When Does Uncertainty Become Expansionary? The Role of Composition and State Dependence

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When Does Uncertainty Become Expansionary? The Role of Composition and State Dependence*

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Abstract

When does uncertainty become expansionary? While the empirical literature generally concludes that uncertainty depresses economic activity, recent theoretical contributions suggest that some forms of uncertainty may instead stimulate investment and output. This paper argues that the macroeconomic effects of uncertainty depend jointly on its composition and the prevailing uncertainty regime. Using sixteen U.S. uncertainty indicators over the period 1990–2024, we construct two orthogonal latent factors through principal component analysis. The first captures the overall level of uncertainty, whereas the second distinguishes financial from non-financial uncertainty. An independent VARIMAX rotation validates this interpretation. We then estimate state-dependent local projections to examine how different uncertainty shocks affect industrial production and employment across low-, moderate-, and high-uncertainty regimes. We find that financial uncertainty shocks generate the conventional contractionary effects. In contrast, non-financial uncertainty shocks significantly increase economic activity when aggregate uncertainty is moderate or high, while they have no significant effect during low-uncertainty periods. These findings suggest that the composition of uncertainty is a key determinant of its macroeconomic consequences and provide new aggregate evidence supporting recent theories predicting expansionary effects of non-financial uncertainty.

Keywords: Uncertainty shocks, non-linear local projection methods, PCA, VARIMAX.
JEL Codes: C32; C38; E32

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1 Introduction

The macroeconomic effects of uncertainty have long been regarded as predominantly contractionary. Following the seminal contributions of Bloom (2009) and Jurado *et al.* (2015), a large empirical literature concludes that increases in uncertainty reduce investment, employment, and output[1]. The standard explanation combines the real-options mechanism, whereby firms postpone irreversible investment decisions, with precautionary behaviour that encourages households to increase savings and delay consumption. As a result, uncertainty is generally viewed as a force amplifying business-cycle downturns.[2]

However, this consensus has recently been challenged by a growing empirical literature documenting expansionary effects of uncertainty under specific circumstances. Rather than questioning the existence of contractionary uncertainty shocks, these studies identify particular forms of uncertainty that may stimulate economic activity. Segal *et al.* (2015), for example, show that uncertainty associated with future industrial opportunities may raise investment and identify positive uncertainty shocks within a VAR framework. Using a different approach, Forni *et al.* (2021) distinguish between downside and upside uncertainty and find that upside uncertainty exerts a modest but positive effect on economic activity.

This empirical evidence gives rise to an important question. Why do some forms of uncertainty appear to stimulate economic activity? Recent theoretical developments offer a possible explanation. Building on earlier contributions in the real-options literature, several models argue that the macroeconomic effects of uncertainty depend not only on its overall level but also on its underlying source. Segal *et al.* (2015) show that uncertainty associated with future technological opportunities may increase current investment. Other contributions emphasize mechanisms related to investment-good productivity (Segal, 2019), downstream *versus* upstream price un-

[1]Extending the analysis beyond investment and output, Nam *et al.* (2021) show that uncertainty also affects household consumption. Using household-level panel data, they find that increases in financial, real, and macro uncertainty significantly reduce consumption growth, with real and macro uncertainty exerting the most persistent effects.

[2]Applying a standard Barro-style growth regression to a panel of 143 countries spanning 1960–2023, Jalles & Karras (2026) demonstrates that uncertainty, measured by the World Uncertainty Index (WUI), has a significantly negative effect on economic growth. The adverse impact is found to be larger in advanced economies than in developing countries. To complement these findings with a dynamic analysis, the author also employs Jordà's (2005) panel local projection method and likewise finds that uncertainty exerts a significant negative effect on economic growth.

certainty (Grigoris & Segal, 2026), or the informational value of irreversible investments such as RD (Crouzet & Eberly, 2026). Although these mechanisms differ substantially, they share a common implication: uncertainty is not intrinsically contractionary. Its macroeconomic effects depend on the nature of the underlying shocks. Importantly, these expansionary mechanisms are driven by sources of uncertainty originating in the real economy rather than by financial disturbances.

Why, then, does the vast majority of the empirical literature continue to find predominantly contractionary effects? We argue that the answer lies in the way uncertainty shocks are identified. Most empirical approaches combine several economically distinct sources of uncertainty into a single aggregate shock. If financial and non-financial uncertainty have different or even opposite macroeconomic effects, estimating their average response is unlikely to recover either effect correctly. Instead, the estimated response is likely to be dominated by the strongest contractionary component, thereby masking expansionary effects predicted by recent theory.

This issue is not limited to the distinction between financial and macroeconomic uncertainty (Jurado *et al.*, 2015). The empirical literature has proposed several other decompositions, including policy *versus* non-policy uncertainty, commodity-specific uncertainty, and upside *versus* downside uncertainty. While these classifications have generated valuable insights, they are generally imposed *ex ante* and do not necessarily isolate independent structural sources of uncertainty. The distinction between financial and non-financial uncertainty is directly motivated by recent theory. Existing models predicting expansionary effects are driven by uncertainty originating in the real economy, whereas the traditional contractionary literature largely emphasizes financial disturbances. Consequently, separating financial from non-financial uncertainty is not simply another classification of uncertainty shocks. Rather, we provide a direct empirical test of two competing views of how uncertainty is transmitted to the macroeconomy.

A second issue concerns state dependence. Even if uncertainty were perfectly identified, estimating a single average response implicitly assumes that uncertainty has the same macroeconomic consequences during tranquil periods as during episodes of elevated uncertainty. Yet recent theoretical contributions suggest precisely the opposite. Whether uncertainty delays investment or accelerates it is likely to depend on the prevailing uncertainty environment. Estimating a single linear response therefore averages together heterogeneous effects and may conceal expansionary responses that arise only under particular uncertainty regimes[3].

This paper proposes a unified empirical framework designed to address both issues. Using sixteen monthly U.S. uncertainty indicators over the period 1990–2024, we first extract two orthogonal latent factors using Principal Component Analysis (PCA). The first factor measures the overall level of uncertainty, whereas the second captures a distinct latent dimension related to the composition of uncertainty. As shown below, the pattern of factor loadings indicates that this second dimension separates financial from non-financial sources of uncertainty, while the sign of the factor scores identifies the nature of individual uncertainty shocks. Importantly, this interpretation is not simply assumed. We assess it independently using an orthogonal VARIMAX rotation, which confirms that the second principal component indeed reflects the distinction between financial and non-financial uncertainty. The VARIMAX analysis therefore validates the economic interpretation of the second principal component. We then estimate the macroeconomic effects of these uncertainty shocks using state-dependent local projections that allow the responses to differ across low, moderate, and high uncertainty regimes.

We find that the macroeconomic effects of uncertainty cannot be understood without jointly considering both its composition and the prevailing uncertainty regime. Financial uncertainty shocks produce the familiar contractionary effects on industrial production, and employment. By contrast, non-financial uncertainty shocks increase economic activity, but only when aggregate uncertainty is moderate or high. No significant effect is found during periods of low uncertainty. These findings remain robust to a wide range of alternative specifications, including controlling for the COVID-19 episode, restricting the sample to the pre-pandemic period, modifying the recursive identification scheme, and altering the construction of the uncertainty factors.

Our findings are consistent with aforementioned models in which uncertainty increases the value of investing immediately, as well as with bounded-rationality models in which greater un-

[3]The empirical evidence of Iván Alfaro & Lin (2024) suggests that the macroeconomic effects of uncertainty are state dependent. Using an instrumental-variable approach, the authors show that uncertainty shocks have considerably stronger adverse effects during periods of tight financial conditions and for financially constrained firms, highlighting the amplifying role of financial frictions.

certainty is associated with stronger cognitive myopia (Gabaix, 2020). Our objective, however, is not to discriminate among these mechanisms but rather to establish an empirical regularity: once uncertainty is decomposed into economically distinct components and analyzed across different uncertainty regimes, expansionary effects become observable in aggregate U.S. data.

Our paper makes three contributions. First, we show that understanding the macroeconomic effects of uncertainty requires considering both its level and its composition. Financial and non-financial uncertainty are not interchangeable and may have fundamentally different macroeconomic consequences. Second, we propose an endogenous identification strategy in which the composition of uncertainty emerges as a latent economic dimension of the data rather than as an *ex ante* classification. An independent VARIMAX analysis then validates the interpretation of this latent dimension as the distinction between financial and non-financial uncertainty. Third, we provide new aggregate evidence that the expansionary effects predicted by several recent theoretical models become observable once uncertainty is properly identified and state dependence is taken into account.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical mechanisms linking uncertainty to macroeconomic activity. Section 3 presents the data, the construction of the uncertainty factors, and the VARIMAX validation of their economic interpretation. Section 4 reports the linear results. Section 5 analyzes the nonlinear state-dependent effects. Section 6 presents a series of robustness checks. Section 7 concludes.

2 Positive effect of uncertainty: literature review

2.1 Positive effect in the data

One of the earliest study that find a positive effect is provided by Segal *et al.* (2015), who argue that uncertainty can benefit economic activity when it relates to future industrial prospects. They develop a theoretical model in which uncertainty shocks—both positive and negative—affect consumption growth and expectations. The key insight is that uncertainty about favourable outcomes can enhance investment by shifting expectations. Using a VAR framework, they empirically identify positive uncertainty shocks based on the positive semivariance of industrial production, and find that these "good" shocks have lasting positive effects on macroeconomic variables, dampening the adverse effects of "bad" uncertainty.

A similar decomposition approach is adopted by Forni *et al.* (2021), who distinguish between downside and upside uncertainty—defined respectively as the distance from the median forecast to the 10th and 90th percentiles of future growth. Their results confirm that downside uncertainty exerts a negative effect on activity, while upside uncertainty has a modest positive impact. These findings suggest that the negative component of uncertainty tends to dominate in aggregate data, explaining why most studies report an overall contractionary effect.

Ludvigson *et al.* (2021) take a different angle by decomposing uncertainty into macroeconomic versus financial components, following the methodology of Jurado *et al.* (2015). They construct a financial uncertainty index based on a panel of 148 financial indicators (e.g., Treasury bill yields, P/E ratios, Fama & French (1992) risk factors, etc), and find that financial uncertainty is closely associated with recessions. While their structural VAR approach identifies a positive effect of certain uncertainty shocks, subsequent analysis by Himounet *et al.* (2024) questions the robustness of these findings, suggesting that such effects may be artifacts of event constraints tied to post-recession recoveries rather than genuine uncertainty dynamics.

More novel methodologies have also been explored. Larsen (2021), for instance, employs machine learning techniques to classify and quantify uncertainty in Norwegian newspapers. Using topic modelling and SVAR with narrative sign restrictions (*à la* Antolín-Díaz & Rubio-Ramírez (2018)), he finds that while most topic-specific uncertainties reduce economic activity, certain domains—like Mergers & Acquisitions—show a positive impact. This highlights that the economic effects of uncertainty may vary depending on its informational content.

Ferrara *et al.* (2022b) examine commodity price uncertainty by identifying three distinct commodity factors: agricultural, metals, and energy. They find that while general and most commodity-specific uncertainties depress activity, uncertainty in energy prices may have a short-term positive effect. This result is interpreted through anticipatory behavior *à la* Punzi (2019): When firms expect energy prices to rise, they may increase current consumption or investment, temporarily boosting output. Building on this, the authors developed a classification scheme in which uncertainty is deemed "good" when commodity prices are falling and "bad" when rising. A related study (Ferrara *et al.* (2022a)) further finds that positive global commodity uncertainty shocks lead to a short-term depreciation followed by a medium-term appreciation in commodity-linked currencies, driven by investor expectations of future returns.

Together, these studies suggest that the economic impact of uncertainty is heterogeneous and contingent on its type (financial vs. non-financial), direction (upside vs. downside), and content (industrial, commodity-related, etc.). Nonetheless, most empirical approaches either rely on mechanical decompositions or are limited to specific sectors or events, limiting the generalizability of their conclusions. Moreover, few studies offer a behavioral mechanism that can explain when and why uncertainty might be expansionary.

2.2 Positive effect in the theory

Long before the recent literature, several theoretical contributions had already questioned the conventional view that uncertainty is necessarily contractionary: Oi (1961), Hartman (1972) and 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.

Segal *et al.* (2015) propose a new mechanism 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"*. An important aspect is that agents may dislike uncertainty—whether good or bad—so the overall effects of uncertainty tend to be skewed toward the negative. Nevertheless, favorable uncertainty can generate positive indirect effects that outweigh the adverse impact of higher volatility. In such cases, asset prices respond positively to favorable uncertainty, as expectations of future growth improve.

Segal (2019) provides a possible microfoundation of these mechanisms. It is related to technological volatility. The basic idea is that volatility may originate from consumption or it may originate from investment. Basically, an increase in volatility implies to opposed effects. First a negative income effect that should boost investment and second a positive substitution effect that leads investment to decrease. If TFP volatility of the investment sector increases, then the probability of having sub-optimal amount of investment goods increases for future periods so households have a strong incentive to invest more and consume less to avoid this, due the precautionary saving. This leads investment to rise. More investment means more resources in the future. This contrasts sharply with the effect an increase of TFP volatility in the consumption sector has: households are more impatient and then consume more so they invest less. However, these two opposed effects are not enough to explain why uncertainty may have a positive effect. For this to work, given that investment and consumption are substitutes, monopolistic competition and sticky prices are necessary inputs. These ingredients create time-varying markups which explain the positive effect because volatility in the investment sector turns out to have long term effect contrary to volatility in the consumption sector. Hence volatility in the investment sector may induce growth and stock prices to increase.

An alternative explanation has been put forward by Grigoris & Segal (2026). They develop a model of real option with time to build. They distinguish upstream and downstream uncertainties. The first implies variability about future input prices while the second is about future output prices. It turns out that upstream uncertainty affects short term while downstream uncertainty affects long term. Firms may exert a growth option (literally, that is an investment that will allow them to grow such as an increase in the size of their factories). Both uncertainties increase the interest to wait before raising the option. But waiting implies a cost that corresponds to the additional profit firms could have obtained had they exercised the growth option. This opportunity cost depends on the future output price, hence the downstream uncertainty, but not from the input price. Thus there is an asymmetry between both uncertainties. Consequently, upstream uncertainty induces investment to fall while downstream uncertainty implies investment may increase because waiting too long means too high a cost.

A last very recent paper that tries to explain these firms' behaviour is Crouzet & Eberly (2026). The authors argue that investment in equipment is very cyclical. For instance, it is very sensitive to employment. The opposite is true for investment in R & D that is quite stable. In order to find something that may be profitable, a firm should not cease her research activity. So different types of investment respond differently to uncertainty. The original logic that there is value in waiting when facing uncertainty rests on a key assumption: information about the project arrives even if the firm does not invest (i.e she waits). Investment in equipment and structure depends on changes of values (material price, labor price,...) that are independent of the firm decision to invest. As for investment in R & D, it is needed to know whether the output of R & D is good or not. That is, investment in R&D (but it may be true for others) reveals the project value. In that cases, uncertainty may cause investment to rise, not fall, because, as the author put it, the "resolution effect" (we need to know) may dominate the "delay effect" (we should wait).

Hence, while the first two theoretical channels are rather related to industrial prospects that may have positive effects on future growth, the last three are about wait (or not) and see behaviour of firms that may be encouraged or discouraged by uncertainties.

A last argument is worth evoking: Ricardian equivalence may not hold anymore when there is an important uncertainty. This conclusion is due to a recent paper by Xavier Gabaix (Gabaix,

2020) that itself builds on several previous papers by the same author. One important implication of that kind of models is that Ricardian equivalence is not holding anymore because agents are partly myopic. This myopia comes from the fact that a typical behavioral new Keynesian agent is not able to analyze all the information available. We hence conjecture that uncertainty may raise their myopia, hence increasing this effect. When agents are limited in their ability to process information they receive, it is possible that uncertainty increases agents' myopia by raising the amount of information agents may need to process, or by raising the difficulty of processing each piece of information as we depart from business as usual. As a consequence, in a period of uncertainty, a raise in government spending should have a positive effect.

A complementary explanation emerges from the behavioral New Keynesian literature developed by Gabaix (2020), building on several earlier contributions by the same author. In these models, agents have limited attention and process information imperfectly, implying that they are partly myopic. One important implication is that Ricardian equivalence no longer holds exactly, as households do not fully internalize the future tax liabilities associated with current fiscal expansions.

Building on this framework, we conjecture that uncertainty may further strengthen agents' cognitive myopia. When uncertainty rises, economic agents are confronted with a larger amount of information and a more complex economic environment. Processing this additional information is costly, so limited-attention agents may rationally devote less attention to distant outcomes and focus more heavily on current conditions. As uncertainty increases, forward-looking behavior may therefore become weaker, reducing the perceived future tax burden associated with fiscal stimulus.

This mechanism suggests that uncertainty may amplify the short-run effects of expansionary fiscal policy and therefore contribute to positive macroeconomic responses under certain circumstances. Our objective is not to test this behavioral mechanism directly. Rather, we regard it as one possible demand-side interpretation, alongside the supply-side mechanisms discussed above, that may help explain why some forms of uncertainty generate expansionary effects.

3 From Global Uncertainty Shocks to Financial an Non Financial Uncertainty Shocks

In this section, we propose an econometric framework to estimate both a global uncertainty index and a methodology for characterizing the nature of uncertainty. More specifically, our objective is to distinguish between uncertainty shocks originating from the financial sphere and those arising from the non-financial economy. The literature already provides measures of both macroeconomic and financial uncertainty. For instance, Ludvigson *et al.* (2021) construct a financial uncertainty index, while Jurado *et al.* (2015), using a similar methodology, develop a macroeconomic uncertainty index. However, these indicators, particularly the macroeconomic uncertainty measure, are not without limitations. One important concern is that the two indices are constructed entirely independently of one another. Consequently, there is no guarantee that the macroeconomic uncertainty index is not contaminated by financial shocks (Himounet, 2022). Indeed, even Jurado *et al.* (2015) acknowledge that their macroeconomic uncertainty index may fluctuate in response not only to uncertainty surrounding real economic activity, such as output and unemployment, but also to uncertainty associated with price dynamics and financial market variables.

In this section, we develop a methodology that allows the two types of uncertainty shocks to be estimated simultaneously while preserving their independence. Our approach extends the framework proposed by Himounet (2022). Specifically, he shows that the second principal component factor obtained from Principal Component Analysis (PCA) can be used to discriminate between different sources of uncertainty shocks, namely, macroeconomic versus financial shocks. However, the underlying justification remains relatively limited. We therefore provide a more rigorous treatment by employing a VARIMAX rotation framework. We demonstrate that the second factor of the PCA indeed effectively separates financial uncertainty shocks from non-financial uncertainty shocks, thereby offering a clear interpretation of the underlying sources of uncertainty.

3.1 Global Uncertainty Composite Indexes

In the empirical literature, numerous measures of uncertainty have been developed using a variety of methodologies (see Himounet (2022) for a detailed review). Typically, each measure captures a specific dimension of uncertainty—be it financial, economic policy, geopolitical, trade policy, or pandemic-related. As such, each indicator conveys distinct information. To account for this heterogeneity, some researchers advocate for the construction of composite indices. For example, using Principal Component Analysis (PCA), Haddow *et al.* (2013) developed a global uncertainty indicator for the United Kingdom, and Himounet (2022) did so for the United States using several different uncertainty measures. Similarly, Charles *et al.* (2018) constructed a composite index for the United States using a dynamic factor model.

In this paper, we adopt a similar strategy and extend the methodology proposed by Himounet (2022). First, we update the data until December 2024. Second, we broaden the scope by incorporating 16 distinct uncertainty measures [4]. To the best of our knowledge, we incorporate all existing uncertainty measures available in the literature for the USA.

There are two broad types of variables in the list of uncertainty indicators applied in Himounet (2022): those that measure uncertainty directly and those that capture it indirectly through its economic effects. On the one hand, several indicators are explicitly designed to quantify uncertainty. Following the seminal paper of Bloom (2009), the VIX measures option-implied volatility on the S&P 500 and directly reflects market expectations about future stock price fluctuations. Baker *et al.* (2016) develop a range of text-based indicators. The News index (NewsUS) captures the frequency of newspaper articles referring to economic conditions and uncertainty. The Economic Policy Uncertainty (EPU_Index) index aggregates three components: a newspaper-based measure, an index of temporary federal tax code provisions capturing fiscal legislative instability, and forecast disagreement from the Survey of Professional Forecasters for policy-relevant variables. The EPU Access World News version (EPU_Access) extends the newspaper component using a broader media database. Thematic indices refine this approach by focusing on specific policy domains: Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Health Policy Uncertainty (HPU), and Trade Policy Uncertainty

[4] Appendix Table A.1 provides the full list of uncertainty indicators applied.

(TPU) isolate instability related to central banking, fiscal decisions, healthcare regulation, and trade policy, respectively.[5] Similar textual methodologies underpin the Geopolitical Risk (GPR) index of Caldara & Iacoviello (2022), the newspaper-based Equity Market Volatility (EMV) tracker of Baker *et al.* (2019), and the Infectious Disease EMV index (Disease) of Baker *et al.* (2020), that measures the share of stock market volatility attributable to pandemics.

On the other hand, some variables proxy uncertainty indirectly by reflecting its consequences for expectations and risk premia. Survey-based measures such as consumer (IDC) and business (IDE) confidence indices capture households' and firms' expectations about future economic conditions; as emphasized by Ludvigson (2004), declining confidence signals rising uncertainty about income, employment, and activity.[6] Financial spreads provide another indirect channel. Corporate bond spreads (Bspread), defined as the difference between the yield on Baa-rated corporate bonds and the yield on 30-year Treasury securities. An increase in the spread is generally interpreted as a sign of heightened market tension reflecting investors' heightened demand for compensation in response to greater uncertainty about the creditworthiness and financial health of corporations (Bachmann *et al.*, 2013; Gilchrist *et al.*, 2014). Similarly, yield curve spreads such as the 10 year–2 year (Spread) differential may reflect a higher term premium when long-horizon uncertainty increases (Bauer & Mertens, 2018).

Broader macroeconomic and financial uncertainty measures rely on econometric frameworks that isolate the unpredictable component of large datasets. Jurado *et al.* (2015) construct a macroeconomic uncertainty index (MU) by aggregating the conditional volatility of forecast errors across a wide range of macroeconomic variables, while Ludvigson *et al.* (2021) develop a comparable financial uncertainty index (FU) based on financial series. However, as discussed at the beginning of this section, the macroeconomic uncertainty index (MU) may be contaminated by financial shocks. As the interpretation of this variable is uncertain, so we prefer not to include it in the PCA.[7]

[5] Although global versions of policy uncertainty index have been developed—either as GDP-weighted averages of national EPU indices (Davis, 2016) or as worldwide textual measures (Ahir *et al.*, 2018)—we do not apply them in this paper. Our aim is to focus exclusively on U.S.-specific uncertainty measures.

[6] We apply the inverse of both indexes to have an interpretation identical to the other uncertainty proxies listed above.

[7] The results are qualitatively similar if we include this variable in the PCA, see section 6.5.

We then apply PCA to these 16 indicators to construct composite indices. Figure 1 presents the variable factor map for the first two principal components. All uncertainty measures are positively loaded on the first factor, indicating that an increase in this factor corresponds to a rise in uncertainty across one or more of the 16 dimensions. We label this component the General Uncertainty index, denoted GU.

As noted in Himounet (2022), the second factor differentiates between two types of uncertainty: financial and non-financial. The uncertainty indicators can be broadly grouped into two categories. The first group comprises non-financial indicators, such as the Economic Policy Uncertainty Index of Baker *et al.* (2016), the Consumer Confidence Index, and the Geopolitical Risk Index of Caldara & Iacoviello (2022). The second group includes predominantly financial indicators such as the VIX, corporate bond spreads, and the Financial Uncertainty Index of Ludvigson *et al.* (2021) (see Figure 1). In the PCA, the second factor is essentially a weighted combination of uncertainty indicators, with financial indicators receiving negative weights and non-financial ones positive weights.[8]

In summary, while the first factor captures the overall level of uncertainty, the second factor reflects the nature of uncertainty shocks by distinguishing between financial and non-financial sources.[9]

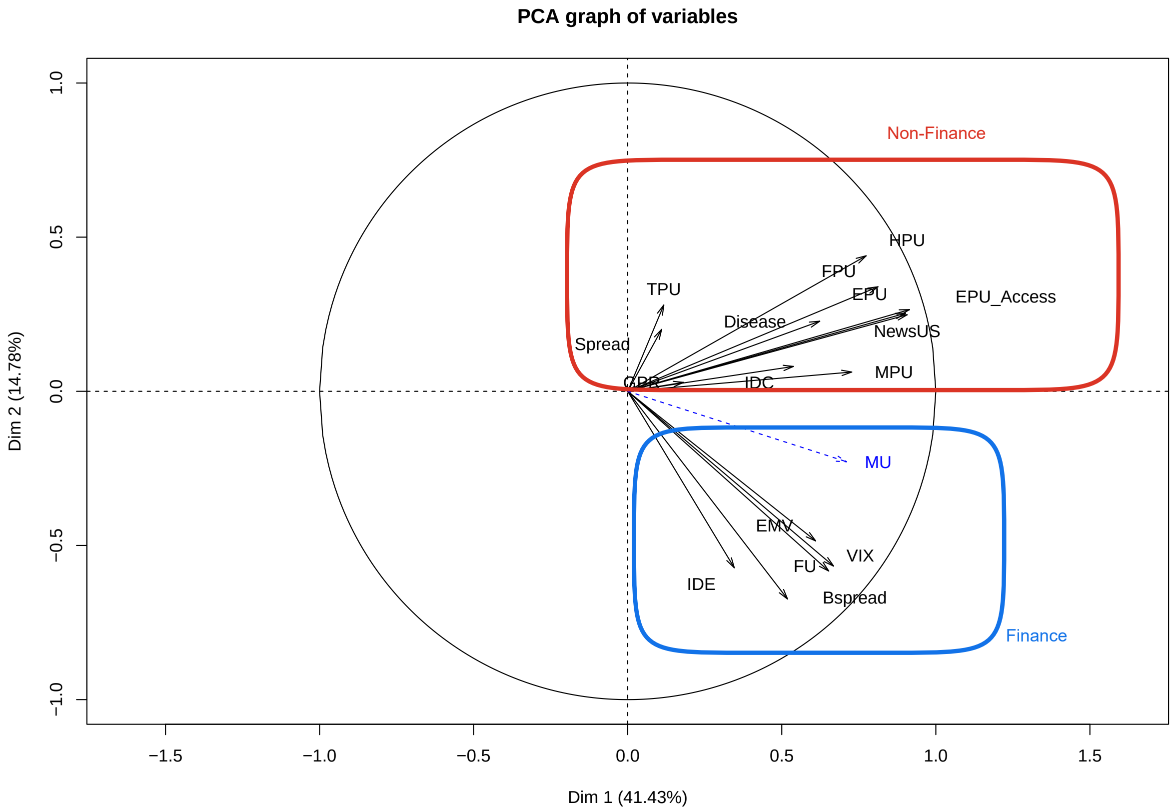
Figure 2 displays the evolution of our synthetic General Uncertainty Index (GU) over the sample period. Several peaks correspond to well-known historical events, such as the Gulf War, the 1998 Russian financial crisis and the collapse of Long-Term Capital Management, the 9/11 attacks, the Lehman Brothers collapse, and the 2011 US debt-ceiling crisis. As expected, the COVID-19 pandemic is recorded as the most pronounced spike. These events —whether financial, macroeconomic, geopolitical, or policy-related— are all associated with significant increases in general uncertainty.

Figure 3 presents the second factor (denoted $Nature\_uncertainty$) of the PCA. This com-

[8]Interestingly, the macroeconomic uncertainty index, included as a supplementary variable, clusters with the financial indicators, suggesting that this measure is more closely associated with financial uncertainty. This remains true when the macroeconomic uncertainty index is included in the PCA.

[9]For comparison, we also computed the aggregate indicators using the Dynamic Factor model. The correlation between the first PCA factor and the first dynamic factor is 0.96, and 0.84 for the second factors. We nevertheless favor the PCA approach, as it offers a more transparent interpretation of the factors. The dynamic factors are available upon request.

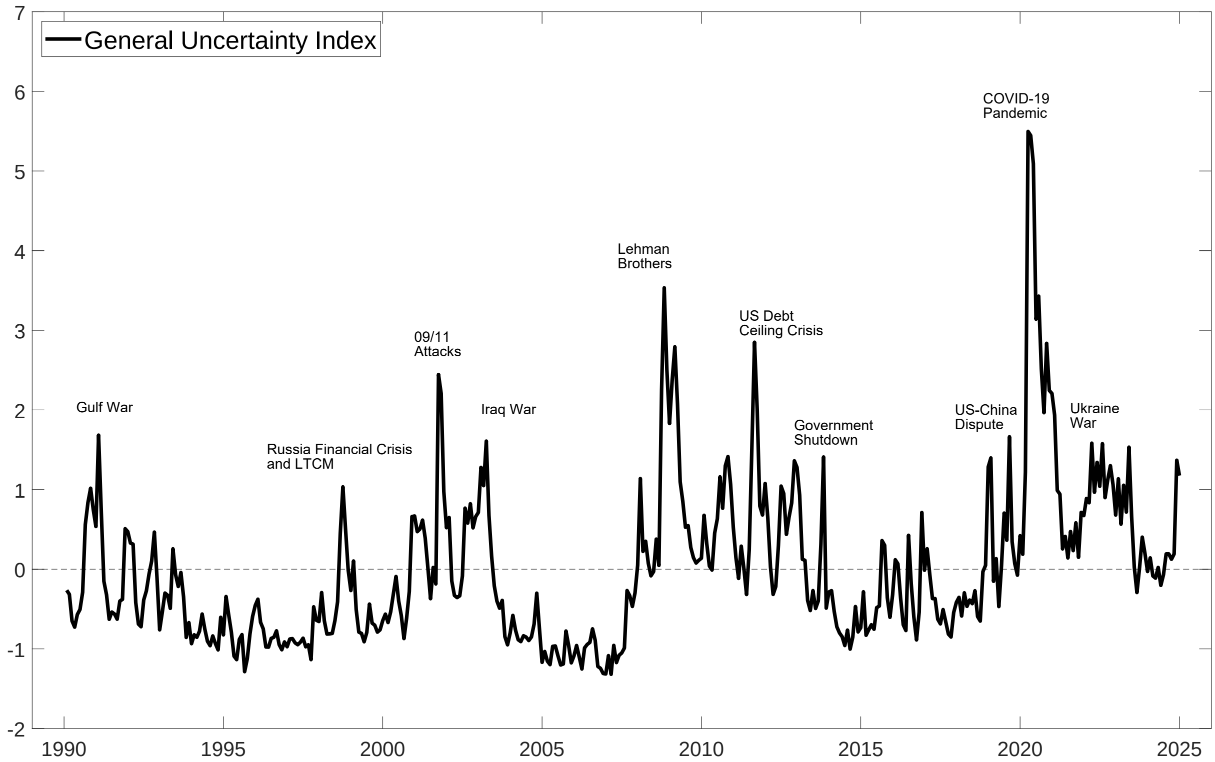
Figure 1: Variable Factor Map (Factors 1 and 2)



Note: The figure shows the variable factor map based on a PCA of 16 uncertainty indicators. The macroeconomic uncertainty (MU) index of Ludvigson *et al.* (2021) is included as a supplementary quantitative variable.

ponent distinguishes between financial and non-financial uncertainty shocks. High values of this factor are associated with non-financial shocks (e.g., the Gulf War, the Iraq War, US government shutdowns), while low values correspond to financial shocks (e.g., the collapse of LTCM, the Dot-Com bubble, the Lehman Brothers bankruptcy). We use this factor to classify the nature of uncertainty shocks. Since both GU and $Nature\_uncertainty$ are derived from the same PCA, they are orthogonal by construction. This result will be crucial in order to interpret the outcomes of our non-linear econometric framework in section 5.

Figure 2: General Uncertainty Index



Note: The index is standardized over the 1990–2024 period. A negative value implies that the level of uncertainty is below its average in that period.

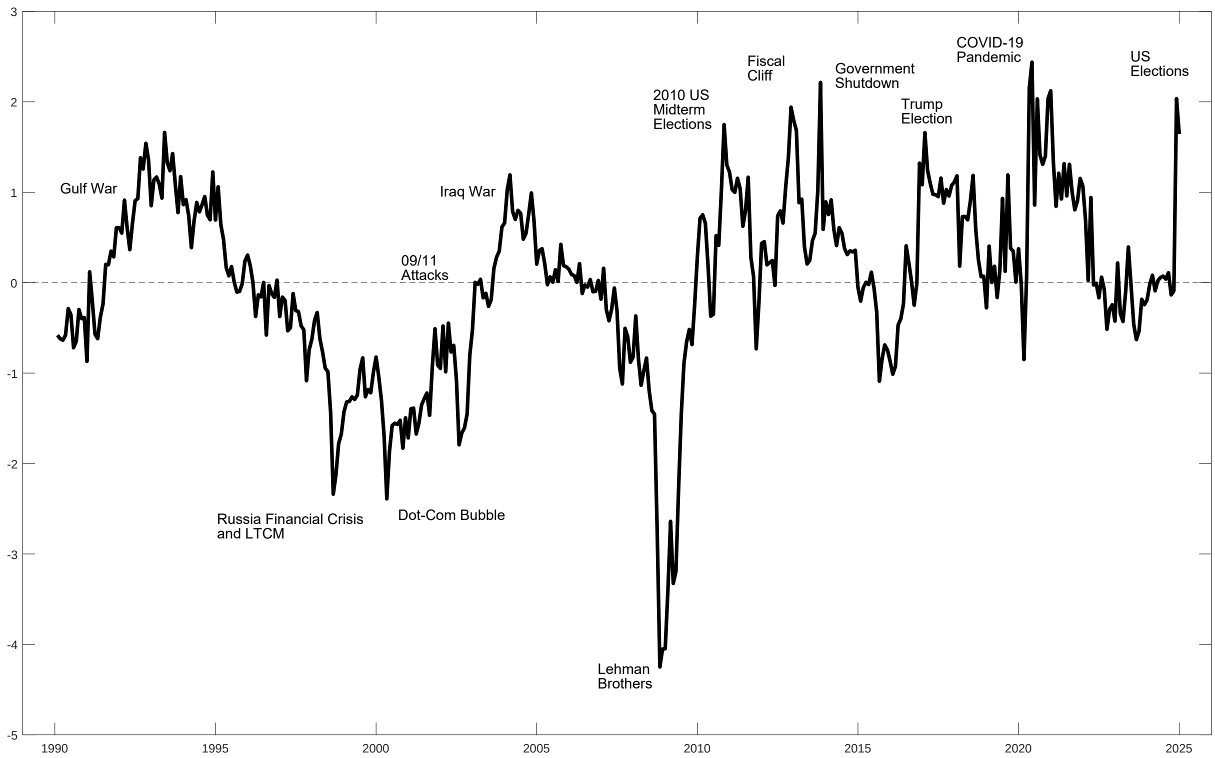
3.2 Disentangling financial uncertainty shocks from non-financial uncertainty shocks

To further assess the interpretation of the second principal component, we will apply a VARIMAX rotation framework to the estimated PCA factors and we will examine whether it reveals a distinct financial-versus-non-financial dimension of uncertainty.

3.2.1 The VARIMAX rotation methodology

To improve the interpretability of the PCA factors, we apply a Varimax rotation to the estimated principal components (Kaiser, 1958). Although PCA constructs orthogonal linear combinations of the original variables that successively maximize explained variance, the associated loading matrix is often difficult to interpret in practice, making it hard to assign a clear economic meaning to individual components. Varimax rotation helps address this issue by taking advantage of

Figure 3: The Nature of Uncertainty: Financial vs. Non-Financial



Note: This graph shows the second principal component from the PCA. The index is standardized over the 1990–2024 period.

the rotational indeterminacy of the factor space. In particular, it applies an orthogonal transformation that preserves both the total explained variance and the orthogonality of the factors, while yielding a simpler structure in which each variable tends to load strongly on only a few factors and weakly on the others (Jolliffe, 2002). Importantly, this procedure does not alter the subspace spanned by the retained components but rather reorients the axes to facilitate interpretation. This has made it a common step in macroeconomic and macro-financial applications, where uncovering interpretable latent dimensions from large datasets is often key. For instance, Akkaya *et al.* (2024) use Varimax rotation on principal components derived from monetary policy surprises to distinguish between different policy dimensions, such as conventional policy, forward guidance, and asset purchases. In the same spirit, we rely on rotated factors to better separate financial from non-financial uncertainty shocks. It is worth noting that as stated by Rohe & Zeng (2023), Varimax framework identifies correctly the "structural" dimensions of the data if the true loadings are sparse and the principal components factors have fat tails. This is arguably the case in our dataset, as the uncertainty measures under consideration are generally understood to reflect a combination of heterogeneous shocks, including financial, macroeconomic, trade, climate, and geopolitical shocks, among others.

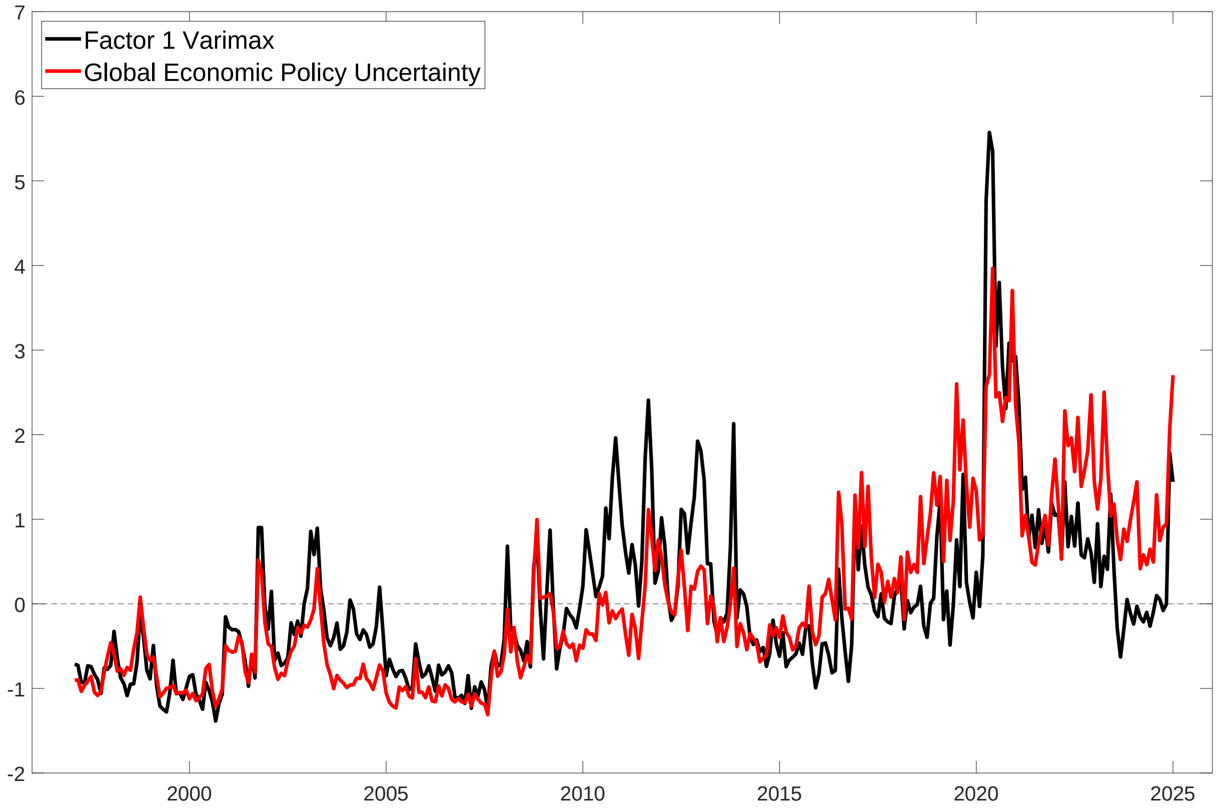
3.2.2 VARIMAX rotation results

Table 1 reports the Varimax-rotated factor loadings for the first two factors. The first Factor from VARIMAX (F1VMAX) exhibits high loadings for EPU (0.92), HPU (0.91), NewsUS (0.90), EPU_Access (0.89), FPU (0.86), Disease (0.69), and MPU (0.63). These indicators are primarily associated with economic policy uncertainty and broader macroeconomic sources of uncertainty. Consequently, F1VMAX can be interpreted as a macroeconomic and economic policy uncertainty factor. This interpretation is supported by Figure 4, which highlights the strong correlation between F1VMAX and the Global Economic Policy Uncertainty index (0.77) of Davis (2016). In contrast, Figure 5 shows that F1VMAX and MU have many differences. This finding is consistent with the argument developed earlier that this macroeconomic uncertainty index is more linked to financial uncertainty.

Table 1: VARIMAX Factor Loadings

	F1VMAX	F2VMAX
VIX	0.27	0.85
EPU	0.92	0.24
NewsUS	0.90	0.25
MPU	0.63	0.31
GPR	0.09	0.01
IDC	0.47	0.18
IDE	-0.04	0.64
Bspread	0.08	0.83
Spread	0.18	-0.13
EPU_Access	0.89	0.24
FU	0.29	0.83
FPU	0.86	0.12
TPU	0.22	-0.20
HPU	0.91	0.03
EMV	0.29	0.75
Disease	0.69	0.15

Figure 4: Factor 1 Varimax vs. Global Economic Policy Uncertainty

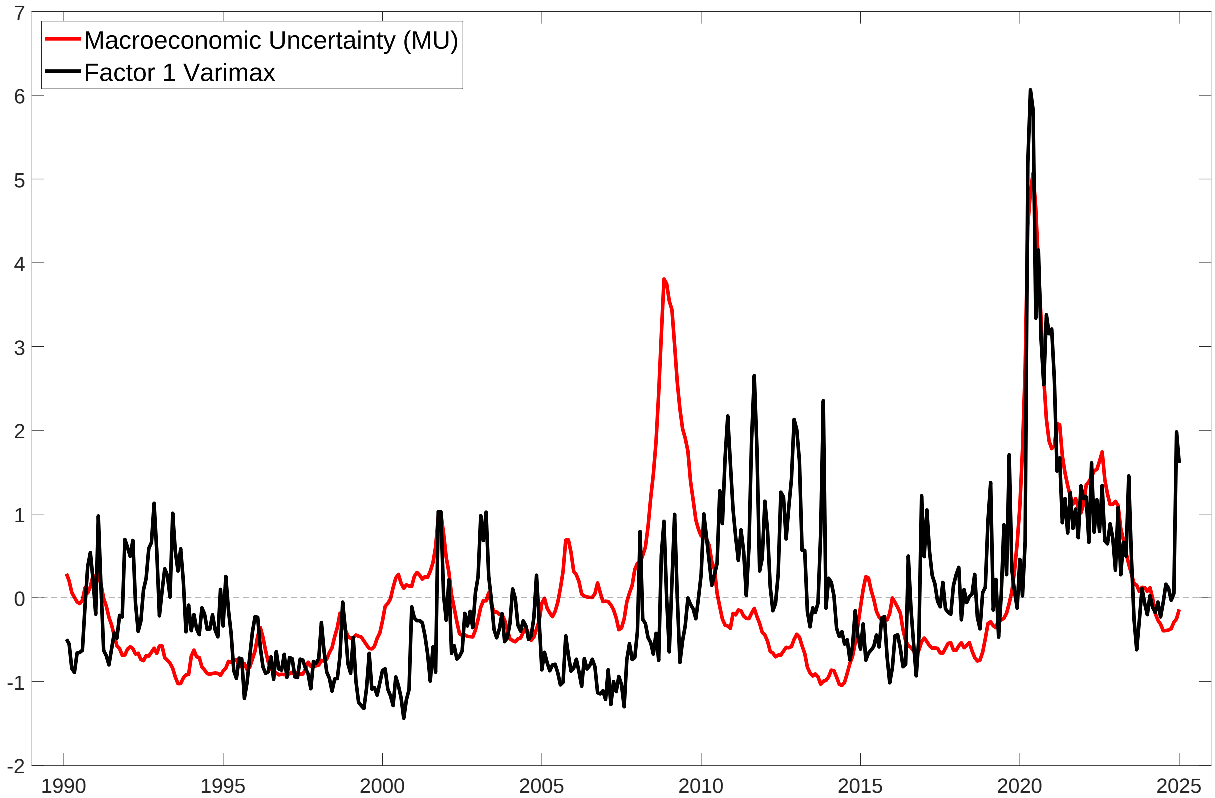


Note: The solid black line represents the first factor from the varimax. The solid red line represents the global economic policy uncertainty index. Indexes are standardized over the 1990–2024 period.

The second factor from the VARIMAX rotation (F2VMAX) is mainly driven by VIX (0.85), Bspread (0.83), FU (0.83), EMV (0.75). These variables are related to financial uncertainty. This interpretation is supported by Figure 6, which shows many similarities between F2VMAX and the financial uncertainty index developed by Ludvigson *et al.* (2021). Furthermore, Figure 7 underlines a strong similarity between F2VMAX and the negative component of the second principal component obtained from the PCA, interpreted as the financial dimension of uncertainty.

In a nutshell, the results from the VARIMAX confirms the interpretation we propose as its first factor seems related to macroeconomic uncertainty while its second factor clearly exhibits similarities with financial uncertainty.

Figure 5: Factor 1 Varimax vs. Macroeconomic Uncertainty



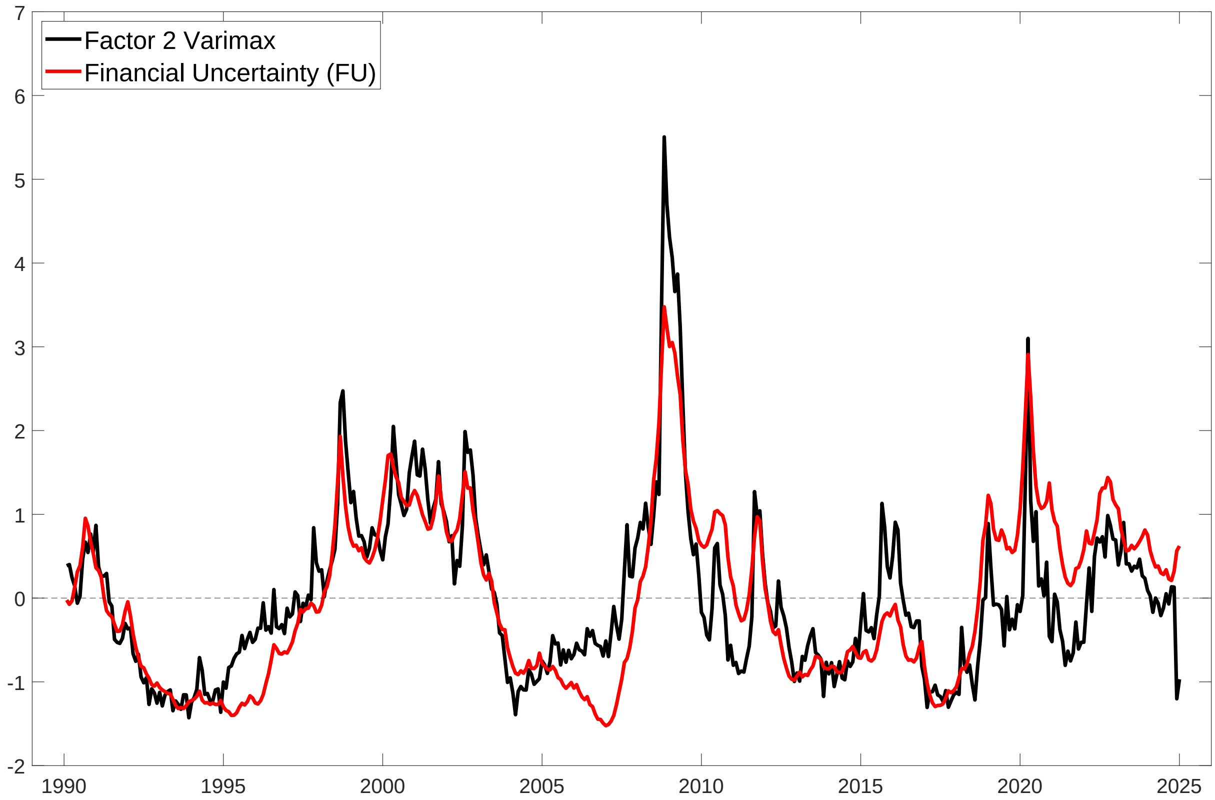
Note: The solid black line represents the first factor from the varimax. The solid red line represents the macroeconomic uncertainty index of Ludvigson *et al.* (2021) . Indexes are standardized over the 1990–2024 period.

4 Impact of Uncertainty shocks: the linear case

Most empirical studies estimating the effect of uncertainty shocks on macroeconomic activity applied Structural VAR (SVAR) models [10]. However, in this section, we will estimate impulse responses to uncertainty shocks using the local projection approach introduced by Jordá (2005). The main reason for this choice is that our analysis is geared towards capturing potential nonlinear effects. While nonlinear VAR models provide a natural framework for dealing with such issues, they typically require specifying the full nonlinear structure of the system, which can be both restrictive and cumbersome in practice. By contrast, local projections offer a simpler and more transparent alternative, allowing us to recover regime-specific responses by interacting the shock with observable state variables. In our context, this is particularly convenient, as our

[10] See, among many others,Bloom (2009); Colombo (2013); Jurado *et al.* (2015); Baker *et al.* (2016); Leduc & Liu (2016, 2020)

Figure 6: Factor 2 Varimax vs. Financial Uncertainty



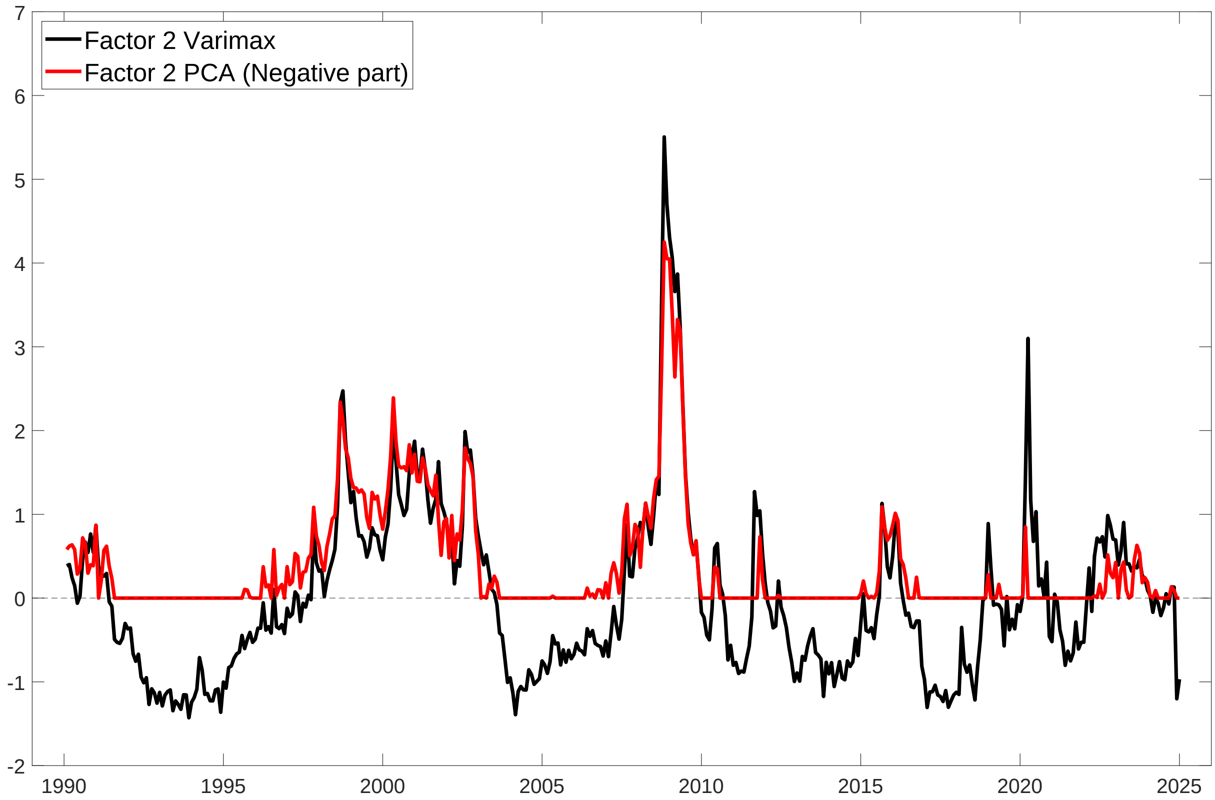
Note: The solid black line represents the first factor from the varimax. The solid red line represents the financial uncertainty index of Ludvigson *et al.* (2021).

objective is not to take a stand on the exact form of the non linearity, but rather to investigate whether the effects of uncertainty shocks vary across different uncertainty regimes. For the remainder of the paper, we therefore use the local projection framework as a way to document these differences across regimes.

4.1 The linear Local Projection (LP) framework

According to Jordá (2005), VAR-based Impulse Response functions (IRFs) can be highly sensitive to model misspecification. So, he proposes a LP framework as a more robust alternative to identify the impact of policy shocks on the economy. LPs offer several advantages: they are robust to misspecification, and easily adaptable to nonlinear frameworks. Furthermore, as demonstrated by Jordá (2005), IRFs from a SVAR and LP model are theoretically equivalent

Figure 7: Factor 2 Varimax vs. Negative part of Factor 2 from the PCA



Note: The solid black line represents the second factor from the varimax. The solid red line represents the negative part of the second factor from the PCA, expressed in absolute value.

when the SVAR coincides with the true data generating process (DGP) [11]. Recent contributions of Montiel Olea & Plagborg-Møller (2021) and Plagborg-Møller & Wolf (2021) extend this property for more general cases. Plagborg-Møller & Wolf (2021) demonstrates that LP and SVAR will produce, asymptotically, the same IRFs if the lag length used for estimation tends to infinity. Montiel Olea & Plagborg-Møller (2021) shows that both methodologies lead to the same median impulse responses in the short term and medium term. However, Plagborg-Møller & Wolf (2021) also emphasizes an important trade-off: LPs exhibit greater robustness to misspecification but suffer from higher variance, while VARs provide more efficient estimates but may introduce bias under model misspecification. It is worth noting, however, that even with LPs, the bias could be important in small sample sizes (Herbst & Johannsen, 2024) if data is highly persistent. Another advantage of LPs lies in the computed standard errors. As stated

[11] See Li *et al.* (2024) for a recent review of the advantages and drawbacks of LPs

by Olea-Montiel *et al.* (2024), "*when the goal is to construct confidence intervals for impulse responses that have accurate coverage in a wide range of empirically relevant DGPs—as opposed to minimizing MSE— then the smaller bias of LPs documented in simulations Li* et al. *(2024) is more valuable than the smaller variance enjoyed by VAR estimators*". Given these arguments against and in favor of the use of LPs, we believe that our data is clearly suitable to LPs as we fall out most of the cases underlined above as necessitating caution with LPs.

According to Plagborg-Møller & Wolf (2021) and Li *et al.* (2024), the core idea behind local projections is to estimate impulse responses at each horizon separately by directly regressing future outcomes on current covariates:

$$y_{t+s} = \alpha_s + \beta_s x_t + \gamma_s^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k}^{'} w_{t-k} + u_{t+s}^s,\ s = 0, \ldots, h \tag{1}$$

where u_{t+s}^s is the projection residual. Suppose that the researcher observes data $w^{'} = (r_t^{'}, x_t, y_t, q^{'})^{'}$ where y denotes the endogenous variables, x the policy variable and r_t and q_t are two vectors of control variables (which may each be empty). It is worth noting that in equation (1), we control for the contemporaneous value of r_t but not that of q_t. In order to have a structural interpretation of equation (1), x_t must be predetermined with respect to y_t and r_t must be predetermined with respect to $\{y_t, x_t\}$ (Plagborg-Møller & Wolf, 2021).

The LP impulse response function of y with respect to x at horizon s is then defined as the coefficient $\{\beta_s\}_{s\geq 0}$ as:

$$\beta_s = E\Bigg[y_{t+s}/x_t = 1, r_t, \{w_\tau\}_{\tau<t}\Bigg] - E\Bigg[y_{t+s}/x_t = 0, r_t, \{w_\tau\}_{\tau<t}\Bigg] \tag{2}$$

The "observed shock" identification corresponds to the case where $x_t = \epsilon_t^{UNC}$ where ϵ_t^{UNC} is defined as an exogenous uncertainty structural shock. If x_t is endogenous (or if the shock is not observed) then we can apply the recursive identification methodology which corresponds to a Cholesky decomposition in the SVAR framework. In this case, the r_t variables will control for confounding factors. These variables correspond to the contemporaneous values of the variables that should be ordered before the uncertainty index, x_t, in the VAR (Li *et al.* (2024).

As changes in the uncertainty indicator cannot be interpreted as exogenous uncertainty shocks, we will rely on the identification scheme advocated by Bloom (2009) which relies on an eight-variable VAR model. The vector w includes the variables in the following order : the log level of the S&P 500 index, an uncertainty measure, the Federal Funds rate, the log of manufacturing wages, the log of aggregate CPI, average hours worked in manufacturing, log manufacturing employment (EMP), and log industrial production (IPI) [12]. Except uncertainty, all variables are detrended applying the Hodrick–Prescott filter as in Bloom (2009).[13]

4.2 Empirical results

To evaluate the impact of uncertainty shocks on employment and output, we use monthly data from January 1990 to December 2024 ($T = 420$). Sources and descriptive statistics of the macroeconomic variables are provided in Table A.2 in appendix A. We will start by analysing the impact of the general uncertainty shocks. In this case, the variable $x_t = GU_t$ in the vector w. The number of lags included in the regression, $p = 4$, has been estimated by minimizing the AIC criteria. The LPs impulse function responses are reported in Figure E.1. We estimate a statistically negative impact on economic activity examining the impulse response functions both for output (IPI variable) and employment (EMP variable).[14] The (significant) negative effect lasts around 6 month for industrial production and 8 month for employment (Figure E.1). These results translate a wait-and-see behavior, with firms postponing investment and hiring decisions. Our finding of a negative impact of uncertainty shocks on economic activity is consistent with results in the existing literature, but we estimate a more persistent effect. For instance, in comparison to Bloom (2009), who reports that uncertainty shocks dissipate after approximately four months, our estimates suggest effects lasting up to 8 months—roughly two times longer. This extended persistence may be attributable to the time span of our sample,

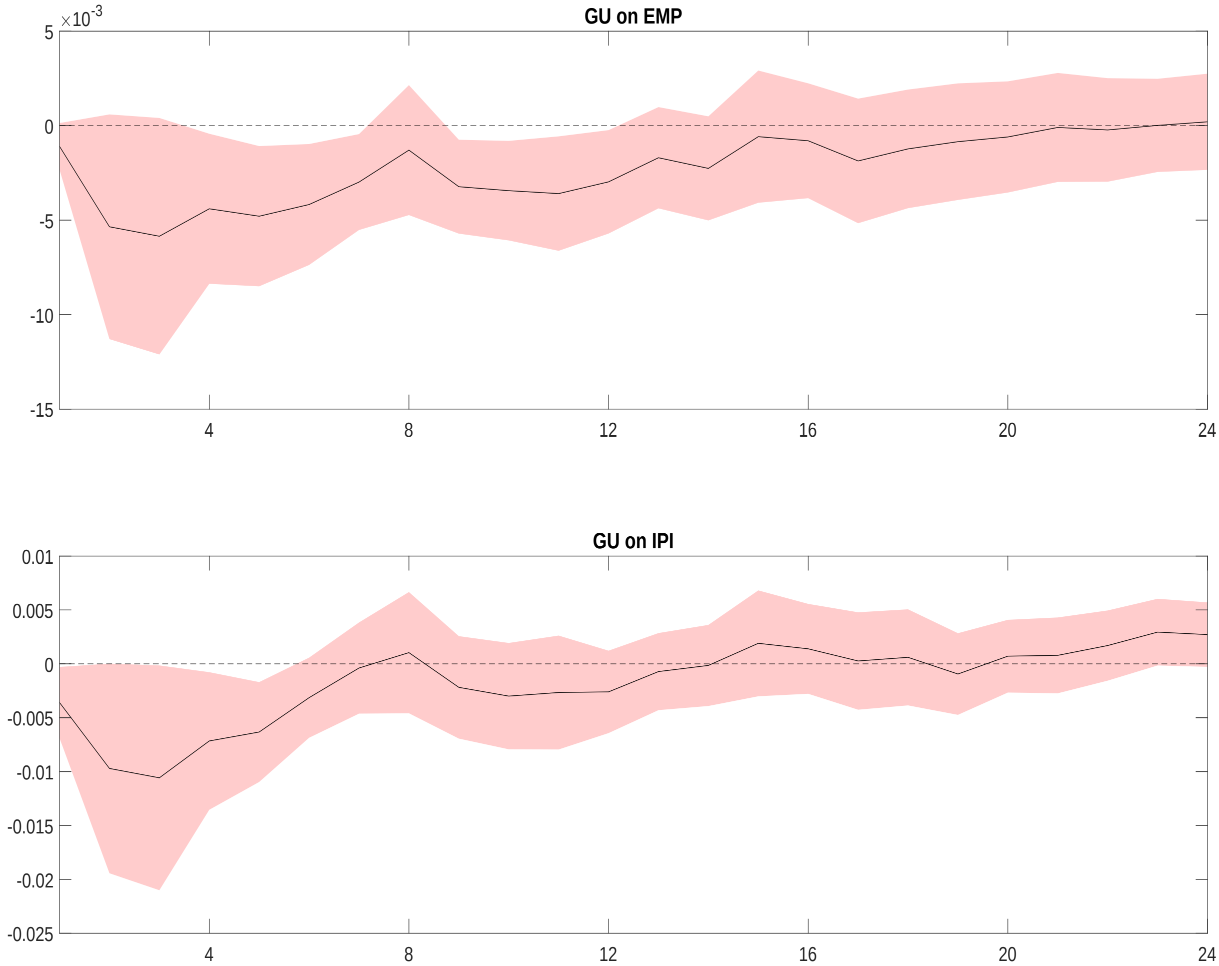
[12]With this recursive identification, the r_t variable corresponds to the log level of the S&P 500 index only.As stated by Bloom (2009), this ordering relies on the assumption that shocks affect the stock market instantaneously, followed by prices (such as wages, the Consumer Price Index, and interest rates), and subsequently by quantities (including hours worked, employment, and output). Placing stock-market index as the first variable in the VAR ensures that their influence is already accounted for when assessing the impact of uncertainty shocks.

[13]Following Ravn & Uhlig (2002), we take the smoothing parameter $\lambda = 129600$ for monthly data.

[14]The effect is significant at the 10% level. Applying local projections, the residuals u^t_{t+s} are a moving average of the forecast errors. To correct heteroskedasticity, we compute error bands applying the Newey & West (1987) method.

which captures major episodes of heightened and prolonged uncertainty, such as the U.S. debt ceiling crisis, the U.S.-China trade dispute, and, most notably, the COVID-19 pandemic.

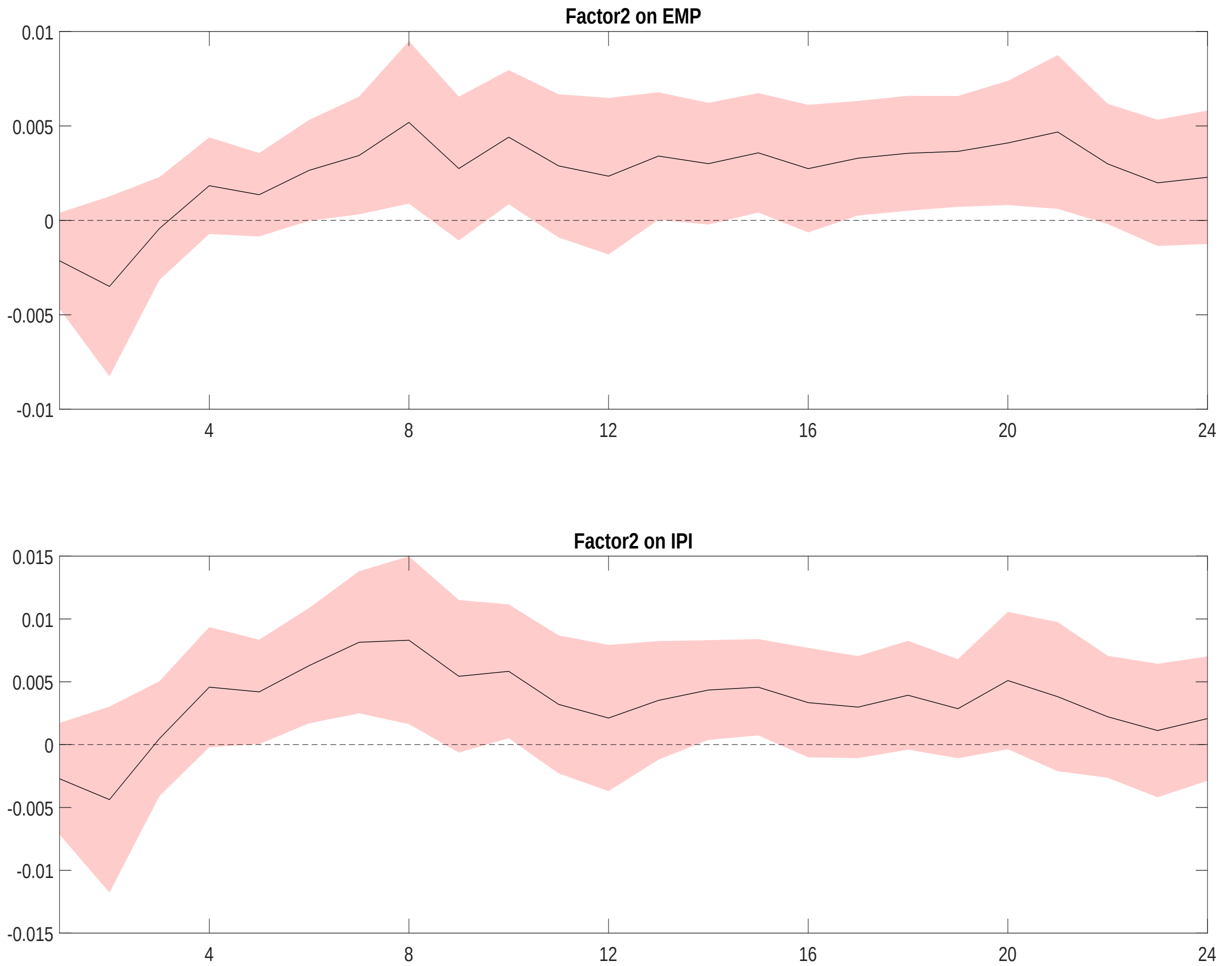
Figure 8: Impulse Response Functions: Effects of a General Uncertainty shock



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 90% confidence interval.

We run the same exercise by analyzing now the impact of uncertainty shocks according to their nature. The x_t variable in the w vector is now the NU variable (see Figure 3). According to its interpretation, a positive shock to this factor could be analyzed as a non financial uncertainty shock. The LPs impulse response functions are reported in Figure 9. We find that after a negative impact of within 2 or 3 month, economic activity bounce back and we estimate a slightly positive effect on industrial production and employment (see Figure 9).

Figure 9: Impulse Response Functions: Effects of a non-financial uncertainty shock



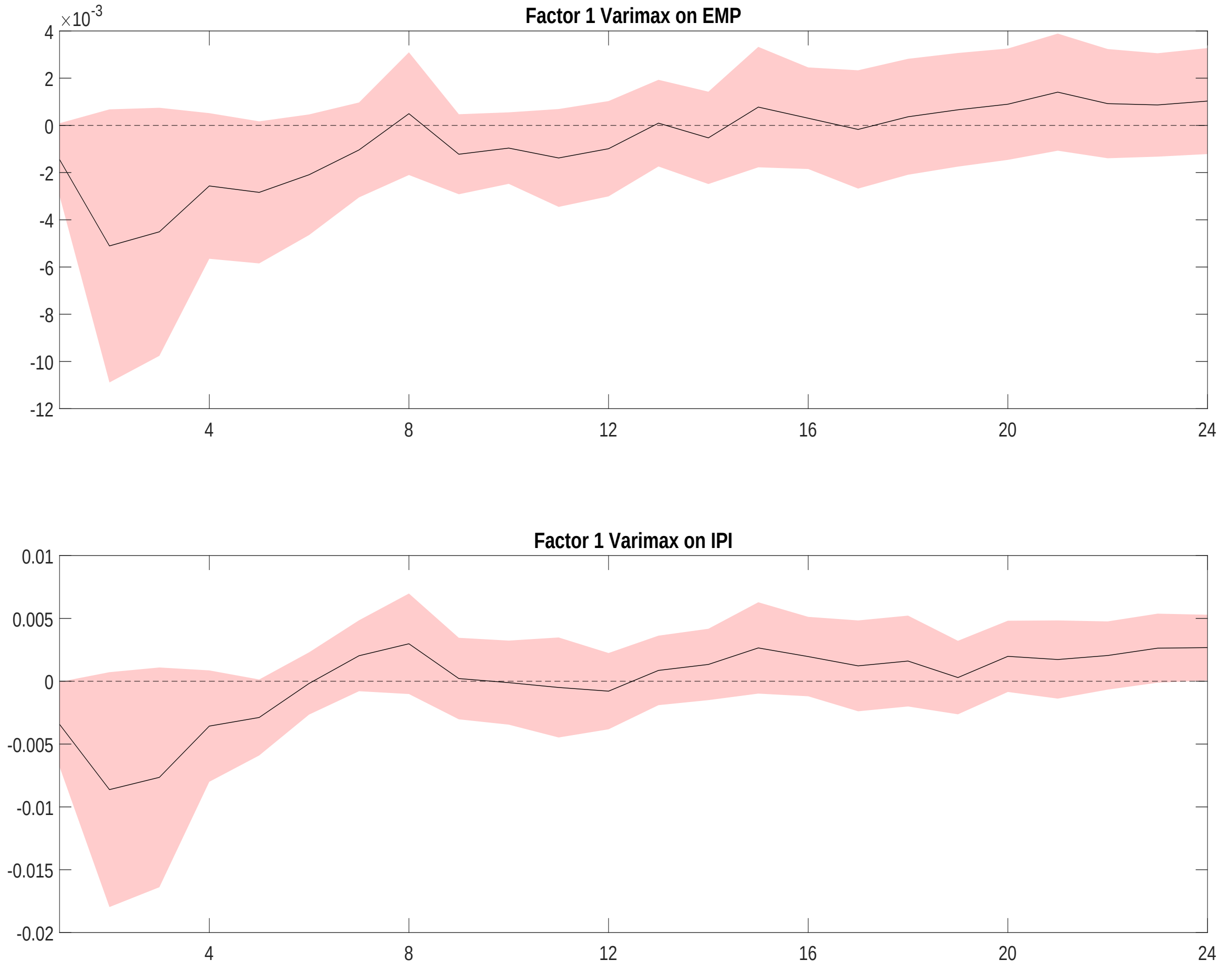
Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 90% confidence interval.

4.3 VARIMAX LPs IRF Results

Figure 10 exhibits the impulse response functions following a positive shock to F1VMAX, interpreted as a macroeconomic policy uncertainty shock, for both output and employment.The responses are not statistically significant at the 90% confidence level.

Figure 11 shows the impulse response functions both for output and employment following a positive shock to F2VMAX which is interpreted as a financial uncertainty shock. We estimate now a significant adverse effects on economic activity. Both employment and industrial production exhibit negative responses following the financial shock, consistent with the existing literature. Furthermore, the negative estimated effect is quite persistent. These results are in line with works underlying that financial uncertainty increases precautionary behavior, tightens financing conditions, and discourages investment and hiring decisions leading to a decline in economic activity. Overall, our results show that uncertainty shocks have a negative effect on economic activity, with this effect being driven primarily by financial uncertainty.

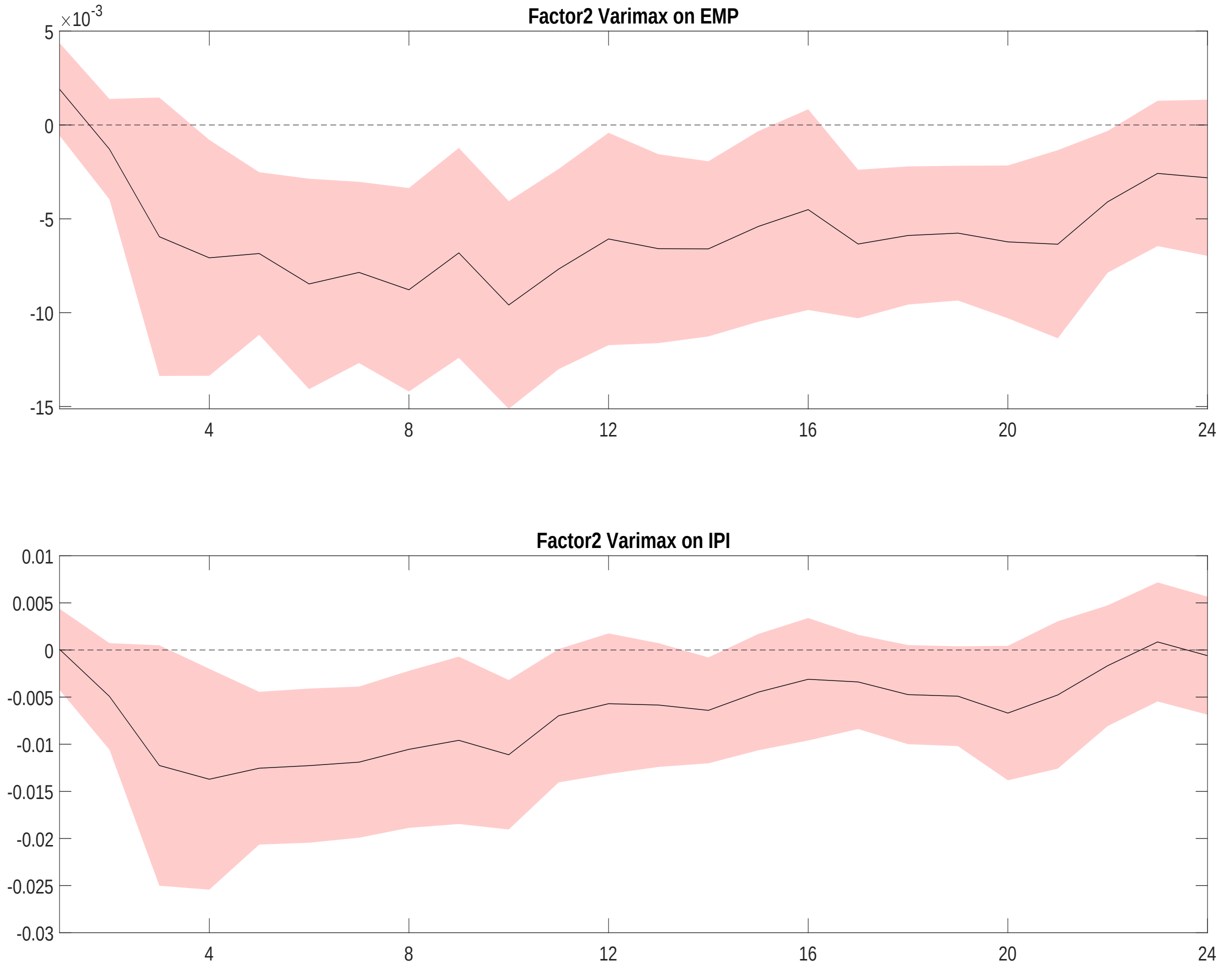
Figure 10: Factor 1 Varimax: Impulse Response Functions



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 90% confidence interval.

In the next section, we investigate how our results may change when introducing non-linear effects into the model. More specifically, we will show that the nature of uncertainty shocks can have either negative or positive effects on economic activity, depending on the prevailing uncertainty regime in which the economy is situated.

Figure 11: Factor 2 Varimax: Impulse Response Functions



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 90% confidence interval.

5 State Dependence of Uncertainty Shocks: Thresholds estimates

The adoption of a nonlinear framework is motivated by the theoretical literature emphasizing that the effects of uncertainty shocks are inherently state-dependent as emphasized in section 2. For example, Bloom (2009) shows that uncertainty shocks generate two offsetting forces. On the one hand, higher uncertainty raises the "free boundary" at which firms optimally exercise growth options, inducing firms to postpone investment and hiring decisions. On the other hand, as realized volatility accumulates over time, firms are eventually pushed above that boundary, triggering a rebound in investment activity that may lead to a medium-run overshoot. This mechanism implies that the effects of uncertainty are not constant across states of the economy but depend on the interaction between uncertainty and firms' decision thresholds. While Bloom (2009) does not explicitly distinguish between different sources of uncertainty, his framework suggests that the transmission of uncertainty shocks depends on the prevailing uncertainty environment, thereby providing a natural rationale for regime-dependent specifications. Such considerations suggest that linear models may fail to capture important state-dependent dynamics. Moreover, if different sources of uncertainty, such as financial and non-financial uncertainty or downstream and upstream uncertainties as in Grigoris & Segal (2026), affect firms through distinct transmission channels, their macroeconomic consequences may diverge precisely when aggregate uncertainty is elevated and precautionary behaviour becomes more pronounced. Lastly, the explanation related to Gabaix' works and the vanishing of Ricardian equivalence is assumed to uniquely work when uncertainty is high enough. These theoretical considerations provide a strong rationale for employing a threshold framework that allows the effects of uncertainty shocks to vary with the prevailing level of aggregate uncertainty.[15]

This argument justifies why the first PCA factor is used as the threshold variable in the

[15] An extensive empirical literature now emphasizes the nonlinear effects of uncertainty shocks on macroeconomic outcomes (among many others, Caggiano *et al.*, 2014; Ismailov & Rossi, 2018; Alessandri & Mumtaz, 2019; Colombo & Paccagnini, 2020; Candelon *et al.*, 2021). Andreasen *et al.* (2024) show that the macroeconomic consequences of uncertainty are state dependent. Specifically, for shocks of identical magnitude, increases in uncertainty lead to a larger and more persistent decline in U.S. real economic activity during periods of weak growth than during periods of strong growth.

analysis. Our empirical framework distinguishes between the level and the composition of uncertainty shocks. The first factor captures the dominant source of common variation across the set of uncertainty indicators and is therefore naturally interpreted as a proxy for aggregate uncertainty. In contrast, the second factor isolates a distinct orthogonal dimension related to the nature of uncertainty shocks, distinguishing in particular between financial and non-financial sources. Within this framework, the nonlinear specification is designed to examine whether the macroeconomic effects associated with this compositional dimension depend on the prevailing level of aggregate uncertainty. A natural conjecture is that, in low-uncertainty environments, financial and non-financial uncertainty shocks may generate broadly similar macroeconomic responses. However, when aggregate uncertainty is high, their transmission may diverge markedly owing to the amplification of uncertainty-related frictions and precautionary behaviour. From this perspective, conditioning the impact of the second factor on the level of the first is conceptually well grounded: the specification tests whether the macroeconomic consequences of different types of uncertainty shocks are state-dependent. In this sense, the framework extends the state-dependence mechanism emphasized by Bloom (2009) by allowing not only the magnitude but also the composition of uncertainty shocks to matter for macroeconomic dynamics. Moreover, the orthogonality between the two factors is particularly useful in this setting because it ensures that the threshold variable and the shock variable capture distinct dimensions of uncertainty. Consequently, the estimated nonlinear effects cannot be attributed to simple linear comovement between the two factors, but instead reflect differences in the transmission of uncertainty shocks across aggregate uncertainty regimes.

5.1 Non Linear LP framework

We use local projection methods to investigate the impact of the nature of uncertainty shocks in different regimes estimating the state-dependent impulse response functions [16]. We apply a three regimes set-up as our preferred specification in order to properly distinguish the high uncertainty regime from the low uncertainty regime, thus implying that a moderate uncertainty

[16]Many works have applied local projections to study non linear effects (See, among many others, Owyang *et al.*, 2013; Ramey & Zubairy, 2018; Ahmed & Cassou, 2021).

regime also exists.[17]

The LPs framework adapted to a three regime framework is as follows:

$$y_{t+s} = I(z_{t-1} \leq \gamma_1)\left[\alpha_s^L + \beta_s^L x_t + \gamma_{s,L}^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k,L}^{'} w_{t-k}\right] +$$
$$I(\gamma_1 < z_{t-1} \leq \gamma_2)\left[\alpha_s^M + \beta_s^M x_t + \gamma_{s,M}^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k,M}^{'} w_{t-k}\right] +$$
$$I(z_{t-1} > \gamma_2)\left[\alpha_s^H + \beta_s^H x_t + \gamma_{s,H}^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k,H}^{'} w_{t-k}\right] + \mu_{t+s}^s$$

The regime-specific impulse response functions are traced out by the coefficient sequences $\{\beta_s^H\}_{s\geq 0}$, $\{\beta_s^M\}_{s\geq 0}$ and $\{\beta_s^L\}_{s\geq 0}$, corresponding respectively to the high-, moderate-, and low-uncertainty regimes.

5.2 Empirical Results

We first test for the existence of different uncertainty regimes by running non linear tests and then we comment the LPs impulse response functions.

5.2.1 Non Linear tests

Likelihood Ratio (LR) Test are applied to test the null hypothesis of linearity against the alternative of a threshold VAR model:

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

where w_t is a vector of endogenous variables including our measure of the nature of uncertainty (as the x_t variable) and the set of monthly macroeconomic variables that we have used in the linear framework; z_t is the switching variable which will be the measure of general uncertainty, GU; $I(.)$ denotes an indicator function which takes the value of 1 alternatively if the switching variable is above the threshold value γ_2 (high uncertainty regime, H), between the two threshold

[17]We extent the R code of the package *lpirfs* of Adämmer (2019) to add the third regime. The code is available upon request

values γ_2 and γ_1 (moderate uncertainty regime, M), or below γ_1 (low uncertainty regime, L); and finally $\Pi_H(L)$ (resp. $\Pi_M(L)$ and $\Pi_L(L)$) is a lag-polynomial of matrices in the high (resp. moderate and low) uncertainty regime. Because the threshold parameters are not identified under the null hypothesis, standard asymptotic distributions do not apply, and the p-value should be computed using bootstrapping methods.

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 it is trimmed at a lower and an upper bounds to ensure a minimal percentage of observations in each regime. In practice, the level is chosen arbitrarily. However, a minimum of about 20% of observations in each regime has often been used. The estimation of the threshold values corresponds to the model with the smallest determinant of the covariance matrix of the error terms μ_t.

Likelihood Ratio (LR) test to assess the presence of nonlinearity in the model are reported in Table 2. First, we test the null hypothesis of linearity against the alternative of a two-regime specification. The null is strongly rejected, with an LR statistic of 594.0465 and a p-value of 0.000. Next, we consider a three-regime alternative and again reject the null of linearity. Finally, we test the null hypothesis of a two-regime model against the alternative of three regimes. This test also rejects the null, with an LR statistic of 222.271 and a p-value of 0.000. These results provide strong statistical support for a non-linear specification with at least three distinct regimes.

Table 2: LR test

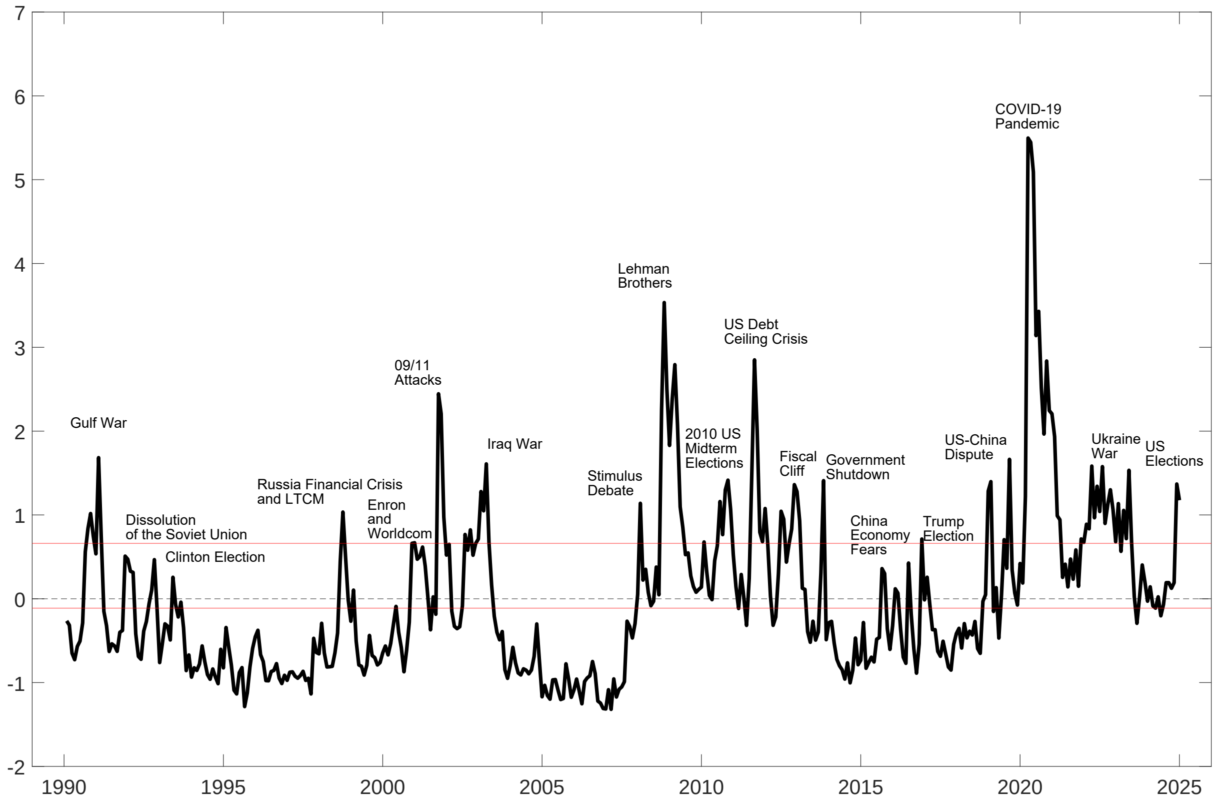
	Linearity VS Two regimes	Linearity VS Three regimes	Two regimes VS Three regimes
LR statistic	725.576	1107.6	382.024
p-value	0.000	0.000	0.000
Estimated threshold	0.628	(-0.112; 0.661)	(-0.112; 0.661)

Source: Author's own calculations.

The estimated threshold values of -0.112 and 0.661 allow to separate shocks of the last three decades as Figure 12 highlights. Most of the peaks observed in the General Uncertainty (GU) indicator correspond to major uncertainty shocks, as they fall within the high-uncertainty regime.

In the moderate regime, we identify events such as U.S. presidential elections—specifically, the election of Bill Clinton and the first election of Donald Trump [18]. This regime also includes the dissolution of the USSR and concerns about the Chinese economy in 2016. Periods of low uncertainty are primarily clustered in the mid-1990s and in the interval between the collapse of the dot-com bubble in the early 2000s and the onset of the global financial crisis in 2008. It is worth noting that in the high uncertainty regime, both financial and non-financial shocks are included.

Figure 12: The three different regimes of uncertainty: High, Moderate and Low



Source: Author's own calculations.
Notes: The black line corresponds to the first factor of the PCA analysis (the *GU* variable). The horizontal red lines correspond to the estimated threshold values obtained with the TVAR model (-0.112 and 0.661)

[18]It is worth noting that the second election of Donald Trump corresponds to significant high peak in the uncertainty index.

5.2.2 LPs IRF under different uncertainty regimes

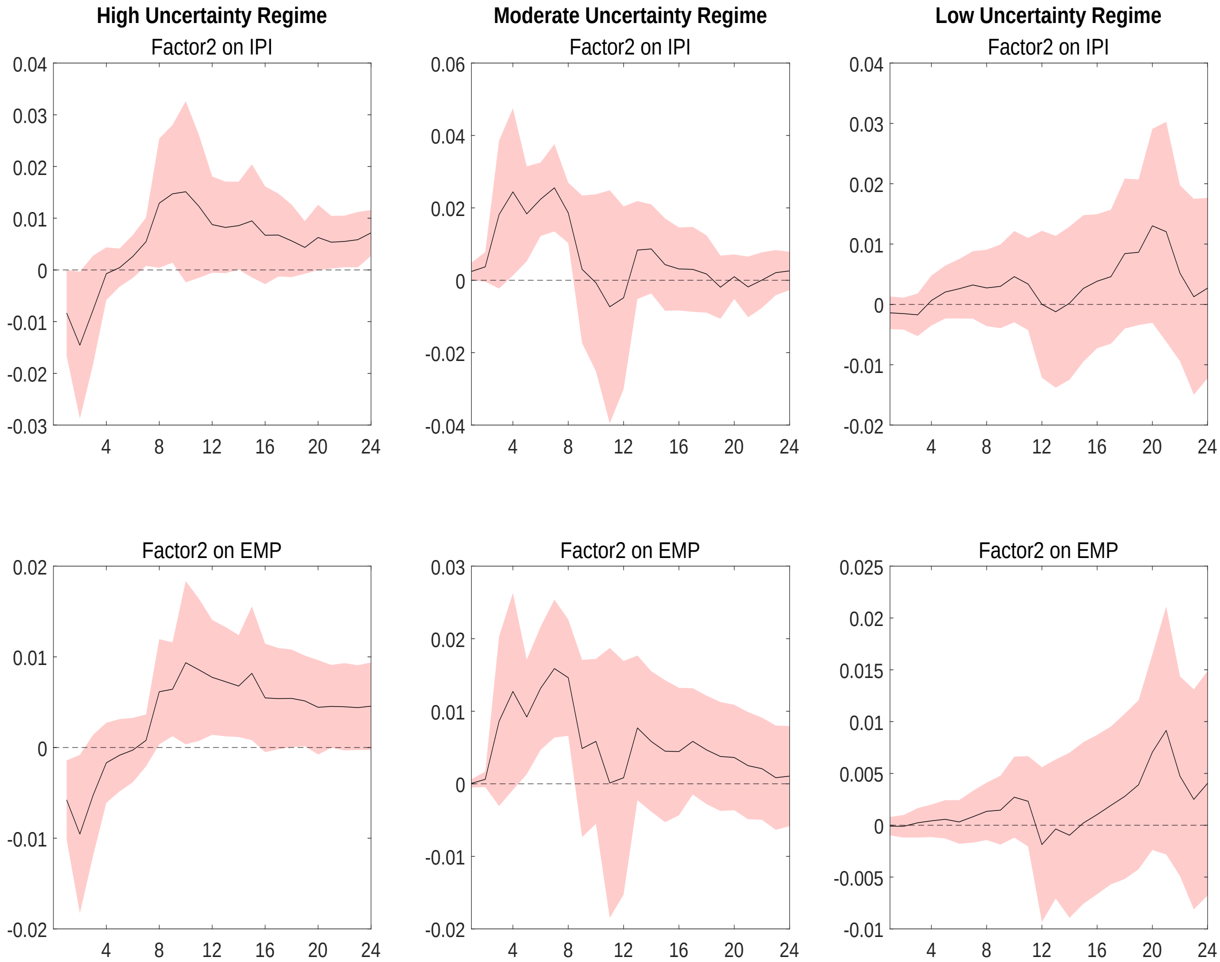
The LPs impulse response functions for the three identified regimes are presented in Figure 13. Since we estimate the effects of a positive shock to the $Nature\_uncertainty$ index, this can be interpreted as a non-financial uncertainty shock. Accordingly, the responses illustrate how economic activity reacts to non-financial uncertainty shocks under different levels of general uncertainty—low, moderate, and high. Two main findings emerge from our results. First, non-financial uncertainty shocks do have now a statistically significant impact on both industrial production and employment in the high uncertainty and moderate uncertainty regimes. The effect is not statistically significant only in the low uncertainty regime (see Figure 13). This pattern is consistent with Bloom (2009), who emphasizes the role of the prevailing level of uncertainty. Uncertainty must be strong for shocks to matter.

Second, and more importantly, under moderate and high uncertainty regimes, non-financial uncertainty shocks have a positive and statistically significant effect. Specifically, we observe a short-lived positive effect on industrial production and employment in the moderate regime. In the high uncertainty regime, the effect takes longer to become statistically significant. Notably, the short-term effects on employment and industrial production are strongest in the moderate-uncertainty regime, suggesting that non-financial uncertainty shocks may stimulate economic activity only when uncertainty is sufficiently elevated to induce precautionary behavior, yet not so high as to generate widespread economic disruption.

5.3 Interpretation of our results

Our empirical findings can be related to two distinct strands of the theoretical literature. Firstly, the "growth options" literature suggests that certain forms of uncertainty—particularly those related to technological change—can have positive effects on economic activity. This theoretical perspective focuses on uncertainty as a driver of future growth opportunities, especially when linked to non-financial sources such as innovation. Over the past decades, economies have experienced a succession of major technological breakthroughs, with many others still unfolding. The emergence of the digital economy following the diffusion of the Internet is one notable

Figure 13: Impulse Response Functions under different regimes of uncertainty



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 90% confidence interval.

example, while the recent rapid advances in artificial intelligence (AI) provide perhaps the most salient illustration of this ongoing process. While the widespread adoption of AI is expected to generate substantial economic benefits, the distribution of those gains across firms remains uncertain both in terms of which firms will benefit and to what extent. This may explain why we do not observe a significant increase in industrial production. At this stage, firms mainly invest in AI-related R&D, which tends to generate employment before resulting in higher output.

Secondly, relying on the attention-based framework of Gabaix (Gabaix, 2014, 2020), we may argue that higher uncertainty could increase agents' myopia by reducing the attention they devote to future outcomes. As agents become more short-sighted, they attach less weight to the future tax burden required to finance current government spending. This weakens Ricardian equivalence, as households become less inclined to offset fiscal expansions through higher precautionary savings. Consequently, the short-run fiscal multiplier increases and expansionary fiscal policy becomes more effective in stimulating aggregate demand. This mechanism is particularly relevant in the case of non-financial uncertainty shocks, which increase agents' myopia without generating the strong contractionary effects typically associated with financial uncertainty.

The finding that the employment response is strongest in the moderate-uncertainty regime may appear counter-intuitive at first. We offer two complementary explanations. First, from the perspective of growth option theory, the uncertainty associated with technological innovation is not characterized by short-lived spikes but rather by a persistent environment of elevated uncertainty. Such a setting is more consistent with a moderate-uncertainty regime than with episodes of exceptionally high uncertainty. Second, the mechanism derived from Gabaix also provides a plausible interpretation. As emphasized by Segal *et al.* (2015), even "good" uncertainty has an inherent downside because it increases volatility. Consequently, when uncertainty reaches very high levels, the adverse effects associated with heightened volatility may outweigh the positive effects arising from agents' increased myopia. By contrast, under moderate levels of uncertainty, the beneficial effects of reduced short-termism can materialize without being dominated by the disruptive consequences of excessive volatility.

6 Robustness Check

In this section, we assess the robustness of our baseline results through five alternative specifications. Specifically, we (i) control for the COVID-19 shock by including a specific exogenous variable measuring COVID19 pandemics, (ii) re-estimate the model over the pre-pandemic sample (1990–2019), (iii) consider a specification with two uncertainty regimes instead of three, (iv) modify the ordering of the variables in the VAR used to identify uncertainty shocks, and (v) include macroeconomic uncertainty (MU) in the principal component analysis (PCA).

6.1 Taking into account the COVID-19 shock

Our sample covers the COVID-19 period. The COVID-19 pandemic represents an unprecedented, exogenous shock that severely disrupted economic activity, causing unprecedented variation in many key macroeconomic variables. Ignoring this could bias estimates. We address this issue in two different manners.

First, we add the Infectious Disease Equity Market Volatility Index of Baker *et al.* (2020) as a new exogenous variable in the list of the control variables. More precisely, we add this variable in the former vector of the (q_t) variables, as we want to take into account current and past values of this variable. The Infectious Disease Equity Market Volatility Index should control for the disturbances associated with the COVID-19 pandemic.[19] LPs impulse responses are reported in Figure B.1 in the appendix. Our main conclusions remain unchanged. In the linear specification, we keep finding that a general uncertainty shock has a negative effect on both employment and industrial production (see Figure B.1). In contrast, a shock to non-financial uncertainty yields a slightly positive impact (Figure B.2). Consistent with our expectations, the non-linear framework reveals more nuanced dynamics: non-financial uncertainty shocks generate positive effects on economic activity in both the moderate and high uncertainty regimes (Figure B.3), while in the low uncertainty regime, there is no significant effect.

6.2 Analysis with reduced time span: 1990-2019

An second way to address the potential influence of the COVID-19 shock is to replicate the analysis using a subsample that excludes the pandemic period—specifically, the 1990–2019 period. We re-estimate the PCA using the same set of uncertainty indicators over this subsample. The results indicate no substantial changes in the structure of the first two principal components (see Figure C.1). As before, the first factor captures the general level of uncertainty, while the second factor continues to distinguish between non-financial and financial uncertainty shocks. In the low uncertainty regime, non-financial uncertainty shocks have a slightly negative effect on

[19]The infectious disease developed by Baker *et al.* (2020) quantifies economic uncertainty related to infectious diseases by counting newspaper articles that jointly mention economic conditions, market volatility, and epidemic-related terms.

industrial production (Figure C.3). In contrast, in the moderate uncertainty regime, we observe a significant positive effect on both employment and industrial production. A positive effect on industrial production is also present in the high uncertainty regime, although the magnitude is smaller. As in the baseline results, the positive effect is most pronounced in the moderate uncertainty regime, even when the COVID-19 period is excluded from the sample.

6.3 Non linear framework with two regimes

We try here to do the same exercise than before but with two regimes instead of three. We apply local projections adapted to the non-linear framework in order to estimate the impulse reponse functions in two regimes:

$$y_{t+s} = \left(1 - I(z_{t-1} \leq \gamma)\right)\left[\alpha_s^L + \beta_s^L x_t + \gamma_{s,L}^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k,L}^{'} w_{t-k}\right] + I(z_{t-1} > \gamma)\left[\alpha_s^H + \beta_s^H x_t + \gamma_{s,H}^{'} r_t + \sum_{k=1}^{p} \lambda_{s,k,H}^{'} w_{t-k}\right] + \mu_{t+s}^s$$

We impose an exogenous threshold value of zero. Since the general uncertainty index is standardized, the value of zero represents the mean. Consequently, observations above zero correspond to periods of general uncertainty higher than the average, whereas observations below zero indicate periods of general uncertainty lower than the average. We will now investigate the impact of the nature of shocks on economic activity when we are either in a high uncertainty regime or in a low uncertainty regime. We get a positive effect of non-financial uncertainty on employment and industrial production in the high uncertainty regime (Figure D.1).

6.4 Alternative ordering in the recursive identification

Following the VAR specification proposed by Bloom (2009), the uncertainty variable is initially ordered second in the vector w_t, with the S&P 500 index placed first. This implies that only financial shocks can contemporaneously affect the uncertainty variable. However, several authors argue that all macroeconomic variables may contemporaneously influence uncertainty. In such cases, the uncertainty indicator is placed as the last element in the vector of endogenous variables (see, among others, Colombo, 2013; Jurado *et al.*, 2015; Charles *et al.*, 2018). Since there is no consensus in the literature on the appropriate ordering of the uncertainty variable, we re-estimate the local projections model using this alternative identification scheme. Specifically, all macroeconomic variables are now included in the r_t vector in equation (1). Importantly, this alternative ordering does not qualitatively alter our main results.[20]

Finally, we adopt the opposite assumption by ordering uncertainty first, allowing an uncertainty shock to affect all other variables instantaneously, but not the reverse. In this case, all the variables are included in the q_t vector and there is no variable in the r_t. Again, the results remain unchanged.

6.5 Estimates including Macroeconomic Uncertainty (MU)

As a final robustness check, we re-estimate our baseline specification by including the macroeconomic uncertainty (MU) index in the PCA. The resulting general uncertainty factor is almost identical to our baseline measure, with a correlation coefficient of 0.99. Likewise, the interpretation of the second factor as capturing the composition of uncertainty—distinguishing between financial and non-financial uncertainty—is preserved, as reflected in its correlation of 0.99 with the baseline second factor.

The impulse response analysis delivers virtually identical results to those obtained in the baseline specification. In the linear framework, a general uncertainty shock continues to depress economic activity. In the nonlinear framework, our main findings also remain unchanged: non-financial uncertainty shocks continue to exert positive effects on economic activity in both the moderate- and high-uncertainty regimes (see appendix E).

7 Conclusion

This paper revisits the macroeconomic effects of uncertainty by arguing that uncertainty should not be treated as a homogeneous concept. Rather than focusing solely on its overall level, we

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

show that understanding its macroeconomic effects requires considering both its level and its composition. This distinction proves essential for reconciling the predictions of recent theoretical models with the empirical evidence. One of the major difficulty in disentangling the various components of uncertainty is to ensure they are the least permeable to each other possible.

To address this issue, we develop a unified empirical framework based on sixteen U.S. monthly uncertainty indicators covering the period 1990–2024. Principal Component Analysis identifies two orthogonal latent factors. The first captures the overall level of uncertainty, while the second captures a latent dimension related to the composition of uncertainty. Rather than imposing an economic interpretation on this second factor, we validate it independently through an orthogonal VARIMAX rotation, which confirms that it is economically interpretable as the distinction between financial and non-financial uncertainty. We obtain then a clearcut and general distinction between both components. We then estimate the dynamic effects of these uncertainty shocks using state-dependent local projections.

Our empirical results reveal a clear asymmetry. Consistent with the conventional literature, financial uncertainty shocks exert contractionary effects on industrial production, and employment. By contrast, non-financial uncertainty shocks generate positive and statistically significant effects on economic activity, but only when the economy is characterized by moderate or high levels of aggregate uncertainty. No significant effects are found during low-uncertainty periods. These results remain robust to a wide range of alternative specifications, including alternative recursive identification schemes, the exclusion of the COVID-19 period, different sample periods, and alternative constructions of the uncertainty factors.

Our findings make three contributions to the uncertainty literature. First, they show that the macroeconomic effects of uncertainty depend jointly on its composition and the prevailing uncertainty regime, suggesting that treating uncertainty as a single aggregate shock may conceal important sources of heterogeneity. Second, we propose an endogenous identification strategy in which the composition of uncertainty is recovered as a latent dimension of the data rather than imposed through an *ex ante* classification. An independent VARIMAX analysis then provides statistical support for interpreting this latent dimension as the distinction between financial and non-financial uncertainty. Third, we provide aggregate empirical evidence showing that the expansionary effects predicted by several recent theoretical models become observable once uncertainty is decomposed according to its composition and analyzed across different uncertainty regimes.

Although our results are consistent with several theoretical mechanisms proposed in the recent literature, they do not allow us to distinguish among them. The expansionary effects associated with non-financial uncertainty may reflect supply-side investment responses emphasized by recent real-options models, demand-side mechanisms based on limited attention and cognitive myopia, or a combination of these channels. Identifying the relative importance of these mechanisms remains an important avenue for future research.

More generally, our findings suggest that the apparent discrepancy between the predominantly contractionary effects reported in the empirical literature and the expansionary effects predicted by several recent theoretical contributions largely reflects an identification problem. Once uncertainty is decomposed according to its composition and analyzed across different uncertainty regimes, these seemingly contradictory findings become mutually consistent. More fundamentally, our results suggest that the relevant question is no longer whether uncertainty is contractionary or expansionary, but rather which type of uncertainty matters and under which uncertainty regime it operates.

References

Adämmer, Philipp. 2019. lpirfs: An R Package to Estimate Impulse Response Functions by Local Projections. *The R Journal*, **11**(2), 421–438.

Ahir, H., Bloom, N., & Furceri, D. 2018. World Uncertainty Index. *Stanford mimeo*.

Ahmed, M. Iqbal, & Cassou, Steven P. 2021. Asymmetries in the effects of unemployment expectation shocks as monetary policy shifts with economic conditions. *Economic Modelling*, **100**, 105502.

Akkaya, Yıldız, Bitter, Lea, Brand, Claus, & Fonseca, Luís. 2024 (Oct.). *A statistical approach to identifying ECB monetary policy*. Working Paper Series 2994. European Central Bank.

Alessandri, Piergiorgio, & Mumtaz, Haroon. 2019. Financial regimes and uncertainty shocks. *Journal of Monetary Economics*, **101**(C), 31–46.

Andreasen, Martin M., Caggiano, Giovanni, Castelnuovo, Efrem, & Pellegrino, Giovanni. 2024. Does risk matter more in recessions than in expansions? Implications for monetary policy. *Journal of Monetary Economics*, **143**, 103533.

Antolín-Díaz, Juan, & Rubio-Ramírez, Juan F. 2018. Narrative Sign Restrictions for SVARs. *American Economic Review*, **108**(10), 2802–29.

Bachmann, R., Elstner, S., & Sims, E.R. 2013. Uncertainty and Economic Activity: Evidence from Business Survey Data. *American Economic Journal: Macroeconomics*, **5**(2), 217–249.

Baker, S. R., Bloom, N., & Davis, S.J. 2016. Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, **131**(4), 1593–1636.

Baker, Scott R., Bloom, Nicholas, Davis, Steven J., & Kost, Kyle J. 2019 (Mar.). *Policy News and Stock Market Volatility*. NBER Working Papers 25720. National Bureau of Economic Research, Inc.

Baker, Scott R, Bloom, Nicholas, Davis, Steven J, Kost, Kyle, Sammon, Marco, & Viratyosin, Tasaneeya. 2020. The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*, **10**(4), 742–758.

Bauer, M. D., & Mertens, T. M. 2018. Information in the Yield Curve about Future Recessions. *FRBSF Economic Letter*, **2018**(20).

Bloom, N. 2009. The Impact of Uncertainty Shocks. *Econometrica*, **77**(3), 623–685.

Caballero, Ricardo J. 1991. On the Sign of the Investment-Uncertainty Relationship. *American Economic Review*, **81**(1), 279–288.

Caggiano, G., Castelnuovo, E., & Groshenny, N. 2014. Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions. *Journal of Monetary Economics*, **67**(C), 78–92.

Caldara, Dario, & Iacoviello, Matteo. 2022. Measuring Geopolitical Risk. *American Economic Review*, **112**(4), 1194–1225.

Candelon, Bertrand, Ferrara, Laurent, & Joëts, Marc. 2021. Global financial interconnectedness: a non-linear assessment of the uncertainty channel. *Applied Economics*, **53**(25), 2865–2887.

Charles, Amélie, Darné, Olivier, & Tripier, Fabien. 2018. Uncertainty and the macroeconomy: evidence from an uncertainty composite indicator. *Applied Economics*, **50**(10), 1093–1107.

Colombo, Valentina. 2013. Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, **121**(1), 39 – 42.

Colombo, Valentina, & Paccagnini, Alessia. 2020 (Aug.). *The asymmetric effects of uncertainty shocks*. CAMA Working Papers 2020-72. Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Crouzet, Nicolas, & Eberly, Janice. 2026. R&D Uncertainty and Cycles. *Pages 504–509 of: AEA Papers and Proceedings*, vol. 116. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Davis, Steven J. 2016 (October). *An Index of Global Economic Policy Uncertainty*. Working Paper 22740. National Bureau of Economic Research.

Fama, Eugene F., & French, Kenneth R. 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, **47**(2), 427–465.

Ferrara, Laurent, Karadimitropoulou, Aikaterina, Triantafyllou, Athanasios, & Bermpei, Theodora. 2022a. *Commodity currencies revisited: The role of global commodity price uncertainty*. EconomiX Working Papers 2022-24. University of Paris Nanterre, EconomiX.

Ferrara, Laurent, Karadimitropoulou, Aikaterini, & Triantafyllou, Athanasios. 2022b (Jan.). *Commodity price uncertainty comovement: Does it matter for global economic growth?* CAMA Working Papers 2022-08. Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Forni, Mario, Gambetti, Luca, & Sala, Luca. 2021 (Mar.). *Downside and Upside Uncertainty Shocks*. CEPR Discussion Papers 15881. C.E.P.R. Discussion Papers.

Gabaix, Xavier. 2014. A Sparsity-Based Model of Bounded Rationality. *The Quarterly Journal of Economics*, **129**(4), 1661–1710.

Gabaix, Xavier. 2020. A Behavioral New Keynesian Model. *American Economic Review*, **110**(8), 2271–2327.

Gilchrist, Simon, Sim, Jae W, & Zakrajšek, Egon. 2014 (April). *Uncertainty, Financial Frictions, and Investment Dynamics*. Working Paper 20038. National Bureau of Economic Research.

Grigoris, Fotis, & Segal, Gill. 2026. Investment under upstream and downstream uncertainty. *The Journal of Finance*, **81**(1), 413–457.

Haddow, Abigail, Hare, Chris, Hooley, John, & Shakir, Tamarah. 2013. *Macroeconomic Uncertainty: What Is It, How Can We Measure It and Why Does It Matter?* Quarterly Bulletin Q2. Bank of England.

Hartman, Richard. 1972. The effects of price and cost uncertainty on investment. *Journal of Economic Theory*, **5**(2), 258–266.

Herbst, Edward P., & Johannsen, Benjamin K. 2024. Bias in local projections. *Journal of Econometrics*, **240**(1), 105655.

Himounet, Nicolas. 2022. Searching the nature of uncertainty: Macroeconomic and financial risks VS geopolitical and pandemic risks. *International Economics*, **170**, 1–31.

Himounet, Nicolas, Serranito, Francisco, & Vauday, Julien. 2024. A positive effect of uncertainty shocks on the economy: Is the chase over? *The World Economy*, **47**(1), 268–297.

Ismailov, Adilzhan, & Rossi, Barbara. 2018. Uncertainty and deviations from uncovered interest rate parity. *Journal of International Money and Finance*, **88**, 242 – 259.

Iván Alfaro, Nicholas Bloom, & Lin, Xiaoji. 2024. The Finance Uncertainty Multiplier. *Journal of Political Economy*, **132, Issue 2**, 337721.

Jalles, João Tovar, & Karras, Georgios. 2026. Sailing through uncertainty: Inspecting mechanisms in advanced and developing economies. *Journal of Macroeconomics*, **88**, 103741.

Jolliffe, Ian T. 2002. *Principal Component Analysis*. 2 edn. Springer Series in Statistics. New York, NY: Springer.

Jordá, Òscar. 2005. Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, **95**(1), 161–182.

Jurado, Kyle, Ludvigson, Sydney C., & Ng, Serena. 2015. Measuring Uncertainty. *American Economic Review*, **105**(3), 1177–1216.

Kaiser, H. F. 1958. The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, **23**(3), 187–200.

Larsen, Vegard Høghaug. 2021. Components of Uncertainty. *International Economic Review*, **62**(2), 769–788.

Leduc, Sylvain, & Liu, Zheng. 2016. Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, **82**, 20 – 35.

Leduc, Sylvain, & Liu, Zheng. 2020. The Uncertainty Channel of the Coronavirus. *FRBSF Economic Letter*, **2020**(07), 1–05.

Li, Dake, Plagborg-Møller, Mikkel, & Wolf, Christian K. 2024. Local projections vs. VARs: Lessons from thousands of DGPs. *Journal of Econometrics*, **244**(2), 105722.

Ludvigson, Sydney C. 2004. Consumer Confidence and Consumer Spending. *Journal of Economic Perspectives*, **18**(2), 29–50.

Ludvigson, Sydney C., Ma, Sai, & Ng, Serena. 2021. Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? *American Economic Journal: Macroeconomics*, **13**(4), 369–410.

Montiel Olea, José Luis, & Plagborg-Møller, Mikkel. 2021. Local Projection Inference Is Simpler and More Robust Than You Think. *Econometrica*, **89**(4), 1789–1823.

Nam, Eun-Young, Lee, Kiryoung, & Jeon, Yoontae. 2021. Macroeconomic uncertainty shocks and households' consumption choice. *Journal of Macroeconomics*, **68**, 103306.

Newey, Whitney, & West, Kenneth. 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, **55**(3), 703–08.

Oi, Walter Y. 1961. The Desirability of Price Instability Under Perfect Competition. *Econometrica*, **29**(1), 58–64.

Olea-Montiel, J. L., Plagborg-Møller, M., Qian, E., & Wolf, C. K. 2024. Double Robustness of Local Projections and Some Unpleasant VARithmetic. *NBER Working paper*, June.

Owyang, Michael T., Ramey, Valerie A., & Zubairy, Sarah. 2013. Are Government Spending Multipliers Greater during Periods of Slack? Evidence from Twentieth-Century Historical Data. *American Economic Review*, **103**(3), 129–34.

Plagborg-Møller, Mikkel, & Wolf, Christian K. 2021. Local Projections and VARs Estimate the Same Impulse Responses. *Econometrica*, **89**(2), 955–980.

Punzi, Maria Teresa. 2019. The impact of energy price uncertainty on macroeconomic variables. *Energy Policy*, **129**(C), 1306–1319.

Ramey, Valerie A., & Zubairy, Sarah. 2018. Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of Political Economy*, **126**(2), 850–901.

Ravn, Morten O., & Uhlig, Harald. 2002. On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *The Review of Economics and Statistics*, **84**(2), 371–376.

Rohe, K., & Zeng, M. 2023. Vintage factor analysis with Varimax performs statistical inference. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, **85**(4), 1037–1060.

Segal, Gill. 2019. A tale of two volatilities: Sectoral uncertainty, growth, and asset prices. *Journal of Financial Economics*, **134**(1), 110–140.

Segal, Gill, Shaliastovich, Ivan, & Yaron, Amir. 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, **117**(2), 369 – 397.

Tisdell, Clement. 1978. Estension of Oi's price. *Journal of Economic Theory*, **17**(07), 130–133.

Appendix

A Data

Table A.1: Uncertainty Data and Sources

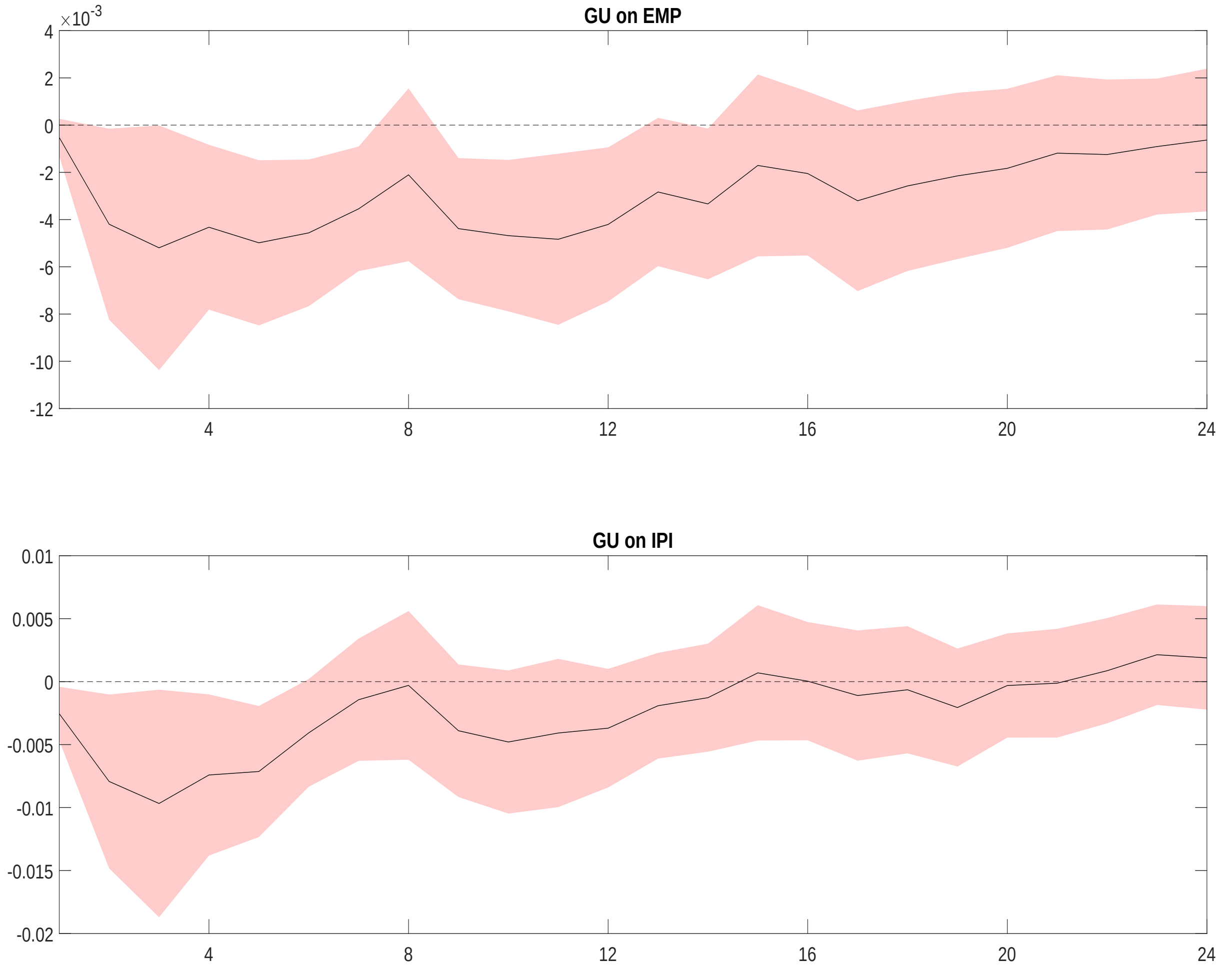
Index	Acronym	Source	Related Literature
Volatility Index	VIX	Yahoo finance	Bloom (2009)
Economic Policy Uncertainty	EPU_Index	policyuncertainty.com	Baker *et al.* (2016)
Monetary Policy Uncertainty	MPU	policyuncertainty.com	Baker *et al.* (2016)
News Index	NewsUS	policyuncertainty.com	Baker *et al.* (2016)
Economic Policy Uncertainty (Access World News)	EPU_Access	policyuncertainty.com	Baker *et al.* (2016)
Fiscal Policy Uncertainty	FPU	policyuncertainty.com	Baker *et al.* (2016)
Health Policy Uncertainty	HPU	policyuncertainty.com	Baker *et al.* (2016)
Trade Policy Uncertainty	TPU	policyuncertainty.com	Baker *et al.* (2016)
Business Confidence Index	IDE	OECD database	Bachmann *et al.* (2013)
Consumer Confidence Index	IDC	OECD database	Haddow *et al.* (2013)
Macroeconomic Uncertainty	MU	sydneyludvigson.com	Jurado *et al.* (2015)
Financial Uncertainty	FU	sydneyludvigson.com	Ludvigson *et al.* (2021)
10Y-2Y yield spread	Spread	FRED database	Bauer & Mertens (2018)
Corporate Bond Spreads	Bspread	FRED database	Bachmann *et al.* (2013)
Geopolitical Risk Index	GPR	matteoiacoviello.com	Caldara & Iacoviello (2022)
Equity Market Volatility Tracker	EMV	policyuncertainty.com	Baker *et al.* (2019)
Infectious disease	Disease	policyuncertainty.com	Baker *et al.* (2020)

Table A.2: US Macroeconomic Variables: Descriptive statistics and Sources

Variable	N	Mean	St. Dev.	Min	Max	Source
Standard Poors 500 Index (SP500)	420	1,694.988	1,252.640	307.120	6,010.910	Yahoo Finance
Industrial Production (IPI)	420	90.127	13.086	60.297	104.104	FRED
Federal Funds rate (Fed)	420	2.841	2.365	0.050	8.290	FRED
Consumer price index (CPI)	420	207.062	48.853	127.500	317.603	FRED
Manufacturing employment (EMP)	420	14,344.680	2,204.853	11,382	17,893	FRED
Average Hourly Earnings in manufacturing (Wages)	420	17.471	4.479	10.520	28.330	FRED
Average hours worked in manufacturing (Hours)	420	41.150	0.617	38.400	42.400	FRED

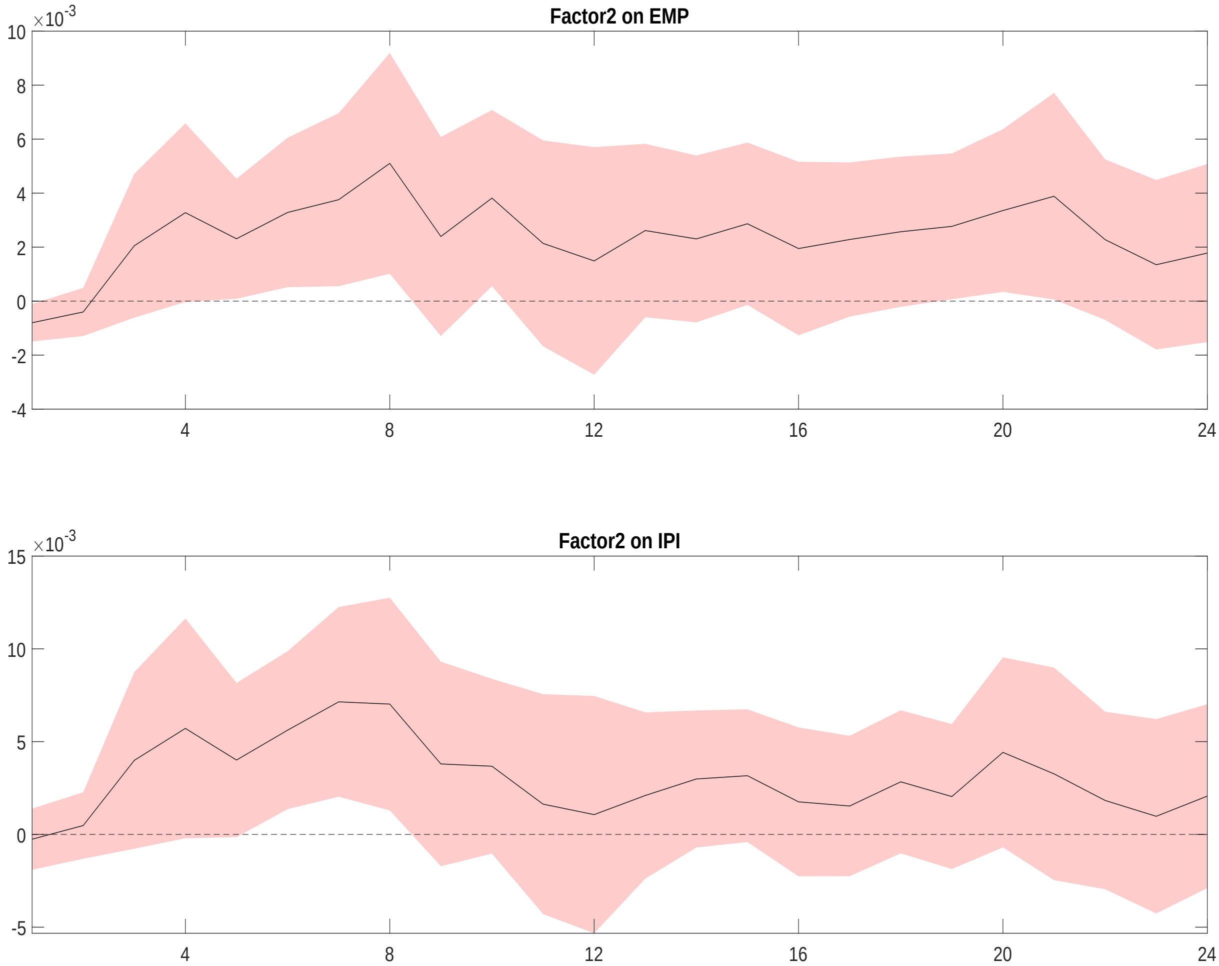
B Robustness Check: Exogenous Variable

Figure B.1: Impulse Response Functions: Effects of a general uncertainty shock



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 80% confidence interval. The light shaded area denotes the 90% confidence interval.

Figure B.2: Impulse Response Functions: Effects of a non-financial uncertainty shock



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The shaded area denotes the 80% confidence interval. The light shaded area denotes the 90% confidence interval.

Figure B.3: Impulse Response Functions under different regimes of uncertainty

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 shaded area denotes the 80% confidence interval. The light shaded area denotes the 90% confidence interval.

C Robustness Check: Subsample 1990-2019

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

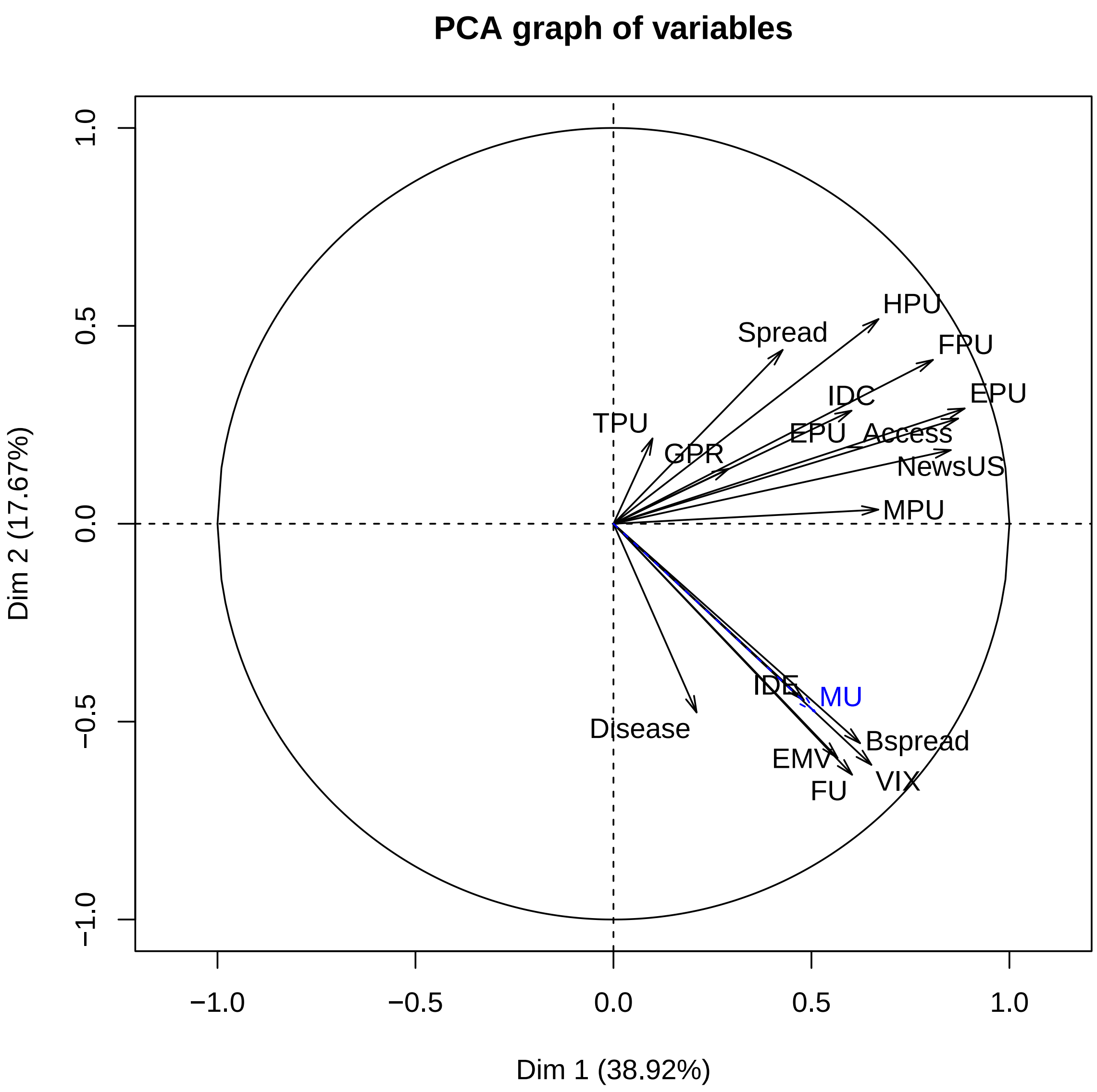
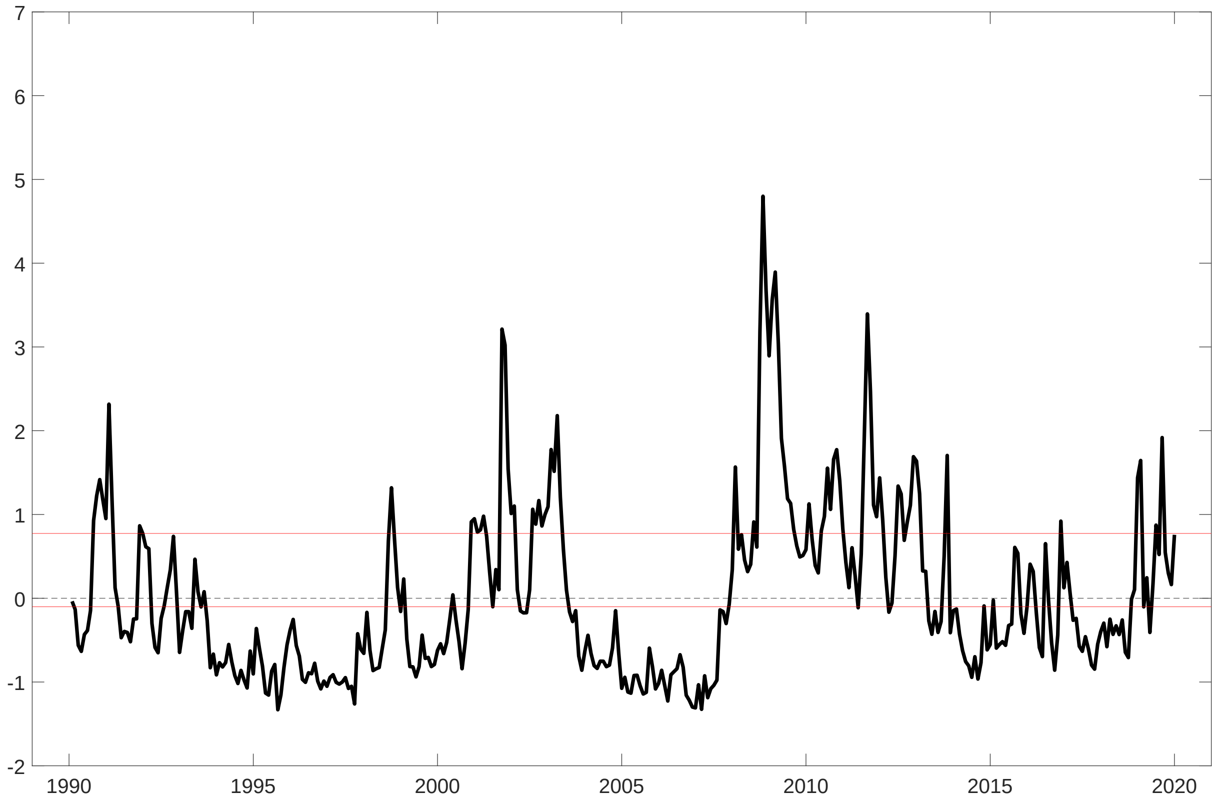


Figure C.2: Estimated Threshold values



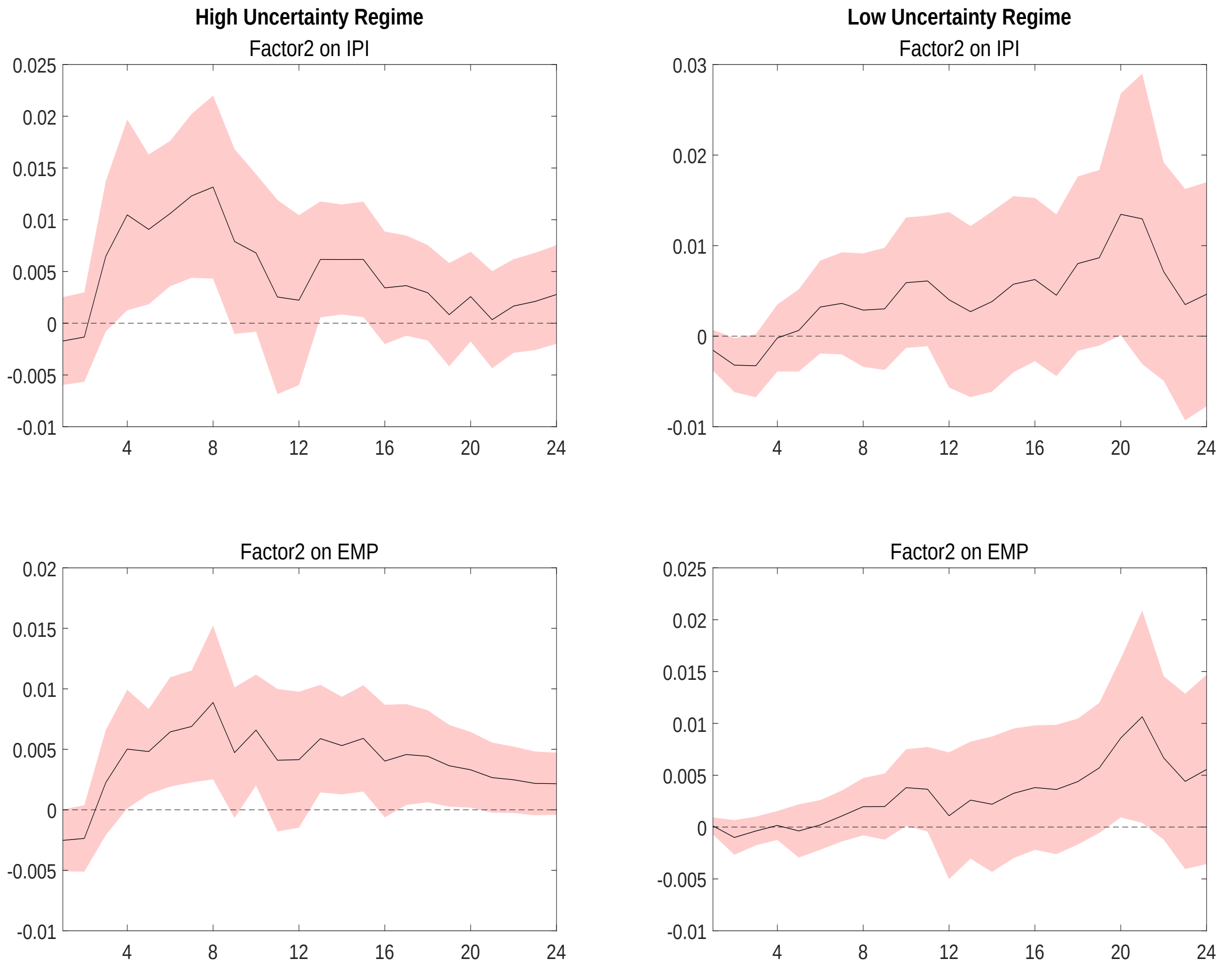
Source: Author's own calculations.
Notes: The horizontal red lines correspond to the estimated threshold values (-0.073 0.727).

Figure C.3: Impulse Response Functions under different uncertainty regimes

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 shaded area denotes the 80% confidence interval. The light shaded area denotes the 90% confidence interval.

D Robustness Check: Nonlinear Framework: Two Regimes

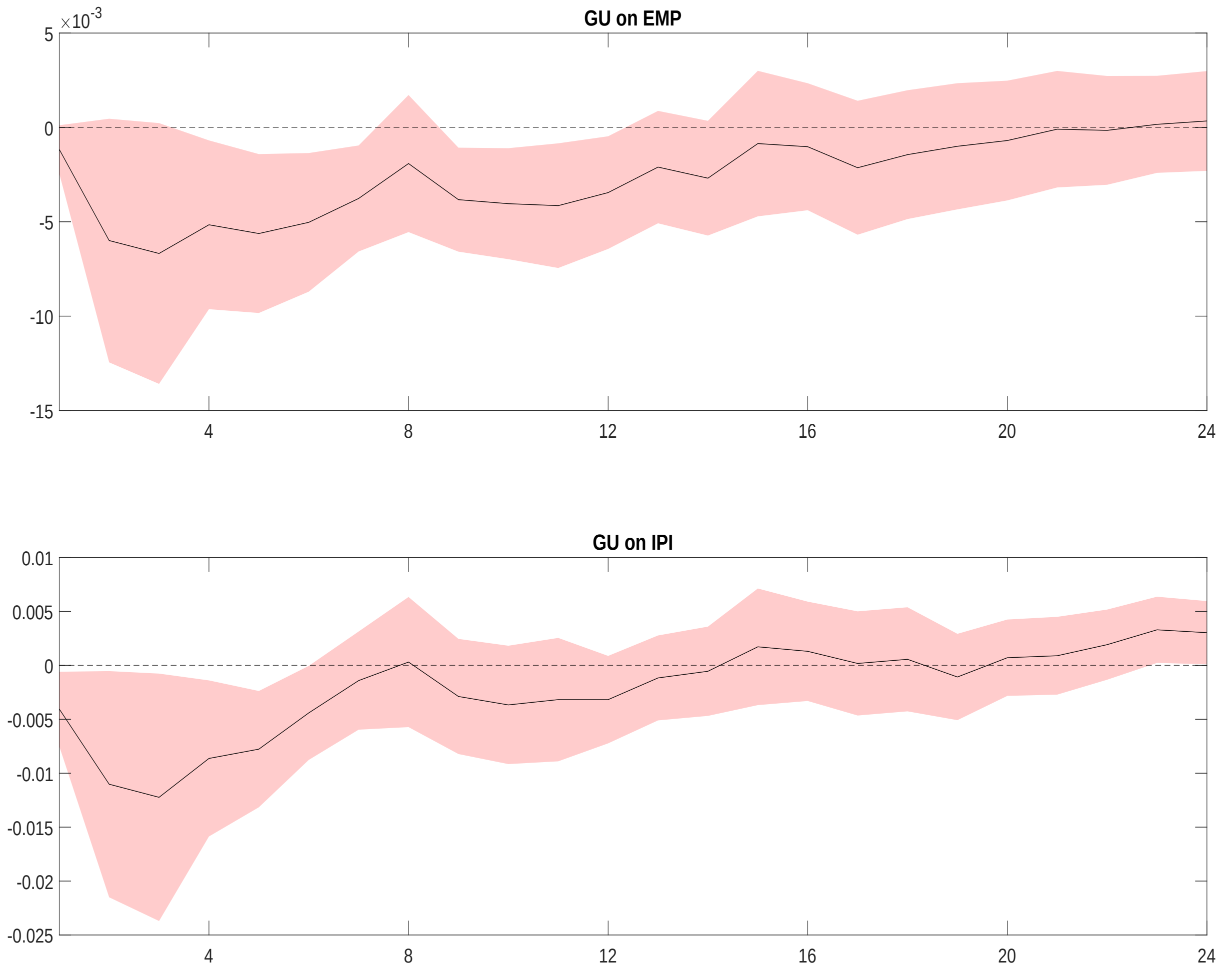
Figure D.1: Impulse Response Functions under two uncertainty regimes



Source: Author's own calculations.
Notes: The threshold value is set to 0. Graphs on the left panel represents impulse response functions in the high 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 shaded area denotes the 90% confidence interval.

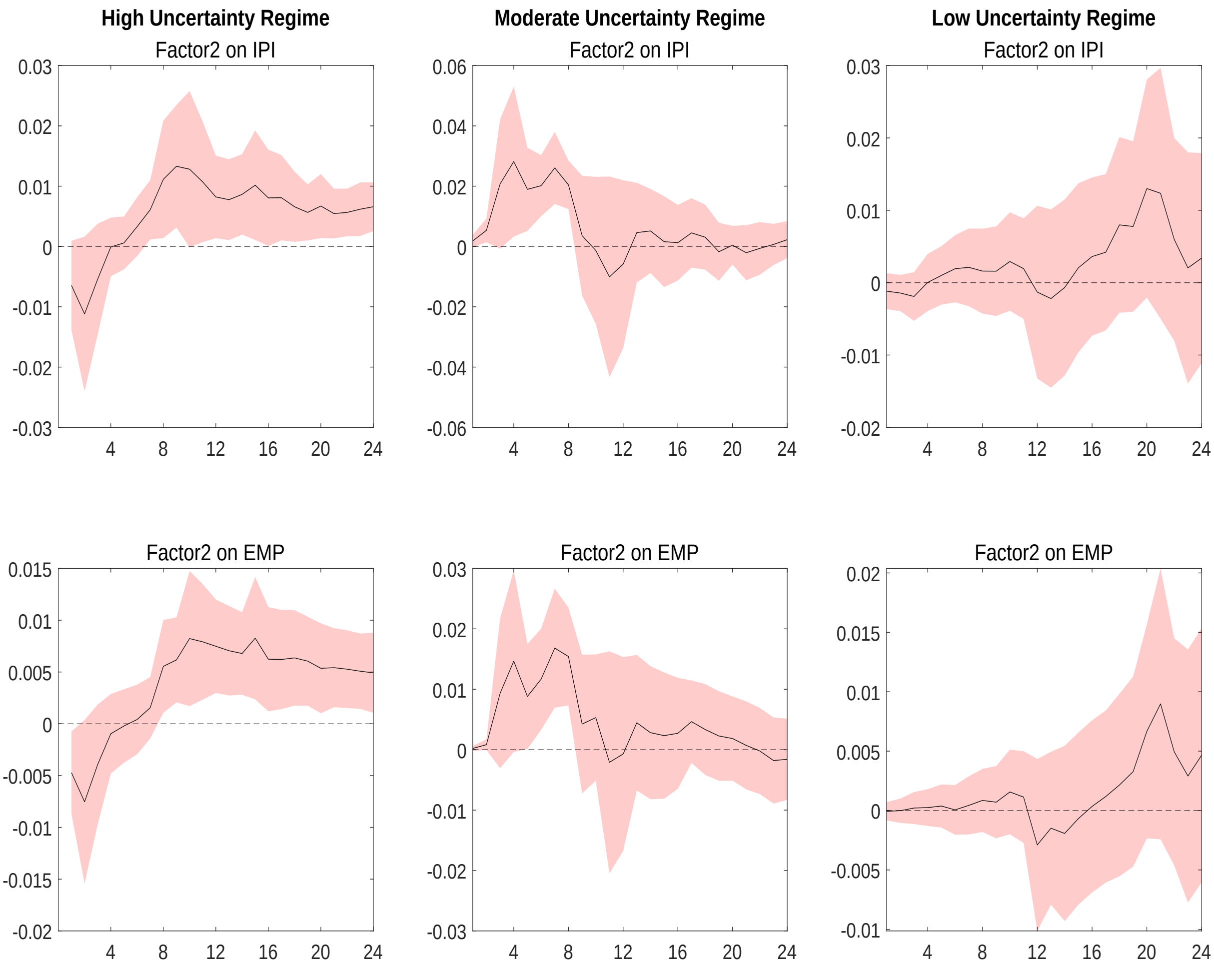
E Robustness Check: Estimates including Macroeconomic Uncertainty (MU)

Figure E.1: Impulse Response Functions: Effects of a General Uncertainty shock



Source: Author's own calculations.
Notes: The solid black lines correspond to the IRFs. The red shaded area denotes the 90% confidence interval.

Figure E.2: Impulse Response Functions under different regimes of uncertainty



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 90% confidence interval.