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Uncertainty about the War in Ukraine: Measurement and Effects on the German Business Cycle[*]

Moritz Grebe Sinem Kandemir Peter Tillmann

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Abstract

We assemble a data set of more than eight million German Twitter posts related to the war in Ukraine. Based on state-of-the-art methods of text analysis, we construct a daily index of uncertainty about the war as perceived by German Twitter. The approach also allows us to separate this index into uncertainty about sanctions against Russia, energy policy and other dimensions. We then estimate a VAR model with daily financial and macroeconomic data and identify an exogenous uncertainty shock. The increase in uncertainty has strong effects on financial markets and causes a significant decline in economic activity as well as an increase in expected inflation. We find the effects of uncertainty to be particularly strong in the first months of the war.

Key Words: war, Twitter, geopolitical risk, machine learning, business cycle
JEL Classification: D8, E3, G1

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1 Introduction

The Russian attack on Ukraine in February 2022 was a huge blow for the world economy. As a consequence of the war, many countries in Europe and beyond have to adjust their military and security policies in light of new geopolitical realities. In addition, countries in Europe, most notably Germany, have to revise their energy policy and, with an eye on future geopolitical conflicts, their economic inter-dependencies with other countries. These adjustments entail large macroeconomic costs (Garicano et al., 2022).

One key economic dimension of the Russian attack on Ukraine is uncertainty: households and firms are uncertain about a potential escalation of the war, the duration of the conflict and the post-war order. Fluctuations in this uncertainty should be a driver of financial markets, real economic activity and inflation expectations.

In principle, uncertainty can impact the economy through three main channels. First, irreversible investment in light of fixed costs implies that uncertainty prompts firms to rethink their investment plans and wait until uncertainty is resolved. Second, risk-averse households respond to an increase in uncertainty by reducing consumption expenditure. Third, uncertainty increases risk premia, which makes investment and consumption more expensive. All three channels imply that an increase in uncertainty has contractionary effects on the real economy.

In this paper, we study the consequences of the uncertainty about the war in Ukraine for the business cycle in Germany. There are two main obstacles for this analysis. First, we need to measure the uncertainty perceived by households and firms about the evolution of the war. Second, we need to trace the causal effect of a change in uncertainty on the German economy. We make two contributions that address these problems.

As a first contribution, we assemble a data set of more than eight million German-speaking tweets, i.e. short messages on Twitter. These tweets are drawn from the Twitter API based on a list of specific keywords, i.e. "Ukraine", "Putin" etc. Twitter is a particularly useful source of data on perceived uncertainty because users can express their own views as a response to geopolitical events and can do so in real time. Both aspects are clear advantages compared to newspaper-based measures of uncertainty. The drawback is that the content of Twitter posts is probably more noisy than curated newspaper reporting.[1]

We then apply a state-of-the-art technique from the field of Natural Language Processing (NLP) to explore the public perception of the war. In this regard, we use zero-shot classification with German Bidirectional Encoder Representations from Transformers (GBERT), i.e. a transformer-based language model. For each tweet, we obtain a probability of being classified as expressing uncertainty. In contrast to dictionary-based uncertainty indicators such as Baker et al. (2016) and others, this method does not rely on identifying words in a given tweet that are included in a pre-specified dictionary. This procedure also enables us to classify tweets into different predefined categories such as "energy", "war", "sanctions" etc. and eliminates the need for explicit training on labeled examples specific to those categories. We then compute the daily averages of the uncertainty probabilities. As a result, we obtain a daily indicator of uncertainty, which clearly reflects the evolution of the war and peaks on February 24, 2022, the day of the attack.

The second contribution of this paper is an identified vector autoregression (VAR) model that allows us to estimate the causal effect of uncertainty shocks on the German economy. We include daily variables such as stock prices, the volatility of the stock market, the price of natural gas, a daily measure of real economic activity and break-even inflation expectations from the bond market for the period January 2022 to February 2023. As a matter of fact, uncertainty is an endogenous variable and responds to the state of the economy and the financial market. To achieve identification, we exploit the fact that Twitter is active around the clock, while the stock market is subject to trading hours and most economic activity takes place during the day. Specifically, we separate uncertainty expressed on Twitter during the night from uncertainty during the day and order uncertainty at night first in the VAR model. A recursive ordering of the variables implies that on a given day, uncertainty at night, i.e. before the opening of the stock market, can

[1] Twitter is also affected by Russian propaganda as investigated by Geissler et al. (2022).

drive financial markets and economic activity, while the reverse effect takes place after at least one day. In contrast to other papers in the literature relying on a recursive identification of uncertainty shocks, e.g. Bachmann et al. (2013), Baker et al. (2016), Altig et al. (2020) and Jurado et al. (2015), the recursiveness assumptions holds by construction and allows us to obtain a clean identification. We also report results from an alternative identification, i.e. a "hybrid VAR" following Romer and Romer (2004), Coibion (2012) and Caldara and Herbst (2019), among others.

We find that an uncertainty shock has strong adverse effects: stock prices fall, stock market volatility increases, the price of natural gas increases, real economic activity falls and expected inflation rises. All these responses are significant and have economically relevant magnitudes. An increase of uncertainty of one standard deviation, for example, depresses the equity market valuation by one percent and raises gas prices by two percent. The opposite responses of activity and expected inflation suggest that the effect of uncertainty resembles the effect of an adverse supply shock. The different categories of uncertainty have similar effects, though some aspects of uncertainty, e.g. migration-related uncertainty, do not cause a drop in activity. A subsample analysis reveals that the effect of uncertainty is much larger in the first subsample, i.e. before August 2022, compared to the second subsample. Overall, our results suggest that geopolitical risks as reflected in the uncertainty expressed in tweets about the war in Ukraine, have strong and significant adverse effects on the German business cycle.

This paper is contributing to the literature on the macroeconomic effects of economic uncertainty, e.g. Bachmann et al. (2013), Baker et al. (2016), Jurado et al. (2015), Altig et al. (2020) and Ludvigson et al. (2021). Most of the papers use identified VAR models and find negative effects of uncertainty shocks on output. Bloom (2014) and Castelnuovo (2022) survey the vast literature on uncertainty shocks. In line with the notion of Bloom (2014), we use the concepts of uncertainty and risk synonymously. The work by Baker et al. (2016) is particularly relevant as these authors establish the construction of uncertainty indicators from text data using pre-specified dictionaries. In contrast to their paper, we use high-frequency Twitter data and apply a machine learning approach.[2] We follow Bachmann et al. (2013), Baker et al. (2016), Altig et al. (2020) and Jurado et al. (2015) and use a recursive ordering of the endogenous variables in order to identify an exogenous uncertainty shock. Importantly, in our model the recursive ordering holds by construction of the variables. Hence, our paper avoids the critique of Kilian et al. (2023) of recursively identified uncertainty shocks.

A recent literature sheds light on the economic effects of fluctuations in geopolitical risk. The pioneering contribution of Caldara and Iacoviello (2022) is the construction of the Geopolitical Risk Index. The authors search a century of newspaper articles in the U.S. for keywords associated with geopolitical threats, wars, terrorism and other tensions. A recursively identified VAR shows that shocks to geopolitical risk cause a persistent fall in investment, employment and equity prices. Caldara et al. (2022) update the Geopolitical Risk Index to include the war in Ukraine. Based on an estimated VAR model, they show that an increase in risk causes a strong fall in global economic activity and an increase in global inflation. The opposite responses of activity ad inflation suggests that the geopolitical risk shock resembles a supply-side shock, which is consistent with our findings. Bondarenko et al. (2023) build a monthly index of geopolitical risk from articles in local newspapers. They find that risk shocks derived from Russian-speaking newspapers have strong effects on the Russian economy.

An alternative to the construction of uncertainty indices based on text data is an identification of uncertainty shocks based on the high-frequency responses of asset prices around important geopolitical events. Piffer and Podstawski (2018) estimate a VAR model and identify an uncertainty shock from the variation in the price of gold in a tight window around geopolitically important events. Ha et al. (2022) estimate the consequences of geopolitical risk shocks on the Korean economy instrumenting risks by the asset price responses around important events.

Another relevant but still small literature addresses the specific consequences of the war in Ukraine. Federle et al. (2023) analyze the stock mar-

[2] Naboka-Krell (2020) constructs economic policy indices based on newspaper articles in Germany, Russia and Ukraine.

ket response to the Russian attack and document a proximity penalty, i.e. a stronger negative response of stock markets in countries which are geographically closer to Ukraine. The authors show that this excess response reflects closer trade integration. Neuenkirch et al. (2023) study how financial markets respond to Western support for Ukraine. In the first weeks after the invasion, stock prices fall as a response to announcements of support. Thereafter, hawkish announcements in support of Ukraine increase stock prices.[3]

The paper is organized as follows. Section two explains the data collection. Section three outlines the construction of our uncertainty indicators. Section four introduces the VAR model and the identification of uncertainty shocks, while section five discusses the empirical results. Section six concludes. An online appendix contains additional material.

2 Data

2.1 Data Collection

We focus on German-speaking tweets containing selected keywords related to the war, i.e. *Zelenskyj*, *Putin*, *Ukraine*, *Kiev*.[4] More precisely, we collect tweets and user information from January 1, 2021 until February 28, 2023 using the Twitter API. The data collected contains user information and includes the account name, number of followers and followees, total number of tweets, user location, and whether the account has been verified by Twitter. Note that Twitter users have to actively choose to add their location to their accounts and tweets. As a result, only a small percentage of tweets include geotags. With that in mind, we do not limit our analysis solely to Germany as geographical location. As a result, we obtain over nine million tweets sent by a total of 468,596 distinct twitter users.

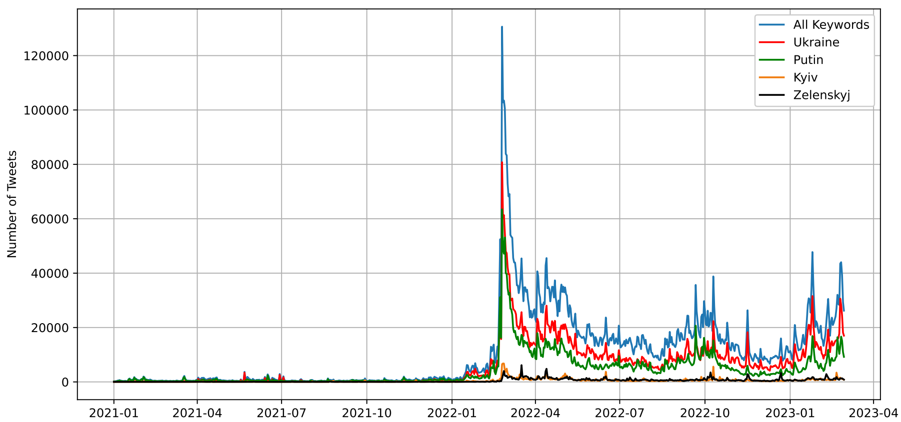
In order to focus on the textual component only, we then apply the fol-

[3]Other papers conducting event studies on the effects of the war on equity markets are Ahmed et al. (2022), Boungou and Yatié (2022), Huang and Lu (2022) and Izzeldin et al. (2023).

[4]To ensure that we also consider the Ukrainian and Russian spellings of these keywords, our analysis further includes the corresponding transcription and transliteration.

lowing preprocessing steps for each tweet. First, we remove Twitter handles such as profile names starting with @, hashtags, hyperlinks, RT (retweet) tags, digits, special characters and line breaks. Second, to ensure that the tweets collected are unique, we remove any retweets, duplicates and empty entries. As a result, we end up with a database of 8,457,134 unique tweets. Figure (1) shows the total number of unique tweets according to the respective keywords.

Figure 1: Number of tweets



Notes: The figure shows the total number of unique tweets according to the respective keywords, i.e. All keywords (n=8,457,134), Ukraine (n=4,948,399), Putin (n=3,441,673), Kyiv (n=346,305) and Zelenskyj (n=364,049). Note that the category *Kyiv* (*Zelenskyj*) also includes alternative transliterations, i.e. *Kiew*, *Kyjiw*, and *Kiev* (*Selenskyj* and *Selenski*).

2.2 Measuring uncertainty

To measure the perceived uncertainty expressed in tweets, we first make use of state-of-the-art machine learning methods. Over the past few years, the use of transformer based models has gained in popularity. The most prominent example in the field of Natural Language Processing is the approach introduced by Devlin et al. (2018), namely Bidirectional Encoder Represen-

tations from Transformers (BERT). Using a transformer architecture and the concept of transfer learning, these models are usually trained on large text corpora, which enables them to achieve a deeper learning and understanding of general language patterns and semantic relationships.[5]
The latter is achieved by using the masked language model approach, namely the masking out of specific words in a text. By training the model to predict the original word using the surrounding text context, these models learn to understand general language patterns and human language structure.

Since we are primarily interested in the classification of tweets in different categories, i.e. "uncertainty", "war", "energy" etc., we make use of zero-shot classification with German BERT (GBERT), a pre-trained transformer model for the German language that allows for multi-class classification.[6] The main idea is to utilize pre-trained models for a specific task and apply them to a different target task or application than their original training purpose. As in our case, the main advantage of zero-shot classification with GBERT lies in the extensive acquisition of general language during the pre-training phase. For the pre-training data set for GBERT, Chan et al. (2020) use over 160 GB of German text data and cover a wide variety of domains such as, among others, Wikipedia articles, parliament speeches, books and German court decisions. By incorporating different text data during the pre-training phase, this approach enables a deeper and more nuanced understanding of human language.[7] Thus, it allows the model to perform different classification tasks without the need for domain-specific training for each individual class, making it highly efficient and flexible in the adaptation to new domains. Using generalized labels, this approach allows us to assign probabilities to categories that were not explicitly included in the training data. Note that

[5] Malte and Ratadiya (2019) provide an overview of the evolution and advantages of transfer learning techniques.

[6] For a detailed model description see https://huggingface.co/Sahajtomar/German_Zeroshot. The model performs with 85.5 and 83.6 accuracy depending on the training data set.

[7] However, it is noteworthy to mention that the results of pre-trained language models should be interpreted with caution. As the training data set may inadvertently inherit preexisting cultural biases or contain false and misleading information, it cannot be ruled out that these biases might potentially be incorporated during the pre-training phase and consequently impact the model results.

the probability distribution is independent for each category and does not sum up to 1. The model assigns probabilities to our pre-defined categories, namely ”uncertainty”, ”energy”, ”war”, ”migration”, ”inflation”, ”politics” and ”sanctions”.

Next, we utilize the ”uncertainty” probabilities as a measure of uncertainty inherent in a given tweet. As for the remaining categories, their probabilities serve to differentiate between different aspects of uncertainty. Note that the reason for this distinction lies in the nature of tweets containing ambiguous language. For example, a tweet that has a distinct reference to politics will have a higher probability in the ”politics” category but a lower probability in other categories. On the contrary, tweets that are related to multiple categories or use ambiguous language will display a more evenly distributed probability across these categories.

To better understand how our approach measures the uncertainty expressed in a tweet, we shed light on two examples from leading German politicians. The first tweet is from German Chancellor Olaf Scholz, who tweeted the following on May 5, 2022:

> Olaf Scholz (@Bundeskanzler) on May 05 2022
>
> **Tweet:** Es ist wieder Krieg in Europa – unser ganzer Kontinent lebt gerade in einer Ausnahmesituation. Es gibt kein Drehbuch für das, was vor uns liegt. Meine Aufgabe ist es, unser Land sicher durch diese Zeit zu steuern. Und das tue ich.
>
> **Translation:** There is war again in Europe - our entire continent is currently living in an exceptional situation. There is no script for what lies ahead of us. My task is to safely navigate our country through this time. And that’s what I’m doing.

This is an example of a tweet for which the model assigns a very high uncertainty value, with the probability of the label ”uncertainty” being 0.92. Interestingly, this value is high even though the word ”sicher” (”safely”) appears in the tweet. The phrase ”Es gibt kein Drehbuch für das, was vor uns liegt.” (”There is no script for what lies ahead of us.”) effectively conveys uncertainty without using uncertainty-specific vocabulary. As a result, dictionary-based methods, e.g. used by Baker et al. (2016) and others, might struggle to detect the uncertainty expressed in this sentence. However, in our approach, the model takes the context of a word into account, thus detecting uncertainty even when uncertainty-specific words are absent. The model assigns an even higher uncertainty value of 0.94 to the mentioned sentence alone.

The second tweet is from Foreign Minister Annalena Baerbock, who tweeted:

> Annalena Baerbock (@ABaerbock) on May 10 2022
>
> **Tweet:** Ich bin unfassbar froh, hier im freien #Kiew zu sein. Der dafür notwendige Mut der Ukrainer*innen ist ergreifend. Meine Botschaft ist klar: Die #Ukraine kann sich auf unsere Unterstützung verlassen - nicht nur militärisch, nicht nur heute.
>
> **Translation:** I am incredibly happy to be here in free #Kyiv. The courage of the Ukrainian people is moving. My message is clear: Ukraine can rely on our support - not only military, not only today.

The probability of the label "uncertainty" for this tweet is a very low value of 0.01. This low level of uncertainty can be largely attributed to the last sentence: "Die #Ukraine kann sich auf unsere Unterstützung verlassen - nicht nur militärisch, nicht nur heute."("Ukraine can rely on our support - not only military, not only today.").

3 A Twitter-based uncertainty indicator

3.1 Index construction

Using the probabilities obtained from the zero-shot classification, we construct our index based on the assumption that a higher probability value for the "uncertainty" label corresponds to a high level of uncertainty inherent in a given tweet. To create this index, we calculate daily averages of uncertainty probabilities across all tweets. As illustrated in Figure (1), there is a significant change in the number of tweets over the sample period. The huge difference between the quantity of tweets at the beginning of this period and the onset of the war could pose a challenge to the construction of the index. To account for the varying number of tweets, we assign weights to each day and then multiply the average uncertainty values by these weights. The weights w_t are constructed as follows

$$w_t = \frac{\log(\#tweets_t + 1)}{\sum_{t=1}^{T} \log(\#tweets_t + 1)}, \tag{1}$$

where $\#tweets_t$ is the number of tweets used to construct the average uncertainty of day t over the sample $t = 1, ..., T$. This method of calculation results in what we refer to as the Ukraine Uncertainty Index.[8] In our construction, we assume that each tweet contributes equally to aggregate uncertainty. However, to account for the potential influence of a tweet's reach, we also compute an alternative index that weights tweets based on their number of retweets. Since this index is extremely similar to our baseline index, we relegate it into the online appendix.

Figure (2) depicts the standardized uncertainty index, alongside the uncertainty associated with specific events.[9]

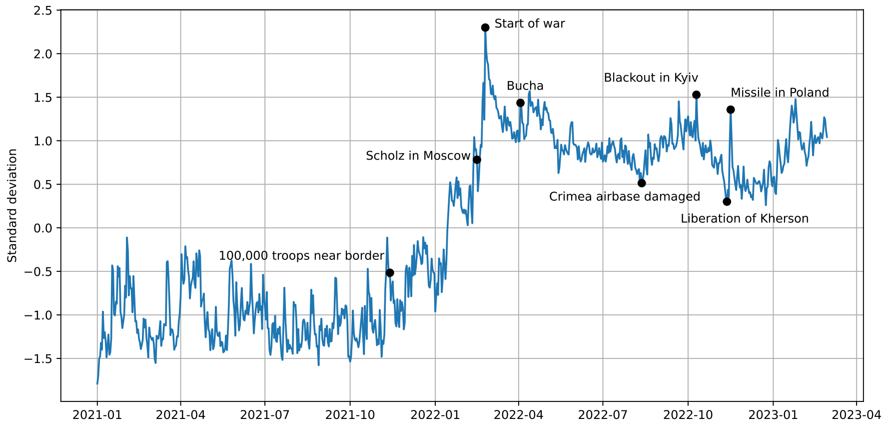
The index fluctuates at a relatively low level from January 2021 to November 2021. As early as April 2021, information surfaced about Russia amplifying its military presence near the Ukrainian border and in occupied Crimea. Correspondingly, the uncertainty index exhibits brief initial spikes around this period, even though the general level of uncertainty remains low until November 2021. On November 13, 2021, Ukrainian President Volodymyr Zelenskiy reported that approximately 100,000 Russian troops had amassed at the Ukrainian border. The situation continued to escalate thereafter, and the uncertainty index surges correspondingly.

In the German Twitter-sphere, a notable event was the visit of German

[8]This uncertainty index will soon be available at www.ukraine-uncertainty.de.

[9]A comprehensive chronology of the events during the war can be found at https://edition.cnn.com/interactive/2023/02/europe/russia-ukraine-war-timeline/index.html or https://commonslibrary.parliament.uk/research-briefings/cbp-9476/.

Figure 2: The Ukraine Uncertainty Index



Notes: The figure shows the standardized daily Ukraine Uncertainty Index derived from German tweets.

Chancellor Olaf Scholz to Russian President Vladimir Putin on February 15, 2022. This was when the escalating conflict and troop deployment along the Ukrainian border were discussed directly. Following the visit, there was increased talk that the visit had contributed to a de-escalation of tensions. The index also shows a decrease in uncertainty on this day and the day following the visit. However, as subsequent events unfolded, it became clear that the situation had not improved. On the contrary, Russian President Putin declared the commencement of a "special military operation" on February 24, 2022, effectively signaling the outbreak of war. This date corresponds to the highest recorded value of uncertainty for the entire sample. After this peak, the index declines but stays at an elevated level. The beginning of April 2022 sees a noticeable surge in uncertainty, coinciding with the disclosure of the Bucha massacre.

Counteroffensives from the Ukrainian army characterized the following summer. As they sought to reclaim territories seized by Russia, the uncertainty index decreases, reaching a low on August 9, 2022, when the Ukrainian military targeted the Crimean airport. From this point forward, uncertainty starts increasing again. October 10, 2022, records a significant level of uncertainty, a day marked by severe attacks on Ukraine's water and electricity infrastructure, which led to blackouts in Kiev and seven other regions. November 2022 experiences a considerable fluctuation in day-to-day uncertainty. On November 11, the index records its lowest value since the start of the war, a day when the Ukrainian army successfully recaptured the city of Kherson and other regions. However, a few days later, on November 15, the uncertainty index increases significantly following a missile strike on Polish territory near the Ukrainian border.

3.2 Comparing our index

We now compare our Twitter-based uncertainty index with three alternatives. The first is the Geopolitical Risk Index of Caldara and Iacoviello (2022) for Germany. The second is the Economic Policy Uncertainty (EPU) Index of Baker et al. (2016) for Germany. Both of these indicators are newspaper-based measure of uncertainty or risk. Our third benchmark is the ifo Dispersion Measure (Grimme, 2017), which measures the dispersion of firms' responses in the monthly ifo business survey.[10] As these three indices are available only at a monthly frequency, we aggregate our index to the same frequency by selecting the last observation for each month.

Figure (3) shows that all indices are strongly correlated. When our index is compared with the Geopolitical Risk Index for Germany, it is apparent that the increase in geopolitical risk from January to March 2022 is larger than for our index. Despite this, the uncertainty indicated by our Twitter-based index remains elevated, while the Geopolitical Risk Index falls. It is important to stress that our index does not rely on the occurrence of specific words in a given tweet, in contrast to the dictionary-based Geopolitical Risk or EPU indices.

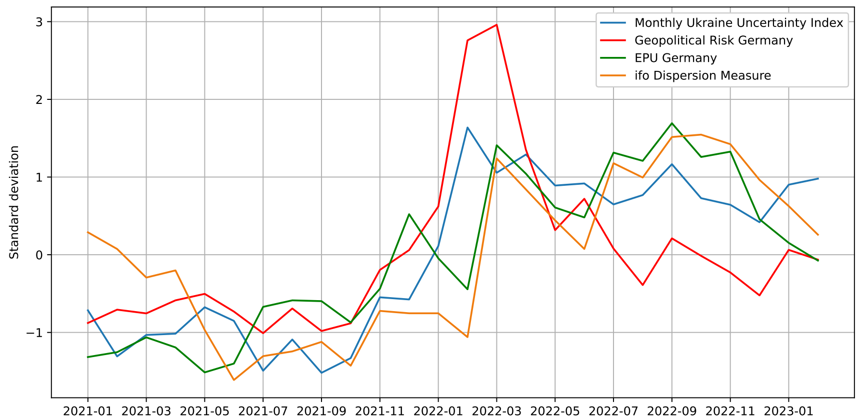
Both the EPU Germany and the ifo Dispersion Measure exhibit similar

[10] Bachmann et al. (2022) shows that firm-level uncertainty remained moderate at the beginning of the war in Ukraine. In fact, uncertainty was much lower than during pandemic.

dynamics, yet our index signals an earlier increase in uncertainty - observable from December 2021 and reaching its peak in February 2022. By comparison, the EPU Germany and the ifo Dispersion Measure do not exhibit a rise until January, reaching their respective peaks in March 2022.

In conclusion, our index is particularly suited for our analysis due to its specific focus on the uncertainty surrounding the Ukraine war. Furthermore, the use of high-frequency Twitter data allows our index to detect changes early on, maintaining this advantage even when the data is aggregated into a monthly format.

Figure 3: Comparing our index with alternative indices



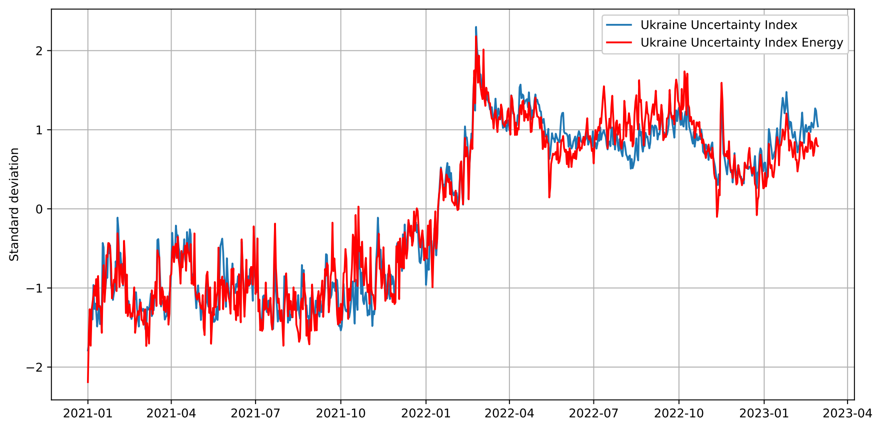
Notes: The figure shows the monthly Ukraine Uncertainty Index derived from German tweets, the Geopolitical Risk Index for Germany, the EPU index for Germany and the ifo Dispersion Measure. Each index is standardized.

3.3 Uncertainty categories

So far, we have discussed the general concept of uncertainty caused by the war in Ukraine. However, it is worth considering that uncertainty resulting from specific war events, such as a missile attack by Russia, may have a different economic impact than uncertainty caused by the war-related energy situation. Since the zero-shot classification provides us with probabilities not only for the "uncertainty" label, but also for the labels "energy", "war", "politics", "sanctions", "migration" and "inflation", we can more accurately pinpoint the sources of uncertainty. For instance, we can differentiate between uncertainty related to the war itself (using the "war" label) and uncertainty about the energy supply (using the "energy" label).

A specific label is assigned to a tweet if the probability of that label is the highest among the labels "energy", "war", "politics", "sanctions", "migration", and "inflation", and if this probability exceeds 0.5. This threshold ensures that tweets without a clear association with the chosen labels are not taken into account. Subsequently, we calculate the average daily uncertainty value by considering, for each category, only the tweets designated to that category. We then weigh the uncertainty value by the number of tweets using equation (1). Here, $\#tweets_t + 1$ represents the number of tweets associated with the respective topic on a given day.

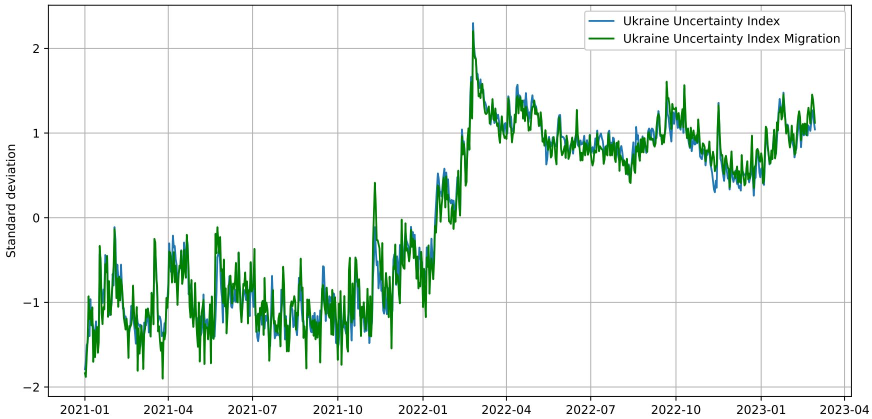
Figure 4: The Ukraine Uncertainty Index (energy)



Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Energy) derived from German tweets.

The indices across categories, each compared with our baseline index, are presented in Figures (4) to (9). It is important to stress that our procedure does not provide us with orthogonal categories of content. Hence, there is a

Figure 5: The Ukraine Uncertainty Index (migration)



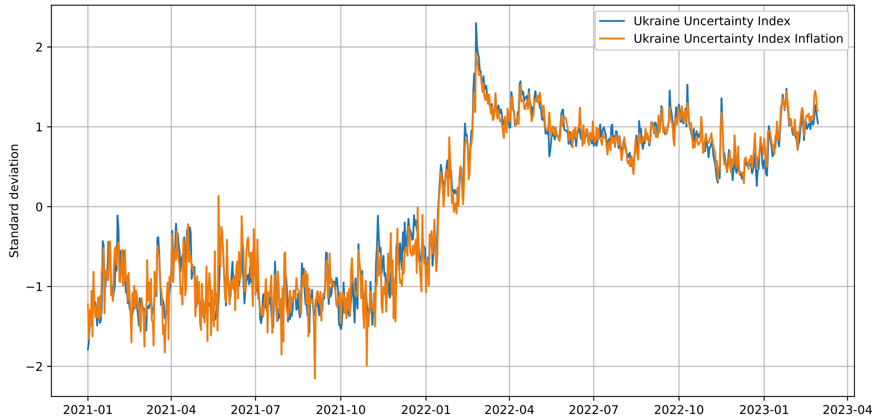
Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Migration) derived from German tweets.

strong resemblance between these indices and the baseline index. The most noticeable difference is seen in the energy index between July and November 2022, where the uncertainty regarding energy is distinctly higher. On the other hand, the index associated with tweets about politics aligns most closely with the baseline index.

4 Estimating the economic effects for the German economy

In this section, we estimate the consequences of an increase in uncertainty about the war in Ukraine on the German economy. Our preferred tool is a structural VAR model, in which we identify an exogenous increase in uncertainty and trace its effect on real and financial variable. The key challenge is identification. Therefore, we will discuss our approach to identification first before we introduce the model.

Figure 6: The Ukraine Uncertainty Index (inflation)



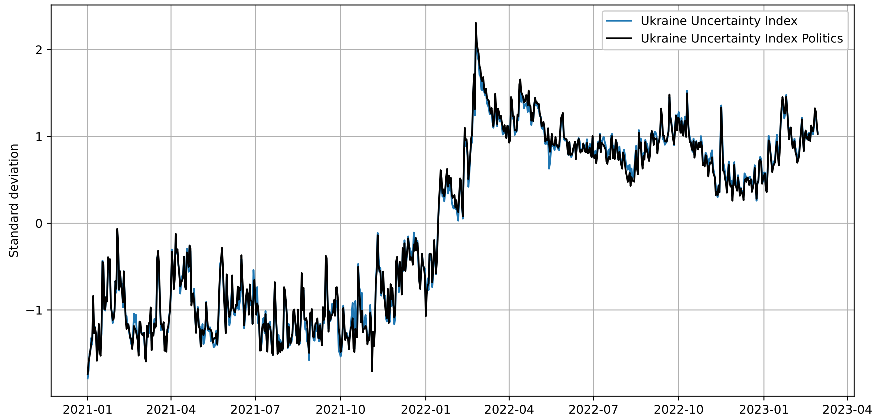
Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Inflation) derived from German tweets.

4.1 Identification and data

The previous sections provide us with daily indicators of Uncertainty about the war in Ukraine as perceived by German Twitter users. We estimate a VAR model for a vector of endogenous variables that consists of the alternative uncertainty indicators as well as economic and financial data such as a measure of economic activity, stock prices and stock market volatility. As a matter of fact, changes in uncertainty are not exogenous with respect to the state of the German economy. Real and financial variables respond to an increase in uncertainty, but at the same time uncertainty is sensitive to the state of the economy. This mutual, contemporaneous interaction requires a careful identification of exogenous variation in uncertainty.

Our identification scheme draws on the fact that Twitter is active around the clock while the financial markets are active during trading hours only. This key difference allows us to isolate variations in uncertainty that are exogenous with respect to financial variables and most forms of economic activity. Consider an increase in uncertainty over night, i.e. before the stock market opens. This increase is clearly exogenous with respect to the

Figure 7: The Ukraine Uncertainty Index (politics)



Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Politics) derived from German tweets.

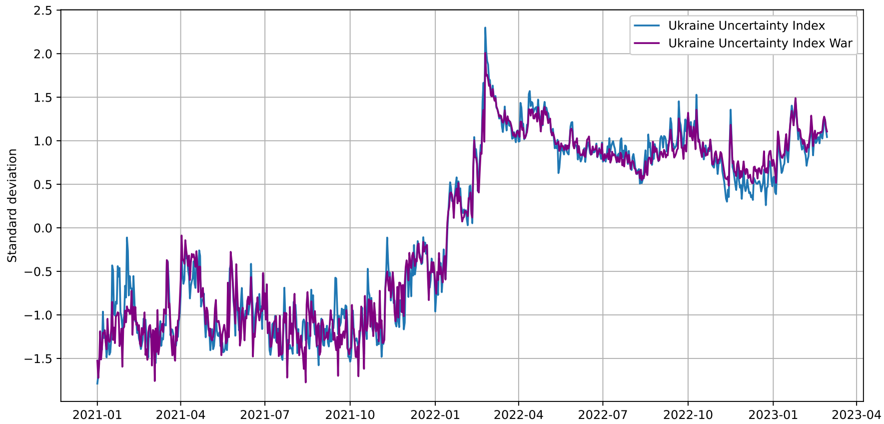
stock market opening in the morning. In contrast, consider an increase in uncertainty at noon. This could equally well drive stock prices or could itself be the result of events on the stock market. Our identifying assumption is that Twitter activity at night is exogenous with respect to financial variables and economic activity realizing during the following day.

To implement this identification scheme, we split our uncertainty indicators of type j into two parts: the first is uncertainty as reflected by Twitter activity between 05:30pm on day $t-1$ and 08:59:59am on day t. We refer to this as $unc_{t,j}^{night}$. The second part is $unc_{t,j}^{day}$ and reflects uncertainty on twitter between 09:00am and 05:29:59pm on day t. On a given day t, $unc_{t,j}^{night}$ should affect financial variables and economic activity, while the reverse effect can safely be excluded. Hence, we study the response of the endogenous variables to an increase in $unc_{t,j}^{night}$, where j indicates either the aggregate uncertainty index or one of the categories, i.e. war, sanctions, energy, migration or policy.

The vector of endogenous variables is

$$\mathrm{y}_t' = \begin{bmatrix} unc_{t,j}^{night} & unc_{t,j}^{day} & stockp_t & stockv_t & gasp_t & activity_t & infl_t^e \end{bmatrix}. \quad (2)$$

Figure 8: The Ukraine Uncertainty Index (war)



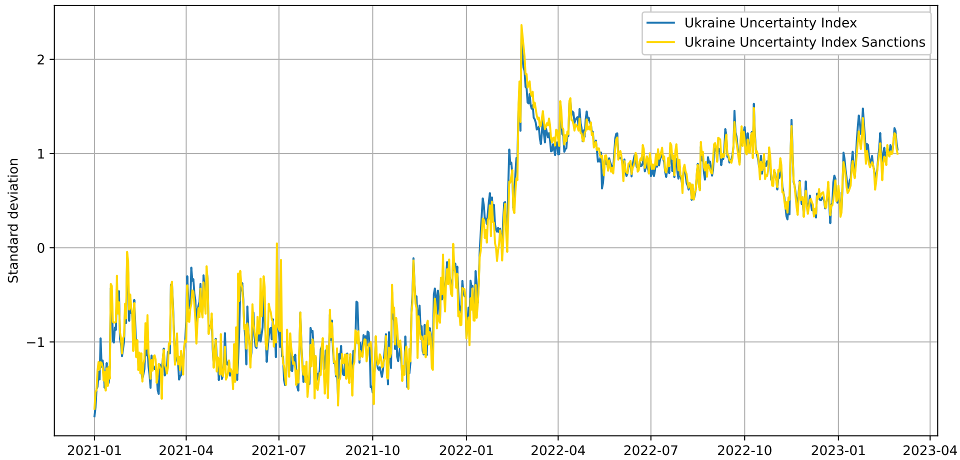
Notes: The figure shows the standardized daily Ukraine Uncertainty Index (War) derived from German tweets.

We include the log (×100) of the German stock market index DAX, $stockp_t$, the log (×100) of the volatility index (VDAX) of the German stock market, $stockv_t$, and the log (×100) of the gas price (Dutch TTF), $gasp_t$. These variables are easily available from standard data bases. In an alternative specification, we replace stock prices with German 10-year government bond yields.

We also want to include a measure of real economic activity in our VAR model. We need an activity measure at a daily frequency, which is naturally noisy. We use the weekly activity index provided by Deutsche Bundesbank, see Eraslan and Götz (2020), which is the common component of several high-frequency indicators such as electricity usage, Google search volume for "unemployment", pedestrian frequency, air pollution, credit card transactions and many more.[11] We interpolate the weekly index (seasonally adjusted and calendar adjusted) to daily frequency using the Chow-Lin procedure with the daily truck toll mileage index as a reference series. The

[11]The data is available at https://www.bundesbank.de/en/statistics/economic-activity-and-prices/weekly-activity-index/weekly-activity-index-for-the-german-economy-833976.

Figure 9: The Ukraine Uncertainty Index (sanctions)



Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Sanctions) derived from German tweets.

resulting daily index of activity is $activity_t$. In the online appendix, we depict this series as well as all other macroeconomic and financial time series used in the estimation. As an alternative to the interpolated activity indicator, we use the daily Perceived Economic Situation indicator provided by trendEcon.[12] This indicator summarizes the Google search intensities on the following keywords: "Wirtschaftskrise" (economic crisis), "Kurzarbeit" (short-term work), "arbeitslos" (unemployed) and "Insolvenz" (insolvency).

The final variable, $infl_t^e$, is expected inflation measured as the break-even inflation rate, i.e. the difference between yields on inflation-indexed and conventional German government bonds. In the baseline model, we use five-year break-even inflation rates, but will also show results for ten-year expectations. The data is retrieved from Refinitiv Datastream.

As we separated uncertainty into night and day, we can now safely impose a recursive ordering onto the endogenous variables. This implies that we restrict the contemporaneous interaction of the variables such that an

[12] See https://www.trendecon.org/.

increase in unc_t^{night} can contemporaneously impact all the remaining variables in the system, while unc_t^{night} itself responds with a lag of one day to all other variables. Consistently, we will estimate the responses of the endogenous variables to an increase in unc_t^{night}. We expect equity prices to fall, stock market volatility and gas prices to increase and economic activity to contract as a response to an increase in uncertainty. Uncertainty during the trading hours is also expected to increase following higher uncertainty the night before.

We estimate the VAR model over the sample period January 3, 2022 to February 28, 2023. All weekends are excluded. The uncertainty indicators are standardized to have a standard deviation of one over the sample period. This allows us to compare the responses of the endogenous variables to different types of uncertainty.

4.2 VAR model

Based on the 7×1 vector of endogenous variables, y_t, we estimate a VAR model with p lags

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t, \tag{3}$$

where $A_1, ..., A_p$ are 7×7 coefficient matrices. The model also includes a vector of intercept terms, which we ignore in the exposition. The vector of error terms, ε_t, follows a multivariate normal distribution, $\varepsilon_t \sim N(0, \Sigma)$, where Σ is the variance-covariance matrix with $E(\varepsilon_t \varepsilon_t') = \Sigma$. The residuals are mutually uncorrelated at all leads and lags.

We estimate the VAR model using Bayesian methods. Assuming a Normal-Wishart prior, we interpret the VAR parameters as random variables drawn from a probability distribution.[13]

As outlined in the previous section, the identification of the structural uncertainty shock is based on the exogenous variation in twitter-based uncertainty at night when the stock market is closed. This amounts to a recursive

[13] All estimations are carried out using the BEAR toolbox for MATLAB, see https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html.

identification scheme, such that we can write the model in its structural form

$$D_0 y_t = D_1 y_{t-1} + ... + D_p y_{t-p} + \eta_t, \tag{4}$$

where $\eta \sim N(0, \Gamma)$ is the vector of structural shocks and the D matrices are defined appropriately. With $D = D_0^{-1}$, the reduced-form error terms and the structural shocks are linked by $\varepsilon_t = D\eta_t$. We assume that D is lower triangular, thus imposing restrictions on the contemporaneous relationship between the variables.

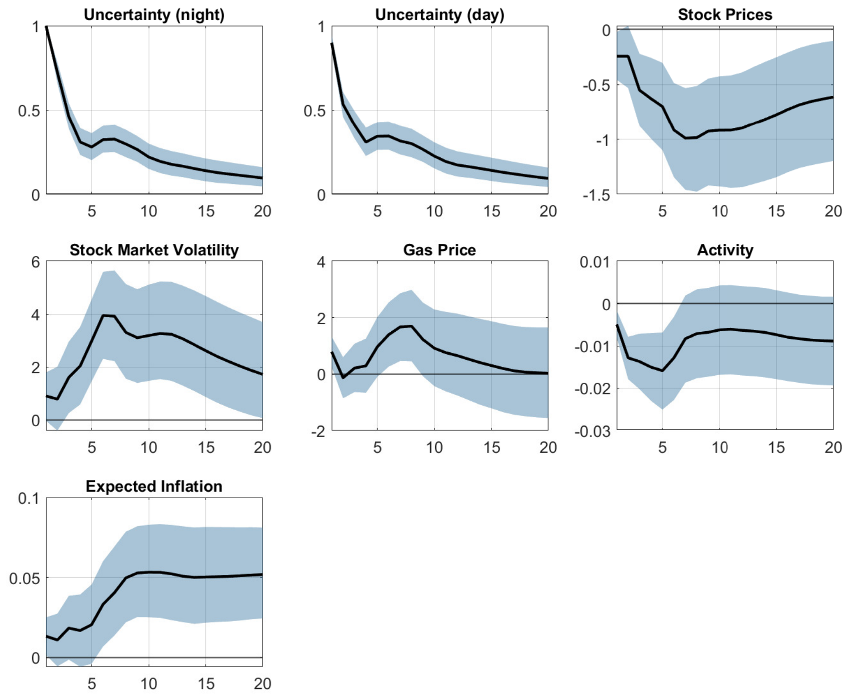
5 The effects of uncertainty

We now present the estimated impulse response functions, i.e. the responses of the endogenous variables to an exogenous increase in uncertainty outside the trading hours. The size of the uncertainty shock is one standard deviation. Each figure also shows 68% probability bands.

5.1 Baseline results

The baseline results for the aggregate uncertainty index are shown in Figure (10). A higher uncertainty at night immediately raises uncertainty at day. Both measures of uncertainty remain significantly above their mean for four weeks. The increase in uncertainty has strong and significant effects on financial markets, economic activity and expected inflation. Stock prices fall by one percent and stock market volatility increases by four percent. Both responses are highly persistent. Higher uncertainty about the war in Ukraine also increases the price of natural gas. A week after the shock, gas prices are about one to two percent higher. The daily measure of economic activity falls upon an increase in uncertainty. This drop in activity is consistent with the fall in the stock market valuation. However, the fall in economic activity is relatively short-lived. Finally, the uncertainty shock causes a persistent increase in expected inflation. Two weeks after the shock, five-year expected inflation is 0.05 percentage points higher.

Figure 10: The response to an uncertainty shock (baseline model)



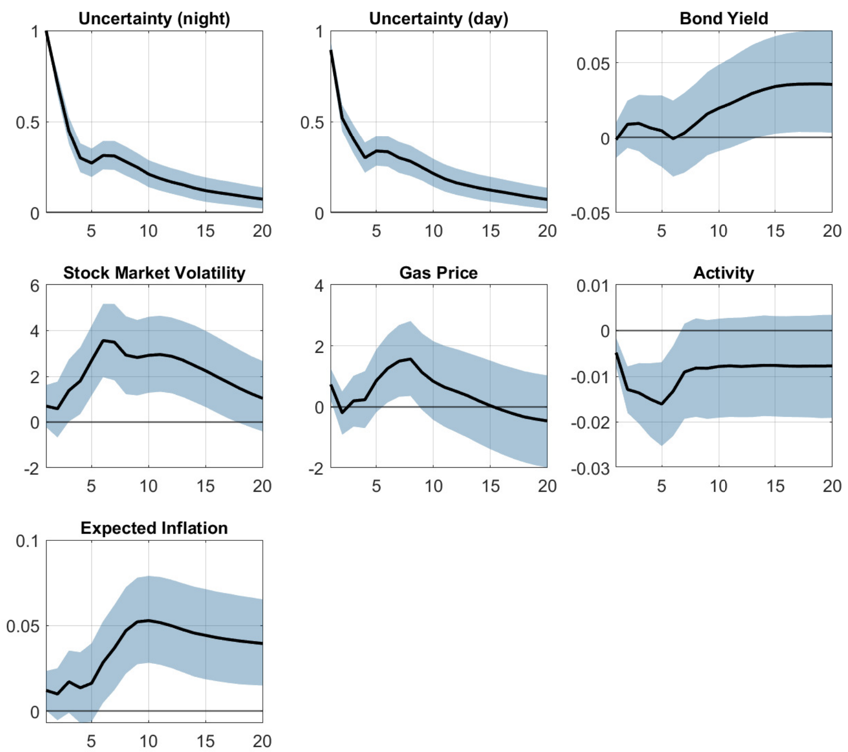
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

The responses of economic activity and break-even inflation have opposite signs. This stands in contrast to the influential work of Leduc and Liu (2016), who show that the effects of an uncertainty shock on the U.S. economy resemble those of a negative aggregate demand shock, i.e. a fall in both output and prices. In contrast, our results suggest that uncertainty about the war in Ukraine resembles an adverse aggregate supply shock.

The results for the model with ten-year bond yields are shown in Figure (11). We find that the uncertainty shock causes an increase in yields by about three basis points after three weeks. This increase in consistent with the higher expected inflation rate and also with markets' anticipation of higher financing needs of the government. All other impulse responses remain unchanged.

Figure (12) shows the effect of the uncertainty shock in a model with the economic perception indicator as a measure of real activity. The perceived situation deteriorates after an exogenous increase of uncertainty. In contrast to the baseline specification, this response is not statistically significant. All other results remain unchanged.[14]

Figure 11: The response to an uncertainty shock (with bond yields)

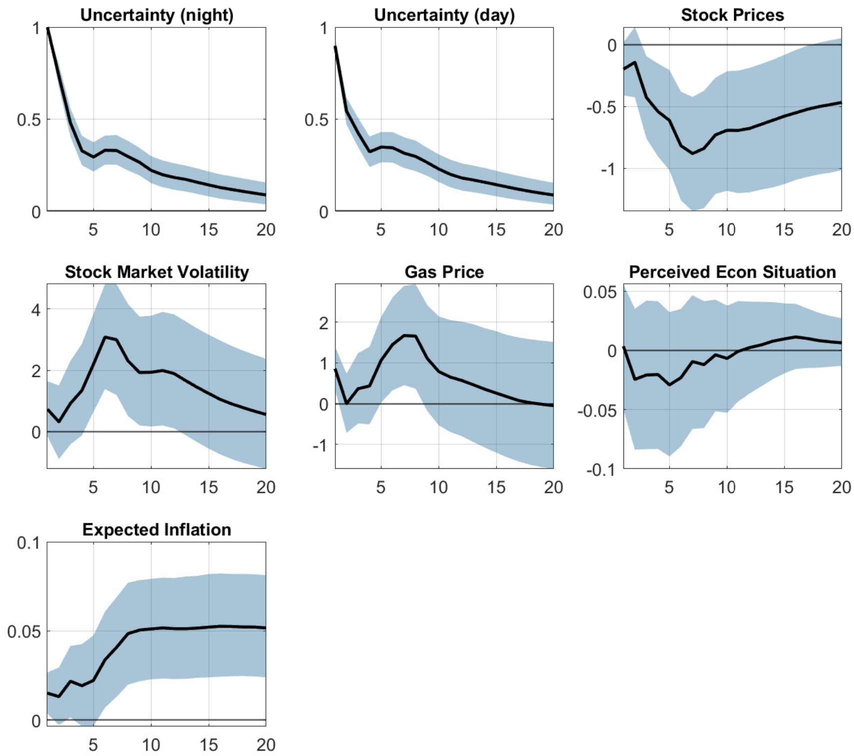


Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

[14]All results also remain unchanged if we include numerical information on the military events in Ukraine. For that purpose, we use the total number of daily fatalities available from the Ukraine Conflict Monitor at https://acleddata.com/ukraine-conflict-monitor.

The online appendix to this paper contains additional results. We show that the results remain unchanged if we replace five-year by ten-year expected inflation. We also provide a comparison of the impulse responses for models with alternative lag orders. The appendix contains responses of additional variables. We find that online job postings fall, though this response remains insignificant, that the number of tweets increases and that page views on Wikipedia for "Ukraine" and "Kiew" increase strongly after an uncertainty shock. Finally, we show the results for a VAR model estimated using least-squares rather than Bayesian methods.

Figure 12: The response to an uncertainty shock (with perceived economic situation)

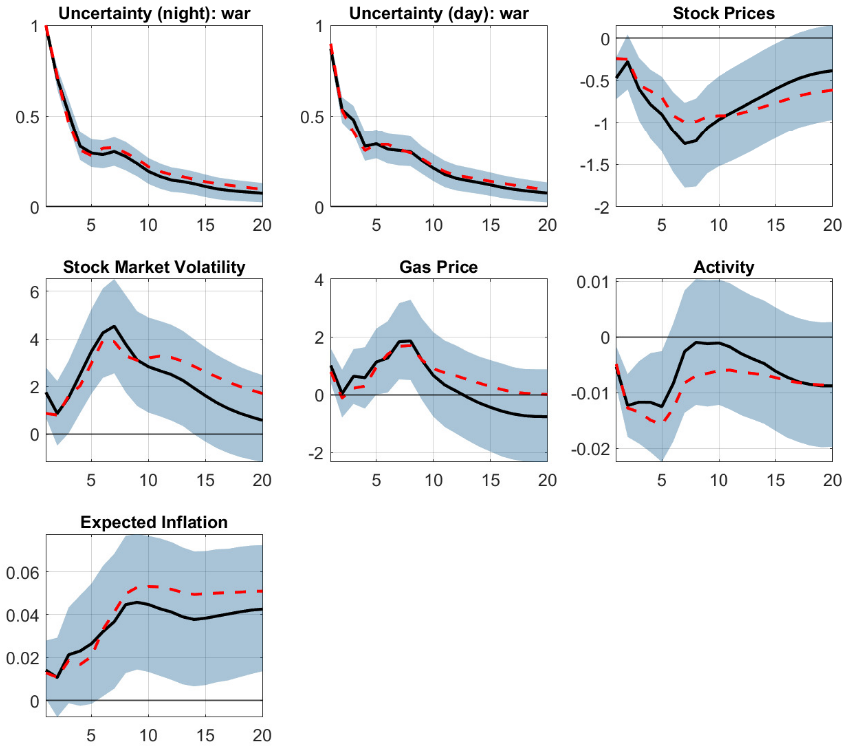


Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

We now report the effects of a shock to one of the categories of uncertainty at night, i.e. uncertainty related to war, politics, migration, sanctions, inflation or energy, on the endogenous variables. In each of the following figures, we also plot the response to aggregate uncertainty at night as a reference. It is important to remember that the categories do not reflect orthogonal dimensions of uncertainty. Rather, the different categories of uncertainty are highly correlated.

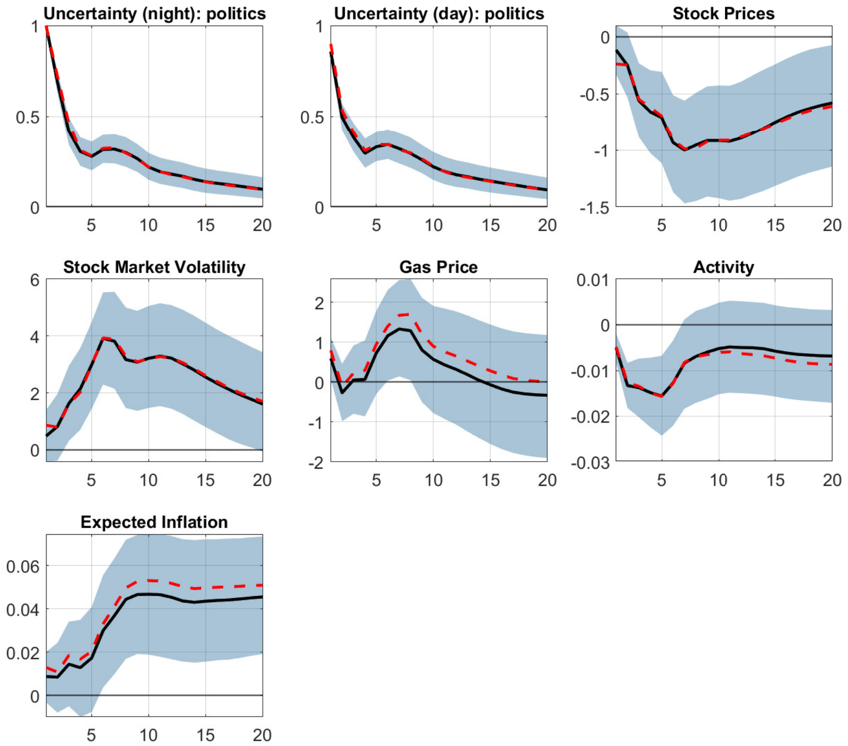
Figure (13) shows the responses to a war-related uncertainty shock. All results remain qualitatively and quantitatively unchanged. The fall of economic activity tends to be slightly smaller, but the difference with respect to the baseline responses is not statistically distinguishable. When we use politics-related uncertainty, see Figure (14), we find impulse responses that are very close to the baseline findings. This similarity does not come as a surprise since the uncertainty indicators are highly correlated. A shock to migration-related uncertainty, see Figure (15), also depresses the stock market, increases the volatility of the equity market and raises expected inflation. However, the responses of gas prices and economic activity, are no longer distinguishable from zero. Hence, this dimension of uncertainty affects financial markets, but not the real economy or inflation.

Figure 13: The response to a war-related uncertainty shock



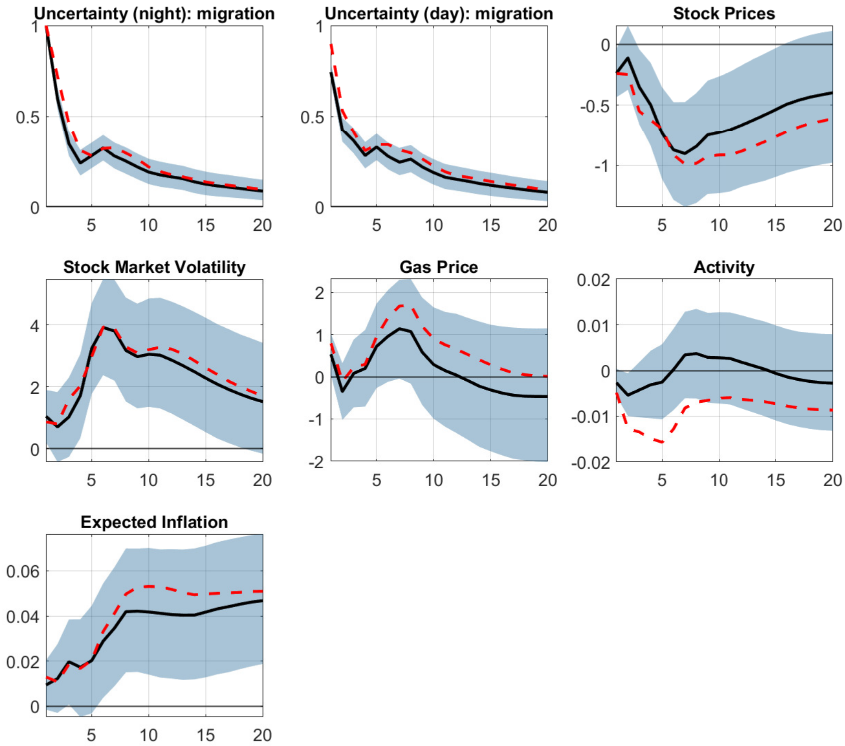
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

Figure 14: The response to a politics-related uncertainty shock



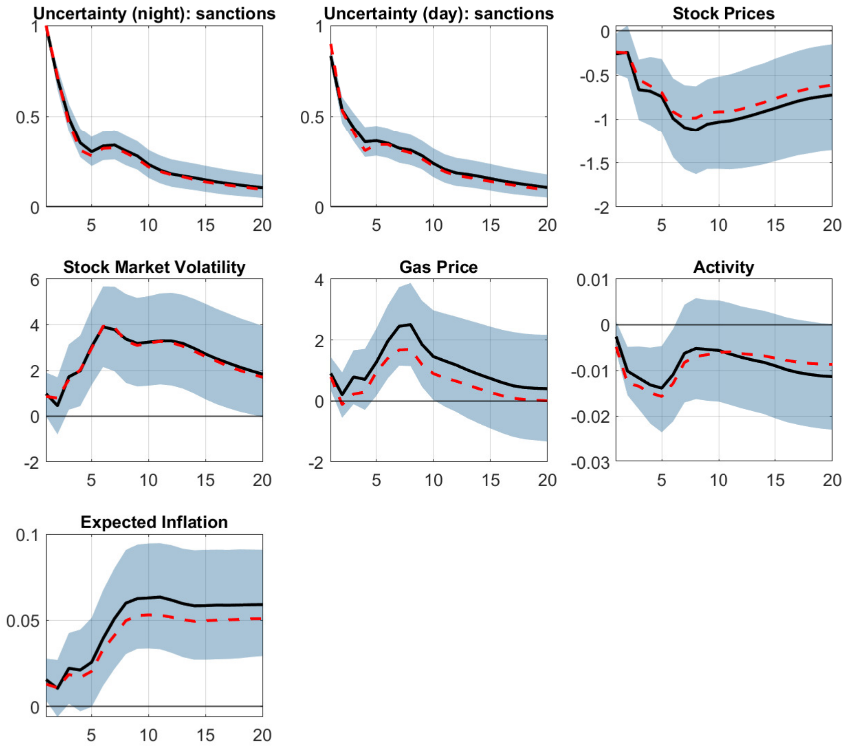
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

Figure 15: The response to a migration-related uncertainty shock



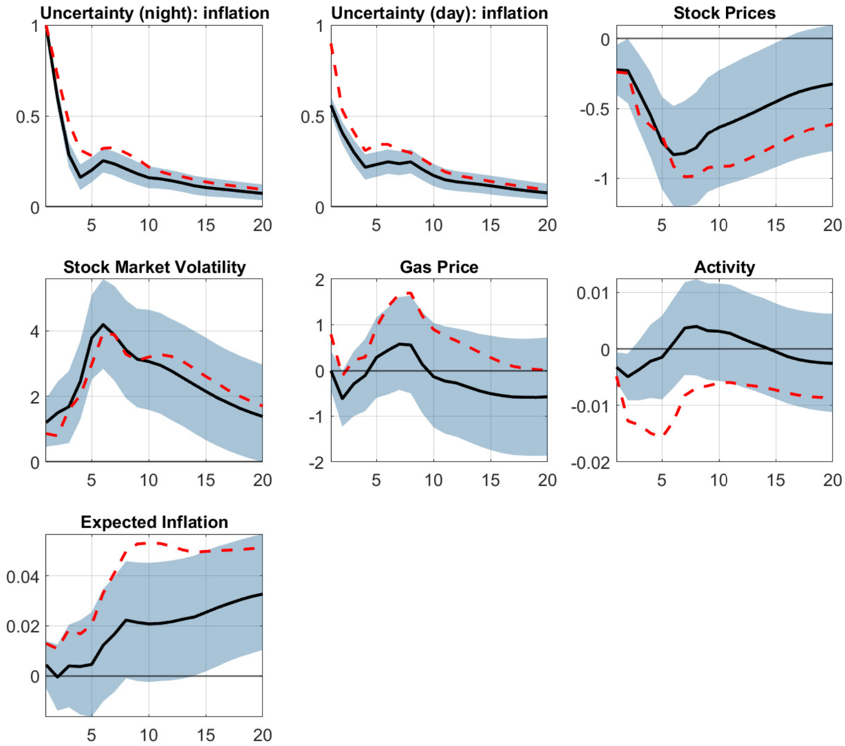
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

Figure 16: The response to a sanctions-related uncertainty shock



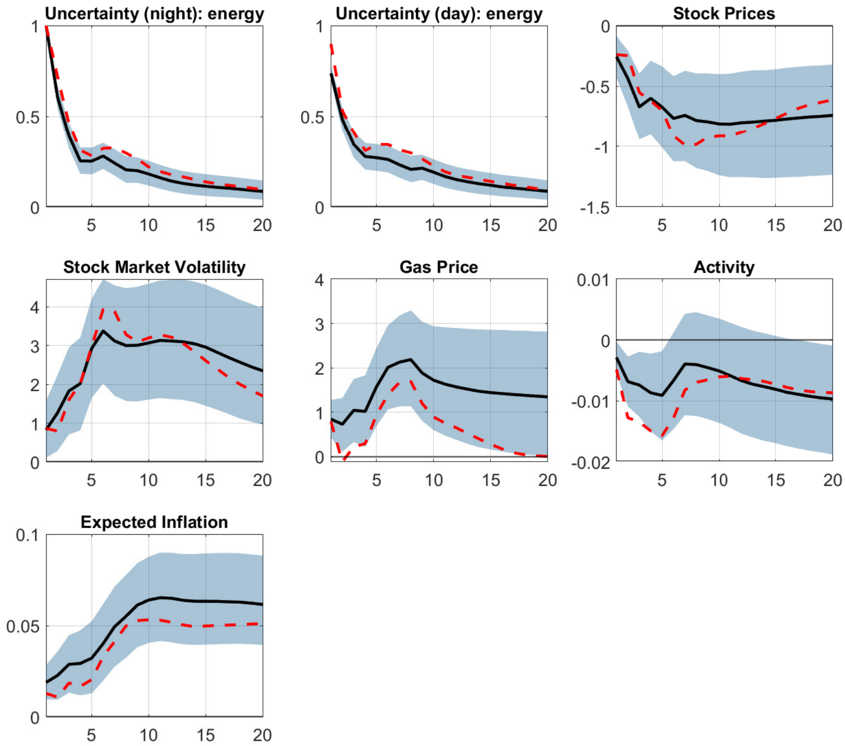
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

Figure 17: The response to an inflation-related uncertainty shock



Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

Figure 18: The response to an energy-related uncertainty shock



Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

Figure (16) depicts the responses to uncertainty related to the sanctions against Russia. Again, the results do not differ from the baseline findings. When uncertainty is related to inflation, the responses of gas prices and economic activity as shown in Figure (17) are no longer significant. Put differently, the business cycle in Germany is particularly sensitive to uncertainty related to the war unfolding in Ukraine, but less so to the indirect effects of uncertainty about war such as uncertainty about inflation or about migration. As expected, gas prices are particularly susceptible to energy-related uncertainty, whose effects are shown in Figure (18). Gas prices increase more strongly than in our baseline model. In contrast, economic activity is less responsive.

5.2 Alternative identifications

While the identification of uncertainty shocks in our baseline model rests on the distinction between Twitter posts before and during trading hours, we now pursue two alternative identifications. First, we adopt a straightforward recursive ordering with daily uncertainty ordered first. Hence, we no longer separate tweets at night from tweets at day. The results are reported in Figure (19) and are essentially unchanged compared to the baseline model.

Second, we follow Romer and Romer (2004), Coibion (2012) and Caldara and Herbst (2019), among others, and adopt a hybrid approach. Specifically, we select a number of dates with important news about the Ukraine and calculate the change in the uncertainty index on these dates. These news are all unrelated to the business cycle in Germany. Hence, changes in uncertainty on these days can be considered exogenous. We do no longer differentiate between day and night but use all tweets. Finally, we put the cumulative sum of the changes of uncertainty on these dates as the first variable in the vector of endogenous variables. Hence, the exogenous news is allowed to contemporaneously affect the remaining variables in the system. The VAR structure is needed to model the dynamic effect of the uncertainty shock. The vector of endogenous variables now is

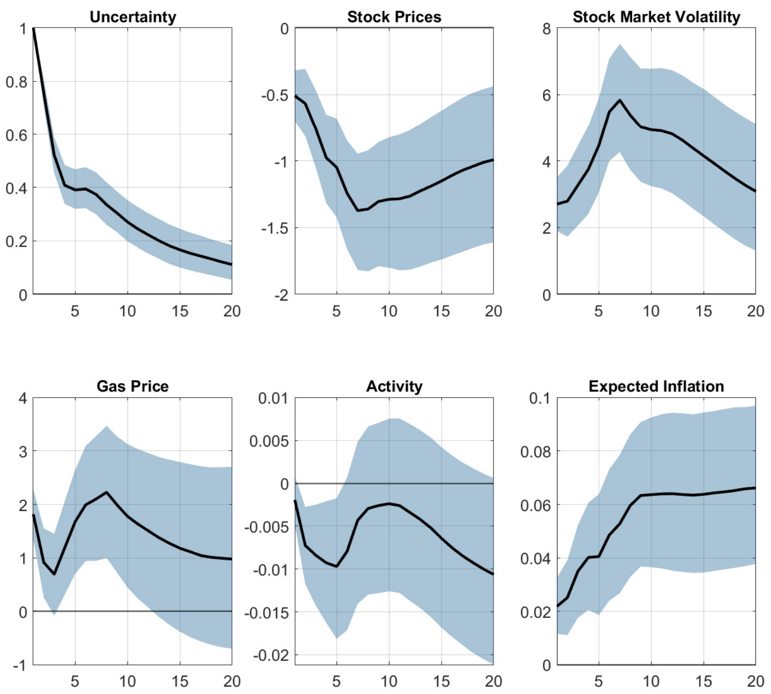
$$\mathrm{y}_t' = [\Delta^{cum} unc_t \quad unc_t \quad stockp_t \quad stockv_t \quad gasp_t \quad activity_t \quad infl_t^e]. \quad (5)$$

where $\Delta^{cum} unc_t$ is cumulative change of the main uncertainty indicator on the following days: February 11 2022 (White House warns Russian invasion of Ukraine may be imminent); February 15 2022 (Chancellor Scholz in Moscow); February 21 2022 (Russia sends troops into Eastern Ukraine); February 24 2022 (Russian invasion begins); March 24 2022 (fighting near Zaporizhzhia nuclear power plant); April 4 2022 (news about Bucha massacre emerge); April 28 (Bundestag decides to send heavy weapons); July 22 2022 (Black Sea grain deal); August 19 2022 (Gazprom announces pipeline maintenance);

September 21 2022 (Russia declares partial mobilization); November 15 2022 (misguided Ukrainian missile hits Poland); January 25 2023 (German government decides to send Leopard tanks to Ukraine); February 20 2023 (President Biden in Kyiv).

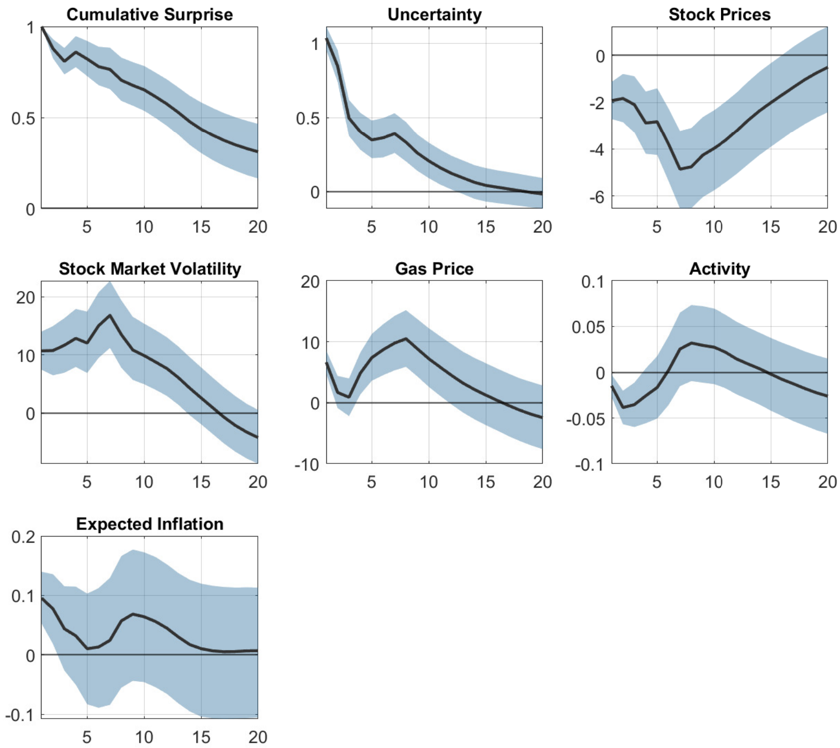
Figure (20) shows the estimated responses to an increase in $\Delta^{cum} unc_t$. The results are very similar to the baseline results. We find that higher uncertainty strongly depresses the stock index, increases stock market volatility, raises natural gas prices, causes a drop in economic activity and a higher expected rate of inflation. Hence, the effects of uncertainty are not dependent on the baseline identification scheme based on the distinction between night and day. Note that the dimensions of the responses are not comparable across identification schemes. The alternative identification is based on the most important events only, such that the magnitude of the responses is larger than in the baseline model.

Figure 19: The response to an uncertainty shock (alternative identification I)



Notes: The figure shows the responses of the endogenous variables to an uncertainty shock one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

Figure 20: The response to an uncertainty shock (alternative identification II)



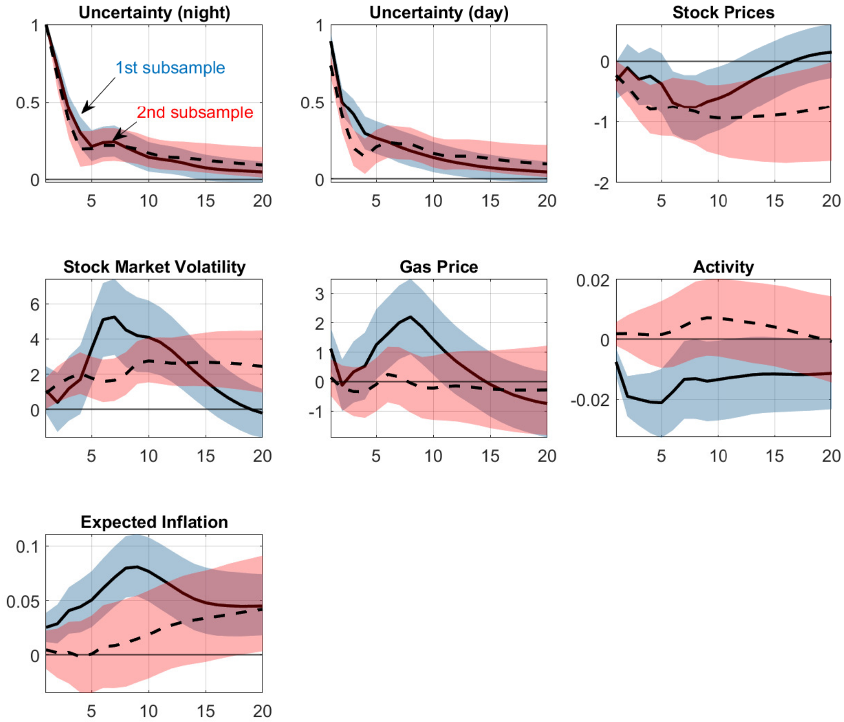
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

5.3 War fatigue?

Our sample period ends one year after the Russian invasion. It is well known that the public's attention to geopolitical events diminishes over time. We see that in the number of tweets in Figure (1), which continuously fall after the peak in February 2022. Does this "war fatigue" imply that the economy becomes less sensitive to an uncertainty shock? A given increase in uncertainty could have a smaller effect because households and firms adapted to the new geopolitical situation or because the government introduced policies in order to mitigate the consequences such as the cap on average costs of natural gas for households by the German government in October 2022.

In order to assess this question, we split the sample into two parts. The first subsample covers January 2022 to August 2022, while the second subsample covers September 2022 to February 2023. We re-estimate the baseline model over each subsample and present the resulting impulse response functions in Figure (21). The results clearly suggest that an uncertainty shock has a larger effect in the first subsample compared to the second. The increase in volatility, gas prices and expected inflation is much larger in the first subsample. In fact, gas prices and inflation expectations are no longer responding to uncertainty in the second subsample. An unexpected increase in uncertainty causes a drop in real activity in the first subsample, but not in the second. Put differently, most of responses over the full sample discussed before reflect the economic adjustment in the early months of the war in Ukraine.

Figure 21: The response to an uncertainty shock (subsamples)



Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The model is estimated for January 2022 to August 2022 (first subsample, blue) and September 2022 to February 2023 (second subsample, red). The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

6 Conclusions

The uncertainty about the war in Ukraine, in particular about its potential escalation, its duration and its long-term consequences, is a determinant of the European business cycle. This paper estimates the effect of uncertainty on Germany. We quantify the evolution of uncertainty using Twitter data. Based on more than eight million tweets, we apply a machine learning approach in order to construct alternative indices of uncertainty. In the second step, we estimate VAR models on daily data and identify an exogenous shock to uncertainty.

We find that an uncertainty shock causes a strong and persistent drop in equity valuations, a strong increase in stock market volatility, an increase in natural gas prices and inflation expectations as well as a significant fall in real economic activity. These results are robust with respect to the measurement of uncertainty and the identification of uncertainty shocks. We also find that the consequences of an uncertainty shock are particularly severe in the first six months of the war and weaker thereafter.

Our conclusions are threefold. First, activity on Twitter and potentially also on other social media channels is a useful source of information in order to learn about the evolution of uncertainty. In future work, we will further exploit the cross-section of Twitter users, i.e. how different the perceived degree of uncertainty is across accounts, in addition to the time-series dimension of average uncertainty used in this paper. Second, uncertainty about the war in Ukraine does not only cause military and political upheaval, but also leads to macroeconomic adjustments that resemble those after adverse supply shocks. This also implies that an eventual resolution of uncertainty about the war will be expansionary for the German economy. Third, our results support the broader notion that geopolitical risks in general are an important source of economic fluctuations.

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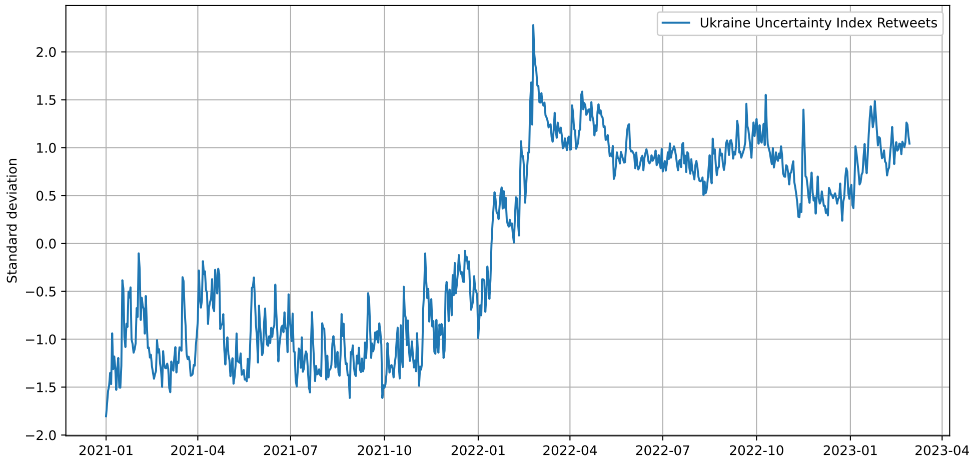
Appendices

Appendix A The role of retweets

In our construction, we assume that each tweet contributes equally to aggregate uncertainty. However, to account for the potential influence of a tweet's reach, we compute an alternative index that weights tweets based on their number of retweets. Following the methodology of Baker et al. (2021), each tweet is weighted by $(1 + \log(1 + \#retweets_i))$, where $\#retweets_i$ denotes the number of retweets of tweet i. Next, we adjust for the daily tweet count by applying equation (1).

Figure A.1: The Ukraine Uncertainty Index (weighted by retweets)



Notes: The figure shows the standardized daily Ukraine Uncertainty Index (Retweets) derived from German tweets.

Comparing this retweet-weighted index with our baseline index as illustrated in Figure (A.1), we observe only minor differences.[15] Given this minimal deviation, we derive all results from our baseline index.

[15]Similar results are obtained when using likes or the number of followers of the tweet author as alternative weighting metrics instead of retweets.

Appendix B Additional empirical results

Figure (B.2) depicts this series as well as all other macroeconomic and financial time series used in the estimation.

The series of the structural uncertainty shock estimated in the baseline model is shown in Figure (B.3). We observe particularly large realizations of the uncertainty shock around the begin of the Russian invasion in late February 2022 and in the night between November 15 and 16 2022, when the misguided Ukrainian missile hits a village in Poland.

In an alternative specification, we replace five-year expected inflation by ten-year expected inflation. The results are shown in Figure (B.4). The results are very similar to the baseline findings.

Figure (B.5) shows the estimated impulse response functions for the baseline model with eight lags and compares them to alternative models with six and four lags, respectively. For shorter lag lengths, the stock prices response becomes smaller, while the response of real economic activity becomes stronger. Most importantly, all of our results remain qualitatively unchanged.

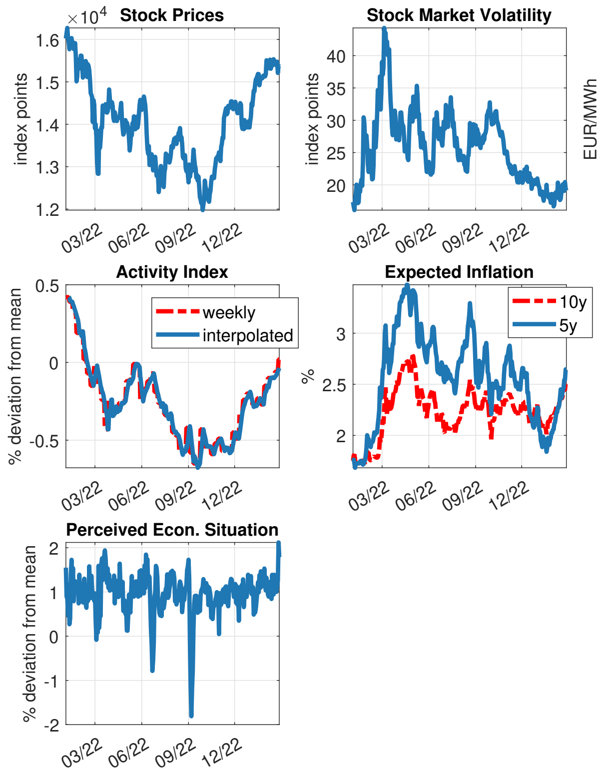
Figure (B.6) shows the responses of additional variables, i.e. the number of online job postings on indeed.com, the number of tweets in our sample and the views of the Wikipedia page on "Ukraine" and "Kiew". All four series are included in logs ($\times 100$).[16] Both Wikipedia pages are in German. We estimate the baseline model and replace the seventh variable, i.e. expected inflation, by the three alternative variables discussed here one at a time. In order to save space, we show only the responses of these additional variables. The remaining variables do not change in an important way. Job postings fall as a response to an adverse uncertainty shock. However, the fall in postings is significant only on impact. An uncertainty shock causes a strong increase in the number of German tweets on the war by about 45%. We also find a large increase in the interest in Wikipedia pages on Ukraine. Both sites, on "Ukraine" and "Kiew", experience 20% more views following an uncertainty shock.

Figure (B.7) depicts the estimated impulse response from the baseline

[16] The job postings are available at https://www.hiringlab.org/de/.

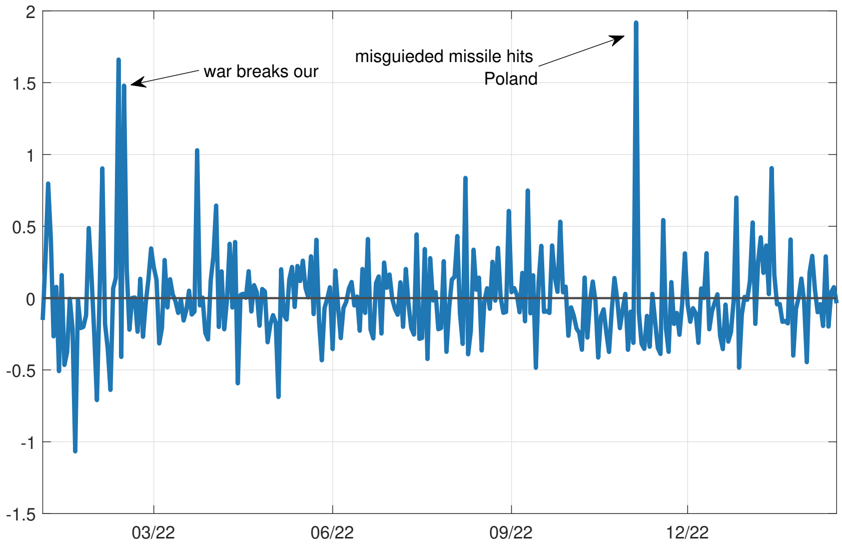
model estimated by least squares rather than Bayesian methods. We plot 90% confidence bands, which are more common in the frequentist VAR literature than the 68% bands from the Bayesian literature. All main results remain unchanged.

Figure B.2: Data series for the VAR model



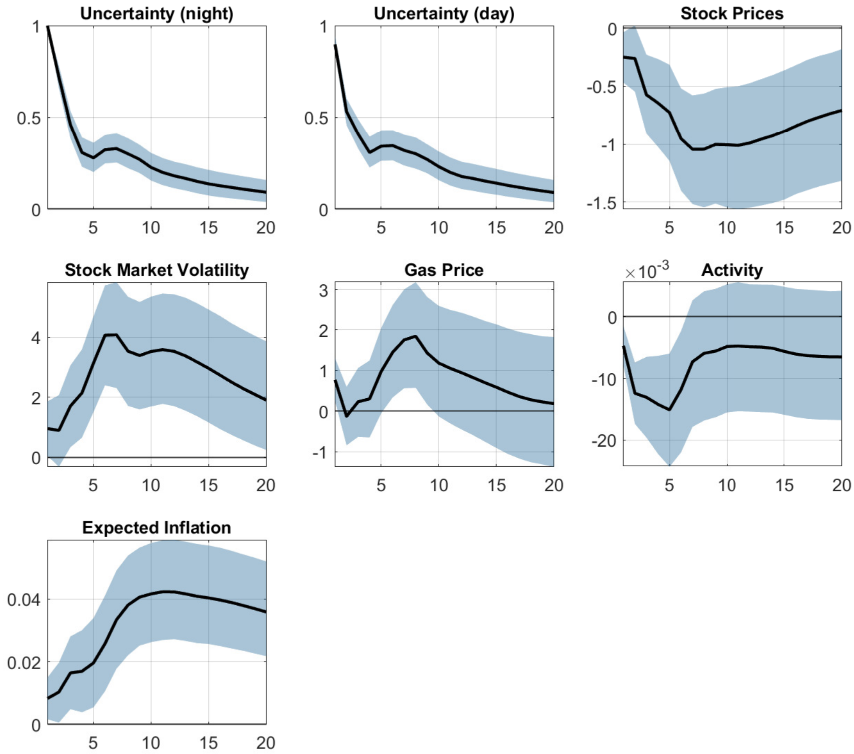
Notes: The figure shows the data series used in the estimated VAR model. The weekly activity index is interpolated to daily frequency using the Chow-Lin procedure with the daily truck toll mileage index as a reference series. All series are explained in the text.

Figure B.3: Structural uncertainty shock



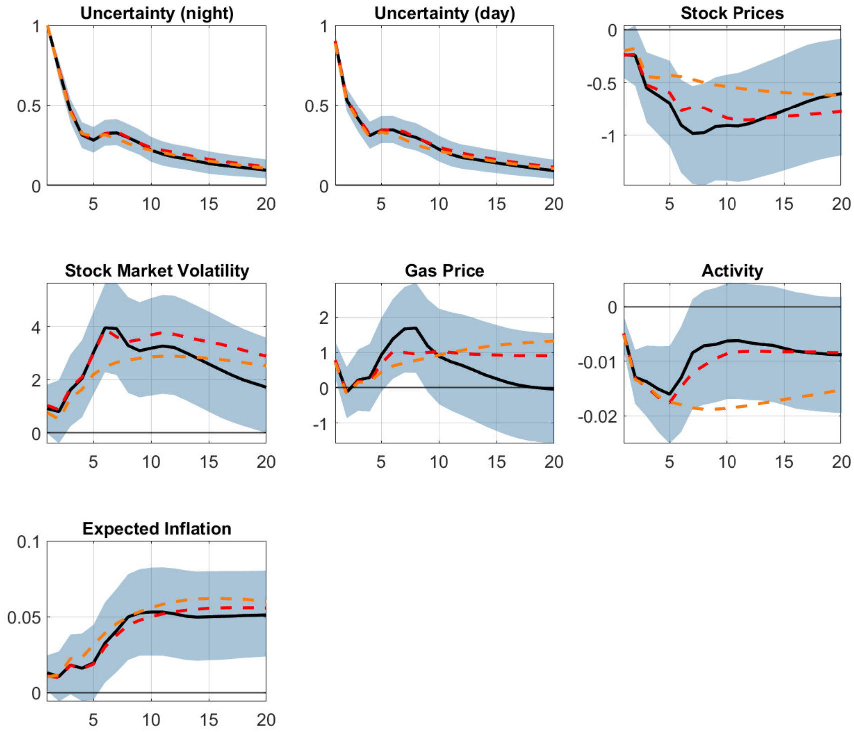
Notes: The figure shows the series of estimated structural uncertainty shocks (in standard deviations).

Figure B.4: The response to an uncertainty shock (with ten-year expected inflation)



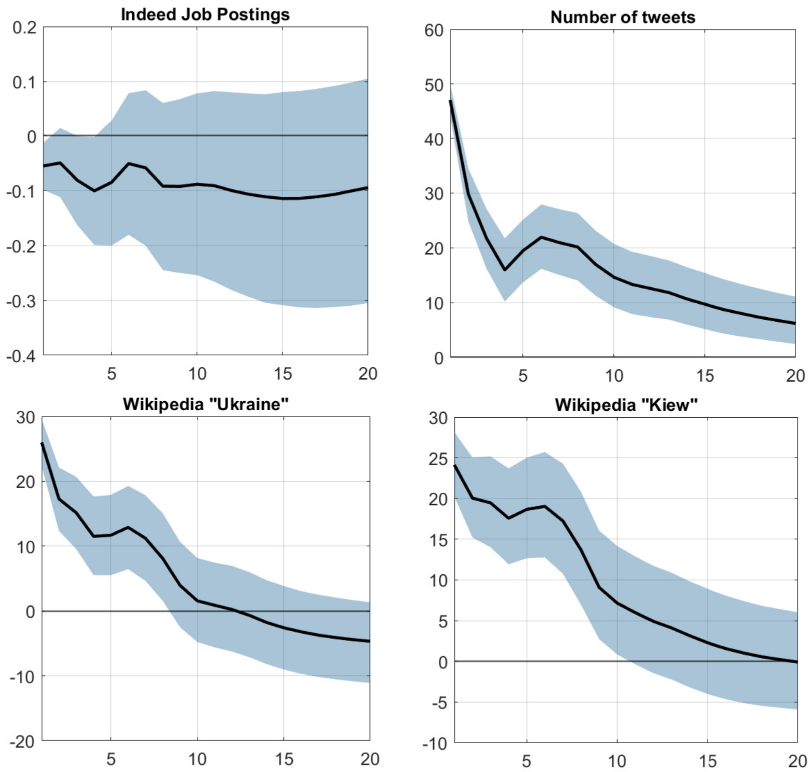
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

Figure B.5: The response to an uncertainty shock (alternative lag orders)



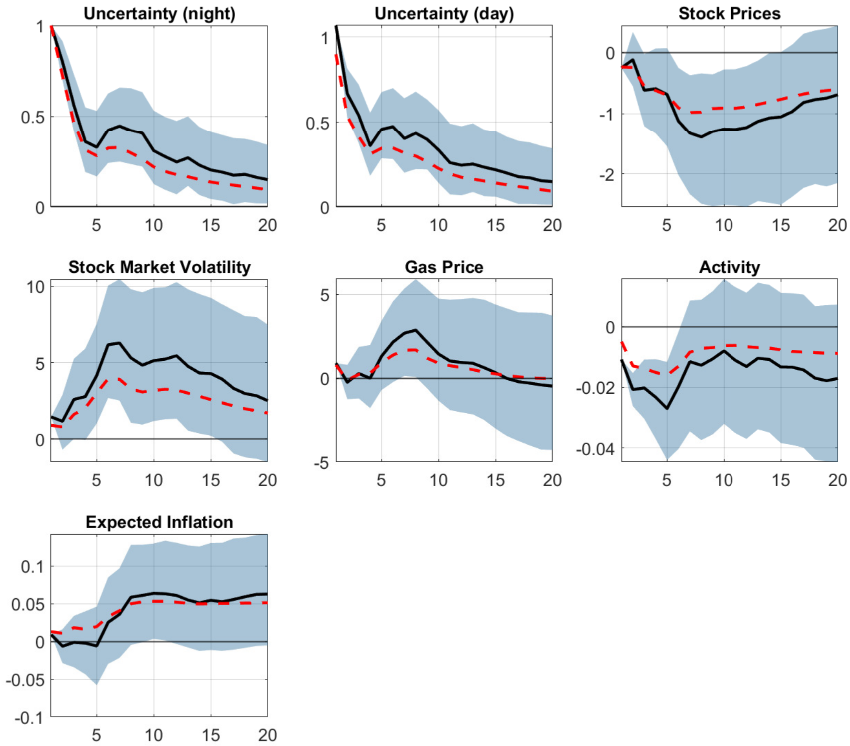
Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size for the model with eight lags (black line) and alternative models with six (red line) and four (orange line) lags. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

Figure B.6: The response to an uncertainty shock (additional variables)



Notes: The figure shows the responses of the additional variables, each used as the alternative seventh variable replacing expected inflation, to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 68% probability bands and the horizontal axis denotes days after the shock.

Figure B.7: The response to an uncertainty shock (OLS-VAR)



Notes: The figure shows the responses of the endogenous variables to an uncertainty shock at night one standard deviation in size. The shaded areas reflect 90% probability bands. The red dashed line is the response in the baseline model and the horizontal axis denotes days after the shock.

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