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Sources of Economic Policy Uncertainty in the euro area[☆]

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ABSTRACT

We create economic policy uncertainty (EPU) indicators for the four largest euro area countries by applying two unsupervised machine learning algorithms to news articles. The procedure allows to uncover components of EPU endogenously for the four European languages. The uncertainty indices computed from January 2000 to May 2019 capture episodes of regulatory change, trade tensions and financial stress. In an evaluation exercise, we use a structural vector autoregression model to study the effects of uncertainty on investment and on private consumption. We document considerable effects for the political and domestic regulation uncertainty components on investment, while the other types show heterogeneous effects across countries. For instance, trade uncertainty influences Germany's investment more than its counterparts. Moreover, we observe strong negative effects of uncertainty on consumption for countries such as Italy (political) and Spain (fiscal, political and domestic regulation).

1. Introduction

Europe has been affected by an unprecedented number of episodes of uncertainty, including the euro area sovereign debt crisis, the sanctions imposed on Russia by the European Union (EU) following the annexation of Crimea in March 2014, the Brexit vote (June 2016), or the recent disputes over global trade to name a few. These episodes have contributed to high levels of policy-related uncertainty (ambiguity regarding which and when new policies will be implemented) in the euro area. Understanding the sources and dynamics of uncertainty affecting the economy is valuable for policymakers, including central banks. Firms are particularly sensitive to uncertainty when making their investment decisions. In response to uncertainty shocks they may reduce their investment, hiring or orders from foreign intermediates, leading to a slowdown in trade and aggregate investment. In turn, consumers may react to increased uncertainty by postponing consumption and increasing precautionary savings.

The purpose of this paper is to provide a comprehensive set of uncertainty indicators and to measure the effect of the different episodes of policy-related uncertainty on consumption and investment in the euro area. Economic policy uncertainty (EPU) reflects the ambiguity regarding who will make economic policy decisions, and what and when economic policy actions will be undertaken

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(Baker et al., 2016). The overall EPU is built by aggregating different components such as fiscal policy, monetary policy and geopolitical issues, to name a few. Several studies have reported a strong negative relationship between investment and overall policy uncertainty (Baker et al., 2016; Gulen and Ion, 2015; Meinen and Röhe, 2017). However, there has not been a study that focuses on specific categories of policy uncertainty in the euro area. This is mainly due to the limitations involved in creating conventional EPU indicators.

The first contribution that this paper makes is to use a method that can consistently categorise the wide sources of economic uncertainty from the media in a wide range of languages and contexts. We derive our uncertainty indicators in two steps. First, we characterise news articles describing economic uncertainty using a continuous bag-of-words (CBOW) model that represents words as vectors based on their context. This method allows us to distinguish the words most closely related to "economy" and "uncertainty" in the context of each language, namely German, French, Italian and Spanish, and therefore to retrieve all those articles relevant to economic uncertainty for each country irrespective of language. Failing to do so would induce an increase in the number of false negatives, that is, we would not collect all the news articles relevant to economic uncertainty.

Second, we use the Latent Dirichlet Allocation (LDA) algorithm to identify relevant components of economic uncertainty. This approach uses an unsupervised machine learning algorithm that categorises news articles into specific categories of economic uncertainty. The unsupervised nature of the algorithm classifies news articles into topics without the need for previous knowledge of the themes covered in the articles. The advantage of this algorithm is that the researcher does not need to provide individual lists of keywords to define each topic, but can apply this method to uncover the structural patterns of any text endogenously. Nonetheless, the algorithm has to be given a number of topics to unveil. In order to make the decision as sound as possible, we use the log-likelihood approach to do so. For each country, we retrieve around 40 to 50 topics in total. Out of these topics, we select the ones that compose EPU.

We compare the indices produced with this approach to several existing ones. First, we compare our aggregate EPU index (the aggregation of eight individual categories) with the EPU indicator developed by Baker et al. (2016), the BBD-EPU index, for each European country under consideration. The BBD-EPU indices for the four largest euro area countries rely on a list of keywords that are an extrapolation of the ones used for the United States. Also, LDA allows endogenously (i.e. without the need to come up with ad hoc list of words) to retrieve components of policy uncertainty (monetary, fiscal, geopolitical etc.) while the BBD is an aggregated index. Despite the differences in the methodologies, we observe strong correlations in the aggregate index (since BBD-EPU does not include individual components of EPU) at the country level between the two indices (0.69 for Germany, 0.78 for France, 0.67 for Italy and 0.86 for Spain). Besides, we compare two additional indices (outside a purely EPU connotation). First, we compare a financial uncertainty index created by adding the components of finance-related topics with the Eurostoxx implied volatility index (VSTOXX). Once again, we observe a strong correlation between the two (0.61 correlation). Secondly, we compare our European trade/manufacturing index (created by adding each country's trade/manufacturing index) with the world trade uncertainty indicator created by Ahir et al. (2022).[1] Although this involves less of a one-to-one mapping (the WTU is global, while ours is European), these two items display some similarities (0.55 correlation) and have both remained at relatively high levels since the beginning of 2018.

In the second part of the paper, we investigate the effects of uncertainty on several macroeconomic variables. To assess the effect of uncertainty on the variable of interest we use the procedure of Caldara et al. (2016) which uses a penalty function to trace out the impact of uncertainty on the economy. The key idea behind the penalty function approach is that structural innovations are identified using as criterion that each shock should maximise the *impulse response* of its respective target variable over a pre-specified horizon. The identifying assumptions are more general than zero restrictions, as they allow for variables to react immediately to an uncertainty shock. We, therefore, avoid the traditional recursive (Cholesky) identification scheme, which is overly tight and depends on the ordering of the variables.

We document stronger effects on investment for two particular types of uncertainties: political and domestic regulation. This goes in line with the extensive literature that finds strong negative effects of political uncertainty on investment (see Julio and Yook (2012), Azzimonti (2018), Jens (2017), Hassan et al. (2019) and of regulatory policy uncertainty on investment (Lopez et al., 2017). Note that regulatory uncertainty does not relate to environmental policy uncertainty which is embedded under the energy uncertainty component. Energy uncertainty does display a short-lived positive sign, consistent with the idea that changes in energy regulation either by imposing carbon taxes, feed-in-tariffs, or tax incentives for energy-related R&D can encourage firms to invest in energy-efficient capital (Barradale, 2010; Reuter et al., 2012). Besides we find that German investment is particularly sensitive to trade uncertainty. This is not surprising as Germany is the biggest exporter of the euro area, and hence especially vulnerable to trade disputes.

Our analysis also includes private consumption. Using our battery of uncertainty indices, we explore a proposed channel by which uncertainty affects the real economy: the *precautionary savings* behaviour of consumers. This channel states that in order to reduce exposure related to the increase in uncertainty and to preserve a smooth consumption pattern, agents reduce consumption. We find signs of this channel for some uncertainty indicators and in some countries more than others. At the country level, for example, we observe that the effects of uncertainty shocks on consumption tend to be more pronounced in countries like Spain, in particular under uncertainty regarding domestic regulations. In Italy, private consumption reacts most to political uncertainty, while in the case of France consumption is more sensitive to European regulation and energy uncertainty.

[1] See https://www.policyuncertainty.com/wui_quarterly.html.

The rest of the paper is structured as follows: Section 2 outlines those research closer to ours in the form of a literature review. Section 3 describes the algorithms and news media data used to produce the EPU indices for Germany, France, Italy and Spain, and compares the resulting aggregate indices with the existing ones; Section 4 describes in detail the individual components that form the aggregate EPU index; Section 5 displays the empirical findings of the effect of EPU components on the real economy; Section 6 concludes.

2. Literature review

This paper relates to at least two streams of literature. The first concerns the impact of uncertainty on the real economy. There are three main channels by which policy uncertainty might influence the economic activity through business investment. The first channel is based on models of the *real option* effects of uncertainty (Bernanke, 1983; McDonald and Siegel, 1986; Dixit, 1989; Bloom, 2000). When investment is at least partially irreversible (capital can only be resold at a lower price than its original purchase price), firms only invest when demand for their products raises above some threshold level. Under uncertainty, this threshold level rises, causing a delay in investment.[2] The second channel builds from models in which uncertainty influences *financing constraints* (Gilchrist et al., 2013; Arellano et al., 2010; Byrne et al., 2016). An increase in uncertainty carries a rise in asymmetric information which in turn reduces credit access. A natural response of firms with difficult access to credit (more financially constrained) is to cut down on investment. Finally, as previously discussed, the third channel has to do with *precautionary savings* behaviour of consumers which ultimately affects firms investment (Basu and Bundick, 2017; Leduc and Liu, 2016; Fernández-Villaverde et al., 2011; Coibion et al., 2021). This latter work, Coibion et al. (2021) finds that after taking into account first moments, higher macroeconomic uncertainty induces households to significantly and persistently reduce their total monthly spending in subsequent months.

Moreover, recently developed macroeconomic models also show that uncertainty has a strong impact on the business cycle. For example, in models with heterogeneous agents, households face periods of high uncertainty in the lower part of the cycle given that uncertainty is endogenously procyclical.[3] From an empirical perspective, there has been an extensive amount of work documenting the detrimental effects of uncertainty on investment (see for example Gulen and Ion (2015), Meinen and Röhe (2017), Jens (2017), Azzimonti (2018), Ludvigson et al. (2021), Kumar et al. (2022). Kumar et al. (2022) employ a survey of firms to document exogenous variation in the macroeconomic uncertainty perceived by firms. They find that as firms become more uncertain, they reduce their prices, employment, and investment, their sales decline, and they become less likely to invest in new technologies or open new facilities.

This paper is also related to a rapidly growing body of literature on textual methods which produce quantitative measures of concepts that are normally difficult to observe. In their seminal contribution, Baker et al. (2016) use newspaper coverage frequency and simple dictionary techniques to measure EPU.[4] Tobback et al. (2017) build an indicator of the degree of “hawkishness" or “dovishness" of the media perception of the ECB’s tone using semantic orientation and support vector machine text classification. In addition, they use LDA to detect the dominant topics in the news articles. The LDA algorithm is also used by Hansen et al. (2017) to study communication patterns in the Federal Open Market Committee talks. Using simple text-mining techniques, Hassan et al. (2019) build a political risk measure as the share of firm quarterly conference calls that are devoted to the political risk for the United States.[5] Finally, Azqueta-Gavaldón (2020) uses LDA and sentiment analysis to study how narratives propagated by the media influence cryptocurrency prices.

3. Data and methods

Fig. 1 describes the process going from gathering news articles to modelling individual components of uncertainty as a time series. This is done in a few simple steps: i) collecting all news articles that contain the words “economy" and “uncertainty"; ii) extending the sample of news articles describing economic uncertainty by including those words that are closest semantically to the above two words in each language (“word2vec" algorithm); iii) running topic modelling algorithms (LDA) to unveil distinctive topics of economic uncertainty; and iv) forming the time series with these topics.

3.1. News articles containing references to economic uncertainty

The first step in creating our indices is to gather all news articles containing any form of the word “economy” and “uncertainty” (or corresponding translations of these two terms). It should be noted that the EPU index developed by Baker et al. (2016) (BBD) is created using a set of three terms: “uncertainty" or “uncertain”; “economic” or “economy”; and one of the following policy terms: “Congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation”, or “White House”. To be as broad as possible, we select all articles containing any type of the terms “economy” and “uncertainty" for the most read newspapers in each country:

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[2] Empirical evidence of capital irreversibility can be found in Ramey and Shapiro (2001). The authors show using equipment-level data from aerospace plants in the 1990’s that even after age-related depreciation is taken into account, capital sells for a substantial discount relative to the replacement cost; the more specialised the type of capital, the greater the discount.

[3] For example, in Bayer et al. (2019), there is a reduction in physical investment as a response to the decline in consumption demand caused by higher uncertainty.

[4] EPU indices have been replicated using more advanced methods (see Azqueta-Gavaldón (2017) and Saltzman and Yung (2018).

[5] To come up with political topics, they first filter political topics by correlating them to sources using a priori political vocabulary, e.g. political sciences textbooks. They then count the number of instances in which these politics-related words appear together with synonyms of “risk" or “uncertainty".

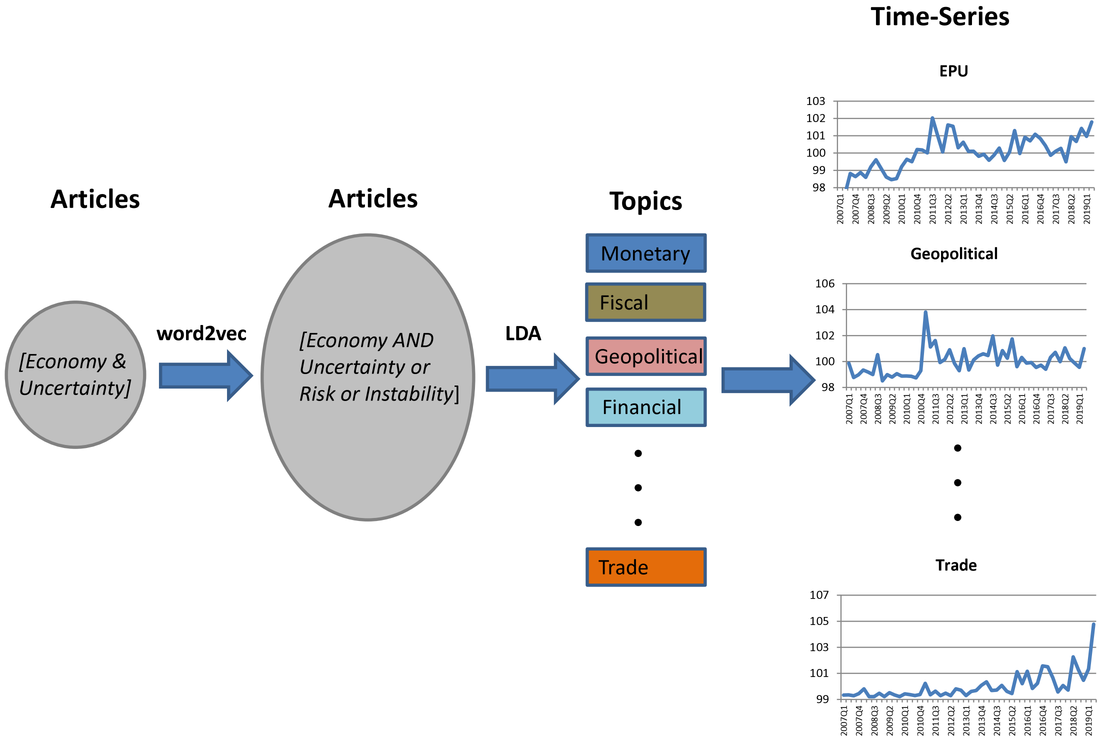

Fig. 1. From News to Time-Series. Notes: The grey circles represent the corpus, i.e. the set of all news articles; "word2vec" stands for the continuous bag of words model developed by Mikolov et al. (2013); and LDA stands for the Latent Dirichlet Allocation algorithm developed by Blei et al. (2003).

- **German newspapers:** Handelsblatt, Frankfurter Allgemeine Zeitung, Die Welt, Süddeutsche Zeitung
- **French newspapers:** Le Figaro, Le Monde
- **Italian newspapers:** Corriere della Sera, La Repubblica, La Stampa
- **Spanish newspapers:** El País, El Mundo, La Vanguardia

Table 1 displays the daily circulation of the seven to eight most read newspapers for each country considered in this analysis. All in all, this highlights that the sample used our analysis is representative of what the population in each country reads. Note that the selection of newspapers include sports newspapers and tabloids, which tend to be on top of the list. Even if we include these media outlets in the total press, our coverage (in 2019) amounts to 33% in Germany, 41% in France, 54% in Italy, and 39% in Spain.[6]

From January 2000 to May 2019, the total number of news articles containing any form of the word "economy" and "uncertainty" was 14,695 for Germany, 11,308 for France, 30,346 for Italy and 32,289 for Spain. However, while the words "economy" and "uncertainty" might be well-suited for the English language, this might not hold for other languages. For example, German has various synonyms for the word "economy" ("Wirtschaft", "Konjunktur", "Volkswirtschaft", "Ökonomie") while the word "uncertainty" ("Unsicherheit") might not map one-to-one onto the English word "uncertainty".[7] Similar complications are also likely to arise in the other languages considered here. For this reason, we need a flexible tool that can perform well in language-specific contexts in order to select all news articles that describe overall economic uncertainty.

To identify the words most similar to "economy" and "uncertainty" for each country (language) we use the continuous bag-of-words model developed by Mikolov et al. (2013), also known as the "word2vec" algorithm. Continuous bag-of-words models are based on the idea that words have similar meaning if they appear near similar words. For example, since "ECB" or "Fed" tend to appear next to words like "inflation" or "target" one would infer that the two words "ECB" and "Fed" have similar meanings. Continuous-bag-of words models represent words as vectors, with the elements in each vector measuring the frequency with which other words are mentioned nearby. Given this vector representation, two words are similar if the inner product of their vectors is

[6] If we exclude the German tabloid newspaper *Bild*, the media outlets selected for Germany in our analysis represent 91% of the seven most read newspapers in Germany. If we exclude the sport-orientated newspaper *L'Equipe* from the French sample, the percentage increases from 41% to 50%. If we exclude from the Italian sample the sport-orientated newspaper *Gazzetta dello Sport*, the percentage of the newspapers selected adds to 59% of the 6 most read Italian newspapers. Similarly, if we exclude the two newspapers from the Spanish sample, *Marca* and *As*, the percentage of the outlet selected amounts to 69% of the most 5 most read Spanish newspapers.

[7] For example, in German the word "Ungewissheit" is often used to express the idea that something is unknown.

Table 1
Average daily circulation of the seven most read newspapers in Germany, France, Italy and Spain as in 2019.

GERMANY		
Newspaper	Daily Sold Copies	Percentage
Bild	1,182,699	63.1
Sudeutsche Zeitung	279,079	**14.9**
Frankfurter Allgemeine	192,770	**10.3**
Handelsblatt	87,560	**4.7**
Die Welt	69,957	**3.7**
Taz	42,113	2.2
Neues Deutschland	19,010	1.0
Percentage of total press		**33.6**
FRANCE		
Newspaper	Daily Sold Copies	Percentage
Le Figaro	313,837	**21.3**
Le Monde	303,613	**20.6**
Le Parisen	290,355	19.7
L'Equipe	245,059	16.6
Les Echos	129,755	8.8
Aujourd'hui en France	104,061	7.1
La Croix	87,289	5.9
Percentage of total press		**41.9**
ITALY		
Newspaper	Daily Sold Copies	Percentage
Gazzetta dello Sport	3,318,000	27.8
Corriere della Sera	2,044,000	**17.1**
La Repubblica	1,883,000	**15.8**
Corriere dello Sport	1,442,000	12.1
La Stampa	1,133,000	**9.5**
Resto del Carlino	1,123,000	9.4
Il Messagero	998,000	8.4
Percentage of selected press		**54.4**
SPAIN		
Newspaper	Daily Sold Copies	Percentage
Marca	1,672,000	29.4
El Pais	1,013,000	**17.8**
As	772,000	13.6
El Mundo	671,000	**11.8**
La Vanguardia	549,000	**9.7**
La Voz de Galicia	514,000	9.0
ABC	496,000	8.7
Percentage of selected press		**39.3**

Notes: The daily number refers to the average sales of the news papers per day in 2019. Information for Germany is taken from deutschland.de (https://www.deutschland.de/en/topic/knowledge/national-newspapers) whereas the information for the rest of countries is taken from Statista.com.

large (they are used in similar contexts and phrases). In practice, two synonyms have a cosine similarity of 1, whereas two antonyms have a cosine similarity of 0.

The most well-known purpose of "word2vec" is to group the vectors of similar words together in the vector space. For example, Atalay et al. (2017) use "word2vec" to create a list of words in newspaper job advertisements. Using this method, they show that words related to non-routine tasks have been increasing in frequency, while words related to routine tasks (especially routine manual tasks) declined in frequency between 1960 and 2000. In our case, we want to retrieve the words most similar to "economy" and "uncertainty" across the four different languages. The results reveal that the closest words for "Wirtschaft" are "Konjunktur" (0.61), "Volkswirtschaft" (0.59) and "Ökonomie" (0.56) while for "Unsicherheit" they are "Verunsicherung" (0.73) and "Ungewissheit" (0.63). The number in parenthesis indicates the vector proximity which ranges from 0 (completely opposite or orthogonal) to 1 (exact synonyms).[8] These results seem reasonable, given that, as previously mentioned, "Konjunktur", "Volkswirtschaft", and "Okonomie" are straight synonyms of the word "economy", while "Ungewissheit" (unknown) is often used to refer to a situation when something is not clear and "Verunsicherung" tends to express a worrisome or a daunting outlook. To see the words retrieved for the rest of the countries, see Table 2.

[8] The results are based on the standard specification in this literature: size=150; window=10; minimum count=2; and workers=10. For the documentation, see https://radimrehurek.com/gensim/models/word2vec.html.

Table 2
Closest words to the Target word according to the *word2vec* algorithm.

Target Word	Word I	Word II	Word III
wirtschaft	(0.61) konjunktur	(0.59) volkswirtschaft	(0.56) ökonomie
unsicherheit	(0.73) verunsicherung	(0.63) ungewissheit	
économie	(0.40) conjoncture		
incertitude	(0.53) flou	(0.52) inquiétud	
economia	(0.38) congiunturali		
incertezza	(0.56) instabilitá	(0.49) preoccupazione	
economía	(0.58) economico		
incertidumbre	(0.65) inquietud	(0.55) desconfianza	

Notes: This table presents the results of the *word2vec* algorithm when finding the closest semantically words to the target word. In brackets the inner product between the target word and the words retrieved by the algorithm. The results are based on the standard specification in this literature: size=150; window=10; minimum count=2; and workers=10. For the documentation, see https://radimrehurek.com/gensim/models/word2vec.html.

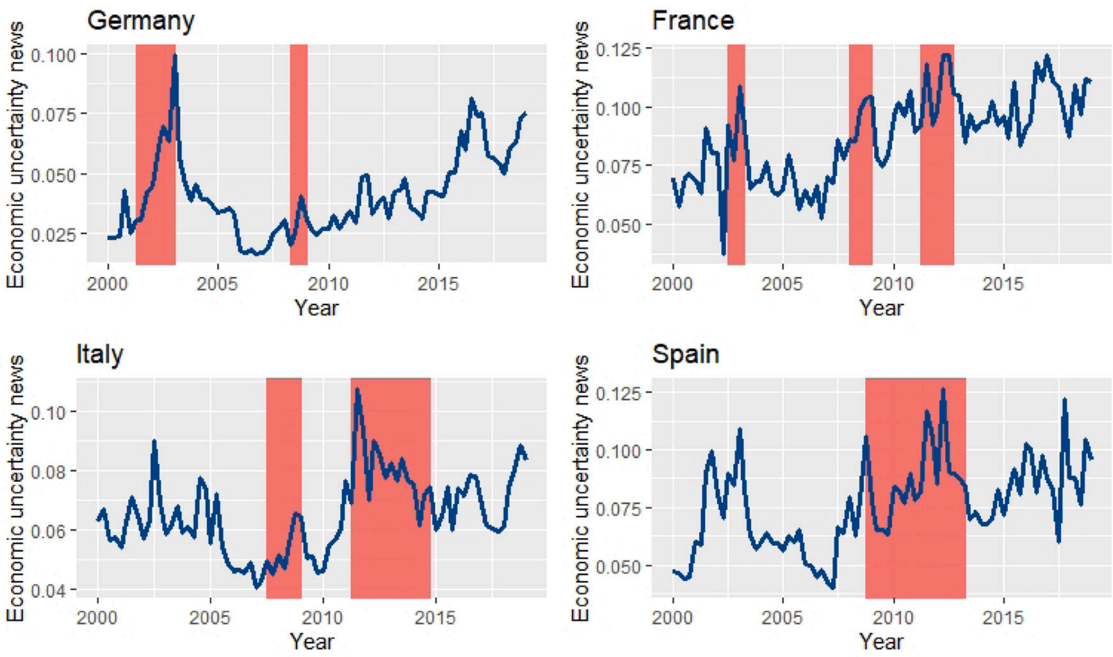

Fig. 2. Proportion of news articles describing economic uncertainty in the press (blue line) and recession bands (red bars) by country. Notes: The blue line is the ratio of the total number of news articles containing words related to "economy" and "uncertainty" over the total number of news articles containing the word "today". Recession bars in red are obtained from the Economic Cycle Research Institute (ECRI), see https://www.businesscycle.com/. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

When using the new, expanded set of keywords related to "economy" and "uncertainty" the total amount of articles increases substantially in each country: from 14,695 to 28,941 in Germany's press; from 11,308 to 31,434 for France; from 30,346 to 74,144 for Italy; and from 32,289 to 54,550 for Spain. Fig. 2 shows the monthly propagation of this set of news articles (scaled by the total number of them containing the word "today") per country and recession periods indicated by the red bars. As can be seen, the proportion of news articles describing overall economic uncertainty tends to increase during periods of negative growth rates. While not officially under recession during 2018 and 2019, Germany and France suffered from anaemic growth during these years, a period where also economic uncertainty news spiked in both countries. This highlights the fact that they are mainly capturing negative events and therefore we do not expect a high level of false positives, e.g. articles being labelled as characterising rises in economic uncertainty while actually describing falls in economic uncertainty.

3.2. Topic modelling

Before feeding all the data (raw words per document) into the LDA algorithm to obtain unique topics, we need to pre-process them. *Stopwords*, punctuation, and numbers are removed.[9] All words are converted to lower case, and each word is converted to its root in a process known as "stemming".[10]

As mentioned, in order to unveil the distinctive sources of uncertainty, we use the methodology described in Azqueta-Gavaldón (2017). This approach applies an unsupervised machine learning algorithm to all news articles describing economic uncertainty to unveil their topics. The unsupervised machine learning algorithm, called Latent Dirichlet Allocation (LDA) was developed by Blei et al. (2003). Intuitively, the algorithm assumes that each document can be described by a distribution of topics, and each topic can be described by a distribution of words. These two distributions are found in an unsupervised way, meaning that the algorithm forms these two hidden (or latent) distributions without any previous labelling of the articles or training of the model before the articles are classified.

The text is converted into a document-term matrix (DTM) which is usually a sparse matrix where each row represents a document, each column represents a term and each value will contain the number of appearances of that term within the document. As an example, in the German corpus this matrix contains 28,941 documents and 255,770 unique terms. The LDA is feeded with this document-term matrix, and the only ex-ante input needed by the algorithm is the total number of topics K to be found. Formally, within each article the probability of a word w_i is:

$$P(w_i) = \sum_{j=1}^{K} P(w_i|z_i = j)P(z_i = j) \tag{1}$$

where z_i is a latent variable indicating the topic from which the *ith* word was drawn and $P(w_i|z_i = j)$ is the probability of word w_i being drawn from topic *j*. $P(z_i = j)$ is the probability of drawing a word from topic *j* in the current article, which will vary across different articles. In other words, $P(w|z)$ indicates which words are important to a topic, whereas $P(z)$ is the frequency of those topics within an article. The algorithm maximises $P(w_i|z_i = j)$ and $P(z_i = j)$ from Eq. (1).

Direct maximisation turns out to be susceptible to problems of slow convergence or the algorithm getting stuck in local maxima (Griffiths and Steyvers, 2004). The two most common methods used to approximate the posterior distribution given by these two probabilities are sampling methods (SM) and variational methods (VM). Although SM are asymptotically exact, they are very time consuming as they rely on techniques such as the Gibbs sampler. Alternatively, VMs approximate the posterior distribution of $P(w_i|z_i = j)$ and $P(z_i = j)$ using an alternative and simpler distribution: $P(z|w)$, and associated parameters. We use an advanced type of VM called *online variational Bayes* as proposed by Hoffman et al. (2010) and the practical implementation of Rehurek and Sojka (2010).

We mentioned that the implementation of the LDA algorithm requires the number of topics K as an input parameter. To endogenize K and remove this last element of discretionarity, we maximise the likelihood of the probability of words for a different number of topics $P(w|K)$. This method commonly applied in the literature determines how plausible model parameters are given the data. For a different numbers of topics, from 10 to 80 in intervals of 10, we calculate a likelihood that the data (words) predicted by different models (with different number of topics) is the actual data (words). Let us suppose we select 10 random words of a document describing monetary policy. Given our corpus, we assess which model (different number of K) describes best the data generation process. Note that this probability cannot be directly estimated since it requires summing over all possible assignments of words to topics but can be approximated using the harmonic mean of a set of values of $P(w|z, K)$, when z is sampled from the posterior distribution (Griffiths and Steyvers, 2004). Based on this method we set K to 30 for Germany, France, and Italy, and 40 for Spain.

4. Economic policy uncertainty in the euro area

Baker et al. (2016) used eight components to produce their original EPU index for the United States: monetary policy; healthcare; national security; regulation; sovereign debt; entitlement programmes; and trade policy. Although some of these components will be common to our four euro area countries, not all will have an exact match. On the one hand, there are components that are not as relevant in Europe as in the United States. This is the case of national security and healthcare. While there has been some debate over the financing of healthcare systems in some EU countries, in particular during the sovereign debt crisis, this debate did not reach the uncertainty levels of Obama Care in the United States. In the case of the United States, healthcare was a major topic during the 2008 Democratic presidential primaries, as it was meant to affect 30 million uninsured people and went to the Supreme Court in 2012. In addition, while there have been some military interventions by EU states, these did not reach the engagement levels of the United States.

There are also policy-related events that are unique to EU-countries and are not present in the United States. This is the case of political referendums, such as the Brexit vote or the illegal Catalan referendum for independence, which have greatly contributed to policy uncertainty but do not match any of the eight components described by Baker et al. (2016). Further differences arise from

[9] *Stopwords* are words that do not contain informative details about an article, e.g., "that" or "me". Note that the list of stopwords is language-specific. We use the *NLTK* library, see www.nltk.org/.

[10] Stemming is language-specific and to carry it out, we use the *SnowballStemmer*: https://www.nltk.org/modules/nltk/stem/snowball.html.

Table 3
Most relevant words representing given by the LDA for each component.

	Germany Articles = 28,941	France Articles = 31,434	Italy Articles = 74,144	Spain Articles = 54,550
Monetary	ezb, notenbank, geldpolit, prozent, zentralbank, fed, europa, euro, stark, zins, inflation, draghi	taux, économ, euro, monétair, bce, banqu, inflat, baiss, ralent, croissanc	banc, bce, spread, monetar, deb, drag, tass, central, eurozon, titol, inflazion	tipos, bce, monetaria, inflación, draghi, euro, interés, banco, economía
Fiscal	rent, riest, gewerkschaft, arbeitgeb, hartz, iv, metall, ig, tarifvertrag, zeitarbeit	fiscal, impôt, dépens, financ, budget, milliard, tax, retrait, défic, publiqu, réform, prélev	fiscal, manovr, bilanc, pubblic, spes, tagl, deficit, padoan, commission	gobierno, ley, medidas, pensiones, fiscal, reforma, impuestos, presupuestos, déficit
Political	spd, cdu, merkel, koalition, grun, csu, fdp, kanzlerin, schaubl, partei, minist	ministr, président, sarkozy, gouvern, chef, franc, macron, réform, elys	renz, pd, salvin, premier, vot, part, elettoral, leg, polit, palazz, president, leghist	pp, rajoy, psoe, cataluña, partido, elecciones, voto, gobierno, presidente
Geopolitical	russland, russisch, iran, ukrain, putin, sanktion, syri, israel, iran, arabi, krim, irak, barrel, konflikt	militair, iran, armé, arab, iranien, syr, turqu, sécur, irak, guerr, terror, immigr, migr, réfugi, russ, ukrain	terror, lib, sir, iran, arab, iraq, guerr, militar, russ, cines, sanzion, jihad, saud, tunis, sunn, curd	irán, siria, turquía, saudí, guerra, ejército, irak, militar, arabia, refugiados, islámico
Trade / Manufacturing	china, usa, global, trump, weltwirtschaft, zoll, strafzoll, iwf, weltweit, import, protektionismus	produit, agricultur, commerc, lait, viand, omg, industriel, export, producteur, automobile, véhicul, psa	trump, aut, fiat, diesel, automobilist, produtt, industr, settor, export, competit, pmi, manifattur, merc, paes	china, rusia, mundial, pekín, aranceles, comercio, unidos, comerciales, ventas, diésel, fabricantes, seat
European Regulation	eu, brexit, britisch, london, pfund, austritt, brussel, binnenmarkt, votum, parlament, komission	européen, europ, union, ue, brex, grec, bruxel, britainn, allemagn, pay, irland, euro, commiss, referendum, zon	europe, ue, german, tedesc, union, grec, merkel, migrant, bruxelles, brexit, vot, referendum, popul, part	europea, ue, bruselas, grecia, unión, comisión, comunitario, eurozona, socios, brexit, referéndum
Domestic Regulation	regier, kommission, nutzungsrecht, schaubl, rechststaat, justiz, dat, kund, internet, ausbild, fluchtling, arbeit	syndicat, text, cgt, salari, syndical, tribunal, jurid, commiss, emploi, enterpris, travail, embauch	pag, pension, red, gentilon, univers, pdl, scuol, sindac, contratt, sindacal, lavor, sentenz, tribunal	justicia, tribunal, supremo, deuda, bancos, crisis, rescate, laboral, sindicatos, ugt, universidades
Energy	energi, strom, gas, erneuerbar, klimaschutz, rwe, bio, offshor	énerg, électr, edf, gaz, nucléair, pétroli, baril, réacteur, carbon, alstom	ambiental, carbon, energ, climat, elettr, inquin, petrol, gas, baril, petrolifer	energía, climático, emisiones, carbón, gases, electricidad, contaminación

the fact that in the case of the EU, there are policies at the European Union level (e.g. monetary policy), at the individual country level (e.g. military interventions) and at both the EU and country levels (e.g. fiscal policies in the context of the EU Stability and Growth Pact).

Our aim is to select those topics that best describe sources of policy uncertainty in the European context. We then select those components that best suit the European context: fiscal; monetary; political; geopolitical; trade/manufacturing; European regulation; domestic regulation; and energy. As can be seen in Table 3, with the words that the LDA algorithm gives we can easily label each component/topic. For example, the political topic is framed by words such as "ministry", "president" or names of heads of states, while the monetary policy topic contains words such as "ECB", "inflation" and "central bank".

In addition, we observe some interesting differences across countries regarding the stance taken on specific topics. For example, in 2014 the words describing the geopolitical component are heavily tuned towards the Russian annexation of Crimea in the case of Germany, France and Italy, but not in the case of Spain; words relating to Russian-EU tensions such as "Russia", "sanctions" and "Ukraine" appear in all geopolitical indices except in the Spanish one. This is not entirely surprising since the three largest euro area economies (Germany, France and Italy) experienced the highest export losses with Russia in absolute terms as a consequence of the sanctions imposed by the EU (as until 2019). In addition, Germany and Italy are very dependent on Russian gas. On the other hand, the words in the fiscal component relate to pension and labour reform in the case of Germany (e.g. "Tarifvertrag" meaning collective agreement or "Rente" meaning pension) while for the rest of countries they also include budgetary terms (e.g. "deficit").

To form the aggregate EPU time series at the country level, we follow two simple steps. First, we sum the topic proportions of these five components by month. This gives us a raw aggregation of the fraction of news articles describing EPU per country. Second, we normalise topics by the volume of news published in the period by dividing each raw aggregation by the total number of news articles containing the word "today". Fig. 3 shows the quarterly EPU indices computed for the four largest economies in the euro area (blue line) and the BBD-EPU index obtained by Baker et al. (2016) (red line). Overall, the time series produced by grouping the EPU topics retrieved by the LDA algorithm and the BBD-EPU indices are fairly similar (correlations of 0.69 for Germany, 0.78 for France, 0.67 for Italy and 0.86 for Spain).

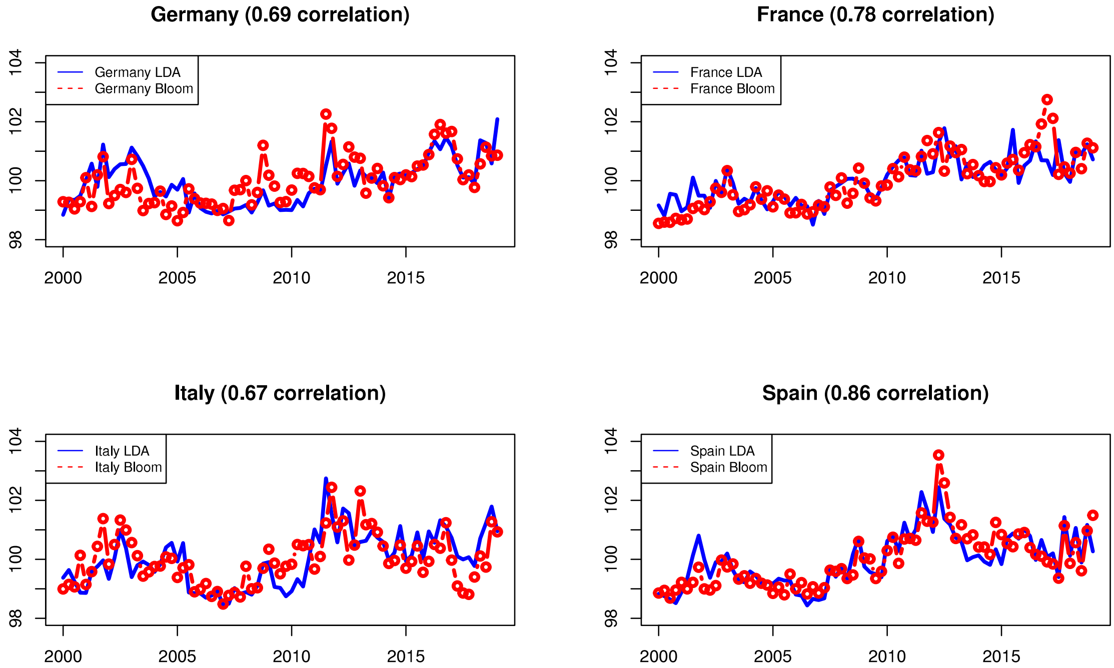

Fig. 3. Evolution of EPU indices produced using LDA and Bloom's EPU indices for the four biggest EU economies. Notes: Quarterly time series for the period Q1:2000–Q1:2019. Each time series is normalised to mean 100 and 1 standard deviation. BBD-EPU indices are obtained from http://www.policyuncertainty.com.

There are three particular episodes where EPU picked up in the four major euro area economies. The first peak occurred in the first quarter of 2003 with the invasion of Iraq. The second peak corresponds to the European sovereign debt crisis between 2010 and 2012 when the risk premiums of several EU countries reached historically high levels. Finally, the third peak is found around the Brexit vote in the third quarter of 2016. For Germany and France we find high uncertainty peaks during and after the Brexit referendum. This is not entirely surprising since these two countries have stronger trade linkages with the United Kingdom.[11] For Italy and Spain, the EPU indices display the highest level during the sovereign debt crisis, in particular when the Spanish government requested financial assistance to recapitalise its banking sector (third quarter of 2012), and when the financial turmoil led to a sharp increase in Italian spread and to the resignation of Berlusconi in favour of the technocrat Mario Monti in Italy (fourth quarter of 2011). For a detailed description and visualisation of the individual components of EPU by country please the Online Appendix.

5. EPU and economic activity

This section focuses on identifying the effect of different types of uncertainty on business investment and consumption through the lenses of a VAR model. Throughout the analysis, we use a Bayesian estimation approach with standard, uninformative priors as proposed by Jeffrey.[12] The Bayesian approach allows a sufficient number of variables and lags to be included in the model without the risk of overfitting, while remaining relatively agnostic about the relationship between the variables.

Empirically, it is unclear whether uncertainty is an exogeneous source of business cycle fluctuations or an endogeneous response to them (see Ludvigson et al. (2021)). Moreover, theoretical work is ambiguous on the sign of the relationship between uncertainty and the business cycle.[13] For these reasons, we want to identify the uncertainty shock by using minimal restrictions, to minimise the probability of imposing wrong restrictions and misspecification. We therefore avoid the traditional recursive (Cholesky) identification scheme, which is overly tight and depends on the ordering of variables (see, for example Baker et al. (2016)). We follow instead the procedure of Caldara et al. (2016) and use a penalty function approach to trace out the impact of uncertainty on the economy.[14]

The penalty function approach dates back to Faust (1998) and Uhlig (2005) which examine the interactions of economic uncertainty and financial conditions in order to trace out the impact of associated shocks on the macroeconomy. The key idea

[11] For example, UK imports in 2016 totalled £75.1bn with Germany, £37.6bn with France, £28.0bn with Spain, and £22.6bn with Italy. See https://www.ons.gov.uk/businessindustryandtrade/internationaltrade/articles/whodoestheuktradewith/2017-02-21.

[12] A robustness check using priors in the spirit of Litterman (1986) leads to very similar results.

[13] For example the *growth option* theory states that firms will actually increase investment as a response to uncertainty (see Bar-Ilan and Strange (1996) and Pástor and Veronesi (2006)).

[14] We thank the Editor and an anonymous Referee for suggesting this identification procedure. The Cholesky scheme is computed for robustness and reported in the online Appendix.

behind this approach is that within the SVAR framework, structural innovations are identified using the criterion that each shock should maximise the *impulse response* of its respective target variable over a pre-specified horizon. The identifying assumptions are more general than zero restrictions, as they allow for variables to react immediately to an uncertainty shock.

In the original contribution, this identification scheme is used to achieve a sequential identification of two shocks: uncertainty and financial shocks. In our case, we only want to identify the uncertainty shock. Therefore, we search for an identification scheme such that the structural "uncertainty shock" maximises the response of the uncertainty indicator over a given horizon. Following Caldara et al. (2016), we maximise the effect of the uncertainty shock on the uncertainty indicator as follows. Consider $IRF_Q(s, v, h)$, the Impulse Response Function of shock s on variable v at horizon t. These impulse responses depend on the identification matrix Q. Assuming that the uncertainty indicator is ordered first, we chose Q so that

$$Q = \arg\max_{Q} \sum_{h=0}^{5} IRF_Q(s_1, v_1, h) \tag{2}$$

After choosing Q, the identified "uncertainty shock" (s_1) has maximum cumulative effect on the uncertainty indicator (v_1) after six periods, for instance. The other shocks are left unidentified. We emphasise again that this identification scheme is independent on the ordering of the variables.

The variables that we include in the model are the natural logarithm of EPU, the natural logarithm of the stock market index, the shadow short term interest rate (SSR) for the euro area[15], the natural logarithm of real investment in machinery and equipment as a proxy for business investment and the natural logarithm of real GDP. Including the stock market index mitigates concerns of endogeneity because stock markets are forward-looking and stock prices react to all sources of information (Baker et al., 2016). The data for each stock market index comes from Datastream, while the rest of the data is obtained from Eurostat.[16]

5.1. Uncertainty and investment

Fig. 4 displays the impulse responses of investment in machinery and equipment for the euro area to shocks in the different EPU components. Note that the aggregate index at the euro area level is the GDP weighted sum of the different country components. For example, to obtain the euro area monetary policy uncertainty index, we aggregate the monetary policy uncertainty indices of the four countries. Similarly, we construct aggregate indices for the eight components and the aggregate EPU index.

Overall, we observe a strong and significant impact of increases in EPU uncertainty on business investment in the euro area. This significant negative impact lasts around four quarters and rebounds after the fifth quarter. This is consistent with the idea that once uncertainty is resolved, firms increase investments to satisfy pent-up demand (Gulen and Ion (2015)). In addition, two uncertainty indicators distinguish themselves for having a stronger detrimental effect on investment as compared to the others. These are political and domestic regulation uncertainties. The negative impact of political uncertainty on investment has been extensively documented (see Julio and Yook (2012), Azzimonti (2018), Jens (2017), Hassan et al. (2019)). These studies find that increases in political risk/uncertainty are associated with significant increases in firm-specific stock return volatility as well as with significant decreases in firms' investment, planned capital expenditures, and hiring. Hence, we can expect reductions in investment at the aggregate level. Besides, there are also studies connecting regulatory uncertainty to investment (see for example Lopez et al. (2017)). Domestic regulation captures events such as labour reforms, banking regulation and fiscal adjustments while environmental regulation would be framed under the energy component.[17] This latter component, energy uncertainty, displays a short-lived positive sign. This is consistent with the idea that changes in energy regulation either by imposing carbon taxes, feed-in-tariffs, or tax incentives for energy related R&D can encourage firms to invest in energy-efficient capital (Barradale, 2010; Reuter et al., 2012).

The relationships between uncertainty and investment at the aggregate level might be heterogeneous at the country level. For this reason, we run the same VAR exercise at the country level. Figures 6, 7, 8 and 9 in the Appendix show the impulse response functions (IRFs) for each EPU component (including aggregate EPU) for Germany, France, Italy and Spain. Just as before we also display the IRF with the BBD index.[18] Altogether, the responses of investment to overall policy uncertainty are negative. However, the impact and significance of our index seems higher than the BBD-EPU indices for all countries except for Italy. Considering that the measurement of uncertainty is not an objective per se, but is only useful to the extent that it is meaningful to predict economic developments, we take the higher significance as suggesting that our method provides value added when constructing uncertainty indices. In addition, our methodology allows examining which particular uncertainty shocks play a more important role on investment.

The particular strong effect of political and domestic regulation on investment and consumption repeats itself at the country level. Nonetheless, there are certain uncertainty types that affect some countries more than others. For example, trade uncertainty matters

[15] Following the common practice in the literature, we use the shadow short rate (SSR) (see Meinen and Röhe (2017)). The SSR aims to measure the accommodation in monetary policy when the short rate is at the zero lower bound (ZLB). The SSR is obtained from Leo Krippner's website at the https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures.

[16] Alternatively, we could have implemented the variables in first differences. Nonetheless, since GDP and investment are likely to be cointegrated, this would result in a misspecification of the model (see Sims et al. (1990)). We thank the Editor and an anonymous Referee for highlighting the issue and providing a reference.

[17] For example, we can see words such as "klimaschutz" (climate protection), "ambiental" (envirment), "climatico" (climate), or "contaminacion" (pollution) in the energy uncertainty component.

[18] Note that for Spain, we use the original uncertainty index: https://www.policyuncertainty.com/europe_monthly.html.

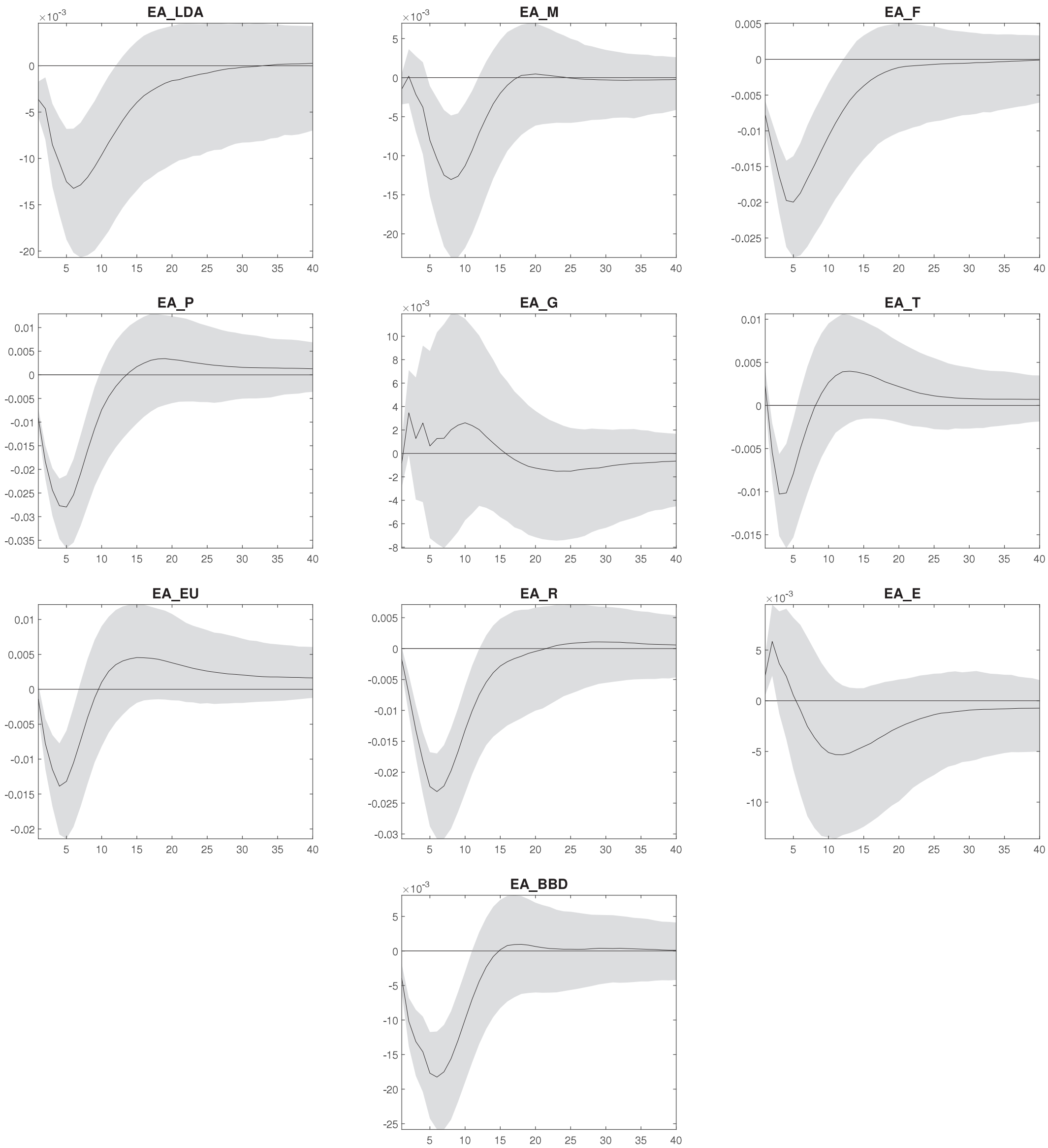

Fig. 4. Impulse response functions of **machinery and equipment investment** in the euro area to shocks in EPU index and its components. Notes: SVAR-estimated impulse response functions for machinery and equipment investment to a positive EPU shock (one standard deviation). The SVAR is identified using Caldara et al. (2016). Sample Q1:2000–Q1:2019. The grey bands represent the 68% confidence interval. LDA stands for EPU index using LDA, M is the monetary policy uncertainty, F is the fiscal policy uncertainty, P is the political uncertainty, G is the geopolitical uncertainty, T is the trade policy uncertainty, EU is the EU regulation uncertainty, R is the regulation uncertainty, E is the energy policy uncertainty and BBD is the Baker at al (2016) EPU index.

in particular to German investment (negative and statistically significant while long lasting effects). This is not entirely surprising given that, as the biggest exporter of the euro area, we would expect Germany to be especially vulnerable to trade disputes.

5.2. Uncertainty and private consumption

This section investigates how uncertainty affects private consumption, the largest component of the GDP. Uncertainty might influence consumption and economic activity through consumers' *precautionary savings* channel (Basu and Bundick, 2017; Leduc and Liu, 2016). This channel states that in order to reduce exposure related to the increase in uncertainty, and to preserve a smooth consumption pattern, agents reduce consumption (ultimately, firms react to this drop in demand by lowering investment).[19]

[19] The literature has also identified a financial channel of transmission, where macroeconomic uncertainty directly influences the risk-taking behaviour of households, therefore reducing their exposure to more risky assets (Coibion et al., 2021).

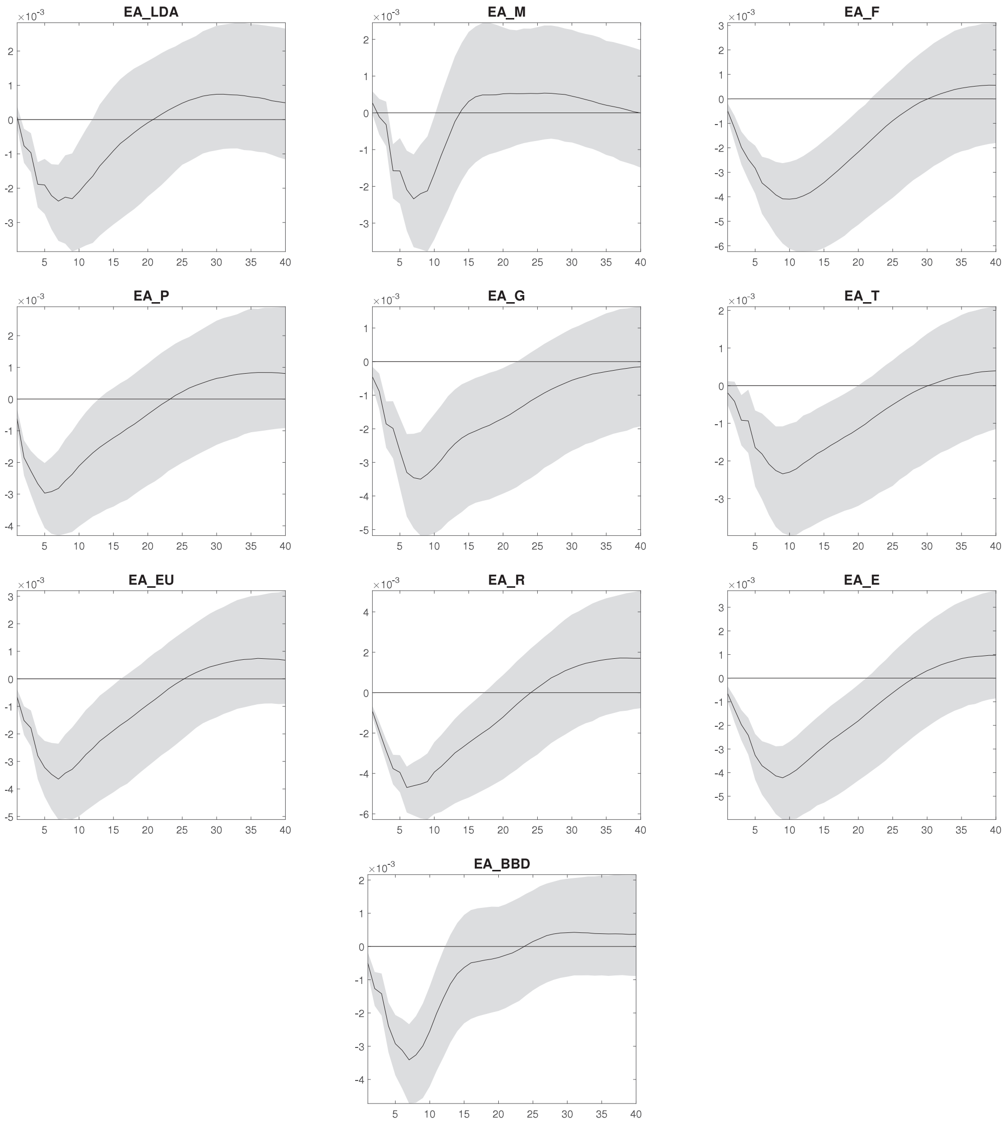

Fig. 5. Impulse response functions of **private consumption** in the euro area to shocks in EPU index and its components. Notes: SVAR-estimated impulse response functions for consumption to a positive EPU shock (one standard deviation). The SVAR is identified using Caldara et al., 2016. Sample Q1:2000–Q1:2019. The grey bands represent the 68% confidence interval. LDA stands for EPU index using LDA, M is the monetary policy uncertainty, F is the fiscal policy uncertainty, P is the political uncertainty, G is the geopolitical uncertainty, T is the trade policy uncertainty, EU is the EU regulation uncertainty, R is the regulation uncertainty, E is the energy policy uncertainty and BBD is the Baker at al (2016) EPU index.

Following the choice of variables in Banbura et al. (2018), we expand our previous VAR setup to account not only for private consumption but also for national exports.[20] The latter variable will allow us to control for international shocks on exports, which may also affect domestic demand. As previously done, we adopt the identification scheme of Caldara et al. (2016).

We report the IRFs we obtain for the euro area as a whole (Fig. 5), and in Appendix those for the four countries (Figures to 10 13). At the European level, we observe negative and significant effects of uncertainty on consumption for the aggregate level as well as across all components. These effects tend to last between 2.5 and 5 years (i.e. 10 to 20 quarters) and are particular strong for the regulation, fiscal and energy uncertainties.

Given the exhaustive comment on the investment IRFs, we emphasise comparisons in the context of other results, rather than describing all IRFs. We first notice that our results are overall consistent with the results of Bloom (EA BBD), suggesting a significant

[20] The variables fed into the VAR (without ordering) are: the natural logarithm of exports, the natural logarithm of EPU, the natural logarithm of private consumption, the natural logarithm of business ivnesment, the shadow rates and the natural logarithm of the stock market index.

and prolonged negative effect of uncertainty on private consumption. Using the indicator of Bloom in the SVAR, we obtain a negative effect in 4 cases out of 5 (EA and four countries), with the only exception being Germany (where Bloom's indicator has a positive effect on private consumption in our VAR setup). We interpret this result as evidence of a flight-to-safety effect for Germany, whereby consumption reacts negatively to uncertainty with the exception of "safe heaven" countries, where the effect can even be positive. Indeed, the resilience of German domestic consumption during the Great Recession has been a puzzle.

Looking at the different uncertainty indicators, their effect squares with the evidence provided for investment. However, the effect is more homogeneous across indicators, suggesting that uncertainty is more of an all-encompassing concept for consumer, no matter its origin. Differently from investment, consumption strongly reacts at impact (for Germany in particular). This is due to the fact that private consumption can be swiftly adjusted while investment is at least partly irrevocable. We also observe a more persistent effect of uncertainty on consumption than on investment. This is plausible since waves of pessimism tend to last longer consistently with persistence of consumption and a more optimising nature of investment.

At the country level, we observe once again heterogeneous effects of uncertainty on consumption. For Germany, as it was the case with the indicator of Bloom, again we observe lower (and sometimes even positive) effects of uncertainty on consumption, and these effects are comparatively short-lived. As discussed above, this result is probably related to the "safe heaven" nature of the German market. By contrast, we observe strong negative effects of uncertainty for countries such as Italy (political) and in particular Spain (fiscal, political and regulation).

All in all, these results are similar to those for investment providing evidence of an overall negative effect of uncertainty on private consumption. Out of the 45 impulse responses, 37 are statistically significant and negative.[21] In conclusion, consumption shows a strong and persistent negative reaction to an increase in EPU, with only Spain showing a rebound effect that, instead, characterises investment in all countries.

6. Conclusion

This paper presents a bottom-up approach to estimate economic policy uncertainty in the euro area and its member countries. We run two unsupervised machine learning algorithms on news articles describing overall economic uncertainty as published in German, French, Spanish and Italian newspapers. This allows us to endogenously extract individual uncertainty components and to assess their weight in the overall EPU.

We document particular strong effects of political and domestic regulation uncertainty on investment and consumption in all countries. Nonetheless, there are particular uncertainty types that affect investment in some countries more than in others. For example, trade uncertainty matters for German investment more than its counterparts. The reaction in consumption is often faster. This might be due to the fact that private consumption can be swiftly adjusted while investment is more thought through and is at least partly non revocable. At the country level, we observe strong negative effects of uncertainty for countries such as Italy (political) and Spain (fiscal, political and regulation). Contrasting this result, we observe low and sometimes positive effects of uncertainty on consumption in Germany. We could interpret this result as new evidence of a flight-to-safety effect for Germany: consumption reacts negatively to uncertainty with the exception of "save heaven" countries, where the effect can even be positive.

Our results suggest that when building text-based economic policy uncertainty measures, in particular in a multi-lingual context, our technique reduces the amount of discretionarity and may be a useful complement to existing techniques based on word counting. In this respect, we have shown how using a continuous bag-of-words model makes it possible to retrieve those articles relevant to economic uncertainty for each country, while LDA can be useful when categorising the individual components of EPU. There are common features that we observe from our results. First, investment reacts strongly to uncertainty. Second, consumption reacts to a lower extent to uncertainty, suggesting more relevant effect of uncertainty on the supply side. Thirdly, our results highlight the heterogeneity in the relationship between different types of uncertainty and the real economy: national features can be relevant and country-specific fragilities matter. National regulators and politicians should then be aware of which type of uncertainty is materialising since, depending on the source, they will be more or less detrimental to the real economy and require different policy responses.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2023.104373.

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[21] These are the 9 IRF at European level plus the 36 (4 × 9) IRF across all four countries. In the case of investment we counted 38 out of 45 to be statistically significant and negative.

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