VILNIUS UNIVERSITY

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

KRISTIJONAS KIRLYS

Quantitative Economics, 3rd year

Bachelor thesis

UNCERTAINTY IN THE EURO AREA AND ITS MACROECONOMIC EFFECTS

Student _____________

(signature)

Supervisor Dr. Mariarosaria Comunale

____

(signature)

Date_______________

Registration No._______________

Evaluation of the academic paper

____

(Date, assessment score, signature)

Vilnius, 2021

ABSTRACT

In this thesis, I construct several uncertainty measures for the euro area during 2000Q1-2020Q4 based on financial market data, newspaper coverage, and professional forecaster data. I test the constructed individual and composite uncertainty indices for their empirical plausibility via correlation analysis and Granger causality tests. I discuss the evolution and history of uncertainty in the euro area during the past two decades and provide background evidence of such movements. Using a VAR approach and a Cholesky decomposition, I analyze the macroeconomic impact of various uncertainty shocks on GDP, investment, consumption, productivity and hours worked. The findings show heterogeneity in persistence, timing and overall impact of such shocks depending on the type of uncertainty and the response macroeconomic variable. Nevertheless, the results suggest that uncertainty has a strong adverse impact on activity in the euro area. The inclusion of the Covid-19 period shows a significantly greater impact of uncertainty compared to previous literature, indicating a huge surge in uncertainty during the pandemic.

TABLE OF CONTENTS

INTRODUCTION

Economic uncertainty and its role have become subjects receiving increasing amounts of attention in the literature and among policy makers recently. It appears to significantly rise during major economic and political unexpected events. Examples include the 9/11 terrorist attacks, the Great Recession, and the sovereign debt crisis – uncertainty has remained elevated at these periods and is assumed to have been one of the factors of the slow recovery afterward.[1] More recent political events, like Brexit and the election of President Donald Trump, also spread uncertainty across the globe. The most important event to mention is the current Covid-19 pandemic, which caused a spike of uncertainty of historically high levels. Uncertainty surrounds almost every aspect – the infectivity and lethality of the virus, the availability of a vaccine, effectiveness of remote work, and the speed and timing of the economy's recovery. Government implemented lockdown restrictions stagnated travel, closed down businesses, and disrupted markets. According to theory, uncertainty adversely affects the economy through multiple channels. As these recent events have caused such major spikes in uncertainty, quantifying the effect of these fluctuations and understanding its role in the economy has become ever more important.

The goal of the thesis is to perform an extensive econometric analysis of macroeconomic uncertainty, with a special focus on the euro area. Firstly, the aim is to gather information from various economic series and to combine them into one composite measure of uncertainty, which then shall be tested for empirical plausibility related to existing literature. Then, the history and evolution of uncertainty for the period 2000Q1-2020Q4 are to be analyzed supported by background information and evidence of such movements. The analysis shall then go deeper to use a specified econometric model to allow for economic interpretation regarding the macroeconomic effect of uncertainty by taking into account the endogeneity of the main macroeconomic variables of interest, also through the application of impulse response functions. Finally, I quantify and interpret the results of the model, providing inference and comparisons to previous literature.

In my bachelor thesis, I follow the work of Gieseck and Largent (2016). The paper constructs several measures of macroeconomic uncertainty from various datasets for the euro area and uses a Structural Vector Autoregression (SVAR) approach to investigate the impact of uncertainty on economic activity during the period 1999Q1-2015Q4.[2] I use a similar approach and

[1] See European Central Bank (2009); Born, et al. (2014).
[2] Recent updates by Gieseck and Rujin (2020) are available on the ECB website.

datasets for the construction of my uncertainty measure, expanding the range of macroeconomic indicators within the analysis. I also use a different, longer time span, including the Covid-19 pandemic, i.e., analyzing the period from 2000Q1-2020Q4.

Before starting the analysis, I firstly build multiple measures of macroeconomic uncertainty, following Gieseck and Largent (2016), covering different aspects of uncertainty. The underlying datasets include financial market data, political uncertainty derived from newspaper coverage (as in Baker, et al., 2016) and the disagreement of professional forecasters regarding macroeconomic projections. Individual measures and one composite measure of uncertainty are computed using dispersions, arithmetic and weighted averages, and principal component analysis. The reliance on multiple uncertainty measures instead of a single one allows for more flexibility and comparability in the inferences, as the measures capture different types and channels of uncertainty, distinguishing its effects. Finally, the robustness and empirical plausibility of the measures are tested. The main two criteria are counter-cyclicality and unidirectional causality with macroeconomic indicators. This is proven by correlation analysis and Granger-causality tests.

The specified empirical model is a multivariate Vector Autoregression (VAR). This approach is popular in the existing literature and allows to measure the impact of fluctuations in uncertainty through impulse response functions. The macroeconomic variables in the model, whose responses are investigated together with uncertainty, are real GDP, investment, consumption, productivity, and hours worked.[3] To control for contemporaneous correlation between uncertainty and other variables, I use a Cholesky decomposition with a measure of uncertainty as the first variable and a macroeconomic indicator as the second. The model also includes additional explanatory variables – employment, inflation, and a shadow rate. The results show that uncertainty has a strong adverse effect on all the macroeconomic variables, although they tend to differ in total impact, timing and persistence depending on the types of uncertainty and macroeconomic activity. The effect is also stronger than in previous literature, which relates to the surge of uncertainty induced by the Covid-19 pandemic.

The thesis is composed of multiple sections as follows – in Section 1, I describe the relevant scientific literature about uncertainty – proxies and ways to measure it, the channels through which it influences the economy and the relationships between uncertainty and key economic variables. The data and methods used for the construction of the uncertainty measure are presented in Section 2. The testing of the measure's empirical plausibility and preliminary analysis is performed in Section 3. In section 4, I specify the empirical approach used to quantify the impact of uncertainty in the euro area and discuss the results.

[3] All variables are taken in year-on-year growth rates.

1. LITERATURE REVIEW

In this section, I present relevant literature and the main contributions in terms of research on uncertainty. I start with introducing the term, various ways to measure and proxy uncertainty, and then discuss literature on the channels and effects of uncertainty on the macroeconomy, other variables, its financial effects and uncertainty during the Covid-19 pandemic.

The early concept of uncertainty was introduced by Frank Knight (1921). Knight defined uncertainty as the inability to predict or forecast the likelihood of future events. The author formalized a distinction between risk and uncertainty and separated the two terms. In risky situations, the odds of something happening can be measured, but it is impossible to know the outcome of that specific event, while in the presence of uncertainty there is not enough information to determine the odds in the first place. Such uncertainty has been named "Knightian uncertainty" and is often compared to risk. Knight was one of the first to propose that no perfect measure for uncertainty exists, which is true to this day as given the broad definition, numerous proxies are used to quantify uncertainty.

Recently, there has been an increase in research regarding uncertainty in the literature. Uncertainty is related to numerous relevant problems, like climate change, natural disasters, financial crises, political tensions, and disease outbreaks. Because of this, uncertainty is a high priority and rewarding research area for economists and policy makers and the literature has tried to find new, better ways of measuring uncertainty. As no direct measure of economic uncertainty exists, research was based on various proxies to capture it. However, most proxies refer to only specific markets (such as financial markets) or groups of economic agents (like forecasters). In these ways, the perception of uncertainty might not be representative of the whole economy.

I start describing the uncertainty measures based on dispersion and volatility of financial data and forecasting, then I move to political and real-time trends, and also discuss more novel measures, swaying away from the traditional literature, concluding with measures and effects of macroeconomic uncertainty.

1.1. Measures of uncertainty

Previously, literature relied on measures of dispersion and volatility (most commonly financial data) as measures of uncertainty.[4] However, the applicable methods expanded widely in

[4] See e.g. Bloom (2009) and Bekaert et al. (2013).

recent years. Disagreement among professional forecasters has become one of the traditional proxies for uncertainty (Bomberger, 1996). The variance of such forecasts is used to measure the uncertainty surrounding the expectations. With higher uncertainty, it becomes more difficult to project future economic variables, states, and developments. Surveys among professional forecasters are another proxy to quantify aggregate and individual forecast uncertainty (Lahiri and Sheng, 2010). In such surveys, the Survey of Professional Forecasters (SPF) conducted by the European Central Bank (ECB) for example, forecasters are asked to provide a precise projection and a probability distribution around a point estimate, which corresponds to the uncertainty faced by an individual forecaster. Measures associated with forecasts have been proven to be counter-cyclical, strongly risen during the Great Recession and tests have shown that changes in disagreement have predictive power over changes in GDP (Legerstee and Frances, 2015).

A recently developed proxy for uncertainty is the frequency of newspaper articles referring to economic policy uncertainty (EPU) (Baker, et al., 2016). The measure was developed to investigate the role of policy uncertainty and observe political uncertainty. The index for the US is based on 10 leading newspapers and the frequency of the words "economic", "uncertainty", and a policy term used in those newspapers. The criteria are expanded with similar words and synonyms to better catch the usage of the terms. The measures capture both short-term and long-term concerns and are constructed for 11 more countries.[5] The constructed EPU measure shows strong positive correlation with the commonly used VIX stock market index, but they also have distinct movements – the EPU index did not rise as sharply during events that have financial and stock market connections but had strong responses to political events. Baker et al. (2016) also constructed an equity market uncertainty index using the same approach as for the EPU.[6] It proved to have an even higher correlation with VIX, indicating that newspapers can be a useful source to identify important different types of uncertainty and can be extended backward in time. The authors also use two different approaches to investigate policy uncertainty effects on economic outcomes – one with firm-level data and another with macro data in VAR analyses. The results show that fluctuations in policy uncertainty have a significant effect on investment, employment growth and output in government-exposed sectors. Castelnuovo and Tran (2017) a similar uncertainty index based on real-time Google Trends data. The indices are based on uncertainty-related keywords by economic agents, represented by Internet users. These are searched upon economic documents like the Federal Reserve's Beige Book for the US and the Reserve Bank's Monetary Policy Statement in Australia. The Google Trends Uncertainty (GTU) indexes are

[5] The measures were also constructed for Canada, Russia, China, France, Germany, India, Italy, Japan, South Korea, Spain and the UK.

[6] Specifically, they retained the Economic and Uncertainty terms, but replaced the Policy term with "stock market", "equity price" and "stock price".

uncovered by searching for phrases, corresponding to uncertain economic conditions in the publicly available Google trends data. The measure exhibits a positive relationship and similar characteristics with other earlier proposed measures of uncertainty. Similar news-media textual indicators have been proposed by Alexopoulos and Cohen (2015) based on New York Times to quantify the effects of uncertainty on the economy, equity and asset markets and Eckley (2015) extracted key phrases from Financial Times with improved index construction methodology and comparisons with other measures.

Knowledge about the future prices of oil also presents similar results to traditional uncertainty measures. For instance, Elder (2010) composes an index of oil price uncertainty to check its relationship and effects on the real economy. The main empirical result is that uncertainty about the price of oil had a negative effect on real GDP, durables consumption, some parts of investment, and industrial production. Pindyck (1987) suggested that oil price uncertainty contributed to the recessions of 1980 and 1982, while Ferderer (1996) found that it adversely affected output in the US over the 1970-1990 period.

Lately, more novel, and interesting proxies of uncertainty, swaying away from the traditional literature, have been proposed. Meinusch (2013) uses the social media platform Twitter as a source to model monetary policy uncertainty and uncertainty shocks. Market participants' beliefs and their uncertainty is extracted from Twitter messages according to words of interest, like in previous literature. The results showed that shocks to market beliefs have a strong effect on bond yields, exchange rates, and asset prices. An index that summarizes recent economic surprises, optimism/pessimism about the economy was used to construct a novel uncertainty index (Scotti, 2013). The surprise index is constructed through macroeconomic announcements and news. It is done by taking the unobservable factor of the component that measures the difference between the actual release and its forecast and averaging over the squared surprises. The constructed index passes the traditional tests of an uncertainty index and is empirically plausible. Collard (2018) uses the equity premium of a financial asset returns model as a measure of macroeconomic uncertainty revealed by equilibrium behavior. The premium is a compensation for a possible forecast error of the payoff, and since parameters towards time and uncertainty have been held fixed, the premium movements are said to be driven by macro uncertainty. The paper compares its index to the one proposed by Jurado, et al. (2015) and finds coinciding results and conclusions, specifically the persistence of the index compared to other proxies due to a smaller number of greater recessionary episodes shown. Bekaert (2016) also captures uncertainty with high correlation to the latter index through an asset pricing model. The model is based on the fundamental dynamic asset pricing literature and the measures unfold from observed time series of the variance premium, conditional variance, and other asset prices. The results suggest that the credit spread carries a large amount of information on uncertainty. The paper uses the approach of combining information from multiple sources to reduce noise. The measures also show strong correlation with political uncertainty, financial stress indices, are counter-cyclical and pass the Granger causality tests.

1.2. Macroeconomic uncertainty

My thesis will instead mostly reflect on and be based on the approach of Gieseck and Largent (2016) and focus on the macroeconomic aspects of uncertainty. The authors construct measures of macroeconomic uncertainty for the euro area and use a multivariate SVAR approach to investigate the impact of uncertainty on economic activity during the period 1999-2015. The measure is created by compiling a wide range of uncertainty measures from a rich dataset that covers a variety of indicators. The index ingredients include measures of systemic stress, financial market uncertainty, political uncertainty, and forecaster disagreement, instead of relying on a single proxy. An aggregate measure of uncertainty is calculated by combining these indicators through the first principal components and being standardized to mean zero and unit standard deviation. The final index is the unweighted average of all the individual uncertainty measures that have passed the tests of theoretical plausibility and empirical evidence. The two main criteria were negative correlation with macroeconomic indicators and unidirectional causality. The selected uncertainty measures were proven to have an adverse effect on activity in the euro area. The impact on investment was shown to be more significant than overall activity. Granger causality tests were performed to determine the direction of the effect, which is important in the topic of uncertainty. The overall measure, political, financial and systemic stress measures all shown a significant effect on activity, but not the other way around. Forecast uncertainty measures did not Granger-cause activity, while activity showed to have a causal effect on these uncertainty indices. The index rose sharply during certain economic events for the analyzed time period – the 9/11 terrorist attack, the Gulf war, the Great Recession, and the sovereign debt crisis. The results suggested a significant impact of changes in uncertainty on the euro area in recent years and were easily comparable to other countries in the euro area or the US. The index's high correlation with uncertainty measures for the US and the UK proves the globality of these shocks over these periods. The paper applies an SVAR model to measure uncertainty's effect on real GDP, private consumption, or total investment. With this approach, it is possible to interpret the results and estimate shocks from the VAR residuals (Sims, 1980). The optimal number of lags has been chosen according to the Akaike Information Criterion (AIC), supplemented by a Portmanteau test, which tests whether any of a group of autocorrelations of the residual time series are different from zero.[7] The activity variables of interest are in log differences, while Augmented Dickey-Fuller tests are present to confirm that the uncertainty measures are stationary. After constructing the model, generalized impulse response functions are computed.

The approach of focusing on an encompassing dataset is in line with the ideas proposed in Jurado, et al. (2015). The paper proposes a measure going beyond the literature at the time by compiling a composite measure of uncertainty which captures the information content of a large number of uncertainty proxies. The model is created to capture estimates of the volatility in the unforecastable component of economic indicators – the common variation in uncertainty across many series. The main idea in the following proxy is not whether particular economic indicators have become more or less variable, but rather whether the economy itself has become more or less predictable. This proxy gives significant independent variation and persistence compared to commonly used proxies, indicating that much of the variation in the other proxies is not caused by uncertainty. The formal notion of uncertainty in the paper is defined as the conditional volatility of the purely unforecastable component. The authors distinguish between uncertainty in a series and its conditional volatility; thus, the forecastable component is removed. This is done to better capture forecastable variations and not identify them as "uncertain". The first step is to acquire estimates of a forecast of the conditional expectation mentioned above, from which the arising forecast errors will be used for computing the uncertainty measures. A large set of predictors are used for approximation by a diffusion index forecast. A parametric stochastic volatility model is specified to acquire estimates of the conditional volatility of the forecast error. Finally, an equally weighted average of individual uncertainties form estimates of macroeconomic uncertainty. This is done for two datasets – one with macroeconomic and financial indicators, and another on firm-level profit growth normalized by sales. The constructed uncertainty measures hint at fewer large uncertainty episodes and fluctuate differently compared to other proxies proposed in the literature and quantitatively significant periods of uncertainty occur far less frequently than implied. The findings show that most movements in proxies like stock market volatility, various cross-sectional dispersion measures, are not caused by a fluctuation in economic uncertainty and thus spike far more frequently. Only three big uncertainty episodes were identified for the investigated period 1960-2011 – around the 1973-74 and 1981-82 recessions and the Great Recession of 2008. During these periods, the uncertainty index showed more persistent correlations with real activity, like decreases in production, working hours, employment, and was strongly counter-cyclical. The approaches and goals of Jurado et al. (2015) and Gieseck and Largent (2016) are similar, however the preparation leading up to the estimation of the uncertainty shocks differs. Jurado et al. (2015)

[7] For more details, refer to Ljung and Box (1978).

also includes firm-level data and computes uncertainty measures through the unforecastable component of economic indicators across multiple models, while Gieseck and Largent (2016) uses arithmetic and weighted averages, dispersions and principal component analysis. Due to the simpler approach of measuring uncertainty and data accessibility as in Gieseck and Largent (2016), I have decided to focus on the latter. It is also the better choice for comparability – as the paper specifically focuses on the euro area.

Another paper that investigates specifically macroeconomic uncertainty is Berger (2017). Macro uncertainty is measured through the conditional variances regarding inflation and output growth from a bivariate dynamic factor model with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) errors. The uncertainty measures exhibit spikes during significant economic shocks and crises and the findings coincide with previous literature – uncertainty shows a strong negative influence on inflation and output growth. Rossi (2016) uses the previously mentioned SPF to identify sources of macroeconomic uncertainty and propose a decomposition between Knightian uncertainty (ambiguity) and risk. Results show that the effects of different uncertainty components and types differ, although show a similar adverse effect. Although, the author does criticize forecast disagreement to underestimate the effect of uncertainty, but still holds it an important component of uncertainty over the past three decades.

1.3. Channels of uncertainty

Along with ways of measuring uncertainty, it is important to understand and investigate through which channels and how does uncertainty affect the economy and key economic variables. One of the main channels of uncertainty is the “real options” effect (Bernanke, 1983; Brennan and Schwartz, 1985). The idea is that when uncertainty is high, the option value to wait is high, so various adjustment costs make people more cautious, thus creating the preference to wait out an uncertain decision and avoid a costly mistake until uncertainty has declined or new information has become available. Because of this, firms refrain from actions like investment or hiring. In the case when investment is irreversible, the “real options” channel of uncertainty helps explain the short-run investment fluctuations during the business cycle. Dornbusch (1987) points out the same issue in labor markets, as various costs, which are higher during uncertainty, impede labor markets. Through this channel, higher uncertainty also makes expansionary stabilization tools less effective. Consumers are more aware of tax cuts and changes in interest rates, dampening the effect of the policy (Bloom, 2016). Overall, economic agents are less sensitive to changing conditions and the policies must be executed more aggressively in order to be effective but may even reduce uncertainty through the reassurance that the government is taking action to stabilize the economy. Fernandez-Villaverde (2015) suggests that the authorities could be the origin of policy uncertainty in cases of frequent fiscal policy adjustments. Aastveit (2013) estimates VAR models for several countries and provides strong empirical evidence regarding the adverse effect of uncertainty on expansionary policies, consistent with the “real options effect”. The reduced firms’ sensitivity explains procyclical productivity – productive firms are less aggressive at expanding during recessions and high levels of uncertainty, thus higher uncertainty can stall aggregate productivity growth (Bloom, 2014). This might also be affected by increases in borrowing costs due to increased risk premia, as investors want to be compensated for higher risk during times of uncertainty. Managers might also become more risk averse in general during periods of heightened uncertainty, thus shying away from decisions about new investment projects or hiring, especially where chief executive officers own a larger fraction of the firm and are exposed to higher risks (Panousi, 2012).

Uncertainty can similarly influence the decisions of private households when it comes to purchases of durable consumer goods. Dreze (1975) and Sandmo (1970) investigate consumption decisions under uncertainty and the choice between saving and immediate consumption. High uncertainty about the economic outlook and in particular employment could induce households to reduce consumption and increase precautionary savings. The authors show that postponing consumption in times of uncertainty yields higher utilities, as the consumer must be aware of limited future resources and thus uncertainty has an adverse effect on the decision. The precautionary savings channel of uncertainty is even greater when it comes to income uncertainty and is defined by Leland (1968) as “the extra saving caused by future income being random rather than determinate” (p. 465). A rising notion between economists is that the Great Recession was accompanied by a surge in saving rates, further suggesting that uncertainty can affect household consumption decisions (Ferrara, 2018). Mody (2012) finds a strong and positive relationship between saving rates and labor income uncertainty during the period of the Great Recession for numerous Organization for Economic Cooperation and Development (OECD) countries. More than two-fifths of the increase in savings are directly related to increases in uncertainty, unemployment risk, and GDP volatility. The results are robust to controlling for other determinants of saving rates and are amplified when uncertainty is affecting labor income rather than investment returns. This intuition is further analyzed by Basu (2017) using a simple VAR. An uncertainty shock, measured by stock market volatility, has an adverse effect on output, consumption, investment and hours worked. The key point is that the fall in consumption is not necessarily compensated by higher investment, which implies an increase in precautionary household savings.

Uncertainty shocks have a stronger impact with present financial frictions, thus financial intermediaries play a significant role in terms of its fluctuations. Christiano (2014) and Caldara (2016) show the relationships and interactions between financial markets and uncertainty. The results show that uncertainty shocks have a significantly stronger impact in cases of financial frictions.

1.4. Possible positive effects

Uncertainty does not always have an adverse effect on the economy. Growth options in the presence of uncertainty have the potential to increase long-term growth. These are the reverse of previously mentioned real options and are sometimes referred to as the "good news principle" compared to the real options that focused on bad news. These principles and uncertainty's effect on investment decisions are discussed by Bernanke (1983). The meaning of growth options is that only good news matters, because bad news is constrained, and the costs can be easily avoided. This is often used to explain the internet boom of the late 1990s. Firms were unsure about the Internet, but uncertainty encouraged investment. The worst outcome for firms was losing their website development costs, while the best outcome looked ever more profitable (Bloom, 2014). Kraft, et al. (2013) have shown how Tobin's Q is related to firm-level volatility. The paper shows significant evidence that the market value of a company increases in firm-level idiosyncratic volatility, which is consistent with growth options theory. Kulatilaka (1998) presents the strategic approach of the optimal use of investment under uncertainty. Under the assumption of imperfect and strategic competition, increased uncertainty encourages investment in growth options – as it results in higher opportunity rather than larger risk.

Another mechanism through which uncertainty could have a positive effect on growth is the Oi-Hartman-Abel effect (Oi, 1961; Hartman, 1972; Abel, 1983). The idea is that if firms or agents can flexibly expand to benefit from good outcomes and contract during bad outcomes, they may benefit from increased uncertainty. Instable prices will always result in greater total returns if firms have the ability to easily respond to such news by increasing production and maximizing short-run profits. If this is the case, the intuition that competitive firms should prefer stable prices is questioned. The writers show that uncertainty growth indeed has a positive effect on investment growth with a linearly homogenous production function. Oi-Hartman-Abel is believed to be strong in the medium and long run, but not in the short run due to adjustment costs

1.5. Uncertainty and business cycles

Bloom (2018) investigates the relationship between uncertainty and business cycles. Uncertainty is counter-cyclical, meaning it is high during recessions and low during booms. The paper develops new empirical measures of uncertainty through the volatility of an idiosyncratic component, which represents firm performance and an aggregate component regarding aggregate variables, like GDP or the S&P500 index. The model implies that productivity and demand dispersion across firms is time-varying and that all firms are more affected by more volatile shocks. Given the calculated measures, robust counter-cyclicality is proven on several economic levels – shocks at the establishment, firm and industry levels all increase in variance during recessions. The results suggest a strong relationship between slow industry growth and heightened uncertainty, relating to the idea that uncertainty caused a slower recovery from the Great Recession. The authors also address uncertainty's endogeneity problem, as uncertainty is said to increase endogenously during recessions, thus determining the direction of causality is crucial. Using trade and exchange rate instrumental variables the paper proves that this is not the case. Uncertainty is an exogenous process, signaling that recessions are driven by a combination of first moment (the mean) and second moment (the variance) shocks. Simulations in a dynamic stochastic general equilibrium (DSGE) model with heterogeneous firms allow for investigation of how components of the economy react to uncertainty shocks. An increase in uncertainty reduces firms' labor decisions – increased adjustment costs decrease both hiring and firing employees, along with adverse effects on investment, capital stock, and overall productivity. Results suggest uncertainty shocks can play an important role in driving business cycles. A theoretical model is built to show how increases in uncertainty dampen the effectiveness of expansionary policies due to lower responsiveness and sensitivity of firms and the economy as a whole. The authors show that the effect of a wage subsidy policy declines significantly more rapidly when uncertainty in the economy is high and suggests that policymakers should respond to this by making expansionary policies more aggressive.

The fundamental endogeneity problem, of whether uncertainty is the driver of business cycles or uncertainty is instead an endogenous response to their fluctuations, is investigated further by Ludvigson et al. (2015). The question of the direction of causality has established itself as a challenge to the uncertainty literature. This is due to the absence of a single unified uncertainty model, hence there is missing theoretical consensus whether it is a primary cause or response of fluctuations in economic activity. The paper discusses how the endogeneity of uncertainty is related to the understanding of the role of uncertainty in business cycles, as uncertainty can co-move with real activity because it might be able to drive business cycles, but also endogenously respond to first moment shocks - wherein most VAR models in the literature, real activity is the first moment variable. The problem is addressed using a novel SVAR approach, where macro and financial uncertainty is distinguished, and their effects are forced to be orthogonal, which means the explanatory variables are uncorrelated – an assumption necessary for consistent estimation and economic interpretation. Shock-based restrictions and constraints of events and external variables are imposed to also capture the feedback between uncertainty and real activity. Shock-based restrictions is a new identification strategy proposed by the authors and are achieved not through structural parameters, but inequality constraints on the behavior of structural shocks. The results prove that positive shocks to financial uncertainty indeed are an exogenous impulse that causes recessions by causing a decline in activity. Increases in policy and macro uncertainty are shown to be endogenous responses to such activity variation. Finally, fluctuations in macro uncertainty also play an important role in amplifying downturns caused by other shocks during recessions.

1.6. Uncertainty and Covid-19

Lastly, as above-mentioned, there has been a surge in contributions following the current Covid-19 pandemic, as this has resulted in a huge spike of uncertainty. The crisis escalated and spread out at incredible speeds. Because of this, assessing the impact of the caused crisis is rather difficult, but nevertheless important. The security measures and lockdowns that countries have implemented, named "The Great Lockdown" by the International Monetary Fund (IMF) (Gopinath, 2020) have stagnated whole economies and had a substantial effect on people's lives and livelihoods. Overall, the pandemic has caused a massive spike in uncertainty. The uncertainties surround many aspects: the infectivity, lethality of the virus, the availability of a vaccine, the effectiveness of social distancing and new government lockdown policies, and how long will they last. Strong interest is also in business and market lockdowns, their survival and the speed at which they and the whole economy can recover afterward, the effectiveness of online education, online work and many other factors that affect the overall production in the economy in the long run. All this results in countries facing multiple crises at the same time – health, financial, and a collapse in commodity prices. IMF states and predicts that the Great Lockdown is the worst recession since the Great Depression and will be far worse than the Global Financial Crisis. Both advanced and developing economies are facing recessions, with some countries going into lockdown for the second or even third time. Although the start of the distribution of a vaccine and successful attempts in containing the virus in some parts of the world give positive signs of the crisis diminishing, there is still huge amounts of uncertainty about the future of the Covid-19 pandemic and its recovery.

Baker, et al. (2020) assess the short and medium-term macroeconomic effects of Covid-19 induced uncertainty. The authors use forward-looking uncertainty measures – stock market volatility, newspaper based economic uncertainty and business expectation surveys and an empirical model developed by Baker, Bloom and Terry (2020) to estimate these effects using natural disasters. The model is a VAR with shock identification, where disasters are instruments and the causal impact is estimated through first-moment and uncertainty channels. The results suggest that the pandemic will cause a huge shock to output – a more significant one than the financial crisis of 2008, and in which most of it can be explained by Covid-19 induced economic uncertainty. The authors also discuss that the results might even understate the adverse effect of the crisis. The model, however, was only estimated for the US and while the results may differ in the euro area or other individual countries, there is no doubt that there would be a negative effect on output. Altig, et al. (2020) use similar uncertainty indices to discuss economic uncertainty before and during the Covid-19 pandemic. All indicators show massive spikes of uncertainty during this time, with some reaching their highest values on record. Differences between uncertainty measures were uncovered, as some uncertainty measures peaked earlier than broader indices with significantly different amplitudes. The paper also mentions two factors that help explain the tremendous increase in economic uncertainty during Covid-19 – the suddenness of a large number of job losses and the size of the mortality shock.

2. DATA PRESENTATION

Here, I will present the data used for the computation of the uncertainty measure, describe the characteristics of the datasets and the methods used to combine the latter information. As previously mentioned, no specific measure of macroeconomic uncertainty exists, but various proxies are used to quantify it. As the literature grows ever richer, there are numerous different ways to capture uncertainty, and each measure can assess a different type or aspect of economic uncertainty. Because of this, some proxies are more preferred to others, depending on the concept or channel of uncertainty that is wished to be investigated or estimated. In my empirical analysis, I will use similar datasets to Gieseck and Largent (2016), GL hereafter, and use a variety of indices proposed in the literature to construct one broad measure of uncertainty for the euro area that covers a large part of the economy. The datasets include multiple indicators of systemic stress and implied equity market volatility to represent financial market uncertainty, policy uncertainty from newspaper coverage and forecast disagreement from the SPF conducted by the ECB.

The financial market uncertainty measure is composed of numerous systemic stress indicators (the composite indicator of systemic stress (CISS), euro exchange rate volatility, bond market volatility, equity market volatility, and financial intermediation), supplemented by implied equity market volatility. The CISS is computed for the euro area as a whole and is based on 15 financial stress measures split equally into five categories.[8] Other datasets include the realized volatility of the euro exchange rate vis-a-vis the US dollar, the Japanese yen, and the British pound, the realized volatility of the German 10-year benchmark government bond index. The equity market volatility index is the realized volatility and maximum cumulated loss of the non-financial sector stock market index and stock-bond correlation. The financial intermediation dataset is the realized volatility of the idiosyncratic equity return of the bank sector stock market index. The financial market uncertainty index is also supplemented by an implied equity market volatility measure – the EURO STOXX 50 Volatility Index (VSTOXX), which is based on real-time option prices. More specifically, it is the square root of the implied variance across all options to reflect market expectations of near-term to long-term volatility. It would be beneficial to also include measures of implied exchange rate volatility and implied bond market volatility, however, these indices are not openly available, thus were not included in the construction of the uncertainty measure. The systemic stress indicators can be accessed in the ECB database for the euro area and are available at weekly frequency, while the VSTOXX index is available daily. I have transformed

[8] For more details, please refer to Hollo (2012).

the VSTOXX index to weekly frequency by using weekly averages. To combine the latter set of variables, I used Principal Components Analysis. This method allows me to obtain a lower-dimensional measure while preserving and capturing common variation in the data as much as possible. For my analysis, I use the first principal component of the mentioned indicators as an index for financial market uncertainty as it best represents the maximum variance direction in the data.

The Economic Policy Uncertainty (EPU) data by Baker, Bloom and Davis (2016) is used to measure political uncertainty. Data is available for the US, EU, Canada, Japan, and 18 other countries. The index for policy-related uncertainty for individual countries is constructed based on the same approach as for the US – the number of newspaper articles that contain the terms „uncertain“ or „uncertainty“, „economic“ or „economy“, and a policy term. All searches are conducted in the respective native languages, the data is scaled, standardized to unit standard deviation, normalized to mean zero and averaged across each country‘s two newspapers. To construct a proxy for the euro area, I take data for the big four euro area countries – Germany, France, Italy and Spain, and calculate the final measure as a weighted average according to country-level GDP. The newspapers used for the compilation of the data are Le Monde and Le Figaro for France, Handelsblatt and Frankfurter Allgemeine Zeitung for Germany, Corriere Della Sera and La Stampa for Italy, El Mundo and El Pais for Spain.

For forecast uncertainty or disagreement, I use data from the SPF conducted by the ECB. Increasingly diverse opinions among forecasters suggest that it is more difficult to project future economic states, indicating that uncertainty exists about the economic outlook. The survey is conducted quarterly and collects information on real GDP growth, unemployment, and inflation in the euro area at multiple horizons – from the current year to long term. For the uncertainty measure calculation, the variance of all the point forecasts is taken, quantifying the disagreement between professional forecasters. Uncertainty of individual forecasters can be used in combination with forecast disagreement to form a measure of aggregate uncertainty of forecasters (Bowles, 2007). In the SPF, participants also provide a probability distribution around their point estimates, which quantifies the individual uncertainty of a specific forecaster. However, this requires analyzing and computing the distributions for every forecaster, which, due to time constraints, was omitted from the final calculation. Forecast disagreement about certain economic indicators by Consensus Economics would also be a good proxy and addition to the overall measure of uncertainty, however, this data is not available publicly for free and thus was not included. Using the same approach as for the financial market uncertainty index, I calculate and use the first principal component of the forecast dispersion datasets as a measure of forecast disagreement.

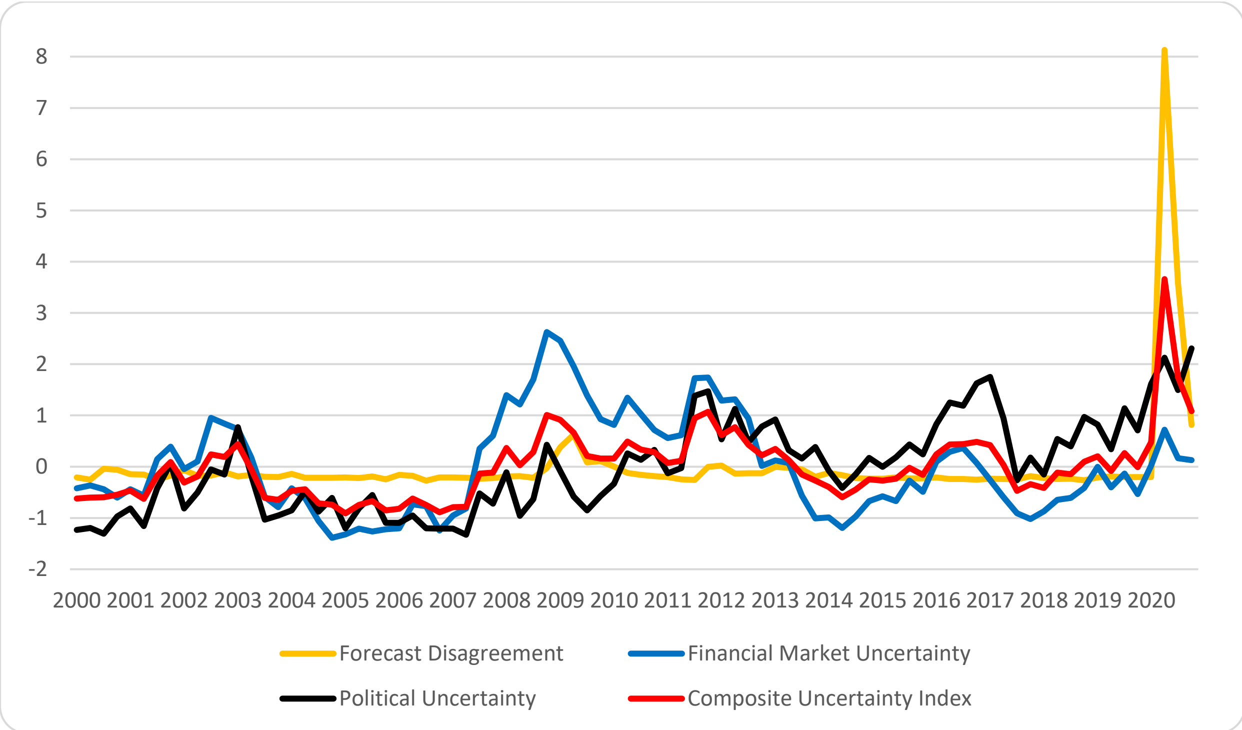
Lastly, to combine the three main uncertainty measures into one broad index, I transform the weekly frequency Financial Market uncertainty and monthly Economic Policy uncertainty indices to quarterly frequencies by using quarterly averages. This is done to match the quarterly frequency of forecast disagreement, which does not have more frequent data, as it is only conducted quarterly, but plays a vital role in terms of assessing increases in uncertainty, especially in recent years, which will be described in more detail in the upcoming section. The final uncertainty measure is then calculated as the unweighted average of all individual measures, which were all standardized to mean zero and unit standard deviation. I provide a summary of all the used datasets, their sources and transformations in Annex 2.

3. PRELIMINARY ANALYSIS

In this section, I present the movement and evolution of uncertainty in the euro area, prove that the indices are counter-cyclical, identify the direction of causality between uncertainty and economic activity, confirming the empirical plausibility of the measures and compare them to other uncertainty indices proposed in the literature. All three individual uncertainty measures along with the composite index are visualized for the period 2000Q1-2020Q4 in Figure 1:

Figure 1

Movement of different uncertainty measures for the euro area during 2000Q1-2020Q4.



Note: The main axis denotes units (standard deviations) for the uncertainty indices.

Source: Own calculations based on data from ECB Statistical Data Warehouse and Baker et al. (2016).

The graph shows that all uncertainty measures fluctuate and rise during significant economic, political and global events during this time frame. The first events causing an increase in economic uncertainty were the invasion of Iraq, also called the Gulf War, in 2003 and a temporary spike of political uncertainty can be identified after the 9/11 terrorist attacks in the US in 2001. The Iraq War spread economic slowdown across countries, shrinking investments, savings and severely affecting global economic health. The financial market uncertainty index peaked during the Great Recession in 2008/2009, as the crisis heavily revolved around the financial system and its vulnerabilities. The severe economic crisis shows significant increases in all economic uncertainty indicators – including a spike in forecast disagreement. The outcome of the crisis is reflected in an increase of the composite uncertainty measure of about two standard deviations from its 2007 levels. The events that started from the US housing bubble were fueled by subprime lending, excessive risk taking. This led to the European mortgage crisis and exposed the flaws of the financial system during that time. Uncertainty decreased as a result of unconventional monetary policy in response to the crisis but remained elevated in 2010-2011 compared to the pre-crisis period. This was caused by the Greek government-debt crisis that unfolded after the events of the Great Recession due to the weakness of the Greek economy and poor monetary policy flexibility. Due to the monetary policy of the euro area, Greece could not use the benefit of an isolated monetary of policy by printing money as a way out, thus the risk of a sovereign debt crisis was higher (Lachman, 2015). The sovereign debt crisis expanded into multiple euro area countries, as they were unable to repay or refinance their government debt, which was accompanied by multiple institutional failures and a currency crisis. As seen in the graph, these events resulted in heightened levels of uncertainty during 2011-2013, with the political uncertainty index reaching one of its few peaks during the period – around two standard deviations above the pre-crisis average. Throughout the next few years, uncertainty gradually declined during the recovery from the crisis events. The economy stabilized and uncertainty returned close to its pre-crisis level in 2014. Financial market uncertainty remained mostly contained during this period and a small increase of uncertainty can be identified during mid-2015 at the height of the Greek crisis. Starting from 2016, a period of elevated political uncertainty began. Two major political events happened that year - the UK's vote in a referendum to leave the European Union and Donald Trump winning the US election. Oil prices experienced a significant drop in 2016, along with widespread terror-related incidents throughout the world – the bombings of airports in Belgium and Turkey and a nightclub massacre in Orlando. These events sparked a steep increase in the EPU index as well as financial market uncertainty. Inaugurated in 2017, the controversial president and the election played a significant role in the direction of the global economy and its outlook. Brexit was in its infancy stage and a lot of uncertainty was present at the time. After the events settled, uncertainty gradually declined. In the next few years, various protests and demonstrations, such as those in Algeria, Iraq, Lebanon, Sudan, and Iran caused spikes in uncertainty, both political and financial, creating tension and negatively affecting international trade. The Arab protests and events quickly spread across the news, with governments and militaries from other countries also getting involved in the feuds. The composite uncertainty index reaches its all-time peak in 2020 – spiking nearly four standard deviations above the mean. This is a result of a global health crisis caused by the Covid-19 pandemic, accompanied by several political and world events. First infected cases were identified at the end of 2019 in Wuhan, China, quickly spreading among other countries and soon the entire globe. On March 11, the World Health Organization (WHO) declared the Covid-19 outbreak a global pandemic. One of the biggest euro area countries – Italy, was one of the first to be severely affected by the pandemic, with daily new cases and deaths rising to record numbers at the time compared to other EU countries. Countries went into lockdown due to government implemented restrictions and policies in order to contain the virus, resulting in closed businesses, impaired markets, closed borders, triggering a global recession. Uncertainty surrounded many aspects – the infectivity, the lethality of the virus, the effectiveness of social distancing, masks, remote-work and education, the availability of a cure or vaccine. As the virus spread at incredible speeds, it was impossible to predict the future outcome of the pandemic, raising questions on how and when the economy will recover. This is reflected by the forecast disagreement index, which skyrocketed to an all-time high of eight standard deviations above the mean in the second quarter of 2020, indicating how much uncertainty surrounded the economic outlook. The pandemic caused supply shortages, price spikes, market disruption and more than a third of the world's population went into lockdown. What has been named by the IMF as "The Great Lockdown" has proven to be the worst economic downturn since the Great Depression, with -3% projected global economic growth at the time (Gopinath, 2020). Hence, it is no surprise that the composite uncertainty index reaches record-heights of nearly four standard deviations above the mean during the Covid-19 crisis year. Amid the pandemic, Brexit formally happened in January, accompanied by yet another US presidential election that featured Donald Trump, who lost to Joe Biden. Race and social justice topics quickly spread from the US across the world after the killing of George Floyd – initiating movements and even violent protests in Berlin, Paris, and other euro area countries. The spike in financial market uncertainty is not as significant compared to the Great Recession due to the crisis not being directly revolved around the financial system – it is rather a response and consequence of the global health crisis.

As discussed previously, measures of economic uncertainty should be counter-cyclical and vary throughout different stages of the business cycle. This means uncertainty should increase and be high during recessions and low during economic booms and times of recovery. Thus, it is expected that the uncertainty indicators will have an adverse effect on macroeconomic variables and will be negatively correlated with economic activity. The correlations and relationships between the uncertainty measures and activity variables are presented in Table 1:

Table 1

Correlations between uncertainty measures and economic activity indicators.

Uncertainty measure	*Growth*						*Aggregate*		
	GDP	Investment	Consumption	Employment	Hours worked	Productivity	GDP	Investment	Consumption
Uncertainty Index	-0.78	-0.66	-0.80	-0.66	-0.78	-0.72	0.22	0.31	0.35
Financial Market Uncertainty	-0.45	-0.56	-0.33	-0.52	-0.37	-0.34	-0.03	0.01	0.05
Policy Uncertainty	-0.44	-0.30	-0.58	-0.37	-0.43	-0.41	0.57	0.56	0.67
Forecast Disagreement	-0.75	-0.56	-0.79	-0.53	-0.84	-0.78	-0.04	0.12	0.07

Source: ECB Statistical Data Warehouse and own calculations.

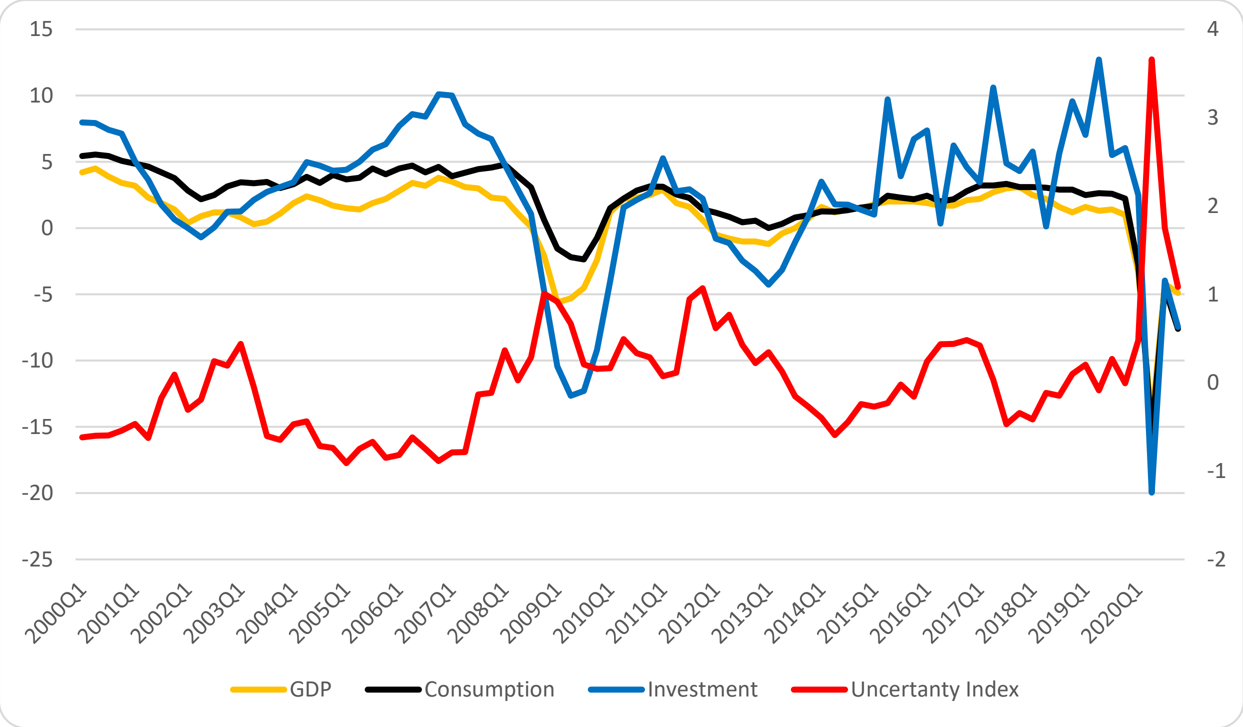
The relationships were checked for six variables in their year-on-year percent change – real GDP, real gross fixed capital formation (investment), real private consumption, total employment, total hours worked, and productivity.[9] Additionally, correlations between uncertainty measures and the three main variables of interest in aggregate were calculated. Although, real aggregate amounts of GDP, investment, and consumption did not yield the expected results due to the nature of the variables – aggregate level does not show the over-the-period trends of the data and is usually increasing in level, but uncertainty does not have consistent growth. Due to this, I was not able to find the desired relationship, as correlations show there is no relationship between financial market uncertainty and forecast disagreement with aggregate-level variables. Economic policy uncertainty, however, even showed positive correlations of around 0.60 with the aggregate variables – also pushing the composite uncertainty index to have a small positive relationship. This finding coincides with Biswas (2019), who also finds a positive relationship between EPU and aggregate real GDP. EPU is looking to be increasing throughout this period, just like the aggregate levels of GDP, investment, and private consumption, suggesting a positive relationship. GL did not note that they have used growth in variables and lacked comments or remarks on what could be the differences in these relationships. When using the year-on-year percent change in activity variables, all uncertainty measures are negatively correlated with all indicators of economic activity in the euro area. Differences can be identified in the relationships between individual uncertainty measures and activity, with forecast disagreement showing the strongest negative correlations. This is most likely due to the Covid-19 period, as the large increase in forecast uncertainty was accompanied by huge decreases in activity during that time. Financial market uncertainty shows weaker correlations with consumption and productivity but adversely

[9] All macro variables data is from ECB Statistical Data Warehouse. For more details, please see Annex 2.

impacts investment the most. The political uncertainty index has a weaker relationship with investment, but a more significant one with consumption. The composite uncertainty index exhibits stronger negative correlations than the individual measures, indicating that its components reflect on different areas of the economy and capture different types of uncertainty, allowing the main measure to be more counter-cyclical. The strongest relationships are with consumption, GDP and hours worked, while correlations with investment and employment are slightly weaker. The counter-cyclical movement of the uncertainty index and three main activity variables can be seen in Figure 2.

Figure 2

Counter-cyclical movement of the composite uncertainty index and economic activity.



Note: The main axis denotes percentage points for economic activity indicators, while the secondary axis represents units for the uncertainty index.

Source: ECB Statistical Data Warehouse and own calculations.

Along with being counter-cyclical, uncertainty measures should have an impact on euro area activity, not the other way around. This means fluctuations in uncertainty should not be an endogenous response to changes in activity and the negative relationship discussed before must be unidirectional. This is analyzed using Granger-causality tests.[10] This statistical hypothesis test

[10] The definition of Granger causality was presented by Granger (1969).

is used for determining whether one time series is useful for forecasting another. It checks whether lagged values of one series provide statistically significant information about future values of another series. If the lagged value coefficients are significantly different from zero, then one series is considered to Grange cause another. The bivariate tests were performed for all uncertainty measures and economic activity in the euro area indicators, choosing the optimal number of lags according to the AIC.[11] The results are summarized in Annex 1. Conclusions for Granger-causality are reached with respect to the 5% significance level. We can see that all uncertainty indicators have an adverse effect on activity variables, but the causality tends to differ. Results show that the composite uncertainty index Granger causes all euro area activity variables, except for employment, but activity does not have an impact on the overall measure. Financial market uncertainty is seen to have a unidirectional causality with GDP and investment, but not consumption, which coincides with the same finding as in GL. The index also causes employment, but this relationship goes both ways. Economic policy uncertainty is seen to only cause consumption at the 5%-level and not vice versa, but it is important to mention that with low p-values regarding GDP, hours worked and productivity, we could reject the null at the 10%-level and conclude that the measure causes these activity indicators. High p-values in hypotheses revolving around activity impact on political uncertainty indicate that they do not Granger cause this type of uncertainty. Many bidirectional relationships can be identified between forecast disagreement and activity. Tests results show that all euro area activity indicators Granger cause forecast disagreement, while the measure itself does not affect investment, but has an impact on all other variables. This is the same case as in GL, indicating that forecast disagreement and measures from surveys tend to be caused by euro area activity. This can be explained by survey participants using the current and prior period economic outlook and data to forecast future economic states, meaning fluctuations a few periods before the survey disrupt the expectations of professional forecasters, resulting in more disperse answers and more uncertainty. Considering the conducted tests, I can conclude that the used and constructed uncertainty measures meet the two expected criteria of an uncertainty index – they are counter-cyclical, they have an adverse effect and cause economic activity in the euro area, but do not respond endogenously to movements in these variables.

When comparing the constructed final measure with the one in Gieseck and Largent (2016), the measures are indeed alike. This is due to a similar approach used for constructing the index on the same composition – the euro area. My constructed measure covers a slightly larger period – from 2000Q1 to 2020Q4, whereas GL's is 1999Q1-2015Q4. Data used for the

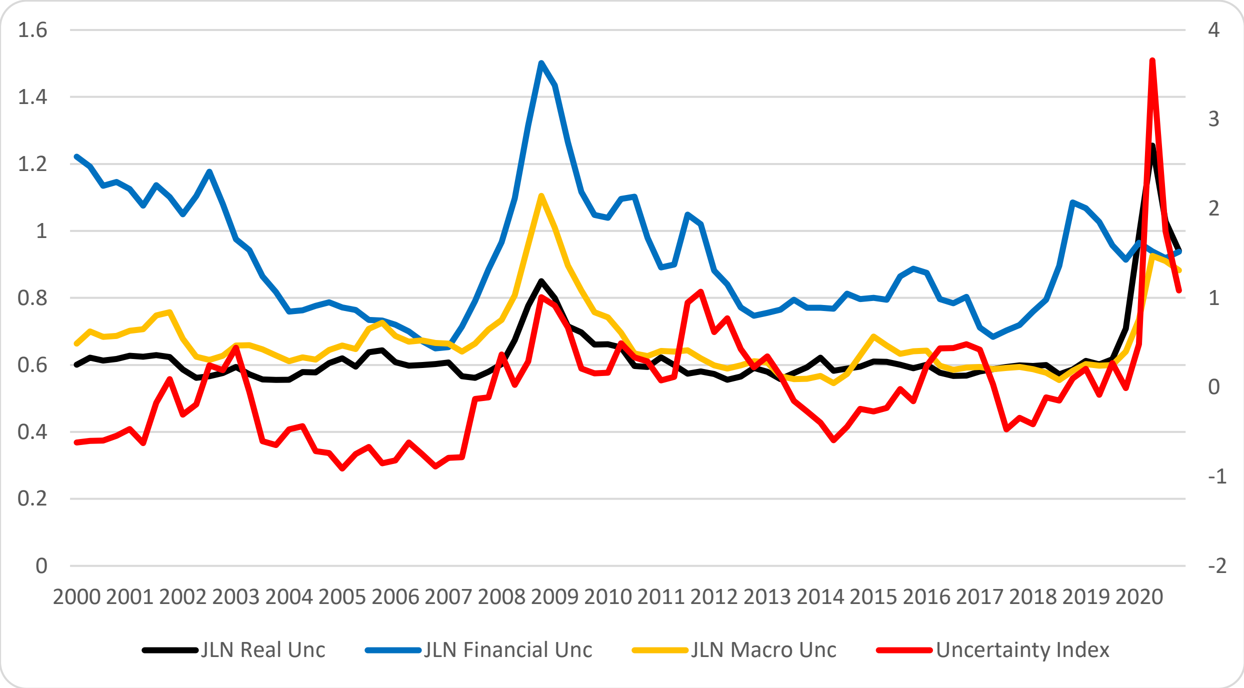
[11] For more details, see Akaike (1969).

construction are mostly from the same sources and have many datasets in common. Although, the data used in GL is richer – in the financial market uncertainty index, they also use implied exchange rate volatility and implied bond market volatility. They also include disagreement from forecasts provided by Consensus Economics, along with distributions around the point forecasts from the SPF. However, measures of forecast uncertainty did not pass the tests of empirical plausibility and statistical evidence and were excluded from the final measure calculations in GL. When looking at the period 2000-2015, coinciding fluctuations are identified, although they are steeper in GL. This is due to the Covid-19 period uncertainty levels smoothing out other fluctuations because of standardization. Gieseck and Rujin (2020) used the same methodology as in GL to cover a larger time span for the analysis of uncertainty in the euro area. When comparing the fluctuations to the updated analyzed period 1991-2020, the uncertainty indices look alike during the past five years. The coinciding findings are the fluctuations of political uncertainty during 2016-2017 and the huge spike of uncertainty during the Covid-19 pandemic. Forecast disagreement rises by more than 8 standard deviations in both the updated article and my analysis, although my composite uncertainty index seems to show a smaller spike during 2020. This difference can be explained once again by the different time span, as all uncertainty indices are standardized, and the fluctuations that are measured in standard deviations tend to differ. However, both the article and my analysis lead to the same conclusion – uncertainty has spiked to record levels during the Covid-19 pandemic.

It is also worth comparing the constructed measure with indices constructed according to the approach of Jurado, Ludvigson and Ng (2015) (JLN, hereafter). Ludvigson publicly provides calculated uncertainty data, which is updated twice per year, thus it can be compared for my whole investigated period. It is important to note, that these measures are constructed globally, not only for the euro area – however, it nevertheless provides a strong basis for comparison. Macro, financial and real uncertainty indexes by JLN along with my uncertainty measure are presented in Figure 3.

Figure 3

Uncertainty measures in the literature compared to the constructed uncertainty index



Note: The main axis denotes units for uncertainty measures proposed by JLN, while the secondary axis represents units for my uncertainty index.

Source: Compiled based on Jurado, Ludvigson and Ng (2015) and own calculations.

All measures exhibit similar fluctuations and rise during significant economic and world events. These similarities between the measures show that uncertainty is shared across the globe. All measures rise significantly during the Covid-19 pandemic, as well as the Great Recession, which is in line with heightened levels of uncertainty during those times. The composite uncertainty index showed correlations of 0.66 and 0.44 with the JLN real and macro uncertainty indices respectively, while the correlation between my financial market uncertainty measure and JLN's is 0.67.

4. EMPIRICAL ANALYSIS

4.1. Methodology

As discussed in the literature review, research has proposed various methods and different approaches to quantify and evaluate the effect of uncertainty on the economy. A possible option is adding a measure of uncertainty into already specified macroeconomic or financial models. Then it is easy to compare the baseline model to the augmented one and check whether the results outperform previous estimates or become more significant. A more popular way proposed in the literature is to use bivariate or multivariate Vector Autoregressive (VAR) models. This approach allows simulating uncertainty shocks and then measuring the dynamic response of economic variables to such fluctuations. A more extensive Structural Vector Autoregressive (SVAR) approach has been developed recently, which allows imposing restrictions on the model to control for contemporaneous correlation between the residuals. These models allow us to estimate the impact of structural shocks on economic variables.

In my thesis, I specify a low-dimensional multivariate vector autoregressive model.[12] The VAR model allows to generalize the single variable univariate model to capture the relationship between multiple variables that change over time. The main time series equation includes the variable's own past values, lagged values of other variables, an intercept, and an error term. The modeling approach is to measure the impact of an uncertainty measure on an indicator of macroeconomic activity – GDP, investment, consumption, hours worked, or productivity. Four uncertainty measures are used in the model: financial market uncertainty (FMU), economic policy uncertainty, the composite uncertainty index, and a modified uncertainty index that includes only FMU and EPU. This is because forecast disagreement, unlike other measures, did not fully pass the tests of empirical plausibility – it had a bidirectional causality with activity. Thus, it was excluded from the impulse response analysis and a new composite measure was computed as the average of the remaining two measures for comparability of the results.[13] All other measures were proven to be strictly counter-cyclical and Granger caused activity but were not affected the other way around. The following model is specified in reduced form:

$$\boldsymbol{Y}_t = \boldsymbol{\beta} + \sum_{i=1}^{n} \boldsymbol{A}_i \boldsymbol{Y}_{t-i} + \boldsymbol{e}_t \tag{1}$$

[12] The following discussion is based on Zivot and Wang (2006).

[13] Note, that forecast disagreement was still used as part of the composite uncertainty index, as the composite measure passed the tests of empirical plausibility, which can be seen in Annex 1 and Table 1.

The optimal lag length of two quarters was chosen according to the AIC for all models. Thus, it can be rewritten with $n = 2$ as:

$$\boldsymbol{Y}_t = \boldsymbol{\beta} + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + \boldsymbol{A}_2\boldsymbol{Y}_{t-2} + \boldsymbol{e}_t \tag{2}$$

Y_t denotes the vector of the observed time series of length k (the number of variables), β is the vector of length k representing the intercepts, e_t denotes the error term vector of length k, while A_i for $i = 1, 2$ is a k x k coefficient matrix. $Y_t = [unc_t, y_t, l_t, p_t, r_t]'$, where unc_t represents a measure of economic uncertainty, y_t is an indicator of economic activity that can be either GDP, investment, consumption, hours worked, or productivity, l_t is a measure of employment, p_t denotes the inflation rate, while r_t is the shadow rate by Wu and Xia (2016). The number of variables in each model is five, thus $k = 5$. The model is defined in the following expanded matrix form:

$$\begin{bmatrix} unc_t \\ y_t \\ l_t \\ p_t \\ r_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} a_{1,1}^i & a_{1,2}^i & a_{1,3}^i & a_{1,4}^i & a_{1,5}^i \\ a_{2,1}^i & a_{2,2}^i & a_{2,3}^i & a_{2,4}^i & a_{2,5}^i \\ a_{3,1}^i & a_{3,2}^i & a_{3,3}^i & a_{3,4}^i & a_{3,5}^i \\ a_{4,1}^i & a_{4,2}^i & a_{4,3}^i & a_{4,4}^i & a_{4,5}^i \\ a_{5,1}^i & a_{5,2}^i & a_{5,3}^i & a_{5,4}^i & a_{5,5}^i \end{bmatrix} \begin{bmatrix} unc_{t-i} \\ y_{t-i} \\ l_{t-i} \\ p_{t-i} \\ r_{t-i} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \\ e_{4,t} \\ e_{5,t} \end{bmatrix} \tag{3}$$

Augmented Dickey-Fuller tests confirmed that all four uncertainty measures – financial market uncertainty, political uncertainty and both the composite and modified uncertainty indicators are stationary. The test's null hypothesis is that a unit root is present in a time series, which is a feature of a non-stationary, stochastic process. Stationarity means that the time series revolves around a stable mean and variance and does not change its statistical properties over time. All economic activity variables (GDP, investment, consumption, hours worked, and productivity) are expressed in real terms, by year-on-year growth. These are the variables of interest, on which I will be measuring the impact of uncertainty. The measure of total employment is also included in year-on-year growth. The Harmonized Index of Consumer Prices (HICP) was used for the inflation rate, but not in growth, as the variable itself already represents growth in prices. The shadow rate by Wu and Xia (2016) was used as it includes monetary policy at the zero lower bound. These shadow rates were selected instead of regular short-term interest rates because they capture the effect of unconventional monetary policy. I use the rate constructed specifically for the euro area from 2004 and the official overnight interest rate EONIA for the period leading up to it, which holds when the zero lower bound is not binding.

After the model is specified, the approach is to see how uncertainty shocks affect the macroeconomy. This is done by computing impulse response functions and looking at how the variable of interest – economic activity reacts to such a fluctuation of an uncertainty measure.[14]

[14] The further specification of the model benefited from the work of Kirchgassner et al. (2012).

Firstly, we can rewrite the 5-variable VAR process from eq. (2) in its infinite order moving-average form to measure the effect of shocks after, say, *i* periods:

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{e}_{t-i} \tag{4}$$

where Y_t is the vector of endogenous variables, μ is the vector of the time-invariant mean values of Y_t, e_t is the vector of reduced-form error terms. Φ_i are the simple Impulse Response Functions (IRFs), which can be determined from the estimated coefficient matrix:

$$\boldsymbol{\Phi}_i = \begin{cases} \boldsymbol{I}_k & \text{if } i = 0 \\ \sum_{j=1}^{i} \boldsymbol{\Phi}_{i-j} \boldsymbol{A}_j & \text{if } i = 1, 2, \ldots \end{cases}$$

Here, I_k is the initial, zero-point response to a shock in variable *k*. The *j*, *k* element of Φ_i gives the effect of a change in the *k*th element of e_t on the *j*th element of Y_t after *i* periods, holding everything else constant. However, no direct economic interpretation could be made from these effects, because the VAR residuals in the reduced form are in general cross-correlated. This means a shock to uncertainty would have a contemporaneous impact on the other variables as well, thus we cannot assume that everything else is constant. Contemporaneous correlation implies that a shock to one variable would most likely be accompanied by shocks to some other variables. Because of this, (4) cannot provide a causal interpretation.

To overcome this, it makes sense not to investigate shocks with respect to the residuals e, but in terms of mutually uncorrelated innovations. To orthogonalize e_t, we need a matrix P, such that $\Sigma_{ee} = PP'$.[15] Sims (1980) has popularized the method of using the lower triangular Cholesky decomposition of the variance-covariance matrix of the reduced form residuals. Then, the innovations can be calculated as

$$\boldsymbol{w}_t = \boldsymbol{P}^{-1} \boldsymbol{e}_t \tag{5}$$

and the errors are uncorrelated because

$$\boldsymbol{\Sigma}_{\boldsymbol{ww}} = \boldsymbol{P}^{-1} \boldsymbol{\Sigma}_{ee} \boldsymbol{P}^{-\mathbf{1}'} = \boldsymbol{P}^{-1} \boldsymbol{P} \boldsymbol{P}' \boldsymbol{P}^{-\mathbf{1}'} = \boldsymbol{I}_k$$

Thus, we can rewrite (4) as

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{P} \boldsymbol{P}^{-1} \boldsymbol{e}_{t-i}$$

$$= \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Theta}_i \boldsymbol{P}^{-1} \boldsymbol{e}_{t-i}$$

[15] Where Σ_{ee} is the variance-covariance matrix of the reduced-form residuals.

where the new coefficient matrix is

$$\boldsymbol{\Theta}_i = \boldsymbol{\Phi}_i \boldsymbol{P}$$

and finally, inserting the innovations (5) to get

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Theta}_i \boldsymbol{w}_{t-i} \tag{6}$$

In the case of such a P, w_k is mutually orthogonal and not contemporaneously correlated, meaning no information is lost and Θ_t yields the causal interpretation that we seek. The transformation with matrix P depends on the ordering of the variables in the system, which is arbitrary. In the specified model, the variables in the estimation order are as proposed by GL – a measure of uncertainty, an indicator of economic activity, employment, inflation, and the shadow rate. We can then expand equation (6) to get the following decomposition for the sub-vectors:

$$\begin{aligned}\boldsymbol{Y}_t = \begin{bmatrix} unc_t \\ y_t \\ l_t \\ p_t \\ r_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} + \begin{bmatrix} \Theta_{1,1}^0 & 0 & 0 & 0 & 0 \\ \Theta_{2,1}^0 & \Theta_{2,2}^0 & 0 & 0 & 0 \\ \Theta_{3,1}^0 & \Theta_{3,2}^0 & \Theta_{3,3}^0 & 0 & 0 \\ \Theta_{4,1}^0 & \Theta_{4,2}^0 & \Theta_{4,3}^0 & \Theta_{4,4}^0 & 0 \\ \Theta_{5,1}^0 & \Theta_{5,2}^0 & \Theta_{5,3}^0 & \Theta_{5,4}^0 & \Theta_{5,5}^0 \end{bmatrix} \begin{bmatrix} w_{1,t} \\ w_{2,t} \\ w_{3,t} \\ w_{4,t} \\ w_{5,t} \end{bmatrix} \\ + \sum_{i=1}^{2} \begin{bmatrix} \Theta_{1,1}^i & \Theta_{1,2}^i & \Theta_{1,3}^i & \Theta_{1,4}^i & \Theta_{1,5}^i \\ \Theta_{2,1}^i & \Theta_{2,2}^i & \Theta_{2,3}^i & \Theta_{2,4}^i & \Theta_{2,5}^i \\ \Theta_{3,1}^i & \Theta_{3,2}^i & \Theta_{3,3}^i & \Theta_{3,4}^i & \Theta_{3,5}^i \\ \Theta_{4,1}^i & \Theta_{4,2}^i & \Theta_{4,3}^i & \Theta_{4,4}^i & \Theta_{4,5}^i \\ \Theta_{5,1}^i & \Theta_{5,2}^i & \Theta_{5,3}^i & \Theta_{5,4}^i & \Theta_{5,5}^i \end{bmatrix} \begin{bmatrix} w_{1,t-i} \\ w_{2,t-i} \\ w_{3,t-i} \\ w_{4,t-i} \\ w_{5,t-i} \end{bmatrix}\end{aligned} \tag{7}$$

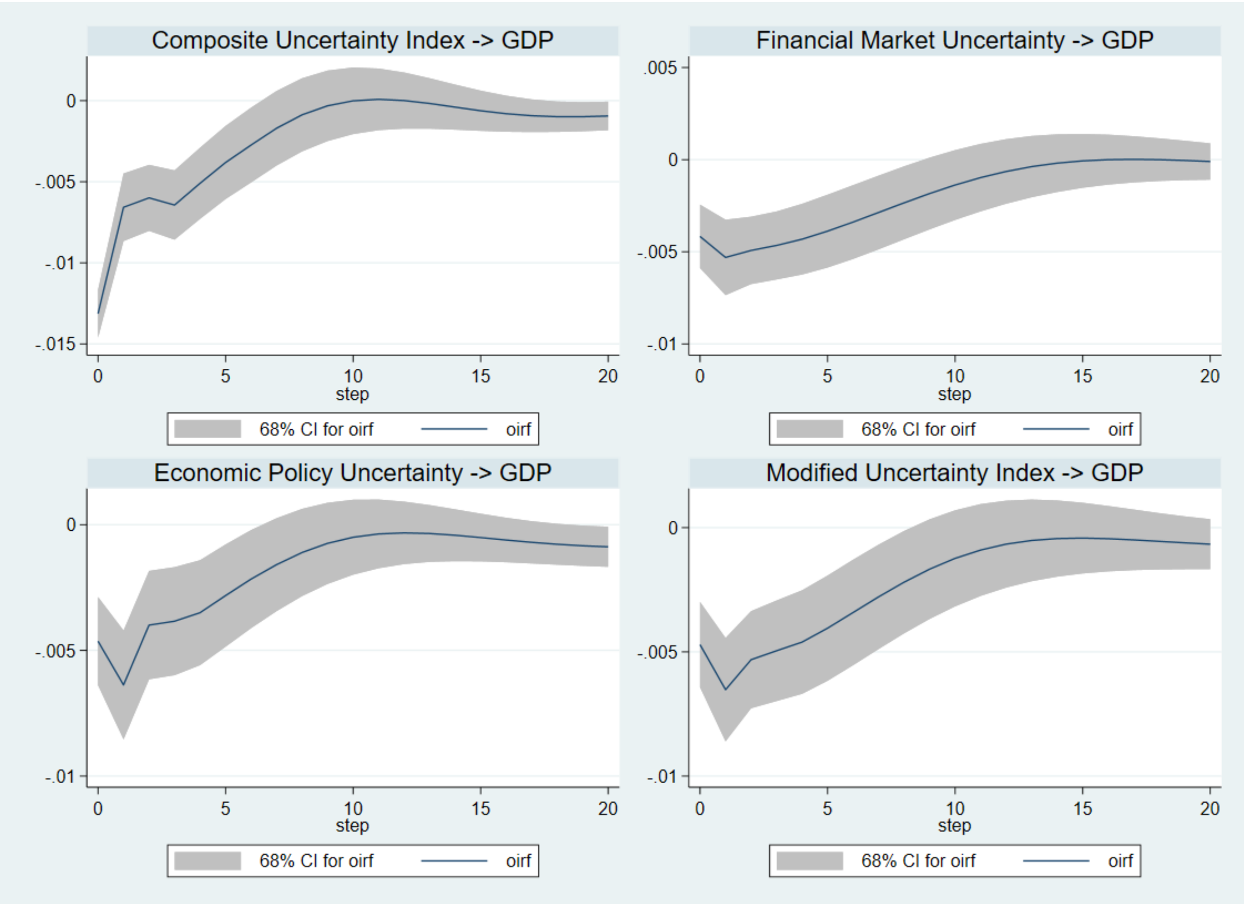
Having performed this transformation with a Cholesky decomposed P and based on the ordering of the variables, uncertainty can have an instantaneous impact on all other variables, while the relation in the reverse direction is excluded. The model is also constructed in a way that all other variables from the third one onwards cannot impact the activity indicator at time t, but they can with lags. Thus, it is possible to measure the effect of a shock in uncertainty on economic activity. These restrictions are only imposed on impact – at the initial zero point. From the next period onwards, all variables can influence others with no further imposed restrictions. With these specifications, the model is identified, and the parameters can be consistently estimated using Ordinary Least Squares (OLS). Orthogonalized impulse response functions and 68% confidence intervals were computed in Stata.

4.2. Results

In the following section, I present the results of the model and comment on the graphs of the impulse response functions and the impact of uncertainty shocks. The results indeed follow the initial intuition that an increase in uncertainty adversely affects macroeconomic activity. The graphs were grouped by economic activity indicators for better visual comparison on how one standard deviation shocks to different types of uncertainty affect a single part of the economy. Figure 4 depicts the dynamic response of real GDP growth to such fluctuations of economic uncertainty.

Figure 4

Real GDP growth response to a one standard deviation shock in different uncertainty indices

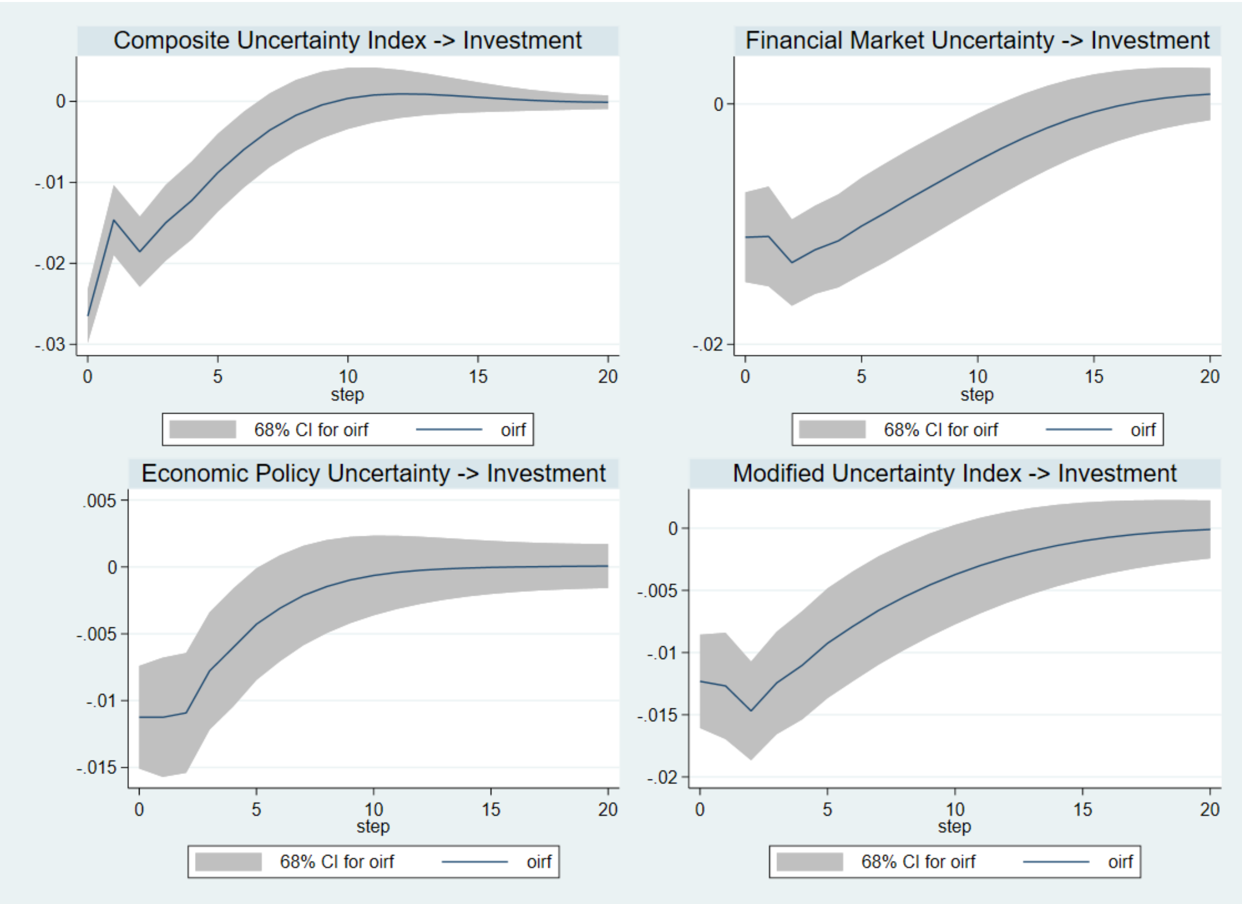


Source: Own calculations.

All graphs show a strong initial negative response from GDP, especially to a shock in the composite uncertainty index, where GDP drops by about -1.3 percentage points at impact, meaning the strongest effect is when the shock in uncertainty takes place. In all cases, real GDP growth gradually comes back to initial levels after about six quarters, indicating that a shock in uncertainty persists for about 1 year and a half. During a shock in financial market uncertainty, GDP does not dip as heavily as compared to the other measures, meaning the response is smoother and does not result in huge unexpected fluctuations but it is slightly more persistent. Overall, the impulse response functions show that uncertainty adversely affects economic growth, which happens through multiple previously discussed channels and supports the fact of the economic downturn during the Covid-19 pandemic. The response of investment can be seen in Figure 5.

Figure 5

Real Investment growth response to a one standard deviation shock in different uncertainty indices

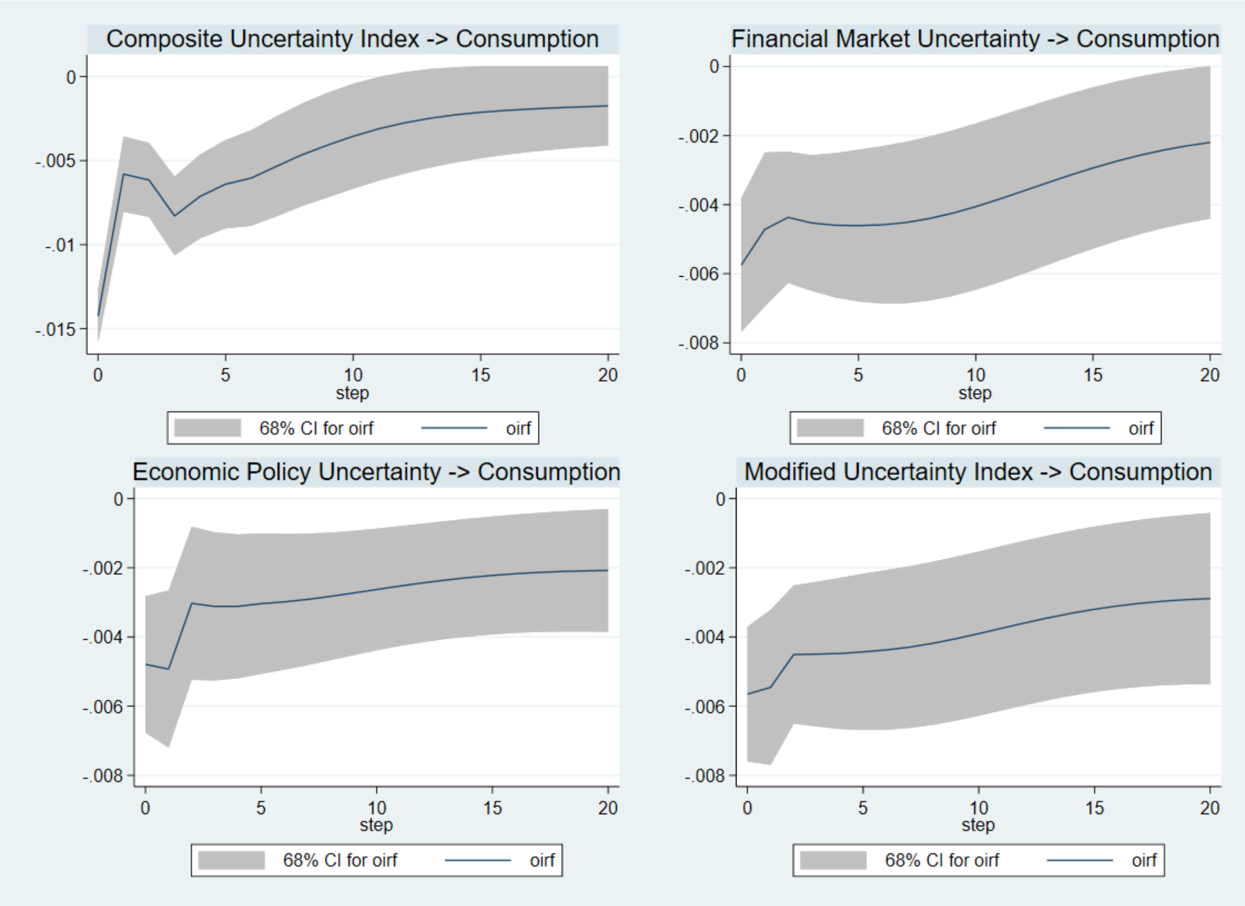


Source: Own calculations.

The impulse response functions of total investment show similar results, with an even stronger adverse initial response, as real gross fixed capital formation growth goes down up to -2.7 percentage points after a one standard deviation shock in uncertainty. A second decline during the second quarter after the shock can be seen, meaning uncertainty adversely affects economic activity not only at impact but also with a delay. This is in line with the literature regarding uncertainty, as the increased risk associated with investment decisions during such times can have a long-lasting impact.[16] Kolev et al. (2013) also find that heightened uncertainty has been an important driver of the decline in investment in the whole EU since 2009, while Buti and Mohl (2014) consider it as one of the three main factors for the euro area. The consumption response to the shock is shown in Figure 6.

Figure 6

Real Private Consumption growth response to a one standard deviation shock in different uncertainty indices



Source: Own calculations.

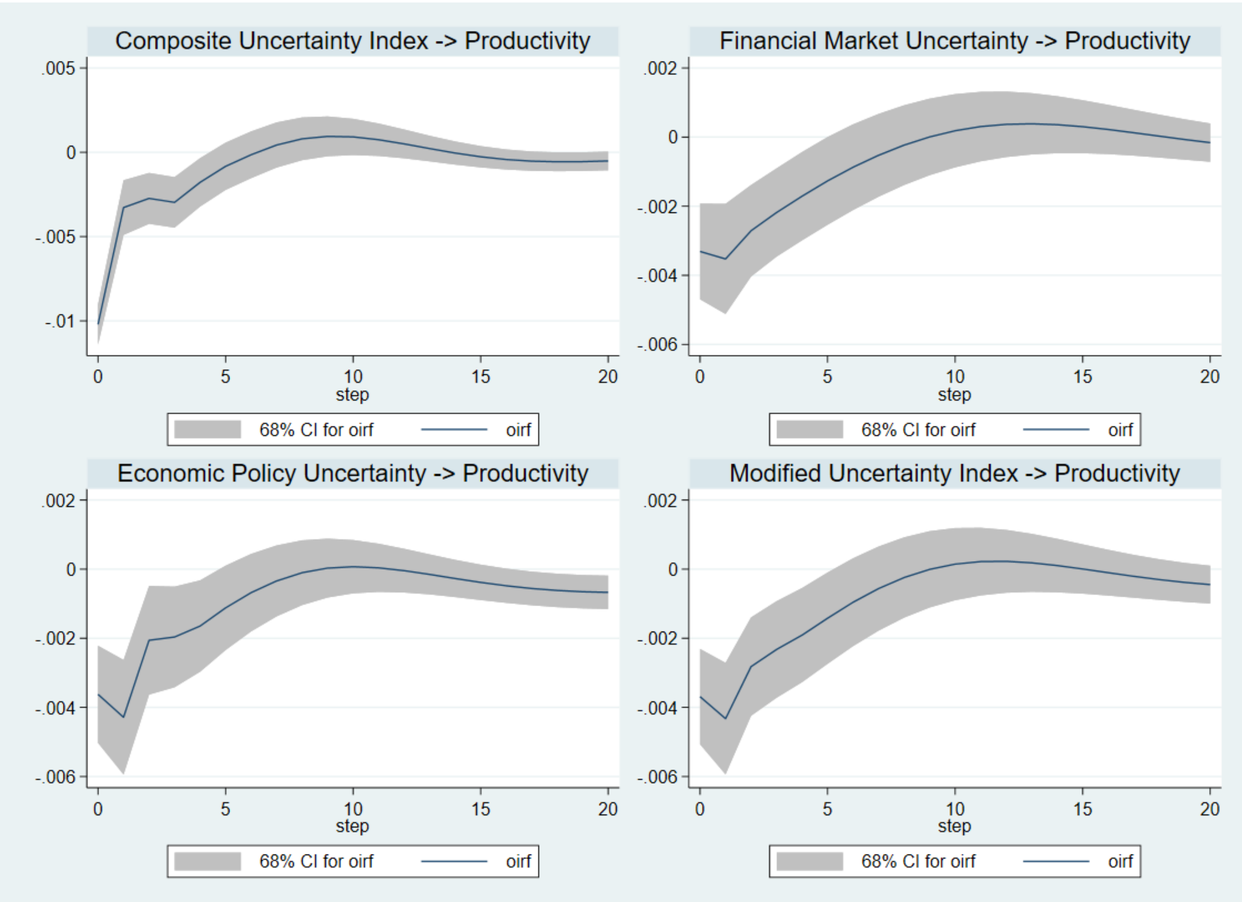
The shock in the composite uncertainty index proposes the strongest adverse effect on consumption at impact, as consumption growth decreases up to -1.4 percentage points, whereas the responses to other shocks show roughly half a percentage point decrease. A shock to economic policy uncertainty peaks the latest of the four – at quarter one, showing a rapid spike of recovery

[16] See e.g. Bonciani and Van Roye (2016) and Bloom (2009).

afterward. Responses to financial market uncertainty and the modified uncertainty index are smoother, although consumption fails to recover back to initial levels throughout the duration of the shock. In general, these are the most persistent IRFs. Only the 68% confidence interval bands of the response to the composite uncertainty index shock can be seen to return to pre-shock levels, indicating less persistence. It is the only measure to include forecast disagreement, thus forecast uncertainty might not have a persistent effect on consumption. The overall impact could be strongly influenced by the Covid-19 pandemic, as people tend to spend less due to an uncertain future regarding their jobs, health and the whole economic situation, hence the long-lasting precautionary savings effect. The real options effect can also be seen, as the value to wait and postpone consumption is higher in times of higher uncertainty. The responses of productivity to different shocks of uncertainty are presented in Figure 7.

Figure 7

Productivity growth response to a one standard deviation shock in different uncertainty indices

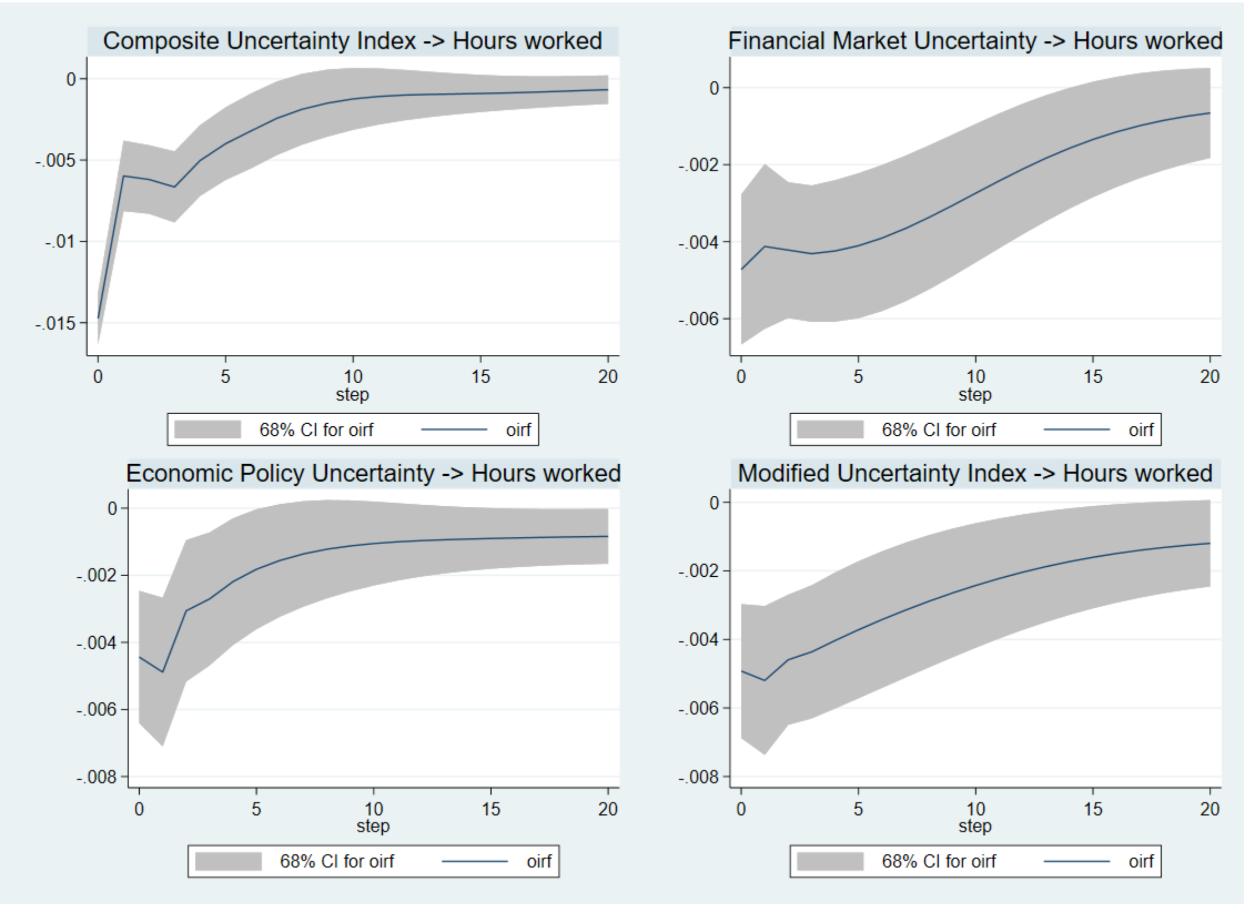


Source: Own calculations.

Productivity shows the least strong response to a one standard deviation shock in uncertainty of all the activity variables, although the response functions follow similar trends to other economic activity indicators in terms of shock duration and dip timing. It can be seen that productivity returns back to pre-shock levels faster than other economic indicators, meaning productivity is not as adversely affected in the long run and it returns to previous levels in a short amount of time. Choi et al. (2018) argue that the effect of uncertainty on productivity growth is related to the investment channel. In times of high uncertainty, firms change their investment by reducing productivity-enhancing investment. Lockdown restrictions during uncertainty induced by the Covid-19 pandemic could be a huge factor for productivity growth, as working from home is generally assumed to be less productive. Finally, the impulse response functions of the total hours worked in the economy are presented in figure 8:

Figure 8

Hours worked growth response to a one standard deviation shock in uncertainty indices



Source: Own calculations.

Just like in previous graphs, it can be concluded that a shock in all uncertainty measures has a negative effect on the growth of total hours worked in the economy. The composite uncertainty index shock effect is larger at impact, as well as in the case of a shock in financial market uncertainty, although the response is weaker. The duration of the shock significantly differs depending on the type of uncertainty shock – hours worked growth takes noticeably longer to get back to initial levels when hit by a spike in financial market uncertainty and the modified uncertainty index. This could be a result of shifts in labor supply and labor demand in a new equilibrium after the rise in uncertainty, as proposed by Basu (2017). As employment was included in the model, it controls for the fluctuations in the labor market and the true effect of uncertainty on hours worked in the economy can be estimated.

The results of the impulse response functions of activity to one standard deviation shocks in uncertainty are summarized in Table 2.

Table 2

Estimated impact of uncertainty on economic activity in the euro area

Response/Impulse variables	Largest impact	Quarter	Duration	Total Impact
GDP growth				
Composite Uncertainty Index	-0.013	0	6	-0.05
Financial Market Uncertainty	-0.005	1	8	-0.04
Economic Policy Uncertainty	-0.006	1	6	-0.04
Modified Uncertainty Index	-0.007	1	8	-0.05
Investment growth				
Composite Uncertainty Index	-0.027	0	6	-0.10
Financial Market Uncertainty	-0.013	2	10	-0.11
Economic Policy Uncertainty	-0.011	1	5	-0.06
Modified Uncertainty Index	-0.015	2	9	-0.11
Consumption growth				
Composite Uncertainty Index	-0.014	0	11	-0.09
Financial Market Uncertainty	-0.006	0	19	-0.08
Economic Policy Uncertainty	-0.005	1	20	-0.06
Modified Uncertainty Index	-0.006	0	20	-0.08
Productivity growth				
Composite Uncertainty Index	-0.010	0	4	-0.02
Financial Market Uncertainty	-0.004	1	4	-0.01
Economic Policy Uncertainty	-0.004	1	4	-0.02
Modified Uncertainty Index	-0.004	1	5	-0.02
Hours worked growth				
Composite Uncertainty Index	-0.015	0	7	-0.06
Financial Market Uncertainty	-0.005	0	14	-0.06
Economic Policy Uncertainty	-0.005	1	5	-0.03
Modified Uncertainty Index	-0.005	1	17	-0.06

Source: Own calculations.

Even though all economic indicators are affected negatively by uncertainty, the impact differs depending on the type of uncertainty shock on specific variables. In all macroeconomic variable response cases, the composite uncertainty index is seen to have a more substantial effect compared to other uncertainty measures. This can be explained by the structure and composition of the measure – it is the only one that included forecast disagreement. The dispersion of professional forecasters' answers was previously discussed to be the most counter-cyclical of all the measures, which means a stronger negative relationship. This is most likely due to the inclusion of the period with the Covid-19 pandemic, where uncertainty spiked significantly and the disagreement index dipped substantially during the same quarter at 2020Q2. Thus, it is no surprise that the information contained in the forecaster index influenced the response to the composite uncertainty index substantially for all economic variables. Responses to the economic policy uncertainty seemed to be least strong; however, the model still proves that uncertainty-inducing political events do have an adverse impact on macroeconomic activity in the euro area. Shocks to the financial market uncertainty index had the strongest impact and lasted the longest on investment growth, which is expected considering investment heavily revolves around the financial system. However, it had the weakest effect on real GDP growth out of the four uncertainty indices. Shocks to the modified uncertainty index without forecast disagreement resulted in stronger adverse effects in most cases than the latter two measures, but less significant than the composite measure.

The strongest adverse effect of uncertainty was on investment – a finding coinciding with the results of Gieseck and Largent (2016). Compared to other macro variables, investment is most influenced by adjustment and fixed costs (real options effect), thus fluctuations in uncertainty have a strong and prolonged effect on the choices and activity related to investment. In terms of total impact, various uncertainty shocks also had a significant adverse effect on consumption. The total estimated impact is relatively high due to the duration of the shock, where the decline lasted for 11 quarters in the case of a shock in the composite index and almost the whole estimated shock period of 20 quarters in the cases of the other measures. GL also finds that the duration of the shock on consumption is longer than on overall activity. During the surge of uncertainty caused by Covid-19, consumption saw decreases with magnitudes from 14% to 69% across multiple sectors in an estimation of 214 cities by Chen (2020). Thus, consumption levels are probable to stay in lower levels for multiple years to come when recovering from the crisis. The cumulative shock impact on real GDP growth throughout the five-year period is estimated to be about 5%. The shock effects between different uncertainty measures do not differ in sign, meaning fluctuations to different types of uncertainty all negatively affect overall macroeconomic activity through different channels one way or another. As uncertainty rose nearly four standard deviations during the Covid-19 pandemic, this strengthens the point that uncertainty severely contributed to the stagnation of the economy during the crisis. Uncertainty shocks least significantly affected productivity growth, with the shock lasting about a year before returning to initial levels. Hours worked growth seemed to be least affected by a shock in political uncertainty and returning to pre-shock levels faster than in cases of other uncertainty shocks. Shocks to financial market uncertainty and the modified index showed to have the same cumulative impact as during a shock in the composite index but lasted considerably longer. This shows that the adjustment costs induced by uncertainty also disrupt the labor market.

The obtained results are similar to those proposed in the literature, however, certain aspects differ. When compared to Gieseck and Largent (2016), the results are relatively coinciding – the strongest adverse effect is on investment, while the shock duration is longest for consumption. However, the length and effect of the shocks are considerably longer and bigger in this analysis. The difference can be explained by the different time period and huge shock in uncertainty during the Covid-19 pandemic. As GL uses data for the period 1999Q1-2015Q4, which mostly reflects on the Great Recession and Greek crisis, I expand the period and use data for 2000Q1-2020Q4. Thus, with the inclusion of the biggest surge of uncertainty during the analyzed time period caused by the global health crisis, the estimated effect of uncertainty is substantially larger. This can also influence the duration of the shocks, as all economic indicators have stayed at extremely lower levels throughout the pandemic. The durations are also longer due to the nature of calculation – as the length is determined by looking at the standard error bands, the confidence interval influences the duration conclusion. I decided to use the basic 68% intervals, whilst GL computed the 95% confidence intervals via Bootstrap methods. Another noticeable difference is in the timing of the most negative effect of uncertainty shocks. In GL, uncertainty has a delayed effect and activity shows the strongest negative response after about two to four quarters, which means it takes a bit of time for the adverse effect of an uncertainty shock to take place. However, my results show a considerable earlier peak effect – from zero up to two quarters at most. This means that the strongest negative effect is at impact, just when uncertainty spikes with no extra considerable delays. This is especially true for the composite uncertainty index, which contains forecast disagreement, which had the large opposite movement with macroeconomic variables during 2020Q2 at the beginning of the Covid-19 pandemic. Although the movements are less significant for the other measures, they are also noticeable and influenced on the results. The unexpected worldwide spike of uncertainty has shown that the impact of surges of uncertainty of this magnitude can have an extremely fast impact. The largest effect also depends on the restrictions imposed on the model, as contemporaneous correlation is a huge issue in this analysis. Even though I have used the Cholesky decomposition to impose restrictions on the model to obtain its structural form, GL initially specified an SVAR model with 35 restrictions to identify the structural shocks along with a Cholesky decomposition, which can also contribute to the differences between the results.

The effect of uncertainty on productivity and hours worked was not analyzed by GL, thus the results can be compared to other relevant research papers. Basu and Bundic (2012) use both a basic and structural VAR to measure the effect of uncertainty shocks on hours worked and other macro indicators. They find that fluctuations in uncertainty indeed have a negative effect on hours worked and other variables; however, here the impact is significantly stronger due to the inclusion of the Covid-19 period. Another coinciding result is the duration of the shock, but the peak of the effects differs due to the same reasons as compared to GL. Choi et al. (2018) find a strong negative relationship between aggregate uncertainty, measured by stock market volatility and economic policy uncertainty, with productivity growth. Although the paper did not simulate uncertainty shocks, the same results that uncertainty has an adverse impact on productivity are achieved. They also find that productivity growth is more affected in industries that rely more on external finance due to the presence of credit constraints. When compared to the popular VAR approach of Bloom (2009), similar findings can be found. That paper measures economic activity via industrial production and finds the same adverse effect as I do on real GDP growth. The biggest difference being that Bloom does not achieve a strong at impact response to a shock in uncertainty and the effect actually turns positive after 3-4 quarters, indicating recovery. However, the time period of 1963-2005 and data for the US was used in that analysis, so different findings are expected, but the main trends of uncertainty shocks remain consistent. When looking at an uncertainty shock analysis by Baker et al. (2020) during the Covid-19 period, the same increased effect of uncertainty can be identified, further proving the point that uncertainty has been an important factor behind the downfall of economic growth and other macro indicators during the pandemic.

Although the obtained results confirm the initial expectations and coincide with the findings in the literature, there are some caveats to the overall approach proposed in this analysis. A place for improvement regarding research that includes uncertainty is the data used to measure it. It would be beneficial to add more datasets in the construction of the uncertainty index to expand and capture more channels of uncertainty in different parts of the economy. In the current state and scope of the internet and social networks in our day-to-day lives, adding uncertainty surrounding these sources would be a great addition. The conditional volatility and the unforecastable component, similar to Jurado et al. (2015) in terms of measuring macro uncertainty might also allow for better inferences and results. Another issue with the approach is the frequency of the data used. Using higher frequency data, like monthly, compared to the quarterly frequency used in this analysis, would result in more accurate conclusions and estimates of uncertainty's impact, especially during the Covid-19 period. This is because the crisis escalated extremely quickly, but started at the beginning of 2020, while the uncertainty index only has a value at 2020Q2. This huge spike could result in an overestimation of the effect of uncertainty, as uncertainty could be shared gradually across the months and would result in a better estimate and measure of the real uncertainty in effect. Due to these fluctuations of uncertainty and macroeconomic variables, the shocks show a greater at impact effect compared to the results proposed in the literature, also having an influence on the direction of causality between uncertainty and economic activity. Thus, forecaster disagreement and the Survey of Professional forecasters might not be best suited for measurement of uncertainty at this frequency, when the current crisis is changing this rapidly. An alternative would be to use surveys of business expectations, as proposed by Baker et al. (2020), where it is possible to extract monthly uncertainty measures from the probability distributions over the firm's future sale growth expectations. The model used in the analysis is a basic Vector Autoregression, and although sometimes simpler is better, it would be worth experimenting with more complex VAR models. The SVAR approach has been popularized in recent literature that has been discussed throughout this thesis and allows to better control for contemporaneous correlation between the variables with the imposed restrictions to obtain better economic interpretations from the residuals. As suggested by GL, it would also be worth trying the approach of Bayesian or threshold VAR models that allow for more flexibility and extra specifications. The final issue that has room for improvement in the econometric analysis is the impact of omitted variable bias. Because of this, it is possible to overestimate the impact of uncertainty. Especially during the Covid-19 period, when multiple factors and rapidly changing conditions in the economy influence each other simultaneously, controlling for such movements would yield better results. Even though the short-term interest rate was changed by the shadow rate compared to GL and allows capturing unconventional monetary policy, there might still be existing monetary policy actions that the model has failed to control for.

CONCLUSION

The aim of this thesis was to investigate the macroeconomic effects and role of uncertainty in the euro area. The approach followed the work of Gieseck and Largent (2016), as multiple uncertainty measures were computed from different datasets through arithmetic and weighted averages, dispersions and principal component analysis. A multivariate VAR model with a Cholesky decomposition was specified, from which impulse response functions were calculated. All in all, the datasets used for the calculation of the uncertainty indices provide sufficient information on the macroeconomic effects of uncertainty. The measures passed the tests of empirical plausibility, as they were strictly counter-cyclical and the relationships were such that uncertainty affects the economic variables and not the other way around. Many uncertainty-inducing events were identified for the analyzed 2000Q1-2020Q4 period, such as the Great Recession, the Greek crisis, Covid-19, and numerous political events. Uncertainty was seen to significantly rise during these periods, while the macroeconomic indicators declined, indicating a negative relationship. The specified model successfully controlled for the contemporaneous correlation between uncertainty and economic activity variables, allowing us to interpret the results from an economic perspective. The impulse response functions showed that uncertainty has an adverse effect on all selected macroeconomic indicators. Various activity indicators were affected to different extents, based on the type of uncertainty. Investment was affected more significantly compared to other macro variables, while the effect on productivity was the least strong and the adverse effect on consumption lasted the longest. Overall, the analysis suggests that uncertainty has remained elevated due to numerous uncertainty shocks of different nature throughout the past two decades and imposes a serious threat to the speed of the recovery from the Covid-19 pandemic. As uncertainty has skyrocketed to record-high levels, it is no surprise that the economy is experiencing such a downfall.

The obtained results are comparable to those in existing literature, as the responses from the macroeconomic variables exhibited similar trends and coinciding inferences about the effect of uncertainty shocks could be made. However, as this analysis used a period containing the large surge of uncertainty during the Covid-19 period, the estimated effect of fluctuations in uncertainty was greater. Differences in the largest moments when the effects of such shocks materialised were identified, because the results mostly showed the strongest effect instantaneously, compared to the slower, more gradual response to uncertainty discussed in recent literature. This can be due to the identification imposed as well, as the literature commonly uses an SVAR approach, where the model allows to better control for the contemporaneous effects between uncertainty and the macro variables through imposed restrictions.

The analysis also has plenty of room for improvements, as more data can be added to the already existing uncertainty measures to capture more channels and types of uncertainty and obtain more robust results. It would be a good idea to use higher-frequency data for more accurate results, especially during the Covid-19 period, as the crisis has been escalating at incredible speeds. I also advise exploring the methodology, as the basic VAR could be replaced with more complex models for extra specifications and additional control variables to better capture financial frictions and movements due to the Covid-19 pandemic.

REFERENCES

Aastveit, K. A., Natvik, G. J. J., & Sola, S. (2013). Economic uncertainty and the effectiveness of monetary policy. https://doi.org/10.1016/j.jimonfin.2017.05.003

Abel, A. B. (1983). Optimal investment under uncertainty. *The American Economic Review*, *73*(1), 228-233. Retrieved from http://repository.upenn.edu/fnce_papers/220

Akaike, H. (1969). Fitting autoregressive models for prediction. Annals of the institute of Statistical Mathematics, 21(1), 243-247. https://doi.org/10.1007/BF02532251

Alexopoulos, M., & Cohen, J. (2015). The power of print: Uncertainty shocks, markets, and the economy. *International Review of Economics & Finance*, *40*, 8-28. https://doi.org/10.1016/j.iref.2015.02.002

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, *191*, 104274. https://doi.org/10.1016/j.jpubeco.2020.104274

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Baker, S. R., Bloom, N., & Terry, S. J. (2020). *Using disasters to estimate the impact of uncertainty* (No. w27167). National Bureau of Economic Research. https://doi.org/10.3386/w27167

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *Covid-induced economic uncertainty* (No. w26983). National Bureau of Economic Research. https://doi.org/10.3386/w26983

Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, *85*(3), 937-958. https://doi.org/10.3982/ECTA13960

Bekaert, G., & Hoerova, M. (2016). What do asset prices have to say about risk appetite and uncertainty?. *Journal of Banking & Finance*, *67*, 103-118. https://doi.org/10.1016/j.jbankfin.2015.06.015

Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), 771-788. https://doi.org/10.1016/j.jmoneco.2013.06.003

Berger, T., Grabert, S., & Kempa, B. (2017). Global macroeconomic uncertainty. *Journal of Macroeconomics*, *53*, 42-56. https://doi.org/10.1016/j.jmacro.2017.05.005

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The quarterly journal of economics*, *98*(1), 85-106. https://doi.org/10.2307/1885568

Biswas, R. (2019). Does Economic Policy Uncertainty Affect Analyst Forecast Accuracy? *Available at SSRN 3407668*. http://dx.doi.org/10.2139/ssrn.3407668

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, *77*(3), 623-685. https://doi.org/10.3982/ECTA6248

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153-76. https://doi.org/10.1257/jep.28.2.153

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, *86*(3), 1031-1065. https://doi.org/10.3982/ECTA10927

Bomberger, W. A. (1996). Disagreement as a Measure of Uncertainty. *Journal of Money, Credit and Banking*, *28*(3), 381-392. https://doi.org/10.2307/2077981

Bonciani, D., & Van Roye, B. (2016). Uncertainty shocks, banking frictions and economic activity. *Journal of Economic Dynamics and Control*, *73*, 200-219. https://doi.org/10.1016/j.jedc.2016.09.008

Born, B., Breuer, S., & Elstner, S. (2014). Uncertainty and the great recession. *Oxford Bulletin of Economics and Statistics*, 80(5), 951-971. https://doi.org/10.1111/obes.12229

Bowles, C., Friz, R., Genre, V., Kenny, G., Meyler, A., & Rautanen, T. (2007). The ECB survey of professional forecasters (SPF)-A review after eight years' experience. *ECB occasional paper*, (59). Retrieved from THE ECB SURVEY OF PROFESSIONAL FORECASTERS (SPF) - A REVIEW AFTER EIGHT YEARS' EXPERIENCE (econstor.eu)

Brennan, M. J., & Schwartz, E. S. (1985). Evaluating natural resource investments. *Journal of business*, 135-157. Retrieved from BrennanSchwartz85.pdf (univr.it)

Buti, M., & Mohl, P. (2014). Lackluster investment in the Eurozone: Is there a puzzle?. *VOX, CEPR's Policy Portal*, *4*, 14. Retrieved from Raising investment in the Eurozone | VOX, CEPR Policy Portal (voxeu.org). [viewed 2021-05-08]

Caldara, D., Fuentes-Albero, C., Gilchrist, S., & Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, *88*, 185-207. https://doi.org/10.1016/j.euroecorev.2016.02.020

Castelnuovo, E., & Tran, T. D. (2017). Google it up! a google trends-based uncertainty index for the united states and australia. *Economics Letters*, *161*, 149-153. https://doi.org/10.1016/j.econlet.2017.09.032

Chen, H., Qian, W., & Wen, Q. (2020). The impact of the COVID-19 pandemic on consumption: Learning from high frequency transaction data. *Available at SSRN 3568574*. https://dx.doi.org/10.2139/ssrn.3568574

Choi, S., Furceri, D., Huang, Y., & Loungani, P. (2018). Aggregate uncertainty and sectoral productivity growth: The role of credit constraints. *Journal of International Money and Finance*, *88*, 314-330. https://doi.org/10.1016/j.jimonfin.2017.07.016

Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk shocks. *American Economic Review*, *104*(1), 27-65. https://doi.org/10.1257/aer.104.1.27

Collard, F., Mukerji, S., Sheppard, K., & Tallon, J. M. (2018). Ambiguity and the historical equity premium. *Quantitative Economics*, *9*(2), 945-993. https://doi.org/10.3982/QE708

Dornbusch, R. (1987). Open economy macroeconomics: new directions (No. w2372). *National Bureau of Economic Research*. https://doi.org/10.3386/w2372

Dreze, J. H., & Modigliani, F. (1975). Consumption decisions under uncertainty. In *Stochastic optimization models in finance* (pp. 459-486). Academic Press. https://doi.org/10.1016/B978-0-12-780850-5.50041-1

Eckley, P. (2015). Measuring economic uncertainty using news-media textual data. *MPRA Paper*, (64874). Retrieved from Measuring economic uncertainty using news-media textual data - CORE Reader

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137-1159. https://doi.org/10.1111/j.1538-4616.2010.00323.x

European Central Bank (2009): Uncertainty and the Economic Prospects for the Euro Area. *ECB Monthly Bulletin*, August 2009, 58–61. Retrieved from Uncertainty and the economic prospects for the euro area (europa.eu). [viewed 2021-04-17].

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy. *Journal of macroeconomics*, *18*(1), 1-26. https://doi.org/10.1016/S0164-0704(96)80001-2

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., & Rubio-Ramírez, J. (2015). Fiscal volatility shocks and economic activity. *American Economic Review*, *105*(11), 3352-84. https://doi.org/10.1257/aer.20121236

Ferrara, L., Lhuissier, S., & Tripier, F. (2018). Uncertainty fluctuations: Measures, effects and macroeconomic policy challenges. In *International Macroeconomics in the Wake of the Global Financial Crisis* (pp. 159-181). Springer, Cham. https://doi.org/10.1007/978-3-319-79075-6_9

Gieseck, A., & Largent, Y. (2016). The impact of macroeconomic uncertainty on activity in the euro area. *Review of Economics*, *67*(1), 25-52. https://doi.org/10.1515/roe-2015-1008

Gieseck, A., & Rujin, S. (2020). The impact of the recent spike in uncertainty on economic activity in the euro area. *Economic Bulletin Boxes*, 6. Retrieved from The impact of the recent spike in uncertainty on economic activity in the euro area (europa.eu). [viewed 2021-03-13].

Gopinath, G. (2020). The great lockdown: Worst economic downturn since the great depression. *IMF blog*, *14*, 2020. Retrieved from page-06.pdf (newsofbahrain.com). [viewed 2021-02-27]

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438. https://doi.org/10.2307/1912791

Hartman, R. (1972). The effects of price and cost uncertainty on investment. *Journal of economic theory*, *5*(2), 258-266. https://doi.org/10.1016/0022-0531(72)90105-6

Hollo, D., Kremer, M., & Lo Duca, M. (2012). CISS-a composite indicator of systemic stress in the financial system. https://doi.org/10.2139/ssrn.1611717

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177-1216. https://doi.org/10.1257/aer.20131193

Kirchgässner, G., Wolters, J., & Hassler, U. (2012). *Introduction to modern time series analysis*. Springer Science & Business Media.

Knight Frank, H. (1921). *Risk, uncertainty and profit*. Boston, MA: Hart, Schaffner & Marx; Houghton Miffl in Company.

Kolev, A., Tanayama, T., & Wagenvoort, R. (2013). Investment and investment finance in Europe. Annual Economic Conference and Publication. https://doi.org/10.2867/21758

Kraft, H., Schwartz, E., & Weiss, F. (2018). Growth options and firm valuation. *European Financial Management*, *24*(2), 209-238. https://doi.org/10.1111/eufm.12141

Kulatilaka, N., & Perotti, E. C. (1998). Strategic growth options. *Management Science*, *44*(8), 1021-1031. https://doi.org/10.1287/mnsc.44.8.1021

Lachman, D. (2015). The Euro Is a Straitjacket for Greece. *The New York Times.* Retrieved from: The Euro Is a Straitjacket for Greece - NYTimes.com. [viewed 2021-03-08].

Lahiri, K., & Sheng, X. (2010). Measuring forecast uncertainty by disagreement: The missing link. *Journal of Applied Econometrics*, *25*(4), 514-538. https://doi.org/10.1002/jae.1167

Legerstee, R., & Franses, P. H. (2015). Does disagreement amongst forecasters have predictive value? *Journal of Forecasting*, 34(4), 290-302. https://doi.org/10.1002/for.2330

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2), 297-303. https://doi.org/10.1093/biomet/65.2.297

Ludvigson, S. C., Ma, S., & Ng, S. (2015). *Uncertainty and business cycles: exogenous impulse or endogenous response?* (No. w21803). National Bureau of Economic Research. https://doi.org/10.3386/w21803

Meinusch, A., & Tillmann, P. (2015). *Quantitative easing and tapering uncertainty: Evidence from Twitter* (No. 09-2015). MAGKS Joint Discussion Paper Series in Economics.

Retrieved from Quantitative Easing and Tapering Uncertainty: Evidence from Twitter (ijcb.org)

Mody, A., Ohnsorge, F., & Sandri, D. (2012). Precautionary savings in the great recession. *IMF Economic Review*, *60*(1), 114-138. https://doi.org/10.1057/imfer.2012.5

Oi, W. Y. (1961). The desirability of price instability under perfect competition. *Econometrica: journal of the Econometric Society*, 58-64. https://doi.org/10.2307/1907687

Panousi, V., & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. *The Journal of finance*, *67*(3), 1113-1148. https://doi.org/10.1111/j.1540-6261.2012.01743.x

Pindyck, R. S. (1990). Irreversibility, uncertainty, and investment (No. w3307). *National Bureau of Economic Research*. https://doi.org/10.3386/w3307

Rossi, B., Sekhposyan, T., & Soupre, M. (2016). Understanding the sources of macroeconomic uncertainty. Retrieved from Paper_10_Sekhposyan.pdf (europa.eu)

Sandmo, A. (1970). The effect of uncertainty on saving decisions. *The review of economic studies*, *37*(3), 353-360. https://doi.org/10.2307/2296725

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*, *82*, 1-19. https://doi.org/10.1016/j.jmoneco.2016.06.002

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48. https://doi.org/10.2307/1912017

Wu, J. C., & Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, *48*(2-3), 253-291. https://doi.org/10.1111/jmcb.12300

Zivot, E., & Wang, J. (2006). Vector autoregressive models for multivariate time series. Modeling Financial Time Series with S-Plus®, 385-429. Retrieved from fmmaster.dvi (washington.edu)

ANNEXES

Annex 1. Granger causality test results at the 5% significance level between uncertainty measures and indicators of economic activity

Variables	P-value	Causality
GDP → Uncertainty Index	0.141	*Unidirectional*
Uncertainty Index → GDP	0.014	***Uncertainty Index → GDP***
Investment → Uncertainty Index	0.066	*Unidirectional*
Uncertainty Index → Investment	0.02	***Uncertainty Index → Investment***
Consumption → Uncertainty Index	0.203	*Unidirectional*
Uncertainty Index → Consumption	0.009	***Uncertainty Index → Consumption***
Employment → Uncertainty Index	0.715	*No causality at 5%*
Uncertainty Index → Employment	0.062	*significance level*
Hours worked → Uncertainty Index	0.183	*Unidirectional*
Uncertainty Index → Hours worked	0.039	***Uncertainty Index → Hours worked***
Productivity → Uncertainty Index	0.113	*Unidirectional*
Uncertainty Index → Productivity	0.023	***Uncertainty Index → Productivity***
GDP → Financial Market Uncertainty	0.079	*Unidirectional*
Financial Market Uncertainty → GDP	0.039	***FMU → GDP***
Investment → Financial Market Uncertainty	0.112	*Unidirectional*
Financial Market Uncertainty → Investment	0.000	***FMU → Investment***
Consumption → Financial Market Uncertainty	0.102	*No causality at 5%*
Financial Market Uncertainty → Consumption	0.283	*significance level*
Employment → Financial Market Uncertainty	0.013	*Bidirectional*
Financial Market Uncertainty → Employment	0.000	***FMU ↔ Employment***
Hours worked → Financial Market Uncertainty	0.086	*No causality at 5%*
Financial Market Uncertainty → Hours worked	0.074	*significance level*
Productivity → Financial Market Uncertainty	0.276	*No causality at 5%*
Financial Market Uncertainty → Productivity	0.254	*significance level*
GDP → Policy Uncertainty	0.925	*No causality at 5%*
Policy Uncertainty → GDP	0.054	*significance level*
Investment → Policy Uncertainty	0.331	*No causality at 5%*
Policy Uncertainty → Investment	0.46	*significance level*
Consumption → Policy Uncertainty	0.392	*Unidirectional*
Policy Uncertainty → Consumption	0.019	***EPU → Consumption***
Employment → Policy Uncertainty	0.572	*No causality at 5%*
Policy Uncertainty → Employment	0.191	*significance level*
Hours worked → Policy Uncertainty	0.832	*No causality at 5%*
Policy Uncertainty → Hours worked	0.057	*significance level*
Productivity → Policy Uncertainty	0.964	*No causality at 5%*
Policy Uncertainty → Productivity	0.061	*significance level*
GDP → Forecast Disagreement	0.000	*Bidirectional*
Forecast Disagreement → GDP	0.000	***FD ↔ GDP***
Investment → Forecast Disagreement	0.014	*Unidirectional*
Forecast Disagreement → Investment	0.067	***Investment → FD***
Consumption → Forecast Disagreement	0.000	*Bidirectional*
Forecast Disagreement → Consumption	0.000	***FD ↔ Consumption***
Employment → Forecast Disagreement	0.001	*Bidirectional*
Forecast Disagreement → Employment	0.000	***FD ↔ Employment***
Hours worked → Forecast Disagreement	0.000	*Bidirectional*
Forecast Disagreement → Hours worked	0.000	***FD ↔ Hours worked***
Productivity → Forecast Disagreement	0.000	*Bidirectional*
Forecast Disagreement → Productivity	0.000	***FD ↔ Productivity***

Source: ECB Statistical Data Warehouse and own calculations.

Annex 2. Summary of datasets used in the thesis, their modifications and sources

Dataset	Description	Transformation	Source
CISS	Composite indicator of systemic stress, euro area, weekly	Combined via the first principal component and transformed into quarterly through averages	ECB Statistical Data Warehouse
Bond market volatility	Stress subindice, bond market volatility, euro area, weekly		
Equity market volatility	Stress subindice, equity market volatility, euro area, weekly		
Exchange rate volatility	Stress subindice, foreign exchange rate market volatility, euro area, weekly		
Financial intermediation	Stress subindice, financial intermediation, euro area, weekly		
VSTOXX	EURO STOXX 50 Volatility, daily	Transformed into weekly through averages, combined as above	Stoxx
Economic Policy Uncertainty	Baker et al. (2015) uncertainty indices	Combined by GDP-weighted average, averaged by quarter	Baker et al. (2015), available at EPU website
Country level GDP data	Gross domestic product at market prices (Italy, Germany, Spain, France), annual		ECB Statistical Data Warehouse
SPF GDP	Euro area, GDP point forecast, variance of forecasts, quarterly	Averaged by year, standardized to mean zero and unit standard deviation, combined via the first principal component	ECB Statistical Data Warehouse
SPF Unemployment	Euro area, Unemployment point forecast, variance of forecasts, quarterly		
SPF Inflation	Euro area, HICP point forecast, variance of forecasts, quarterly		
GDP	Gross domestic product at market prices, euro area, total economy, quarterly	Deflated, year-on-year change	ECB Statistical Data Warehouse
Investment	Gross fixed capital formation, euro area, total economy, quarterly	Deflated, year-on-year change	
Consumption	Individual consumption expenditure, euro area, NPISH, quarterly	Deflated, year-on-year change	
Productivity	Labor productivity (per persons), euro area, total economy, quarterly	year-on-year change	
Hours worked	Total employment (hours worked) euro area, total economy, quarterly	year-on-year change	
Inflation	HICP, euro area, overall index, annual rate of change, monthly	Transformed into quarterly by averages	
EONIA	Money market, Eonia rate, euro area, monthly	Transformed into quarterly by averages. EONIA until 2004, and 2004-2020 Shadow rate	
Shadow rate	Shadow rate by Wu and Xia (2016), monthly		Wu and Xia (2016), available at Wu's personal website
JLN Real uncertainty	Jurado et al. (2015) uncertainty index	none	Jurado et al. (2015), available at S. Ludvigson's personal website
JLN Financial uncertainty	Jurado et al. (2015) uncertainty index	none	
JLN Macro uncertainty	Jurado et al. (2015) uncertainty index	none	

Source: Compiled based on the sources listed in the table.