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The Impact of Macroeconomic and Financial Uncertainty on GDP growth: a Quantile Regression Analysis

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Abbreviations

CDF - Inverse Conditional Distribution Functions

CISS - Composite Indicator of Systemic Stress

CRRA - Constant Relative Risk Aversion

DHFM - Dynamic Hierarchical Factor Model

DSGE - Dynamic Stochastic General Equilibrium

EBP - Excess Bond Premium

EPU - Economic Policy Uncertainty

FED - Federal Reserve System

FRED - Federal Reserve Economic Data

FRED-MD - Federal Reserve Economic Data - Monthly Database

GFU - Global Financial Uncertainty

GDP - Gross Domestic Product

GIRF - Generalized Impulse Response Function

NFCI - National Financial Conditions Index

PCA - Principal Component Analysis

PDF - Probability Distribution Functions

PIT - Probability Integral Transform

RBC - Real Business Cycle

STVAR - Smooth-Transition VAR

VAR - Vector Auto Regression

BVAR - Bayesian Vector Auto Regression

VIX - Volatility Index from Chicago Board Options Exchange

"The very conception of and exact science involves abstraction;
its ideal is analytic treatment, and analysis and abstraction are virtually synonyms."
(Knight 1921)

Abstract

This dissertation investigates the relationship between financial and macroeconomic uncertainty and the business cycle. Utilizing quantile regression analysis and US data, the study examines the effects of changes in uncertainty on the entire conditional distribution of future real GDP growth over different time horizons.

Key findings reveal that financial uncertainty predominantly signals downside risk, while macroeconomic uncertainty enhances both risks and growth opportunities.

The analysis underscores the importance of conditioning on different phases of the business cycle, as different crises episodes show different impacts of uncertainty measures.

Use of vulnerability measures such as relative entropy and expected shortfall highlight asymmetries in GDP growth risks. Addressing reverse causality, the research finds limited reverse impact of output growth on uncertainty. The results emphasize the need for precise identification of uncertainty channels affecting economic outcomes.

This work contributes to understanding the distinct roles of financial and macroeconomic uncertainty, suggesting that policymakers should use detailed uncertainty measures and recognize non-linear transmission channels. Future research should refine uncertainty specifications to better capture its effects, to help achieve more effective policies and improve crisis management.

Chapter 1: Introduction

It is commonly known that expectations on future economic developments have a major role on business cycles. Both firms and policy makers need to understand how uncertainty can influence the path of economic growth. Uncertainty has been firstly described as the impossibility to forecast the likelihood of a certain outcome, as there is not certain information regarding the distribution of the analysed event (Knight 1921, Bloom 2014).

This is reflected in economic literature, as the concept of uncertainty is mainly defined as the change in the second moment of the distribution, given a certain mean-preserving shock (Castelnuovo 2023).

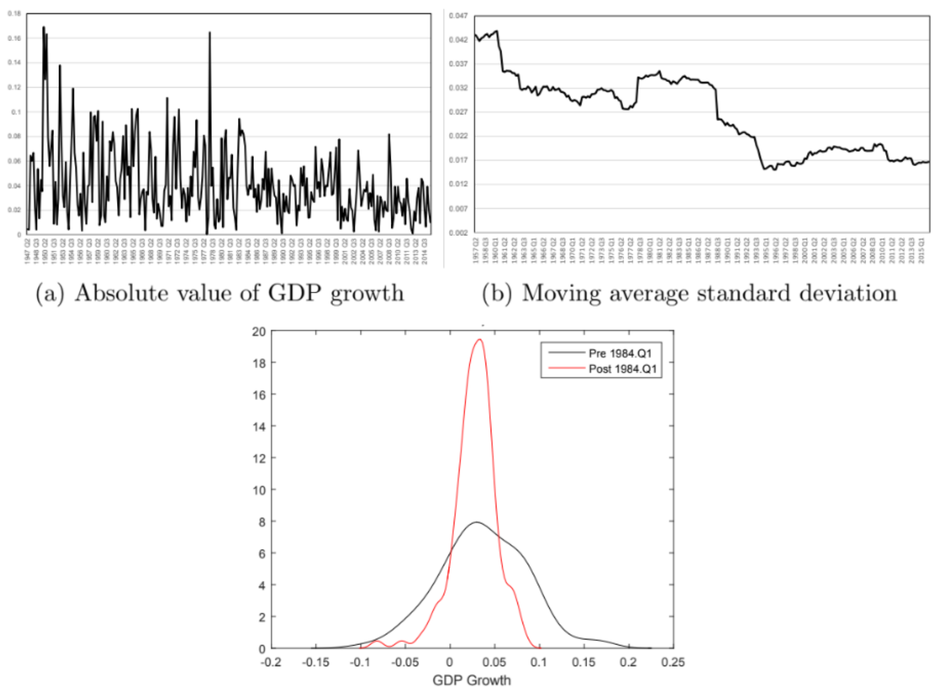
To complete the definition of uncertainty, and properly define the main center of this dissertation, it is important to uncover the differences between the concept of uncertainty and risk. The main parameter to establish this difference is the probability distribution. Risk implies that, although the results in time of a certain variable are not known, is possible to assume the probability distribution that dictates its behaviour; in contrast, uncertainty is more difficult to estimate as it means to enter in a realm of outcomes of which it is not possible to assume the distribution (Cascaldi-Garcia et al. 2023).

It is therefore essential to understand the concept of uncertainty and which of the measures created in literature can shed light on the relationship between uncertainty and economic growth vulnerability. Many literature reviews explore both theoretical models and their empirical applications in order to gather a shared understanding of this matter (Fernández-Villaverde & Guerrón-Quintana 2020, Cascaldi-Garcia et al. 2023, Castelnuovo 2023), but there is an important number of challenges to face. It is complex to determine the impact of uncertainty in a clear way, without explaining the details of theories and measurement used to collect results in this matter.

Indeed, there is extensive research on assessing which could be the transmission channels of uncertainty. The discussion starts when there is the attempt to assess how a macroeconomic variable, like GDP growth, changes over time and what are the main reasons behind these fluctuations. Fernández-Villaverde & Guerrón-Quintana (2020) show this difference by reporting two main figures. Figure 1 plots for a sample after the second World War the absolute value of GDP growth in Panel (a), while Panel (b) is the plot for the same series of the the 10-year moving average standard deviation. Panel (c) shows the Kernel density related to this variable. From Panel

(a) and (b), it seems that there is a difference in the fluctuation of the variable, Panel (c) confirms the argument by setting the turning point at 1984Q1: the figure shows for absolute value of GDP after this chosen year a more concentrated distribution, with thinner tails.

Figure 1: GDP growth



(a) Absolute value of GDP growth

(b) Moving average standard deviation

(c) Kernel densities of GDP growth

Figure 1: GDP as reported by Fernández-Villaverde & Guerrón-Quintana (2020)

The idea of "impact" of uncertainty is related to the possibility of considering that the economical structure of a nation "has undergone some sort of structural transformation" (Fernández-Villaverde & Guerrón-Quintana 2020). These underlying movements spark the interest to gather more information on what could be second moment shocks, that deeply impact the relationships that guide the business cycle.

In line with this, an important number of recent studies concentrate on assessing the impact that uncertainty can have on different outputs to measure the direction of this effect. Theoretical consensus seems really difficult to achieve when talking about what could be in general the relationship between uncertainty and business cycles, therefore looking at empirical analysis, results can suggest a better view on this topic (Cascaldi-Garcia et al. 2023).

The first issue to assess is how uncertainty can be measured. Empirical measures of uncertainty are mainly based either on counting a specific number of words related to uncertainty in a determined database (Baker et al. 2016), or using surveys gathered by different organizations (Leduc & Liu 2016, Rossi & Sekhposyan 2015), otherwise through common movements between the forecast errors (Jurado et al. 2015, Ludvigson et al. 2021). In order to achieve a better identification, recent indexes try to define a more global approach (Caggiano & Castelnuovo 2023), or are constructed specifically to account for downside and upside risk (Forni et al. 2021, Castelnuovo & Mori 2022). Consequently, linear studies assessing the impact of uncertainty on output employ these different measures and generally assess that uncertainty is counter-cyclical and shows ”wait-and-see” effects, after a drop in the economic variables analyzed there is a slow recovery towards the status-quo (Bloom 2009, Bachmann et al. 2013, Bloom et al. 2018, Baker et al. 2016). Therefore, if uncertainty is increasing in the system, there is a moment of ”delay” of the recovery (Bernanke 1983).

In the meantime, still assessing this linear relationship, more specific elaborations of the uncertainty indexes are found. The more this field grows, the more studies are aware that different uncertainty indexes mean that we can have more detailed results, by comparing different indexes or analysing the impact of ”positive” and ”negative” uncertainty (Rossi & Sekhposyan 2015, Caldara et al. 2016). In particular, understanding the best way to identify indexes can be the road to new interesting results: if transmission channels are properly identified, new growth opportunities are included in determined uncertainty measures (Caldara et al. 2021), confirming the theoretical possibility of ”growth effects” (Oi 1961, Hartman 1972, Abel 1983, Bloom 2014).

Finally, there is recent progress on the assessment of more non-linear channels through which uncertainty can be evaluated: through more elaborated versions of VAR specifications, it is important to assess effects of uncertainty in different moments. There is the possibility to compare recession periods with more stable moments, or the effects of uncertainty during a moment of zero lower bound (ZBL), where conventional monetary policy becomes ineffective (Caggiano et al. 2014, 2017, 2021, 2022).

The main focus in this literature, the common thread, has been to analyse the most likely economic output. Policymakers care also, if not mainly, about the likelihood of extreme realizations of the variable of interest, in this case output growth. Therefore, in this thesis, the most important objective is to assess if uncertainty will affect trends in output growth, assessing the impact on the whole distribution. This is achieved through a quantile analysis of the behaviour of macroeconomic and financial uncertainty when regressed on real GDP growth. The methodology used in this dissertation, proposed by Adrian et al. (2019), allows to analyze the relationship without assumptions on the distribution of the variables.

It is particularly interesting to analyze the impact of both these types of uncertainty on GDP growth, as there are some important differences already described in economic literature from a theoretical point of view, therefore the contribute to the literature that this work aims to provide is the effective assessment of this difference. In particular results discuss the concept of counter-cyclicality: although the main relationship of uncertainty an business cycle is negative, it is important to understand under which circumstances uncertainty could be a propulsor of innovation.

The relationship between uncertainty and real GDP is fairly easy to be visualized if time series of data considered for this dissertation are compared: Figure 2 reports real GDP growth compared with changes in Macroeconomic and Financial uncertainty, covering a period from the first quarter of 1970 up to the latest available data point in the second quarter of 2023. Uncertainty indices employed in this research are constructed from the methodologies established in works of Jurado et al. (2015) and Ludvigson et al. (2021). In this way, this dissertation obtains also results related to the question if all uncertainty measures are the same: in particular it is analyzed the difference between a ”wider” set of uncertainty, related to different macroeconomic variables, and a more specific one, more linked with financial conditions of the United States of America. There is a difference, as these are different anchors and create different expectations.

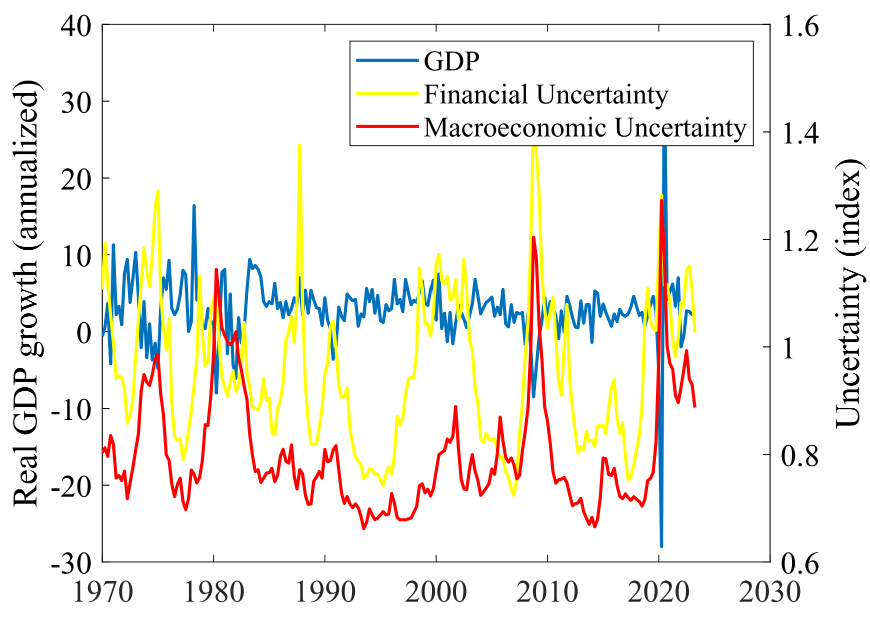


Figure 2: Time series sample 1970Q1 - 2023Q2

Figure 2 shows that there is a negative correlation between the level of unpredictability of a large set of fundamentals and movements of GDP growth: during moments when the level of unpredictability arises, GDP growth declines. Therefore this image and Table 1, show this negative correlation between uncertainty and business cycles.

	Correlation
GDP and Financial Uncertainty	-0.247311981
GDP and Macro Uncertainty	-0.304893386

Table 1: Correlation of GDP with Financial and Macroeconomic Uncertainty

In addition, it is directly visible that there is a significant surge in uncertainty observed in 2020. Specific results seem to be biased by this important jump in GDP growth; therefore, in some sections, the analysis requires to visualize and compare results both in the 1970Q1 - 2019Q4 and 1970Q1 - 2023Q2 sample to get the full picture of the nuances of the main relationship. Differently from GDP growth, the uncertainty index is modeled to be inclusive of biases that could arise from changes happened during the Covid crisis (Ng 2021).

Although general movement suggest a proportionally inverse relationship between both uncertainties and GDP growth, the macroeconomic line behaves slightly differently from financial uncertainty. Movements of the indices seem to depend on the various crises, but from 1980 until just before the 2008 crisis; while the variable of financial uncertainty makes large movements as soon as a fall in GDP growth is experienced, macroeconomic unpredictability does not seem to have the same sensitivity. This is a hint of what will later be visible differences through the analysis of the quantile regression coefficients, as well as the expected GDP growth over a quarter and a year. The analysis is concluded assessing if results are robust to different specification: in particular there is the comparison between the main results that differentiate between the two types of uncertainty with a model where these variables condition GDP-growth simultaneously. Measures of vulnerability are then reported to clearly measure the asymmetries described before. To understand better the question of identification, an endogeneity hypothesis is considered to verify results provided by Ludvigson et al. (2021).

In in the following sections the dissertation is structured as follows: Chapter 2 reviews the economic literature regarding this topic, firstly describing how uncertainty is measured and how its relationship with business cycles is assessed, followed by a depiction of theoretical discussion on the transmission channels between the two main variables. Chapter 3 describes the methodology used in this dissertation, therefore quantile regression method, and lists the data used in this analysis. Chapter 4 reports all the results regarding the relationship between macroeconomic and financial uncertainty and business cycles. Finally, Chapter 5 concludes with the robustness tests, namely the analysis of the impact of the two types of uncertainty together and the assessment of possible endogeneity between uncertainty and GDP growth.

Chapter 2: Assessing the impact of Uncertainty: literature review

2.1 Measuring uncertainty

Cascaldi-Garcia et al. (2023) work is at the basis of any evaluation that involves proxies for uncertainty as they group and define four major areas in which uncertainty indexes can be categorized, giving therefore a clear picture both of the status of studies employing any index of uncertainty to reveal its impact and both the different ways this could be done. Using a determined index is a choice that must be calibrated for the objectives of the analysis. These authors define four main categories.

The first class is indexes that are based on newspapers, as their construction relies mainly on counting the number of article or words that are strictly related to more unpredictable moments in the economy.

The second class are measures that are computed from surveys, therefore there is the attempt to measure the sentiment of uncertainty in different areas by actually collecting data on the beliefs regarding future uncertainty of people and then retrieving an index from the collection of answers.

The third category are econometric based criteria: there is an attempt to find a methodology that measures the ”lack of economic unpredictability”, therefore indexes that want to understand which is the non forecastable component of the variables that measure economic activity.

Lastly, they list asset-based indexes, which mostly reflect volatility in financial markets. Therefore, this categorization serves as a starting point to understand which index can better describe the analyzed variable.

In addition to the indexes collected in this review, new indexes are starting to develop in recent times. Castelnuovo & Mori (2022) use a quantile regression approach, to develop an index that is based on the quantile regression of monthly data of different realizations of the National Financial Conditions Index (NFCI), a measure of financial conditions in the construction and supervision of the Federal Reserve Bank of Chicago (Federal Reserve Bank of Chicago 2024). This index’s creation method is strictly related to the methodology used in this dissertation, therefore, for the sake of clarity, will be mentioned after the exhaustive explanation of this type of regression. Another relevant work similar to the aforementioned is Forni et al. (2021): the importance of considering downside and upside

risk in a different manner will be, as it will be visible at the end of the review of empirical works, a needed distinction in order to account for all the different transmissions mechanism mentioned.
In addition, in the last years there have been more studies concerned with the determination of a more global index of financial movements to explain monetary policy, by collecting the most important financial variables volatility and their co-movements in a single index, the Global Financial Cycle (Miranda-Agrippino & Rey 2020, 2021). A study that is an example of the application of this attention towards different countries when building an index of uncertainty is provided by Caggiano & Castelnuovo 2023. The Global Financial Uncertainty index is retrieved through a Dynamic Hierarchical Factor Model (DHFM) with four levels, explain by the subsequent equations:

$$Z_{rcnt} = \lambda^{n}_{C,rc}(L)C_{rct} + e_{Z_{rcnt}}$$

$$C_{rct} = \Lambda_{R.rc}(L)R_{rt} + e_{C_{rct}}$$

$$R_{rt} = \Lambda_{GFU.r}(L)GFU_t + e_{R_{rt}}$$

$$\Psi_{GFU}(L)GFU_t = e_{GFU_t}$$

Z_{rcnt} is the volatility at time t for a certain variable n, this is computed for a certain country c belonging to region r. C_{rct} is the vector of factors related to each country, R_{rt} the vector compiling region factors. GFU_t is the common factor. This levels create a variable that is such that the global factor evolves on the basis of region variables, which in turn explain the country factors strictly related to Z_{rcnt}. The estimated GFU factor can be consequently used as a proxy of global financial uncertainty.
After this categorization of the uncertainty indexes in the economic field, the next part is devoted to gather main methodologies to collect results on this relationship. First studies and the main part of works related to this objective mainly use linear models to assess effects of uncertainty on business cycles.
One of the first empirical assessments is provided by Bloom (2009). This work highlights for the first time the need to to assess not only ”first moment” shocks, but ”second moment” shocks as well to understand how uncertainty can generate a movement in major economical variable, and in particular define a ”wait and see” effect on the basis of which there is a delay in the recovery because of this second moment shock. This is assessed by using a VAR model in which data are

calibrated through. Results on industrial production and employment show in fact an initial negative effect followed by a delayed recovery. These results will later be confirmed by a more recent study (Bloom et al. 2018), in which a more complex DSGE model with time-varying uncertainty and adjustments-cost that quantify the aforementioned second moment shock. These frictions still lead to a drop in GDP with a quick drop and subsequent fast recovery.

Bachmann et al. (2013) use to main surveys: in Germany they collect information from the the IFO Business Climate Survey (IFO-BCS) and for USA they rely on Philadelphia Fed's Business Outlook Survey (BOS). These studies contain qualitative data on firm's sentiment of future business conditions. In particular, for Germany data are such that a possible evaluation of ex-ante disagreement shown in this survey with ex-post forecast error. They use SVARs to understand which of the channels of uncertainty propagation and effects seems to be the most relevant. They measure the effect on manufacturing production (MP), manufacturing employment (Emp.). German data seems to confirm the "wait-and-see" effects, while in the US the variables chosen seem to be more impaired from the surge in uncertain beliefs. The authors see these results as an avenue for future research on similar effects on USA data.

But a statutory work on surveys is considered to be the index proposed by Baker et al. (2016), the Economic Policy Uncertainty (EPU) index. This index is constructed by counting the frequency of triads of words related to the economy, uncertainty and USA institutions.

They compute the index in 12 different countries. Firstly they assess in a firm-level environment that policy uncertainty is impactful on unemployment and investments. Although these results are not enough as they offer a limited view that does not consider aggregate effects that undergo through different channels that may be ignored. Therefore, they fit a VAR model using the index in 12 different countries. They report the response to a 90-point increase of the value of EPU, as intense as the change from the average value in 2005–2006 (stable economic situation) to 2011–2012 (less favourable economic conditions). The authors conclude that the channel these results imply is that, measuring with EPU, means that increases in uncertainty are linked with a drop in industrial production and employment.

Working instead on the idea of elaborating indexes already present in literature, Caldara et al. (2016) is a really interesting example of a work where different uncertainty indicators are used to distinguish different channels: they use the excess bond premium (EBP) to measure expectations related more to financial variables, while for more economic uncertainty they elaborate on different proxies, three based on stock market volatility, one is the just mentioned EPU index by Baker et al. (2016), then they use the mentioned index gathered from surveys by Bachmann et al. (2013) and the index that will be developed more in this dissertation, the macroeconomic index elaborated by Jurado et al. (2015). They argue that financial uncertainty shocks are firmly related to negative parts of the business cycle, as they have more intense and permenant negative effects on economical variables.

Still in the realm of survey studies, but with a innovative eye on differentiating the index used to gather certain results, is the downside upside approach used by Rossi & Sekhposyan (2015). Their index relies on the cumulative distribution function of the unexpected mistakes in the prediction of economical variables. These authors use this two-fold approach to study the distribution of the uncertainty indexes in order to see two areas.

$$U^{+}_{t+h} = \frac{1}{2} + \max\left\{U_{t+h} - \frac{1}{2}, 0\right\}$$

$$U^{-}_{t+h} = \frac{1}{2} + \max\left\{\frac{1}{2} - U_{t+h}, 0\right\}$$

They proceed to use this differentiation in a VAR model that includes GDP, as well as employment, the FED fund rate stock prices and an uncertainty index (considered separately).

They track the time-varying placement of the forecast error for GDP in relation to its unconditional empirical distribution, finding that their measure of ”good uncertainty” could develop transmission channels on GDP that show possible positive effects of periods of uncertainty. Although this is an interesting result, as in this analysis is first introduced the idea of analysing the asymmetric impact on GDP, the methodology does not allow for a detailed analysis. As this dissertation will confirm, better methodologies provide a specific view of the distribution. This will provide a more interesting result as there is the assessments of effects related not to only to a general area, but more precisely to a quantile of the distribution of the dependent variable. Using quantile regression can be an improvement, as it is possible to visualize and analyze the whole distribution of the analysed variable.

It is in fact important to distinguish and properly identify uncertainty. More recent works Cascaldi-Garcia & Galvao (2021) show that, if financial shock are considered separately from news shocks, there is a term of ”good uncertainty” as a consequence of the opportunities that arise, through new innovations and solutions to actually redefine conventions challenged by news shocks. Financial shocks are more prone to determine a negative impact on output in the short term. They break down the effects to see how much impact there actually is. ”Truly news” means that news has no impact on financial and ”truly uncertainty” means that uncertainties fin have no effect on news shocks. For outcomes related to the impact of ”true news” on major economic variables, the difference between the ”news” variable and the ”true news” measures the attenuation effect after identifying which part of news uncertainty is related to news about technological innovations. The impact on growth, in this case, is positive.

Differently financial uncertainty, if identified separately from news, majorly shows negative effects. They assess the same methodology on macroeconomic effects as well, finding that although ”good uncertainty” effects are also relatable to this variable, for financial uncertainty effects of separation are more important. These studies therefore underline how it is important to distinguish between different types of uncertainty.

There is the need to gather results in a specific way in order to attempt to reach a consensus that theoretically speaking seems difficult to achieve.

Another important uncertainty index that uses a particular computation process that will be developed in detail later in the methodology part of this dissertation is the index is computed by Jurado et al. (2015) and updated in more recent times by Ludvigson et al. (2021). The basis of their computation is the use factors to summarize the co-movement of a large set of variables, to then compute the non forecastable component of the co-variability. This analysis is done both on a really comprehensive dataset summarizing economic activity and on a more specific dataset of financial markets’ values.

What the index tries to measure is the common variability of the non forecastable component of various variables. Uncertainty is not just the variability of the factors chosen to describe the economic situation, but is the part of co-movement that could have not been forecasted with the set of current information available.

The construction starts from the variable $y_{jt} \in Y_t \equiv \{y_{1t}, \ldots, y_{Nt}\}$ which represents the data that constructs the indexes, so that Yt describes the set of variables representing different sectors of which there is the intent to measure uncertainty.

As already explained, $U_{jt}(h)$, the h period ahead uncertainty at time t for the variable j, is mathematically equivalent to the conditional volatility of the unforecastable component of the future value of one of the variables of the dataset as it is described in equation 1,

$$U_{jt}^{y}(h) \equiv \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]} \tag{1}$$

where I_t represents information available at t. The main component of uncertainty is the expectation at the current period of the squared error in forecasting y_{jt+h}, conditional on the information. If the squared error in forecasting rises, uncertainty rises. The computation of $E[y_{jt+h}|I_t]$ is a critical part of the construction of the index, this part is approximated with a forecast of common factors, using Principal Component Analysis (PCA). Common factors are computed from a large dataset that includes all the detailed predictors, the aim of the index is to get the summary of their co-movement. The objective is to determine forecasts of macroeconomic variables and financial movements:

$$y_{j,t+1} = \Phi_j^y(L)y_{jt} + \gamma_j^F(L)\hat{F}_t + \gamma_j^W(L)W_t + \nu_{j,t+1} \tag{2}$$

This is achieved by including current and past values (with the lag operator L) of variables, a set of predictors W and a large dataset of predictors summarised in $\hat{F}_t$. $\hat{F}_t$ collects the estimates of the latent common factors of the predictors $X_t = (x_{1t}, \ldots, x_{N_x t})$, namely the data to construct the indexes.

$$x_{it} = (\Lambda_i^F)' F_t + e_{it} \tag{3}$$

The main achievement of this step is that the factor's number is rather much smaller than the number of series. Factors are then chosen on the basis of their predictive power (Bai & Ng 2006). The conditional expectation of the squared forecast errors is then computed through a parametric stochastic volatility model for the one-step-ahead predictive errors for both the variables forecasts ($y_{j,t+1}$) and the factors. Finally, uncertainty in a specific sector is an aggregate of individual uncertainties:

$$U_t^y(h) \equiv \text{plim}_{N_y \to \infty} \sum_{j=1}^{N_y} w U_{jt}^y(h) \equiv E_w[U_{jt}^y(h)] \tag{4}$$

This measure has been selected in its 1 quarter horizon for both macroeconomic and financial uncertainty, in this dissertation a quarterly frequency of this index is maintained in order to match the frequency of the dependent variable.

This first assessments define the importance of including uncertainty as a predictor of business cycles. In addition, they reflect on the identification as endogeneity of uncertainty and the business cycle presents a significant challenge. The main conclusion is that shocks to financial uncertainty are the main drivers of economic fluctuations, while macroeconomic uncertainty has a different role, it seems to be a consequence of periods of recession. These results have been already discussed in literature, as other assessments find that these indexes show both types of uncertainty have an effect on business cycles (Angelini & Fanelli 2019).

An important and relatively new branch of empirical works underline how linear models are not able to capture specific nuances of the relationship of uncertainty with predetermined variables. This is seen initially in the study conducted by Caggiano et al. (2014). The authors asses the impact of a movement of one standard deviation of VIX on inflation (therefore with a more asset based method of assessing uncertainty), unemployment policy rate and uncertainty itself. This is achieved with a linear VAR model and a non linear Smooth-Transition VAR framework (STVAR), in order to account for two different regimes (recession and no recession) given the use of a logistic transition function $F(z_t)$. The STVAR model therefore is described by:

$$X_t = F(z_{t-1})\Pi_R(L)X_t + (1 - F(z_{t-1}))\Pi_{NR}(L)X_t + \varepsilon_t,$$

$$\varepsilon_t \sim \mathcal{N}(0, \Omega_t),$$

$$\Omega_t = F(z_{t-1})\Omega_R + (1 - F(z_{t-1}))\Omega_{NR},$$

$$F(z_t) = \frac{e^{\gamma z_t}}{1 + e^{\gamma z_t}}, \quad \gamma > 0, \quad z_t \sim \mathcal{N}(0, 1).$$

where X_t are the variables modeled, smoothness of the transition function is controlled by γ and z_t is the transition indicator, controlling for the two different regimes. Π_R and $\Pi_N R$ are the VAR coefficients in the two regimes and Ω_t accounts as the stage-contingent variance-covariance matrix. Therefore, the exogenous variable is described by two different linear VARs and the regime used depends on the transition variable z_t, which determines probabilities through $F(z_t)$. Results from this model show that conducting the study of the impact of uncertainty without assessing potential non-linearity could be an error, as the red dashed lines indicating the non-linear model effects of the uncertainty index on the variables, especially for inflation, unemployment and policy rate. It is important though to notice that there is the basis assumption that there is no switch from a recessionary phase to a period of recovery, therefore these results are more likely to be considered upper bounds of the responses, rather than the average estimate. This is an important and different result than previously seen, as this implies that the intensity of transmission channels, which previously seen to be really difficult to assess with a certain degree of determination, may change on the basis of the business cycle moments in which these shock happen.

Given the different results that a non-linear model provides to the understanding of this relationship, Caggiano et al. (2022) propose Bloom (2009) analysis in a different key. Firstly assess the linear results through a different methodology (using EViews) and secondly they apply the STVAR model described in this section to the same data. Results considering shocks in the VIX variable (as a measure of financial uncertainty) confirm The wait-and-see mechanism and show how this channel is more intense during recession periods. In addition, an interesting point in this study is the actual attempt to understand if monetary policy had an impact on regulating effects of uncertainty. This is assessed by putting to zero the coefficient of the federal funds rate in the VAR analysis, as of to silence the effect of the Fed after uncertainty shocks. Results point to the evaluation of the lower effectiveness of monetary policy during recessions. In ”bad times” the impact of lowering the policy rate is similar to the results gathered when there is not this instrument.

Another way to assess the effects of certain policies, and in particular their impactfulness in a regime of zero lower bound, is through the Interacted-VAR used by Caggiano et al. (2017) and Caggiano et al. (2021)

$$y_t = \alpha + \sum_{j=1}^{k} A_j y_{t-j} + \left[\sum_{j=1}^{k} c_j u_{nc,t-j} \times ff_{r,t-j} \right] + u_t$$

$$E(u_t u_t') = \Omega$$

Therefore, y_t includes measures the exogenous variables chosen, while the interaction term $c_j u_{nc,t-j} \times ff_{r,t-j}$ accounts for VIX as a proxy for uncertainty and the federal funds rate as a proxy of the monetary policy position, which is used as the factor to determine if the analysis is done in a condition of normal times or during a period of ZLB). To measure the responses of this interaction term, Generalized Impulse Response Function (GIRF) are used, accounting for dynamic responses with the interaction term involved.

Again, the quality of action is impaired as during periods of ZLB, when conventional monetary policies cannot be easily implemented, uncertainty shocks are more pronounced. This interacted VAR is at the basis of another important assessment, as it describes a non linear DSGE model in which the result is confirming that a great part of the losses incurred during the great recession in the USA are due to uncertainty shocks (Caggiano et al. 2021).
The focus of this thesis will be therefore the importance of tail risk. There are already studies conducted with an eye on asymmetries of effects of movements of volatility of determined variables on business cycles: analysing growth-at-risk through stochastic volatility models, it is visible that there are asymmetric effects on the distribution (Caldara et al. 2021). This area of research, rapidly growing, shows great potential for understanding and explaining the impact of uncertainty and trying to create a consensus in the literature. This is needed as, both theoretically and empirically, there are difficulties in understanding what the correct explanation might be.

2.2 Uncertainty and the business cycle: theoretical insights

In light of understanding the effects of uncertainty, Guerrón-Quintana (2024) lectures provide an overview on how the different theoretical models accounting for channel of transmission have evolved and which reasons and channels of transmission of uncertainty are the most referred to in economic literature. The main parts of this authors' discourse are the following:

- Oi-Hartman-Abel effect;
- Precautionary behavior;
- Option value effects;
- Nominal and real rigidities.

The objective of this section is to integrate all the information gathered from literature and therefore discuss the following transmittion channels as well:

- Wait and see effects;
- Confidence effects;
- Uncertainty traps.

First theoretical assessments on the effect of uncertainty on production is provided by the series of paper from Oi-Hartman-Abel, their results from the basis to understand how to evaluate the relationship between uncertainty and business cycles (Oi 1961, Hartman 1972, Abel 1983). The basis of this discourse is the Jensen Inequality. Jensen's inequality is a fundamental result in probability theory and statistics; this inequality states that for a convex function f and a random variable X:

$$f(E[X]) \leq E[f(X)]$$

Therefore, if the production function is convex, it could be that an increase in uncertainty could actually benefit for example profits of a company. Investments, hiring and output could benefit from an increase of variability in productivity.

To grasp the setting of the combination of these three models and how these are interconnected, I report the initial ideas of each of these authors to understand how a model that includes all inputs can create the results discussed. Hartman (1972) model described the framework of relationships between main macroeconomic variables, explained in the following equations:

Production function of a firm;

$$Q_t = F(K_t, L_t)$$

Capital accumulation equation where δ is the depreciation rate and $\Phi(I_t, K_t)$ is the adjustment cost function;

$$K_{t+1} = (1-\delta)K_t + I_t - \Phi(I_t, K_t)$$

The objective of the firm, which is to maximize the sum of discounted cash flows in its expected value.

$$\sum_{t=0}^{\infty} \mathbb{E}\left[R^t\left(p_t Q_t - w_t L_t - C(I_t, q_t)\right)\right].$$

Therefore they concentrate on how costs related to investments are impacted by the introduction of uncertainty. Results are not so straight forward as they depend on many parameters. Abel (1983) model then laid down the idea of the value function, representing the expected present value of future profits, account for a discount rate and investments to be made:

Value function $V(K_t)$, where ρ is the discount rate

$$V(K_t) = \max_{I_s, L_s} E\left[\int_t^{\infty} e^{-\rho(s-t)}[p_s L_s^{\alpha} K_s^{1-\alpha} - wL_s - \gamma I_s^{\beta}]ds\right]$$

Stochastic process for the price level

$$dP_t = \mu_P P_t dt + \sigma_P P_t dZ_t$$

Oi (1961) argues that in the context of perfect competition, an increase in uncertainty might impact in a positive way investment by adding price variability, therefore introducing the possibility of future favourable changes in price.

Expected profit function under perfect competition

$$E[\pi_t] = P_t Y_t - W_t N_t - C(K_t)$$

Setting the framework by combining how these authors described economic relationships between output and price variability, investments are impacted in a positive way by option value and possible favourable price variations.

The option value of waiting is described as

$$\text{OptionValue}(I_t) = E\left[\int_0^{\infty} e^{-\rho t}(\pi_t - I_t)dt\right]$$

an the price variability term is described as

$$\text{PriceVariability}(P_t) = E\left[\sigma_P \cdot P_t\right]$$

Therefore, increased uncertainty could have two main effects in this model: it could go on the more intuitive route, increasing a perception of higher probability of less favourable outcomes therefore dampening investments, or it could bring a margin of possible future favourable movements of prices, therefore determining a more investment seeking approach from firms that know how to insure themselves from less desirable results. Another conclusion that could be retrieved from these models is that if the profit function is convex with respect to capital, an uncertainty shock could potentially stimulate investments in periods as expected marginal profitability of capital increases. An example of this effect is shown by Fernández-Villaverde & Guerrón-Quintana (2020). This example explains the model by starting from a Cobb-Douglas production function

$$y_t = A_t k_t^{\alpha} l_t^{\beta}$$

where A is the level of productivity at period t and assuming that $\alpha + \beta < 1$ (the function shows decreasing-returns-to-scale). The optimally conditions for the firm are:

$$k_t^* = \psi_1 A_t^{\frac{1}{1-\alpha-\beta}}$$

$$l_t^* = \psi_2 A_t^{\frac{1}{1-\alpha-\beta}}$$

where $\psi_1 = \left(\frac{\alpha}{r_t}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w_t}\right)^{\frac{\beta}{1-\alpha-\beta}}$ and $\psi_2 = \left(\frac{\alpha}{r_t}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w_t}\right)^{\frac{1-\alpha}{1-\alpha-\beta}}$.
Therefore the profit function is:

$$\Pi_t^* = \psi_3 A_t^{\frac{1}{1-\alpha-\beta}}$$

with $\psi_3 = \psi_1^{\alpha}\psi_2^{\beta} - \psi_1 r_t - \psi_2 w_t$. These findings illustrate that the input demands and profits are convex functions of A_t. Consequently, an increase in uncertainty about A_t, while keeping the mean constant, will lead to greater variability in input demands, profits, and output.

Diving deeper on the theoretical assumptions that could explain and describe transmission of uncertainty effects, a realm of theoretical assumptions is related to precautionary motives agents may have, which implies a dislike for uncertainty. Following Simon (1956) and Theil (1992) which first conceptualize the idea of ”certainty equivalence”, this concept is the basis of the idea that there is a certain threshold in which the optimal choice of agent under uncertainty who maximizes her utility is identical with the choice that ignores uncertainty.

This is declined in the idea of precautionary behaviour, measuring this point of aversion towards uncertainty. In the presence of more realist cost relative risk aversion (CRRA) preferences, precautionary behavior depends on the third derivative of the utility function, and the computation is shown in Figure 3 as reported by Guerrón-Quintana (2024).

Table 1: Utility functions and derivatives

	Quadratic	CRRA
Level	$\alpha_1 c - \frac{\alpha_2}{2} c^2$, $\alpha_1, \alpha_2 > 0$	$\frac{c^{1-\sigma}-1}{1-\sigma}$, $\sigma > 0$
u'	$\alpha_1 - \alpha_2 c$	$c^{-\sigma}$
u''	$-\alpha_2$	$-\sigma c^{-\sigma-1}$
u'''	0	$(\sigma+1)\,\sigma c^{-\sigma-2}$

Figure 3: Quadratic and CRRA preferences by Guerrón-Quintana (2024)

If there are CRRA preferences, demand for saving is increasing in uncertainty. In a real business cycle (RBC) environment this could cause, along with drop in investment due to the same wave of uncertainty, a drop in market rates, followed by an increase in consumption as an answer. Considering only precautionary savings, uncertainty could therefore bring GDP growth both towards higher or lower values. This irrelevance could be surpassed by a different parametrization of preferences, such as the of recursive preferences a la Epstein & Zin (1989) which account for higher levels risk aversion than previously seen with a CRRA or the idea of ambiguity aversion first mathematically developed by Gilboa & Schmeidler (1989).

More complex models have brought other elements to this analysis: for example a channel of transmission could be the ”option-value” channel. This channel was provided by the model and assessment of Leduc & Liu (2016): they emphasize how their model predict that an increase in uncertainty, in this case the Michigan Survey of Consumers, could bring a light surge in unemployment and decrease of inflation. These results are achieved by incorporating a Dynamic Stochastic General Equilibrium (DSGE) model with search frictions (equations that try to establish the difficulties for an individual searching for a job for the right match) in the labor market and nominal rigidities in prices (incorporating the fact that prices adjust with a specific rate that is not obviously immediate to changes in the economic environment). The author’s analysis shows more complex mechanism than before stated in literature, as there has to be kept in mind that uncertainty could be an exacerbator of frictions already in the market, and therefore recovery could be impaired by these delays.

Therefore, if there are nominal rigidities, the channel which they call “option-value” confirms that uncertainty could be a self-reinforcing push to a recession period. This result is different from the RBC model with a spot labor market as seen before, models in which some possibility of growth was allowed. In this version of the problem, the aggregate demand channel is temporarily shut off. Given that the major factor are as said search friction related to the job hunt, in more uncertain moments, the option value of waiting increases and the match value, given by finding the employment, declines. This consequence damps the hiring rate of firms.

There are many theories differentiating between nominal and real frictions as channels of uncertainty repercussions. Studies including nominal friction determine that sticky prices can determine an amplification of shocks of uncertainty. The fact that firms determine their prices before a shock could arise, forces to increase these prices the prospect of not having to incur high costs in the future when these prices will have to be changed (Fernández-Villaverde et al. 2015).

Basu & Bundick (2017) work focuses on nominal frictions but trying to assess how these frictions can create co-movement in different variables of the real economy and financial markets after a certain shock. Their model tries to explain the fact that a model where is difficult to change prices there are important effects on output and employment as well when uncertainty is a variable. Figure 4 is the model intuition behind the idea that these frictions could be an important start for the discussion on transmission mechanisms. Given these equations that characterize most of the models of business cycles, linking together GDP, consumption, investment, hours worked (Nt), and the real wage (Wt/Pt):

Aggregate Demand Equation

$$Y_t = C_t + I_t$$

Production Function

$$Y_t = F(K_t, Z_t, N_t)$$

Euler Equation for Labor Supply

$$\frac{W_t}{P_t} U_1(C_{t-1} - N_t) = U_2(C_{t-1} - N_t)$$

Wage-Price Phillips Curve

$$\frac{W_t}{P_t} = Z_t F_2(K_t, Z_t, N_t)$$

The visual representation of the relationship between nominal wages and hours worked becomes:

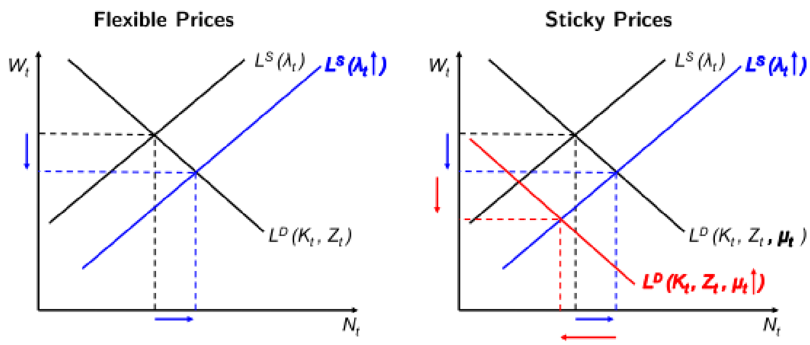


Figure 4: Model intuition in Basu & Bundick (2017)

Households want to save more and decrease consumption when uncertainty level increase. Therefore, in uncertain moments, marginal utility of wealth $t = U1(Ct1{-}Nt)$ increases, which shifts the household labor supply curve outward. If prices are flexible, higher uncertainty does not impact capital (Kt) or technology (Zt). Instead, prices that move slower, output decreases faster, which has an impact on the side that owns capital: investments rates decrease. When prices are ”sticky” the labour demand curve changes and becomes:

$$\frac{W_t}{P_t} = \frac{1}{\mu} Z_t F_2(K_t, Z_t, N_t)$$

This happens as firms markups must increase to balance the effect of uncertainty. This brings the equilibrium to a co-movement in decrease for both nominal wages and hours worked.
Bloom (2009) defines instead the role of real frictions, specifically in its case the surface of non-convex adjustment costs. These costs are such that increased uncertainty widens the range of inactivity where firms have great difficulties to adjust their capital, which brings to greater precaution.
In addition to the mentioned studies collected in try to assess the channels in which uncertainty moves. Bachmann et al. (2013) collect literature on the phenomena that they refer to as the “wait and see” effects. All these scholarly works explain how an important unexpected surge in uncertainty could be in the first moment a source of concern, therefore the first instinct is to cut off on investments with a drop in GDP growth. This happens as there is not a smooth adjustment channel between real economic activity and shocks of uncertainty. But once production has stopped, there could be a “see” moment where new opportunities could arise, and this could produce a moment

of recovery after the initial drop (Bloom 2009, Bloom et al. 2014). The wait is determined by the fact that most of the investments, which will have their impact on future output growth, are not reversible and imply a cost (Bernanke 1983).

These initial negative effects could be explained by confidence effects as well. Ilut & Schneider (2014) explain the theory related to ambiguity aversion of the major players in the economic framework (firms and investors). This aversion refers to the fact that players prefer to make choices in an environment where outcomes are more certain rather than related to a certain level of uncertainty (or, as these authors call it, ambiguity). Therefore, a shock in ambiguity is often related to the first negative effect of uncertainty on business cycles, as the most intuitive choice is to delay any action of entrepreneurship.

Fajgelbaum et al. (2017) determine a theoretical model that implies the idea of uncertainty traps: they demonstrate how an equilibrium that explains business cycles through uncertainties can perceive how an increase in the latter means a more delayed recovery period. Hence, what at first sight seemed to be a quick episode of deterioration of the state of the economy, can become a self-reinforcing vicious cycle.

In this environment where many models point out to a mainly negative relationship between uncertainty and growth, Cascaldi-Garcia & Galvao (2021) poses itself as an example of model where mechanisms of propagation may seem more difficult to assess than it seems. When these authors try to asses macroeconomic unpredictability, it is found that it is possible to have an unexpected positive impact on output growth rather than negative impact. The evolution of literature that tries to effectively explain both negative and positive effects from a theoretical and empirical point of view the effect of uncertainty is growing in time and this dissertation tries to asses if positive effects are possible. The majority of works concentrate on the more established idea that mainly uncertainty is a cause of decreases in business cycles rather than increases. It is important to get a clear picture of the instrument use to measure uncertainty and share instruments to assess the direction of the effects on business cycles.

Chapter 3: Empirical methodology

3.1 The empirical model: quantile regression

Establishing empirically the relationship between uncertainty and business cycles is not only difficult in the step of understanding which index would fit best the needs of the research, but there has to be made a choice regarding the methodology in which the relationship is analysed.

In this dissertation I opt for the methodology steps laid out by Adrian et al. (2019), work based on the quantile regression specified in Koenker & Bassett (1978). Using quantile regression allows to measure the impact of the predictor variables on the whole distribution of the dependent variable, which in this case is real output growth, and not only the behavior of the predictors with respect to the mean value. In this way quantile regression analysis could be a more precise methodology to assessing uncertainty impact, as there is the possibility to gather information about the whole underlying distribution of the dependent variable and assess, in this case, the growth-at-risk impact of uncertainty.

To understand better this methodology that utilizes quantile regression, coefficients of this kind of regression are described by equation 5:

$$\hat{\beta}_\tau = \arg\min_{\beta_\tau \in \mathbb{R}^k} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbf{1}_{(y_{t+h} \geq x_t\beta)} |y_{t+h} - x_t\beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h} < x_t\beta)} |y_{t+h} - x_t\beta_\tau| \right) \tag{5}$$

Therefore, there are two main differences from the OLS estimates. OLS models minimize the sum of squared errors. Meanwhile quantile regression not only fits a linear model by minimizing instead the quantile weighted values of absolute errors though $\hat{\beta}_\tau$, but it also uses an asymmetric loss function, denoted by **1**, an indicator function. This loss function assigns different weights to errors depending whether they fall above or below a specified quantile. In this analysis is the interest is how output growth behaves below and above the median value of the conditional distribution of real output growth. The predicted value from the quantile regression is the quantile of y_{t+h} conditional on x_t, as computed in equation 6:

$$\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) = x_t\hat{\beta}_\tau \tag{6}$$

The model allows to understand if uncertainty shocks can have a different impact on the different parts of the distributions, therefore allowing us to understand which of the many transmission channels identified before in literature could be affected by a change in the index.

This methodology will be used in this dissertation to measure the impact of the chosen uncertainty indexes on GDP growth-at-risk, but is important to mention that there is the possibility to use this methodology to develop an index of uncertainty that measures estimated quantiles of the output growth's conditional density. Castelnuovo & Mori (2022) do so by using Adrian et al. (2019) methodology but with a ”MIDAS” therefore ”unrestricted mixed-frequency approach” approach. The authors show that using mixed frequency data could be beneficial to the understanding of business cycles, by employing the skewness of the measure that is retrieved from the quantile regression.

Forni et al. (2021) is instead an example of a study that takes inspiration from this methodology and applies a different smoothing technique for the quantile regression, employing the one proposed by Fernandes et al. (2021). In this way they are able two construct a two fold measure of uncertainty (that resembles the more ”simplistic” version of Rossi & Sekhposyan (2015)) which can differentiate between shock to the right and left tail of the conditional distribution.

A study that is really similar methodology with respect to this dissertation is Hengge (2019). This thesis completes the analysis by assessing financial uncertainty from the same authors and underlining how there are effectively some differences between these two uncertainty measures that can be further studied in the future, in light of clearly assessing which could be the effects of uncertainty and finalize this complex relationship.

3.2 Data

GDP output The data used in this dissertation are FRED Real Gross Domestic Product for USA. This variable collects the value of goods and services minus the value of good and services used in production. The growth or decline in GDP from one period to another is a crucial indicator for Americans to assess their economic health. Globally, the United States' GDP is monitored as an important economic measure. Real GDP growth data are quarterly and it is an inflation-adjusted time series (Bureau of Economic Analysis 2024).

Uncertainty index All these reviews and empirical assessments of uncertainty circle back to the choice of the index in this thesis. The first choice was the categorical area related to the way the index is constructed. Inspired by the review of Cascaldi-Garcia et al. (2023) and empirical works, I decided to choose an index that was based on economical measures in order to grasp as much as possible a precise movement of uncertainty. In addition, it was in my interest to define and compare the different effects that financial and macroeconomic uncertainty have on business cycles, therefore I chose as the main index to define these movements the ones proposed by Jurado et al. (2015) and Ludvigson et al. (2021). Another important aspect, the index was chosen on the basis of the dataset that it was able to cover. This index is in fact based on a very large dataset, specifically constructed to include as many aspects of the various economic policies as possible. In particular, the range of the macroeconomic index is especially wide as it provides values that try to assess beliefs related to the performance of several variables. A more detailed description of data used to effectively construct both the Macroeconomic and Financial index are reported in detail in Appendix A.
The most important aspect of understanding these indexes is their identification. A point has to be made when examining the dataset of the two variables: macroeconomic uncertainty depends mainly on the FRED-MD dataset. In this dataset there are financial variables as well, to better assess the state of the whole economy. Therefore there could be some ”overlaps” between these macroeconomic and financial dataset. For example, Market Excess Return reported in the financial dataset can potentially be approximated by stock market returns from indices such as the S&P 500, present in the FRED-MD dataset. It has to be said that although there could be some variables aligned, the majority of the financial index is constructed on specific industry portfolios, which are not part of the FRED-MD dataset. In addition, the computation that will be shortly presented, of the factors composing the index, are done in a separate way.

Chapter 4: Empirical analysis: results

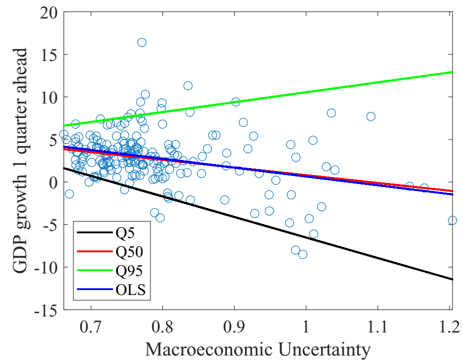
4.1 The difference between Macroeconomic and Financial Uncertainty impact

The next step of this dissertation is to measure the impact of financial and macroeconomic uncertainty on the prediction of real GDP growth. The analysis includes in the model the value of the present value of GDP growth and a measure of uncertainty. The regression is performed firstly considering macroeconomic uncertainty and financial uncertainty separately, while in the robustness check that will follow later these measures are included together. The model describing the quantile regression used in dissertation is explained in equation 7:

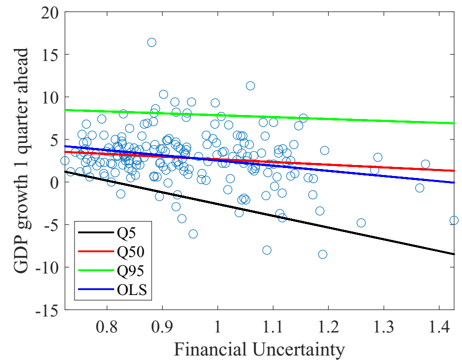
$$GDP_{t+h} = \beta_0 + \beta_1 \cdot GDP_t + \beta_2 \cdot Uncertainty_t + \varepsilon_{t+h} \tag{7}$$

After computing the quantiles using the methodology described in the previous chapter, it is possible to visualise the univariate impact of uncertainty on the prediction the real output growth, both considering one quarter ahead and four quarters ahead. An important note on the computation of the dependent variable, is that the prediction of real GDP growth in this analysis is more correctly described as the prediction of the average value of GDP growth in the chosen horizon, therefore the computations try to predict what will be the average growth of the dependent variable in the h period of time ahead.

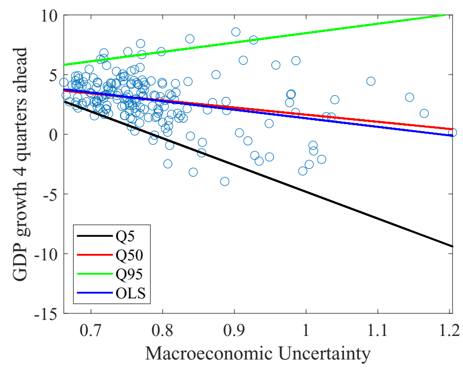
Lines in Figure 5 correspond to the quantile regression lines for specific quantiles indicated (5th, 50th and 95th) and the OLS regression line. Only the sample 1970Q1 - 2019Q4 is reported, as the important sudden change in GDP during the Covid-19 crisis has a major impact on this simple visualization. This figure provides a first intuition of what will be the main results of the more detailed analysis of the coefficients of the quantile regression analysis.



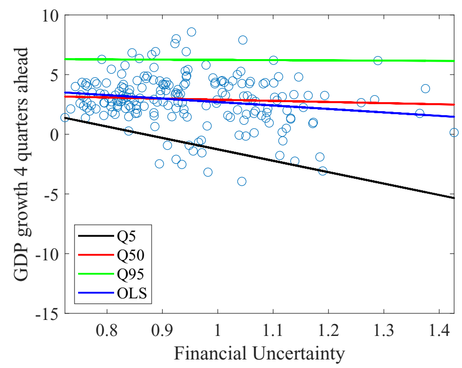
(a) Macroeconomic uncertainty 1 quarter ahead



(b) Financial uncertainty 1 quarter ahead



(c) Macroeconomic uncertainty 1 year ahead



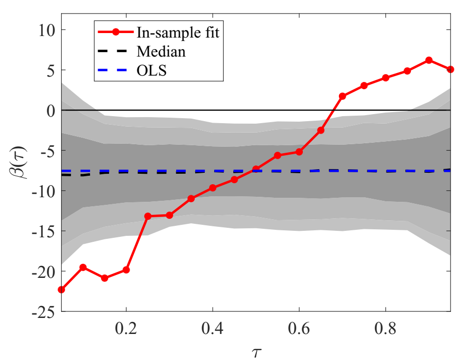
(d) Financial uncertainty 1 year ahead

Figure 5: Uncertainty univariate impact in sample 1970Q1 - 2019Q4

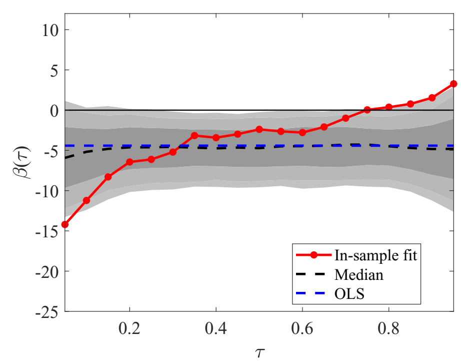
Through this univariate analysis, it can be intuitively understood the impact of different types of uncertainty on GDP growth. Macroeconomic uncertainty can act as a double-edged instrument, the ambiguous effect could result in a potential deepening of a recessionary period or a unexpectedly moment of growth stimulation. It can be explained this way: greater noise around the prediction of a specific macroeconomic variable could reduce the effectiveness of policies which aim was stabilising the economy; however, this increased risk could also promote new ideas and therefore foster entrepreneurship, as there could be a prospect of possible future rewards. This concept forms the basis of the argument that is commonly known as the ”growth option” argument (Bloom 2014). Another theory that might explain this effect is the Oi-Hartman-Abel effect: as previously seen, this theory suggests that if firms can expand in a way that allows them to benefit from favourable future scenarios while insuring themselves against poor results, they may exhibit risk-taking behaviour (Bloom 2009). Therefore this edge of macroeconomic uncertainty will lead the discussion in the next paragraphs regarding results of this regression. It has to be said that the effects of negative shocks are more pronounced than positive ones, therefore there is always a certain level of asymmetry in the response of business cycles to changes in uncertainty. Financial uncertainty, on the other hand, seems to have a predominantly negative impact on GDP growth. Financial markets interpret signals of rising financial uncertainty as indicators of worsening scenarios rather than as opportunities for future prosperity when the situation stabilises. Data seems to suggest that markets need reassurance. Positive signals of reduced uncertainty are perceived but do not significantly affect growth, while when this type of uncertainty increases, it weakens trust of market players and consequently this has a negative impact on output. These findings are consistent with analysis by Adrian et al. (2019), as they would seem to reflect the behaviour of the NFCI.

For both uncertainties, the effects are important in terms of their intensity over both shorter and longer horizon. However, the effects are stronger considering the average computed in a shorter horizon (one quarter ahead). Attempts to predict further time horizons show that the intensity of the effects described earlier diminish but do not change direction.

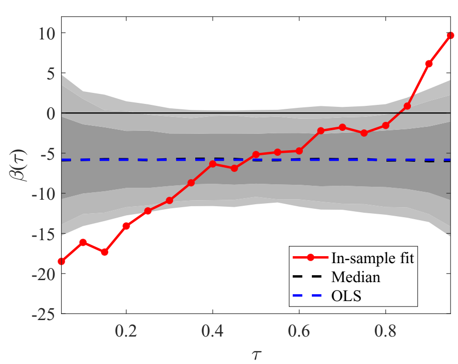
Next, the regression slopes of the quantile regression are evaluated: next figures report the coefficients of uncertainty $\beta(\tau)$ given a specific quantile τ.



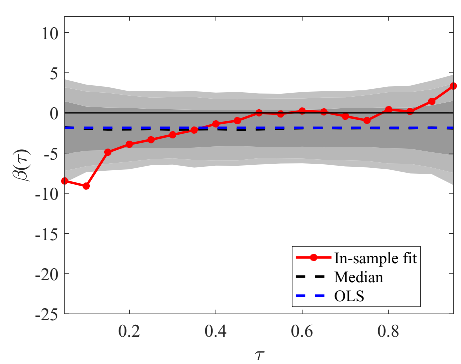
(a) Macroeconomic uncertainty 1 quarter ahead



(b) Financial uncertainty 1 quarter ahead



(c) Macroeconomic uncertainty 1 year ahead



(d) Financial uncertainty 1 year ahead

Figure 6: Uncertainty multivariate impact in sample 1970Q1 - 2019Q4

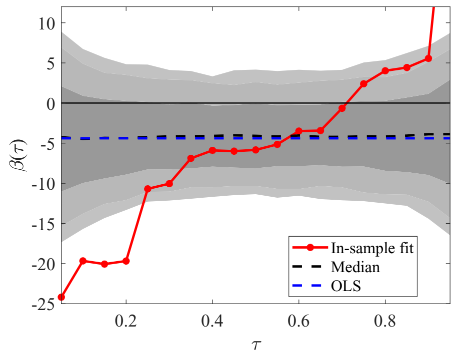
Figure 6 shows the confidence limits corresponding to the 95 % confidence interval around the hypothesis that the model measuring the impact of uncertainty is a general linear model. These limits are represented by the grey areas, whose colour is scaled on the basis of the critical value chosen. Instead, the red line represents the in-sample fit of the estimated quantile coefficients. The test of the general linear model is centered around the possibility that this red line overcomes the bands: if this happens, then the relationship between GDP growth and different types of uncertainty is non-linear. Differently from before, this image is part of the multivariate analysis, so it defines the impact of one of the types of uncertainty considered that the dependent variable is conditioned on the current value of output growth as well.

Results reported, together with the line correspondent to the in-sample fit, confirm the previously observed trends in the univariate analysis. Coefficients related to a change in macroeconomic uncertainty show a pronounced upward trend as the quantile of the uncertainty distribution chosen increases, changing drastically beyond the median of zero. This pattern implies a tendency towards a positive impact on the prediction of GDP growth, especially in the short run. The median, represented by the dashed black line, is utilised as a benchmark.

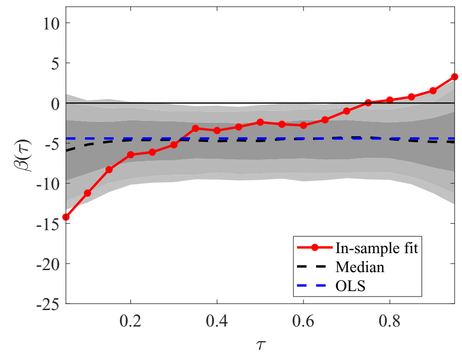
It is worth noting that the curve for macroeconomic uncertainty, the in-sample fit, rises substantially above the median. On the other hand, it is also observed that volatility increases below the median value, therefore when low quantiles are analyzed, the impact on GDP growth is negative.

However, this is not the case for financial uncertainty: most of the in-sample line is located below the median and these results show that the prediction of output growth remains significantly different from the OLS estimate.

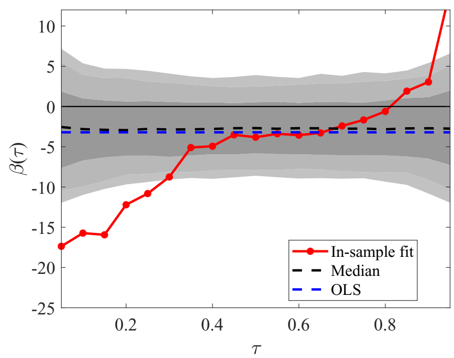
The importance to analyse separately macroeconomic and financial uncertainty is further highlighted in the literature, which emphasizes the endogeneity or exogeneity of these variables in relation to business cycles, which will be analysed deeply further in this dissertation. All these considerations suggest the need to distinguish between the roles of macroeconomic and financial uncertainty in economic dynamics and their respective impacts on output growth.



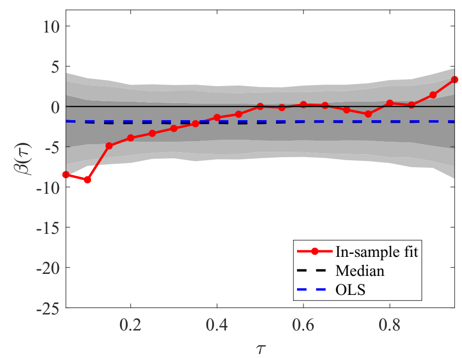
(a) Macroeconomic uncertainty 1 quarter ahead



(b) Financial uncertainty 1 quarter ahead



(c) Macroeconomic uncertainty 1 year ahead



(d) Financial uncertainty 1 year ahead

Figure 7: Uncertainty multivariate impact in sample 1970Q1 - 2023Q2

In Figure 7, despite the change in sample, the underlying dynamics remain consistent, highlighting the distinct role of macroeconomic and financial uncertainty in economic fluctuations. The line of the macroeconomic uncertainty coefficient suggest a tendency towards a positive impact on GDP growth as there is a movement towards higher quantiles of the distribution, especially in the short run. In contrast, this pattern is not observed for financial uncertainty, where the majority of the in-sample line of best fit is consistently below the median, emphasising a significant deviation from the OLS estimate.

Results related to financial conditions are also tested in Europe by Figueres & Jarociński (2020). They analyse first different indexes as in Europe financial markets are not as ”experienced” as American ones. This is reflected in the difficulties encountered while finding a specific index that can be a used as a proxy for financial conditions. Their focus is mostly on understanding which indicators is the best predictor of financial conditions. The authors asses that a simple elaboration of the indicators analyzed with a principal component seems to be not a really informative financial indicator for estimating the same dependent variable, namely risks to growth.

Hence, the very end of the analysis is reached with the CISS (Composite Indicator of Systemic Stress). This index aggregates many individual financial indicators in a nonlinear way, elaboration which allows to represent the ”systemic” nature of events.

The authors compare the principal component index (PC1) and the CISS. In Europe, considering CISS index, the effects of financial conditions seem to be in line with what the previous analysis referred.

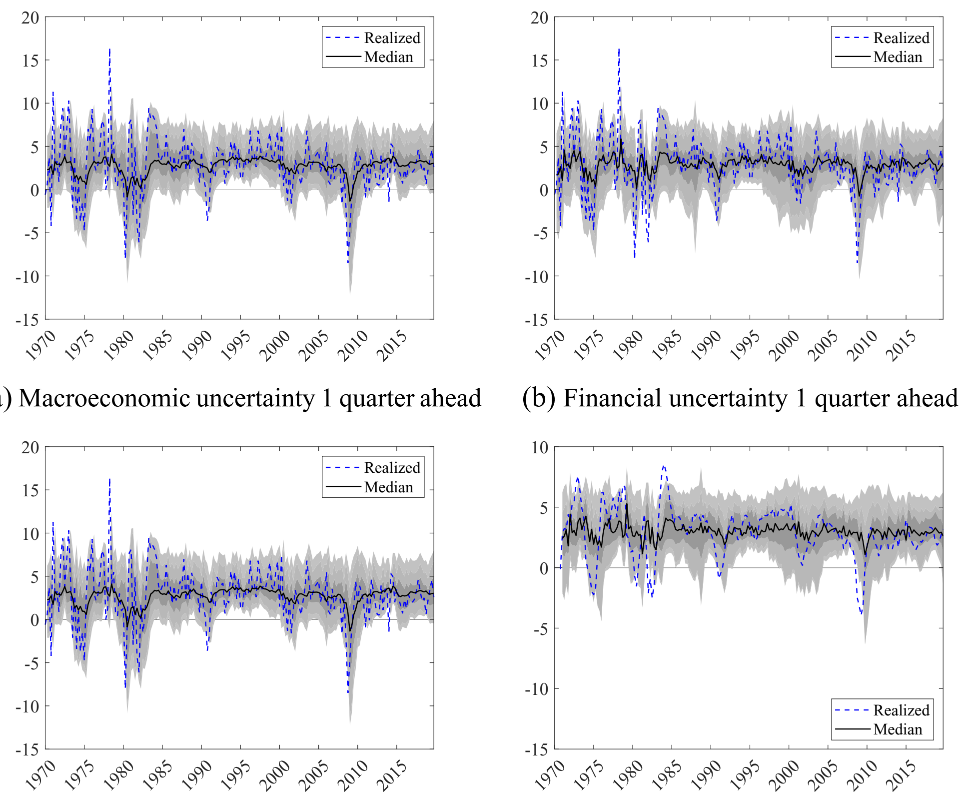
Results are similar to what has been seen with financial uncertainty even in the multivariate analysis with the financial index in Europe. The principal component index is not even significant, while the CISS follows the asymmetry expected from the previous bands from American data.

Fortin et al. (2023) use instead the same index but a different methodology, again to assess the impact of uncertainties in the European area, comparing with the US area.

Their analysis is captivating as they differentiate between local (country specific) and global (US) uncertainty, considering that in their scope are included specific countries (Germany, France, Austria and UK). Therefore here the comparison is almost immediate. In the empirical part of their analysis they report the impulse response function to shocks, calculated using Cholesky factor decomposition, in which a shock is a one standard deviation rise in one of the types of uncertainty chosen. They consider the impact on industrial production and employment in the euro area and the impact on a major index of financial volatility in Europe, the Euro Stoxx 50. What they found is that while global uncertainty is always significant, local uncertainty it is only in the case of the impact of local economic uncertainty in unemployment. In addition, all the effects of financial uncertainty exceed and have indeed a more intense negative effect on all variables with respect to economic uncertainty.

4.2 Predicted distributions: visualising the interquantile range

Figures 8 and 9 provide an effective visualisation of the interquantile range in two different samples, first the 1970Q1 - 2019Q4 sample and secondly the window that includes the large jump associated with the Covid-19 crisis, the 1970Q1 - 2023Q2 sample. These figures show the one-quarter and four-quarter GDP growth together with its conditional median and selected conditional quantiles (5, 25, 75 and 95 per cent). One of the key findings is illustrated in these figures: the asymmetry between the upper and lower conditional quantiles for macroeconomic and financial uncertainty. This highlights the different behaviour of these two types of uncertainty.



(a) Macroeconomic uncertainty 1 quarter ahead (b) Financial uncertainty 1 quarter ahead

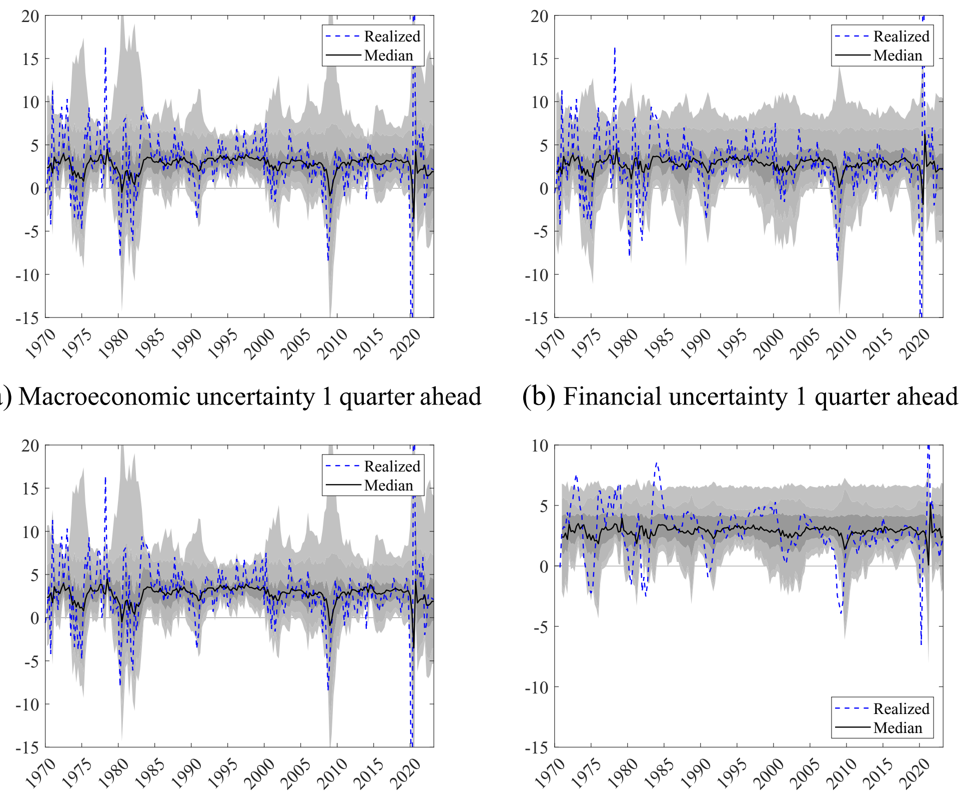
(c) Macroeconomic uncertainty 1 year ahead (d) Financial uncertainty 1 year ahead

Figure 8: Predicted distribution sample 1970Q1-2019Q4

In Figure 8 illustrating macroeconomic uncertainty, the grey band covering the quantiles from the 25th to the 75th percentile tends to widen during recessions. This suggests an upward shift in variability, suggesting that higher levels of macroeconomic uncertainty could be associated with higher economic growth as well as recessions.

On the other hand, when financial uncertainty is visualized, it can be observed that most of the variability is below the line that defines the median. This implies that financial uncertainty behaves differently from macroeconomic uncertainty, as a larger proportion of its fluctuations occurring below the median.

This contrast between macroeconomic and financial uncertainty underlines the different ways in which these two types of uncertainty can affect economic conditions. It highlights the need for a more sophisticated understanding of these variables when analysing their impact on economic growth, particularly during periods of economic downturn. The graphs serve as a visual representation of these complex dynamics, providing a clear and intuitive way to understand the asymmetric behaviour of macroeconomic and financial uncertainty.



(a) Macroeconomic uncertainty 1 quarter ahead (b) Financial uncertainty 1 quarter ahead

(c) Macroeconomic uncertainty 1 year ahead (d) Financial uncertainty 1 year ahead

Figure 9: Predicted distribution sample 1970Q1-2023Q2

In Figure 9, capturing the swift shift in GDP growth during the Covid 19 crisis, it's worth noting that the models seem to accommodate this variability by visibly widening the interquantile range. However, these results could be biased by the major jump in output growth. Indeed, the impact of macroeconomic uncertainty on GDP growth is even more pronounced at both the upper and lower quantiles, while financial uncertainty is more volatile below the median. Macroeconomic uncertainty continues to show its dual effect. For financial uncertainty, even small downward shifts can lead to considerable variability. It's important to note that the scale for a one-year forecast is significantly lower than that for a one-quarter forecast, especially for financial uncertainty. This highlights the sensitivity of both macroeconomic and financial uncertainty to small changes, as well as the different scales used for short-term and long-term forecasts.

4.3 Conditional distribution of GDP growth

Next pages are devoted to the report of the Probability Distribution Functions (PDF) and Inverse Conditional Distribution Functions (CDF) in specific points in time. Subsequently, only the sample until 2019 is reported as results, as seen before, are more reliable. In addition, with these results it will be easy to get a picture of the matching technique used by Adrian et al. (2019). This analysis can be done for specific periods in time: therefore the decision to look both periods of recessions as well as periods of growth between these points in time can help to evaluate the model as best as possible. To understand which periods are needed to be seen in detail, it is possible to detect in the data sequential quarters that showed negative changes in real GDP. Therefore the decision was to chose to analyse the distribution in these specific periods of time reported in Table 2, adding the second quarter of 2006 and the fourth quarter of 2014 to have a comparison with a growth period.

Recession	Observation Date	Real GDP growth
Beginning recession	1974-07-01	-3.7
Beginning recession	1974-10-01	-1.5
Moment to analyse	1975-01-01	-4.8
Beginning recession	1981-10-01	-4.3
Moment to analyse	1982-01-01	-6.1
Beginning recession	2008-07-01	-2.1
Moment to analyse	2008-10-01	-8.5
Slow recovery	2009-01-01	-4.5
Beginning recession	2020-01-01	-5.3
Moment to analyse	2020-04-01	-28.0
Fast recovery	2020-07-01	34.8

Table 2: Recessions in output growth data

The data retrieved from previous analysis can be elaborated to construct a probability distribution function, by smoothing the quantiles to a predetermined distribution. This fitting is achieved by using the skewed t-distribution laid out by Azzalini & Capitanio (2003). The main characteristics of this distribution are better described in equation 8

$$f(y;\mu,\sigma,\alpha,\nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};\nu\right) T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\left(\frac{y-\mu}{\sigma}\right)^2}};\nu+1\right) \tag{8}$$

The four parameters defined by the Greek letters are used to account for location μ, scale σ, fatness ν, and shape α, in order to understand and construct the main parts of the distribution of the dependent variable that is not assumed as given in the beginning of the analysis. For each horizon, the parameters are chosen following equation 9.

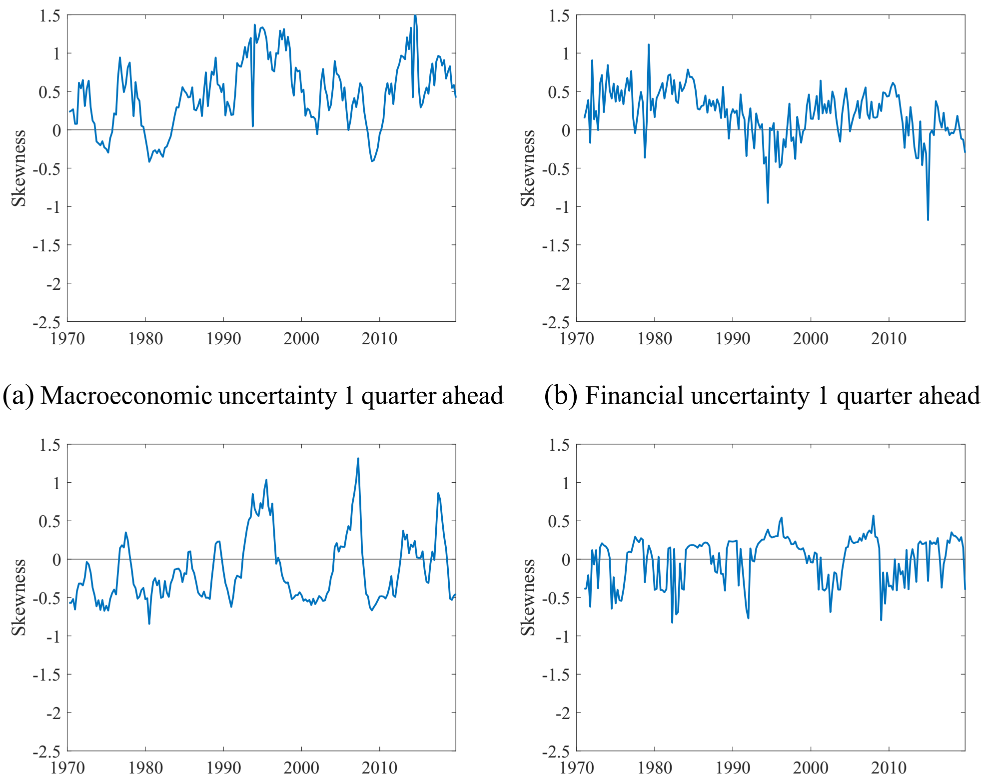
$$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = \underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) - F^{-1}(\tau;\mu,\sigma,\alpha,\nu)\right)^2 \tag{9}$$

Using this calculation means that there is the objective to establish the main parameters of the fitted distribution. This is achieved by the optimization process that minimizes the distance between the quantiles computed in the previous step and the inverse function of the fitted version of Azzalini's curve (the t-skewed distribution). This approach guarantees that the fitted distribution reflects in the most accurate degree possible the underlying structure of the data.

Comparing the probability density functions of the fitted version of the conditional distribution versus not including uncertainty, can explain the impact that accounting for uncertainty could provide if there is the objective to estimate output growth, instead of only taking into consideration the current state of the economic output growth. The result expected from this part of the analysis, given the original analysis considering financial conditions is that including the NFCI in the distribution, is that fitted PDFs have a higher volatility in recession periods if the financial conditions are included. The distribution including data from the NFCI is more left skewed with respect to the distribution that has an explaining variable only the current output growth (Adrian et al. 2019).

Instead with uncertainty, there is the need to consider the differences that the two types of uncertainty yield. As previously seen, macroeconomic uncertainty could result in an ambiguous impact on output growth: this ambiguity is reflected in the images of the PDFs as well as the coefficients of the quantile regression. Figure 11 shows the results related to the PDFs that include macroeconomic uncertainty while Figure 12 displays PDFs associated with the regression that includes financial uncertainty. It is directly visible some significant differences between these two predictors, especially in the moments of recession.

Firstly, it is visible that during recession periods both macroeconomic and financial uncertainty "move" the distribution: the mean is lower and the shape accounts for higher volatility. But considering skewness, reported in Figure 10, there has to be made the already know differentiation between the two types of uncertainty.



(a) Macroeconomic uncertainty 1 quarter ahead

(b) Financial uncertainty 1 quarter ahead

(c) Macroeconomic uncertainty 1 year ahead

(d) Financial uncertainty 1 year ahead

Figure 10: Skeweness in sample 1970Q1 - 2019Q4

Indeed, macroeconomic uncertainty has greater tails during periods of recession: the distribution is more volatile. But, although it results to be more left skewed with respect to the PDF with only uncertainty, in the fourth quarter of 2008 (but in 1975Q1 and 1982Q2 as well) it is possible to see that macroeconomic uncertainty "moves" the distribution in the left side but in the right side as well. In this case, the dimension of the right tail shows that higher probability is related to positive output growth values. Instead, PDFs including financial uncertainty are more left skewed and the right tail is not as important as in the other type of uncertainty.

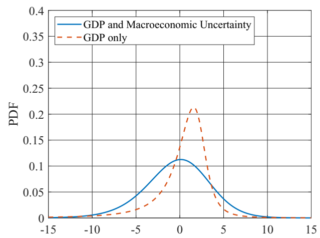
This difference between the two variables is especially visible in the recession period of 1975Q1 and 1982Q2: these moments are crucial, as both represent periods of the end of crisis related to oil shocks, in particular the price increases in 1973-1974 triggered by the aftermath of the October 1973 war, followed by further increases in 1979-1980 due to the Iranian revolution in late 1978 and the outbreak of the Iran-Iraq war in late 1980 (Barsky & Kilian 2001). Therefore, it is intuitively easy to understand why in this case macroeconomic uncertainty seems to be a better predictor of the possible outliers in output growth happening in this period, while financial uncertainty "moves" more the distribution in 2008Q4.

The fact that volatility increases both tails of the distribution only for the macroeconomic variable, captures the differences between the two types of uncertainty compared. It is an important result that confirms previous results and effectively assesses that there are opportunities following an increase of macroeconomic uncertainty. Therefore, the story these distributions tell is different. If output growth is described through the lenses of macroeconomic variables movement, what is expected is ambiguous, as if could not only show future decreases. Therefore, there seem to be inherently in this index a measurement of a window of hope for a different future if there is the right investment and the right insurance. In periods of growth, 2006Q2 and 2014Q4, when uncertainty is included, the PDFs are less volatile with respect to the ones with current GDP only and the skewness parameter is similar for both smoothed distributions.

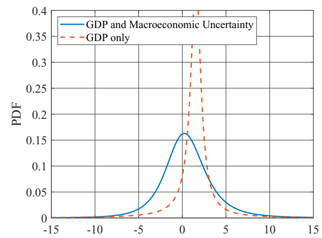
Having analysed PDFs, Figure 13 describes the inverse CDF of macroeconomic uncertainty while Figure 14 Inverse CDF of financial uncertainty. This image determines the matching step of the analysis, how the quantiles have been smoothed to the curve chosen to describe the distribution. This figures plots $\hat{Q}_{y_{t+h}|x_t}(\tau|x_t)$ with the yellow line (so the raw values of the conditional quantile distribution) and the inverse function $F^{-1}(\tau; \mu, \sigma, \alpha, \nu)^2$ both with and without one of the types of uncertainty, keeping fixed the presence of current output growth. The interest has to be placed in the distance between the "raw" line, containing the quantiles of the distribution without any matching, and the "matched" lines, and their respective position, as it changes in moments of recession or growth.

Results assess that the inverse CDFs for both uncertainties are better fitted if uncertainty is considered, and all the previous results regarding the PDFs are confirmed. Results regarding the conditional distribution during COVID period (and, for comparison, the other recession periods highlighted) are included in Appendix B. But due to the major jump in 2020, the figure showing the inverse CDFs show that matching data to the Azzalini curve seems very difficult and non reliable.

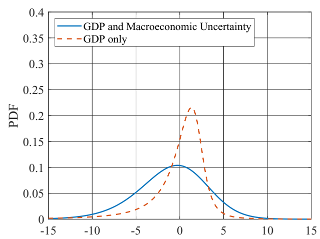
Macroeconomic Uncertainty PDFs 1970Q1-2019Q4



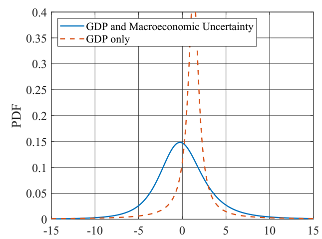
(a) PDF H1 1975Q1



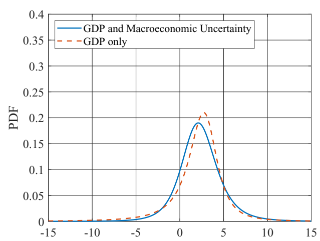
(b) PDF H4 1975Q1



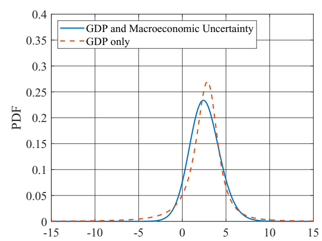
(c) PDF H1 1982Q2



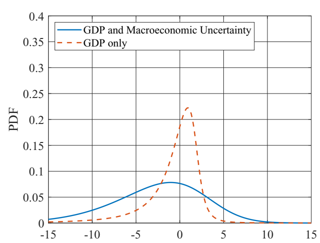
(d) PDF H4 1982Q2



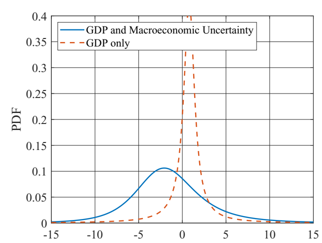
(e) PDF H1 2006Q2



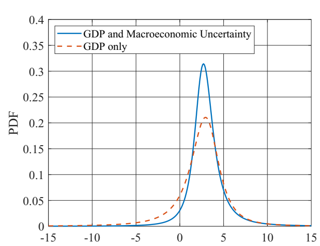
(f) PDF H4 2006Q2



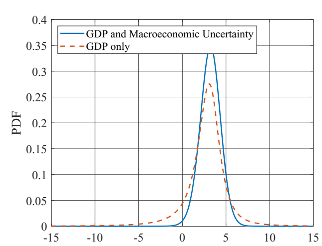
(g) PDF H1 2008Q4



(h) PDF H4 2008Q4



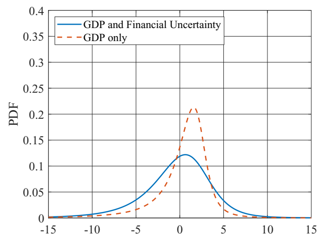
(i) PDF H1 2014Q4



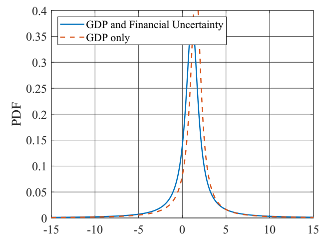
(j) PDF H4 2014Q4

Figure 11: Macroeconomic Uncertainty PDFs 1970Q1-2019Q4

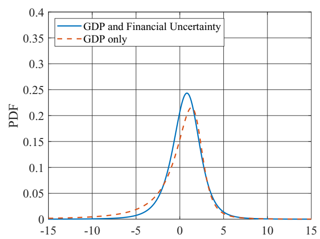
Financial Uncertainty PDFs 1970Q1-2019Q4



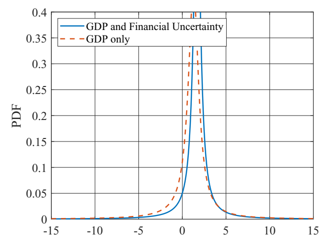
(a) PDF H1 1975Q1



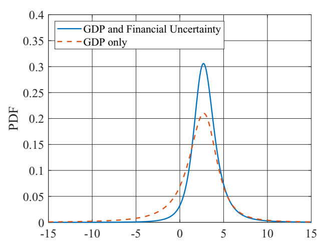
(b) PDF H4 1975Q1



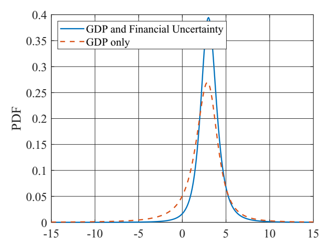
(c) PDF H1 1982Q2



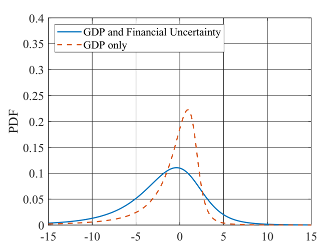
(d) PDF H4 1982Q2



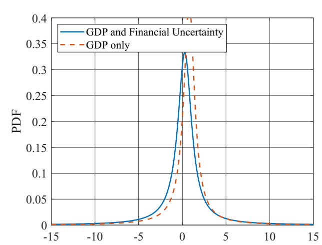
(e) PDF H1 2006Q2



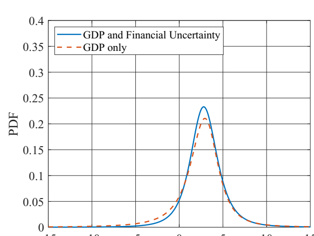
(f) PDF H4 2006Q2



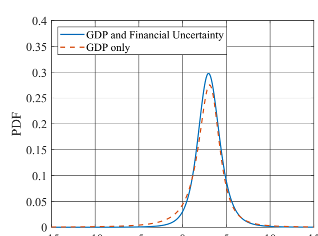
(g) PDF H1 2008Q4



(h) PDF H4 2008Q4



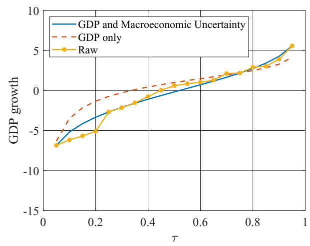
(i) PDF H1 2014Q4



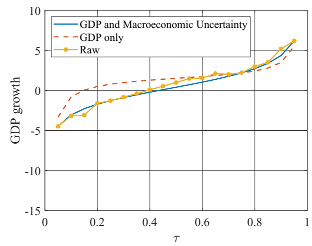
(j) PDF H4 2014Q4

Figure 12: Financial Uncertainty PDFs 1970Q1-2019Q4

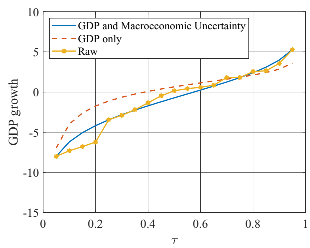
Macroeconomic Uncertainty Inverse CDFs 1970Q1-2019Q4



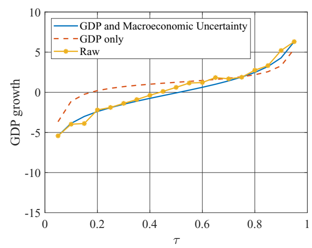
(a) InverseCDF H1 1975Q1



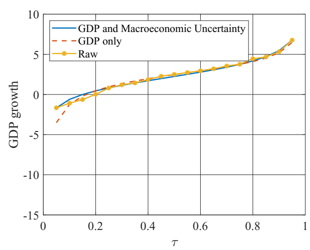
(b) InverseCDF H4 1975Q1



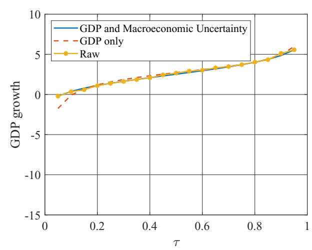
(c) InverseCDF H1 1982Q2



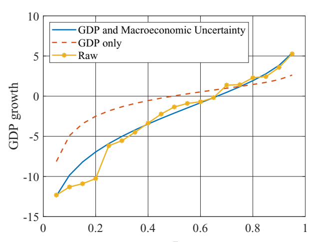
(d) InverseCDF H4 1982Q2



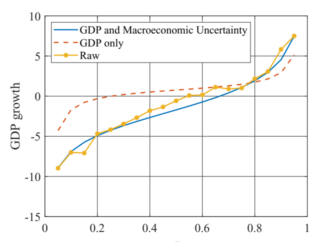
(e) InverseCDF H1 2006Q2



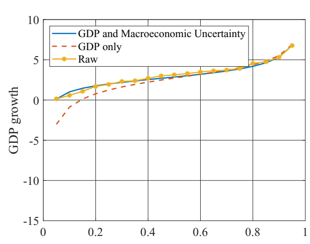
(f) InverseCDF H4 2006Q2



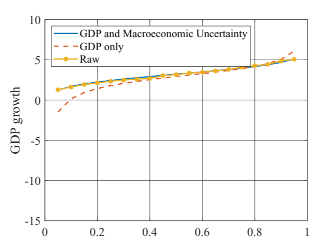
(g) InverseCDF H1 2008Q4



(h) InverseCDF H4 2008Q4



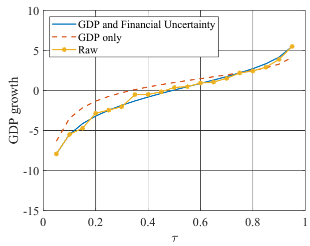
(i) InverseCDF H1 2014Q4



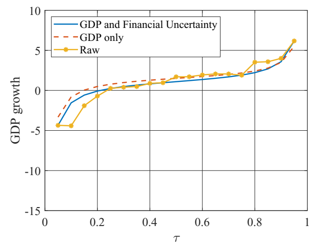
(j) InverseCDF H4 2014Q4

Figure 13: Macroeconomic Uncertainty Inverse CDFs 1970Q1-2019Q4

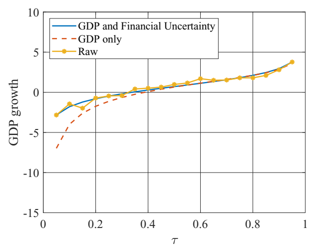
Financial Uncertainty Inverse CDFs 1970Q1-2019Q4



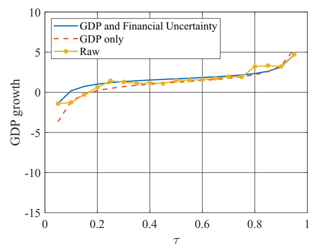
(a) InverseCDF H1 1975Q1



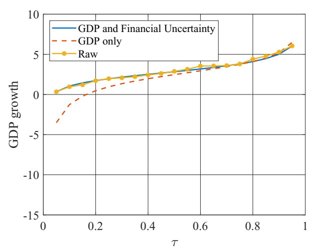
(b) InverseCDF H4 1975Q1



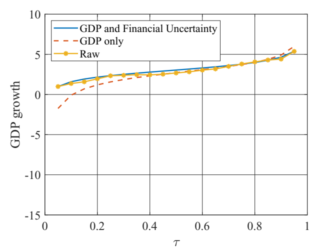
(c) InverseCDF H1 1982Q2



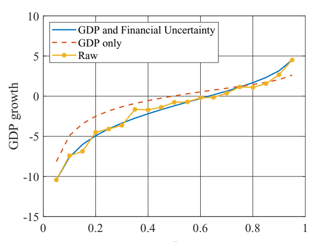
(d) InverseCDF H4 1982Q2



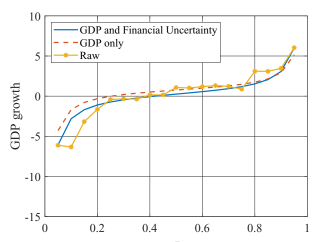
(e) InverseCDF H1 2006Q2



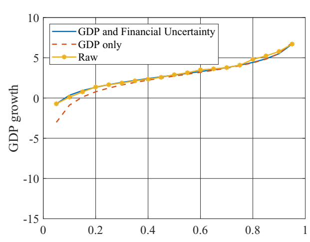
(f) InverseCDF H4 2006Q2



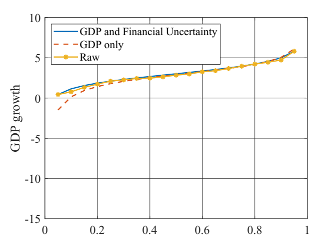
(g) InverseCDF H1 2008Q4



(h) InverseCDF H4 2008Q4



(i) InverseCDF H1 2014Q4



(j) InverseCDF H4 2014Q4

Figure 14: Financial Uncertainty Inverse CDFs 1970Q1-2019Q4

4.4 Vulnerability measures: the upside and downside risk related to the forecast of real GDP growth

All the analysis before shed light on two main aspects: macroeconomic uncertainty can be both a input to growth as well as predictor of recession, whereas financial uncertainty rising is seen only as a bad signal for business cycles. Hence, there is the need to understand, given these results, what is the downside and upside risks with respect to the forecast. This means trying to evaluate what happens after an unexpected shock in uncertainty to the outlook of output growth. Thus, this part of the analysis wants to assess what is the decrease in GDP output after unexpected changes in uncertainty. The aim is to effectively assess what was just intuited by defining how PDFs moved if in the analysis is included uncertainty.

To measure this distance there is a specific calculation that uses the outputs of the matching technique described before. The first is $\hat{g}_{y_{t+h}}(y)$, which is the unconditional density computed by matching the unconditional empirical distribution of only current output growth. The second is the estimated skewed t-distribution $\hat{f}_{y_{t+h}|x_t}(y \mid x_t) = f(y; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h})$, therefore the fitting of the conditional distribution to the already described Azzalini curve.

Then the analysis proceeds with the computation of their distance, described in equation 10 for the downside entropy and in equation 11 for the upside entropy:

$$\mathcal{L}_t^D\left(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}\right) = -\int_{-\infty}^{\hat{F}^{-1}_{y_{t+h}|x_t}(0.5|x_t)} \left(\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)\right) \hat{f}_{y_{t+h}|x_t}(y|x_t)\, dy \tag{10}$$

$$\mathcal{L}_t^U\left(\hat{f}_{y_{t+h}|x_t}; \hat{g}_{y_{t+h}}\right) = -\int_{\hat{F}^{-1}_{y_{t+h}|x_t}(0.5|x_t)}^{\infty} \left(\log \hat{g}_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t)\right) \hat{f}_{y_{t+h}|x_t}(y|x_t)\, dy \tag{11}$$

Where $\hat{F}_{y_{t+h}|x_t}(y|x_t)$ is the cumulative distribution associated with $\hat{f}_{y_{t+h}|x_t}(y|x_t)$, and $\hat{F}^{-1}_{y_{t+h}|x_t}(0.5|x_t)$ is the conditional median.

As the equations explain, downside entropy measures the distance between the unconditional density and the conditional density below conditional median. This means that higher downside entropy is related to the fact that the conditional density gives more probability to more extreme negative events, therefore placed in the left tail of the distribution, with respect to the PDF that is describing the model with only GDP as a explanatory variable. In the same mirrored way, upside entropy is measuring the difference between the unconditional and conditional density above the conditional median. This means that when upside entropy takes higher values, there is more probability that events in the right tail, so extremely higher than the median events happen. A peculiar attribute of this measure of vulnerability is that, unlike the complete entropy, this upside and downside measures can be negative but if one on the two measures is negative, the other has to be positive. Therefore, while the overall entropy is positive, one side (downside or upside) could have a higher tail.

Another measure of the vulnerability are the expected shortfall and expected longrise:

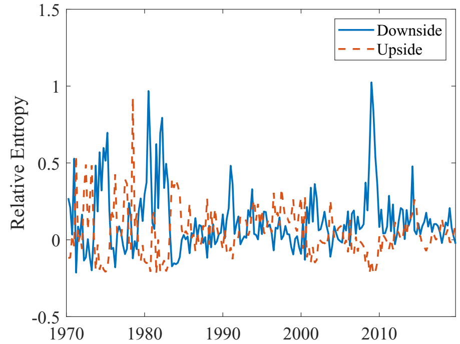
$$SF_{t+h} = \frac{1}{\pi} \int_0^{\pi} \hat{F}^{-1}_{y_{t+h}|x_t}(\tau|x_t)\, d\tau \tag{12}$$

$$LR_{t+h} = \frac{1}{\pi} \int_{1-\pi}^{1} \hat{F}^{-1}_{y_{t+h}|x_t}(\tau|x_t)\, d\tau \tag{13}$$

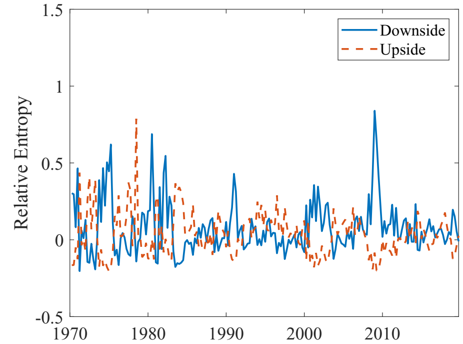
Equation 12 describes expected shortfall, which measures the average value of the distribution quantiles from 0 to π, while in equation 13 displays the mathematical description of how expected longrise measures the average value of the distribution quantiles from $1-\pi$ to 1. Therefore these measures both provide an average value for the lower and upper part of the distribution.

To summarize, while shortfall and longrise describe the tail behaviour of the conditional distribution in absolute terms, downside and upside entropy measure the tail behaviour of the conditional distribution in excess of the tail behaviour of the unconditional distribution (Adrian et al. 2019).

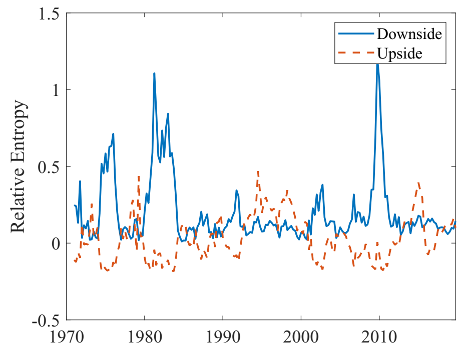
Next figures show the realizations of all the vulnerability measures described considering the more stable sample of 1970Q1 - 2019Q4, while in the appendix are reported results for the sample that includes the COVID crisis.



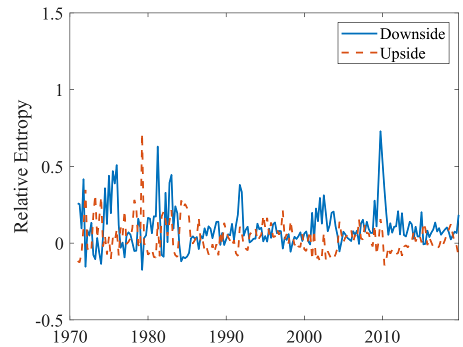
(a) Macroeconomic uncertainty 1 quarter ahead



(b) Financial uncertainty 1 quarter ahead



(c) Macroeconomic uncertainty 1 year ahead



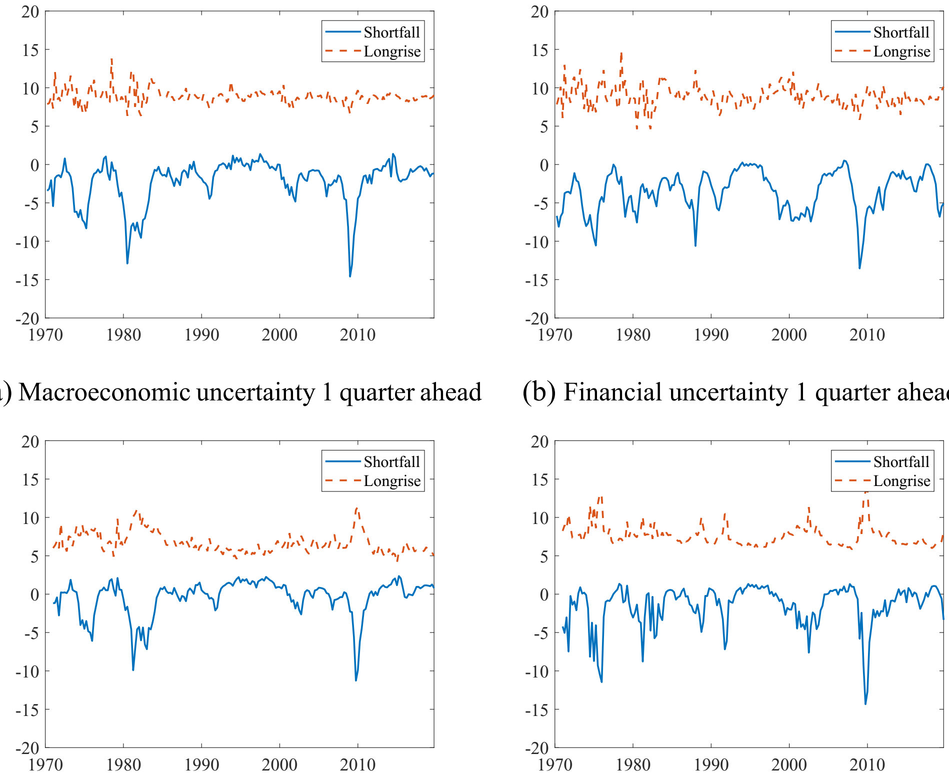
(d) Financial uncertainty 1 year ahead

Figure 15: Relative Entropy in sample 1970Q1 - 2019Q4

Relative Entropy To summarise, in Figure 15 results of the measure of entropy in the horizons chosen (3 months and 1 year) are shown. The window of one quarter shows higher variability both upside and downside for all entropy measures. When one quarter ahead prediction on GDP growth are analysed, there is a difference when specific crisis are observed. As it is expected, during 1974-1975 and 1981-1982, macroeconomic uncertainty shows a downside and upside entropy that are more volatile, especially the upside entropy.

In general, there is higher variability for upside entropy in the case macroeconomic uncertainty, but overall downside entropy is similar for financial and macroeconomic uncertainty. Hence, the main results that strikes is that upside entropy shows higher entropy for macroeconomic uncertainty and is higher at the moment of crisis, which is equivalent to say that it is higher at the moment of extreme uncertainty. Instead, financial uncertainty shows a stable upward entropy.

In a longer horizon of prediction, results remain the same but seem to last longer for macroeconomic uncertainty and still the upside entropy shows a high variability. It has to be said that overall downside entropy shows that considering a linear model could be detrimental to the analysis, as negative signals of uncertainty are clearly reflected in the distribution of the dependent variable. The sample until 2023Q2 confirms the mentioned results considering the major COVID crisis (see Appendix B).



(a) Macroeconomic uncertainty 1 quarter ahead
(b) Financial uncertainty 1 quarter ahead
(c) Macroeconomic uncertainty 1 year ahead
(d) Financial uncertainty 1 year ahead

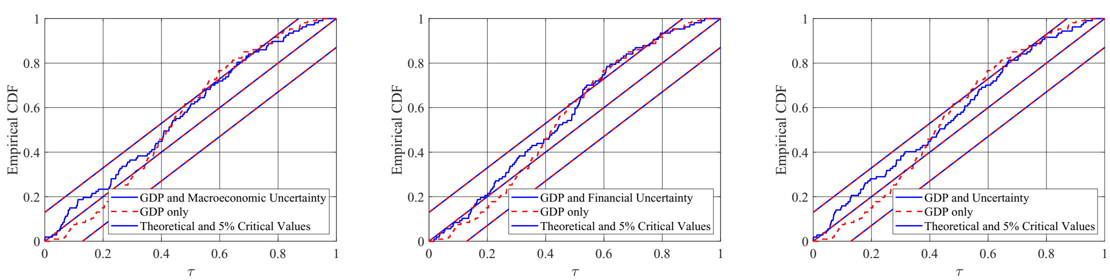
Figure 16: Shortfall and longrise in sample 1970Q1 - 2019Q4

Expected Shortfall and Longrise In Figure 16 are show then the average movements of the tail of the distributions, so the graphical description of the 5 percent expected shortfall and the 95 percent expected long rise. To understand the results it has to be taken in consideration that this measure is different from entropy. While expected shortfall measures changes in the tail in absolute terms, downside entropy considers the distance between the area of unconditional and conditional distributions. Therefore, if these distributions are both negatively skewed, downside entropy will decrease while expected shortfall will show higher values (Adrian et al. 2019). The considerations to be made seem to be in line to the results seen before, both measures of vulnerability show movements during in higher recession moments, but for financial uncertainty is more visible the difference between shortfall and long rise. This is due to the fact that the asymmetry is more visible with this variable, as in moments of recession higher macroeconomic uncertainty could be a signal of positive real GDP growth, while financial uncertainty is more a symptom of future declines in output.

4.5 Models in comparison: out-of-sample analysis of the quantile regression

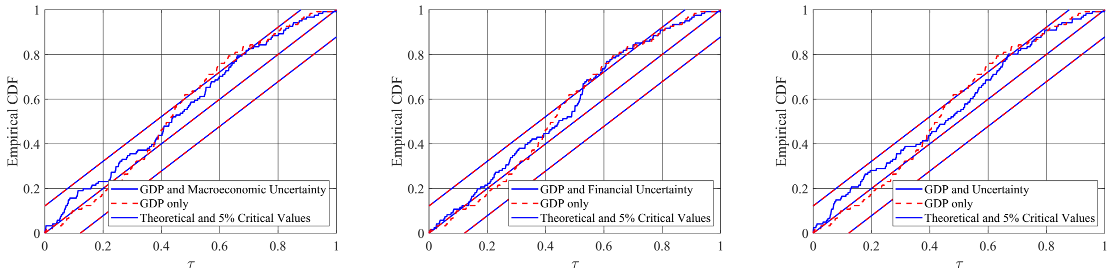
In this section, previous results are finalized by examining the Probability Integral Transforms (PITs). The object of this analysis is to understand what would have been the real-time evaluations an economist would perform using the methodology before described to assess and analyse forecast distributions in the one-quarter horizon. Therefore, using data from 1973Q1 to 1992Q4, the forecast distribution from 1993Q1 (one quarter ahead) is estimated. To get the wanted outcome, this process is applied to the estimation sample one quarter at a time until the sample period ends. The out-of-sample performance and calibration of the density forecasts are assessed by analyzing the prediction score and the PIT, which correspond to the predicted density and cumulative distribution evaluated at the outcome, respectively. At the end of the out-of-sample evaluation, the calibration of the predictive distribution is examined.

The empirical cumulative distribution of the PITs is calculated, indicating the percentage of observations below a given quantile. The closer this empirical distribution is to the 45-degree line, the better the model's prediction. In a perfectly calibrated model, the cumulative distribution of PITs forms a 45-degree line, meaning the proportion of realizations below any given quantile $Q_{y_{t+h}|x_t}(\tau)$ of the predictive distribution is exactly equal to τ. Following Rossi & Sekhposyan (2019), confidence bands around the 45-degree line are included to verify if the lines of the sample are significantly different from the identity line (Adrian et al. 2019).



(a) Macroeconomic uncertainty model OOS (b) Financial uncertainty model OOS (c) Macro and Financial uncertainty model OOS

Figure 17: OOS analysis in sample until 2019Q4



(a) Macroeconomic uncertainty model OOS (b) Financial uncertainty model OOS (c) Macro and Financial uncertainty model OOS

Figure 18: OOS analysis in sample until 2023Q2

Here there is the possibility to compare the models analysed. Previous results indicated how keeping the conditioning set differentiated between macroeconomic and financial uncertainty is important, but also considering the impact of both variables in the same moment has its own results. Therefore the question that naturally rises is what model fits best the main intention to describe the future course of business's cycles.

Incorporating both types of uncertainties appears to result in predictions that are closer to observed reality, intuitively the prediction is formed on the basis of more information which allows for a better perspective. Although the difference may not be immediately apparent, the additional information provided by considering both uncertainties seems to add to the overall predictive accuracy, as the PITs are more contained in the bands and near the 45 degree line. Consequently, the forecast for GDP growth is likely to be more accurate, reflecting a closer alignment with actual economic outcomes.

In conclusion, this section provided an opportunity to compare the models that have been analyzed. In doing so, it becomes apparent that while the main model allows for the differentiation of the effects of macroeconomic and financial uncertainty, a question that could arise is if combining these uncertainties might lead to a more robust predictive performance. The performance seems slightly improved, but, as will be seen in the robustness test, it is important to differentiate the different effects that different variables could have on output growth, in order to understand the underlying dynamics better.

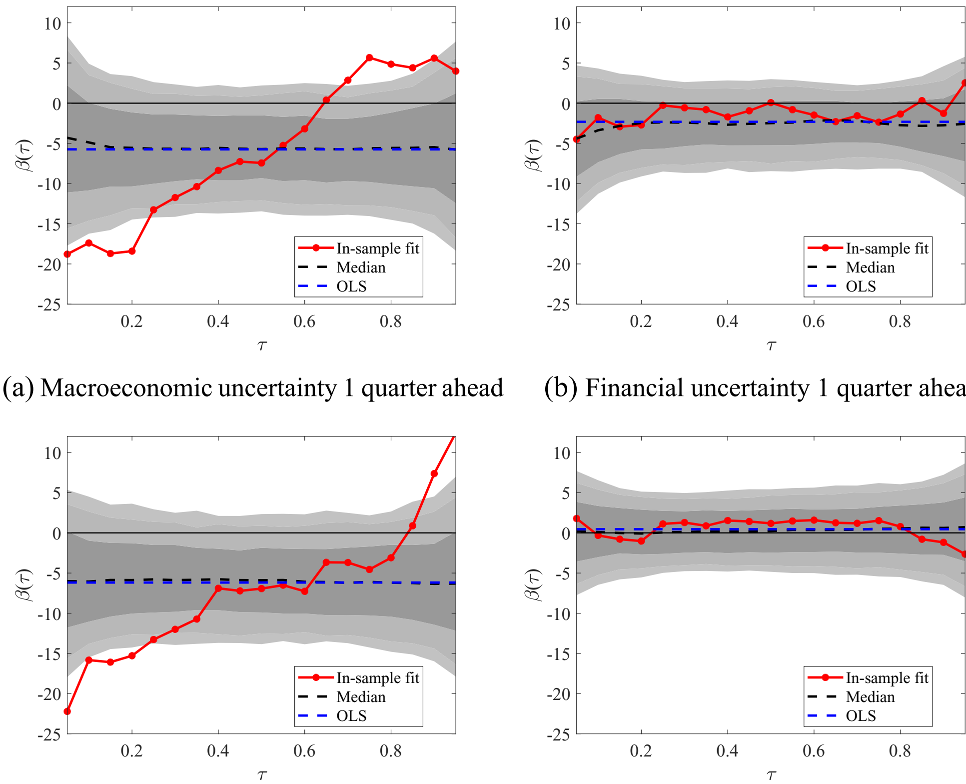
Chapter 5: Robustness analysis

5.1 Macroeconomic Uncertainty and Financial Uncertainty: joint impact

In the previous parts, results reported were related to models where uncertainties were considered separately, therefore it is possible to look at the differences of the effects that these variables had on the prediction of GDP growth. The following results will instead analyse whether conditioning output growth on both types of uncertainty could benefit the analysis. The question now is if the forecast is more accurate when both these inputs are considered to create a belief about what will happen during the window of a quarter or of a year.

It has to be considered that although the two indexes do not overlap, the macroeconomic index contains a group of data related to financial variables, but the tendency of macroeconomic uncertainty is to collect data in many different areas, and in some way the financial index completes it by defining more precise information in the area of stock markets. (see Appendix A for more details on data).

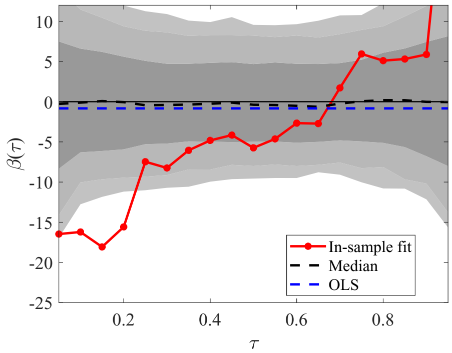
Therefore, with a variable that can capture a in a more comprehensive manner the dynamics of the anchor, the question now becomes how does this wider vision influence the expectations of the general public, if these beliefs are conditioned on a more complete set of predictors. The next step therefore is to perform the same analysis in the complete model.



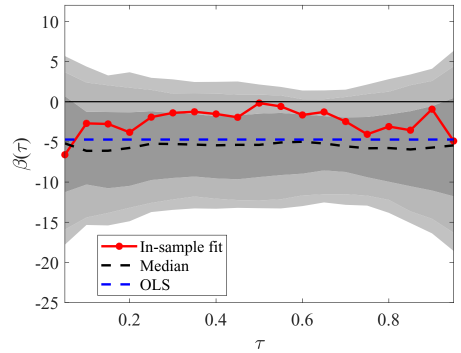
(a) Macroeconomic uncertainty 1 quarter ahead
(b) Financial uncertainty 1 quarter ahead
(c) Macroeconomic uncertainty 1 year ahead
(d) Financial uncertainty 1 year ahead

Figure 19: Uncertainty multivariate impact in sample 1970Q1 - 2019Q4

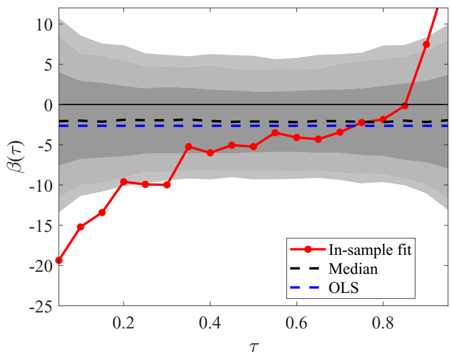
In the sample between 1970Q1 and 2019Q4 reported in Figure 19, it is visible that the in sample fit is significantly deviant from the grey areas when it concerns macroeconomic uncertainty, while it is more included for the financial index. The information provided from macroeconomic uncertainty seems to be stronger and again it is visible the double-edged nature of this uncertainty, as the sample fit lies both below and above the median. Financial uncertainty results are less stronger, the moment where the coefficients seem to be different from zero at a high critical value, the line lies almost always below the zero, therefore it is expected mainly a negative impact of this type of uncertainty on output growth, regardless of the quantile of the distribution chosen.



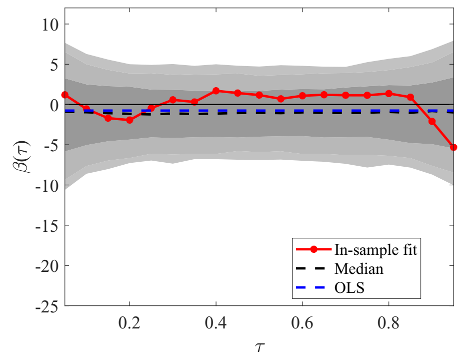
(a) Macroeconomic uncertainty 1 quarter ahead



(b) Financial uncertainty 1 quarter ahead



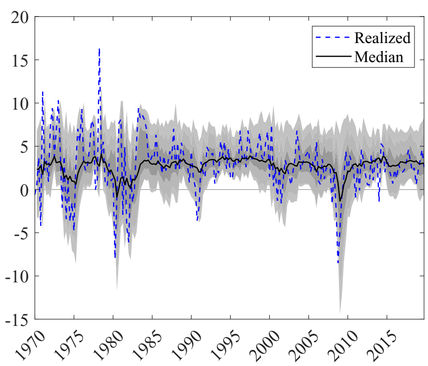
(c) Macroeconomic uncertainty 1 year ahead



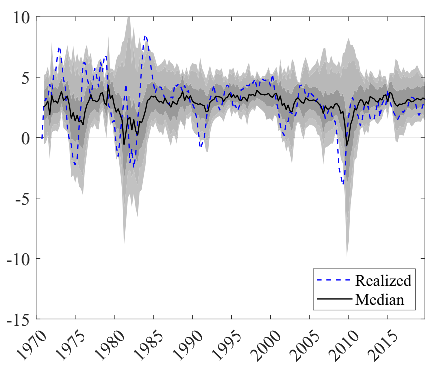
(d) Financial uncertainty 1 year ahead

Figure 20: Uncertainty multivariate impact in sample 1970Q1 - 2023Q2

The analysis of the coefficients in Figure 20 show that the variables behaviour does not change if the model in which the variables influence GDP growth in the same moment in a larger sample, which includes the COVID crisis, is considered. On the other hand, the predicted distributions do not show significant results, as it is difficult to distinguish between the two different effects.

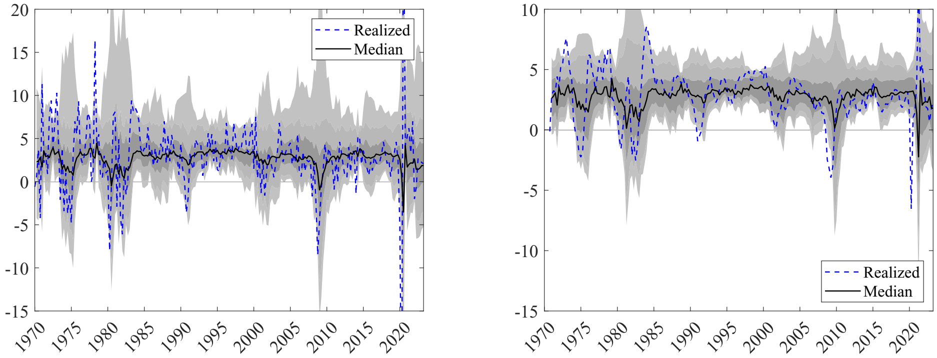


(a) Uncertainty 1 quarter ahead



(b) Uncertainty 1 year ahead

Figure 21: Predicted distribution sample 1970Q1-2019Q4

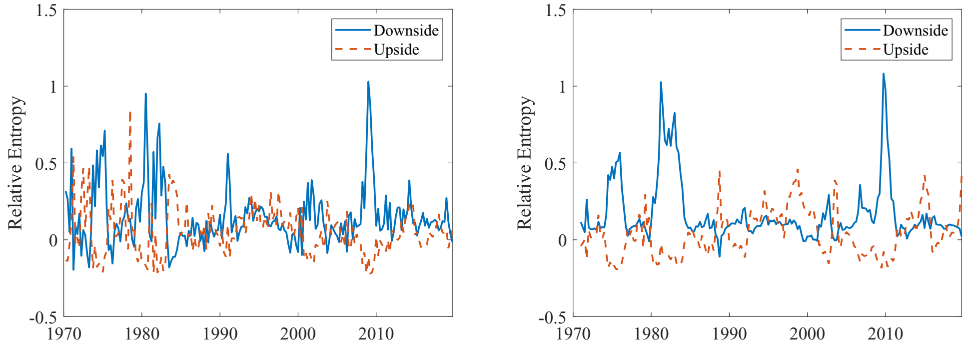


(a) Uncertainty 1 quarter ahead (b) Uncertainty 1 year ahead

Figure 22: Predicted distribution sample 1970Q1-2023Q2

Therefore, from Figure 21 and 22, when it comes to understanding the relationship that a movement in uncertainty has on business cycles, it is important to remember that is critical to separate the impact of financial and macroeconomic variables on GDP growth, as there could be different effects and higher uncertainty could have different meanings. In this case, the results seem to be aligned with macroeconomic uncertainty predictions, and this could be given by the way the indexes are formed. As said in the data section of this dissertation, macroeconomic uncertainty captures a wide variety of data and categories, with respect to the financial aspect, which is more specific. So it seems that the macroeconomic index could be described as the summary measure of uncertainty from both real and financial shocks (Berger et al. 2023). In the moment were a forecast of the GDP growth is needed, including both indexes to explain the variable, means that results show higher volatility on the upper side of the spectrum as well, but this is mainly given by the fact that there is the macroeconomic uncertainty boosting possibilities of future possible growth.

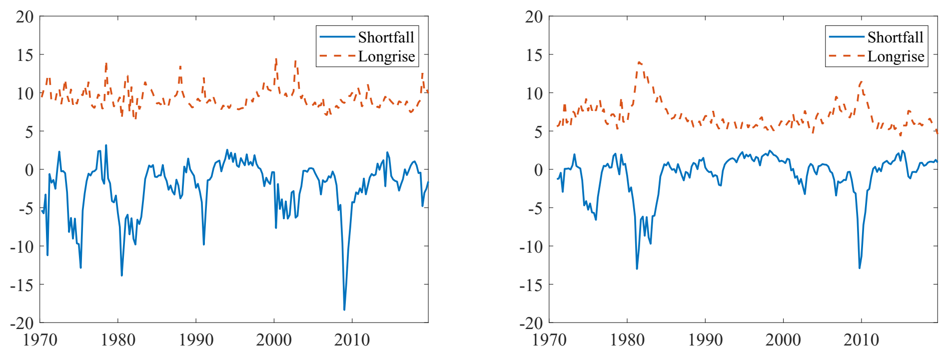
When both variables are considered together, Relative Entropy, shown in Figure 23, seems to remain similar to what happens when the analysis is performed separately for each type of uncertainty. In moments of recession, downside entropy is high for both financial and macroeconomic uncertainty, while upside entropy peaks more in the macroeconomic uncertainty framework.



(a) Macroeconomic uncertainty 1 year ahead (b) Financial uncertainty 1 year ahead

Figure 23: Relative Entropy in sample 1970Q1 - 2019Q4

In Figure 24 expected longrise shows a more stable and higher mean in the macroeconomic uncertainty variable, while financial uncertainty displays higher variability in expected shortfall. Results seem to confirm what previously seen with the analysis with separated indexes.



(a) Macroeconomic uncertainty 1 year ahead (b) Financial uncertainty 1 year ahead

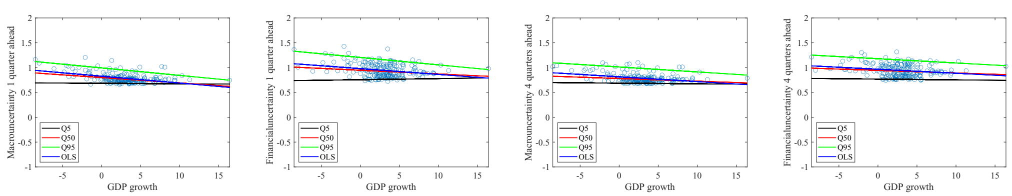
Figure 24: Shortfall and Longrise in sample 1970Q1 - 2019Q4

5.2 Endogeneity: evaluating the impact of GDP growth on Uncertainty

At the time these indices were updated, the endogeneity or exogeneity of their impact on business cycles was considered a one of the main concerns. In the latest version of the indexes, not only are these indexes constructed, but the authors conclude that shocks to financial uncertainty are the main drivers of economic fluctuations, with macroeconomic uncertainty playing more the role of deteriorating the prospect of future output growth once the business cycle faces a downturn (Ludvigson et al. 2021). The question this section wants to answer is if GDP growth could be a predictor of changes in uncertainties in the future, therefore if the start of a negative relationship between higher uncertainty and recessions could be caused by a period of recession first.
This is measured including both uncertainties in the regression simultaneously, so the model now becomes the one described by equation 14

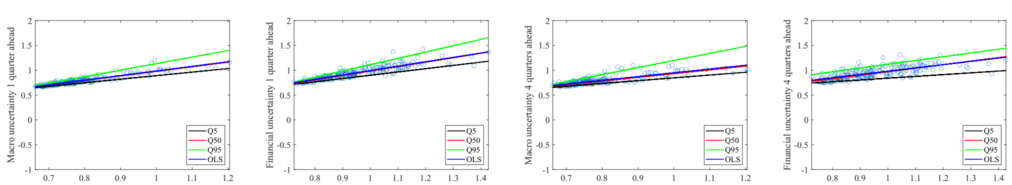
$$Uncertainty_{t+h} = \beta_0 + \beta_1 \cdot Uncertainty_t + \beta_2 \cdot GDP_t + \varepsilon_{t+h} \tag{14}$$

Univariate results effect of one type of uncertainty on future output growth over the horizon chosen.



(a) GDP on Macroeconomic uncertainty 1 quarter ahead (b) GDP on Financial uncertainty 1 quarter ahead (c) GDP on Macroeconomic uncertainty 1 year ahead (d) GDP on Financial uncertainty 1 year ahead

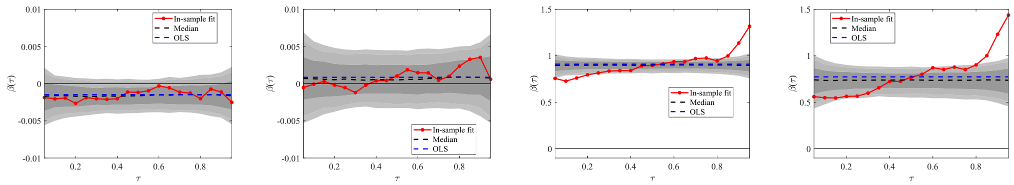
Figure 25: GDP growth impact in sample 1970Q1 - 2019Q4



(a) Macro uncertainty on Macro uncertainty 1 quarter ahead (b) Financial uncertainty on Financial uncertainty 1 quarter ahead (c) Macro uncertainty on Macro uncertainty 1 year ahead (d) Financial uncertainty on Financial uncertainty 1 year ahead

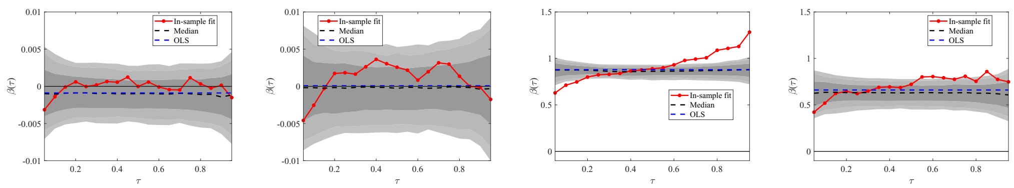
Figure 26: Uncertainty univariate impact in sample 1970Q1 - 2019Q4

Multivariate results effect of uncertainty on future output growth over the horizon chosen.



(a) GDP on Macro Uncertainty 1 quarter ahead (b) GDP on Macro Uncertainty 1 quarter ahead (c) Macro Uncertainty on Macro Uncertainty 1 quarter ahead (d) Macro Uncertainty on Macro Uncertainty 1 year ahead

Figure 27: Impact on Macroeconomic uncertainty in sample 1970Q1 - 2019Q4



(a) GDP on Financial Uncertainty 1 quarter ahead (b) GDP on Financial Uncertainty 1 year ahead (c) Financial Uncertainty on Financial Uncertainty 1 quarter ahead (d) Financial Uncertainty on Financial Uncertainty 1 year ahead

Figure 28: Impact on Financial Uncertainty in sample 1970Q1 - 2019Q4

Already in the univariate results GDP growth relationship with uncertainty, depicted in Figure 25, impact is almost none and obviously there is not a clear definition of asymmetry as seen before: the OLS line is almost coincident the extreme values of quantiles chosen (5th and 95th quantile). The impact of current uncertainty on the prediction over a certain horizon on the same type of uncertainty is really low, as seen in Figure 26. For multivariate results, both financial and macroeconomic uncertainty, in Figure 27 and 28 it seems that there is a slight significant effect of these variables, and the sample fit moves outside the grey areas indicating that a general linear model is not be the most efficient way to describe this relationship. Instead for GDP growth the in sample fit is inside the grey area and the zero coefficient is included bands: there is not a real necessity to differentiate for quantiles and the regression slopes seem to confirm the idea that neither macroeconomic or financial uncertainty are impacted by the level of current output growth in a significant way. The sample until 2023Q2 confirms the mentioned results considering the major COVID crisis (see Appendix).

Conclusion

The main question of assessing uncertainty impact is, considering common beliefs regarding the economic and financial developments of a nation, if it is possible to reach, with a certain extent of truthfulness, a prediction that is near the actual value of a certain variable in the future. By collecting the economic literature on this topic, it is difficult to find a theoretical consensus. This analysis itself reveals different results when different features in the indices used are considered. A major problem in this part of literature and empirical assessments will be the determination and identification of the uncertainty shocks in a detailed manner in order to distinguish the different channels of effects.

This dissertation was an empirical attempt to measure the impact of macroeconomic and financial uncertainty on business cycles, considering quarterly USA data. This is mainly achieved through the application of a quantile regression analysis of the indexes on the value of output growth over one quarter and one year ahead. Results of this attempt show that macroeconomic uncertainty accounts for a share of progress inherent in a certain part of uncertainty.

The main results are the asymmetries between upside and downside risk to of real GDP growth considering the distribution conditional on uncertainty. Considering financial uncertainty, downside risk seems more prominent: an increase regarding uncertainty on financial variables is is felt to be a bad signal. Considering macroeconomic uncertainty instead, although downside risk is more important, there is an important part of upper side risk which is a interesting result: it incorporates that part of uncertainty that accounts for the positive effect on output growth when uncertain situation could be a source of new opportunities.

This model showed in addition the importance of understanding the nature of the moment analysed: results are analysed in detail for the crises during 1974-1975 and 1981-1982 and 2008, with a specific note on 2020 as data seems biased from the large jump in GDP growth due to the virus period. Signals starting the crisis are different and therefore results have to be considered in different lights.

Vulnerability measures then effectively assess the asymmetry of uncertainty in GDP growth. Both computing relative entropy and with measures of expected shortfall and longrise this thesis gathers information on the different effects of macroeconomic and financial uncertainty.

To test the robustness, a model with both variables is analysed. Results suggest that although considering both types of uncertainty simultaneously could give more information, important nuances are lost. Both the revision of the literature, regarding other works, as well as results of this dissertation pointed clearly to the need of the right identification of the cahnnel in which uncertainty operates.

Regarding the endogeneity hypothesis, by assessing the impact of output growth on both types of uncertainties, results show that while both types of uncertainties have an impact on business cycles, the contrary cannot be said as results regarding this effect are small and not significant.

This dissertation shows that it is significant considering different robustness hypotheses, but it is important to understand the differences between macroeconomic and financial uncertainty.

Although many works are applying always better indexes and models to grasp this relationship, there is still a lot of space for future research. It would be really interesting to understand if different specification, based on a better identification of uncertainty, could better explain the channels in which this variable is in part responsible for positive but short fluctuations in GDP growth.

This analysis underlines how policy makers should use all information gathered on uncertainty: new policies should not forget about non linearities in the transmission channels of uncertainty and understand the importance of instruments used to measure this relationship.

This could lead in a level of progress in the way crisis are handled, as it is possible understand how to take advantage of a factor that has always been seen as negative signal by being more aware on its possible positive sides. In uncertainty there may be an inherent variable, a fair share of ”hope” in the future, that makes us realise what opportunities may arise if we know how to seize it.

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Chapter 6: Appendix

6.1 Appendix A: Summary of specific data of the uncertainty indexes

To understand better their peculiarities of the indexes and to better interpret following results of the quantile regression analysis, here are reported the details regarding the data constructing the indexes.

Macroeconomic data The FRED-MD (Federal Reserve Economic Data - Monthly Data) dataset is the basis used to construct the macroeconomic index. It is a dataset that collects a vast number of variables explain the general status of the U.S. economy. Explained in detail in the study by McCracken & Ng (2016), is mainly constructed with variables described in Table 3

Here's a summarized version of the dataset:

Group	Category	Description
Group 1	Industrial Production	Real Personal income and Industrial production indexes.
Group 2	Labor Market	Includes indexes describing the labor market, employment levels, and average hours worked.
Group 3	Housing Market	Data on the Housing market, with details on Building Permits.
Group 4	Sales and Manufacturing	Details on consumer sentiment and sales performance.
Group 5	Money Stock	Money stock and monetary base indexes, various types of loans.
Group 6	Interest Rates	Various data on US and other countries interest rates.
Group 7	Prices Indexes	PPI for various goods, CPI for items and services, and Crude Oil Prices.
Group 8	Stock Market	S&P 500 data including Dividend Yield and Price-Earnings Ratio.

Table 3: Descriptions and Indicators in FRED-MD Groups

As it can be seen, financial variables are somehow included in group 8. These then referenced and more detailed in the construction of the dataset of financial uncertainty.

Financial data Data used to construct the financial uncertainty index comes from two main sources: the Center for Research in Security Prices (CRSP) and Kenneth French's data library. CRSP data include several important financial measures. For example, the index looks at changes in dividends, prices, and other related financial activities over time. In addition to CRSP data, the index uses several factors from Kenneth French's library as described in Table 4:

Variables	**Description**
R15-R11	This variable compares small companes return with the ones of bigger companies, to see their difference.
Cochrane-Piazzesi Factor	Based on the work of Cochrane & Piazzesi (2005), this factor predicts expected excess returns in the market.
Market Excess Return	Shows the extra returns over a risk-free rate
Size	Measures how smaller companies perform compared to larger ones
Value	Assesses the performance of value stocks versus growth stocks
Momentum	Looks if stocks that had high performance before continue to do well

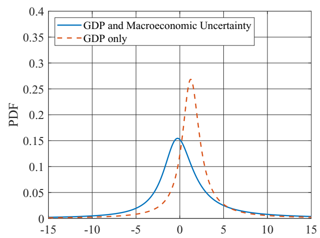
Table 4: Kenneth French's library

In addition, in financial uncertainty data there is a lot of detail on the performance of more specific industry portfolios. Therefore this data adds a lot of nuance to the measurement of uncertainty, giving an idea on how specific markets react.

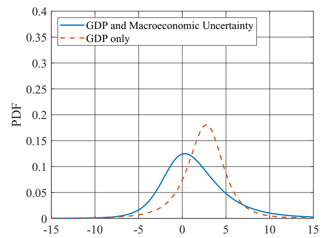
6.2 Appendix B: additional results in the sample 1970Q1 - 2023Q2

6.2.1 Distributions in sample 1970Q1 - 2023Q2

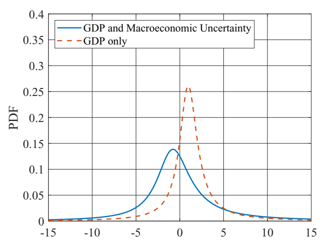
Macroeconomic Uncertainty PDFs



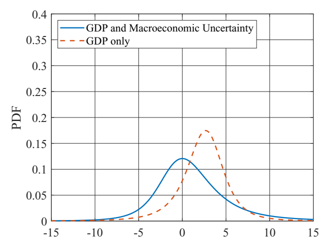
(a) PDF H1 1975Q1



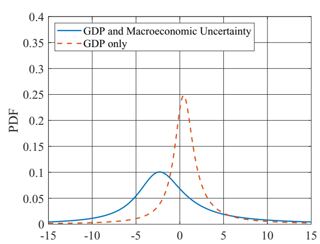
(b) PDF H4 1975Q1



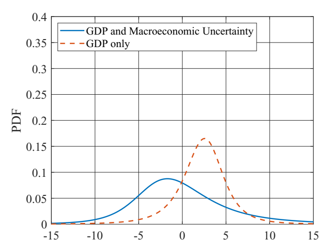
(c) PDF H1 1982Q2



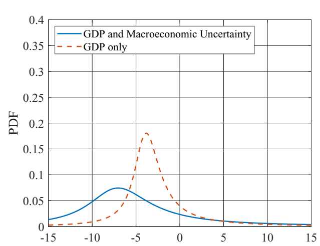
(d) PDF H4 1982Q2



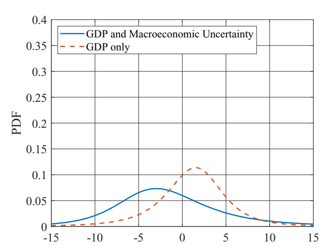
(e) PDF H1 2008Q4



(f) PDF H4 2008Q4



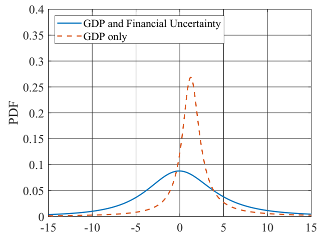
(g) PDF H1 2020Q2



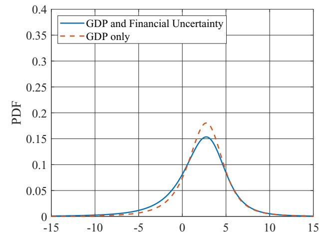
(h) PDF H4 2020Q2

Figure 29: Macroeconomic Uncertainty PDFs 1970Q1-2023Q2

Financial Uncertainty PDFs



(a) PDF H1 1975Q1



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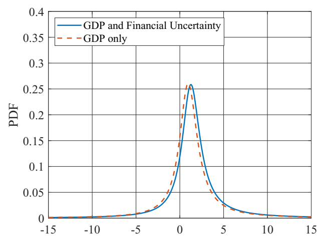
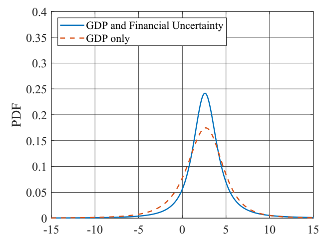
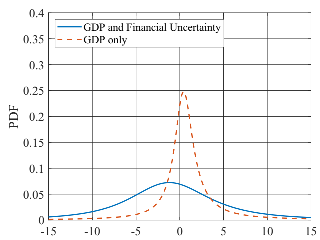


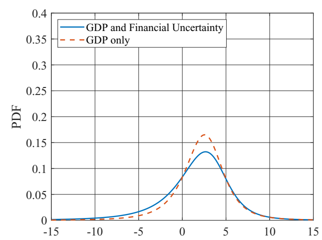
(c) PDF H1 1982Q2



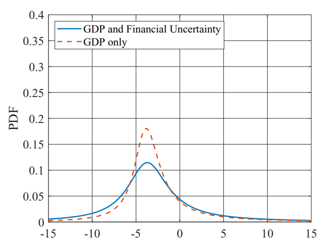
(d) PDF H4 1982Q2



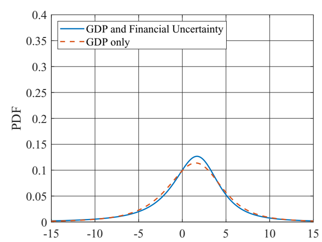
(e) PDF H1 2008Q4



(f) PDF H4 2008Q4



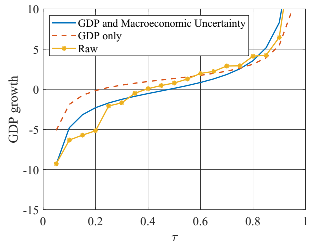
(g) PDF H1 2020Q2



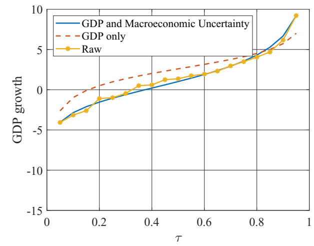
(h) PDF H4 2020Q2

Figure 30: Financial Uncertainty PDFs 1970Q1-2023Q2

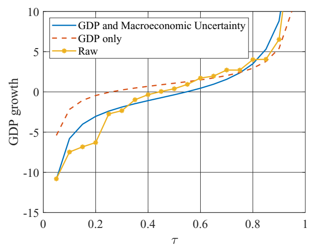
Macroeconomic Uncertainty Inverse CDFs



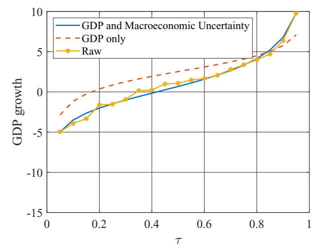
(a) InverseCDF H1 1975Q1



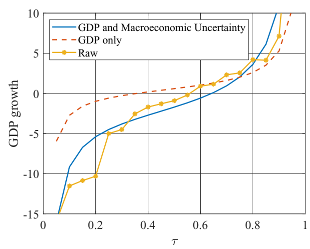
(b) InverseCDF H4 1975Q1



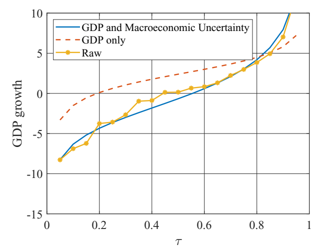
(c) InverseCDF H1 1982Q2



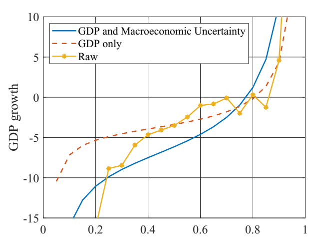
(d) InverseCDF H4 1982Q2



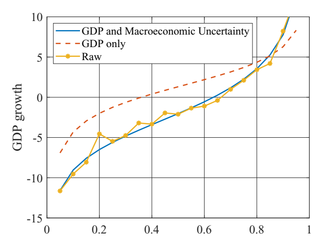
(e) InverseCDF H1 2008Q4



(f) InverseCDF H4 2008Q4



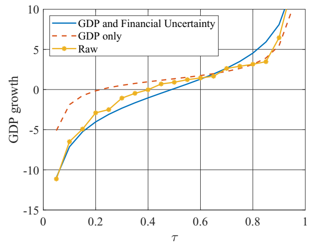
(g) InverseCDF H1 2020Q2



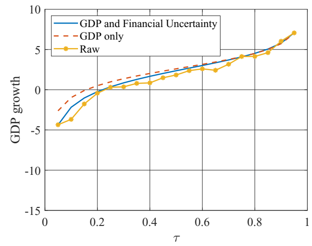
(h) InverseCDF H4 2020Q2

Figure 31: Macroeconomic Uncertainty Inverse CDFs 1970Q1-2023Q2

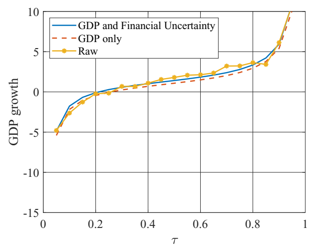
Financial Uncertainty Inverse CDFs



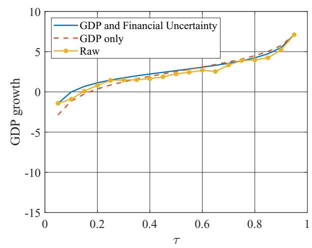
(a) InverseCDF H1 1975Q1



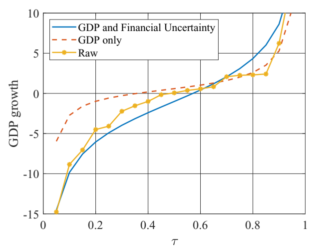
(b) InverseCDF H4 1975Q1



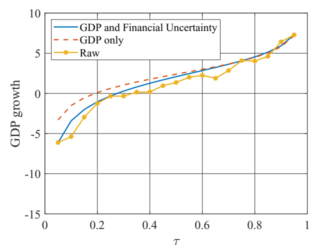
(c) InverseCDF H1 1982Q2



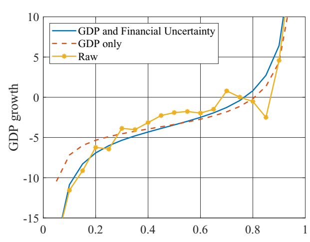
(d) InverseCDF H4 1982Q2



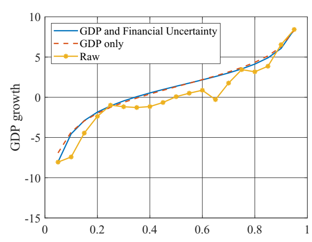
(e) InverseCDF H1 2008Q4



(f) InverseCDF H4 2008Q4



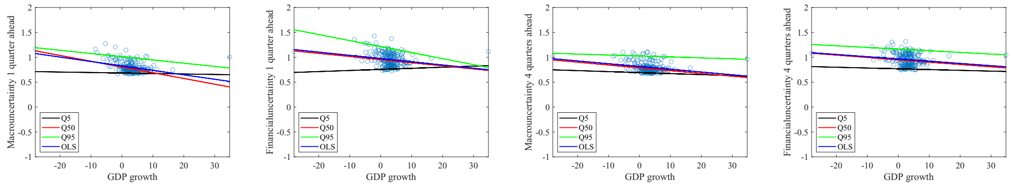
(g) InverseCDF H1 2020Q2



(h) InverseCDF H4 2020Q2

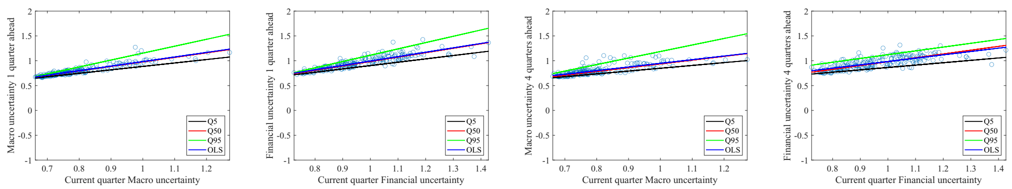
Figure 32: Financial Uncertainty Inverse CDFs 1970Q1-2023Q2

6.2.2 Endogeneity in sample 1970Q1 - 2023Q2



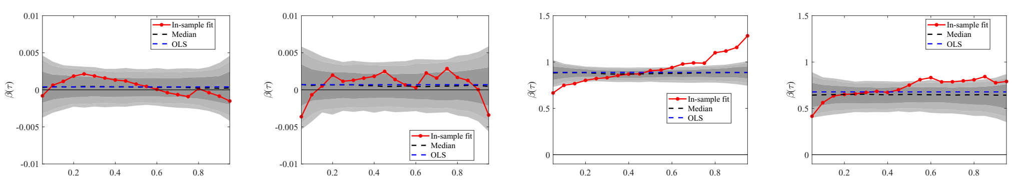
(a) GDP on Macroeconomic uncertainty 1 quarter ahead (b) GDP on Financial uncertainty 1 quarter ahead (c) GDP on Macroeconomic uncertainty 1 year ahead (d) GDP on Financial uncertainty 1 year ahead

Figure 33: GDP growth univariate impact in sample 1970Q1 - 2023Q2



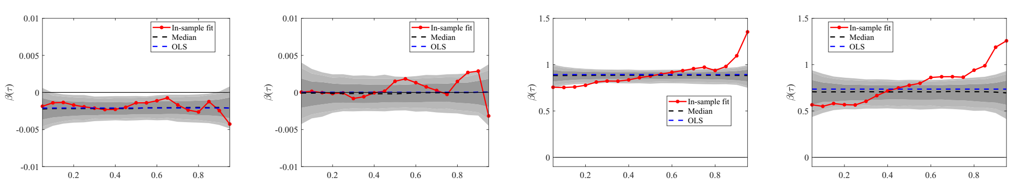
(a) Macroeconomic uncertainty 1 quarter ahead (b) Financial uncertainty 1 quarter ahead (c) Macroeconomic uncertainty 1 year ahead (d) Financial uncertainty 1 year ahead

Figure 34: Uncertainty univariate impact in sample 1970Q1 - 2023Q2



(a) GDP on financial uncertainty 1 quarter ahead (b) GDP on financial uncertainty 1 year ahead (c) Financial uncertainty on financial uncertainty 1 quarter ahead (d) Financial uncertainty on financial uncertainty 1 year ahead

Figure 35: Impact on Financial Uncertainty in sample 1970Q1 - 2023Q2

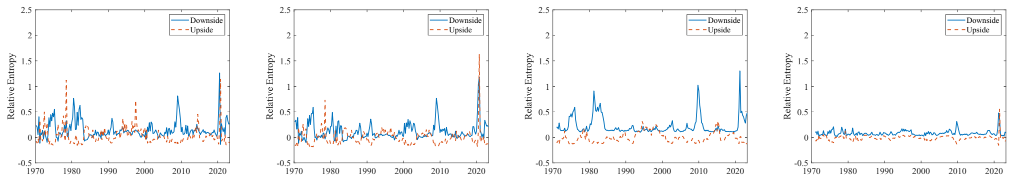


(a) GDP on Macroeconomic uncertainty 1 quarter ahead (b) GDP on Macroeconomic uncertainty 1 year ahead (c) Macro uncertainty effect on macro uncertainty 1 quarter ahead (d) Macro uncertainty effect on macro uncertainty 1 year ahead

Figure 36: Impact on Macroeconomic uncertainty in sample 1970Q1 - 2023Q2

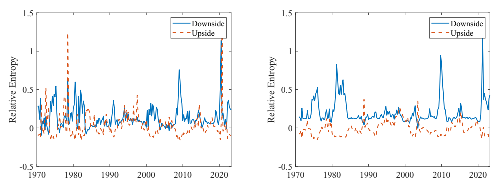
6.2.3 Vulnerability measures in sample 1970Q1 - 2023Q2

Vulnerability measures, with Macroeconomic and Financial uncertainty considered together or separately. Relative Entropy in sample 1970Q1 - 2023Q2



(a) Macroeconomic uncertainty 1 quarter ahead (b) Financial uncertainty 1 quarter ahead (c) Macroeconomic uncertainty 1 year ahead (d) Financial uncertainty 1 year ahead

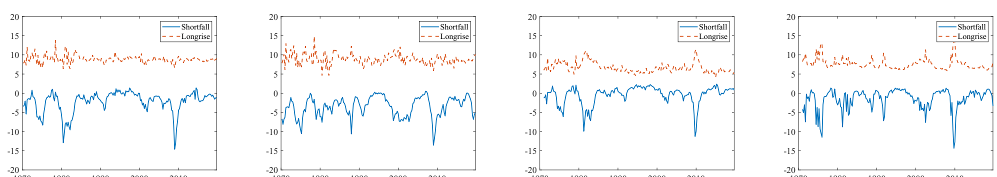
Figure 37: Relative Entropy, Uncertainty considered separately in sample 1970Q1 - 2023Q2



(a) Macroeconomic uncertainty 1 year ahead (b) Financial uncertainty 1 year ahead

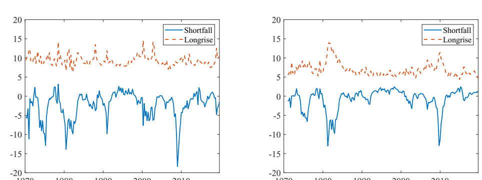
Figure 38: Relative Entropy, Uncertainty considered together in sample 1970Q1 - 2023Q2

Expected Shortfall and Longrise in sample 1970Q1 - 2023Q2



(a) Macroeconomic uncertainty 1 quarter ahead (b) Financial uncertainty 1 quarter ahead (c) Macroeconomic uncertainty 1 year ahead (d) Financial uncertainty 1 year ahead

Figure 39: Expected Shortfall and Longrise, Uncertainty considered separately in sample 1970Q1 - 2023Q2



(a) Macroeconomic uncertainty 1 year ahead (b) Financial uncertainty 1 year ahead

Figure 40: Expected Shortfall and Longrise, Uncertainty considered together in sample 1970Q1 - 2023Q2

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