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Working Paper The macroeconomic impact of asymmetric uncertainty shocks

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Henrik Müller, Boris Blagov, Torsten Schmidt, Jonas Rieger, and Carsten Jentsch

The Macroeconomic Impact of Asymmetric Uncertainty Shocks





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The Macroeconomic Impact of Asymmetric Uncertainty Shocks

Abstract

We present an Uncertainty Perception Indicator (UPI) for Germany based on the dynamic topic modelling technique RollingLDA. In contrast to conventional LDA, where all data is processed in one go, the recursive structure of RollingLDA ensures that data is made available for modeling as soon as it is actually published, which prevents information leakage. Employing this approach facilitates the close-to-realtime identification of both the magnitude of an uncertainty shock as well as its specific characteristics. Thereby, more precise predictions about the likely impact are possible, as different sources of uncertainty have different repercussions in the macroeconomy. Employing a Bayesian VAR approach, we analyze the effects of various uncertainty shocks on fixed investment and other macroeconomic variables. Our results document the asymmetric nature of uncertainty shocks, as their consequences are highly dependent on the respective sources of uncertainty. We find that international shocks only have weak effects on the German macroeconomy, while domestic policy shocks prove to be highly significant. Uncertainty hurts most when it originates close to home. These results markedly differ from earlier studies that, in the case of Germany, tend to maintain the opposite. Interestingly, the results for the entire UPI (the sum of all individual UPI time-series) are broadly insignificant. In contrast, some single uncertainty topics show quite strong effects. We attribute this to information losses that occur when the entirety of uncertainty-related reporting is employed. Different UPI topics tend to offset one other. The RollingLDA technique helps disentangling the information hidden in the analysis corpus.

JEL-Codes: C32, C82, D80, E20

Keywords: Uncertainty; topic modeling; business cycle; fixed investment; geoeconomics

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1. Introduction

If humans knew what the future looked like, our lives would be pretty dull. There'd be no pleasant surprises, no good or bad luck, no catastrophes, no revolutions, no crises. We'd be prepared, no matter what. Fortunately, there is little reason to fear the boredom of clairvoyance, as the world repeatedly proves to be a place of profound uncertainty.

Economists, for their part, tend to view uncertainty as an adverse aberration. The farther real-world circumstances deviate from the theoretical ideal of perfect foresight, the more efficiency suffers; individuals get their decisions wrong, economic aggregates sputter, growth is being depressed. More recently, though, psychologists and behavioral economists have stressed that mankind is actually pretty good at dealing with uncertainty and have turned their attention to the question how people act in unknown circumstances, i.e., when neither probability distributions nor incident rates can be identified. To name just one example of this class of approaches, Tuckett and Nicolic (2017) show how people use narratives as cognitive frameworks to gauge the consequences of different paths of action.

Humans are well-equipped to deal with incalculable unknowns. In fact, most of the time people don't even think about all the unknowns that impact the outcomes of their actions, as Frank Knight observed more than a hundred years ago: *"It probably occasions surprise to most persons the first time they consider seriously what a small portion of our conduct makes any pretense to a foundation in accurate and exhaustive knowledge of the things we are dealing with." (Knight 1921, p. 210).* Due to the complexity of the world, its state at the current juncture, let alone in the future, is largely unknowable. Yet, billions of people make decisions – consume, trade, invest – every single day. How they go about their business and what that implies for the movement of economic aggregates has been a matter of research in economics for many years. Since Knight's days economists' toolboxes have greatly improved. Forecasts, projections and scenario analyses are available in great number and detail. But even equipped with myriads of data, Al tools and IT capacity we are still confronted with "radical uncertainty" (Kay and King 2020). The excitement never ends.

Insofar as the perception of uncertainty is a social phenomenon, a heightened interest in detecting its origins has proliferated. To this end, the media are an obvious data source. Economic agents, even professional economists (Boumans et al. 2023), largely obtain information about the state of the world from the media. Indeed, individuals do not have to find convincing what they read or watch. To have an impact on their outlook, and potentially on their behavior, it is sufficient that they believe everybody else to be influenced by media coverage (the "third-person effect", e.g., Perloff 1999). Patterns of herd behavior reenforce the persuading power of the media: at times the tides of issue attention capture

entire media systems (Downs 1972, Waisbord & Russell 2020). When all the media, journalistic and social, focus on a single issue, it influences the self-perception of society, and potentially alters collective behavior. Thematic shifts in media coverage matter. That's why media-based indicators have come widely into use in recent years, particularly to get to grips with bouts of uncertainty (e.g., most prominently, Baker et al. 2016).

This paper contributes to this strand of literature. It makes use of a dynamic news-based uncertainty indicator that is constructed with the help of the topic modeling technique RollingLDA (Rieger et al. 2021). Our approach enables researchers to conduct consistent textual analyses that lend themselves to construct updatable issue-specific uncertainty time-series In contrast to the classical LDA (Blei et al. 2003), where all the available data is processed in one go *after* the whole data set has been collected, the iterative structure of RollingLDA prevents information leakage by generally using only the data that is actually available at a certain time point. Employing this approach facilitates the close-to-real-time identification of both the magnitude of an uncertainty shock as well as its specific characteristics. Thereby, more realistic predictions about the likely impact are possible, as different sources of uncertainty have different repercussions in the macroeconomy. A geopolitical shock, say, varies in its effects from a monetary policy one, or a pandemic. Our Uncertainty Perception Indicator (UPI) lays open the asymmetries in the nature of uncertainty shocks, so that they can be dealt with more aptly.

The model we present in this paper focusses on Germany. The indicators we derive from it can be used to analyze the effects of different sources of uncertainty on macroeconomic variables like investment, consumption, and exports. Applying a Bayesian VAR approach, our results show a quite different picture in terms of causes and effects compared to earlier studies. For example, Azqueta-Gavaldón et al. (2023) find that trade uncertainty has a substantial effect on German economic activity while other sources of uncertainty do not. In contrast, our results suggest that shocks emanating from international sources only have small effects on domestic macroeconomic variables, while domestic factors have significant and partly long-lasting consequences, particularly on private investment. Importantly, we find that uncertainty concerning domestic economic *policies* impacts macro variables most strongly. Similar, though less pronounced effects can be observed for uncertainty arising from the realms of society. However, *politics* – i.e., the performative appearance of democratic institutions, such as the public bickering of ministries, political figures or parties that tend to feature prominently in news media and is often blamed for disappointing economic developments – does not lead to measurable negative consequences within our framework.

Overall, the results show that uncertainty, as captured by UPI time-series, has statistically significant and economically meaningful effects on economic development. Contrary to some empirical studies, domestic issues do matter a great deal.

This paper is organized as follows: Section 2 provides a brief review of the literature. Section 3 exposits the construction of the UPI model. Section 4 shows the results of the econometric analysis, while Section 5 draws some conclusions and suggests further paths of research.

2. Review of the Literature

In this section we start with theoretical considerations and get to empirical strategies to capture uncertainty a little farther below.

Uncertainty affects economic behavior through different channels (see Bloom 2014 for an overview). Plenty of research has focused on investment. Since investing involves assumptions about future income streams, expectations are central to assessing potential projects. Keynes (1936, chap. 12) stressed the *"confidence* with which we make this forecast" (italics in original). Therefore, a sense of uncertainty blurs the outlook and reduces the reliability of expectations, prompting some investors to put projects on hold.

The real-options literature (e.g., Bernanke 1983, Dixit & Pindyck 1994), in contrast, highlights the sunkcosts, or "irreversibility", that is part of the investment process. Once a project is started, the option to invest at another point in time and gather more information meanwhile to reduce uncertainty, or pursue a different project altogether, is lost. With increasing uncertainty, opportunity cost rise. Waiting becomes more attractive, so that projects are delayed, in effect reducing aggregate investment. Bloom (2009) ties in with this line of thought and finds that uncertainty shocks reduce investment, output, and hiring. Sunk-costs are particularly pronounced with regard to investments in intangible assets, such as R&D, design, or branding. Once taken, an investment decision is irrevocable as intangible assets can mostly not be sold off. Hence, uncertainty is particularly damaging to investments in intangibles, that are thought to be a key to productivity growth (Haskel & Westlake 2022, pp. 60-61). Indeed, Palombo (2020) finds links between the rise of uncertainty and subdued investments in intangibles in the course of the Financial Crisis of 2008/09 and the ensuing Great Recession that can partly explain the prolonged slowdown in productivity growth in the aftermath.

As far as consumption is concerned, life-cycle models of household behavior imply that rising uncertainty induces higher precautionary savings to ensure future consumption, thereby reducing current consumption. Different empirical strategies to test these hypotheses have been employed. A large body of literature draws from survey data. Balta et al. (2013) use business and consumer surveys conducted in the euro area. Coibion et al. (2024) draw from a population-representative survey of households in Europe, while Kumar et al. (2023) use data from business surveys conducted in New

Zealand. Bloom et al. (2022) measure subjective uncertainty based on interviews with senior management in US companies. Kolev & Randall (2024) use business surveys conducted for the European Investment Bank. In a recent contribution the International Monetary Fund (2024) emphasizes that different measures of macroeconomic uncertainty tend to be positively but not strongly correlated and strives to build an integrated framework.

Financial markets-focused indicators, such as volatility indices of the VIX type, might be well-equipped to gauge the effects of uncertainty, but not its causes, which are, by definition, exogeneous and therefore unpredictable within the context of economic models (Moore 2017). Carrière-Swallow & Céspedes (2013) assess the impact of uncertainty shocks on emerging economies. To quantify policy uncertainty, different indicators of news media content have been constructed in recent years. This strategy seems justified since economically relevant political, social and technological developments should be reflected in day-to-day news reporting at early stages. The most popular indicator of this type is the afore mentioned EPU (Baker et al. 2016) that makes use of a broad set of international newspaper corpora. The EPU is available for a growing number of countries and specific kinds of uncertainty (trade, monetary policy etc.). News-based approaches have also been proposed by Brogaard & Detzel (2015), Husted et al. (2020), Caldara & Iacoviello (2022), Manela & Moreira (2017), and Azzimonti (2018). For their World Uncertainty Index Ahir et al. (2022) use country reports from the Economist Intelligence Unit.

EPU data have become widely used. For instance, Antonakakis et al. (2019) measure Europe-wide uncertainty shocks originating in the Greek debt crisis. Chen et al. (2019) show in an EPU-based analysis how oil price shocks are affecting Chinese economic growth. Degiannakis & Filis (2018) find that economic uncertainty not just originates in politics but that there is also a feedback loop from financial markets to politics. Yu et al. (2018) show that global economic policy uncertainty leads to increasing volatility of financial market indicators. Alqahtani et al. (2019) come to the conclusion that US-originated uncertainty spills over to the Gulf region's stock markets, while Caggiano et al. (2020) calculate that it effects unemployment rates in Canada and the UK. Nguyen et al. (2020) associate elevated EPU levels with decreasing tourism consumption; Dash et al. (2019) find decreasing stock market liquidity in G7 economies with increasing EPU levels.

Much of the existing news-based literature suffers from one of two shortcomings. Either, indicators like the EPU and the Global Uncertainty Index are based on simple counts of articles containing a predefined query. In this case researchers are able to build updatable time-series, but are systematically unable to detect newly arising sources of uncertainty. Or, they use machine learning techniques, such as Latent Dirichlet Allocation (LDA), to carve out thematic reporting patterns. In this

vein, Azqueta-Gavaldón et al. (2023) construct uncertainty indicators for the biggest euro area countries, applying a topic modeling approach, as does Larsen (2017). Both find asymmetric economic effects of different sources of uncertainty. However, their *static* LDA topic modeling approach is inherently backward-looking as is uses all the available data *after* the whole data set has been collected. Hence, it does not lend itself to construct updatable time series since it utilizes data from future time points to model topics' distributions in the past.

The Uncertainty Perception Indicator we introduce in this paper is a measure that combines the timeinherent stability of the counts of articles-approach with the thematic openness and flexibility of topic models.

3. The Uncertainty Perception Indicator (UPI) and its components

In this section, we exhibit our approach to the textual analysis. Figure 1 aims at clarifying the sequence of steps; the econometric analysis is shown in the following section. It is noteworthy that the procedure combines quantitative and qualitative stages. Since the initial input is text, a complex and inherently ambiguous type of data, human coders are consulted to check the relevance of the machine-processed results and to (re-)calibrate the algorithm.^f

To be sure, our approach shares several features with earlier ones, some of which have been widely employed. Like the Economic Policy Uncertainty Index (Baker et al. 2016), the World Uncertainty Index (Ahir et al. 2022), or the Geopolitical Risk Index (Caldara & Iacoviello 2022) the UPI is based on news content aggregated in large text corpora; it filters for uncertainty-related articles; and, like Azqueta-Gavaldón et al. (2023), it makes use of sophisticated text-mining techniques. Yet it differs in several important aspects. For one, we do not presuppose specific sources of uncertainty. Instead, the UPI is fundamentally open to *unknown unknowns*, i.e., entirely novel external developments. As recent history has shown, uncertainty shocks at times come from unanticipated directions. Indicators that filter for precise areas, such as fiscal, monetary or trade policy, run the risk of overlooking potential hazards arising outside of their frames. In contrast, our textual-analysis model is constructed in an initially unsupervised manner, allowing the algorithm to classify content without interference, and hence researchers' biases. What's more, the dynamic RollingLDA approach allows topics to evolve over

¹ Statistical text analyses often rely on automated selection to select parameter settings, such as "perplexity optimization" (Grün & Hornik 2011). However, Chang et al. (2009) showed that selection mechanisms aiming at optimizing likelihood-based measures do not correspond with the human perception of a well-adapted model of text data. In fact, the authors observe a negative correlation.

time and its iterative structure guarantees that only the part of the data is used that is available at the time the indicator value is calculated. This ensures the timeliness and stability of UPI time-series over longer periods of time, a property that greatly enhances the indicator's usefulness in econometric analyses capturing several business cycles. Moreover, this indicator allows for a better and more realistic description of the level and the actual sources of uncertainty at a specific point in time.





Source: authors

3.1 Data and Method

The UPI is based on a corpus of three leading nation-wide German newspapers: Süddeutsche Zeitung (center left), Die Welt (center right) and Handelsblatt (business). This choice of media is meant to capture the reporting patterns of the country's broad media mainstream. The data were obtained from LexisNexis and the publishing houses. Articles published between 1 January 2001 and 31 January 2024 are considered. The entire corpus has a size of roughly three million texts. In a first step the corpus is cleaned; all words are converted to lower case, umlauts are resolved. Afterwards, an extended selection of meaningless stop words is erased to dampen undue noise. Following these preprocessing steps an issue-specific analysis corpus is carved out by applying a rather open query:

"unsicherheit" OR "unsicher" OR "unsicherheiten"

AND "wirtschaftlich" OR "wirtschaft"g

The subsequent analysis corpus has a size of 42079 articles.

^g Uncertainty OR uncertain AND economy OR economic. Note that the query is identical to the one used by Baker et al. (2016) minus policy area-specific items.

As indicated above, we make use of the well-established topic modeling method Latent Dirichlet Allocation, albeit in a modified way. Original LDA (Blei et al. 2003) has the disadvantage that the random initialization of the Gibbs sampler (Griffiths & Steyvers 2004) can result in markedly different models when run several times on the same data with identical parameter settings. This property of probabilistic topic models has been a nuisance to researchers and has limited the scientific reproducibility of results. Furthermore, it obstructs the construction of consistent time-series. Whenever new textual data come in, a new model needs to be computed. Fitting together subsequent models creates a host of additional problems. Hence, LDA may be useful for analyzing thematic developments in the media in a backward-looking manner, that is, by using all the data in one go after having collected the whole data set. But a series of one-shot LDAs does not amount to a meaningful exercise. One strategy to overcome this problem is "seeding", i.e., new data are fitted to a predefined model derived from past observations. To this end, the topic assignments of all previously modeled articles are held stable so that assignments for all new articles to the existing topics are obtained. However, over longer periods of time this approach proves to be too rigid. Assuming the thematic stability of news coverage is incompatible with the fluid nature of real-world events – the very thing an uncertainty indicator is supposed to capture. Therefore, a more flexible approach is needed to reconcile flexibility with stability.

To construct the UPI, we use a dual approach. First, the arbitrariness of LDA results is tamed by applying the selection method LDAPrototype (Rieger et al. 2024). The method improves the reliability of findings drawn from LDA results: for a given combination of parameters a number of models is calculated (usually about 100), from which the LDA is determined that is most similar to all other LDAs in the set of models. Second, we refine the "seeding" approach mentioned above by implementing it on a time-varying basis to get to a RollingLDA (Rieger et al. 2021). The first modeling step is limited to all the articles published between 1 January 2001 and 31 December 2005. We modeled 100 conventional LDAs on this five year subset and determined the PrototypeLDA as visualized in by Fig. 2. As suggested by Rieger et al. (2024), similarities between two LDAs are calculated

$$s_{i;j} = 1 - \frac{1}{2K} \sum_{g \in G^*}^{\square} |g| \left(\left| |g_{|i}| - 1 \right| + \left| |g_{|j}| - 1 \right| \right) \in [0,1]$$

where $g \in G^*$ are sets representing cluster groups from joint clustering of topics from two LDA runs iand j. Accordingly, $g_{|j}$ is the set restricted to topics from LDA run i and G^* is the set of sets that maximizes the similarity $s_{i;j}$ according to the LDAPrototype algorithm.



Using a rather low threshold, we determine the vocabulary for this initial modeling: all the words that occur more than five times in this time interval are considered. This procedure removes the long tail of very infrequently occurring words that provide very little information. The result is a sub-corpus of 10,806 texts with an average of 251 tokens from a 44,942 words vocabulary for the first modeling period. These texts from the first five-year-period are modeled using the LDAPrototype procedure. To determine the parameter settings, we conducted a pretest: two human coders labeled different PrototypeLDA models derived from the identical database, identifying 14 topics to be the most appropriate number for our purpose. Accordingly, we model K = 14 topics and choose as Dirichlet parameters $\alpha = \eta = 1/K$ as common, while the Gibbs sampler iterates 200 times over the dataset.

In a second modeling step we consider the articles from the subsequent first quarter of 2006. By applying the "seeding" procedure, we model the topic assignments to these 303 articles. We only use the last three quarters as memory, i.e., the model is initialized with the 1222 articles from April to December 2005 as displayed in Fig 3.



Figure 3: Initializing new chunks of data with RollingLDA

Source: authors

The vocabulary is extended by words that occur more than five times in the new articles and that were not included in the vocabulary before. The topic assignments of the new articles are initialized randomly and the Gibbs sampler iterates over each of the new articles again 200 times, while the topic assignments of all articles acting as initializing memory remain constant. This procedure of initializing new media content by using the results of the last three respective quarters can be likened to a rolling window, hence RollingLDA. The initial modeling procedure based on the LDAPrototype approach ensures the reliability of the method, while the seeding with the restriction of three quarters as memory opens up the possibility for topics to mutate over time. That is, certain actors may change, new terms may be coined, some words may fade from vocabulary while others become fashionable, nonetheless an evolving topic contains articles about similar issues over the entire time horizon.^h In principle, this type of topic model could be updated on a permanent (e.g., hourly) basis whenever new meaningful data are available. However, to carve out relevant thematic trends we find monthly updates appropriate.

3.2 Results from the textual analysis

The qualitative analysis reveals that 13 topics comprise content relevant to our research interest. To assess the topics' content characteristic articles and words as well as topic frequencies over time were consulted. Table 1 provides an overview of the topic structure.

^h To ensure thematic consistency of RollingLDA models over time, Rieger et al. (2021) recommend to calculate the cosine similarity of the word frequency vector of each topic from the current quarter to the previous one. If substantial breaks from earlier observations are noted, human coders should look into the content of recent quarters and facilitate a recalibration if necessary. However, the UPI model has proven remarkably stable over time.

Topic	Label	Share in	Content
No.		analysis	
		corpus	
		(per	
		cent)	
1	Corporate Culture	6.6	Labor relations, Trust, Technology, Entrepreurship,
			Digitalization, Knowledge, Workplace, Career
2	EU Conflicts	5.4	Brexit, Greek debt, democratic values, Russia, Turkey,
			Ukraine war etc.
3	Energy & Climate	4.5	Energy market developments, transition to renewables,
	Change Mitigation		Fukushima disaster (2011), Russia sanctions and resulting
			energy crunch (2022)
4	Companies & Markets	7.3	Developments at quoted international corporates
5	Geopolitics	6	Geopolitical tensions
6	Society	11.3	Debates on capitalism, globalization, democracy, populism,
			immigration, national identity, war and peace
7	Financial Markets I	6.1	Trouble concerning financial institutions (banks, insurance
			companies), retail investor aspects
8	German Politics I	7	Structural Reforms, labor Markets, welfare state, fiscal
			stance, taxes, subsidies
9	Miscellaneous	10.1	Diverse
10	Financial Markets II	9.5	How to invest, retail investor perspective
11	Services	4.4	Leisure, hospitality, entertainment, arts, sports, travel,
			corona-related peak
12	Central Banks	7.3	Monetary policy, ECB, Fed etc. actions against crises
13	German Economy	8.9	Business cycle, forecasts, surveys
14	German Politics II	5.6	Institutions, political parties and figures

Table 1: Overview of the UPI model's topics and labels

Political topics with domestic and European or international focus.

There are two broad categories of topics, representing political and economic sources of uncertainty. Political uncertainty (highlighted in Table 1) stems from both domestic and European or international origins, with three topics each. Domestic political uncertainty comes in three categories: "German Politics I" deals with economic policies, "German Politics II" with quarrels among political actors. "Society" entails political issues involving more fundamental long-term issues such as immigration or questions of war and peace.

European and international sources of uncertainty are captured by the topics "Central Banks" (predominantly ECB) and "EU Conflicts". "Geopolitics" includes economically relevant international developments, from trade conflicts to the war in Ukraine.

The remaining topics cover real-economy and financial market-aspects of uncertainty. Their content ranges from strongly cyclical topics, such as "German Economy" and "Companies & Markets", to structural ones such as "Corporate Culture". One topic, "Energy & Climate Change Mitigation", falls between categories. It contains a wide range of issues that are all closely related to energy markets, and include market developments (e.g., oil prices), policies (regulation to reduce carbon emissions) and shifting public opinion towards climate change (such as the Fridays for Future movement of the late 2010s).

Figure 4 depicts the frequency of the UPI corpus relative to the entire newspaper coverage over time, before differentiating for sources of uncertainty, akin to the EPU for Germany. Among the major peaks different types of shocks stand out. The first two local maxima are (geo)political in nature: 9/11 (peak 1, coinciding with the fallout from the bursting of the dot.com bubble, a market-based event preceding the period covered by our data) and the Iraq war (peak 2). The third local maximum is associated with the financial crisis, a market-centered event. The fourth one is triggered by the financial stress surrounding the Euro area in 2011. Clearly politics-related shocks occurred in the second half of 2016, with the twin peaks of populism resulting from the Brexit vote (5a) and Donald Trump's election (5b). The subsequent maximum, and the most severe one so far, is associated with the Covid- 19 shock (6), followed by the War in Ukraine, energy shortages, inflation, domestic budget squabbles and such.



Figure 4: Frequency of the overall UPI and related events*

*UPI analysis corpus relative to entire news corpus; dotted line: 12-month backward-looking moving average. Source: authors

Three provisional observations are noteworthy:

Outbreaks of uncertainty seem to come in waves. A major event is typically being followed by subsequent (smaller) ones. Major uncertainty shocks seem to be cumulations of underlying tensions in the political economy. Once laid bare, these tensions tend to unload in a series of additional eruptions. The two geopolitical shocks of the early 2000s were related to each other, the US-led war in Iraq being a direct consequence of the terror attacks of 9/11. The financial crisis, in turn, triggered the Euro crisis, when troubles of over-extended financial sectors called the solvency of some member states into question. The populist shocks of 2016 were related to each other in so far as British and American political debates are closely intertwined due to intense mutual media attention.

Uncertainty perception has been following a rising trend. Since 2008 the relative volume of uncertainty-related reporting has risen substantially. This increase has come in several steps, with each major peak leaving behind subsequently higher levels of uncertainty attention, as the 12-month moving average line in Fig. 4 indicates. The world seems to have become more unstable.

In the past, however, phases of relative calm tended to follow uncertainty shocks. An initial bout of uncertainty subsided as societies learned more about the respective phenomenon and recalibrated their institutions accordingly. Once the geopolitical shocks of 2001/03 were digested, several years of low perceived uncertainty followed. Also, after the episode of financial market turmoil several years

of stability ensued. Even after Trump took office in January 2017 and the Brexit talks between the UK and the EU stalled, a rather relaxed mood prevailed for a while. The most recent experiences, though, have resulted in an extraordinarily rapid succession of shocks, casting doubt on whether a period of relative calm will again set in any time soon.

Making use of the UPI methodology reveals the differences in the nature of individual uncertainty shocks. Figure 5 displays their composition at each juncture. Note that at each point in time uncertainty is perceived from different angles. Consider peak 5b as an example: Donald Trump's election, widely unexpected in Germany and elsewhere in Europe, was predominantly a geopolitical shock. At the same time, it was an issue with strong domestic resonances (see Society topic). The Covid shock (peak 6), in contrast, is reflected in strong showings of the Central Banks topic, as the ECB and others sprang to the rescue by immediately introducing emergency measures.



Figure 5: Thematic composition of uncertainty coverage at UPI peaks*

*Designation of peaks as in fig. 4;; relative weight of different sources of uncertainty in the month of occurrence of respective local maximum. Each observation total=1; Source: authors

Figures 6 and 7 illustrate the asymmetric behavior of the six policy topics. There are several events that are reflected in idiosyncratic frequency variations. The Brexit vote, for example, plays out mainly in "EU Conflicts". Trump's election leads to a peak in "Geopolitics". Economic policy uncertainty surrounding the Euro crisis is captured by "Central Banks" as the ECB was central in keeping stressed debtors afloat (Fig. 7). At the domestic level, the rise of immigration figures in 2015/16 and the subsequent success of the hard-right AfD party prompted a pronounced surge in the "Society"

frequency graph. During the pandemic "Society" and "German Politics I" shoot up simultaneously, indicating the severity of the related uncertainty shock (Fig. 6), a result that was also underlined by the local peak in "Central Banks" (Fig. 7).

Apart from Covid-19, until recently major uncertainty shocks were mostly centered around events that stayed in the realm of one particular topic, a feature that helped soften the blow. Insofar as other aspects of uncertainty remained barely affected, the overall repercussions on general uncertainty perception were dampened. However, towards the end of the observation period, a new pattern is showing. Starting in the Winter of 2022/23 domestic uncertainty increases across the board, with all three related topics rising in tandem (Fig. 6). A host of critical issues dominate political debates – in particular, war, inflation, immigration – accompanied by a domestic political system that itself projects the impression of increasing uncertainty. It's both the substance and the appearance of domestic politics, led by a disparate-looking three-way coalition government, that contribute to high and rising uncertainty. This is all the more remarkable as for decades domestic politics in Germany used to be characterized by enduring stability.





*Topics' share of total corpus; three-month backward-looking moving average, source: authors



Figure 7: European and international contribution to perceived uncertainty*

*Topics' share of total corpus; three-month backward-looking moving average, source: authors

4. Econometric Analysis

The textual analysis of the preceding section has produced plausible patterns of uncertainty perception. Our hypothesis is that the economic consequences of shocks differ depending on the sources of uncertainty. Hence, when an uncertainty shock hits, determining its size and sources should enable economic agents and policymakers to estimate the potential macroeconomic effects and thus potential remedies. To this end, we analyze the effects of various uncertainty shocks on private investment and other macroeconomic variables employing a Bayesian VAR approach.

4.1 Econometric Framework and data

We use data for real investment in machinery and equipment (inv_equip), real private consumption (cons) as well as real exports (exports) from the German quarterly system of National Accounts. In addition, we use monthly data for consumer prices (cpi) and the three-month money market rate (interest). Consumer prices as well as the uncertainty indicators are aggregated to quarterly data by taking averages. For the national accounts data as well as consumer prices we calculate quarter to quarter growth rates. Moreover, we use the log-transformation for the uncertainty indicators.

We estimate a Bayesian VAR model with Minnesota priors from 2001 Q1 to 2024 Q1. The VAR model is given in a reduced form

$$y_t = c + \sum_{j=1}^p A_j y_{t-1} + u_t, \ u_t \sim N(0, \Sigma),$$
(1)

where y_t collects our variables in time t, c is a vector of constants and A_j are parameter matrices for each of the respective p lags of the variables. With Bayesian vector autoregressions (VARs) having become workhorse models in macroeconomic modelling ever since the seminal contribution of Doan, Litterman, and Sims (1984), we use Bayesian methods for estimating model (1). For this purpose we utilize the Minnesota prior that implies the following distributions on the parameters before introducing the model to the data:

$$\theta^i \sim N(\theta_{Mn}, V_{Mn}),$$

where θ_{Mn} are entries of 1s corresponding to the first lag of each variable and 0 otherwise and the elements of V_{Mn} have the following structure:

$$\underline{V}_{i,jj} = \begin{cases} \frac{\lambda_1}{l^{\lambda_3}}, & \text{for coefficients on own lag } l \text{ for } l = 1, \dots, p \\ \frac{\sigma_{ii}\lambda_1\lambda_2}{l^{\lambda_3}\sigma_{jj}}, & \text{for coefficients on lag } l \text{ of variable } j \neq i, \text{ for } l = 1, \dots, p \\ \sigma_c^2\lambda_5 & \text{for the constant} \\ \sigma_{ii}(\lambda_1,\lambda_4), & \text{for coefficients on eventual exogenous variables} \end{cases}$$

The parameters λ_1 , λ_2 , λ_3 , λ_4 , λ_5 are called hyperparameters and control the degree of shrinkage on the prior. For example, low values of λ_1 would impose tighter variance of the prior and hence more weight in the posterior distribution. In the literature it is common to take fixed values for these parameters, for example in US data it is often stipulated that $\lambda_1 = 0.1$. However, in our application we are dealing with a German dataset and nothing ensures that these values are appropriate. Therefore, we take a data-driven approach and in a first step we estimate the hyperparameters for the priors. We do this by doing a grid search over the hyperparameter space and choose the values that maximize the marginal likelihood. We do this for every variable set before estimation. In the second step we estimate the coefficients of the VAR model given the priors. Given that the Minnesota prior has an analytical distribution we draw the parameters directly from the posterior. We use the Schwarz Information Criterion to specify the lag-length of the VAR model. We find that for all models one lag is sufficient. As in the original paper by Caldara et al. (2016) we use 1000 draws from the posterior distribution. For the identification of uncertainty shocks we follow Caldara et al. (2016), an approach also employed by Azqueta-Gavaldón et al. (2023). The key idea of this approach is that structural innovations should have a maximum effect on its respective target variable over a given horizon. As in Azqueta-Gavaldón et al. (2023) we are interested in identifying uncertainty shocks. We therefore maximize the effect of the uncertainty shock on the uncertainty index in the four quarters after the shock. In addition, we impose the restriction that the effect of an uncertainty shock on the uncertainty indicator is positive and an increase in uncertainty generates a prolonged period of heightened uncertainty.

4.2 Results

In this subsection, we present the impulse response results for various uncertainty shocks to selected macroeconomic variables. Most importantly, we find that the UPI's uncertainty topics have significant effects on macroeconomic variables. However, the strength of the effects varies between topics. In contrast to Azqueta-Gavaldón et al. (2023), we find that mainly domestic uncertainty topics have an effect on macroeconomic variables. What's more, the results for the entire UPI – i.e., the sum of all individual UPI time series, comparable to Baker et al.'s (2016) EPU – are rather disappointing, particularly with regard to investment and consumption. In contrast, some single uncertainty topics show quite strong effects. At first glance, that might be surprising, as one might assume that the overall UPI is the most information-rich time-series in our model. However, on many occasions different UPI topics offset one other. As discussed in the previous section, a peak in one time-series may be accompanied by a trough elsewhere, diluting the essence of the shock. Therefore, disentangling the information by applying the RollingLDA technique serves a highly valuable purpose: sorting out high-impact information in terms of uncertainty perception and separate it from weaker signals.

Table 2 summarizes the results. Among the six politics-oriented uncertainty topics the two domestic ones "Germany Politics I" and "Society" are the ones with the strongest impact by far, while the three European/international topics prove to be broadly insignificant.

Table	2: S	ummary	of	results
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Shock/Response	Investment	Consumption	Interest rate	СРІ	Exports
UPI total	0	0	-	-	0
Central Banks	0	0	-	0	0
EU Conflicts	0	0	_	0	0
Geopolitics	0	+	0	0	0
German Politics I	_	_	_	_	-
German Politics II	0	0	0	0	0
Society	_	_	-	-	_
German Economy	0	0	_	0	
Companies & Markets	-	0	_	0	_
Corporate Culture	-	0	-	0	-
Energy & Climate Change Mitigation	0	0	_	+	0
Services (form. Leisure)	-	_	_	+	_
Financial Markets I	0	0	-	0	_
Financial Market II	0	0	-	0	0

European and international topics, domestic politics topics, see also table 1

0 no significant effect, + positive, –negative significant effect within 68 per cent confidence interval Source: authors

An interesting distinction was found between shocks to "German Politics I" and "German Politics II". Shocks to the former have strong negative effects on all variables of the system (Fig. 8). With regard to private consumption the negative effect is much more pronounced and not compensated by the following positive effect. In this case there is a significant negative effect on inflation. We find similar results for "Society" (Fig. 9), though with smaller magnitudes. In contrast, the impulse responses of shocks to "German Politics II" are insignificant, bar an interest rate effect.



Figure 8: Responses of macroeconomic variables to a "German Politics I" topic shock

We present the mean and 68% confidence bands of a standard deviation shock to the uncertainty indicator. Source: authors

This is a highly interesting result. "German Politics I" deals with substantial questions of *policies*, such as taxes, social or environmental protection. An unclear future path in these policy areas plausibly impacts investment, and to a lesser extent consumption (think: regulatory uncertainty concerning electric vehicles and consumers' resulting aloofness). By depressing aggregate demand, a decline in interest rates is prompted. In contrast, "German Politics II" mainly deals with the petty bickering of politicians and parties, that makes up a large part of what's reported about politics, even though there's little substance in it. While the public appearance of democratic politics is rarely joyful, our results show that it's not economically hurtful either, contrary to popular beliefs. "



Figure 9: Responses of macroeconomic variables to a "Society" topic shock

We present the mean and 68% confidence bands of a standard deviation shock to the uncertainty indicator. Source: authors

To highlight some more results: an unexpected increase in the overall UPI leads to a negative rate of change in equipment investment and exports (Fig. 10). In contrast, the initial decline in private consumption is being offset in subsequent periods. This temporary decline in real economic activity is accompanied by a lasting drop in interest rates, which is the only statistically significant effect concerning this time-series.

Figure 10: Responses of macroeconomic variables to an overall UPI shock



We present the mean and 68% confidence bands of a standard deviation shock to the uncertainty indicator. Source: authors

Uncertainty shocks that are related to the "Central Banks" topic reveal similar patterns as shocks to the general UPI. Here, the effect on the growth rate of private consumption is a bit more pronounced. An increase in uncertainty leads to an immediate reduction in private consumption. After the shock has petered out, however, private consumption increases significantly and more pronounced than after an UPI shock. Again, the results are broadly insignificant.

Uncertainty shocks that have international sources only have small effects on domestic macroeconomic variables. Uncertainty shocks that are related to EU Conflicts or Geopolitical topics have small positive effects on consumption and investment.

As far as economic uncertainty in narrow sense is concerned, "Companies & Markets" is the most promising topic. A shock prompts investment and exports to decline and is accompanied by lower interest rates (Fig. 11). "German Economy", a topic that encompasses news reports about business cycle developments, reacts with exports in particular, a feature that can be explained by the high trade-dependency of the domestic economy.



Figure 11: Responses of macroeconomic variables to an overall "Companies & Markets" shock

We present the mean and 68% confidence bands of a standard deviation shock to the uncertainty indicator. Source: authors

"Energy & Climate Change Mitigation" reacts strongly with inflation and interest rates, but little with other variables, a property that is due to oil and gas price shocks featuring prominently in this topic.

Overall, the results show that uncertainty as measured by the UPI has a statistically significant and economically meaningful effect on economic development. Contrary to other empirical studies, domestic issues do have an impact.

5. Conclusion

In this paper, we presented an economic uncertainty indicator, making use of the dynamic topic modelling technique RollingLDA. We constructed an Uncertainty Perception Indicator (UPI) for Germany, based on a corpus of German broadsheet newspapers. Our model produces well-interpretable time-series each of which contains distinct aspects of economic uncertainty. Since RollingLDA allows topics to evolve so that it adapts to changing circumstances and vocabulary, our UPI model proves to be both flexible and stable over time. Most importantly, the UPI can be updated with new data frequently and hence serve as an indicator for business cycle (or financial market) analyses. This feature differentiates our approach from earlier ones that use static topic models, like the original LDA (Blei et al. 2003), and allow only one-shot backward-looking analyses. (The code and data are available at https://github.com/JonasRieger/upi.)

Subsequently we subjected our 14 UPI time-series to econometric analysis. Employing a Bayesian VAR approach, we analyzed the effects of various uncertainty shocks on fixed investment and other macroeconomic variables. Our results document the asymmetric nature of uncertainty shocks, as their consequences are highly dependent on the respective sources of uncertainty. We find that international shocks such as geopolitical shocks only have weak effects on the German macroeconomy, while shocks emanating from domestic politics and society prove to be highly significant, particularly as far as negative impacts with regard to business investment are concerned. Uncertainty hurts most when it originates close to home. These results markedly differ from earlier studies that, in the case of Germany, tend to maintain the opposite.

Interestingly, the results for the entire UPI (the sum of all individual UPI time-series) are broadly insignificant. In contrast, some single uncertainty topics show quite strong effects. We attribute this to information losses that occur when the entirety of uncertainty-related reporting is employed. Different UPI topics tend to offset one other. As discussed in the Section 3.2, a peak in one time-series may be accompanied by a trough elsewhere, diluting the essence of the shock. The RollingLDA technique helps disentangling the information hidden in the analysis corpus.

Our findings open up a wide range of possible paths for future research. For example, an entire family of UPI models covering other countries could be built and tested. Obvious candidates would be other larger euro area economies (e.g., France, Italy, Spain, Netherlands), the United Kingdom, and the US.

An interesting characteristic of the UPI is the secular rise of uncertainty that took off around the time of the Financial Crisis. Investigating this trend and its effects, for instance on potential growth, would be worthwhile. There might be a causal connection to the enduringly low rates of business investment accompanied by high capital outflows (the mirror image of record-breaking current account surpluses) that have plagued Germany during this period.

As mentioned in the literature review, psychology and behavioral economics have identified narratives as key to understanding decision-making under uncertainty. Accordingly, narrative analyses of the UPI news content might shed light on its shape and structure. These findings could be cross-checked by the uncertainty narratives that company executives or private investors harbor at a given time. Participants could be asked to formulate brief stories they tell themselves to make sense of the present and the immediate future, along the lines of Andre et al. (2022).

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