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Searching for the Nature of Uncertainty: Macroeconomic VS Financial

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Abstract

A growing empirical literature on how to measure uncertainty has emerged following the 2007-2008 financial crisis. This paper review the different methods measuring uncertainty. From a principal component analysis (PCA) including the various measures of uncertainty provided by this growing empirical literature, a monthly global measure of uncertainty for the United States on the period 1990-2015 has been developed and the factors explaining fluctuations in uncertainty have been determined. The US global measure from the PCA has similarities with a composite index from a dynamic factor model. The same methodology is used using euro area data. We find many similarities between US uncertainty peaks and the uncertainty peaks of the euro area. The second factor provides a switch between two natures of uncertainty: macroeconomic and financial. Finally, we extend our analysis adding a measure related to the pandemic risk to take into account the current COVID-19 pandemic.

Keywords: Uncertainty, principal component analysis, economic activity, COVID-19.
JEL Codes: C38 ; D80 ; E32

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1 Introduction

The effects of uncertainty on macroeconomic environment have become an important topic in both economic policy and academic research in recent years. However, the topic of uncertainty is not recent where Knight (1921) has established the modern definition of this concept in economy where he distinguished risk from uncertainty: *"It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all".* Risk is associated to situations where all outcomes are identified and their probabilities of occurrences are computed and are known. Uncertainty is defined as situations where the possible outcomes of a choice like an investment decision or the probability distribution associated are unknown for the agents. Keynes (1921, 1936, 1937) defined uncertainty as the case where the risk in the decision is not objectively measurable in advance because of lack knowledge regarding future. The future is unpredictable and does not follow a predetermined probability distribution unlike mainstream perspectives involving uncertainty which are based on a statistical analysis of past data (Davidson, 1991). We can also find the idea of unpredictable future in Shackle (1953, 1956) referring to the situation where we can't produce *ex-ante* an exhaustive list of all possible outcomes of a choice because of lack knowledge regarding future.[1] The Brexit case is a perfect example of uncertainty according to these definitions. We can't know the future trajectory of the UK economy and we can't objectively compute probabilities of potential scenarios using past observations given that there is no previous case since the United-Kingdom has been the first country to leave the European Union.

From these large definitions and concepts, a quite old theoretical literature have investigated the effects of uncertainty on the macroeconomic environment through the behavior of households, firms and investors (See, among many others, Leland, 1968; Bernanke, 1983; Dixit, 1989; Pindyck, 1991). The 2007-2008 financial crisis has sparked a renewed interest in the effects of uncertainty on the economy where uncertainty has been one of the main explanations for the weak global recovery (Blanchard, 2009; Stock & Watson, 2012; Bloom *et al.*, 2013) and has

[1] We will not discuss the different definitions on the concept of uncertainty in this paper. There are other definitions, concepts of uncertainty in the literature. See, among many others, Savage (1954), Davidson (1991), Ferrari-Filho & Conceição (2005), Dequech (1997, 2000, 2011).

brought a new path on this topic that has been widely used today: the empirical dimension. To better understand what are the effects of uncertainty in empirical works, one variable reflecting or approximating uncertainty is necessary. Since uncertainty is an intrinsically unobservable phenomenon, a booming economic research has emerged on how to quantify uncertainty in recent years where no consensus has yet been able to lead to a single measure. This recent literature can't make the distinction between risk and uncertainty as in Knight (1921) but refer to a mixture of risk and uncertainty (Bloom, 2014). Many methodologies have been developed and the resulting indexes have been used to investigate empirically the effects of uncertainty on macroeconomic environment where we can find different effects according to the measure used (Rossi & Sekhposyan, 2015). In this paper, we present different approaches measuring uncertainty. The literature review on this topic shows that a multitude of proxies have been developed in recent years. Mainly, the literature has tried to measure two natures of uncertainty shocks: macroeconomic and financial. The first measures have quantified financial uncertainty through the volatility on financial markets. Then, other works have been interested in the development of macroeconomic uncertainty indexes using this notion of volatility and other various approaches (survey-based measure, forecast errors, . . .). Recent works have tried to decompose uncertainty shocks between macroeconomic and financial uncertainty shocks from econometric models. Other works have used textual analysis techniques and big data frameworks to develop news-based measures of uncertainty. In front of the diversity of methods proposed, the resulting measures differ from each other providing different information. That is why composite indexes have been developed to get a synthetic index of uncertainty. To achieve it, two methods have been proposed: a dynamic factor model (DFM) and a principal component analysis (PCA).

This paper contributes to this growing empirical literature by the estimation of a US global uncertainty index over the time period 1990M1:2015M3 combining different measures of uncertainty from different categories and provides an analysis in order to identify the nature (or determinants) of uncertainty shocks (financial, macroeconomics, news, geopolitical risk, . . .). We apply the same method to the euro area and we have developed a general index using 6 measures only but gathering the different natures (financial, macroeconomic, policy,. . .).[2] On

[2]Most measures have been developed for the United States. There are less indexes developed for the euro area.

the one hand, this paper stands out from the other works using the composite index approach with the estimation of a US global index using more recent measures developed. On the other hand, we conduct an analysis in order to understand and interpret the factors provided by the PCA and the DFM explaining the fluctuations of uncertainty and more precisely, the nature of uncertainty shocks (financial, macroeconomic policy, news, geopolitical risk, ...). The first factor of the PCA can be interpreted as a measure of the global level of uncertainty for the United States. Interestingly, the second factor establishes the distinction between two natures of uncertainty shocks. More precisely, the second factor underlines the importance to distinguish macroeconomic uncertainty shocks and financial uncertainty shocks as mentioned in the literature review providing a switch between macroeconomic uncertainty shocks and financial uncertainty shocks in a single variable. Given that some uncertainty peaks can be represented both in a macroeconomic uncertainty measure and in a financial uncertainty index like the Gulf War or the collapse of Lehman Brothers, this variable allows to determine what is the nature associated with the uncertainty shock. Is the nature of the uncertainty shock related to finance or macroeconomics ? In the best of our knowledge, there are no works which have developed a unique variable establishing this distinction.[3] The other factors of the PCA consider the public broadcasting and geopolitical risk as dimensions of uncertainty. The interpretation of the results for the DFM are the same for the first two factors where we find similarities between the factors from both methods. For the euro zone, the analysis is less complex because there are less measures available but we can keep the interpretation of the first two factors. We extend our analysis adding a measure of uncertainty related to the pandemic developed by Baker *et al.* (2020b) to take into account the current COVID-19 pandemic running a PCA over the time period 1990M1:2020M6. It is worth nothing that the COVID-19 pandemic is the highest uncertainty peak and we find that the pandemic risk is a new dimension of uncertainty.

Two lessons can be drawn from this paper and its results. The first lesson concerns the method used to get a synthetic index where we find many similarities between indexes from both methods with a strong correlation like in Charles *et al.* (2018). So, using a mathemati-

[3]Jurado *et al.* (2015) and Ludvigson *et al.* (2021) have decomposed uncertainty shocks separately using two indexes.

cal procedure less complex, *i.e.* , using a PCA rather than a DFM, we can find a satisfactory general index of uncertainty. More, the PCA provides graphs and tools allowing to understand and interpret the different factors contrary to the DFM where it is more difficult to interpret the factors. Thus, about the interpretation of factors explaining fluctuations in uncertainty, the PCA approach seems better than the DFM approach. The second lesson concerns the macroeconomic uncertainty index developed by Jurado *et al.* (2015). In addition to our general uncertainty index, we have developed a variable switching between macroeconomic uncertainty shocks and financial uncertainty shocks that is represented by the second factor. Examining the variables factor map concerning the second factor, we can reconsider the nature of the measure of macroeconomic uncertainty proposed by Jurado *et al.* (2015) that is part of a group made up of financial variables. Therefore, we should be careful with this index which seems more linked to financial uncertainty.

The rest of this paper is organized as follows. The second section reviews the different measures of uncertainty where we propose a new classification to analyze these measures according to the nature of uncertainty. The third section computes a global index of uncertainty from a PCA and a DFM framework for the United States. The fourth section presents the application to the euro zone. The fifth section extends the previous sections by adding the measure of uncertainty related to the pandemic risk. The sixth section presents robustness checks. The last section presents conclusions and directions for future works.

2 Measuring Uncertainty: literature review

There are no consensual and objective methods on how to measure uncertainty. A recent literature has emerged proposing different uncertainty proxies. Ferrara *et al.* (2017) have classified these measures into different categories: uncertainty on financial markets, macroeconomic uncertainty, micro-level and economic policy uncertainty. New measures of uncertainty have been developed using new methodologies. This section aims at improving their classification with new measures and approaches. More, this literature review will allow to select measures that we are going to use to develop our global uncertainty index in the next section. In order to get a great set of measures, we will select and will plot monthly measures of uncertainty which can span over the time period January 1990 to March 2015. The other uncertainty measures have been proposed on a shorter period or a different frequency or data are not available.

2.1 Financial Uncertainty

In the empirical literature, the first measure of uncertainty developed was based on financial market fluctuations and more precisely, on the volatility. For example, Bloom (2009) uses the Volatility Index (VIX) as a measure of uncertainty. The VIX, developed by Chicago Board Options Exchange (CBOE) since 1990, is a measure of 30-day option-implied volatility in the S&P 500 index. Using historical data, a high level of this index means a high volatility in financial markets which corresponds to period of crisis. This "fear index" (Whaley, 2000, 2009) can reflect agents' expectations in the equity market. A rise of this index is a sign of a growing uncertainty. Figure A.1 plots the VIX index showing that the greatest uncertainty peaks are related to the COVID-19 pandemic, the collapse of Lehman Brothers in 2008 and the 1998 Russian financial crisis. We can find other peaks which are related to periods of geopolitical tensions like the Gulf War, the Iraq War or 09/11 attacks. This index has been used to build other measures like the variance risk premium in Zhou (2018) defined as the difference between an *ex-ante* risk-neutral expectations and the *ex-post* observation of the return variance represented by the realized variance. The risk-neutral expectation of variance (or the implied variance) is measured using the VIX translating stock market's expectation.[4] The realized variance is the volatility of the S&P 500 index using high-frequency returns (Bollerslev *et al.*, 2009).[5] The difference between both variables is strong during crisis periods and recessions (Figure A.2). When the implicit variance exceeds the realized variance, traders have increased the price of options as a hedge against a potential transition to a riskier economic environment. Market participants are willing to pay more in order to hedge against unexpected market volatility (Carr

[4]The implied variance corresponds to the estimate of the underlying future volatility of assets derived from option prices which can be approximated by the VIX reflecting the stock market's expectation of volatility based on S&P 500 index options (Bollerslev *et al.*, 2009; Whaley, 2009).

[5]The academic literature has demonstrated that the realized variance measure computed from high-frequency data provided a more accurate ex-post observation of the return variance than a variance computed from daily returns (Barndorff-Nielsen & Shephard, 2002; Meddahi, 2002).

& Wu, 2008; Feunou *et al.*, 2018) and hence, reflecting a growing future uncertainty. The variance risk premium is moderately high and positive with the Gulf War in 1990, the 1997 Asian financial crisis, the 1998 Russian financial crisis, the Iraq War (Figure A.2). On the other hand, when the realized variance exceeds the implicit volatility, the interpretation is more difficult and the literature does not really explain what happens when there is a negative level. Considering the implied variance as an *ex-ante* uncertainty and the realized as an *ex-post* uncertainty, the interpretation that we can make is that the hedge has been insufficient against risks that have already occurred. For example, taking the highest negative peak of this variable representing the collapse of Lehman Brothers (Figure A.2), either we have underestimated the importance of occurrence of the bankruptcy, or we could not predict that bankruptcy. We should be careful with this index. If the variance risk premium is equal to 0, it does not mean necessary that that the level of uncertainty remains unchanged or is low but that both variances are equal. The VIX can be high translating high uncertainty like the realized variance too but if the difference is small or close to 0 at time t, we could misinterpret the fact that there is no uncertainty at time t. More, some authors don't consider the variance risk premium as a measure of uncertainty but could be interpreted as a measure of the agents' risk-aversion (Rosenberg & Engle, 2002; Beckaert & Hoerova, 2016). Another shortcoming of the VIX based uncertainty measures relies on the limited time span. Manela & Moreira (2017) have remedied it from the VIX and machine learning techniques using front of articles from the Wall-Street journal to develop a new measure which can cover a very large time period to extend options implied measures of uncertainty back to the end of the 19^{th} century where variation in the topics in the business press could reflect the evolution of investors' concerns about these topics. That's why they have estimated a measure based on the co-movement between news and the VIX capturing the fears of the investors over history. We can consider the NVIX an extension of VIX combined with information from words of the business press. The NVIX is high for the 1929 crisis, the 1998 Russian financial crisis and Long Term Capital Management, the Iraq War in 2003 and the collapse of Lehman Brothers in 2008 (Figure A.3). This method is very interesting to have data on a very large period with a variable that can replace the VIX until the end of the 19^{th} century. Unsurprisingly, we find many similarities between between the VIX and the NVIX with a correlation equal to 0.80 (Figure A.4) over the time period 1990-2016.

Some measures are based on firm-level stock market returns following the introduction of volatility indexes to measure uncertainty. Usually, a standard deviation is computed for a specific company. Bloom (2009) has proposed to compute the cross-sectional standard deviation of US firm-level stock returns. Gilchrist *et al.* (2014) have constructed a measure of idiosyncratic uncertainty ($IVOL$) using daily stock returns data from a panel of 11303 nonfinancial corporations.[6] They propose a three step approach. Firstly, the authors have removed the forecastable variation in daily excess returns with a four-factor advocated by Carhart (1997). Secondly, they have computed a quarterly firm-specific standard deviation of daily returns with the OLS residuals. This standard deviation provides a firm-specific measure of uncertainty. Thirdly, to construct their measure at an aggregate level, the authors use a dynamic panel data model where time fixed effects capture common shocks in the idiosyncratic volatility. Figure A.5 plots the monthly version of Caldara *et al.* (2016) where the collapse of Lehman Brothers is the highest peak. We find other peaks related to financial crises like the 1997 Asian financial crisis, the 1998 Russian crisis. As the VIX, we have other peaks which are related to geopolitical tensions like the Gulf War, the Iraq war.[7]

Corporate bond spreads have been used as an indicator of tension on financial markets (Bachmann *et al.*, 2013). This measure is defined as the difference between the yield of Baa-rated corporate bonds and the 30-year Treasury yield. A rise is assumed to reflect a greater tension in the financial markets which can be a sign of a growing uncertainty where the investor demands compensation with a higher yield because of uncertainty about the financial health of corporates.[8] Corporate bond spreads exhibits the higher spikes during financial crises with the 2000 dot-com bubble, the collapse of Lehman Brothers (Figure A.6) where there was a real doubt about the financial health of each company, bank, financial institution, etc…

[6] The authors have chosen firms with at least 1250 trading days of data. However, there is no justification about this selection criteria.

[7] The data of this index are available until March 2015 and therefore, determines the choice of the end date of the sample in the next section.

[8] Following Bachmann *et al.* (2013), the 30-year Treasury bond was missing between March 2002 and January 2006. That's why we complete data using difference between the yield of Baa-rated corporate bonds and the 20-year Treasury yield.

2.2 Macroeconomic Uncertainty

2.2.1 Dispersion among forecasters

As financial uncertainty indexes, measures of dispersion have been proposed to represent macroeconomic uncertainty like the dispersion of forecast disagreements. Professional forecasters are asked about the future evolution of a macroeconomic variable. These forecasters may have the same data but everyone will have their own interpretation. Therefore, these forecasters will make different forecasts. If there is a strong disagreement among forecasters on the future evolution of a macroeconomic variable, the evolution of this variable will be more uncertain in the future. It is assumed that there is a positive relationship between uncertainty about the future and forecast disagreements (Giordani & Soderlind, 2003). Bloom (2009) has proposed the standard deviation of GDP forecasts using the survey of professional forecasters at the Federal Reserve Bank of Philadelphia about the one-year-ahead GDP.[9] Istrefi & Mouabbi (2018) have developed a subjective measure of interest rate uncertainty based on the Consensus Economics survey for some advanced economies.[10] Their measure is defined as the sum of the variance of disagreement among professional forecasters and the conditional variance of mean forecast errors exploiting the difference between expected and observed interest rates.[11]

2.2.2 Confidence Indexes

Other survey-based measures have been proposed like confidence indexes which can represent an alternative measure to proxy uncertainty (Leduc & Liu, 2016). Bachmann *et al.* (2013) construct a measure of forecast dispersion using the Philadelphia Fed's Business Outlook Survey giving qualitative information on the current state of firms' business conditions and their expectations about future business conditions. Firms answer this question: "What is your evaluation of the level of general business activity six months from now vs [current month]: decrease; no change; increase?" However, this question is too general and large. In the business confidence

[9]At a micro-level, Bloom (2009) proposed to compute the cross-sectional standard deviation of firm profit growth from Compustat quarterly accounts and the annual standard deviation of the five-factor total-factor productivity (TFP) growth rates from the National Bureau of Economic Research (NBER).

[10]The United States, France, Germany, Japan, Spain, Italy, the United Kingdom, Sweden, Canada.

[11]This second component has been used to construct other measures of uncertainty.

index of the Organisation for Economic Co-operation and Development (OECD), questions are more specific. This index is based on firms' assessment of production, orders and stocks, the current situation and their short-term expectations. The questions are more specific and concern job prospects, production, sales prices and order books. An index above 100 signals a boost in the confidence towards the future economic situation. Inversely, an index below 100 translates a pessimistic attitude and a growing uncertainty (Figure A.7). The index is low during the Gulf War, the 09/11 attacks, the 2007-2008 financial crisis and during the current COVID-19 pandemic with lockdown measures stopping economic activities.

Similarly, a consumer confidence has been developed. On the one hand, a consumer may be optimistic if there is no uncertainty about a favorable change in his future income. On the other hand, if there exists a doubt about an adverse change, this confidence will decline and therefore, the consumer will prefer to save rather than to consume. This is the concept of "precautionary saving" (Leland, 1968). The consumer confidence index developed by the OECD gives an indication of future evolution of households' consumption and savings with answers about their expected financial situation, their sentiment about the economic situation, unemployment and capability of savings. The questions concern the expectations about the financial situation of households, the expectations for the economic situation and the number of unemployed in the next twelve months. An index above 100 signals a boost in the confidence towards the future economic situation and an index below 100 translates a pessimistic attitude and a growing uncertainty (Figure A.7). This growing uncertainty increases rapidly in recessions like during the period following the 2007-2008 financial crisis where the pessimistic attitude has been persistent. This index exhibits a spike during the current COVID-19 pandemic with associated lockdown measures which is a high period of uncertainty for consumers regarding their future situations (financial, job,...) and the future macroeconomic situation.

2.2.3 Interest Rate Spreads

Like with financial indexes, interest rate spreads can be use. From the difference between long-term interest rates and short-term interest rates, we can try to infer macroeconomic information on the future. This difference is considered as a predictor of a recession or a signal of an economy in bad health one year later if this difference is small or negative (Estrella & Mishkin, 1998; Rudebusch & Williams, 2009; Bauer & Mertens, 2018a,b). In practice, for long-term rates, it is a common choice to use the 10-year Treasury bill rate that reflects the visions of investors in the bond market. About short-term rates, there are several possibilities: 2-year, 1-year, 3-month Treasury bill rates. In the academic literature the 3-month rate is often used. Financial commentators use the 2-year rate which is seen as an indicator of the stance of monetary policy. Interest rate spreads are high during the period following the collapse of Lehman Brothers (Figure A.8) and it is interesting to see that interest rate spreads are high during period of geopolitical tensions (Gulf War, Iraq War and 09/11 attacks) and increase rapidly during recessions. During the European debt crisis with the Greek crisis, medias and financial commentators have focused on the spread between the Greece 10-year Government Bond yield and the Germany 10-year Government Bond yield to try to infer macroeconomic information on the future for Greece.

2.2.4 Forecast Errors

Forecast errors have been used by Scotti (2016) to construct a daily index of macroeconomic uncertainty for some countries.[12] The uncertainty index is computed as the square root of a weighted average of the squared of the difference between the Bloomberg forecasters median expectation for certain variables and the realization of these variables for a set of macroeconomic variables. Rossi & Sekhposyan (2015) have proposed a macroeconomic uncertainty index based on comparing the realized forecast error of real GDP with historical forecast error distribution. However, we can't construct a macroeconomic index using the real GDP only. Ismailov & Rossi (2018) have used the same method to develop an exchange rate uncertainty index for the European Union and a set of developed countries. [13]

Another approach consists to estimate an econometric model with time-varying volatility where the volatility of the forecast errors is considered as a proxy of uncertainty. Bali *et al.* (2014) have developed a US macroeconomic measure of uncertainty using variables that could affect investor consumption and investment opportunities.[14] This econometric approach has

[12]The United States, Canada, Japan and the United Kingdom and the euro area.

[13]The United States, Switzerland, the United Kingdom, Japan, Canada.

[14]The difference between yields on BAA-rated and AAA-rated corporate bonds, the aggregate dividend yield on

been used for the estimation of an interest rate uncertainty index (Fernández-Villaverde *et al.*, 2011), an uncertainty index about fiscal policy (Fernández-Villaverde *et al.*, 2015) and inflation (Chan, 2017).

2.3 Decomposition of Uncertainty Shocks: Macroeconomics VS Finance

More recent works try to decompose uncertainty shocks using the econometric approach. Ludvigson *et al.* (2021) have decomposed uncertainty between macroeconomic uncertainty and financial uncertainty. According to them, financial uncertainty could be very linked to the recessions, both as a cause and as a propagating mechanism. The measure of macreconomic uncertainty is based on the method of Jurado *et al.* (2015) using a panel of macroeconomic and financial time series (industrial production, real income, hours, unemployment, prices, stock market indices, ...). According to Jurado *et al.* (2015), volatility measures are partly predictable. So, in order to get a "true" measure of uncertainty, the predictable component of each series must be removed. Moreover, they have argued that a great panel of macroeconomic time series should be used and not only one time series like in Rossi & Sekhposyan (2015). These authors have computed the conditional volatility from volatility stochastic model of the unforecastable component of the future values of each series by taking the difference between the conditional forecasts obtained from a large dynamic factor model the realization. The measure of macroeconomic uncertainty is an average of the conditional volatility of each series (Figure A.15). Using the same methodology, Ludvigson *et al.* (2021) have developed a financial uncertainty index (Figure A.15) from a panel of 148 monthly financial indicators: Treasury bill yields, price-earnings ratio, risk factors of Fama & French (1992). Both indexes exhibit a spike with 1973 oil crisis but they also have differences before 1990 where financial uncertainty is high during the 1987 financial crisis and macroeconomic uncertainty is high during the 1981–1982 recession (Figure A.15). Even if the Russian financial crisis in 1998 is higher for the financial uncertainty index, we can note that these indexes have many similarities after 1990 with

the S&P500 index, monthly growth rate of real GDP per capital, monthly inflation, monthly unemployment, the difference between yields on ten-year and three-month Treasury securities, the difference between the three-month T-bill and its 12-month backward moving average and the excess return on the value-weighted NYSE / Amex / Nasdaq equity market index.

a correlation equal to 0.69. Redl (2020) has used this econometric framework to decompose uncertainty between macroeconomic and financial uncertainty shocks for some countries.[15]

The approach of the decomposition of shocks has been used for another aspect instead of macroeconomics versus finance only. Mumtaz & Theodoridis (2017) decomposed uncertainty shocks between common (or world) shock and country-specific shock for a set of 11 OECD countries.[16] In order to develop common and country-specific measures of uncertainty, they have used a dynamic factor model with stochastic volatility and decompose time-varying volatilities. Their common uncertainty can be interpreted like the average volatility of the unpredictable part of the common component. Similarly, their country-specific uncertainty can be interpreted like the average volatility of the unpredictable part of the country-specific component (Carriero *et al.*, 2016).

2.4 Textual Analysis

Recently, textual analysis has been used as an alternative approach in order to construct new measures of uncertainty. Baker *et al.* (2016) have developed the Economy Policy Uncertainty (EPU) indexes for some countries.[17] As the measure can be computed for a wide range of countries, it is possible to compare the effects of uncertainty shocks. To measure US policy-related economic uncertainty, the authors have used an average of several components. The first component is the news index (Figure A.9), based on the frequency of newspaper references to economic policy uncertainty. The authors have searched digital archives of 10 leading newspaper [18] since 1985 and more precisely, articles containing terms related to the economy ("economic" or "economy"), policy ("congress", "legislation", "white house", "regulation", "federal reserve" or "deficit") and uncertainty ("uncertainty" or "uncertain").[19] The second component relies on

[15]France, Germany, Italy, Spain, Sweden, Switzerland, Netherlands, Japan, Canada, the United Kingdom.

[16]The United-States, the United-Kingdom, Canada, Germany, France, Italy, Spain, Netherlands, Sweden, Japan and Australia.

[17]The United States, the United Kingdom, France, China, Japan, Russia, Australia, Brazil,...

[18]USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal

[19]For the other countries, they conduct all searches in the native language of the newspaper in question. For example, for France, they search the following words: "incertitude", "économie", "réglementations", "BCE", "Banque Centrale", "dépenses",...

reports by the Congressional Budget Office which establishes lists of temporary federal tax code provisions.[20] The last components draw on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters using the dispersion of the forecast variables directly influenced by fiscal and monetary policy: the consumer price index and federal government purchases. An alternative is the news index but where the authors have used the Access World News database of over 2000 US newspapers which allows to take into account more articles (Figure A.9). These indexes exhibits spikes during events affecting uncertainty like the Gulf War, presidential elections, the terrorist attacks on September 11, 2001, the stimulus debate in early 2008, the collapse of Lehman Brothers, the 2011 debt ceiling dispute or the current COVID-19 pandemic. Even if there exists many similarities between these measures concerning their construction, we can see that some uncertainty peaks are higher or lower according to the measure used like the Gulf War which is higher for the measure based on Access World News database (Figure A.9).

From textual analysis methods, new measures can be derived. Baker *et al.* (2016) have developed a measure of US monetary policy uncertainty (Figure A.10). This measure draws on the news index but also includes terms related to monetary policy ("quantitative easing", "fed funds rate", "Volker", "open market operations", ...). Other indexes are linked to fiscal policy, trade policy and health policy using adapted categorical policy terms. On the one hand, the additional keywords allow to modify the initial level of some peaks like the 09/11 attacks which is higher for the monetary policy index. On the other hand, we can identify new peaks like with the trade policy uncertainty index which exhibits spikes for two periods only: the negotiations of the North American Free Trade Agreement (NAFTA) and during the trade policy conflicts between China and the United States in 2018-2019. The fiscal policy uncertainty index is mainly high during periods of political tension within the US with the debt ceiling crisis in 2011, elections in 2012, the *fiscal cliff* and the government shutdown in 2013. The health policy uncertainty index presents peaks with the Clinton health care plan of 1993, the Affordable Care Act (ACA) in 2010 and with the current COVID-19 pandemic. These authors have also constructed a quarterly migration-related policy uncertainty index using the same methodology

[20]This component is US-specific and can't be used to construct the measure of economic policy uncertainty of another country.

as the news index adding terms related to migration ("Schengen", "migrant", "immigration", "refugee", etc. . .).

Davis (2016) has developed a worldwide economic policy uncertainty index using a GDP-weighted average of national economic policy uncertainty indices. Ahir *et al.* (2018) have developed another global uncertainty measure. They have constructed quarterly indices of economic uncertainty for 143 countries whose population exceeds 2 million and a world uncertainty index with the Economist Intelligence Unit (EIU) reports since 1996.[21] In order to construct a world uncertainty index, they count the number of times "uncertainty" is mentioned in the quarterly EIU reports. Caldara & Iacoviello (2018) have developed a global geopolitical risk index counting the occurrence of terms related to geopolitical tensions in 11 international newspaper.[22] The authors have identified articles containing related to mentions of geopolitical risk like military-related tensions involving large regions of the world and the United States, terms related to nuclear tensions, war threats, terrorist threats, war acts and terrorist acts, respectively. This index reaches its highest values with the Gulf War, the Iraq War and the 09/11 attacks (Figure A.13) and thus, during periods of geopolitical tensions only but also during the trade policy conflicts between China and the United States more recently. The same methods are used to construct a newspaper-based Equity Market Volatility (EMV) tracker (Baker *et al.*, 2019b) where the key words are linked to economy ("economic","economy"), equity market ("financial","stock market, "Standard and Poors",. . .) and uncertainty or volatility ("uncertainty','volatile",. . .). This index is high during financial crisis (Russian financial crisis in 1998, dot-com bubble in 2000, Lehman Brothers in 2008) but also during the debt ceiling crisis in 2011, with the COVID-19 crisis (Figure A.11) and has many similarities with the VIX with a correlation close to 0.8 (Figure A.12).

However, the search of terms like "uncertainty" only is very vague and abstract. It can refer to different concepts and ideas. To take into account the context in which keywords have been used, Puttman (2018) has used a new approach of textual analysis using big data methodol-

[21] These reports examine and discuss the main economic, financial and political trends in a country.

[22] The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal and The Washington Post

ogy and the emotional content of newspapers in order to construct a financial stress indicator. Puttman (2018) have used articles of five leading newspapers since 1889 and have selected articles which one term related to financial markets in the title.[23] In order to measure the emotional content of these articles, he has used sentiment dictionaries where words are separated into two categories: "positive" and "negative" words.[24] According to the dictionary, he considers a title as having a negative connotation if it includes more "negative" than "positive" words. However, language has evolved for a century. Language in the end of the 19^{th} century isn't the same as today. Especially in tweets, new words and expressions have appeared which were not used at the end of the 19^{th} century or at the beginning of the 20^{th} century. Similarly, there are certainly words at the end of the 19^{th} century that we no longer use today. So, tweets wouldn't really be appropriate to measure emotional content of newspapers in the end of the 19^{th} century and the the first half of the 20^{th} century. This index exhibits spikes during the 1933 great depression, the 1987 financial crisis, the 1997 Asian financial crisis, the dot-com bubble and during the 2007-2008 financial crisis but also during the European sovereign debt crisis in 2011 (Figure A.14).

In addition to the news-based measures, textual analysis of internet research constitutes another possibility like in Castelnuovo & Duc (2017) who have developed a measure for the United States using Google Trends and terms that are often cited in the Beige Book of the Federal Reserve.[25] Baker *et al.* (2020a) have developed a Twitter-based Economic Uncertainty index extracting tweets containing the terms related to economy and uncertainty.

[23]The word must belong to a list 120 words divided in 11 topics: bonds; business; central banks; economy; general; gold; silver; inflation; railroads; stocks; trade and trouble.

[24]To be more precise, Puttman (2018) has used four sentiment dictionaries where the first is very general where a word like "evil" is considered as a negative word (Mohammad & Turney, 2013). The second serves to evaluate customer reviews (Liu *et al.*, 2005). The third dictionary measures language on microblogs and tweets (Nielsen, 2011). The last is more applied to the financial press (Loughran & Mcdonald, 2011) where a word like "bankrupt" is considered as a negative word.

[25]The Beige Book is a report published by the Federal Reserve Board. Each Federal Reserve Bank gives information on current economic condition in its district. The Beige Book summarizes information by district.

2.5 Composite Indexes and Lessons

Despite their obvious interests, many measures represent just one dimension of uncertainty. In the previous categories, we have seen that a great set of indicators and methodologies have been developed for the last 10 years. Some authors have proposed a global measure using these different measures of uncertainty. To achieve it, two methods have been proposed: the principal component analysis and the dynamic factor model. The aim is to identify the common component of the indexes to develop an overall uncertainty index since most of uncertainty measures are positively correlated with each other (Table A.1). Hence, they tend to vary together suggesting there is a common component to all these measures. Haddow *et al.* (2013) have developed a global index of uncertainty for the United Kingdom based on a principal component analysis (PCA) with several indicators measuring uncertainty in the United Kingdom[26]. The global index is the first factor of the PCA. Larsen (2017, 2021) has developed a set of uncertainty indexes (macroeconomics, financial, mergers & acquisitions,. . .) from textual analysis methods for Norway and has used a PCA to develop a general index for this country. Charles *et al.* (2018) have developed a global measure for the United States from another method using six measures: the VIX, the economic policy uncertainty index developed by Baker *et al.* (2016), the macroeconomic uncertainty index proposed by Jurado *et al.* (2015), the measure of dispersion developed by Bachmann *et al.* (2013), the corporate bond spreads and the financial uncertainty index proposed by Ludvigson *et al.* (2021). The authors have used a dynamic factor model (DFM) to capture the common component of these measures and the estimation relies on the procedure of Doz *et al.* (2012) based on the quasi-maximum likelihood approach.

The next section will consist to develop a general measure of uncertainty from both methods but using more measures than previous works. More, we will interpret other factors allowing to explain fluctuations in uncertainty like in Larsen (2017, 2021).

[26] Three-month option-implied volatility of the FTSE All-Share index, the number of press articles citing "economic uncertainty", the results of a survey about the forecast on the evolution of the number of unemployed in one year and the score of the following question in the Confederation of British Industry surveys : "What factors are likely to limit your capital expenditure authorizations over the next twelve months ?"

3 Measuring general uncertainty: PCA VS DFM

3.1 Data

Some measures are not available on authors website and most of the measures are available at a monthly frequency and for the United States. We propose a US monthly measure of general uncertainty which spans over the period January 1990 to March 2015[27]. To achieve it, we use the following monthly measures: the VIX, the macroeconomic uncertainty index (MU) of Jurado *et al.* (2015), the financial uncertainty index (FU) developed by Ludvigson *et al.* (2021), the economic policy uncertainty index (EPU_Index), the news index (NewsUS), the economic policy uncertainty index using Access World News database (EPU_Access), the monetary policy uncertainty index (MPU), the trade policy index (TPU), the fiscal policy uncertainty (FPU), the health policy uncertainty index (HPU), the consumer confidence index (IDC)[28], the business confidence index (IDE), the financial stress indicator (FI), the geopolitical risk index (GPR), the monthly idiosyncratic uncertainty index (IVOL) modified by Caldara *et al.* (2016), the corporate bonds spread (Bspread), the 10Y-2Y yield spread (Spread)[29], the news-implied volatility (NVIX), the newspaper-based Equity Market Volatility tracker (EMV) and the variance premium risk (VRP).[30]

3.2 Motivation

In the first section, we have seen that a multitude of indicators measuring uncertainty have been developed. These indicators vary in different ways over time. We can note a significant negative correlation between Spread and IDE (Table A.1). If we consider that an increase of Spread could indicate future growth (Bauer & Mertens, 2018a,b), firms can be able to anticipate this future growth because they have more knowledge than consumers. Therefore, there will be

[27]The beginning of the period is determined by the VIX. The VIX is available since January 1990 and the measure of idiosyncratic uncertainty (IVOL) isn't available after March 2015.

[28]In the rest of this paper, we are going to use the inverse of the consumer confidence index in order to have an interpretation of a variation of this measure identical to the others. We use the same transformation for the the business confidence index.

[29]Using 10Y-3m yield spread, the results are qualitatively the same. These results are available upon request.

[30]The results are robust if we remove this index. The results are available upon request.

a boost in the business confidence towards the future economic situation. This can explain why there is a negative relationship between Spread and IDE and positive between Spread and IDC. The trade policy uncertainty (TPU) is negatively correlated with many measures. TPU focuses on periods of trade tensions where the level is high for this index and low for the other indexes like the geopolitical risk index or the VIX which don't take into account the trade dimension. The matrix of correlation shows that some measures are highly correlated like the VIX and the financial uncertainty index (FU). However, this correlation isn't equal to 1. In other words, these measures vary together but also have distinct variations. Figure A.16 represents the evolution of four measures from different categories.[31] There is a great disparity between these measures. Some events are not identified as uncertainty peaks for some indicators but they are for others. For example, for the collapse of Lehman Brothers in 2008, the VIX is higher than other measures while the geopolitical measure is lower for this event and does not consider it as an uncertainty shock. In other words, each of these indicators provides different information. To synthesize these measures in a single index losing as little information as possible, we have seen that two methods have been proposed: the principal component analysis (PCA) and the dynamic factor model (DFM). Charles *et al.* (2018) have run both methods to develop a composite index and have found many similarities between the resulting composite indexes with a correlation close to 0.99.

3.3 PCA Results

In appendix B, Table B.1 reports the eigenvalues of the matrix of correlation (Table A.1) between the 19 measures.[32] This table shows that most of the variance can be explained by the first factor (41.14%). We retain the factors with eigenvalues greater than 1 following the Kaiser criterion and therefore, we select five factors .[33] In the variables factor map[34] (Figure B.1), except the trade policy uncertainty index , all measures are positively correlated with the first factor (Table B.2). The following variables are highly correlated with the first factor: VIX (0.80), FU

[31] Other combinations are possible. We plot this graph to have a clear example.

[32] The indexes don't have the same scale. In order to solve this problem, we use a normalized principal component analysis.

[33] The elbow method selects three factors only.

[34] Also called the correlation circle.

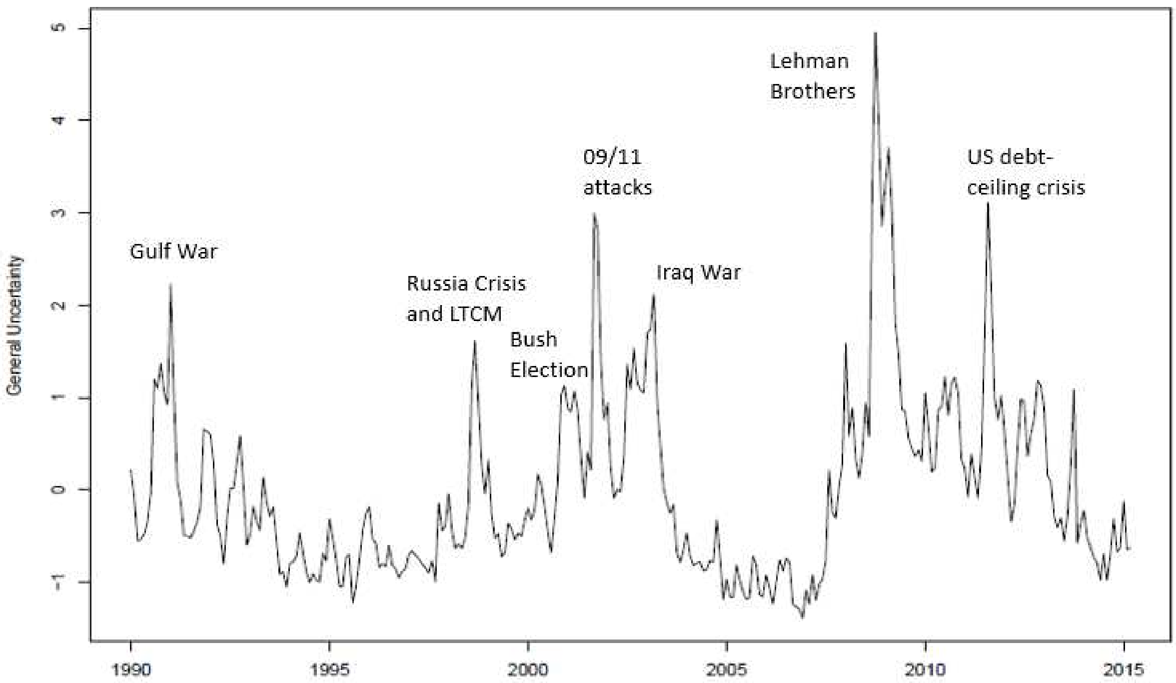
(0.72), Bspread (0.74), NewsUS (0.86), EPU_Index (0.81), EPU_Access (0.82), EMV(0.66) and the NVIX(0.85). The variables MU (0.63), MPU (0.65), IDC (0.57), FI (0.60), IDE (0.57), IVOL (0.59), FPU(0.72) are less correlated. GPR and Spread have a low correlation with the first factor (0.31 and 0.38 respectively). We compute the squared cosines (cos^2) to measure the quality of the representation of the measures on this first factor (Table B.3). A value close to one indicates that the measure is well represented. On the first factor, the squared cosine of the VIX is equal to 0.64 meaning that 64% of the VIX is represented on the first factor only. Globally, the measures are mainly represented on the first factor, except for GPR (0.09) and Spread (0.14). Given that the squared cosines of TPU and VRP are very close to 0, we can't interpret these variables on the first factor. [35] Thus, on this first factor, it's a shock (policy, macroeconomic, financial, geopolitical) which causes an increase of uncertainty. This first factor will constitute the general measure of uncertainty (GU), is computed as a weighted average of these indexes where the weights are given by the eigenvector associated with the greatest eigenvalue. Figure 1 represents the general measure where it is important to examine the evolution of this graph and not just the value on a specific date. For example, the level of uncertainty is around 0.3 in January 1990 which, taking alone, isn't very meaningful. However, if we compare this level to October 2008 which is close to 5, we can interpret that 0.3 isn't a high level of uncertainty.

We can identify different uncertainty peaks corresponding to well identified events like the Gulf War, the Russian financial crisis and Long-Term Capital Management in 1998, the 9/11 attacks, the Iraq War, the collapse of Lehman Brothers or the US debt-ceiling dispute in 2011.[36] These are shocks (financial, macroeconomic, geopolitical, policy,...) that increase the general uncertainty. Here, we refer to the magnitude of the shock. Figure B.2 represents the comparison between our synthetic measure and the composite uncertainty index (CUI) proposed by Charles *et al.* (2018). We find similarities between both composite indexes with a correlation is close to 0.91 but also some differences. Bloom (2009) and Jurado *et al.* (2015) have identified uncertainty events using a threshold of 1.65 standard deviations above the mean corresponding to

[35]For the other factors, we will not refer to the squared cosines (or occasionally).

[36]As sensibility analysis tests, we run 20 PCA using 19 measures, *i.e.* , removing a different measure among the selected indexes each time. The resulting synthetic measures are very similar with a high level of correlation. These results are available upon request.

Figure 1: General measure of uncertainty



Note: The index is standardized.

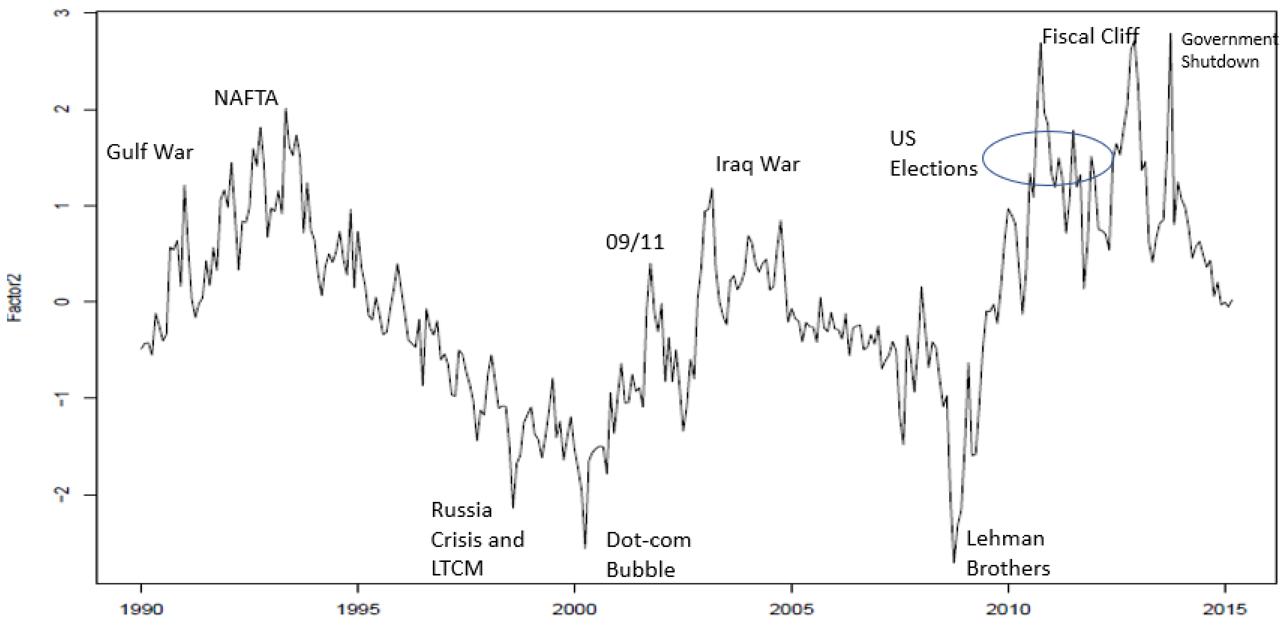
a significance threshold at the 5% level. Using this threshold, our synthetic measure highlights the Gulf War and the Iraq War as events that have generated uncertainty peaks contrary to the composite index of Charles *et al.* (2018). We can explain these differences by the introduction of more uncertainty indexes in the PCA and especially more policy indexes. Beyond the first factor that approximates general uncertainty, the other factors can allow to identify other dimensions.

On the second factor, we can see that there are two groups. EPU_Index, EPU_Access, NewsUS, MPU, Spread, IDC, TPU, FPU, HPU and GPR constitute the first group where these indexes are positively correlated with the second factor. In the second group, we can see that financial variables are negatively correlated with the second factor.[37] The second factor seems to discriminate between two types of uncertainty shock: macroeconomic and financial. However, there are two measures which should be more related to macroeconomics in this second group:

[37]The NVIX and VRP do not belong to either of the two groups given that their squared cosines are very close to 0 and thus, can't be interpreted on the second factor.

IDE and MU. In front of these results, it is more difficult to interpret the second factor. In order to better understand the second factor, we plot the second factor in Figure 2.

Figure 2: Second Factor



Examining the graph, when the second factor is low, we find events which are related to the major financial events of the last two decades: the Dot-com bubble in 2000; the collapse of Lehman Brothers in 2008; the Russian financial crisis and Long-term capital management in 1998. When this second factor is low, uncertainty is financial. Inversely, when the second factor is high, we can find events which are not linked to financial crises but more related to macroeconomics and politics like the Gulf War, the Iraq War, the 09/11 attacks. We can identified elections in the United States like the 2010 midterm elections, the 2012 United States presidential election, the 2012 United States House of Representatives elections. An election can generate uncertainty about future macroeconomic performances. The result of an election will influence the future economic policy and therefore the future macroeconomic performances. We can take the example of the 2012 United States House of Representatives elections where the Republican Party has kept the control of the House of Representatives and the problem of the *fiscal cliff* in January 2013. The US Federal Government has been divided. Without an agreement between the Democratic Party and the GOP, the United States could have gone into recession with the rise in taxes and the decrease in public spending scheduled in January 2013. There is also the US federal government shutdown in 2013 following the disagreement between the Republican-led House of Representatives and the Democratic-Led Senate. These observations confirm that the second factor highlights an opposition between financial uncertainty and nonfinancial uncertainty. However, how can we explain the troubling results about the measures MU and IDE ? About the business confidence index (IDE), the financial sector has taken an increasing importance for three decades. Firms are more dependent on the financial markets, especially in the US. That explains why firms can answer according to their expectations on financial markets. Hence, this measure is oriented towards finance. Concerning the measure of macroeconomic uncertainty of Jurado *et al.* (2015), we had already started to evoke similarities between the macroeconomic uncertainty and the financial uncertainty index. By examining more the construction of MU, their are 25 financial series among the 132 variables used to develop the index. With financialization, these financial series could have become more important, hence increasingly biasing the measure towards the financial side. As a consequence, the second factor indeed discriminates between financial and nonfinancial uncertainty (or macroeconomic uncertainty).

We plot the second and the third factor on the variables factor map (Figure B.3).[38] MPU, TPU, EMV and EPU_Access are the measures the most positively correlated with the third factor and therefore the best represented. The third factor distinguishes a group of variables where measures of uncertainty are based on textual analysis of the other variables. So, the underlying variable behind the third factor would be the public broadcasting surrounding uncertainty peaks. Even if the fifth factor restitutes a small part of the available information, it allows to identify another dimension of uncertainty. The strongest variable is the geopolitical risk index on this factor (Figure B.5). The correlation between the fifth factor and the geopolitical risk index is equal to - 0.50 and seems to distinguish this index from the other indexes highlighting the geopolitical risk as a particular dimension of uncertainty. The variance risk premium is mainly represented on the fourth factor (Figure B.4) with a correlation equal to 0.77 representing its

[38] We could have plotted the variables factor map with the first and the third factor. However, this visualization is clearer to interpret the third factor.

distinction between *ex-ante* uncertainty and *ex-post* uncertainty.[39]

3.4 Dynamic Factor Model Results

As in Charles *et al.* (2018), we use a dynamic factor model (DFM) proposed by Doz *et al.* (2012) based on the quasi maximum likelihood. Extracting the first factor from the DFM, we note that the most of the measures are positively correlated with the first factor of the DFM (Table F.1.1). The trade policy uncertainty and the VRP are weakly correlated with this first factor (-0.09 and -0.03 respectively). Thus, the first factor captures the common component of the uncertainty indexes. As in Charles *et al.* (2018), we find that the composite index from the DFM has many similarities with the composite index from the PCA (Figure F.1.1) where the coefficient of correlation is close to 0.96. We identify the same uncertainty peaks: the Gulf War, the Russian financial crisis and Long-Term Capital Management, 9/11 attacks, the Iraq War, Lehman Brothers and the US debt-ceiling dispute. So, from a PCA and a simpler mathematical procedure, we have found an equivalent result to a DFM. More, the second factor from the DFM resembles that from the PCA (Figure F.1.2) with a correlation close to 0.89. When this second factor is high, we can find uncertainty shocks related to macroeconomics and politics (the Gulf War, the Iraq War, 09/11 attacks, 2012 US elections and Fiscal Cliff). When this second factor is low, we can find uncertainty shocks related to finance (Russian crisis, Dot-Com Bubble, Lehman Brothers).On the one hand, the measures which are related to finance including MU and IDE are negatively correlated with the second factor (Table F.1.1). On the other hand, measures which are more related to macroeconomics are positively correlated with the second factor like with the PCA. Using a DFM only, it would have been difficult to underline the distinction between macroeconomic uncertainty shocks and financial uncertainty shocks and thus, to interpret the factor. Examining the third factor, we note that indexes from textual analysis methods are the most correlated variables with this factor. More, we find similarities with the factor from the PCA (Figure F.1.3) with a strong correlation (0.85). Thus, we keep the public broadcasting as a dimension of uncertainty.

However, we don't have the same interpretation about the fourth factor of the DFM where

[39]By removing the VRP from the PCA, the fourth factor represents the geopolitical risk only.

we have many differences with the fourth factor of the PCA where the correlation is equation to 0.25 (Figure F.1.4). The correlations with uncertainty indexes don't allow to give an interpretation for this factor from the DFM. We have the same results about the fifth factor with a correlation equal to 0.20 (Figure F.1.5).

In front of these results, the PCA approach seems the better approach from two points of view: on the one hand, using simpler mathematical tools, we can find equivalent results to a DFM if you want to develop a composite index. On the other hand, the PCA can allow to better understand and interpret the interpretation of the factors in our analysis while it is more difficult to interpret the factors from a DFM.

4 An application to the euro area

Most of the methodologies that have been described in the first section have been applied to the US. However, some authors have constructed measures of uncertainty for some European countries. Baker *et al.* (2016) have developed a news index for France, Germany, Spain and Italy which constitutes the economic policy uncertainty index for these countries. Using a weighted average of these indexes, we can have a proxy of the economic policy uncertainty for the euro area.[40] Redl (2020) have decomposed uncertainty shocks between macroeconomic uncertainty shocks and financial uncertainty shocks for European countries combining macroeconomic and financial datasets following the methodology of Jurado *et al.* (2015) and Ludvigson *et al.* (2021). As previously, we use a weighted average of these measures to get a proxy of macroeconomic uncertainty and financial uncertainty for the euro area. There exists a consumer confidence index and a business confidence index for the euro area in the OECD database. The equivalent of the VIX for the Euro Area is the Vstoxx index. This index measures the 30-day implied volatility of the Euro Stoxx 50 index. The matrix of correlation (Table E.1) and the figure E.1 shows that these measures vary together but also have distinct variations providing different information. Like in the second section, we run a PCA with these six measures in order to get a synthetic

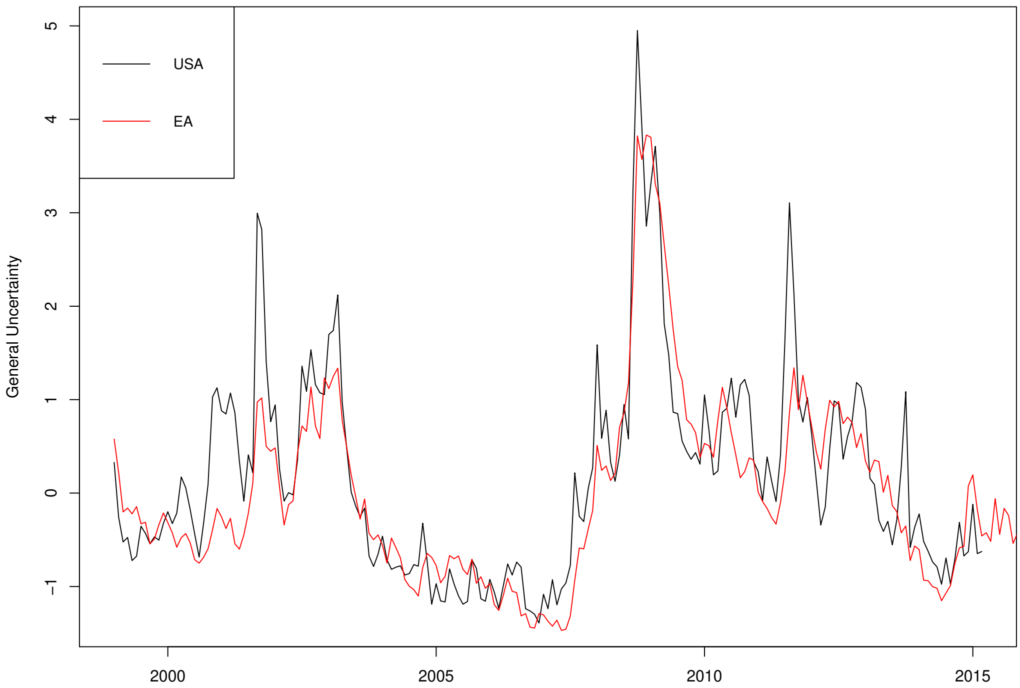
[40] The weights are given by the weights of these countries in the GDP in the euro area. France represents around 21%, Germany represents 29%, Italy represents 15% and Spain represents 10%. We recover 75% of the euro area using these four countries.

measure of uncertainty for the euro area which spans over the time period 1999M1:2015M12.

In appendix E, Table E.2 reports the eigenvalues of the matrix of correlation between these measures. This table shows that most of the variance can be explained by the first factor (52.04%). Following the Kaiser rule, we retain the first two factors. Like in the US case, all measures are positively correlated with the first factor (Table E.3) where MU (0.81), FU (0.81), IDE (0.76) and the Vstoxx (0.78) are highly correlated with the first factor. Like in the US case, the first factor is going to constitute the general measure of uncertainty for the euro area. We identify uncertainty peaks corresponding to events like the 09/11 attacks, the Iraq War in 2003, the collapse of Lehman Brothers or the European debt crisis (Figure E.3). On the second factor (Figure E.2), we can distinguish two groups. EPU, IDE and IDC constitute the first group. These measures are positively correlated with the second factor. In the second group, we can see that the Vstoxx, MU and FU are negatively correlated with the second factor. Visualizing this second factor, we can do a distinction between two types of uncertainty shock. On the one hand, we distinguish macroeconomic or nonfinancial uncertainty shocks with the 09/11 attacks as for the United States, the 2005 German elections and the euro crisis in the 2010s. On the other hand, we distinguish financial uncertainty shocks with the collapse of Lehman Brothers in 2008. This distinction is less clear because there are less measures than in the US case. We can remark that the measure of the macroeconomic uncertainty based on the methodology of Jurado *et al.* (2015) is still linked to finance. The other factors do not allow to identify other dimensions.

We can see many similarities between the euro area composite index and the United States composite index with a high level of correlation (0.88). Especially, it is interesting to note that we find many US uncertainty peaks examining the peaks of the euro area (e.g, 09/11 attacks, the Iraq War) but not inversely. Interestingly, except for the euro crisis, the euro area uncertainty measure reaches its highest values with US peaks. However, what is happening in Europe is susceptible to affect US uncertainty like with the sovereign debt crisis in Europe in 2010. Since Europe is an important trade partner of the United States, there could be a negative impact on the US growth and thus, could affect the US macroeconomic uncertainty. However, since the United States is not directly affected, the level of uncertainty is not very high regarding its general uncertainty index in 2010. In some works, it is assumed that uncertainty shocks in the

Figure 3: US uncertainty VS EA uncertainty over the period 1999M1:2015M3



Note: Indexes are standardized

United States have an immediate impact on uncertainty in the euro area (Favero & Giavazzi, 2008; Colombo, 2013; Cheng *et al.*, 2016; Balcilar *et al.*, 2017). Balcilar *et al.* (2017) argue that the actions of the US government regarding policy changes in the United States is a source of uncertainty for the euro area and its investors suggesting that economic policy uncertainty peaks in the Euro area are partially driven by US uncertainty with the evidence on financial integration across international markets. Candelon *et al.* (2018) have find that the United States is the main source of connectedness within the global equity system and support the idea that uncertainty is a channel of contagion on financial markets. This argument is in line with Baker *et al.* (2019a) which have underlined the dominance of the United States in global stock markets. The general measure for the euro area seems to underline the sensibility of the euro area uncertainty to US uncertainty shocks.

Running a dynamic factor model for the euro area, we find that indexes from both methods have similarities too (Figure F.2.1 and Figure F.2.2). The both general indexes from these methods have a correlation close to 0.94. Similarities are less clear than in the US case concerning the second factor but the correlation is high (0.84).

5 COVID-19 and Uncertainty

The COVID-19 pandemic is currently disrupting the global economy stopping economic activities with worldwide lockdown measures and increasing uncertainty on many aspects (employment, growth, health, policy,...). From textual analysis methods, Baker *et al.* (2020b) have developed a newspaper-based infectious disease equity market volatility tracker quantifying the role of infectious diseases (COVID-19, ebola, sars,...) in US stock market volatility. The key words in newspapers are related to economy (economic, economy, financial), equity market (stock market, equity, equities, Standard and Poors), volatility (volatility, volatile, uncertain, uncertainty, risk, risky) and pandemic (epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1) to construct the daily index (Figure G.1). Unsurprisingly, the highest peaks are related to the current COVID-19 pandemic. We convert the daily index to a monthly frequently using the average for each month (Figure G.2) to insert this new variable in the PCA that we denote $COVID$.

5.1 The United States

We add this monthly variable in our baseline PCA over the period 1990M1:2015M3 for the US. We find that this index is positively correlated with the first factor but its squared cosine is weak (Table G.1.2). Unsurprisingly, the general index computed by this PCA is very similar to the general index of our baseline PCA (Figure G.1.3).[41] Adding this variable does not change the interpretation of the first and the second factor. Comparing the second factor with the second factor of our baseline PCA, we find many similarities too and we keep the distinction between

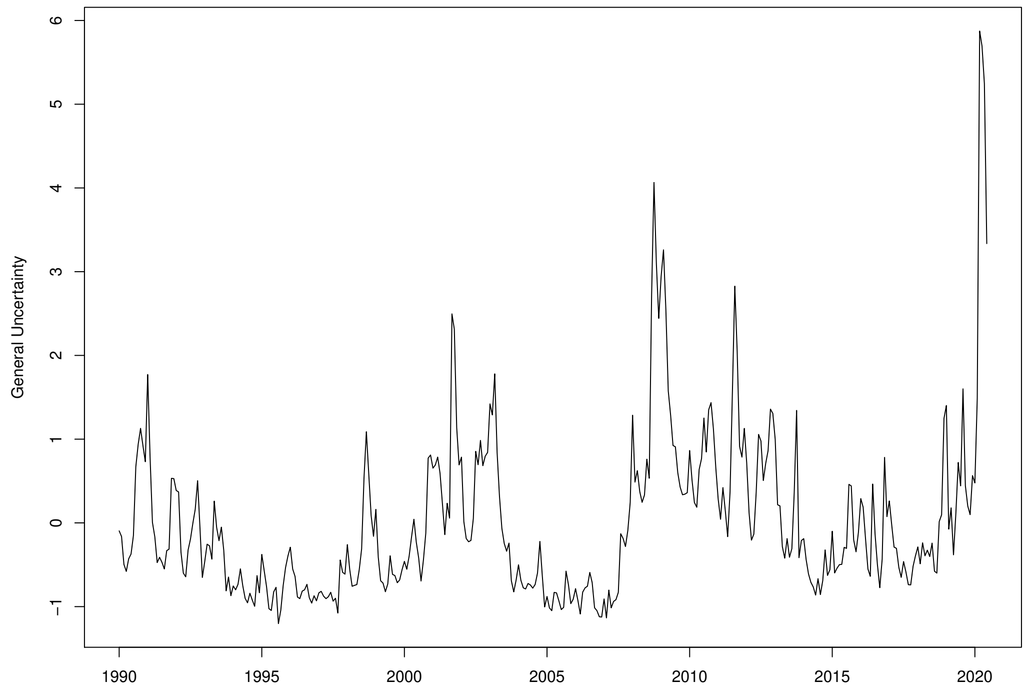
[41] Adding the variable COVID in the DFM does not change the results, we find many between similarities between both general indexes from both methods.

financial shocks and nonfinancial shocks (Figure G.1.4). On this second factor, COVID is included in the financial group. The research of key words related to equity market could be the explanation of the position of this variable which is close to the financial news-based index (FI) of Puttman (2018) and the equity market volatility tracker of Baker *et al.* (2019b). More, since this measure tries to quantify the role of infectious diseases in US stock market volatility, this result is not very surprising. Hence, this result reinforces our interpretation of the second factor distinguishing financial uncertainty shocks and nonfinancial uncertainty shocks and the results of the macroeconomic index of Jurado *et al.* (2015) which seems more linked to finance.

Regarding the other factors, we plot the second and the third factor on the variables factor map (Figure G.1.2). TPU, GPR, MPU, GPR, FI and EMV are the measures the most positively correlated with the third factor. We have always the public broadcasting surrounding uncertainty peaks on this factor with these news-based measures. Interestingly, examining the squared cosines, the only measure that we can interpret on the eighth factor is COVID even if this factor restitutes a small part of the available information. The correlation between this factor and COVID is equal to 0.60. Thus, the pandemic risk constitutes a new dimension of the fluctuations in uncertainty.

Finally, in order to determine the level of the COVID-19 pandemic in a general uncertainty index, we run a PCA over the time period 1990M1:2020M6 adding the pandemic measure to the other available uncertainty indexes. We lost the following measures used in our baseline PCA because there are not available over this sample: IVOL, FI, VRP and the NVIX. Unsurprisingly, the COVID-19 pandemic in 2020 is considered as an uncertainty peak (Figure 4). More, it is considered as the highest uncertainty peak over this sample. Examining the second factor, we keep the distinction between financial uncertainty shocks and macroeconomic uncertainty shocks where the macroeconomic index of Jurado *et al.* (2015) is still linked to finance Figure G.2.1). Plotting this second factor, we keep the switch between financial uncertainty shocks and macroeconomic (or nonfinancial) uncertainty shocks where the COVID-19 pandemic and associated lockdown measures stopping economic activities are related to macroeconomic uncertainty shocks (Figure G.2.2). Interestingly, the fourth factor distinguishes the geopolitical risk and the pandemic risk highlighting these two particular dimensions of the fluctuations in uncertainty (Figure G.2.1).

Figure 4: US General Uncertainty (1990-2020)



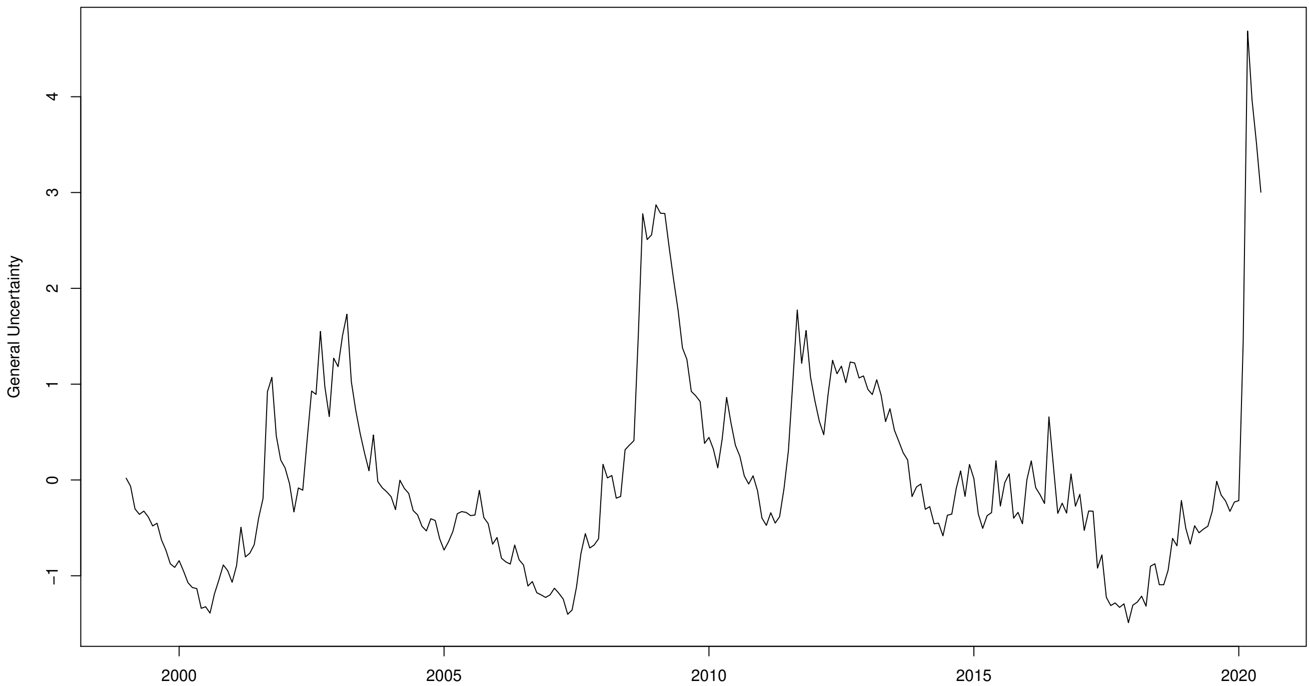
Note: The index is standardized.

5.2 The Euro Area

Adding the variable COVID in the PCA over the period 1990M1:2015M12 for the euro area, it is positively correlated with the first factor (Table G.3.2) but its squared cosine is weak (Table G.3.3). Unsurprisingly, the general index computed by this PCA is very similar to the general index of our baseline PCA (Figure G.1.3). Examining the second factor, as in the US case, we can remark that the measure of the macroeconomic uncertainty of Redl (2020) based on the methodology of Jurado *et al.* (2015) is still linked to finance. Adding this variable does not change the interpretation of the first and the second factor like previously with the United States. More, on the third factor, there is only the variable COVID that we can interpret. Thus, the pandemic risk constitutes a new dimension of the fluctuations in uncertainty for the euro area.

In order to determine the level of the COVID-19 pandemic in a general uncertainty index for the euro area, we run a PCA over the period 1999M1:2020M6 adding this pandemic measure to the other available uncertainty indexes. We lost the financial uncertainty index and the macroeconomic uncertainty index of Redl (2020) because there are no data available over this sample. Unsurprisingly, the COVID-19 pandemic in 2020 is considered as the highest uncertainty peak (Figure 5).

Figure 5: EA General Uncertainty Index



Note: The index is standardized.

6 Robustness Checks

In order to check whether the assumption of financialization mentioned in the US case is credible, we run a PCA on a longer sample. Therefore, the variables MU and IDE could have a different position on the variables factor map. More, we have seen in the literature review that MU and FU have many similarities after 1990 but have differences before 1990 too. That's why we redo a PCA on a sample that is very close to the sample of the measure of macroeconomic uncertainty of Jurado *et al.* (2015). We run a PCA on 1962-2016 with the following measures where data are available: VIX, MU, FU, IDC, IDE and FI.[42] There is no change about the first factor. Examining the second factor, MU and IDE are not with the financial variables (Figure C.1). However, the business confidence index has a squared cosine close to 0 on the second factor (Table C.3), making this variable difficult to interpret. Over a longer period, MU and IDE are not on the financial side. The uncertainty index of Jurado *et al.* (2015) is macroeconomic on a longer period. However, when we are on a recent period and when we use more measures of uncertainty related to macroeconomics and hence, have more information in the PCA, this measure is more linked to finance. The difference of results between these different PCA is in line with the increasing weight of finance in the economy and the fact that some variables have progressively leaned towards finance. This interpretation reinforces the observation that there is a distinction between macroeconomic uncertainty and financial uncertainty on the second factor.[43] Therefore, we can reconsider the decomposition of uncertainty shocks in Ludvigson *et al.* (2021) for the last three decades.

7 Conclusion

There is no consensus leading to a unique measure of uncertainty. There are many methods approximating uncertainty which are very interesting. The most of the measures that we have described in the literature review refer to one dimension of uncertainty (macroeconomic, finance, policy, geopolitical risk, ...) providing different information. From various uncertainty indexes, we have developed a synthetic measure of uncertainty for the Unites States taking into account all these aspects using two methods: the PCA and the DFM. Our general measure has

[42]We complete our data using Bloom's (2009) data who has used the monthly standard deviation of the S&P500 index that measures the realized volatility. These data are available since 1962. The results are qualitatively the same replacing the VIX with the NVIX.

[43]In Appendix D, we run a PCA with these 6 measures over the time period 1990-2016. On the second factor, the results don't allow to interpret MU and IDE.

profound similarities with the composite index proposed by Charles *et al.* (2018). However, we have inserted more variables than these authors did (and especially more of economic policy variables). That is why, our general measure identifies the Gulf War and the Iraq war as uncertainty peaks. We find equivalent composite indexes with a strong correlation from the PCA and the DFM but we argue that the PCA seems to be the best method to determine and to interpret the factors explaining the fluctuations in uncertainty. On the first factor, these are shocks (policy, financial, geopolitical, ...) that will generate uncertainty. Other factors are related to the public broadcasting and geopolitical risk. More, adding an uncertainty related to the pandemic, we find that the pandemic risk is a new dimension in uncertainty.

Examining the second factor, we can observe a disturbing result. The second factor has established a distinction between financial uncertainty and an uncertainty more related to macroeconomics like in the decomposition of uncertainty shocks proposed by Ludvigson *et al.* (2021). Therefore, the PCA has underlined the importance of their decomposition between these two natures of uncertainty shocks. However, on the variables factor map, the measure of macroeconomic uncertainty of Jurado *et al.* (2015) is more linked to finance. So, their decomposition of uncertainty shocks isn't completely accomplished. Over a longer period, this measure is no longer with the financial variables on the second factor. In other words, if we want to study the impact of macroeconomic uncertainty shocks over a relatively recent sample, we should be careful with this index. Given that finance can be macroeconomic, we can understand one methodological choice of Jurado *et al.* (2015). These authors have inserted financial time series to build their indicator of macroeconomic uncertainty. However, these financial series may have become more important in the construction of this measure with financialization of the economy in the last decades. We should research a better measure of macroeconomic uncertainty that would be more independent of finance. This task is all the more important since many empirical works use and refer, perhaps wrongly, to this so-called macroeconomic uncertainty index. A track work could be to rework with the measure of Jurado *et al.* (2015) applying their methodology and removing the financial series in order to get a measure more independent of finance.

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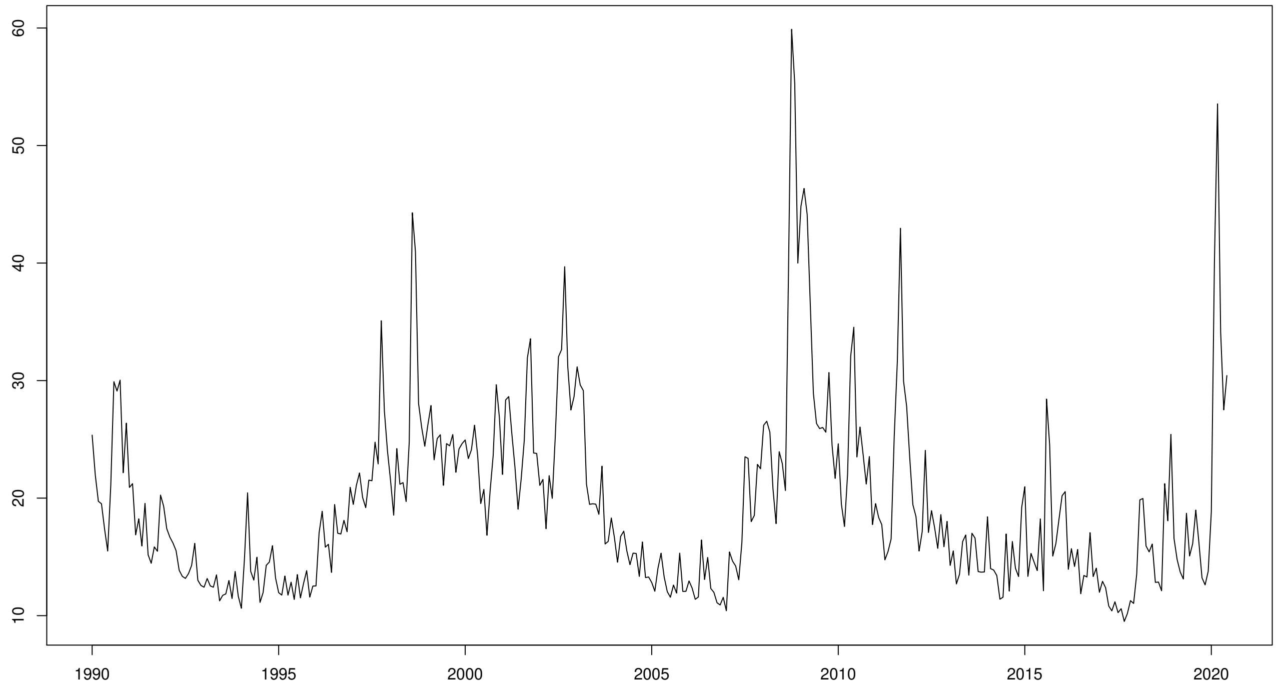
Appendix

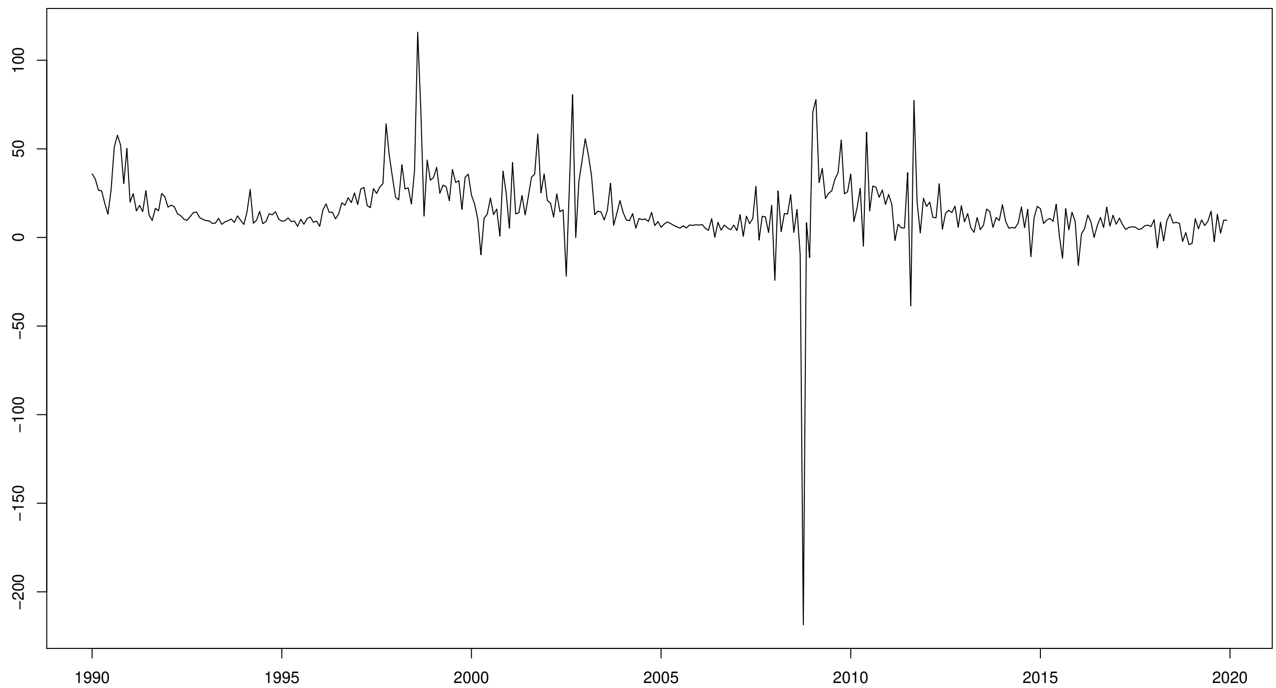
A Measures of Uncertainty

Figure A.1: VIX Index



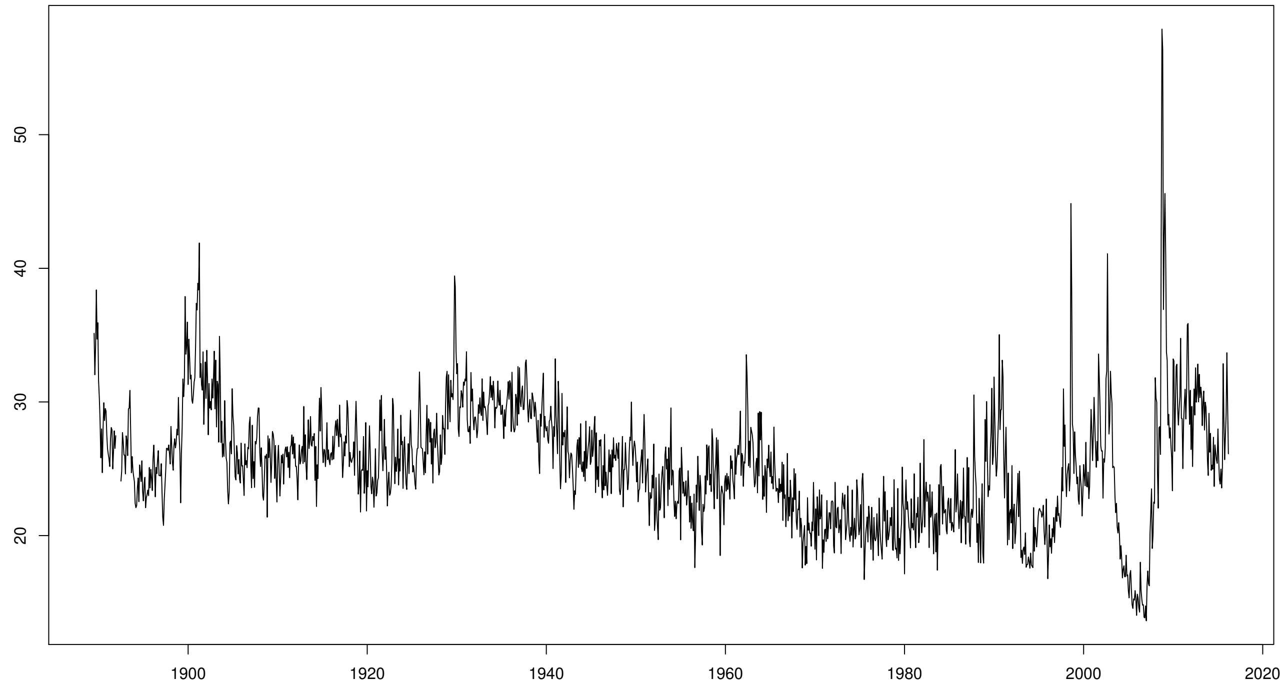
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.2: Variance Risk Premium



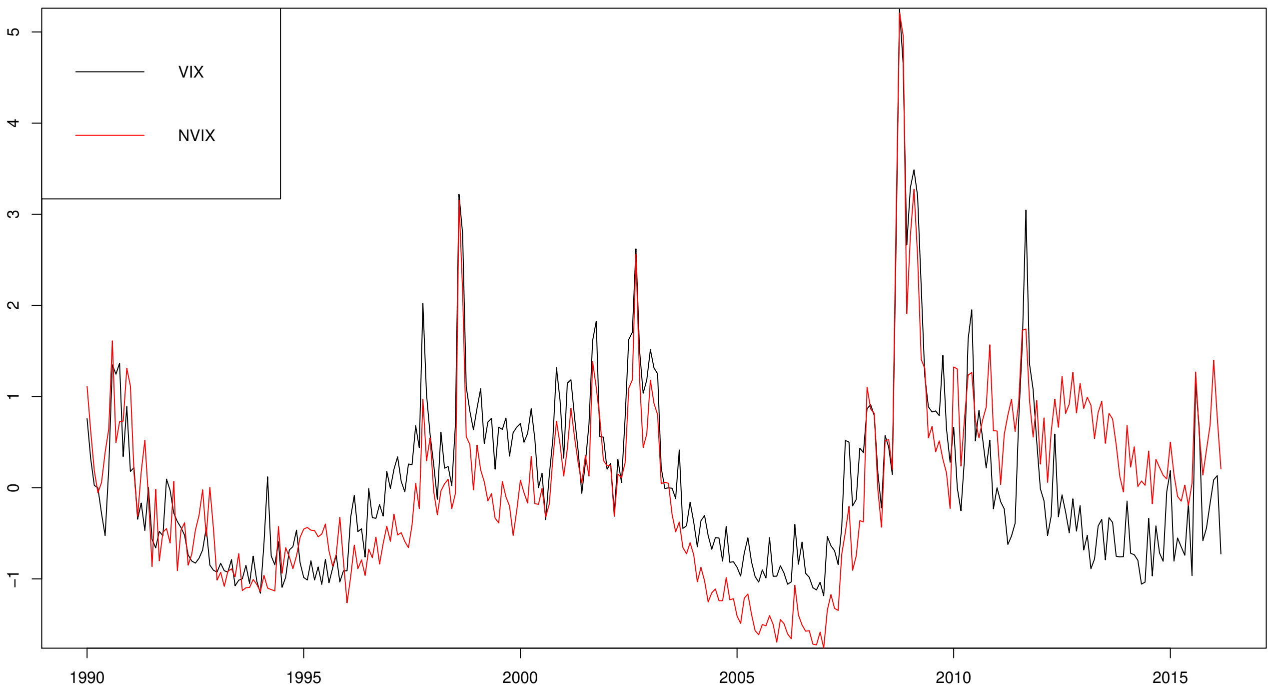
Note: The measure spans the time period 1990:M1-2019:M12

Figure A.3: News Implied Volatility Index of Manela & Moreira (2017)



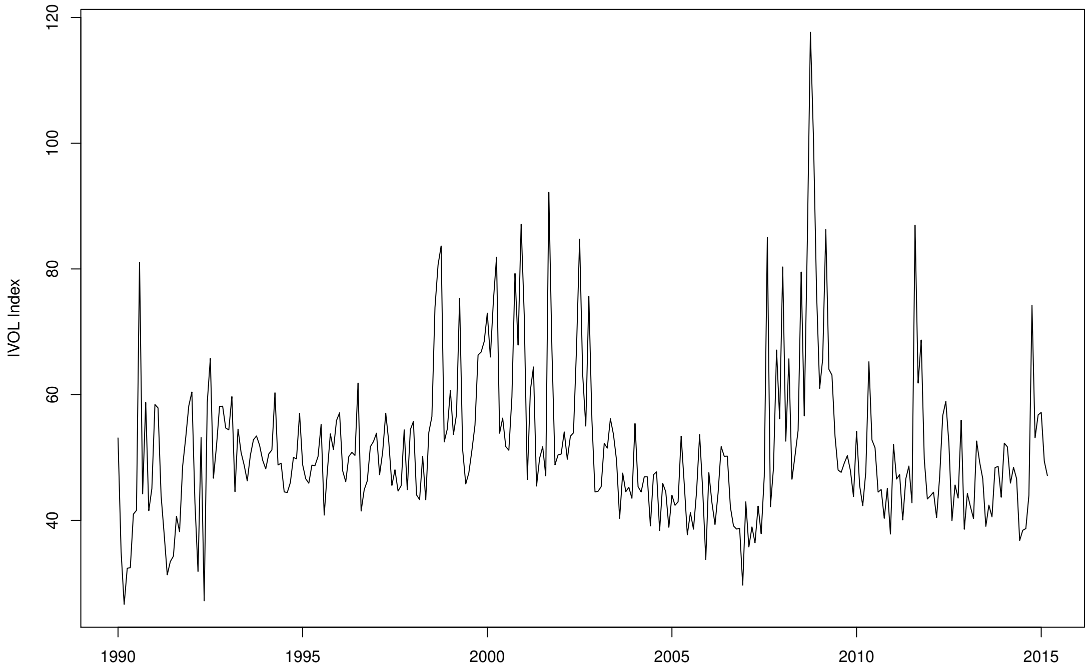
Note: The measure spans the time period 1889:M7-2016:M3

Figure A.4: Comparison: News Implied Volatility Index of Manela & Moreira (2017) and the VIX



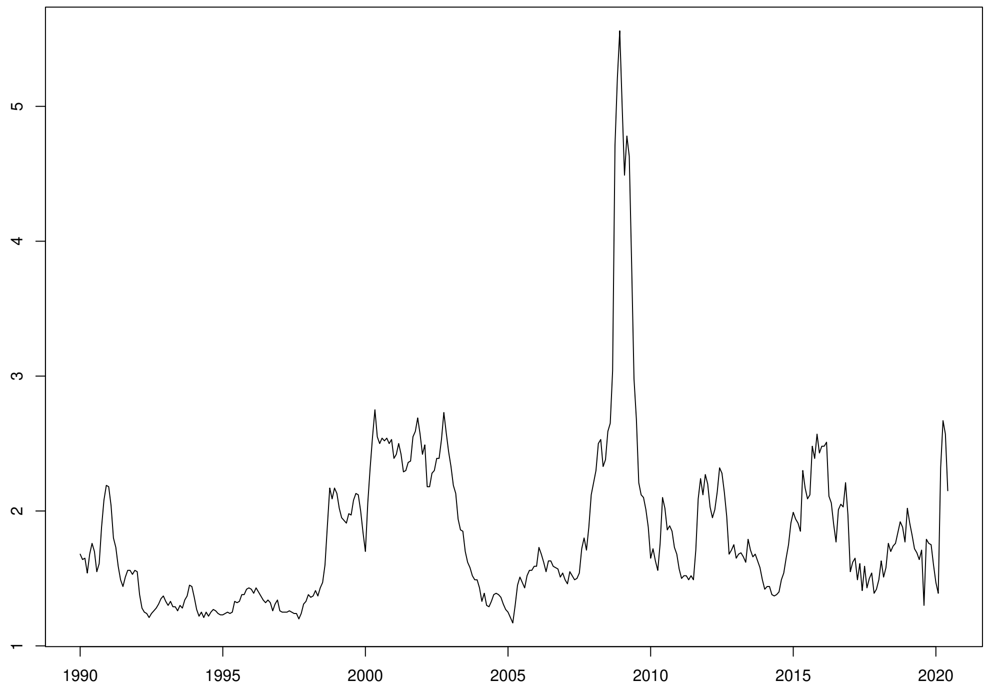
Note: The indexes are standardized.

Figure A.5: IVOL Index



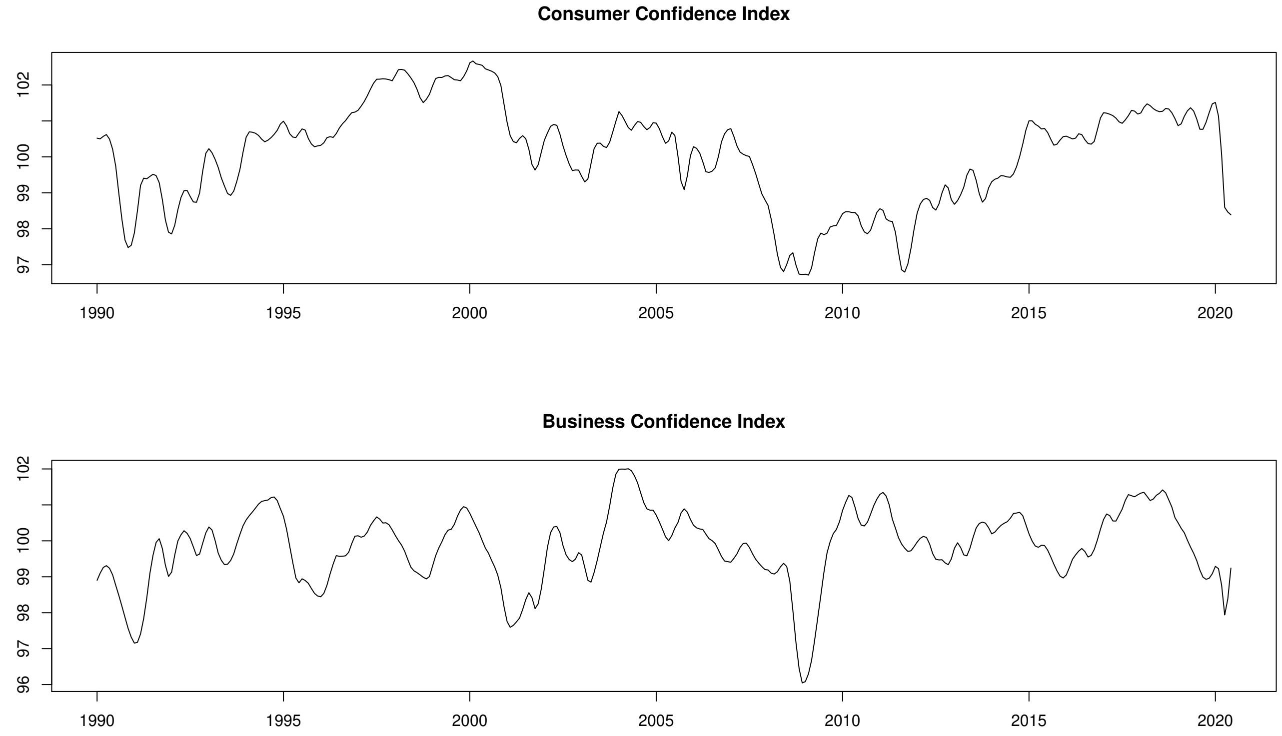
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.6: Corporate Bond Spread



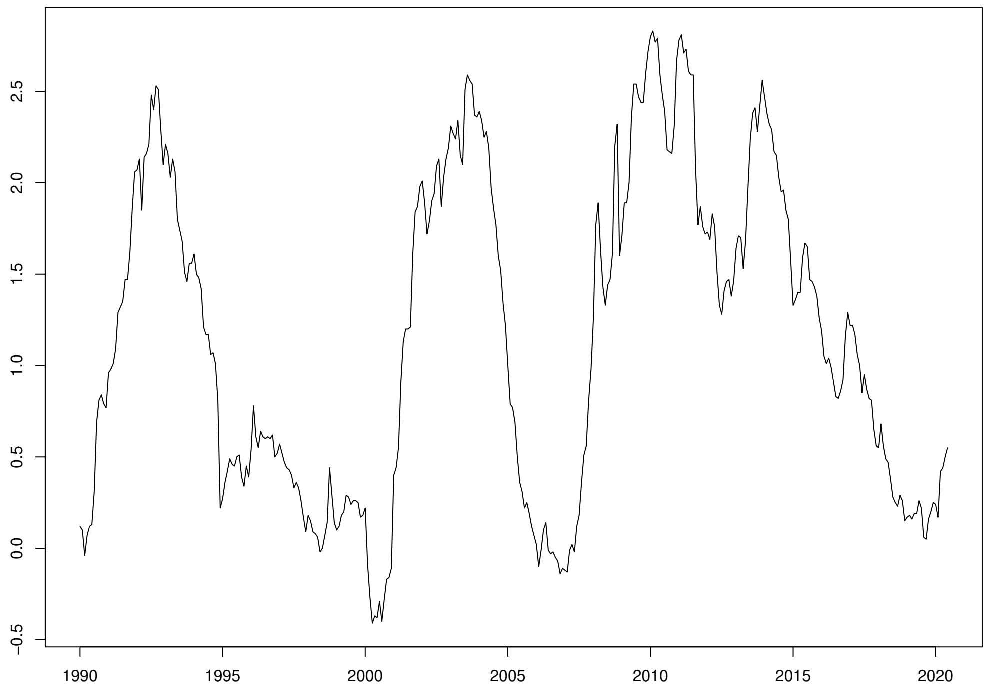
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.7: Confidence Indexes



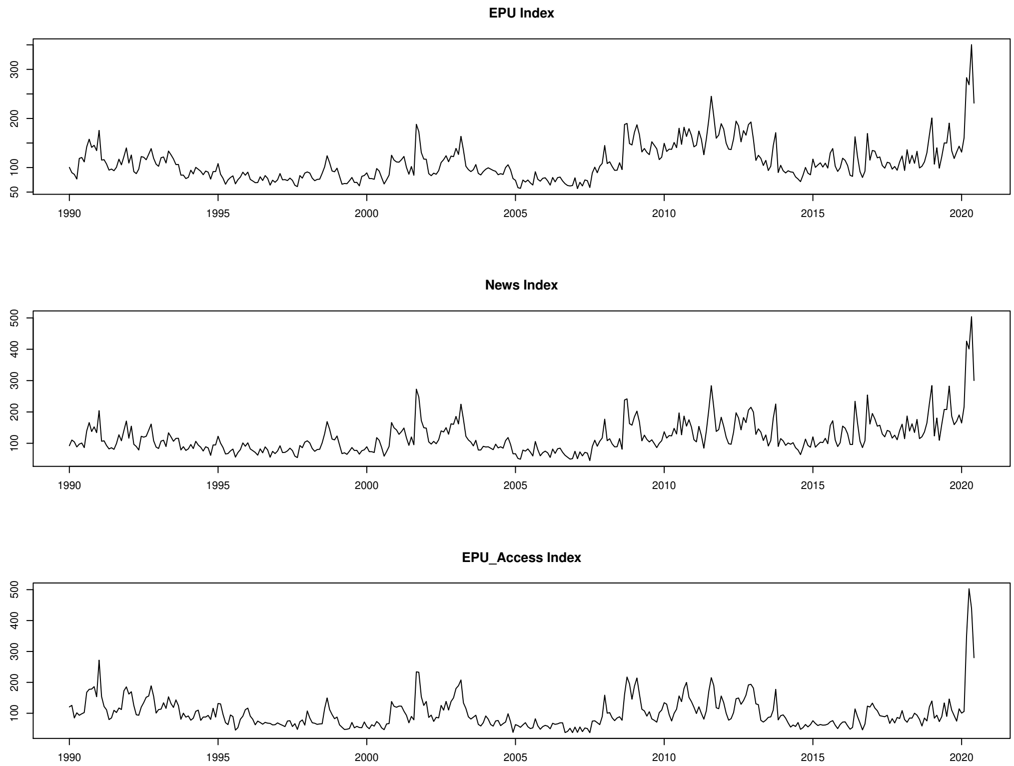
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.8: Spread 10Y-2Y



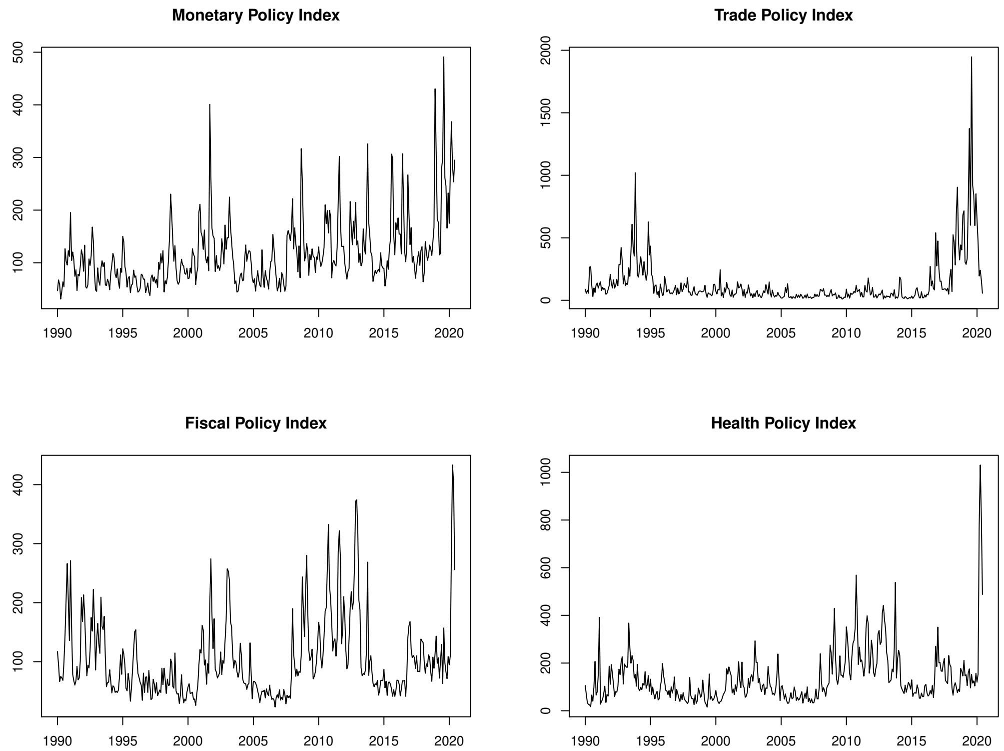
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.9: Economic Policy Uncertainty Indexes of Baker *et al.* (2016)



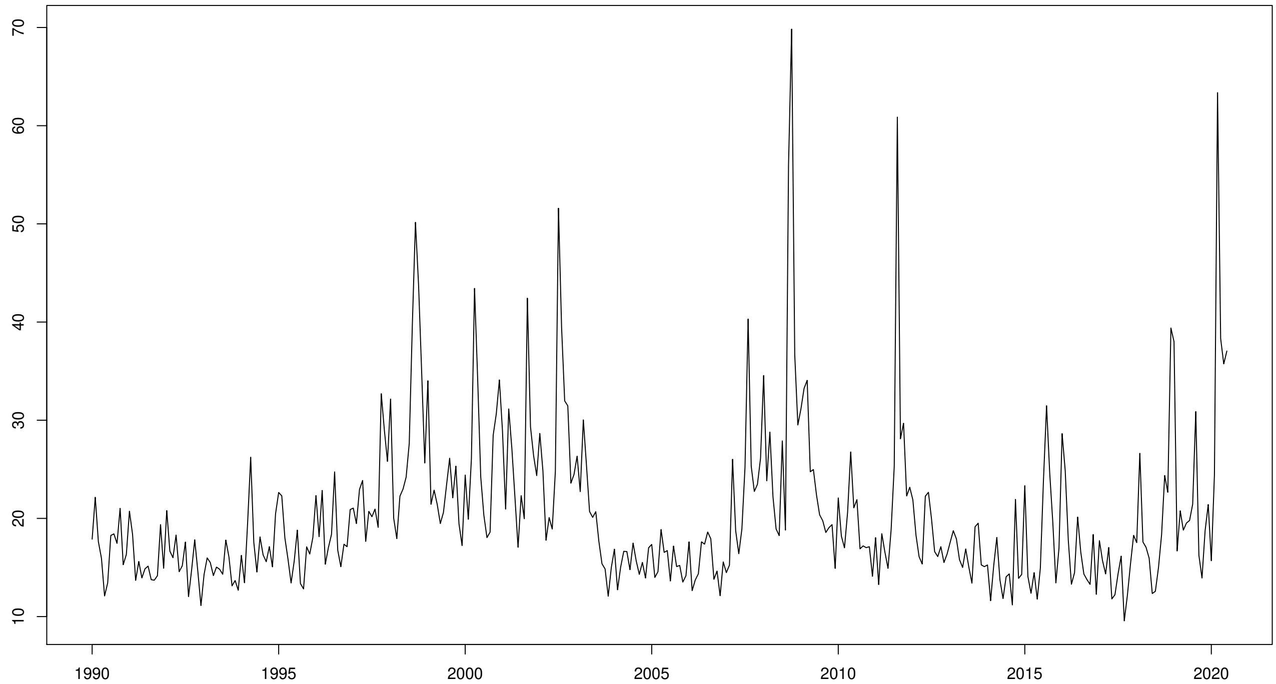
Note: The measures span the time period 1990:M1-2020:M6

Figure A.10: Derived Economic Policy Uncertainty Indexes of Baker *et al.* (2016)



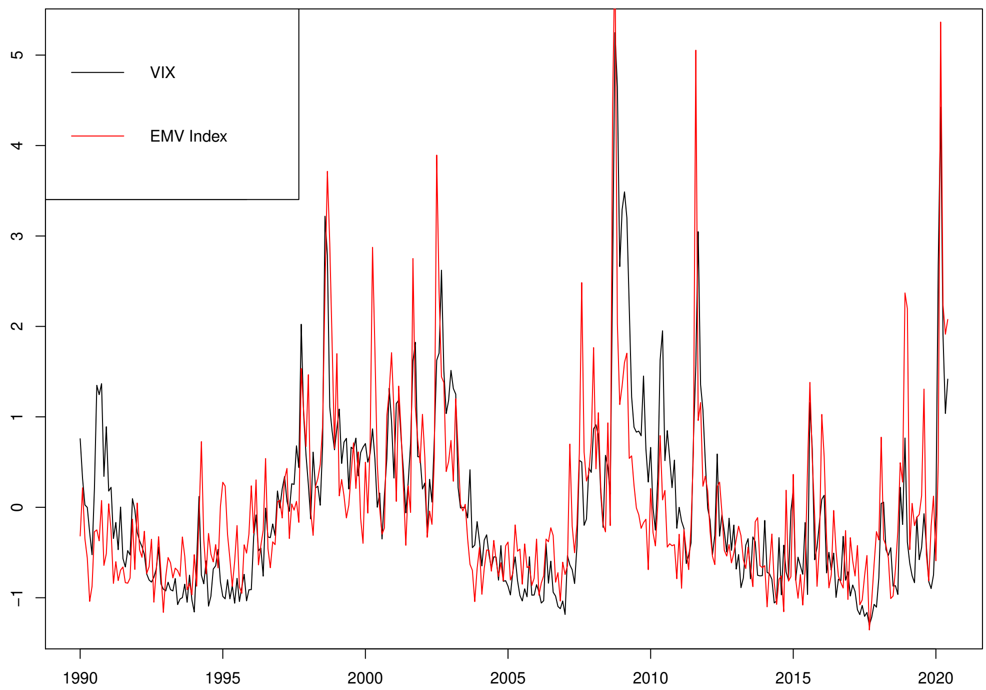
Note: The measures span the time period 1990:M1-2020:M6

Figure A.11: Equity Market Volatility tracker of Baker *et al.* (2019b)



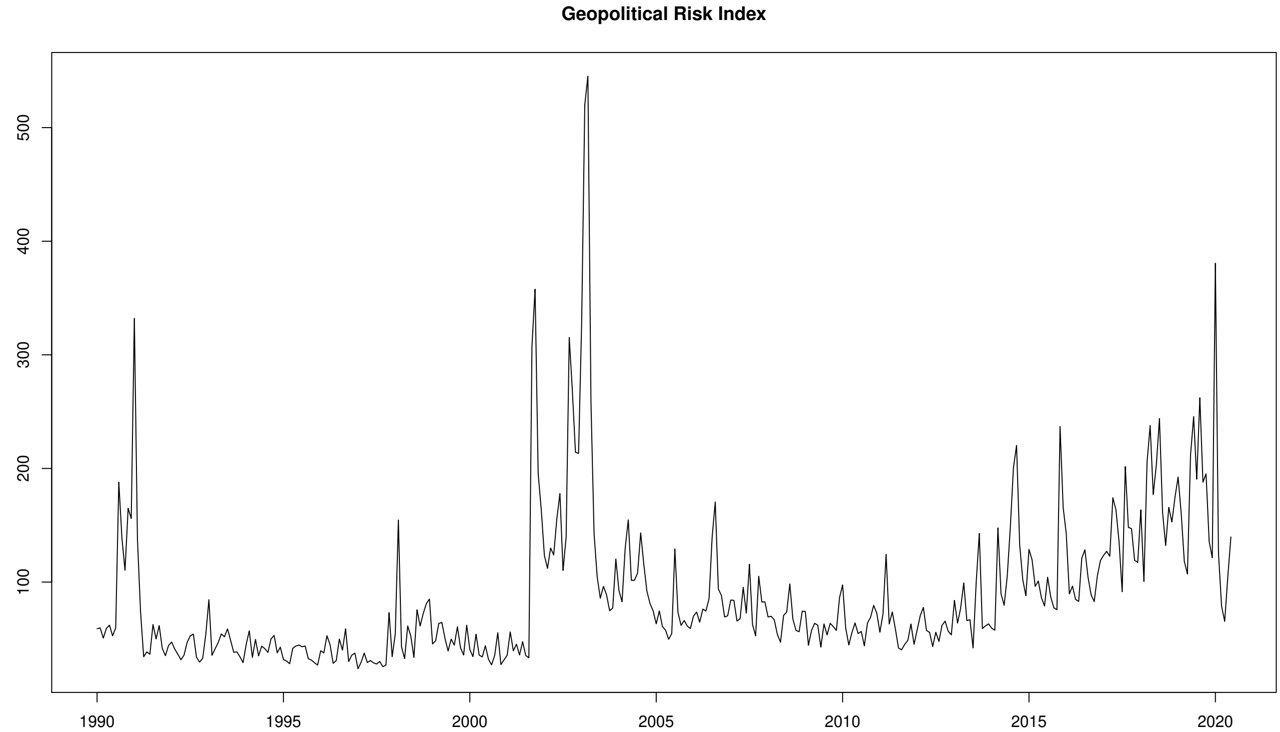
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.12: Comparison between the VIX and the Equity Market Volatility index of Baker *et al.* (2019b)



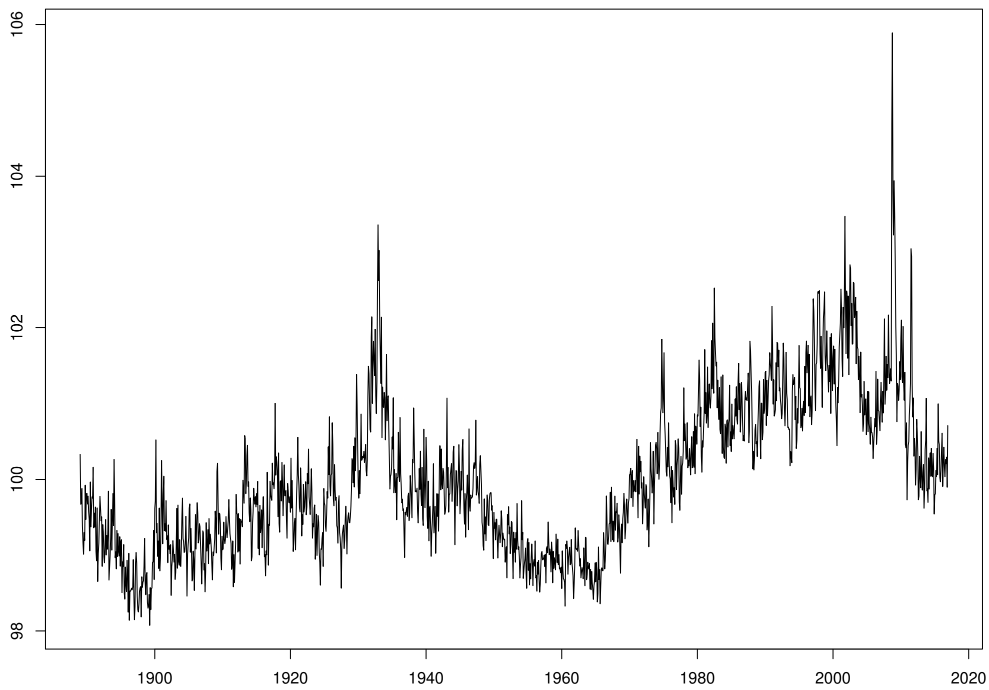
Note: The measures are standardized

Figure A.13: Geopolitical Risk Index



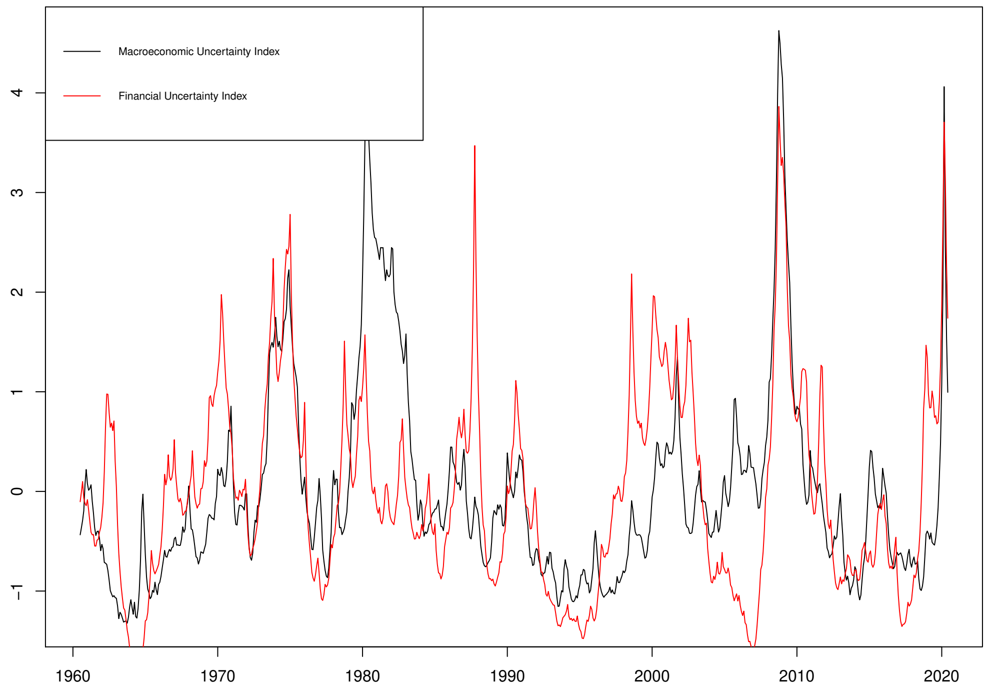
Note: The measure spans the time period 1990:M1-2020:M6

Figure A.14: Financial Stress Index of Puttman (2018)



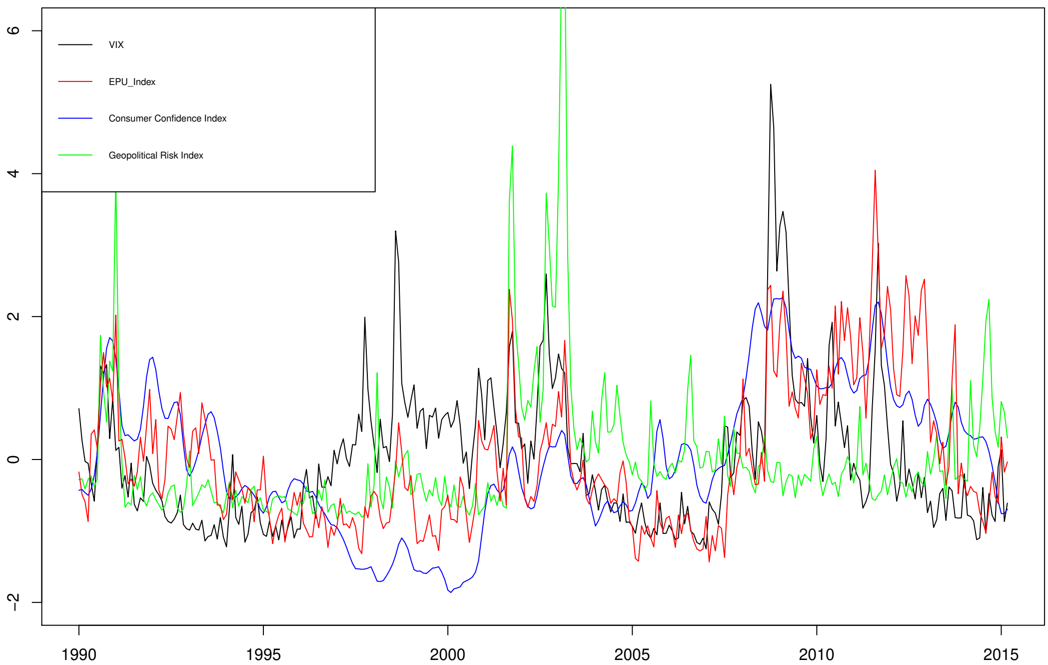
Note: The measure spans the time period 1889:M1-2016:M12

Figure A.15: Macroeconomic Uncertainty Index of Jurado *et al.* (2015) and Financial Uncertainty Index of Ludvigson *et al.* (2021)



Note: The measures are standardized and span the time period 1960:M7-2020:M6

Figure A.16: Comparison of various uncertainty indexes



Note: Indexes are standardized

Table A.1: Table of Correlation

	VIX	FU	MU	EPU_Index	NewsUS	EPU_Access	MPU	Spread	IDC	Bspread	FI	IDE	IVOL	GPR	NVIX	VRP	TPU	EMV	FPU	HPU
VIX	1.00																			
FU	**0.85**	1.00																		
MU	**0.61**	**0.69**	1.00																	
EPU_Index	**0.45**	**0.38**	**0.33**	1.00																
NewsUS	**0.51**	**0.42**	**0.31**	**0.90**	1.00															
EPU_Access	**0.43**	**0.32**	**0.25**	**0.82**	**0.88**	1.00														
MPU	**0.38**	**0.28**	**0.19**	**0.52**	**0.70**	**0.77**	1.00													
Spread	0.09	0.08	0.10	**0.56**	**0.43**	**0.42**	**0.12**	1.00												
IDC	**0.22**	**0.18**	**0.45**	**0.70**	**0.53**	**0.58**	**0.25**	**0.62**	1.00											
Bspread	**0.74**	**0.79**	**0.83**	**0.41**	**0.44**	**0.35**	**0.25**	**0.12**	**0.36**	1.00										
FI	**0.70**	**0.61**	**0.50**	**0.19**	**0.35**	**0.35**	**0.44**	-0.00	0.05	**0.50**	1.00									
IDE	**0.48**	**0.46**	**0.52**	**0.26**	**0.36**	**0.44**	**0.40**	**-0.16**	**0.30**	**0.63**	**0.45**	1.00								
IVOL	**0.62**	**0.57**	**0.41**	**0.27**	**0.38**	**0.30**	**0.41**	-0.00	0.06	**0.53**	**0.54**	**0.34**	1.00							
GPR	**0.19**	**0.12**	**0.13**	**0.19**	**0.33**	**0.31**	**0.45**	**0.24**	**0.11**	**0.16**	**0.18**	0.08	0.04	1.00						
NVIX	**0.80**	**0.72**	**0.48**	**0.67**	**0.68**	**0.59**	**0.37**	**0.33**	**0.43**	**0.67**	**0.44**	**0.46**	**0.51**	**0.19**	1.00					
VRP	**0.25**	**0.20**	-0.07	0.04	0.03	0.09	0.10	-0.07	-0.10	-0.00	0.02	0.09	**-0.17**	**0.16**	**0.12**	1.00				
TPU	**-0.18**	**-0.23**	**-0.27**	-0.03	-0.01	**0.18**	**0.12**	-0.01	-0.04	**-0.21**	-0.07	-0.04	0.02	**-0.17**	**-0.18**	-0.02	1.00			
EMV	**0.75**	**0.64**	**0.43**	**0.32**	**0.49**	**0.34**	**0.47**	-0.08	0.03	**0.54**	**0.70**	**0.36**	**0.74**	0.11	**0.59**	-0.10	-0.10	1.00		
FPU	**0.31**	**0.21**	**0.18**	**0.83**	**0.83**	**0.90**	**0.57**	**0.47**	**0.58**	**0.27**	**0.19**	**0.30**	**0.17**	**0.24**	**0.53**	0.06	0.04	**0.20**	1.00	
HPU	**0.18**	0.10	**0.10**	**0.75**	**0.67**	**0.69**	**0.32**	**0.54**	**0.55**	**0.21**	-0.01	0.07	0.10	0.06	**0.44**	-0.01	0.06	0.10	**0.84**	1.00

Notes: The measures are monthly and span the time period over January 1990 to March 2015. The correlations which are not in bold are not statistically significant at the 5% level.

B Baseline PCA 1990-2015

Table B.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	8.23	41.14	41.14
Factor 2	3.49	17.43	58.57
Factor 3	1.63	8.14	66.71
Factor 4	1.36	6.79	73.50
Factor 5	1.08	5.38	78.88
Factor 6	1.00	5.02	83.90
Factor 7	0.76	3.78	87.67
Factor 8	0.48	2.38	90.05
Factor 9	0.38	1.90	91.95
Factor 10	0.36	1.79	93.74
Factor 11	0.30	1.50	95.24
Factor 12	0.23	1.17	96.41
Factor 13	0.16	0.80	97.21
Factor 14	0.15	0.73	97.93
Factor 15	0.11	0.55	98.48
Factor 16	0.09	0.45	98.93
Factor 17	0.08	0.42	99.35
Factor 18	0.06	0.30	99.66
Factor 19	0.04	0.20	99.85
Factor 20	0.03	0.15	100.00

Table B.2: Factor Loadings

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20
VIX	0.80	-0.45	-0.01	0.12	0.02	-0.26	0.08	-0.03	-0.02	-0.05	-0.05	0.11	-0.07	-0.05	-0.01	-0.12	-0.04	-0.17	-0.03	0.01
FU	0.72	-0.51	-0.17	0.11	0.06	-0.20	0.10	0.04	0.08	0.05	-0.05	-0.22	-0.08	-0.03	0.22	0.05	0.03	0.02	-0.01	-0.00
MU	0.63	-0.40	-0.44	-0.03	0.07	0.30	0.11	-0.04	0.19	0.25	-0.05	0.04	-0.04	-0.01	-0.11	0.14	-0.04	-0.04	0.00	-0.01
EPU_Index	0.81	0.47	-0.09	-0.03	0.01	-0.11	-0.09	0.04	-0.06	0.10	-0.16	-0.05	0.00	0.16	-0.02	-0.02	0.09	-0.05	0.12	-0.01
NewsUS	0.86	0.35	0.16	0.00	-0.08	-0.03	-0.13	0.05	-0.01	0.04	-0.15	-0.08	0.09	0.14	-0.05	0.02	0.01	0.01	-0.14	0.02
EPU_Access	0.82	0.44	0.27	0.00	0.11	0.10	-0.02	-0.06	-0.00	-0.01	0.01	-0.06	-0.09	-0.03	-0.01	-0.03	-0.09	0.02	-0.01	-0.13
MPU	0.65	0.14	0.58	0.10	-0.10	0.26	-0.05	-0.02	-0.09	0.22	0.02	-0.13	0.03	-0.20	-0.03	-0.03	0.05	-0.02	0.02	0.04
Spread	0.38	0.58	-0.36	0.00	-0.30	-0.13	0.42	-0.12	-0.12	-0.09	0.16	-0.14	0.14	-0.03	-0.01	0.04	-0.06	-0.04	0.01	0.00
IDC	0.57	0.46	-0.45	-0.10	0.11	0.25	0.16	-0.09	-0.26	0.12	-0.05	0.20	-0.06	-0.03	0.09	-0.06	0.03	0.06	-0.03	0.02
Bspread	0.74	-0.41	-0.32	-0.02	0.13	0.14	0.07	0.19	0.18	-0.02	0.04	-0.07	0.14	-0.01	-0.05	-0.17	-0.02	0.08	0.02	0.01
FI	0.60	-0.49	0.23	-0.04	-0.11	0.04	0.14	-0.51	0.09	-0.12	0.04	0.02	-0.03	0.07	-0.04	-0.02	0.09	0.05	0.00	0.01
IDE	0.57	-0.30	0.05	0.03	0.47	0.46	-0.15	0.03	-0.16	-0.24	0.12	-0.02	0.09	0.04	0.05	0.07	0.02	-0.06	0.01	0.00
IVOL	0.59	-0.43	0.22	-0.38	-0.19	-0.13	0.05	0.22	-0.13	0.14	0.34	0.05	-0.08	0.11	-0.02	0.01	0.01	0.01	-0.01	-0.00
GPR	0.31	0.11	0.18	0.59	-0.50	0.36	0.20	0.22	0.11	-0.12	-0.02	0.12	-0.04	0.05	0.05	0.02	0.03	0.00	0.01	-0.01
NVIX	0.85	-0.09	-0.15	0.05	0.02	-0.27	-0.03	0.16	-0.15	-0.26	-0.09	0.00	-0.10	-0.12	-0.13	0.07	0.04	0.07	0.01	0.01
VRP	0.07	-0.03	0.16	0.77	0.43	-0.34	0.12	-0.03	-0.06	0.16	0.11	0.08	0.07	0.04	-0.03	0.03	-0.01	0.04	0.00	-0.00
TPU	-0.10	0.24	0.51	-0.39	0.38	-0.01	0.57	0.13	0.11	-0.05	-0.12	0.04	-0.00	0.01	0.00	0.02	0.01	-0.00	0.00	0.02
EMV	0.66	-0.48	0.26	-0.22	-0.23	-0.17	-0.10	-0.03	-0.06	0.02	-0.15	0.17	0.19	-0.04	0.08	0.06	-0.09	0.04	0.04	-0.01
FPU	0.72	0.58	0.10	0.01	0.08	-0.02	-0.18	-0.07	0.16	-0.07	0.08	0.02	-0.11	0.04	0.04	0.01	-0.15	0.03	0.03	0.09
HPU	0.56	0.65	-0.09	-0.13	0.07	-0.21	-0.16	0.01	0.29	-0.02	0.16	0.14	0.08	-0.10	0.04	0.03	0.12	-0.02	-0.02	-0.02

Table B.3: Squared Cosines

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20
VIX	0.64	0.20	0.00	0.02	0.00	0.07	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.00
FU	0.52	0.26	0.03	0.01	0.00	0.04	0.01	0.00	0.01	0.00	0.00	0.05	0.01	0.00	0.05	0.00	0.00	0.00	0.00	0.00
MU	0.40	0.16	0.19	0.00	0.01	0.09	0.01	0.00	0.04	0.06	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00
EPU_Index	0.65	0.22	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.02	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.01	0.00
NewsUS	0.74	0.12	0.03	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.02	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.02	0.00
EPU_Access	0.67	0.20	0.07	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02
MPU	0.43	0.02	0.34	0.01	0.01	0.07	0.00	0.00	0.01	0.05	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00
Spread	0.14	0.34	0.13	0.00	0.09	0.02	0.17	0.01	0.01	0.01	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IDC	0.32	0.21	0.20	0.01	0.01	0.06	0.02	0.01	0.07	0.02	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Bspread	0.55	0.17	0.10	0.00	0.02	0.02	0.01	0.04	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.03	0.00	0.01	0.00	0.00
FI	0.36	0.24	0.05	0.00	0.01	0.00	0.02	0.26	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00
IDE	0.33	0.09	0.00	0.00	0.22	0.21	0.02	0.00	0.02	0.06	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IVOL	0.35	0.19	0.05	0.14	0.04	0.02	0.00	0.05	0.02	0.02	0.11	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
GPR	0.09	0.01	0.03	0.34	0.25	0.13	0.04	0.05	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NVIX	0.72	0.01	0.02	0.00	0.00	0.07	0.00	0.03	0.02	0.07	0.01	0.00	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.00
VRP	0.00	0.00	0.03	0.60	0.18	0.12	0.01	0.00	0.00	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TPU	0.01	0.06	0.26	0.15	0.15	0.00	0.32	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EMV	0.44	0.23	0.07	0.05	0.05	0.03	0.01	0.00	0.00	0.00	0.02	0.03	0.04	0.00	0.01	0.00	0.01	0.00	0.00	0.00
FPU	0.52	0.34	0.01	0.00	0.01	0.00	0.03	0.01	0.03	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01
HPU	0.32	0.42	0.01	0.02	0.00	0.04	0.03	0.00	0.08	0.00	0.03	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00

Figure B.1: Variables factor map (Factor 1 and Factor 2)

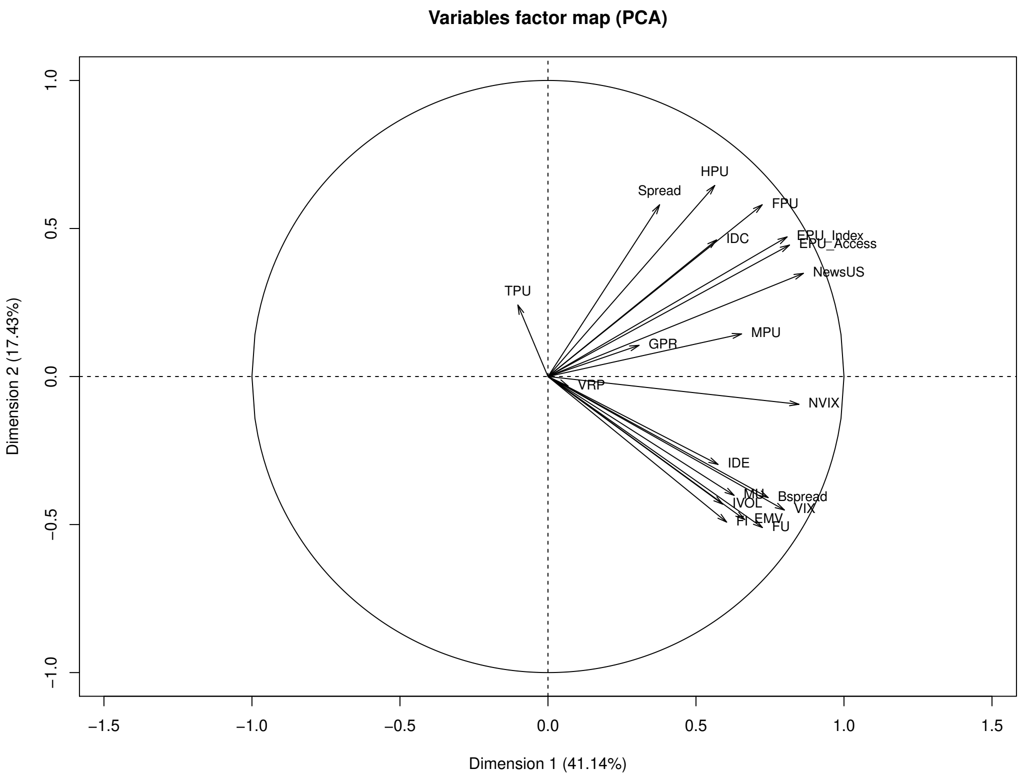
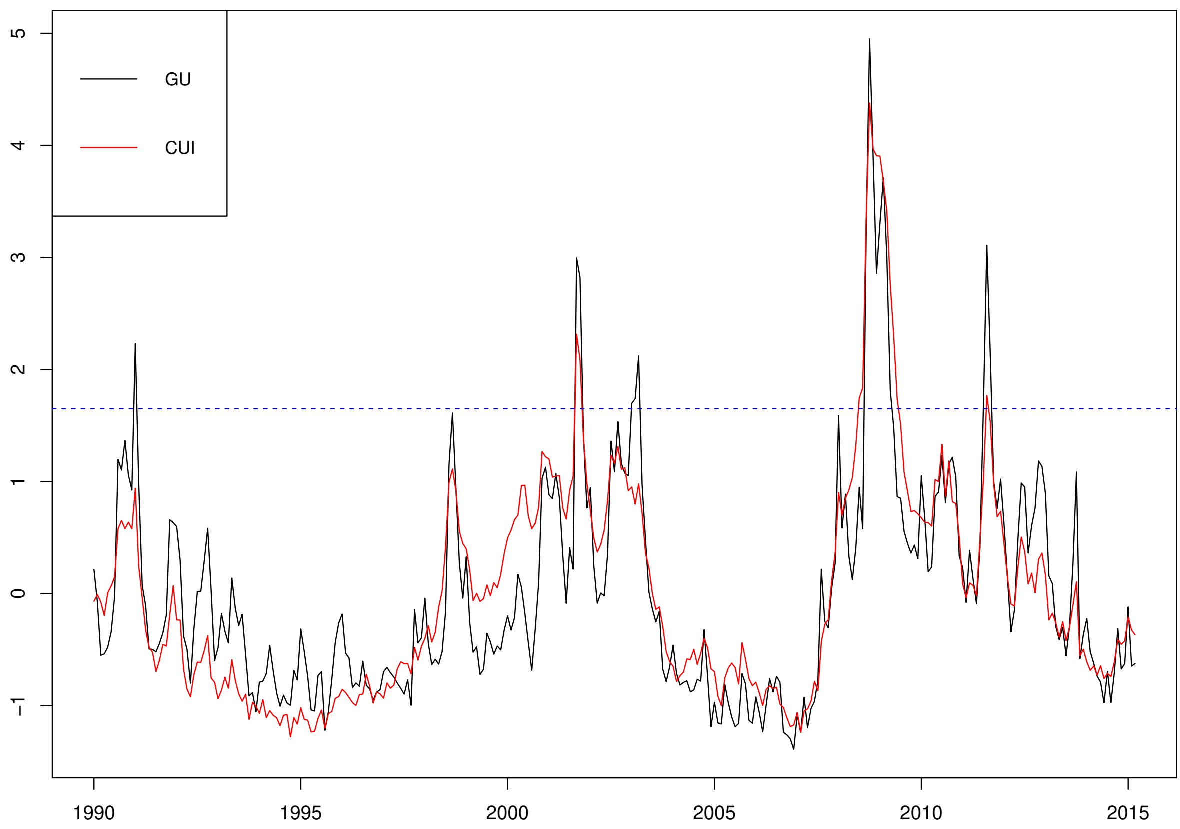


Figure B.2: General Uncertainty (GU) VS CUI



Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65.

Figure B.3: Variables factor map (Factor 2 and Factor 3)

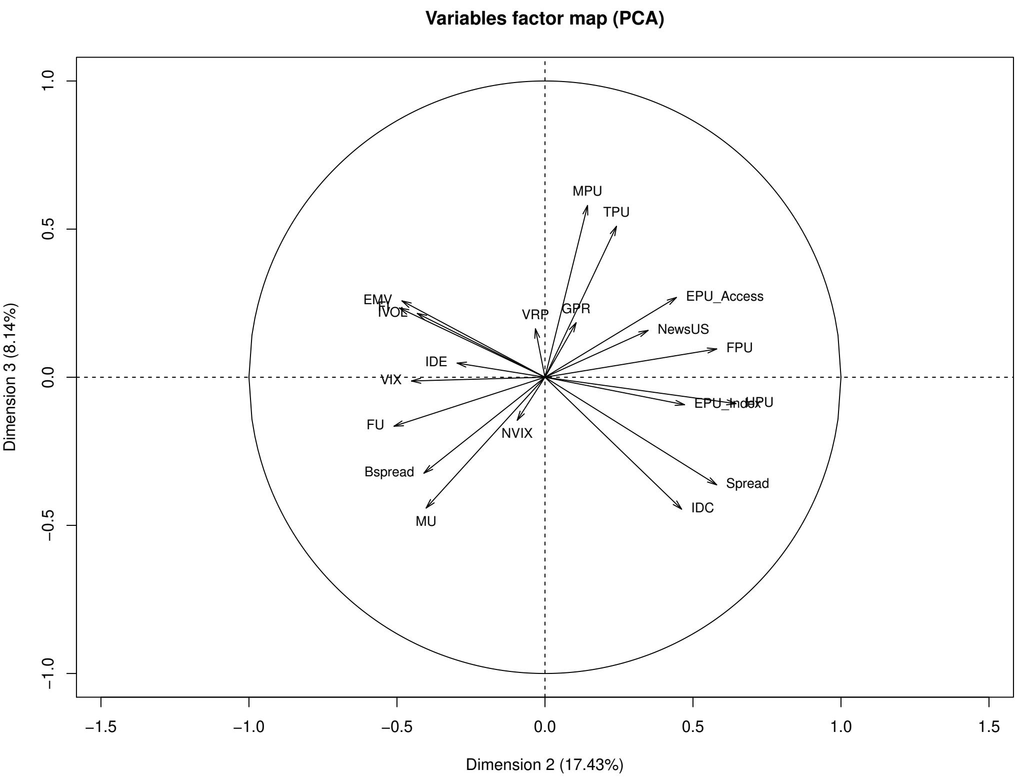


Figure B.4: Variables factor map (Factor 2 and Factor 4)

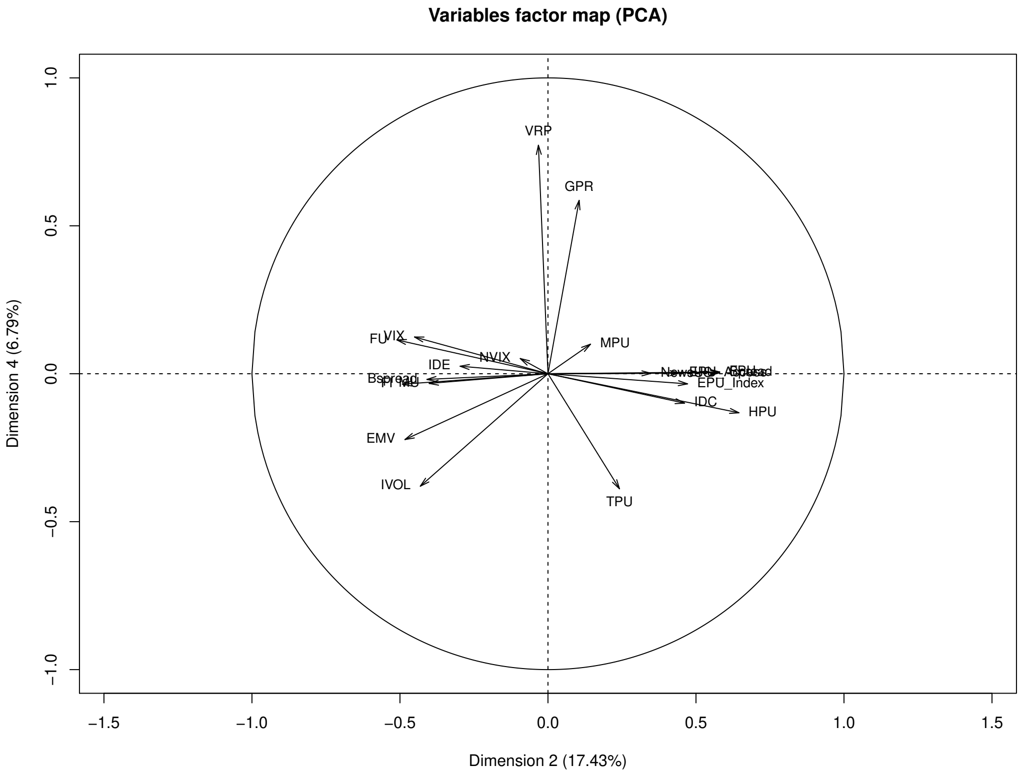
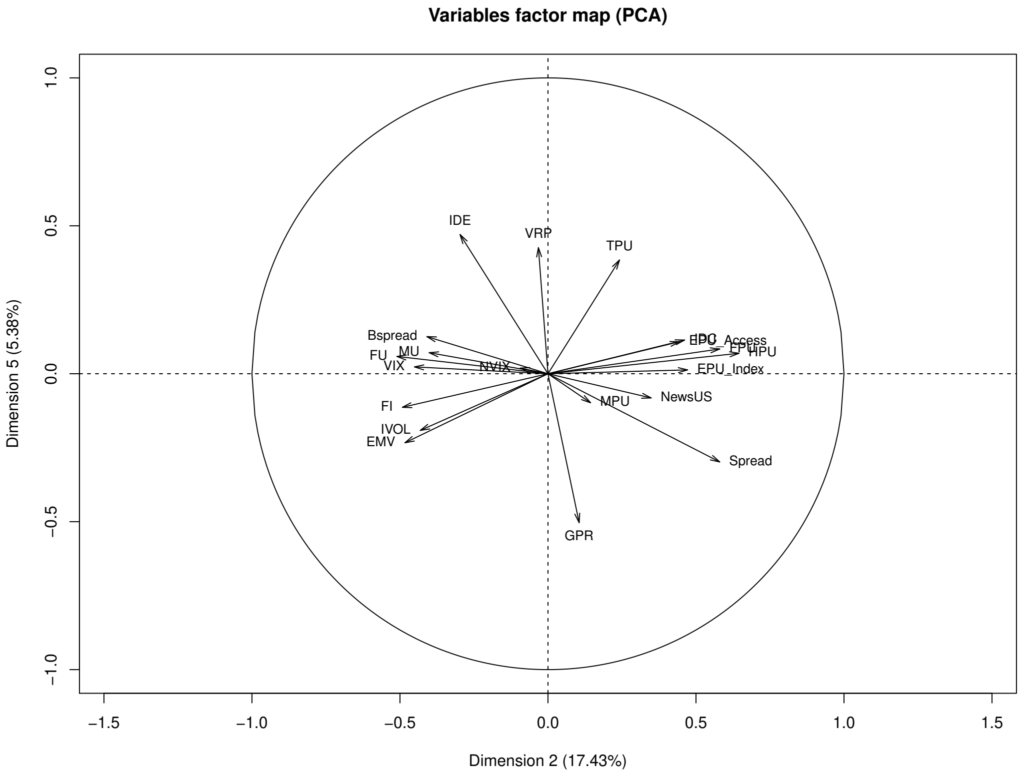


Figure B.5: Variables factor map (Factor 2 and Factor 5)



C PCA over the period 1962-2016

Table C.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	3.27	54.48	54.48
Factor 2	1.00	16.62	71.09
Factor 3	0.79	13.22	84.31
Factor 4	0.46	7.67	91.98
Factor 5	0.29	4.80	96.78
Factor 6	0.19	3.22	100.00

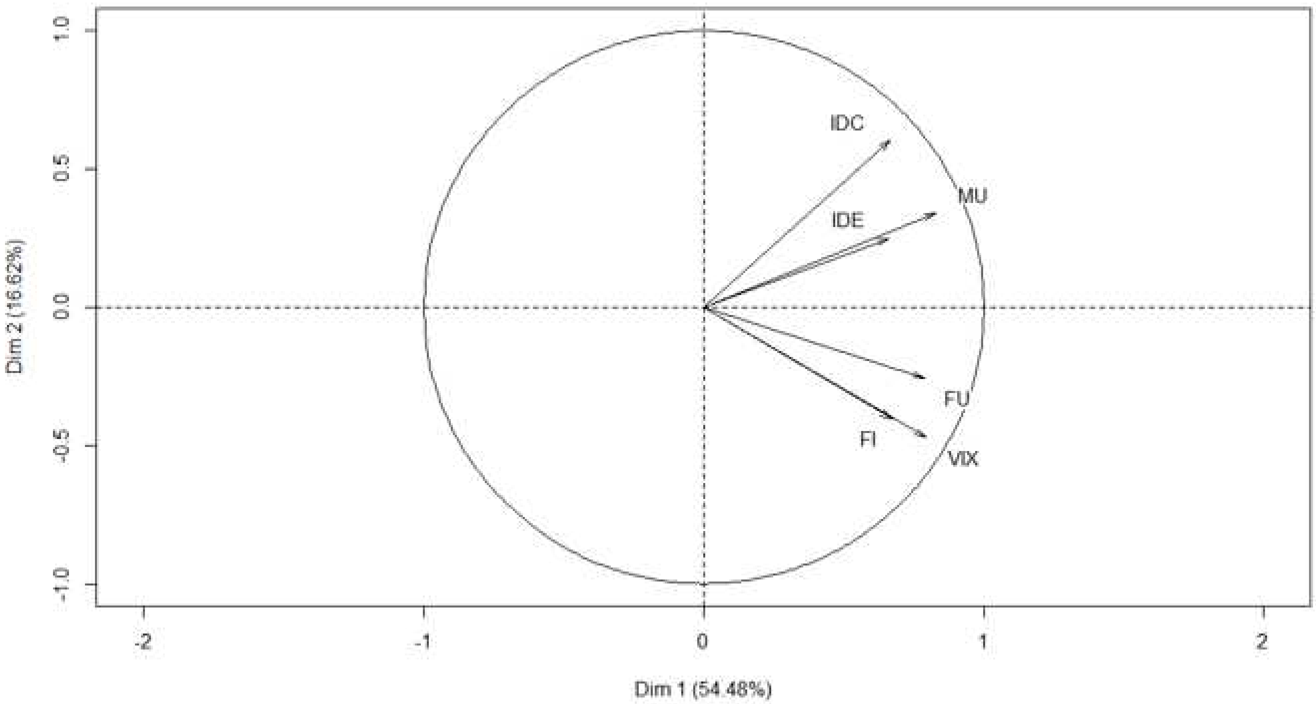
Table C.2: Factor Loadings

	F1	F2	F3	F4	F5	F6
VIX	0.79	-0.47	-0.18	-0.02	0.18	-0.29
MU	0.83	0.34	-0.13	0.02	-0.41	-0.12
FU	0.79	-0.26	-0.42	-0.25	-0.01	0.28
IDC	0.66	0.60	-0.17	0.30	0.27	0.05
FI	0.67	-0.40	0.46	0.39	-0.08	0.13
IDE	0.66	0.25	0.57	-0.40	0.10	-0.01

Table C.3: Squared Cosines

	F1	F2	F3	F4	F5	F6
VIX	0.63	0.22	0.03	0.00	0.03	0.08
MU	0.69	0.12	0.02	0.00	0.16	0.02
FU	0.62	0.07	0.17	0.06	0.00	0.08
IDC	0.44	0.36	0.03	0.09	0.08	0.00
FI	0.45	0.16	0.22	0.15	0.01	0.02
IDE	0.44	0.06	0.33	0.16	0.01	0.00

Figure C.1: Variables factor map (Factor 1 and Factor 2)



D PCA over the period 1990-2016 with 6 measures

Table D.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	3.45	57.51	57.51
Factor 2	1.06	17.71	75.22
Factor 3	0.61	10.17	85.39
Factor 4	0.43	7.16	92.55
Factor 5	0.33	5.42	97.97
Factor 6	0.12	2.03	100.00

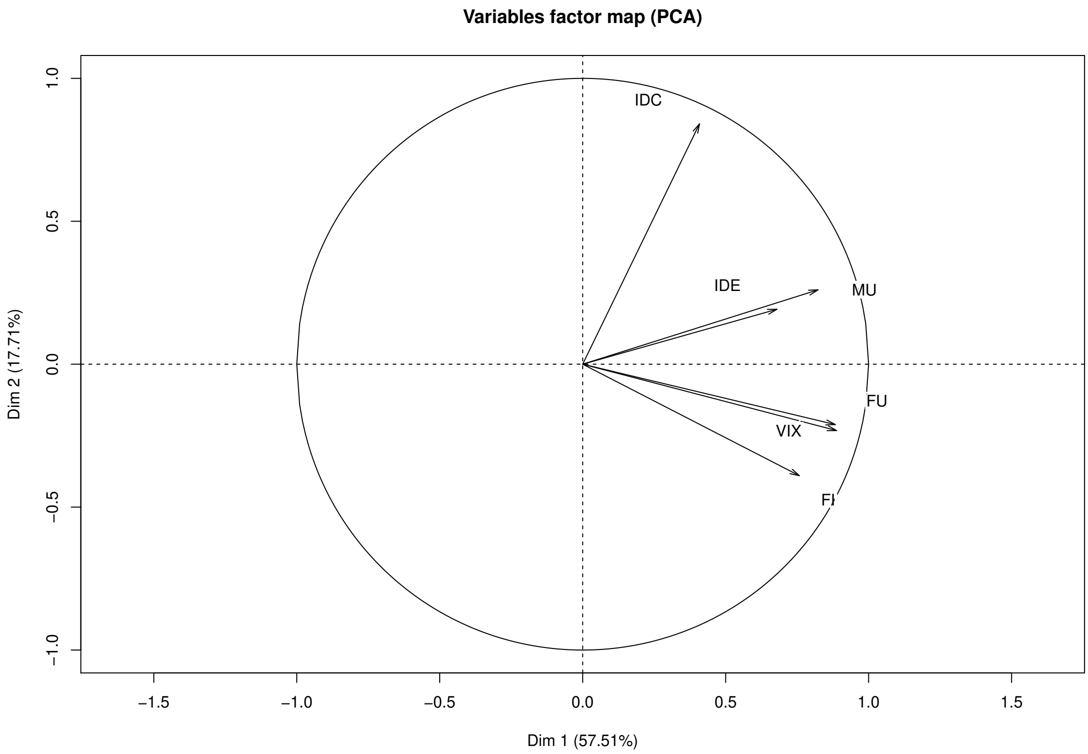
Table D.2: Factor Loadings

	F1	F2	F3	F4	F5	F6
VIX	0.89	-0.23	-0.16	0.01	0.28	-0.23
MU	0.82	0.26	-0.12	-0.28	-0.39	-0.08
FU	0.88	-0.21	-0.18	-0.25	0.16	0.24
IDC	0.41	0.84	-0.21	0.26	0.12	0.05
FI	0.76	-0.39	0.01	0.47	-0.22	0.06
IDE	0.68	0.19	0.70	-0.04	0.07	0.01

Table D.3: Squared Cosines

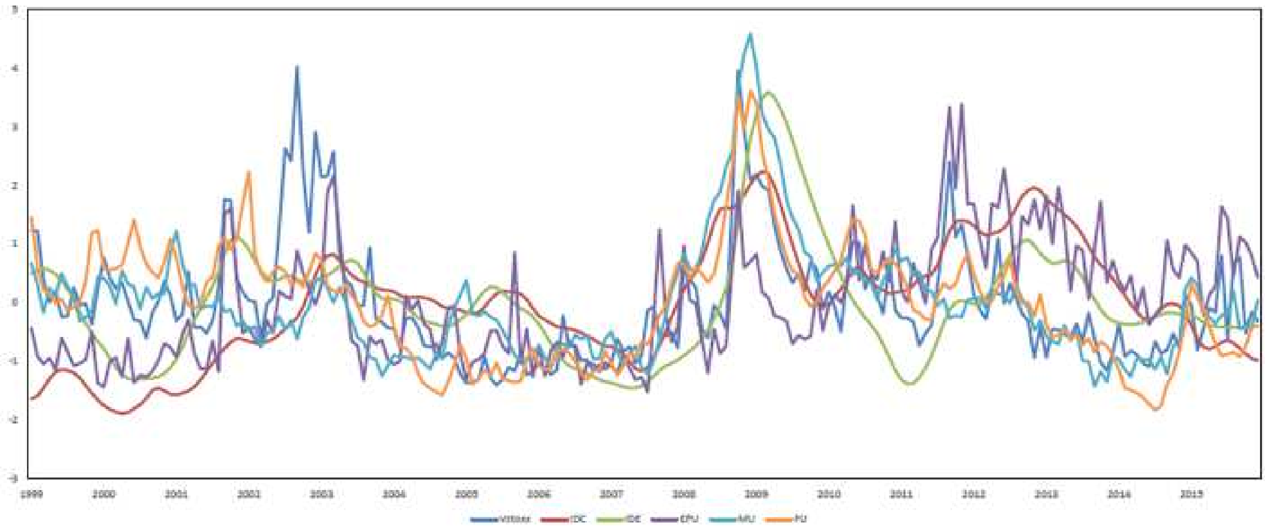
	F1	F2	F3	F4	F5	F6
VIX	0.79	0.05	0.03	0.00	0.08	0.05
MU	0.68	0.07	0.01	0.08	0.15	0.01
FU	0.78	0.04	0.03	0.06	0.03	0.06
IDC	0.17	0.71	0.04	0.07	0.01	0.00
FI	0.57	0.15	0.00	0.22	0.05	0.00
IDE	0.46	0.04	0.49	0.00	0.01	0.00

Figure D.1: Variables factor map (Factor 1 and Factor 2)



E PCA: Results for the euro area

Figure E.1: Comparison between various of uncetainty indexes for the euro area



Note: Indexes are standardized.

Table E.1: Correlation

	Vstoxx	*IDC*	*IDE*	*EPU*	*MU*	*FU*
Vstoxx	**1.00**					
IDC	**0.23**	**1.00**				
IDE	**0.46**	**0.57**	**1.00**			
EPU	**0.39**	**0.57**	**0.23**	**1.00**		
MU	**0.54**	**0.35**	**0.51**	0.10	**1.00**	
FU	**0.69**	**0.20**	**0.45**	**0.17**	**0.79**	**1.00**

Notes: The measures are monthly and span the period over January 1999 to December 2015. The correlations which are not in bold are not statistically significant at the 5% level.

Table E.2: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	3.12	52.08	52.08
Factor 2	1.30	21.66	73.74
Factor 3	0.77	12.85	86.58
Factor 4	0.45	7.52	94.11
Factor 5	0.20	3.32	97.43
Factor 6	0.15	2.57	100.00

Table E.3: Factor Loadings

	F1	F2	F3	F4	F5	F6
Vstoxx	0.78	-0.19	0.43	-0.32	-0.25	0.03
IDC	0.63	0.64	-0.31	0.20	-0.22	-0.13
IDE	0.76	0.12	-0.47	-0.41	0.17	0.04
EPU	0.49	0.69	0.47	0.09	0.20	0.09
MU	0.81	-0.39	-0.17	0.33	-0.03	0.25
FU	0.81	-0.46	0.14	0.15	0.16	-0.26

Table E.4: Squared Cosines

	F1	F2	F3	F4	F5	F6
Vstoxx	0.62	0.03	0.19	0.10	0.06	0.00
IDC	0.39	0.41	0.09	0.04	0.05	0.02
IDE	0.57	0.01	0.22	0.17	0.03	0.00
EPU	0.24	0.48	0.22	0.01	0.04	0.01
MU	0.65	0.15	0.03	0.11	0.00	0.06
FU	0.65	0.21	0.02	0.02	0.02	0.07

Figure E.2: Variables Factor Map (Factor 1 and Factor 2)

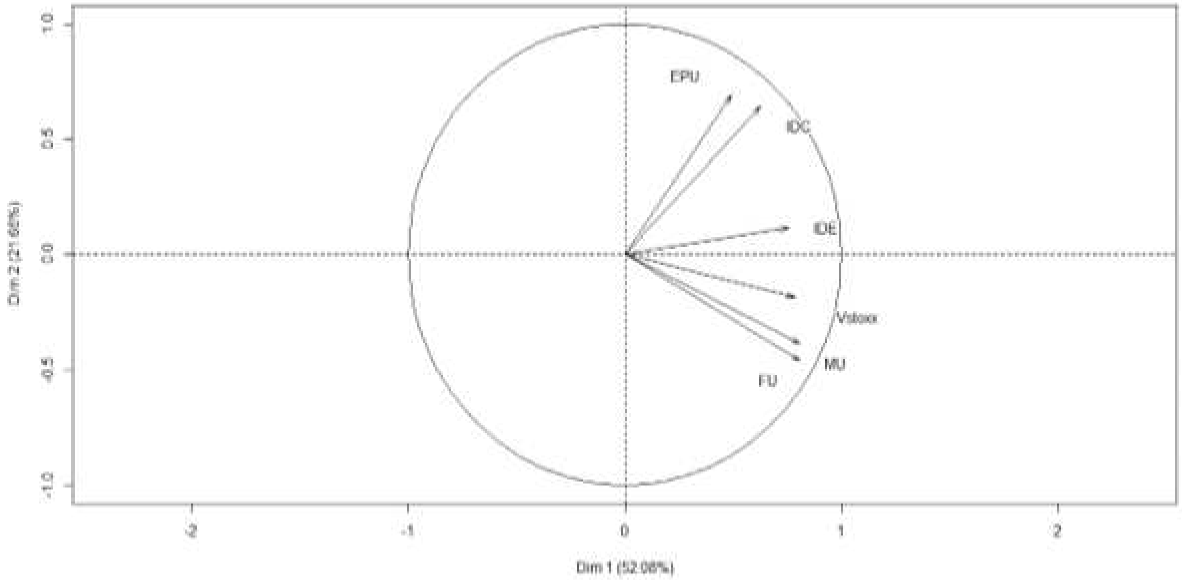


Figure E.3: EA General Uncertainty

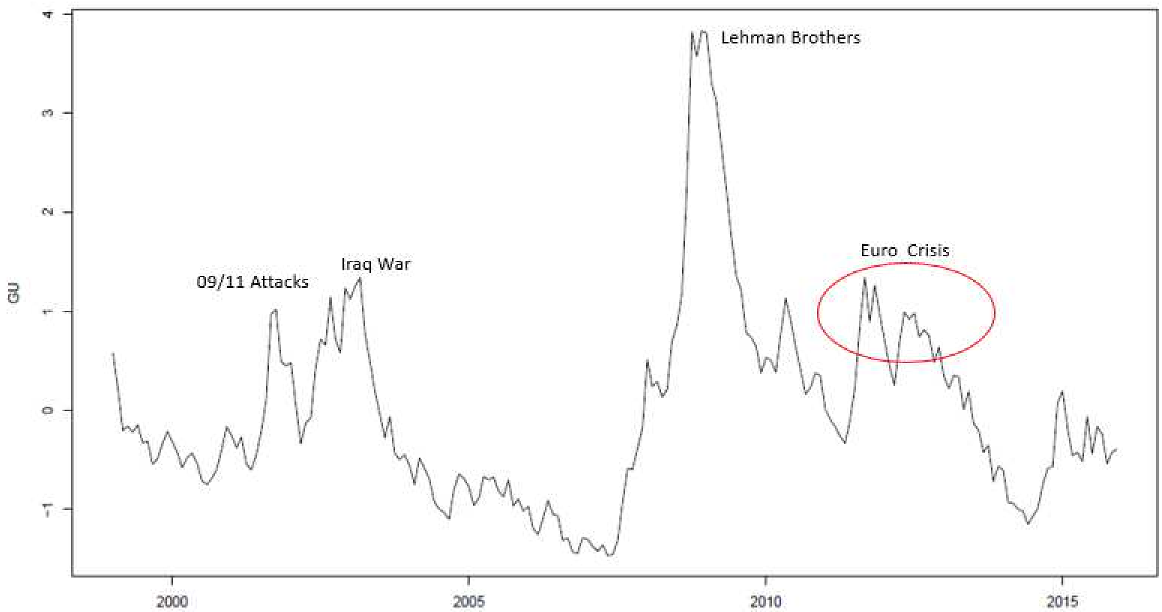
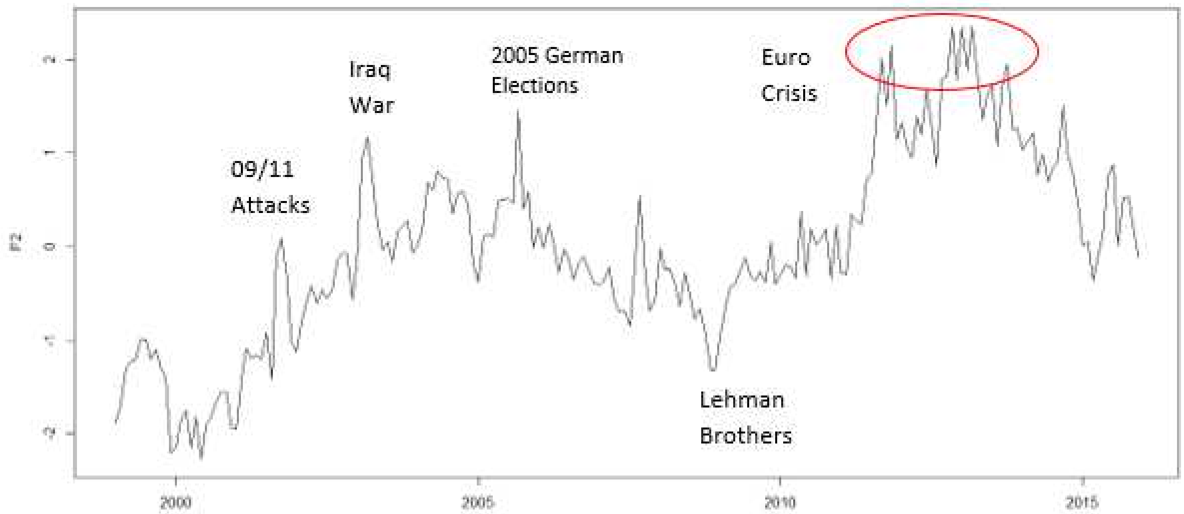


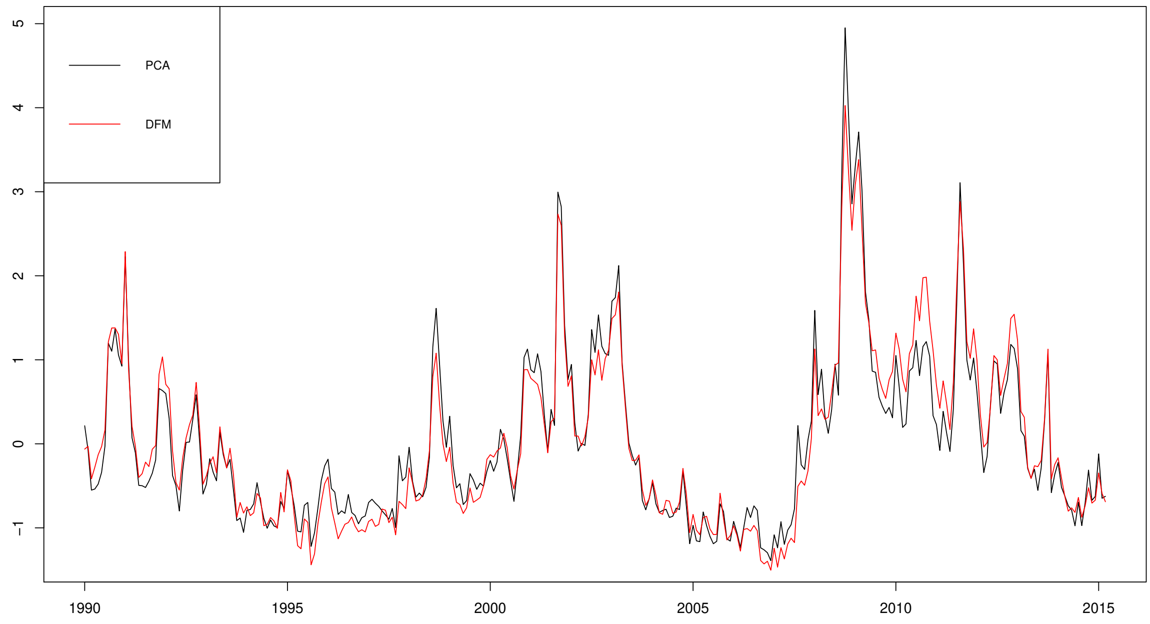
Figure E.4: EA Second factor



F Dynamic Factor Model

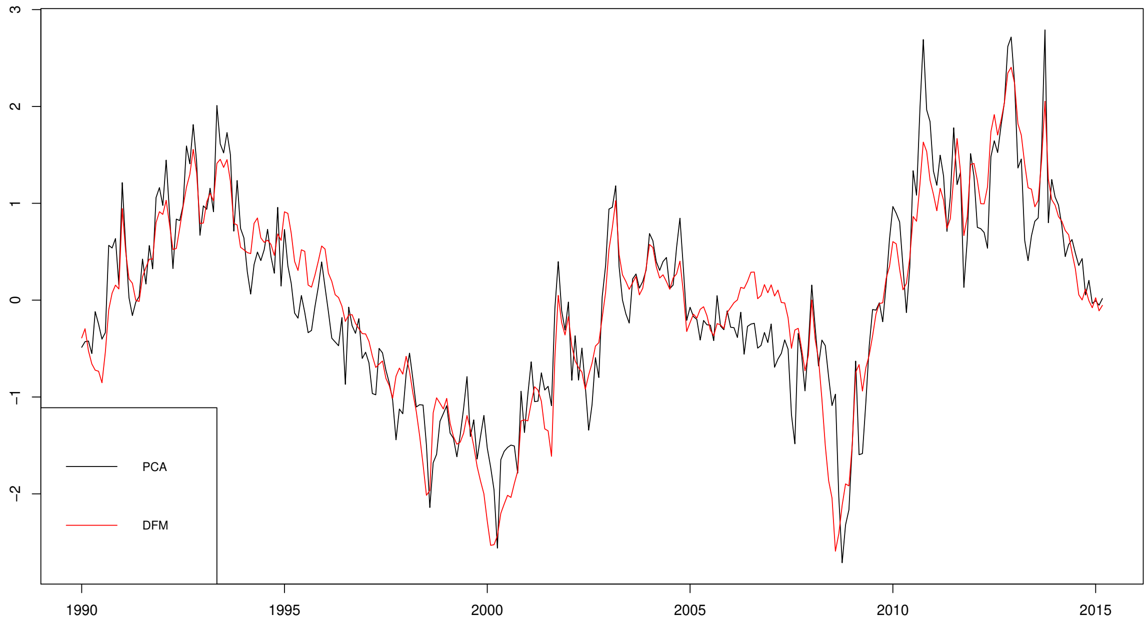
F.1 The United States

Figure F.1.1: Comparison between the first factor from the PCA and the DFM



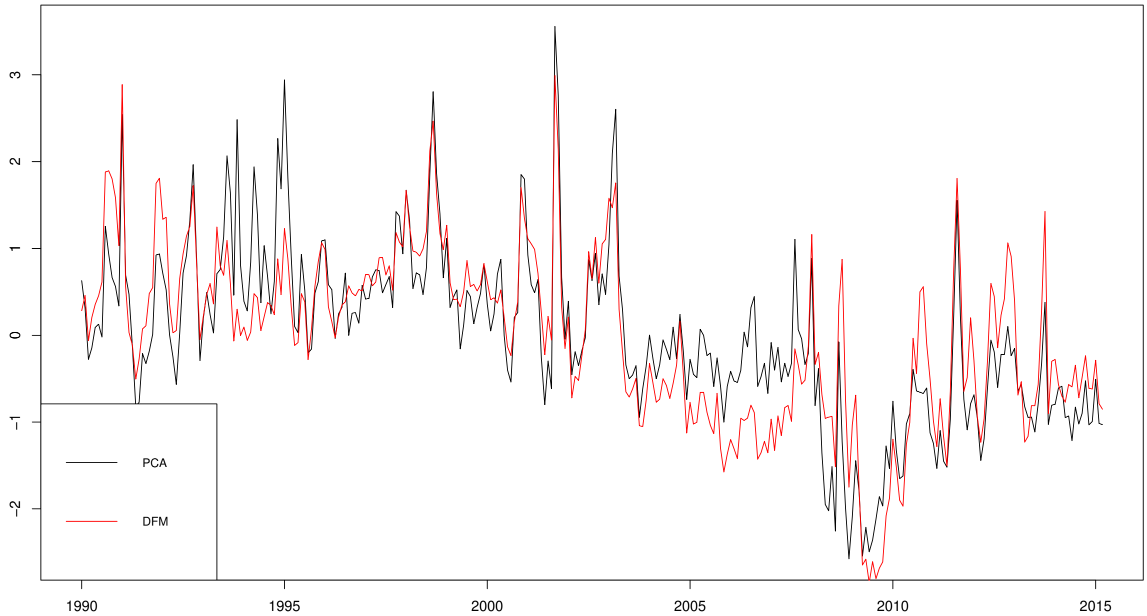
Note: Indexes are standardized.

Figure F.1.2: Comparison between the second factor from the PCA and the DFM



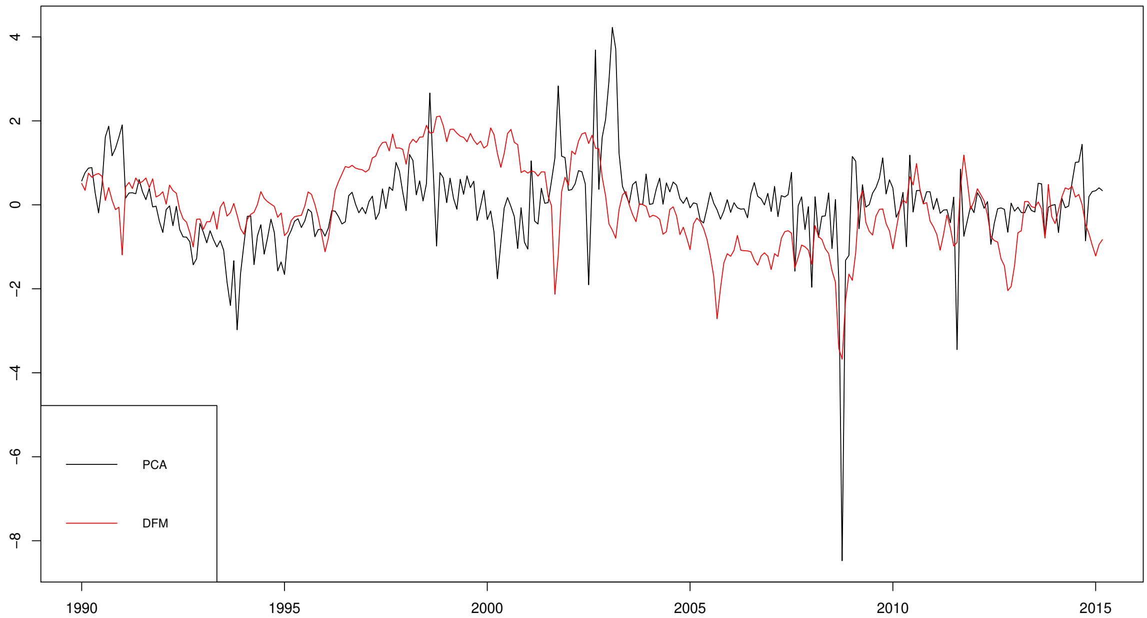
Note: Indexes are standardized.

Figure F.1.3: Comparison between the third factor from the PCA and the DFM



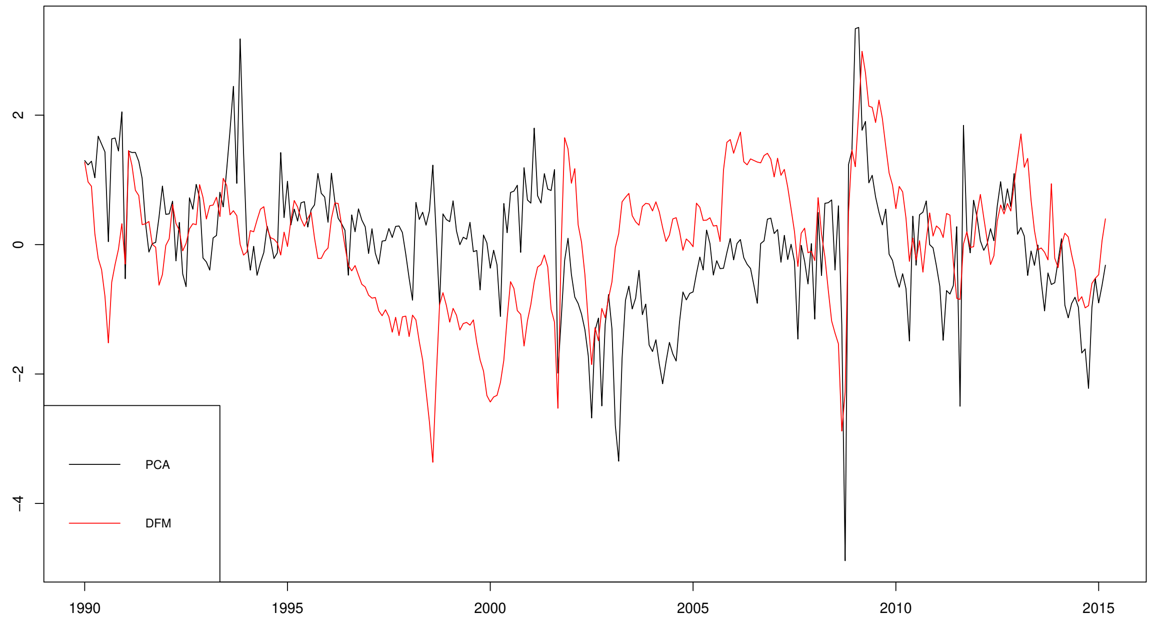
Note: Indexes are standardized.

Figure F.1.4: Comparison between the fourth factor from the PCA and the DFM



Note: Indexes are standardized.

Figure F.1.5: Comparison between the fifth factor from the PCA and the DFM



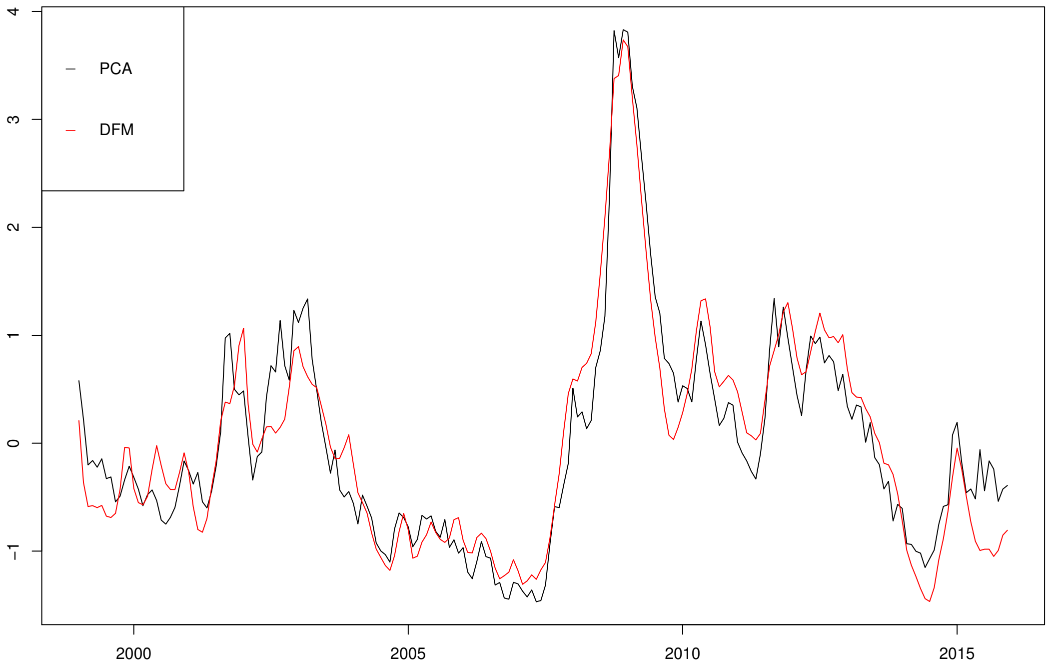
Note: Indexes are standardized.

Table F.1.1: Correlation with factors of the DFM

	F1 DFM	F2 DFM	F3 DFM	F4 DFM	F5 DFM
VIX	0.71	-0.46	0.18	0.14	-0.31
FU	0.70	-0.63	0.07	0.27	-0.38
MU	0.59	-0.46	-0.37	-0.41	0.16
EPU_Index	0.88	0.40	0.14	-0.30	0.09
NewsUS	0.88	0.28	0.38	-0.26	-0.07
EPU_Access	0.85	0.37	0.47	-0.26	0.04
MPU	0.61	0.10	0.61	-0.16	-0.17
Spread	0.48	0.51	-0.24	-0.26	0.28
IDC	0.65	0.43	-0.28	-0.56	0.43
Bspread	0.68	-0.43	-0.15	-0.10	0.03
FI	0.48	-0.47	0.29	0.07	-0.26
IDE	0.48	-0.26	0.21	-0.08	0.07
IVOL	0.47	-0.40	0.29	0.02	-0.41
GPR	0.28	0.07	0.14	-0.13	-0.01
NVIX	0.82	-0.12	0.15	0.01	-0.21
VRP	0.09	-0.10	0.17	0.39	-0.07
TPU	-0.08	0.20	0.31	0.02	-0.01
EMV	0.53	-0.42	0.33	0.07	-0.43
FPU	0.79	0.49	0.33	-0.30	0.13
HPU	0.64	0.56	0.10	-0.32	0.20

F.2 The Euro Area

Figure F.2.1: Comparison between the first factor from the PCA and the DFM

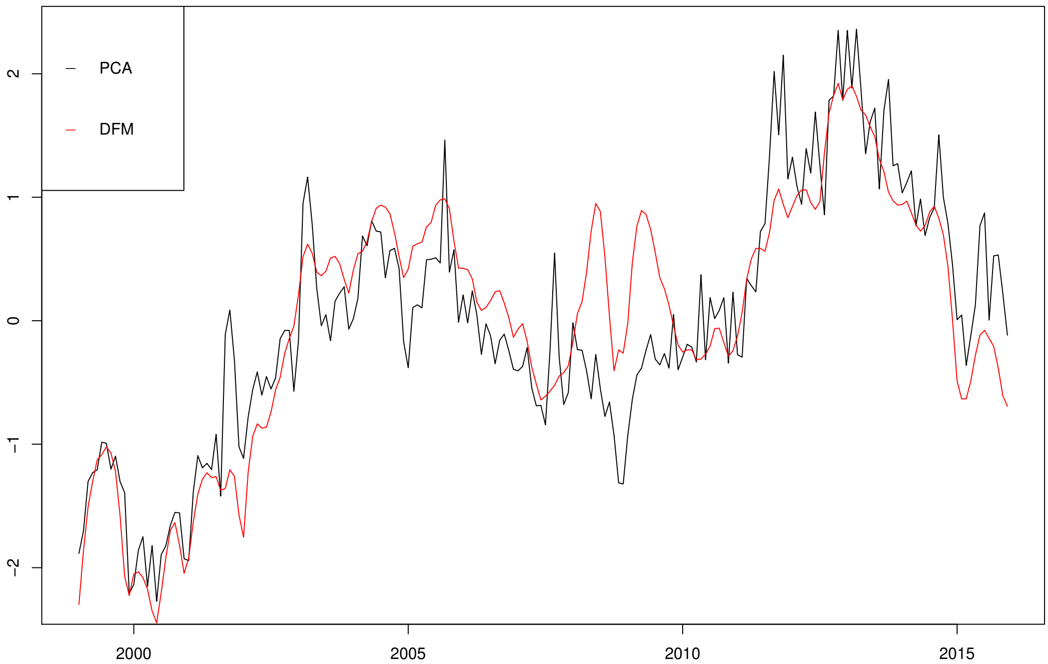


Note: Indexes are standardized.

Table F.2.1: Correlation with factors of the DFM

Correlation	F1 DFM	F2 DFM
Vstoxx	0.64	-0.20
IDC	0.69	-0.81
IDE	0.64	0.26
EPU	0.43	0.43
MU	0.78	-0.16
FU	0.85	-0.41

Figure F.2.2: Comparison between the second factor from the PCA and the DFM



Note: Indexes are standardized.

G Introduction of the COVID index

Figure G.1: Daily newspaper-based infectious disease equity market volatility tracker of Baker *et al.* (2020b)

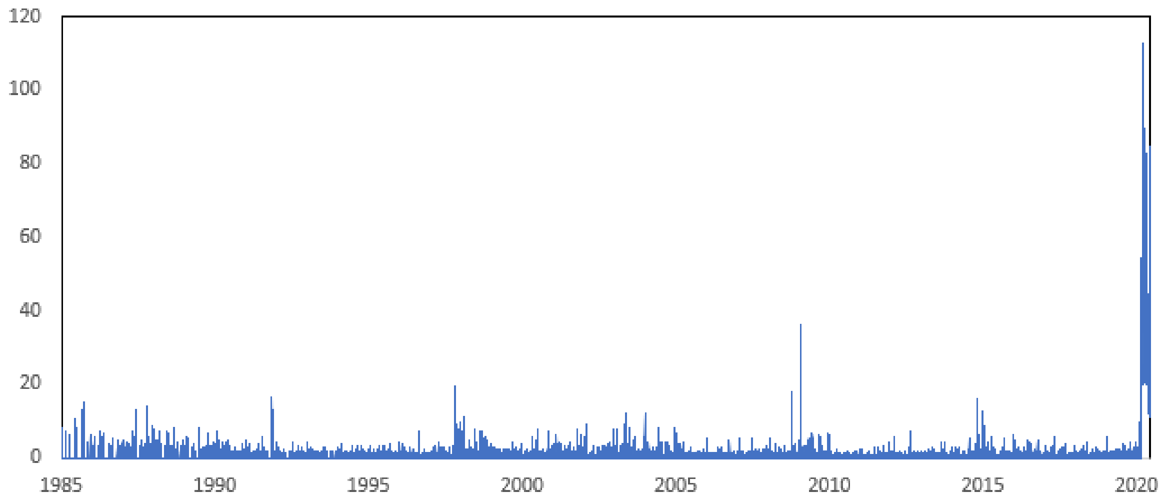
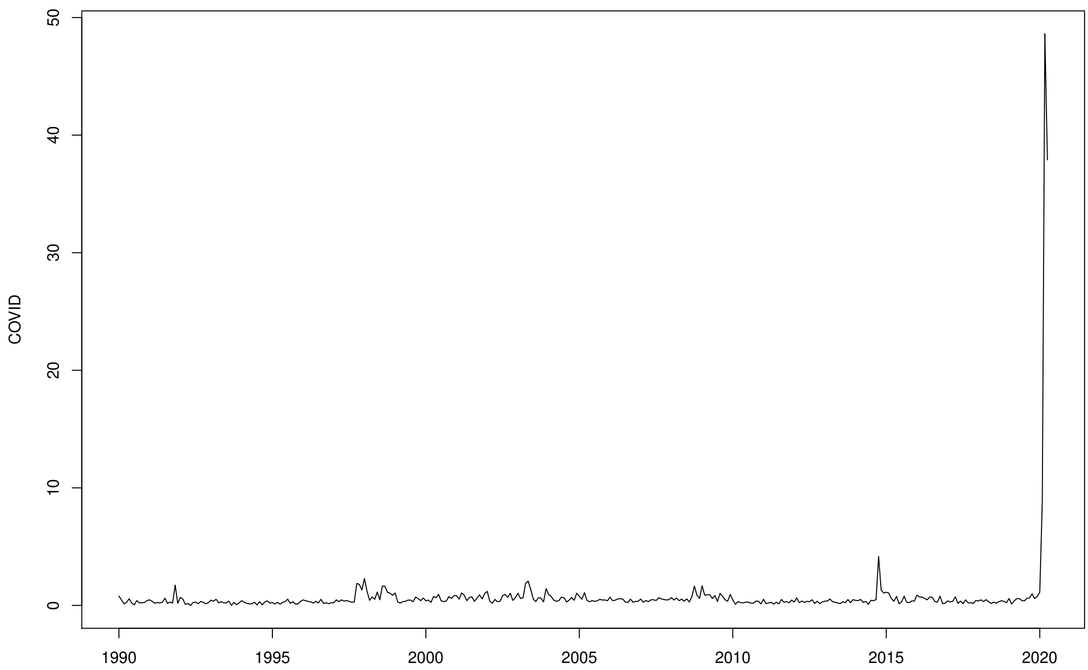


Figure G.2: Monthly COVID measure



Note: The index spans the time period 1990M1:2020M6.

G.1 US:1990-2015

Table G.1.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	8.30	39.54	39.54
Factor 2	3.61	17.19	56.73
Factor 3	1.64	7.80	64.53
Factor 4	1.38	6.57	71.10
Factor 5	1.20	5.71	76.80
Factor 6	1.01	4.80	81.61
Factor 7	0.77	3.66	85.26
Factor 8	0.65	3.11	88.37
Factor 9	0.47	2.26	90.63
Factor 10	0.38	1.80	92.43
Factor 11	0.36	1.70	94.13
Factor 12	0.30	1.41	95.53
Factor 13	0.23	1.10	96.64
Factor 14	0.16	0.74	97.38
Factor 15	0.14	0.69	98.07
Factor 16	0.11	0.52	98.58
Factor 17	0.09	0.42	99.00
Factor 18	0.08	0.38	99.38
Factor 19	0.06	0.29	99.67
Factor 20	0.04	0.19	99.86
Factor 21	0.03	0.14	100.00

Table G.1.2: Factor Loadings

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21
VIX	0.81	-0.43	-0.02	0.10	0.06	0.24	0.11	-0.08	-0.02	-0.01	-0.06	-0.04	0.12	-0.05	-0.05	-0.02	-0.12	0.00	-0.17	-0.03	0.01
FU	0.73	-0.48	-0.18	0.08	0.10	0.20	0.13	-0.08	0.05	0.10	0.03	-0.02	-0.21	-0.06	-0.03	0.22	0.04	0.04	0.02	-0.01	-0.00
MU	0.63	-0.38	-0.46	-0.05	0.11	-0.28	0.07	0.11	-0.05	0.21	0.23	-0.06	0.03	-0.05	-0.03	-0.09	0.12	-0.09	-0.04	-0.00	-0.01
EPU_Index	0.80	0.49	-0.09	-0.02	-0.03	0.12	-0.07	-0.06	0.04	-0.04	0.09	-0.16	-0.05	-0.02	0.16	-0.03	0.02	0.08	-0.05	0.12	-0.01
NewsUS	0.86	0.36	0.17	0.02	-0.08	0.02	-0.11	-0.07	0.05	-0.00	0.03	-0.15	-0.09	0.06	0.15	-0.05	0.02	-0.00	0.01	-0.14	0.02
EPU_Access	0.81	0.46	0.27	-0.03	0.12	-0.07	-0.04	0.03	-0.06	-0.00	-0.01	0.01	-0.06	-0.09	-0.04	-0.00	-0.07	-0.06	0.02	-0.01	-0.13
MPU	0.65	0.15	0.58	0.06	0.04	-0.29	-0.02	-0.10	-0.01	-0.06	0.22	0.03	-0.13	0.06	-0.20	-0.04	-0.01	0.05	-0.02	0.02	0.05
Spread	0.37	0.58	-0.33	0.10	-0.33	0.06	0.43	0.10	-0.12	-0.14	-0.07	0.15	-0.14	0.13	-0.01	-0.01	0.02	-0.07	-0.04	0.01	0.00
IDC	0.56	0.49	-0.46	-0.10	0.10	-0.21	0.11	0.09	-0.08	-0.25	0.15	-0.07	0.20	-0.04	-0.03	0.09	-0.05	0.06	0.06	-0.03	0.02
Bspread	0.75	-0.38	-0.34	-0.05	0.14	-0.11	0.04	0.10	0.18	0.18	-0.04	0.04	-0.07	0.14	0.02	-0.07	-0.16	0.03	0.08	0.02	0.01
FI	0.61	-0.48	0.22	-0.06	-0.03	-0.08	0.18	-0.06	-0.51	0.07	-0.13	0.05	0.02	-0.03	0.07	-0.05	0.02	0.08	0.05	0.00	0.01
IDE	0.58	-0.27	0.01	-0.09	0.51	-0.34	-0.25	0.18	0.02	-0.20	-0.21	0.11	-0.02	0.08	0.05	0.05	0.07	-0.01	-0.06	0.01	0.00
IVOL	0.60	-0.42	0.20	-0.36	-0.24	0.08	0.08	-0.05	0.22	-0.12	0.16	0.33	0.06	-0.09	0.10	-0.02	0.02	0.00	0.01	-0.01	-0.00
GPR	0.31	0.09	0.23	0.63	-0.22	-0.48	0.25	-0.07	0.22	0.11	-0.14	-0.00	0.13	-0.03	0.05	0.04	0.03	0.02	0.00	0.01	-0.01
NVIX	0.85	-0.08	-0.15	0.06	-0.01	0.26	-0.00	-0.06	0.16	-0.16	-0.25	-0.08	0.00	-0.09	-0.14	-0.12	0.09	0.01	0.07	0.01	0.01
VRP	0.07	-0.03	0.18	0.68	0.51	0.42	0.09	0.09	-0.04	-0.06	0.18	0.08	0.07	0.06	0.05	-0.03	0.02	-0.03	0.04	0.00	-0.00
TPU	-0.11	0.25	0.47	-0.48	0.29	0.10	0.47	0.34	0.12	0.09	-0.06	-0.12	0.03	-0.01	0.01	0.01	0.02	0.00	-0.00	0.00	0.02
COVID	0.29	-0.40	0.14	0.24	-0.48	0.07	-0.22	0.62	-0.04	-0.05	0.04	-0.05	-0.02	-0.03	-0.01	0.02	-0.01	0.02	0.00	0.00	0.00
EMV	0.68	-0.48	0.25	-0.20	-0.24	0.11	-0.04	-0.15	-0.02	-0.05	0.02	-0.16	0.16	0.19	-0.01	0.08	0.02	-0.10	0.04	0.04	-0.02
FPU	0.71	0.59	0.10	0.01	0.03	0.04	-0.20	0.02	-0.08	0.14	-0.08	0.08	0.02	-0.12	0.02	0.05	-0.05	-0.14	0.03	0.03	0.09
HPU	0.55	0.65	-0.08	-0.10	-0.07	0.23	-0.18	0.05	0.00	0.27	-0.04	0.16	0.15	0.10	-0.08	0.03	0.08	0.10	-0.02	-0.02	-0.02

Table G.1.3: Squared Cosines

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21
VIX	0.65	0.19	0.00	0.01	0.00	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.00
FU	0.54	0.23	0.03	0.01	0.01	0.04	0.02	0.01	0.00	0.01	0.00	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
MU	0.40	0.14	0.21	0.00	0.01	0.08	0.01	0.01	0.00	0.04	0.05	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00
EPU_Index	0.64	0.24	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.01	0.00
NewsUS	0.74	0.13	0.03	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00
EPU_Access	0.65	0.21	0.07	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02
MPU	0.43	0.02	0.33	0.00	0.00	0.08	0.00	0.01	0.00	0.00	0.05	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00
Spread	0.14	0.33	0.11	0.01	0.11	0.00	0.18	0.01	0.01	0.02	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00
IDC	0.31	0.24	0.21	0.01	0.01	0.04	0.01	0.01	0.01	0.06	0.02	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Bspread	0.56	0.15	0.12	0.00	0.02	0.01	0.00	0.01	0.03	0.03	0.00	0.00	0.00	0.02	0.00	0.01	0.03	0.00	0.01	0.00	0.00
FI	0.38	0.23	0.05	0.00	0.00	0.01	0.03	0.00	0.26	0.01	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00
IDE	0.33	0.07	0.00	0.01	0.27	0.11	0.06	0.03	0.00	0.04	0.04	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IVOL	0.36	0.18	0.04	0.13	0.06	0.01	0.01	0.00	0.05	0.01	0.03	0.11	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
GPR	0.10	0.01	0.05	0.40	0.05	0.23	0.06	0.00	0.05	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NVIX	0.72	0.01	0.02	0.00	0.00	0.07	0.00	0.00	0.03	0.03	0.06	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00
VRP	0.00	0.00	0.03	0.46	0.26	0.17	0.01	0.01	0.00	0.00	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TPU	0.01	0.06	0.22	0.23	0.08	0.01	0.22	0.12	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
COVID	0.09	0.16	0.02	0.06	0.23	0.00	0.05	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EMV	0.46	0.23	0.06	0.04	0.06	0.01	0.00	0.02	0.00	0.00	0.00	0.03	0.03	0.04	0.00	0.01	0.00	0.01	0.00	0.00	0.00
FPU	0.51	0.35	0.01	0.00	0.00	0.00	0.04	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01
HPU	0.30	0.43	0.01	0.01	0.01	0.05	0.03	0.00	0.00	0.07	0.00	0.03	0.02	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00

Figure G.1.1: Variables Factor Map (Factor 1 and Factor 2)

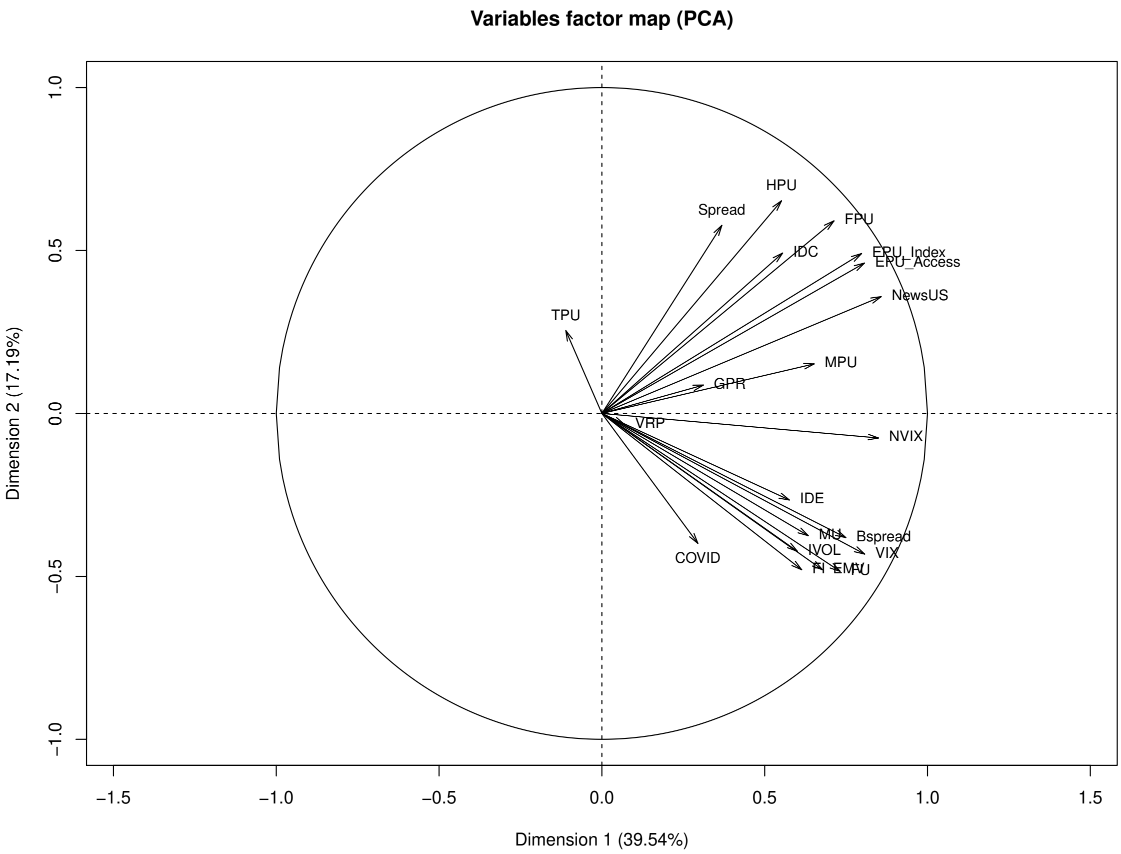


Figure G.1.2: Variables Factor Map (Factor 2 and Factor 3)

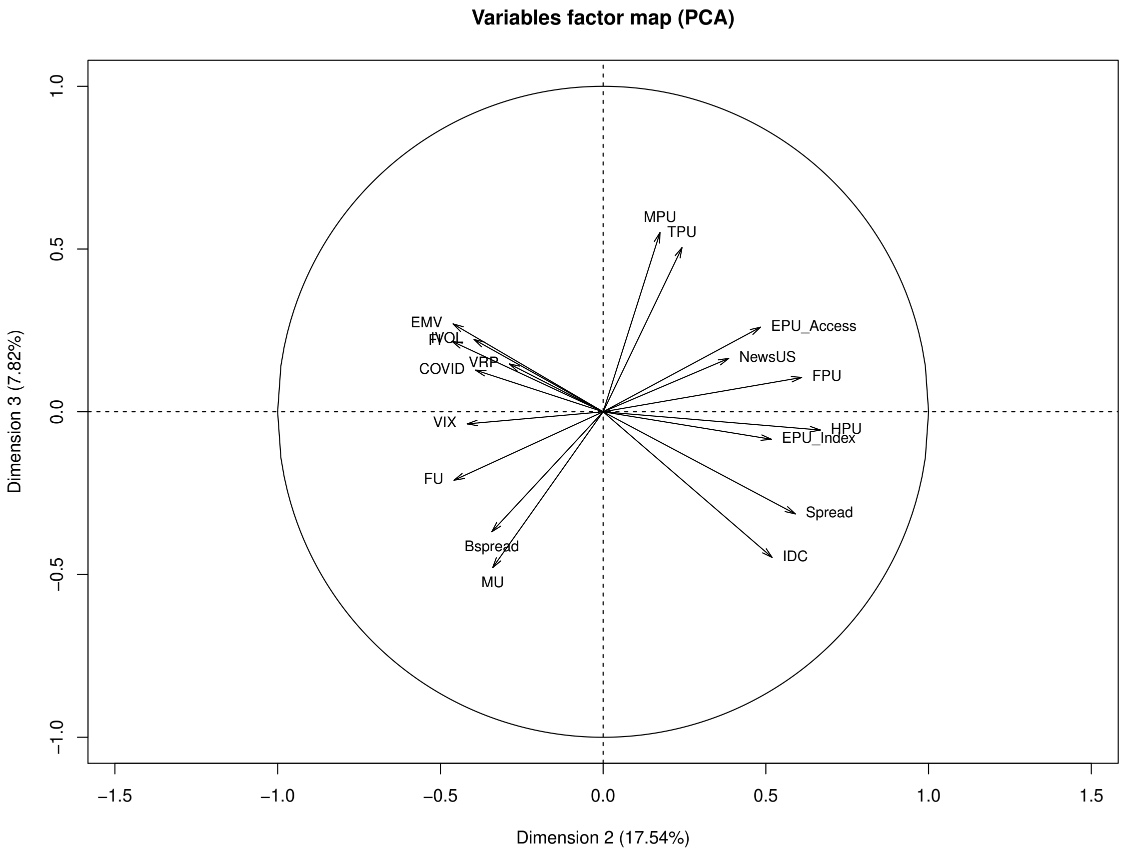
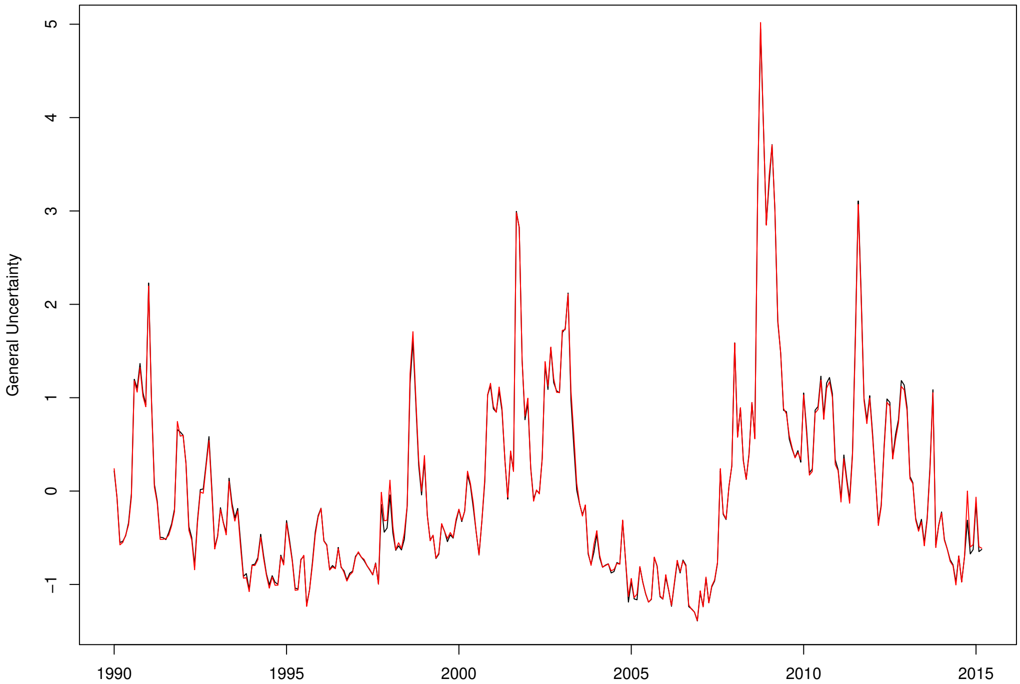
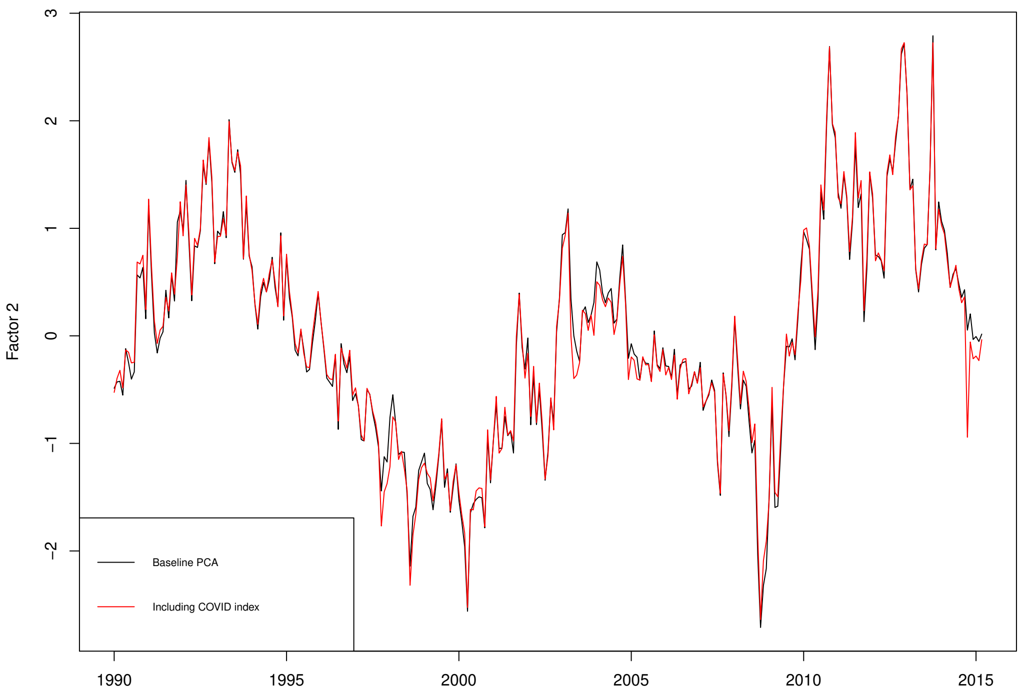


Figure G.1.3: Comparison of US General Uncertainty Indexes



Note: The indexes are standardized.

Figure G.1.4: Comparison of Factor 2



Note: The indexes are standardized.

G.2 US:1990-2020

Table G.2.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	7.12	41.91	41.91
Factor 2	2.66	15.64	57.54
Factor 3	1.97	11.61	69.15
Factor 4	1.25	7.38	76.53
Factor 5	0.85	5.01	81.54
Factor 6	0.71	4.16	85.70
Factor 7	0.58	3.43	89.13
Factor 8	0.45	2.67	91.80
Factor 9	0.36	2.10	93.91
Factor 10	0.27	1.57	95.48
Factor 11	0.22	1.30	96.77
Factor 12	0.15	0.91	97.68
Factor 13	0.13	0.74	98.43
Factor 14	0.11	0.65	99.08
Factor 15	0.09	0.52	99.59
Factor 16	0.04	0.26	99.85
Factor 17	0.03	0.15	100.00

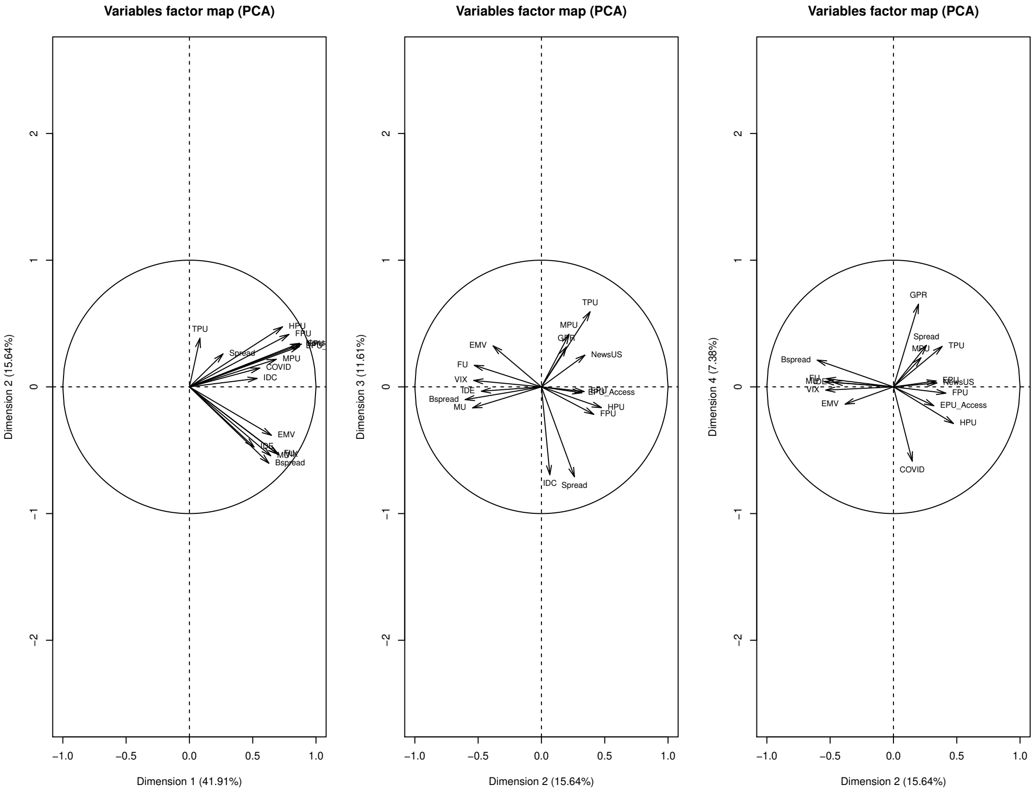
Table G.2.2: Factor Loadings

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17
VIX	0.71	-0.54	0.05	-0.03	-0.24	-0.10	-0.13	0.20	0.13	-0.05	-0.08	0.00	0.16	-0.19	0.02	-0.01	-0.01
EPU	0.88	0.34	-0.04	0.05	-0.01	-0.10	0.03	-0.06	-0.09	-0.03	-0.14	-0.18	-0.05	-0.04	0.11	-0.00	0.09
NewsUS	0.87	0.34	0.25	0.03	-0.01	-0.00	-0.02	-0.10	-0.08	0.04	-0.05	-0.11	-0.09	-0.05	0.04	-0.02	-0.12
MPU	0.69	0.22	0.42	0.23	-0.05	-0.19	-0.02	-0.40	-0.06	0.08	-0.07	0.17	0.09	-0.01	-0.07	0.01	0.02
GPR	0.23	0.20	0.32	0.65	-0.21	0.56	-0.07	0.05	0.08	-0.07	0.03	-0.00	0.03	0.04	0.03	-0.00	0.01
IDC	0.53	0.07	-0.69	0.20	0.18	-0.09	0.10	-0.15	0.21	-0.19	-0.04	-0.09	0.12	0.09	-0.05	0.01	-0.03
IDE	0.51	-0.47	-0.03	0.04	0.60	0.15	-0.24	-0.05	0.14	0.20	-0.02	0.04	-0.00	0.01	0.10	-0.00	0.00
Bspread	0.63	-0.60	-0.10	0.21	0.07	0.06	0.10	0.02	-0.29	0.14	0.18	-0.14	0.05	-0.01	-0.10	0.02	0.01
Spread	0.27	0.26	-0.71	0.33	-0.33	-0.13	0.08	0.06	0.14	0.28	0.06	0.06	-0.08	-0.02	0.03	0.00	-0.00
EPU_Access	0.87	0.32	-0.05	-0.15	0.12	0.09	-0.14	0.12	0.10	-0.02	0.00	0.01	-0.09	-0.02	-0.17	-0.11	0.03
MU	0.64	-0.54	-0.17	0.04	0.06	0.12	0.38	-0.11	-0.03	-0.19	0.06	0.14	-0.13	-0.09	0.05	-0.02	0.00
FU	0.70	-0.53	0.17	0.06	-0.13	-0.10	0.12	0.24	-0.05	0.04	-0.23	0.06	-0.04	0.19	-0.02	0.00	-0.01
FPU	0.79	0.41	-0.22	-0.05	0.10	0.03	-0.23	0.18	-0.11	-0.12	0.02	0.10	-0.05	-0.02	-0.03	0.14	-0.00
TPU	0.08	0.38	0.59	0.32	0.33	-0.32	0.29	0.25	0.15	-0.00	0.12	-0.01	0.01	-0.02	0.01	0.01	0.00
HPU	0.74	0.47	-0.16	-0.29	-0.01	0.03	0.05	0.11	-0.18	-0.00	0.14	0.09	0.15	0.08	0.11	-0.07	-0.01
EMV	0.65	-0.38	0.32	-0.14	-0.28	-0.23	-0.24	-0.11	0.17	-0.09	0.24	-0.04	-0.07	0.10	0.04	0.01	0.01
COVID	0.56	0.15	0.22	-0.59	-0.11	0.31	0.31	-0.05	0.21	0.14	-0.00	-0.04	0.04	0.00	-0.03	0.07	0.01

Table G.2.3: Squared Cosines

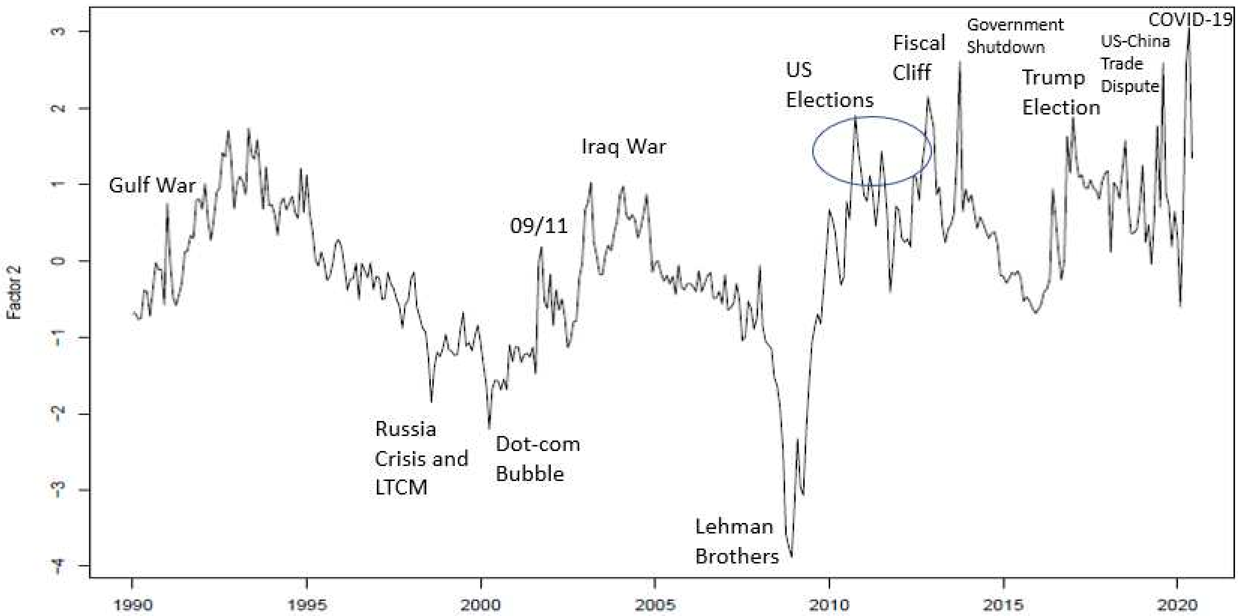
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17
VIX	0.50	0.29	0.00	0.00	0.06	0.01	0.02	0.04	0.02	0.00	0.01	0.00	0.03	0.04	0.00	0.00	0.00
EPU	0.78	0.11	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.00	0.01	0.00	0.01
NewsUS	0.76	0.12	0.06	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01
MPU	0.47	0.05	0.17	0.05	0.00	0.04	0.00	0.16	0.00	0.01	0.00	0.03	0.01	0.00	0.00	0.00	0.00
GPR	0.05	0.04	0.10	0.43	0.04	0.32	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IDC	0.29	0.00	0.48	0.04	0.03	0.01	0.01	0.02	0.04	0.04	0.00	0.01	0.01	0.01	0.00	0.00	0.00
IDE	0.26	0.23	0.00	0.00	0.36	0.02	0.06	0.00	0.02	0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Bspread	0.39	0.36	0.01	0.04	0.00	0.00	0.01	0.00	0.08	0.02	0.03	0.02	0.00	0.00	0.01	0.00	0.00
Spread	0.07	0.07	0.50	0.11	0.11	0.02	0.01	0.00	0.02	0.08	0.00	0.00	0.01	0.00	0.00	0.00	0.00
EPU_Access	0.76	0.10	0.00	0.02	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.03	0.01	0.00
MU	0.41	0.30	0.03	0.00	0.00	0.01	0.14	0.01	0.00	0.04	0.00	0.02	0.02	0.01	0.00	0.00	0.00
FU	0.48	0.28	0.03	0.00	0.02	0.01	0.02	0.06	0.00	0.00	0.06	0.00	0.00	0.03	0.00	0.00	0.00
FPU	0.62	0.17	0.05	0.00	0.01	0.00	0.06	0.03	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00
TPU	0.01	0.15	0.35	0.10	0.11	0.10	0.09	0.06	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
HPU	0.54	0.22	0.03	0.08	0.00	0.00	0.00	0.01	0.03	0.00	0.02	0.01	0.02	0.01	0.01	0.01	0.00
EMV	0.42	0.15	0.10	0.02	0.08	0.05	0.06	0.01	0.03	0.01	0.06	0.00	0.01	0.01	0.00	0.00	0.00
COVID	0.31	0.02	0.05	0.34	0.01	0.10	0.09	0.00	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure G.2.1: Variables Factor Map



Notes: The left variables factor map represents the factor 1 and the factor 2. The middle variables factor map represents the factor 2 and the factor 3. The right variables factor map represents the factor 2 and the factor 4.

Figure G.2.2: Second Factor



G.3 EA:1990-2015

Table G.3.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
Factor 1	3.18	45.48	45.48
Factor 2	1.37	19.53	65.02
Factor 3	0.90	12.85	77.87
Factor 4	0.77	10.93	88.80
Factor 5	0.43	6.16	94.96
Factor 6	0.20	2.85	97.81
Factor 7	0.15	2.19	100.00

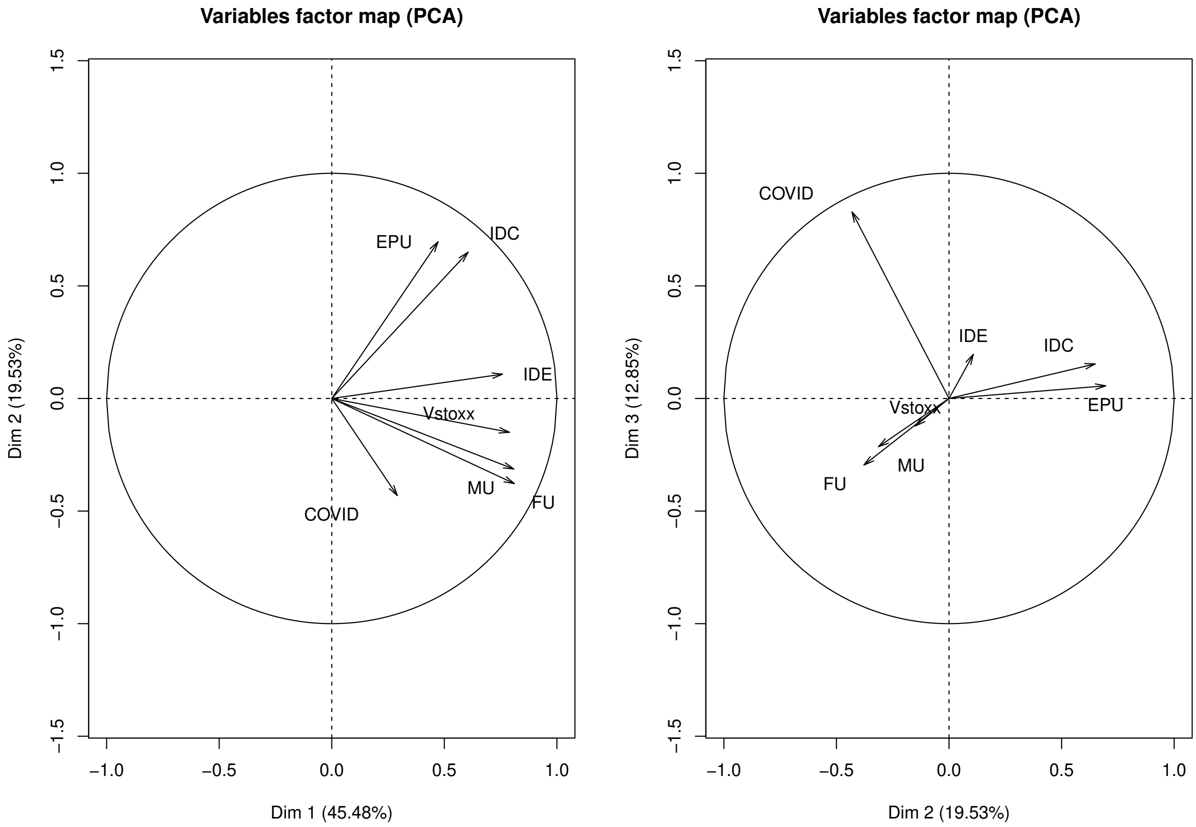
Table G.3.2: Factor Loadings

	F1	F2	F3	F4	F5	F6	F7
Vstoxx	0.79	-0.15	-0.12	0.43	-0.31	-0.25	-0.03
IDC	0.61	0.65	0.15	-0.30	0.19	-0.22	0.13
IDE	0.76	0.11	0.20	-0.43	-0.40	0.17	-0.04
EPU	0.47	0.70	0.06	0.48	0.11	0.20	-0.09
MU	0.81	-0.31	-0.21	-0.22	0.31	-0.03	-0.24
FU	0.81	-0.38	-0.30	0.09	0.12	0.16	0.26
COVID	0.29	-0.43	0.83	0.16	0.13	-0.00	0.01

Table G.3.3: Squared Cosine

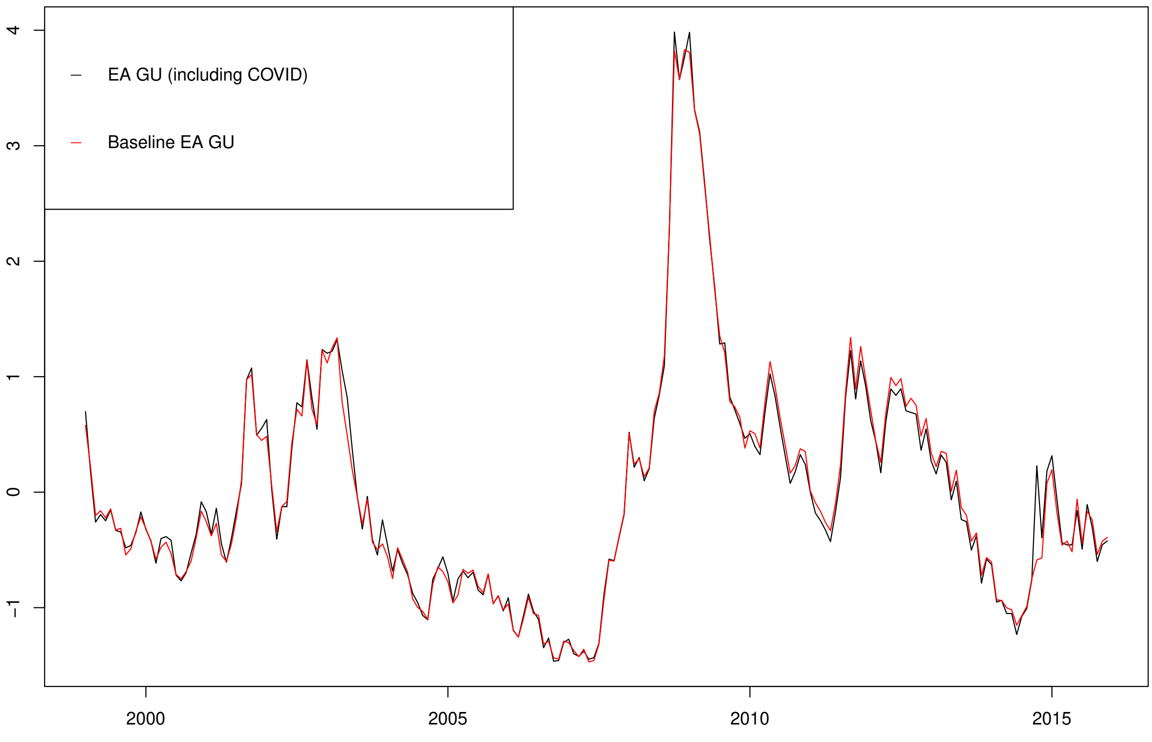
	F1	F2	F3	F4	F5	F6	F7
Vstoxx	0.62	0.02	0.01	0.18	0.10	0.06	0.00
IDC	0.37	0.42	0.02	0.09	0.04	0.05	0.02
IDE	0.57	0.01	0.04	0.18	0.16	0.03	0.00
EPU	0.22	0.48	0.00	0.23	0.01	0.04	0.01
MU	0.65	0.10	0.05	0.05	0.09	0.00	0.06
FU	0.66	0.14	0.09	0.01	0.02	0.02	0.07
COVID	0.08	0.19	0.69	0.03	0.02	0.00	0.00

Figure G.3.1: Variables Factor Map



Notes: The left variables factor map represents the factor 1 and the factor 2. The right variables factor map represents the factor 2 and the factor 3.

Figure G.3.2: Comparison of EA general uncertainty indexes



Note: The indexes are standardized.

G.4 EA:1990-2020

Table G.4.1: Eigenvalues and Variance

Factor	eigenvalue	percentage of variance	cumulative percentage of variance
F1	2.26	45.11	45.11
F2	1.09	21.89	67.00
F3	0.73	14.66	81.66
F4	0.62	12.39	94.04
F5	0.30	5.96	100.00

Table G.4.2: Factor Loadings

	F1	F2	F3	F4	F5
Vstoxx	0.71	-0.15	-0.35	0.57	0.13
EPU	0.49	0.65	0.50	0.26	-0.13
COVID	0.50	0.65	-0.43	-0.36	0.11
IDE	0.82	-0.35	-0.09	-0.19	-0.39
IDC	0.75	-0.33	0.40	-0.25	0.31

Table G.4.3: Squared Cosines

	F1	F2	F3	F4	F5
Vstoxx	0.51	0.02	0.13	0.32	0.02
EPU	0.24	0.42	0.25	0.07	0.02
COVID	0.25	0.42	0.19	0.13	0.01
IDE	0.68	0.12	0.01	0.04	0.15
IDC	0.57	0.11	0.16	0.06	0.10