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Abstract

The proliferation of economic uncertainty indicators —ranging from text-based indices like the Economic Policy Uncertainty (EPU) index to market-based measures such as the VIX and the ECB's Country-Level Index of Financial Stress (CLIFS)— has enriched the analytical toolkit of economists and policymakers. Yet these indicators often diverge, sending conflicting signals about the state of uncertainty in the economy. This paper argues that such divergence is not a flaw but a feature: each indicator captures a distinct dimension of uncertainty. Using topic modeling techniques applied to national news corpora, we construct a taxonomy of uncertainty narratives across five European countries and classify episodes of divergence between the EPU and CLIFS indicators. Our findings reveal systematic patterns: EPU peaks are predominantly driven by political and institutional developments, CLIFS peaks by financial market stress and joint peaks by systemic crises. These results underscore the multidimensional nature of uncertainty and highlight the need for structured interpretative frameworks. By linking narrative content to indicator behavior, our approach offers a novel lens for understanding uncertainty dynamics and provides practical tools for researchers and policymakers navigating an increasingly complex informational environment.

Keywords: economic policy uncertainty, financial uncertainty, natural language processing, open access data.

JEL classification: D8, C43, C55, E32.

Resumen

La proliferación de indicadores de incertidumbre económica —que abarca desde los índices basados en texto, como el índice de incertidumbre de política económica (EPU, por sus siglas en inglés), hasta las medidas basadas en el mercado, como el VIX y el índice de estrés financiero a nivel país del Banco Central Europeo (CLIFS)— ha enriquecido el conjunto de herramientas analíticas de los economistas y responsables de políticas públicas. Sin embargo, estos indicadores a menudo divergen, emitiendo señales contradictorias sobre el estado de la incertidumbre en la economía. En este documento sostenemos que dicha divergencia no constituye una deficiencia, sino una característica inherente: cada indicador capta una dimensión distinta de la incertidumbre. Mediante técnicas de modelado de temas aplicadas a los corpus de noticias nacionales, construimos una taxonomía de narrativas de incertidumbre en cinco países europeos y clasificamos los episodios de divergencia entre el EPU y el CLIFS. Nuestros hallazgos revelan patrones sistemáticos: los picos del EPU están impulsados predominantemente por los desarrollos políticos e institucionales, los del CLIFS por las tensiones en los mercados financieros, y los picos conjuntos por las crisis sistémicas. Estos resultados subrayan la naturaleza multidimensional de la incertidumbre y destacan la necesidad de desarrollar marcos interpretativos estructurados. Al vincular el contenido narrativo con el comportamiento de los indicadores, nuestro enfoque ofrece una perspectiva novedosa para comprender la dinámica de la incertidumbre y proporciona herramientas prácticas para los investigadores y responsables de políticas en un entorno informativo cada vez más complejo.

Palabras clave: incertidumbre sobre la política económica, incertidumbre financiera, procesamiento del lenguaje natural, datos de acceso abierto.

Códigos JEL: D8, C43, C55, E32.

1 Introduction

In recent years, the proliferation of economic uncertainty indicators has transformed the way researchers and policymakers monitor risk and volatility in the macroeconomic environment. From text-based indices such as the Economic Policy Uncertainty (EPU) index (Baker et al., 2016a) and the World Uncertainty Index (WUI) (Ahir et al., 2025a), to market-based measures like the VIX[1] and composite financial stress indices such as ECB's Country-Level Index of Financial Stress (CLIFS), the landscape of uncertainty measurement has become increasingly diverse. While this expansion has enriched the analytical toolkit, it has also introduced a fundamental puzzle: these indicators often diverge, sending conflicting signals about the state of uncertainty in the economy (see Fig.1).

This divergence is not merely anecdotal. For instance, during the 2024–2025 period, text-based indicators such as the EPU and WUI reached historically high levels, reflecting heightened political and geopolitical tensions, while market-based measures like the VIX remained subdued amid strong equity market performance (Ahir et al., 2025a; Cascaldi-Garcia et al., 2023; Martorana and Mistak, 2025a). Survey-based indicators, such as the Survey of Business Uncertainty (SBU), showed little movement, further complicating the picture (Ahir et al., 2025a). A similar pattern was observed in earlier episodes, such as the 2016 U.S. presidential election and the Brexit referendum, where political uncertainty spiked without a corresponding rise in market volatility (Aït-Sahalia et al., 2025; Martorana and Mistak, 2025b). Recent empirical work by Yang (2025) and Aït-Sahalia and Xiu (2025) confirms that such divergences are not measurement errors but reflect the multidimensional nature of uncertainty, with text-based and market-based indicators responding to different underlying shocks and time horizons.

Along these lines, recent speeches by policymakers —including ECB President Christine Lagarde and IMF Managing Director Kristalina Georgieva— underscore the complexity of the current uncertainty regime and the need for nuanced interpretation of indicators (Lagarde, 2025). The European Central Bank has explicitly acknowledged the growing disconnect between financial market volatility and policy uncertainty, attributing it to factors such as equity market momentum and the evolving nature of geopolitical risk (Martorana and Mistak, 2025a). Several explanations have been proposed for these disconnects. One view is that text-based indices like EPU may be inflated by media amplification of political events, even when the underlying economic risk is limited (Ahir et al., 2025b). Another perspective emphasizes the role of market sentiment: during periods of strong asset performance, investors may discount political risks, leading to muted volatility despite elevated policy uncertainty (Martorana and Mistak, 2025b). These interpretations suggest that EPU and market-based indicators capture different facets of uncertainty—EPU reflecting the salience of uncertainty in public discourse, and CLIFS/VIX capturing perceived financial risk. The critical question about these discrepancies is thus: are these divergences indicative of measurement error, or do they reflect meaningful differences in the underlying forces driving each indicator?

This paper argues for the latter. We posit that the divergence among uncertainty indicators is not a flaw but a feature—each measure is inherently designed to capture distinct dimen-

[1] Cboe Volatility Index calculated by the Chicago Board Options Exchange (Cboe).

sions of uncertainty. Text-based indices are sensitive to political and institutional narratives, market-based indicators respond to financial volatility and investor sentiment, and survey-based measures reflect firm-level expectations and confidence. This multidimensionality is increasingly recognized in the literature (Cascaldi-Garcia et al., 2023; Larsen, 2021; Aït-Sahalia and Xiu, 2025), yet a comprehensive framework to interpret these divergences remains underdeveloped. As emphasized by Cascaldi-Garcia et al. (2023) and echoed in recent policy commentary by the ECB and IMF (Martorana and Mistak, 2025a; Ahir et al., 2025b), there is a growing need for structured interpretative frameworks that can disentangle the drivers of uncertainty across different domains.

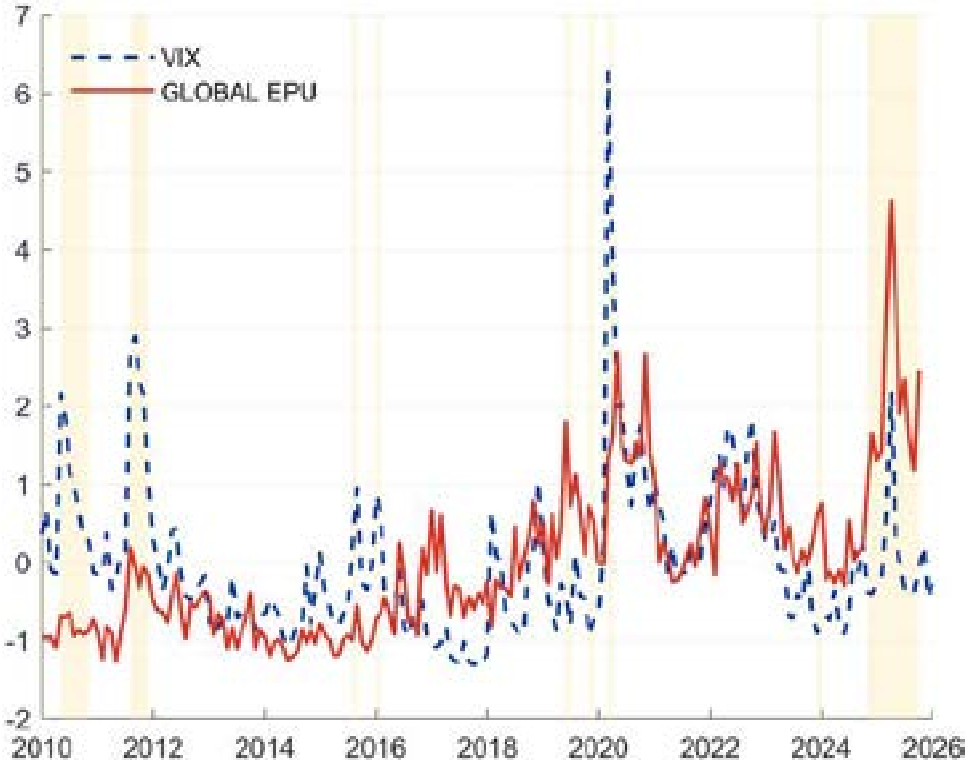
Our contribution is the following: we provide empirical evidence supporting the hypothesis that uncertainty indicators are driven by different underlying shocks. We use topic modeling techniques to unveil different types of uncertainty themes in several countries (along the lines of Azqueta-Gavaldón et al. (2023)). In particular, we decompose press-based uncertainty narratives and classify episodes of divergence between EPU and CLIFS – as a better cross-country measure of financial uncertainty than VIX[2]– across five European countries. Our taxonomy of "EPU-only", "CLIFS-only", and "joint" uncertainty episodes offers a novel lens to interpret divergence patterns, linking them to the nature (political, financial, military) and origin (domestic or external) of the underlying shocks. This responds directly to recent calls in the literature for interpretative tools that go beyond parallel use of multiple indicators.

Our findings reveal systematic patterns: EPU peaks are predominantly associated with political and policy-related topics, while CLIFS peaks correspond to financial market stress and social concerns. Joint peaks, in contrast, tend to coincide with systemic crises such as the Global Financial Crisis or the COVID-19 pandemic. These results are consistent with recent findings by Martorana and Schmitz (2025) and Naboka et al. (2023), who show that topic-specific uncertainty narratives can help explain the behavior of different uncertainty proxies across countries and time.

Using text offers several advantages: (i) news data is readily available for each country, capturing what people in each region are reading or exposed to. This contrasts with econometric methods that rely on a predetermined number of macro series to capture specific types of uncertainty; (ii) using news is a much more cost-effective way to unveil uncertainty indicators compared to surveys, which only represent a small fraction of individuals; (iii) text-based methods allow us to uncover endogenous categories of uncertainty, ranging from financial and geopolitical to regulatory and energy uncertainties. This provides a comprehensive and nuanced understanding of the various uncertainty themes present in different regions. Unlike other methods that define a very specific source of uncertainty, text methods reveal the different themes important for each region. Although our approach is based on Latent Dirichlet Allocation (LDA), recent advances in natural language processing—including the use of large language models (LLMs) (Audrino et al., 2024) and multilingual contextualized topic modeling (Naboka et al., 2023)—highlight the growing potential of AI-enhanced methods to measure uncertainty.

[2]Although the VIX is widely used as a global benchmark for market volatility, we exclude it from our baseline analysis due to its U.S.-centric scope and limited country coverage. Similarly, we do not include the World Uncertainty Index (WUI) of Ahir et al. (2022), despite its prominence, as our topic-based indicators are constructed at the national level and require country-specific alignment.

Figure 1: Decoupling between VIX and EPU



Note: Standardized series. Global EPU is the global economic policy uncertainty index constructed by Davis (2016); VIX is the Cboe Volatility Index calculated by the Chicago Board Options Exchange. Yellow bands indicate periods in which the discrepancy between VIX and Global EPU exceeds the standard deviation of their difference series, highlighting significant divergences between the two indices.

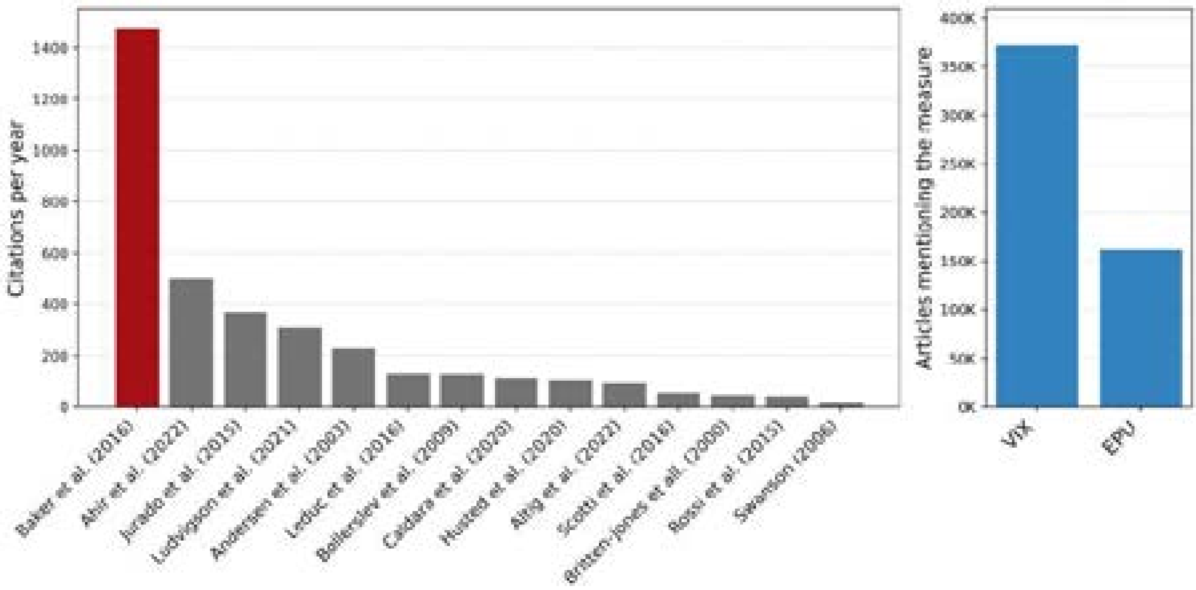
Finally, our findings have direct policy relevance. As uncertainty becomes an increasingly salient feature of the global economic environment, central banks and international institutions are actively seeking tools to interpret diverging signals from multiple indicators (Martorana and Mistak, 2025a; Ahir et al., 2025b). Our taxonomy and topic-based decomposition provide a structured approach that can inform scenario analysis, risk assessment, and communication strategies.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on uncertainty measurement and indicator divergence. Section 3 describes the data sources and the methodological framework of topic modeling and composite-peak taxonomy. Section 4 presents the empirical findings, highlighting the distinct narrative drivers of EPU and CLIFS. Finally, Section 5 concludes with reflections on the future of uncertainty measurement and avenues for further research.

2 Literature Review

The proliferation of economic uncertainty indicators has given rise to a diverse methodological landscape. This section reviews the main approaches to measuring uncertainty, grouped into four broad families: text-based, survey-based, econometric, and market-based. While each method captures distinct facets of uncertainty, recent contributions have increasingly highlighted the multidimensional nature of the concept and the frequent divergence among indicators (see Fig.2).

Figure 2: Academic attention to the main uncertainty proxies.



Note: The left panel reports citations per year for the main uncertainty proxies, selected following Cascaldi-Garcia et al. (2023). The red bar highlights the proxy used in this paper. The right panel shows the total number of academic articles mentioning the relevant proxy.

This review outlines the key developments in each strand, with particular attention to recent work that underscores the need for more structured interpretative frameworks.

Text-based indicators. Text-based measures derive uncertainty from the frequency and content of news articles. The Economic Policy Uncertainty (EPU) index introduced by Baker et al. (2016a) remains the most influential example, with numerous extensions targeting specific domains such as trade and monetary policy (e.g., Caldara and Iacoviello, 2022; Ghirelli et al., 2019). The World Uncertainty Index (WUI) by Ahir et al. (2025a) extends this approach globally using country reports. These indices offer high-frequency, zero-lag signals and are particularly sensitive to political and institutional developments. More recent work has moved beyond simple keyword-based methods to incorporate richer text-as-data techniques. For instance, Larsen (2021) and Azqueta-Gavaldón et al. (2023) apply Latent Dirichlet Allocation (LDA) to uncover thematic structures within uncertainty narratives, revealing that different topics—such as politics, markets, or sectoral disruptions—exhibit distinct dynamics and macroeconomic effects. Building on this, recent studies leverage advanced natural language processing: Audrino et al. (2024) employ large language models (GPT-based) to construct refined news-based uncertainty indices that show stronger correlations with macro-financial fluctuations than traditional EPU measures, while Martineau et al. (2023) use a fine-tuned BERT model to create a daily "narrative" monetary policy uncertainty index, capturing linguistic nuances beyond keyword counts. Cross-country comparability has also improved; for example, Naboka-Krell (2024) develop a multilingual topic modeling approach that aligns uncertainty topics across languages, enabling consistent national EPU indexes that remain predictive of economic activity across different countries. These advances have greatly improved the granularity and context-sensitivity of text-based indicators. Nonetheless, challenges remain regarding media bias, cross-country differences, and the interpretability of topics. For instance, Schröder (2025) demonstrates that raw news-based trade uncertainty indices can be inflated by unrelated news coverage, underscoring the importance of careful content filtering in text-derived measures.

Survey-based indicators. Survey-based measures capture uncertainty through the expectations and confidence intervals reported by firms, households, or professional forecasters. These include the Survey of Business Uncertainty (SBU) in the United States, the European Commission's business and consumer surveys, and the University of Michigan's Survey of Consumers. For example, Leduc and Liu (2016) use dispersion in consumer expectations to proxy inflation uncertainty. A notable recent contribution is the SBU developed by Altig et al. (2022), which elicits subjective probability distributions from business executives about their own-firm outcomes, providing a direct quantification of firm-level uncertainty. Such measures offer direct insight into perceived uncertainty at specific horizons and are well-suited to studying micro-level decision-making. However, their limited frequency, geographic coverage, and cross-country comparability constrain their use in high-frequency or cross-national analyses.

Econometric indicators. Econometric approaches define uncertainty as the conditional volatility of forecast errors in macroeconomic or financial variables. The macroeconomic uncertainty index of Jurado et al. (2015) and the financial uncertainty index of Ludvigson et al. (2021) are prominent examples. These indices aggregate information from a broad set of time series, isolating the unpredictable component of economic dynamics. While theoretically grounded and empirically robust, such measures are typically low-frequency and less transparent, and they do not readily distinguish among different sources of uncertainty. Recent research has begun to refine these approaches—for example, by separating macroeconomic versus financial uncertainty factors or examining international commonalities in uncertainty—but the fundamental trade-off between breadth and frequency remains (Ludvigson et al., 2021).

Market-based indicators. Market-based measures infer uncertainty from asset prices, particularly derivatives. The VIX index, derived from S&P 500 option prices, is the most widely used proxy for expected stock market volatility (Andersen et al., 2003). Other measures include realised volatility and credit spreads. These indicators are forward-looking and available at high frequency, making them useful for real-time monitoring. However, they are narrowly focused on financial market perceptions and may not reflect broader economic or policy-related uncertainty. Composite indices such as the ECB's Country-Level Index of Financial Stress (CLIFS) attempt to address this limitation by aggregating stress across multiple market segments (equities, bonds, foreign exchange, etc.). CLIFS offers a more comprehensive view of financial stress, though its complexity can obscure the specific drivers of uncertainty within it. Notably, researchers have also explored market-implied measures of policy uncertainty — for instance, using interest rate options to gauge uncertainty about future monetary policy (e.g., Bauer et al., 2021). Such measures complement the VIX by targeting other asset classes or risk facets, but like the VIX they primarily capture investors' risk perceptions.

Towards a multidimensional view. Recent literature increasingly recognises that these indicators capture different dimensions of uncertainty and often diverge in their signals. Cascaldi-Garcia et al. (2023) provide a systematic classification of uncertainty measures by construction method, noting that divergence is common and typically reflects underlying differences in scope, time horizon, and shock sensitivity. Ahir et al. (2025a) document episodes where text-based and market-based indicators moved in opposite directions, while Martorana and Mistak (2025a) highlight the disconnect between financial market volatility and policy uncertainty in the euro area. Larsen (2021) further show that even within a single text-based index, different topics can have heterogeneous macroeconomic impacts. In the same vein, Yang (2025) find that EPU and stock market volatility are more closely aligned over longer horizons than in the short run, implying that news-based indices may capture forms of uncertainty that take time to influence markets. Bontempi et al. (2025) take a complementary approach, using human experts and large language models to identify "uncertainty-generating events" and testing how various indices correspond to those events; their analysis confirms that different uncertainty measures tend to flag different events, reflecting their distinct foci. These findings underscore the need for interpretative frameworks that go beyond the parallel use of multiple indicators. While the literature has made significant progress in documenting and classifying uncertainty measures, it has yet to develop a structured taxonomy that links specific types of shocks to the observed configuration of indicator responses. Existing reviews — including the comprehensive survey by Cascaldi-Garcia et al. (2023) — stop short of offering such a framework. By proposing a taxonomy of divergence episodes and mapping them to underlying political, financial, and geopolitical shocks, our empirical analysis aims to help fill this gap in the literature.

3 Data and Topic Modelling Approach

3.1 Reference Indices

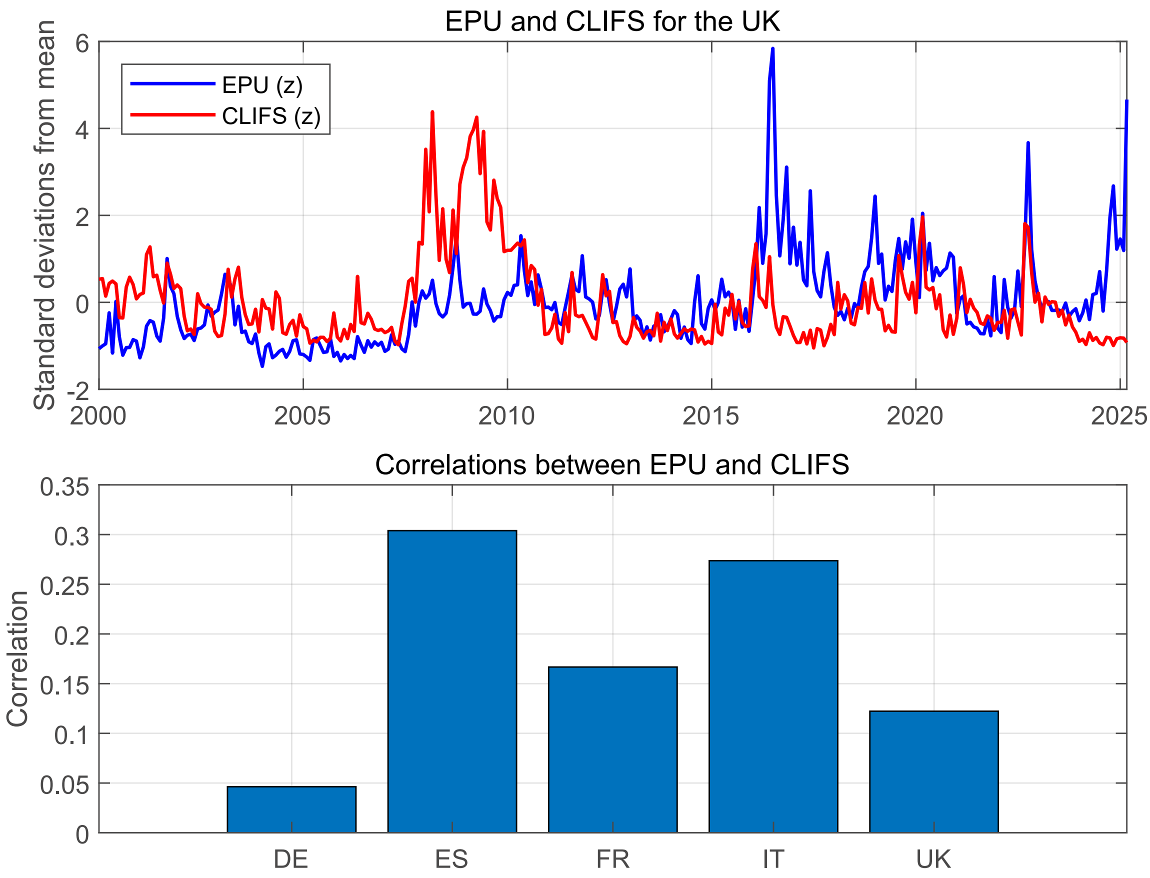
Our analysis focuses on two national-level proxies of economic uncertainty: the Economic Policy Uncertainty (EPU) index of Baker et al. (2016b) and the Country-Level Index of Financial Stress (CLIFS) developed by the European Central Bank. These indicators are selected for their broad country coverage and consistent availability over the full sample period (2000–2025) across the five countries in our study: the United States, United Kingdom, Germany, France, and Italy.

EPU captures narrative and policy-related uncertainty as reflected in national press coverage, while CLIFS aggregates financial stress across equity, bond, and foreign exchange markets, serving as a national-level analogue to the VIX. Although the VIX is widely used as a benchmark for market volatility, it is excluded from our baseline due to limited country coverage—e.g., the French VIX series is discontinued after January 2021. A visual comparison of CLIFS and VIX, presented in Appendix A, supports the interpretation of CLIFS as a suitable market-based counterpart to EPU.

We also exclude the World Uncertainty Index (WUI) of Ahir et al. (2022), despite its global scope, as our topic-based indicators are constructed at the national level and require alignment with country-specific press corpora.

Figure 3(a) illustrates the empirical divergence between EPU and CLIFS. In the UK, for

Figure 3: Evolution of uncertainty measures



Note: Monthly standardized values of EPU and CLIFS. The two indices exhibit distinct dynamics across countries and time.

instance, CLIFS peaks during the Global Financial Crisis, while EPU spikes around the Brexit referendum. Similar patterns are observed across countries (Appendix Figure D.1). Correlations between EPU and CLIFS range from 0.05 to 0.3 (Figure 3(b)), indicating limited co-movement. This divergence motivates our effort to interpret these indicators through the lens of topic-specific press narratives, with the aim of uncovering the distinct sources of uncertainty each proxy reflects.

3.2 Topic Modelling Approach

To construct topic-specific uncertainty indicators, we use newspaper articles from five European countries: the United Kingdom, Germany, France, Italy, and Spain. Articles are sourced from the Dow Jones repository, covering a broad set of national newspapers (see Table 1).

We restrict the corpus to articles containing the terms "economy" and "uncertainty" (translated into each country's language). Following Azqueta-Gavaldón et al. (2023), we expand this set by including articles with semantically related terms, identified using the word2vec algorithm (Mikolov et al., 2013).[3]

Text preprocessing includes standard steps: lowercasing, removal of stopwords, punctuation,

[3] Word2vec represents words as vectors based on their co-occurrence in text. Words with similar meanings have high cosine similarity.

Table 1: List of newspapers by country and period

Country	Newspapers	Period
Germany	Handelsblatt, Die Welt, Süddeutsche Zeitung, Der Tagesspiegel, Die Tageszeitung, Börsen-Zeitung, Berliner Zeitung	Starting year: 1997
France	Les Echos, Le Figaro, La Tribune, Le Monde, Libération, L'AGEFI Quotidien, La Croix, L'Opinion	Starting year: 1996
Italy	Il Sole 24 Ore, Corriere della Sera, Il Giornale, La Repubblica, ItaliaOggi, La Stampa, Il Fatto Quotidiano	Starting year: 1997
Spain	La Vanguardia, El Mundo, Expansión, ABC, El País, El Economista, Cinco Días	Starting year: 1997
United Kingdom	The Times, The Guardian, The Independent, The Daily Telegraph, The Herald, The Economist, City AM	Starting year: 1981

Note: Press and time coverage used to construct the topic-specific uncertainty indices for each country.

and numbers, and stemming. We then apply Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to extract $k = 30$ latent topics per country. Each article is represented as a distribution over topics, and each topic as a distribution over words.

Topic labeling follows a multi-stage process combining AI-generated suggestions and manual validation. We first generate candidate labels using Copilot and compare them with independent manual labels. Within each country, we resolve overlapping or ambiguous labels by prompting Copilot to distinguish between similar topics. We then harmonize labels across countries to ensure comparability, while preserving national specificity. For example, topics related to *EU affairs* are labeled consistently, while geopolitical topics are differentiated (e.g., "Middle East geopolitics" in Italy vs. "Russia geopolitics" in France).

Each topic indicator is computed monthly as the normalized sum of topic shares across relevant articles, scaled by the total number of published articles. This normalization ensures comparability across time and countries and aligns the indicators with the frequency and construction of the EPU.

The value of a topic indicator in a given month reflects three components:

- the average share of the topic within relevant articles,
- the number of relevant articles,
- the total number of published articles.

An increase in the indicator may thus reflect more intense coverage of the topic, a greater volume of relevant articles, or a decline in overall news volume—each implying greater narrative salience of the topic in question.

3.2.1 Topic aggregation

To enhance interpretability and facilitate cross-country comparison, we group the 30 machine-generated topics into eight thematic categories. This dimensionality reduction allows us to analyze broader uncertainty themes while preserving the richness of the underlying narratives.

The grouping follows a hybrid approach. We begin with heuristic expert judgment and validate the resulting clusters using intra- and inter-topic correlations. To ensure international comparability, we impose a consistency constraint: each category must be represented in the majority of countries. This requirement limits the inclusion of highly country-specific topics. For example, a topic centered on "Brexit" appears prominently in the UK press but is largely absent elsewhere. Rather than assigning it to a standalone category, we incorporate it into a broader thematic group—such as *Politics* or *International*—that is present across countries.

The final eight categories are defined as follows:

- **International:** Global geopolitical events and international trade.
- **Policy:** Fiscal and monetary policy issues.
- **Outlook:** Economic forecasts and macroeconomic indicators.
- **Markets:** Financial markets and commodity-related topics.
- **Corporate:** Business performance, investment, and firm-level developments.
- **Society:** Labour markets, social unrest, and public services.
- **Politics:** Elections, government formation, and institutional dynamics.
- **Segments:** Sector-specific issues (e.g., real estate, energy, tourism).

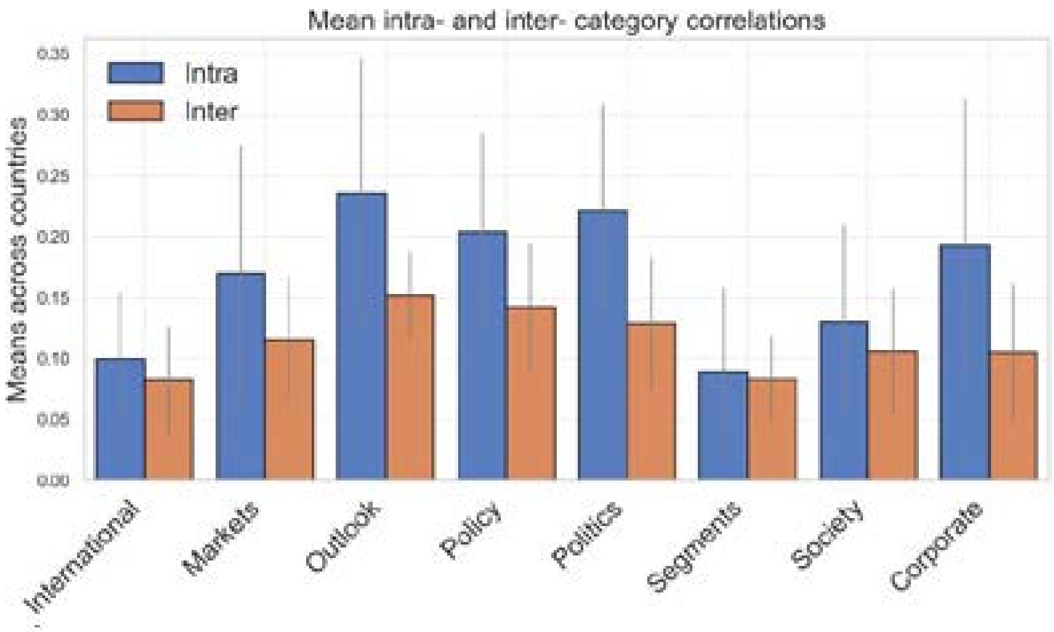
See Appendix B for detailed topic-to-category mappings in each country (Figures B.1–B.4). While the categories are harmonized across countries, the specific topics assigned to each category may vary to reflect national context and media salience.

3.2.2 Validation

To evaluate the internal consistency of the thematic categories, we compute average pairwise correlations among topic indicators within and across categories. As shown in Figure 4, intra-category correlations (blue bars) are consistently higher than inter-category correlations (orange bars), supporting the validity of the grouping scheme.

Categories such as *Outlook*, *Policy*, and *Politics* exhibit particularly strong internal coherence, indicating that the topics grouped under these labels tend to co-move over time. In contrast, the *Segments* category displays lower internal correlation, reflecting its broader and more heterogeneous thematic scope. These results confirm that the thematic aggregation preserves meaningful structure in the underlying topic dynamics while enabling more tractable cross-country comparisons.

Figure 4: Intra- and inter-category correlations (UK)



Note: Mean pairwise correlations among topics within (blue) and across (orange) thematic categories in the UK.

3.2.3 Statistical Properties of Topics

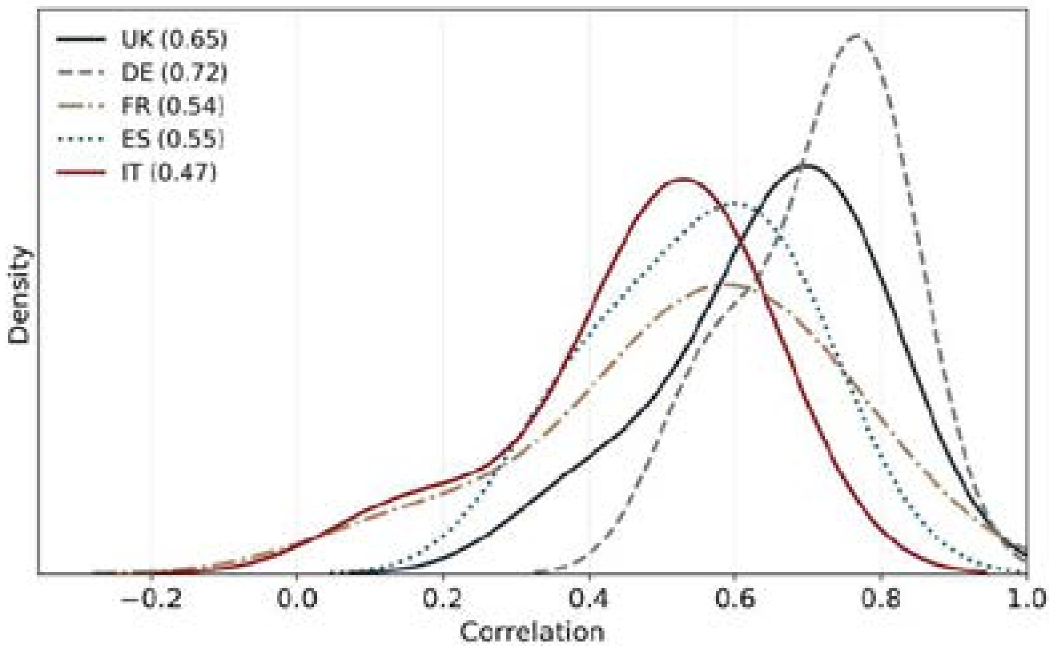
Topic indicators exhibit substantial heterogeneity across countries. Figure 5 summarizes the distribution of pairwise correlations among topics within each country.[4] Germany displays the highest internal coherence (mean correlation = 0.74), while France shows the lowest (mean = 0.51), suggesting differences in the thematic structure and co-movement of uncertainty narratives.

The most central topics—defined as those with the highest average correlation with other topics—also vary by country. In the UK, *Politics* emerges as the most central theme, while *Outlook* dominates in Germany and Italy. In France and Spain, *Society*-related topics are most central. These patterns indicate that national uncertainty narratives are anchored in different thematic domains, reflecting country-specific institutional, political, and media dynamics.

4 Unveiling the narrative drivers of EPU and CLIFS

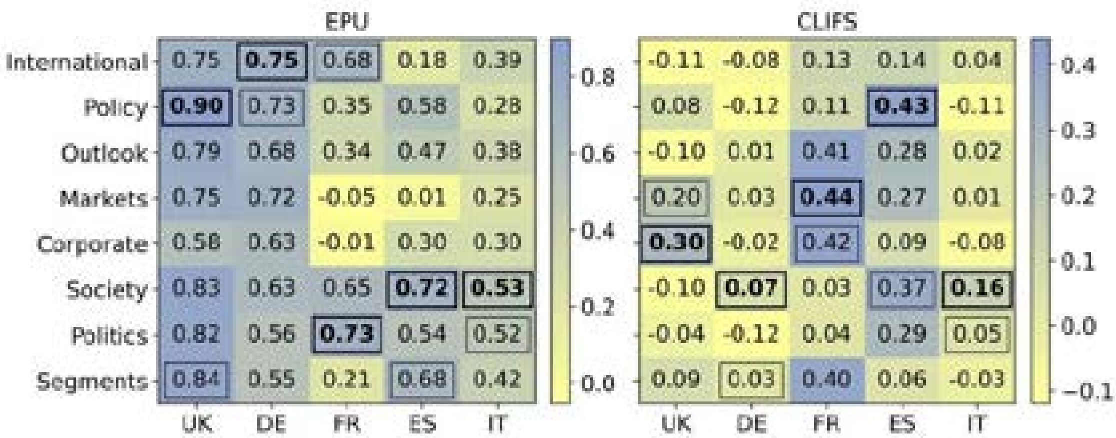
This section examines the relationship between topic-based press narratives and the two selected uncertainty proxies—EPU and CLIFS—across five European countries. The objective is to assess whether these indicators respond to common underlying drivers or instead reflect distinct dimensions of uncertainty. The analysis draws on newspaper data available through April 2025 and focuses on the extent to which thematic narratives can account for the observed divergence between the two proxies.

Figure 5: Pairwise topic correlations



Note: Distribution of pairwise correlations among topic indicators by country. Kernel density estimates shown; means indicated in the legend.

Figure 6: Correlations between topics and proxies



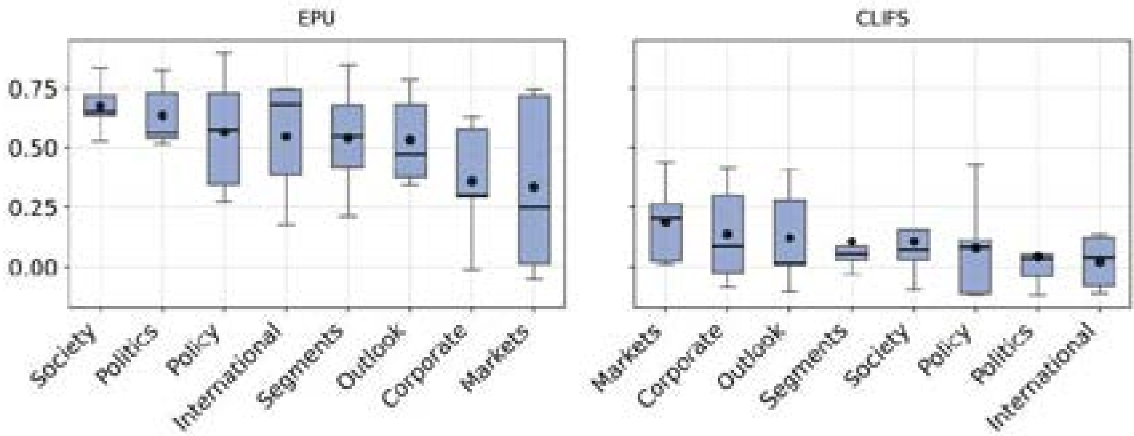
Note: Pairwise correlations between the topics and the proxies. The highest correlation dislayed by a topic with the proxy is boxed and shown in bold, and the second highest is boxed only.

4.1 Pairwise correlations

We begin by examining the pairwise correlations between each topic-based uncertainty indicator and the two benchmark proxies: EPU and CLIFS. As shown in Figure 6, topic indicators exhibit systematically stronger correlations with EPU than with CLIFS. This is expected, as both EPU and the topic indicators are derived from national press narratives and thus capture similar dimensions of uncertainty, albeit with different levels of thematic granularity. In contrast, CLIFS is constructed from market-based variables, and its relationship with press narratives is more indirect, reflecting the transmission of financial stress into public discourse.

There is considerable cross-country heterogeneity in the topics most correlated with each

Figure 7: Average correlation between topics and proxies



Note: The correlation between topics and the proxy, as averaged across the five countries. The box defines the 25-75 percentile, the horizontal line is the median, the circle is the mean, and the whiskers are the most extreme datapoints.

proxy. For EPU, five distinct topics emerge as top correlates when considering the two most correlated topics per country. For CLIFS, the picture is even less consistent, with some topics showing negligible correlations. For example, in Germany, correlations between CLIFS and most topic indicators are particularly low.[5]

To extract broader patterns, we compute average correlations across countries. As shown in Figure 7, the topics most correlated with EPU are *Society*, *Politics*, and *Policy*, while those most correlated with CLIFS are *Markets*, *Corporate*, and *Outlook*. This pattern aligns with the conceptual distinction between the two proxies: EPU reflects political and institutional uncertainty, whereas CLIFS captures financial and corporate stress. It is important to note, however, that these are unconditional correlations and do not account for confounding factors or directionality. The regression analysis in the following sections provides a more structured assessment of these relationships.

4.2 Exploring the tails

Both the topic indicators and the uncertainty proxies exhibit substantial volatility, suggesting that the most informative relationships are likely to emerge during periods of elevated uncertainty. To focus on these episodes and mitigate the influence of noise, we adopt two complementary modeling strategies.

First, we estimate quantile regressions to examine how the relationship between topic indicators and uncertainty proxies varies across the conditional distribution of the proxies, with particular emphasis on the upper tail. Second, we discretize the proxies into binary peak indicators and estimate classification models to capture the presence or absence of extreme uncertainty episodes.

The binary peak series are constructed using a semi-automated procedure that combines

[5]This suggests that CLIFS and topic-based indicators may capture different dimensions of uncertainty. Nonetheless, we retain CLIFS in the analysis to assess whether press narratives contain predictive information about financial stress. While estimated coefficients are generally small, some significant results—especially for market-related topics in the upper quantiles—are consistent with expectations.

statistical thresholds with expert judgment. We define two versions of the peak indicators:

- **H0:** Peaks defined using baseline thresholds (see Table D.1).
- **H3M:** Peaks defined using the same thresholds, but requiring a minimum duration of three consecutive months.

Appendix D provides a detailed description of the peak construction process and displays the resulting binary series alongside the original proxies.

For each country and uncertainty proxy, we estimate quantile regressions across the conditional distribution of the dependent variable. This approach allows us to assess how the relevance of each topic varies with the level of uncertainty. Country-specific results are presented in Appendix E. Each panel displays the relative importance of a given topic across quantiles, alongside the corresponding OLS coefficient and the average of the upper-half quantile coefficients. Since our interest lies in periods of heightened uncertainty, we focus on the upper quantiles.

Several patterns emerge. In some countries, topic relevance is relatively stable across quantiles, suggesting that certain narratives are consistently associated with uncertainty. In others, topic relevance increases sharply in the upper tail. As summarized in Table 2, the most influential categories for EPU are typically *Politics* and *Policy*, reflecting the index's sensitivity to institutional and fiscal developments. However, country-specific deviations are notable: in Germany, *Outlook* dominates, while in Spain and Italy, *Segments* becomes more prominent, highlighting the role of sector-specific narratives. For CLIFS, the leading topics are *Society* and *Markets*. The prominence of *Markets* aligns with the financial nature of CLIFS, while the relevance of *Society* likely reflects the lagged transmission of financial stress into public discourse.

As a robustness check, we complement the quantile regression analysis with a set of classification models aimed at predicting peak uncertainty episodes. Specifically, we estimate three standard classifiers: logistic regression with L2 (ridge) regularization, logistic regression with L1 (lasso) regularization, and a linear Support Vector Machine (SVM).

Figure 8 summarizes the results by combining standardized coefficients from both quantile regressions and classification models, offering a unified view of topic relevance across methods.[6] For EPU, the most influential topics are *Outlook* and *Policy*, followed by *Politics* and *Segments*. For CLIFS, *Society* and *Markets* dominate, with a substantial margin over other categories. Table 3 summarizes the most important topics for each proxy. The leading topics for EPU—*Politics*, *Policy*, *Outlook*, and *Segments*—are closely tied to institutional and policy-related uncertainty. For CLIFS, the dominance of *Markets* and *Society* reflects the financial and social dimensions of economic stress.

Appendix F provides a detailed description of the methodology and full results. We also explore two alternative aggregation strategies to synthesize results across models and specifications (see Appendix G for details of the aggregation strategies and results). The findings from both approaches are broadly consistent and align with theoretical expectations.

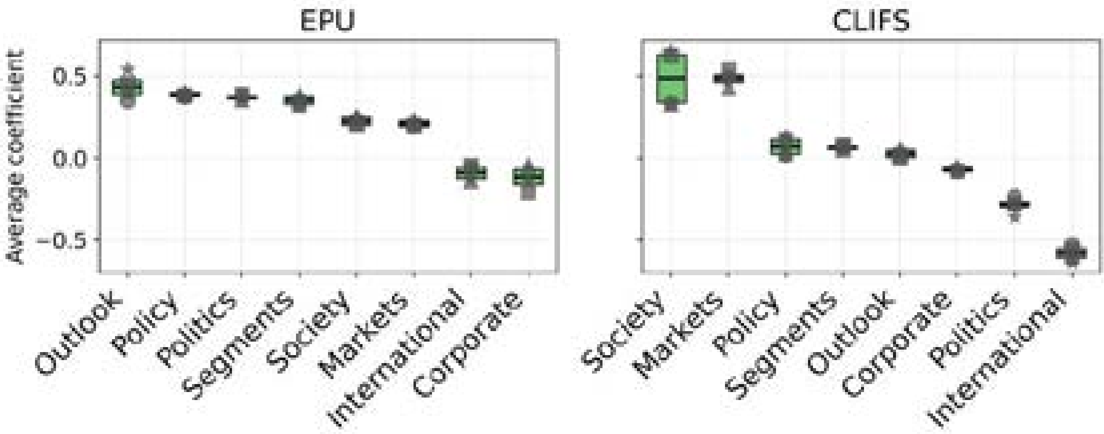
[6]The figure averages results across multiple model specifications, including different quantile thresholds and peak definitions. Full methodological details are provided in Appendix F.

Table 2: Quantile results: most relevant topics in uncertainty peaks

Country	EPU	CLIFS
UK	Policy, Markets, Politics	Society, Policy, Outlook
DE	Outlook, International	Markets, Segments, Society
FR	Politics, International, Outlook	Markets, Segments, Outlook
ES	Policy, Segments	Society, Policy, Outlook
IT	Politics, Segments, Society	Markets, Outlook, Politics

Note: We select largest positive significant coefficients beyond percentile 0.8: in black, coefficients larger than 0.4, in gray coefficient larger than 0.25.

Figure 8: Aggregated results averaging across models



Note: Average coefficient across countries, where each country's value is the mean across quantile regressions and classification models. Symbols indicate different parameter configurations (τ refers to the set of quantiles considered in the average, while the second parameter refers to the peak definition): circle = ($\tau_{\min} = 0.5$, H0); triangle = ($\tau_{\min} = 0.5$, H3M); square = ($\tau_{\min} = 0.7$, H0); star = ($\tau_{\min} = 0.7$, H3M). Horizontal lines show the overall mean. See Appendix F for methodological details.

Table 3: Results of the formal analysis of national proxies

Uncertainty Proxy	**Most important topics**
EPU	Outlook, Policy, Politics, Segments
CLIFS	Society, Markets

Note: The most important topics, as chosen by either of the aggregation methods.

4.3 Composite Peak Analysis

We now turn to the joint dynamics of EPU and CLIFS by systematically identifying episodes in which the two indicators either move together or diverge. We develop a taxonomy of what we term "composite peaks," capturing periods of elevated uncertainty in at least one of the two proxies. Figures H.1–H.5 in Appendix H illustrate the temporal alignment and decoupling of EPU and CLIFS across countries.

To operationalize this taxonomy, we construct a joint indicator based on the binary peak series for EPU and CLIFS introduced earlier. Each country is associated with two binary time series indicating the presence or absence of peaks in each proxy. Combining these yields a two-dimensional composite indicator, where each observation is a tuple $c = (a, b)$ with $a, b \in \{0, 1\}$. The four possible states are:

- $(0, 0)$: No peak in either EPU or CLIFS — low uncertainty overall.
- $(1, 0)$: EPU-only peak — elevated narrative or policy uncertainty without financial stress.
- $(0, 1)$: CLIFS-only peak — financial stress without elevated policy uncertainty.
- $(1, 1)$: Joint peak — simultaneous narrative and financial uncertainty.

We define composite peaks as any state in which at least one of the two proxies registers a peak. These are further classified into three mutually exclusive types: EPU-only, CLIFS-only, and joint peaks. The composite peak series are constructed using the hybrid peak definitions (**H0** and **H3M**) introduced earlier. In addition, we define a third version, **Rev**, based on manual revisions of the **H3M** series. This revision process involves reviewing all peak and non-peak periods and reclassifying them when necessary, retaining only those episodes for which we have high confidence in the classification. Details on the construction of these series are provided in Appendix H, and the resulting composite peaks are overlaid on the original proxies in Figures H.1–H.5.

Across countries, we observe that all three types of composite peaks—EPU-only, CLIFS-only, and joint—occur with meaningful frequency. Table H.2 in Appendix H summarizes the distribution of event types using the **H3M** dataset. The most common state is the absence of any peak, accounting for 50–60% of the sample. CLIFS-only peaks occur in approximately 18% of months, followed by EPU-only peaks (14%) and joint peaks (13%). This distribution confirms that divergence between narrative and financial uncertainty is not only frequent but also persistent across countries and over time.

In the next section, we analyze the narrative content associated with each type of composite peak to uncover the thematic drivers of joint and decoupled uncertainty episodes.

4.3.1 A taxonomy of composite peaks

We now turn to a direct examination of the empirical structure of composite peaks. While these peaks are defined by the co-occurrence (or absence) of EPU and CLIFS spikes, the underlying events that trigger them are highly heterogeneous. To better understand what composite peaks represent, we classify each episode based on the nature of the originating shock, thereby developing a phenomenology of uncertainty events.

The first step involves assigning a likely cause to each composite peak using expert judgment. For each country, we reviewed the timeline of composite peaks—defined as periods in which either EPU, CLIFS, or both registered a spike—and identified the most plausible underlying event. The full list of classified peaks is provided in Table I.3 in Appendix I. For clarity, we also group these events into broader episodes (e.g., the Global Financial Crisis, the COVID-19 pandemic), summarized in Table 4. A single episode may generate different types of composite peaks across countries or over time, depending on the nature and transmission of the shock. For instance, the onset of the COVID-19 pandemic typically triggered joint peaks, while subsequent waves or reopening phases often resulted in EPU-only peaks, as financial markets stabilized.

Table 4: Suggestive Mapping of Uncertainty Events to (EPU, CLIFS) Peak Types

Period	Timeline	DE			UK			FR			IT			ES		
		EPU	CLIFS	BOTH	EPU	CLIFS	BOTH	EPU	CLIFS	BOTH	EPU	CLIFS	BOTH	EPU	CLIFS	BOTH
2000-01	Dot-com Bubble		✓	✓		✓			✓					✓		
2001	9/11 Attacks			✓			✓			✓			✓			
2002	Post-Dot-com financial weakness					✓				✓		✓		✓		
2003	Iraq war buildup			✓			✓			✓			✓			
2004	Market-driven stress		✓			✓			✓	✓				✓		
2007-09	Global Financial Crisis			✓	✓	✓	✓		✓	✓		✓			✓	✓
2010-11	Eurozone Debt Crisis-Greek bailout			✓		✓	✓	✓		✓			✓			✓
2012	Eurozone Debt Crisis-Draghi pledge	✓		✓						✓						✓
2013	Domestic political uncertainty							✓			✓		✓	✓		✓
2014-15	Greek Debt Crisis			✓		✓					✓		✓	✓		
2016	Brexit Referendum	✓		✓	✓		✓	✓								
2018-19	US–China Trade War			✓						✓			✓	✓		
2020-21	COVID-19 Pandemic	✓		✓	✓		✓			✓	✓		✓	✓		✓
2022	Russia–Ukraine War+energy shock			✓			✓			✓			✓		✓	✓
2023	Inflation shock							✓		✓	✓		✓			✓
2024	US Presidential Election	✓			✓					✓	✓			✓		

Note: The table reports peak episodes lasting at least three months and observed in two or more countries. Orange cells indicate EPU-only peaks (1,0), blue indicate CLIFS-only (0,1), and green denote joint peaks (1,1). Dates are approximate, as timing may vary by country and indicator. Events marked as (1,0), (0,1), and/or (1,1) may reflect multiple successive spikes linked to the same event; only (1,1) events denote truly simultaneous increases in both indicators.

To interpret these patterns, we propose a conceptual taxonomy linking the nature of the shock to its expected manifestation in the uncertainty proxies. Specifically, we distinguish whether a shock is likely to affect policy uncertainty (EPU), financial stress (CLIFS), or both, based on its transmission channels:

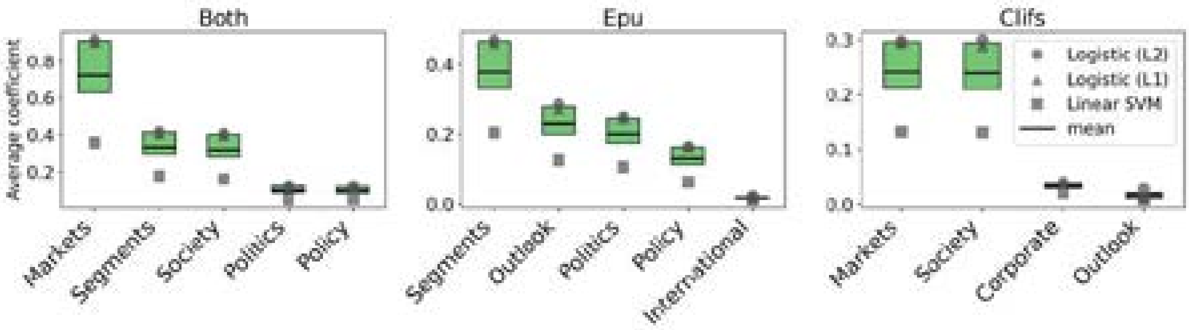
- **Pure Financial / Market Events → CLIFS-only.** Shocks driven by financial market dynamics—such as asset price corrections, liquidity shortages, or credit events—that do not materially alter the political or institutional landscape.

- **Military / Geopolitical / Security Events → BOTH.** Events that simultaneously affect political expectations and financial markets, including military conflicts, geopolitical escalations, and security threats.

- **Systemic Macroeconomic Crises → BOTH.** Deep, system-wide disruptions—such as global financial crises or sovereign debt crises—that propagate through both financial and political channels.

- **External Macro / Policy Shocks → EPU-only or BOTH.** Shocks originating outside the domestic economy that influence domestic policy debates or institutional responses, with varying degrees of financial market impact depending on country-specific exposure.

Figure 9: Topic effects on composite peak prediction



Note: Average coefficients from the three classifiers estimated on the pooled cross-country dataset using the H0 composite peak definition. The only values shown are those where the coefficient is positive. Topics are ordered from left to right according to the magnitude of their average coefficient, with those on the left contributing most strongly to the prediction of composite peaks. Boxes are only shown if all three classifiers are present (meaning all three give the coefficient to be positive).

Importantly, the same event can generate different types of composite peaks across countries or over time. This may reflect (i) the sequential unfolding of events—as with Brexit, which began with EPU-only peaks, followed by a joint peak after the referendum, and later intermittent EPU-only spikes during negotiations; (ii) delayed spillovers across domains—as in the Global Financial Crisis, which initially triggered CLIFS-only peaks and later led to widespread political uncertainty; and (iii) country-specific exposure—where global shocks, such as commodity price swings, affect countries differently depending on their economic structure or financial vulnerabilities.

To formalize this taxonomy, we classify each composite peak along three dimensions: (i) the nature of the shock (Political, Financial, or Military), (ii) its origin (Domestic or External), and (iii) its manifestation in the uncertainty proxies (EPU-only, CLIFS-only, or Both). Table 5 summarizes the results of this empirical categorization.

The results confirm the validity of our conceptual framework. EPU-only peaks are predominantly driven by domestic political events. CLIFS-only peaks are almost exclusively triggered by external financial shocks. Joint peaks—where both EPU and CLIFS rise—are typically associated with systemic or geopolitical crises, such as the Global Financial Crisis, the COVID-19 pandemic, or the Russia–Ukraine war. These events propagate through both financial and political channels, generating simultaneous stress in markets and policy narratives.[7]

In sum, our empirical classification aligns closely with the conceptual taxonomy. Political and institutional shocks tend to manifest as EPU-only peaks, financial shocks as CLIFS-only peaks, and systemic or geopolitical shocks as joint peaks. This correspondence reinforces the value of our topic-based framework in disentangling the nature and transmission of uncertainty shocks.

[7] Selected examples drawn from the full list of country-specific peaks (see Appendix I) illustrate these dynamics. Spain's 2015–2016 government formation deadlock and France's 2023–2024 pension reform crisis triggered EPU-only peaks, reflecting institutional uncertainty without financial distress. In contrast, Germany's 2003–2004 post-dot-com market weakness and Spain's 2006 real estate overheating led to CLIFS-only peaks, with little narrative uncertainty. Systemic crises—such as the GFC, COVID-19, and the Russia–Ukraine conflict—produced joint peaks across countries, as both financial markets and policy narratives were simultaneously affected.

Table 5: Categorization of composite peaks by type of shock

Origin	**Type**	**EPU-only** ($n = 34$)	**CLIFS-only** ($n = 25$)	**Both** ($n = 57$)
Inside	Political	74%	0%	26%
	Financial	0%	4%	0%
	Military	0%	0%	0%
	Total	74%	4%	26%
Outside	Political	15%	0%	4%
	Financial	12%	96%	47%
	Military	0%	0%	23%
	Total	26%	96%	74%
Grandtotal		100%	100%	100%

Note: Percentages shown; counts in parentheses. Composite peaks are restricted to events lasting at least three months and pooled across countries to increase sample size. All peaks are listed in Table I.3, Section D, Appendix. "Origin" distinguishes domestic ("Inside") from external/global ("Outside") drivers. "Nature" classifies events as Political (e.g., elections, policy shifts), Military (e.g., wars, terrorism), or Financial (e.g., crises, market volatility, debt/banking stress).

4.3.2 Modeling Composite Peaks with Pooled Data

To formally assess the narrative structure of composite peaks, we estimate classification models that identify which uncertainty-related topics are most salient during each type of peak. To ensure sufficient statistical power, we pool events across all countries, effectively constructing a "virtual country" that abstracts from national idiosyncrasies and emphasizes generalizable patterns.

Figure 9 presents results from three classifiers—logistic regression with L1 and L2 regularization, and a linear Support Vector Machine—using the **H0** peak definition. While the absolute magnitudes of the coefficients vary, the relative ranking of topics is highly consistent across models, suggesting robustness in the mapping between topic activity and peak probabilities. To further validate these findings, we replicate the analysis using all three composite peak definitions (**H0**, **H3M**, and **Rev**) and compute average topic rankings across specifications. The aggregated results are shown in Figure J.1 in Appendix J.

For CLIFS-only peaks, the dominant topics are *Society* and *Markets*. The prominence of *Markets* is expected, given CLIFS's financial construction. The relevance of *Society* suggests that financial stress often coincides with concerns about labor markets, public services, and social cohesion—dimensions that are captured in the press under this category. These results indicate that financial stress episodes are frequently accompanied by broader socio-economic repercussions.

EPU-only peaks are most strongly associated with *Segments*, followed by *Outlook* and *Politics*. The prominence of *Segments* implies that political or institutional uncertainty often transmits rapidly to the real economy, with sector-specific narratives—such as energy, real estate, or manufacturing—becoming salient even in the absence of financial stress.[8] [9]

For joint peaks—where both EPU and CLIFS are elevated—the dominant topics are *Markets*, *Segments*, and *Society*. This combination is intuitive: *Markets* reflects direct financial pressures; *Segments* captures sector-specific vulnerabilities; and *Society* encompasses broader social and institutional consequences. Subtopics within *Society* include public health, labor markets, regional tensions, and governance issues. These results suggest that joint peaks arise when financial stress, sectoral disruptions, and socio-political strains interact and reinforce one another, producing a broad-based uncertainty environment.

Linking Narrative Structure to Shock Taxonomy The classification results provide empirical validation for the shock taxonomy developed in Section 4.3.1. The taxonomy hypothesized that different types of shocks—political, financial, or systemic—would manifest in distinct combinations of uncertainty indicators. The narrative composition of composite peaks confirms these expectations.

There is a clear mapping between topics and economic transmission channels: *Politics* and *Policy* correspond to governance uncertainty; *Markets* to financial stress; *Segments* to real economy disruptions; *Outlook* to forward-looking macroeconomic expectations; and *Society* to the social consequences of uncertainty. The prominence of specific topics during each peak type thus provides insight into both the origin and propagation of the underlying shock.

For joint peaks, the co-occurrence of *Markets*, *Segments*, and *Society* suggests a multi-channel shock affecting financial markets, key economic sectors, and the broader social environment—consistent with systemic macroeconomic or geopolitical crises.

EPU-only peaks are characterized by the prominence of *Segments*, *Outlook*, and *Politics*, indicating that political or institutional uncertainty is transmitted to the real economy without triggering financial stress. The absence of *Markets* reinforces the interpretation that these are non-financial shocks.

CLIFS-only peaks are associated with *Markets* and *Society*, with a notable absence of *Segments* and *Politics*. This configuration suggests that the shock originates in financial markets and may have social consequences, but does not yet manifest in sectoral narratives or political discourse.

In sum, the presence—and absence—of specific narratives across peak types corresponds closely with the hypothesized transmission channels. The narrative composition of each peak type not only signals the origin of the shock but also reveals the pathways through which uncertainty propagates. These findings underscore the value of topic-based press analysis in interpreting the divergence and co-movement of uncertainty indicators.

[8] For example, EPU-only peaks are often linked to narratives around energy and climate policy in the UK, automotive and green transition debates in Germany and France, real estate concerns in Spain, or business technology in Italy. These sectors are particularly sensitive to regulatory and policy shifts, making their prominence under EPU-only peaks consistent with expectations.

[9] Although the *Corporate* topic rarely ranks among the top three, it frequently appears within the top four for both composite and CLIFS peaks. *Corporate* captures firm-level developments—profitability, restructuring, investment decisions, and mergers or acquisitions. Its consistently lower ranking relative to *Segments* suggests that sector-level stress is more prominently reflected in the press than firm-specific responses, which tend to be second-order effects.

5 Concluding remarks

Our findings offer a new lens through which to interpret the divergence between narrative- and market-based uncertainty indicators. The empirical evidence presented in this paper strongly supports the hypothesis that EPU and CLIFS capture distinct underlying forces rather than serving as interchangeable proxies for a single latent "uncertainty" factor, underscoring the multidimensional nature of uncertainty (Cascaldi-Garcia et al., 2023; Aït-Sahalia and Xiu, 2025). This multidimensionality is both theoretically grounded and empirically observable across countries and over time. The classification of composite peaks reveals that EPU-only episodes are predominantly triggered by domestic political and institutional events, while CLIFS-only peaks are typically associated with external financial shocks. Joint peaks, in contrast, are concentrated around systemic crises—such as the Global Financial Crisis, the COVID-19 pandemic, and the Russia–Ukraine war—that simultaneously affect both financial markets and policy narratives. These patterns validate our proposed taxonomy and reinforce the idea that different uncertainty proxies respond to distinct transmission channels. In other words, each indicator captures a specific "slice" of the uncertainty environment, a point emphasized in recent research (Larsen, 2021).

Our results also resonate with ongoing academic and policy discussions. Central banks and international institutions have increasingly acknowledged the need to interpret uncertainty indicators in context. For instance, the European Central Bank has highlighted the persistent disconnect between low financial-market volatility and high policy uncertainty, linking it to unusual equity market momentum and shifting geopolitical risks (Martorana and Mistak, 2025a). Likewise, IMF analyses caution that no single indicator can fully capture today's complex uncertainty landscape (Ahir et al., 2025a). By linking topic-based press narratives to the behavior of EPU and CLIFS, our framework provides a structured approach to interpreting uncertainty dynamics. It helps explain when and why indicators diverge or converge, offering a practical tool for deciphering seemingly conflicting signals.

This has important implications for both researchers and policymakers, who must navigate an increasingly complex and fragmented information environment. In particular, our taxonomy can assist policymakers in identifying whether a spike in uncertainty is driven by political narratives or financial stress, informing more targeted policy responses. For researchers, the framework helps reconcile conflicting signals from different proxies and addresses calls for interpretative tools that bridge the gap between various uncertainty measures. Furthermore, while our analysis employs LDA-based topic indices, the rise of more advanced NLP techniques—such as transformer models and multilingual topic alignment—presents promising avenues for refining uncertainty measurement (Audrino et al., 2024; Naboka et al., 2023). Integrating these innovations could enhance cross-country comparability and capture greater nuance in uncertainty narratives, thereby strengthening the robustness and scope of future analyses.

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Appendix

A Comparison VIX - CLIFS

Table A.1: Pairwise correlation between VIX and CLIFS

Country	Common period	Monthly correlation	Quarterly correlation
Germany	2000m01–2025m03	0.76	0.79
Italy	2010m04–2025m03	0.61	0.63
Spain	2007m01–2024m11	0.72	0.75
United Kingdom	2000m01–2025m03	0.61	0.65
France	2000m01–2021m01	0.76	0.78

The following figures compare the monthly evolution of CLIFS and VIX indices for the selected countries for the common period.

Figure A.1: Comparison CLIFS - VIX: UK

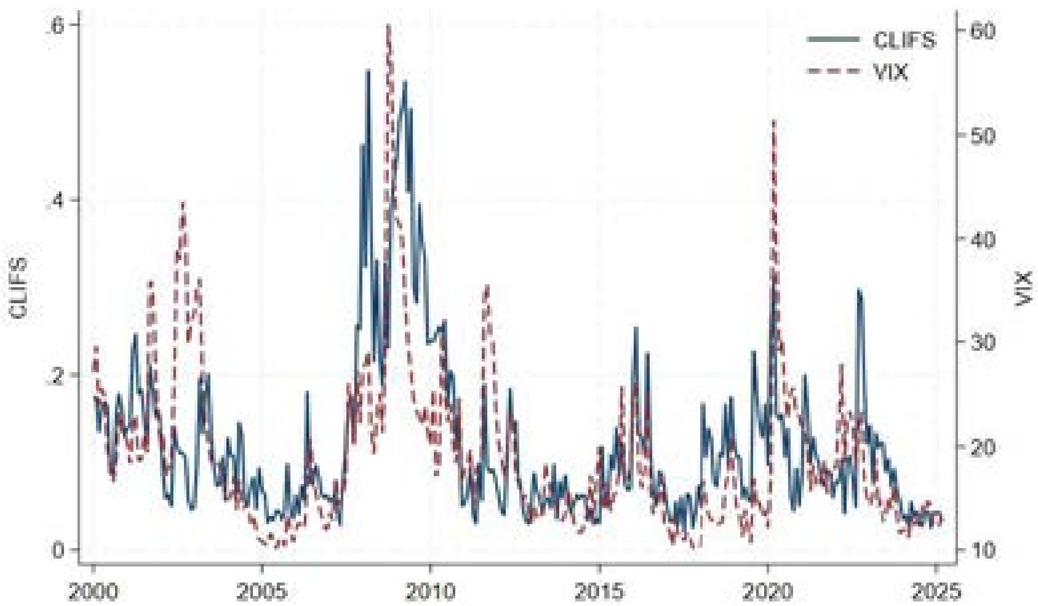


Figure A.2: Comparison CLIFS - VIX: France

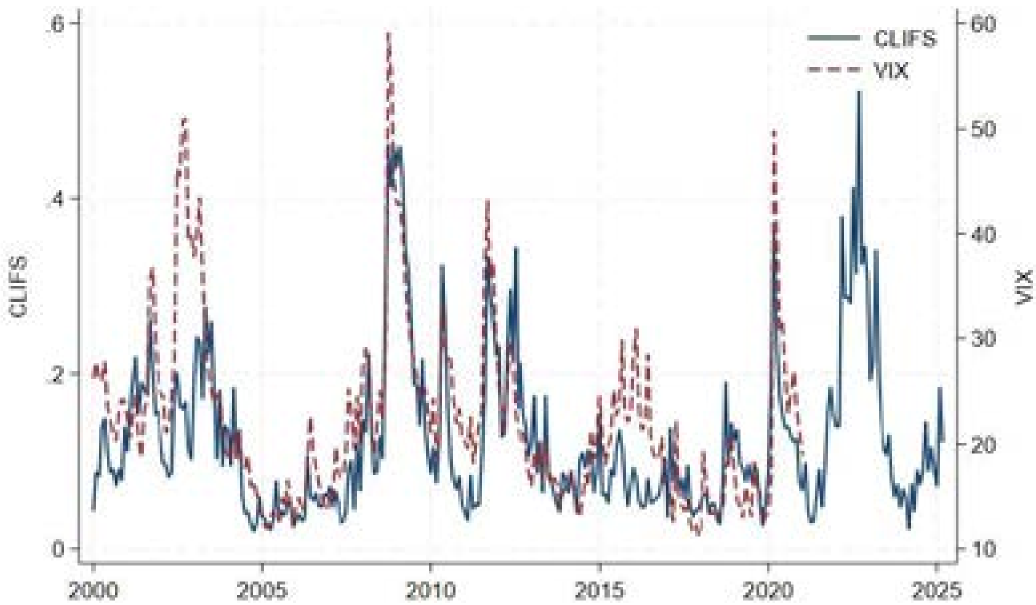


Figure A.3: Comparison CLIFS - VIX: Germany

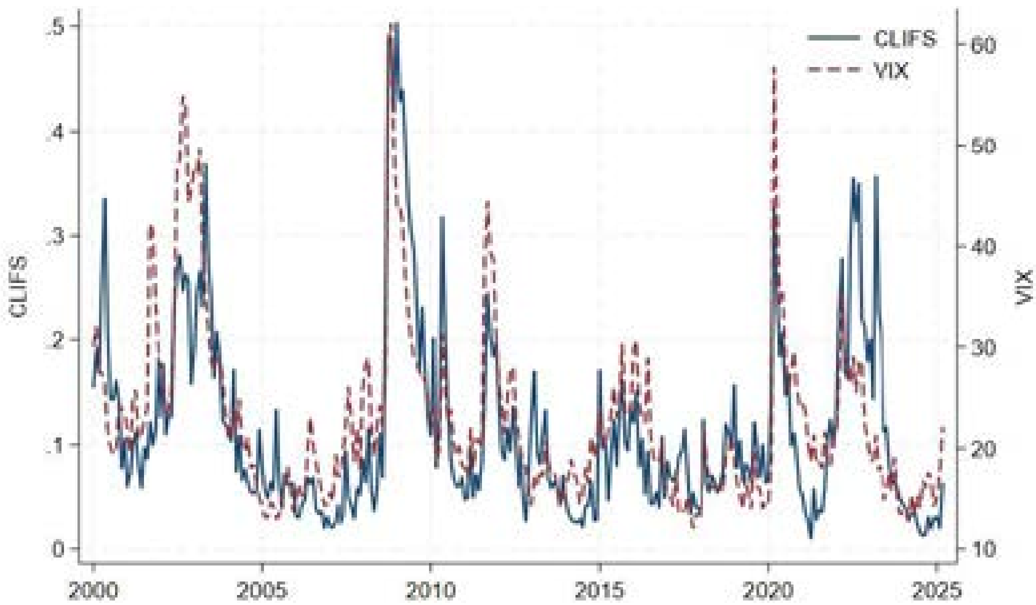


Figure A.4: Comparison CLIFS - VIX: Italy

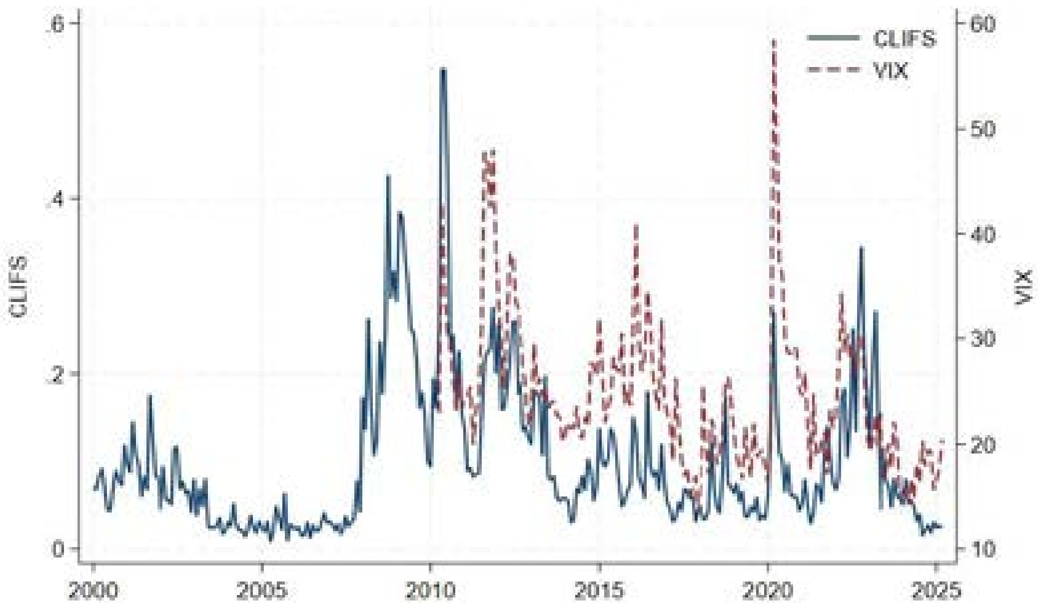
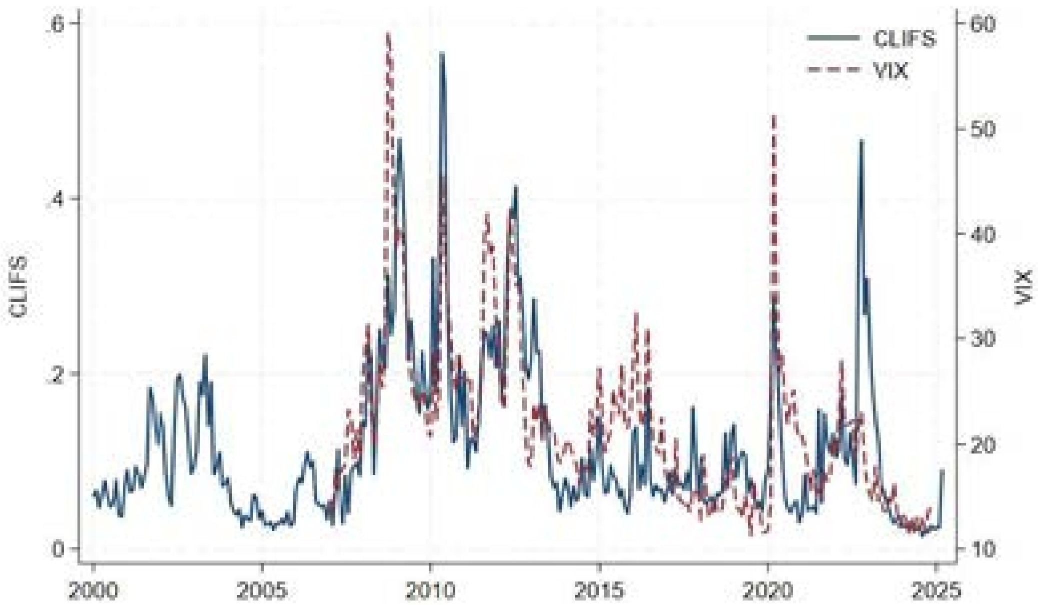
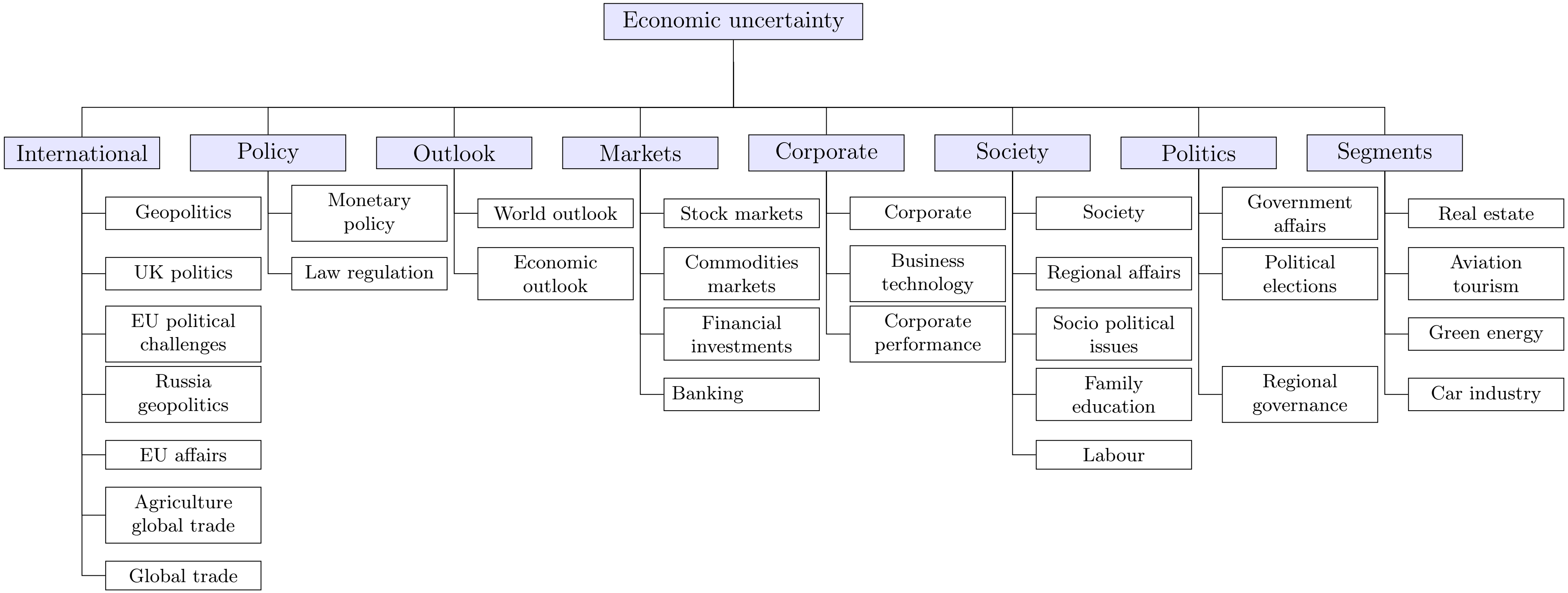


Figure A.5: Comparison CLIFS - VIX: Spain



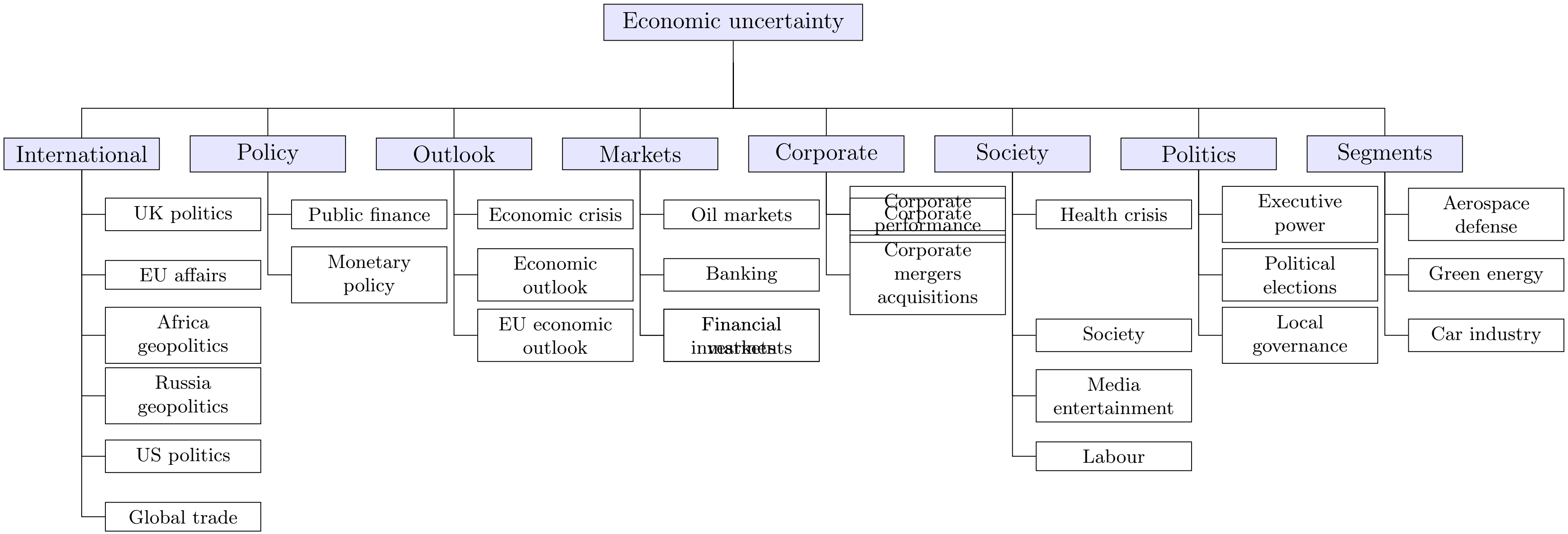
B Topic aggregation for each country

Figure B.1: Topic Aggregation for Germany



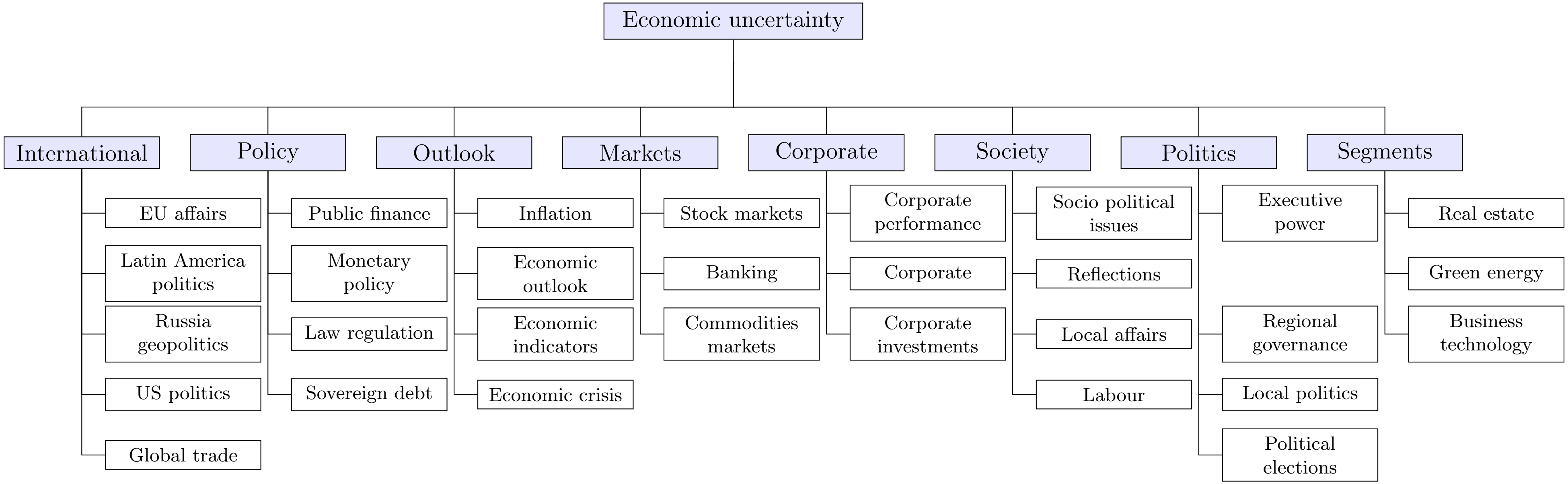
Note:This Figure represents the current aggregation of topics (white rectangles) into our 8 main categories (light blue rectangles), for Germany.

Figure B.2: Topic Aggregation for France



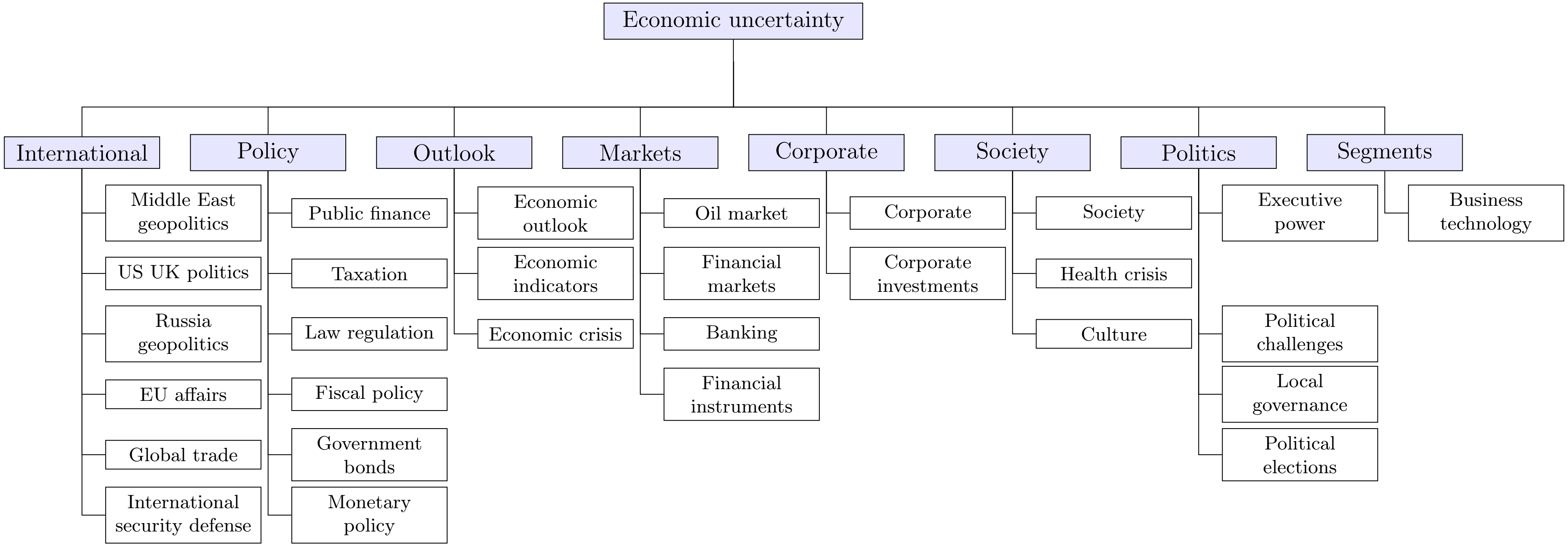
Note: This Figure represents the current aggregation of topics (white rectangles) into our 8 main categories (light blue rectangles), for France.

Figure B.3: Topic Aggregation for Spain



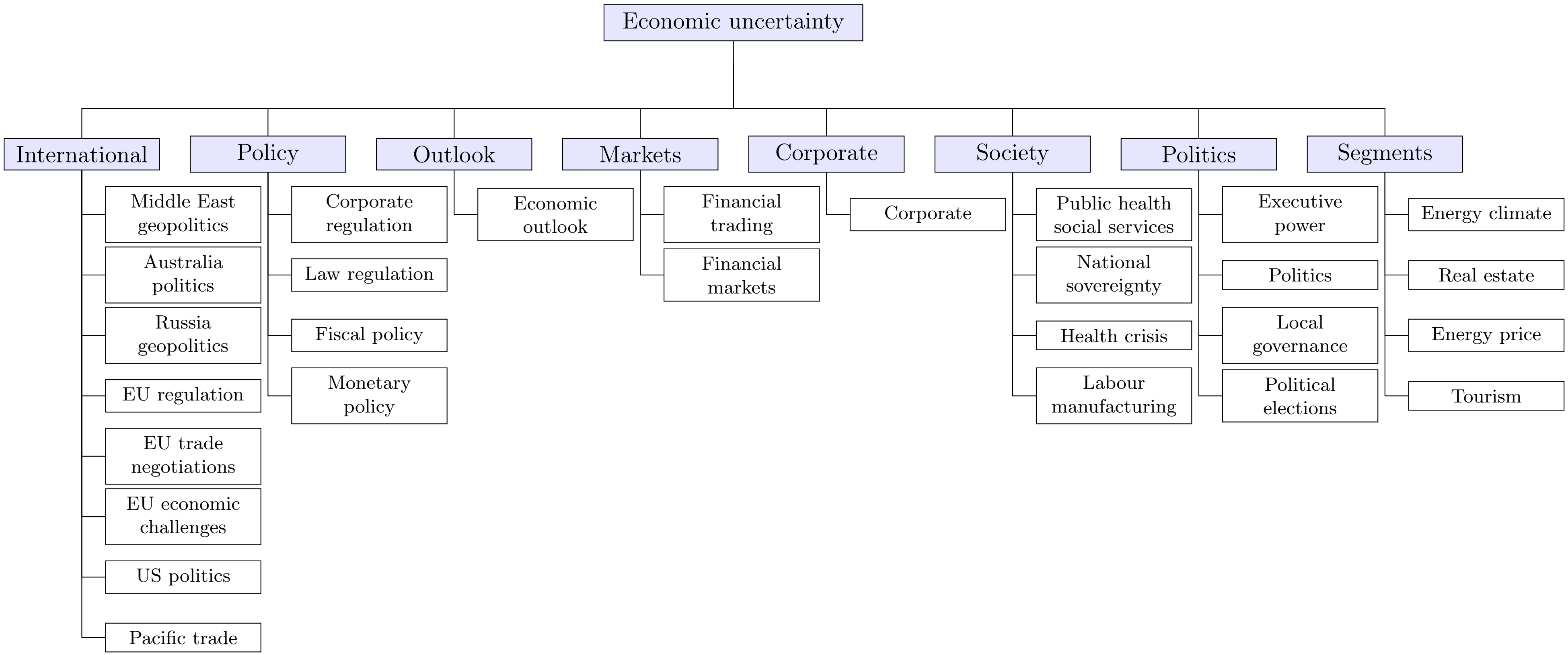
Note: This Figure represents the current aggregation of topics (white rectangles) into our 8 main categories (light blue rectangles), for Spain.

Figure B.4: Topic Aggregation for Italy



Note: This Figure represents the current aggregation of topics (white rectangles) into our 8 main categories (light blue rectangles), for Italy.

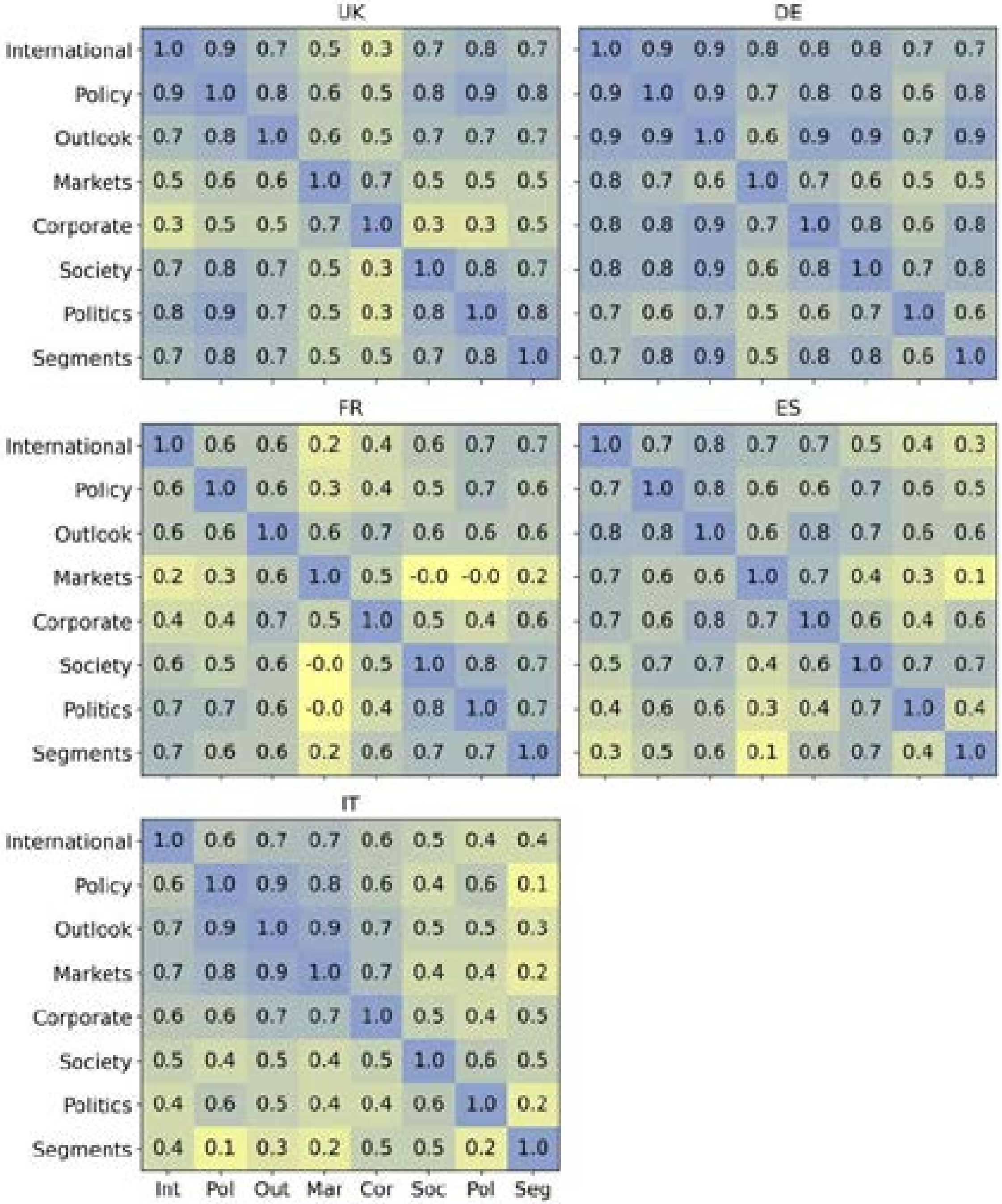
Figure B.5: Topic Aggregation for UK



Note: This Figure represents the current aggregation of topics (white rectangles) into our 8 main categories (light blue rectangles), for UK.

C Statistics about topics

Figure C.1: Correlations between topics



Note: Pairwise correlations between topics reported.

D Discretising the Proxies

The objective is to map the continuous values of the uncertainty proxies to $0, 1$, where 1 corresponds to the times of high uncertainty. A method that is at once naive yet entirely suitable for a variety of situations is one where the 1s are defined as being above some minimum number of standard deviations from the mean, usually computed using a rolling window. For these particular proxies this approach had several important drawbacks, one being that the set of peaks this definition captured appeared incomplete, and the second that this failed to capture periods of prolonged uncertainty, so characteristic of these series with non-negligible autocorrelationTo check.. We therefore created a semi-automatic (hybrid) approach to define periods of heightened uncertainty. This is based on an iterative approach of adding various statistical conditions, and evaluating whether the resulting selection is closer to our intuition as to what should be defined as a peak. Finally, this is supplemented by specific additions and subtractions from the final set. The complete table specifying the criteria for each country is given in Table D.1.

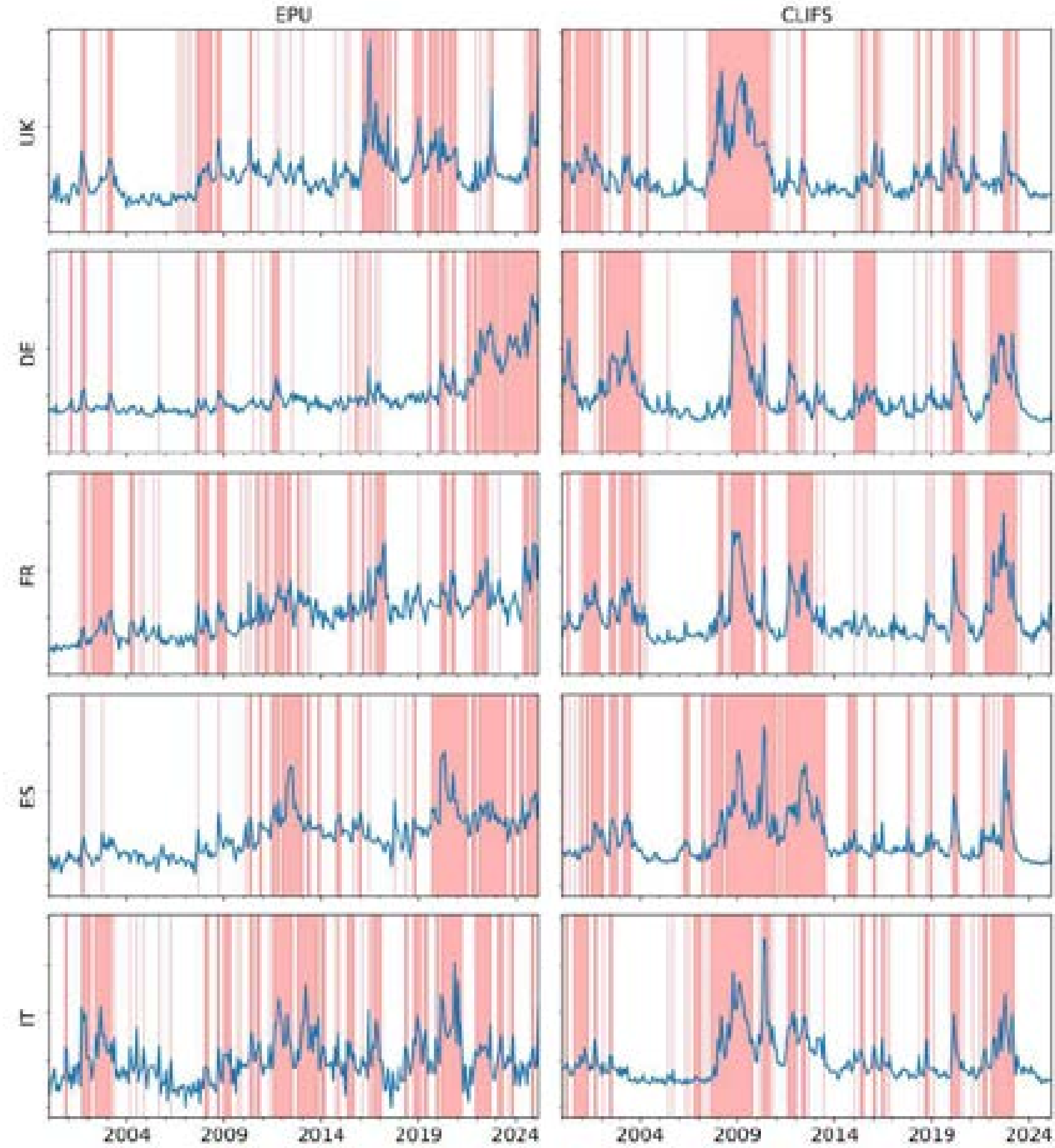
From this set of conditions we define two series of peaks for each proxy. The first one, "Hybrid" or "H0", is simply given by adhering to the criteria from D.1. The second series, "Hybrid 3M" or "H3M", is based on the same set of criteria, except that the peak times defined by the Windows need to have minimum duration of three months (note that no such minimum length is imposed on the other elements). This results in an equilibrium between having too many peaks of low duration, and not considering them at all. The result can be seen in Figures D.1 and D.2.

Table D.1: Country-Specific Criteria for Defining Uncertainty Peaks

	Method	**DE**	**ES**	**FR**	**IT**	**UK**
EPU	**Rolling Window**	size: 36, offset: 1		size: 36, offset: 0.5	size: 36, offset: 1	size: 36, offset: 1
	Stationary Window	offset: 1	offset: 0.5		offset: 0	offset: 0.5
	Peaks	size: 36, offset: 3	size: 36, offset: 2.5	size: 36, offset: 2.5	size: 36, offset: 2	size: 36, offset: 2
CLIFS	**Rolling Window**		size: 36, offset: 0.5		size: 36, offset: 0	size: 36, offset: 1
	Stationary Window	offset: 0	offset: 0	offset: 0	offset: 1	offset: 0
	Peaks	size: 36, offset: 3	size: 36, offset: 2.5	size: 36, offset: 3	size: 36, offset: 2	size: 36, offset: 3
	Extra	(2015-01, 2016-02)	(2014-09, 2015-02)			
	Remove		(2016-06, 2016-06), (2019-02, 2019-06)			

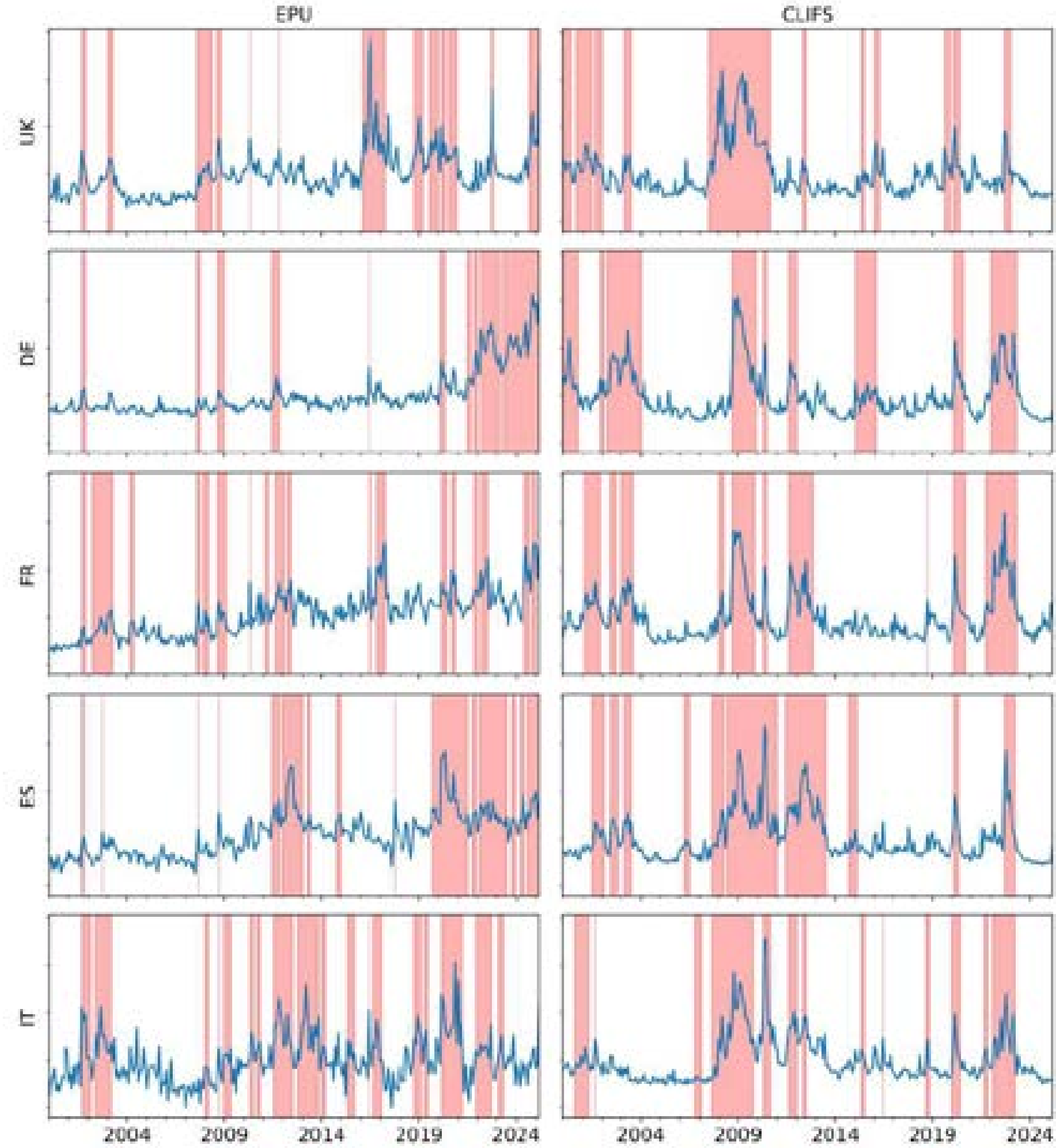
Note: The settings to distretise the proxy (EPU or CLIFS) for each of the countries. In the context of Rolling and Stationary window *offset* refers to the minimum number of standard deviations above the mean that the value needs to exceed to be mapped to a 1, with *size* referring to width of the Rolling window, in months. The elements selected by the two windows are then only retained if they are span at least a minimum peak length (an external parameter). The Peaks are defined in the same way as the Rolling window but without the minimum peak length. The brackets in the Extra and Remove fields define, correspondingly, the start and end of extra periods to add or remove.

Figure D.1: Peaks periods (no minimal length)



Note: The uncertainty proxy and the times when the proxy is said to peak (in red), according to the algorithm in Table D.1. No minimum peak length is imposed.

Figure D.2: Peaks periods (some minimal length)

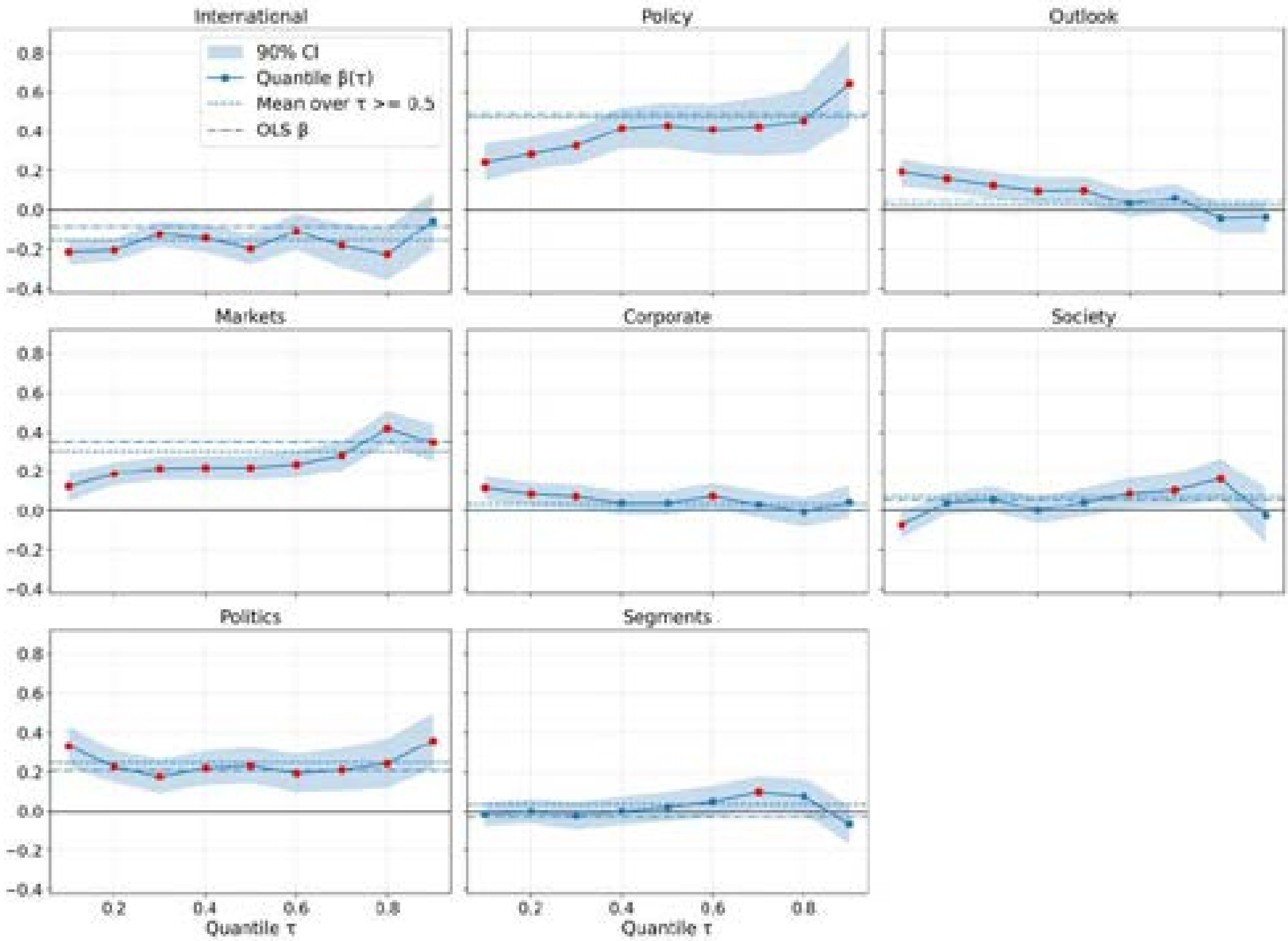


Note: The uncertainty proxy and the times when the proxy is said to peak (in red), according to the algorithm in Table D.1. Minimum peak length of three months is imposed on the peaks defined by the "Windows" criteria.

E Robustness: Quantile Regression on the National Uncertainty Proxies

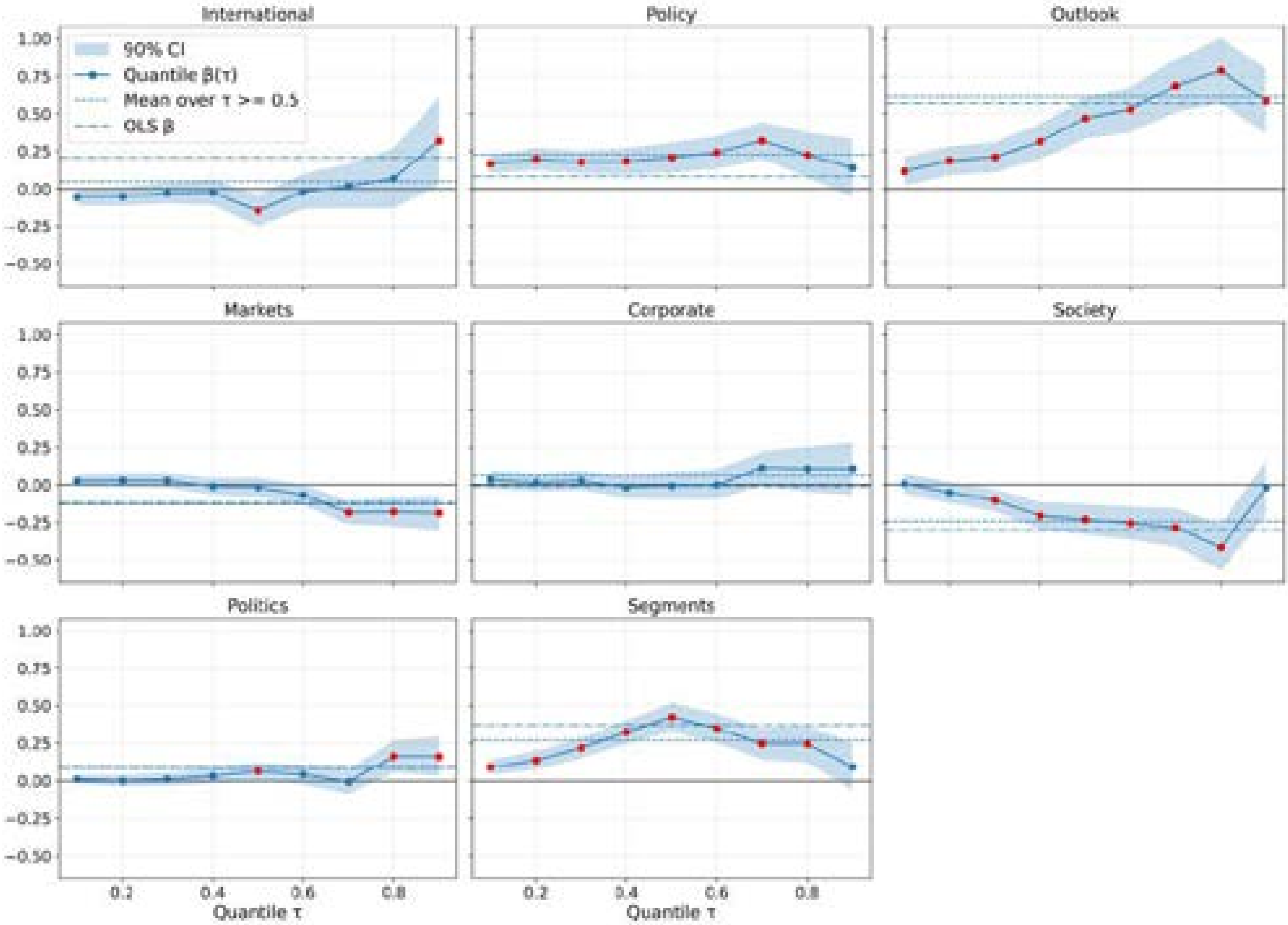
This section presents the results of quantile regressions run for each of the two uncertainty proxies, for the five countries in our sample. We take both the dependent and independent variables to be in level.

Figure E.1: Quantile regression for EPU in the UK



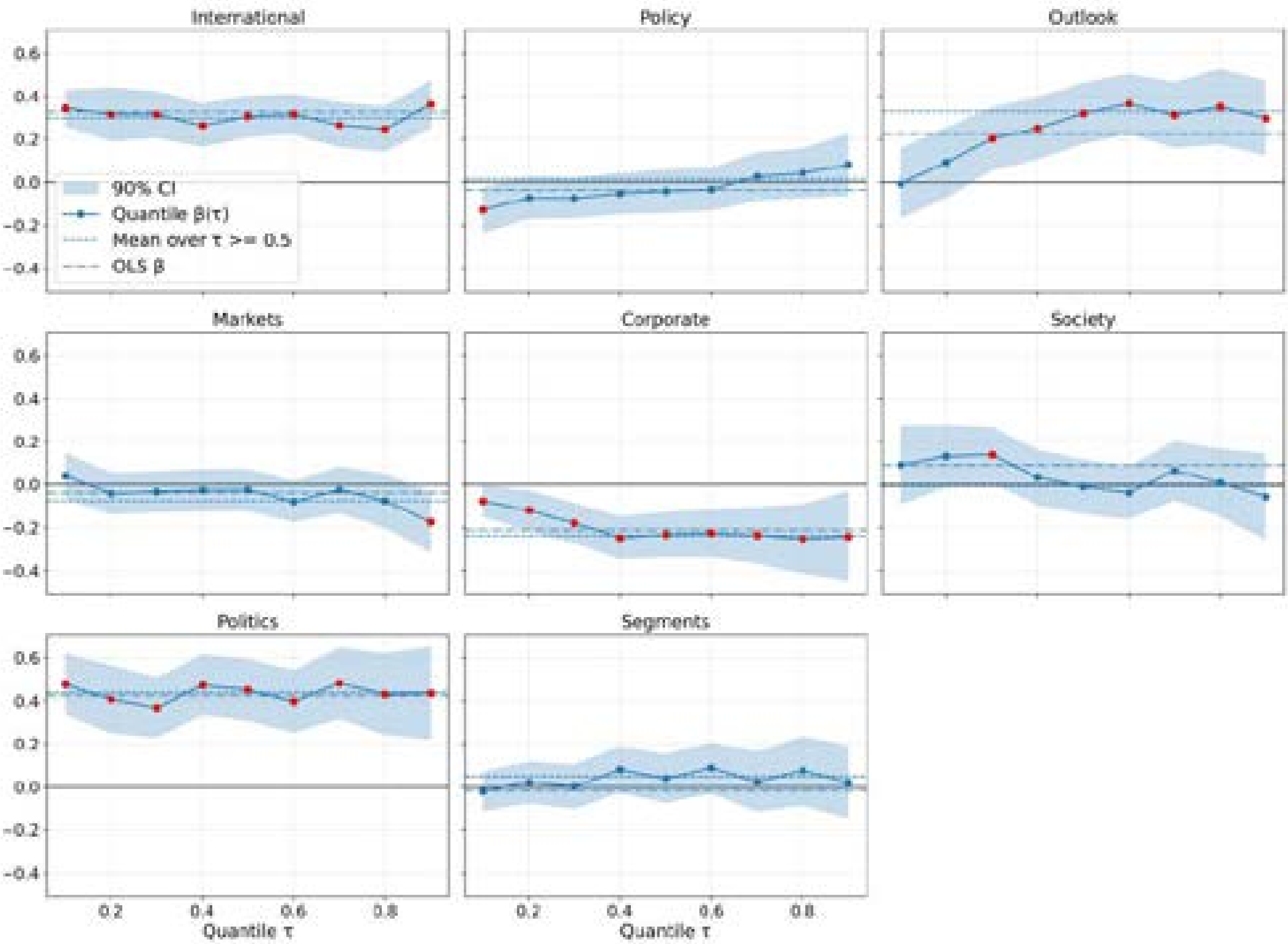
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.2: Quantile regression for EPU in Germany



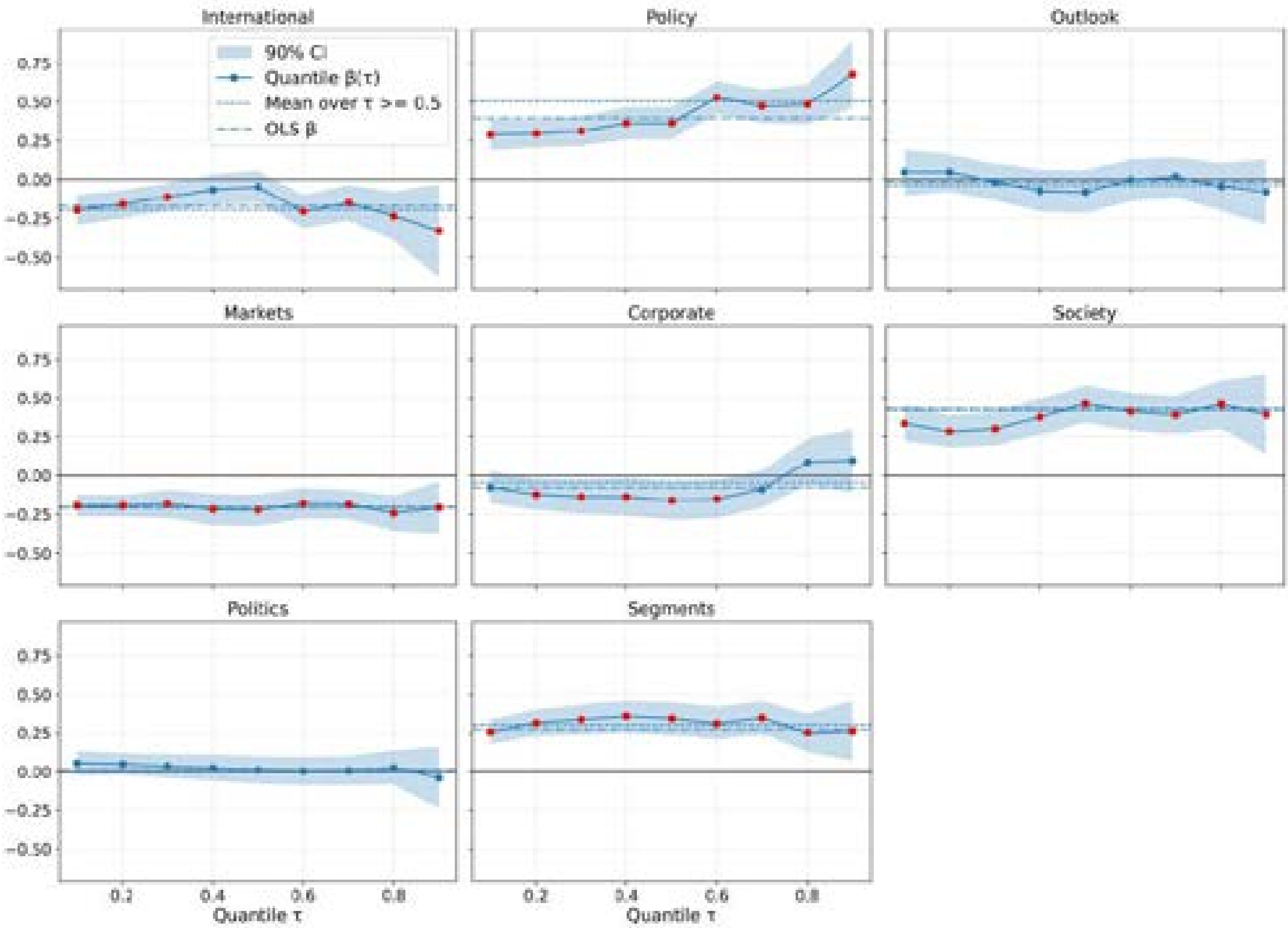
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.3: Quantile regression for EPU in France



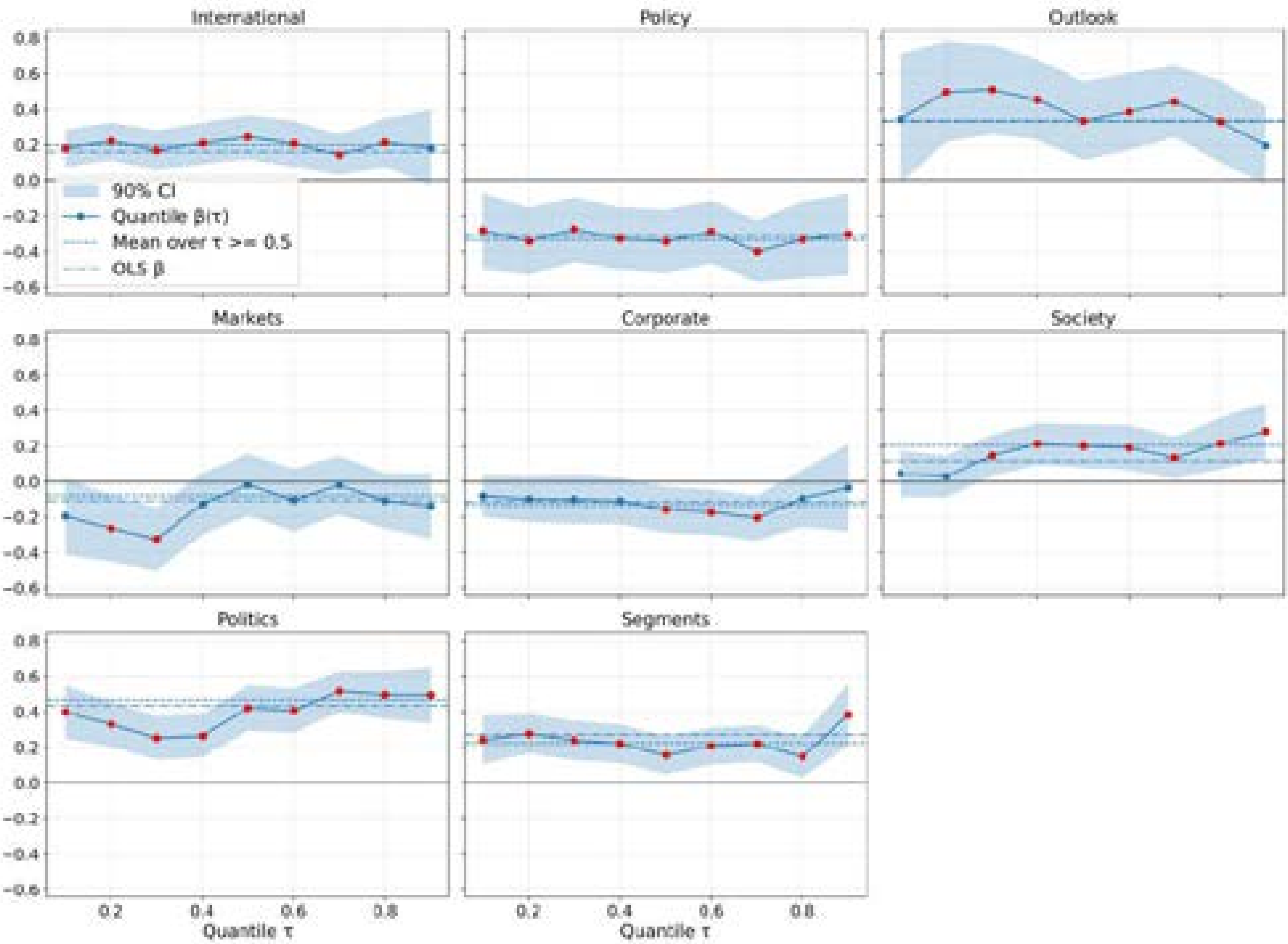
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.4: Quantile regression for EPU in Spain



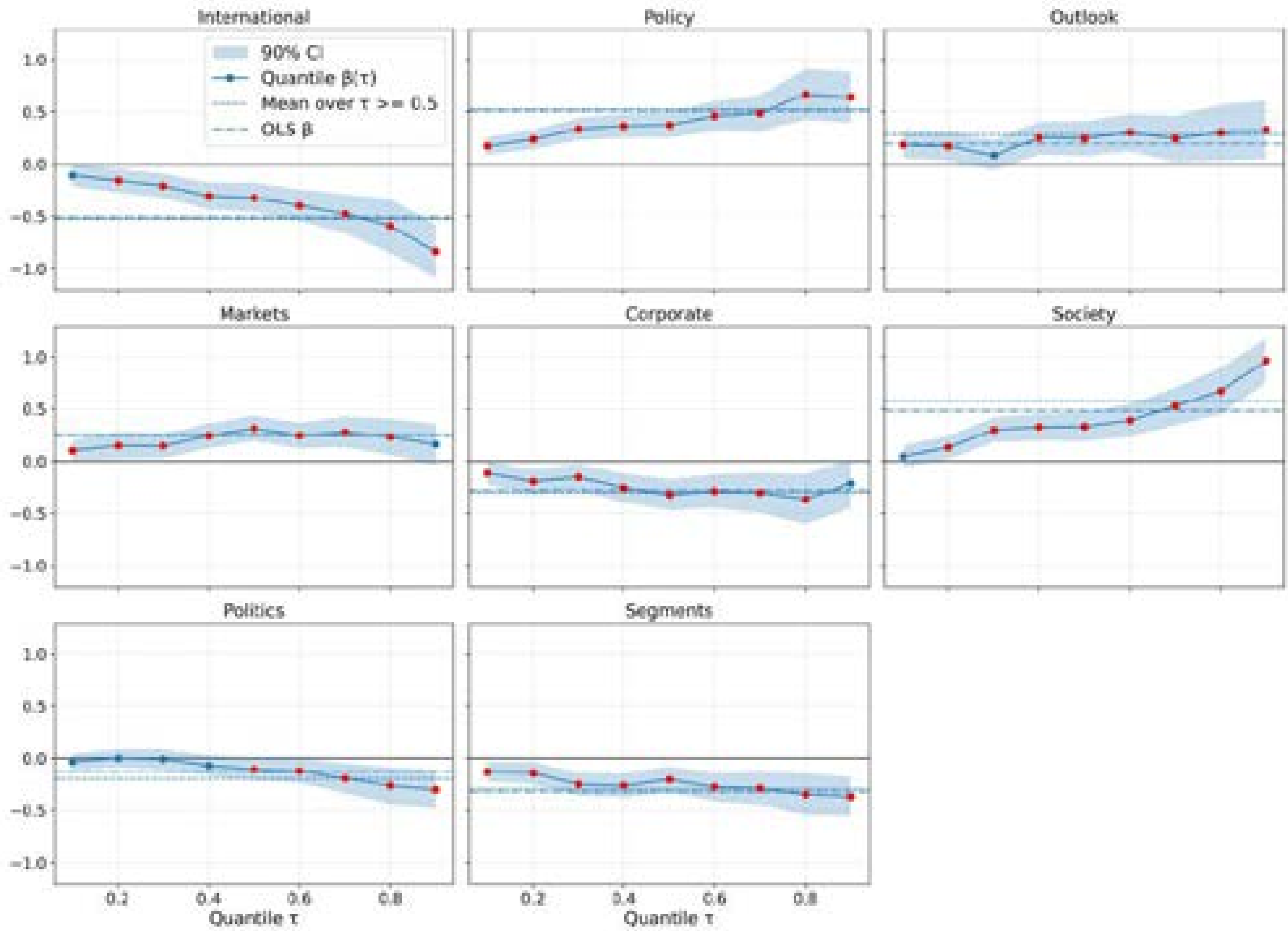
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.5: Quantile regression for EPU in Italy



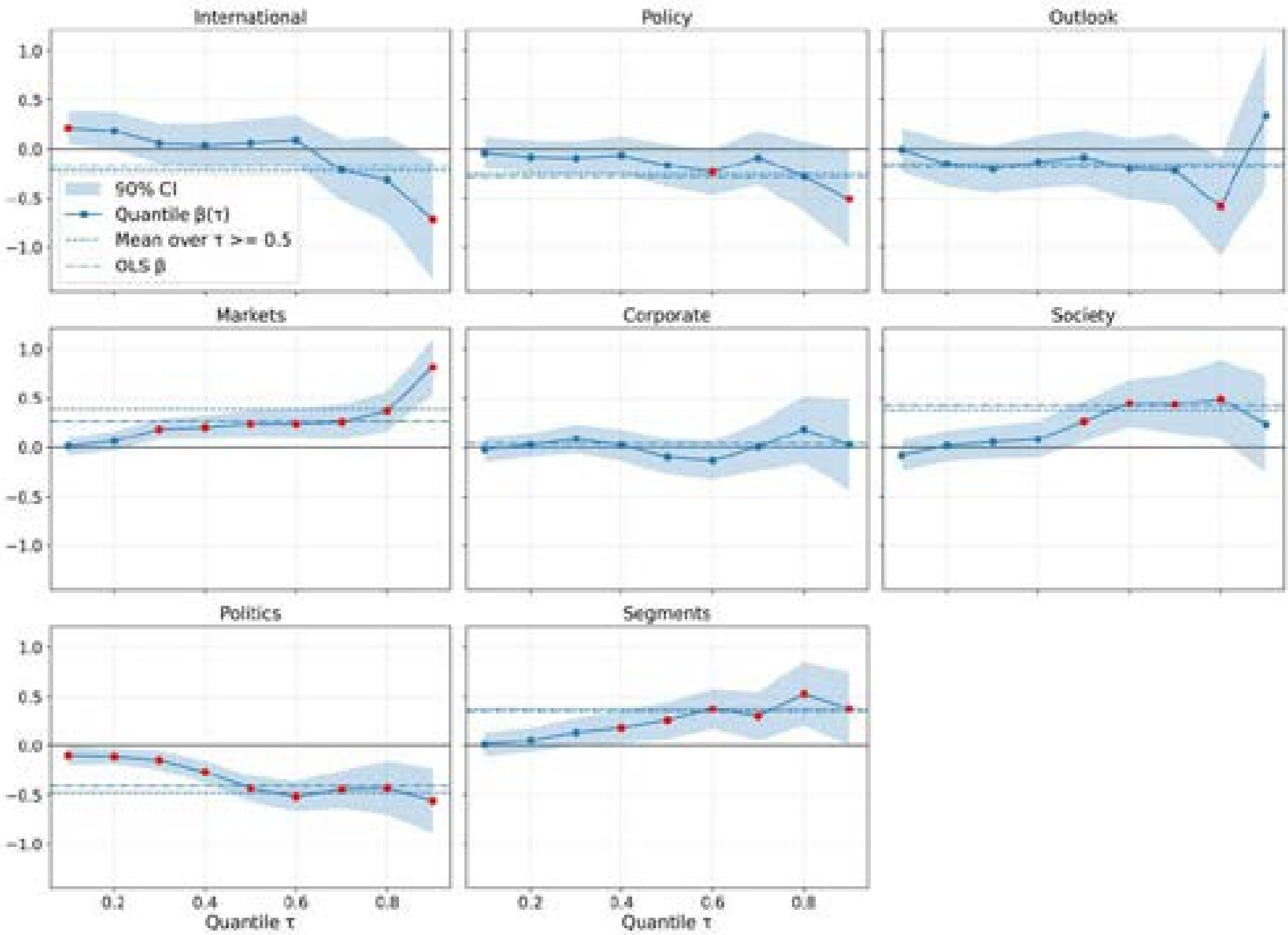
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.6: Quantile regression for CLIFS in the UK



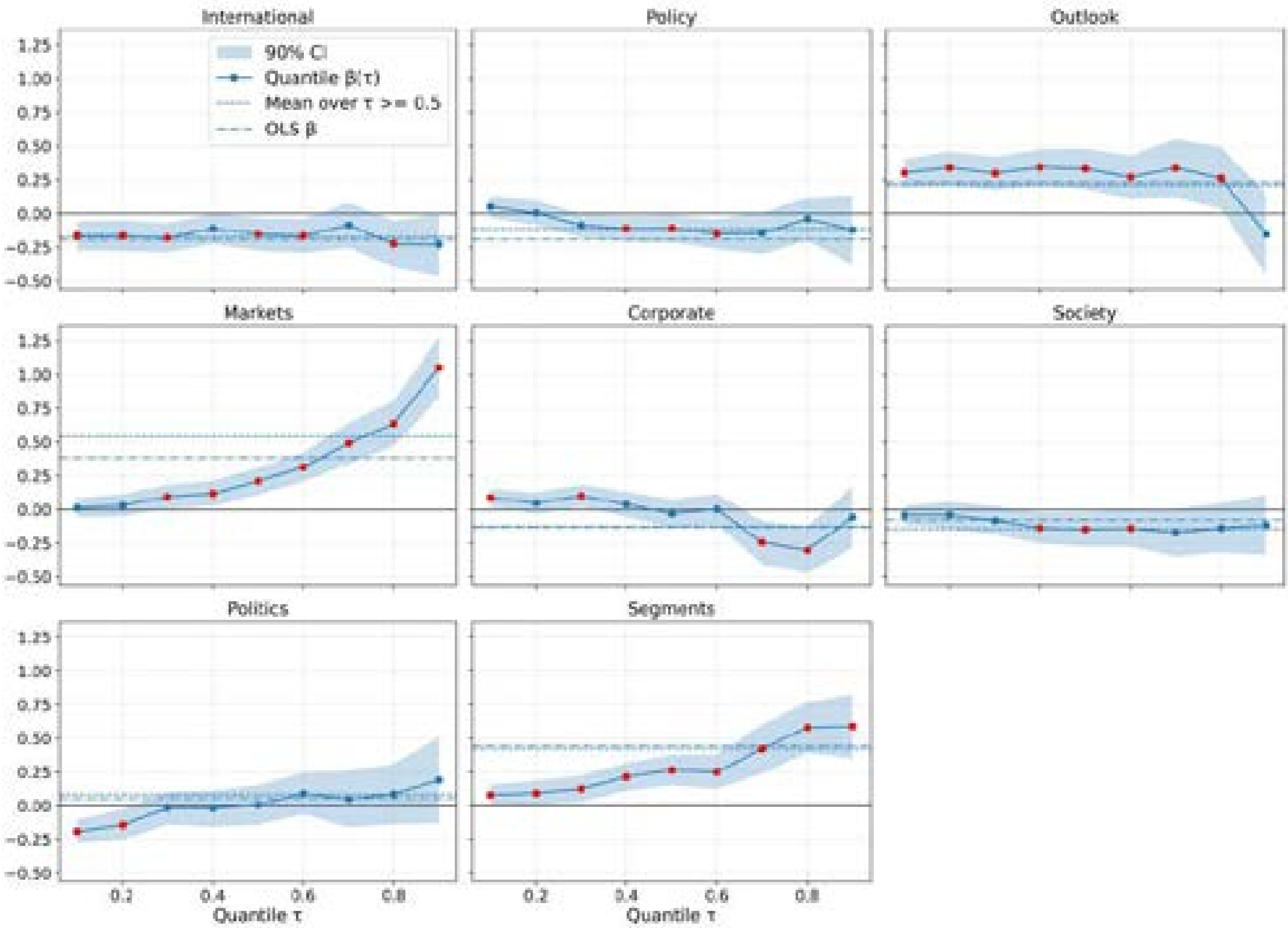
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.7: Quantile regression for CLIFS in Germany



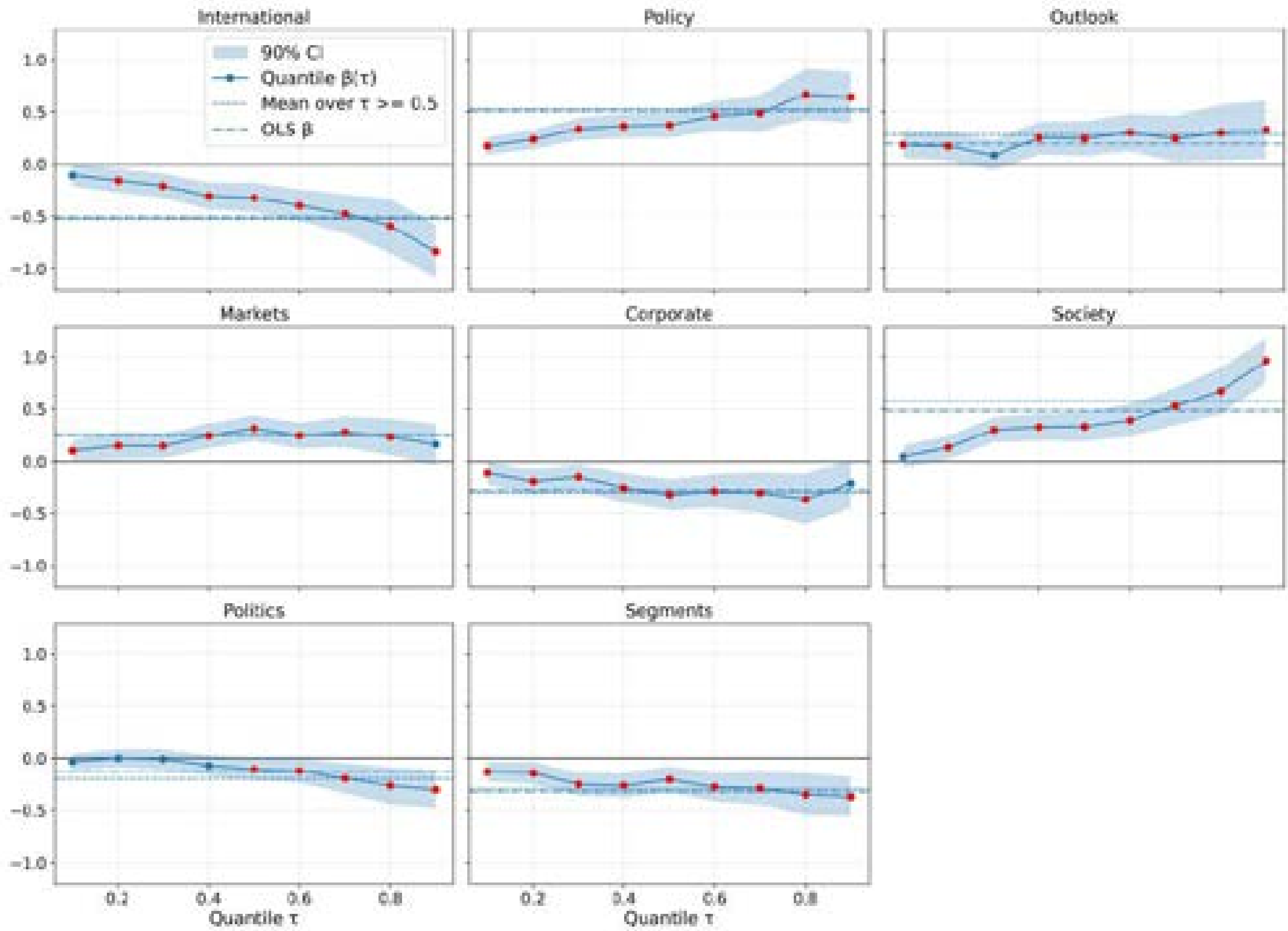
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.8: Quantile regression for CLIFS in France



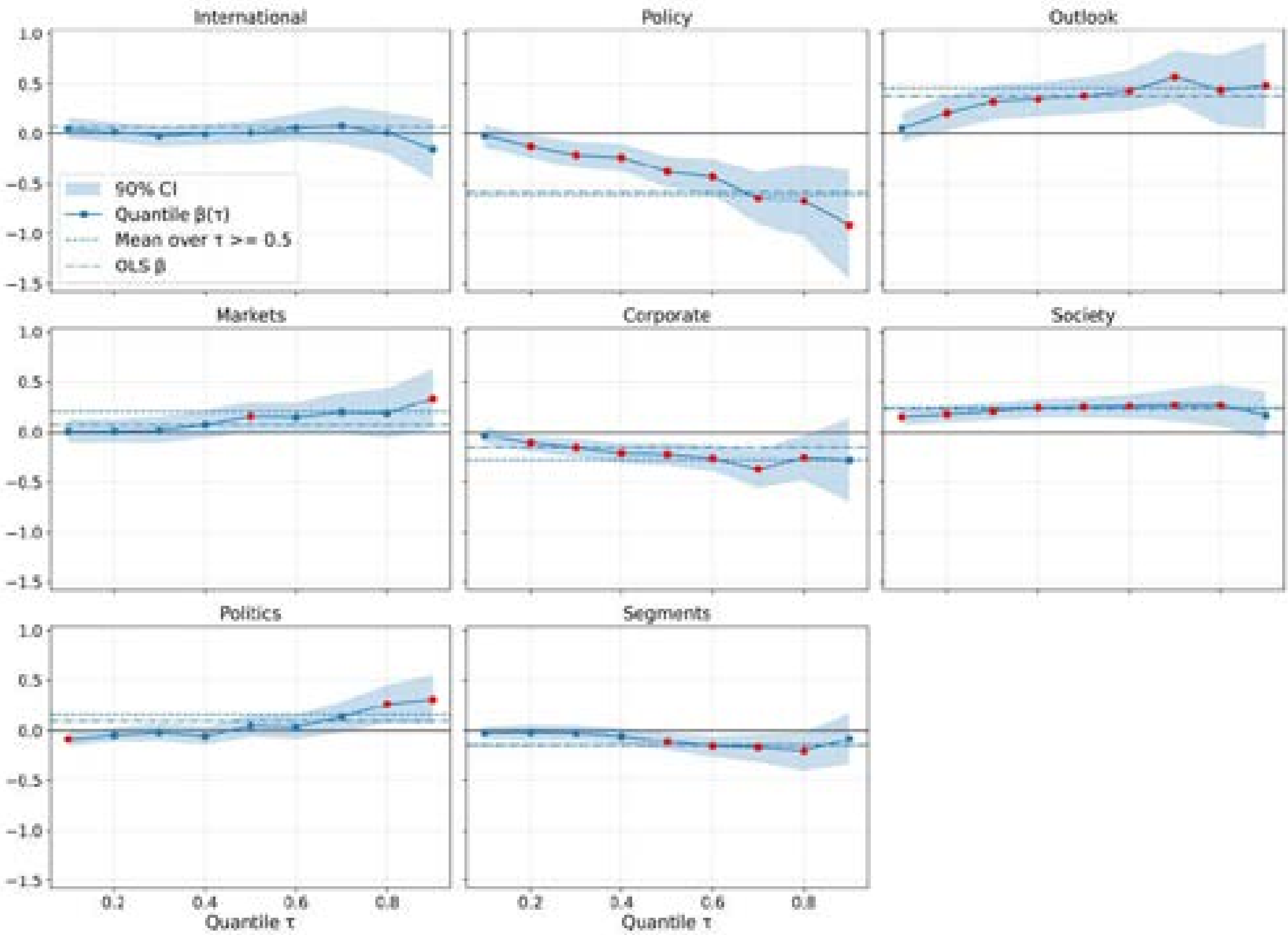
Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.9: Quantile regression for CLIFS in Spain



Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

Figure E.10: Quantile regression for CLIFS in Italy



Note: Coefficients β of the eight aspects of economic uncertainty for various quantiles τ. The critical p-value of 0.1 determines both the markers shown in red, and the confidence interval of 0.9.

F Robustness: Discrete-State Modeling via Classification Methods

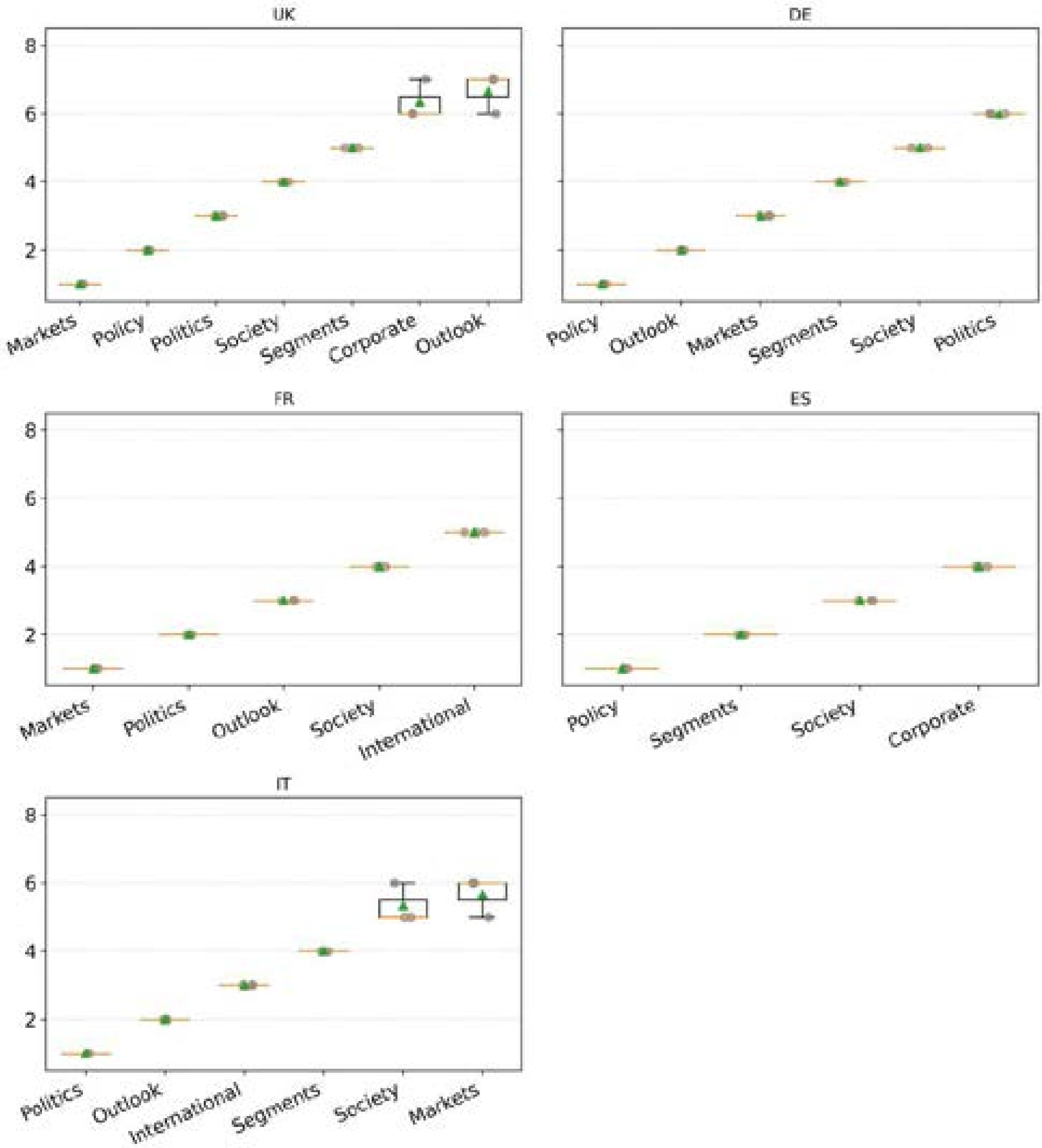
As an alternative approach, we discretize the uncertainty proxies into binary variables indicating the presence (1) or absence (0) of a peak. These peaks are defined using a hybrid procedure that combines statistical thresholds with expert judgment to ensure comprehensive coverage of relevant events.

We then estimate three standard linear classifiers to assess the predictive relevance of each topic:

- Logistic regression with L2 (ridge) regularization, which stabilizes estimates.
- Logistic regression with L1 (lasso) regularization, which promotes sparsity and variable selection.
- Linear Support Vector Machine (SVM), which maximizes the classification margin and is robust to outliers.

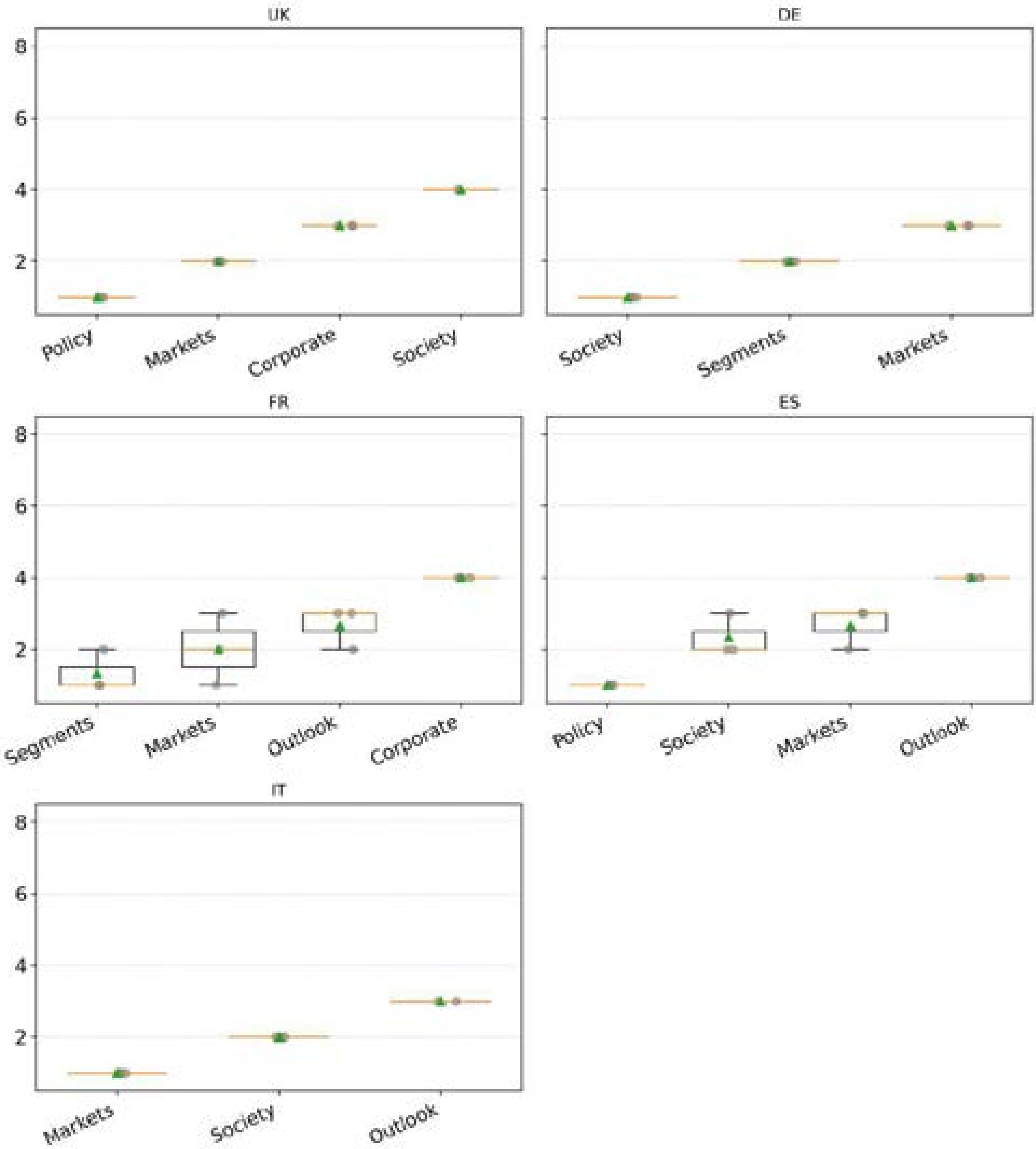
All models are estimated in-sample using standardized predictors and class-weight balancing to address class imbalance. Results are reported below as average rankings of standardized coefficients across the three classifiers, where lower ranks indicate greater importance. The classification results show that the topics most consistently associated with EPU peaks are *Politics*, *Policy*, and *Segments*, while *Markets* and *Society* are the most robust predictors of CLIFS peaks across countries, model specifications, and peak definitions.

Figure F.1: Variable Importance for Identifying Peaks in EPU



Note: Rankings (1=best) of most relevant variables for explaining the peaks in the EPU proxies, averaged across the three models described in the above section. The y variable is discretized without setting minimal peak duration. The rankings for each model are obtained by sorting the positive coefficients in ascending order.

Figure F.2: Variable Importance for Identifying Peaks in CLIFS



Note: Rankings (1=best) of most relevant variables for explaining the peaks in the CLIFS proxies, averaged across the three models described in the above section. The y variable is discretized without setting minimal peak duration. The rankings for each model are obtained by sorting the positive coefficients in ascending order.

G Robustness: Aggregating Strategies Across Models

We aggregate the results from both quantile regressions and classification models to identify the most influential topics across countries and proxies. For the quantile regressions, we compute the average coefficient for each country–topic–proxy triplet, using all quantiles $\tau \geq 0.5$ and retaining only those with $p \leq 0.1$. For the classifiers, we average the standardized coefficients across the three models without applying significance thresholds. This yields a matrix of topic–country–proxy coefficients from both methods, which are displayed below.

For each cell, we assess whether the two methods agree on the sign of the effect and whether the result is robust across parameter choices. Specifically, we consider four configurations: two values of $\tau_{\min} \in 0.5, 0.7$ for the quantile regressions, and two peak definitions (H0 and H3M) for the classifiers. The results show high consistency: when both methods indicate a positive association under one configuration, they typically do so across all four. Only a small number of cases are sensitive to parameter changes, suggesting that the underlying signals are robust.

- **Aggregate Averaging Strategy.** We first compute the average coefficient across methods and countries to obtain a global ranking of topic relevance. While this approach does not account for country-specific heterogeneity, it provides a clear picture of which topics are most strongly associated with each proxy. To ensure robustness, we average across all four parameter configurations. As shown in Figure G.1, the most important topics for EPU are *Outlook* and *Policy*, followed closely by *Politics* and *Segments*. For CLIFS, the dominant topics are *Society* and *Markets*, with a substantial margin over the rest.

- **Consensus-Based Strategy.** This strategy applies a stricter relevance criterion. We retain only topics with positive coefficients in both methods and count the number of countries in which this condition holds. Topics that are consistently relevant across countries are interpreted as having broader explanatory power. As shown in Figure G.2, the most universally relevant topics for EPU are *Politics*, *Segments*, and *Outlook*. For CLIFS, *Markets* emerges as the dominant topic in all five countries.

Table G.1: Average coefficients for EPU

	UK	DE	FR	ES	IT
International	-0.17 (-0.3)	0.08 (-0.54)	0.31 (0.05)	-0.24 (-0.44)	0.2 (0.45)
Policy	0.47 (0.7)	0.24 (0.83)	N/A (-0.23)	0.54 (1.29)	-0.33 (-0.77)
Outlook	0.1 (0.02)	0.59 (0.46)	0.34 (0.24)	N/A (-0.73)	0.37 (0.64)
Markets	0.3 (0.82)	-0.18 (0.37)	-0.18 (1.04)	-0.22 (-0.43)	N/A (0.1)
Corporate	0.07 (0.04)	N/A (-0.1)	-0.24 (-0.04)	-0.17 (0.18)	-0.18 (-0.33)
Society	0.12 (0.17)	-0.29 (0.08)	N/A (0.17)	0.45 (0.77)	0.2 (0.14)
Politics	0.24 (0.27)	0.13 (0.05)	0.45 (0.53)	N/A (-0.02)	0.47 (0.87)
Segments	0.1 (0.12)	0.31 (0.22)	N/A (-0.35)	0.32 (1.0)	0.22 (0.34)

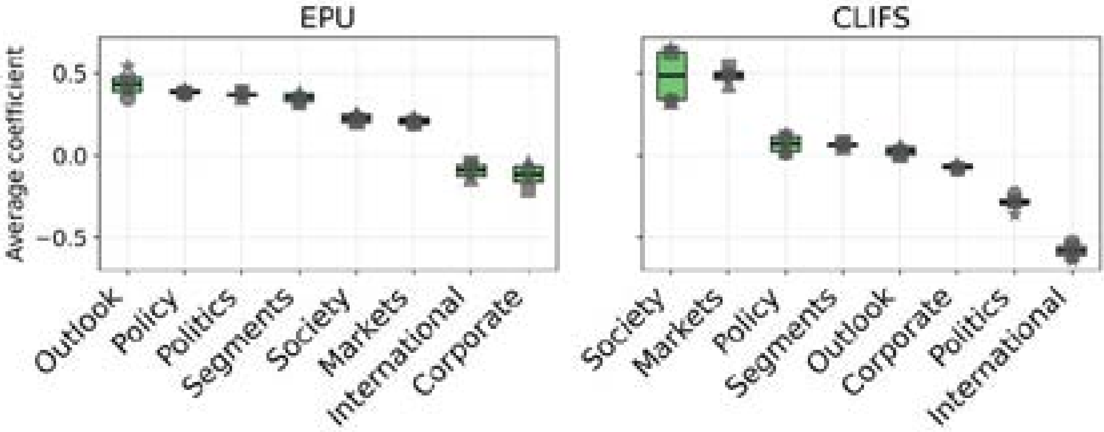
Note: The first number is the average coefficient of the Quantile models, with $\tau \geq 0.5$, and $p <= 0.1$. The number in brackets is the average coefficient of the three Classifiers (with the H0 peak definition). Cell colours correspond to the following: Green - both methods agree on the coefficient being positive (and significant, for the Quantile regression); Blue - negative and significant; Red - the two methods disagree on the sign or the regression coefficient is not statistically significant. Cells are coloured only if that colour is robust to a) varying the peak definitions (H0 and H3M) and b) the minimum τ (0.5 and 0.7). The non-robust cells are never outliers from an otherwise well-defined mean.

Table G.2: Average coefficients for CLIFS

	UK	DE	FR	ES	IT
International	-0.52 (-0.84)	-0.66 (-0.03)	-0.15 (-0.43)	-0.47 (-1.12)	N/A (-0.08)
Policy	0.58 (0.59)	-0.36 (-0.14)	-0.13 (-0.53)	0.52 (0.98)	-0.61 (-0.71)
Outlook	-0.35 (-0.36)	-0.57 (-0.6)	0.3 (0.64)	0.28 (0.26)	0.46 (0.01)
Markets	0.32 (0.52)	0.38 (0.4)	0.54 (0.72)	0.27 (0.83)	0.24 (0.74)
Corporate	0.3 (0.32)	N/A (-0.05)	-0.27 (0.12)	-0.31 (-0.29)	-0.27 (-0.26)
Society	0.16 (0.01)	0.4 (0.82)	-0.14 (-0.18)	0.57 (0.83)	0.26 (0.66)
Politics	-0.21 (-0.03)	-0.48 (-0.99)	N/A (-0.07)	-0.19 (-0.15)	0.28 (-0.09)
Segments	N/A (-0.03)	0.37 (0.48)	0.4 (0.76)	-0.29 (-0.78)	-0.16 (-0.22)

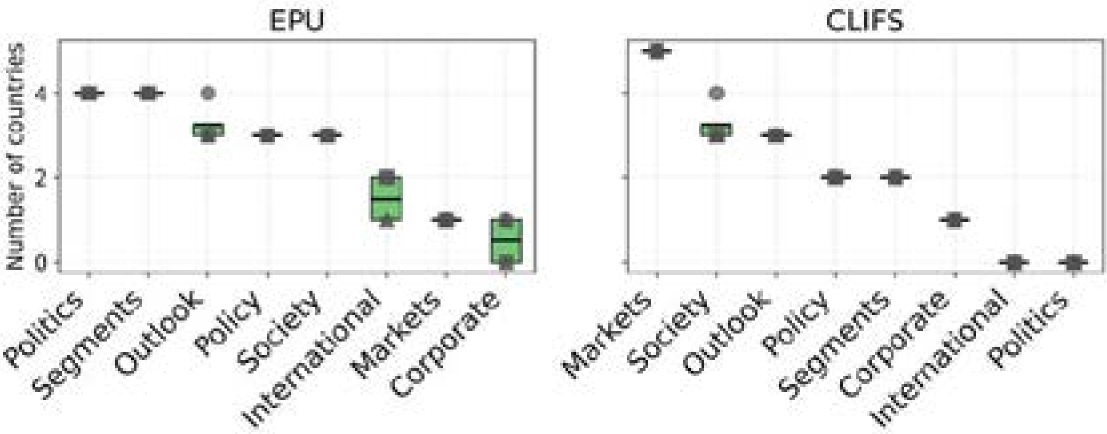
Note: The first number is the average coefficient of the Quantile models, with $\tau \geq 0.5$, and $p <= 0.1$. The number in brackets is the average coefficient of the three Classifiers (with the H0 peak definition). Cell colours correspond to the following: Green - both methods agree on the coefficient being positive (and significant, for the Quantile regression); Blue - negative and significant; Red - the two methods disagree on the sign or the regression coefficient is not statistically significant. Cells are coloured only if that colour is robust to a) varying the peak definitions (H0 and H3M) and b) the minimum τ (0.5 and 0.7). The non-robust cells are never outliers from an otherwise well-defined mean.

Figure G.1: Results of the Aggregate Averaging strategy



Note: Average coefficient across countries, where each country's value is the mean across both methods and all four parameter configurations. Symbols indicate parameter sets: circle = ($\tau_{\min}$ = 0.5, H0); triangle = ($\tau_{\min}$ = 0.5, H3M); square = ($\tau_{\min}$ = 0.7, H0); star = ($\tau_{\min}$ = 0.7, H3M). Horizontal lines show the overall mean.

Figure G.2: Results of the Consensus-Based strategy



Note: Number of countries in which a topic has a positive coefficient in both methods, with $p \leq 0.1$ for quantile regressions. Symbols correspond to the parameter sets defined in Figure G.1.

H Composite Peaks

Table H.1: Composite Peak Definition

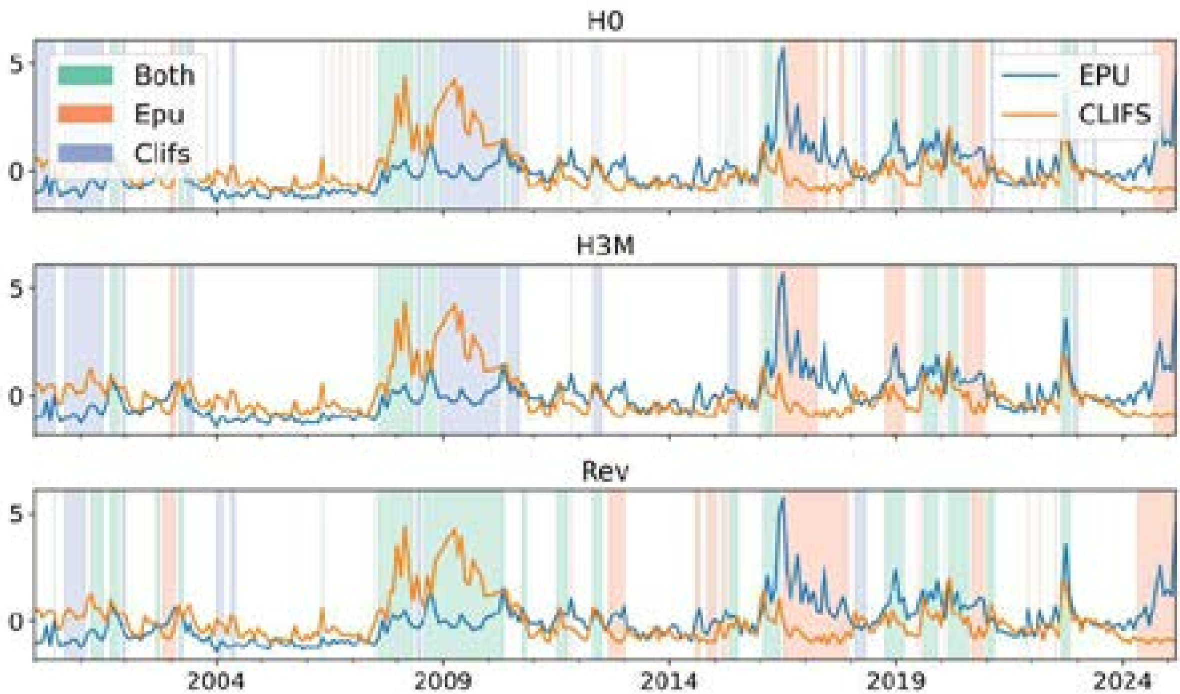
Composite Peak Type	Abbreviation	Description
Hybrid, no minimal length	H0	Composite peaks defined by coincidence of individual proxy peaks determined by Table D.1
Hybrid, some minimal length	H3M	Peaks defined by table D.1, where minimal length of three months is imposed on the Rolling and Stationary windows
Manual revision of H3M	Rev	H3M peaks but where all four peak categories (including None) are revised manually, and only the more certain times are kept

Table H.2: Prevalence of peak episodes

%	Both	Epu	Clifs	None
UK	11	11	18	58
DE	9	11	23	55
FR	14	10	15	59
ES	14	15	21	48
IT	14	22	14	48

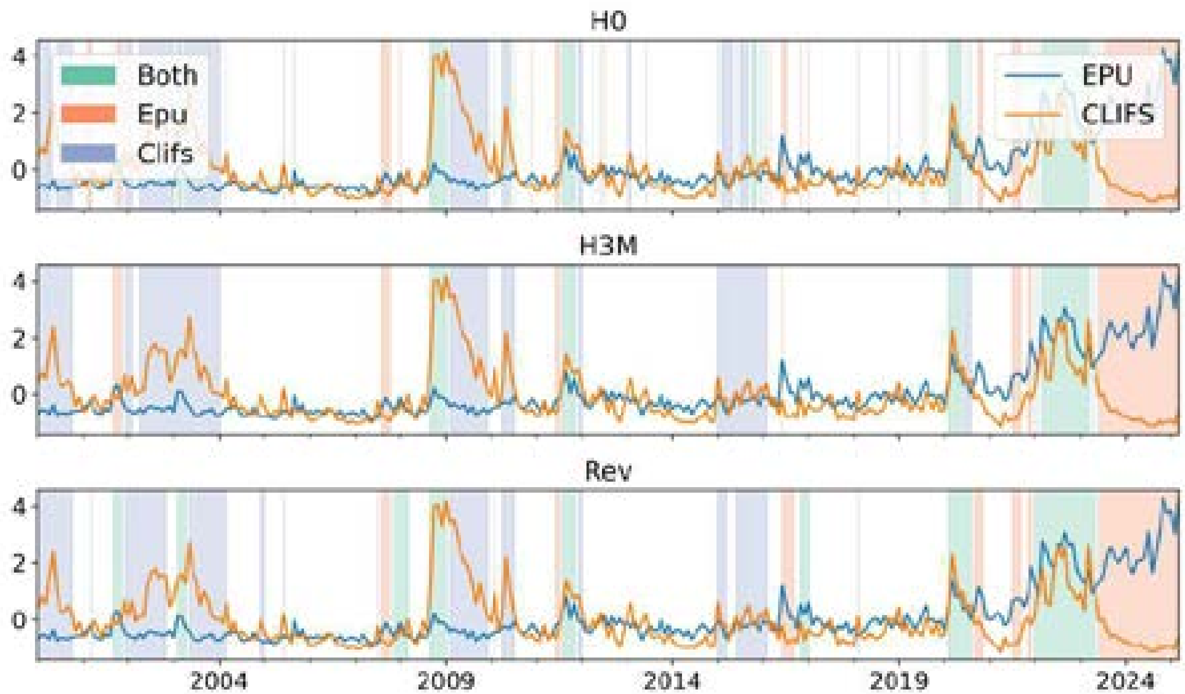
Note: Peak Statistics for the *H3M* dataset. Shown is the fraction of time a country spends in each peak type.

Figure H.1: Composite peaks in the UK



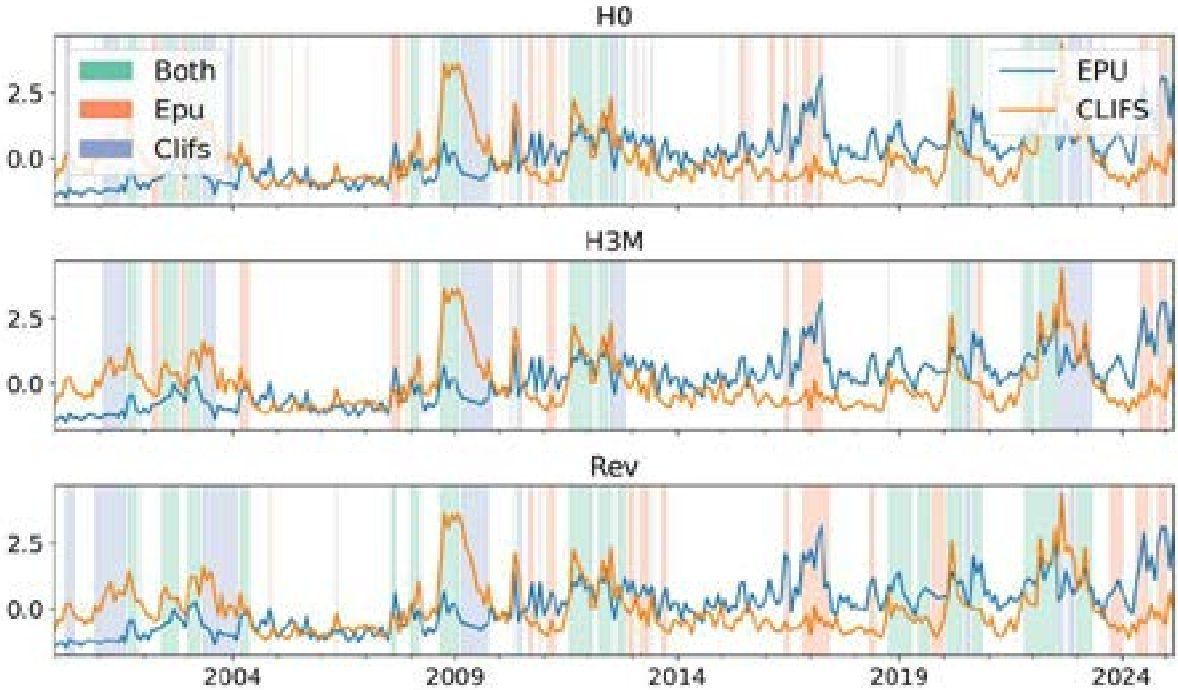
Note: The plots show how the three composite peak types (Both, meaning that both EPU and CLIFS peak; and Epu and Clifs, meaning that only the relevant proxy peaks, without a corresponding peak in the other) vary with the peak definition. The three peak definitions are given in H.1. H0 corresponds to hybrid peaks with no minimal length; H3M corresponds to the same but with some minimal length imposition; Rev is the H3M but revised manually.

Figure H.2: Composite peaks in Germany



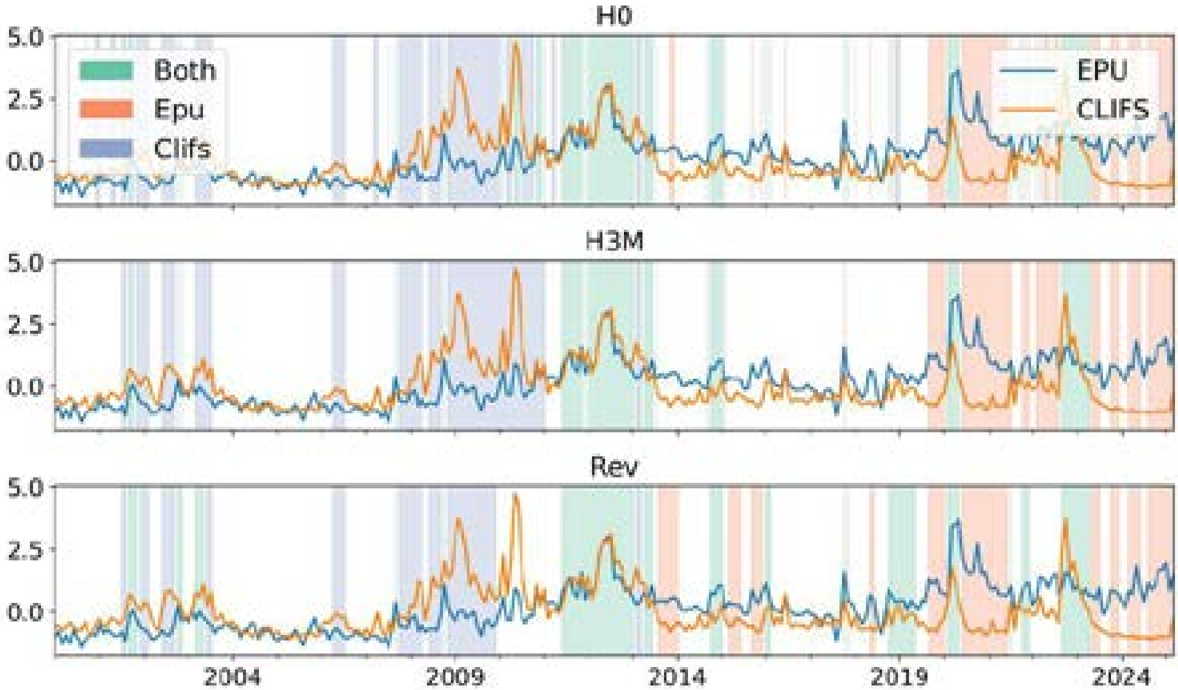
Note: The plots show how the three composite peak types (Both, meaning that both EPU and CLIFS peak; and Epu and Clifs, meaning that only the relevant proxy peaks, without a corresponding peak in the other) vary with the peak definition. The three peak definitions are given in H.1. H0 corresponds to hybrid peaks with no minimal length; H3M corresponds to the same but with some minimal length imposition; Rev is the H3M but revised manually.

Figure H.3: Composite peaks in France



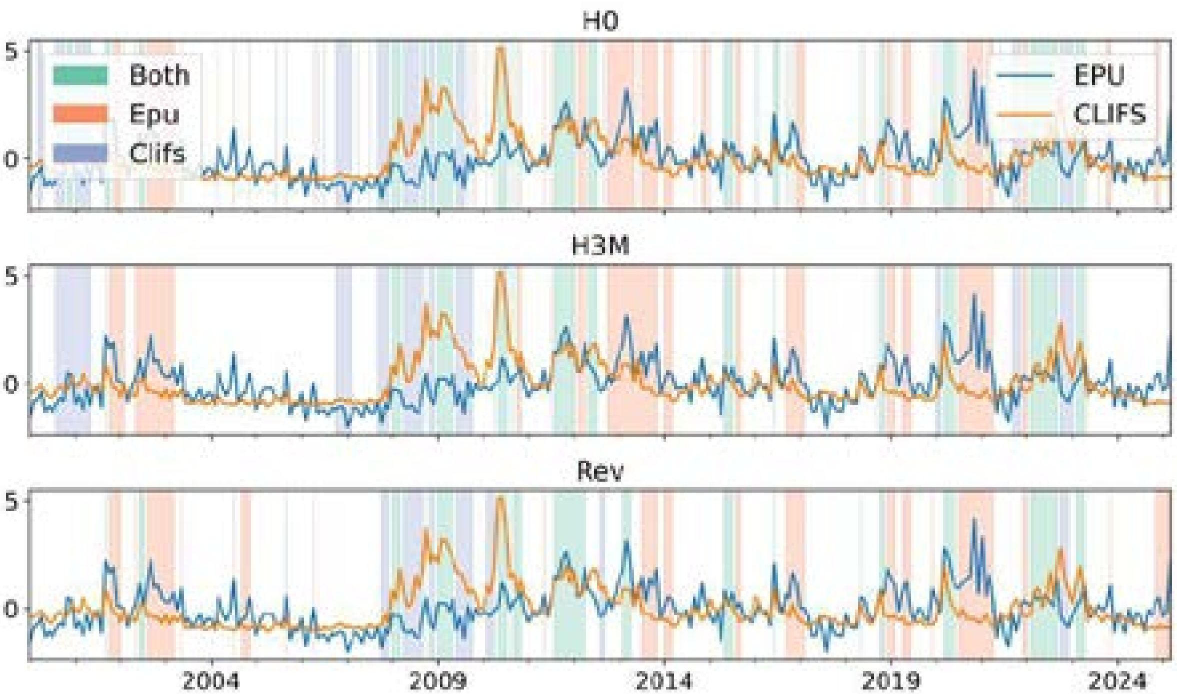
Note: The plots show how the three composite peak types (Both, meaning that both EPU and CLIFS peak; and Epu and Clifs, meaning that only the relevant proxy peaks, without a corresponding peak in the other) vary with the peak definition. The three peak definitions are given in H.1. H0 corresponds to hybrid peaks with no minimal length; H3M corresponds to the same but with some minimal length imposition; Rev is the H3M but revised manually.

Figure H.4: Composite peaks in Spain



Note: The plots show how the three composite peak types (Both, meaning that both EPU and CLIFS peak; and Epu and Clifs, meaning that only the relevant proxy peaks, without a corresponding peak in the other) vary with the peak definition. The three peak definitions are given in H.1. H0 corresponds to hybrid peaks with no minimal length; H3M corresponds to the same but with some minimal length imposition; Rev is the H3M but revised manually.

Figure H.5: Composite peaks in Italy



Note: The plots show how the three composite peak types (Both, meaning that both EPU and CLIFS peak; and Epu and Clifs, meaning that only the relevant proxy peaks, without a corresponding peak in the other) vary with the peak definition. The three peak definitions are given in H.1. H0 corresponds to hybrid peaks with no minimal length; H3M corresponds to the same but with some minimal length imposition; Rev is the H3M but revised manually.

I Chronology of Identified Uncertainty Peaks

Table I.3: Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
UK	2000-09 to 2001-02	Clifs	Dot-com Bubble unwinding and equity-market correction	Outside	Financial
UK	2001-04 to 2001-07	Both	Global showndown and early 2001 Recession concerns	Outside	Financial
UK	2001-09 to 2001-11	Both	9/11 Attacks	Outside	Military
UK	2002-11 to 2003-02	Both	Iraq war buildup and geopolitical tensions	Outside	Military
UK	2004-01 to 2004-03	Clifs	Market-driven stress	Outside	Financial
UK	2007-08 to 2008-05	Both	Global Financial Crisis - Early phase: Northern rock; credit-market freeze	Outside	Financial
UK	2008-08 to 2010-05	Both	Global Financial Crisis - Lehman collapse; deep recession	Outside	Financial
UK	2011-07 to 2011-10	Both	Eurozone Debt Crisis - Italy/Spain bond crisis	Outside	Financial
UK	2012-05 to 2012-07	Both	Eurozone Debt Crisis Peak - the peak until "Whatever it takes"	Outside	Financial
UK	2012-09 to 2013-01	EPU	U.S. Fiscal Cliff negotiations	Outside	Political
UK	2014-11 to 2015-01	Both	Greek Debt Crisis - Grexit fears; early crisis	Outside	Financial
UK	2015-05 to 2015-07	Both	Greek Debt Crisis - referendum, bank closures, bailout negotiations	Outside	Financial
UK	2016-02 to 2016-06	Both	Brexit Referendum - Campaign and result shock	Inside	Political
UK	2016-07 to 2017-12	EPU	Brexit Referendum - Political uncertainty, Article 50 negotiations	Inside	Political

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
UK	2018-02 to 2018-05	CLIFS	Early 2018 Market Volatility - and global market correction	Outside	Financial
UK	2018-10 to 2019-03	Both	U.S.–China Trade War and UK Brexit-related legislative gridlock	Inside/Outside	Political
UK	2019-08 to 2019-12	Both	UK Brexit Constitutional Showdown (Illegal prorogation of Parliament, Dec election)	Inside	Political
UK	2020-03 to 2020-08	Both	COVID-19 Pandemic - initial outbreak	Outside	Financial
UK	2020-09 to 2020-12	EPU	COVID-19 Pandemic - Covid-19 policy and reopening uncertainty	Inside	Political
UK	2021-01 to 2021-03	Both	COVID-19 Pandemic - winter wave and renewed restrictions	Inside	Political
UK	2022-09 to 2022-11	Both	Energy-price shock and Truss mini-budget (imported energy-market disruption and domestic fiscal shock)	Inside	Financial
UK	2024-05 to 2025-03	EPU	U.S. Presidential Election	Outside	Political
Germany	2000-01 to 2000-10	Clifs	Dot-com Bubble unwinding and equity-market correction	Outside	Financial
Germany	2001-09 to 2001-11	Both	9/11 Attacks	Outside	Military
Germany	2001-12 to 2002-11	Clifs	Post-dot-com financial weakness and early 2000s recession conditions	Outside	Financial
Germany	2003-02 to 2003-04	Both	Iraq war buildup and geopolitical tensions	Outside	Military
Germany	2003-05 to 2004-03	Clifs	Slow Eurozone recovery and corporate-sector restructuring	Outside	Financial
Germany	2007-08 to 2007-10	Epu	Subprime Mortgage Crisis (pre-GFC turmoil)	Outside	Financial
Germany	2007-11 to 2008-03	Both	Deepening global credit turmoil	Outside	Financial

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
Germany	2008-09 to 2009-01	Both	Global Financial Crisis - Lehman collapse; deep recession	Outside	Financial
Germany	2009-02 to 2009-12	Clifs	GFC aftermath: credit weakness and recessionary financial conditions	Outside	Financial
Germany	2010-04 to 2010-07	Clifs	Eurozone Debt Crisis - Greek bailout	Outside	Financial
Germany	2011-08 to 2011-11	Both	Eurozone Debt Crisis - Italy/Spain bond crisis	Outside	Financial
Germany	2015-01 to 2015-03	Clifs	Greek Debt Crisis - pre-referendum tensions	Outside	Financial
Germany	2015-06 to 2016-02	Clifs	Greek Debt Crisis - Green referendum, bailout negotiations	Outside	Financial
Germany	2016-06 to 2016-09	EPU	Brexit Referendum	Outside	Political
Germany	2016-11 to 2017-01	Both	US election shock	Outside	Political
Germany	2020-02 to 2020-08	Both	COVID-19 Pandemic - initial outbreak, lockdown concerns	Outside	Financial
Germany	2020-09 to 2020-11	Epu	COVID-19 Pandemic - second wave uncertainty	Outside	Financial
Germany	2021-07 to 2021-09	EPU	COVID-19 Pandemic delta wave and Federal elections uncertainty	Inside	Political
Germany	2022-01 to 2023-05	Both	Russia-Ukraine War and energy crisis	Outside	Military
Germany	2023-06 to 2025-03	EPU	energy transition, fiscal rules, coalition tensions, external geopolitics, US elections, etc	Inside	Political
France	2000-04 to 2000-06	Clifs	Global Dot-com downturn and equity-market adjustment	Outside	Financial
France	2000-12 to 2001-08	Clifs	Extended post–dot-com financial weakness leading into the early-2000s recession	Outside	Financial

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
France	2000-09 to 2001-11	Both	9/11 attacks and global geopolitical/financial shock	Outside	Military
France	2002-06 to 2002-10	Both	Post-election political uncertainty & Iraq War buildup	Outside	Military
France	2003-01 to 2003-04	Both	Iraq War onset (March 2003)	Outside	Military
France	2003-05 to 2004-02	Clifs	Market volatility during sluggish Eurozone recovery	Outside	Financial
France	2004-03 to 2004-05	Both	European constitutional treaty uncertainty & related political turbulence	Outside	Political
France	2008-01 to 2008-03	Both	Pre-Lehman Global Financial Crisis stress	Outside	Financial
France	2008-09 to 2009-02	Both	Lehman collapse & Global Financial Crisis	Outside	Financial
France	2009-03 to 2009-10	Clifs	GFC aftermath: weak credit, recessionary pressure	Outside	Financial
France	2011-02 to 2011-04	Epu	Eurozone fiscal tensions + French presidential pre-campaign uncertainty	Inside	Political
France	2011-08 to 2012-02	Both	Eurozone Debt Crisis escalation (Italy/Spain crisis; French rating downgrade)	Outside	Financial
France	2012-04 to 2012-07	Both	French presidential election + ongoing Eurozone turmoil	Inside	Political
France	2012-09 to 2012-11	Both	Eurozone crisis resolution phase (OMT announcement)	Outside	Financial
France	2013-03 to 2013-05	Epu	French domestic political uncertainty (labor reform debates, weak coalition support)	Inside	Political
France	2016-11 to 2017-06	Epu	Global political realignment + French election uncertainty	Inside	Political

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
France	2018-10 to 2019-04	Both	U.S.–China Trade War + Yellow Vest protests	Inside/Outside	Political
France	2019-06 to 2019-09	Both	Intensification of U.S.–China Trade War + French domestic reform tensions	Inside/Outside	Political
France	2019-10 to 2020-01	Epu	French pension reform protests & political uncertainty	Inside	Political
France	2020-02 to 2020-06	Both	COVID-19 outbreak, lockdown, and initial economic shock	Outside	Financial
France	2020-09 to 2020-11	Both	Second COVID wave & renewed economic uncertainty	Outside	Financial
France	2021-11 to 2022-07	Both	Russia–Ukraine War and European energy crisis	Outside	Military
France	2023-01 to 2023-05	Both	French pension reform crisis + inflation shock + global banking anxiety	Inside	Political
France	2023-10 to 2024-01	Epu	Domestic political uncertainty + global geopolitical tensions (Israel–Hamas conflict)	Inside	Political
France	2024-05 to 2024-08	Epu	European Parliament elections + French domestic political instability	Inside	Political
France	2024-11 to 2025-01	Epu	Global political uncertainty around U.S. 2024 election outcomes	Outside	Political
Spain	2001-09 to 2001-11	Both	9/11 attacks and global geopolitical/financial shock	Outside	Military
Spain	2001-12 to 2002-02	Clifs	Post–dot-com financial weakness and early-2000s slowdown	Outside	Financial
Spain	2002-06 to 2002-09	Clifs	Market volatility during weak Eurozone growth phase	Outside	Financial
Spain	2003-03 to 2003-05	Both	Iraq War onset	Outside	Military

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
Spain	2006-04 to 2006-07	Clifs	Spanish real estate and credit-market overheating concerns	Inside	Financial
Spain	2007-10 to 2008-04	Clifs	Subprime crisis spillovers and pre-Lehman stress	Outside	Financial
Spain	2008-06 to 2008-09	Clifs	Financial tensions ahead of the Lehman collapse	Outside	Financial
Spain	2008-11 to 2009-12	Clifs	Global Financial Crisis and deep Spanish recession	Outside	Financial
Spain	2011-06 to 2013-01	Both	Eurozone Debt Crisis (Greece, Italy, Spain's sovereign/bank crisis)	Outside	Financial
Spain	2013-04 to 2013-06	Both	Aftershocks of Eurozone crisis and banking recapitalization	Outside	Financial
Spain	2013-08 to 2014-01	Epu	Domestic political fragmentation and early territorial tensions	Inside	Political
Spain	2014-10 to 2015-01	Both	Ebola case in Spain + Eurozone deflation fears	Inside/Outside	Financial
Spain	2015-03 to 2015-06	Epu	Political fragmentation + Andalusian elections + Podemos rise	Inside	Political
Spain	2015-09 to 2015-12	Epu	Spanish general election deadlock and government-formation uncertainty	Inside	Political
Spain	2018-10 to 2019-05	Both	Catalan crisis aftermath + global trade-war volatility	Inside	Political
Spain	2019-09 to 2020-01	Epu	Repeat Spanish elections and government-formation deadlock	Inside	Political
Spain	2020-02 to 2020-05	Both	COVID-19 outbreak and initial economic shock	Outside	Financial
Spain	2020-06 to 2021-06	Epu	Pandemic management uncertainty + EU recovery fund negotiations	Outside	Financial

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
Spain	2021-10 to 2021-12	Both	Energy price shock + European inflation spike	Outside	Financial
Spain	2022-09 to 2023-04	Both	Russia–Ukraine war consequences + inflation + energy crisis	Outside	Military
Spain	2023-05 to 2023-07	Epu	Spanish general election announcement + uncertainty around coalition outcomes	Inside	Political
Spain	2023-10 to 2023-12	Epu	Post-election government-formation tensions	Inside	Political
Spain	2024-08 to 2025-02	Epu	Likely driven by political uncertainty and external geopolitical factors (U.S. 2024 election and EU political dynamics)	Outside	Political
Italy	2001-10 to 2002-01	Epu	Global Dot-com downturn and equity-market adjustment	Outside	Financial
Italy	2002-08 to 2003-03	Epu	Political uncertainty and institutional tensions under Berlusconi II	Inside	Political
Italy	2004-09 to 2004-11	Epu	Domestic political instability and constitutional reform debates	Inside	Political
Italy	2007-10 to 2007-12	Clifs	Pre-GFC financial turbulence	Outside	Financial
Italy	2008-01 to 2008-03	Both	Early phase of the Global Financial Crisis + Italian political uncertainty	Inside	Political
Italy	2008-04 to 2008-09	Clifs	Deteriorating financial conditions prior to Lehman collapse	Outside	Financial
Italy	2009-01 to 2009-05	Both	Global recession + Italy-specific macro/political concerns	Outside	Financial
Italy	2009-06 to 2009-10	Clifs	GFC aftermath: market-driven weakness	Outside	Financial
Italy	2010-02 to 2010-04	Clifs	Early Eurozone sovereign stress (Greece bailout concerns)	Outside	Financial
Italy	2010-05 to 2010-07	Both	Eurozone Debt Crisis onset	Outside	Financial

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Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
Italy	2010-09 to 2010-11	Both	Mounting concerns about Italy's fiscal position + market volatility	Inside	Financial
Italy	2011-08 to 2012-04	Both	Italian sovereign crisis, Berlusconi resignation, technocratic Monti government	Inside	Financial
Italy	2013-02 to 2013-04	Both	Hung parliament after 2013 elections + market concerns	Inside	Political
Italy	2013-07 to 2013-11	Epu	Government instability under Letta and Berlusconi's legal battles	Inside	Political
Italy	2014-01 to 2014-03	Epu	Renzi replaces Letta; institutional reshuffling	Inside	Political
Italy	2015-05 to 2015-07	Both	Greek crisis (Grexit fears) + Italy's spillover vulnerability	Outside	Financial
Italy	2016-09 to 2017-02	Epu	Renzi constitutional referendum and his resignation	Inside	Political
Italy	2018-12 to 2019-02	Epu	Budget conflict with the European Commission under the Lega–M5S government	Inside	Political
Italy	2019-04 to 2019-06	Epu	Coalition tensions and threats of government collapse	Inside	Political
Italy	2020-03 to 2020-03	Both	COVID-19 outbreak (Italy as first European epicenter)	Outside	Financial
Italy	2020-07 to 2021-04	Epu	Pandemic management + collapse of Conte government + formation of Draghi government	Inside	Political
Italy	2022-02 to 2022-09	Both	Russia–Ukraine War + energy shock + Draghi resignation (July 2022)	Outside	Military
Italy	2022-10 to 2022-12	Clifs	Energy-price volatility and inflation-driven market stress	Outside	Financial

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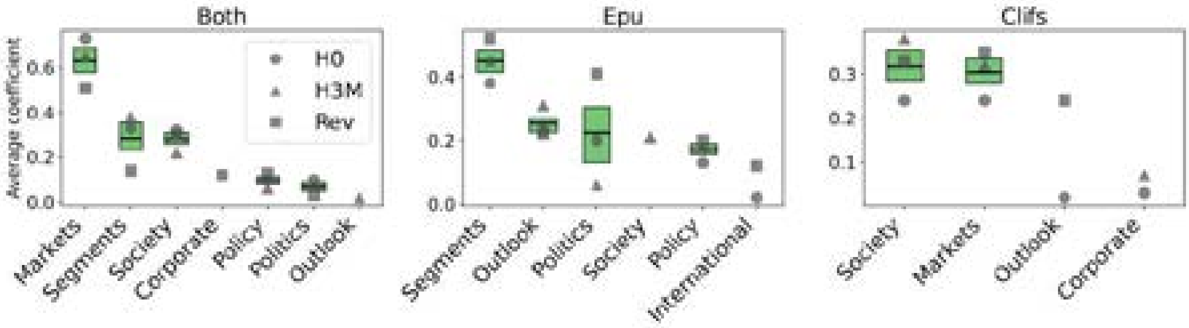
Table I.3 (continued): Main Uncertainty Peaks by Country, Origin and Nature

Country	Period	Peak	Likely Associated Event(s)	Origin	Nature
Italy	2023-02 to 2023-04	Both	European banking turbulence (Credit Suisse, U.S. regional banks) + Italian fiscal concerns	Outside	Financial
Italy	2024-11 to 2025-03	Epu	Likely driven by political uncertainty (domestic coalition tensions + global 2024 US election spillovers)	Inside	Political

Note: The table reports spikes identified using the procedure described above, limited to events lasting at least three months. The "Peak" columns classify episodes as follows: EPU (1,0) when only EPU rises, CLIFS (0,1) when only CLIFS rises, and BOTH (1,1) when both rise simultaneously. Labels indicate major contemporaneous events, though other local factors may also contribute; the timeline is thus not exhaustive. "Origin" distinguishes domestic ("Inside") from external/global ("Outside") drivers. "Nature" categorizes events as Political (e.g., elections, policy shifts), Military (e.g., wars, terrorism), or Financial (e.g., crises, market volatility, debt/banking stress).

J Robustness for composite peak analysis

Figure J.1: Topic Effects on Composite Peak Prediction Across Peak Definitions



Note: Average classifier coefficients for the pooled cross-country dataset under the three composite peak definitions (H0, H3M, and Revisions). Each point represents the average coefficient across classifiers for a given topic and peak definition. The only values shown are those where the coefficient is positive. Boxes are only shown if all three of the peak definitions have at least one classifier estimating the coefficient to be positive..

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