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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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# Financial disruptions and heightened uncertainty: a case for timely policy action

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**Abstract**

We examine whether the response of the euro area economy to uncertainty shocks depends on the state of financial conditions. We find strong evidence that uncertainty shocks have much more powerful effects on key macroeconomic variables in episodes marked by financial distress than in normal times. We document that the recovery of economic activity is state-dependent following an adverse uncertainty shock. More precisely, it is gradual in normal times, but displays a more accelerated rebound when the shock hits during financial distress. These findings are based on a non-linear data-driven model that accounts for regime switching and time-varying volatility. Finally, from a policy perspective, we argue that whether financial markets are calm or distressed matters when it comes to the appropriate policy responses to uncertainty shocks.

**Keywords**: Uncertainty, financial regime asymmetries, non-linear VAR, time-varying volatility
**JEL codes**: C32, E32, E44, E52

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# I Introduction

The interaction between financial market disruptions and heightened economic uncertainty is frequently identified among the culprits of the Great Recession. At the current juncture, marked by elevated uncertainty with respect to the macroeconomic implications of the ongoing COVID-19 pandemic, we think that the link between the two has re-emerged at the forefront of policy and research debates. Therefore, we seek to contribute to this discussion and aim at answering the following question. *Does uncertainty affect the euro area economy differently in periods of normal versus distressed financial conditions?*

We find strong empirical evidence that uncertainty shocks have much more powerful effects on key macroeconomic variables in episodes marked by financial distress than in normal times, based on a non-linear data-driven model that accounts for regime switching and time-varying volatility. The latter feature allows us to estimate aggregate economic uncertainty as a common component of all the modelled structural shocks' volatilities. Our results show that the effects of a change in uncertainty also depend on the size of the shock. In tranquil episodes responses are essentially linear in the size of the shock, while in financial turmoil uncertainty perturbations give rise to amplification effects. We also document sign asymmetries in the case of large uncertainty shocks that hit during financial distress: an adverse perturbation leads to a larger decline in industrial production compared to mild positive effects following a decrease in uncertainty (of the same magnitude). We find that the recovery of economic activity is state-dependent after an adverse uncertainty shock. More precisely, it is gradual in normal times, but displays a more accelerated rebound when the shock hits during financial distress. Finally, from a policy perspective, whether financial markets are calm or distressed matters when it comes to the appropriate policy responses to uncertainty shocks.

Our motivation is based on the recent re-enforcement of financial distress and heightened uncertainty. Measures of uncertainty (such as equity market volatility) have increased sharply in countries around the world (i.e. the United States, the euro area, Japan), amid concerns about the economic impact of the pandemic. These fast-moving measures reacted swiftly to developments in the health sector, anticipating the declines in economic indicators that are released with a significant lag. Stock markets in major economies plummeted and witnessed a surge in implied volatility, reflecting a major repricing of risks posed by the broad-based spread of the coronavirus. With the spike in volatility, market liquidity has deteriorated significantly, and credit spreads have widened broadly across markets, as investors have started to reallocate from relatively risky to safer assets ("flight to safety"). As a result, emerging markets have experienced unprecedented capital outflows. Therefore, a sharp rise in uncertainty coupled with financial turmoil can put both economic growth and financial stability at risk. Our ultimate aim is to better understand this link and to assess how instrumental financial markets are to the transmission of uncertainty shocks.

Financial conditions have tightened markedly as the economic disruption caused by the pandemic outbreak intensified. This translates in higher funding costs for firms when they need to tap equity and bond markets to finance their working capital. A sharp tightening of financial conditions and heightened uncertainty can have powerful effects on economic activity, as companies delay investment projects and individuals postpone consumption due to precautionary motives or binding financial constraints. Nevertheless, major central banks acted quickly and in a coordinated manner by injecting liquidity and/or cutting policy interest rates. These measures aim at improving the overall market functioning, easing financial conditions and supporting the flow of credit to businesses and households.

There is widespread agreement in both academic and policy circles that uncertainty shocks have powerful recessionary effects, with financial frictions at the core of the propagation of the shocks to the real economy. The conjecture here is that when financial contracts are subject to agency or moral hazard problems, a rise in uncertainty increases the premium on external finance, leading to a surge in the cost of capital and a fall in firms' investment – in line with the financial accelerator mechanism proposed by Bernanke et al. (1999).

Against this background, we analyse the nexus between credit market disruptions and uncertainty for the euro area economy. To the best of our knowledge, there is no empirical evidence to document the macroeconomic implications of uncertainty shocks for the eurozone studied in the context of non-linearities. To explore the state-dependent link between financial conditions and uncertainty we employ a non-linear vector autoregressive (VAR) model. In this setting, uncertainty is captured by the overall volatility of the economy's structural shocks and impacts macroeconomic developments directly. We document that uncertainty has different macroeconomic implications depending on whether financial markets are clam or in distress when the shock hits the economy. Furthermore, it is essential to better understand how long it takes for the uncertainty shocks to fully dissipate and for the economy to recover (return to "normal"), depending on the prevailing financial stress level and size of the shock.

## 1.1 Related literature

In this subsection we briefly review some of the contributions to the ongoing assessment of the macroeconomic implications of uncertainty shocks in an environment characterised by financial frictions. The theoretical underpinning of why financial distortions should be incorporated in macroeconomic models stems from the feedback loop between credit constraints and the economic activity. More precisely, financial constraints may lead to amplification and persistence of (standard) shocks, which in turn shape and magnify the macroeconomic cycles. In conjunction with this, financial factors can influence the transmission mechanism of macroeconomic policies and economic shocks.

The global financial crisis (GFC) has ignited extensive discussions on the impact of macroeconomic shocks and how they shape the financial and business cycles. Considerations on the interactions between uncertainty and financial frictions have emerged at the forefront of the policy discussion. With the benefit of hindsight, broad-based and heightened uncertainty is seen by both researchers and policymakers as one of the main factors behind the depth and duration of the Great Recession. Frequently, the explanation is linked to two transmission channels. Risk premium, which is often invoked, as uncertainty typically leads to an increase in the cost of external financing. Concurrently, risk aversion is advocated to have also been at play because uncertainty undermines consumer and business confidence, which hold back spending and investment (due to precautionary motives). At the current juncture, the unfolding coronavirus pandemic appears to illustrate that financial markets are critical to the propagation of uncertainty shocks to the real economy.

Theoretical studies document that elevated uncertainty typically generates a decline in economic activity. A frequently cited channel that links uncertainty to the real economy relates to firms' investment and hiring irreversibility, following the lead of Bernanke (1983) and Bloom (2009). A more recent stream of research argues that financial frictions are at the core of the transmission mechanism of uncertainty shocks to the real economy. In other words, this view advocates that credit markets are the crucial link in the propagation of uncertainty shocks (for example, Christiano et al., 2014; Gilchrist et al., 2014, among others). The reasoning is the following: when financial contracts are subject to agency or moral hazard problems, a rise in uncertainty increases the external finance premium, leading to an increase in the cost of capital and a fall in firms' investment. More precisely, the impact on financing conditions and on market expectations prompted by increased uncertainty may lead to adjustments in asset prices (e.g. equities, high-yield bonds, commodities). This, in turn, has adverse implications for consumption and investment via wealth effects.

For instance, when equity prices fall, individuals might reduce their consumption to make-up for the loss in their net wealth. Furthermore, abrupt asset price moves can also impact the aggregate demand via the value of collateral, which typically allows borrowers to gain access to credit and receive funding. Finally, broad-based uncertainty might also prompt households to increase their precautionary savings.

On the empirical front, the VAR literature has largely abstracted from taking into account the interaction between uncertainty and financial conditions. Only in the aftermath of the GFC a few studies have been focusing on this link. For instance, Popescu and Smets (2010) analyse the interaction between perceived uncertainty[1] and financial risk premia for Germany. Their results point to a modest but temporary impact on economic activity following an exogenous uncertainty shock. However, they emphasise the identification issues arising in a VAR setting when simultaneously incorporating a credit spread measure and a proxy to capture aggregate uncertainty. Benati (2013) investigates the role of policy uncertainty shocks[2] in the United States, the euro area, the United Kingdom, and Canada using a Bayesian time-varying parameters structural VAR framework with stochastic volatility. The author finds that, depending on the identification strategy, these shocks have either a marginal or a non-negligible contribution in explaining macroeconomic fluctuations. Caldara et al. (2016) show that uncertainty shocks have important macroeconomics implications when operating through the financial channel, that is, when allowing financial conditions to respond to changes in uncertainty. Otherwise, these have a more muted effect. A first attempt to offer some empirical evidence on the global impact of COVID-19-induced uncertainty is provided by Caggiano et al. (2020). However, their empirical framework relies on VIX as a proxy for global financial uncertainty.

Our work is closely related to the novel approach proposed by Alessandri and Mumtaz (2019). They engineer a regime-switching structure in a VAR model where the structural shocks have time-varying volatilities, which influence the first-moment dynamics of the system (see Mumtaz and Surico, 2018; Mumtaz and Zanetti, 2013, for instance). Based on this non-linear VAR model, they document that in the USA, uncertainty shocks have recessionary effects at all times, but their impact on economic activity is significantly larger when the economy is experiencing financial turmoil.

The remainder of the paper proceeds as follows. In Section II, we describe the model used to conduct our empirical analysis. Then, in Section III, we present the quantitative exercises, which deliver our results. In Section IV we show how this framework can be used as a device to track the current state of financial markets in real time. Finally, Section V provides a set of robustness checks, and Section VI concludes.

# II The Model

In this section, we provide an overview of the empirical model that follows closely the approach proposed by Alessandri and Mumtaz (2019)[3]. To examine whether uncertainty affects the euro area economy differently in times of normal versus distressed financial conditions, we resort to estimating a VAR model, with two key non-linear features: regime switching and time-varying volatility. This modelling framework allows for the existence of two regimes characterized by arguably different dynamics. In this environment, the regime is determined by the level of financial distress (based on high-yield bond spreads[4]) relative to some unobserved

[1] They measure the perceived uncertainty about the performance of the German economy based on the disagreement in forecasts (of consumption, output, investment, industrial production, interest rates, and prices) responses from Consensus Economics.

[2] As uncertainty is not directly observable, the author uses the policy uncertainty index proposed by Baker et al. (2016) for each country.

[3] We gratefully acknowledge using as a starting point the programming codes available at one of the authors webpage.

[4] Represents the Option-Adjusted Spread of the ICE BofAML Euro High Yield Index which tracks the performance of Euro denominated below investment grade corporate debt publicly issued in the euro domestic or euro-bond markets.

threshold, endogenously determined as a by-product of the estimation procedure.

To estimate the baseline model, we use four variables for the euro area economy: monthly industrial production growth, monthly HICP inflation, the shadow rate proposed by Wu and Xia (2016) that accounts for the additional easing through unconventional policies and also for the possibly binding effective lower bound (ELB) on interest rates, and the high-yield bond spread to capture financial conditions. The data has a monthly frequency, covering the period between January 1998 and January 2020.[5] We employ Bayesian techniques to estimate the non-linear VAR model.

The uncertainty measure is treated as a latent state variable and inferred based on the joint volatility of the structural shocks within the model. Instead of plugging in observable proxies such as realized equity price volatility or an index of implied volatility, i.e. the EURO STOXX 50 Volatility Index (VSTOXX)[6], we opt for a model-based measure of uncertainty that is directly linked to agents' ability to form predictions on the future state of the economy. In essence, this econometric approach has the advantage of modelling the economy's first and second moments in a unified, internally consistent setting.

Through the lenses of this model, the intuition underlying the transmission mechanism of uncertainty shocks to the economy can be summarised as follows. An adverse volatility shock triggers an increase in the economy-wide uncertainty. This, in turn, leads to a worsening of agents' ability to formulate predictions on the future state of the economy. This heightened uncertainty translates into tighter financial conditions. Now, depending on whether the financial markets are distressed or calm, the agents respond accordingly, delaying investment projects and postponing consumption due to precautionary motives or binding financial constraints, via effects on wealth and/or on the value of collateral.

**Structure of the non-linear VAR model**

The modelling setting is based on a threshold VAR model with time-varying volatility. More precisely, the dynamics of the system are allowed to differ across two regimes, linked to periods of calm and distressed financial markets. In this environment, volatility effects are accounted for. In particular, uncertainty is captured by the volatility of the economy's structural shocks and impacts macroeconomic developments directly, as we explain below. The structure of the model is formalised as follows:

$$\begin{aligned} Y_t = &\left( c_1 + \sum_{p=1}^{P} \beta_{1p} Y_{t-p} + \sum_{p=0}^{L} \gamma_{1p} \ln \sigma_{t-p} + \Omega_{1t}^{1/2} e_t \right) I_t \\ &+ \left( c_2 + \sum_{p=1}^{P} \beta_{2p} Y_{t-p} + \sum_{p=0}^{L} \gamma_{2p} \ln \sigma_{t-p} + \Omega_{2t}^{1/2} e_t \right) (1 - I_t) \end{aligned} \tag{1}$$

where $Y_t = \{IP_t, HICP_t, IR_t, FC_t\}$ represents a set of four variables for the euro area: industrial production growth, HICP inflation, the policy (shadow) rate, and a proxy to capture financial conditions. The system is enriched with a measure of uncertainty, $\sigma_t$, treated as a latent state variable that stems directly from the volatility of the shocks that hit the economy (during the analysed period). Regarding the lagged terms, given the monthly frequency of the model, we impose $P = 13$ (a standard choice). We set $L = 3$, assuming that the uncertainty characterizing the previous quarter might impact the current state of

[5] The sources of the data are Eurostat and the FRED database. Appendix A provides a detailed description of the dataset.

[6] Volatility is implied by at-the-money options observed in the market. Since these reflect the amounts investors are willing to pay to protect themselves from the risk of price fluctuations, VSTOXX captures also financial market risk aversion. We report in Section V a robustness exercise that examines an alternative model augmented with VSTOXX to account for a wider information spectrum.

the economy.[7]

Regime switching is embedded in the model using an indicator function, $I_t$, that distinguishes between calm and financially distressed periods. In our benchmark application, the regime is determined based on the movements of the financial condition indicator (proxied by the high-yield bond spread) relative to a critical threshold $FC^*$: $I_t = 1$, if $FC_{t-d} \leq FC^*$, and $I_t = 0$, otherwise ($FC_{t-d} > FC^*$). Note that both the threshold and the delay ($d$ – number of lags) needed for the system to shift are parameters that must be estimated. Also, all parameters of the system $\{c_i,\ \beta_{ip},\ \gamma_{ip}, \Omega_i\}_{i=\overline{1,2}}$ vary across regimes. We can view these two sets of parameters as reflecting (in a reduced form) the dynamics of the economy during calm ($I_t = 1$) and financial distressed times ($I_t = 0$).

In this framework, the reduced-form innovations in equation (1) are assumed to be zero-mean normally distributed, with time-varying variance-covariance matrix, $\Omega_{it}$. Following established practice, this is factored as follows:

$$\Omega_{it} = A_i^{-1}\Sigma_t \left(A_i^{-1}\right)', \quad i = \overline{1,2}, \tag{2}$$

where $A_i$ is a lower triangular matrix. Turning to the uncertainty measure ($\sigma_t$), this is characterized by the following two equations:

$$\Sigma_t = \sigma_t S, \text{ where } S \equiv \operatorname{diag}(\sigma_1, \sigma_2, \sigma_3, \sigma_4) \tag{3}$$

$$\ln \sigma_t = \alpha + \rho \ln \sigma_{t-1} + \zeta_t \tag{4}$$

where $\zeta_t$ is an independent and identically distributed innovation with variance $\omega$. As equation (4) shows, the volatility is assumed to follow a first order autoregressive process – AR(1). At this point, an important remark is in order. Following Carriero et al. (2016) and Alessandri and Mumtaz (2019), we assume that the time variation of the variance-covariance matrix of the shocks is shaped by the economy-wide volatility process $\sigma_t$, estimated exploiting the volatility of all the level shocks considered in the system.

Next, we focus on describing the intuition behind the transmission mechanism of uncertainty shocks to the economy through the lenses of this data-driven model. An adverse uncertainty shock (that is, $\zeta_t > 0$) triggers an increase in the economy-wide uncertainty ($\sigma_t$). This in turn leads to an upward shift in the variance-covariance matrix of the shocks $e_t$. In essence, this translates into a worsening of the forecasting accuracy of the future states of the economy, $Y_{t+k}$ ($k > 0$). In addition, uncertainty impacts the dynamics of the economy directly through the volatility-in-mean mechanism ($\gamma_{ip}$, $i = \overline{1,2}$).

To estimate the model, we resort to Bayesian techniques. We follow closely the approach proposed by Alessandri and Mumtaz (2019). The Appendix of their paper provides an in-depth discussion of the Gibbs sampling algorithm employed to estimate the posterior distributions of all parameters. Here we focus primarily on the intuition and refrain from delving into all technical details. At this stage, two remarks are in order. First, note that given a draw of the volatility process, $\sigma_t$, the model reduces to a threshold VAR with a presumed form of heteroscedasticity. Secondly, following a generalised least square (GLS) transformation of the model, the conditional posterior distributions of the state-dependent parameters, the critical threshold and its associated delay mirror those obtained based on a standard threshold VAR.

The following steps help streamline the Markov Chain Monte Carlo (MCMC) algorithm, which is a sampling technique based on drawing from a given conditional probability distribution. As established by Chen and Lee (1995), the threshold parameter ($FC^*$) can be drawn from its non-standard posterior relying on a random walk Metropolis step and the conditional posterior of the delay parameter follows a

[7] We show in Section V that our findings are robust to this timing assumption.

Multinomial distribution. Next, with the estimated values for the threshold and delay parameters, the dataset can be divided into observations that are regime-specific. Now, given a draw for $\sigma_t$, the left- and the right-hand side variables of the VAR can be transformed to remove heteroscedasticity. Then, the conditional posterior distribution for the autoregressive coefficients in each regime is standard, sampled from the normal distribution. After the regime-specific residuals are obtained, given a draw for the VAR parameters, the threshold, and a value for $\sigma_t$, the conditional posterior distribution for matrix $A_i$ is standard (after a GLS transformation to make the errors homoscedastic). At this point, conditional on all the parameters, the residuals of the model can be pinned down and their variances, $S$, sampled from an inverse Gamma distribution. Equipped with the values of all the parameters, the model can be casted into a non-linear state-space representation. Recall that the volatility process is treated as a latent variable. Therefore, its values are inferred via the independent Metropolis algorithm designed for time-varying volatility models, as proposed by Jacquier et al. (2002). Lastly, the coefficients governing the transition equation (4) must be estimated. As this is a linear regression, the normal and inverse Gamma conditional posteriors apply.

After the estimation of the posterior distributions of all parameters, we proceed to construct the history dependent impulse response functions (generalised IRF)[8]. They account for the fact that the variables' responses can determine the system to change the regime after a shock. The impulse-responses are computed as the difference between two conditional expectations based on simulating the model under a shock scenario and a no change alternative, where there is no perturbation that hits the system. In essence, for a given financial regime, $I_t = \{0,\ 1\}$, and a regime-specific history $\left(Y_{t-1}^I\right)$, the responses are computed as:

$$IRF_t^I = E\left(Y_{t+h}|\Theta, \sigma_t, Y_{t-1}^I, \zeta \neq 0\right) - E\left(Y_{t+h}|\Theta, \sigma_t, Y_{t-1}^I, \zeta = 0\right),$$

where $\Theta = \{c_i, \beta_{ip}, \gamma_{ip}, A_i, S, \omega, FC^*, d, \alpha, \rho\}_{i=\overline{1,2}}$ represents all the parameters of the VAR model, $h$ denotes the number of periods ahead (in our case, this is 36 months) we want to generate the responses and $\zeta$ is the uncertainty shock imposed in the first period of the simulation interval. As emphasised above, the regime-switching is treated as endogenous. Note that the impulse responses depend on the history of the system before the realisation of the shock, $Y_{t-1}^I$. In other words, during the simulation horizon the economy may transition from normal to distressed dynamics or the other way around, conditional on the size and sign of the shock. This is particularly relevant, as the dynamics of the economy might be different depending on the prevailing level of financial stress relative to its critical threshold, i.e. close to or far below, even though both cases are assigned to normal times.

# III Quantitative Analysis

In this section, we deliver our main results that can be summarised as follows. The quantitative analysis that we conduct provides strong empirical evidence that uncertainty shocks (of the same size) have much more powerful effects on key macroeconomic variables in periods experiencing financial distress than in normal times. We show that the effects of a change in uncertainty also depend on the size of the shock. In tranquil episodes responses are essentially linear in the size of the shock, while in financial turmoil uncertainty perturbations give rise to amplification effects. Moreover, we also document sign asymmetries in the case of large uncertainty shocks that hit during financial distress. In particular, an adverse perturbation leads to a larger decline in industrial production compared to milder positive effects following a decrease in uncertainty (of the same magnitude). Our findings suggest that following an uncertainty shock, the recovery of the key macroeconomic variables is state-dependent: it is gradual in normal times as compared to a more

[8] These are obtained following the methodology proposed by Koop et al. (1996); it takes into account that the effect of a shock depends on the joint influences of history and of the perturbation itself.

accelerated rebound when the shock hits during financial distress. We conclude this section by quantifying the role of uncertainty shocks in explaining the dynamics of endogenous variables. We resort to a forecast error variance decomposition and show that they emerge as a major driver of financial conditions in both regimes. Furthermore, uncertainty proves to be more important for output fluctuations during financial distressed episodes. Finally, we are also interested to pin down the contribution of uncertainty shocks to macroeconomic dynamics from a historical perspective. To this end, a counterfactual exercise reveals that uncertainty shocks account for about: (i) 1.7 and 0.5 percentage points of the largest drop in industrial production during the GFC and the sovereign debt crisis, respectively; (ii) 0.3 percentage points of the missing inflation at the peak of the GFC; (iii) 14.5 percentage points of the tighter financial conditions at the height of the financial turmoil.

## 3.1 Gauging economic uncertainty and its macroeconomic implications

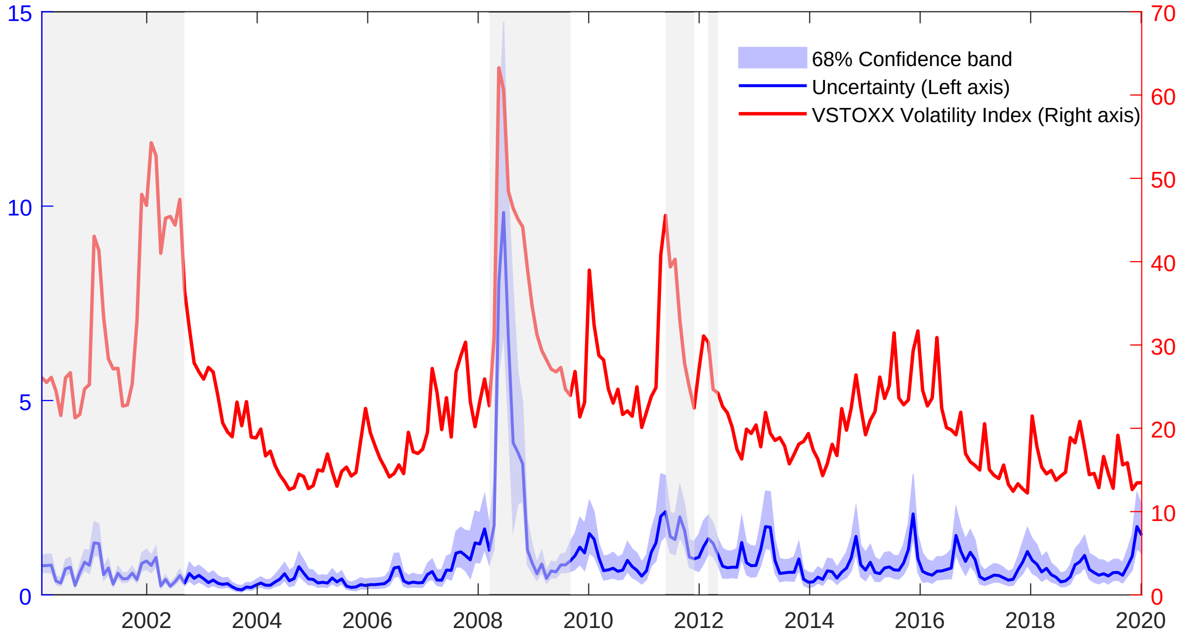
In this subsection we report our model-based measure of economic uncertainty, the identified timeline of financial distressed episodes, and conclude with the macroeconomic implications following uncertainty shocks. In sum, the main message is that uncertainty has different macroeconomic implications depending on whether financial markets are clam or under stress when the shocks hit the economy.

Figure 1 reveals a high correlation (approximately 60%) between the model-based measure of economic uncertainty and a widely used proxy – VSTOXX volatility index. Note that our uncertainty measure is directly linked to agents' ability to form predictions on the future state of the economy, while the implied volatility index derived from option prices[9] captures financial market risk aversion. The graph also reports the financial regimes identified according to our framework. The episodes when the euro area's financial markets are assessed to be in distress, defined as a state where the high-yield bond spread exceeds the critical threshold, are the following: (i) October 2000 – April 2003, (ii) August 2008 – January 2010, (iii) September 2011 – March 2012 and (iv) June – August 2012. The first period marks the adverse spill-overs from the dot-com bubble and the 9/11 terrorist attack. The second interval coincides with the GFC and its aftermath, while the last two episodes reflect the turmoil due to the European sovereign debt crisis. Historically, high uncertainty overlaps with episodes characterised by lower growth and tighter financial conditions. Note the sharp increase witnessed by the uncertainty measure at the end of our sample, which gives credit to the ability of the model to timely distil the volatility effects of the ongoing COVID-19 pandemic.

Figure 2 shows the impulse response functions for both small and large uncertainty shocks (defined as one and five standard deviations) in normal and distressed times, respectively. The reasoning underlying our choice of a five standard deviations is supported by Caggiano et al. (2020). The authors propose a calibration of the COVID-19-induced uncertainty shock of a similar order of magnitude based on VIX values[10]. This figure helps clarify our main findings. Irrespective of the financial regime, a rise in uncertainty triggers recessionary effects. Allowing credit conditions to respond to changes in uncertainty proves critical in order for these shocks to affect economic activity. Following a volatility shock the financial conditions tighten and the model implies that the monetary authority should cut interest rates in order to stabilise the economy. The response of industrial production differs in magnitude across financial regimes. The cumulative 12-month response to a one standard deviation uncertainty shock is estimated at -0.29% in normal times and at near -0.9% during financial turmoil; the results in response to a large shock suggest a 1.53% decline in calm periods versus 5.0% during financial distress. These results show that the effects of a change in

[9] Entail the amounts investors are willing to pay to hedge themselves from the risk of price fluctuations.
[10] They attribute 90% of the observed increase in the VIX (between its peak in mid-March 2020 and its value precisely one month earlier, on February 16) to the COVID-19 outbreak. This delivers a scaling factor of about 5.

Figure 1: Financial regimes and economic uncertainty – model-based versus VSTOXX volatility index




Note: The blue line is uncertainty measured as the average volatility of the structural shocks in the euro area economy according to the threshold VAR model (median estimate and 68% confidence band). The red line represents the implied volatility based on EURO STOXX 50 Volatility Index (VSTOXX). The correlation between the two indicators is near 60%. The shaded areas represent the periods when the euro area economy is estimated to be in financial distress.

uncertainty also depend on the size of the shock. In tranquil episodes responses are essentially linear in the size of the shock, while in financial turmoil uncertainty perturbations give rise to amplification effects.

The response of inflation changes significantly across regimes – prices increase in normal times (except on impact), while they decline during financial distress.[11] These different dynamics can be rationalised as follows. When financial markets are calm, uncertainty on the economic outlook and future marginal costs introduces a precautionary upward bias in firms' pricing decisions. Notwithstanding, when financial markets are in distress, aggregate demand is more sensitive to uncertainty because of binding borrowing constraints (via wealth and balance sheet effects) and firms adjust their mark-ups accordingly.

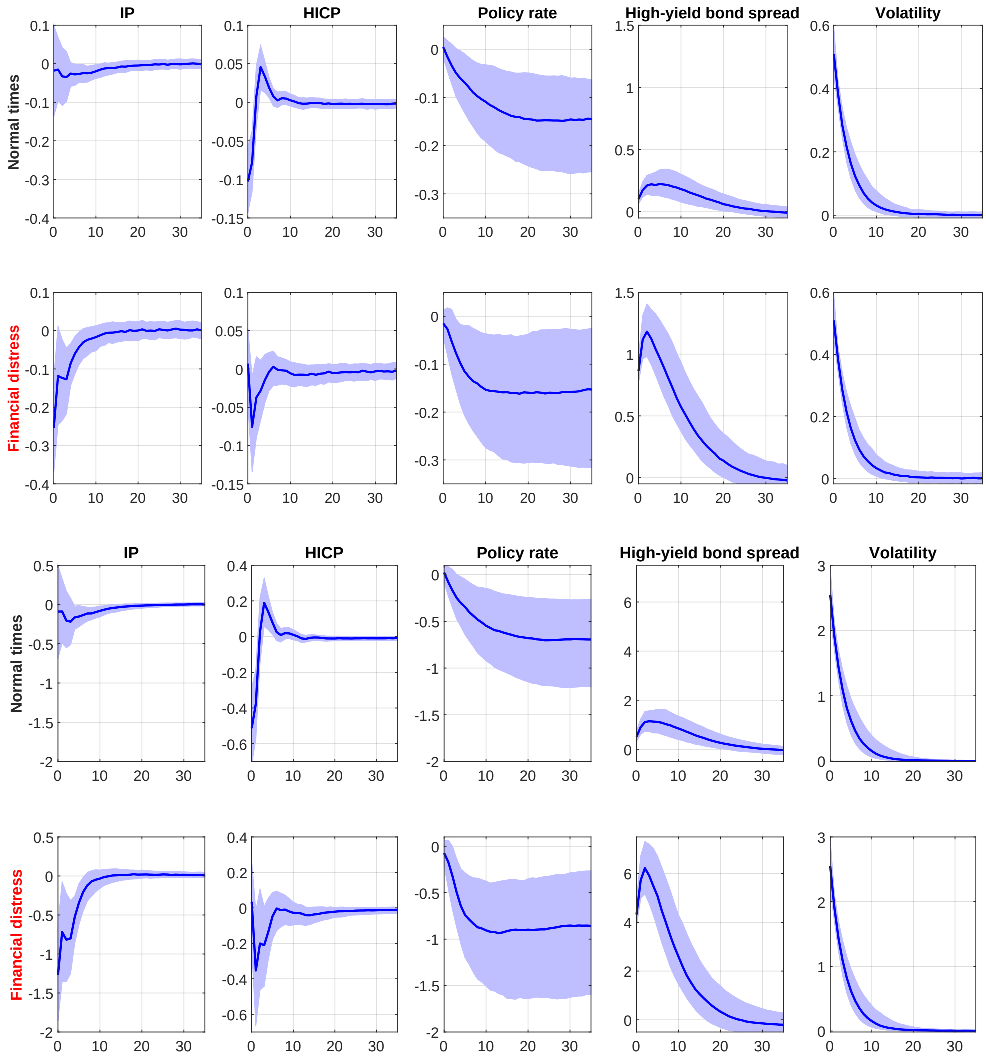
Finally, our findings suggest that the recovery of the key macroeconomic variables is state-dependent following an uncertainty shock. More precisely, it is gradual in normal times, but displays a more accelerated rebound when the shock hits during financial distress. This behaviour reflects the dynamics of financial conditions. In normal times the normalisation of credit spreads is more protracted.

### 3.2 Asymmetric effects of uncertainty shocks

Here we further elaborate the discussion regarding asymmetric effects of uncertainty shocks mentioned above. Figure 3 helps demonstrate that there are size and sign asymmetries in the response of industrial production following uncertainty shocks. We report the cumulative responses to small versus large shocks and positive versus negative shocks, while distinguish between normal and financial distressed episodes.

[11] The literature provides mixed evidence on the relation between uncertainty and inflation. Uncertainty shocks can be deflationary, when they act as aggregate demand shocks (e.g. Christiano et al., 2014). Or, they can be inflationary, when uncertainty on future demand and marginal costs shapes firms' pricing decisions (e.g. Fernández-Villaverde et al., 2015). Which mechanism prevails is ambiguous a priori.

Figure 2: Impact of a small/large (one/five standard deviation) adverse uncertainty shock in normal and distressed times

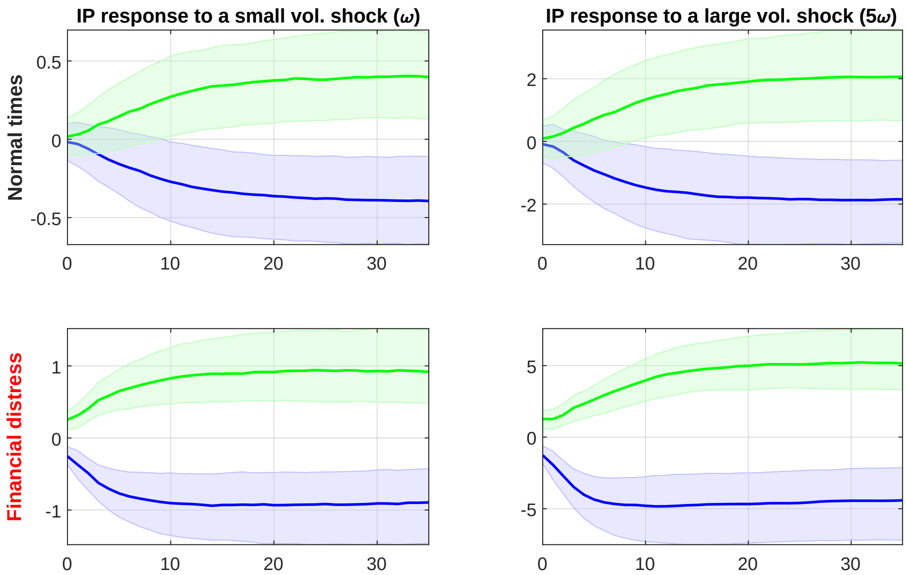



Note: In the upper panel (first two rows), the blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distress (i.e. the high-yield bond spread exceeds an endogenously determined critical threshold). In the bottom panel (last two rows), the blue line shows the impact of a five standard deviation uncertainty shock. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), the policy rate, a proxy for financial conditions and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months. The estimation period is January 1998 – January 2020.

This exercise shows that in calm periods the responses are essentially linear in the size of the shock (first row). In contrast, during financial turmoil uncertainty perturbations give rise to amplification effects (second row). Furthermore, when the economy is experiencing financial distress, large volatility shocks give rise to sign asymmetries. More specifically, an increase in uncertainty leads to a larger fluctuation in industrial production in the short run compared to a protracted response of output after a drop in uncertainty of equal magnitude (lower-right chart).

This asymmetry is the result of two factors: (i) the strong impact that volatility has on credit conditions and (ii) the state-dependent nature of the linkage between financial markets and the real economy. The intuition can be summarised as follows. During financial distress, an escalation in volatility retains the economy in a state where financial conditions are tight; this, in turn, generates feedback effects. On the other hand, a fall in volatility leads to an easing of financial conditions that can trigger a regime switching back into normal times, where borrowing constraints bind less and amplification effects are partly mitigated.

Figure 3: Size and sign asymmetries of uncertainty shocks – an illustration for industrial production (IP)




Note: The first/second column shows the cumulative response of IP to a small/large uncertainty shock, differentiating between normal and distressed financial episodes. The blue and green shaded areas represent the 68% confidence bands associated to increases and drops in uncertainty, respectively. The horizontal axis is time, measured in months.

### 3.3 Role of uncertainty shocks

To assess whether uncertainty is a major source of business cycle fluctuations, we follow the literature and conduct a forecast error variance (FEV) decomposition exercise. Table 1 and Figure 4 reveal the contribution of uncertainty perturbations to the forecast error variances of all variables included in the model. We document that these shocks are a major driver of financial conditions in both regimes.

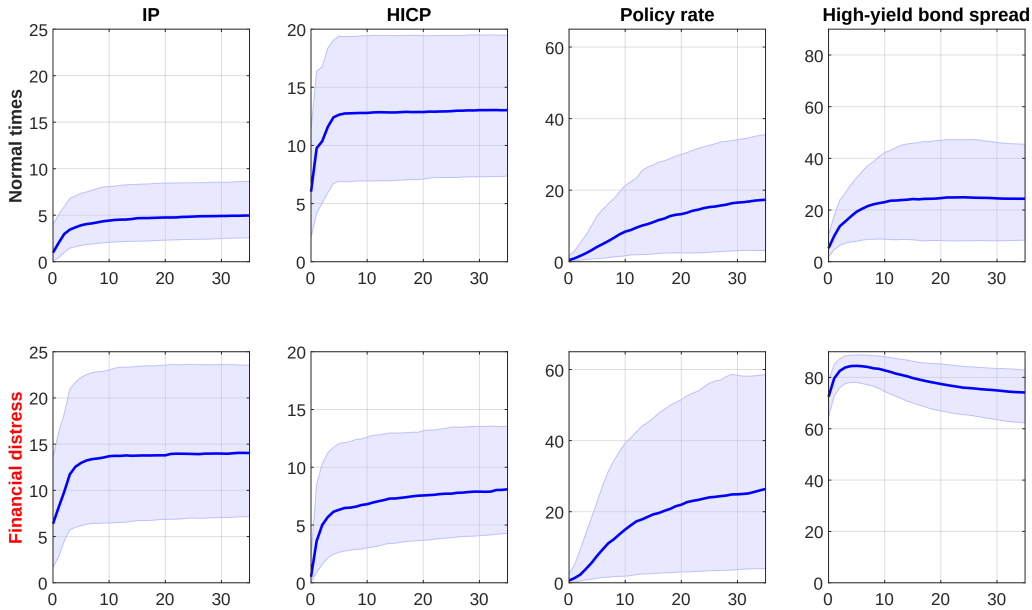
For industrial production (which is our proxy for output), we find that uncertainty is more important in financial distressed episodes. For instance, the proportion of industrial production variance accounted for by uncertainty shocks is three-fold higher when the economy is experiencing financial distress, approximately 14% versus 4.5%. These results are in line with other findings obtained for the US economy, see Alessandri and Mumtaz (2019) or Caldara et al. (2016) among others. Nevertheless, our results suggest that for inflation the opposite appears to be supported by the data. In particular, in normal times uncertainty shocks explain about 13% of inflation's variance, while only 7-8% during financial distressed episodes. This result could be partly explained by the fact that in normal times the monetary authority is more focused on stabilising inflation and achieving its target, while during financial turmoil it might pay more attention to economic activity.

Table 1: Role of uncertainty shocks based on a FEV decomposition

| Variable | IP | HICP | Policy rate | High-yield bond spread |
|---|---|---|---|---|
| 12-months-ahead forecast error variance decomposition | | | | |
| Normal times | 4.5 | 12.8 | 8.9 | 23.6 |
| Financial distress | 13.7 | 6.9 | 16.2 | 82.2 |
| 24-months-ahead forecast error variance decomposition | | | | |
| Normal times | 4.8 | 12.9 | 14.5 | 24.9 |
| Financial distress | 14.0 | 7.7 | 23.3 | 76.4 |

Note: Each row shows the fraction of forecast error variance explained by uncertainty shocks for all variables included in the model, conditioning on whether financial markets are assessed to be clam or in distress. The table reports the results for 12- and 24-months-ahead forecast error variance.

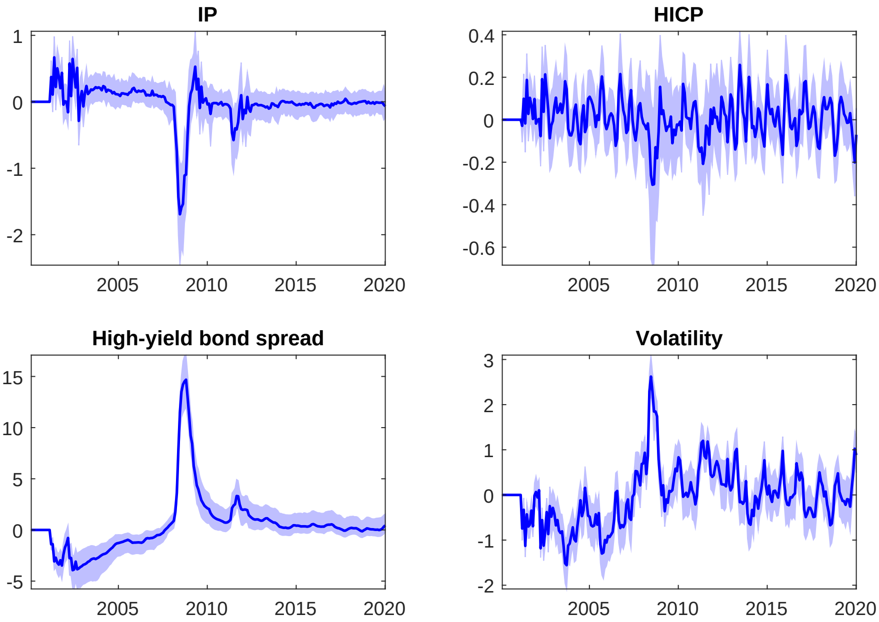
Figure 4: Role of uncertainty shocks through the lenses of a FEV decomposition exercise




Note: Each panel shows the share of forecast error variance explained by uncertainty shocks for each of the variables included in the model. The first row reports the results obtained for normal times and the second row corresponds to financial distress. The figure reports the median response and a 68% confidence band. The horizontal axis is the forecast horizon measured in months.

From a narrative perspective, we are interested to quantify the role of uncertainty shocks for macroeconomic dynamics over time. To this end, we conduct the following counterfactual analysis. Using an alternative version of our benchmark model, with the embedded working assumption of no uncertainty shocks, we generate the corresponding model-implied time series for each endogenous variable. Figure 5 shows the difference between actual and alternative model-simulated data, pinning down the role of uncertainty shocks. The charts capture the loss of fit caused by the counterfactual assumption that volatility remained constant instead of varying over time. Through the lenses of this exercise, the key takeaway from the figure is that uncertainty shocks account for about: (i) 1.7 and 0.5 percentage points of the largest drop in industrial production during the GFC and the sovereign debt crisis, respectively; (ii) 0.3 percentage

Figure 5: Counterfactual exercise to infer the historical contribution of uncertainty shocks




Note: The figure reports the difference between actual data and model simulated time series under the assumption of no uncertainty shocks. More precisely, the blue lines and the corresponding 68% confidence bands are based on the benchmark threshold VAR model, but with constant volatility.

points of the missing inflation at the peak of the Great Recession; (iii) 14.5 percentage points of the tighter financial conditions at the height of the financial turmoil.

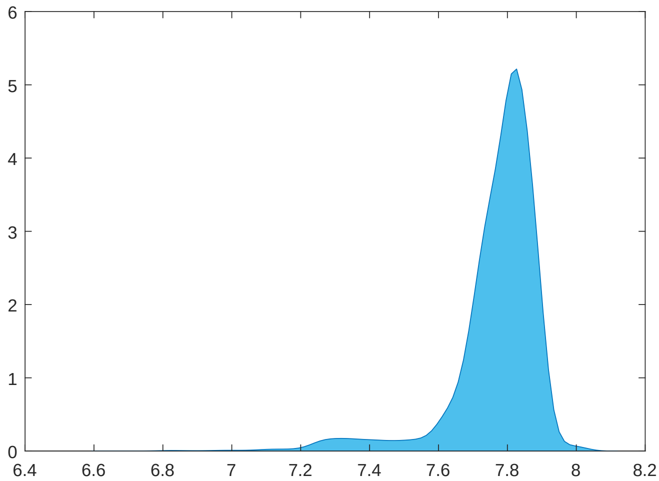
# IV Tracking the current state of financial markets in real time

Given that we estimate the model using Bayesian techniques, we obtain the posterior distribution of the critical threshold. In our framework, this is a key parameter as it is used to evaluate whether the financial markets are calm or in distress, defined as a state where the high-yield bond spread is below or exceeds the threshold, respectively. We first describe the moments characterizing the threshold's estimated distribution and afterwards we show how we can use these values to gauge the current state of financial markets in real time. More specifically, closely monitoring real time movements in our proxy for financial conditions, the high-yield bond spread, and mapping those into the posterior distribution of the critical threshold offers a metric to trace the transition between financial regimes.

## 4.1 Threshold's posterior distribution

Figure 6 reports the estimated posterior distribution of the threshold parameter. It shows that most of its values are clustered between 7.7% and 7.9% (approximately 68% of the distribution's mass lies within this range). The median of the posterior distribution is 7.8% and its standard deviation is around 0.13%. These values are highly instructive. They could be used as a device to trace in real time whether financial markets are calm, heading towards a distressed episode, in turmoil or transitioning back to normal times. This is of particular importance in the context of economic data (like inflation rate, industrial production, unemployment rate) being of lower frequencies and released with significant lag, while financial market data being available at a daily frequency.

Figure 6: Threshold's posterior distribution




Note: The figure reports the posterior distribution for the endogenously determined critical threshold estimated based on our model. The horizontal axis represents its estimated values (expressed in %) across simulations; we run 500000 Gibbs simulations and retain the last 10% draws.

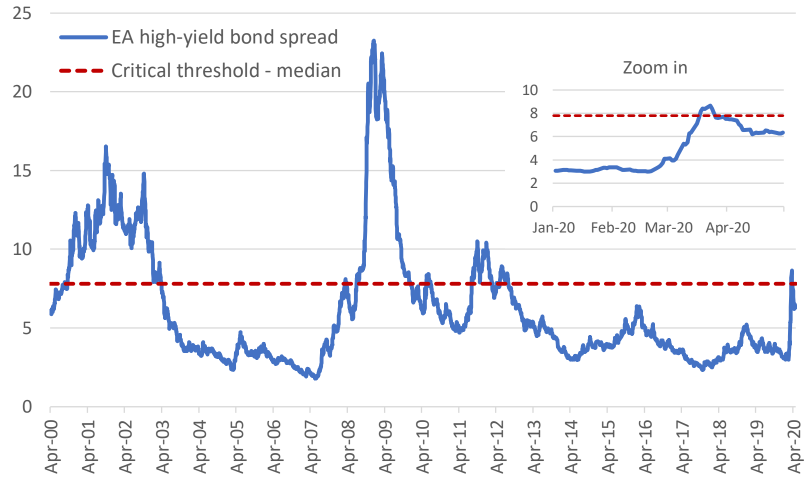
Therefore, we propose to monitor the high-yield bond spread real-time readings and compare them with the median value of the threshold's posterior distribution, that is 7.8% (this procedure can be interpreted as an out-of-sample forecast). For instance, the early March 2020 readings of the euro area high-yield bond spread – that was available in real time, as opposed to industrial production and consumer inflation data, for which the latest observation was January 2020 (at the moment of our estimations) – signal that we might transition towards a financial distressed episode (see Figure 7). Then, the late March values already place euro area in financial turmoil. As a result of the recent targeted set of measures deployed by the ECB aimed primarily at improving overall market functioning and easing financing conditions, the mid-April high-yield bond spread readings have stabilised close but below our 7.8% estimated threshold.

# V Robustness checks

In this section we conduct a sensitivity analysis to prove that our results are robust when changing some of the key elements of our modelling framework. First, as we acknowledge that the recursive identification of the structural shocks can influence our findings, we consider alternative orderings of the variables. Then, we expand the information set included in the VAR model. Next, we stress-test our findings against alternative measures to capture financial conditions and economic activity, respectively. Subsequently, we focus on the assumptions related to the volatility-in-mean mechanism. We first test if this feature improves the empirical fit of our baseline specification and then examine whether the timing assumption of how uncertainty affects the system's dynamics matters for the impulse-response analysis. We also explore an alternative smooth-transition VAR model[12]. In essence, it accounts for the possibility that the transitions across financial regimes are smooth, in contrast to our benchmark assumption that implies sudden regime changes. In a nutshell, these exercises help demonstrate that our findings are to a large extent robust when varying some of the key ingredients of our empirical setting. Finally, we provide evidence that our main findings emerge also in an environment that distinguishes across states that are associated with economic expansion and downturn episodes.[13]

[12] This framework nests our baseline threshold specification.
[13] Appendix B provides all the figures that support and help clarify this sensitivity analysis.

Figure 7: Tracking the current state of financial markets in real time




Source: FRED database (last observation 30th of April), own estimations.

**Different orderings of variables.** Because the recursive identification of the structural shocks (implicit in the factorization of the matrices $A_i$) can influence our results, via the estimation of the average volatility process $\sigma_t$, we consider alternative orderings of the variables included in our analysis. These sensitivity checks suggest that the correlation of the (model-based) uncertainty measures is relatively high and the impulse responses remain qualitatively similar to the baseline, particularly in terms of asymmetries across financial regimes (see Figure 8 in Appendix B).

**Extending the VAR dataset.** Since VSTOXX is often used as a proxy for uncertainty, we also consider a VAR model that includes it. Allowing financing conditions to respond to fluctuations in aggregate uncertainty appears critical in order for these shocks to affect economic activity. Therefore, we check whether our results change when embedding a measure of implied volatility as an observable variable in the model. We conclude that the impulse-responses are broadly in line with our baseline results (see Figure 9 in Appendix B). Also, the model-based uncertainty measures are highly correlated. Next, we also study an open-economy version of our baseline. To this end, we include the nominal effective exchange rate (NEER)[14]. Our findings point to an exchange rate depreciation following an increase in uncertainty, while the other impulse responses are qualitatively similar to our baseline results (see Figure 10 in Appendix B).

**Alternative measures to capture financial conditions.** The indicator that summarizes in an aggregate way the cost of credit is critical in our framework. Therefore, we are interested to examine whether our findings are sensitive to alternative measures of credit spreads. Taking into account also the data availability, we explore two alternative proxies: (i) the Option-Adjusted Spread (OAS) of the ICE BofA Euro Corporate Index, which tracks the performance of Euro denominated corporate debt (publicly issued in the euro domestic or euro-bond markets), and (ii) the OAS of the ICE BofA BBB Euro Corporate Index.[15] Our findings can be summarized as follows. First, the aggregate uncertainty measures, obtained based on these alternative proxies for financing conditions, exhibit a very high correlation with our baseline estimate: 86% and 91%, respectively (see Figure 11 in Appendix B). Second, the impulse responses in both cases reveal similar findings as in our baseline setting (see Figure 12 in Appendix B). As emphasised before, we can use

[14] It represents an useful aggregate measure of the exchange rate fluctuations relative to the currencies of the euro area's principal trading partners. We consider a broad set of 38 trading partners. The ordering of the VAR variables is the following: industrial production, inflation, NEER, policy rate, financial conditions.

[15] These credit spreads proxies are highly correlated with our baseline measure: 62% and 78%, respectively.

this framework to track the current state of financial markets in real time. To illustrate this point, Figure 13 (in Appendix B) reports the real-time readings of these alternative bond spread measures and compares them with their corresponding median values of the threshold's posterior distribution (these are 1.5% and 2.1%, respectively). According to the results, as of end-April, the mapping for both alternative financial conditions suggests that the euro area is in financial distress. Notwithstanding, the end-April readings of the high-yield bond spread (our baseline proxy for financial conditions) are close, but below the critical threshold.

**Alternative proxies for economic activity.** Since industrial production captures the manufacturing sector and abstracts from services, we also explore alternative measures for monthly output. We opt for a monthly frequency of the data because of three reasons: (i) a rather short sample for the euro area, (ii) the nature of this threshold VAR approach, that ultimately splits the sample between normal and distressed episodes in the estimation process, and (iii) the need to obtain estimates that are relevant in a timely manner. Using quarterly data is not a viable option, as it will result in very few observations for the financial distressed regime, rendering the results very uncertain and unreliable. Therefore, we need to use indicators that capture economic activity, but at a monthly frequency. We repeat our analysis using the economic sentiment indicator (ESI) as an alternative signal to capture monthly activity. This exercise delivers (i) an aggregate economic uncertainty measure highly correlated with our baseline estimate (i.e. 93%) and (ii) qualitatively similar impulse responses following adverse uncertainty shocks, with the already established asymmetries across financial regimes (see Figure 14 in Appendix B).

**Volatility-in-mean effects.** First, we estimate an alternative model assuming no direct impact of uncertainty on the endogenous variables included in our system: that is, setting $\gamma_{ip} = 0$ in equation (1). Our goal is to test whether the volatility-in-mean feature improves the empirical fit of our baseline model. Therefore, we conduct a model comparison using the Deviance Information Criterion (DIC) proposed by Spiegelhalter et al. (2002). This metric is computed based on the mean likelihood of the model amended for its complexity (i.e. the number of estimated parameters). Our results reveal that the benchmark model, that allows for uncertainty effects, is preferred by the data.[16]

Next, we examine whether the timing assumption of how uncertainty affects the system matters for the impulse-response analysis. Our baseline assumes that the uncertainty characterizing the previous quarter might impact the current state of the economy. Here we amend this conjecture by allowing only the prevailing uncertainty from the previous month to affect macroeconomic developments, i.e. setting $L = 1$ in equation (1). This exercise confirms that our results are robust to this timing assumption (see Figure 15 in Appendix B). Then, we conduct a more extreme inquiry: we assume that uncertainty affects the dynamics of the economy only contemporaneously (i.e. setting $L = 0$ in equation (1)). Our main findings survive this scenario as well (see Figure 16 in Appendix B). Nonetheless, we emphasise that when the volatility-in-mean channel is muted, uncertainty shocks appear to act as aggregate demand shocks, irrespective of the financial regime. Yet, the inflation response is not statistically significant. Regarding the estimated overall uncertainty measures, these are highly correlated (above 95%) with our baseline estimate.

**A smooth transition across regimes.** Our benchmark specification assumes that a threshold determines the transitions across states. Therefore, the implied regime changes are discrete by construction. Note however that this feature seems to be broadly consistent with the onset of financial distressed episodes in our sample.[17] To account for the possibility that the transitions are smooth, we also estimate an alternative

[16] The DIC is worsening when the direct uncertainty channel is removed: it is evaluated at -175.56 as compared to -410.84 in the benchmark case.

[17] This claim is also corroborated by our estimate for the delay parameter ($d$ – number of lags needed for the system to shift): the median of the posterior distribution is around one month, reflecting a sudden regime change.

version of the model that uses a logistic function to describe regime changes. This process is defined as follows:

$$I_t = 1 - \left[1 + \exp\left(-\gamma\left(FC_{t-d} - FC^*\right)\right)\right]^{-1},$$

where $\gamma > 0$ determines the smoothness of the transition function; as $\gamma \to \infty$ the specification collapses to the threshold VAR. The regime estimates delivered by this smooth-transition VAR model are in fact quite similar to those obtained in the benchmark case and the transitions across regimes appear to be quite abrupt (see Figure 18 in Appendix B), which confirms that a threshold specification represents a fair description of the data. The impulse response analysis suggests qualitatively similar findings (see Figure 19 in Appendix B), but the estimation precision is worsening (stemming from the increased complexity of this model).

**Regime switching across expansion and downturn.** Finally, we conclude this section by considering a somewhat related, but still different, perspective in terms of regimes. In essence, next we show that our main findings also survive in a setting that differentiates across states that are associated with economic expansion and downturn episodes. We conduct this analysis by substituting our state variable that captures financial conditions with a measure that is linked to economic activity. For this we use the composite output Purchasing Managers Survey – PMI[18] (which is the weighted average of the manufacturing output index and the services business activity index). Interestingly, this exercise delivers an aggregate economic uncertainty that is still highly correlated with our baseline measure: 87%. Lastly, the impulse-response analysis reveals that our benchmark results are also validated when accounting for regime changes linked to the current state of economic activity (see Figure 21 in Appendix B).

# VI Conclusion

There is broad consensus that elevated uncertainty has powerful recessionary effects, with financial frictions at the core of the transmission mechanism to the real economy. In this paper we study the interplay between credit market disruptions and heightened uncertainty, focusing on the euro area economy. Our motivation is underpinned by the current environment which is marked by substantial uncertainty with respect to the macroeconomic implications of the unfolding COVID-19 pandemic. The economic lockdown in an effort to contain the virus led to unforeseen disruptions in several segments of the financial market.

We aim to answer the following question. *Does uncertainty affect the euro area economy differently in periods of normal versus distressed financial conditions?* We employ a non-linear data-driven model to study the state-dependent link between financial conditions and uncertainty – captured by the overall estimated volatility of the economy's structural shocks and directly impacting macroeconomic developments. In this setting, an adverse volatility shock triggers an increase in the economy-wide uncertainty. This, in turn, affects agents' ability to assess the most likely future path of the economy. This increased uncertainty translates into tighter financial conditions, which typically impairs the flow of credit to businesses and consumers. Conditional on whether the financial markets are distressed or calm, the agents respond accordingly, delaying investment projects and postponing consumption due to precautionary motives or binding financial constraints (via wealth effects and/or the value of collateral).

We find strong empirical evidence that uncertainty shocks have much more powerful effects on key macroeconomic variables in episodes marked by financial distress than in normal times. We also document sign asymmetries when large uncertainty shocks hit during financial distress: an adverse perturbation prompts a

[18] This is a seasonally adjusted diffusion index. Values above 50 are typically associated with an expansion of economic activity. Our framework reveals a median estimate of 50.8 for the critical threshold that determines the transition across states.

larger decline in industrial production compared to milder positive effects after a decrease in uncertainty (of the same magnitude). Following an adverse uncertainty shock, our results reveal a state-dependent economic recovery: it is gradual in normal times but displays a more accelerated rebound when the shock materializes during financial distress. A by-product of our analysis is that we can quantify the role of uncertainty shocks for historical macroeconomic dynamics. We show they are a major driver of financial conditions in both regimes and account for 1.7 percentage points of the largest drop in industrial production during the GFC.

We add to the empirical evidence that financial markets are instrumental to the transmission of uncertainty shocks. Accordingly, whether financial markets are calm or in distress matters when it comes to the appropriate policy responses following an adverse uncertainty shock. In the euro area, the space of manoeuvre is limited by the effective lower bound (ELB) on interest rates. Thus, timely and targeted policies (i.e. balance sheet, credit easing, forward guidance, macroprudential, or a mix) might be warranted during episodes of financial distress. These policies can help boost confidence, anchor agents' expectations, and provide stability to the economy. Moreover, appropriate macroprudential tools aimed at enhancing the resilience of the financial system could limit the amplification effects arising from heightened uncertainty. Lastly, policymakers should also take into account that uncertainty might trigger a re-allocation toward less innovation-oriented sectors, leading to persistent growth slowdown, as documented by Bansal et al. (2019).

In normal times, an uncertainty disturbance resembles a supply shock, while in periods marked by financial distress it acts like a demand shock. The latter case, in principle, poses no trade-off for the monetary authority. Therefore, depending on the assessment of the state of financial markets, our data-driven results imply that a potentially different policy response should be deployed. This framework can guide policymakers in determining in real time whether financial markets are heading towards a distress episode. More precisely, closely monitoring real time movements in our proxy for financial conditions, the high-yield bond spread, and mapping those into the posterior distribution of the critical threshold estimated with the model provides a metric to gauge the transition between financial regimes.

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# VIII Appendices

## Appendix A: Data set

*Macroeconomic aggregate data.* The industrial production data is taken from Eurostat and for the estimation of the model we use its monthly growth rate (i.e. logarithmic first-difference). This time series includes the following sectors: (i) mining and quarrying, (ii) manufacturing, (iii) electricity, gas, steam and air conditioning supply, and (iv) construction. The data is seasonally and calendar adjusted. We think that industrial production represents a good proxy for the economic activity. Nevertheless, we acknowledge its limitation in capturing services, as these account for a substantial share of output. Next, we use monthly consumer inflation measured by the logarithmic first-difference in headline HICP. The source of the data is Eurostat.

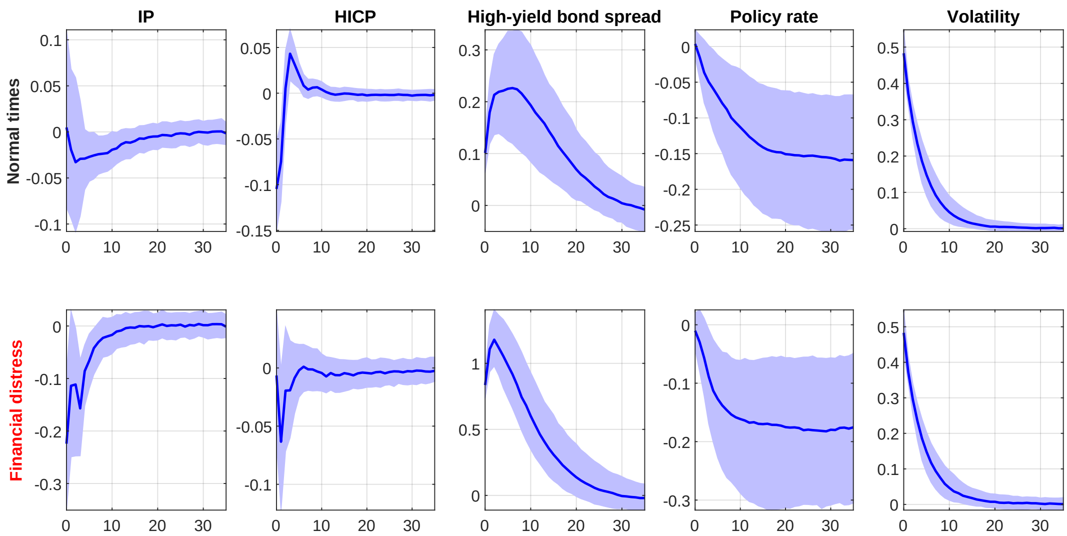
*Financial data.* The key financial variable used in the empirical analysis is a measure for credit spreads, which is approximated by the high-yield bond spread for the euro area. More precisely, this data represents the Option-Adjusted Spread (OAS) of the ICE BofAML Euro High Yield Index which tracks the performance of Euro denominated below investment grade corporate debt publicly issued in the euro domestic or euro-bond markets. We think that the high-yield bond spread captures fairly well aggregate financial conditions in the eurozone. It is available at FRED database and it has a daily frequency. Finally, for the policy interest rate we use the estimates based on the Wu and Xia (2016) model of the shadow rate.[19] Our motivation for this choice is the following. We want to capture the effective stance of monetary policy by also taking into account the unconventional measures that have been adopted by the ECB in the aftermath of the GFC. Moreover, our estimation sample includes the period when at least the zero lower bound on interest rates was binding (if not also the effective lower bound) and, therefore, we think it is appropriate to use the shadow rate.

## Appendix B: Figures underpinning the robustness analysis

This section provides all the figures that support and help clarify our sensitivity analysis. Due to space constraints, here we display only the generalised impulse response functions (IRFs) following a small (one standard deviation) uncertainty shock, while the ones for a large shock are available upon request.

**Different orderings of variables.** Here we present the results obtained in one alternative ordering; the rest are available upon request[20]. Figure 8 displays the impulse responses when switching the policy (shadow) rate with the financial conditions' proxy (i.e. high-yield bond spread). The results are broadly in line with our baseline findings. The two alternative model-based uncertainty measures are highly correlated (near 99%). This implies that the indirect effect on the overall volatility process (via the recursive factorisation of the matrices in equation 2) is negligible.

Figure 8: IRFs when using an alternative ordering



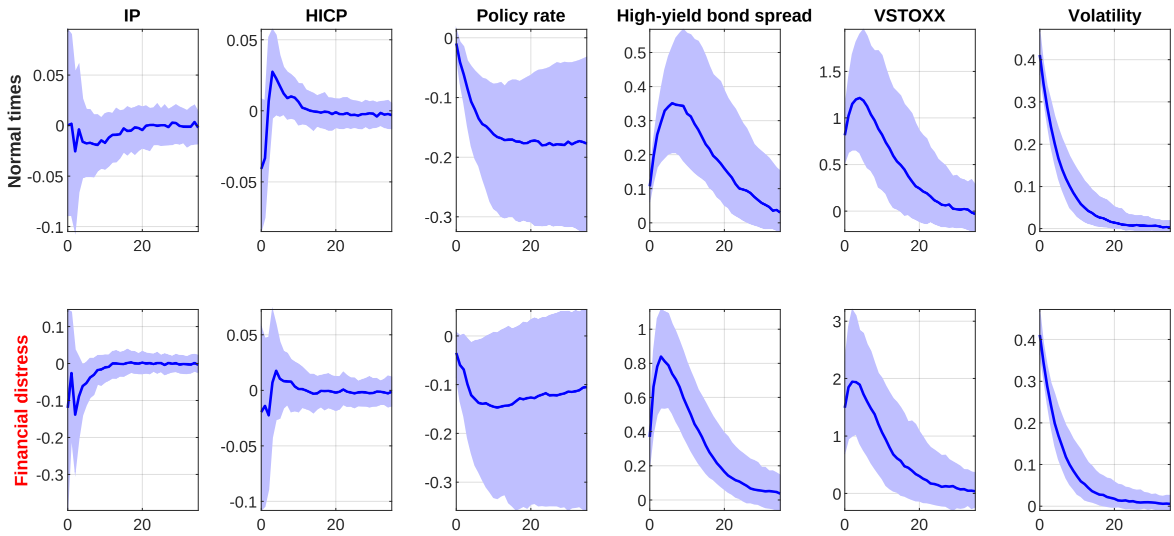

Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), a proxy for financial conditions, the policy rate and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

**Extending the VAR dataset.** We start by considering a version of the model that also incorporates a common proxy for uncertainty, i.e. the implied volatility index – VSTOXX. In our view this measure captures more financial risk aversion than overall economic uncertainty. Figure 9 shows the impulse responses following a small (one standard deviation) uncertainty shock. The increased overall uncertainty leads to

[19] The euro area shadow policy rate is available at Haver Analytics.
[20] We think that these alternative orderings are harder to justify from a theoretical perspective.

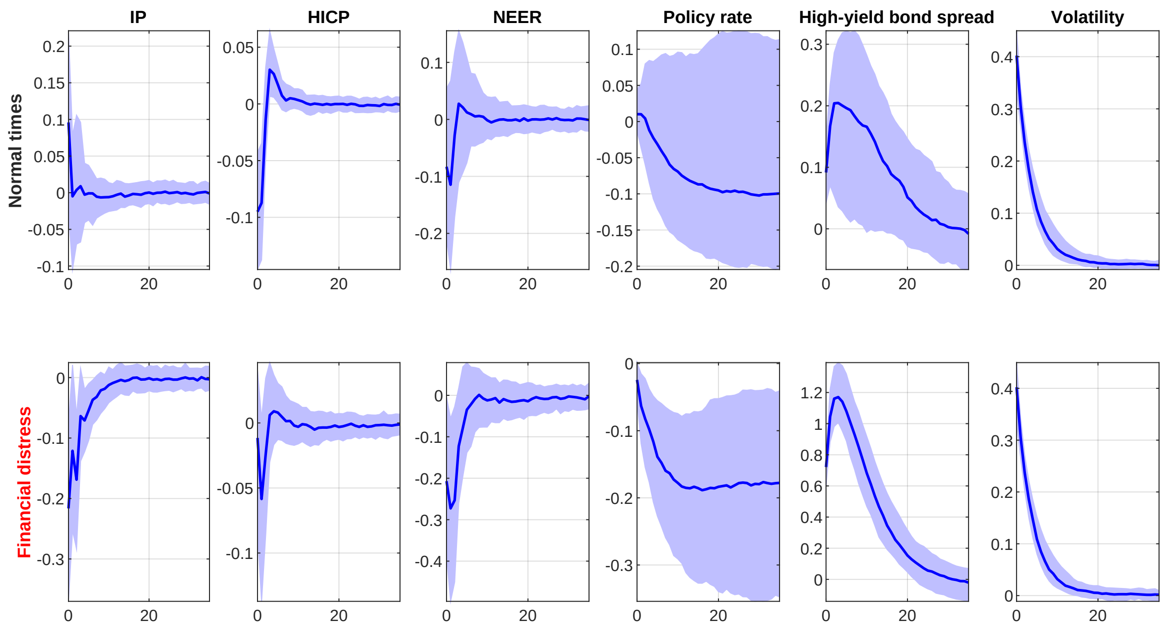
a rise in VSTOXX, which triggers a tightening of financing conditions. These responses are qualitatively similar to our baseline results.

Figure 9: IRFs when adding VSTOXX




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), the policy rate, a proxy for financial conditions, the implied volatility index (VSTOXX) and the model-based overall volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

Figure 10: IRFs when adding the exchange rate (NEER)

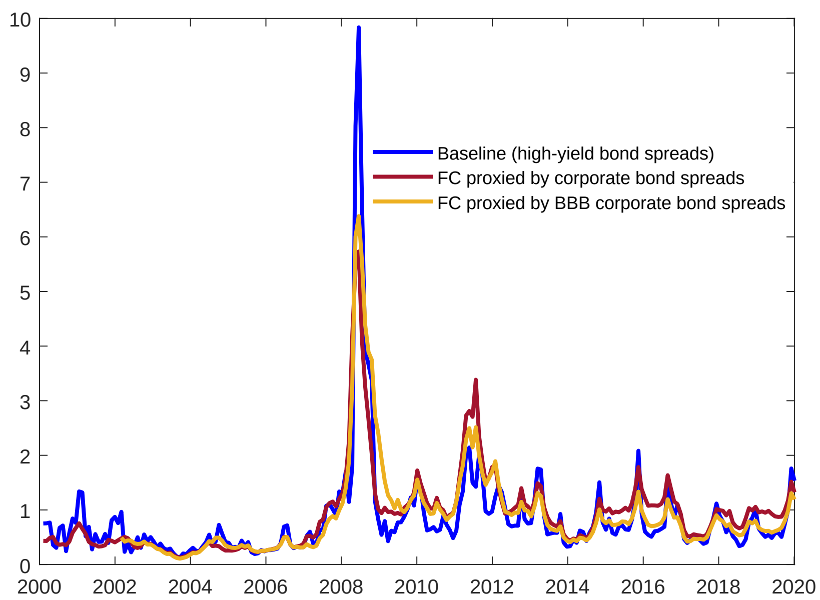



Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), the nominal effective exchange rate (NEER), the policy rate, a proxy for financial conditions, the implied volatility index and the model-based overall volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

Next, in Figure 10 we report the impulse responses based on an open-economy version of our baseline (formalised by expanding the information set with the broadest available measure of NEER). This exercise reveals an exchange rate depreciation after an increase in uncertainty, while the other responses are qualitatively in line with our benchmark findings. Note that by adding an extra variable the number of parameters to be estimated rises significantly and this affects the model's precision (also reflected in somewhat wider confidence bands). The two model-based uncertainty measures exhibit high correlations with our benchmark estimate: 95% (with VSTOXX) and 97% (with NEER), respectively.

**Alternative measures to capture financial conditions.** Figure 11 shows that the aggregate uncertainty measures, obtained based on two different proxies for financing conditions, exhibit a very high correlation (86% and 91%, respectively) with our baseline estimate. Figure 12 displays the impulse responses for both cases, revealing similar findings as in our baseline setting. Figure 13 reports the real-time readings of these alternative bond spread measures and compares them with their corresponding median values of the threshold's posterior distribution: these are 1.5% and 2.1%, respectively.

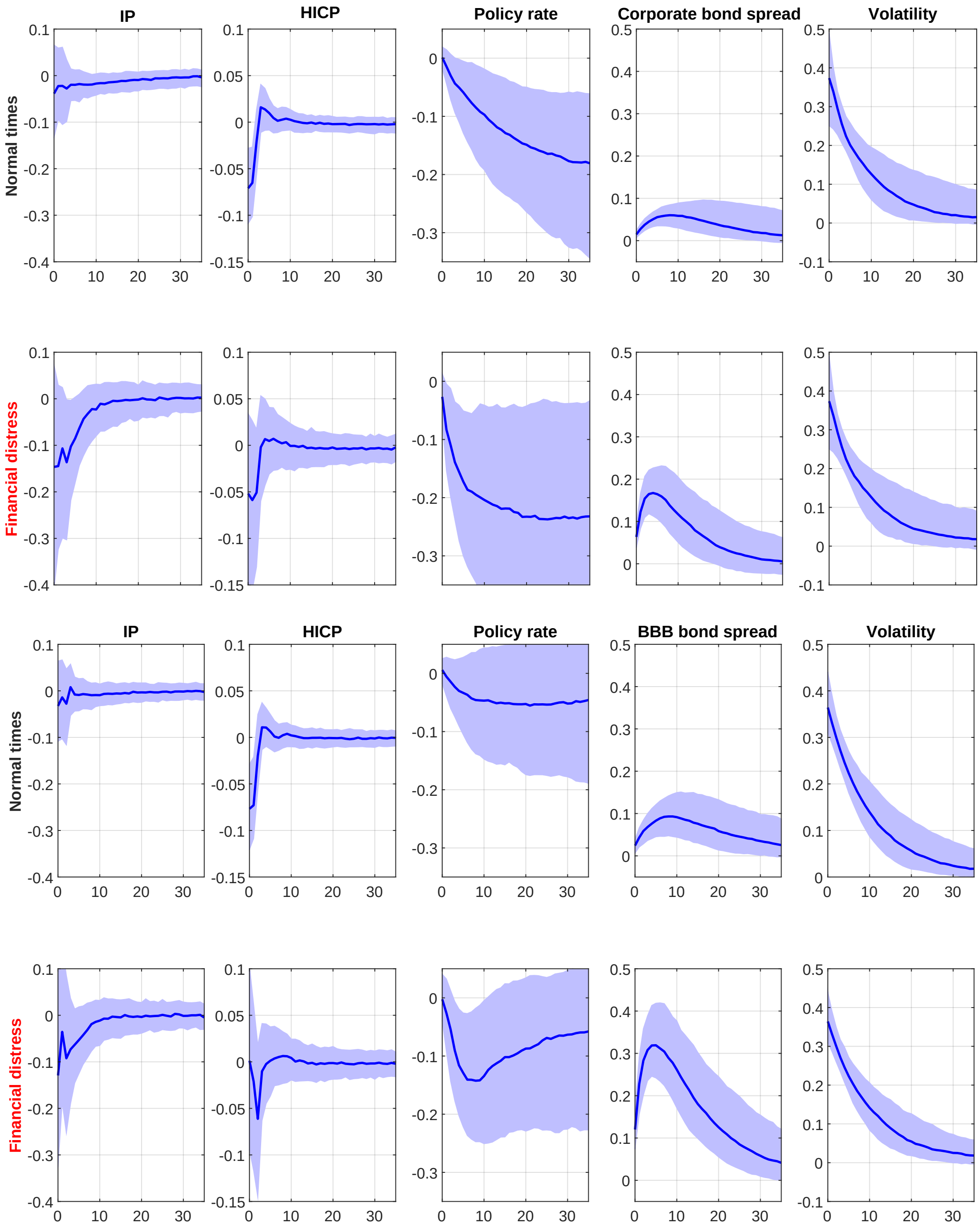
Figure 11: Model-based uncertainty comparison across alternative proxies for financial conditions (FC)




**Alternative proxies for economic activity.** Figure 14 reveals qualitatively similar impulse responses following adverse uncertainty shocks, in an alternative estimation with ESI replacing industrial production, with the already established asymmetries across financial regimes.

**Volatility-in-mean effects.** This sensitivity analysis is focused on the timing assumption of volatility effects. Figure 15 shows the impulse responses when allowing only the prevailing uncertainty from the previous month to affect macroeconomic developments. These are broadly in line with our baseline results. Not surprisingly, the uncertainty shock exhibits a lower persistence as compared to our benchmark setting. Then, we also report the responses when we assume that volatility effects are present only contemporaneously. Figure 16 reveals that our main findings survive this test, as well. Nevertheless, it is worth noticing that in normal times, inflation declines on impact and quickly returns to zero; yet its response is mostly statistically insignificant over the simulation horizon. In essence, when the volatility-in-mean channel is muted, uncertainty shocks appear to act as aggregate demand shocks, irrespective of the financial regime. Lastly, both measures of overall uncertainty are highly correlated (above 95%) with our baseline estimate.

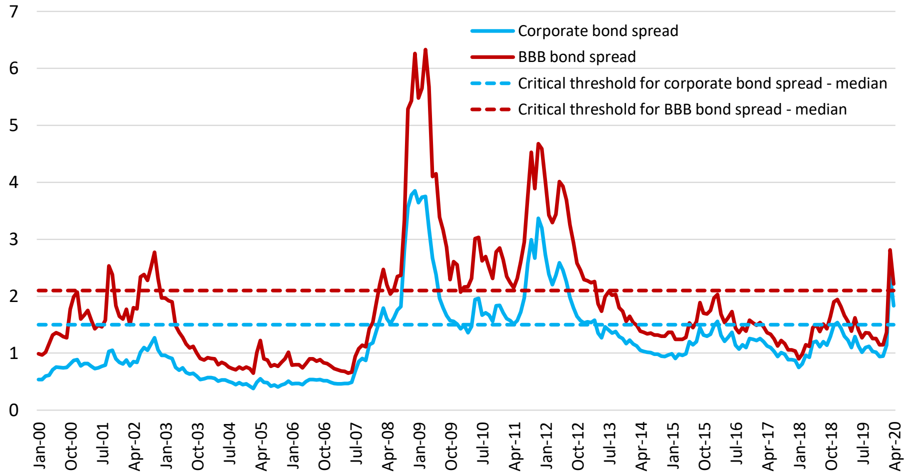
Figure 12: IRFs when financial conditions are captured by alternative credit spreads




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), an alternative proxy for financial conditions, the policy rate and the model-based volatility estimate. The upper panel (first two rows) reports the results when financial conditions are captured by the corporate bond spread, while the bottom panel (last two rows) displays the responses obtained in the case of the BBB bond spread. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

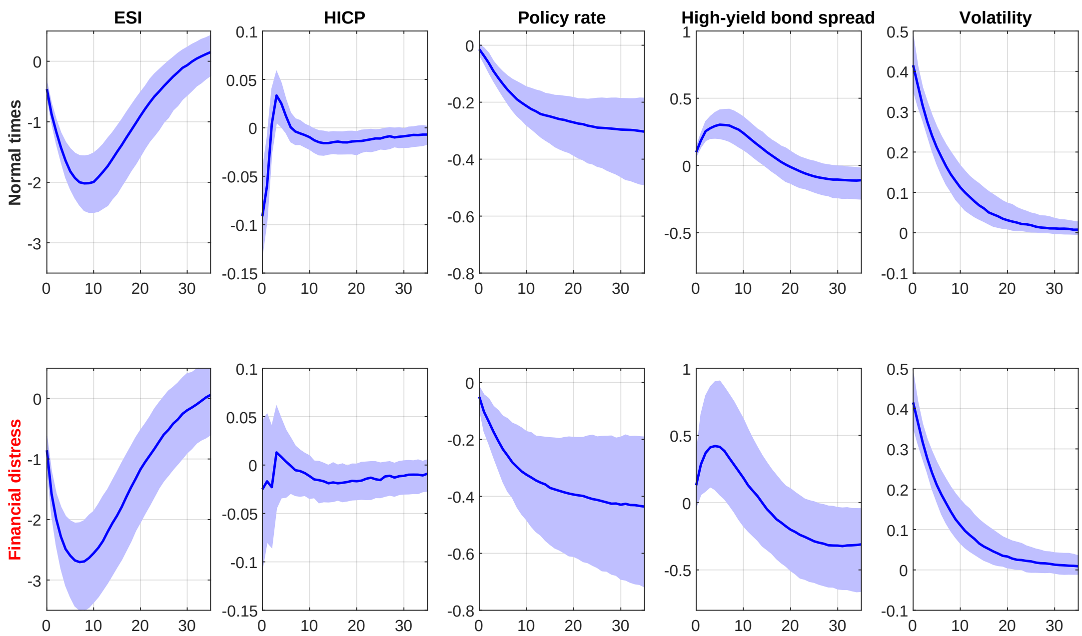
**A smooth transition across regimes.** The uncertainty measure based on this alternative model exhibits a 92% correlation with the one generated with our baseline framework (see Figure 17). The estimates are less precise, reflecting the higher complexity of the model, but the median responses are broadly in line with the ones based on the benchmark model. Figure 18 displays the episodes when the euro area economy is experiencing financial distress identified based on the smooth transition logistic function

Figure 13: Tracking the current state of financial markets in real time




Source: Bloomberg (last observation 30th of April), own estimations.

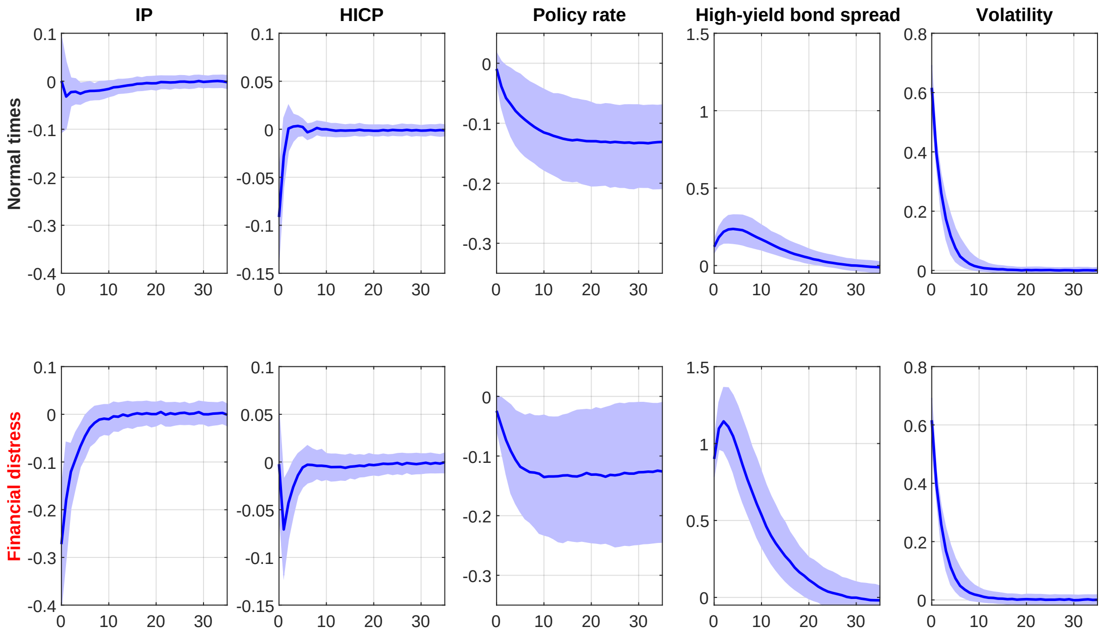
Figure 14: IRFs when economic activity is captured by the economic sentiment indicator (ESI)




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are the economic sentiment indicator (ESI), consumer price inflation (HICP), a proxy for financial conditions, the policy rate and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

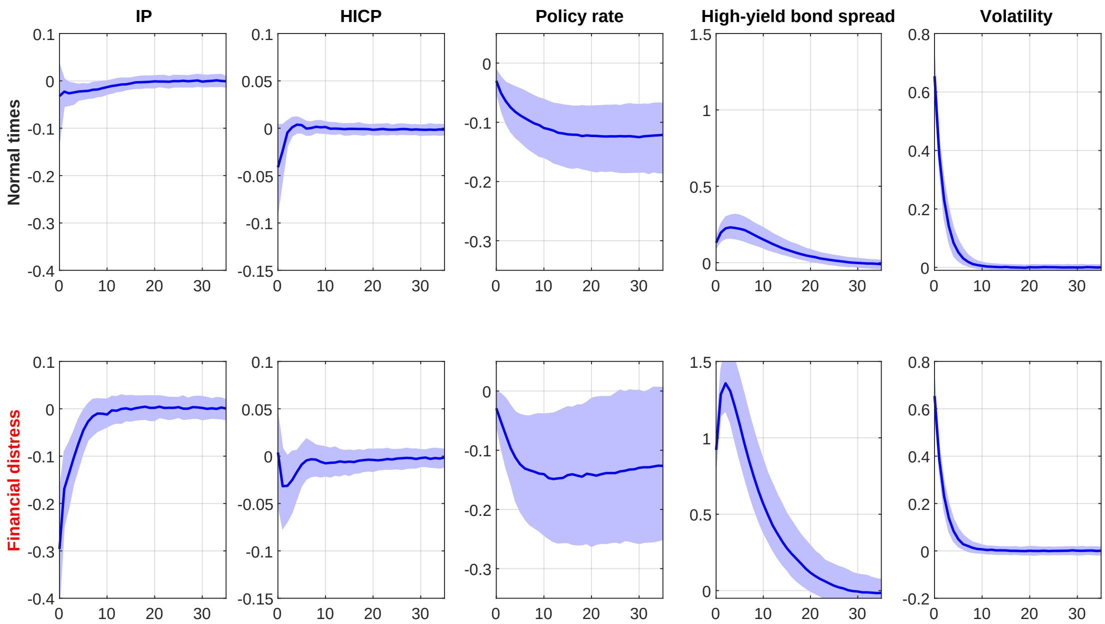
versus the indicator function (used in our baseline setting). These episodes are largely overlapping. Figure 19 reports the generalised impulse responses based on an alternative Smooth Transition VAR model (STVAR). Finally, we also report the threshold's posterior distribution: the mode is quite similar across the alternative STVAR approach and our baseline model (see Figure 20). This gives credit to the robustness of the estimated threshold. However, the much wider distribution in the alternative specification encompasses relatively less precise estimates.

Figure 15: IRFs when allowing only the prevailing last month's uncertainty to affect the system




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), a proxy for financial conditions, the policy rate and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

Figure 16: IRFs when volatility effects are present only contemporaneously




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), a proxy for financial conditions, the policy rate and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

Figure 17: Model-based uncertainty: TVAR versus STVAR

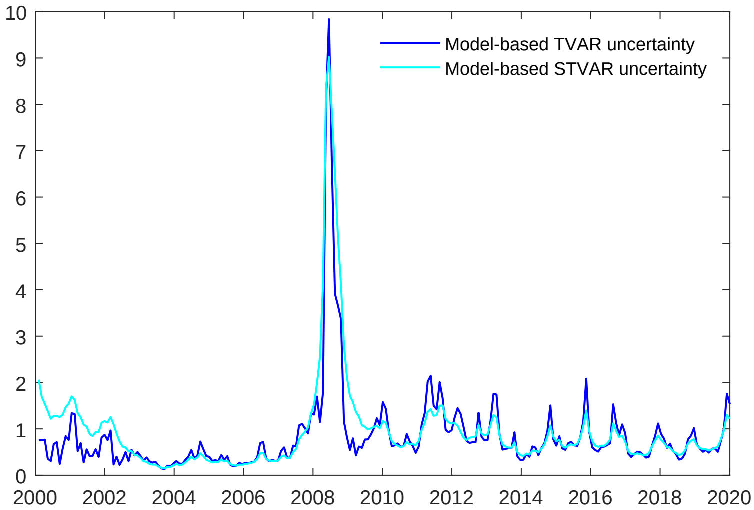
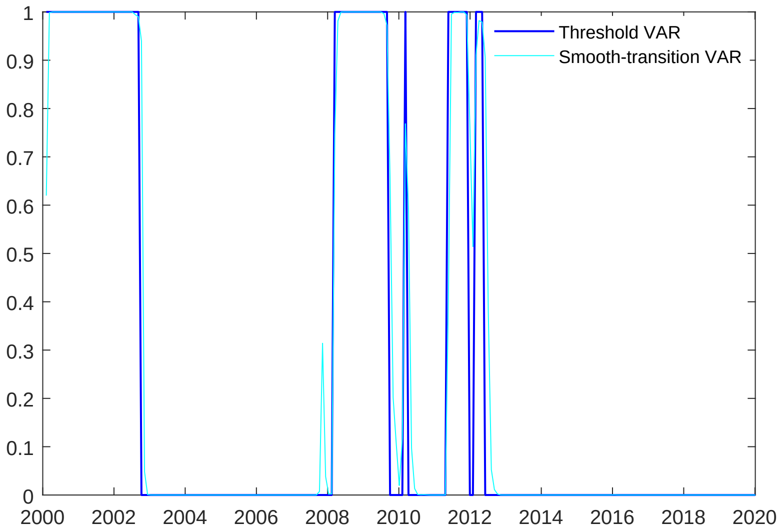


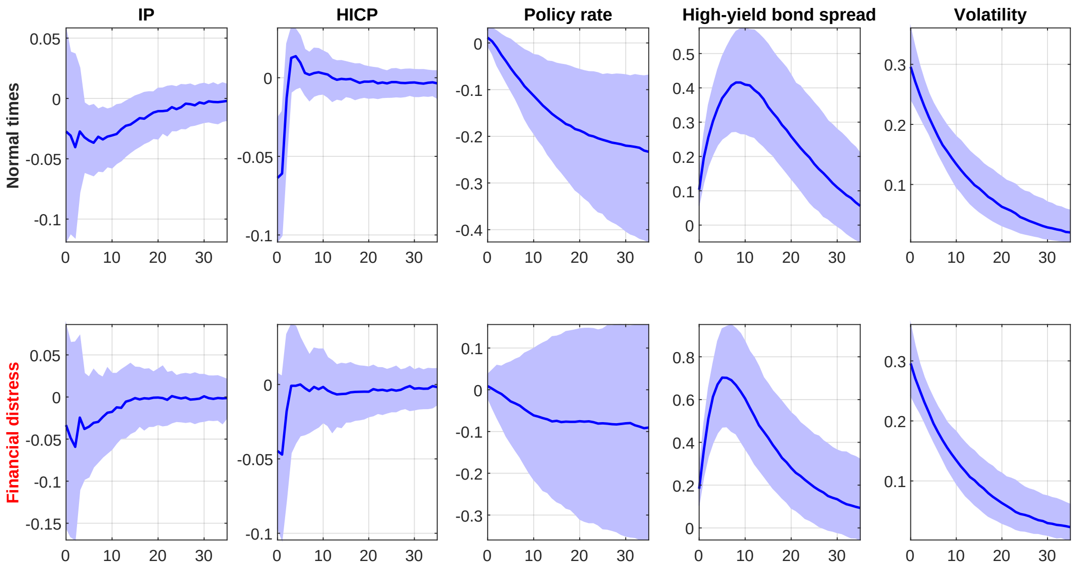

Figure 18: Financial distressed episodes according to TVAR and STVAR models




Note: TVAR stands for threshold VAR (our baseline model) and STVAR represents the alternative smooth transition VAR model.

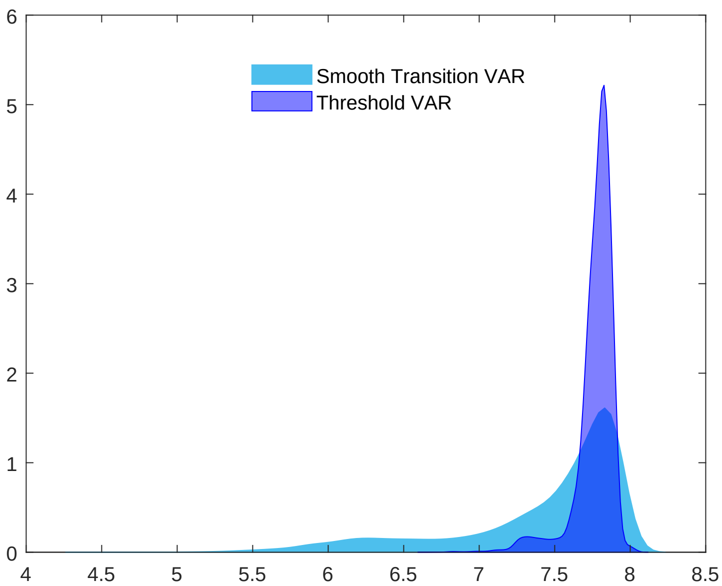
**Regime switching across expansion and downturn.** This exercise delivers an aggregate economic uncertainty that is still highly correlated with our baseline measure (i.e. 87%). Figure 21 shows that our baseline findings survive also when accounting for regime changes linked to economic activity.

Figure 19: IRFs when employing the alternative STVAR model



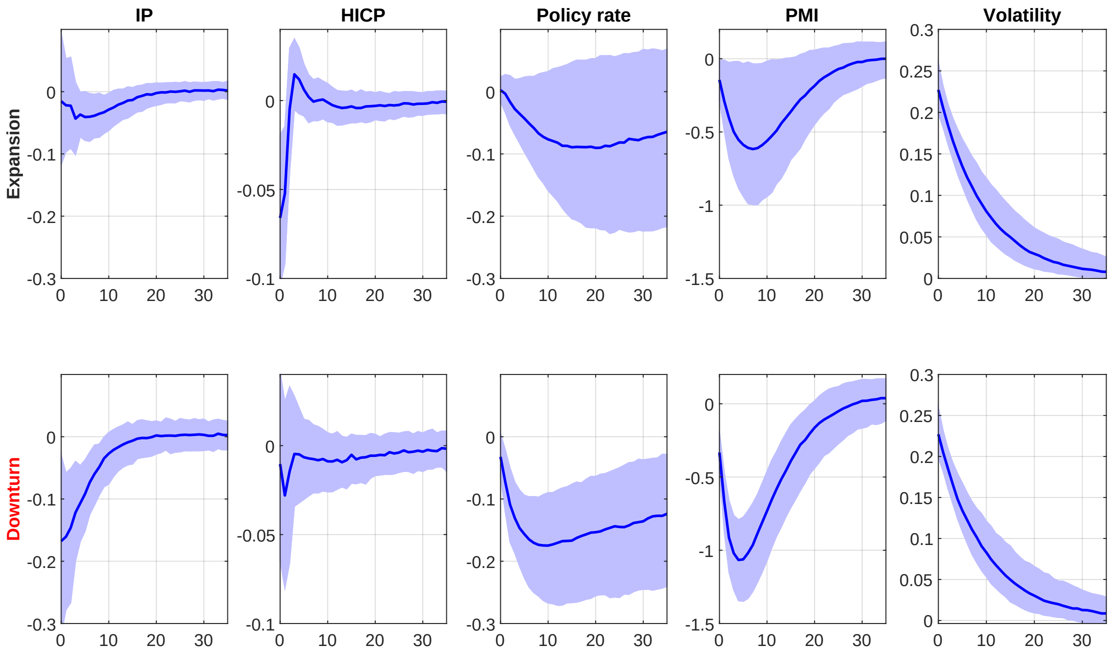

Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in normal times versus financial distressed episodes (identified according to a smooth transition function). From left to right, the variables are industrial production (IP), consumer price inflation (HICP), the policy rate, a proxy for financial conditions and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

Figure 20: Threshold's posterior distribution TVAR and STVAR models




Note: The horizontal axis represents the estimated values across simulations; we run 500000 Gibbs simulations and retain the last 10% draws.

Figure 21: IRFs when accounting for regime changes linked to economic activity




Note: The blue line shows the impact of a one standard deviation increase in the volatility of the euro area economy in expansion versus downturn episodes. From left to right, the variables are industrial production (IP), consumer price inflation (HICP), the policy rate, the composite output PMI and the model-based volatility estimate. For each variable and regime, the figure reports the median response and a 68% confidence band. The horizontal axis is time, measured in months.

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