Uncertainty is bad for Business. Really?

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Abstract

We investigate the impact of uncertainty shocks according to their nature applying local projection methods in a nonlinear framework. More precisely, we investigate the impact of uncertainty shocks according to their nature (nonfinancial and financial) in different regimes of general uncertainty: high, moderate and low. We get a positive and significant effect of the nonfinancial uncertainty shocks when the general level of uncertainty is high or moderate.

Keywords: Uncertainty, local projection methods, economic activity.
JEL Codes: C32; C38; E32

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1 Introduction

The common wisdom about uncertainty is that it is negative. The last financial crisis and the following surge of papers in the literature that study the effects of uncertainty were perceived as empirical validations of this consensus. However, since the middle of the last decade some papers have started to consider the possibility that some forms of uncertainty may instead have a positive impact on the economy.

This recent and still rare literature has started with a paper by Segal *et al.* (2015) that states uncertainty may also be about positive growth perspectives. For instance one may think to recent developments on Artificial Intelligence (AI). Despite forecasting what will be the industrial achievements due to AI in ten years is highly uncertain, predicting that these achievements will generate very large profits is a safe bet. Some authors refer to this theory as the "growth option" theory. Segal *et al.* (2015) postulate that uncertainty may be good or bad, they develop a theoretical model in which they introduce good and bad shocks and study the effect of uncertainty surrounding those shocks. They show theoretically that good uncertainty may have a positive effect on various variables when there is a channel through which uncertainty influences future growth. They then confirm this empirically.

Another paper that highlights a positive effect of uncertainty is Ludvigson *et al.* (2021). They use an index of macroeconomic uncertainty (developed in a previous paper, Jurado *et al.*, 2015) and an index of financial uncertainty which is newly built for this work. They have various results but focusing on a possible positive effect of uncertainty, they find that a shock on the macroeconomic uncertainty generally has a positive effect on industrial production on the short term that turns negative in the long-run. They argue that the positive effect they identify confirms the "growth option" theory.

Forni *et al.* (2021), rely on the work by Adrian *et al.* (2022) to estimate quantiles of predicted growth to also distinguish good and bad uncertainty. They show that despite the main effect on real economic activity of uncertainty is related to its bad component, it is possible that its positive one may have a positive effect. They explain that the reason why they, as well as the other papers of this literature, mostly find a negative effect of uncertainty is due to the

predominance of its negative components in the data.

Larsen (2021) uses machine learning techniques that autonomously identify some types of uncertainty by analyzing many Norwegian business press articles. Then the author introduces these various types in SVARs and it appears that some of them, especially those related to business (e.g. Mergers & acquisitions), have a positive effect.

One last paper that finds a short run positive effect of uncertainty is Ferrara *et al.* (2022). They show that an energy-specific uncertainty shock may have a short run positive effect on economic activity. This result being especially true for countries that produce energy.

This paper is in line with this very recent literature in that it is about finding under which conditions uncertainty may have a positive effect. Despite very rare, previous empirical results highlight that positive uncertainty may come from industrial prospects or be more broadly macroeconomic. Arguably, industrial perspectives are a subset of the macroeconomic context. To the contrary, uncertainty is not positive when it is about finance. The three papers above as well as the other works analyzing the effects of uncertainty starting with the seminal paper of Bloom (2009) do all conclude that uncertainty related to financial variables has a clear negative impact. So we first propose a mean to empirically distinguish endogenously financial uncertainty from non financial one. Second, we show that non financial uncertainty may have a positive effect under some conditions. Contrary to previous works that find a positive effect of uncertainty, we provide a more general approach that allows to identify a positive effect of uncertainty.

Concerning the theoretical mechanisms that may explain a positive effect of uncertainty. Segal *et al.* (2015) proposes a model based on the intuition that when it concerns industrial prospects, uncertainty may be good. Ludvigson *et al.* (2021) refer to this mechanism as the "growth option" theory and connect it to several old papers (Oi, 1961; Hartman, 1972; Tisdell, 1978; Abel, 1983) that in fact are not really directly about growth (Larsen, 2021, does a distinction). They rather show that because firms are not risk averse, they may prefer price instability because the best uncertain issues generate very large profits. Nevertheless, they all relate to industry inasmuch firms are at the center of these mechanisms. In this paper, we add to these possible mechanisms another one that is inferred from recent works by Gabaix (2014, 2020)

on behavioral new Keynesian models. Simply put, the idea is as follows. The second article shows that agents, because they are partly myopic, fail to perfectly anticipate future taxes after a stimulus is enacted. This implies that Ricardian equivalence does not hold. The first article as for it models how agents decide what degree of attention to bring to each existing information in order to process an action aimed at optimizing their utility. We develop what we may call an intuitive demonstration, despite not a formal proof, that conditions under which increased uncertainty may lead to a reduced mean attention do exist. As a consequence, by increasing agent's myopia, uncertainty may lead stimuli to have a stronger (positive) effect. This leads us to posit that uncertainty may have a positive effect not only when it concerns industrial aspects but more generally when it is non-financial.

Come back to the empirics of uncertainty. This is an unobservable phenomenon and measuring it is clearly a challenge. In recent years, a booming economic research has emerged to take up this challenge and to propose how to quantify uncertainty. Ferrara *et al.* (2017) review all the different methodologies to measure uncertainty and their impact on macroeconomic variables. In this paper, we contribute to this growing empirical literature and we propose three new improvements. Firstly, using a new measure of general uncertainty (See Himounet, 2022), we provide an empirical analysis in order to identify not only changes in the overall level of uncertainty in the US but also the determinants of an uncertainty shock (financial, macroeconomic policy, news index, geopolitical risks, ...). Secondly, we identify the conditions under which uncertainty could have a positive effect on the economy by testing an intuition derived from Gabaix? results in a linear VAR model. Thirdly, we validate this intuition using a non linear VAR model hence empirically proving that conditions which for uncertainty has a positive effect on the economy do exist.

As in Himounet (2022), we apply a principal component analysis (PCA) in order to build up a global measure of uncertainty for the US using new measures recently developed in the literature. The novelty of our approach is to interpret and use both the first and the second factors of the PCA. In particular, if as expected the first factor can be interpreted as a measure of the general level of uncertainty, the second one of this PCA is more about the nature of uncertainty. This second factor is high when uncertainty is industrial/macroeconomic, hereafter

we will write non-financial, and low when it is financial. We use these factors to study the impact of uncertainty shocks using local projection methods (Jordá, 2005) on US data on the period 1990-2019.

Our US global uncertainty variable (Factor 1) is shown to have a negative and significant effect on all the macroeconomic variables used in the estimations as the literature generally finds. Then, we conduct the same analysis using the factor that discriminates between financial and non-financial uncertainty (Factor 2) and find no significant effect. Strikingly, using a nonlinear framework, we obtain a positive and significant effect of this second dimension of uncertainty on industrial production and a negative one on the unemployment when the general level of uncertainty is high. Several robustness checks confirm this result.

The rest of this paper is organized as follows. In section 2, we present a brief literature review on the positive effect of uncertainty and develop our intuitive demonstration from Gabaix' works. In section 3, we use local projection methods to investigate the dynamics between uncertainty and economic activity in a linear and a non linear framework. In section 4, we present robustness checks. The last section presents our conclusions and directions for future research.

2 Positive effect of uncertainty: Literature review and theoretical discussion

A recent literature has emerged proposing different measures of uncertainty based on various methodologies making the task of establishing a consensus on how to measure uncertainty very hard, if not impossible. This section presents the papers that have put forward a positive effect of uncertainty and then discusses the possible theoretical arguments for this positive effect. For those interested, Himounet (2022) proposes a very detailed literature review of all the papers that develops some measures of uncertainty with the aim of improving the Ferrara *et al.* (2017)'s classification and uncertainty approximation with new measures and approaches.

2.1 Positive effect in the data

Segal *et al.* (2015) is the first paper to break the consensus about the negative effect of uncertainty. They start from a conjecture: uncertainty may be good for business activities when considering future industrial perspectives. They give the example of the high tech revolution of the 1990s during which it was hard to guess what would be the concrete achievements for the business. However, many business analysts and specialists were almost certain that many firms would benefit from these new technologies. Arguably, it was true. Then, they first develop a theoretical model in which both kind of uncertainty shocks exist, negative and positive. These shocks affect consumption growth as well as consumption expectation. This last effect allows uncertainty to have opposed effects. The authors confirm empirically the existence of a positive component of uncertainty using a VAR. Their methodology implies that positive shocks are by nature positive since they correspond to positive semivariances of industrial production. Then they use the predictable component of this measure to capture ex-ante uncertainty. It results that shocks on good uncertainty have lasting (positive) effects on several key macro variables and that it dampens the negative effects of bad shocks. In a similar way, Forni *et al.* (2021) decomposed uncertainty between two components relying on the methodology of Adrian *et al.* (2022): downside uncertainty and upside uncertainty. Downside uncertainty is considered as uncertainty on the future decrease of growth while upside uncertainty is considered as uncertainty on the future increase of growth.[1] As expected, the authors get a negative effect of downside uncertainty and a slightly positive effect of upside uncertainty. Their results seem to underline that the negative component of uncertainty dominates the positive component in uncertainty data explaining the fact that most studies have got a negative effect.

Ludvigson *et al.* (2021) have decomposed uncertainty between macroeconomic uncertainty and financial uncertainty. According to them, financial uncertainty could be very linked to recessions, both as a cause and as a propagating mechanism. Macroeconomic uncertainty and financial uncertainty are computed using Jurado *et al.* (2015)'s methodology. Jurado *et al.* (2015) have constructed a measure of macroeconomic uncertainty using a panel of macroeconomic and

[1] Forni *et al.* (2021) defined downside uncertainty as the difference between the forecast of the median and the 10th percentile of the future growth. Upside uncertainty is defined as the difference between the forecast of the 90th percentile and the median of the future growth.

financial time series (industrial production, real income, hours, unemployment, prices, stock market indexes, ...).They argue that volatility measures are partly predictable. So, in order to get a "true" measure of uncertainty, the predictable component of each series must be removed. Using this methodology, Ludvigson *et al.* (2021) have developed a financial uncertainty index from a panel of 148 monthly financial indicators (Treasury bill yields, price-earnings ratio, risk factors of Fama & French (1992), ...).

Then, they propose a new method to estimate a SVAR model with several event constraints. One of their side result, this was not the objective of their paper to show this, is to find a positive effect of uncertainty. Himounet *et al.* (2023) have showed that this result is at best to be considered very carefully. Indeed, it appears that the positive effect of uncertainty is fully explained by one constraint. This constraint is supposedly related to the end of Bretton-Woods but we show that it is also related to the end of a one year recession. Hence the positive effect of uncertainty would be in fact the surge of growth that followed the recession.

Larsen (2021) relies on a different approach to measure uncertainty since he uses machine learning techniques to analyse Norwegian business articles published in a daily newspaper. In a first step, the author uses an unsupervised learning algorithm that will both classify by topic the articles and quantify the degree of uncertainty. Each of the 80 topics may vary in time according to the degree of uncertainty that is related to it. For instance, the measure linked to the topic on *Oil price* varies whether events related to this topic generate more or less uncertainty. Then he runs SVAR with narrative sign restrictions *à la* Antolín-Díaz & Rubio-Ramírez (2018). Some topics exhibit the usual pattern of uncertainty as more uncertainty results in a decrease in variables used to evaluate the health of an economy. However, it appears that the opposite is true for the topic on *Mergers & acquisitions* which for uncertainty has a positive effect on the economy.

Ferrara *et al.* (2022) is the more recent paper to obtain a positive effect. The paper aims at analyzing the effect of commodity prices shock on real economic activity. They use three commodities categories, agricultural, metals and energy that each contain four different commodity prices. They first show that there is a common commodity factor that they interpret as the general uncertainty component as in many studies of the literature. Then, they isolate each pure

factor related to each of the three categories of commodities. It appears that the general factor as well as those related to agricultural and metal have a negative effect. However, it turns out that the third pure factor, related to energy, has a short run positive effect. They refer to Punzi (2019) that argue that the risk that oil price goes too high in a near future may induce firms and households to anticipate their energy consumption hence inducing a short run positive effect of uncertainty. Then, they build on this result to construct a more systematic way to identify good and bad uncertainty: bad uncertainty would be in action when commodity prices are increasing whereas good uncertainty would be an action when commodity prices are decreasing. This last estimation yields negative or non significant effects of uncertainty.

To sum up this brief literature review, some studies posit that uncertainty may be good or bad and the others find a positive effect without especially looking for it. Among these studies three of them highlight a very specific component of uncertainty related to business activities or energy prices that indeed has a positive effect. Among the two remaining works, one is in the category of assuming that uncertainty is either good or bad and finds a small positive effect while the other's result that identifies a positive effect of uncertainty is fragile. Our paper is the first to explicitly look for a positive effect of uncertainty without trying to isolate ex ante the positive component of uncertainty.

2.2 Positive effect in the theory

Among the papers referred to above, the last two do not develop a theoretical explanation of the positive effect of uncertainty. They instead refer to two old papers by Oi (1961) and Hartman (1972) to which Larsen (2021) adds Tisdell (1978). Oi (1961) shows that competitive firms that maximize short term profits always prefer price instability, hence uncertainty, over price stability. Tisdell (1978) extends the results of Oi (1961) to factors' price instability which is also preferred by competitive firms under the same conditions and shows that both output price instability and factors price instability are simultaneously preferred by competitive firms. Hartman (1972) shows that optimal investment of firms increases or remains unchanged with increased uncertainty in future output prices and/or wage rates and that it is invariant to uncertainty in future investment costs. Using a mean preserving uncertainty, he shows that this

result holds quite generally except that it requires the production function to be homogeneous of degree 1. Without going too far in analyzing these results, they mostly lay on the fact firms are risk-neutral. The explanation of Oi (1961) and Hartman (1972) is based on the assumptions of perfect competition. Caballero (1991) shows that if the assumptions of perfect competition are relaxed, firms' investments may fall when uncertainty increases but this relationship could also remain positive if firms have increasing returns to scale under imperfect competition.

As already written above, in Segal *et al.* (2015) the authors develop a theoretical model in which uncertainty shocks may either be positive or negative. As in Hartman (1972), the two shocks are mean zero. Both consumption shocks have time varying volatilities that depend on two state variables that represent good and bad macroeconomic uncertainties. They allow a feedback effect of the macro volatilities in that they also affect expected consumption. This means that good and bad macro uncertainties have direct effects on future economic growth as well as on the shocks. As the authors put it, they do not provide a *"primitive micro-foundation for this channel*, [but they] *show direct empirical evidence to support our volatility feedback specification"*. One important aspect is that agents may dislike uncertainty be it good or bad which implies that the overall effects of uncertainty will be skewed towards bad uncertainty. That is, good uncertainty has a negative component because it implies volatility. As a consequence, the equity risk premium the authors obtain exhibit a second order moment that is positive, i.e the risk premium increases, whereas the third order moment may be either positive or negative, i.e the risk premium increases or decreases.

These two first theoretical channels are rather related to industrial prospects that may have positive effect on future growth. Here we want to suggest another mechanism that would explain a positive effect of uncertainty. This mechanism is related to recent works by Gabaix (Gabaix, 2014, 2020). In the first of these two articles Gabaix proposes the sparse max operator in which agents do not observe all the information available at time *t*. In order to decide which action to undertake they will first have to allocate for each available information x_i an amount m_i of attention for $i = 1, \ldots, N$. Consequently, the agent does not take into account most of the information available because it is costly to analyze it. The agent observes $x_i^s := m_i x_i$ instead of x_i and there may have a lot of null m_i depending on some parameters.

In the second article, Gabaix develops a behavioral new Keynesian model that is built on a simplified version of Gabaix (2014) as he mostly uses a macroeconomic attention parameter $\bar{m}$ which somehow represent the mean of the above m_i. Similarly, this means that agent are partly myopic since they only observe $\bar{m}x_i$. As a consequence, $\mathbb{E}_t^{BR}[z(X_{t+k})] = \bar{m}^k \mathbb{E}_t[z(X_{t+k})]$ where the left hand side (LHS) is the expected value of the behavioral agent at time t of the vector of variable X_t in k periods and the last term of the right hand side (RHS) is the expectation of a rational agent that corresponds to $\bar{m} = 1$ coefficiented by $\bar{m}^k$ which indicates that myopia is increasing with distance to the future.

One of the (many) insights of Gabaix (2020) is that with behavioral agents, Ricardian equivalence does not hold anymore. Proposition 7 of this paper is about fiscal policy and concerns a situation with a public deficit $d_t := \mathcal{T}_t + \frac{r}{R} B_t$ financed with debt in order to allow a lump-sum transfer $\mathcal{T}$ to the agents. The value of the government debt evolves as $B_{t+1} = B_t + Rd_t$. This proposition establishes that the new IS curve becomes

$$x_t = M\mathbb{E}_t[x_{t+1}] + b_d d_t - \sigma(i_t - \mathbb{E}_t[\pi_{t+1}] - r_t^{n0}) \tag{1}$$

We want to focus here on the second term of the RHS: $b_d d_t$. It measures the sensitivity to deficits of the agent. It is null if $\bar{m} = 1$ (agents are rational) but it is positive otherwise and decreasing in $\bar{m}$. As exposed in the appendix of Gabaix (2020), this part of the paper requires an additional state vector $\mathbf{Z}_\tau$ that complements the original vector X_τ. The agent has then to observe now some additional information that concern precisely deficits. The perceived future taxes are then given by

$$\mathbb{E}_t^{BR}[\mathcal{T}(Z_\tau)] = -\frac{r}{R} B_t + \bar{m}^{\tau - t} \mathbb{E}_t \left[d_\tau - r \sum_{u=t}^{\tau-1} d_u \right] \tag{2}$$

The first term of the RHS reflects a Ricardian behavior: If debt was to remain at its level in t, namely B_t, then the behavioral agent correctly anticipates that the debt will have to be repaid. The second term reflects the myopia of the behavioral agent that fails to precisely taking into account of future deficits and their fiscal consequences on its revenues, i.e futures taxes implied by the future deficits.

Now come back to Gabaix (2014) that explains how an agent chooses the degree of attention it will bring to each available information. Proposition 1 of this paper establishes the behavior of a behavioral agent that uses the sparse max procedure to choose which x_i he will consider and with which degree of attention. The consequences of proposition 1 are that (i) many x_i are eliminated, (ii) more attention is paid to more variable x_i, (iii) more attention is paid to x_i that matter more for the action the agent considers to undertake, (iv) more attention is paid to x_i that may generate great losses and (v) more attention is paid generally if the cost of attention is low.

Where do we see uncertainty in this model? One could argue that this is the variance of x_i. If this is so, then proposition 1 establishes that more attention is paid to an information that varies more. However, what if the number of x_i increases temporarily? What if the number of more variable x_i^s increases temporarily? We believe that these two possibilities better reflect the idea of a general uncertainty. In order to answer intuitively to these questions, let see how the attention vector is chosen by a behavioral agent (Definition 1 in Gabaix (2014)):

$$\underset{m\in[0,1]^n}{argmin}\frac{1}{2}\sum_{i,j=1..n}(1-m_i)\Lambda_{ij}(1-m_j)+\kappa\sum_{i=1..n}m_i^{\alpha} \tag{3}$$

where $\Lambda_{ij}=-\sigma_{ij}a_{x_i}u_{aa}a_{x_j}$. σ_{ij} is the covariance of x_i and x_j, a_{x_i} is the marginal effect of x_i on the optimal action of the agent and u_{aa} is the second derivative of the utility function with respect to a, the action. κ and α parameterize the psychological cost of paying attention to any variable, the first part is the quadratic loss associated to the fact of not taking the right action because the agent observes m_ix_i instead of x_i.

Assume as Gabaix mostly does that the agent considers the variables as uncorrelated. Consider first the possibility of an increase of the number of variables. If one assumes that the initial total psychological cost paid by the agent before the increase in the number of variables is the maximum the agent can bear[2], then adding any new variable implies that the mean attention vector is reduced, even when $\alpha=1$, the value recommended by Gabaix. Indeed, the agent has to allocate the same total cost on $n+1$ variables instead on n.

Consider now the second possibility of more variable x_i^s. Under the same hypothesis on the

[2]It is admittedly a strong assumption but it reflects the more general idea that an agent may be constrained by a maximal psychological cost he can bear.

total psychological cost then, if $\alpha > 1$, increasing attention on variable x_j if m_j was already positive may necessitate to reduce at least one m_i such that $\Delta m_j < -\Delta m_i$. Consequently, the mean attention is also reduced. If m_j was null before its importance increased, then it is when $\alpha < 1$ that the same could happen. When $\alpha = 1$, then nothing happens since $\Delta m_j = -\Delta m_i$.

We may add that even without the assumption on the total psychological cost those effects should exist under some conditions. The characterization of those conditions is let for future work.

Finally, if one considers that variables are correlated as in 3. Note first that an increase of a_{x_j} implies that more attention should be paid to variable x_j. But as it is clear in 3, this increase will also affect the choice of the optimal m_i. There is no reason to consider that this relationship could not imply a reduction of m_i. This being true whatever the values of κ and α.

To conclude, there are a lot of reasons to believe that uncertainty may result in a decrease of $\bar{m}$ in 1. As a consequence, increased uncertainty would increase myopia of the agents if they are behavioral and then would reinforce the effect of the stimulus enacted by the government. It is important to be aware that the three theoretical explanations are complementary.

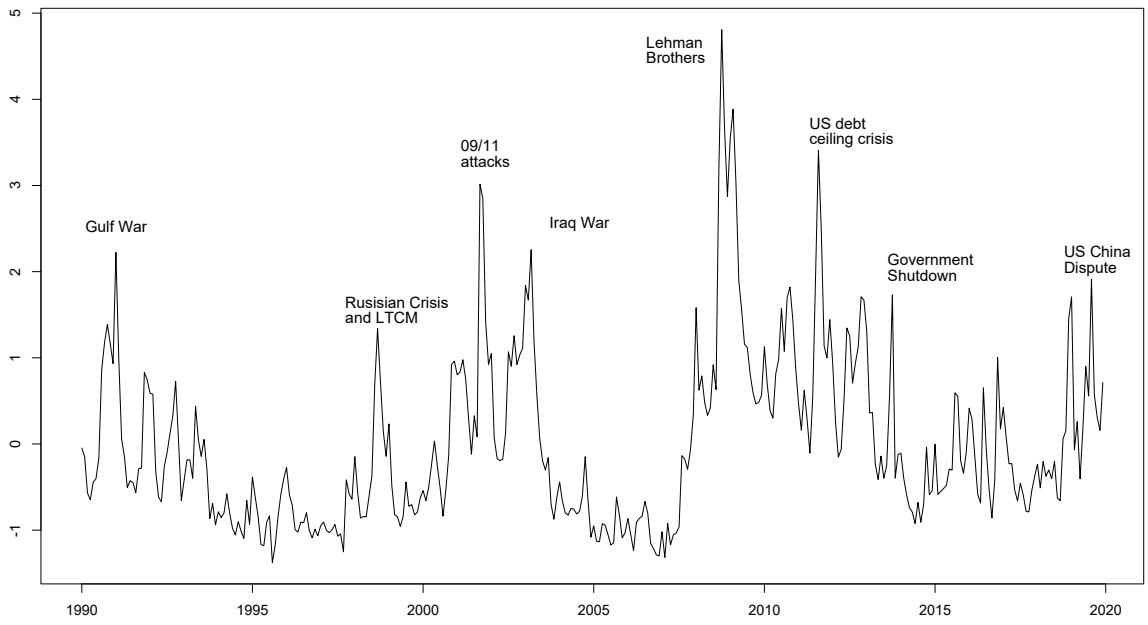
3 Uncertainty and Macroeconomy: a local projection approach

3.1 Uncertainty Data

To investigate the impact of uncertainty shocks on economic activity, many measures of uncertainty have been developed from different methodologies. However, many measures represent just one dimension of uncertainty: financial, economic policy, geopolitical,... As these indexes are provided from different methodologies, they provide different information. To take into account this heterogeneity, some works have developed composite indexes. Haddow *et al.* (2013) have constructed a global indicator of uncertainty for the United Kingdom based on a principal component analysis (PCA) with several indicators measuring uncertainty in the United Kingdom. Charles *et al.* (2018) have developed a global measure for the United States applying a dynamic factor model.

We are going to apply the measure estimated in Himounet (2022) from a PCA on the period January 1990 to December 2019. Figure 1 represents this synthetic or general measure over this sample. It can identify different uncertainty peaks corresponding to well identified events like the Gulf War, the Russian financial crisis and Long-Term Capital Management in 1998, the 9/11 attacks, the collapse of Lehman Brothers or the US debt-ceiling dispute in 2011. These are shocks (financial, macroeconomic, geopolitical, policy,...) that increase the general uncertainty.

Figure 1: General Uncertainty Index

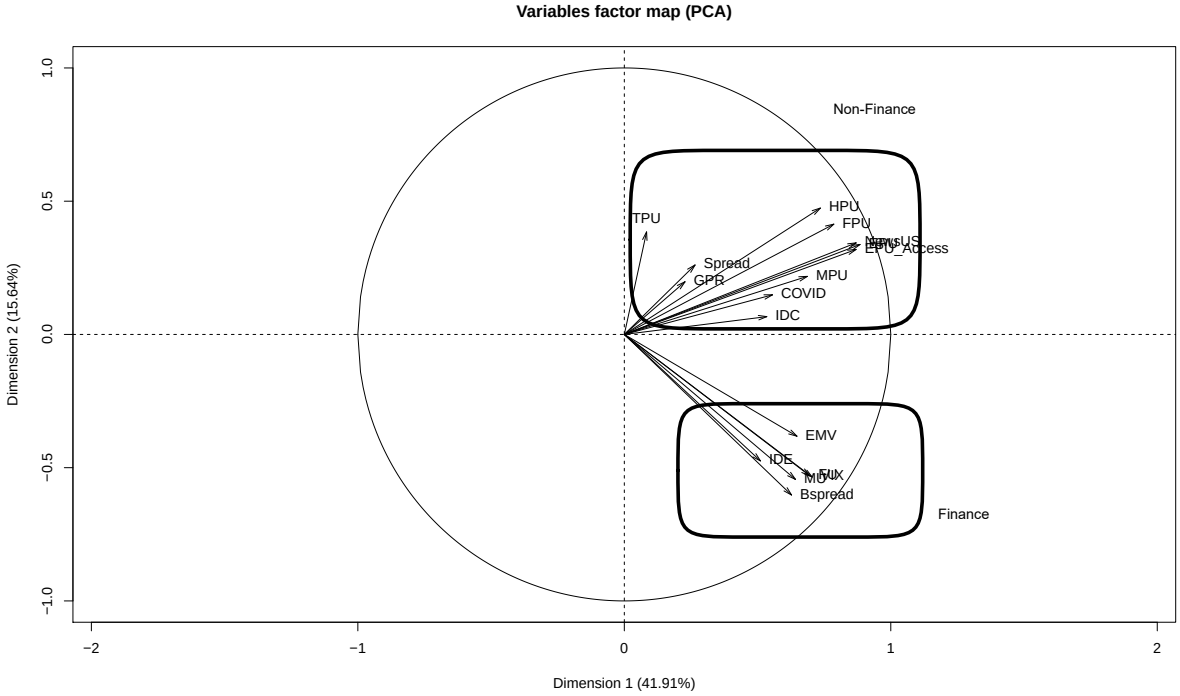


Note: The index is standardized over the period 1990-2019.

Beyond the first factor that approximate general uncertainty, the second factor of Himounet (2022) concerns the nature of uncertainty shocks by distinguishing two groups of uncertainty variables. On the Figure 2, the first group of the variables factor map includes non-financial uncertainty: economic policy uncertainty indexes of Baker *et al.* (2016), the consumer confidence index, the geopolitical risk index of Caldara & Iacoviello (2022),... The second group includes variables that are mainly linked to finance: the VIX index, the corporate bond spreads, the financial uncertainty index of Ludvigson *et al.* (2021),.... So, the second factor is a weighted sum of uncertainty indexes where financial indexes have a negative weight and non-financial indexes

have a positive weight. Figure 3 plots the second factor ($Factor2$) of the PCA of Himounet (2022). This variable discriminates two types of uncertainty shocks: non-financial and financial. The interpretation of this variable is that when this factor is high, the nature of uncertainty shocks is associated with macroeconomics or non-finance (Gulf War, Iraq War, Government Shutdown,...). Inversely, when this variable is low, the nature of uncertainty shocks is linked to finance (LTCM, Dot-Com bubble, Lehman Brothers). We will use this variable to investigate the nature of uncertainty shocks. As both variables are provided by the same PCA, they are orthogonal by construction.

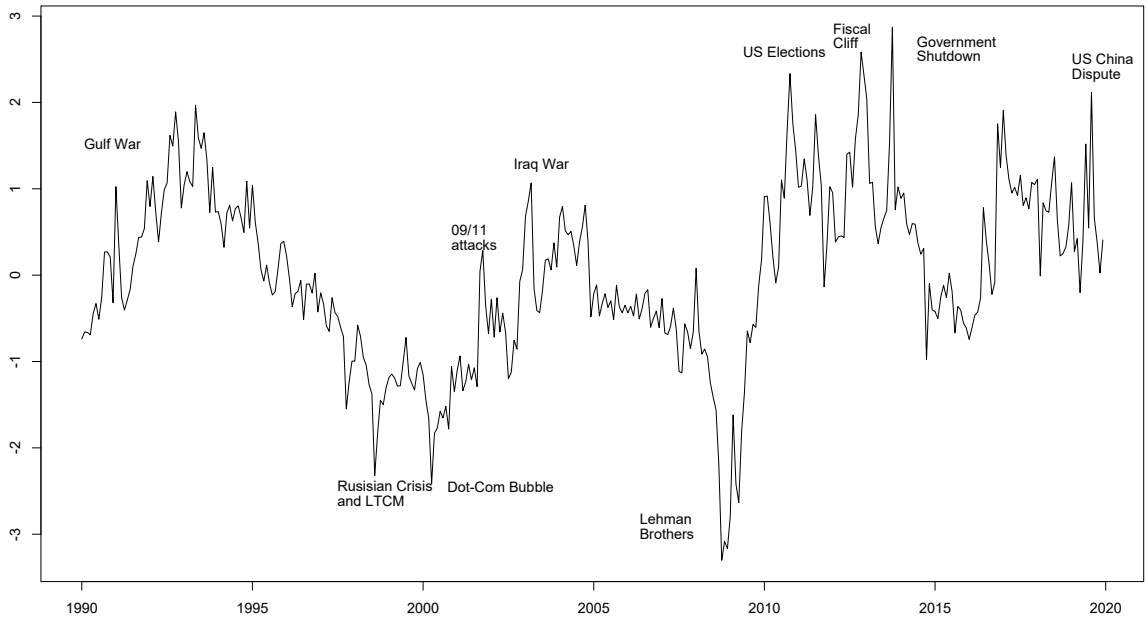
Figure 2: Variables Factor Map (Factor 1 and Factor 2) in Himounet (2022)



3.2 Linear Framework

To investigate the dynamics between macroeconomy and uncertainty, vector autoregressive (VAR) models developed by Sims (1980) have been traditionally used in the empirical literature to construct impulse responses. Based on the conventional reduced form VAR model, the notation for the impulse response function is based on the difference between two forecasts (Hamilton, 1994):

Figure 3: Factor 2



Note: The index is standardized over the period 1990-2019.

$$IR(t, s, d_i) = E\left(y_{t+s}|v_t = d_i; X_t\right) - E\left(y_{t+s}|v_t = \mathbf{0}; X_t\right) \quad s = 0, 1, ... \tag{4}$$

where $E(.|.)$ denotes the best mean squared error predictor, y_t is a $n \times 1$ vector, X_t denotes the lags of y_t (y_{t-1}, y_{t-2}, y_{t-3},...), $\mathbf{0}$ is a $n \times 1$ vector containing 0, v_t denotes a vector of reduced-form disturbances, and D is an $n \times n$ matrix, whose columns d_i contain the relevant experimental shocks.

Jordá (2005) has pointed out that this methodology is not optimal if the VAR does not coincide with the underlying data generating process and has developed a popular alternative approach to impulse responses from VAR: local projection methods. This methodology consists in running a series of predictive regressions of our variable of interest. The impulse responses are computed using regression coefficients. According to the author this method has many advantages. Local projections can be estimated by one equation, they are more robust to misspecification of the data generating process and can easily be adapted to a nonlinear framework. Jordá

(2005) has demonstrated that impulse responses from a VAR and local projection are equivalent if the VAR coincides with the true data generating process. Montiel Olea & Plagborg-Møller (2021) and Plagborg-Møller & Wolf (2021) have showed that local projections are more robust than the SVAR methodology. Both methodologies lead to the same median impulse responses in the short and medium term.

Applying the local projections of Jordá (2005), we run the following regressions:

$$y_{t+s} = \alpha_s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + ... + B_p^{s+1} y_{t-p} + u_{t+s}^s \qquad (5)$$
$$s = 0, 1, ..., h$$

where y_t is a vector of endogenous variables including our synthetic measure of uncertainty and a set of monthly macroeconomic variables:[3] industrial production, unemployment rate, inflation, oil prices, the S&P500 index and the fed funds rate. Impulse responses are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{B}_1^s d_i \qquad (6)$$
$$s = 0, 1, ..., h$$

where d_i corresponds to the i^{th} column of the experimental matrix D and the identified structural shock. We construct this matrix following the suggestion of Jordá (2005), which essentially follows methodologies applied in the traditional VAR literature and begins by estimating a SVAR with a Cholesky decomposition as identification scheme. If the shock is already identified and/or considered as exogenous, there is no need to apply a VAR model and

[3]The data used for the analysis are downloaded from FRED database on the Federal Reserve Bank of St. Louis' website.

the Cholesky decomposition:[4]

$$x_{t+h} = a^h + b^h shock_t + \gamma z_t + \epsilon_{t+h} \tag{7}$$

x_t represents the variable of interest, z_t a vector of control variables and $shock_t$ represents the identified or exogenous shock. The impulse response of $shock_t$ on x_t will correspond to the series of coefficients b^h for each horizon h.

We apply a Cholesky decomposition as many works which have used VAR models to identify our shocks (See, among many others, Bloom, 2009; Colombo, 2013; Jurado *et al.*, 2015; Baker *et al.*, 2016; Leduc & Liu, 2016, 2020). Therefore, to compute the impulse response functions, we have to determine the contemporaneous impact matrix with a VAR model applying Cholesky decomposition to identify structural shocks. d_i denotes the i^{th} column of the Cholesky decomposition and therefore represents the structural shock to the i^{th} element in y_t. A crucial point is to estimate the contemporaneous impact matrix applying the Cholesky decomposition. The impact of shocks can differ with the ordering of our variables. We order our variables such that:

$$y = \begin{bmatrix} \text{SP500} \\ \text{OIL} \\ \text{GU} \\ \text{Inflation} \\ \text{Unemployment rate} \\ \text{Fed funds rate} \\ \Delta\text{log(Industrial production)} \end{bmatrix}$$

where GU denotes our measure of general uncertainty. We use $\Delta \log(\text{Industrial Production})$ to have a stationary variable (IPI). We order our measure of uncertainty third under the assumption that uncertainty shocks will have an immediate impact on the macroeconomic variables. $SP500$ is the $\Delta \log(\text{Stock market index})$, it is usually placed first in the literature. We

[4]Other identification scheme can be applied with local projections: long-run restrictions, identification with external instruments (Jordá, 2005; Stock & Watson, 2018; Plagborg-Møller & Wolf, 2021).

collected this variable on Yahoo! Finance. The second one is OIL, the monthly price of crude oil (West Texas Intermediate) deflated by the consumer price index and also in log difference to have a stationary variable. It is aimed at capturing possible geopolitical foreign influence on US economics contrary to previous works that who did not take it into account. We order these both variables before uncertainty index under the assumption that these variables are unaffected by the uncertainty shock to take into account expectations and identify an unanticipated uncertainty shock. Inversely, the macroeconomic variables will not have an immediate impact on uncertainty. This is a common choice in the empirical literature (See, among others, Bloom, 2009; Baker *et al.*, 2016; Caggiano *et al.*, 2014; Istrefi & Mouabbi, 2018). The idea is that agents do not have information about the current macroeconomic conditions (Leduc & Liu, 2016) because data are not yet available. $Inflation$ (I) is ranked fourth since price may react quickly after a shock. We place the fed funds rate (Fed) after the unemployment rate (U) under the assumption that the Federal Reserve will react instantly to an unemployment shock. Indeed, one objective of the Federal Reserve is a low level of unemployment.[5] The results reported in Figure A.1.1 demonstrate that no unit root lies outside the unit root circle, indicating the stationarity of the VAR. The estimated coefficients of each equation are display in Table A.1.1. A result which can be surprising is the value of the R^2 for the unemployment and the Fed funds rate which is close to 0.99 even if we have shown the stationarity of the VAR.[6] These results could be due to the fact that their past values are statistically significant contrary to other variables meaning that these variables are strongly linked to their past values.[7]

Examining the impulse response functions from the local projections, the impact of uncertainty on macroeconomic variables, we find a statistically negative impact on economic activity as almost all works.[8] We get a negative effect on employment during the months following the uncertainty shock with an increase in unemployment (Figure 4). These results highlight a *wait and see* behavior where firms delay investment and hiring decisions. We get a slightly negative

[5]To determine the number of lags, we apply the Akaike information criteria (AIC).

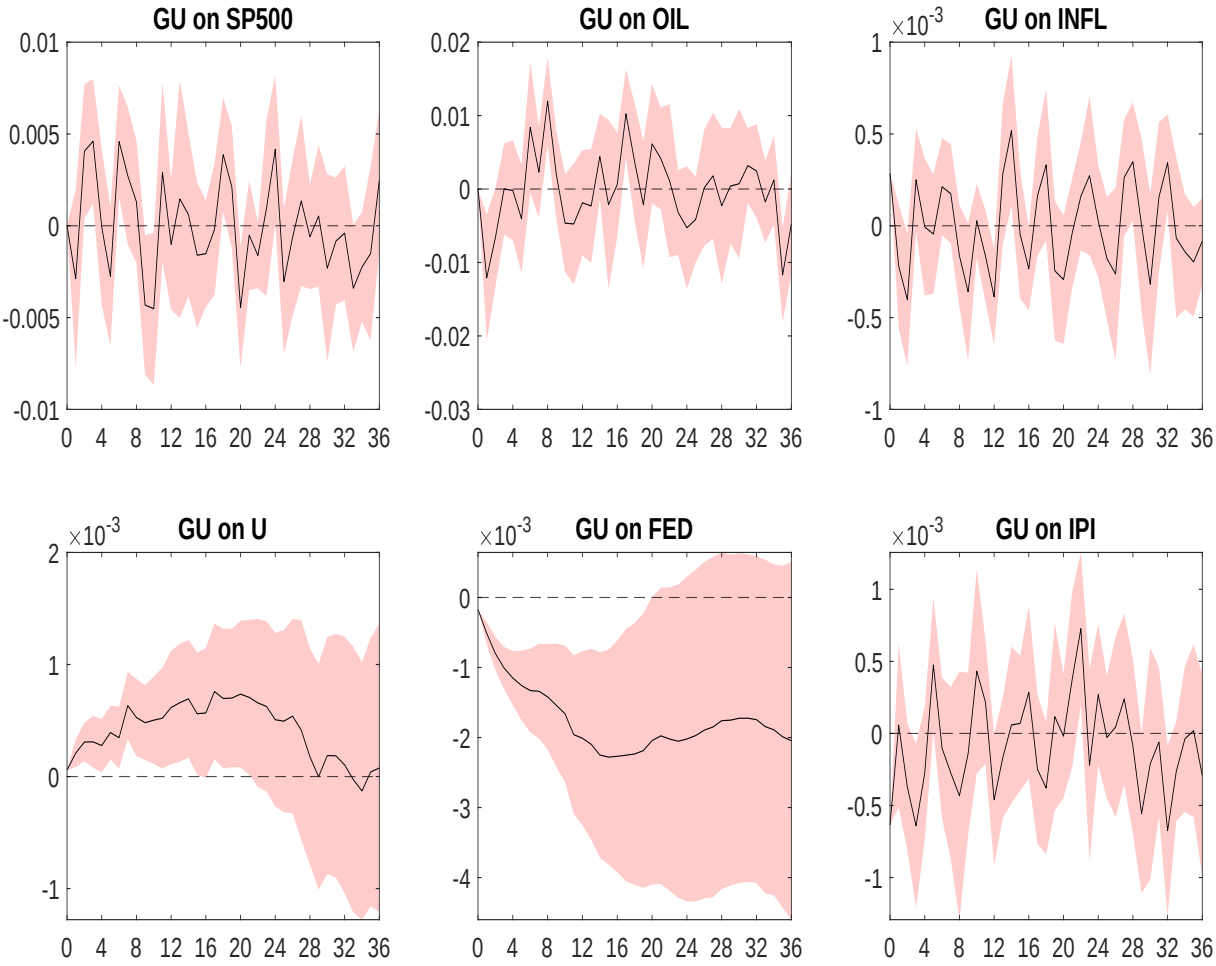
[6]Moreover, both variables do not have a unit root applying the Elliott-Rothenberg-Stock (ERS) test.

[7]We get the same results if we apply the Hodrick-Prescott filter in robustness checks. The VAR of the seminal paper of Bloom (2009) also presents high values of the R^2.

[8]The effect is significant at the 5% level. Applying local projections, the residuals u_{t+s}^t are a moving average of the forecast errors. To correct heteroskedasticity, we compute error bands applying the Newey & West (1987) method.

effect on industrial production in the near term. The Fed decreases its rate in order to boost the economy.

Figure 4: Impulse Response Functions

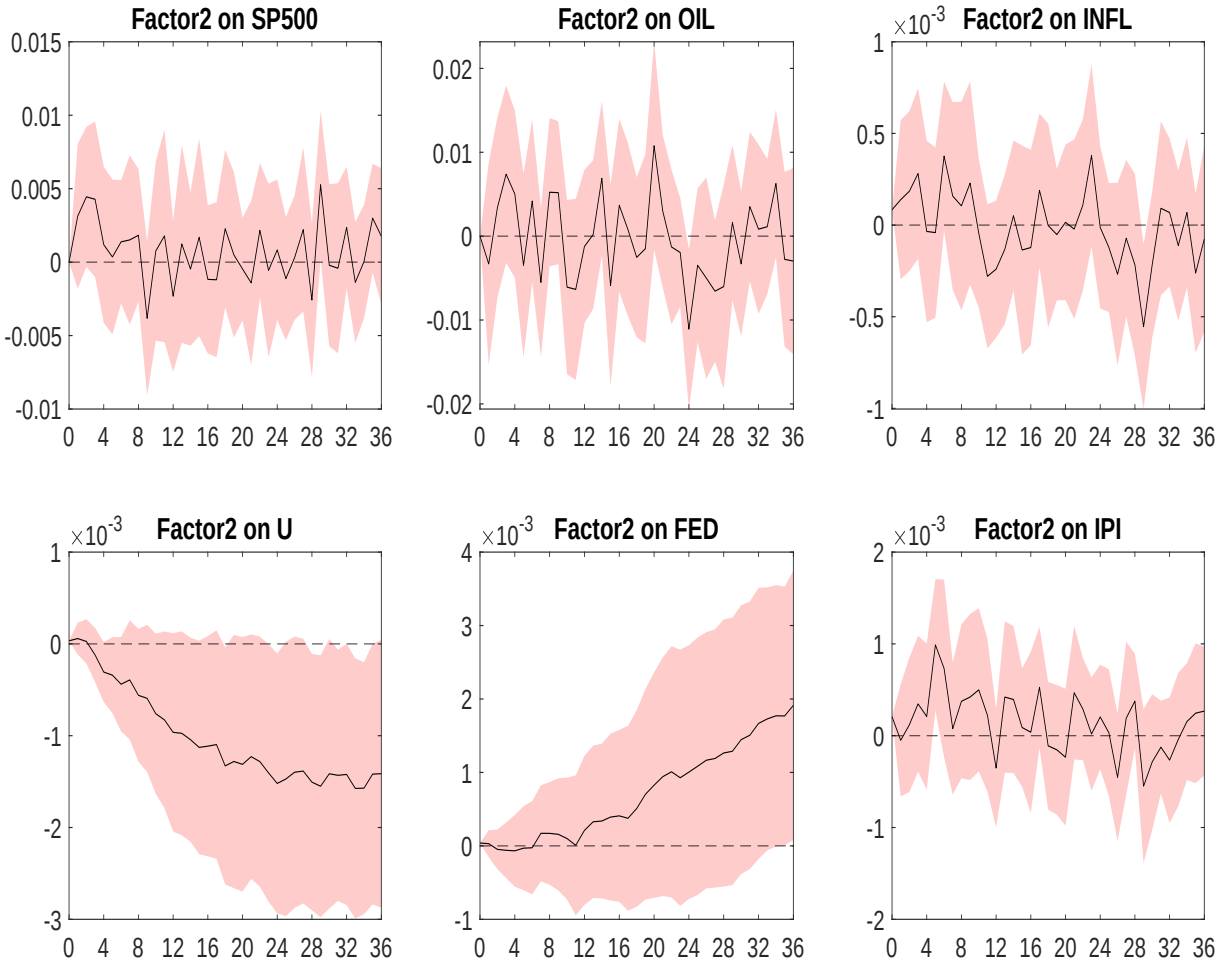


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

We run the same exercise with $Factor2$ as uncertainty variable to investigate the effect of the nature of uncertainty shocks. We replace the general uncertainty index by the second factor ($Factor2$) in the model. According to its interpretation, a positive shock to this second factor indicates more non-financial uncertainty. We find that a non-financial uncertainty shock has no significant effects on industrial production and unemployment during the months following the shock (Figure 5). We run a VAR but we introduce the product of both factors ($GU * Factor2$) instead of each factor alone. It is worth noticing that no caution is needed when introducing

this product since these two factors present the quality of being independent from each other by construction from the PCA. Hence this variable is high when both factors are high, i.e when uncertainty is high and non-financial. Remind here that both theoretical frameworks that, according to us, may explain why uncertainty could be positive rely on non financial uncertainty. Growth option theory relies on an industrial uncertainty whereas Gabaix's theory relies on a general macroeconomic uncertainty.

Figure 5: Impulse Response Functions

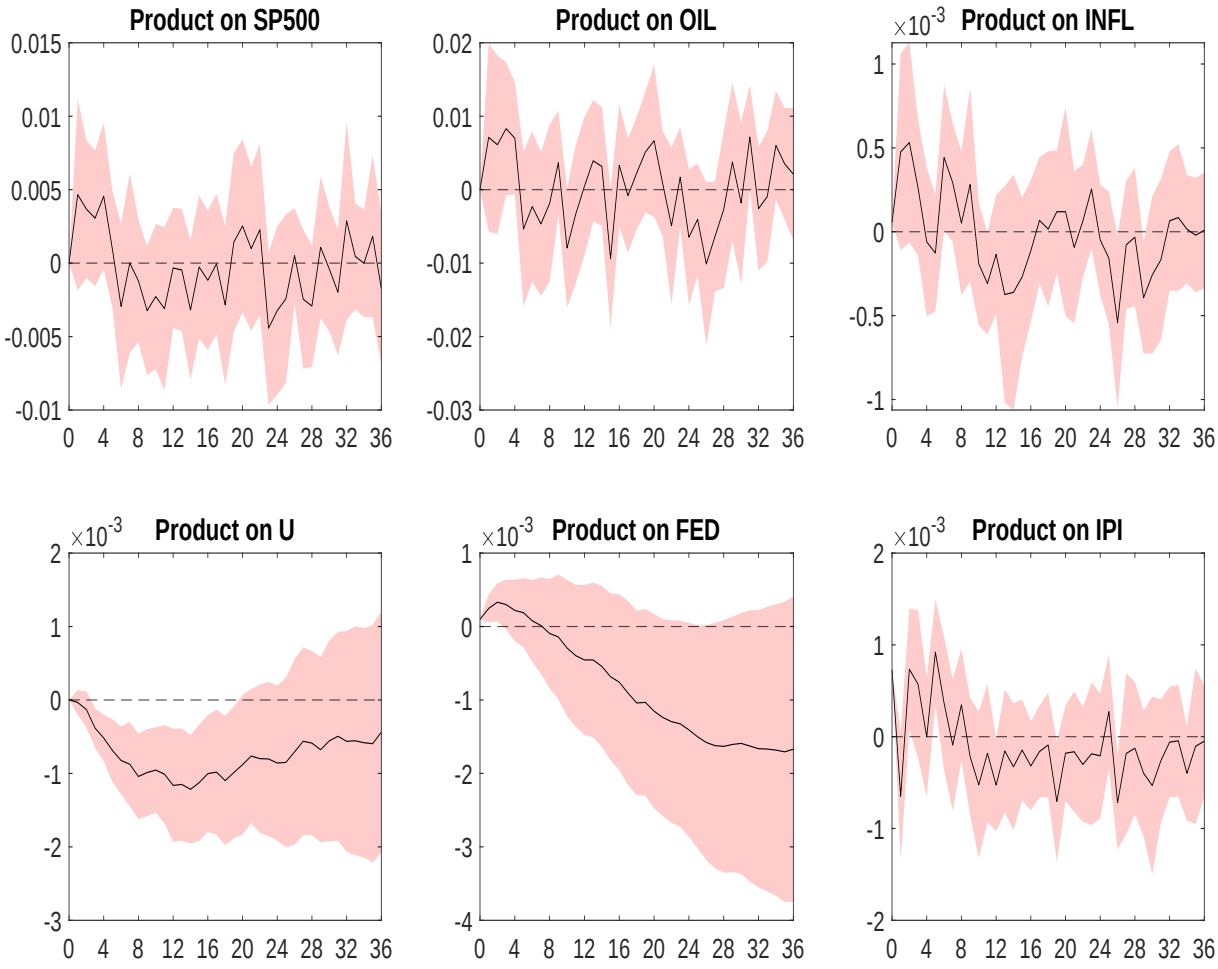


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

The striking result we obtain is that when the product is shocked it has a short positive and significant impact on industrial production and a lasting negative and significant effect on unemployment (Figure 6). These results show that the variable $Factor2$ representing the nature

of uncertainty does not have a significant effect but its interaction with the overall level of uncertainty can provide a much richer set of results. Hence, as we hypothesized, uncertainty can have a positive effect on the economy. More specifically, uncertainty has a positive effect when it is non financial interacting it with the overall level of uncertainty. However, we do not know exactly what happens in the product $GU * Factor2$. For instance, the product of both factors may be as high when uncertainty is high and the nature of uncertainty is indeterminate as when the nature of uncertainty is non-financial and uncertainty is moderate. This result is rather a confirming intuition than a robust proof. In order to check whether this intuition is correct using a proper estimation method, we turn to a non linear framework.

Figure 6: Impulse Response Functions



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

3.3 Non linear framework

In the linear framework, we have found that a shock of the nature of uncertainty doesn't have a significant effect whereas uncertainty does have an effect. However, the nature may have an effect depending on the general level of uncertainty or uncertainty may have a different impact depending on the nature of uncertainty. This is what suggests the previous intuitive test using the product of both factors. A non linear framework allows to study the effect of a shock on a variable conditioned to the level of another variable. This intuition comes from the theoretical model of Gabaix (2020) assuming that agents are partly myopic. Therefore, they fail to perfectly anticipate future taxes after a stimulus generating an effective stimulus. A corollary of these results is that myopia is exacerbated when uncertainty is high. Following these theoretical arguments, taking the second factor of the PCA of Himounet (2022) distinguishing non-financial uncertainty from financial uncertainty as a threshold variable makes no sense given its non cardinal nature. Therefore, we are going to use the measure of general uncertainty representing the overall level of uncertainty as the threshold variable. Concretely, we aim at studying the effect of a shock on the nature of uncertainty conditioned to various levels of the general uncertainty. This strategy allows to examine the interaction between both measures in another way.

3.3.1 High, moderate and low uncertainty regimes

A great advantage of the local projection methodology is that it can easily be adapted to a nonlinear framework. Many works have applied local projections to study non linear effects, threshold effects (See, among many others, Owyang *et al.*, 2013; Ramey & Zubairy, 2018; Ahmed & Cassou, 2021).[9] We apply local projection methods to investigate the impact of the nature of uncertainty shocks in different regimes estimating the state-dependent impulse response functions. We have decided to use a three regimes set-up as our preferred specification in order to properly distinguish the high uncertainty regime from the low uncertainty regime,

[9]This section is linked to a branch of empirical studies investigating non-linear effects of uncertainty (See, among many others, Caggiano *et al.*, 2014; Ismailov & Rossi, 2018; Alessandri & Mumtaz, 2019; Colombo & Paccagnini, 2020; Candelon *et al.*, 2021).

thus implying that a moderate uncertainty regime also exists.[10]

We consider the extension of our baseline model with threshold effects:

$$y_t = I(z_{t-1} < \gamma_1)\Pi_L(L)y_{t-1} + I(\gamma_1 \leq z_{t-1} < \gamma_2)\Pi_M y_{t-1} + I(z_{t-1} > \gamma_2)\Pi_H y_{t-1} + \mu_t$$

where y_t is a vector of endogenous variables including our measure of the nature of uncertainty and the set of monthly macroeconomic variables that we have used in the linear framework. z_t is the switching variable which is the measure of general uncertainty. I denotes an indicator function which takes the value of 1 alternatively if the first factor is above the threshold value γ_2 (high uncertainty regime, H), or between the two threshold values γ_2 and γ_1 (moderate uncertainty regime, M), or below γ_1 (low uncertainty regime, L). $\Pi_H(L)$ is a lag-polynomial of matrices in the high uncertainty regime. $\Pi_M(L)$ is a lag-polynomial of matrices in the moderate uncertainty regime. $\Pi_L(L)$ is a lag-polynomial of matrices in the low uncertainty regime. The threshold values are estimated applying a TVAR model. The threshold values of the switching variable are determined endogenously by a grid search over possible values of the switching variable. The grid is constructed such that the grid is trimmed at a lower and upper bound to ensure a minimal percentage of observations in each regime. In practice, the level is chosen arbitrary. It doesn't exist a general guideline. However, a level around 20% of observations in each regime has often been used. The estimation of the threshold value corresponds to the model with the smallest determinant of the covariance matrix of the error terms μ_t.

We apply the Likelihood Ratio (LR) test to test the linearity (Table A.2.1). The LR test rejects the null hypothesis of linearity. A nonlinear framework is more appropriate to study the impact of shocks. Moreover, the LR test rejects the null hypothesis of two regimes against three regimes. It means that three regimes are more appropriate to study the effect of the non linear effects of the nature of the shocks instead of two regimes. As in the linear framework, we apply local projection that we adapt to a non linear framework such that:

$$y_{t+s} = I(z_{t-1} < \gamma_1)\Pi_L^{s+1}(L)y_{t-1} + I(\gamma_1 \leq z_{t-1} \leq \gamma_2)\Pi_M^{s+1} y_{t-1} + I(z_{t-1} > \gamma_2)\Pi_H^{s+1} y_{t-1} + \mu_{t+s}^s$$

[10] We extent the R code of the package *lpirfs* of Adämmer (2019) to add the third regime.

Impulse responses in a high uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}^s_{1,H} d_i \qquad (8)$$
$$s = 0, 1, ..., h$$

Similarly, impulse responses in a low uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}^s_{1,L} d_i \qquad (9)$$
$$s = 0, 1, ..., h$$

And for the moderate uncertainty regime:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}^s_{1,M} d_i \qquad (10)$$
$$s = 0, 1, ..., h$$

where d_i is the i^{th} column of the Cholesky decomposition as in the linear framework.

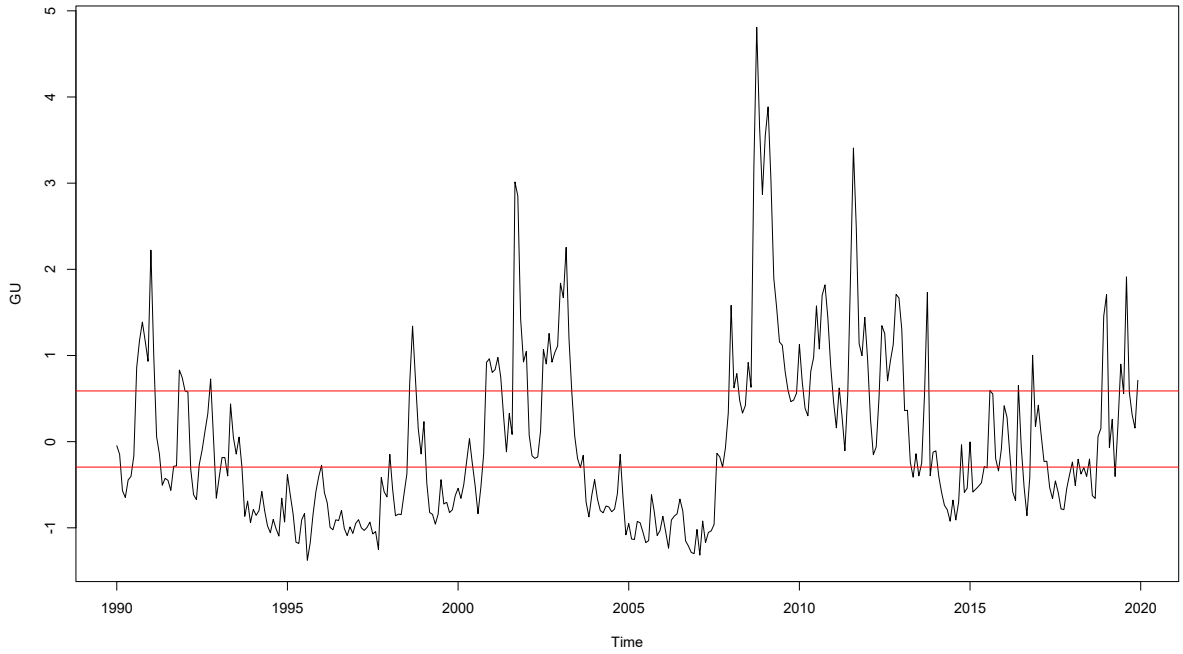
The estimated threshold values of -0.2953414 and 0.5885597 allow to separate shocks of the last two decades as the following graph highlights.

The results for the three different regimes are provided in Figure 8, Figure 9 and Figure 10. As for the linear framework, we do not have any significant effect of the nature of uncertainty under the low uncertainty regime and there is a very short negative effect on industrial production. However, it turns out that under both the moderate and the high uncertainty regimes, the nature of uncertainty has a positive significant and lasting effect on unemployment. There is a short (a quarter) positive effect on production industrial production under the moderate regime. One should note that the effect on unemployment is stronger in the moderate uncertainty regime whereas it lasts longer in the high uncertainty regime.[11]

In the theoretical literature, "growth options" theories argue that some forms of uncertainty

[11] We get results which are qualitatively equivalent for the moderate and high uncertainty regimes extending the regression 7 to our non-linear specification even if they are less significant (Figure A.2.1). $Factor2$ is considered as the identified shock and the vector of control variables contains the lags of $Factor2$ and the lags of other macroeconomic variables of our baseline model.

Figure 7: Two thresholds of general uncertainty

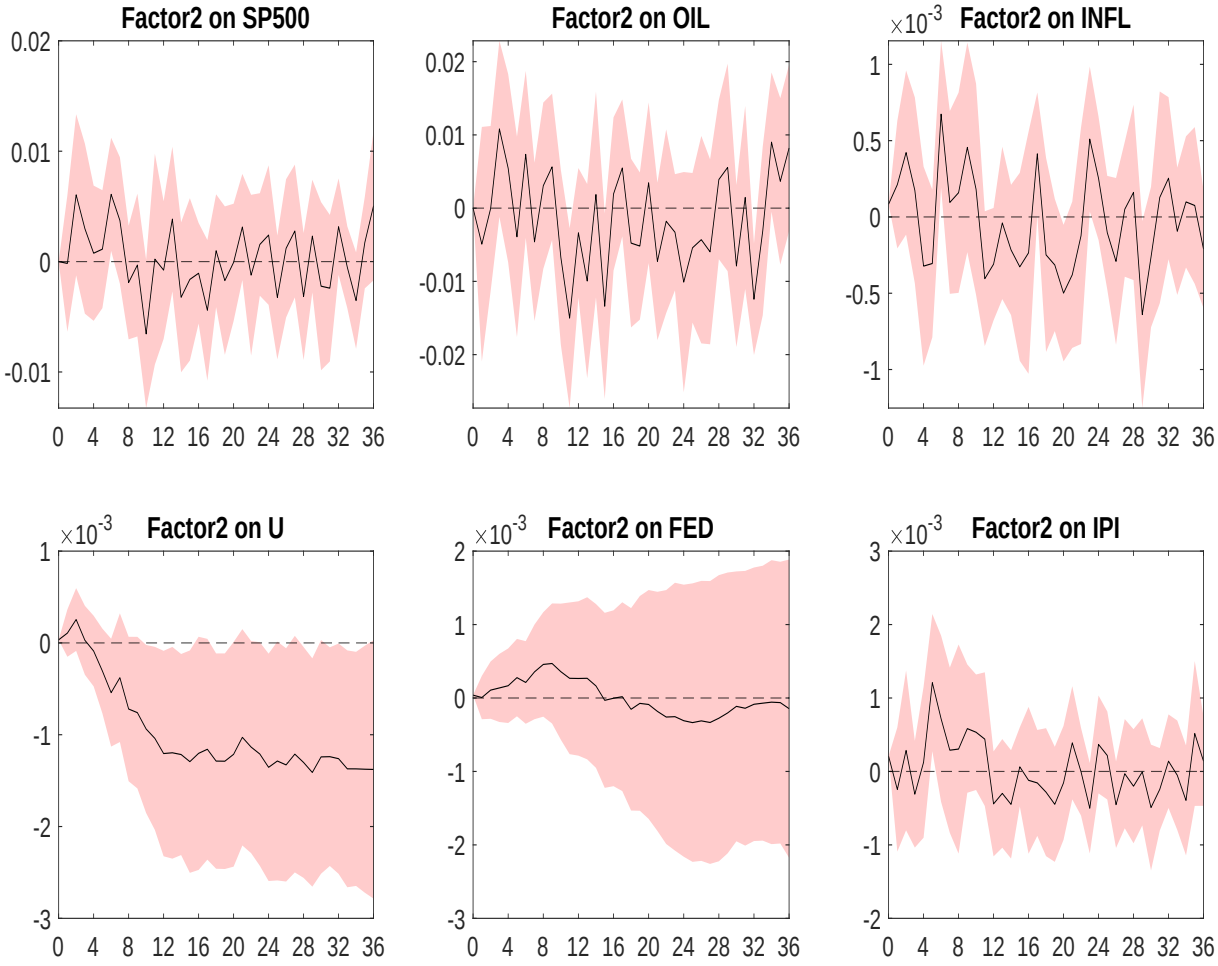


Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.2953414 and 0.5885597)

can have a positive effect on economic activity. This theory refers more specifically to macroeconomic uncertainty related to technology. During the last decade, many technological advances have appeared and other advances are developing. We can take the example of the rapid development of artificial intelligence (AI). AI will provide growth opportunities that will benefit firms and the economy in the future. However, we do not know which firms and by how much. That is why, there isn't a consequent gain when we examine the response of industrial production since most of the work firms do on AI is R & D.

Another explanation which is not exclusive of the previous one is as follows. Gabaix (2014, 2020) has shown that when a lot of information is available then individuals have to choose which information to analyze and by how much they will do so. It results that when a lot of information is available, individuals are not able to anticipate that an economic stimulus will certainly induces taxes to rise in a quite near future and hence, accordingly, to save money thus suppressing the positive expected effect of the stimulus. In other words, the quantity of

Figure 8: Impulse Response Functions in a high uncertainty regime

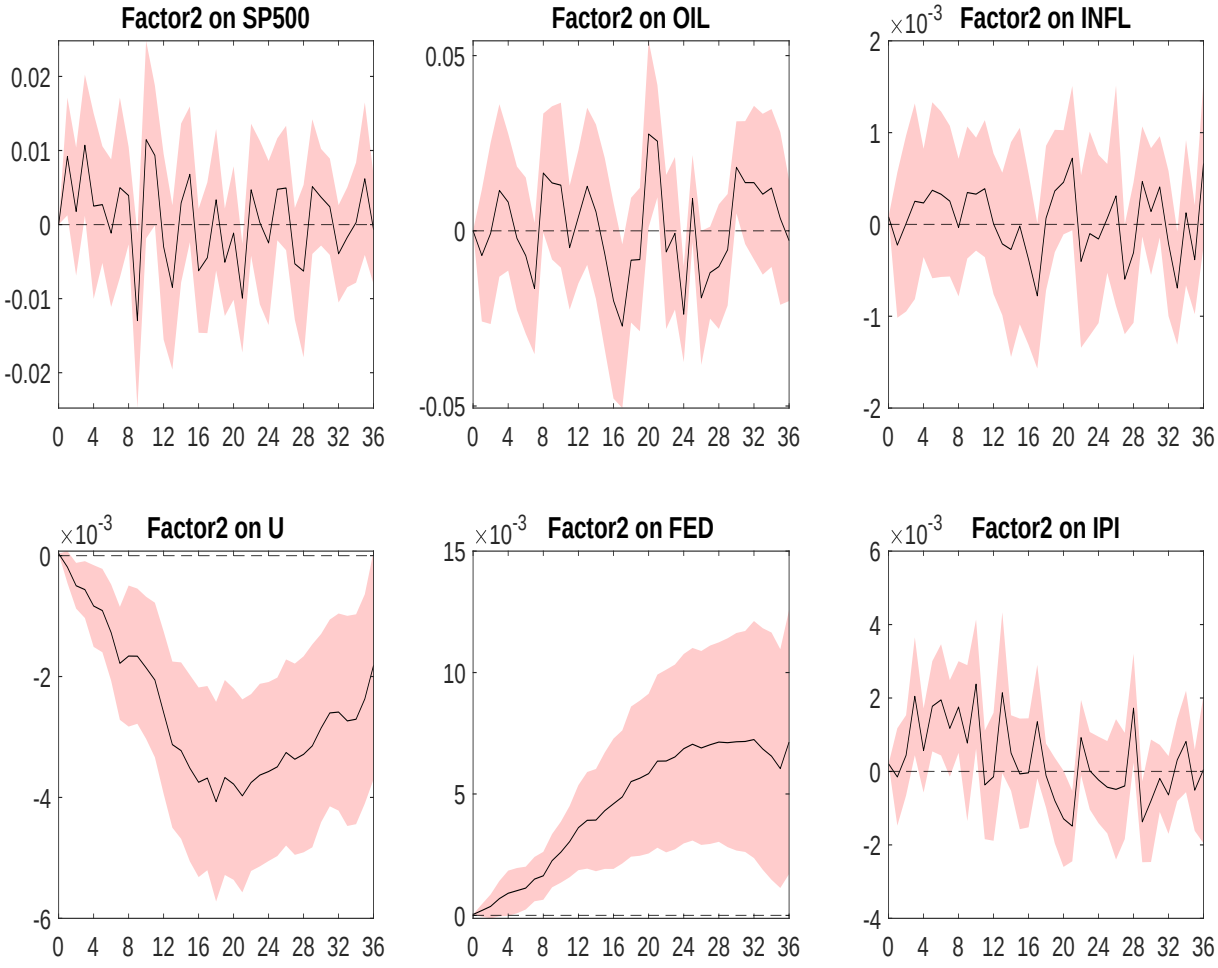


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

available information shuts down the ricardian equivalence. Importantly, this effect works on the theoretical set-up of Gabaix uniquely when myopia is strong. So, behind this second factor, we could have a distinction between a "positive" macroeconomic uncertainty that could refer to technological progress and a "negative" uncertainty which is financial.

The fact the effect on unemployment is stronger in the moderate regime may seem counter-intuitive. We argue however that, concerning the growth theory explanation, the technical uncertainty it involves is not surging as a peak but is rather a lasting phenomenon that corresponds quite well with a moderate uncertainty regime. As for the Gabaix explanation, we argue that under the high uncertainty regime, the negative financial uncertainty is also often there. The negative effect of financial uncertainty on unemployment may attenuate the positive effect in-

Figure 9: Impulse Response Functions in an intermediate uncertainty regime

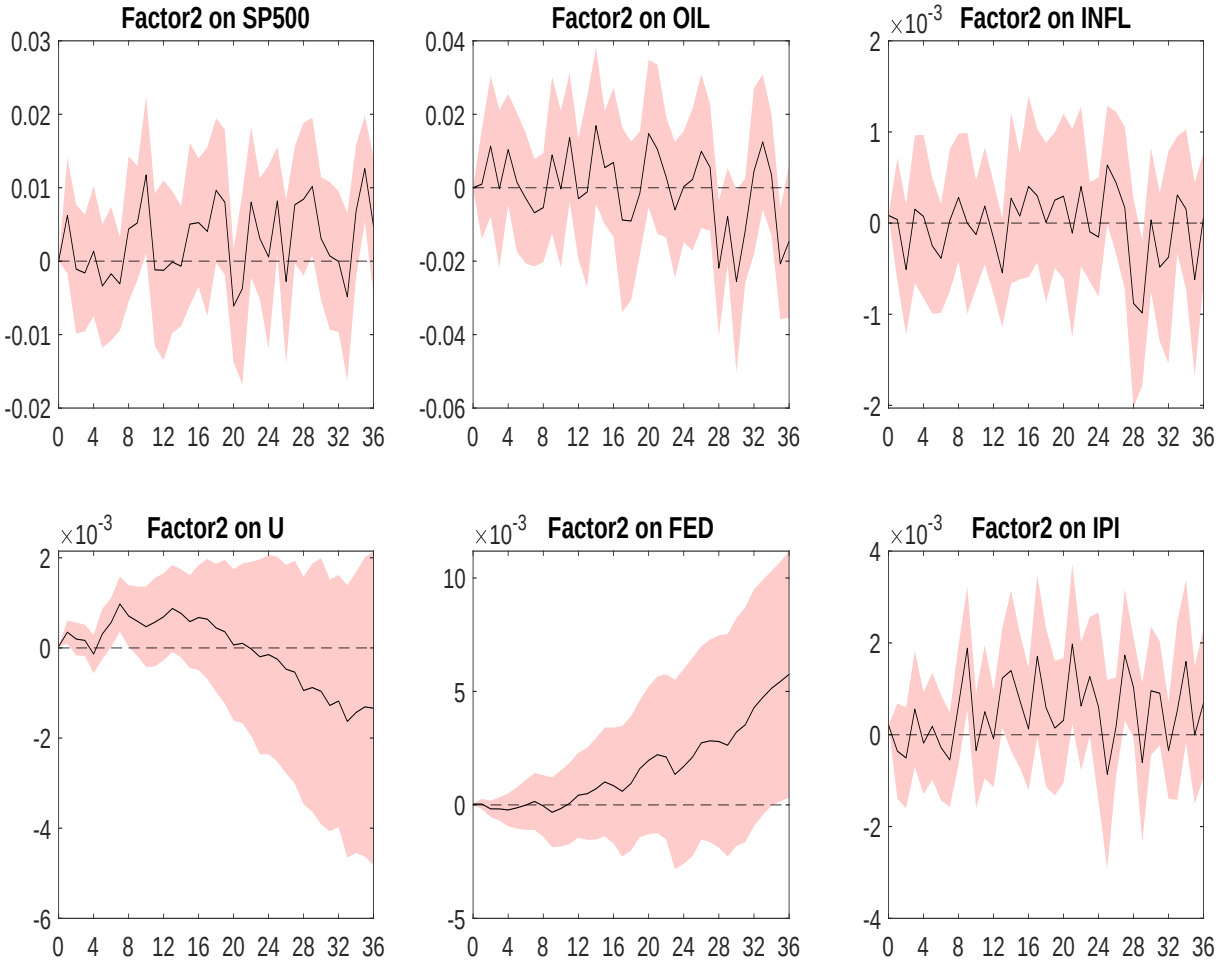


Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

duced by the increased myopia of the agents. In other words, the remedy is working but the illness it has to cure is very damaging.

To add an additional evidence to validate these assumptions, we redo our procedure on a subsample as a robustness check: 1990-2006. By doing so we suppress the financial crisis during which uncertainty unambiguously has had a massive negative effect. We redo the PCA of Himounet (2022) applying the same set of uncertainty indexes on this subsample. We do not observe major changes concerning the first two factors of this new PCA (Figure B.1.1). The first factor represents the overall level of uncertainty and the second factor also represents the distinction between non-financial and financial uncertainty shocks. A shock of non-financial

Figure 10: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

uncertainty in a low uncertainty regime has no significant effects on macroeconomic variables (Figure B.1.5) as in a high uncertainty regime (Figure B.1.3). However, in the intermediate uncertainty regime, there is a significant positive effect on unemployment and a significant negative effect on the industrial production in the short term (Figure B.1.4).

Several explanations may hold. By suppressing the 2007-2019 period, we originally aimed at reinforcing the positive effect we have highlighted by removing the negative effect of the financial crisis. It appears that we obtain the opposite result: uncertainty is again negative. In fact we have also removed all the positive effect of the industrial uncertainty, i.e all the high-tech innovations of the 2007-2019 decade that according to our "growth option" explanation

have had a positive effect. Another relies on the theoretical result of Gabaix (2014, 2020) that we interpret simply as the fact that uncertainty restores its efficiency to economic stimulus. As a matter of fact, there has been a large stimulus in the US during the period 2007-2019 that we have also suppressed by shortening the sample.

This additional exercise does not help us to disentangle between both explanations but confirms that they can be convincing. In addition, note that both explanations are not mutually exclusive and may therefore be both valid. We nevertheless can notice that the effect of the nature of uncertainty on the fed's rate is in line with the Gabaix's explanation since the rate increases as usually happens after a stimulus in order to avoid an overheated economy. In order to better test our assumption linked to high-tech innovations, we should construct a measure of uncertainty related to technology. We let this task for future works.

4 Robustness Check

4.1 Non linear framework with two regimes

We try here to do the same exercise than before but with two regimes instead of three. The VAR is then the following:

$$y_t = (1 - I(z_{t-1} > \gamma))\, \Pi_L(L) y_{t-1} + I(z_{t-1} > \gamma) \Pi_H y_{t-1} + \mu_t$$

As we proceed in the whole paper, we use local projections that we adapt to the non–linear framework:

$$y_{t+s} = (1 - I(z_{t-1} > \gamma))\, \Pi_L^{s+1}(L) y_{t-1} + I(z_{t-1} > \gamma) \Pi_H^{s+1} y_{t-1} + \mu_{t+s}^s$$

Impulse responses in a high uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}_{1,H}^s d_i \tag{11}$$
$$s = 0, 1, ..., h$$

Similarly, impulse responses in a low uncertainty regime are computed according to:

$$\hat{IR}(t, s, d_i) = \hat{\Pi}_{1,L}^{s} d_i \tag{12}$$
$$s = 0, 1, ..., h$$

The estimated threshold value is equal to 0.5938924 (Table A.2.1) It means that when we are above this threshold, the situation is very more uncertain than the average. Here, we investigate the impact of the nature of shocks when we are in a high uncertainty regime and a low uncertainty regime. We find that a non-financial uncertainty shock doesn't have significant effects when we are in the low uncertainty regime (Figure B.2.2). However, we a negative and significant effect on unemployment when we are in the high uncertainty regime (Figure B.2.1). The decrease of unemployment is persistent for many months. Consequently, the results are qualitatively the same than with three regimes. Note that by construction under two regimes, these are the moderate and the low regimes that are merged into one regime. It is interesting that when doing so, the results of the low regimes "dominate" those of the moderate regime.

4.2 Alternative ordering

Uncertainty has been ordered third in the VAR. However, uncertainty has been ordered last by some authors (See, among others, Colombo, 2013; Jurado *et al.*, 2015; Charles *et al.*, 2018). Uncertainty has been ordered last to remove the measure of uncertainty of the contemporaneous movements of the macroeconomic variables (Colombo, 2013). There is no consensus on how to order the measure of uncertainty in the vector of endogenous variables. We redo local projections and a SVAR model with a Cholesky Decomposition to identify shocks in ordering our measure of uncertainty in last. This novel ordering implies that all shocks of the system can have a contemporaneously impact on our measure of uncertainty. This alternative ordering could change the dynamic of the system. However, our results are very similar.[12] We have a short-term negative impact on industrial production with our general uncertainty using local projections. There is an effect which isn't statistically different from zero with the second factor.

[12]The results and figures are available upon request.

Applying this ordering in our nonlinear framework, the results are qualitatively identical.

4.3 Hodrick Prescott Filter

Following the seminal paper of Bloom (2009), we detrend the variables that are applied in the VAR model applying the Hodrick-Prescott filter except the uncertainty variable. Following Ravn & Uhlig (2002), we take the smoothing parameter $\lambda = 129600$ for monthly data. The results are qualitatively equivalent with a negative effect of a general uncertainty shock (Figure B.3.1) on economic activity with the decline in industrial production and the rise in unemployment. Applying our non linear framework with the general uncertainty as threshold variable, a positive shock on the second has a negative effect on economic activity in a low uncertainty regime (Figure B.3.4). We keep the positive effect in an intermediate uncertainty regime (Figure B.3.5). In the high uncertainty regime, we have a decrease in unemployment and an increase in industrial production which are not significant a 5% level (Figure B.3.6).[13]

4.4 VAR-8

In this subsection, we run local projections with our non-linear specification applying the eight-variable VAR model of Bloom (2009); Jurado *et al.* (2015); Charles *et al.* (2018) ordered as follows: the S&P 500 stock index, the manufacturing production (IPI), the level of employment (EMP), the average hours worked in manufacturing, the wage in manufacturing, the log aggregate CPI, the Federal Funds rate, and uncertainty. The measure of uncertainty is ordered at the end. We identify the shocks with a Cholesky decomposition as previously. The results are less significant but we keep a slightly positive effect of $Factor2$ on the industrial production and the employment under the high and the moderate regime of uncertainty (Figure B.4.1).

[13]These results are more significant at a 10% level.

5 Conclusion

This paper has investigated the effects of uncertainty applying a local projection approach in a linear and a non linear framework. We apply the second factor of the PCA of Himounet (2022) distinguishing financial uncertainty from non-financial uncertainty, hence it is about the nature of uncertainty. In the linear framework, this variable doesn't have a significant effect but its interaction with the overall level of uncertainty provides a significant positive effect. Applying a nonlinear framework to measure the interaction of this variable with the overall of uncertainty in another way, the estimation of a positive effect of the second factor when general uncertainty is above its mean confirms that uncertainty may indeed have a positive effect. Uncertainty associated with this second dimension can refer to macroeconomic uncertainty related to technological progress. Firms don't doubt that technological progress is a source of value creation. However, there is uncertainty on the final gain only. This uncertainty can lead firms to invest and hire. The estimation of a negative effect on the subsample 1990-2006 seems to be another sign of our assumption of technological progress. Another explanation relies on the theoretical works of Gabaix (2014, 2020). He shows that when agents are strongly myopic, economic stimuli regain in effectiveness. The simple interpretation that we make of his results is that by increasing myopia, uncertainty suppresses the Ricardian equivalence. Therefore, an increased uncertainty restores the effectiveness of an economic stimulus. Again, the results with the subsample 1990-2006 seem to confirm this hypothesis since the large economic stimulus that followed the 2007-2008 crisis disappears from the sample.

All in all, we have showed that uncertainty may indeed be positive when it is non-financial and strong. We have proposed two explanations on this positive effect which both are credible and not exclusive of each other. In order to test whether one is more valid one should construct a measure of technological uncertainty which represents another quite challenging perspective.

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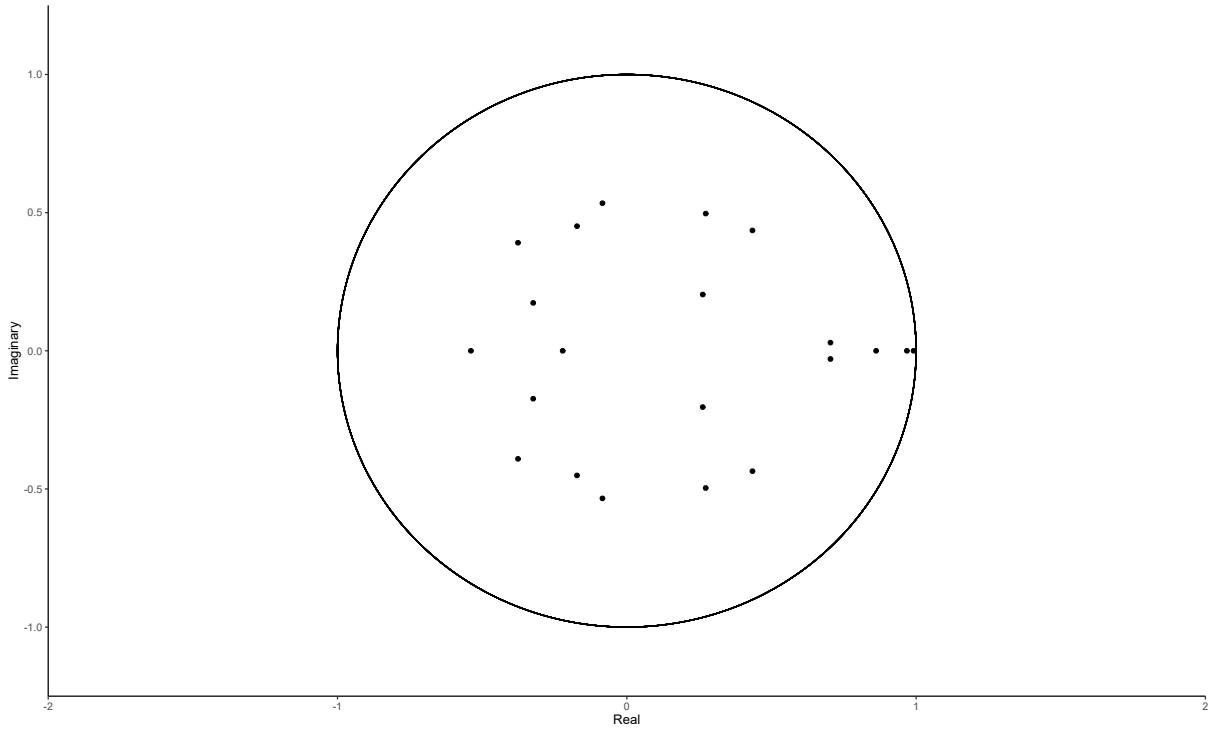
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Appendix

A Local Projections: Impulse response functions

A.1 Linear Model

Figure A.1.1: Inverse roots of AR characteristic polynomial



Source: Author's own calculations.
Note: The VAR is specified with 3 lags.

Table A.1.1: Linear Model Results: GU as Uncertainty variable

	SP500	OIL	GU	Infl	U	FED	IPI
(Intercept)	0.00	0.01	-0.19	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
SP500_{t-1}	-0.03	-0.02	-3.69^{***}	0.00	-0.00	0.00	0.01
	(0.06)	(0.12)	(0.72)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.01	0.24^{***}	-0.27	0.01^{***}	-0.00	0.00	0.01
	(0.03)	(0.06)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-1}	-0.00	-0.02^{*}	0.73^{***}	-0.00	0.00	-0.00^{**}	0.00
	(0.01)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	-0.35	-0.31	7.02	0.34^{***}	-0.01	-0.04	0.00
	(0.69)	(1.33)	(8.24)	(0.06)	(0.02)	(0.02)	(0.09)
U_{t-1}	-0.78	6.91^{*}	17.44	0.16	0.85^{***}	0.01	-0.43^{*}
	(1.63)	(3.14)	(19.40)	(0.14)	(0.05)	(0.05)	(0.22)
FED_{t-1}	1.59	4.34	-30.89	0.10	-0.07	1.39^{***}	0.25
	(1.78)	(3.44)	(21.29)	(0.15)	(0.06)	(0.05)	(0.24)
IPI_{t-1}	1.16^{**}	1.49	-13.74^{**}	0.01	-0.04^{**}	0.05^{***}	-0.03
	(0.40)	(0.78)	(4.81)	(0.03)	(0.01)	(0.01)	(0.05)
SP500_{t-2}	0.01	-0.06	-1.05	-0.00	-0.00	0.00	0.03^{**}
	(0.06)	(0.12)	(0.74)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.04	0.01	-0.31	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-2}	0.02^{*}	0.01	-0.13	0.00	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	-0.77	0.60	1.07	-0.17^{**}	-0.00	0.04	-0.05
	(0.72)	(1.38)	(8.56)	(0.06)	(0.02)	(0.02)	(0.10)
U_{t-2}	-1.02	-11.07^{**}	5.93	-0.15	0.15^{*}	0.03	0.56^{*}
	(2.11)	(4.06)	(25.12)	(0.18)	(0.07)	(0.06)	(0.28)
FED_{t-2}	0.01	-2.46	39.93	-0.31	0.10	-0.24^{*}	-0.22
	(3.07)	(5.92)	(36.62)	(0.26)	(0.10)	(0.09)	(0.41)
IPI_{t-2}	1.03^{*}	0.16	-7.53	0.09^{**}	-0.03^{*}	0.00	0.07
	(0.42)	(0.80)	(4.96)	(0.03)	(0.01)	(0.01)	(0.06)
SP500_{t-3}	0.07	0.19	-1.23	0.01	-0.00	-0.00	0.04^{***}
	(0.06)	(0.11)	(0.68)	(0.00)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.01	-0.10	0.99^{**}	0.00	0.00^{*}	-0.00	-0.00
	(0.03)	(0.06)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
GU_{t-3}	0.00	0.02^{*}	0.11	0.00	0.00	0.00	-0.00
	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	0.11	0.02	3.68	-0.06	-0.03	-0.03	0.11
	(0.65)	(1.26)	(7.78)	(0.05)	(0.02)	(0.02)	(0.09)
U_{t-3}	1.70	3.90	-18.43	-0.02	-0.00	-0.04	-0.08
	(1.64)	(3.17)	(19.58)	(0.14)	(0.06)	(0.05)	(0.22)
FED_{t-3}	-1.44	-1.77	-10.13	0.20	-0.01	-0.17^{**}	-0.01
	(1.77)	(3.42)	(21.15)	(0.15)	(0.06)	(0.05)	(0.24)
IPI_{t-3}	-0.22	1.24	-0.55	0.07^{*}	-0.04^{**}	0.01	0.17^{**}
	(0.41)	(0.79)	(4.86)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.11	0.18	0.78	0.29	0.98	0.99	0.32
Adj. R^2	0.05	0.12	0.77	0.25	0.98	0.99	0.28
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.1.2: Linear Model Results: Factor2 as Uncertainty variable

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	-0.00	-0.00	-0.22	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
SP500$_{t-1}$	-0.00	0.16	-1.01	0.01	-0.00	0.00^{*}	0.01
	(0.06)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-1}$	0.01	0.26^{***}	0.76^{*}	0.01^{***}	-0.00	0.00	0.01
	(0.03)	(0.06)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2$_{t-1}$	0.01	-0.01	0.72^{***}	0.00	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-1}$	-0.67	-0.75	-0.70	0.33^{***}	-0.01	-0.04	0.01
	(0.70)	(1.35)	(7.37)	(0.06)	(0.02)	(0.02)	(0.09)
U$_{t-1}$	0.48	6.98^{*}	-11.75	0.13	0.84^{***}	-0.02	-0.45^{*}
	(1.65)	(3.19)	(17.45)	(0.14)	(0.05)	(0.05)	(0.22)
FED$_{t-1}$	0.73	4.77	-19.70	0.13	-0.12^{*}	1.43^{***}	0.30
	(1.76)	(3.41)	(18.64)	(0.15)	(0.06)	(0.05)	(0.23)
IPI$_{t-1}$	0.98^{*}	1.47	4.88	0.01	-0.04^{**}	0.06^{***}	-0.02
	(0.40)	(0.78)	(4.26)	(0.03)	(0.01)	(0.01)	(0.05)
SP500$_{t-2}$	-0.02	0.06	0.09	0.00	-0.00	0.00^{*}	0.02^{**}
	(0.06)	(0.11)	(0.59)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-2}$	0.03	0.01	-0.19	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.33)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2$_{t-2}$	0.00	0.01	0.13^{*}	0.00	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-2}$	-0.74	0.53	-0.96	-0.17^{**}	-0.00	0.04	-0.05
	(0.72)	(1.40)	(7.66)	(0.06)	(0.02)	(0.02)	(0.10)
U$_{t-2}$	-0.89	-10.68^{*}	-9.96	-0.14	0.16^{*}	0.04	0.53
	(2.13)	(4.12)	(22.58)	(0.18)	(0.07)	(0.07)	(0.28)
FED$_{t-2}$	-0.36	-5.75	24.59	-0.37	0.12	-0.28^{**}	-0.17
	(3.07)	(5.94)	(32.53)	(0.25)	(0.10)	(0.09)	(0.41)
IPI$_{t-2}$	0.68	0.04	0.23	0.09^{**}	-0.03^{*}	0.01	0.08
	(0.42)	(0.81)	(4.41)	(0.03)	(0.01)	(0.01)	(0.05)
SP500$_{t-3}$	0.00	0.18	0.28	0.01	-0.00^{*}	0.00	0.04^{***}
	(0.06)	(0.11)	(0.59)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-3}$	0.01	-0.12^{*}	0.38	0.00	0.00	-0.00	-0.00
	(0.03)	(0.06)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)
Factor2$_{t-3}$	-0.01	-0.01	0.01	-0.00	-0.00^{*}	0.00	0.00
	(0.01)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-3}$	-0.05	-0.11	-5.02	-0.06	-0.02	-0.03	0.11
	(0.66)	(1.28)	(7.00)	(0.05)	(0.02)	(0.02)	(0.09)
U$_{t-3}$	0.46	3.72	25.96	-0.01	0.01	-0.02	-0.06
	(1.67)	(3.24)	(17.72)	(0.14)	(0.06)	(0.05)	(0.22)
FED$_{t-3}$	-0.27	0.87	-6.11	0.22	0.01	-0.16^{**}	-0.11
	(1.75)	(3.39)	(18.57)	(0.14)	(0.06)	(0.05)	(0.23)
IPI$_{t-3}$	-0.58	1.01	-0.37	0.07^{*}	-0.04^{**}	0.01	0.18^{***}
	(0.41)	(0.79)	(4.33)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.08	0.15	0.83	0.29	0.98	0.99	0.31
Adj. R^2	0.02	0.10	0.81	0.24	0.98	0.99	0.27
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.1.3: Linear Model Results: Product as Uncertainty variable

	SP500	OIL	Product	Infl	U	FED	IPI
(Intercept)	-0.00	0.00	-0.17	0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
SP500$_{t-1}$	-0.01	0.12	1.56	0.01	-0.00	0.00^{*}	0.01
	(0.06)	(0.11)	(1.28)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-1}$	0.00	0.26^{***}	1.56^{*}	0.01^{***}	0.00	0.00	0.01
	(0.03)	(0.06)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
Product$_{t-1}$	0.00	0.01	0.78^{***}	0.00^{*}	0.00	0.00	-0.00^{*}
	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-1}$	-0.75	-0.90	1.85	0.32^{***}	0.00	-0.04	-0.01
	(0.70)	(1.36)	(16.13)	(0.06)	(0.02)	(0.02)	(0.09)
U$_{t-1}$	0.37	6.88^{*}	8.94	0.15	0.80^{***}	-0.07	-0.43
	(1.67)	(3.23)	(38.39)	(0.14)	(0.05)	(0.05)	(0.22)
FED$_{t-1}$	0.37	3.93	-25.60	0.10	-0.15^{**}	1.40^{***}	0.33
	(1.78)	(3.44)	(40.89)	(0.15)	(0.06)	(0.05)	(0.23)
IPI$_{t-1}$	1.00^{*}	1.42	50.32^{***}	0.00	-0.03^{*}	0.06^{***}	0.01
	(0.41)	(0.79)	(9.39)	(0.03)	(0.01)	(0.01)	(0.05)
SP500$_{t-2}$	-0.04	0.04	1.24	-0.00	-0.00	0.00^{**}	0.02^{**}
	(0.06)	(0.11)	(1.29)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-2}$	0.03	0.01	-0.58	-0.00	-0.00	-0.00	0.00
	(0.03)	(0.06)	(0.70)	(0.00)	(0.00)	(0.00)	(0.00)
Product$_{t-2}$	0.00	0.00	-0.04	-0.00	-0.00	-0.00	0.00^{**}
	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-2}$	-0.75	0.58	6.63	-0.17^{**}	0.01	0.04^{*}	-0.05
	(0.73)	(1.40)	(16.64)	(0.06)	(0.02)	(0.02)	(0.09)
U$_{t-2}$	-1.12	-10.75^{**}	-66.19	-0.16	0.16^{*}	0.04	0.53
	(2.13)	(4.12)	(48.86)	(0.17)	(0.07)	(0.06)	(0.28)
FED$_{t-2}$	0.20	-4.12	2.12	-0.31	0.16	-0.24^{*}	-0.25
	(3.10)	(5.98)	(71.01)	(0.25)	(0.10)	(0.09)	(0.40)
IPI$_{t-2}$	0.55	-0.33	9.40	0.07^{*}	-0.03^{*}	0.01	0.11
	(0.43)	(0.83)	(9.85)	(0.04)	(0.01)	(0.01)	(0.06)
SP500$_{t-3}$	-0.01	0.16	-0.06	0.01	-0.00	0.00	0.04^{***}
	(0.06)	(0.11)	(1.28)	(0.00)	(0.00)	(0.00)	(0.01)
OIL$_{t-3}$	0.01	-0.12^{*}	0.78	0.00	0.00	-0.00	-0.00
	(0.03)	(0.06)	(0.69)	(0.00)	(0.00)	(0.00)	(0.00)
Product$_{t-3}$	-0.00	-0.01	-0.02	-0.00	-0.00^{**}	-0.00^{**}	-0.00
	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
Infl$_{t-3}$	-0.08	-0.11	-21.02	-0.07	-0.00	-0.01	0.11
	(0.67)	(1.30)	(15.38)	(0.05)	(0.02)	(0.02)	(0.09)
U$_{t-3}$	0.88	3.79	58.52	-0.00	0.05	0.03	-0.07
	(1.69)	(3.27)	(38.83)	(0.14)	(0.05)	(0.05)	(0.22)
FED$_{t-3}$	-0.53	0.17	22.95	0.19	0.01	-0.17^{**}	-0.06
	(1.76)	(3.40)	(40.37)	(0.14)	(0.06)	(0.05)	(0.23)
IPI$_{t-3}$	-0.69	0.73	-10.34	0.06	-0.03^{*}	0.01	0.17^{**}
	(0.42)	(0.81)	(9.60)	(0.03)	(0.01)	(0.01)	(0.05)
R^2	0.08	0.15	0.71	0.30	0.98	0.99	0.33
Adj. R^2	0.03	0.10	0.70	0.26	0.98	0.99	0.29
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

A.2 Nonlinear Model

Table A.2.1: LR test

	Linearity VS Two regimes	Linearity VS Three regimes	Two regimes VS Three regimes
LR statistic	351.2817	578.1422	226.8604
p-value	0.000	0.000	0.000
Estimated threshold	0.5938924	-0.2953414 ; 0.5885597	-0.2953414 ; 0.5885597

Source: Author's own calculations.

Table A.2.2: Non linear model Results

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	0.02	-0.00	-0.30^{*}	0.00	-0.00	0.00	-0.00
	(0.01)	(0.03)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
High Uncertainty Regime							
$SP500_{t-1}$	0.09	0.38^{*}	0.30	0.01^{*}	-0.00	0.00	0.00
	(0.08)	(0.15)	(0.83)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-1}	0.03	0.18	0.73	0.01^{*}	-0.00	0.00	0.02^{**}
	(0.05)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
$Factor2_{t-1}$	-0.00	-0.02	0.65^{***}	0.00	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-1}$	-3.06^{*}	2.71	20.18	0.12	0.03	-0.09^{*}	0.09
	(1.38)	(2.76)	(14.98)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-1}	4.41	10.96	-18.87	-0.25	0.84^{***}	0.10	-1.19^{**}
	(3.19)	(6.39)	(34.63)	(0.27)	(0.10)	(0.10)	(0.43)
FED_{t-1}	3.31	10.19	29.66	0.73^{**}	0.01	1.55^{***}	-0.49
	(3.07)	(6.14)	(33.30)	(0.26)	(0.10)	(0.09)	(0.41)
IPI_{t-1}	2.14^{**}	3.57^{**}	7.42	0.02	-0.03	0.07^{***}	-0.04
	(0.65)	(1.29)	(7.01)	(0.05)	(0.02)	(0.02)	(0.09)
$SP500_{t-2}$	-0.04	0.08	1.21	-0.00	-0.00	0.01^{**}	0.02

	(0.08)	(0.16)	(0.89)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-2}	0.09	0.07	−0.28	−0.00	−0.00	0.00	−0.01
	(0.05)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-2}	0.02*	0.02	0.02	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	−1.56	0.82	−10.27	0.05	−0.06	0.08	−0.34
	(1.44)	(2.89)	(15.65)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-2}	−3.83	−10.44	−65.13	0.01	0.24	−0.06	0.21
	(4.41)	(8.81)	(47.77)	(0.37)	(0.14)	(0.13)	(0.59)
FED_{t-2}	−2.07	−14.48	−57.74	−1.26**	−0.00	−0.64***	0.92
	(5.37)	(10.74)	(58.21)	(0.45)	(0.18)	(0.16)	(0.72)
IPI_{t-2}	1.22	1.17	1.52	0.13*	−0.05*	0.04	0.06
	(0.76)	(1.53)	(8.27)	(0.06)	(0.03)	(0.02)	(0.10)
SP500_{t-3}	−0.00	0.13	0.73	−0.00	−0.01**	−0.00	0.06***
	(0.09)	(0.18)	(0.96)	(0.01)	(0.00)	(0.00)	(0.01)
OIL_{t-3}	0.06	−0.29**	0.15	−0.00	0.00	−0.00**	0.00
	(0.05)	(0.10)	(0.56)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-3}	−0.01	−0.01	0.08	−0.00*	−0.00**	−0.00	−0.00
	(0.01)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	−0.45	−0.64	−16.21	−0.26**	0.03	−0.09**	−0.09
	(1.07)	(2.14)	(11.58)	(0.09)	(0.04)	(0.03)	(0.14)
U_{t-3}	−0.79	−0.36	89.19*	0.23	−0.07	−0.05	1.00*
	(3.38)	(6.76)	(36.64)	(0.28)	(0.11)	(0.10)	(0.45)
FED_{t-3}	−0.89	4.03	30.73	0.55*	−0.00	0.07	−0.44
	(3.18)	(6.36)	(34.47)	(0.27)	(0.10)	(0.10)	(0.43)
IPI_{t-3}	−1.48*	0.79	−0.87	0.04	−0.08**	0.00	0.12
	(0.73)	(1.46)	(7.93)	(0.06)	(0.02)	(0.02)	(0.10)

Intermediate Uncertainty Regime							
$SP500_{t-1}$	-0.13	0.05	-3.28^{*}	0.01	0.00	0.00	0.00
	(0.13)	(0.27)	(1.45)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-1}	-0.04	0.18	-0.26	0.00	0.00	0.00	0.00
	(0.06)	(0.13)	(0.70)	(0.01)	(0.00)	(0.00)	(0.01)
$Factor2_{t-1}$	0.02	-0.02	0.88^{***}	-0.00	-0.00	0.00	-0.00
	(0.01)	(0.02)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-1}$	2.26	-0.71	-3.30	0.42^{***}	-0.06	-0.03	-0.11
	(1.29)	(2.58)	(13.97)	(0.11)	(0.04)	(0.04)	(0.17)
U_{t-1}	-8.36^{*}	10.85	-10.80	0.77^{*}	0.88^{***}	-0.25^{*}	-0.12
	(3.59)	(7.18)	(38.91)	(0.30)	(0.12)	(0.11)	(0.48)
FED_{t-1}	-3.76	-14.34	-78.85	-0.41	-0.05	1.26^{***}	0.82
	(4.05)	(8.11)	(43.94)	(0.34)	(0.13)	(0.12)	(0.54)
IPI_{t-1}	-0.29	-0.90	7.67	-0.11	0.01	0.03	-0.09
	(0.99)	(1.97)	(10.69)	(0.08)	(0.03)	(0.03)	(0.13)
$SP500_{t-2}$	0.28^{*}	0.09	0.13	-0.00	-0.00	0.01	0.03
	(0.13)	(0.26)	(1.42)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-2}	-0.02	-0.23	-0.54	-0.00	0.00	-0.00	0.00
	(0.06)	(0.12)	(0.64)	(0.00)	(0.00)	(0.00)	(0.01)
$Factor2_{t-2}$	-0.01	-0.02	0.19	-0.00	-0.00	-0.00	0.00
	(0.01)	(0.02)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
$Infl_{t-2}$	-3.78^{**}	2.53	2.00	-0.19	0.02	0.03	0.07
	(1.40)	(2.79)	(15.12)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-2}	6.66	-19.37^{*}	-8.66	-0.60	0.16	0.23	1.15
	(4.47)	(8.93)	(48.40)	(0.37)	(0.15)	(0.13)	(0.60)
FED_{t-2}	2.00	25.66	153.67^{*}	0.75	-0.01	-0.07	-0.59
	(6.62)	(13.23)	(71.73)	(0.56)	(0.22)	(0.20)	(0.89)

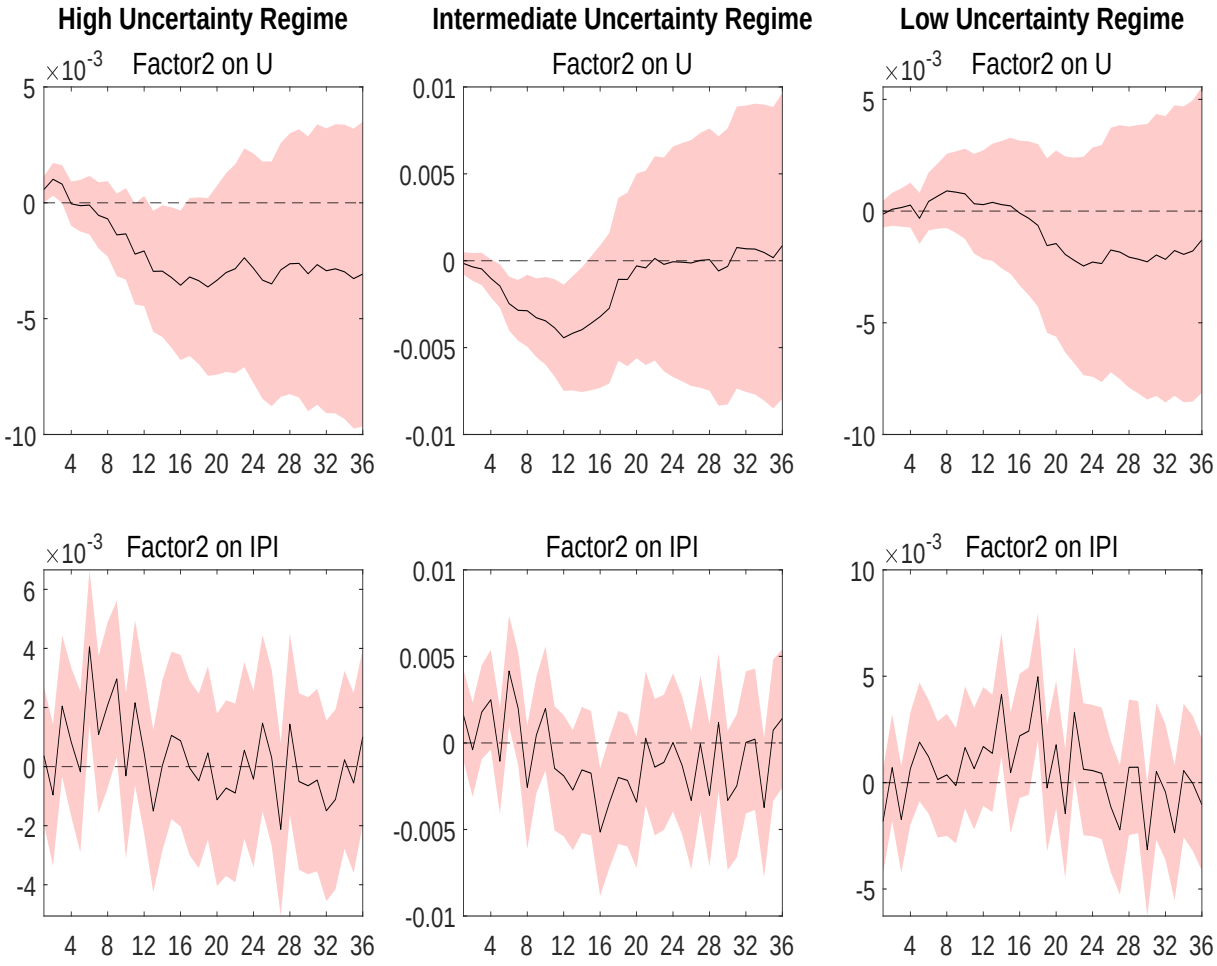
IPI_{t-2}	1.86	1.20	−8.40	0.10	−0.03	−0.03	0.00
	(0.99)	(1.98)	(10.75)	(0.08)	(0.03)	(0.03)	(0.13)
SP500_{t-3}	0.19	−0.15	−0.30	0.00	−0.01	0.00	0.04*
	(0.12)	(0.24)	(1.31)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-3}	−0.14*	0.01	−0.07	0.00	0.00	0.00	−0.00
	(0.06)	(0.13)	(0.69)	(0.01)	(0.00)	(0.00)	(0.01)
Factor2_{t-3}	−0.01	0.03	−0.21*	0.00	0.00	−0.00	0.00
	(0.01)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	1.77	0.83	10.35	0.12	0.04	0.02	0.23
	(1.41)	(2.81)	(15.26)	(0.12)	(0.05)	(0.04)	(0.19)
U_{t-3}	1.35	8.40	26.39	−0.16	−0.03	0.01	−1.01*
	(2.93)	(5.87)	(31.79)	(0.25)	(0.10)	(0.09)	(0.39)
FED_{t-3}	1.35	−10.83	−73.42	−0.35	0.07	−0.20	−0.18
	(3.58)	(7.15)	(38.78)	(0.30)	(0.12)	(0.11)	(0.48)
IPI_{t-3}	1.08	0.68	−13.16	0.06	−0.05	−0.01	0.29*
	(0.94)	(1.89)	(10.22)	(0.08)	(0.03)	(0.03)	(0.13)
Low Uncertainty Regime							
SP500_{t-1}	−0.28*	−0.12	−1.05	0.00	−0.00	0.00	0.02
	(0.11)	(0.22)	(1.22)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-1}	0.01	0.30**	1.18*	0.01**	0.00	−0.00	−0.00
	(0.05)	(0.10)	(0.52)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-1}	0.01	0.00	0.76***	0.00	0.00*	−0.00	−0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-1}	−0.80	−1.63	−20.36	0.29**	−0.02	0.02	0.11
	(1.12)	(2.23)	(12.11)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-1}	0.34	4.07	−4.83	0.06	0.56***	−0.05	−0.14
	(2.56)	(5.12)	(27.77)	(0.22)	(0.08)	(0.08)	(0.34)
FED_{t-1}	−1.07	6.54	−32.01	0.14	−0.22*	1.25***	0.26

	(2.90)	(5.81)	(31.47)	(0.24)	(0.10)	(0.09)	(0.39)
IPI_{t-1}	0.77	0.51	−3.52	0.01	−0.04	0.04	−0.12
	(0.65)	(1.29)	(7.02)	(0.05)	(0.02)	(0.02)	(0.09)
SP500_{t-2}	−0.06	−0.06	−1.17	0.01	0.01	−0.00	−0.00
	(0.12)	(0.24)	(1.30)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-2}	0.02	0.12	0.39	0.00	−0.00	0.00	0.01
	(0.05)	(0.10)	(0.54)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-2}	−0.01	0.05*	0.14	0.00	−0.00	−0.00*	−0.00
	(0.01)	(0.02)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-2}	0.14	−1.43	0.81	−0.36***	0.06	−0.01	−0.04
	(1.13)	(2.25)	(12.22)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-2}	−1.55	−6.88	1.31	−0.03	0.18	0.04	0.48
	(2.84)	(5.69)	(30.82)	(0.24)	(0.09)	(0.09)	(0.38)
FED_{t-2}	3.21	−7.04	36.86	−0.23	0.28	0.05	−0.70
	(4.68)	(9.37)	(50.76)	(0.39)	(0.15)	(0.14)	(0.63)
IPI_{t-2}	0.55	−0.54	0.53	−0.01	−0.01	0.00	0.00
	(0.64)	(1.28)	(6.92)	(0.05)	(0.02)	(0.02)	(0.09)
SP500_{t-3}	0.00	0.42	0.63	0.01	0.01	−0.00	0.01
	(0.11)	(0.22)	(1.22)	(0.01)	(0.00)	(0.00)	(0.02)
OIL_{t-3}	0.01	−0.02	0.61	0.01	0.00	0.00	0.00
	(0.05)	(0.10)	(0.53)	(0.00)	(0.00)	(0.00)	(0.01)
Factor2_{t-3}	−0.00	−0.04*	0.07	0.00	−0.00	0.00*	0.00*
	(0.01)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Infl_{t-3}	−1.14	0.60	−9.48	−0.09	−0.02	0.03	0.25
	(1.13)	(2.26)	(12.24)	(0.09)	(0.04)	(0.03)	(0.15)
U_{t-3}	0.82	2.60	9.73	−0.04	0.25**	0.01	−0.31
	(2.63)	(5.25)	(28.48)	(0.22)	(0.09)	(0.08)	(0.35)
FED_{t-3}	−1.93	0.75	−5.50	0.09	−0.04	−0.30***	0.50

	(2.94)	(5.89)	(31.91)	(0.25)	(0.10)	(0.09)	(0.39)
IPI_{t-3}	0.21	0.93	−1.42	0.02	−0.02	0.02	0.11
	(0.62)	(1.23)	(6.67)	(0.05)	(0.02)	(0.02)	(0.08)
R^2	0.28	0.28	0.86	0.42	0.98	0.99	0.44
Adj. R^2	0.12	0.13	0.82	0.29	0.98	0.99	0.32
Num. obs.	357	357	357	357	357	357	357

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure A.2.1: Impulse Response Functions with Factor2 as Identified or Exogenous shock

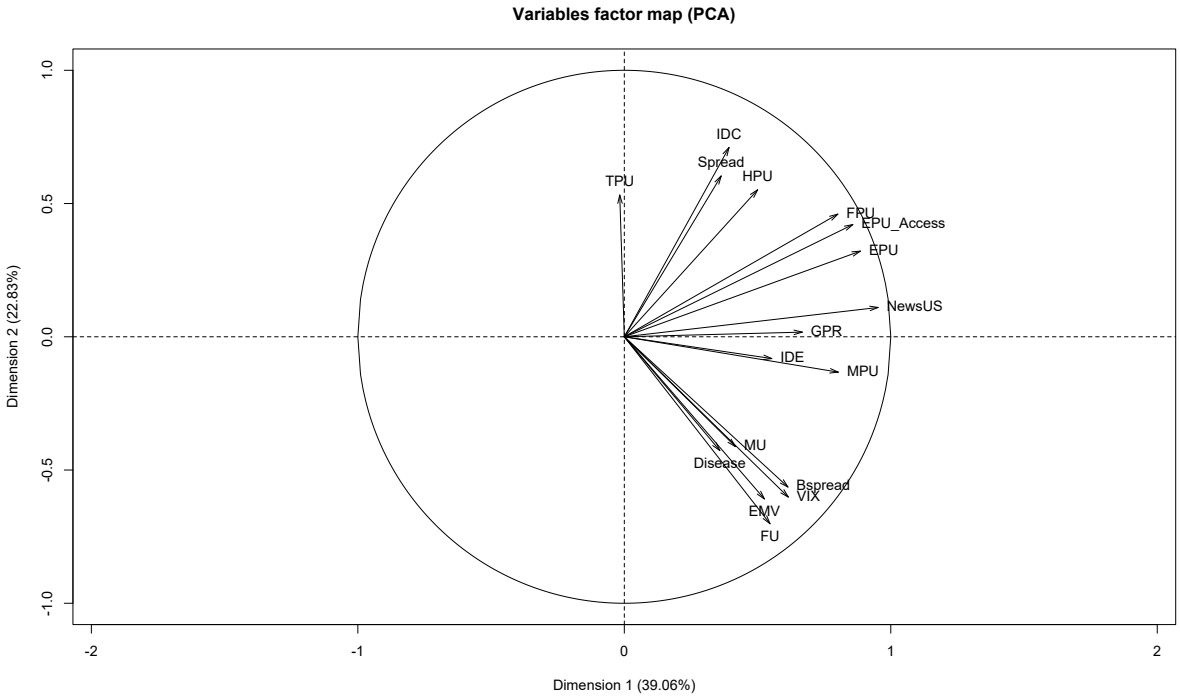


Source: Author's own calculations.
Notes: Graphs on the left panel represents impulse response functions in the high uncertainty regime. Graphs on the middle panel represents impulse response functions in the moderate uncertainty regime. Graphs on the right panel represents impulse response functions in the low uncertainty regime. The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

B Robustness Checks

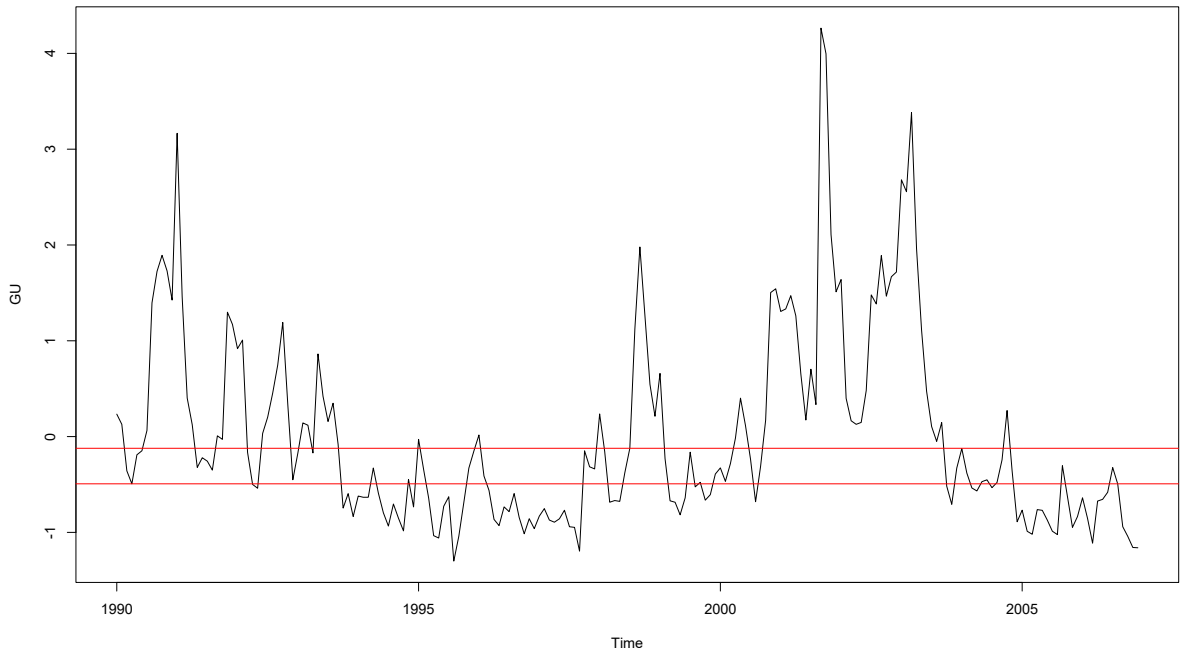
B.1 Subsample 1990-2006

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



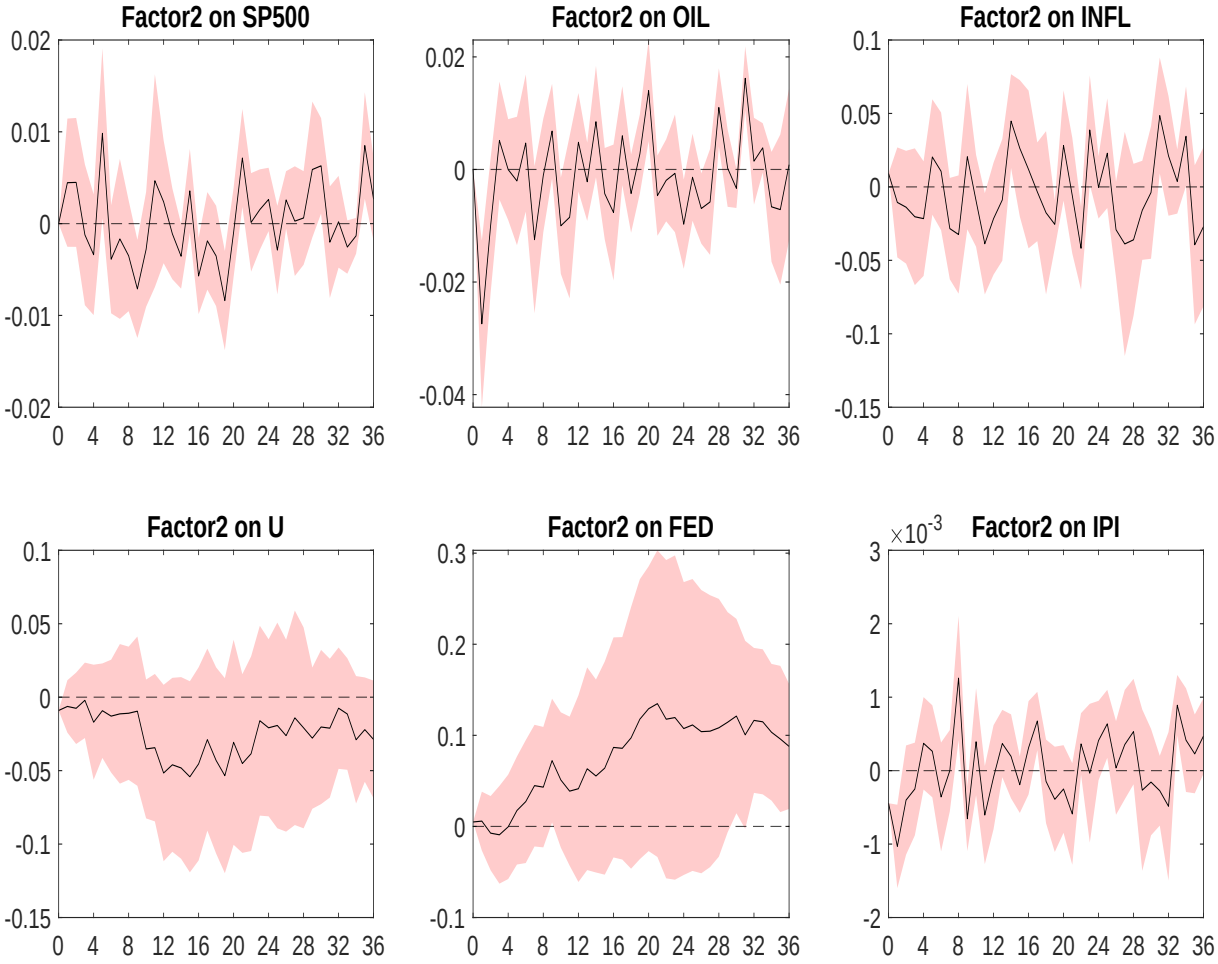
Source: Author's own calculations.

Figure B.1.2: Estimated Threshold values



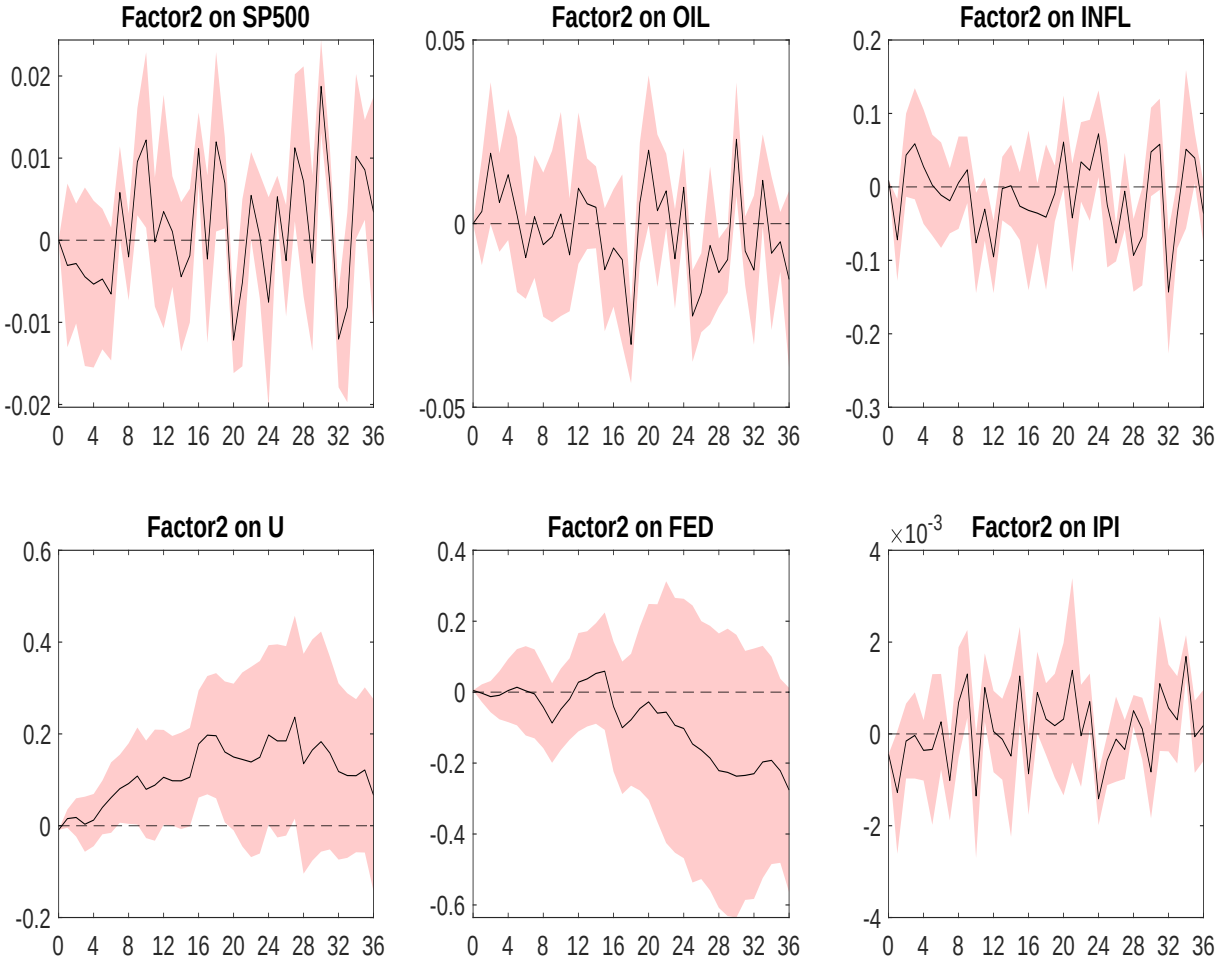
Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.1220759 and -0.4930768)

Figure B.1.3: Impulse Response Functions in a high uncertainty regime



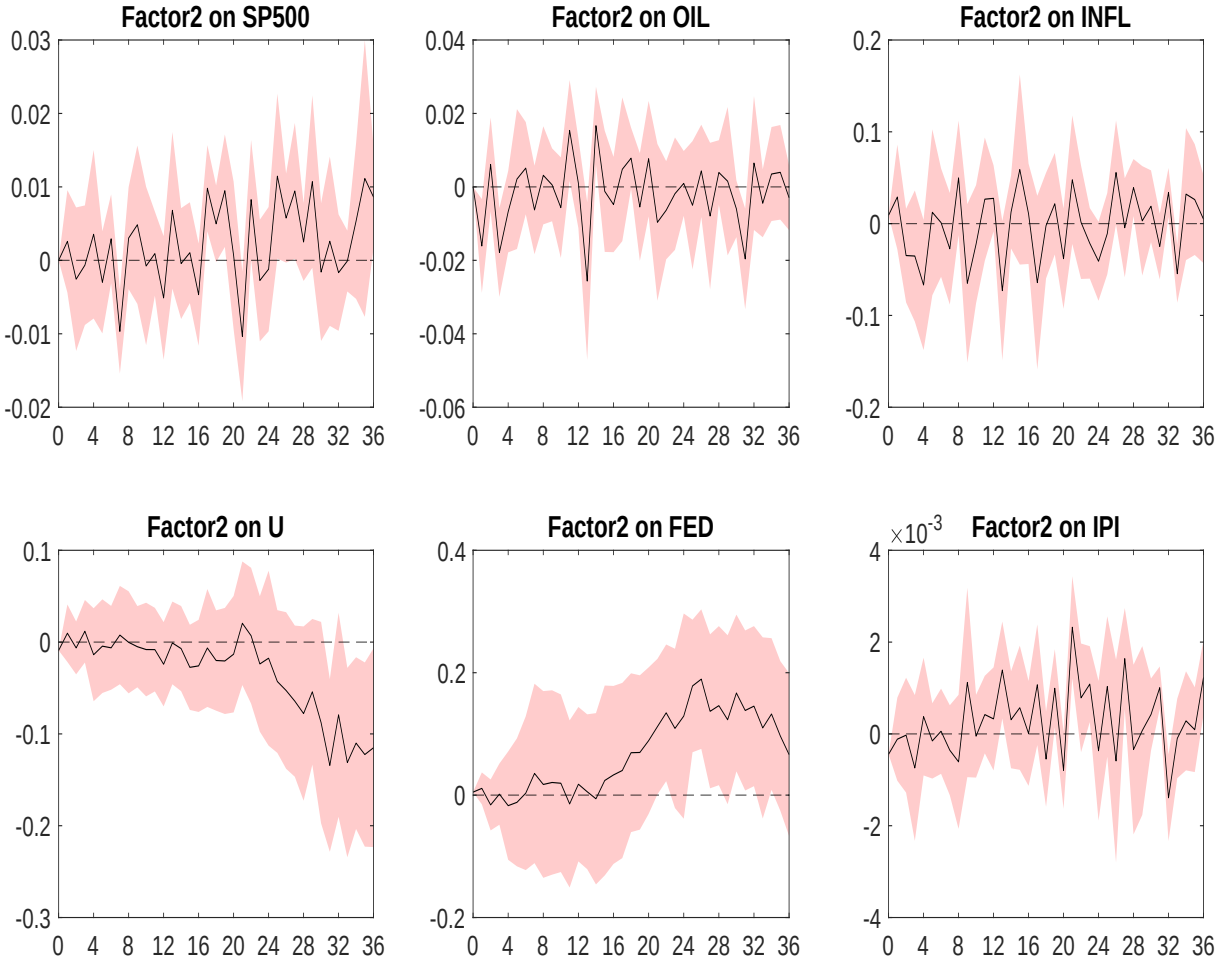
Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.1.4: Impulse Response Functions in an intermediate uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

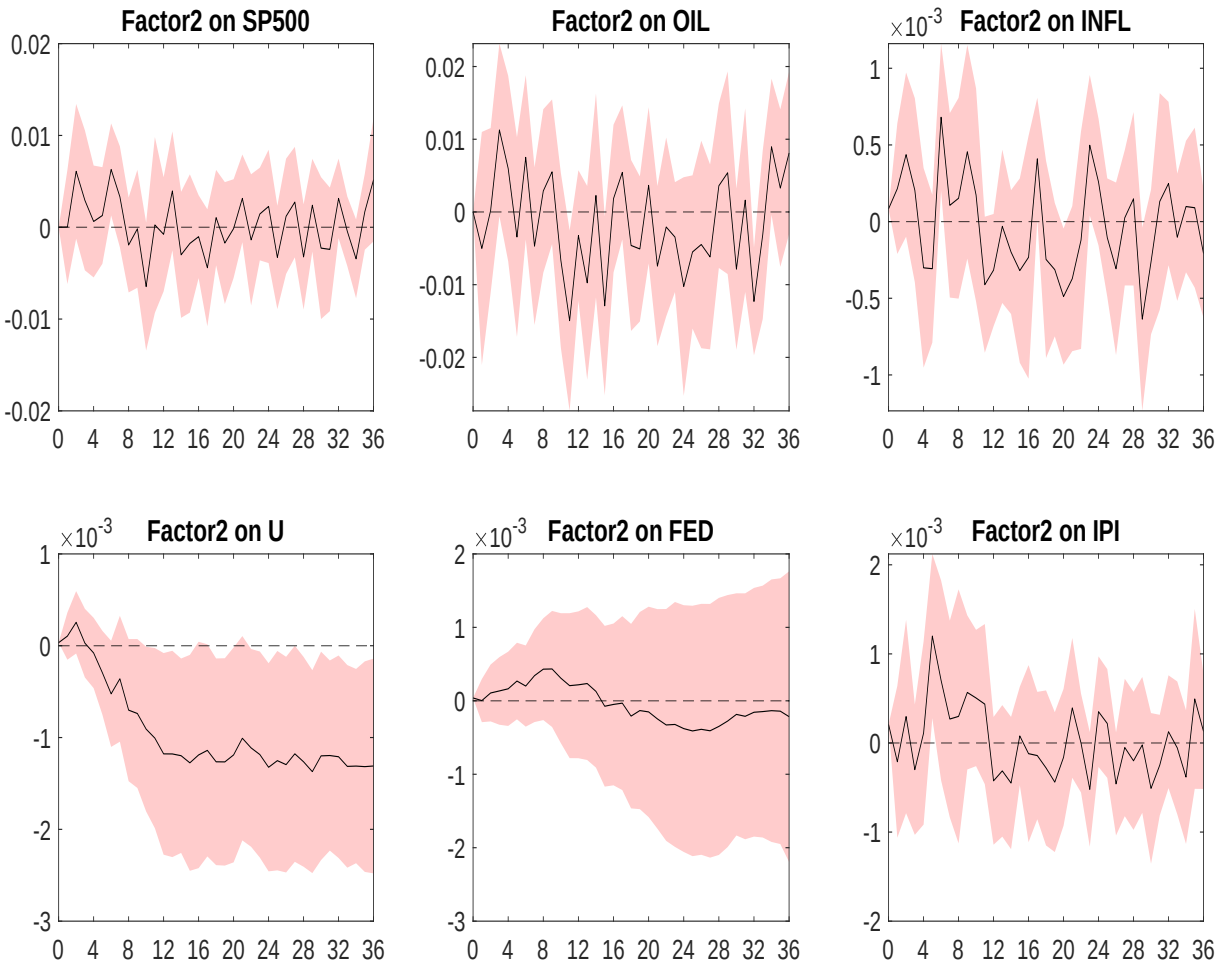
Figure B.1.5: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

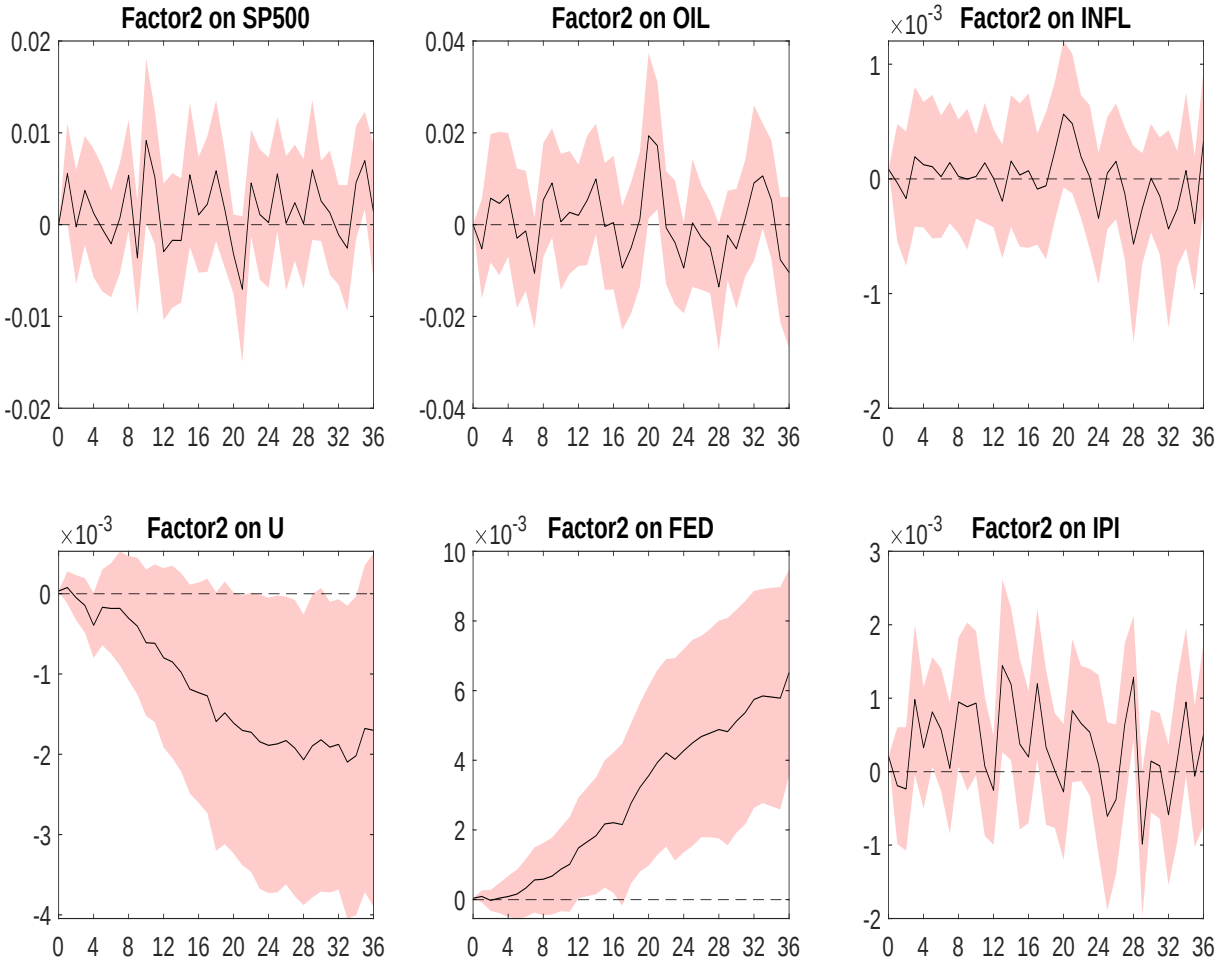
B.2 Nonlinear Framework: Two Regimes

Figure B.2.1: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

Figure B.2.2: Impulse Response Functions in a low uncertainty regime



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.

B.3 Hodrick Prescott Filter

Table B.3.1: Regression Results HP: GU as Uncertainty variable

	SP500	OIL	GU	Infl	U	FED	IPI
(Intercept)	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.03)	(0.02)	(0.01)	(0.01)	(0.00)
$SP500_{t-1}$	0.87^{***}	0.03	-3.26^{***}	0.60	-0.17	0.12	0.01
	(0.06)	(0.12)	(0.76)	(0.50)	(0.19)	(0.19)	(0.01)
OIL_{t-1}	0.02	1.14^{***}	-0.05	0.91^{***}	0.02	-0.01	0.01
	(0.03)	(0.06)	(0.37)	(0.24)	(0.09)	(0.09)	(0.00)
GU_{t-1}	-0.01^{*}	-0.02^{*}	0.79^{***}	-0.06	0.04^{*}	-0.04^{**}	0.00
	(0.00)	(0.01)	(0.06)	(0.04)	(0.01)	(0.01)	(0.00)
$Infl_{t-1}$	-0.01	0.01	0.06	1.19^{***}	-0.03	-0.01	0.00
	(0.01)	(0.01)	(0.08)	(0.05)	(0.02)	(0.02)	(0.00)
U_{t-1}	0.00	0.08^{*}	0.18	0.11	0.69^{***}	-0.05	-0.00
	(0.02)	(0.03)	(0.21)	(0.14)	(0.05)	(0.05)	(0.00)
FED_{t-1}	0.01	0.04	-0.12	0.13	-0.08	1.44^{***}	0.00^{*}
	(0.02)	(0.03)	(0.19)	(0.13)	(0.05)	(0.05)	(0.00)
IPI_{t-1}	1.27^{**}	1.79^{*}	-15.02^{**}	0.17	-3.85^{**}	5.57^{***}	0.91^{***}
	(0.39)	(0.75)	(4.98)	(3.29)	(1.27)	(1.24)	(0.05)
$SP500_{t-2}$	0.00	-0.02	3.47^{***}	-0.44	0.12	-0.20	0.01
	(0.06)	(0.11)	(0.76)	(0.50)	(0.19)	(0.19)	(0.01)
OIL_{t-2}	-0.01	-0.30^{***}	0.22	-0.66^{**}	0.10	-0.07	-0.01
	(0.03)	(0.06)	(0.37)	(0.25)	(0.09)	(0.09)	(0.00)
GU_{t-2}	0.01^{*}	0.02	0.01	0.04	0.01	0.02	-0.00^{*}
	(0.00)	(0.01)	(0.06)	(0.04)	(0.01)	(0.01)	(0.00)
$Infl_{t-2}$	-0.00	-0.00	-0.03	-0.36^{***}	0.00	0.02	-0.00
	(0.01)	(0.01)	(0.08)	(0.05)	(0.02)	(0.02)	(0.00)
U_{t-2}	0.01	-0.05	-0.05	-0.08	0.15^{**}	0.04	0.01^{***}
	(0.02)	(0.03)	(0.20)	(0.13)	(0.05)	(0.05)	(0.00)
FED_{t-2}	0.00	-0.03	0.14	-0.12	0.06	-0.46^{***}	-0.00
	(0.02)	(0.03)	(0.20)	(0.13)	(0.05)	(0.05)	(0.00)
IPI_{t-2}	-0.90^{*}	-1.16	15.55^{**}	1.94	0.88	-5.20^{***}	0.03
	(0.41)	(0.78)	(5.18)	(3.42)	(1.31)	(1.29)	(0.05)
R^2	0.88	0.87	0.77	0.89	0.97	0.99	0.96
Adj. R^2	0.88	0.86	0.76	0.88	0.97	0.99	0.96
Num. obs.	358	358	358	358	358	358	358

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure B.3.1: Impulse Response Functions (General Uncertainty)



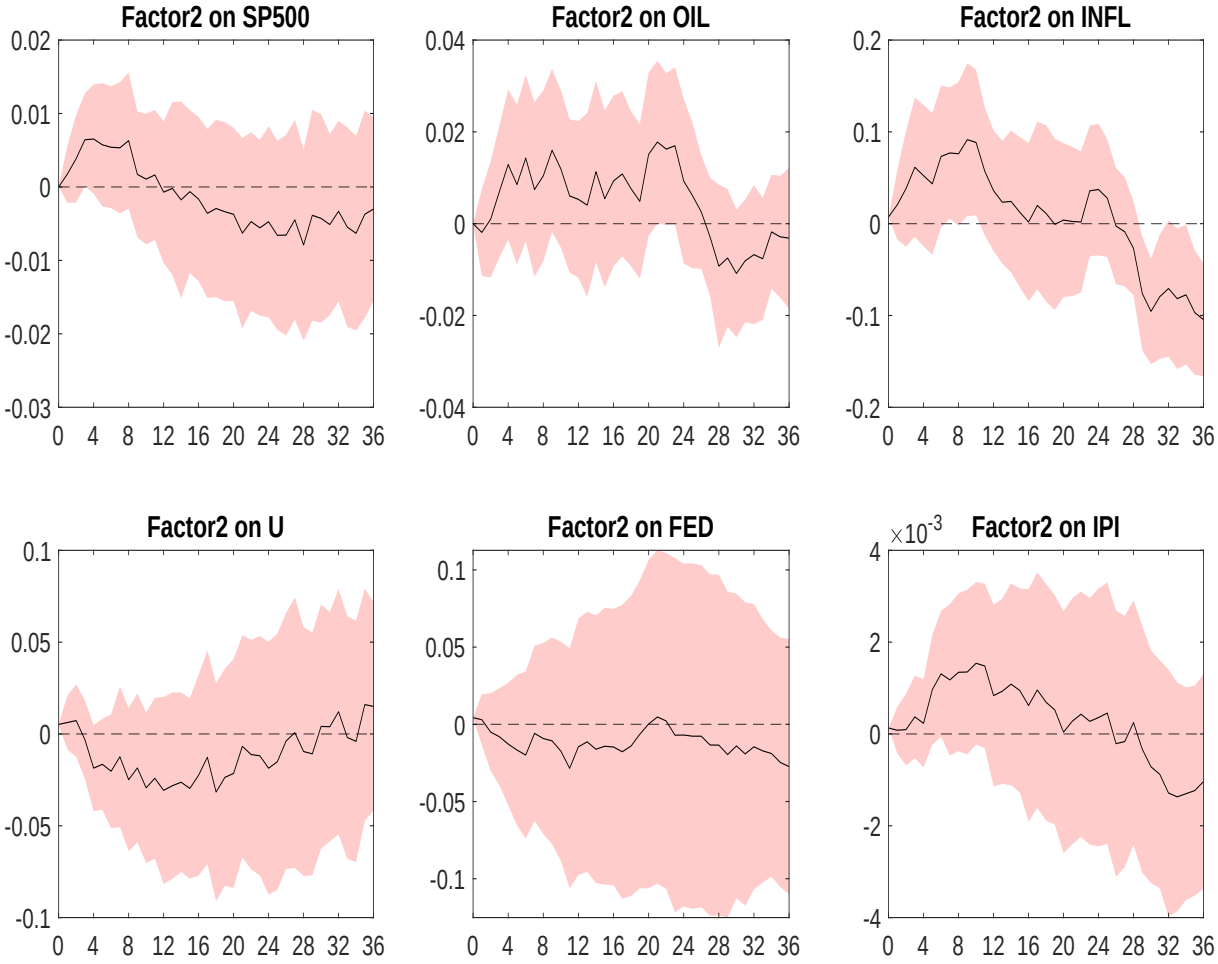
Source: Author's own calculations.
Notes: Except the uncertainty variable (GU), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Table B.3.2: Regression Results HP: Factor2 as Uncertainty variable

	SP500	OIL	Factor2	Infl	U	FED	IPI
(Intercept)	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)
$SP500_{t-1}$	0.91^{***}	0.14	-1.50^{*}	0.79	-0.40^{*}	0.41^{*}	0.01
	(0.06)	(0.13)	(0.67)	(0.51)	(0.20)	(0.19)	(0.01)
OIL_{t-1}	0.02	1.15^{***}	0.69^{**}	0.91^{**}	-0.02	0.03	0.01
	(0.04)	(0.06)	(0.24)	(0.29)	(0.09)	(0.09)	(0.00)
$Factor2_{t-1}$	0.00	-0.01	0.72^{***}	0.03	0.01	-0.01	-0.00
	(0.00)	(0.01)	(0.06)	(0.04)	(0.02)	(0.02)	(0.00)
$Infl_{t-1}$	-0.01	0.00	-0.02	1.17^{***}	-0.02	-0.01	0.00
	(0.00)	(0.01)	(0.03)	(0.06)	(0.02)	(0.02)	(0.00)
U_{t-1}	0.01	0.07^{*}	-0.07	0.10	0.74^{***}	-0.08	-0.01^{*}
	(0.01)	(0.03)	(0.12)	(0.12)	(0.05)	(0.05)	(0.00)
FED_{t-1}	0.00	0.05	-0.15	0.15	-0.17^{***}	1.49^{***}	0.01^{**}
	(0.02)	(0.04)	(0.13)	(0.13)	(0.04)	(0.04)	(0.00)
IPI_{t-1}	1.17	1.83^{**}	5.33^{*}	-0.47	-4.58^{***}	6.42^{**}	0.92^{***}
	(0.63)	(0.60)	(2.68)	(3.00)	(1.22)	(2.12)	(0.05)
$SP500_{t-2}$	-0.03	-0.10	1.12	-0.54	0.17	-0.40	0.01
	(0.07)	(0.13)	(0.72)	(0.56)	(0.19)	(0.24)	(0.01)
OIL_{t-2}	-0.02	-0.31^{***}	-0.71^{*}	-0.68^{*}	0.11	-0.09	-0.01
	(0.04)	(0.07)	(0.28)	(0.27)	(0.10)	(0.10)	(0.00)
$Factor2_{t-2}$	0.00	0.01	0.18^{**}	0.02	-0.03	0.00	0.00
	(0.00)	(0.01)	(0.06)	(0.03)	(0.02)	(0.02)	(0.00)
$Infl_{t-2}$	0.00	-0.00	-0.01	-0.35^{***}	0.01	0.02	-0.00
	(0.00)	(0.02)	(0.03)	(0.07)	(0.02)	(0.02)	(0.00)
U_{t-2}	0.00	-0.06^{*}	0.17	-0.11	0.14^{**}	0.06	0.01^{**}
	(0.01)	(0.03)	(0.11)	(0.12)	(0.05)	(0.05)	(0.00)
FED_{t-2}	0.01	-0.04	0.20	-0.14	0.15^{***}	-0.52^{***}	-0.01^{*}
	(0.02)	(0.04)	(0.12)	(0.11)	(0.04)	(0.04)	(0.00)
IPI_{t-2}	-0.84	-1.38^{*}	-5.25	1.92	2.44^{*}	-6.39^{***}	-0.01
	(0.52)	(0.60)	(2.84)	(2.95)	(1.18)	(1.91)	(0.05)
R^2	0.88	0.87	0.83	0.89	0.97	0.99	0.96
Adj. R^2	0.88	0.86	0.82	0.88	0.96	0.98	0.96
Num. obs.	358	358	358	358	358	358	358

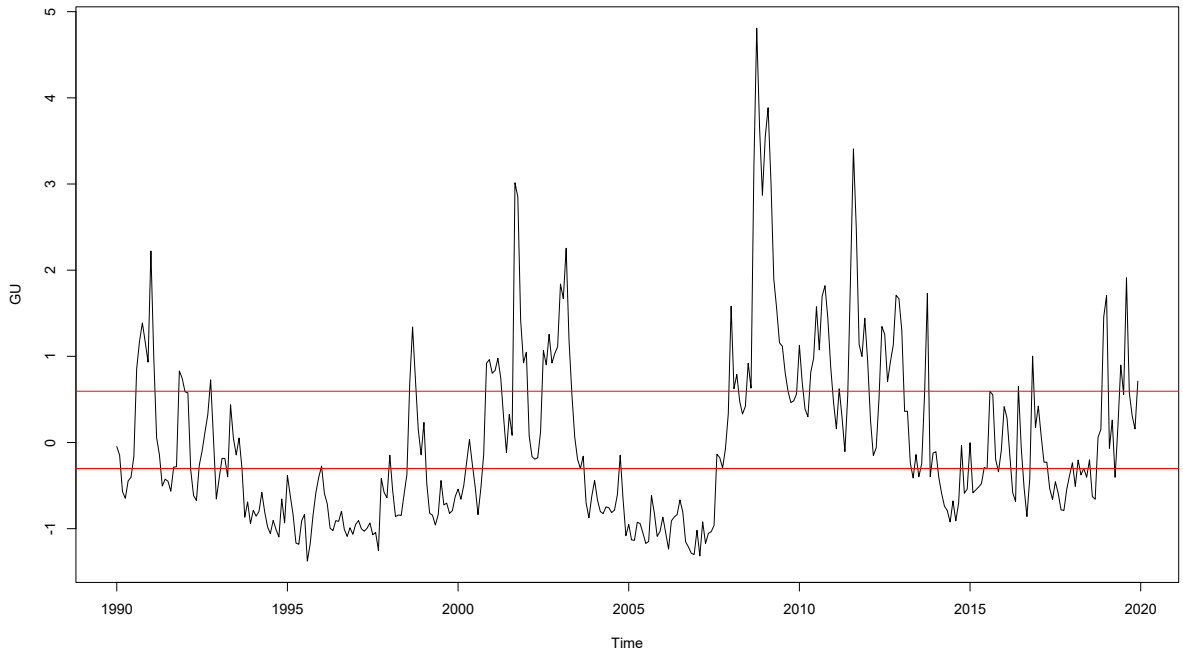
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure B.3.2: Impulse Response Functions (Factor 2)



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.3.3: Two thresholds of general uncertainty



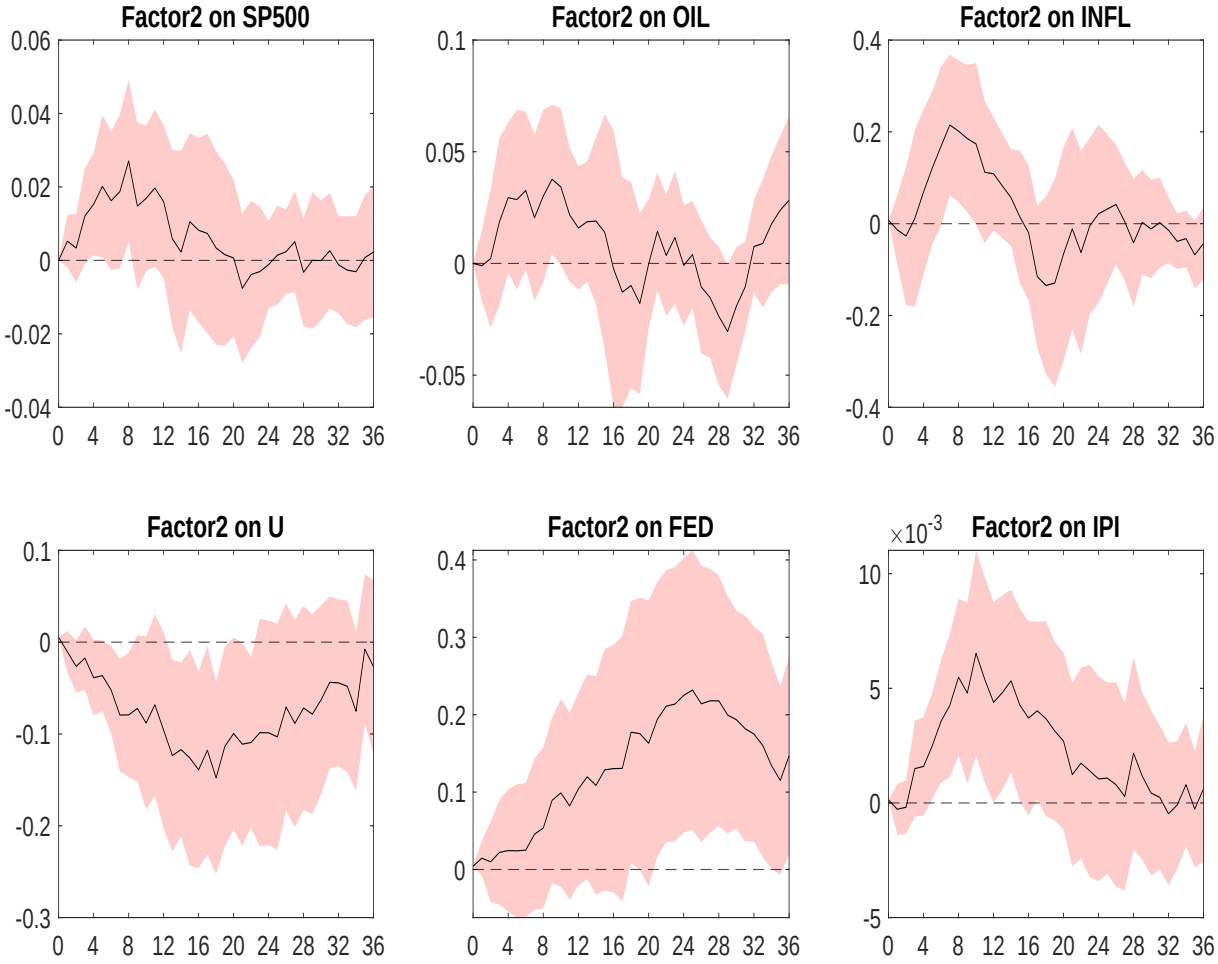
Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.3014314 and 0.6228429)

Figure B.3.4: Impulse Response Functions in a low uncertainty regime



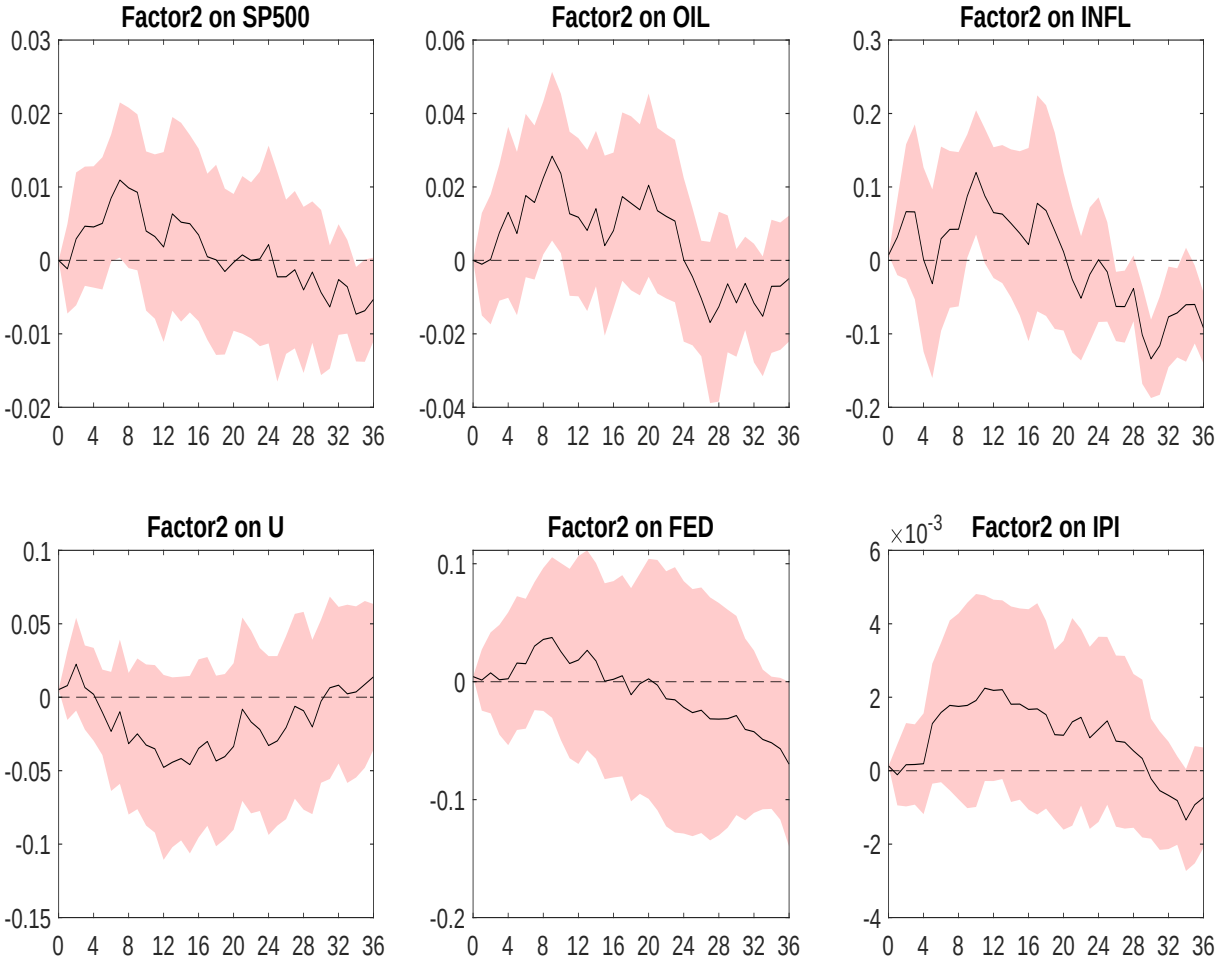
Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

Figure B.3.5: Impulse Response Functions in an intermediate uncertainty regime



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

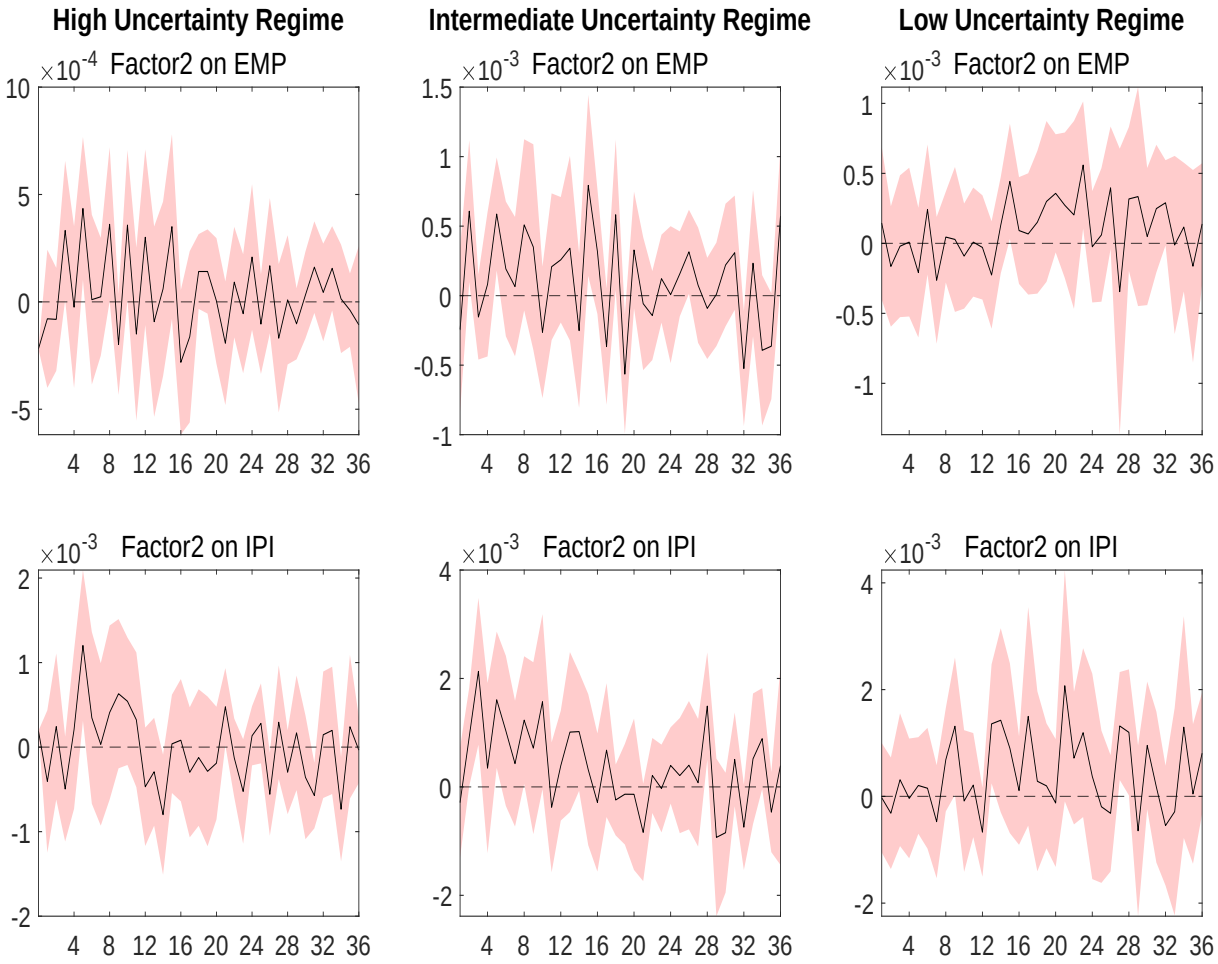
Figure B.3.6: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: Except the uncertainty variable ($Factor2$), all variables are detrending applying the HP filter ($\lambda = 129600$) The solid black lines correspond to the IRFs. The shaded area denotes the 95% confidence interval.

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Figure B.4.1: Impulse Response Functions in a high uncertainty regime



Source: Author's own calculations.
Notes: Graphs on the left panel represents impulse response functions in the high uncertainty regime. Graphs on the middle panel represents impulse response functions in the moderate uncertainty regime. Graphs on the right panel represents impulse response functions in the low uncertainty regime. The solid black lines correspond to the IRFs. The red shaded area denotes the 95% confidence interval.