DOWNSIDE AND UPSIDE UNCERTAINTY SHOCKS

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Abstract

An increase in uncertainty is not contractionary *per se*. What is contractionary is a widening of the left tail of the GDP growth forecast distribution, the downside uncertainty. On the contrary, an increase of the right tail, the upside uncertainty, is mildly expansionary. The reason 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: C32, E32)

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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] 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. Several definitions of uncertainty have been considered in the literature. According to an authoritative one, uncertainty is the expected volatility of real economic activity variables (see Jurado et al., 2015, JLN henceforth, and Ludvigson et al., 2021, LMN henceforth). This is the definition we adopt throughout the paper.

The 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,

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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. (2021), Angelini and Fanelli (2019). For more references, see the survey articles in Cascaldi-Garcia et al. (2020), Fernandez-Villaverde and Guerron-Quintana (2020) and Berger et al. (2020).

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

while the right tail is relatively constant over time.[3] So, in periods of economic slowdowns an increase in expected volatility 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 see this, notice that total uncertainty can be decomposed into the part originating from the left tail of the growth forecast distribution, say the “downside uncertainty”, 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 uncertainty are distinct concepts, which should not be confused with each other.

The above discussion raises a few interesting questions. What are the effects of downside and upside uncertainty? Are they different? What is it that really matters? From a theoretical point of view, it is plausible that downside and upside uncertainty generate different effects. When uncertainty originates from the left tail, both the “real

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.

options" effect[5] and the "risk premium" effect[6] are in place. Both effects tend to depress real economic activity. On the other hand, when uncertainty originates from the right tail, of course the risk premium channel is not active. But there is another effect in place, the "growth options", which tends to push economic activity.[7] To sum up, while downside uncertainty is unambiguously contractionary, the effects of upside uncertainty are ambiguous, depending on which of the two channels, the real options and the growth options, dominates.[8]

The contribution of this paper is twofold. First, we show that what really matters for real economic activity is not uncertainty *per se* but just downside uncertainty.

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5. 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.

6. 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, 2014, and Gilchrist, Sim and Zakrajšek, 2014).

7. 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.

8. See Bloom (2014) for a review of the theoretical literature on the macroeconomic effects of uncertainty. We do not consider here the Oi-Hartman-Abel effect since such effect is likely modest in the short-medium run, owing to adjustment costs.

Second, we develop a relatively simple econometric framework to study how shocks to the expected distribution of growth are related with macroeconomic variables.

Our empirical application provides two main findings. (i) An increase in downside uncertainty is associated with sizable contractions of real economic activity. (ii) An increase in upside uncertainty is related to moderate expansions of real economic activity and large stock price increases. These results unveil a new interesting picture. An exogenous increase in uncertainty is not necessarily contractionary. 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.

These results are obtained using an econometric method which combines quantile regressions and structural VAR techniques. The method involves three steps.

First, we select the target variable and the relevant horizon. Here we use GDP growth and one-quarter ahead. We then estimate the expected quantiles using the smoothed quantile regression recently proposed in Fernandes et al. (2021) and Natal and Horta (2022). This allows us to use several predictors selected on the basis of their significance: real GDP, unemployment, real stock prices and the expected business conditions 1-year ahead (a component of the Michigan consumer confidence index).

With the estimated quantiles, 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. For completeness, we also use the Kelley's (1947) measure of skewness defined as the difference between upside uncertainty and downside uncertainty.

Second, we estimate a VAR model that includes the quantile regression predictors above and additional variables of interest: real investment, a term spread and a risk spread.

Third, we identify two types of shocks to the expected distribution of GDP growth: downside uncertainty shocks and upside uncertainty shocks. These shocks are obtained by combining the VAR residuals and the quantile regression parameters. Similarly, the related impulse response functions are obtained by combining the reduced form VAR responses with the quantile regression parameters.[9]

Our paper is closely related to Adrian et al. (2019). The results obtained in the first step of our procedure confirm their findings. The novelty of our contribution is in the second and third steps, which allow us to identify upside and downside uncertainty shocks along with their different impulse-response functions.

9. Notice that the method can also be used the other way around to study the effects of any macroeconomic shock, i.e. policy shocks, technology shocks, etc., on the expected distribution of GDP growth or any other variable of interest. We do not purse this route here. In an ongoing project we are studying the effects of financial, monetary policy, and technology shocks on the GDP growth expected distribution.

We also contribute to a new and growing literature on asymmetry and the business cycle. Two important papers are Salgado et al. (2019) and Dew-Becker (2020).[10] These papers show that cross-sectional measures of realized skewness matter for economic fluctuations. Here we show, first, that this is also true for the expected skewness of the aggregate GDP growth; second, that the effects are largely driven by the left tail of the growth distribution.

Finally, Segal et al. (2015) represents a first attempt to construct measures of “bad” and “good” uncertainty. The results they obtain, however, are hard to interpret and to reconcile with the existing findings since the effects of total uncertainty on GDP growth are mostly positive. This might depend on the econometric approach which is radically different from ours.

From an econometric point of view, the first step of our procedure is closely related to Chavleishvili and Manganelli (2021); essentially, we estimate a single equation of their quantile VAR (albeit with the ‘smoothed’ method). The distinguishing feature of our procedure is that in the second and third steps we combine quantile estimation with standard VAR techniques. Our shocks, for instance, are obtained from linear combinations of the (standard) VAR residuals, rather than being derived directly from quantile regression.[11]

10. Schüler (2019) measures the effect of shocks increasing and reducing uncertainty as opposed to shocks to various quantiles.

11. Koenker and Xiao (2006) study a univariate autoregressive version of quantile estimation.

One might wonder whether the first step in our procedure, estimating the expected distribution of growth, could be replaced by data from the Survey of Professional Forecasters (SPF). It is important to recall that the distribution of forecasts across individuals in the SPF reflects the dispersion of individual views, which is not the same thing as the expected distribution of growth. To keep outside of the analysis the across-agents dispersion we should in principle extract information about the probability distribution of each forecaster and aggregate such distributions (see Rossi, Sekhposyan and Soupre, 2019, for a thorough discussion of this point). This however is left for further research.

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 two main shocks: downside and upside uncertainty shocks.

The approach consists of three steps. First, the expected distribution 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, we combine the quantile regression coefficients with the VAR residuals to obtain the shock and with the VAR coefficients to obtain the impulse response functions.

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 Fernandes 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.[12] 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.[13] Finally, (iv) it is possible to compute the asymptotic standard deviation of

12. See Koenker and Bassett (1978).

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

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 Fernandes 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. The quantiles allow us to derive several interesting descriptive statistics of the expected distribution of the variables.

First, we define total uncertainty as

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

where the index u stands for *uncertainty*. This measure is conceptually similar to the interquartile range but with different percentiles.[14]

The basic idea of the present paper is to decompose total uncertainty into the sum of downside uncertainty and upside uncertainty. We define downside uncertainty, z_t^l,

14. We choose the 10th and the 90th percentile because, as we shall see, extreme values of the expected distribution play an important role.

as 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 tail*, and upside uncertainty, z_t^r, as 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 tail*. Total uncertainty is simply the sum of the two terms

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

This decomposition turns out to be very useful since our main goal is to assess whether the effects of uncertainty originating from the left tail are different from those originating from the right tail.

Finally, we compute the Kelley's (1947) absolute skewness, z_t^s, as the difference between upside and downside uncertainty:

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

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

$$\gamma_l(L) = \tilde{\beta}_{0.5}(L) - \tilde{\beta}_{0.1}(L)$$

$$\gamma_r(L) = \tilde{\beta}_{0.9}(L) - \tilde{\beta}_{0.5}(L)$$

$$\gamma_u(L) = \tilde{\beta}_{0.9}(L) - \tilde{\beta}_{0.1}(L)$$

$$\gamma_s(L) = \tilde{\beta}_{0.9}(L) + \tilde{\beta}_{0.1}(L) - 2\tilde{\beta}_{0.5}(L).$$

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. Structural VAR

Having measures of downside and upside uncertainty, we can in principle estimate the effects of downside and upside uncertainty shocks either by including our measures within a structural VAR model or by using them within local projection equations.

Notice however that our uncertainty measures are, by construction, linear combinations of the current and past values of the y's, so that including them together with y_t in the same model can generate collinearity or quasi-collinearity. Consider for instance the simple case of z_t^l being a linear combination of current y's: in this case including both z_t^l and y_t in the same model is impossible. A reasonable solution is to exclude one or some variables of the vector y_t from the VAR model, or one or some of the conditioning variables entering the local projection equations.[15] A somewhat unpleasant feature of this solution is that excluding different variables can in principle produce different outcomes. Furthermore, it is not clear whether we should include both measures of uncertainty in the same model or whether we should enter them one by one.

For these reasons we prefer a different, albeit asymptotically equivalent, method. We include in the VAR all of the variables in the vector y_t and keep outside the VAR the uncertainty measures. The relevant impulse response functions are then computed (rather than directly estimated) by combining the quantile-regression coefficients with the reduced-form VAR IRFs, according to the formulas discussed in the next paragraphs.

We assume that y_t follows (abstracting from the constant term) the VAR model

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

where $\varepsilon_t \sim WN(0, \Sigma_\varepsilon)$ 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

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

15. In the empirical application below we do precisely this in a robustness exercise.

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 $u_t = U'C^{-1}\varepsilon_t \sim WN(0, I)$.

By combining (1), (3) and (4) we can derive the implied dynamics for the quantiles

$$z_t^j = \gamma_j'(L)B(L)\varepsilon_t = \gamma_j'(L)B(L)CUu_t. \tag{5}$$

The above equation establishes a link between the quantiles and the shocks in u_t. Below we discuss how to use this equation to identify the desired shock to the expected distribution.[16]

2.3. Internal consistency

At a first sight the linearity of the VAR model for y_t might seem inconsistent with the idea that each conditional quantile of the forecast distribution of y_t is time varying and (linearly) predictable. But it is not. We show that these two assumptions are not inconsistent by providing an example in which both are satisfied.

16. Notice that equation (5) can also be used to study how structural economic shocks affect z_t^j.

Suppose that the n-dimensional vector y_t admits the VAR representation

$$y_t = Ay_{t-1} + \varepsilon_t$$

where ε_t is serially independent. In this case, the τ-th conditional quantile of the i-th variable in the vector y_t, y_{it}, is:

$$Q^{\tau}_{it} = A_i y_{t-1} + Q^{\tau}_{\varepsilon_i}$$

where $Q^{\tau}_{\varepsilon_i}$ is the τ-th conditional quantile of ε_{it}, and A_i is the i-th row of A. Note that the term $A_i y_{t-1}$ is constant for all τ so that the difference between any two quantiles $\overline{\tau}$ and $\underline{\tau}$ is:

$$Q^{\overline{\tau}}_{it} - Q^{\underline{\tau}}_{it} = Q^{\overline{\tau}}_{\varepsilon_i} - Q^{\underline{\tau}}_{\varepsilon_i}.$$

By serial independence, $Q^{\tau}_{\varepsilon_i}$ is constant and does not depend on y_{t-1} so that $Q^{\overline{\tau}}_{it} - Q^{\underline{\tau}}_{it}$ is constant.

Suppose now that ε_t is not serially independent. For instance assume $\varepsilon_t = \alpha' y_{t-1} v_t$, where v_t is a vector white noise, independent of the past history of y_t. Serial uncorrelation of ε_t is fulfilled, since $E(\varepsilon_t \varepsilon'_{t-k}) = \alpha' E(y_{t-1} y'_{t-k}) \alpha \, E(v_t v'_{t-k}) = 0$ for any $k > 0$. The model becomes

$$y_t = Ay_{t-1} + \alpha' y_{t-1} v_t. \tag{6}$$

The τ-th conditional quantile of y_{it} is now

$$Q_{it}^{\tau} = A_i y_{t-1} + \alpha' y_{t-1} Q_{v_i}^{\tau} = (A_i + Q_{v_i}^{\tau}\alpha')y_{t-1}$$

where $Q_{v_i}^{\tau}$ is the τ-th conditional quantile of v_{it}. Interestingly, now the quantiles of y_{it} depend linearly on y_{t-1} and the coefficient $(A_i + Q_{v_i}^{\tau}\alpha')$ is quantile-dependent. The difference between two quantiles is:

$$Q_{it}^{\overline{\tau}} - Q_{it}^{\underline{\tau}} = (Q_{v_i}^{\overline{\tau}} - Q_{v_i}^{\underline{\tau}})\alpha' y_{t-1}.$$

which is now time-varying and is a linear function of the conditioning variables, y_{t-1}.

2.4. 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.[17] In the next subsection we show how to enrich the identification scheme with additional constraints.

From equation (5), the innovation in z_t^j is

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

17. It should be stressed that we do not re-estimate the VAR by adding z_t^j as a new variable. Rather we simply combine the coefficients of the VAR and the quantile regression as discussed below.

(since $B(0) = I$) with variance $\gamma'_{j0}\Sigma_\varepsilon\gamma_{j0}$.[18] Let u_t^j be the structural shock of interest. To identify the structural shock as the innovation in z_t^j, normalized to have unit variance, it suffices to impose that

$$u_t^j = \theta_j'\varepsilon_t, \tag{7}$$

where $\theta_j' = \gamma'_{j0}/\sqrt{\gamma'_{j0}\Sigma_\varepsilon\gamma_{j0}}$. 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. $u_t^j = U_1'C^{-1}\varepsilon_t$, where U_1 is an orthonormal column vector, implying $\theta_j' = U_1'C^{-1}$. The impulse response functions to u_t^j are therefore $d_j(L) = B(L)CU_1$. Using $U_1 = C'\theta_j$ and recalling that $CC' = \Sigma_\varepsilon$, we obtain

$$d_j(L) = B(L)CC'\theta_j = B(L)\Sigma_\varepsilon\theta_j. \tag{8}$$

Notice that the contemporaneous effects are $\Sigma_\varepsilon\theta_j$, 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 $d_j(L)$.

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

2.5. Identification with additional constraints

The identification discussed in the previous subsection is equivalent to assuming that u_t^j is the only shock affecting contemporaneously the variable z_t^j. This assumption in many cases might be inappropriate or too restrictive. Here we show how to relax this assumption and to impose different identifying restrictions.

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 another shock, (structural or not), which moves GDP in the long run (call it $w_{1t} = D_1\varepsilon_t$, where D_1 is a row vector). To do so, we project the innovation to z_t^j onto this long run shock and take the projection residual. The desired shock is this residual, normalized to have unit variance. 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 y_{1t}, the first variable of y_t, it suffices to impose orthogonality with respect to the shock $\varepsilon_{2t} = D_2\varepsilon_t$, where $D_2 = [1\ 0\ \cdots\ 0]$, i.e. to project the innovation to z_t^j onto ε_{2t} and take the normalized residual.

More generally, let D be any $m \times n$ matrix and let $D_1, D_2, \ldots, D_m$ be its rows. If we want to impose orthogonality with respect to $D_1\varepsilon_t, D_2\varepsilon_t, \ldots, D_m\varepsilon_t$, we take the residual of the orthogonal projection of the innovation of z_t^j onto $D\varepsilon_t$, normalized to have unit variance. The shock of interest u_t^j can be computed from the VAR coefficients by applying the formulas

$$u_t^j = \delta_j \varepsilon_t \tag{9}$$

$$\delta_j = \frac{\alpha_j}{\sqrt{\alpha_j' \Sigma_\varepsilon \alpha_j}}$$

$$\alpha_j = \gamma_{j0}' - \gamma_{j0}' \Sigma_\varepsilon D' (D \Sigma_\varepsilon D')^{-1} D.$$

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

$$d_j(L) = B(L) \Sigma_\varepsilon \delta_j. \tag{10}$$

2.6. Inference

To compute the confidence bands for the impulse-response functions we keep fixed the point estimate of the vector γ_{j0} obtained in the quantile regression, and therefore the vectors θ_j and δ_j appearing in equations (8) and (10), respectively. This means that estimation uncertainty from the first step of our procedure is not considered in the second and third steps.

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, real investment,[19] three financial variables –namely, the log of the S&P500 stock market index divided by the GDP deflator, 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)[20]– and the Michigan Survey expected business conditions 1-year ahead (E1Y). The VAR is estimated with two lags, as suggested by the HQC 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 time t. In the baseline specification we focus on the one-quarter ahead horizon (i.e. quarter-on-quarter growth), while 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

19. Investment includes durable consumption.

20. Adrian et al. (2019) use as a benchmark financial indicator the Chicago Fed's National Financial Conditions Index (NFCI), a series available from 1971. Plagborg-Møller et al. (2020) show that, conditional on information on real variables, the NFCI has no forecasting power.

properties: (i) each predictor is significant at the 3% level for at least one of the 10th, 50th and 90th percentile, and (ii) 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.[21]

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, taken in deviation from the median (thin red lines). 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 uncertainty 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

21. Adrian et al. (2019) find that the NFCI is significant in explaining the 10th and 50th percentile of the growth rate of GDP. When we restrict the sample to begin in 1971, the time in which the NFCI becomes available, the index turns out to be significant for the 10th and 50th percentile. Therefore, our estimator delivers similar estimates as those in Adrian et al. (2019).

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. The shaded areas are asymptotic 68% confidence bands. Downside uncertainty increases in every recession, while upside uncertainty 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 uncertainty.

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 Fernandes et al. (2021). 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).

As a robustness exercise, we report in the Online Appendix additional results obtained with the standard quantile regression method, using the regressors above (see Figures **??** and **??**). Results are qualitatively similar to those of Figures 1 and 2 (notice however that different quantiles are much more likely to cross).[22]

3.2. Identification schemes

Here we discuss the restrictions we use to identify the downside and upside uncertainty shocks. To begin with, we identify the shocks as the innovations in downside uncertainty and upside uncertainty, respectively (Identification A).

22. The correlation coefficients of the 10-th percentiles and the 90-th percentiles obtained with the two methods are 0.97 and 0.99, respectively.

Given that downside uncertainty and upside uncertainty are correlated to some extent, to better isolate the effects of each of the two tails we impose that the downside uncertainty shock has no contemporaneous effect on upside uncertainty and, vice versa, the upside uncertainty shock has no effect on downside uncertainty (Identification B). In other words, we study what happens when one of the two tails enlarges (implying an increase of total uncertainty) but the other remains constant.

A drawback of the previous identification schemes is that downside and upside uncertainty are assumed to be unaffected by other macroeconomic shocks contemporaneously. The assumption has been criticized in several recent works, see Bachmann et al. (2013) and Ludvigson et al. (2021). It is important to emphasize that establishing whether uncertainty is exogenous or not is not the focus of this paper. Nonetheless, we try to mitigate the endogeneity problem by imposing that downside uncertainty shocks and upside uncertainty shocks are contemporaneously orthogonal to GDP, unemployment and investment, i.e. uncertainty shocks have zero impact effects on these variables (Identification C). More sophisticated identification schemes like those proposed by Ludvigson et al. (2021) and Brianti (2021) are left for future research.

As anticipated above, for the sake of completeness we also identify a shock to total uncertainty using Identification A.

3.3. Uncertainty shocks

Before discussing our main results about downside and upside uncertainty shocks, we start by investigating the impulse-response functions of a total uncertainty shock to assess whether the results are in line with those obtained in previous works.

The impulse responses to the uncertainty shock (Identification A), u_t^u, are displayed in Figure 4. An unexpected increase in uncertainty is associated with a significant depression of the real economy (see Bloom, 2009, JLN, 2015 or LMN, 2019). A unit variance uncertainty shock, increasing uncertainty by about 0.5% corresponds to a reduction of GDP of about 0.2% on impact, with respect to the previous quarter, and almost 0.5% after one year, while unemployment increases by about 0.3% after one year. From the variance decomposition in 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. All in all, the results are in line with existing studies.

3.4. Downside and upside uncertainty shocks

Let us come now to downside and upside uncertainty shocks. Figure 5 displays the impulse-response functions of downside uncertainty shocks (Panel (a)) and upside uncertainty shocks (Panel (b)) obtained with identification A. If we interpret the shocks as exogenous, we see that 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 uncertainty 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 uncertainty 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 shock 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 uncertainty 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 using Identification B. This scheme imposes that the shock to one tail leave the other tail unchanged on impact. This can be useful to better isolate the effects of the shock to one tail since the two tails are positively correlated (the correlation coefficient is about 0.5, see Table 2). Figure 6 reports the results. The effects of both downside and upside uncertainty are amplified. A shock to downside generates a large, significant and protracted economic downturn while a shock to the upside has now significant positive effects on real economic activity.

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 uncertainty. This helps understanding why the effects of total uncertainty on stock prices are quite small and barely significant (see Figure 4), despite the fact that overall uncertainty is dominated by the left tail.

Finally, we identify the two shocks using Identification C. Figure 7 plots the results. The effects on real economic activity variables, although smaller in magnitude, are still contractionary and significant for the downside and expansionary for the upside, confirming our main conclusions. Table 5 reports the variance decomposition. Even when orthogonalizing the shock with respect to current values of GDP, unemployment and investment, the downside shock remains very important, explaining around 25% and 40% of the short run fluctuations in GDP and unemployment, respectively.

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) that is associated with 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 uncertainty 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 highlight that previous interpretations were somewhat misleading: it is not total uncertainty that matters, but only downside uncertainty.

To sum up, from a theoretical point of view, the effects of downside uncertainty are predicted to be indisputably contractionary, since the risk premium and the real options channels operate. Our results confirm these predictions. In particular, the effect of the downside uncertainty shock on the risk premium is significantly negative. On the contrary, the effects of upside uncertainty on economic activity are ambiguous. The risk premium channel is not active and the real options and the growth options channels work in opposite directions. According to our results, the growth options effect slightly prevails, since the effects of the upside uncertainty shock are expansionary, although quantitatively small. Interestingly, the effects on stock prices are much larger. Since stock prices are not affected by the real options channel, the growth options effect has no counterweight and the effect of upside uncertainty is large.

3.5. Skewness

A recent stream of literature has put forward the idea that changes in the realized cross-sectional skewness of firm-level indicators might play a role for business cycle fluctuations, see Salgado et al. (2019) and Dew-Becker (2020). Our results show that also the expected skewness of the GDP growth matters for economic fluctuations. In our framework, the distribution becomes more left-skewed when downside uncertainty increases or upside uncertainty reduces or both. As we have seen, a widening of the left tail and a shrinkage of the right tail are both contractionary. Therefore an increase in left-skewness is contractionary as well. Notice however that the effects of the right tail are very modest and, in addition, the right tail does not move that much. Therefore the bulk of the effects, as for total uncertainty, are driven by downside uncertainty.

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 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 **??** (online appendix) 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 horizon. Figure **??** (online appendix) 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 uncertainty 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 **??** (online appendix) 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. (2021).

Figure 8 reports the impulse response functions to the downside uncertainty shock (Panel (a)) (identification A) and the upside uncertainty shock conditional to downside uncertainty (Panel (b)) (identification B). The responses to downside uncertainty are similar to those found with the 1-quarter ahead distribution. Table **??** 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. (g) We use standard quantile regression to estimate the relevant quantiles (h) We consider a larger sample ending in 2023:Q2, including the COVID pandemic. The shocks under consideration are the downside and upside uncertainty shocks obtained with Identification A.

Figure 9 reports the results for GDP. 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 are reasonably robust, especially for the downside uncertainty shock. Using standard quantile regression, the effects of a upside uncertainty shock are much larger. When considering the larger sample, including the pandemic, the IRFs are sizably affected by the huge short-run variations related to the lockdown of 2020:Q2. However, robustness checks confirm the basic result: an increase in downside uncertainty is related to a slowdown of economic activity, whereas an increase in upside uncertainty is associated with stable or increased activity.

4.3. Using local projections and "internal uncertainty" VAR

Instead of computing the IRFs according to formulas (8) or (10), we can estimate them by including our measures of uncertainty in the VAR or in a local projection equation. To avoid collinearity we exclude from the information set one of the predictors used in the estimation of the quantiles (see Section 2.2). In the present subsection we show the results obtained by excluding E1Y.

Figure 10 shows the results. The blue dashed lines are the IRFs corresponding to the first shock of a Cholesky VAR(2) including downside (upside) uncertainty as the first variable. The red dotted-dashed lines are the IRFs obtained by local projections (the control variables are the same used in the VAR). The black solid lines and the shaded areas are those of the benchmark model (Identification A).

The results obtained by including our uncertainty measures within the VAR model are almost identical to those computed with formula (8). The result obtained with local projection are very much similar for the first 5-10 lags; after that, they start to be very volatile. All in all, our basic results are confirmed.

5. Concluding remarks

The main conclusion of our study is that 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 uncertainty increases. An increase in uncertainty arising from a widening of the right tail, i.e. higher upside uncertainty, on the contrary, has positive effects on the economy. The results can be rationalized through existing theories of the transmission mechanisms of uncertainty.

We reach such conclusion using a novel econometric method which combines quantile regressions and VAR models. This method enables us to estimate how shocks to the expected distribution of growth (or other macroeconomic variables) affect the macroeconomy. The procedure proposed here can be used in other applications and with other purposes. For instance it would be interesting to study the reverse: how structural macroeconomic shocks, i.e. policy shocks, technology shocks, etc., affect uncertainty and other features of the expected distribution. We plan to pursue this line of research in the future.

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Tables

TABLE 1. p-values of the retained quantile predictors.

	10th percentile	50th percentile	90th percentile
A. One-quarter ahead growth forecast distribution			
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-year 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 2. Correlation of our measures z_t^j and a few uncertainty indexes.

	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 3. Variance decomposition for the 1-quarter horizon uncertainty shock (upper panel), the downside uncertainty shock, conditional on upside uncertainty (middle panel) and the left skewness shock, conditional on uncertainty (lower panel). Standard errors in brakets.

	A. Uncertainty			
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	17.8 (5.0)	30.7 (8.4)	23.5 (8.4)	15.0 (7.2)
Unemployment rate	37.6 (5.6)	46.7 (9.4)	42.2 (10.2)	36.2 (10.4)
S&P500/GDPDEF	4.9 (2.9)	3.3 (4.5)	3.9 (6.1)	4.9 (6.8)
Investment	13.9 (4.8)	24.0 (8.3)	16.8 (7.4)	11.2 (6.5)
Spread GS10-TB3m	1.2 (1.8)	9.2 (6.9)	12.7 (8.0)	12.4 (7.8)
spread BAA-GS10	13.2 (5.0)	22.0 (8.6)	22.3 (8.4)	22.0 (8.2)
E1Y	82.3 (2.5)	47.9 (9.0)	42.5 (8.9)	40.8 (9.0)
Uncertainty	100.0 (0.0)	59.9 (8.2)	53.8 (8.5)	53.4 (8.6)
	B. Downside shock			
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	21.7 (5.2)	39.2 (8.6)	28.0 (8.6)	17.4 (7.2)
Unemployment rate	46.0 (5.4)	63.9 (8.4)	55.5 (10.1)	47.6 (10.8)
S&P500/GDPDEF	14.9 (4.5)	9.5 (6.7)	9.4 (8.1)	10.3 (8.6)
Investment	18.4 (5.3)	33.3 (8.9)	22.4 (8.0)	14.9 (7.1)
Spread GS10-TB3m	1.8 (2.3)	15.5 (8.0)	19.5 (8.9)	18.9 (8.7)
spread BAA-GS10	18.8 (5.0)	32.5 (8.8)	32.0 (8.5)	31.5 (8.3)
E1Y	80.8 (2.4)	49.9 (9.2)	44.1 (9.3)	42.6 (9.3)
Downside uncertainty	100.0 (0.0)	62.1 (8.2)	56.6 (8.4)	56.5 (8.5)
	C. Upside shock			
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	0.1 (1.0)	1.6 (2.5)	1.8 (3.2)	1.4 (4.6)
Unemployment rate	0.2 (0.9)	5.9 (5.4)	3.8 (4.5)	3.8 (4.5)
S&P500/GDPDEF	38.3 (7.0)	24.3 (9.7)	17.8 (9.8)	13.9 (9.4)
Investment	1.0 (1.7)	3.9 (4.0)	2.4 (3.4)	1.9 (3.7)
Spread GS10-TB3m	0.3 (0.9)	7.7 (5.2)	7.1 (4.8)	7.0 (4.7)
spread BAA-GS10	2.5 (3.6)	8.9 (5.8)	9.5 (5.8)	9.5 (5.8)
E1Y	14.2 (5.4)	5.5 (4.3)	5.4 (4.6)	5.9 (4.5)
Upside uncertainty	100.0 (0.0)	73.4 (6.5)	67.0 (7.6)	61.5 (8.1)

TABLE 4. Variance decomposition continued for the 1-quarter horizon uncertainty shock (upper panel), the downside uncertainty shock, conditional on upside uncertainty (middle panel) and the left skewness shock, conditional on uncertainty (lower panel). Standard errors in brakets.

	D. Downside conditional on upside			
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	24.3 (5.4)	46.4 (8.7)	30.8 (8.6)	18.6 (7.0)
Unemployment rate	51.5 (5.3)	80.8 (7.2)	67.5 (10.0)	58.1 (11.2)
S&P500/GDPDEF	33.6 (5.2)	21.1 (8.6)	19.0 (10.0)	19.0 (10.3)
Investment	22.5 (5.7)	42.8 (9.2)	27.7 (8.5)	18.5 (7.7)
Spread GS10-TB3m	2.4 (2.7)	23.8 (8.7)	27.8 (9.3)	26.7 (9.1)
spread BAA-GS10	24.6 (5.5)	44.6 (8.8)	43.0 (8.3)	42.5 (8.2)
E1Y	68.3 (5.0)	46.0 (9.1)	40.6 (9.1)	39.7 (9.1)
Downside Uncertainty	92.4 (4.1)	59.5 (8.2)	55.3 (8.5)	55.2 (8.5)
	E. Upside conditional on downside			
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	2.7 (2.4)	8.8 (4.8)	4.6 (3.6)	2.6 (4.6)
Unemployment rate	5.7 (2.6)	22.9 (7.4)	15.9 (6.9)	14.3 (6.7)
S&P500/GDPDEF	56.9 (5.0)	35.9 (10.2)	27.4 (10.8)	22.5 (10.5)
Investment	5.1 (3.1)	13.4 (6.3)	7.7 (4.9)	5.5 (4.7)
Spread GS10-TB3m	0.9 (1.3)	16.0 (6.8)	15.4 (6.4)	14.9 (6.2)
spread BAA-GS10	8.4 (5.6)	21.0 (7.5)	20.6 (7.3)	20.4 (7.3)
E1Y	1.8 (0.9)	1.6 (2.3)	1.9 (3.4)	3.0 (3.4)
Upside Uncertainty	92.4 (4.1)	64.7 (7.4)	62.9 (7.2)	58.7 (7.3)

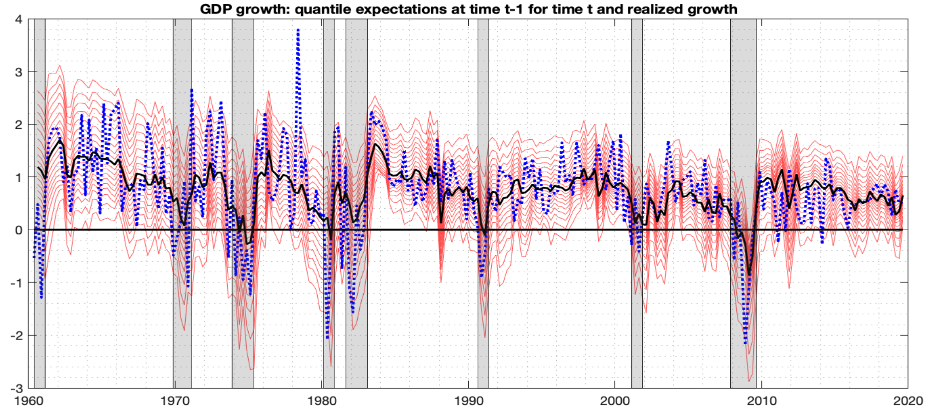
TABLE 5. Variance decomposition continued for the 1-quarter horizon. Upper panel: downside uncertainty shock conditional on GDP, unemployment rate and investment; bottom panel: upside uncertainty shock conditional on GDP, unemployment rate and investment. Standard errors in brakets.

F. Downside conditional on GDP, Unemployment and Investment				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	0.0 (0.0)	25.9 (8.1)	29.2 (8.9)	25.4 (8.1)
Unemployment rate	0.0 (0.0)	35.0 (9.8)	49.8 (10.9)	51.5 (10.7)
S&P500/GDPDEF	54.3 (6.6)	63.3 (10.0)	65.8 (11.5)	65.4 (12.3)
Investment	0.0 (0.0)	31.4 (9.0)	35.6 (9.8)	31.8 (9.4)
Spread GS10-TB3m	0.3 (1.0)	5.0 (4.3)	12.4 (6.6)	13.5 (6.7)
spread BAA-GS10	5.6 (2.7)	28.1 (8.6)	28.9 (8.4)	28.6 (8.4)
E1Y	72.1 (5.7)	73.5 (8.1)	68.6 (9.1)	67.5 (9.2)
Downside uncertainty	41.3 (4.7)	54.1 (7.8)	49.1 (7.8)	49.1 (7.9)

G. Upside conditional on GDP, Unemployment and Investment				
	$h = 0$	$h = 8$	$h = 16$	$h = 40$
GDP	0.0 (0.0)	7.7 (4.4)	4.8 (3.8)	3.5 (4.6)
Unemployment rate	0.0 (0.0)	17.9 (6.8)	16.6 (7.4)	17.9 (7.4)
S&P500/GDPDEF	74.8 (5.1)	62.2 (10.1)	53.9 (11.9)	48.4 (12.4)
Investment	0.0 (0.0)	12.1 (5.6)	8.9 (5.3)	8.7 (5.7)
Spread GS10-TB3m	0.4 (1.0)	8.6 (4.9)	9.6 (5.1)	9.6 (5.0)
spread BAA-GS10	4.6 (3.8)	20.2 (6.5)	19.3 (6.3)	19.1 (6.2)
E1Y	0.0 (0.0)	4.8 (3.1)	4.5 (3.2)	6.6 (3.5)
Upside Uncertainty	80.0 (5.7)	50.4 (7.9)	52.3 (7.9)	51.9 (7.7)

Figures

Panel (a)



Panel (b)

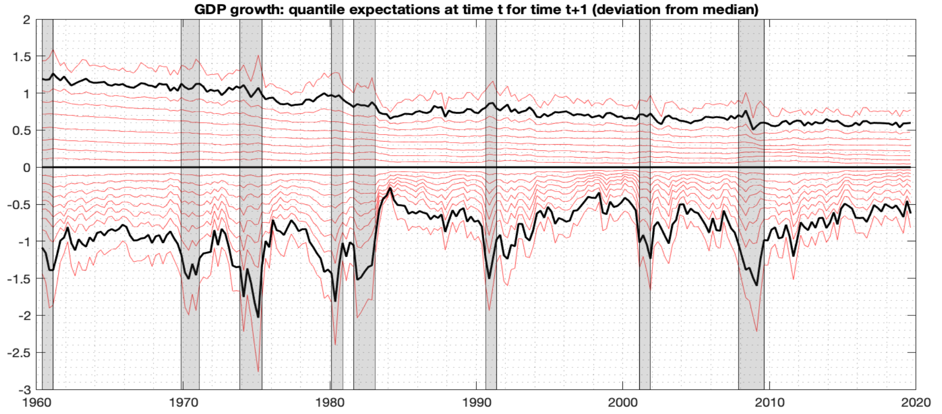


FIGURE 1. Panel (a) - Estimated quantiles of the expected distribution of US quarter-on-quarter GDP growth. Dashed blue line: GDP growth. Solid black line: median of the forecast distribution. Thin red lines: percentiles of the expected distribution. Gray vertical bands: US recessions. Panel (b) - Estimated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

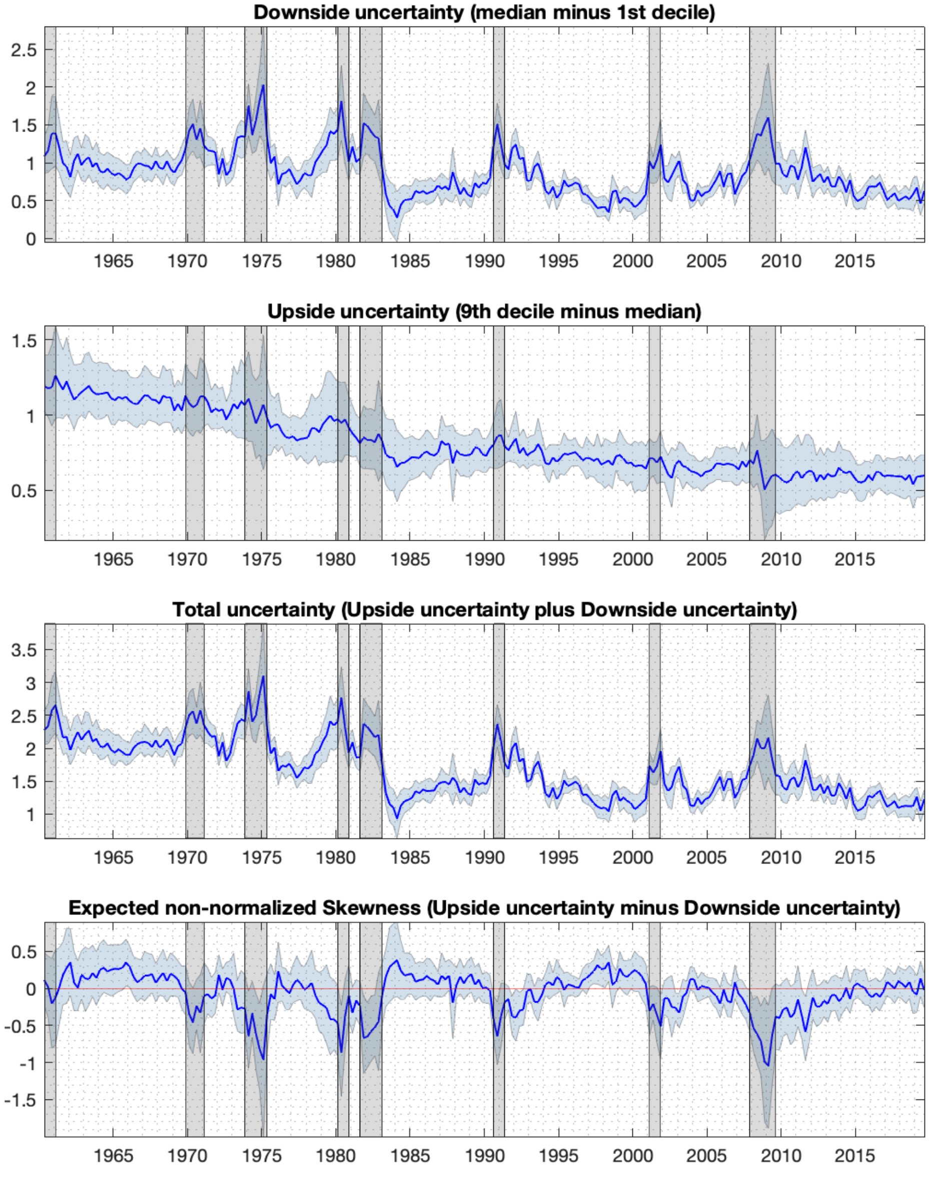


FIGURE 2. Measures of dispersion and asymmetry for the quarter-on-quarter expected growth distribution. From top to bottom: downside uncertainty z_t^l, upside uncertainty z_t^r, total uncertainty z_t^d, expected skewness z_t^s. Sheaded areas: 68% confidence bands. Gray vertical bands: US recessions.

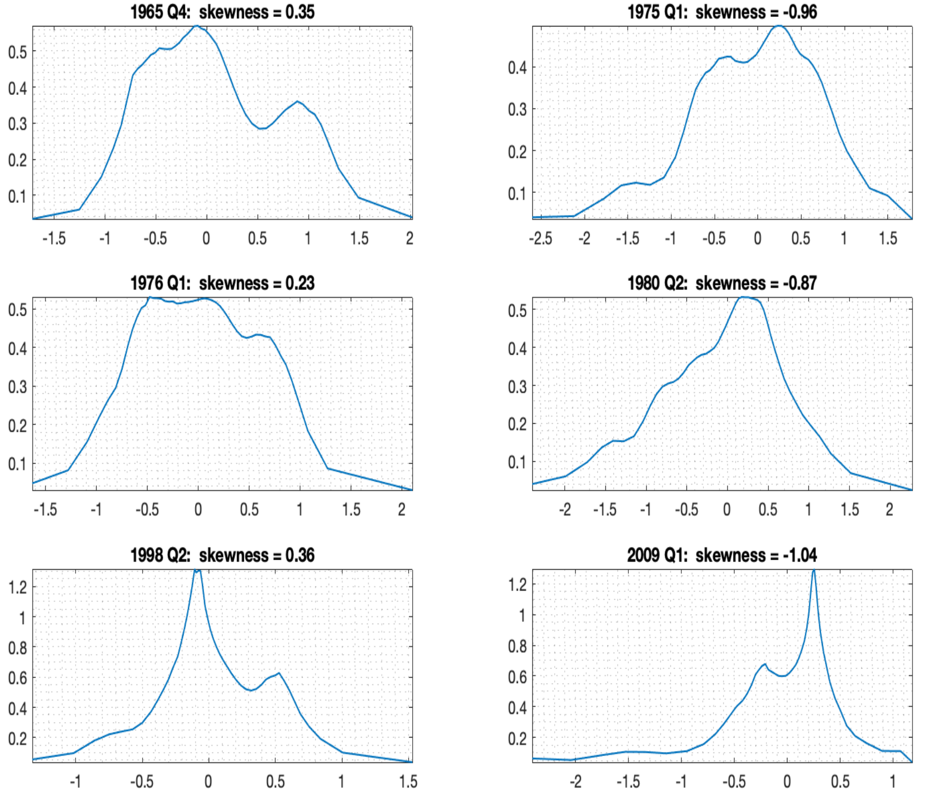


FIGURE 3. The expected quarter-on-quarter growth distribution (centered in the median) in a few selected good times (left column) and bad times (right column).

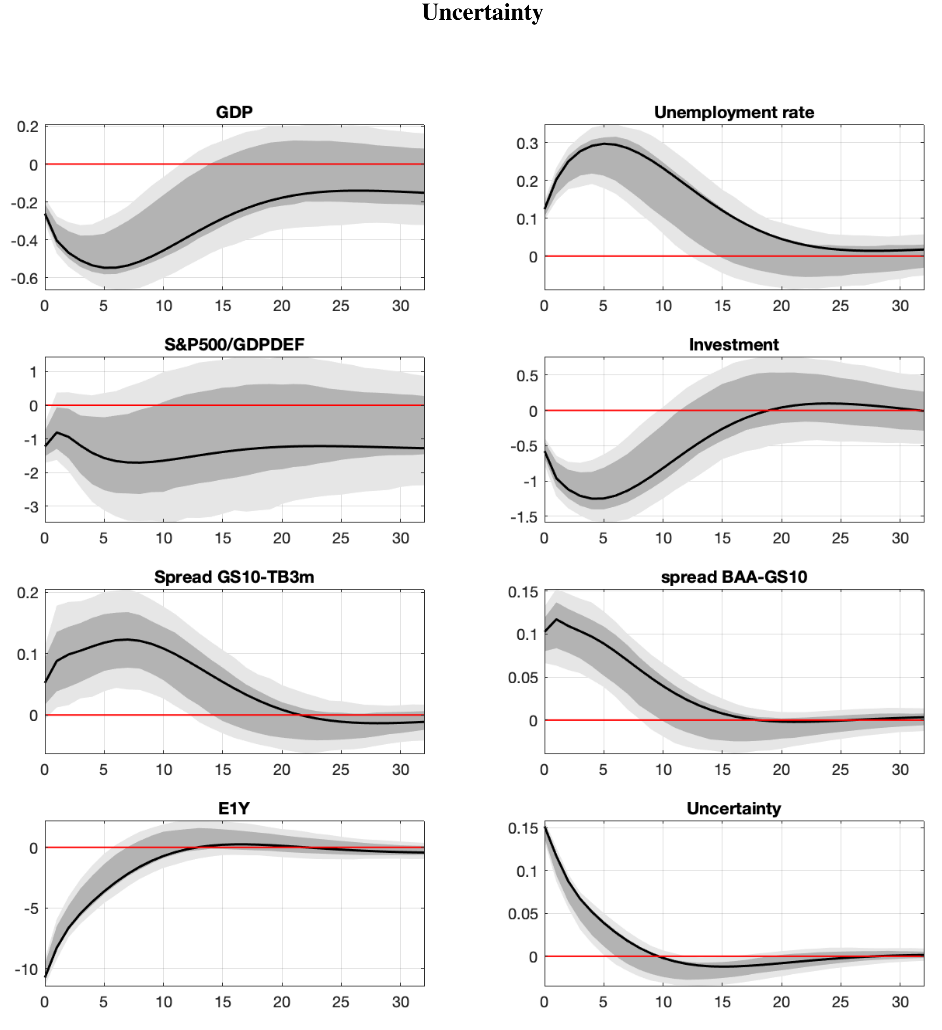


FIGURE 4. Impulse responses to the uncertainty shock. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

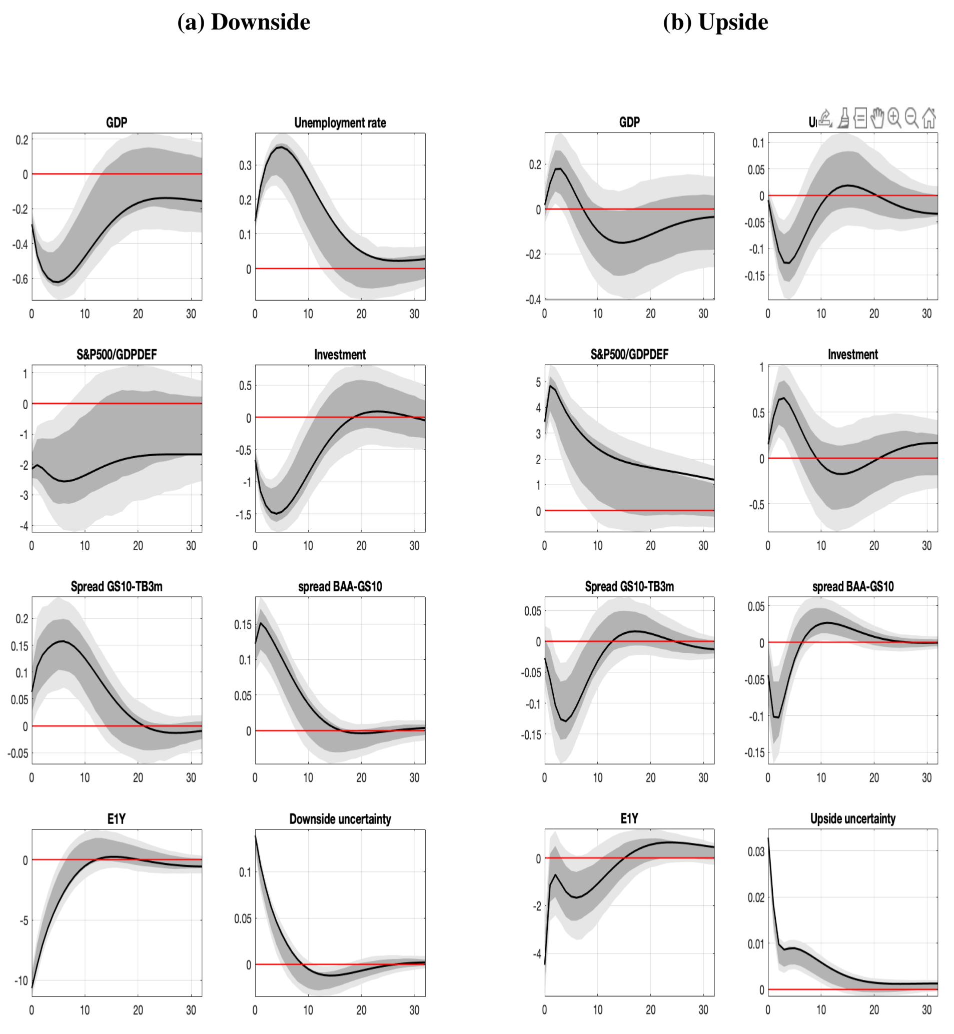


FIGURE 5. Identification A. Panel (a): impulse responses to the downside uncertainty shock. Panel (b): impulse response to the upside uncertainty shock. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

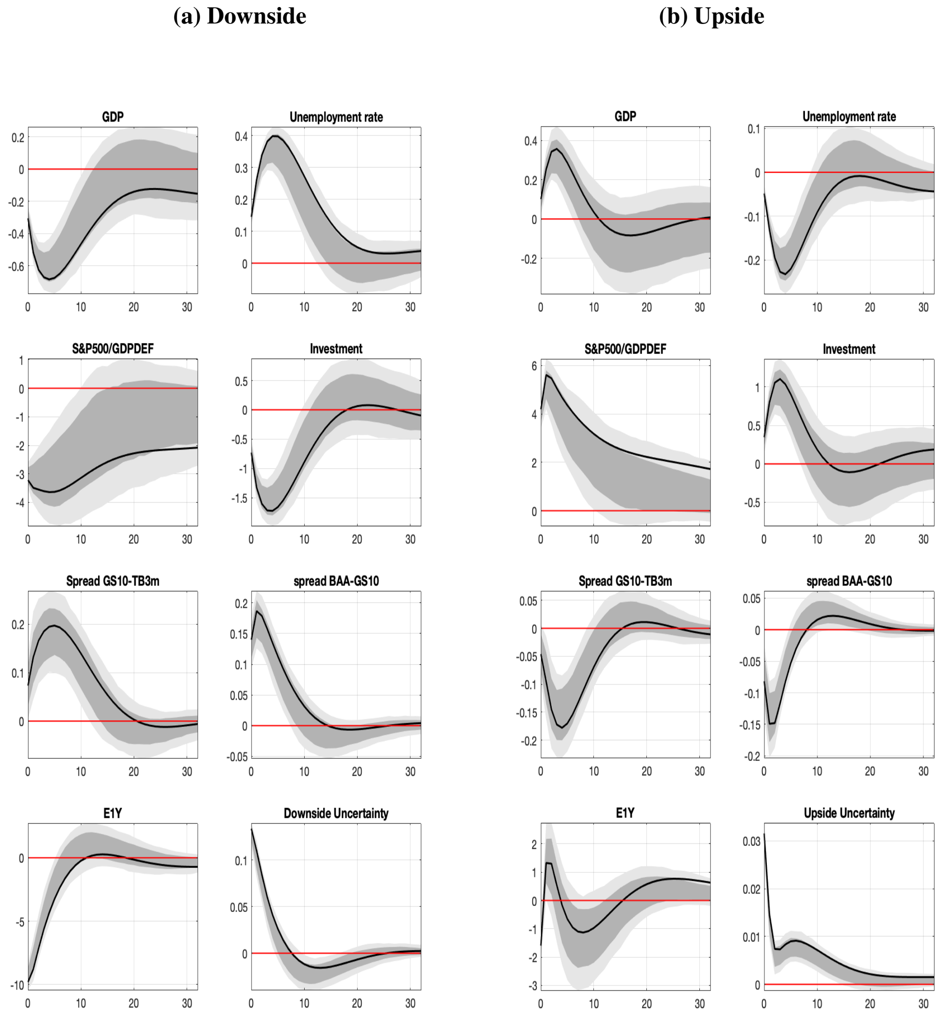


FIGURE 6. Identification B. Panel (a): impulse response to the downside shock conditional on upside uncertainty. Solid lines: point estimates. Panel (b): impulse response to the upside shock conditional on downside uncertainty. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

(a) Downside **(b) Upside**

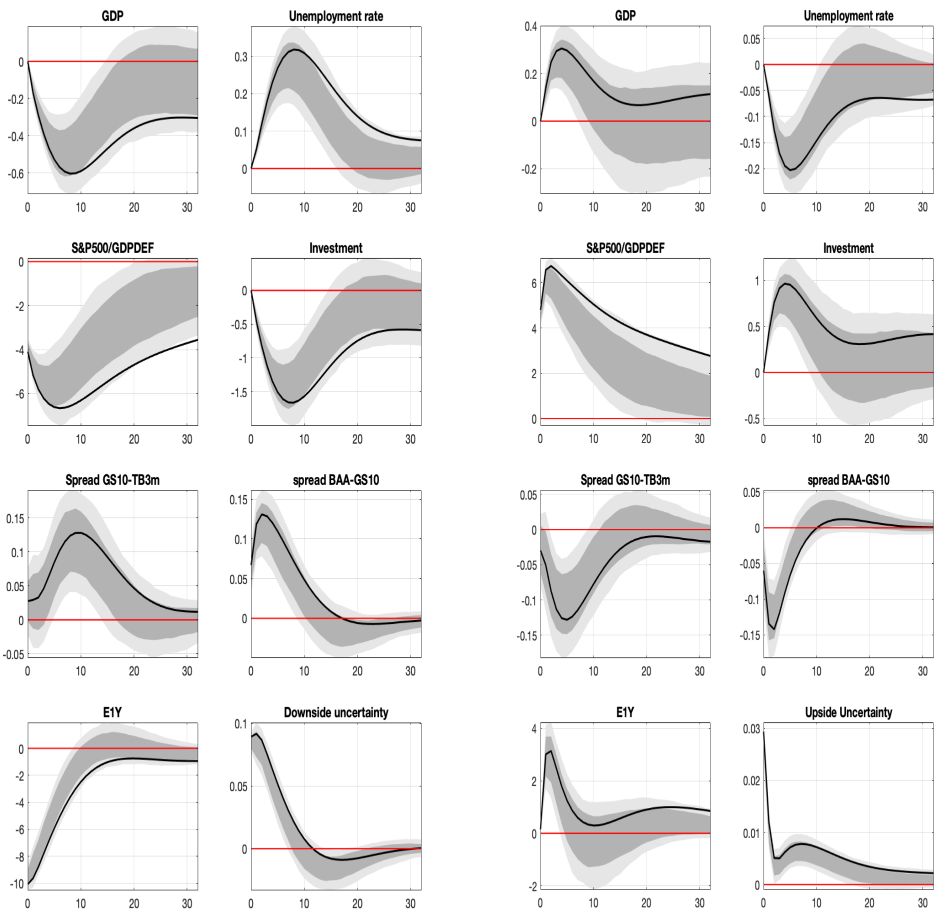


FIGURE 7. Identification C. Panel (a): impulse response to the downside shock conditional on GDP, unemployment and investment. Solid lines: point estimates. Panel (b): impulse response to the upside shock conditional on GDP unemployment and investment. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

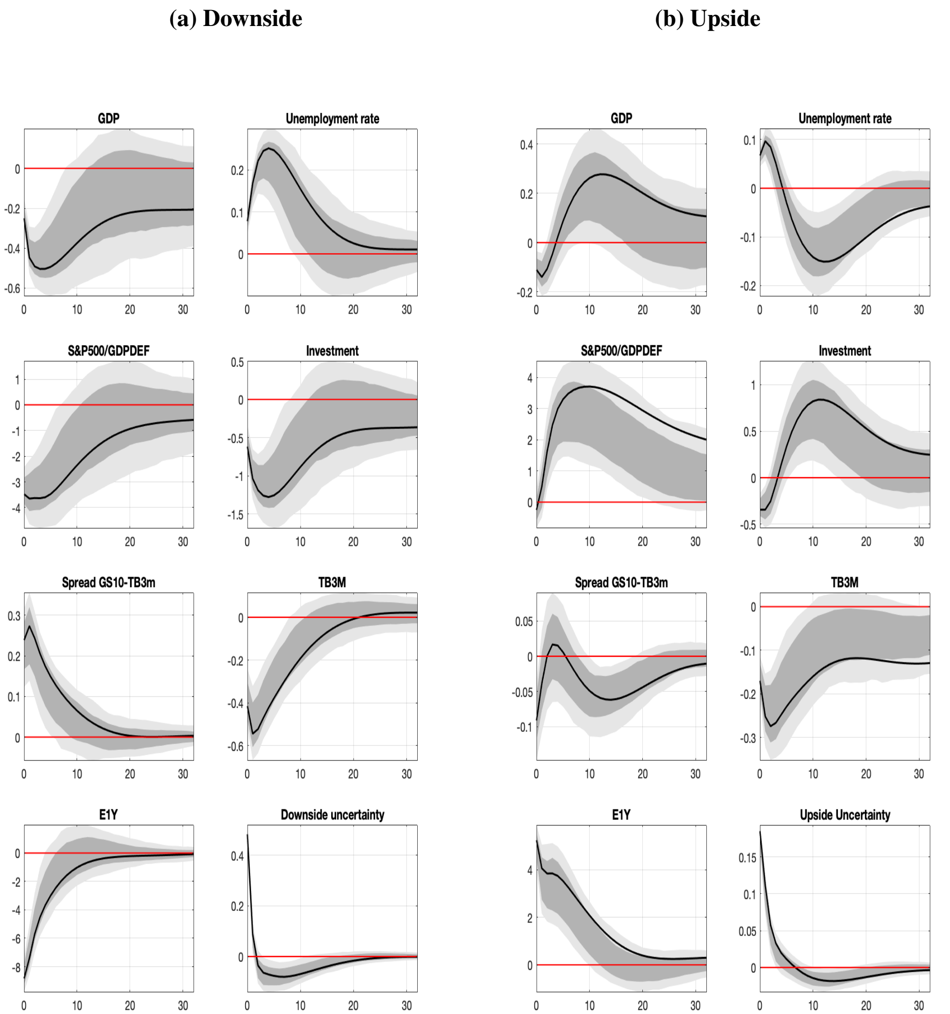


FIGURE 8. Panel (a): impulse responses to the downside uncertainty shock using the one-year forecast distribution and identification A. Panel (b): impulse responses to the upside uncertainty shock conditional on downside uncertainty using the one-year forecast distribution and identification. Solid lines: point estimates. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands.

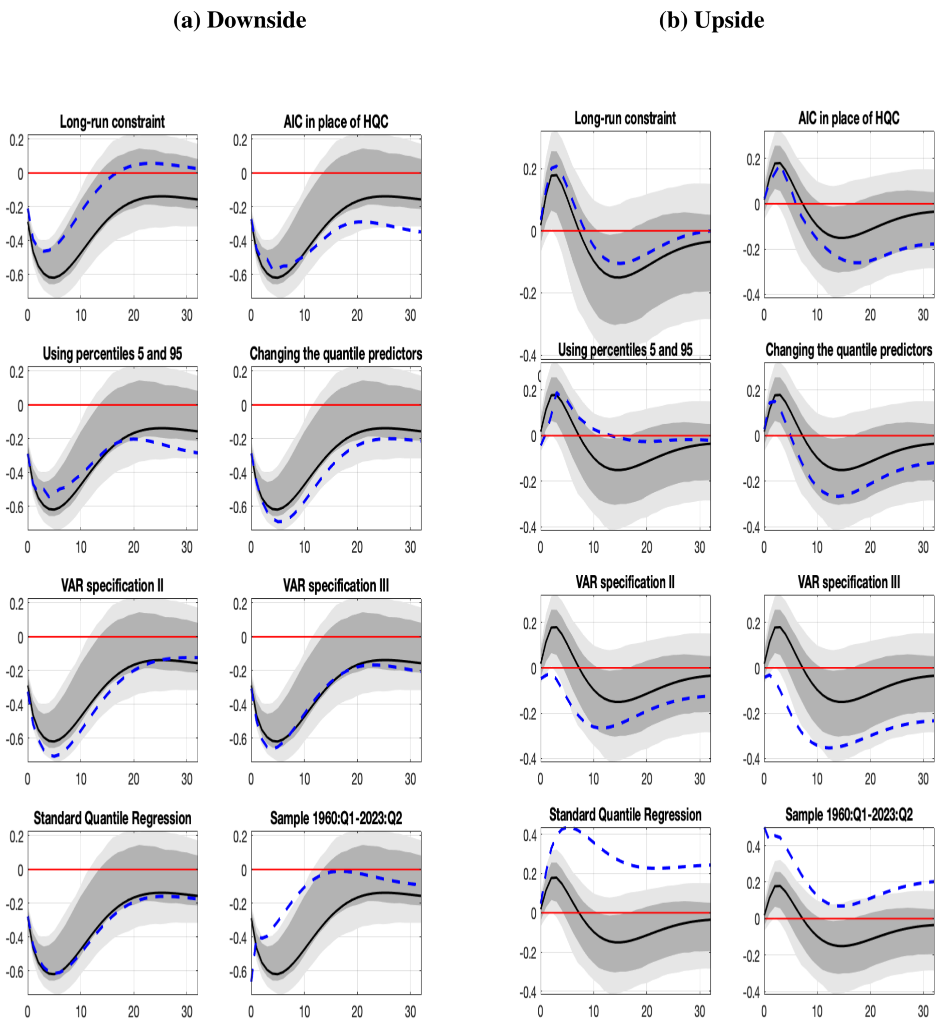


FIGURE 9. Robustness checks. Panel (a) impulse responses of GDP to a downside uncertainty shock. Panel (b) impulse responses of GDP to an upside uncertainty shock. Black solid lines: point estimates of the baseline model. Dark gray areas: 68% confidence bands. Light gray areas: 90% confidence bands. Dashed blue lines, alternative model.

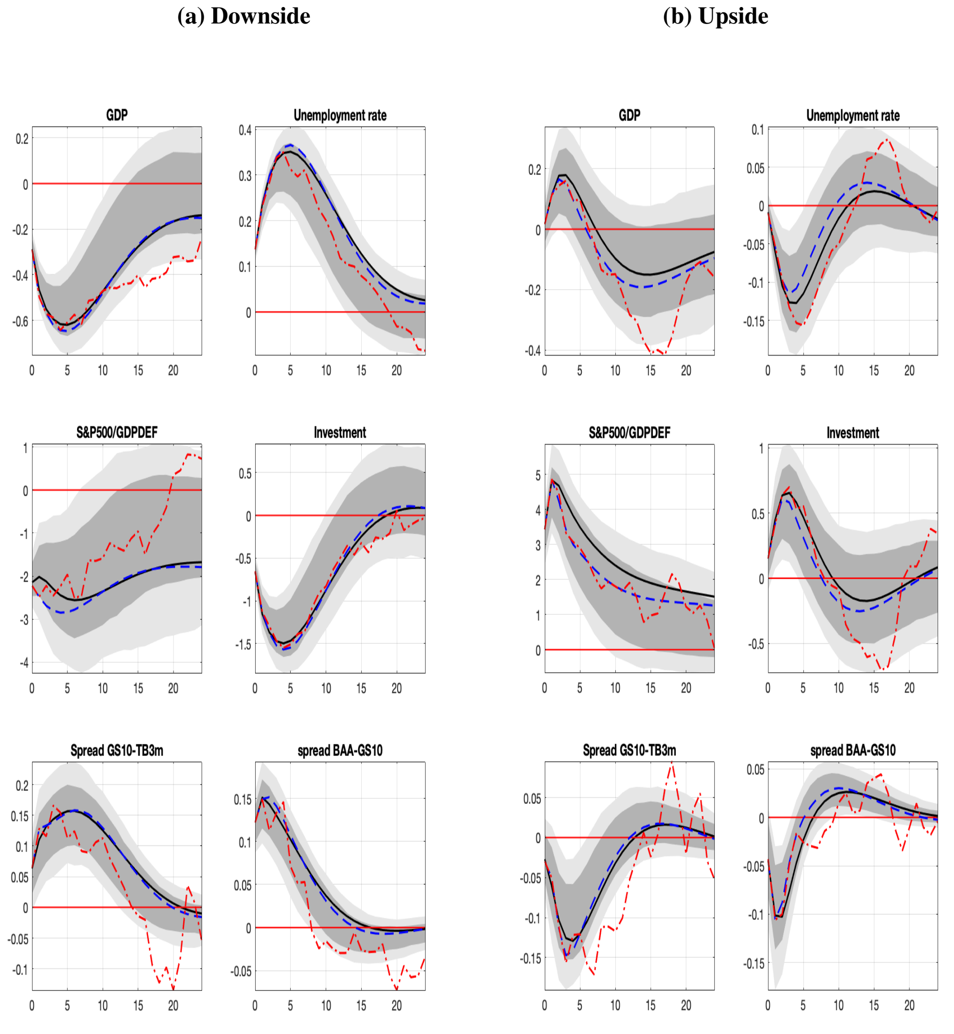


FIGURE 10. Robustness checks. Blue dashed lines: including the uncertainty measure in the VAR. Red dashed-dotted lines: local projections. Black solid lines: benchmark (Identification A). Gray areas: 68% and 90% confidence bands for the benchmark specification (Identification A). Panel (a): downside uncertainty shock. Panel (b): upside uncertainty shock.