tanzania	AFR	3	1966Q4
Côte d'Ivoire	AFR	3	1960Q1	Madagascar	AFR	3	1962Q1	Thailand	APD	2	1953Q3
Croatia	EUR	2	1993Q1	Malawi	AFR	3	1966Q3	The Gambia	AFR	3	1957Q1
Czech Republic	EUR	1	1993Q2	Malaysia	APD	2	1954Q1	Togo	AFR	3	1962Q1
Democratic Republic of the Congo	AFR	3	1963Q1	Mali	AFR	3	1960Q1	Tunisia	MCD	2	1956Q3
Denmark	EUR	1	1952Q1	Mauritania	MCD	3	1967Q1	Turkey	EUR	2	1952Q1
Dominican Republic	WHD	2	1956Q1	Mexico	WHD	2	1952Q1	Turkmenistan	MCD	2	1993Q1
Ecuador	WHD	2	1954Q1	Moldova	EUR	3	1992Q2	Uganda	AFR	3	1966Q4
Egypt	MCD	2	1953Q1	Mongolia	APD	3	1993Q1	Ukraine	EUR	2	1992Q1
El Salvador	WHD	2	1954Q2	Morocco	MCD	2	1956Q3	United Arab Emirates	MCD	2	1971Q1
Eritrea	AFR	3	1993Q3	Mozambique	AFR	3	1974Q1	United Kingdom	EUR	1	1953Q1
Ethiopia	AFR	3	1960Q1	Myanmar	APD	3	1953Q3	United States	WHD	1	1952Q1
Finland	EUR	1	1952Q2	Namibia	AFR	2	1978Q3	Uruguay	WHD	2	1952Q3
France	EUR	1	1952Q2	Nepal	APD	3	1966Q3	Uzbekistan	MCD	3	1993Q1
FYR Macedonia	EUR	2	1993Q1	Netherlands	EUR	1	1952Q1	Venezuela	WHD	2	1953Q3
Gabon	AFR	2	1962Q1	New Zealand	APD	1	1955Q3	Vietnam	APD	3	1956Q1
Georgia	MCD	2	1993Q1	Nicaragua	WHD	3	1954Q2	Yemen	MCD	3	1971Q1
Germany	EUR	1	1952Q2	Niger	AFR	3	1962Q1	Zambia	AFR	3	1966Q3
Ghana	AFR	3	1957Q1	Nigeria	AFR	3	1953Q1	Zimbabwe	AFR	3	1966Q1
Greece	EUR	1	1953Q2	Norway	EUR	1	1955Q1				

Note: For group 1, AFR = Africa, APD = Asia and the Pacific, EUR = Europe, MCD = Middle East and Central Asia, and WHD = Western Hemisphere. For group 2, 1 = advanced economies, 2 = emerging economies, and 3 = low-income economies.

Table 2. WUI Co-movements

	Synchronization	Correlation	Variance Explained by 1 st Factor—PCA
All countries	-0.167	0.071	0.150
Advanced economies	-0.146	0.121	0.221
Emerging and low-income economies	-0.185	0.011	0.144
European	-0.134	0.224	0.283

Note: synchronization between country i and j at time t is defined as: $\varphi_{i,j,t} = -|U_{i,t} - U_{j,t}|$, where U denotes the WUI. The data is from 1996Q1 to 2017Q4.

Table 3. Synchronization of WUI and trade and financial linkages

	(I) ^a	(II) ^a	(III)	(IV)	(V)	(IV)
Trade linkages	0.113** (2.37)		0.741** (2.47)		0.738** (2.49)	0.746** (2.52)
Financial linkages		0.131** (2.32)		0.314** (1.95)	0.313** (2.01)	0.317** (2.06)
Output synchronization						0.011*** (3.10)
Country-pair FE	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15,393	15,393	15,393	15,393	15,393	15,393

Note: synchronization between country i and j at time t defined as: $\varphi_{i,j,t} = -|U_{i,t} - U_{j,t}|$, where U denotes the WUI. Estimates are based on the following equation: $\varphi_{i,j,t} = \alpha_{i,j} + \gamma_t + \beta_1 TR_{i,j,t} + \beta_2 FI_{i,j,t} + \delta O_{i,j,t} + \varepsilon_{i,j,t}$ where $TR_{i,j}$ denotes trade linkages—defined as bilateral trade between country i and j , normalized by the sum of total trade of country i and j ; $FI_{i,j}$ denotes financial linkages—defined as bilateral assets and liabilities between country i and j , normalized by the sum of total assets and liabilities of country i and j . $O_{i,j}$ denotes output synchronization—defined as minus the absolute value GDP growth difference between country i and j , normalized by the sum of GDP growth of country i and j . **, *** denote significance at 5 and 1 percent, respectively. Country-pair and time fixed effects included but not reported. ^a dummy for common language and past or present colonial relationship included. The data is from 1996Q1 to 2017Q4.

Table 4. The WUI during recession and non-recession years

	Recessions years	Non-recession years	P-value for difference
All countries	0.210	0.177	0.000***
Advanced economies	0.195	0.165	0.000***
Emerging and low-income economies	0.226	0.191	0.000**

Note: The World Uncertainty Index (WUI) is computed by counting the frequency of uncertain (or the variant) in EIU country reports. The WUI is then normalized by total number of words and rescaled by multiplying by 1,000. The WUI is then normalized by total number of words, rescaled by multiplying by 1,000. A higher number means higher uncertainty and vice versa. For the list of countries in each income group, see Table 1. Recession years identified as those with negative growth. The data is from 1996Q1 to 2020Q4.

Table 5. Correlation of WUI with EPU, Stock Market Volatility and Growth

	(I)	(II)	(III)
EPU	59.941*** (3.52)		
Stock Vol		0.131*** (4.11)	
GDP Growth Forecast Disagreement			0.092** (2.33)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2053	6208	1822
R ²	0.50	0.61	0.53

Note: *, **, *** denote statically significance at 10, 5, and 1 percent respectively.

T-statics based on clustered standard errors at the country level.

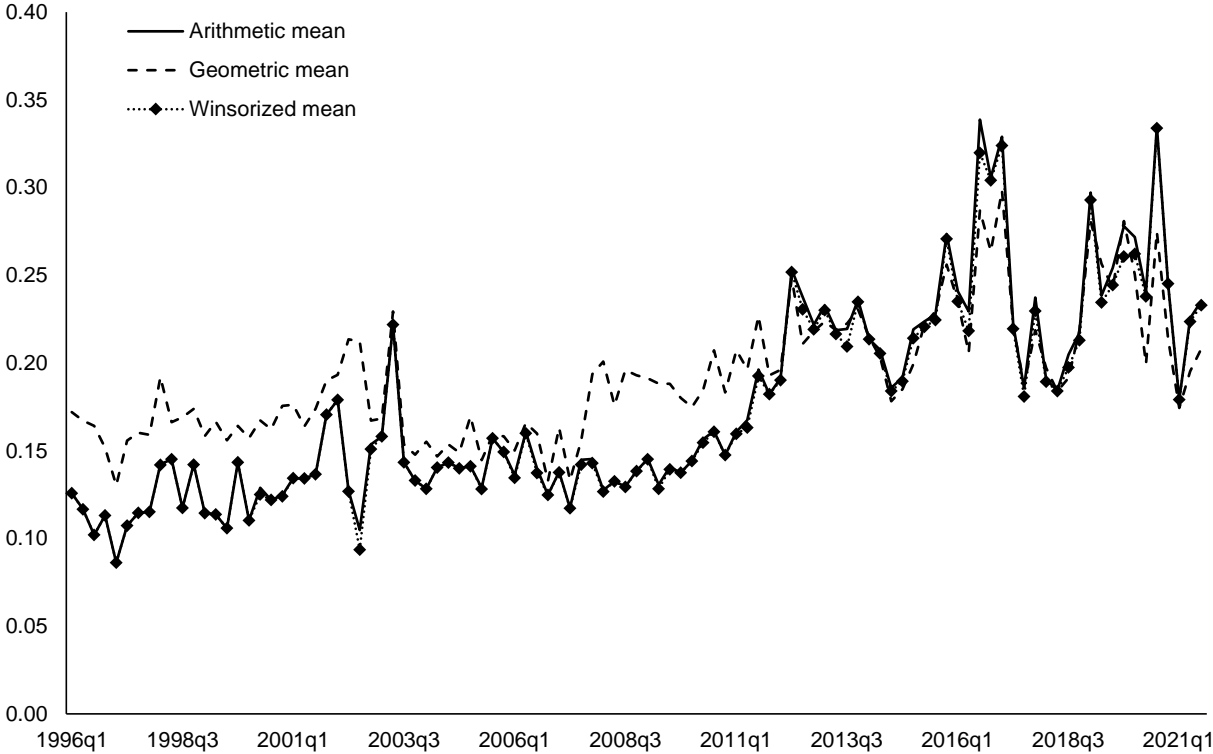
Table 6. WUI, elections and shocks

	t-2	t-1	t	t+1	t+2
All	-0.002 (-0.29)	0.022*** (2.63)	0.044*** (4.64)	0.047*** (4.78)	0.023** (2.90)
Exogenous	-0.003 (-0.19)	0.036** (2.44)	0.074*** (4.21)	0.053*** (3.54)	0.015 (1.17)

Note: *, **, *** denote statically significance at 10, 5, and 1 percent respectively. T-statics in parenthesis.

ANNEX A

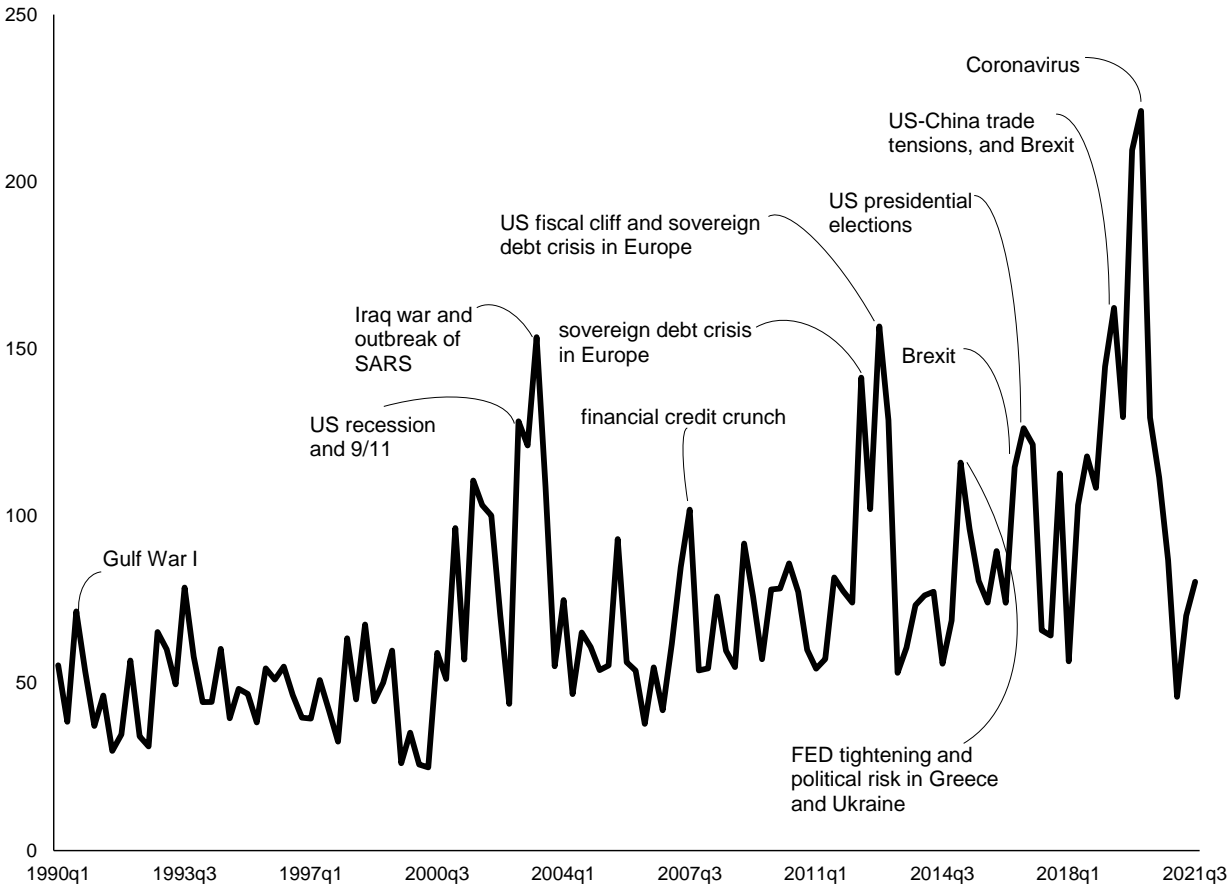
Figure A1. Global WUI



Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. For the list of countries included, see Table 1. The data plotted in the figure is from 1996Q1 to 2021Q3.

Figure A2. World Uncertainty Index (WUI) over time

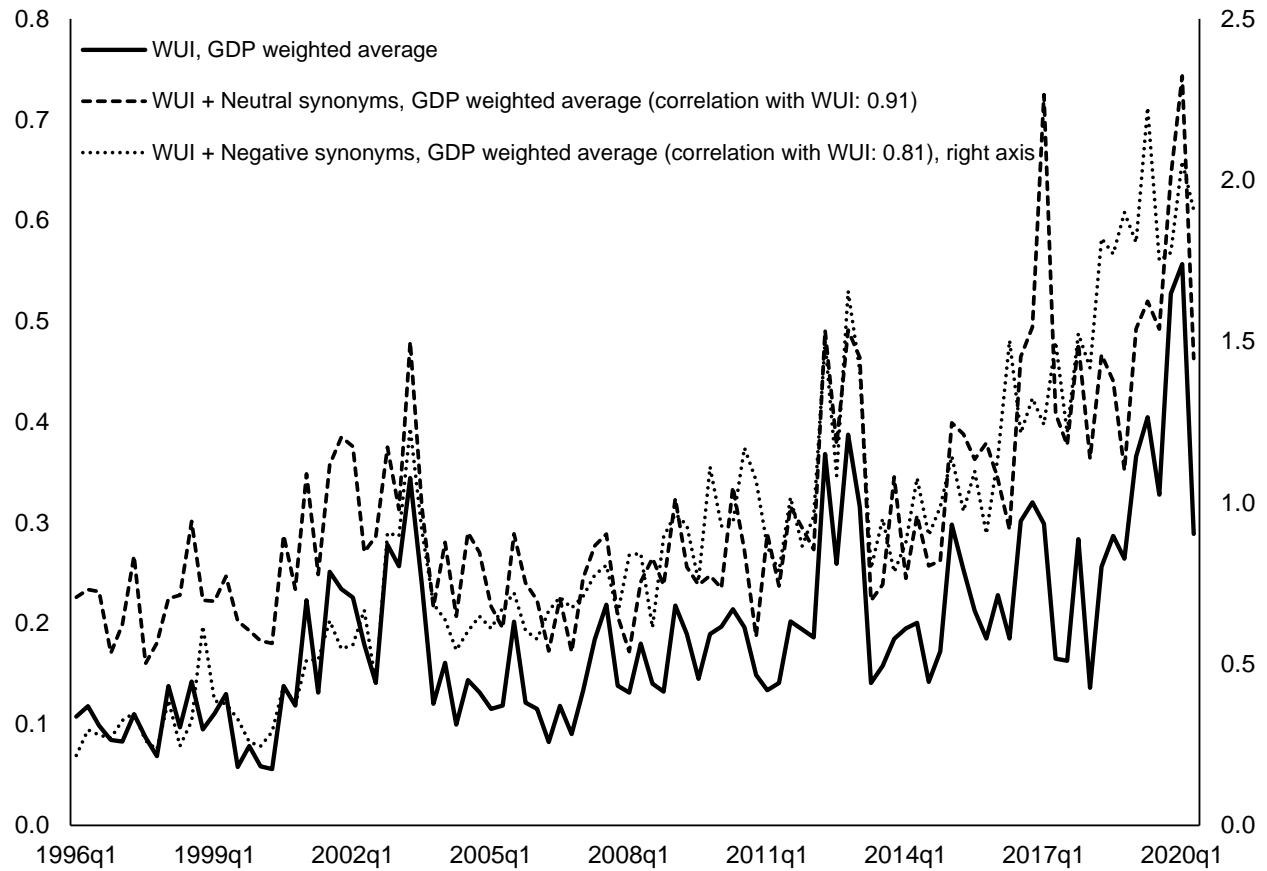
(GDP weighted average and normalize by total number of pages)



Note: The WUI is computed by counting the number of times uncertain (or the variant) is mentioned in EIU country reports. The WUI is then normalized by total number of pages and rescaled by multiplying by 1,000. A higher number means higher uncertainty and vice versa. For the list of countries included in the index, see Table 1. The data plotted in the figure above is from 1990Q1 to 2021Q3.

Figure A3. World Uncertainty Index vs. synonyms of uncertainty

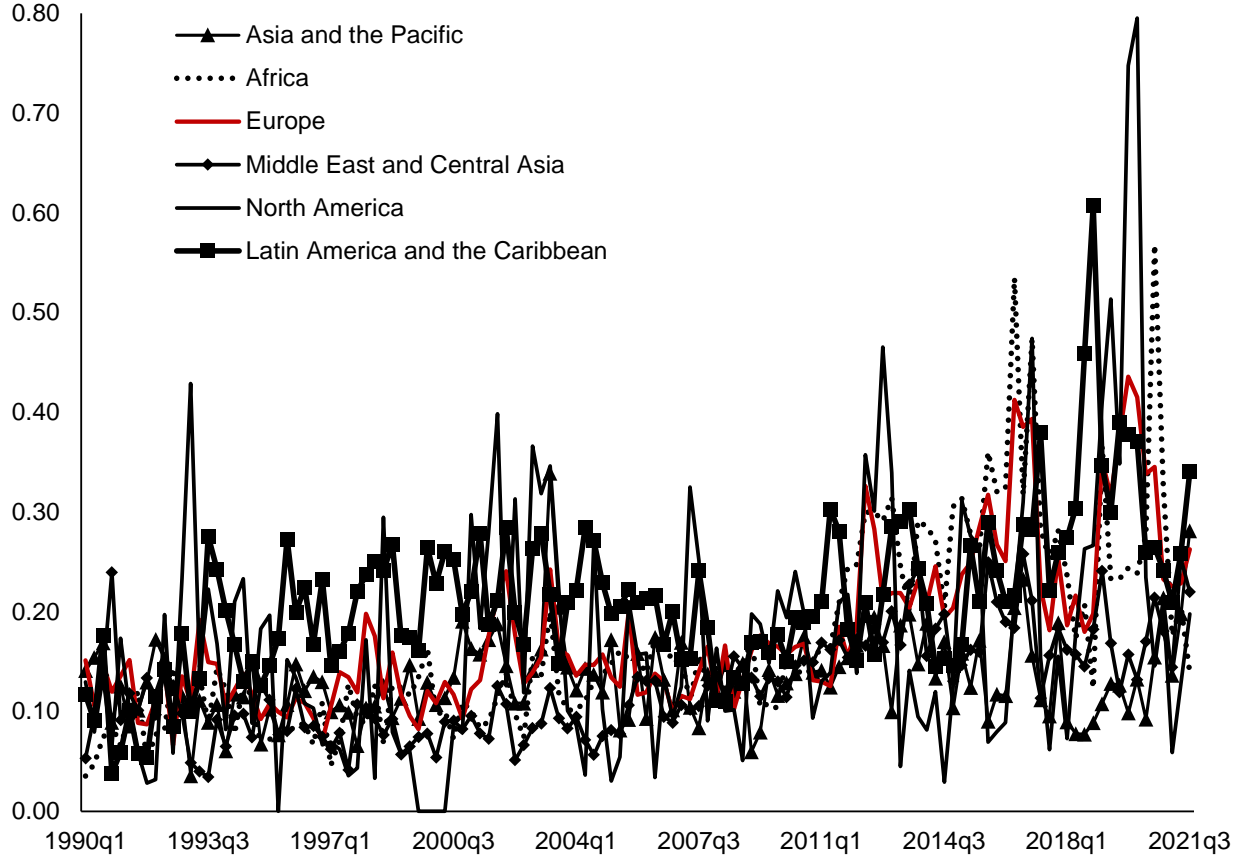
(GDP weighted average)



Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. WUI + neutral synonyms count the following keywords: ambiguous, ambivalent, dubious, erratic, hazy, hesitant, unclear, undecided, undetermined, unpredictable, unreliable, unsettled, unsure, vague, questionable, insecure, plus uncertain (or the variant). Negative synonyms count the following keywords: risk, risks, risky, precarious, unresolved, plus uncertain (or the variant). The three indexes are then normalized by total number of words, rescaled by multiplying by 1,000. A higher number means higher uncertainty and vice versa. For the list of countries included, see Table 1. The data is from 1996Q1 to 2020Q2.

Figure A4. World Uncertainty Index (WUI) by region over time

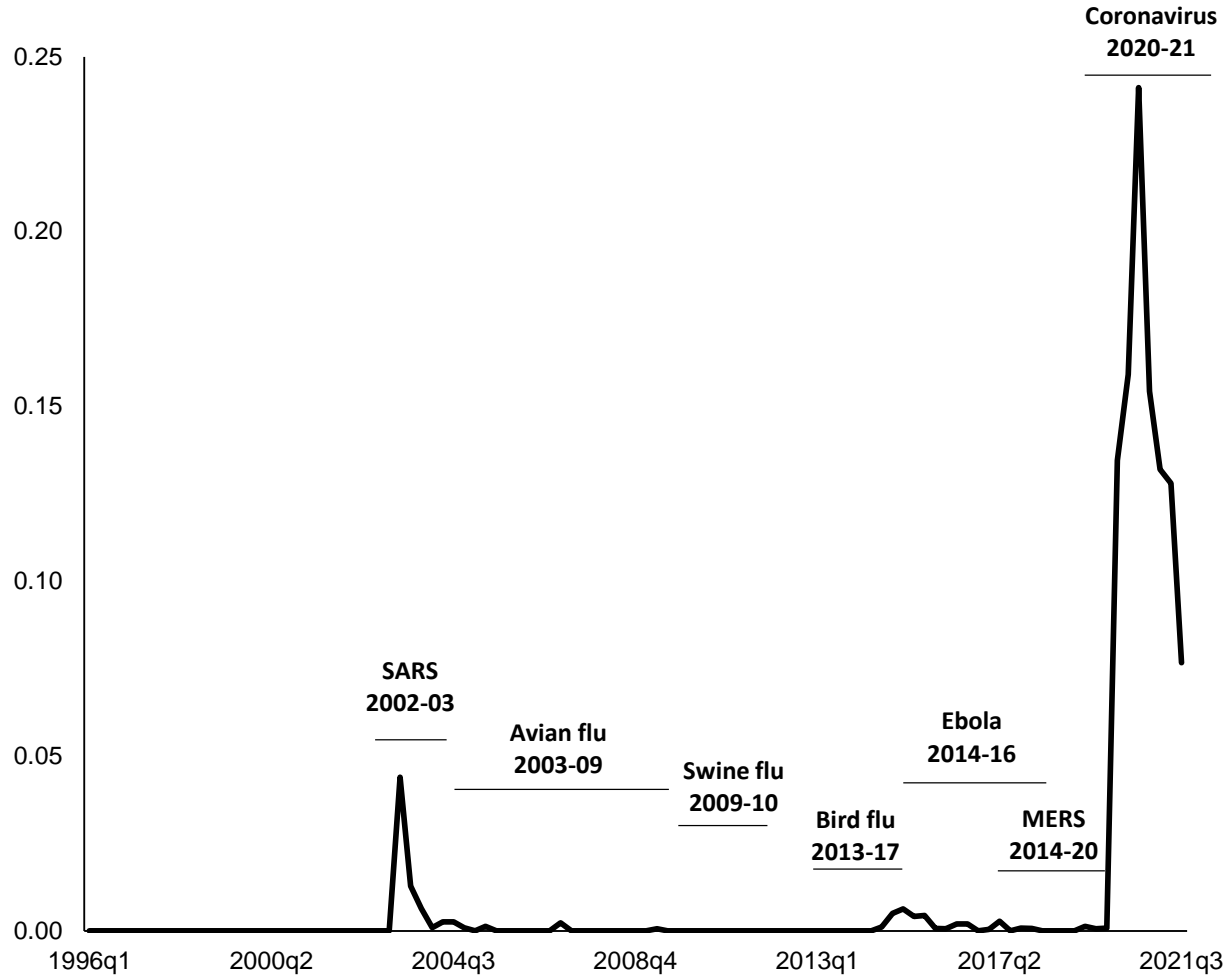
(simple average)



Note: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. For the list of countries included in each region, see Table 1. Note that North America includes Canada and the United States. Latin America and the Caribbean includes all the countries in Western Hemisphere (see Table 1) except Canada and the United States. The data is from 1990Q1 to 2021Q3.

Figure A5. World Pandemic Uncertainty Index (WPUI) over time

(simple average)



Note: The WPUI index is computed by counting the number of times uncertain (or the variant) is near the following words: Severe Acute Respiratory Syndrome (SARS), Avian flu, H5N1, Swine flu, H1N1, Middle East respiratory syndrome (MERS), Bird fu, Ebola, Coronavirus, Covid-19, Influenza, H1V1, and World Health Organisation (WHO) in EIU country reports. The WPUI is then normalized by total number of words and rescaled by multiplying by 1,000. For the list of countries included in the index, see Table 1. The data is from 1996Q1 to 2021Q3.

Figure A6. WUI vs. EPU

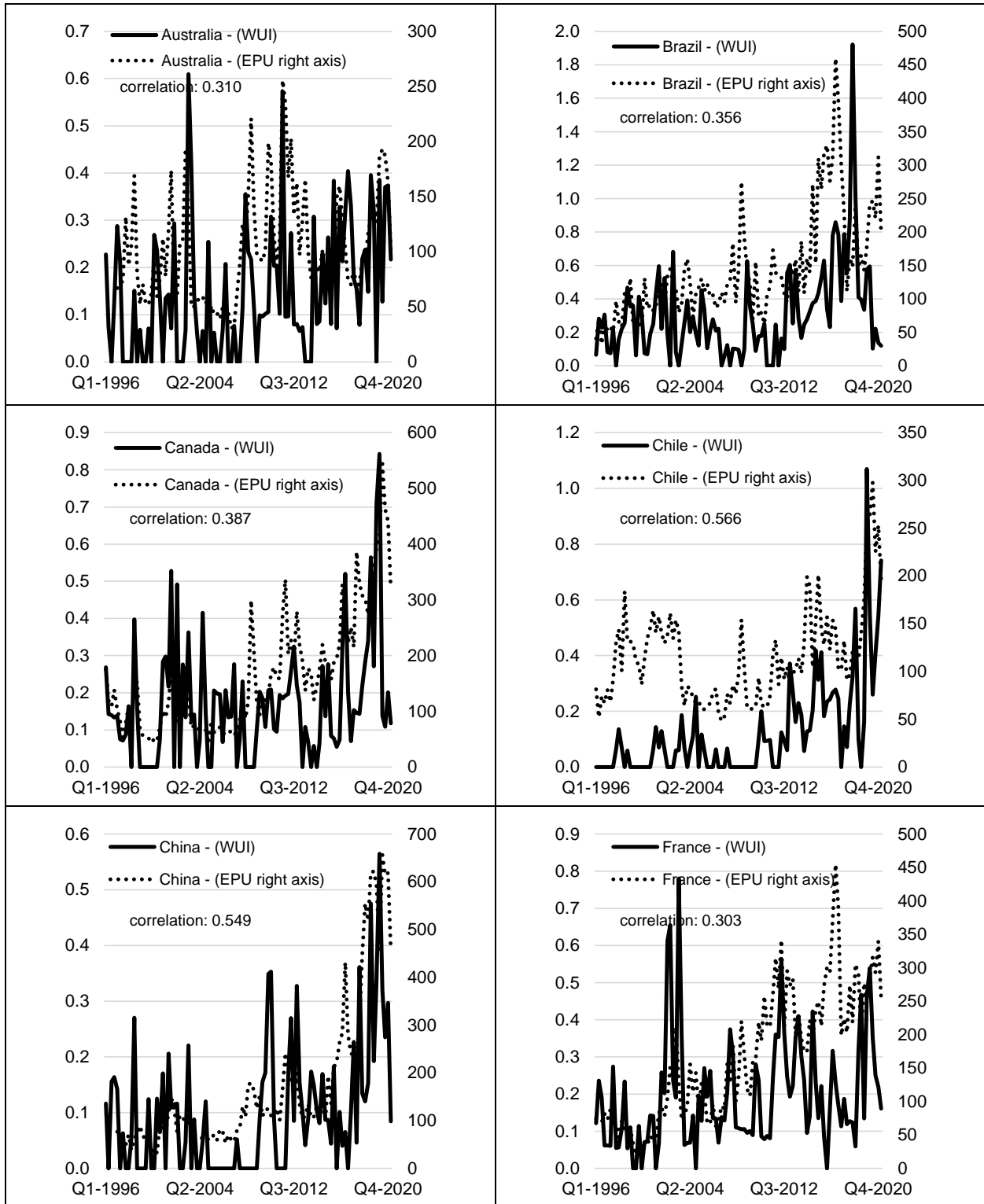


Figure A5. WUI vs. EPU. (continued...)

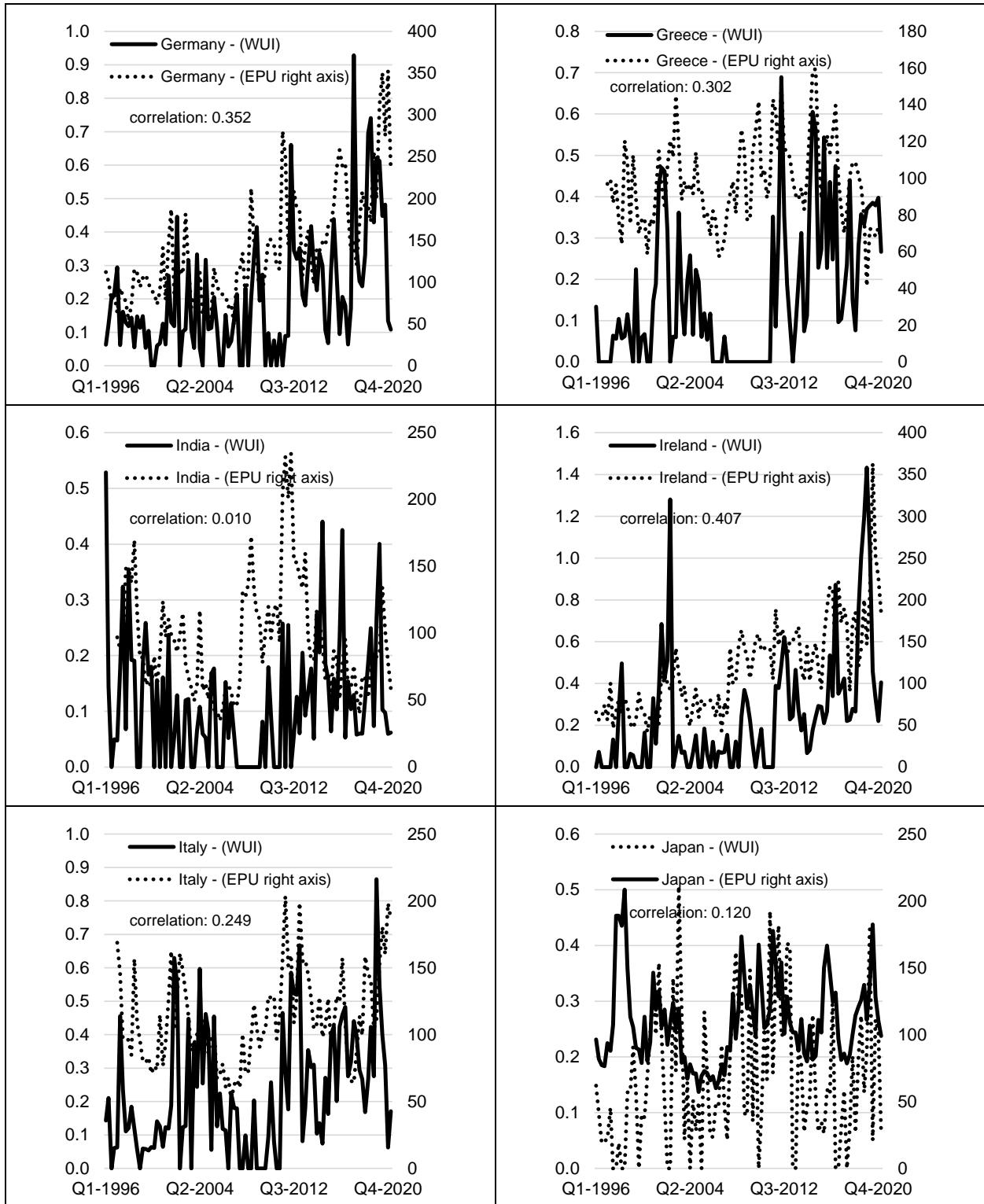


Figure A5. WUI vs. EPU. (continued...)

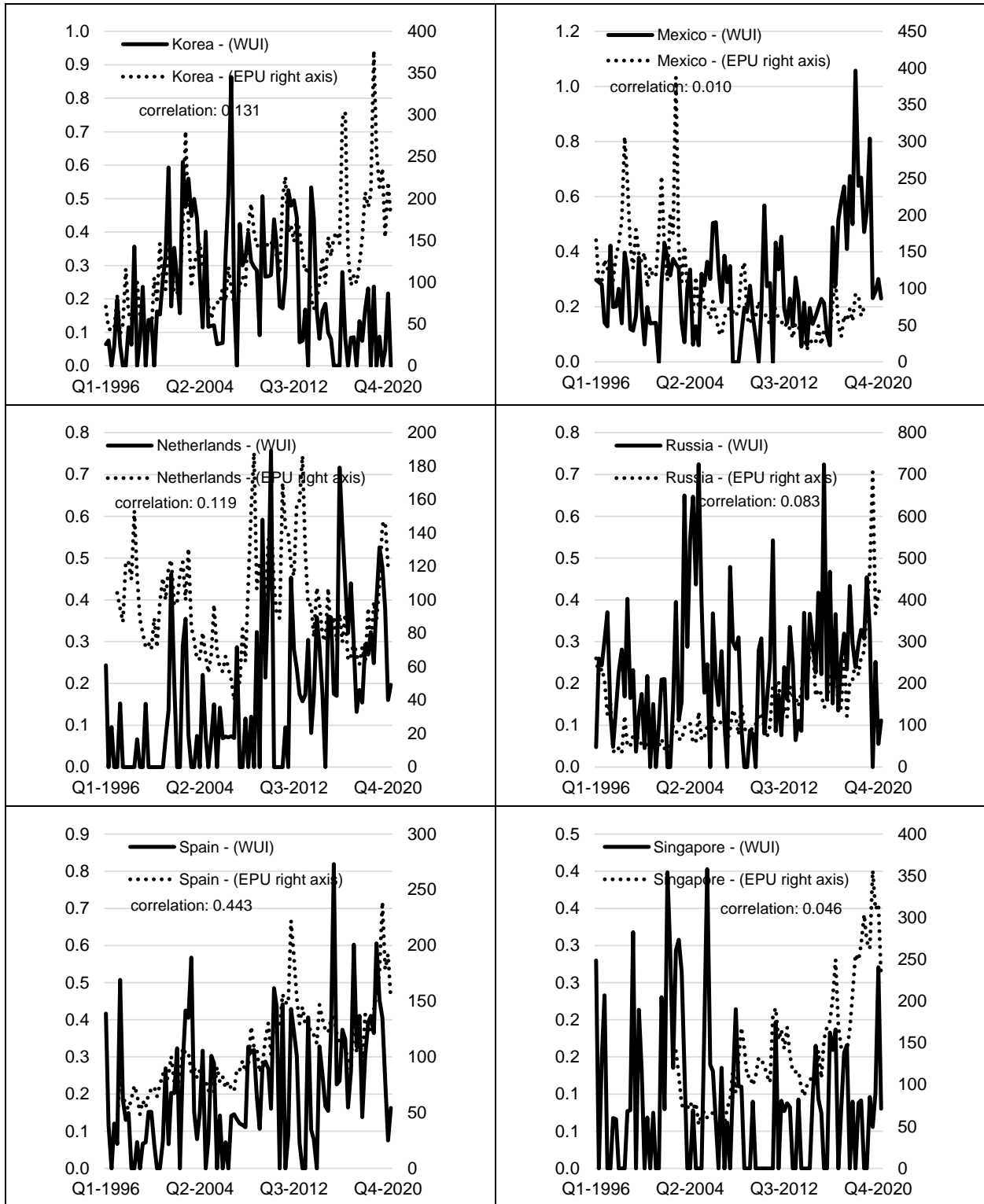
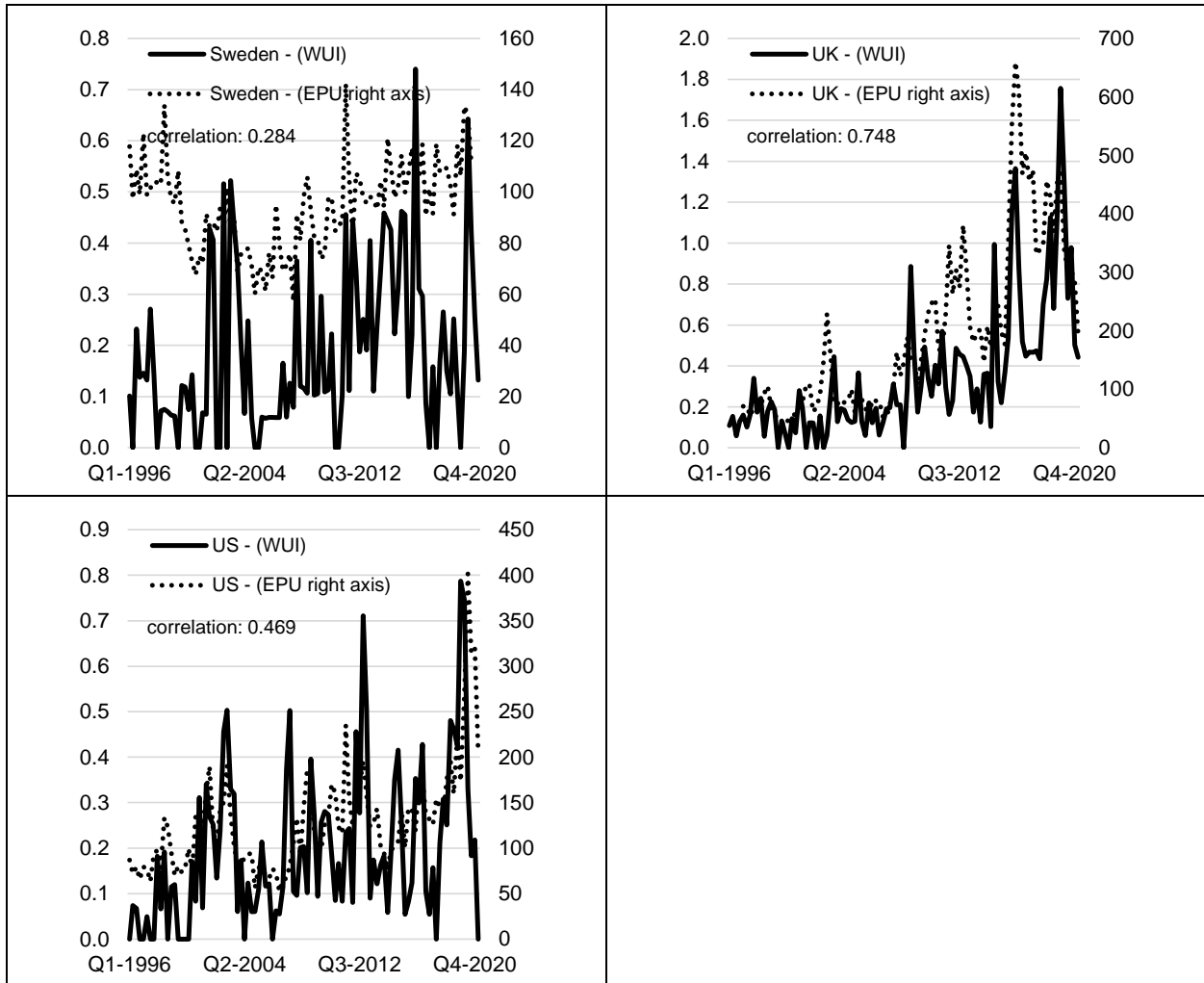
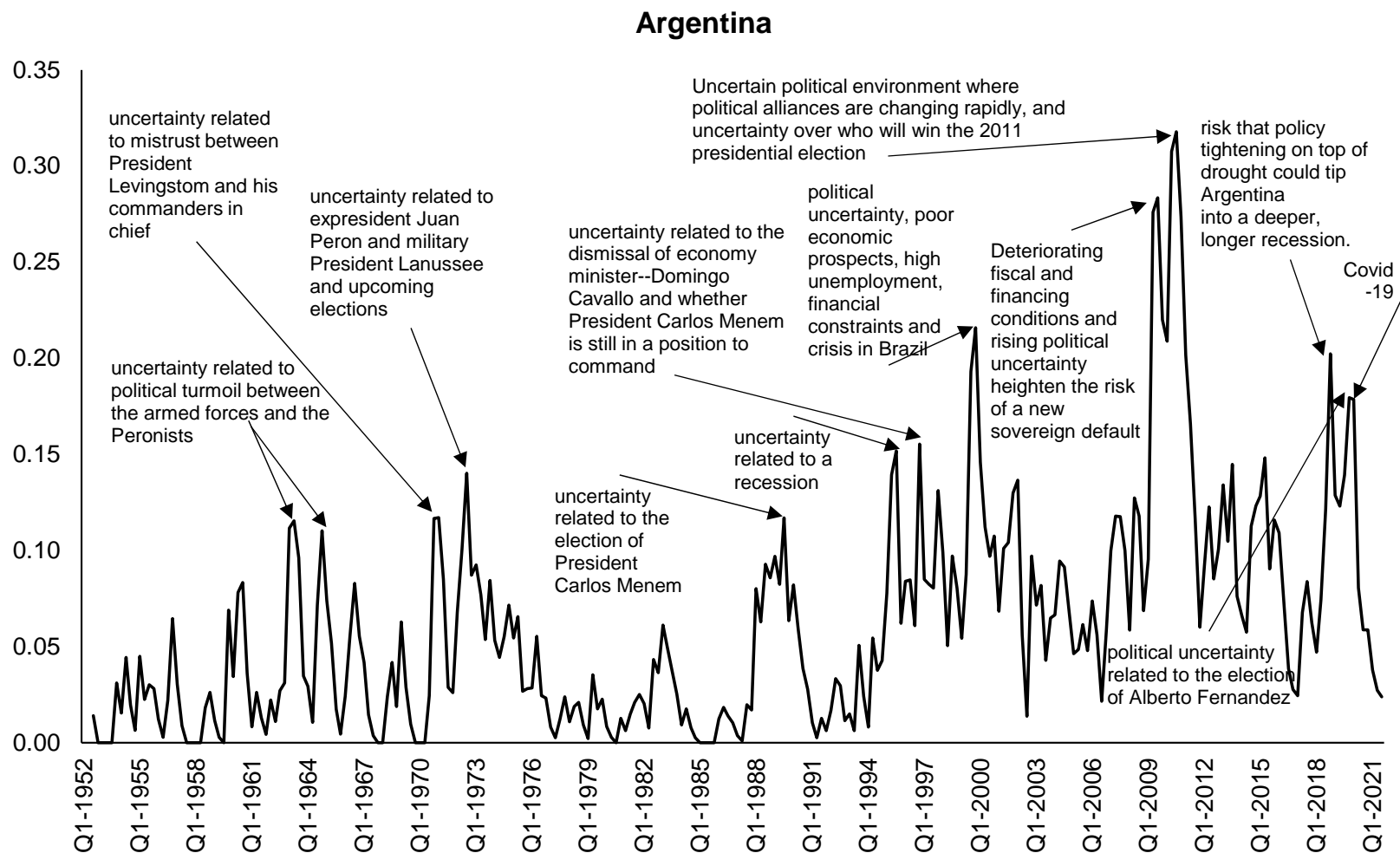


Figure A5. WUI vs. EPU. (continued...)



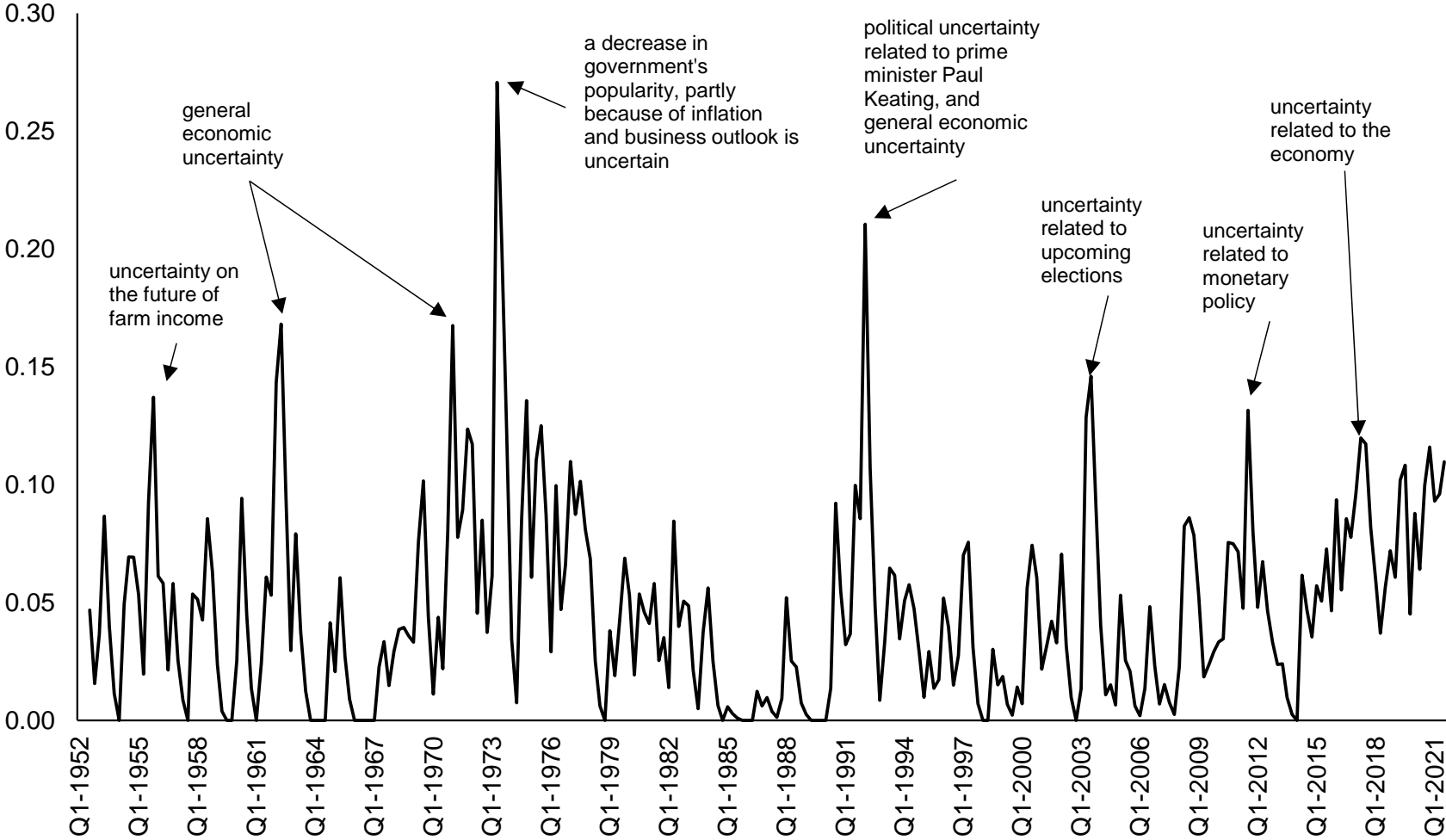
Note. Left Scale: WUI—number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. Right scale: EPU from Baker, Bloom and Davis (2016). The data is from 1996Q1 to 2021Q1.

Figure A6. Historical WUI

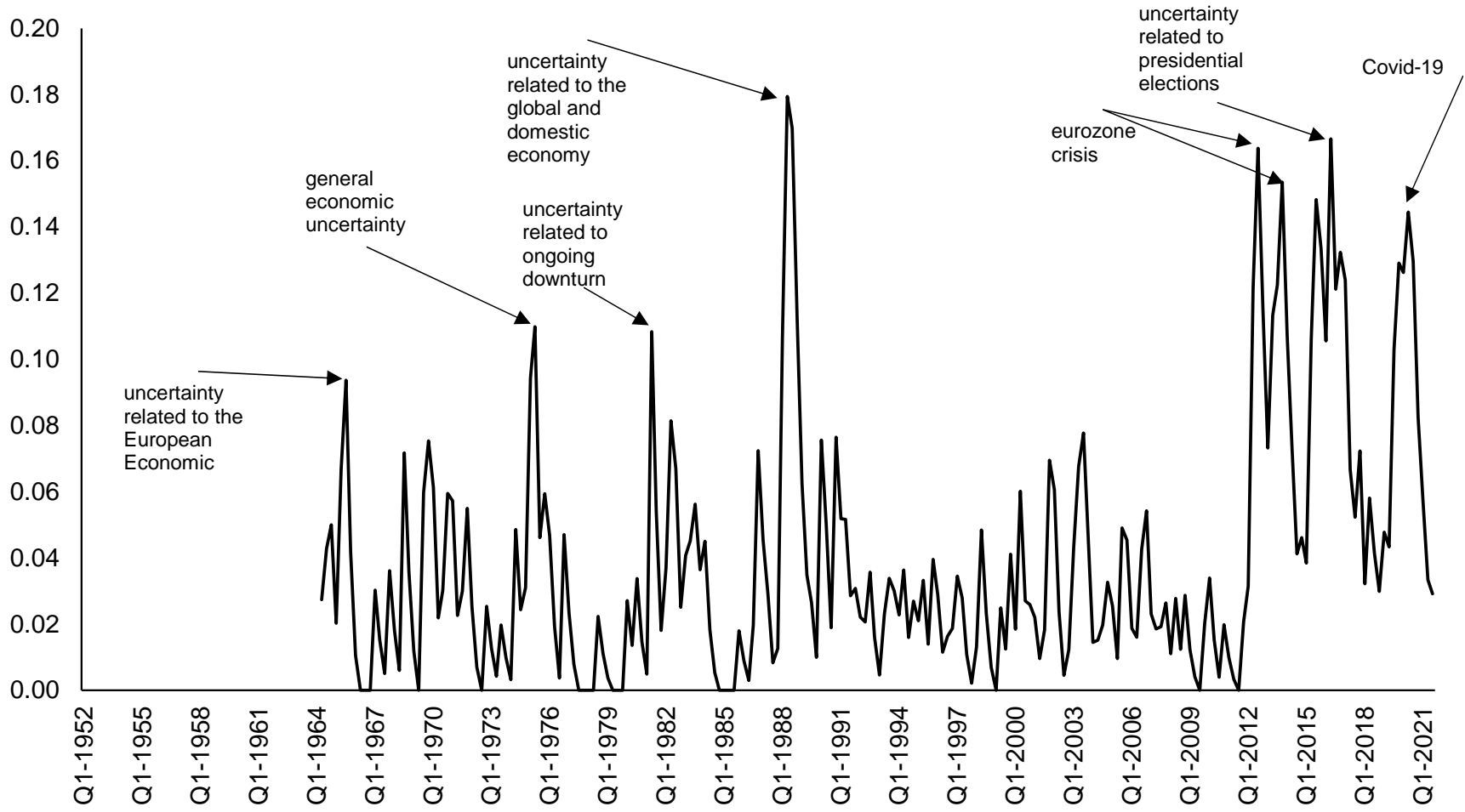


Note for all figures in Appendix A5: The WUI denotes the number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. A higher number means higher uncertainty and vice versa. The data plotted in Appendix A5 is from the earliest available for the respective country to 2021Q3 and it is a 3-quarter weighted moving average. The moving average is computed as follows: $1996Q4 = (1996Q4 \cdot 0.6) + (1996Q3 \cdot 0.3) + (1996Q2 \cdot 0.1) / 3$.

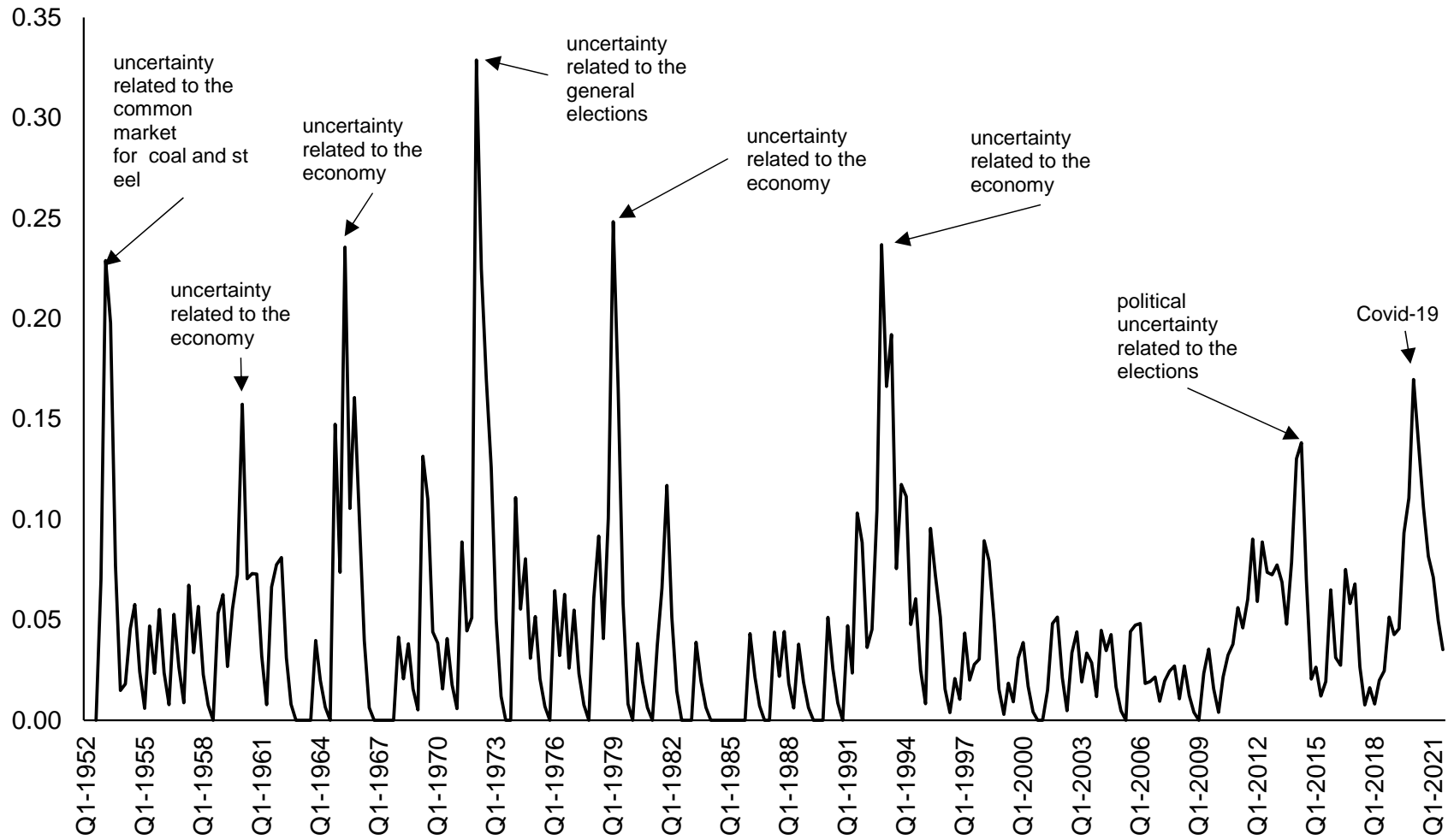
Australia



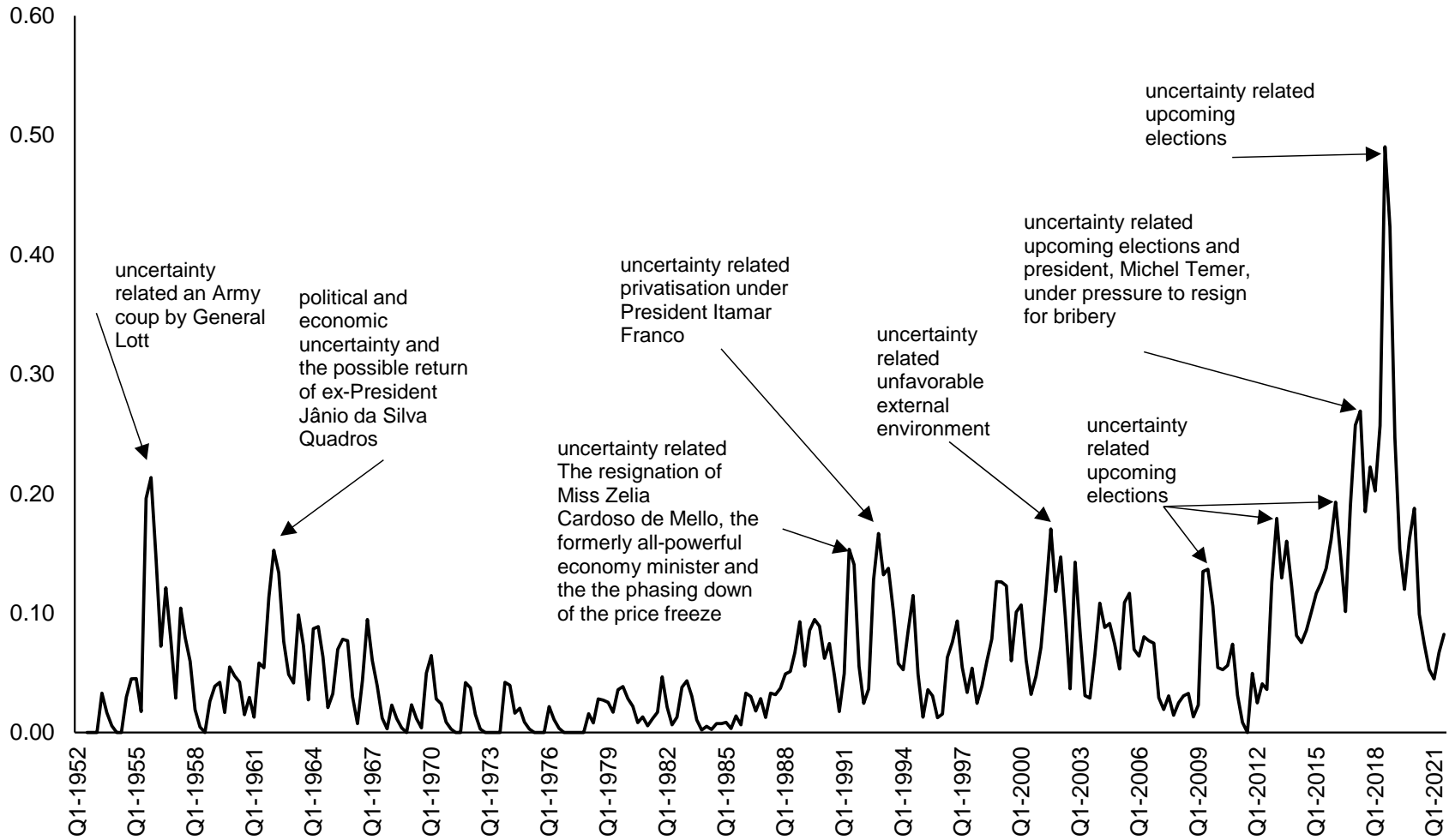
Austria



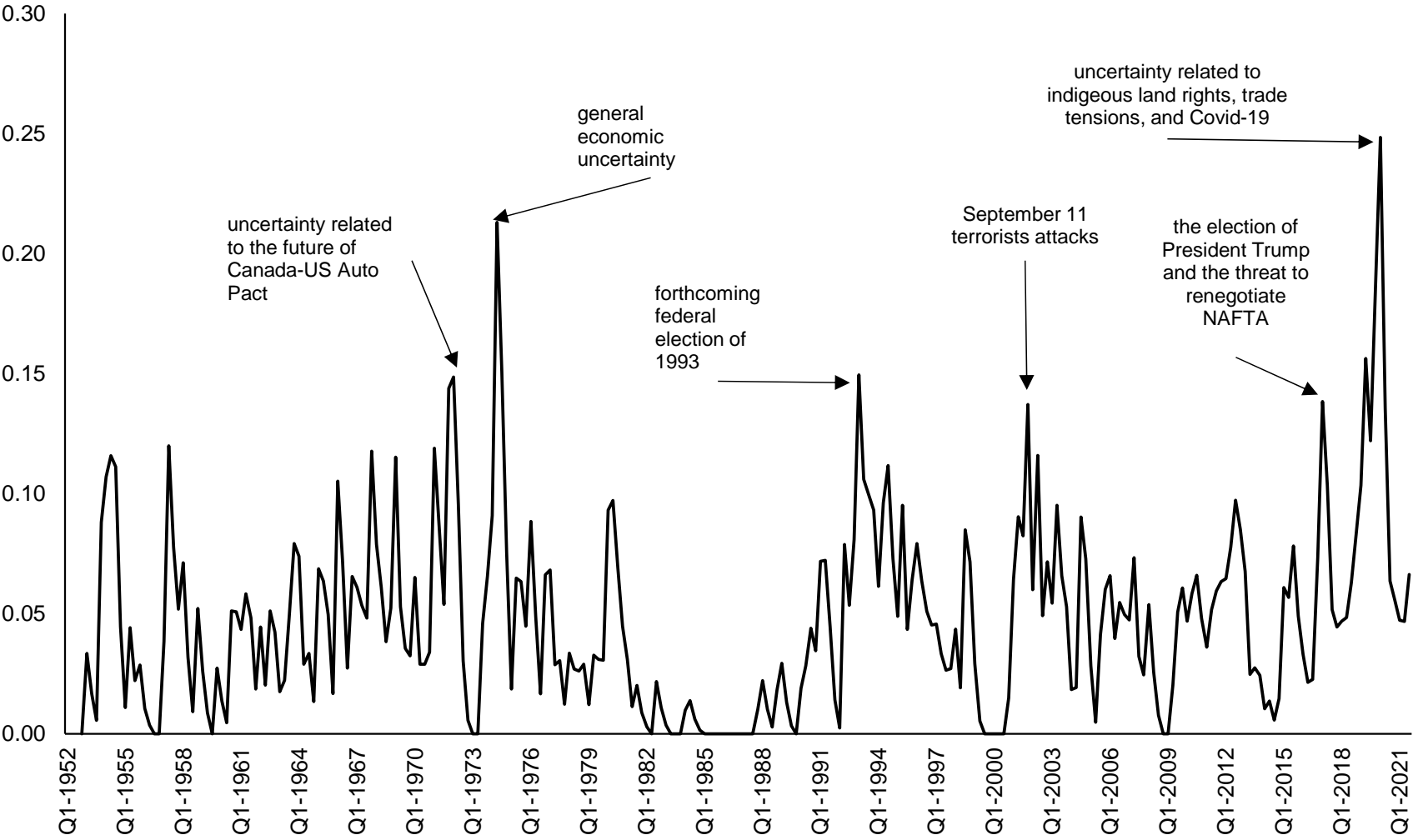
Belgium



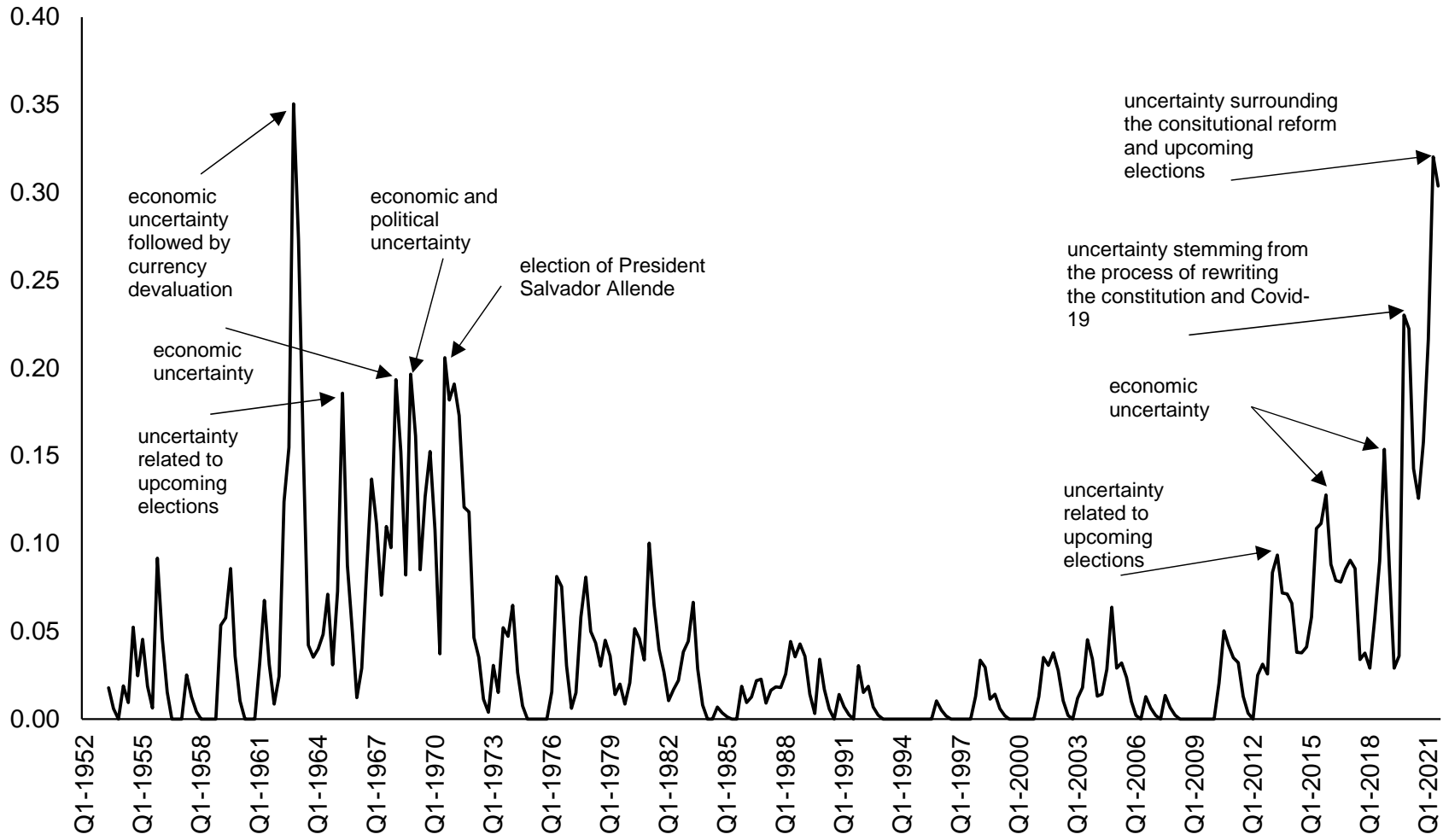
Brazil



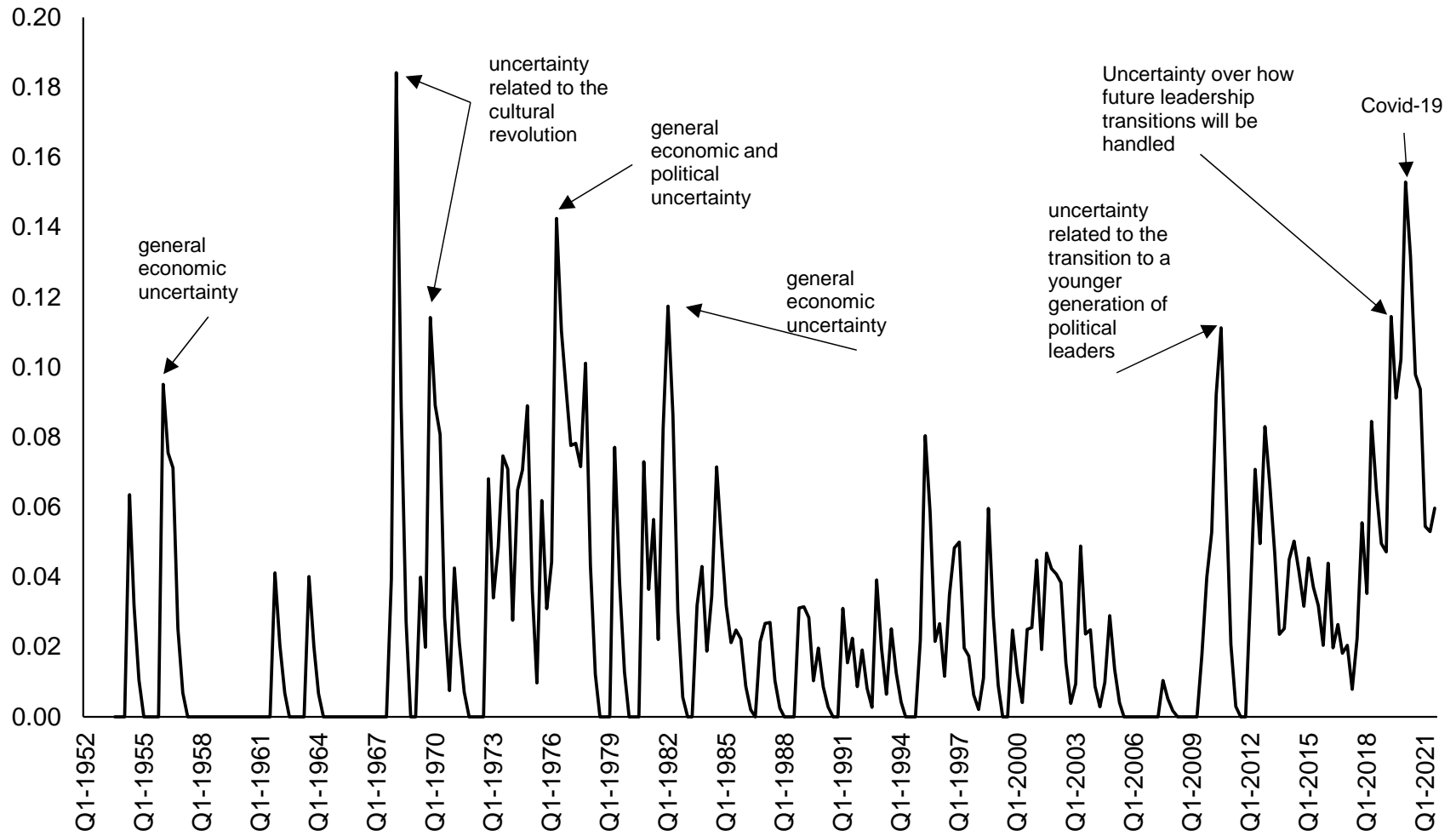
Canada



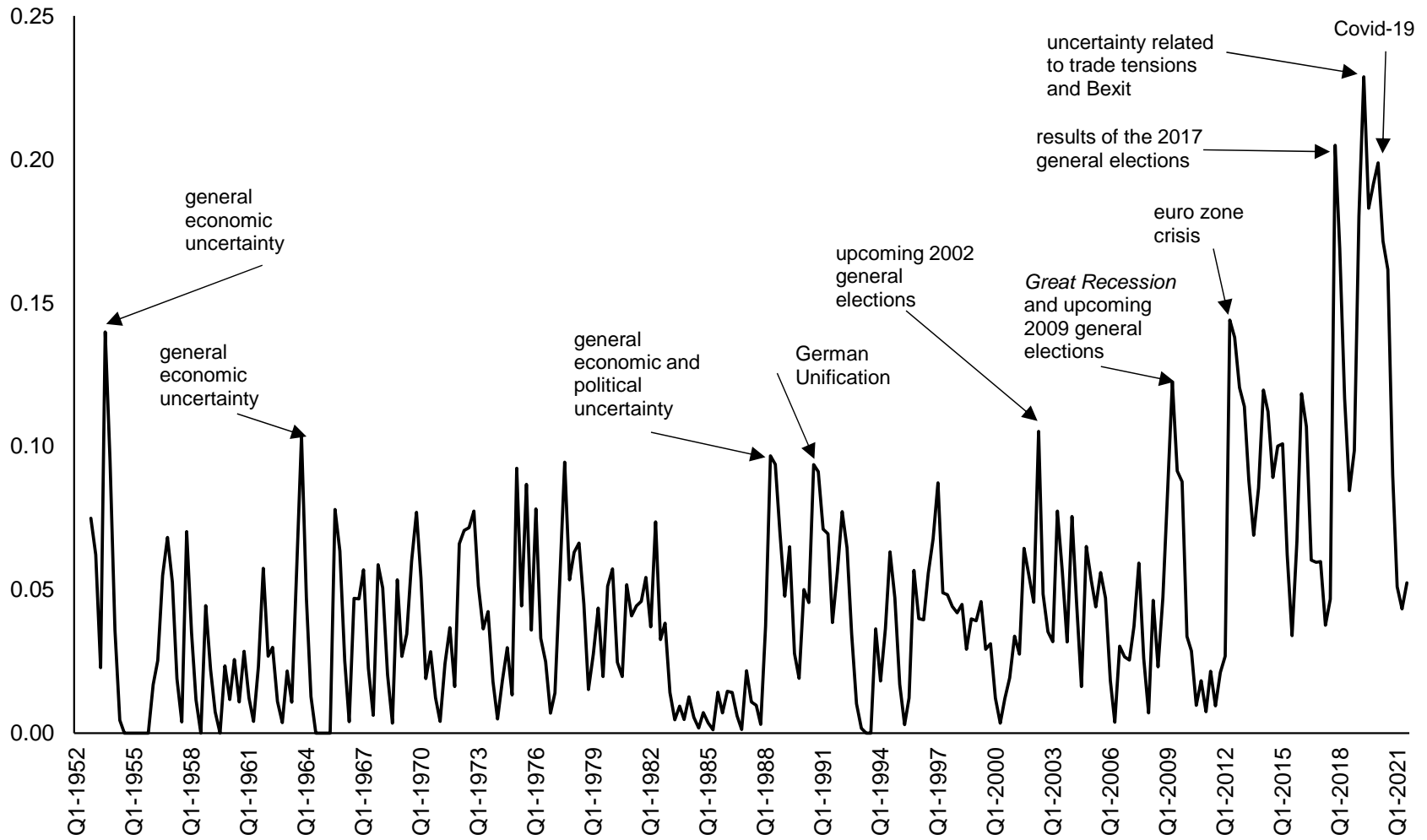
Chile



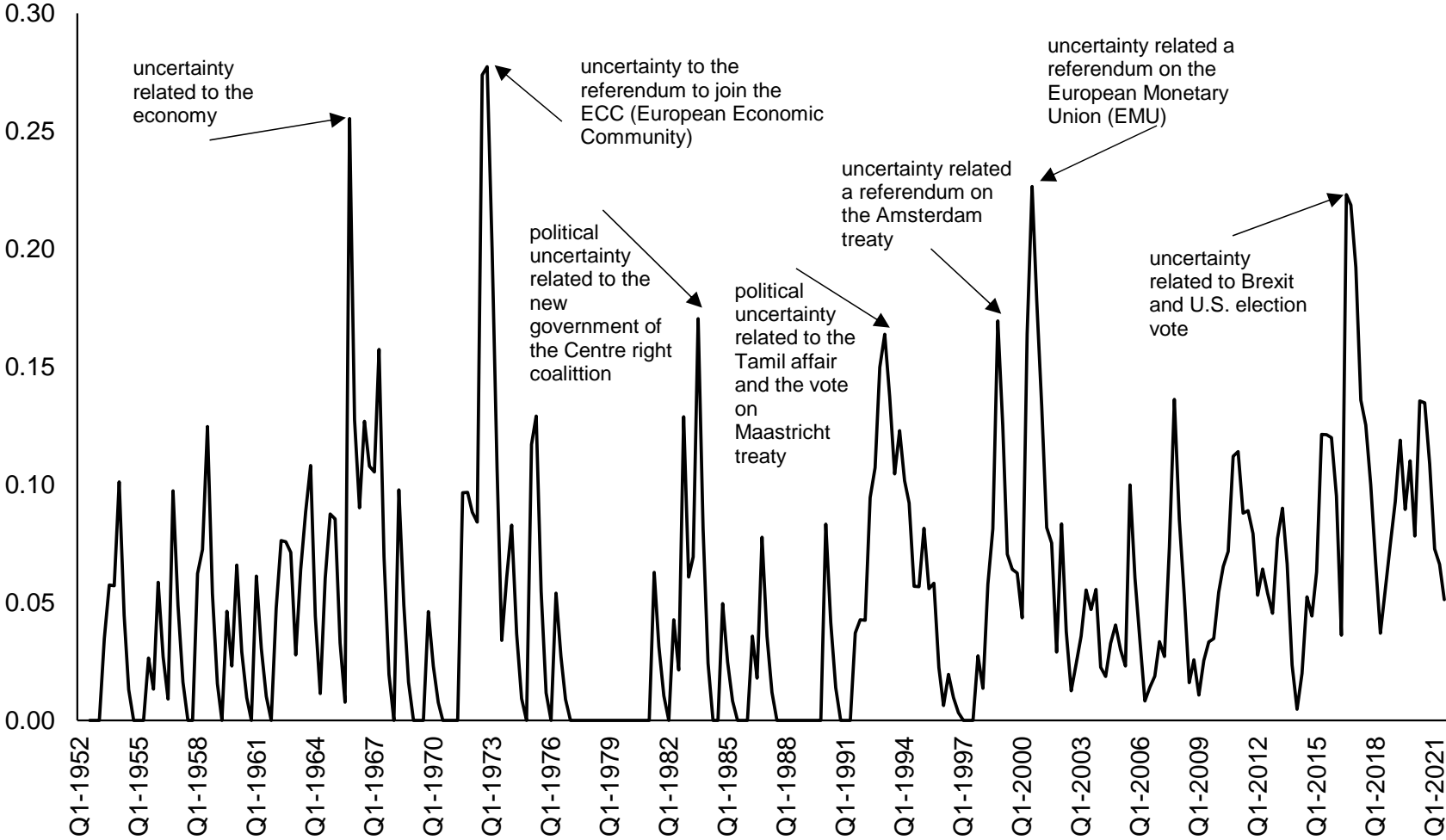
China



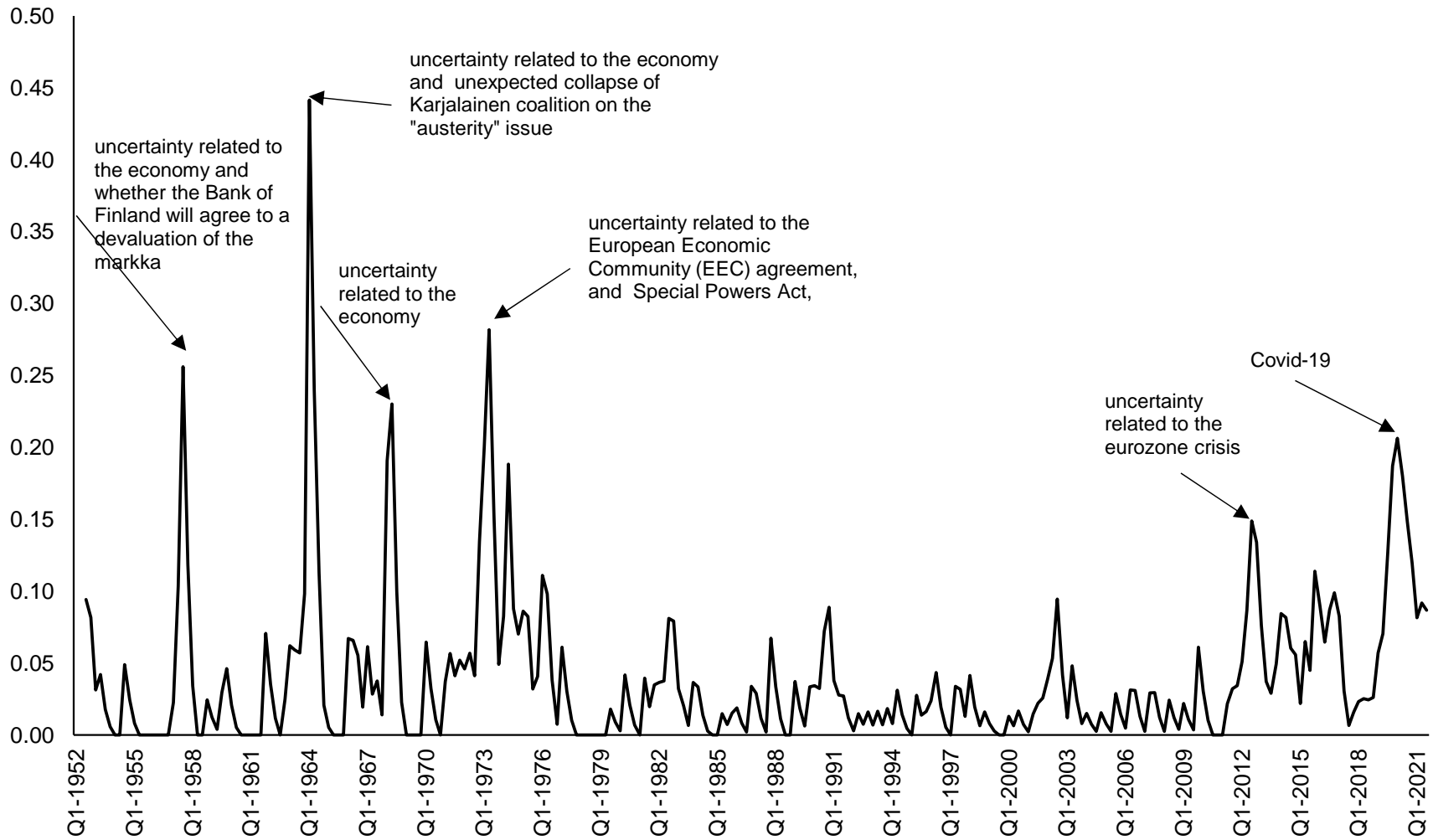
Germany



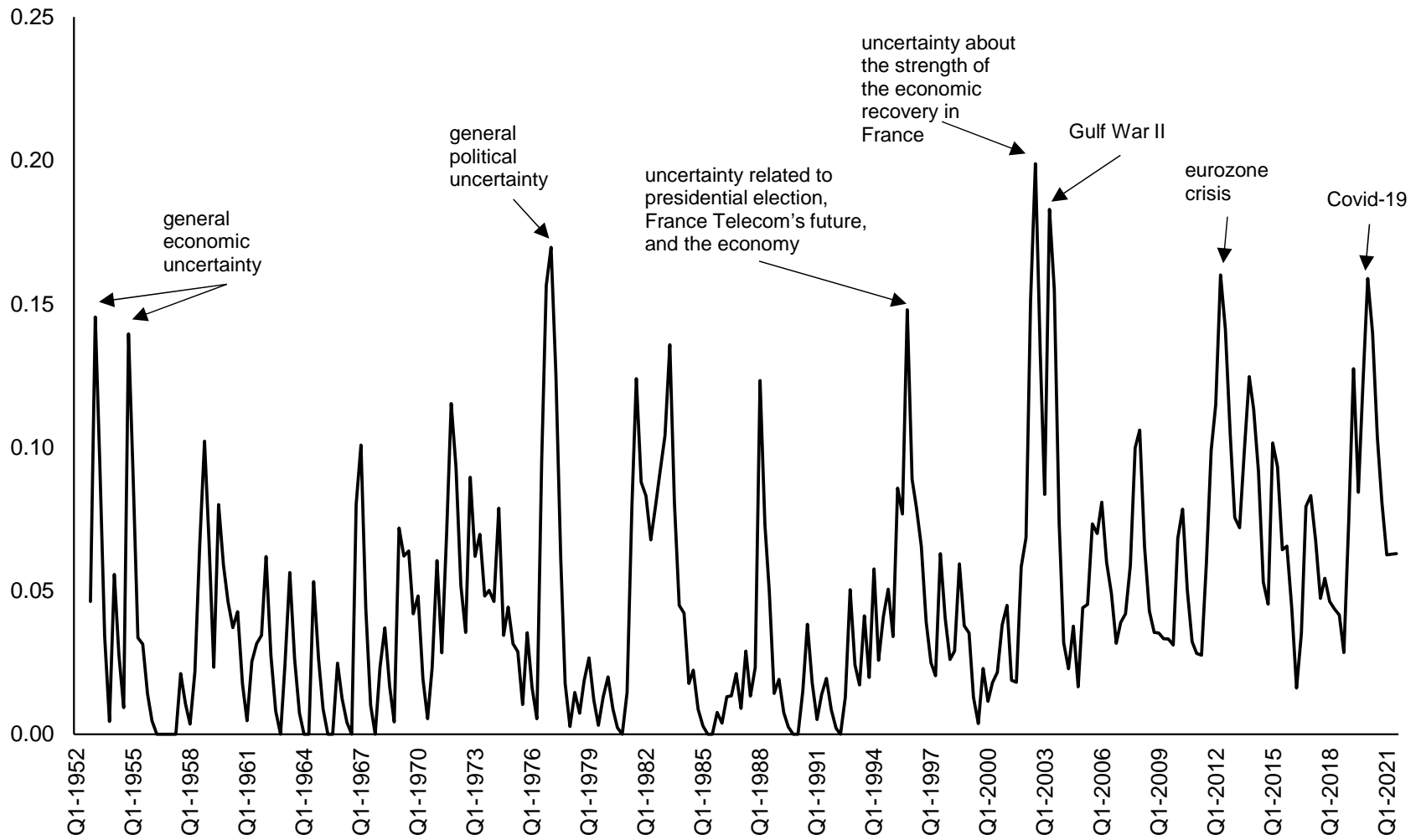
Denmark



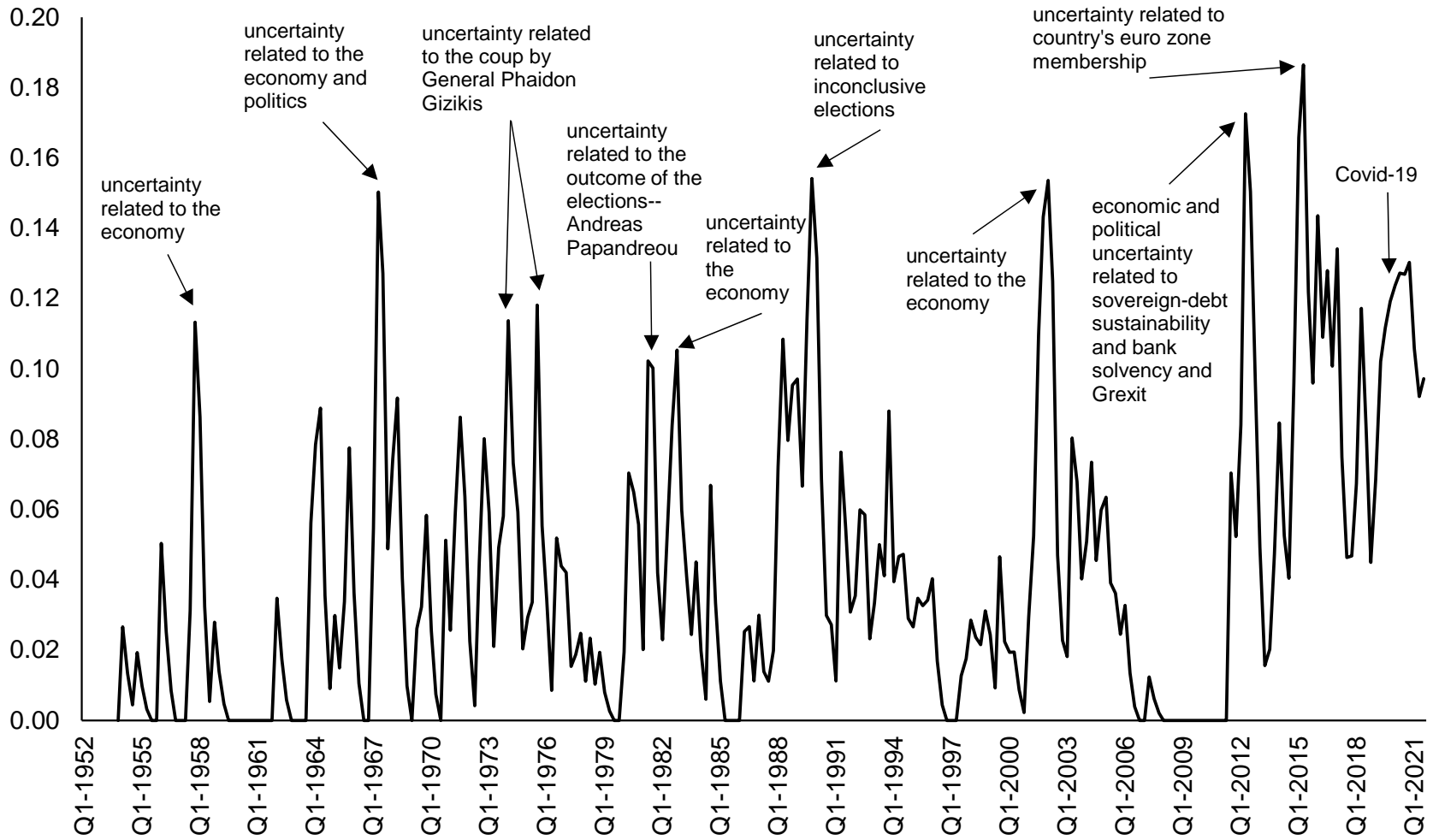
Finland



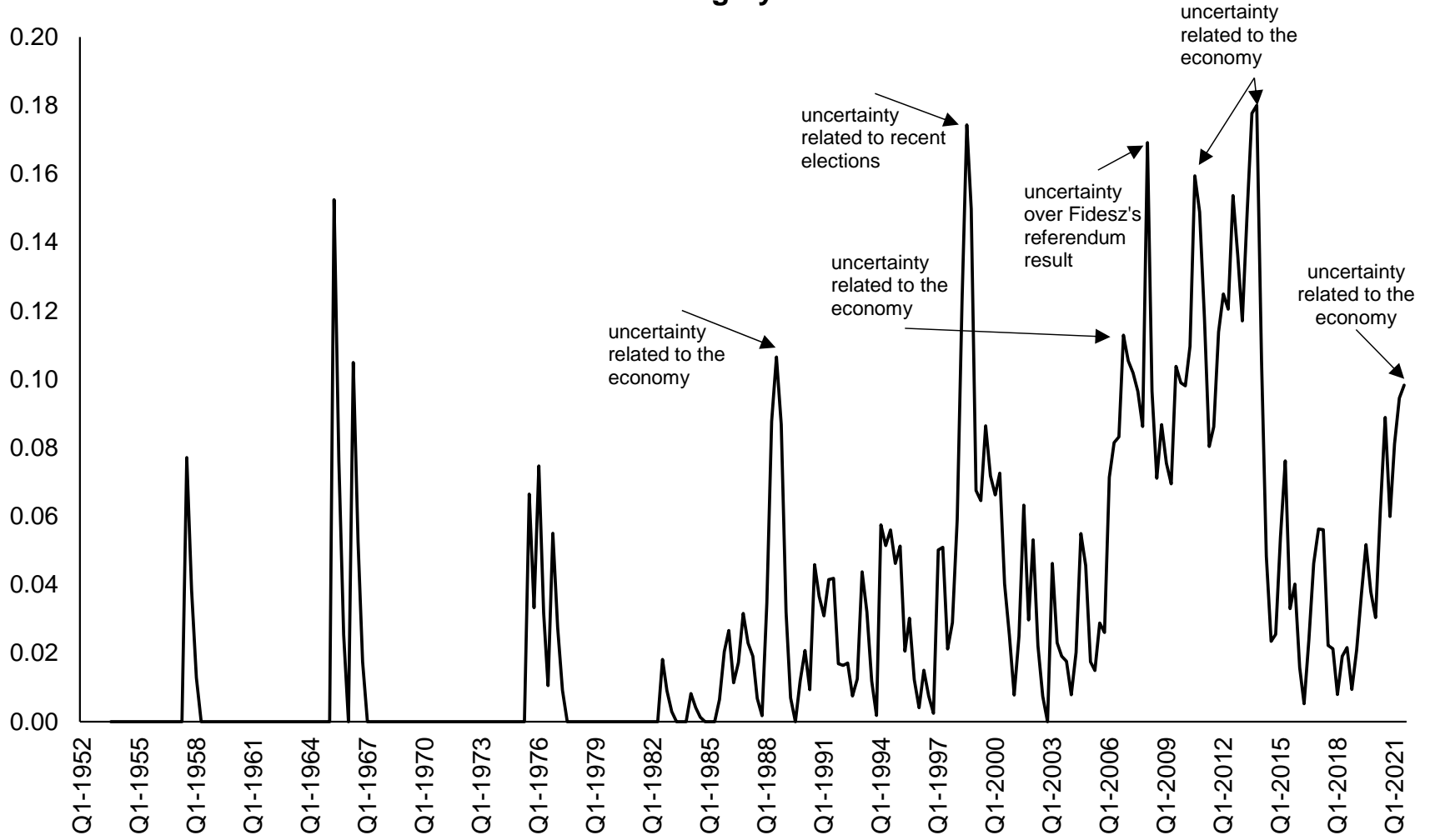
France



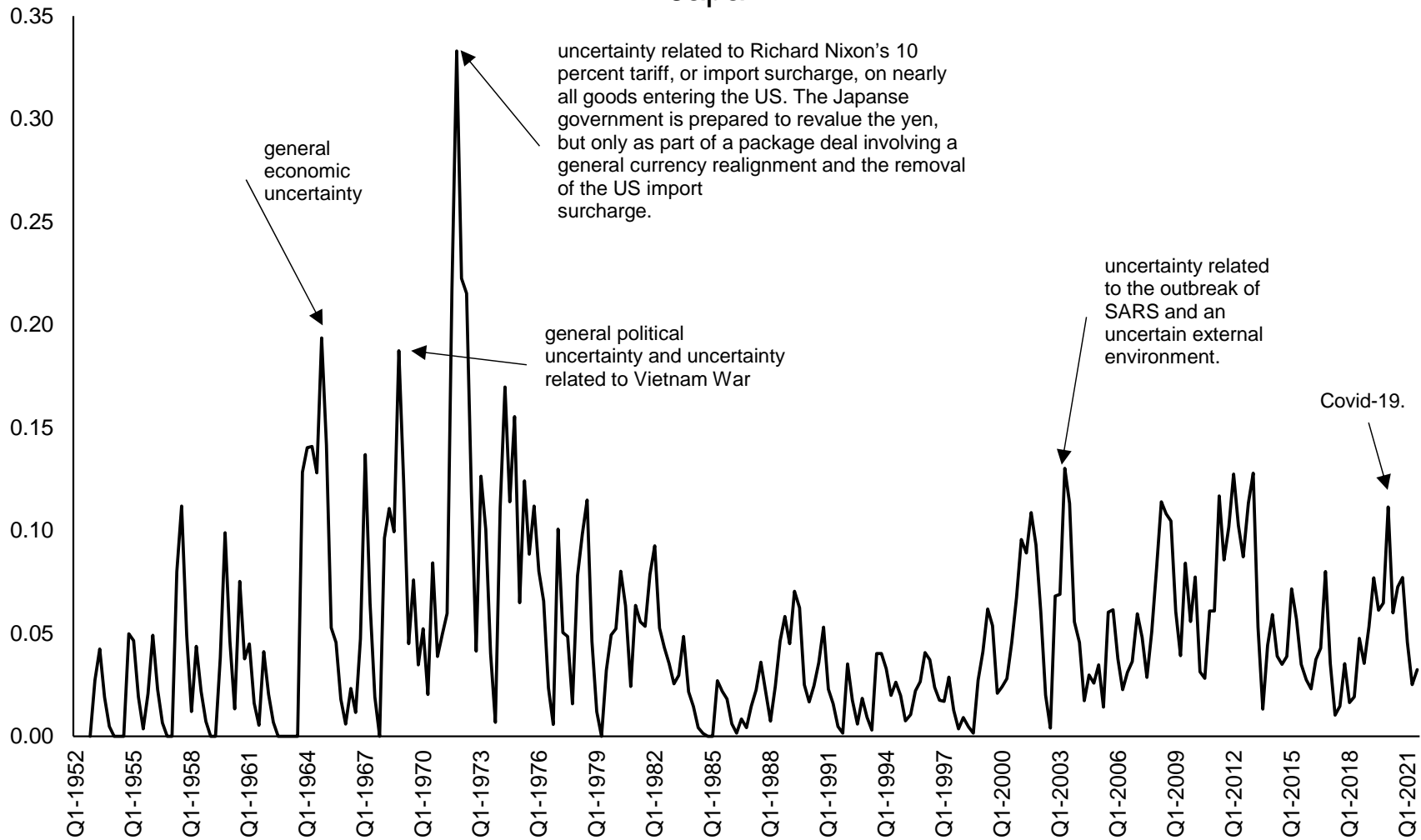
Greece



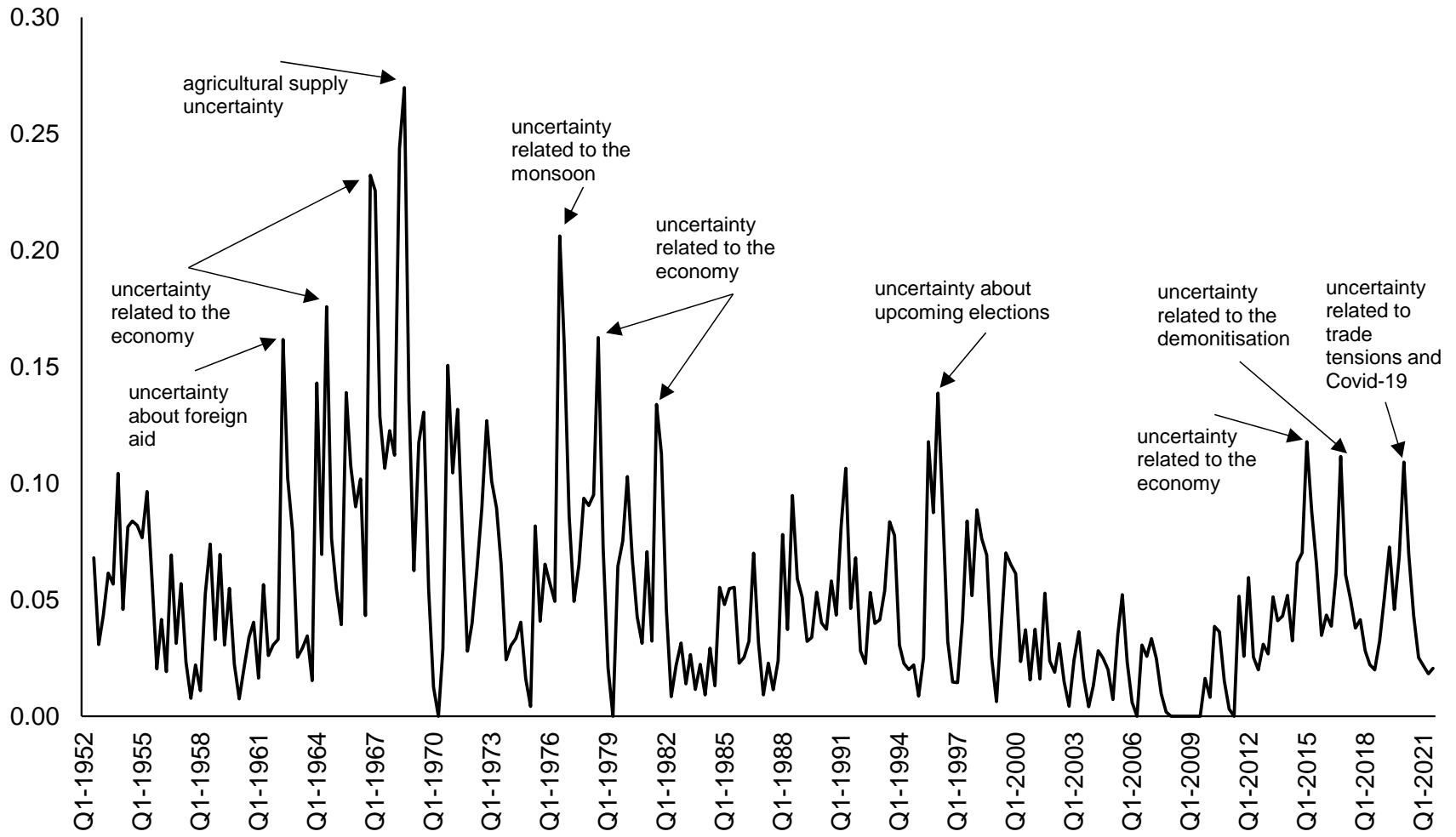
Hungary



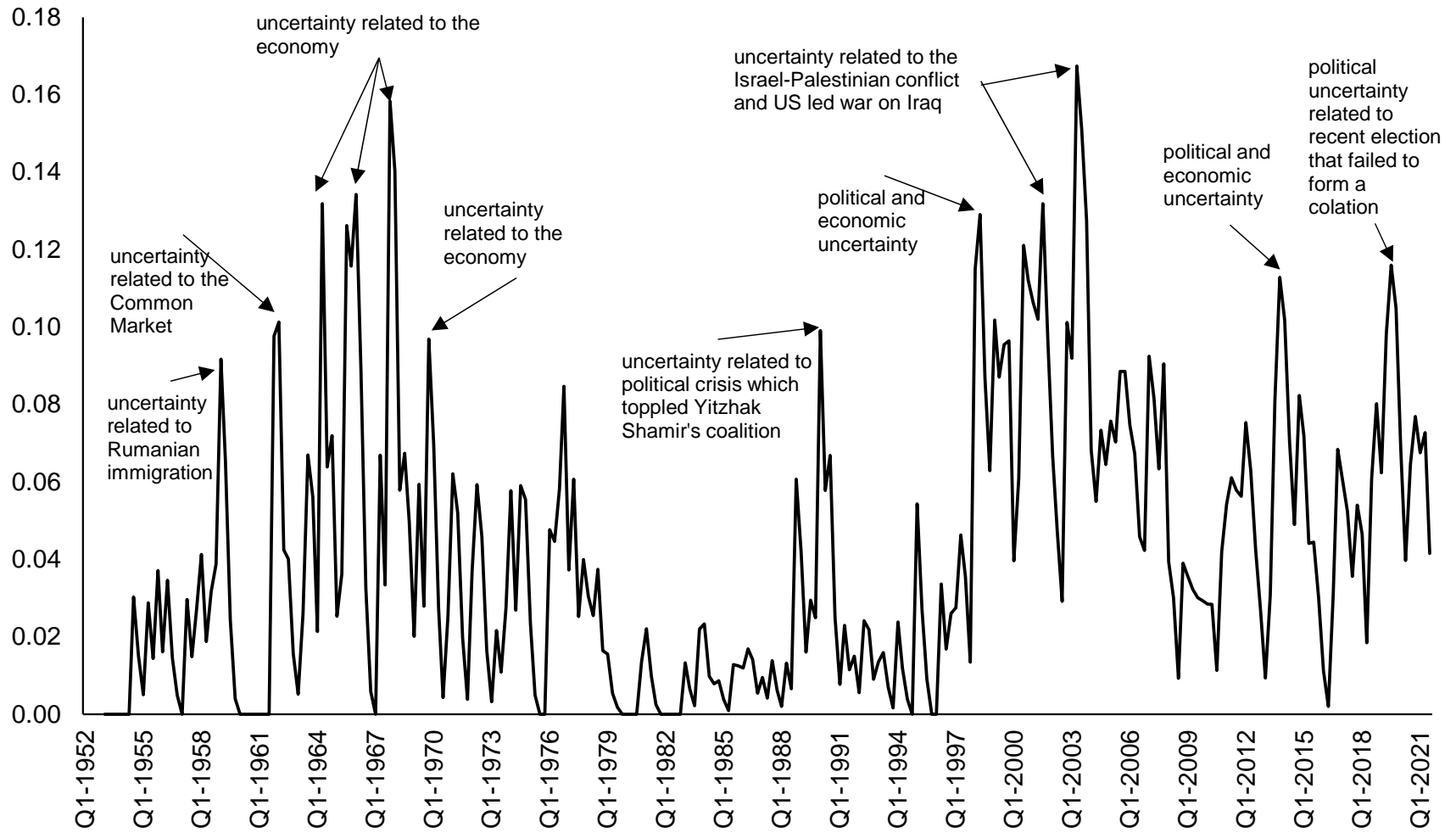
Japan



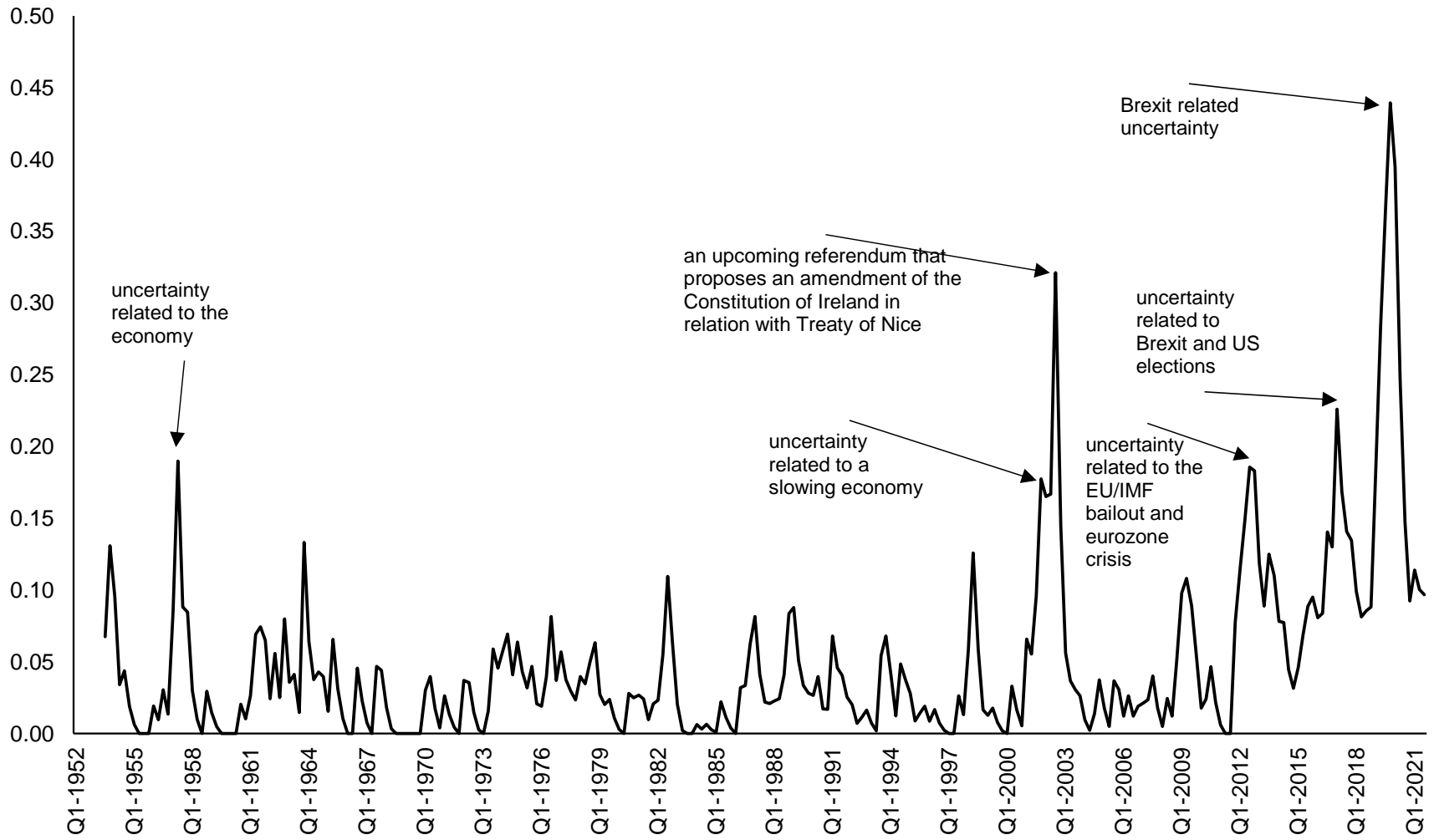
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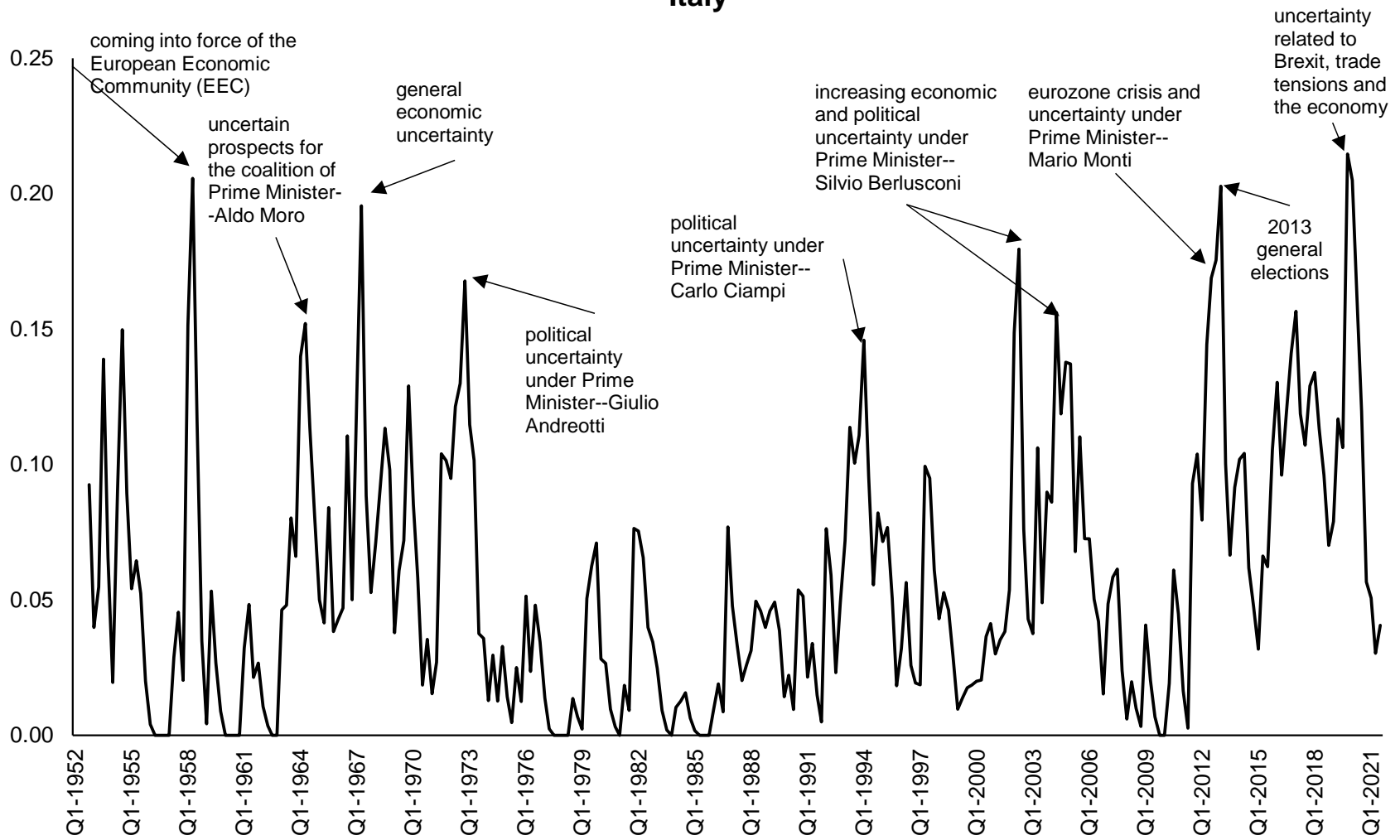
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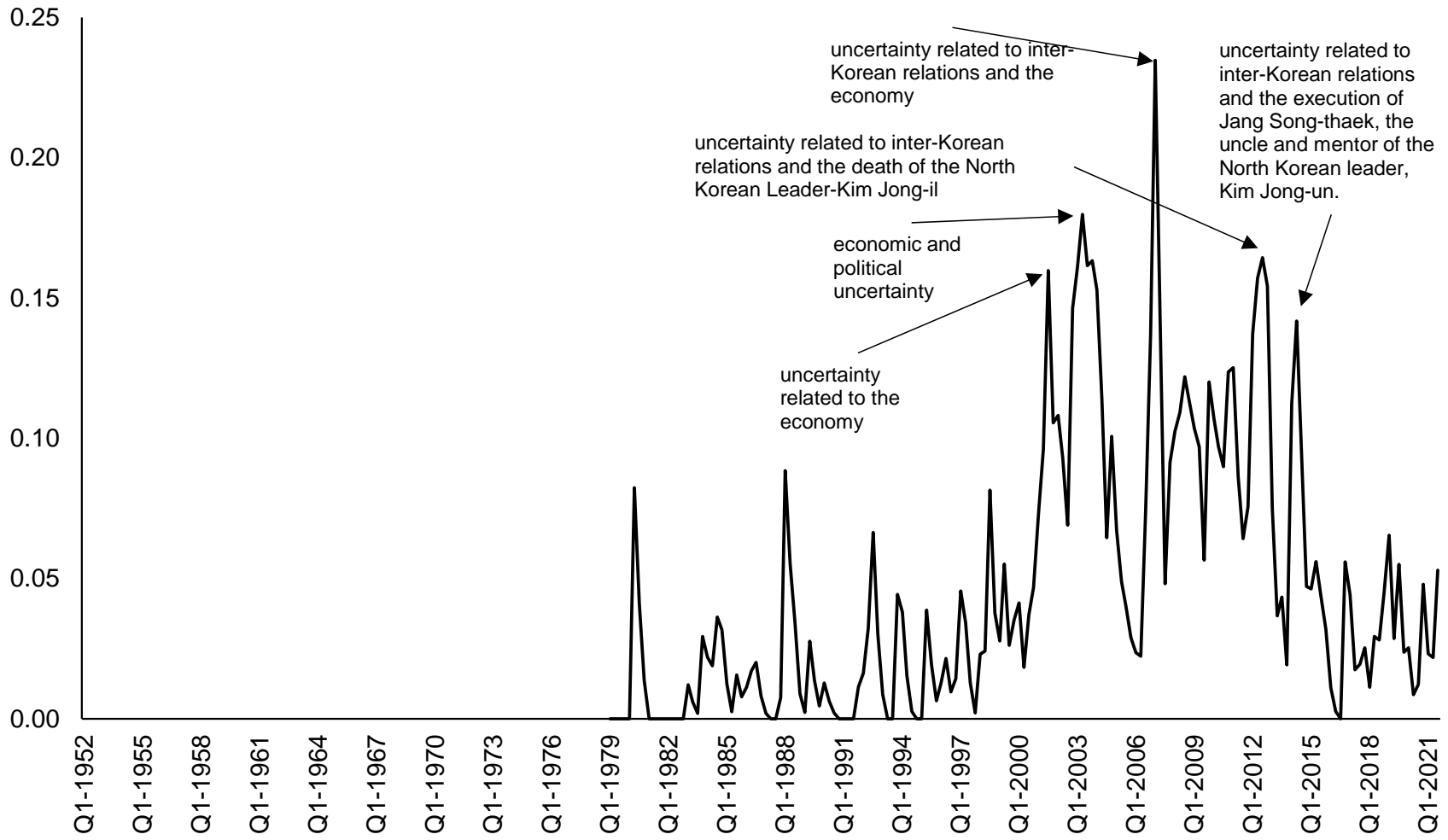
Ireland



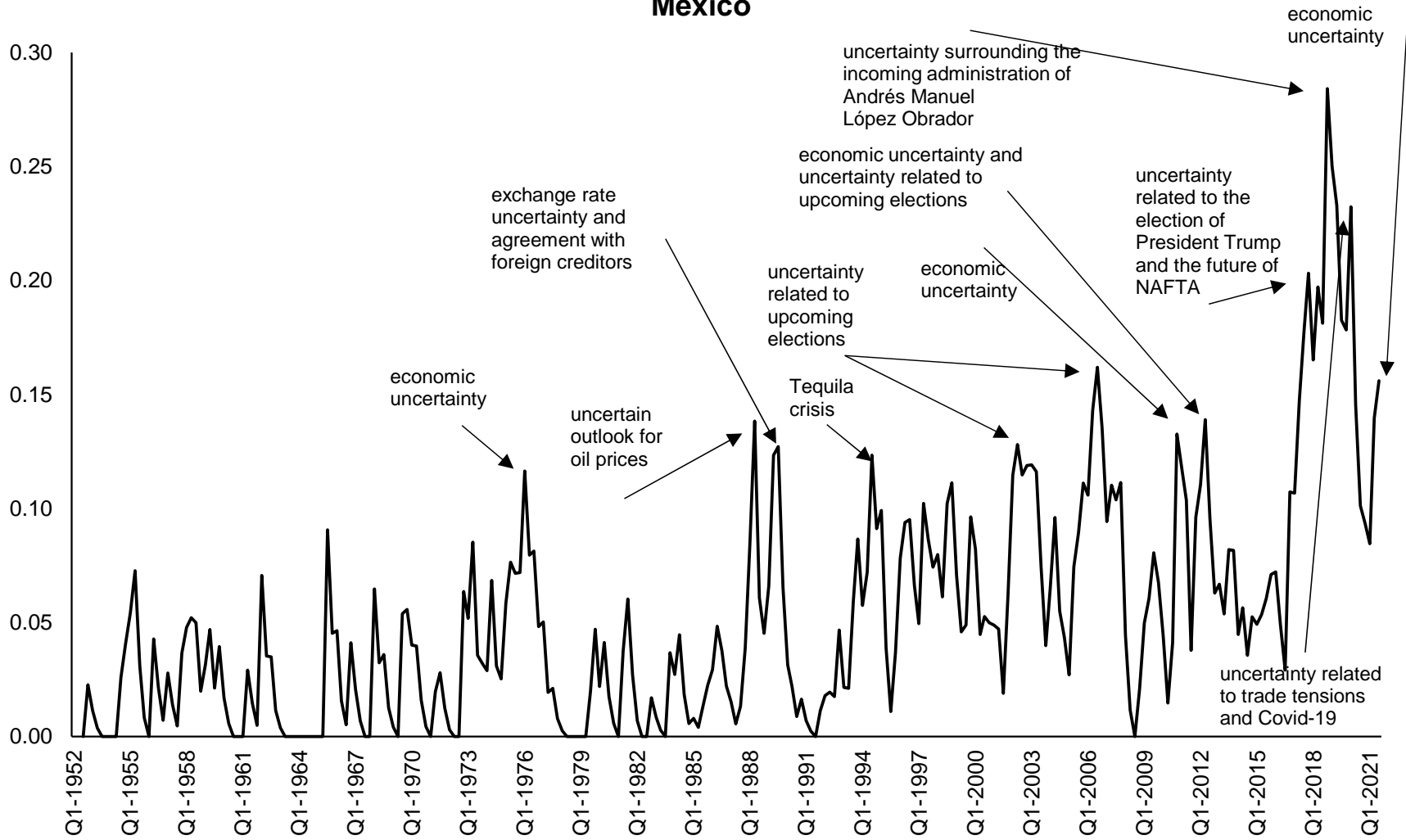
Italy



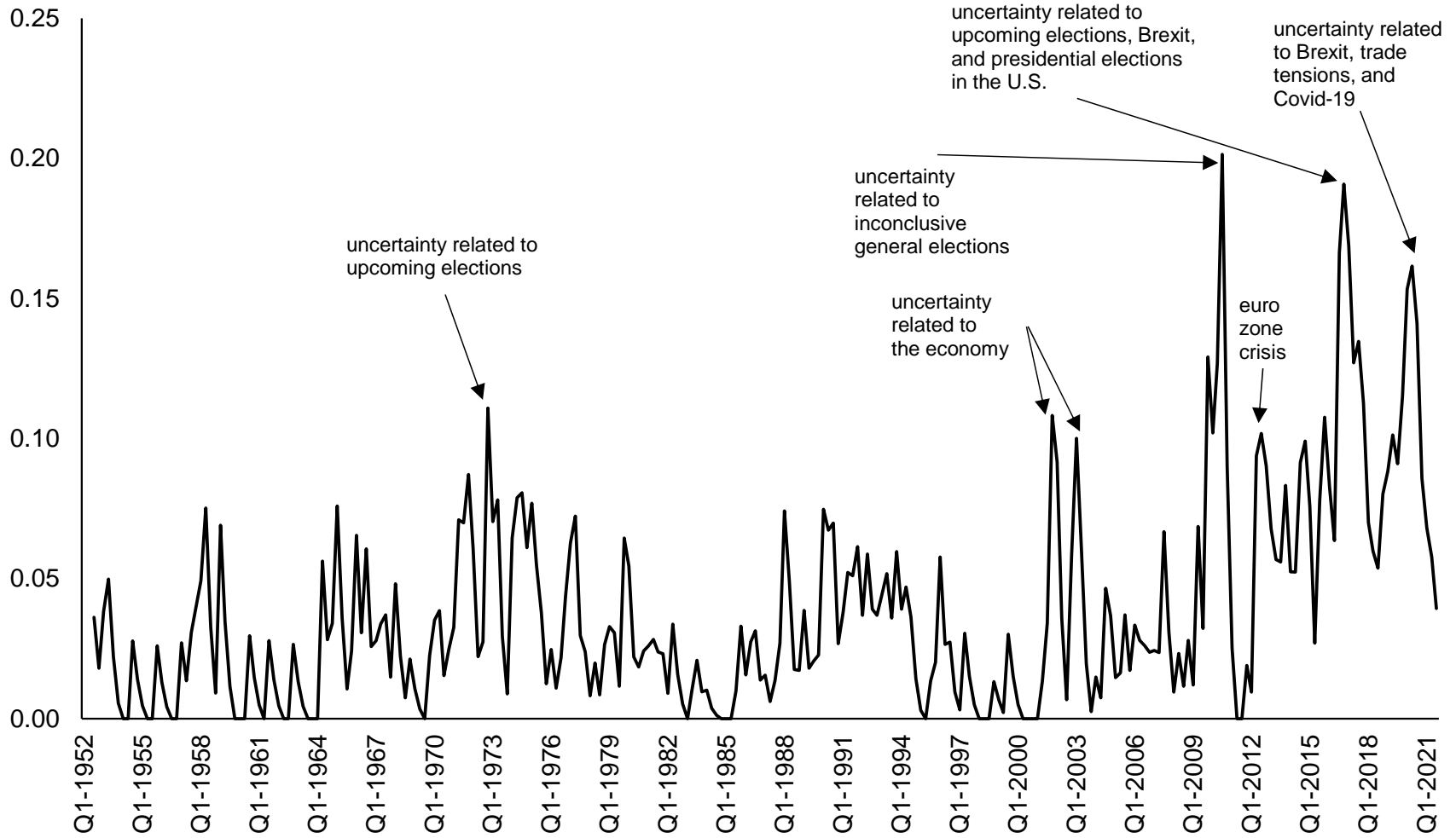
Korea



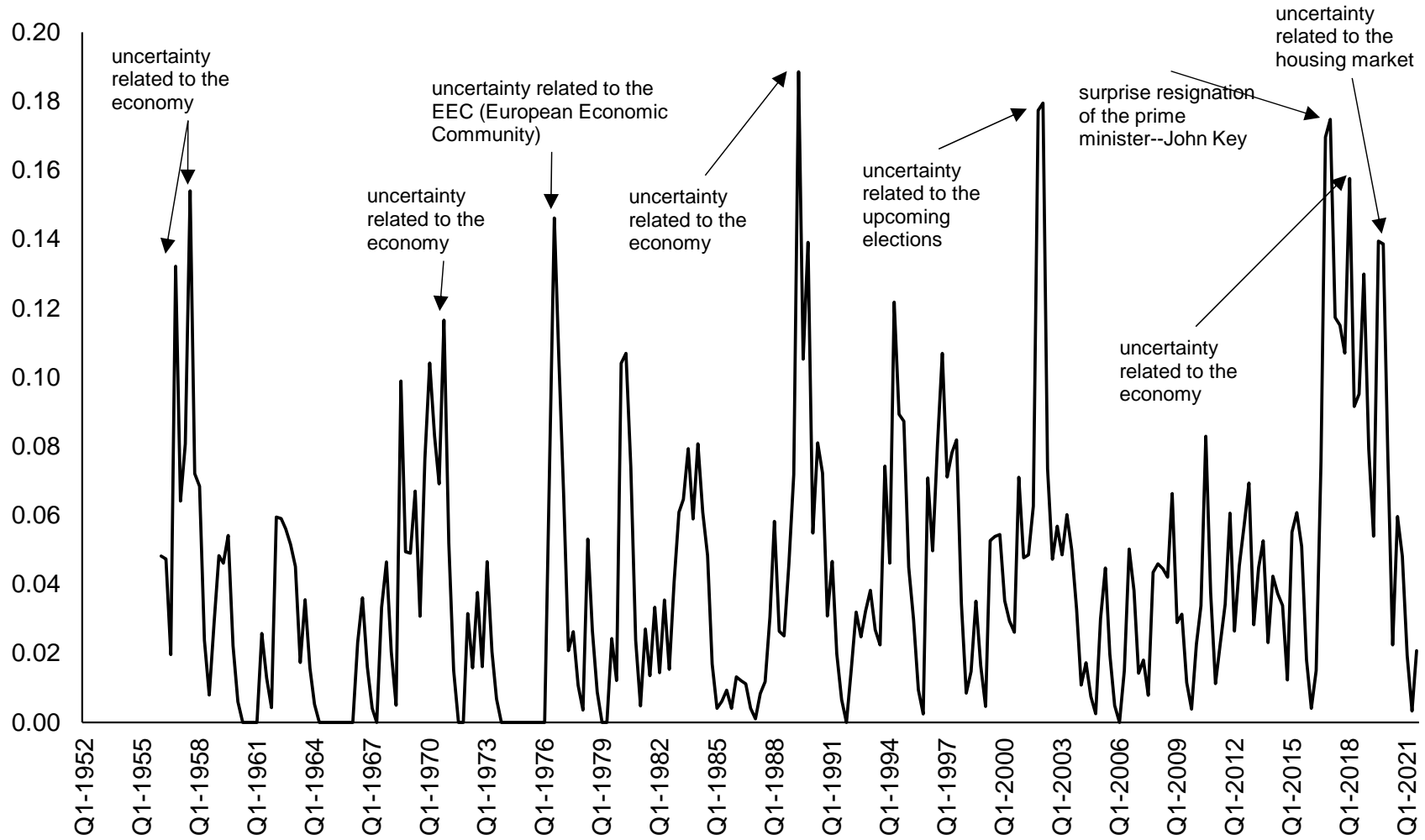
Mexico



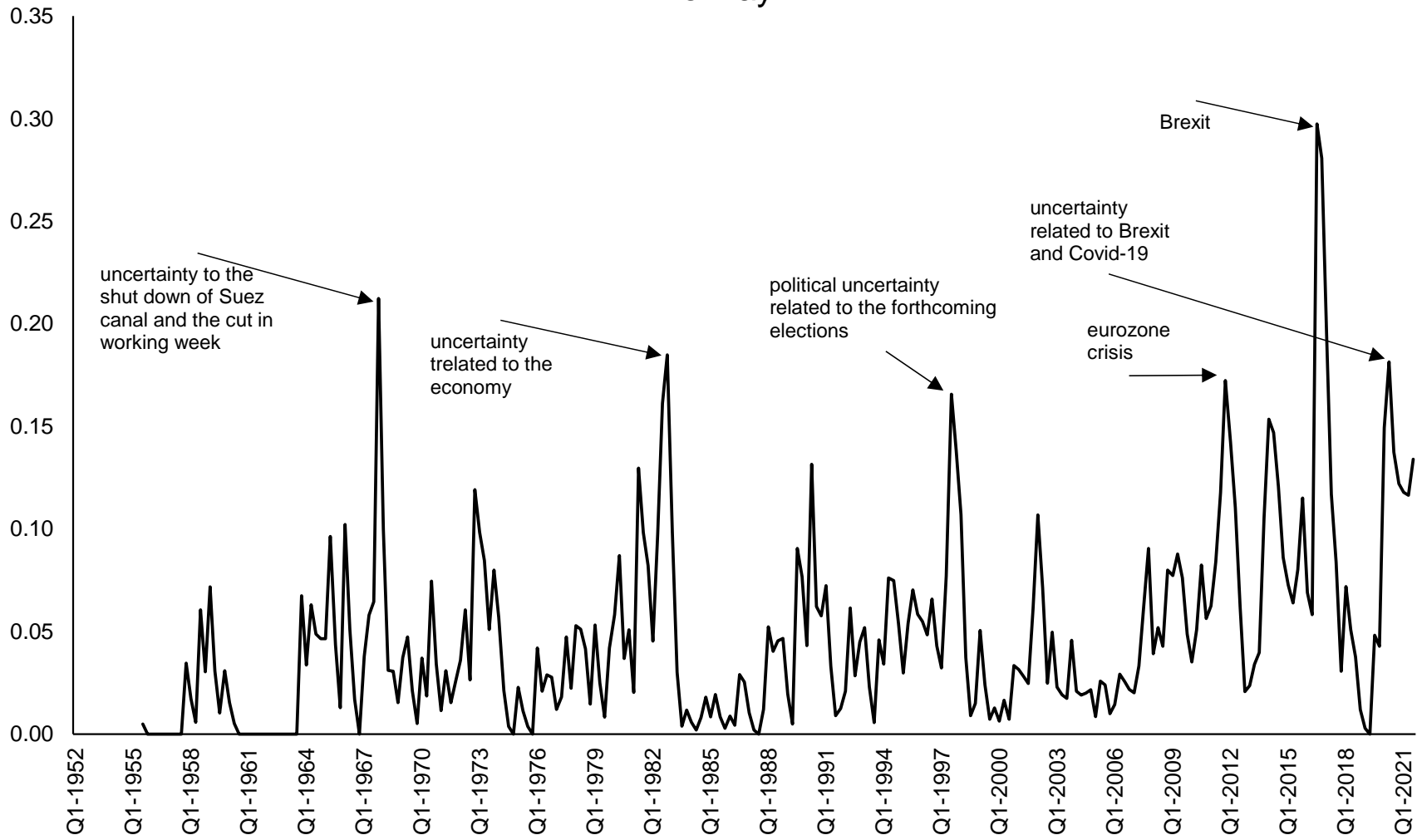
Netherlands



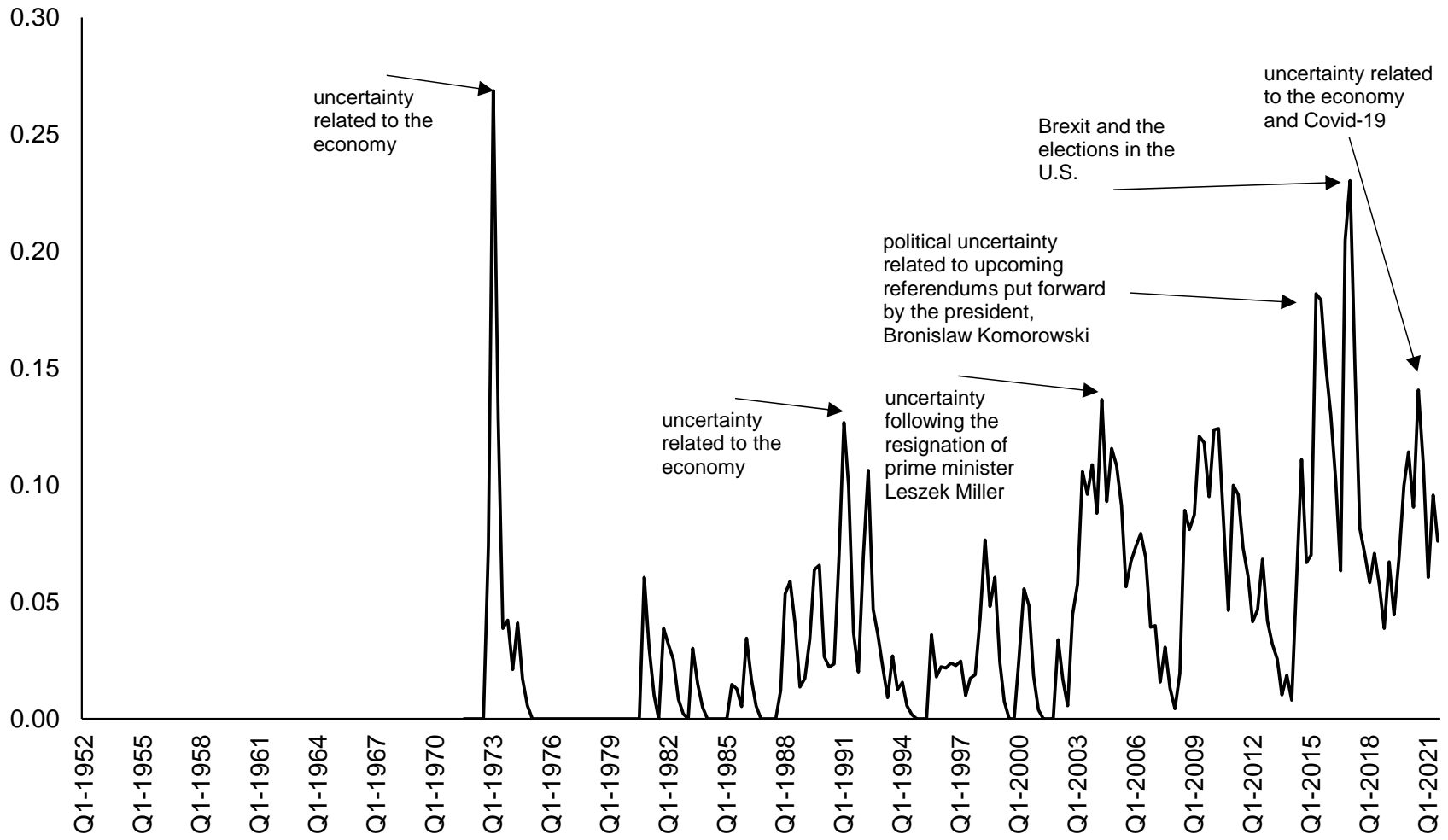
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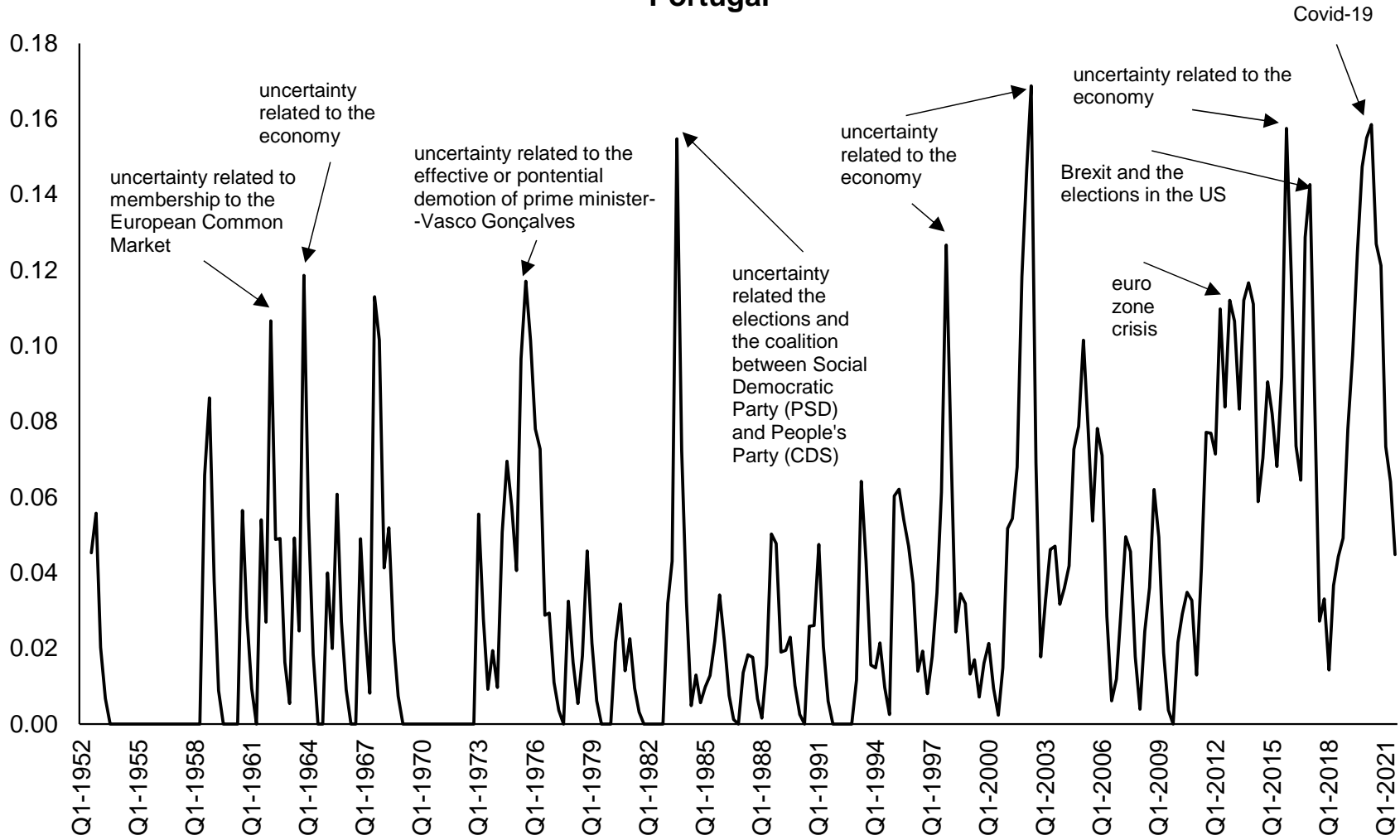
Norway



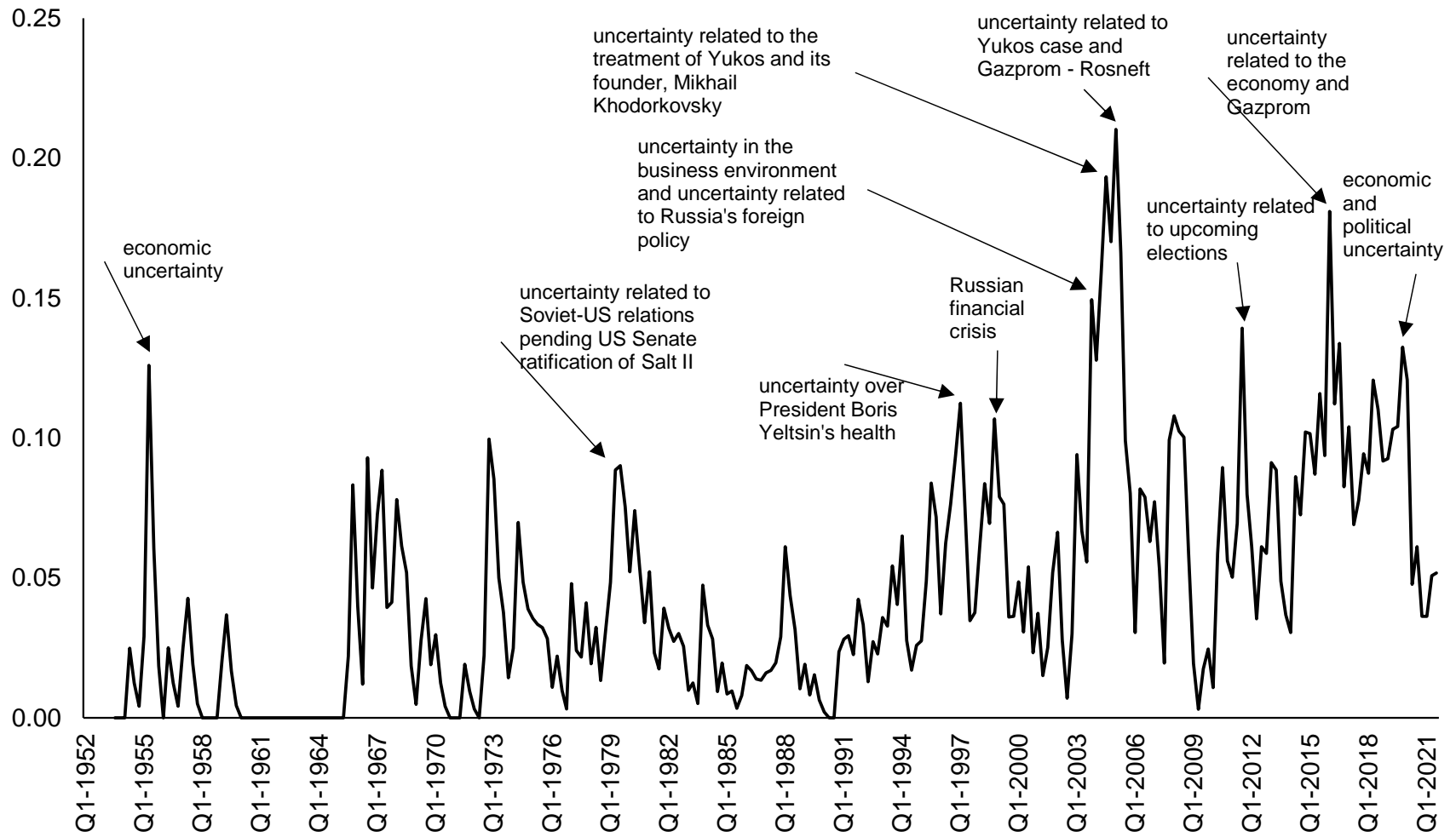
Poland



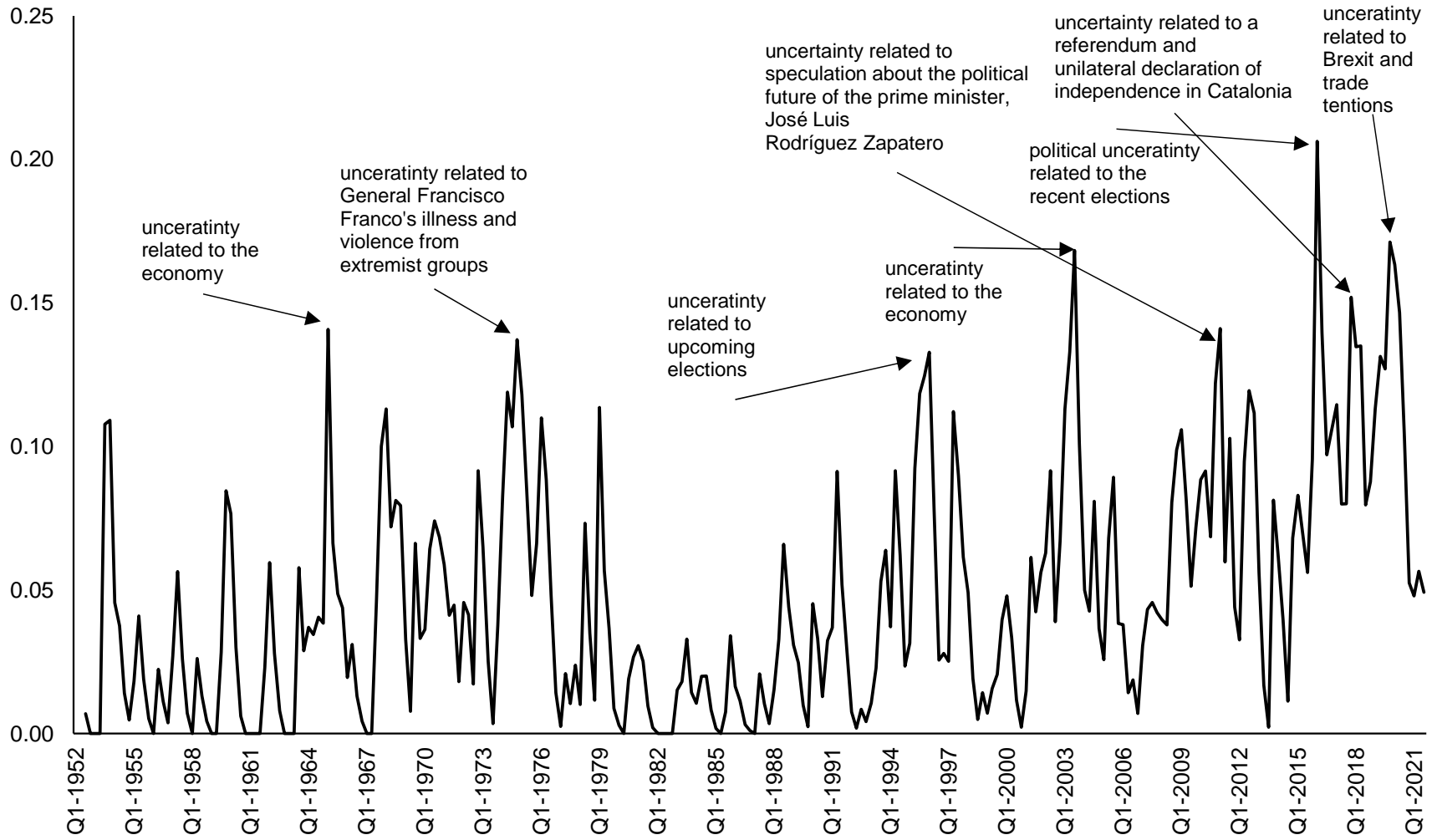
Portugal



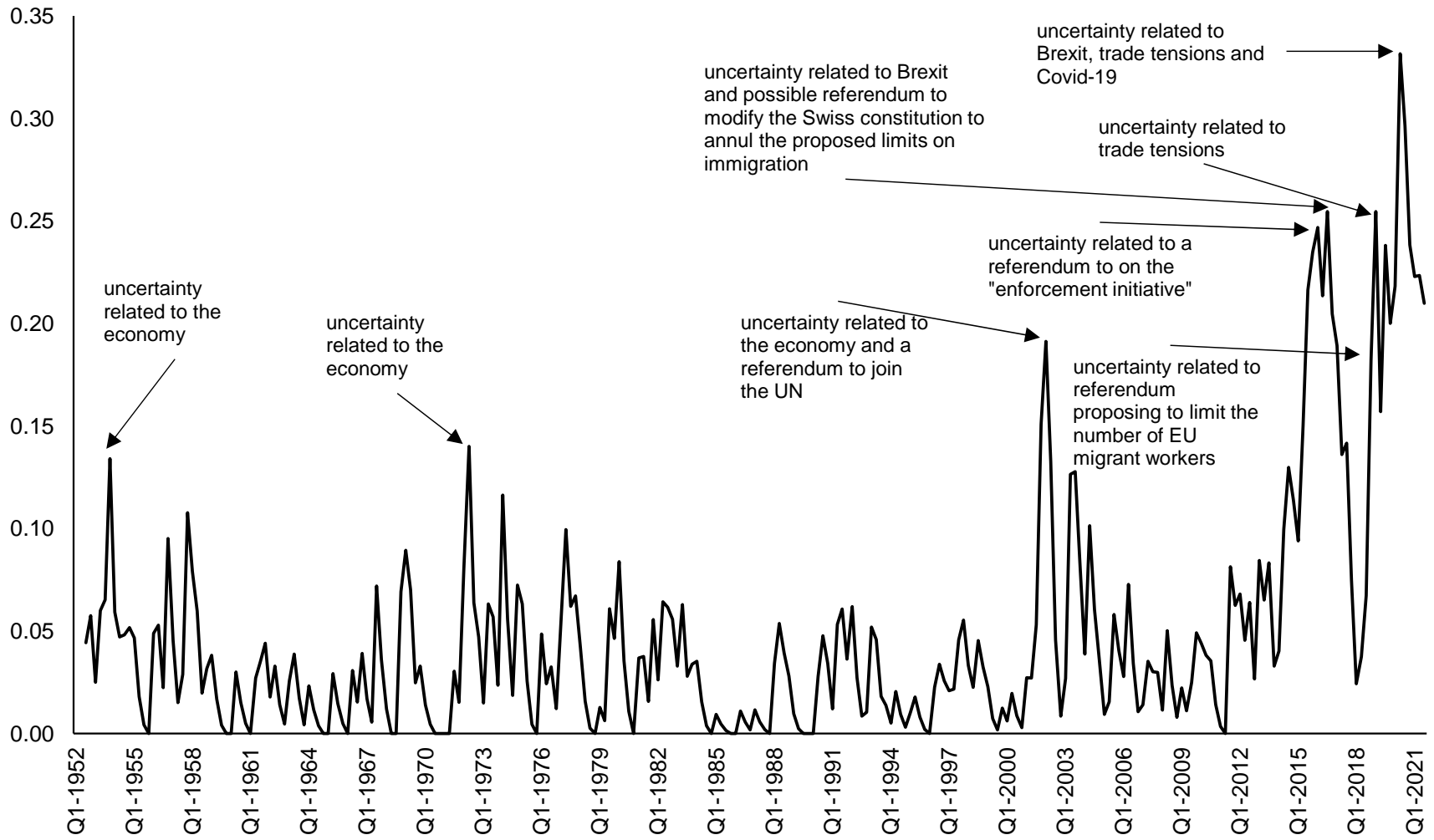
Russia



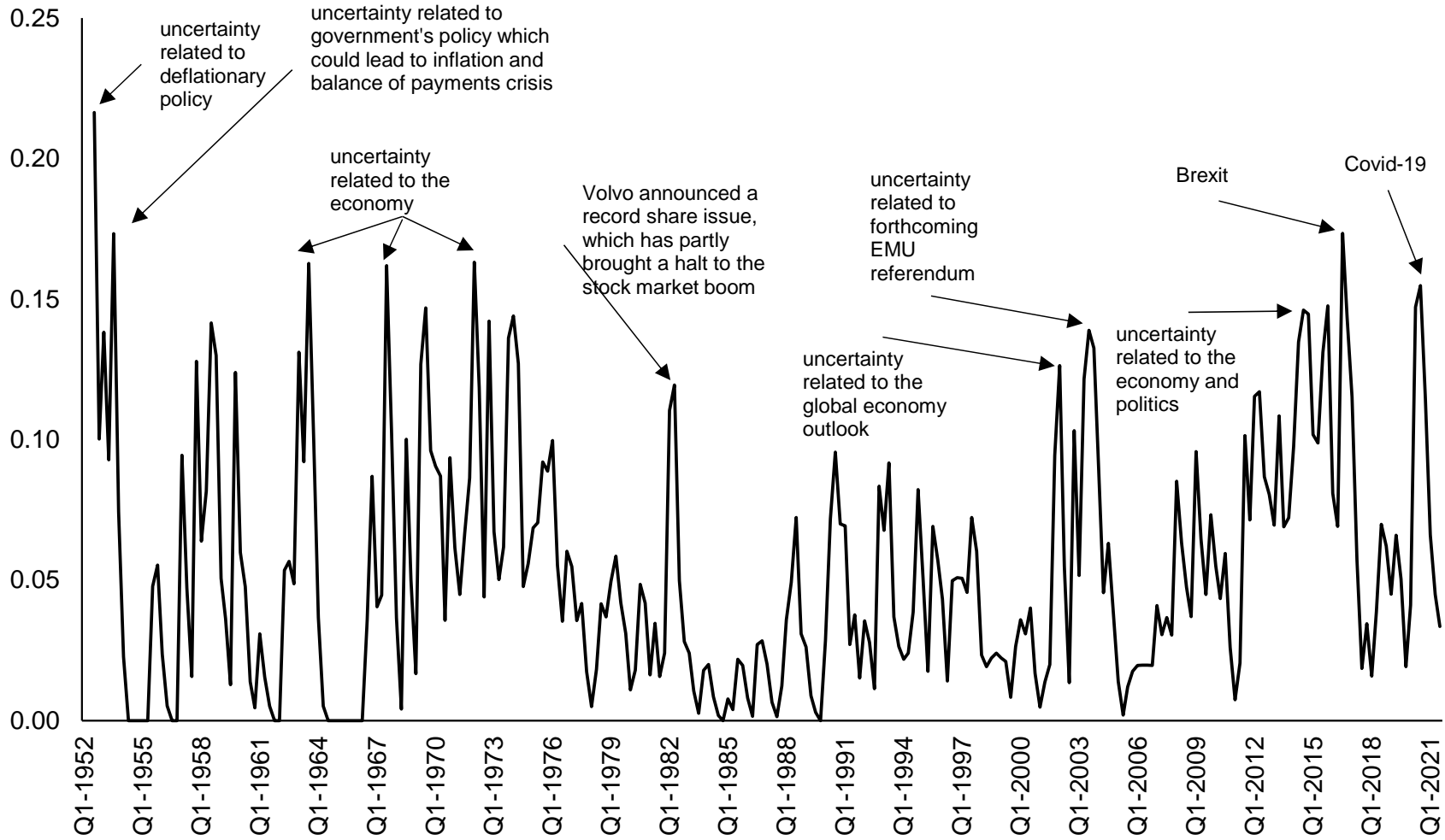
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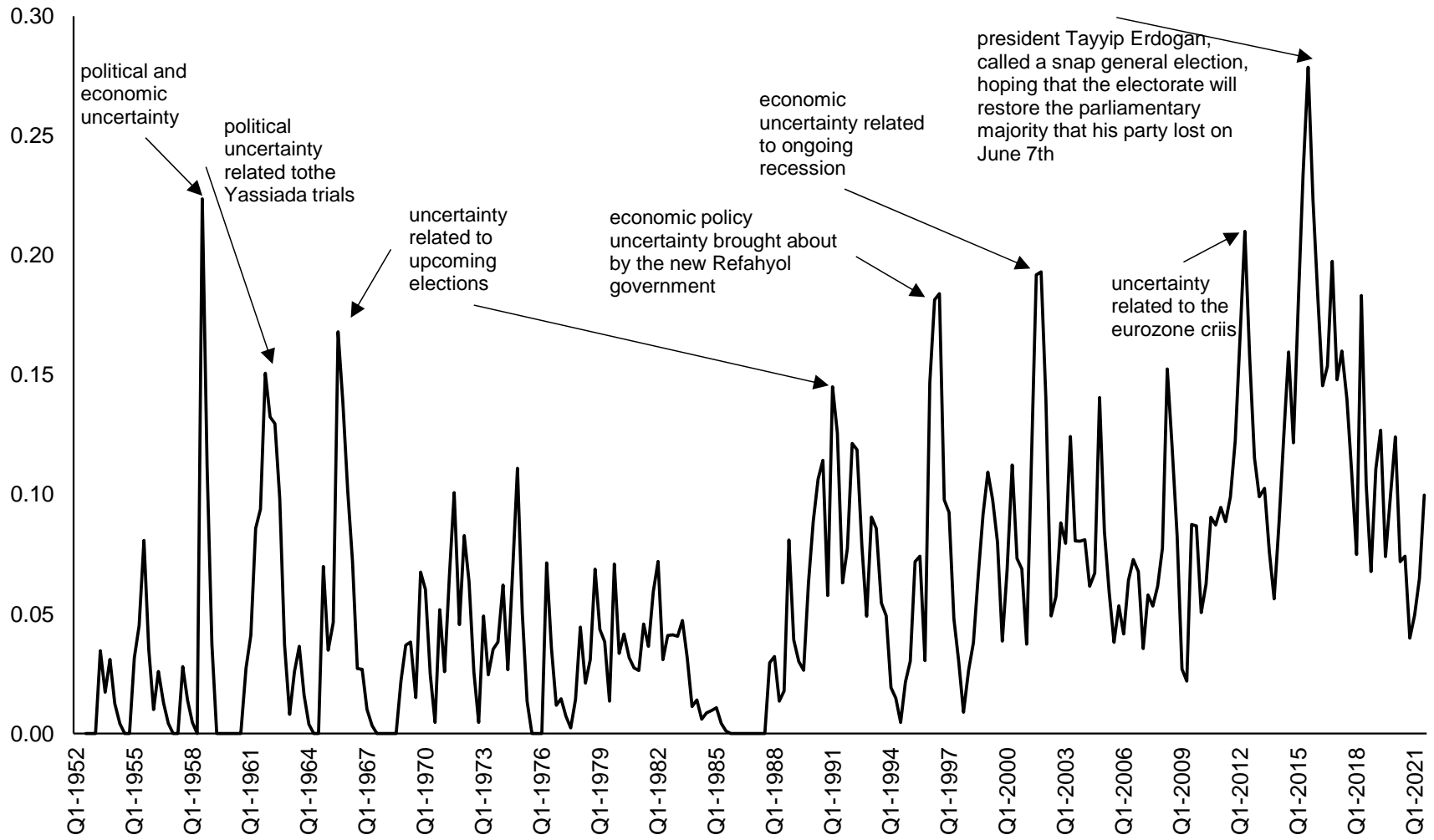
Switzerland



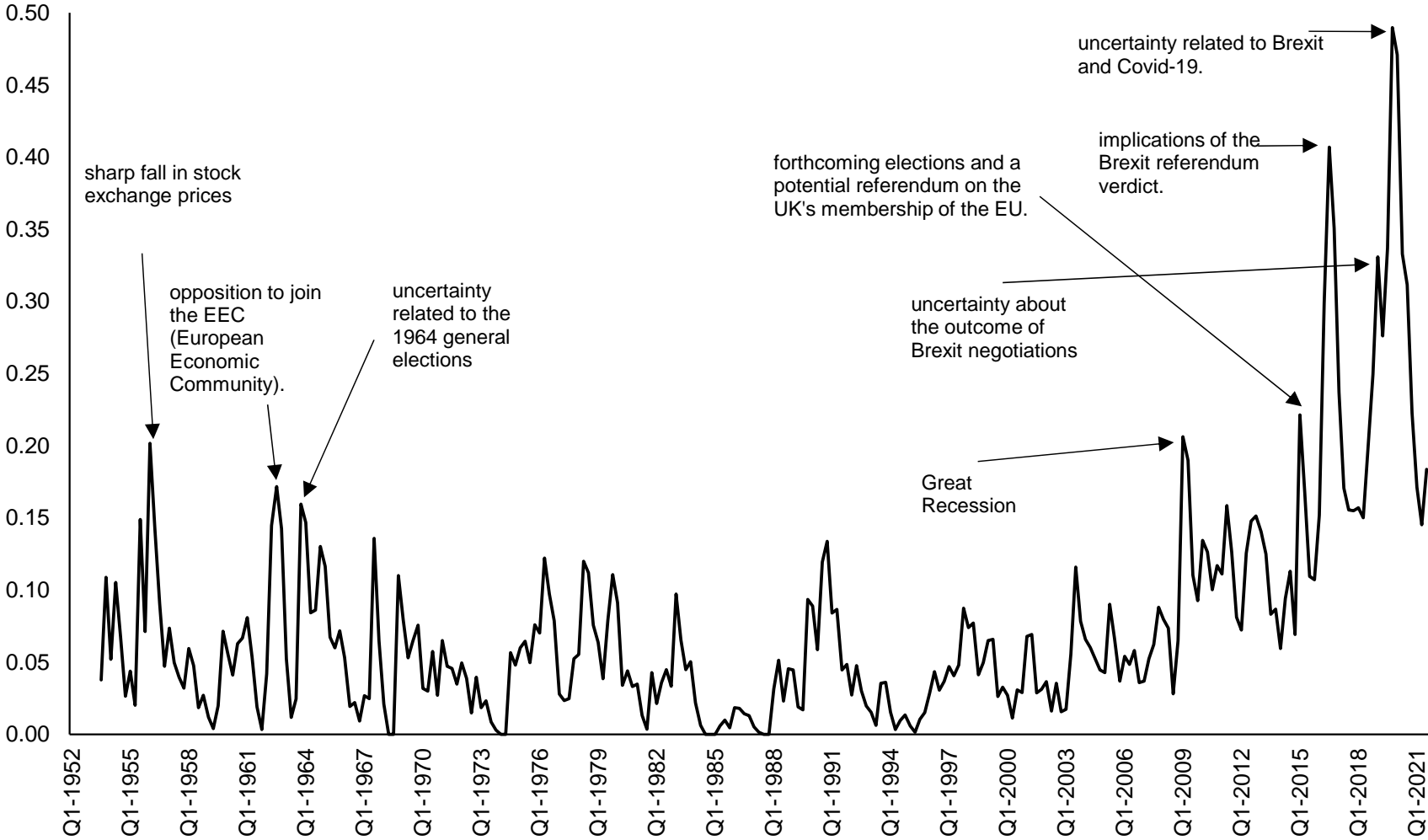
Sweden



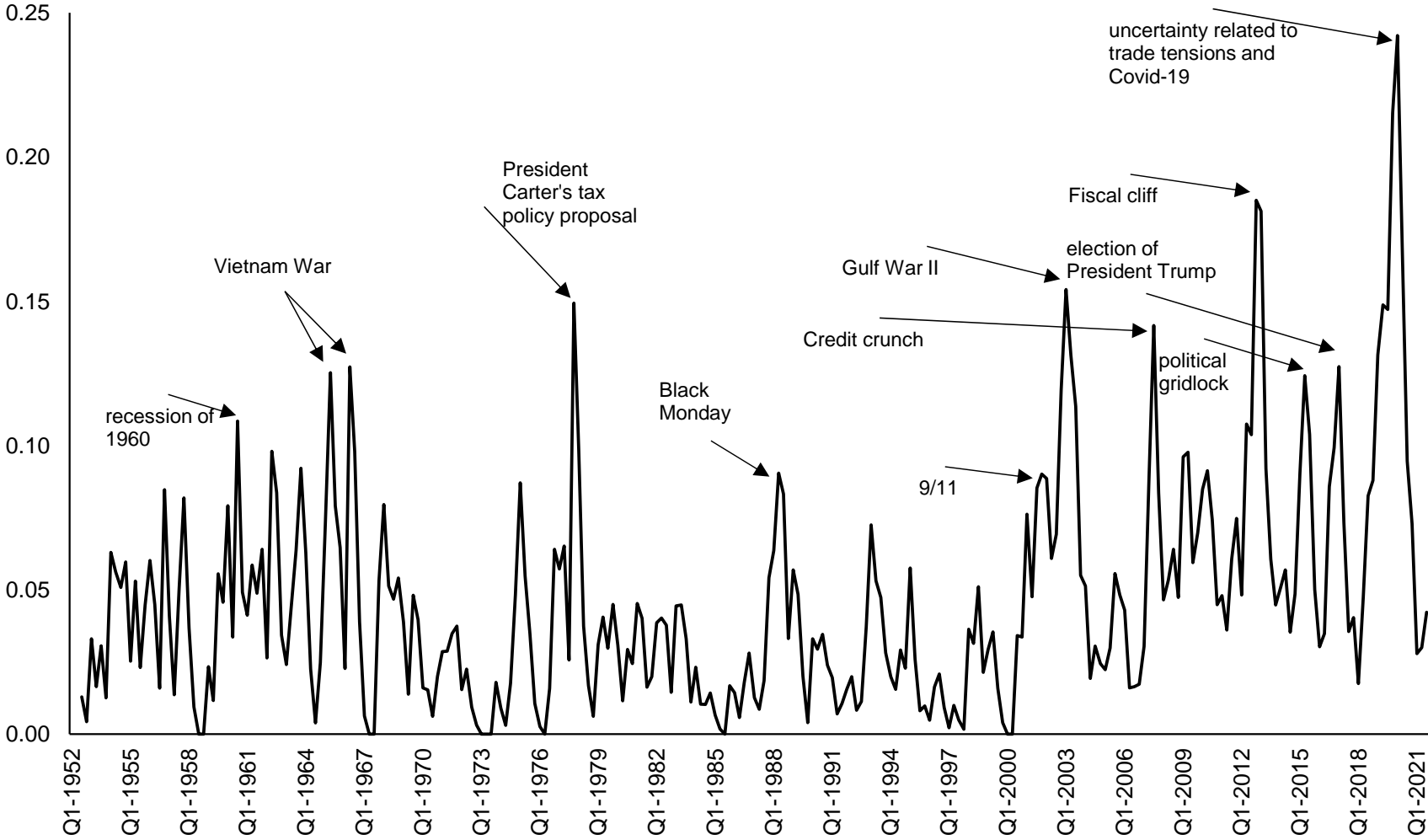
Turkey



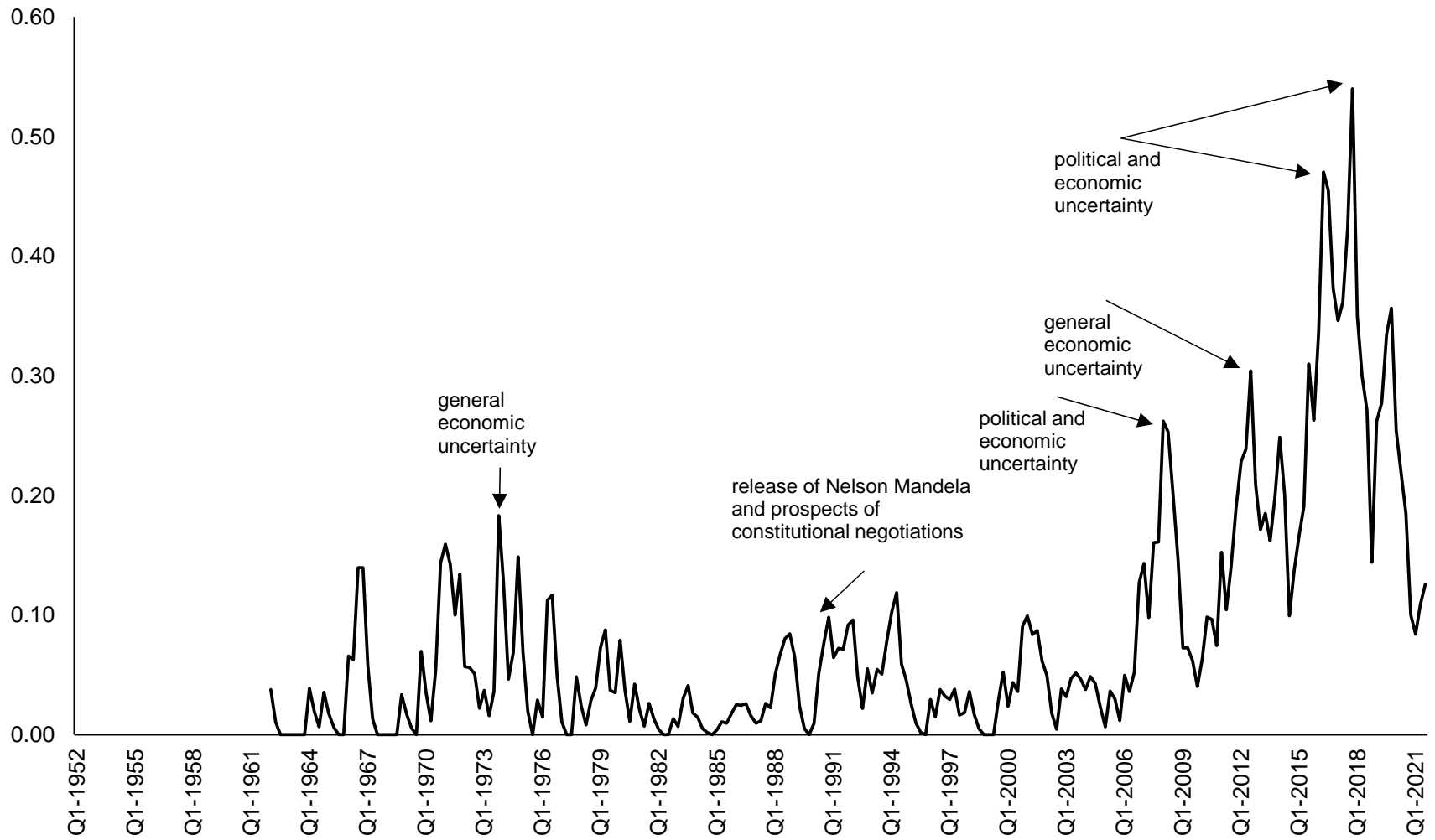
United Kingdom



United States

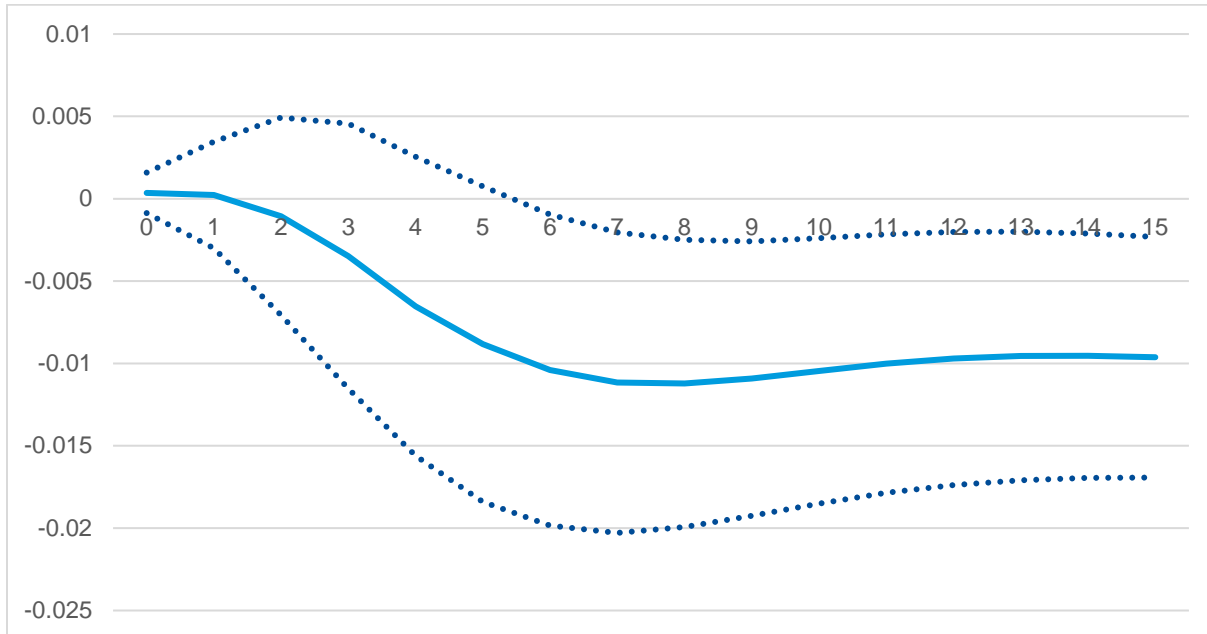


South Africa



ANNEX B

Figure B1. GDP response to WUI innovations—IV exogenous elections and controlling for fiscal balance and short-term rate



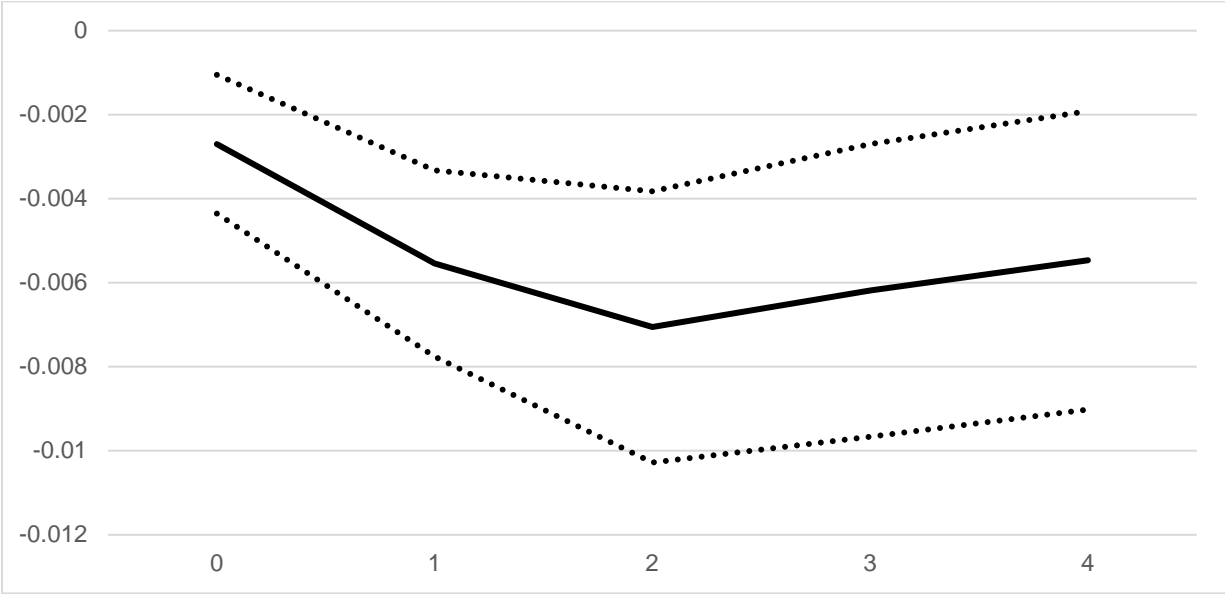
Note: VAR fit to quarterly data for an unbalanced panel of 49 countries from 1970q1 to 2020q4. Impulse responses of GDP to a one-standard deviation increase in WUI—equal to the change in average value in the index from 2014 to 2016—using as instrument exogenous elections and based on a Cholesky decomposition with the following order: exogenous elections, the log of average stock return, short-term interest rate, the WUI, the fiscal balance and GDP growth. The specification includes four lags of all variables. Country and time fixed effects are included. First stage:

$$WUI_{i,t} = 0.185 + 0.099Exogenous\ elections$$

(6.09)

t-statistics in parenthesis.

Figure B2. GDP response to WUI innovations-annual data—Local Projection; full Sample

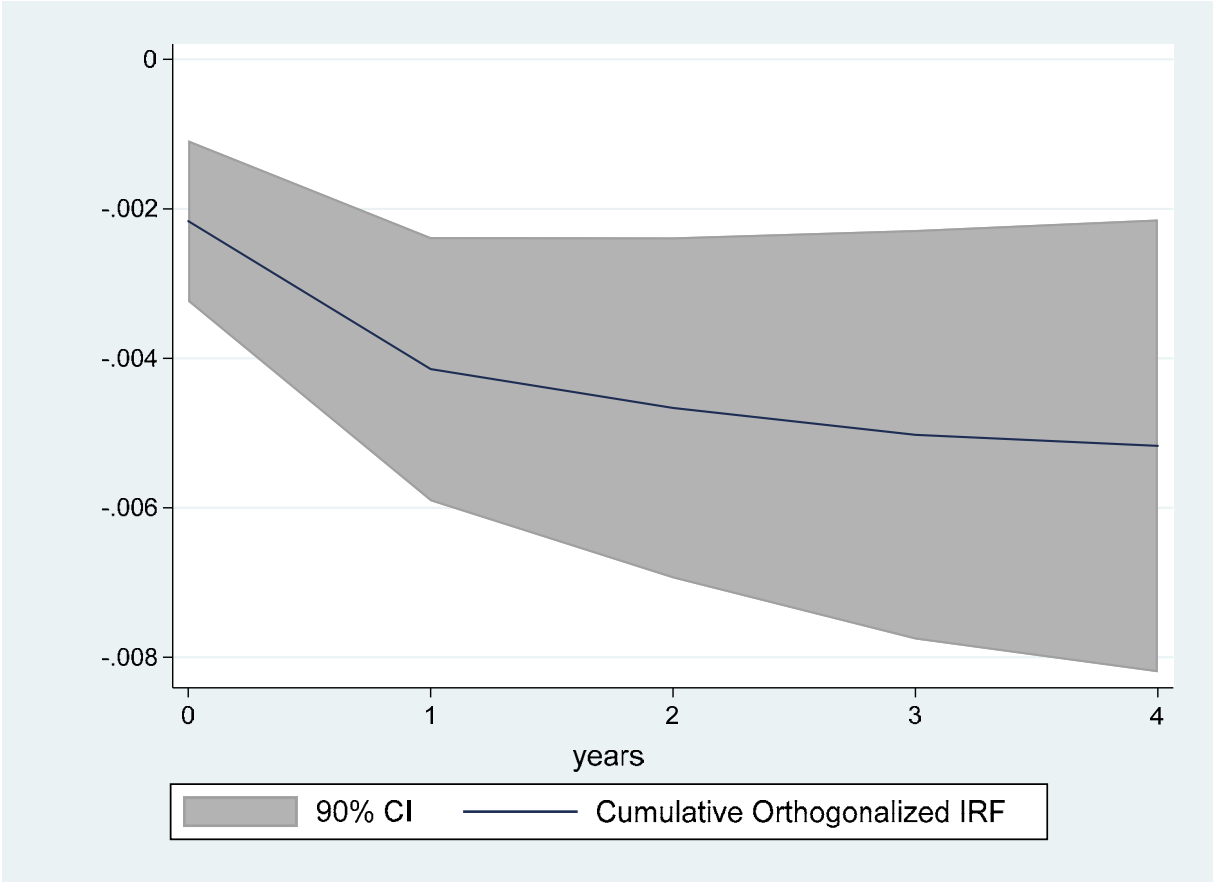


Note: Response estimated using the local projection method (Jorda 2005):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t}$$

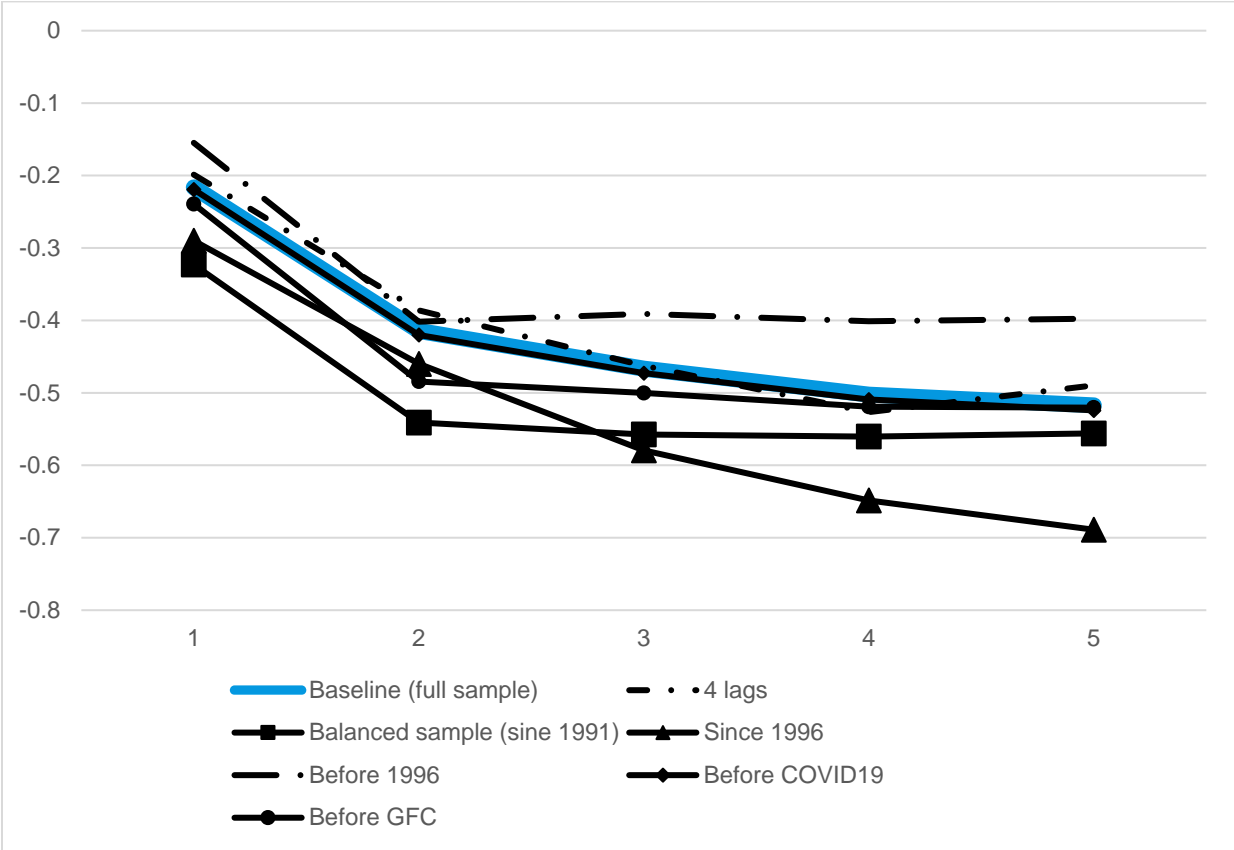
where y is the log of output; α_i are country-fixed effects; γ_t are time-fixed effects; X is a set of controls including lags of the growth rate of output and of the WUI index. Estimates based on annual data for a panel of 143 countries from 1952 to 2020. Solid line denoted the impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016. Dotted lines denote 90 percent confidence bands.

Figure B3. GDP response to WUI innovations—annual data



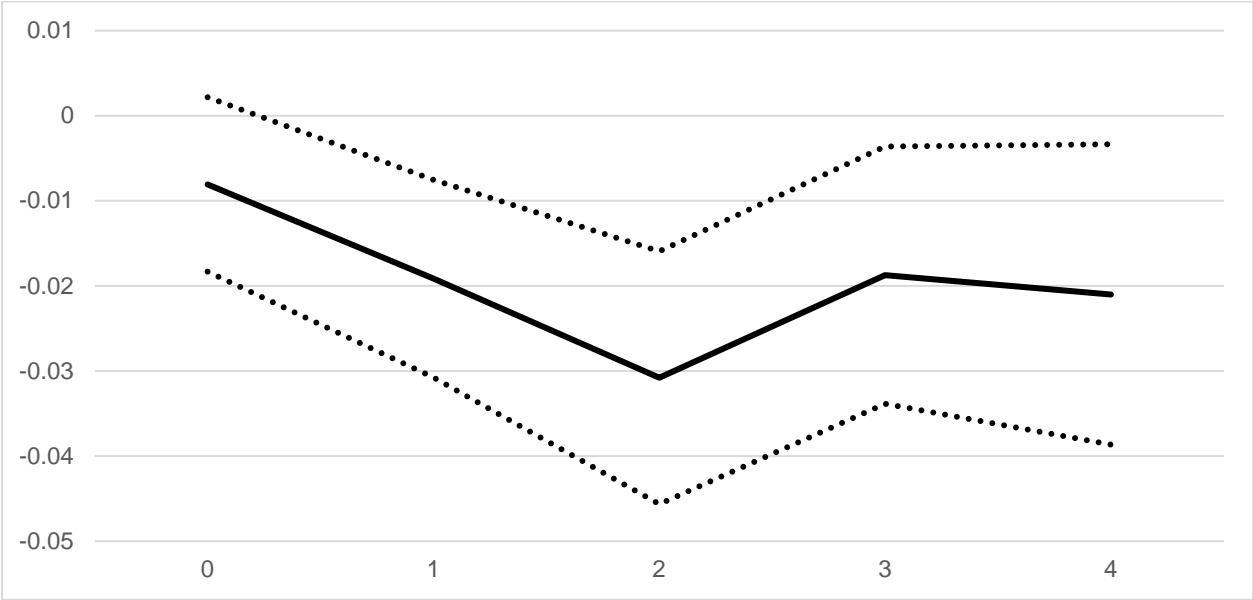
Note: VAR fit to annual data for a panel of 143 countries from 1952 to 2020. Impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—based on a Cholesky decomposition with the following order: the WUI and GDP growth. The specification includes two lags of all variables. Country and time fixed effects are included.

Figure B4. GDP response to WUI innovations—annual data, robustness checks



Note: VAR fit to annual data for a panel of 143 countries from 1952 to 2020. Impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—based on a Cholesky decomposition with the following order: the WUI and GDP growth. The specification includes two lags of all variables. Country and time fixed effects are included.

Figure B5. Investment response to WUI innovations-annual data—Local Projection

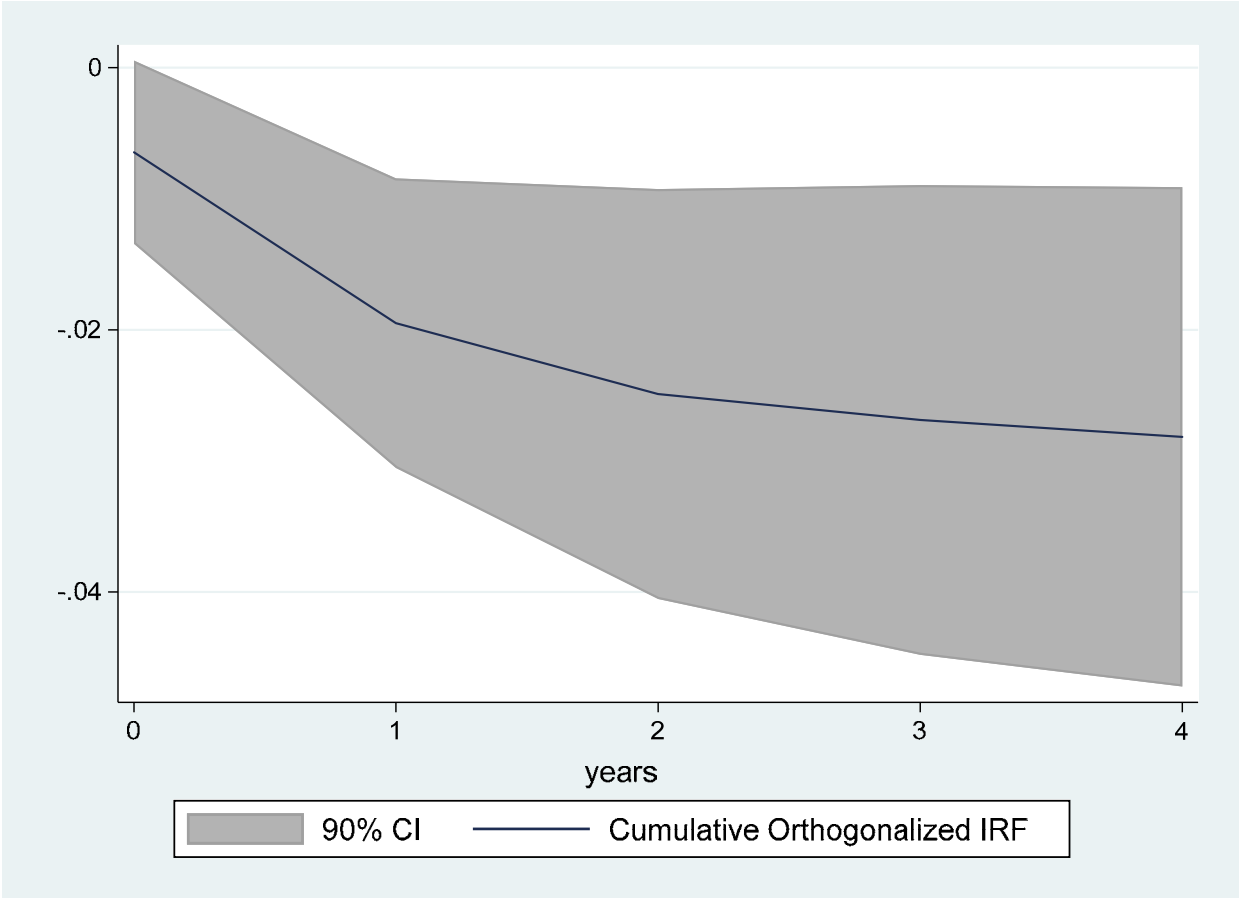


Note: Response estimated using the local projection method (Jorda 2005):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t}$$

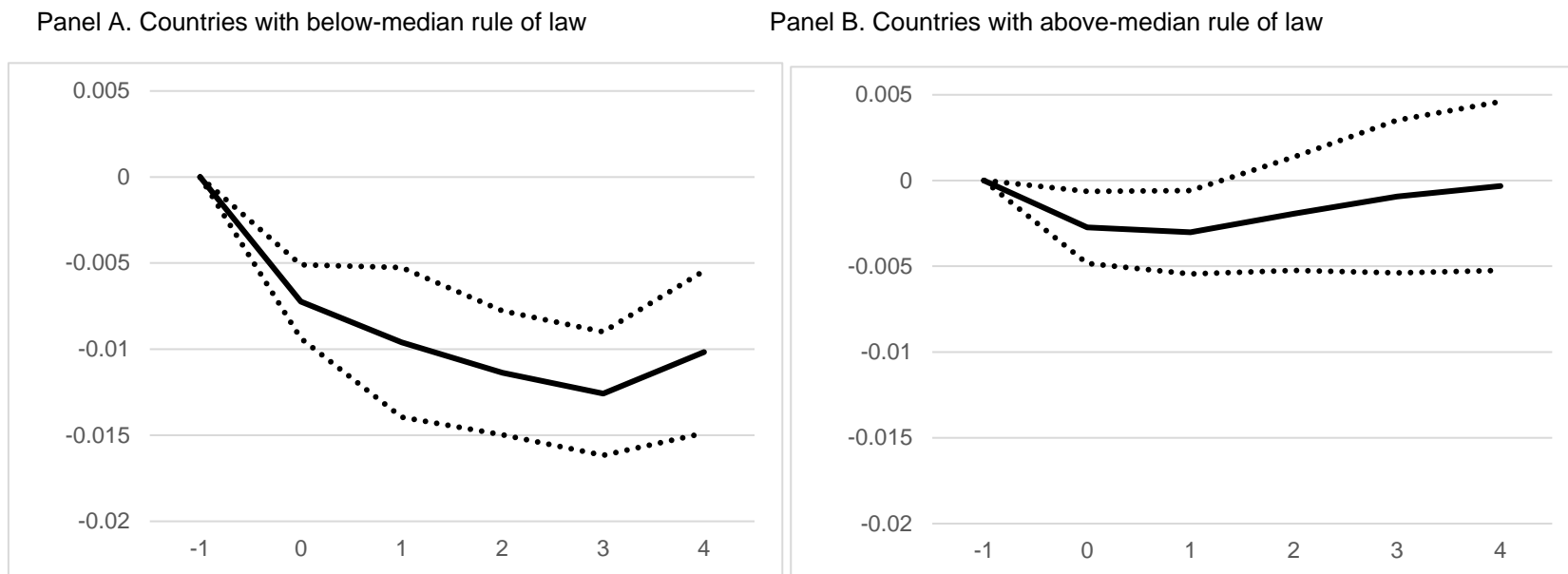
where y is the log of private investment; α_i are country-fixed effects; γ_t are time-fixed effects; X is a set of controls including lags of the growth rate of investment and of the WUI index. Estimates based on annual data for a panel of 95 countries from 1970 to 2020. Solid line denoted the impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016. Dotted lines denote 90 percent confidence bands.

Figure B6. Investment response to WUI innovations—annual data robustness checks



Note: VAR fit to annual data for a panel of 95 countries from 1970 to 2020. Impulse responses of private investment to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—based on a Cholesky decomposition with the following order: the WUI and investment growth. The specification includes two lags of all variables. Country and time fixed effects are included.

Figure B7. GDP response to WUI innovations-annual data—Local Projection, the role of institutions; controlling for interaction with GDP per capita.

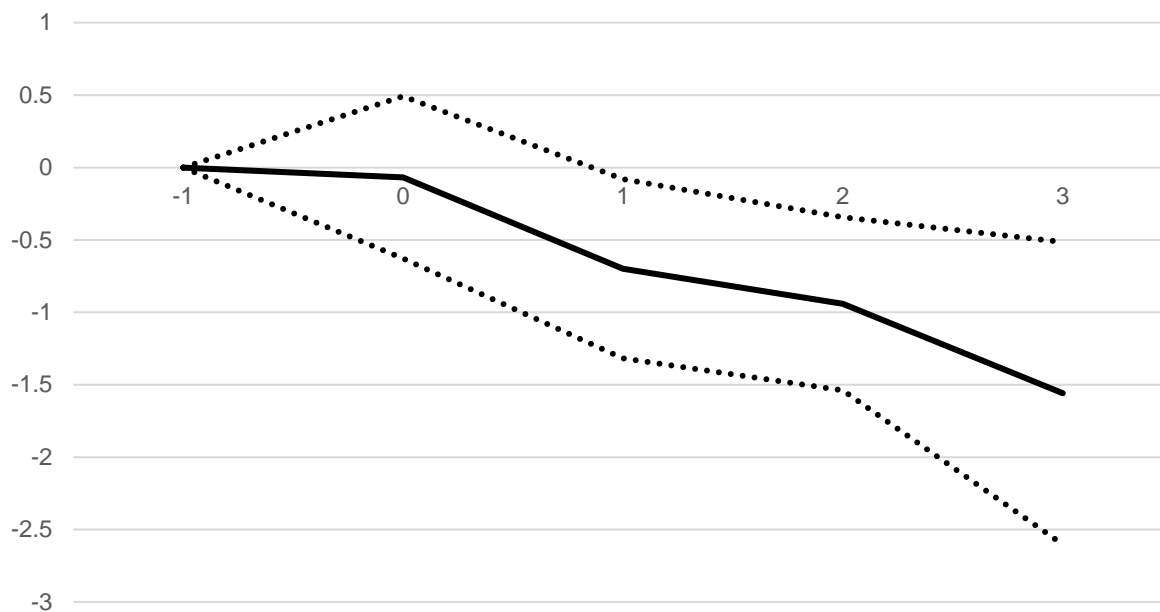


Note: Response estimated using the local projection method (Jorda 2005):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \gamma_t + \beta^l D_i WUI_{i,t} + \beta^h (1 - D_i) WUI_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t}$$

where y is the log of output; α_i are country-fixed effects; γ_t are time-fixed effects; D is a dummy variable which takes value 1 for countries with a score in the indicator of rule of law below median; X is a set of controls including lags of the growth rate of output and of the WUI index. Estimates based on annual data for a panel of 122 countries from 1991 to 2020. Solid line denoted the impulse responses of GDP to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016. Dotted lines denote 90 percent confidence bands.

Figure B8. Sectoral labor productivity response to WUI innovations—role of financial constraints



Note: Response estimated using the following specification:

$$\Delta y_{jit} = \alpha_{ij} + \gamma_{it} + \delta_{jt} + \sum_{k=0}^3 \beta_k WUI_{i,t-k} EFD_j + \varepsilon_{jit}$$

where y is the log of sectoral labor productivity (the output-to-employment ratio); α_{ij} are sector-country fixed effects; γ_{it} are country-time fixed effects; δ_{jt} are sector-time fixed effects; EFD is the Rajan and Zingales's (1998) measure of the degree of dependence on external finance in each industry—measured as the median across all U.S. firms, in each industry, of the ratio of total capital expenditures minus the current cash flow to total capital expenditures. Estimates based on annual data for a panel of 22 industries, 56 countries from 1995 to 2017 (the size of the estimation sample is 24,098 observations). Solid line denotes the differential productivity effect to a one-standard deviation increase in the WUI—equal to the change in average value in the index from 2014 to 2016—of an industry with high external financial dependence (at the 75th percentile distribution of the indicator) compared to an industry with low external financial dependence (at the 25th percentile distribution of the indicator). Dotted lines denote 90 percent confidence bands.

Table B1. Country coverage of the industry analysis

Country	Advanced economies		Country	Developing economies	
	Number of observations	Maximum coverage		Number of observations	Maximum coverage
Australia	378	1988-2013	Algeria	56	1990-1996
Austria	545	1988-2014	Bahrain	25	2001-2005
Belgium	623	1980-2014	Bangladesh	318	1980-2011
Canada	733	1979-2014	Bolivia	405	1981-2010
Denmark	700	1979-2014	Chile	306	1990-2013
Finland	722	1979-2014	China	493	1982-2007
France	699	1980-2014	Colombia	602	1982-2012
Greece	669	1976-2013	Costa Rica	244	1990-2003
Hong Kong	460	1984-2014	El Salvador	104	1993-1998
Iceland	237	1980-1996	Ethiopia	420	1990-2014
Italy	577	1988-2014	Gabon	56	1991-1995
Japan	797	1970-2010	Ghana	178	1980-2003
Netherlands	651	1981-2014	Honduras	107	1990-1995
New Zealand	187	1985-2012	India	550	1988-2014
Norway	723	1978-2014	Iran	554	1990-2014
Portugal	580	1986-2014	Jamaica	63	1990-1996
Singapore	532	1990-2014	Jordan	554	1985-2013
Spain	722	1980-2014	Kenya	315	1982-2013
Sweden	711	1980-2014	Kuwait	430	1990-2013
Switzerland	316	1986-2013	Lebanon	39	1998-2007
U.K.	716	1978-2013	Madagascar	172	1980-2006
			Malaysia	429	1990-2012
			Mexico	348	1990-2013
			Mongolia	345	1990-2011
			Morocco	458	1990-2013
			Oman	437	1993-2014
			Paraguay	55	2001-2010
			Philippines	389	1989-2012
			Qatar	330	1990-2013
			Romania	469	1990-2013
			Sri Lanka	369	1990-2012
			Swaziland	155	1980-2011
			Trinidad and Tobago	236	1988-2003
			Venezuela	188	1988-1998

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