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Abstract

An increase in uncertainty is not contractionary per se. What generates a significant downturn of economic activity is a widening of the left tail of the expected distribution of growth, the downside uncertainty. On the contrary, an increase of the right tail, the upside uncertainty, is mildly expansionary. The reason for why uncertainty shocks have been previously found to be contractionary is because movements in downside uncertainty dominate existing empirical measures of uncertainty. The results are obtained using a new econometric approach which combines quantile regressions and structural VARs.

JEL Classification: C32, E32

Keywords: VAR models, Quantile regression, Skewness, uncertainty

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Abstract

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1 Introduction

Since the seminal contribution by Bloom (2009), a vast literature has investigated the macroeconomic effects of uncertainty, and uncertainty shocks have been at the heart of the business cycle debate.[1] Uncertainty is often defined as the expected volatility of real economic activity variables (see Jurado et al., 2015, JLN henceforth, and Ludvigson et al., 2019, LMN henceforth), and the shock identified using SVAR techniques. Although the exact magnitude of the effects varies across studies, there is by now a widespread consensus that an exogenous increase in uncertainty induces a significant temporary downturn in economic activity.

The very recent contribution by Adrian et al. (2019)[2], in addition to reaffirming the countercyclical behavior of uncertainty, documents a new intriguing finding: the tendency of the expected distribution of GDP growth to become left skewed during recessions. The asymmetry arises because the size of the left tail is counter-cyclical, while the right tail is relatively constant over time.[3] So, in periods of economic slowdown an increase in uncertainty is systematically associated with an increase in the asymmetry of the expected distribution of GDP growth.[4]

The result in Adrian et al. (2019) has important implications for the literature studying the effects of uncertainty shocks. To understand the implication, notice that total uncertainty can be decomposed into the part originating from the left tail of the growth forecast distribution, say the "downside uncertainty" or "downside risk", and the part originating from the right tail, the "upside uncertainty".If the former dominates the latter, as the evidence suggests, then one might confound the effects of an increase in total uncertainty with those of a widening of the left tail. But of course total uncertainty and downside risk are distinct concepts, which should not be confused with each other.

The above discussion raises few interesting questions. What are the effects of downside, upside and total uncertainty? Are they different? What is it that really matters? From a

[1] A few prominent contributions are Fernandez-Villaverde et al. (2011), Bachmann et al. (2013), Bekaert et al. (2013), Caggiano et al. (2014), Rossi and Sekhposyan (2015), Jurado et al. (2015), Scotti (2016), Baker et al. (2016), Caldara et al. (2016), Leduc and Liu (2016), Basu and Bundik (2017), Fajgelbaum et al. (2017), Piffer and Podstawsky (2017), Nakamura et al. (2017), Bloom et al. (2018), Carriero et al. (2018a, 2018b), Shin and Zhong (2018), Jo and Sekkel (2019), Ludvigson et al. (2019), Angelini and Fanelli (2019). For more references, see the survey articles in Cascaldi-Garcia et al. (2020) and Fernandez-Villaverde and Guerron-Quintana (2020).

[2] See also Giglio et al. (2016), Plagborg-Møller et al. (2020) and Delle Monache et al. (2020)).

[3] The paper shows that changes in the left tail are largely driven by changes in financial conditions, the left tail increasing in periods of high financial stress. For a dissenting view, see Plagborg-Møller et al. (2020).

[4] Several studies had previously pointed out that business cycle fluctuations tend to be negatively skewed since recessionary episodes tend to have larger effects on growth than booms, see for instance Neftci (1984), Sichel (1993) and Morley and Piger (2012). Very recently, Jensen et al. (2020) shows that such an asymmetry has been increasing over the last decades in the United States and other G7 economies.

theoretical point of view, it is plausible that upside and downside uncertainty generate different effects. When uncertainty originates from the left tail, both the "real options" channel and the "risk premium" channel operate. According to the real options effect (Bernanke, 1983), uncertainty increases the option value of delaying spending decisions that are to some extent irreversible. Firms and consumers become more cautious, since a wrong decision would be costly. They prefer to postpone investment, hiring and durable consumption to a time when future prospects are clearer. As a consequence, real economic activity slows down. According to the risk premium effect, higher uncertainty increases the probability of bad outcomes for the firm, raising the risk of investment and therefore the cost of finance (see Christiano, Motto and Rostagno, 2009, and Gilchrist, Sim and Zakrajšek, 2014). When uncertainty originates from the right tail, the risk premium channel does not operate, and uncertainty effects are transmitted only through the real option channel. Moreover, a channel which pushes economic activity, the "growth options", operates. A mean-preserving increase in upside uncertainty increases the opportunity of high profits in the good scenario, stimulating investment and growth. This argument was invoked as an explanation for the dot-com bubble of the turn of the century. To sum up, while downside uncertainty has negative effects, the effects of upside uncertainty are ambiguous, depending on which of the two channels, the real options and the growth options, dominates.[5]

The contribution of this paper is twofold. First, we develop a relatively simple econometric framework to study how shocks to the expected distribution of macroeconomic variables affect real economic activity, and, in the opposite direction, how policy or other structural shocks affect the expected distribution of macroeconomic variables. Second, we apply our econometric framework to study the effects of downside, upside and total uncertainty.

The basic idea is to combine quantile regression with structural VAR techniques. More precisely, we proceed in three steps.

First, we select the target variable, which in this paper is GDP growth, and the relevant horizon: here we use one quarter and 4 quarters. We then estimate the expected quantiles, conditional to a selected set of predictors. This part of the procedure is similar to the one in Adrian et al. (2020). The main difference is that here we use the smoothed quantile regression recently proposed in Fernandez et al. (2019); this allows us to use several predictors, in place of a single financial stress indicator. With the estimated quantiles, we can build descriptive statistics of the expected distribution. Here we compute downside uncertainty as the difference between the median and the 10th percentile, upside uncertainty as the difference between the 90th percentile and the median, and total uncertainty as the sum of the two. In a robustness

[5]See Bloom (2014) for a review of the theoretical literature on the macroeconomic effects of uncertainty.

exercise we also use a measure of skewness: the difference between upside uncertainty and downside uncertainty.

In the second step, we estimate a VAR that includes, in addition to the variables of interest, the variables that were used in the first step for quantile prediction. From the VAR, we derive the reduced form impulse response functions.

In the third step, we combine the previous two. The quantiles estimated in the first step are linear combinations of the VAR variables. This allows us to derive, from the VAR coefficients estimated in the second step, the effects of any structural shock on these quantiles, by properly combining the VAR impulse response functions with the quantile regression coefficients. In this way we can study, for instance, the effects of conventional and unconventional monetary policy on the expected distribution of interest rates, economic activity and prices.

The other way round, we can study the effects of shocks to the expected distribution of the target variable on economic activity, as we do in the present paper. For, the innovations of the quantiles are linear combinations of the VAR residuals and the related impulse response functions are combinations of the VAR impulse response functions. The same is true for any statistic describing the relevant expected distribution, provided that this statistic is linear in the quantiles, as is the case for downside and upside uncertainty, as defined above. Since innovations may be partly endogenous, we show how various identification restrictions can be incorporated into the basic scheme, including Cholesky-type restrictions on impact effects, long-run restrictions, and orthogonality restrictions with respect to previously identified structural shocks. In this paper, for example, we condition the effects of the left tail of the expected distribution to those of the right tail and vice versa; in a few robustness exercises, we impose that downside and upside uncertainty have transitory effects on GDP.

In the empirical part of the paper we use quarterly US data from 1960:Q1 to 2019:Q2. We select the predictors on the basis of their significance in predicting the relevant quantiles and retain both financial and non-financial predictors: real GDP, unemployment, real stock prices and a component of the Michigan consumer confidence index: the expected business conditions 1-year ahead. In the baseline VAR specification, we use in addition real investment, a term spread and a risk spread.

Our main results are the following. (i) Uncertainty shocks generate a temporary downturn in real economic activity, confirming the results previously found in the literature. (ii) An increase in downside risk generates significant negative effects on real economic activity. (iii) An increase in upside uncertainty has positive but small effects on real economic activity and larger effects on stock prices. Results (ii) and (iii) unveil a new interesting picture. An increase in uncertainty is not contractionary *per se*. It is contractionary as long as uncertainty originates from a widening of the left tail of the growth forecast distribution. A widening of the right tail is indeed expansionary. The reason why uncertainty is found here and was found in most of the empirical works to have significant negative effects on the economy is that downside uncertainty dominates upside uncertainty in empirical measures of total uncertainty, since downside uncertainty is the only part of the distribution displaying large cyclical variations. Notice that a widening of the left tail makes the distribution more left skewed. So, the shock that matters for fluctuations generates not only an increase in uncertainty, but also an increase in the asymmetry of the distribution.

Our paper is closely related to Adrian et al. (2019). The main difference is that here, in addition to estimating the expected distribution of growth, we estimate the effects of shocks to this distribution on macroeconomic variables. Another important related paper is Salgado et al. (2019). The paper shows that skewness shocks matter for economic fluctuations. The results are very much in line with ours. The main difference is that this paper focuses on the realized cross-sectional distribution of firm-level employment, sales and productivity rather than the expected distribution of aggregate GDP growth. Finally, Segal et al. (2015) analyze "bad" and "good" uncertainty and find results which are qualitatively similar to ours. The main difference is the econometric methodology, whose scope is more limited, as it involves the use of annual data.

The remainder of the paper is organized as follows. Section 2 discusses the econometric approach. Section 3 presents the main results. Section 4 presents some robustness checks. Section 5 concludes.

2 Econometric approach

The goal of our econometric approach is to estimate the impulse response functions of macroeconomic variables to shocks to the expected distribution of a variable of interest. We focus on four types of shocks: uncertainty shocks, downside risk shocks, upside risk shocks and finally skewness shocks.

The approach consists of three steps. First, the expected distribution of a variable of interest is estimated using conditional quantile regressions. Second, a VAR for a vector of macroeconomic variables, including the predictors used in the first step, is estimated. Third, the shock of interest and its impulse response functions are obtained by combining the VAR residuals and coefficients with the coefficients of the quantile regression.

2.1 The expected distribution

Let x_t be the variable whose distribution we want to predict and let y_t be an n-dimensional time series vector, which includes the macroeconomic series of interest. Let $w_t = Wy_t$ be the r-dimensional subvector of variables which are important to forecast x_t, where W is a $r \times n$ matrix of zeros and ones selecting the appropriate predictors in y_t.

The goal is to estimate the conditional distribution of x_{t+h} given w_t. To do so, we use quantile regressions. The τ-th quantile Q_t^τ of x_{t+h}, conditional on the predictors w_t, is a linear function of the predictors:

$$Q_t^\tau = \beta'_\tau(L)w_t = \beta'_\tau(L)Wy_t = \tilde{\beta}'_\tau(L)y_t,$$

where $\tilde{\beta}'_\tau(L) = \beta'_\tau(L)W$. We estimate the parameters $\beta_\tau(L)$ using the smoothed quantile regression estimator recently proposed by Fernandez et al. (2019). The basic novelty of this estimator is that it uses a smoothing of the standard objective function typically used in conditional quantile regressions.[6] The advantage of this estimator is that (i) it is more accurate than the standard estimator and (ii) it does not suffer from the curse of dimensionality, so that it is possible to use several predictors. In addition, (iii) the kernel estimator is continuously differentiable and increasing in the quantiles.[7] Finally, (iv) it is possible to compute the asymptotic standard deviation of the estimated coefficients to get confidence bands and (v) obtain a consistent estimate of the conditional probability density function, without the need of resorting to an interpolation like the one used in Adrian et al. (2019). The estimator has a parameter governing the bandwidth; to set this parameter we use the rule of thumb suggested by Fernandez et al. (2019).

Since the quantiles are linear in y_t, any linear combination z_t^j of the quantiles can be written as a linear combination of current and lagged macroeconomic variables, i.e.

$$z_t^j = \gamma'_j(L)y_t, \tag{1}$$

where $\gamma_j(L) = \gamma_{j0} + \gamma_{j1}L + ...\gamma_{jq}L^q$ is an n-dimensional vector of polynomials in the lag operator L. Here, we are interested in linear combinations which summarize important features of the forecast distribution. The first feature is uncertainty, the dispersion of the forecast distribution, which we measure as the difference between the 90th and 10th percentile

$$z_t^u = Q_t^{0.9} - Q_t^{0.1}.$$

[6] See Koenker and Bassett (1978).

[7] The latter property holds for the average covariates, but in practice it is rarely violated elsewhere.

where the index u stands for *uncertainty*. Uncertainty then can be decomposed as the sum of downside risk, z_t^l, and upside risk, z_t^r,

$$z_t^u = z_t^r + z_t^l$$

where the downside risk is the difference between the median and the 10th percentile,

$$z_t^l = Q_t^{0.5} - Q_t^{0.1},$$

where the index l stands for *left*, and the upside risk is the difference between the 90th percentile and the median,

$$z_t^r = Q_t^{0.9} - Q_t^{0.5}$$

where the index r stands for *right*.

Using the two tail risks, we can also easily derive a measure of the non-normalized Kelley skewness (Kelley, 1947) as the difference between the two:

$$z_t^s = z_t^r - z_t^l = Q_t^{0.9} + Q_t^{0.1} - 2Q_t^{0.5}.$$

As noted above, the four variables are linear functions of the quantiles and therefore can be rewritten as linear combinations of y_t, with parameters

$$\begin{aligned}
\gamma_l(L) &= \tilde{\beta}_{0.5}(L) - \tilde{\beta}_{0.1}(L) \\
\gamma_r(L) &= \tilde{\beta}_{0.9}(L) - \tilde{\beta}_{0.5}(L) \\
\gamma_u(L) &= \tilde{\beta}_{0.9}(L) - \tilde{\beta}_{0.1}(L) \\
\gamma_s(L) &= \tilde{\beta}_{0.9}(L) + \tilde{\beta}_{0.1}(L) - 2\tilde{\beta}_{0.5}(L).
\end{aligned}$$

Estimates of the four polynomials in L can simply be obtained by replacing the quantile parameters $\tilde{\beta}_\tau(L)$ with their estimates obtained from the quantile regression.

2.2 VAR

The second ingredient of our approach is to specify a dynamic representation for the vector y_t. We assume that y_t follows (abstracting from the constant term) the VAR model

$$A(L)y_t = \varepsilon_t, \tag{2}$$

where $\varepsilon_t \sim WN(0, \Sigma_\varepsilon)$, $k > 0$, and $A(L) = I - \sum_{k=1}^{p} A_k L^k$ is a matrix of degree-p polynomials in the lag operator L. By inverting the VAR, we obtain the moving average

$$y_t = B(L)\varepsilon_t, \tag{3}$$

where $B(L) = \sum_{k=0}^{\infty} B_k L^k = A(L)^{-1}$ (with $B_0 = I_n$). From (3) we can derive a representation in terms of orthonormal shocks

$$y_t = B(L)CUu_t, \tag{4}$$

where C is the Cholesky factor of Σ_ε, U is an orthonormal matrix, i.e. $UU' = I$, and the vector of shocks $u_t = U'C^{-1}\varepsilon_t \sim WN(0, I)$.

2.3 Identification with the innovation

We show here how to identify a shock to any linear function of the percentiles of the forecast distribution, z_t^j, and recover its impulse response functions on y_t. We begin by discussing how to identify the shock as the innovation in z_t^j. In the next subsection we show how to enrich the identification scheme with additional constraints.

By combining (1) and (3), the innovation in z_t^j is simply

$$z_t^j - E_{t-1}[z_t^j] = \gamma'_{j0}\varepsilon_t$$

with variance $\gamma'_{j0}\Sigma_\varepsilon\gamma_{j0}$.[8] Let u_t^j be the structural shock of interest. To identify the structural shock as the innovation in z_t^j, it suffices to impose that

$$u_t^j = v'_j\varepsilon_t, \tag{5}$$

where $v'_j = \gamma'_{j0}/\sqrt{\gamma'_{j0}\Sigma_\varepsilon\gamma_{j0}}$. To obtain the impulse response functions, let us assume, without loss of generality, that u_t^j is the first shock in u_t in representation (4), i.e. $u_t^j = U'_1C^{-1}\varepsilon_t$, where U_1 is an orthonormal column vector, implying $v'_j = U'_1C^{-1}$. The impulse response functions of u_t^j are therefore $d_j(L) = B(L)CU_1$. By replacing $U_1 = C'v_j$, we obtain

$$d_j(L) = B(L)CC'v_j = B(L)\Sigma_\varepsilon v_j. \tag{6}$$

Notice that the contemporaneous effects equal to $\Sigma_\varepsilon v_j$, being $B(0) = I_n$. The matrix $B(L)$, the innovation ε_t and their covariance matrix Σ_ε can be simply obtained using OLS. An estimate of the vector γ_0 is obtained from the quantile regression discussed in the previous subsection. This provides an estimate of the impulse response functions $d_j(L)$.

2.4 Identification with additional orthogonality constraints

The identification discussed in the previous subsection is equivalent to assuming that there is only one shock affecting contemporaneously the variable z_t^j. The assumption in many cases

[8]This simply follows from $z_t^j - E_{t-1}[z_t^j] = \gamma'_j(L)y_t - E_{t-1}[\gamma'_j(L)y_t] = \gamma'_{j0}y_t - \gamma'_{j0}E_{t-1}[y_t] = \gamma'_{j0}(y_t - E_{t-1}[y_t]) = \gamma'_{j0}\varepsilon_t$.

might appear too restrictive. Here, we show how to relax this assumption and in turn, how to impose additional restrictions.

This can be done by imposing additional orthogonality restrictions with respect to other identified shocks. It essentially amounts at projecting the innovation to z_t^j onto these shocks and taking the projection residual. Suppose, for instance, that the goal is to impose that the shock to z_t^j has no long run effect on GDP. In this case, it suffices to impose that the shock is orthogonal with respect to the shock identified as the only one driving GDP in the long run (call it $D_1\varepsilon_t$, where D_1 is a row vector). To do so, we impose that the (non-normalized) shock is $[\gamma'_{j0} - \gamma'_{j0}\Sigma_\varepsilon D'_1 D_1]\varepsilon_t$. Under this identification scheme, the shock has only transitory effects on output.

Similarly, one can restrict to zero the impact coefficient of the shock on a given variable by imposing orthogonality with respect to the VAR residual of that variable. For instance, to impose a zero impact effect on the first variable of y_t, y_{1t}, it suffices to impose orthogonality with respect to the shock $\varepsilon_{1t} = D_2\varepsilon_t$, where $D_2 = [1\ 0\ \cdots\ 0]$.

More generally, let D be the $m \times n$ matrix having on the rows the vectors D_1, D_2, ..., D_h, ..., D_m, If we want to impose orthogonality with respect to the corresponding m shocks $D_1\varepsilon_t, D_2\varepsilon_t \ldots, D_m\varepsilon_t$, we have to take the residual of the orthogonal projection of the innovation of z_t^j onto $D\varepsilon_t$, normalized to have unit variance.

Hence the shock of interest u_t^j can be computed from the VAR coefficients by applying the formulas

$$\begin{aligned} u_t^j &= \delta_j \varepsilon_t \\ \delta_j &= \frac{\alpha_j}{\sqrt{\alpha'_j \Sigma_\varepsilon \alpha_j}} \\ \alpha_j &= \gamma'_{j0} - \gamma'_{j0}\Sigma_\varepsilon D'(D\Sigma_\varepsilon D')^{-1}D. \end{aligned} \tag{7}$$

The impulse-response function corresponding to the shock u_t^j are given by

$$d_j(L) = B(L)\Sigma_\varepsilon \delta_j. \tag{8}$$

2.5 Shocks

As mentioned above, we identify four shocks: an uncertainty shock u_t^u, a downside risk shock u_t^l, an upside risk shock u_t^r, and finally a skewness shock u_t^s. The four shocks are identified as follows.

1. The uncertainty shock u_t^u is assumed to be the innovation in z_t^u, $u_t^u = v'_u\varepsilon_t$. This identification imposes the same restrictions used in VAR models to identify the uncertainty shock as the only shock with a non-zero impact effect on the uncertainty measure considered.

2. The downside risk shock u_t^l is found using two alternative identifications:

   (2a) The shock u_t^l is the innovation in z_t^l, and therefore is the only shock driving downside risk on impact.

   (2b) The shock u_t^l increases downside risk but has no contemporaneous effect on (i.e. it is orthogonal to) upside risk. This identification will be used as a check of the previous one. It can be interpreted as an increase in uncertainty exclusively driven by a shift of the left tail of the forecast distribution. In practice, we set $D = v_r$ in equation (7), where v_r is the vector multiplying ε_t in the innovation to upside risk.

3. The upside risk shock u_t^r is found using two alternative identifications.

   (3a) The shock u_t^r is the innovation in z_t^r, and therefore is the only shock driving downside risk on impact.

   (3b) The shock u_t^r increases upside risk but has no contemporaneous effect on (i.e. it is orthogonal to) downside risk. The shock has the same interpretation of the shock identified in (2b) for upside risk. In practice, this amounts at setting $D = v_l$ in equation (7), where v_l is the vector multiplying ε_t in the innovation of downside risk.

4. The skewness shock u_t^s is identified by assuming that the shock increases left-skewness but has no effect on (i.e. it is orthogonal to) total uncertainty. This orthogonality restriction is important to ensure that the effects of the skewness shock are not due to an increase in uncertainty, given that uncertainty and skewness are, as shown below, correlated. In practice, this amounts at setting $D = v_u$ in equation (7).

Notice that the two shocks identified in points 2. and 3. can be interpreted as a decomposition of the total risk in the two components associated to the two tails of the forecast distribution.

3 Empirics

In this section, we discuss the results of our empirical analysis. We use quarterly US data from 1960:Q1 to 2019:Q2. In the baseline specification, the vector y_t includes the following variables: the log of real GDP, the unemployment rate, the log of the S&P500 stock market index divided by the GDP deflator, real investment,[9] the spread between Moody's Baa corporate bond yield and the 10-year government bond yield (BAA-GS10), the spread between the 10-year government bonds yield and the 3-month Treasury Bill rate (GS10-TB3m), the Michigan Survey expected business conditions 1-year ahead (E1Y). The VAR is estimated with two lags, as suggested by

[9] Investment includes durable consumption.

the HQ criterion (the AIC criterion, suggesting 4 lags, is used in a robustness exercise). The variable to forecast, x_t, is the growth rate of GDP, measured as the difference between the log of real GDP at time $t+h$ and the log of real GDP at time t; we focus on the one-quarter ahead horizon (i.e. quarter-on-quarter growth). In the robustness section, we study the 4-quarter ahead horizon (i.e. year-on-year growth).

3.1 The one-quarter ahead expected distribution

Using the statistical significance of the parameters in the smoothed quantile regression, we select the following variables as predictors entering the vector w_t: real GDP at time t, the unemployment rate at time t and $t-1$, the S&P500 stock price index at time t and $t-1$, and E1Y at t. This set of predictors fulfills the following properties: (i) it is a subset of the VAR variables; (ii) each predictor is significant at the 3% level for at least one of the 10th, 50th and 90th percentile, and (iii) no other variable or lagged variable, when added to this set, is significant at the 3% level for at least one of the three targets. In a robustness exercise we include also the term spread, which is significant at the 5% level for the 10th percentile. Table 1 shows the p-values of the coefficients for the 10th, 50th and 90th percentile. Notice that stock prices (both contemporaneous and lagged) are highly significant for the median and the 90th percentile, whereas the confidence index E1Y is highly significant for the 10th percentile and the median.

Panel (a) of Figure 1 reports the 1-quarter ahead (in-sample) expected distribution of real GDP growth. The blue dashed line is the growth rate of real GDP at time t, the black solid line is the median of the distribution expected at time $t-1$ for time t and the red thin lines are percentiles $5, 10, 15, \ldots, 90, 95$. Panel (b) reports the percentiles predicted at time t for time $t+1$ (thin red lines) taken in deviation from the median. The two black solid lines are the 90th and the 10th percentiles, i.e. upside uncertainty and downside uncertainty with the minus sign, respectively. Downside risk appears to be much more volatile than upside uncertainty; in fact, its variance is 0.098 as against 0.039 for upside uncertainty. The left tail of the distribution substantially decreases in recessionary periods, while the right tail is relatively stable and constant over-time. The result confirms the finding in Adrian et al. (2019), obtained with different predictors (and a different quantile regression method).

Figure 2 reports, from top to bottom, the four features of the expected distribution discussed above: downside and upside uncertainty, total uncertainty and expected skewness. Downside risk increases in every recession, while upside risk is not correlated with the state of the business cycle. The third panel shows a sharp reduction in uncertainty after the early 80s crises. This reduction has already been documented in Kim and Nelson (1999); McConnell and Perez-Quiros

(2000); Blanchard and Simon (2001); Giannone, Lenza and Reichlin (2008) and Bernanke (2012). We see from the second panel that the reduction of total uncertainty is almost entirely due to the reduction of upside uncertainty, which exhibits a clear downward trend in the sample, especially between 1960 and 1985. In the bottom panel we see that skewness goes down in each recession, since the low percentiles move away from the median whereas the high percentiles do not. This is essentially a mirror image of the first panel, with skewness reflecting mainly movements in downside risk.

Table 2 shows the correlations between our uncertainty measures and other uncertainty indicators. We report the correlation with the VXO index, a widely used indicator of uncertainty in financial markets (see Bloom, 2009), the JLN (2015) uncertainty indices, 3 and 12 months ahead; the LMN (2019) indices of macroeconomic uncertainty, 3 and 12 months ahead; the Economic Policy Uncertainty index (Baker et al., 2016, EPU henceforth) and the Rossi and Sekhposyan (2015, RS henceforth) index 4 quarters ahead. We see that z_t^u and z_t^l are highly correlated with a few uncertainty indexes, especially the LMN real uncertainty indexes, while z_t^r exhibits a lower (or even negative) correlation.

Figure 3 displays the probability density function in a few selected periods, directly estimated from smoothed quantile regression, without any further smoothing, according to the formulas in Fernandez et al. (2019). During good times (left column) the pdf is symmetric or right-skewed, whereas during bad times (right column) the expected pdf becomes markedly left-skewed. This is in line with the evidence previously found in the literature on skewed business cycle (see Salgado et al., 2019, Adrian et al., 2019).

3.2 Downside and upside uncertainty shocks

Let us now analyze the effects of shocks to the measures of total uncertainty, downside uncertainty and upside uncertainty. To begin, we identify the shocks as the innovations in the corresponding uncertainty measures. This is equivalent, *mutatis mutandis*, to a recursive identification within a VAR where an external measure of uncertainty is order first.

The impulse responses to the uncertainty shock, u_t^u, are displayed in Figure 4. An unexpected increase in uncertainty has a significant depressing effect on the real economy, as already found in existing studies on the effects of uncertainty shocks (see Bloom, 2009, JLN, 2015 or LMN, 2019). The effects are particularly sizable on the variables capturing economic activity, GDP, unemployment and investment. From the variance decomposition of Table 3, we see that the shock explains around 40-50% of the variance of unemployment, around 30% of the variance of GDP and around 25% of real investment at the two-year horizon. The effect on the Michigan Survey expected conditions (E1Y) is huge, especially on impact. The effect of macroeconomic uncertainty to stock prices, on the contrary, appears to be negligible. All in all, the results point out to uncertainty as a major driver of business cycle fluctuations.

By construction, uncertainty is the sum of downside and upside uncertainty. So, to better understand the effects of uncertainty shocks, we study separately the effect of shocks to the two tails of the expected distribution of growth. Figure 5 displays the effects of downside risk shocks and Figure 6 shows the effects of upside uncertainty shocks. The shocks to the two tails have radically different effects. Shocks to the left tail have significant negative effects on the economy, very similar to those obtained for the uncertainty shock. On the contrary, shocks to the right tail have positive, albeit barely significant, effects on economic activity. Importantly, the effects on the BAA-GS10 spread have opposite signs: the downside risk shock increases the risk premium, as expected, whereas the upside uncertainty shock does not, confirming that, for this kind of uncertainty, the risk-premium channel does not operate. Finally, observe that the stock price index is the only one variable, besides uncertainty itself, on which the upside uncertainty shock has large significant effects. We shall come back to this point in a moment.

Table 3 shows that the effects of downside risk are larger than those of total uncertainty for all variables. The explained variance is very large for the three real activity variables and stock prices. Indeed, the shocks explains more than half of the variance of unemployment,around 40% of the variance of GDP and about one third of the variance of investment at the two-year horizon. The shock is also important for stock prices, especially in the short run. On the contrary, upside risk essentially explains nothing of the real economic activity variables. As already observed, however, it has very large effects on stock prices, as it accounts for almost 40% of the prediction error variance on impact. Our explanation is that financial investments are reversible and are not subject to adjustment costs, so the option value is zero, whatever the uncertainty. Hence the real options channel does not operate: waiting is not a good choice. On the other hand, the growth option effect is important. This result is very much in line with the growth options explanation of the dot-com bubble of the late 90s.

We repeat the analysis about the effects of the two tails shocks using the alternative identifications schemes (2b) and (3b). These two schemes impose that the shocks to one tail leave the other tail unchanged on impact. This can be useful to better isolate the effects of the shocks to one tail when the width of the two tails is correlated, as in this case (the correlation coefficient of upside and downside uncertainty is about 0.5, see Table 2). Figure 7 and 8 reports the results. The effects of both downside and upside uncertainty are amplified. In particular, the expansionary effects of upside uncertainty are now significant.

Table 4 reports the variance decomposition. For real activity variables, the negative effects of downside uncertainty are very large, particularly for unemployment, whereas the positive effects of upside uncertainty are much smaller. For stock prices, the ranking is reversed: the positive effects of upside uncertainty are larger than the negative effects of downside risk. This helps understanding why the effects of total uncertainty on stock prices are so small, despite the fact that overall uncertainty is dominated by the left tail.

The above results uncover a new interesting scenario. It is not an increase in uncertainty *per se* (larger variance, caused by changes in both tails) generating a downturn in economic activity, as found in previous studies. It is actually the widening of the left tail, the downside uncertainty. Higher uncertainty originating from higher upside risk is actually beneficial for the economy. The fact that the effects of total uncertainty are similar to those of the downside uncertainty depends on the fact that changes of the left tail, as seen in the previous subsection, are quantitatively much larger that changes of the right tail. As an implication, the effects of total uncertainty are driven by the effects of downside uncertainty. Our results are fully in line with those found in the literature but also highlight that previous interpretations were somewhat misleading: is not uncertainty that matters, but it is just downside uncertainty.

As discussed in the Introduction, from a theoretical point of view the effects of downside uncertainty are predicted to be indisputably negative, since the risk premium and the real options channel operate. Our results confirm these theoretical predictions. In particular, the effect of the downside uncertainty shock on the risk premium is significantly negative. However, the effects on economic activity of the upside uncertainty are uncertain from a theoretical point of view: the real options and the growth options channel work in opposite directions. According to our results, the growth option slightly prevails, since the effects of the upside uncertainty shock are positive, although quantitatively small. For stock prices, where the real options channel is not operational, the growth options effect has no counterweight so that the positive effect of upside uncertainty is large.

3.3 Skewness shocks

The results of the previous subsection suggest that the asymmetry of the expected distribution of growth is related to the business cycle, since an increase in downside risk makes the distribution more left-skewed. To check this prediction, we identify a skewness shock as described in subsection 2.5, point 4. Figure 9 reports the impulse response functions of a skewness shock not affecting uncertainty on impact. The shock has significant contractionary effects on macroeconomic variables which resemble those of downside uncertainty. From Table 4, it can be seen that the skewness shock generates sizable effects on GDP and unemployment, although slightly smaller than those generated by the downside uncertainty shock. On the contrary, the shock appears to have larger effects on stock prices than downside risk.

The result basically confirms the previous evidence, reinforcing our conclusions. Higher macroeconomic uncertainty does generate a downturn in economic activity only if it arises from an increase of the left tail, since an increase in upside risk is found to stimulate the economy. Hence, a shock which does not affect uncertainty but increases left-skewness has negative effects on economic activity.

4 Robustness

Here we assess whether the results are robust to changes in the baseline specification. First, we consider the one-year ahead growth forecast. Second, we use several model specifications.

4.1 The one-year ahead expected distribution

In this subsection we repeat the analysis by changing the horizon of expectations from a quarter to a year. Precisely, we consider the expectation, at time t, of the quantiles of the GDP growth between t and $t+4$. The variables in the VAR are the same as before, except that the the 3-month Treasury Bill rate (TB3m) replaces the risk spread since, as discussed next, the interest rate is a good predictor, while the risk spread is not. To predict the quantiles we use real GDP at time t, the unemployment rate at t, the S&P500 stock price index at t and $t-1$, the term spread at t, the TB3m at t and $t-1$ and E1Y at t. The difference with respect to quarter-on-quarter growth is motivated by the fact that now the interest rate (current and lagged) and the term spread are significant, whereas lagged unemployment is not. This set of predictors fulfills the properties in section 3.1. Table 1 (panel B) shows the p-values of the coefficients for the 10th, 50th and 90th percentile.

Figure 10 reports the estimated percentiles. As for the one-quarter ahead distribution, the left tail is still more volatile than the right tail, although the difference is mitigated relative to the one-quarter ahead. Figure 11 reports, from top to bottom, the main features of the expected year-on-year growth distribution: downside and upside uncertainty, total uncertainty and left skewness. Upside uncertainty is still much less volatile than downside uncertainty, the variance being 0.20 as against 0.60. Overall, the figure is qualitatively similar to the one of quarter-on-quarter growth: downside risk increases at the beginning of every recession and reduces at the end of the recession, whereas upside uncertainty is much less correlated with the state of the business cycle. Skewness is usually close to zero or positive during good times and largely negative during bad times, with the exception of the crisis at the very beginning of the sample.

Figure 12 displays the expected distribution of growth in a few selected periods, corresponding to good and bad times. In good times (left column) the pdf is skewed to the right, whereas in bad times (right column) the density distribution is skewed to the left. Interestingly, during the selected crises the expected distribution is markedly bimodal, as found in Adrian et al. (2020).

Figure 13 and 14 report the impulse response functions to the downside uncertainty shock (identification 2a) and the upside uncertainty shock, conditional to downside uncertainty (identification 3b). The responses to downside risk are similar to those found with the 1-quarter ahead distribution. Table 5 shows that the size of the effects is slightly smaller but the shock still appears to be very important, explaining around one fourth of the variance of GDP and around one third of the variance of unemployment at the two-year horizon. Upside uncertainty generates volatile responses, initially negative and then positive, and again explains a small portion of the variance of the real activity variables.

4.2 Other checks

We assess the robustness of the results to several changes in the model. More specifically, we perform the following robustness checks. (a) We condition the uncertainty shock to a long run shock on GDP, imposing that the long run effect of uncertainty on GDP must go to zero. (b) We use the AIC criterion, selecting 4 lags in the VAR in equation (3). (c) We change the definition of uncertainty by using the 5-th and the 95-th percentiles in the definition of z_t^d. (d) We change the quantile predictors by adding the term spread, which is significant at the 5% level for the 10th percentile. (e) We use a different VAR specification, including only the predictors: GDP, the unemployment rate, stock prices and the confidence index. (f) We use a different VAR specification including the 3-month T-Bill rate, the ISM New Order Index and the GDP deflator in place of investment, the term spread and the risk spread. The shocks under consideration are the downside and upside uncertainty shocks (identifications 2a and 3a).

Figure 15 and 16 report the results. The black lines and gray areas are those displayed in Figure 5. The blue dashed line is the response obtained in the modified model. Overall, the results for the downside uncertainty shock are robust. When imposing zero long run effects (panel 1,1) the magnitude of the effects is reduced. For the other checks, the impulse response functions are very similar. Also the results for the upside risk shock are quite robust in general, except for the medium to long run effect, when using the 95th percentile instead of the 90th. There are a few other quantitative differences but the results confirm the very modest role of the shock.

5 Concluding remarks

We have proposed a novel method to estimate shocks to functions of the forecast distribution percentiles. Our results unveil a new picture about the effects of uncertainty shocks. Higher uncertainty has a negative effect on the economy only when it originates from an increase in the left tail, i.e. when the downside risk increases. An increase in uncertainty arising from an increase in the upside risk has positive effects on the economy. All in all, our findings point to the asymmetry of the expected distribution as a major driver of economic fluctuations.

The methodology proposed here can be used in other applications and with other purposes. For instance, as already observed in the Introduction, it would be interesting to study the reverse: how typical economic structural shocks, or policy shocks, affect uncertainty and other features of the expected distribution of growth and other macroeconomic variables. This can be done by identifying the effects of the shock using standard identification assumptions and then deriving the responses of the percentiles or functions of the percentiles using the estimated quantile regression parameters. We plan to pursue this line of research in the future.

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Tables

A. One-quarter ahead growth forecast distribution			
	10th percentile	50th percentile	90th percentile
Constant	0.015	0.052	0.000
GDP	0.150	0.021	0.000
Unemployment	0.057	0.037	0.024
Stock prices	0.046	0.000	0.000
E1Y	0.000	0.003	0.097
lagged Unemployment	0.021	0.006	0.003
lagged Stock prices	0.042	0.001	0.002

B. One-yer ahead growth forecast distribution			
	10th percentile	50th percentile	90th percentile
Constant	0.275	0.007	0.129
GDP	0.371	0.008	0.164
Unemployment	0.090	0.098	0.001
Stock prices	0.006	0.001	0.089
Term Spread	0.016	0.002	0.377
Interest rate	0.007	0.285	0.009
E1Y	0.000	0.000	0.000
lagged Stock prices	0.001	0.002	0.025
lagged interest rate	0.000	0.366	0.005

Table 1: p-values of the retained quantile predictors

	z_t^u	z_t^l	z_t^r
z_t^l	0.93	1.00	0.53
VXO	0.13	0.29	-0.19
JLN 3 months	0.40	0.59	-0.03
JLN 12 months	0.34	0.53	-0.08
LMN real 3 months	0.73	0.75	0.48
LMN real 12 months	0.62	0.68	0.32
US EPU index	0.36	0.48	-0.27
RS 4 quarters	0.01	-0.02	0.11

Table 2: Correlation of our measures z_t^j and a few uncertainty indexes

A. Uncertainty shock				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	17.8	30.7	23.5	15.0
Unemployment rate	37.6	46.7	42.2	36.2
S&P500/GDPDEF	4.9	3.3	3.9	4.9
Investment	13.9	24.0	16.8	11.2
Spread GS10-TB3m	1.2	9.2	12.7	12.4
spread BAA-GS10	13.2	22.0	22.3	22.0
E1Y	82.3	47.9	42.5	40.8
Uncertainty	100.0	5.0	5.1	5.6

B. Downside risk shock				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	21.7	39.2	28.0	17.4
Unemployment rate	46.0	63.9	55.5	47.6
S&P500/GDPDEF	14.9	9.5	9.4	10.3
Investment	18.4	33.3	22.4	14.9
Spread GS10-TB3m	1.8	15.5	19.5	18.9
spread BAA-GS10	18.8	32.5	32.0	31.5
E1Y	80.8	49.9	44.1	42.6
Downside uncertainty	100.0	12.2	11.3	11.3

C. Upside uncertainty shock				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	0.1	1.6	1.8	1.4
Unemployment rate	0.2	5.9	3.8	3.8
S&P500/GDPDEF	38.3	24.3	17.8	13.9
Investment	1.0	3.9	2.4	1.9
Spread GS10-TB3m	0.3	7.7	7.1	7.0
spread BAA-GS10	2.5	8.9	9.5	9.5
E1Y	14.2	5.5	5.4	5.9
Upside uncertainty	100.0	30.2	20.3	15.2

Table 3: Variance decomposition for the 1-quarter horizon uncertainty shock (upper panel), the downside risk shock, conditional on upside uncertainty (middle panel) and the left skewness shock, conditional on uncertainty (lower panel).

D. Downside risk shock conditional on upside uncertainty				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	24.3	46.4	30.8	18.6
Unemployment rate	51.5	80.8	67.5	58.1
S&P500/GDPDEF	33.6	21.1	19.0	19.0
Investment	22.5	42.8	27.7	18.5
Spread GS10-TB3m	2.4	23.8	27.8	26.7
spread BAA-GS10	24.6	44.6	43.0	42.5
E1Y	68.3	46.0	40.6	39.7
Downside Uncertainty	92.4	25.3	21.6	20.3

E. Upside uncertainty shock conditional on downside risk				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	2.7	8.8	4.6	2.6
Unemployment rate	5.7	22.9	15.9	14.3
S&P500/GDPDEF	56.9	35.9	27.4	22.5
Investment	5.1	13.4	7.7	5.5
Spread GS10-TB3m	0.9	16.0	15.4	14.9
spread BAA-GS10	8.4	21.0	20.6	20.4
E1Y	1.8	1.6	1.9	3.0
Upside Uncertainty	92.4	43.5	31.1	24.4

F. Skewness shock conditional on uncertainty				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	6.6	17.4	9.1	5.0
Unemployment rate	14.1	40.1	29.2	25.8
S&P500/GDPDEF	67.0	42.1	33.0	28.0
Investment	9.6	22.7	13.2	9.2
Spread GS10-TB3m	1.5	22.3	22.2	21.4
spread BAA-GS10	13.9	31.5	30.2	30.0
E1Y	0.3	3.5	3.5	4.7
Skewness	18.7	45.1	33.7	28.1

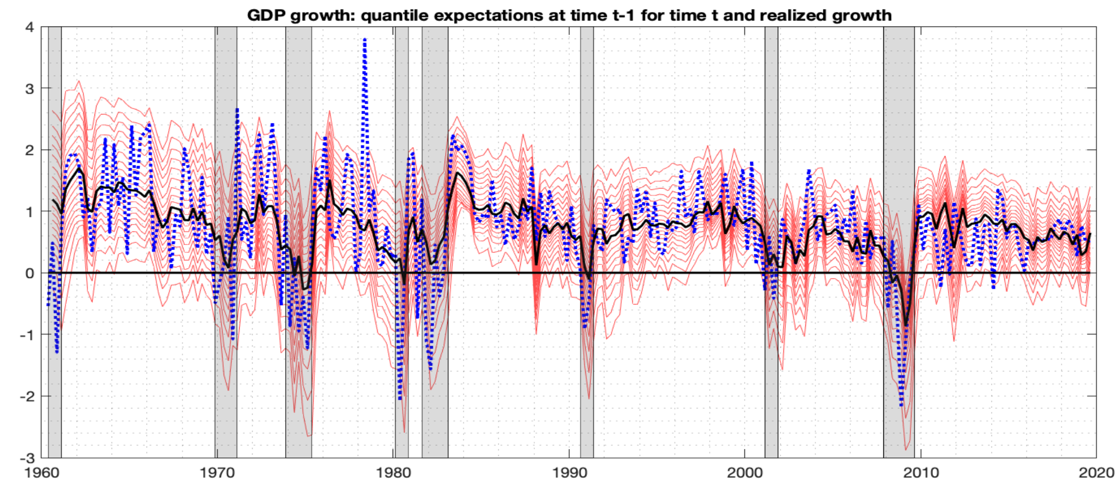
Table 4: Variance decomposition continued for the 1-quarter horizon uncertainty shock (upper panel), the downside risk shock, conditional on upside uncertainty (middle panel) and the left skewness shock, conditional on uncertainty (lower panel).

Downside risk shock				
	$h=0$	$h=8$	$h=16$	$h=40$
GDP	16.2	26.1	17.9	13.7
Unemployment rate	14.8	33.5	25.3	21.3
S&P500/GDPDEF	41.7	22.6	16.0	10.8
Investment	16.3	24.9	17.9	14.7
Spread GS10-TB3m	24.7	29.9	27.8	26.0
TB3M	43.7	44.8	37.6	28.5
E1Y	54.9	33.5	30.1	29.4
Downside uncertainty	100.0	67.1	52.9	43.0
Upside uncertainty shock conditional on Downside risk				
	$h=0$	$h=8$	$h=16$	$h=40$
GDP	3.2	2.2	4.7	4.5
Unemployment rate	11.1	4.1	10.5	13.0
S&P500/GDPDEF	0.2	14.5	20.3	22.4
Investment	5.1	3.4	7.6	7.6
Spread GS10-TB3m	3.6	1.1	3.0	4.2
TB3M	7.3	13.6	13.8	16.5
E1Y	19.4	19.2	19.6	19.5
Upside Uncertainty	72.9	21.5	16.5	16.0

Table 5: Variance decomposition for the 1-year horizon uncertainty shock (upper panel) and the 4-quarter horizon skewness shock, conditional on uncertainty (lower panel).

Figures

Panel (a)



Panel (b)

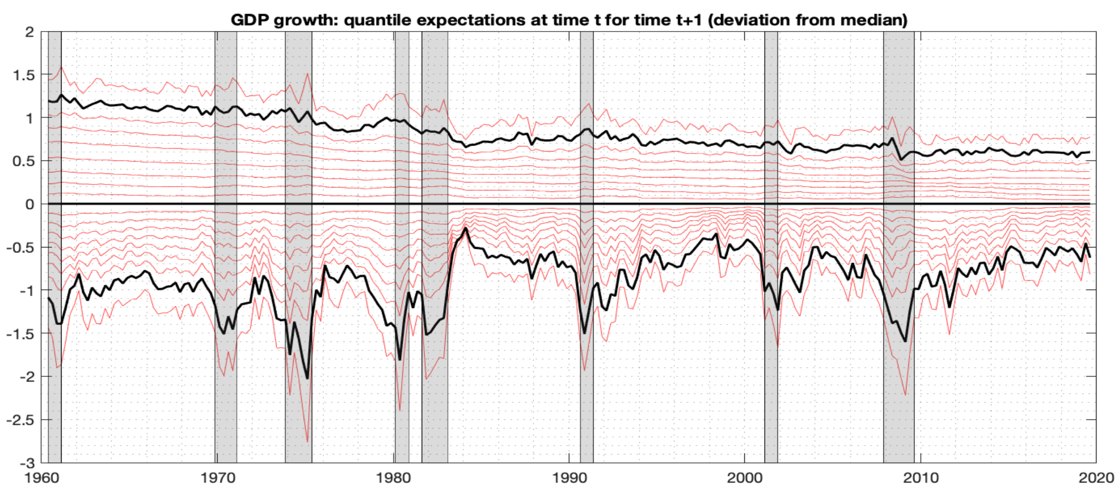


Figure 1: Panel (a) - Estimated quantiles of the expected distribution of US quarter-on-quarter GDP growth. Dashed blue line: GDP growth. Solid black line: median of the forecast distribution. Thin red lines: percentiles of the expected distribution. Gray vertical bands: US recessions. Panel (b) - Estimated quantiles of the expected distribution of US GDP growth minus the median. Solid black lines: upside and (minus) downside uncertainty. Thin red lines: percentiles of the forecast distribution minus the median. Gray vertical bands: US recessions.

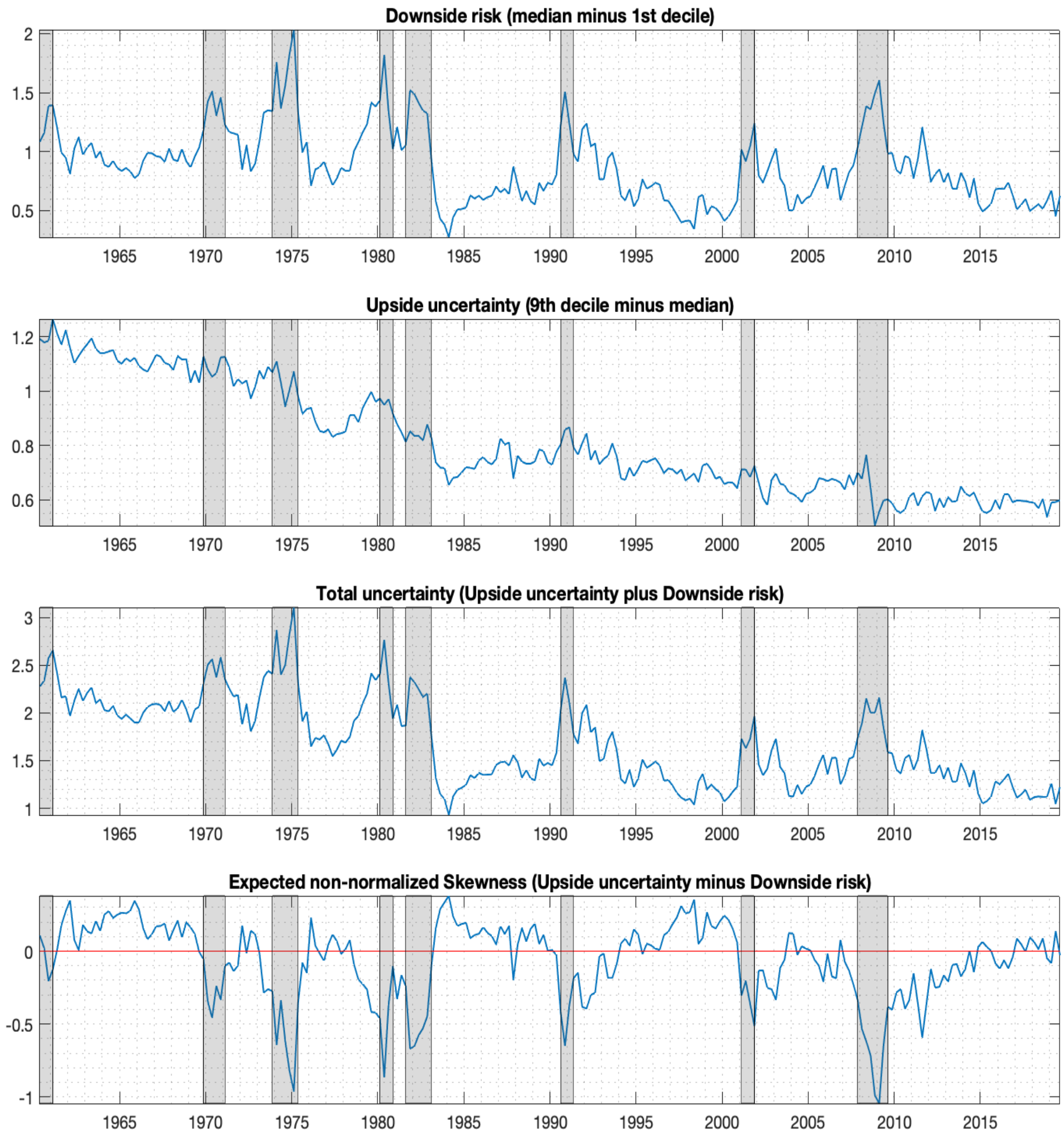


Figure 2: Measures of dispersion and asymmetry for the quarter-on-quarter expected growth distribution. From top to bottom: downside risk z_t^l, upside risk z_t^r, total uncertainty z_t^d, expected skewness z_t^s. Gray vertical bands: US recessions.

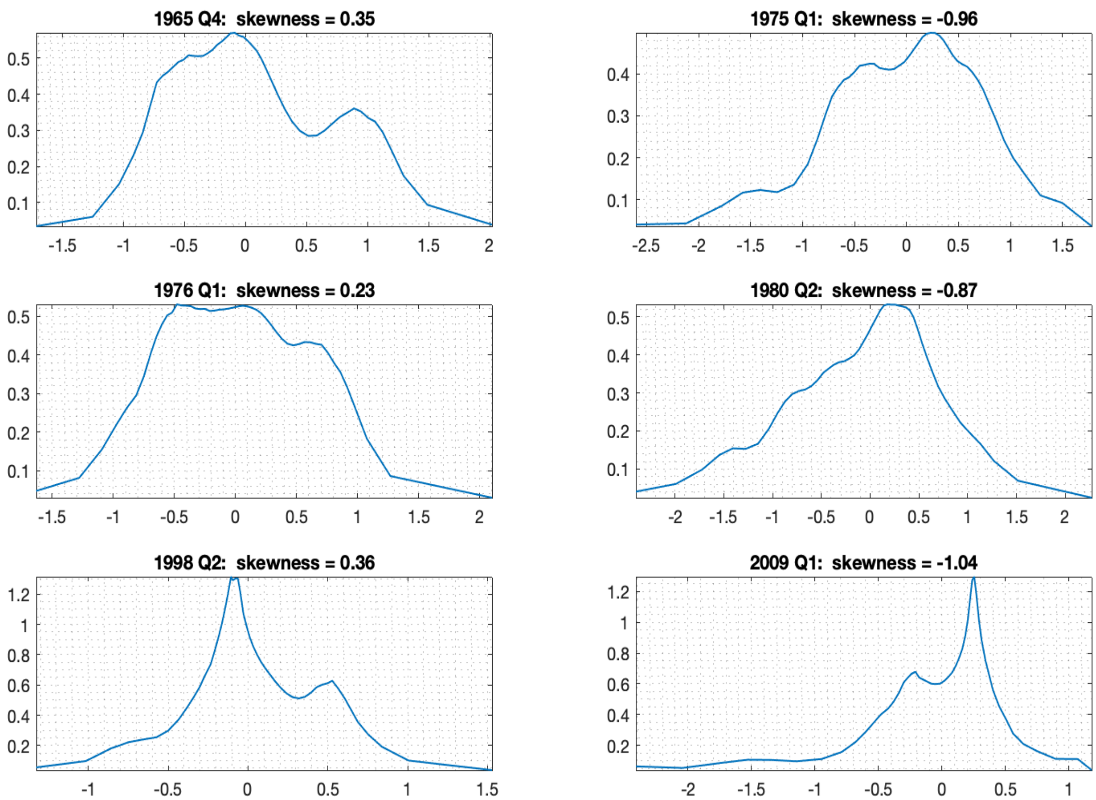


Figure 3: The expected quarter-on-quarter growth distribution (centered in the median) in a few selected good times (left column) and bad times (right column).

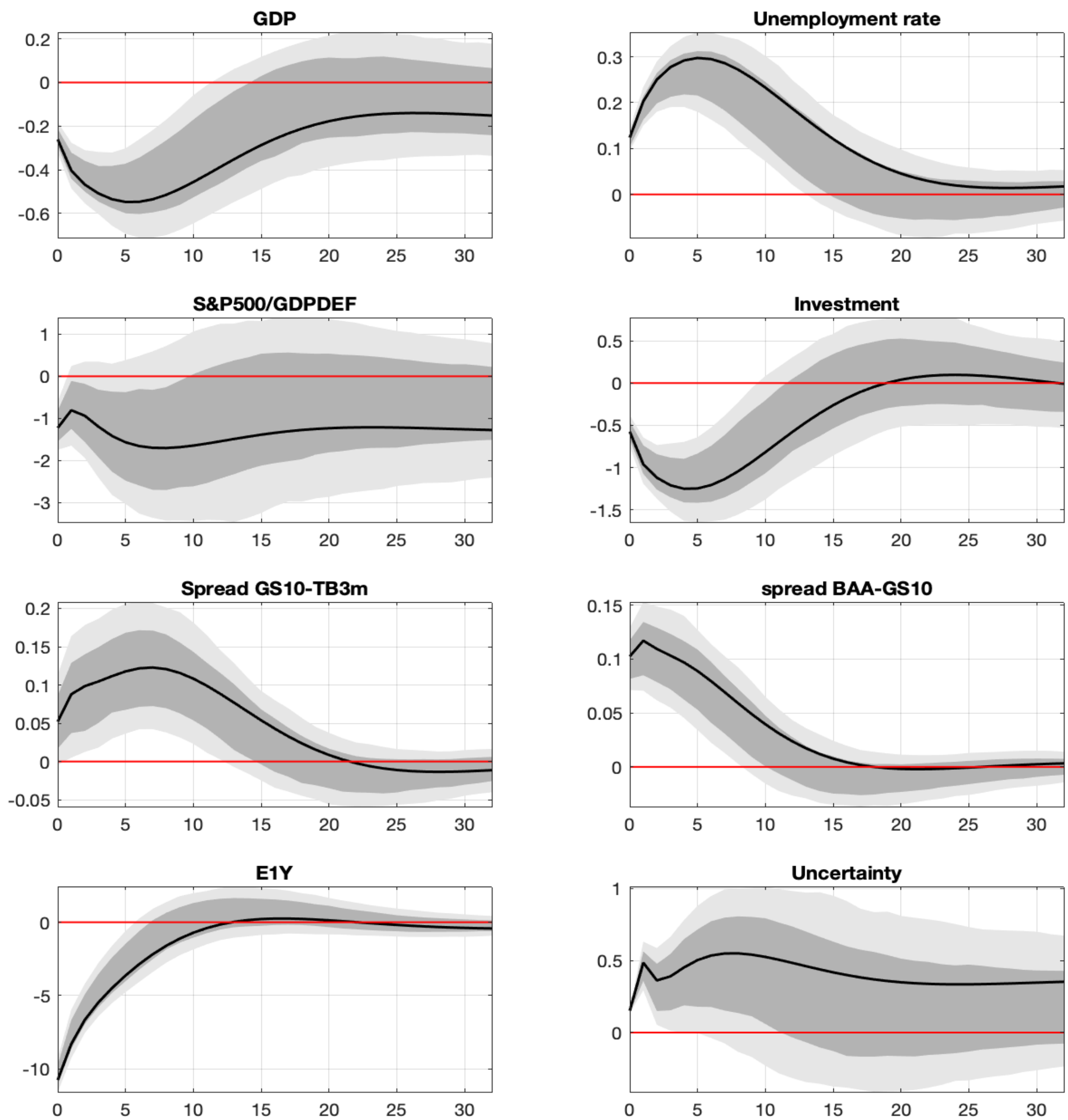


Figure 4: Impulse responses to the uncertainty shock. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

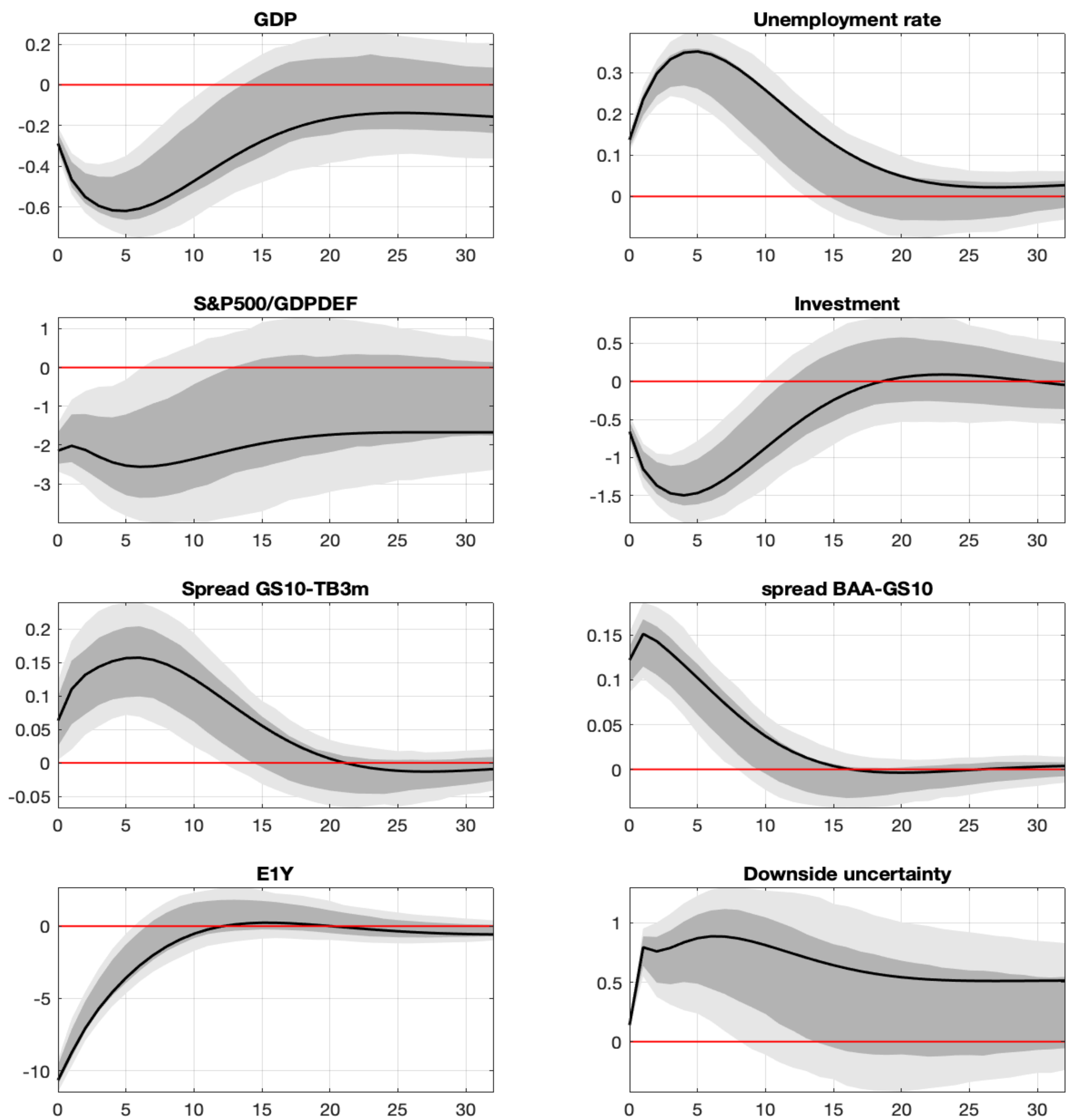


Figure 5: Impulse responses to the downside risk shock. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

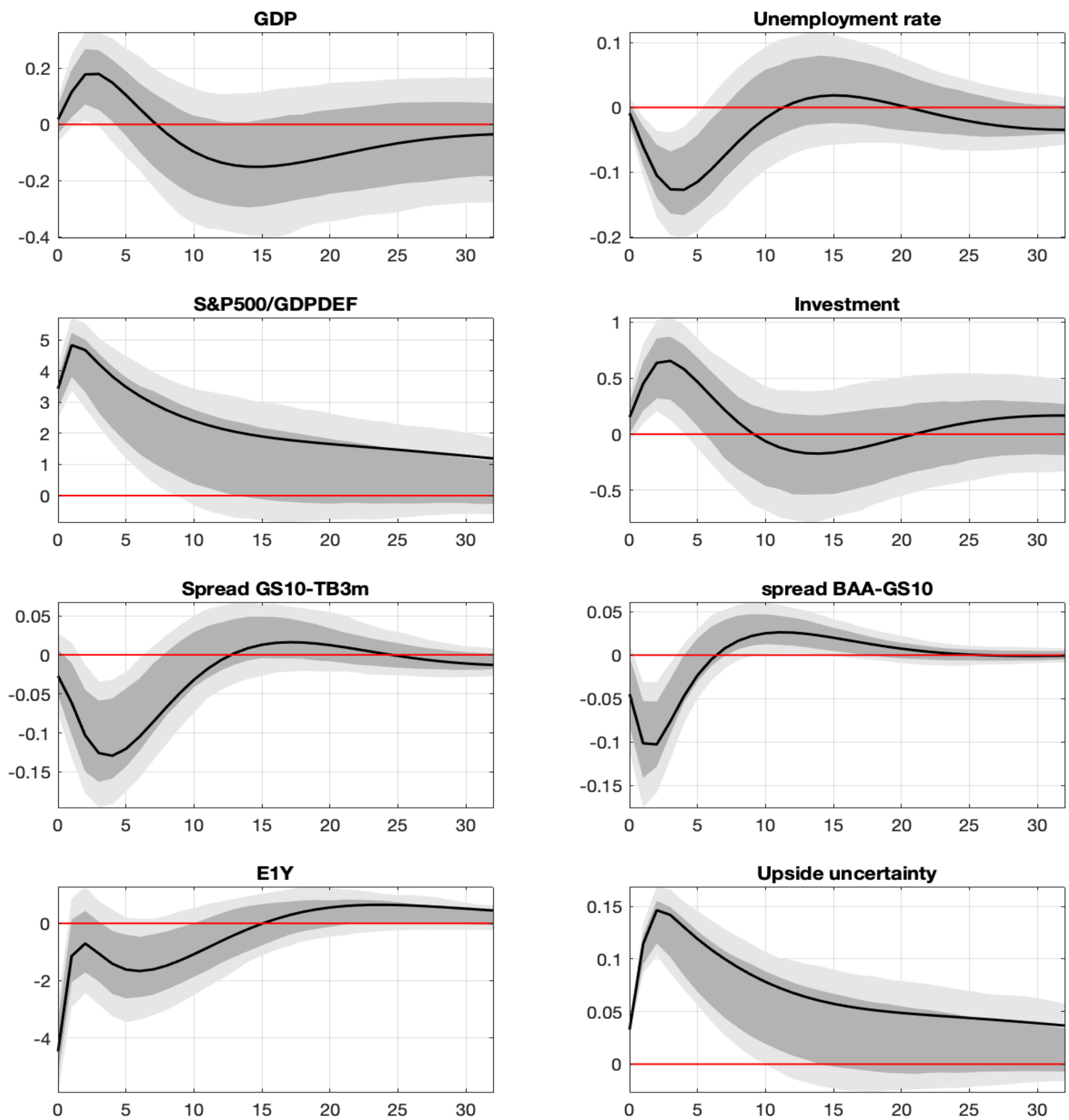


Figure 6: Impulse response to the upside risk shock. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

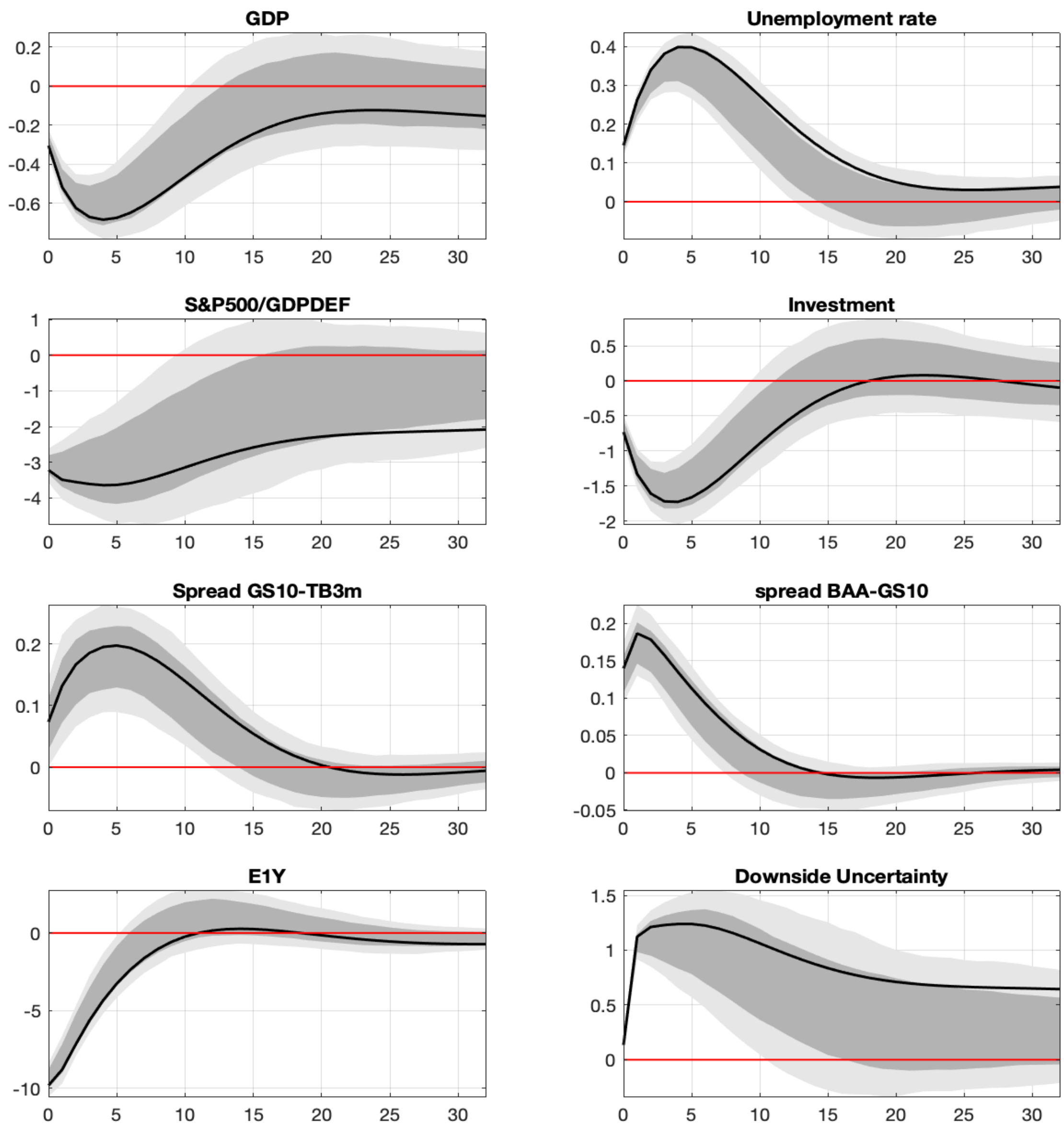


Figure 7: Impulse response to the downside shock conditional on upside risk. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

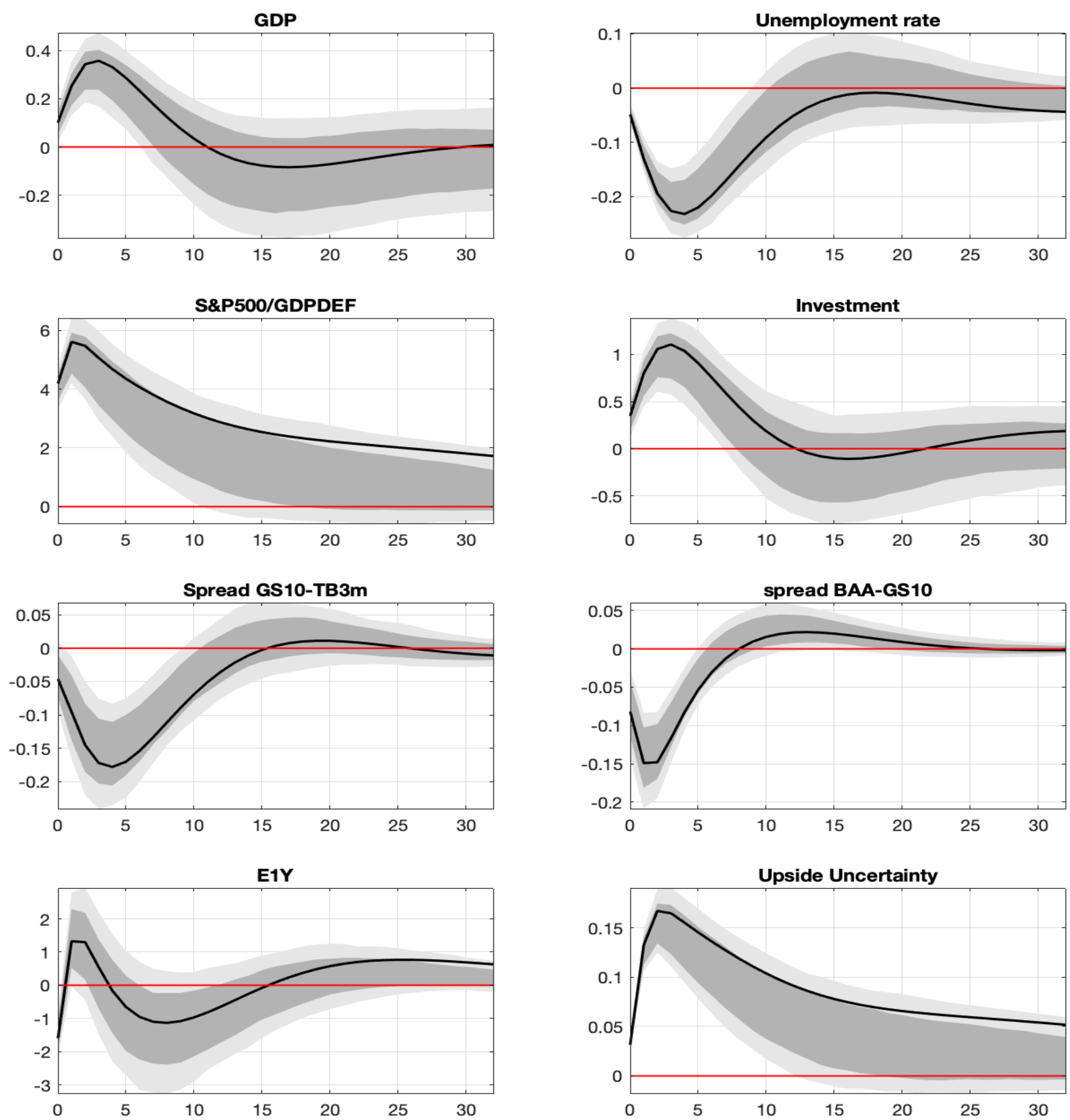


Figure 8: Impulse response to the upside shock conditional on downside risk. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

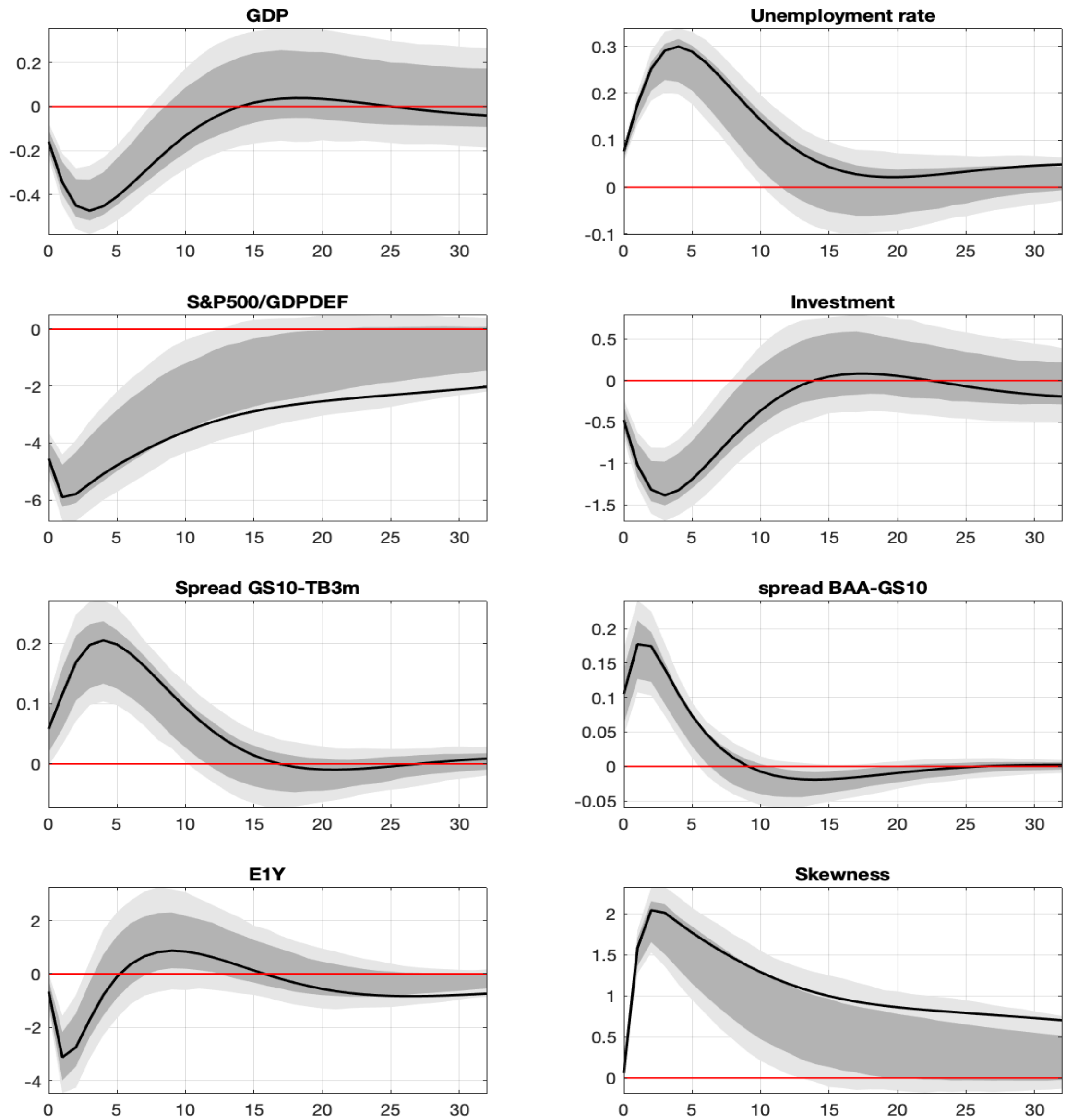
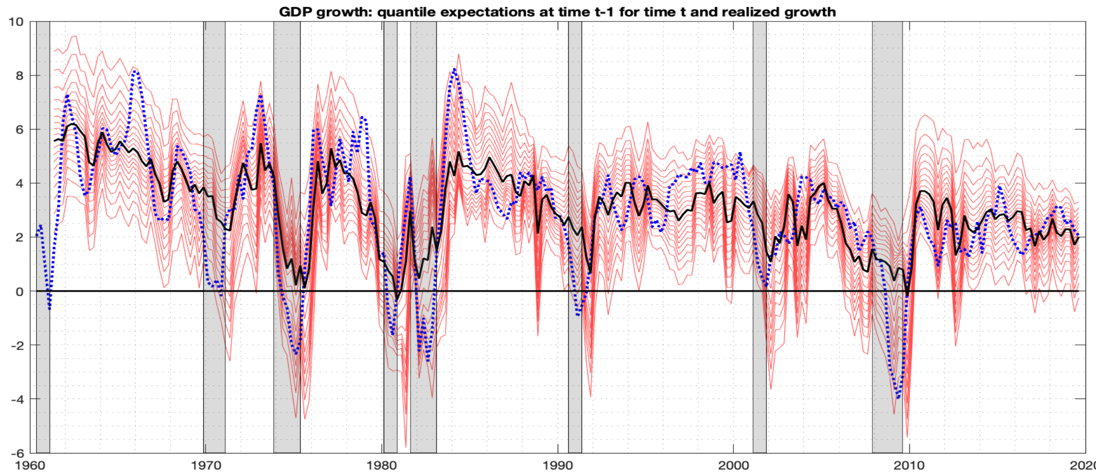


Figure 9: Impulse response to the skewness shock. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

Panel (a)



Panel (b)

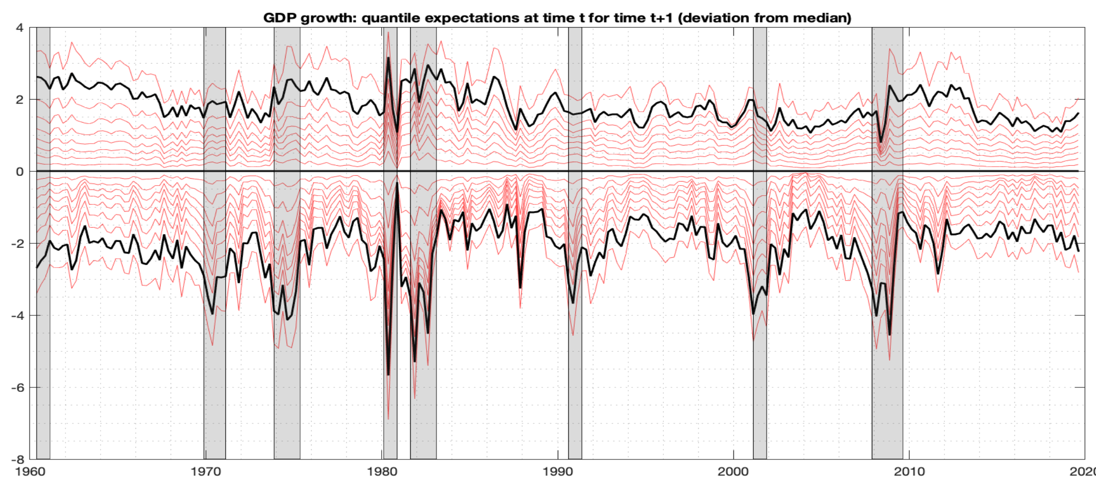


Figure 10: Panel (a) - Estimated quantiles of the expected one-year ahead distribution of US GDP growth. Dashed blue line: GDP growth. Solid black line: median of the forecast distribution. Thin red lines: percentiles of the expected distribution. Gray vertical bands: US recessions. Panel (b) - Estimated quantiles of the expected distribution of US GDP growth minus the median. Solid black lines: upside and (minus) downside uncertainty. Thin red lines: percentiles of the forecast distribution minus the median. Gray vertical bands: US recessions.

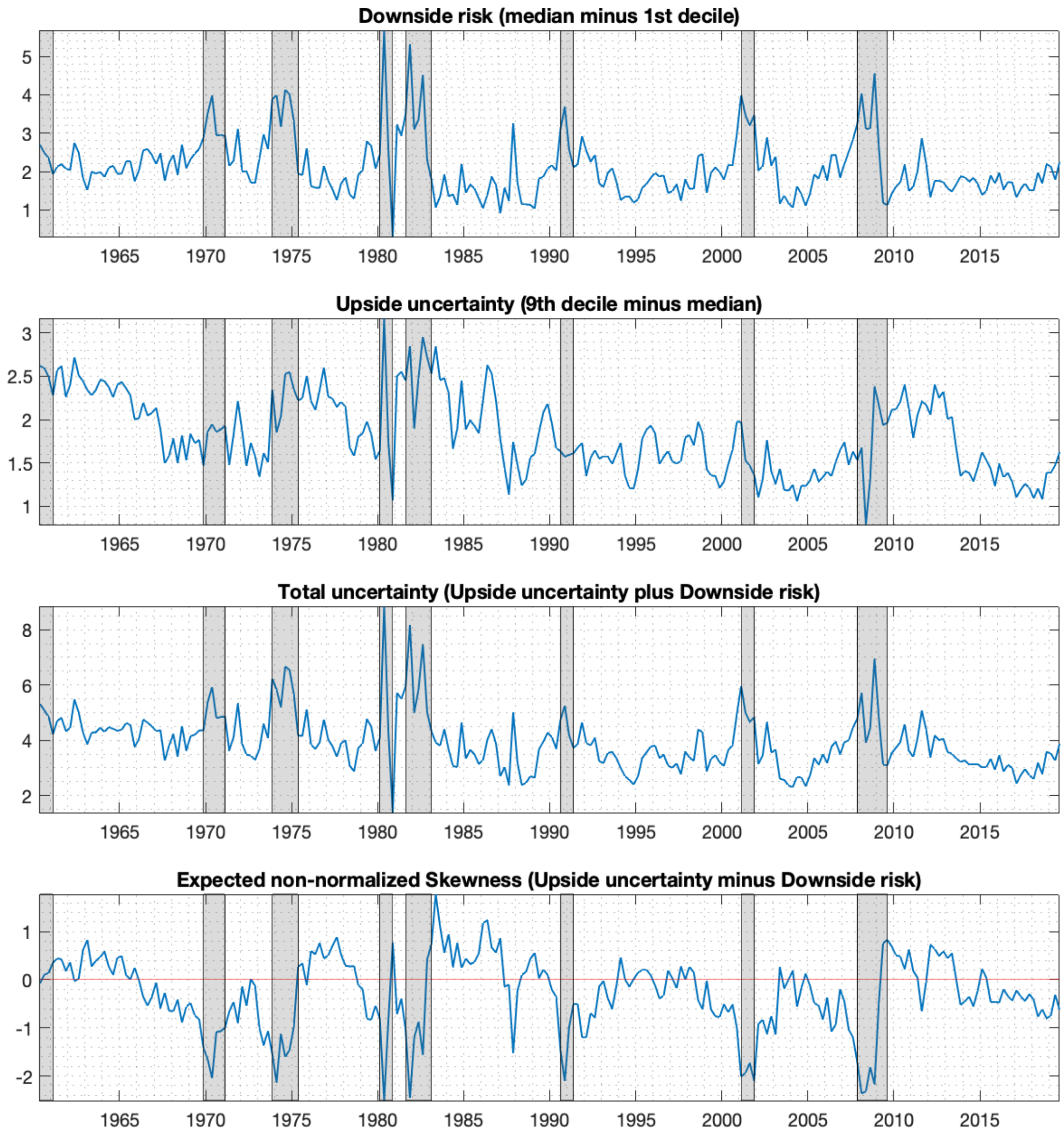


Figure 11: Measures of dispersion and asymmetry for the one-year ahead growth forecast distribution. From top to bottom: downside risk z_t^l, upside risk z_t^r, total uncertainty z_t^d, expected skewness z_t^s. Gray vertical bands: US recessions.

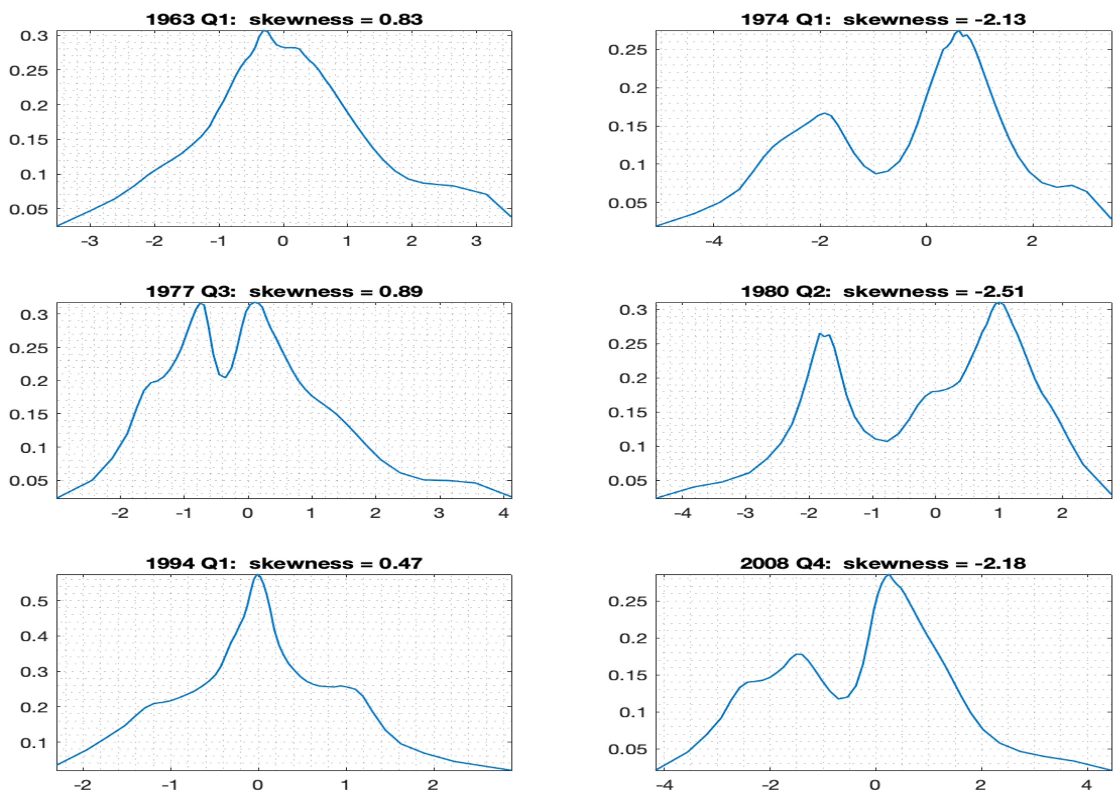


Figure 12: The one-year ahead growth forecast distribution (centered in the median) in a few selected good times (left column) and bad times (right column).

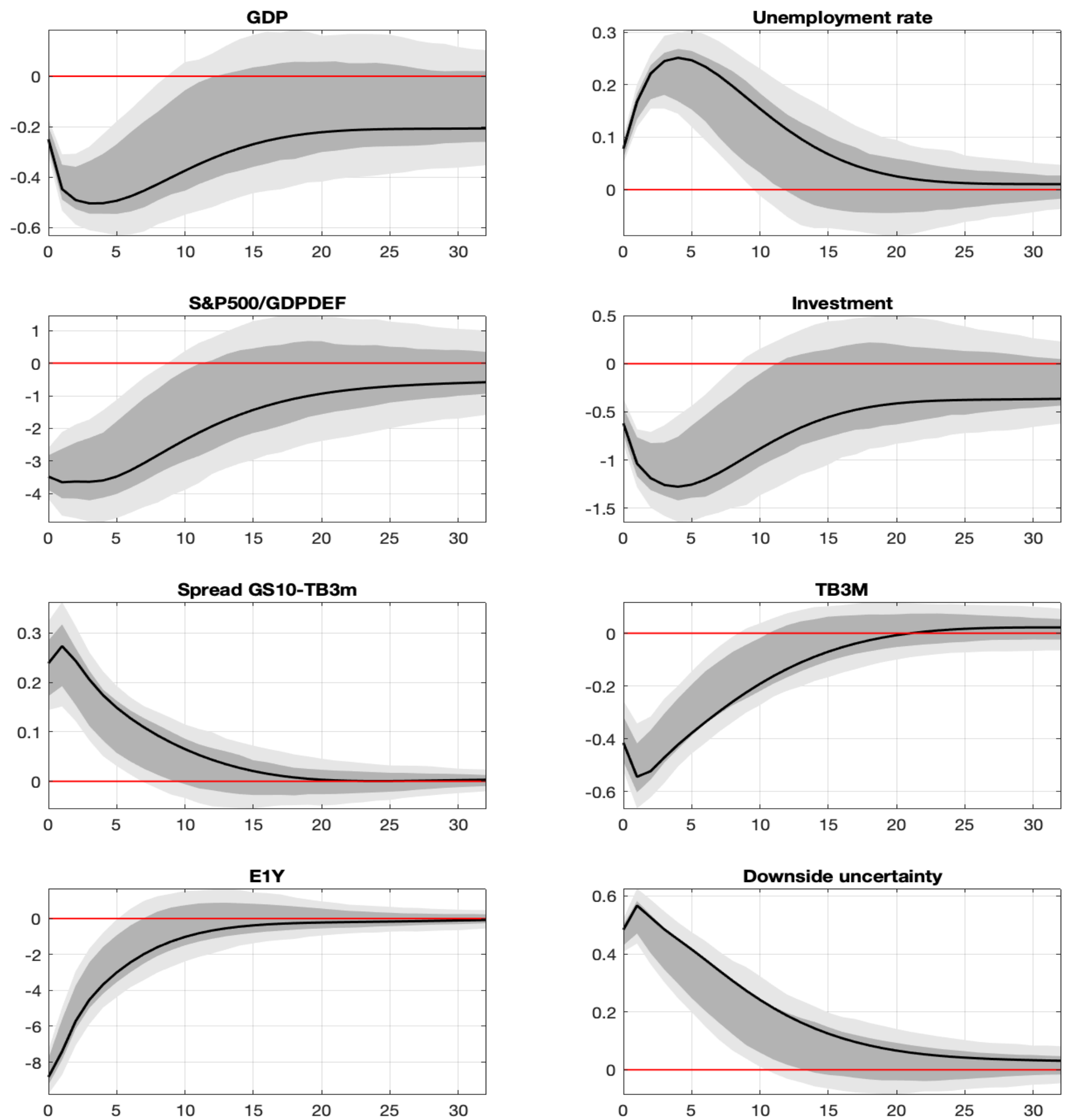


Figure 13: Impulse responses to the downside uncertainty shock using the one-year forecast distribution. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

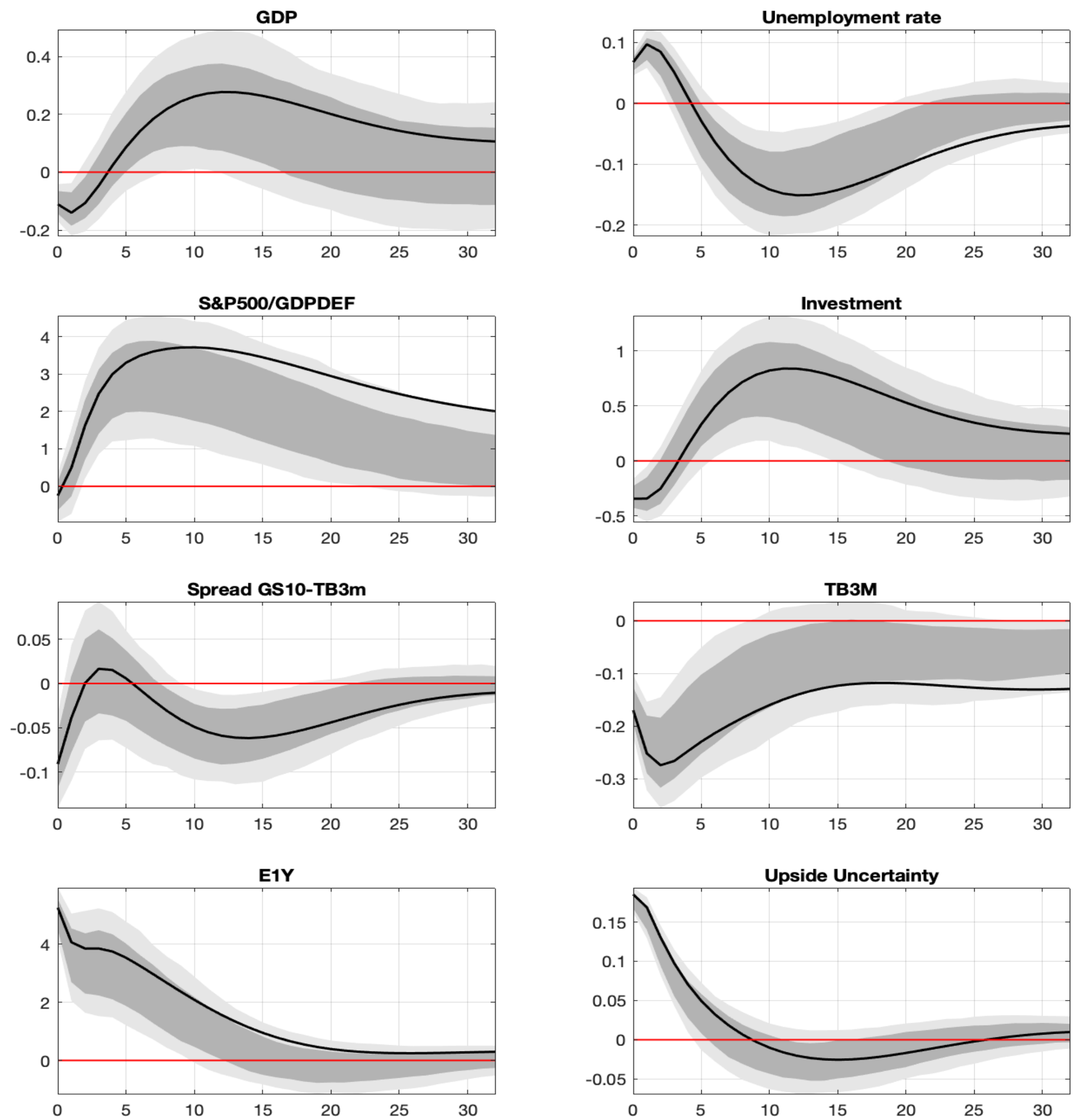


Figure 14: Impulse responses to the upside uncertainty conditional on downside uncertainty using the one-year forecast distribution. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

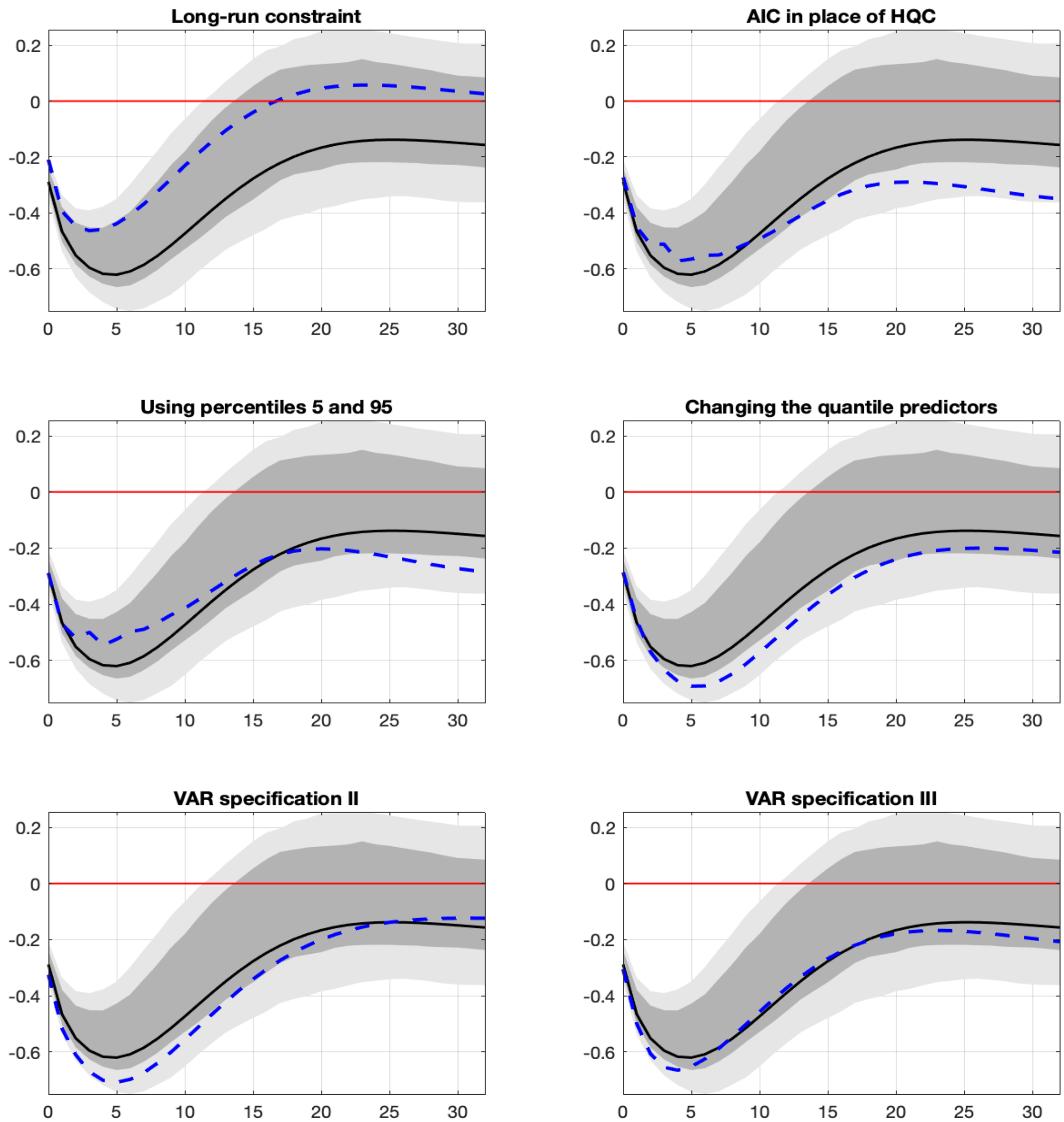


Figure 15: Robustness checks. Response of GDP. Black solid lines: point estimates of the baseline model. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands. Dashed blue lines, alternative model.

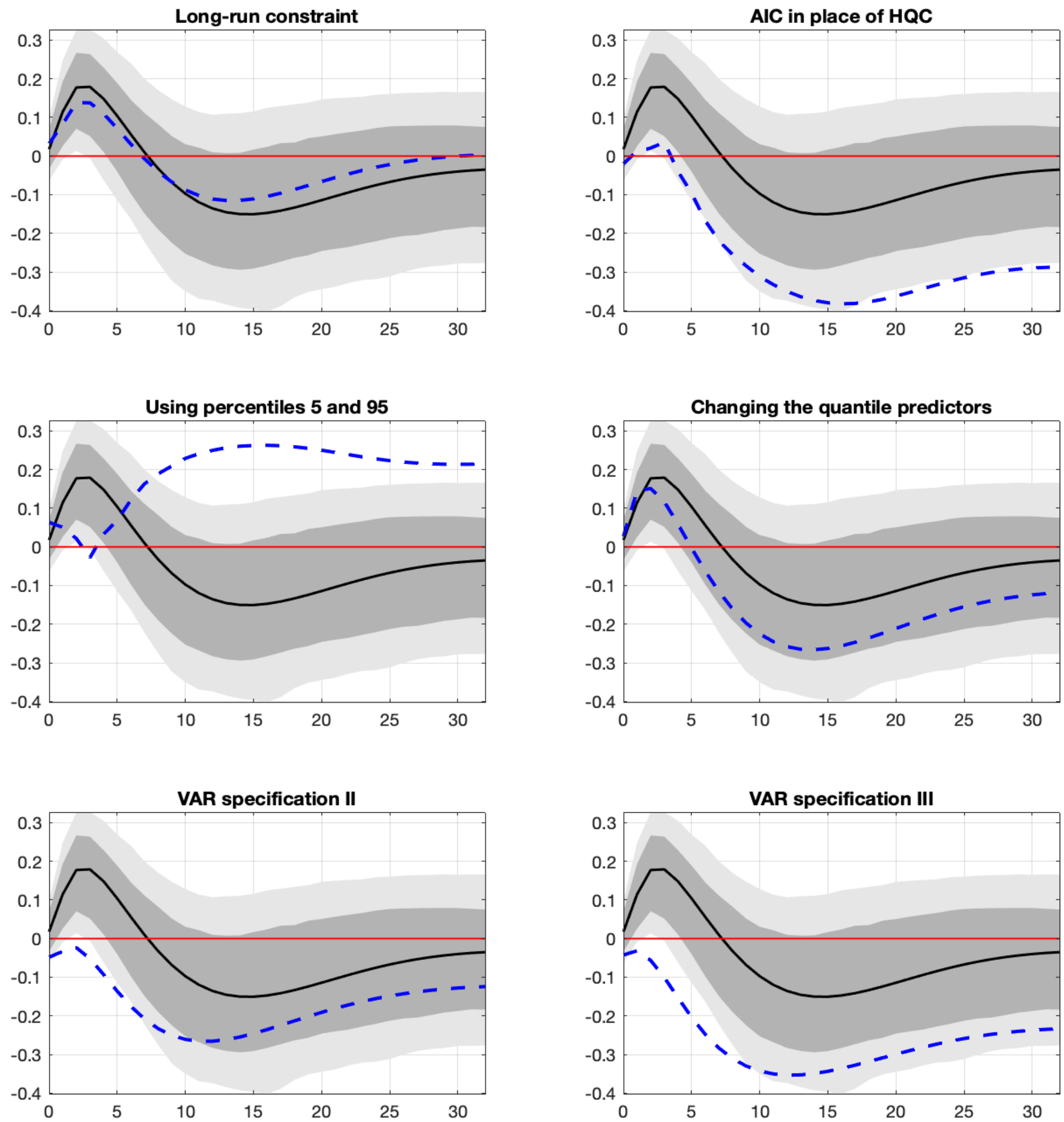


Figure 16: Robustness checks. Response of GDP. Black solid lines: point estimates of the baseline model. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.