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The Impact of Pessimistic Expectations on the Effects of COVID-19-Induced Uncertainty in the Euro Area*

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Abstract

We estimate an Interacted-VAR model allowing for the impact of uncertainty shocks to depend on the average outlook of the economy measured by survey data. We find that, in response to the same uncertainty shock, industrial production and inflation's peak decrease is around three and a half times larger during pessimistic times. We build scenarios for a path of innovations in uncertainty consistent with the COVID-19-induced shock. Industrial production is predicted to experience a year-over-year peak loss of between 15.1% and 19% peaking between September and December 2020, and subsequently to recover with a rebound to pre-crisis levels between May and August 2021. The large impact is the result of an extreme shock to uncertainty occurring at a time of very negative expectations on the economic outlook.

Keywords: COVID-19, Uncertainty shocks, Non-Linear Structural Vector AutoRegressions, Consumer Confidence. JEL codes: C32, E32.

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1 Introduction

The social distancing measures imposed worldwide to respond to the COVID-19 epidemic have resulted in the partial shutdown of economic activity, and immediate losses in output.[1] As countries started planning a gradual reopening of the economy in April 2020, expectations about the future were at their lowest, reflecting a pessimistic outlook for the future.[2] At the same time, measures of uncertainty were still very high, after having experienced levels comparable to those of the Global Financial Crisis.[3]

Using a nonlinear Interacted VAR specification, we assess the effects of heightened uncertainty in the presence of pessimistic expectations about the future economic outlook in the Euro area, and estimate the macroeconomic impact of the COVID-induced uncertainty spike.

The observed increase in uncertainty measures during the COVID pandemic can be interpreted as a perceived increase in the probability of very negative outcomes - for example, future waves of pandemic leading to protracted economic lockdowns – as well as very positive outcomes, such as the rapid procurement of a vaccine or effective antiviral drugs, and a fast rebound of economic activity. It is well known that unexpected surges or "shocks" in uncertainty have a negative effect on real activity (see, e.g., Bloom (2009), Mumtaz and Zanetti (2013), Bachmann, Elstner, and Sims (2013), Jurado, Ludvigson, and Ng (2015), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Leduc and Liu (2016), Baker, Bloom, and Davis (2016), Basu and Bundick (2017), Piffer and Podstawski (2018), Ludvigson, Ma, and Ng (2019)). This outcome can be explained by risk-averse consumers increasing precautionary savings against a rise in the risk of possible negative future outcomes, or by firms postponing partially-irreversible investment to the future and adopting a "wait and see" behavior (see, e.g., Caballero (1990) and Bernanke (1983), respectively).

Given the recent COVID-induced uncertainty shock, similar incentives to modify households' and firms' optimal choices would be at work during this pandemic, with negative effects on output that will add to those given by the lockdowns, and may potentially last longer than the lockdowns. This is confirmed by recent Structural Vector AutoRegression (VAR) studies on the impact of

[1] By the second half of April 2020, the Euro zone-wide composite Purchasing Manager Index (PMI) hit an all-time low of 13.5, implying the Eurozone economy had suffered the steepest ever fall in manufacturing and services activity (European Commission, 2020).

[2] The German ZEW sentiment index, and the consumer confidence indicator released by the European Commission in April 2020 signaled a confidence level approaching the number reached during the 2008-2009 financial crisis.

[3] Baker, Bloom, Davis, and Terry (2020) document the recent enormous increase in economic uncertainty as measured by several US indicators: the VIX index; the U.S. Economic Policy Uncertainty Index; several survey-based measures reporting uncertainty about the outlook among firms.

COVID-19 uncertainty by Baker, Bloom, Davis, and Terry (2020) – estimating a peak impact on year-over-year US GDP growth of about 5.5% – and Leduc and Liu (2020), estimating an impact on US unemployment peaking at one percentage points after 12 months. As regards the global effects of the COVID uncertainty shock, Caggiano, Castelnuovo, and Kima (2020) predict the cumulative loss in world output one year after the shock to be about 14%. However, these studies employ linear VAR models and hence cannot account for the unusual circumstances the economy is facing in terms of both uncertainty and pessimistic outlook during the current COVID pandemic. Further, none of the aforementioned papers study the consequences of the COVID uncertainty shock for the Euro area economy, the economy most hit at the time we are writing.[4]

We provide two novel sets of results by estimating a nonlinear Interacted VAR model. First, we empirically study the role of pessimistic expectations about future outcomes for the historical propagation of uncertainty shocks in the Euro area. Second, we make use of this novel finding to predict the expected propagation of the COVID-induced uncertainty shock.

We measure expectations about the economic outlook with consumer confidence and interpret plummeting consumer confidence as capturing pessimism about the future.[5] In principle, pessimism - that is, a negative outlook about the future of the economy - may influence the impact of uncertainty shocks. Given an average outlook, higher uncertainty increases the risks in the outlook: it implies a higher chance of more extreme outcomes, or an increased probability of large upside or downside risks. The impact of heightened risk on optimal choices may change depending on the state of the economy, since in some states a change in the distribution of future shocks may have a larger impact on the distribution of economic outcomes, or agents may engage in robust-control optimal behaviour overweighing worst-case scenarios. Several economists, including contributions by Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014) and Cacciatore and Ravenna (2020) have suggested models able to explain the time-varying impact of uncertainty shocks.

We empirically test whether pessimism amplifies the impact of uncertainty shocks by modeling a vector of Euro area macroeconomic data with an Interacted VAR (IVAR) model for the period 1999m1-2020m1. The IVAR is a parsimonious nonlinear VAR model which augments a standard

[4] As of 7 July 2020, Europe reported 194,515 deaths – with the most hit countries being, in order, United Kingdom (44,236), Italy (34,869), France (29,920), and Spain (28,388) – and the United States 130,306 deaths (see the COVID-19 situation update worldwide by the European Centre for Disease Prevention and Control, available at https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases).

[5] Autonomous shifts in confidence have been documented to have powerful predictive implications for income and consumption. These shifts may operate through two possible channels: they may reflect changes in 'animal spirits', having a direct effect on the economy, or they may reflect fundamental information, or 'news', about the future state of the economy, available to consumers and not summarized by other measurable variables (Barsky and Sims (2012)).

linear VAR model with an interaction term to determine how the effects of a shock on one variable depend on the level of another variable. We interact an uncertainty measure with a measure of consumer confidence to estimate the impact of an uncertainty shock at times when consumer confidence is in the bottom quintile of its historical distribution. Armed with this model, we build scenarios for a path of innovations in uncertainty consistent with the COVID-19-induced shock. In building the hypothetical response of the economy to the uncertainty shocks, we compute Generalized IRFs (GIRFs) à la Koop, Pesaran, and Potter (1996) to account for the endogenous evolution of the state of the economy – including its impact on uncertainty itself.[6]

Following the seminal work by Bloom (2009) we focus on financial uncertainty, that we measure by the VSTOXX index, a high-frequency measure of implied volatility for the EURO STOXX 50 stock market index (the European-analogue to the VIX index for the US). This is important since - as shown in Ludvigson, Ma, and Ng (2019) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) - indicators proxying this type of uncertainty are likely to capture movements in uncertainty which are relevant to explain the evolution of output at business cycle frequencies.

Our main results can be summarized as follows. First, we find that historically, uncertainty shocks in the Euro area have had a significant impact on the economy only during pessimistic times. Industrial production and inflation decrease in both states of the economy, but their decrease is much larger and more persistent during pessimistic times. The peak response of industrial production (inflation) to a typical uncertainty shock is -1.28% (-0.11%) in pessimistic times and -0.36% (-0.04%) in normal times. Consistently with these findings, uncertainty shocks are found about three times more important in explaining business cycle fluctuations in industrial production and inflation during pessimistic times than during normal times, respectively explaining the 42% and 27% of the fluctuations in the two series. We also assess several alternative economic and econometric hypotheses about the state-dependent impact of uncertainty shocks, including global uncertainty spillovers, the role of financial factors and households mood swings, the impact of firms' pessimism about the outlook, the information contained in survey measures of cross-sectional dispersion, and a Proxy SVAR specification.

Second, our estimates imply that the COVID-19 shock via its uncertainty channel alone will induce a long and deep recession in the Euro area. In our first scenario, we hit the pessimistic-times state of our estimated IVAR with a 10 standard deviations uncertainty shock – corresponding to the

[6] Details on the estimation methodology for the IVAR model are in Caggiano, Castelnuovo, and Pellegrino (2017), Pellegrino (2017) and Pellegrino (2018).

unexpected rise in the level of the VSTOXX measure of uncertainty from February 2020 to March 2020. Industrial production is predicted to experience a year-over-year peak loss of 15.14% peaking after 7 months from the shock, in September 2020, and subsequently to recover with a rebound to pre-crisis levels in May 2021. In terms of GDP, a back-of-the-envelope calculation suggests a corresponding fall in year-over-year GDP of roughly 4.3% at peak.

We also consider two alternative scenarios where either uncertainty goes back to normal levels much more slowly in the current situation than in the past – given the persisting uncertainty in delivering a vaccine could span several months –, or where a second unexpected spike in uncertainty occurs following a possible new wave of the pandemic in the coming fall. Both scenarios would delay the recovery and would prolong the recessionary impact by several months, yielding a larger total loss in industrial production. In the case of a new fall-2020 wave, our simulations predict the trough to happen in December 2020 and the rebound to start in July 2021.

Our findings lend support to the unprecedented policy responses to the pandemic, many of which can be interpreted as providing catastrophic insurance against worst-case outcomes. Provided that the sole impact of the COVID-19 shock via its uncertainty channel will imply large losses as well as a slow and painful return to normality, policymakers are required to enact clear policies aimed not only at boosting confidence in the outlook, but specifically targeted at resolving the uncertainty.

Our study is connected with the empirical literature investigating whether uncertainty shocks have state-dependent effects according to the economic phase when a shock hits. Among others, Caggiano, Castelnuovo, and Groshenny (2014), Chatterjee (2018), and Caggiano, Castelnuovo, and Figueres (2020) employ non-linear Structural VAR techniques to enquire whether contractionary vs. expansionary phases are important in determining the impact of uncertainty shocks, whereas Alessandri and Mumtaz (2019), Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), and Lhuissier and Tripier (2019) investigate whether financial or volatility regimes are important for the real effects of uncertainty shocks. This study focuses on the role of consumer confidence. Its forward-lookingness allows us to pin down the role of agents expectations for the transmission of uncertainty shocks.

The paper is structured as follows. Section 2 presents the empirical model and the data. Section 3 documents our empirical findings. Section 4 concludes.

2 Econometric setting

Interacted VAR. The IVAR is a nonlinear VAR model which augments a standard linear VAR model with an interaction term to determine how the effects of a shock in one variable depend on the level of another variable. Our estimated IVAR reads as follows:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \cdot conf_{t-j} \right] + \mathbf{u}_t \tag{1}$$

where $\mathbf{Y}_t$ is the vector of the endogenous variables, $\boldsymbol{\alpha}$ is a vector of constant terms, $\mathbf{A}_j$ are matrices of coefficients, $\mathbf{u}_t$ is the vector of error terms whose variance-covariance (VCV) matrix is $\boldsymbol{\Omega}$. The interaction term includes a vector of coefficients, $\mathbf{c}_j$, a measure of uncertainty, unc_t, i.e., the variable whose exogenous variations we aim at identifying, and a measure of consumer confidence, $conf_t$, that will serve as our conditioning variable. Both uncertainty and consumer confidence are treated as endogenous variables.

The vector of endogenous variables modeled by our IVAR reads as follows: $\mathbf{Y}_t = [unc_t, \Delta_{12} \ln IP_t, \pi_t, conf_t, i_t]'$, where unc stands for uncertainty, $\Delta_{12} \ln IP$ for year-over-year industrial production growth, π for year-over-year inflation, $conf$ for consumer confidence, and i for the policy rate. We proxy Euro area financial uncertainty with the monthly average of the VSTOXX index, which is the real-time measure of implied volatility for the EURO STOXX 50 stock market index. The VSTOXX index is the European-analogue to the VXO index for the US, the index used in Bloom's (2009) seminal work. We use the Consumer Confidence Index provided by the European Commission, which provides an indication of the next 12 months' developments of households' consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment and capability of savings.[7] To capture the stance of monetary policy, we use the overnight interest rate (EONIA), while industrial production (measured by the manufacturing sector) and inflation (measured by CPI index) are aggregates for the Euro area.[8] The Appendix reports plots of all the data series used in the model.

[7] The series is available at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en (the mnemonic is CONS.EU.TOT.COF.BS.M)

[8] The use of synthetic European data is common among researchers (see, e.g., Smets and Wouters (2003) and Castelnuovo (2016)). The mnemonics for inflation and Eonia are respectively given by CPHPTT01EZM661N and FM.M.U2.EUR.4F.MM.EONIA.HSTA.

Relative to alternative nonlinear VARs like Smooth-Transition VARs and Threshold VARs, the IVAR is particularly appealing in addressing our research question. It enables us to model the interaction between uncertainty and consumer confidence in a parsimonious manner – as it does not require parametric choices for any threshold or transition function in the estimation procedure –, and, at the same time, the IVAR can estimate the economy's response conditional on very low consumer confidence since the definition of a pessimistic regime is only used when simulating generalized impulse response functions conditional on a given initial state, hence making the responses less sensitive to outliers in a particular regime.

The IVAR methodology has been shown through Monte Carlo simulations to be able to recover the true state-dependent impulse responses to an uncertainty shock as implied by a state-of-the-art nonlinear DSGE framework solved via a third-order approximation around its stochastic steady state (Andreasen, Caggiano, Castelnuovo, and Pellegrino (2020)). Details on the estimation methodology for the IVAR model are in Caggiano, Castelnuovo, and Pellegrino (2017), Pellegrino (2017) and Pellegrino (2018). The Appendix provides additional information on the estimation and the GIRF algorithm.

We estimate the IVAR model based on the 1999m1-2020m1 sample. The starting date is dictated by the availability of the VSTOXX index and coincides with the establishment of the Euro area. The model is estimated by OLS. We use 4 lags as suggested by the AIC statistic. A multivariate LR test rejects the null of linearity against our IVAR model ($p - value = 0.00$).

GIRFs for normal and pessimistic times. We compute GIRFs à la Koop, Pesaran, and Potter (1996) to account for the endogenous response of consumer confidence to an uncertainty shock and the feedbacks this can have on the dynamics of the economy. GIRFs acknowledge the fact that, in a fully nonlinear model, responses depend on the sign of the shock, the size of the shock, and initial conditions. Theoretically, the GIRF at horizon h of the vector $\mathbf{Y}$ to a shock in date t, δ_t, computed conditional on an initial condition, $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, is given by the following difference of conditional expectations:

$$GIRF_{\mathbf{Y},t}(h, \delta_t, \boldsymbol{\varpi}_{t-1}) = \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \boldsymbol{\varpi}_{t-1}\right] - \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right], \quad h = 0, 1, \ldots, H. \tag{2}$$

We are interested in computing the GIRFs to an uncertainty shock for normal and pessimistic times. We define the "Pessimistic times" state to be characterized by the initial months corresponding to the bottom 20% of the consumer confidence distribution, while the "Normal times" state is defined by all other initial months in the sample. Figure 1 plots consumer confidence for the Euro area and provides a visual representation of the two states. Pessimistic times mostly capture the period of the Great Financial Crisis of 2008-2009 and the sovereign debt crisis of 2011-2013 but also capture the setback in confidence in 2003.

Uncertainty shocks are identified by means of a Cholesky decomposition with recursive structure given by the ordering of the variables in the vector $\mathbf{Y}$ above, i.e., $[unc, \Delta_{12} \ln IP, \pi, conf, i]'$. Ordering the uncertainty proxy before macroeconomic aggregates in the vector allows real and nominal variables to react on impact, and it is a common choice in the literature (see, among others, Bloom (2009), Caggiano, Castelnuovo, and Groshenny (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Leduc and Liu (2016)). Moreover, it is justified by the theoretical model developed by Basu and Bundick (2017), who show that first-moment shocks in their framework exert a negligible effect on the expected volatility of stock market returns. This is in line with the findings in Ludvigson, Ma, and Ng (2019) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) according to which uncertainty about financial markets is a likely source of output fluctuations, rather than a consequence. The implications of alternative identification choices are included in the next section.

3 Empirical results

3.1 The effects of uncertainty shocks in the Euro area: The role of pessimism

3.1.1 Baseline results

We start by documenting the impact of uncertainty shocks in the Euro area during pessimistic and normal times over the estimation sample. Figure 2 depicts the state-dependent GIRFs to a one standard deviation uncertainty shock along with 90% bootstrapped confidence bands. Figure 3 plots the 68% and 90% confidence bands of the statistical test on the difference of the impulse responses computed in the two states.[9]

We obtain three main results. First, real activity and inflation decrease in both states of the economy, but their decrease is much larger and more persistent during pessimistic times. The peak response of real activity is -1.28% in pessimistic times and -0.36% in normal times, i.e., around

[9] We compute differences between the impulse responses in the two states conditional on the same set of bootstrapped simulated samples. In this way, the construction of the test accounts for the correlation between the estimated impulse responses. The empirical density of the difference is based on 500 realizations for each horizon of interest.

three and a half times bigger. The shock is deflationary, and the fall in inflation is three times as large in pessimistic times (-0.11%) compared to normal times (-0.04%). From a statistical standpoint, the decrease in real activity and inflation is significant only for pessimistic times, and their difference of responses across states is significant too (although only at the 68% confidence level for inflation).

Second, consumer confidence decreases for several months after the uncertainty shock hits before starting to rise again after 6 months in pessimistic times and after roughly one year and a half in normal times. Importantly, the response of consumer confidence is only marginally statistically significant, especially in pessimistic times, supporting the conclusion that shocks to uncertainty contain additional information relative to consumer confidence, and do not simply proxy for the average outlook of the economy.

Third, the difference in the reaction of consumer confidence across the "pessimistic" and "normal" states is significant (at the 68% confidence level). We find that this result is robust across all of the alternative specifications in the next Section. We attribute the faster estimated recovery in consumer confidence during pessimistic times to the estimated faster and larger cut in the policy rate engineered by the European Central Bank when the outlook is negative. The policy rate is slashed in the first 5 months and reaches the peak response of about 20 basis points after 8 months from the shock.

The previous results show that uncertainty shocks have a significant impact on the Euro area economy only during pessimistic times. Next, we investigate how important uncertainty shocks are in explaining business cycle fluctuations in the two states. Table 1 reports the results of a Generalized Forecast Error Variance Decomposition (GFEVD) exercise for a forecast horizon of two years computed by adopting the algorithm proposed by Lanne and Nyberg (2016).[10] Three main findings emerge. First, uncertainty shocks are more important during pessimistic times in explaining fluctuations in key macroeconomic variables such as industrial production, inflation, and the policy rate. In pessimistic times, the contribution of uncertainty shocks is estimated to be 42%, 27%, and 57% for the volatility of industrial production, inflation, and the policy rate, respectively. In normal times, these shares drop to 17, 11, and 20%, i.e., roughly one-third of those in pessimistic times. Our results are in line with both Euro area and US analyses. According to

[10] We are interested in computing the contribution of structural (orthogonalized) shocks to the variance of the forecast errors of the endogenous variables in our nonlinear VAR. Hence, we follow Caggiano, Castelnuovo, and Pellegrino (2017) and modify the Lanne and Nyberg (2016) algorithm to calculate the GFEVD to a one standard deviation shock to all variables included in our analysis.

the ECB Economic Bulletin (2016), uncertainty on average explains 20% of real GDP fluctuations in the Euro area. Jurado, Ludvigson, and Ng (2015) find that uncertainty shocks account for up to 29 percent of the variation in US industrial production at business cycle frequencies, and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) find that uncertainty shocks explain between 20 percent to 40 percent of the same. All these studies adopt linear VAR models. Our results imply that the largest part of the forecast error variance in economic aggregates that linear econometric methodologies attribute to identified uncertainty shocks arise from the impact of these shocks during pessimistic times.

Second, the forecast error variance of the VSTOXX is mainly explained by its own shock in both states (89% in normal times and 92% in pessimistic times). This is consistent with the findings by Ludvigson, Ma, and Ng (2019) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) according to which financial uncertainty is mostly an exogenous source of business cycle fluctuations.

Third, consumer confidence fluctuations are partially explained by uncertainty shocks, although they explain only 10% of the volatility of consumer confidence during pessimistic times. This is interesting as it suggests that during pessimistic times a larger part of the fluctuations in consumer confidence reflects either autonomous shifts – which may be due to both 'animal spirits' or fundamental information, or 'news', about the future state of the economy available to consumers and not summarized by other measurable variables (Barsky and Sims (2012)) – or a reaction to other shocks. Consistently with this interpretation, we find that consumer confidence (monetary policy) shocks explain 33% (3.5%) of the business cycle fluctuations in confidence in pessimistic times, and 27% (2.2%) in normal times.

What explains the result of a severe impact of an uncertainty shock conditional on a pessimistic outlook? Heightened uncertainty translates, from the point of view of consumers and businesses, into a higher chance of more extreme outcomes, that is, a higher chance of large upside or downside risk, for a given average outlook. Consumers are risk-averse: they would prefer a lower income with certainty, compared to an environment with a chance of very negative outcomes - such as becoming unemployed - even if they were guaranteed that their expected lifetime income would be identical under the two environments. Businesses, when faced with more uncertainty about future demand, may find optimal to postpone investments.

At times of low prospects for future economic activity, an increase in the dispersion of future outcomes may have a larger impact on the economy: many more consumers, for example, may be closer to a worst-case scenario where they lose any income stream completely, and may optimally choose to change their behavior because of the increase in risk – even if there is an equally likely probability that the economy will rebound fast and demand growth will raise incomes. The same may be true for firms: with a very negative outlook, the same increase in uncertainty can – for example – dramatically raise the probability of bankruptcy for many firms, leading to a sharper change in behavior than what would be observed in normal times with a less extreme outlook (this intuition is formalized, among others, in Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014) and Cacciatore and Ravenna (2020)).

3.1.2 Alternative Hypotheses on the Impact of Uncertainty Shocks

In this section we study alternative specifications to discuss further findings on the role of pessimism for the transmission mechanism of uncertainty shocks. We explore the transmission of global uncertainty shocks, the relevance of survey-derived measures of expectations dispersion, the specific importance of consumer confidence, and the implications of an alternative interpretation of pessimism based on mood swings. The findings are shown in Figures 4 and 5, for real activity and inflation, respectively.

Non-European financial uncertainty indicators. In our baseline analysis, we use the VSTOXX volatility index, as an index of European financial uncertainty. However, most of its spikes coincide with global, or non-European, events, such as Worldcom and Enron US financial scandals in 2002, Gulf War II in 2003, and the Global Financial Crisis (see the first panel of Figure A1 in the Appendix). We assess whether the spillover effects of *global* uncertainty shocks to the Euro area depend on the *local*, Euro area level of confidence. To this end, we re-estimate the IVAR employing the US VIX index in place of our European uncertainty indicator.

As an alternative indicator, we also use the Ludvigson, Ma, and Ng's (LMN, 2019) US financial uncertainty index in place of the VIX. The index is a computed by adopting the same data-rich methodology proposed in Jurado, Ludvigson, and Ng (2015), i.e., it is the average of the conditional volatilities of the unforecastable components of a large dataset of financial variables. The findings in the top panels of Figures 4 and 5 document that global financial uncertainty shocks have spillover effects in the Euro area that also depend on the European confidence level. Results are very similar to the baseline ones. The key difference is that the LMN financial uncertainty index implies larger and more persistent real effects in both states. Large comovements across the main global trading areas level of output may explain this result, although the correlation of the VSTOXX with the VIX and the LMN measure is respectively 0.86 and 0.69.

European uncertainty indicators based on survey-derived measures of expectations dispersion. Provided that our IVAR makes use of a survey-based measure of consumer confidence, it is interesting to verify whether shocks to survey-based indicators of expectations dispersion, or "disagreement", also affect real activity and inflation in a state-dependent manner according to the level of consumer confidence. We hence use measures of survey-based disagreement in place of our baseline uncertainty indicator. This is close in spirit to Bachmann, Elstner, and Sims (2013) who use survey expectations data from both Germany and the United States to construct empirical proxies for time-varying business-level uncertainty.[11]

To construct a consumer disagreement index, we exploit the dispersion of responses to the following forward-looking survey question[12]:

> *How do you expect the financial position of your household to change over the next 12 months?*
> $++$ *"get a lot better"*; $+$ *"get a little better"*; $=$ *"stay the same"*; $-$ *"get a little worse"*;
> $--$ *'get a lot worse'; NA "don't know"*.

In accordance with the construction of the consumer confidence level index, we assign the values 1, 0.5, 0, -0.5 and -1 to each of those categories (see European Commission's (2020) survey user guide, p. 14). Let, without loss of generality, the weighted fraction of consumers with a very positive outlook at time t be $Frac_t^{++}$. We compute the consumer disagreement index as the standard deviation of response values weighted with the respective fractions, i.e.:

$$EDISP_{cons.} = \sqrt{\begin{array}{c} Frac_t^{++} \cdot (1 - mean)^2 + Frac_t^{+} \cdot (0.5 - mean)^2 \\ +Frac_t^{-} \cdot (-0.5 - mean)^2 + Frac_t^{--} \cdot (-1 - mean)^2 \end{array}},$$

where:

$$mean = 1 \cdot Frac_t^{++} + 0.5 \cdot Frac_t^{+} - 0.5 \cdot Frac_t^{-} - 1 \cdot Frac_t^{--}$$

For the equivalent index of industrial firm responses, we consider the following four questions in the industry subsector of the European Commission's business survey:

1. *Do you consider your current overall order books to be:/*

[11] Bomberger (1996) validates the use of survey-based measures of dispersion across forecasters as proxies for the uncertainty surrounding the mean forecast. Specifically, he shows that the conditional variance of forecast errors from an ARCH model is positively related to the disagreement among forecasters at the time of the forecast.

[12] The following is question 2 of the European Commission (2020) Consumer Survey, one of the questions at the basis of the Consumer Confidence Index we adopt.

2. *Do you consider your current export order books to be:/*

3. *Do you consider your current stock of finished products to be:*
   + "more than sufficient/above normal"; = "sufficient/normal for the season"; − "not sufficient/below normal"; NA "refused/not applicable"?

4. *How do you expect your production to develop over the next 3 months?*
   + "increase"; = "remain unchanged"; − "decrease".

Letting again $Frac_t^+$ ($Frac_t^-$) denote the weighted fraction of firms in the cross-section with "increase" ("decrease") responses at time t, the $EDISP$ dispersion indicators are then computed for each question as in Meinen and Röhe (2017):

$$EDISP_{ind.,i} = \sqrt{Frac_t^+ + Frac_t^- - \left(Frac_t^+ + Frac_t^-\right)^2}; \quad i = 1, 2, 3, 4.$$

We compute an unweighted average across the questions which we refer to as "industry outlook disagreement". The time series is displayed in Figure A4, together with all uncertainty indices used throughout the paper. As the panels in the second row of Figures 4 and 5 document, disagreement shocks also feature a confidence-dependent transmission mechanism. While shocks to industry outlook disagreement have effects similar to our baseline ones, consumer disagreement shocks have milder effects on real activity in both states and have mild inflationary effects in the short run.

Economic sentiment and industry confidence. In our baseline, we use the Consumer Confidence Index provided by the European Commission as indicator of expectations for the economic outlook. We now ask how confidence affects the impact of uncertainty shocks when broadening the measure of confidence to include producers' expectations. We introduce in the IVAR the Economic Sentiment Indicator, which is a composite of indices across consumers and producers in 5 sectors. We also consider its industry component alone. The latter covers firms in the manufacturing sector (2-digit NACE codes 10 to 33), which allows us to have a direct forward-looking equivalent to the industrial production series used in the VAR. The Appendix reports all the economic outlooks series we use and the third row of panels of Figures 4 and 5 reports novel findings. The IVAR results are similar to the baseline ones, with two key differences. First, industry confidence now implies a more persistent drop in real activity in normal times with the peak drop reached after a year. Second, both economic sentiments and industry confidence are only mildly deflationary in the short run.

Definition of pessimistic times related to mood swings. In our baseline analysis, we use the level of consumer confidence to define our pessimistic-times state. The idea behind this choice is that a low value of the index reflects pessimism, i.e., a negative outlook for the future of the economy. However, one may argue that pessimism can also be reflected by sudden negative changes in consumer confidence that are unrelated to the level of the series. In fact, as Figure 1 documents, our pessimistic-times state includes both phases with plummeting consumer confidence and recovering phases. In order to investigate this alternative interpretation of pessimism based on mood swings, we classify an initial month to the pessimistic times state whenever the cumulative change in the last six months of the Consumer Confidence Index is in its bottom 20%. The Appendix reports the visual representation of this alternative pessimistic-times state. Now, pessimistic times only include phases of negative mood swings and more episodes (also outside recessions) are classified into this state. The results – documented in the fourth row of panels of Figures 4 and 5 – are very similar to baseline ones, with the only difference being that now uncertainty shocks have milder effects under this alternative interpretation of pessimistic times.

Overall, we interpret the findings in Figures 4 and 5 as strongly supporting our baseline result, also when exploring alternative connected hypotheses and data measures.

3.1.3 Alternative Econometric Specifications

Before using our baseline results to predict the impact of the Covid-19 induced uncertainty shock, we check that they are robust to perturbations regarding both the control for financial variables, the identification approach adopted, and the definition of pessimistic times. Results for both industrial production and inflation are summarized in Figure 6.

Control for financial variables. Our baseline VAR does not model any financial variable. However, financial stress indicators – such as credit or at least three reasons. First, it is well known that credit spreads have large predictive power for both US and Euro area real activity (see Gilchrist and Zakrajšek (2012) and Gilchrist and Mojon (2018), respectively). Second, as advocated by recent studies, financial frictions and credit spreads are important for the transmission of uncertainty shocks (Alfaro, Bloom, and Lin (2018), Gilchrist, Sim, and Zakrajšek (2014) and Arellano, Bai, and Kehoe (2019)). A recent paper by Görtz, Tsoukalas, and Zanetti (2016) shows that movements in credit spreads are also relevant for the propagation of news shocks. Third, thanks to the consideration of credit spreads we can capture the effects of unconventional monetary policy in the Euro area since it operated at the long-term of the yield curve.

We alternatively add two bond spread indicators to our baseline IVAR and order them just after the VSTOXX uncertainty measure.[13] First, we use a high yield spread that tracks the performance of Euro-denominated below-investment-grade corporate debt publicly issued in the Euro markets with respect to a portfolio of Treasury bonds.[14] Second, we use the Gilchrist and Mojon's (2018) credit spread of Euro area non-financial corporations. The authors follow the methodology of Gilchrist and Zakrajšek (2012) and use individual bond level data to construct bond-specific credit spreads, which are then averaged to obtain credit spread indices at the country level. These credit spread indices are defined as the difference between the corporate bond yield and the country-specific sovereign bond yield. By aggregating this information across countries, they construct credit spreads for the Euro area as a whole.[15] As Figure 6 documents, controlling for financial variables does not affect our main results: the impulse responses under these alternative specifications of our IVAR are within the baseline results confidence bands.

Identification via external instrument: A Proxy Strucural IVAR. In our baseline, we use a recursive (Cholesky) strategy to identify uncertainty shocks. Our recursive identification allows for an immediate impact of uncertainty shocks but treats financial uncertainty as exogenous to the business cycle. To document the robustness of our main results, we adopt an alternative identification scheme, via external instruments, adopted in Proxy Structural VARs (see Stock and Watson (2012), Mertens and Ravn (2013), Mertens and Ravn (2014), Gertler and Karadi (2015), Piffer and Podstawski (2018)). We follow Piffer and Podstawski (2018), who propose an instrument to identify uncertainty shocks within proxy SVARs. Their instrument equals the percentage variations in the price of gold – which is perceived as a safe haven asset – around events associated with unexpected changes in uncertainty. The Appendix shows how to apply the external instrument identification to IVAR models. The gold instrument is used in an IVAR that features the VXO as the uncertainty measure, as in Piffer and Podstawski (2018).[16] Figure 6 shows that our main

[13]The use of a Cholesky decomposition does not allow us to easily disentangle uncertainty from financial shocks provided that both variables are fast-moving and are contemporaneously correlated (see Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016)). We order the credit spread as the second variable so as to allow it to contemporaneously react to uncertainty shocks. In this way, we can account for both their influence on real activity and their crucial role in the transmission of uncertainty shocks.

[14]Our credit spread measure is the ICE/BofA Euro High Yield Index Spread (source: Federal Reserve Bank of St. Louis).

[15]The credit spread indicators proposed by Gilchrist and Mojon (2018) are monthly updated and available at the link https://publications.banque-france.fr/en/economic-and-financial-publications-working-papers/credit-risk-euro-area. We use the variable spr_nfc_dom_ea, which refers to the euro area credit spread for non-financial corporations.

[16]The instrument is available on Michele Piffer's webpage (https://sites.google.com/site/michelepiffereconomics/). For our sample period, the instrument is associated with an F statistic equal to 8.17. Our first-stage regression

results are robust to the use of this alternative external instrument identification scheme. Impulse responses overall lie within the baseline estimation confidence bands except for the short-run response of inflation, which increases after an uncertainty shock, and the short-run response of real activity, which now features a bigger drop in normal times.

Alternative thresholds for the definition of pessimistic times. In our baseline, we use the bottom quintile of the historical distribution of consumer confidence to define our pessimistic-times state. We check that our results are not driven by this definition by alternatively using either the bottom decile or the bottom tertile as the relevant thresholds. Figure 6 documents that results are robust to this perturbation.

Our main results are also robust to the use of alternative lag orders (3 and 6).

3.2 The uncertainty-channel of the COVID-19 shock

We use the baseline IVAR results to predict the possible effects of the COVID-19 shock via its uncertainty channel. COVID-19 has caused enormous increases in financial uncertainty in the first half of 2020. Uncertainty measures have been surging since late February 2020, when the first cases in the Euro area not directly related to China were detected in Italy. During March the index has seen its biggest increase, in the period when the World Health Organization (WHO) declared a pandemic emergency on March 11. In the next few days, most Euro area countries closed their schools and borders (e.g., Germany on March 13 and 15, respectively) and adopted a lockdown (Germany on March 22, the same date when Italy implemented the strictest measures for its lockdown already started on March 9). Only in late April 2020 Euro area's countries have been relaxing the restrictions.

The April release of the European Commission consumer confidence indicator signaled a confidence level approaching the level reached during the 2008-2009 financial crisis. In the previous Section, we computed the effects of a typical uncertainty shock occurring during pessimistic times and found that it has stronger effects than during normal times. The peak reaction of real activity is roughly 3.5 times stronger during pessimistic times than normal times. We now simulate the effects of the COVID-19 related surge in uncertainty by using the pessimistic-times state of our

coefficient is 155.82 which is close to Piffer and Podstawski's (2018, Table 2) one of 166.40, notwithstanding the different sample considered. Differently from Piffer and Podstawski (2018), we do not use a set-identified Proxy SVAR that identifies uncertainty and news shocks jointly, but rather use their instrument to exactly identify the impulse responses associated to uncertainty shocks, an approach common in the Proxy SVAR literature. Piffer and Podstawski (2018, Figure H18) shows that the two approaches produce similar results for their analysis.

estimated IVAR.

The use of a nonlinear VAR is ideal to answer our COVID-19 related question because it can account for the unusual circumstances the Euro area economy is currently facing in terms of both uncertainty and consumer confidence. Moreover, the current values of consumer confidence and uncertainty do not represent outliers in our sample, something that reassures us of the information carried by our IVAR for the assessment of the uncertainty-channel of the COVID-19 shock.

According to our estimated IVAR, the unexpected rise in the level of the VSTOXX measure of uncertainty from February 2020 to March 2020 corresponds to roughly a 10 standard deviation shock. The black line in Figure 7 plots the effects of such an uncertainty shock during the average pessimistic state according to our estimated IVAR.[17] As Table 2 clarifies, industrial production experiences a year-over-year peak loss of 15.41% peaking after 7 months from the shock, in September 2020, and subsequently it recovers with a rebound to pre-crisis levels predicted to happen in May 2021. Given that our measure of industrial production is 2.8 times more volatile than the corresponding measure of GDP, a back-of-the-envelope calculation would translate the IVAR prediction for industrial production into a year-over-year fall in GDP of roughly 4.3% at peak. Inflation's year-over-year peak decrease is predicted to be -1.35% in August 2020.

What if the COVID-19 related uncertainty shock propagated in a way different from the past Euro area experience? In performing the previous exercise, we considered the persistence of a typical uncertainty shock as estimated by our IVAR on past data. Two alternative scenarios are plausible in the COVID-19 pandemic. We first assume that uncertainty can go back to normal levels much more slowly in the current situation than in the past, given the persisting uncertainty in delivering a vaccine could span several months. Alternatively, a second unexpected spike in uncertainty may occur following a new wave of the pandemic in the coming 6 to 9 months. In order to construct these two possible scenarios, we compute GIRFs by feeding a sequence of shocks. We generalize the GIRF definition in equation (2) with the following:

$$GIRF_{\mathbf{Y},t}(h,\boldsymbol{\delta},\boldsymbol{\varpi}_{t-1}) = \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\delta},\boldsymbol{\varpi}_{t-1}\right] - \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right], \quad h = 0,1,\ldots,H, \tag{3}$$

where now $\boldsymbol{\delta}$ is a vector including several unexpected shocks hitting at different times, or $\boldsymbol{\delta} = [\delta_t, \delta_{t+1,}..., \delta_{t+H}]$.

[17] Imposing a shock as big as 10 standard deviations causes our IVAR pessimistic times' response - which is based on the average of 50 initial quarters responses - to discard 5 particularly extreme initial histories which would lead to an explosive response. This implies that the estimated impact of the COVID-related uncertainty shock we report is conservative. However, our pessimistic times' response to a one standard deviation shock at the basis of Figure 2 did not discard any initial quarter.

We operationalize the first scenario assuming our uncertainty indicator, on top of being hit by a 10 standard deviation shock in period 1, is also hit by a sequence of small shocks for six months so as to mimic a scenario in which uncertainty comes back to normal levels only slowly.[18] In the second scenario, our uncertainty indicator is also hit by a 7.5 standard deviation shock after 7 months, or in September 2020, so as to mimic the effects of a possible new epidemic wave.[19]

Figure 7 and Table 2 report the results of these two exercises. Both scenarios would exacerbate the depth and length of the COVID-19 induced recession, by enlarging the maximum loss in industrial production and by shifting the time of the peak loss and the time of the rebound farther in future. In the case of a new fall wave, our simulations predict the trough to happen in December 2020 and the rebound in August 2021.

Notice that the effect of the hypothetical September 2020 shock is relatively small notwithstanding its size. This is because in the simulations consumer confidence endogenously subsides after the initial shock and hence the new uncertainty shock arrives in less pessimistic (or rather normal) times[20]. This implies that we are conservative in our findings. In the Appendix we show that, in a situation in which consumer confidence is not allowed to mean revert for the first 6 months after the shock – a plausible case for the COVID pandemic –, the effects on real activity and inflation are even bigger, with the rebound predicted to happen in September 2021.

The economic relevance of the predicted impact of the COVID-induced uncertainty shock in the Euro area can be assessed in the context of the results in Battistini and Stoevsky (ECB Economic Bulletin, 2020) on the *overall* impact of the COVID pandemic (including lockdowns and falling foreign demand, among other factors). According to their analysis, real GDP will plummet by around 12% in 2020 under their considered severe scenario, reaching a trough of around -15% in the second quarter of 2020. In our case, a back-of-the-envelope calculation would translate the IVAR prediction for industrial production for our severe scenario in Table 2 into a year-over-year fall in GDP of roughly 6.2% at its trough, hence around half of the large contraction predicted to happen because the COVID-19 disaster. This is in line with the predictions by Baker, Bloom, Davis, and Terry (2020) for the US. According to their study, around half of the total contraction

[18] Specifically we use $\boldsymbol{\delta} = [\delta_t, \delta_{t+2}, \delta_{t+3}, \delta_{t+4}, \delta_{t+5}, \delta_{t+6}, \delta_{t+7}] = [10, 1, 1, 1, 0.5, 0.5, 0.5]$.

[19] In an interview on April 1 2020, Yale University Professor Nicholas Christakis (MD, PhD, MPH) states that in Fall 2020 the US will have a 75% chance of getting a second wave of the pandemic (the podcast by the *Journal of American Medical Association* (JAMA) Network is available at https://edhub.ama-assn.org/jn-learning/audio-player/18393767 (around 25')). We use this information to calibrate the size in standard deviations of our Fall shock: $75\% \cdot 10 = 7.5$.

[20] Pellegrino (2017) discusses the effect of mean reversion of the conditioning variable in a fully nonlinear IVAR.

induced by the COVID-19 disaster will be due to the COVID-induced uncertainty shock.

4 Conclusion

We analyze the impact of the COVID-19 shock via its uncertainty channel using an IVAR model for the Euro area. The COVID-19 shock can be interpreted as a rare natural disaster shock that, because of its long-term consequences, also affects economic uncertainty, as documented by Ludvigson, Ma, and Ng (2020) and Baker, Bloom, Davis, and Terry (2020). As the latter studies, we rely on past historical data to predict the macroeconomic impact of the COVID-19 induced uncertainty shock, and as such appropriate caveats apply to our analysis. However, to try mitigating them, we considered alternative scenarios accounting for a possible different propagation of this huge uncertainty shock.

Our results suggest that the impact of an uncertainty shock in the Euro area is highly state-dependent, and varies according to the expectations for the economic outlook as measured by several confidence survey-measures. Using the estimated IVAR model, we assess that the rebound after the COVID-19 epidemics will be slow and painful - even if impact occurred only through the massive increase in uncertainty. This is caused by the uncertainty shock hitting the Euro area economy at a time of a severely negative economic outlook. Even when lockdowns will gradually be relaxed, there will still be a drag on the Euro area economy given by the heightened level of uncertainty about the future.

The current experience is unique, in that measures of uncertainty registered surges in both the US and the Euro area equal to several standard deviations, and measures of economic sentiment simultaneously hit their record bottom. If the uncertainty-channel alone can explain a substantial share of the overall cost of the COVID-19 disaster shock, policymakers ought to seriously consider enacting clear policies aimed not only at boosting confidence in the outlook, but specifically targeted at resolving the uncertainty, by providing to the public contingent scenarios and policies ready to be adopted if the worst-case outcomes materialize.

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Table 1: **Generalized Forecast Error Variance Decomposition: Contribution of uncertainty shocks in the two states.** GFEVD computed according to Lanne and Nyberg's (2016) algorithm for a 1-standard deviation shock to all variables. Forecast horizon: 2 years.

Variable	Normal times	Pessimistic times
VSTOXX	0.89	0.92
Industrial production	0.17	0.42
Inflation	0.11	0.27
Consumer confidence	0.27	0.10
Policy rate	0.20	0.57

Table 2: **Euro area predicted response to the COVID-19-induced uncertainty shock.** 'Time to trough': number of months for the peak impact on industrial production to occur. 'Time to rebound': number of months for year-over-year growth in industrial production to go back to zero.

	March 2020 shock (historical shock persistence)	
	Industrial Production	Inflation
Peak y-o-y loss	−15.41%	−1.35%
Time to trough	7 months (September 2020)	6 months (August 2020)
Time to rebound	15 months (May 2021)	−
	March 2020 shock (increased shock persistence)	
Peak y-o-y loss	−18.96%	−1.90%
Time to trough	7 months (September 2020)	9 months (November 2020)
Time to rebound	17 months (July 2021)	−
	March 2020 shock (historical persistence) and fall 2020 shock	
Peak y-o-y loss	−17.28%	−2.17%
Time to trough	10 months (December 2020)	10 months (December 2020)
Time to rebound	18 months (August 2021)	−

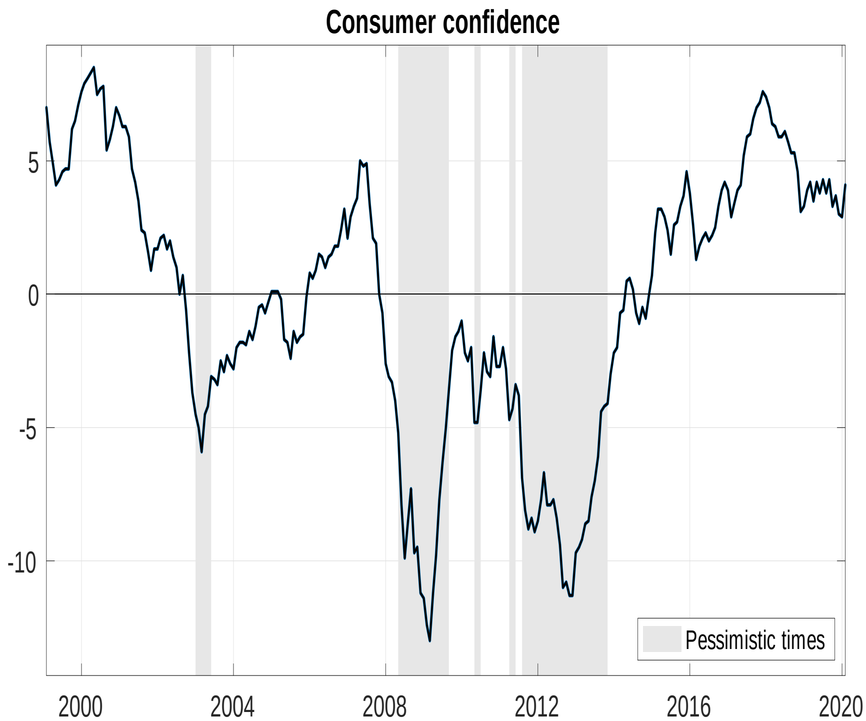

Figure 1: **European Commission Consumer Confidence Index (rescaled).** Solid line: European Commission Consumer Confidence Index. The series is obtained by subtracting the long-run average of the original series. Grey vertical bars: initial quarters in the bottom 20% of the consumer confidence distribution defining the Pessimistic times state.

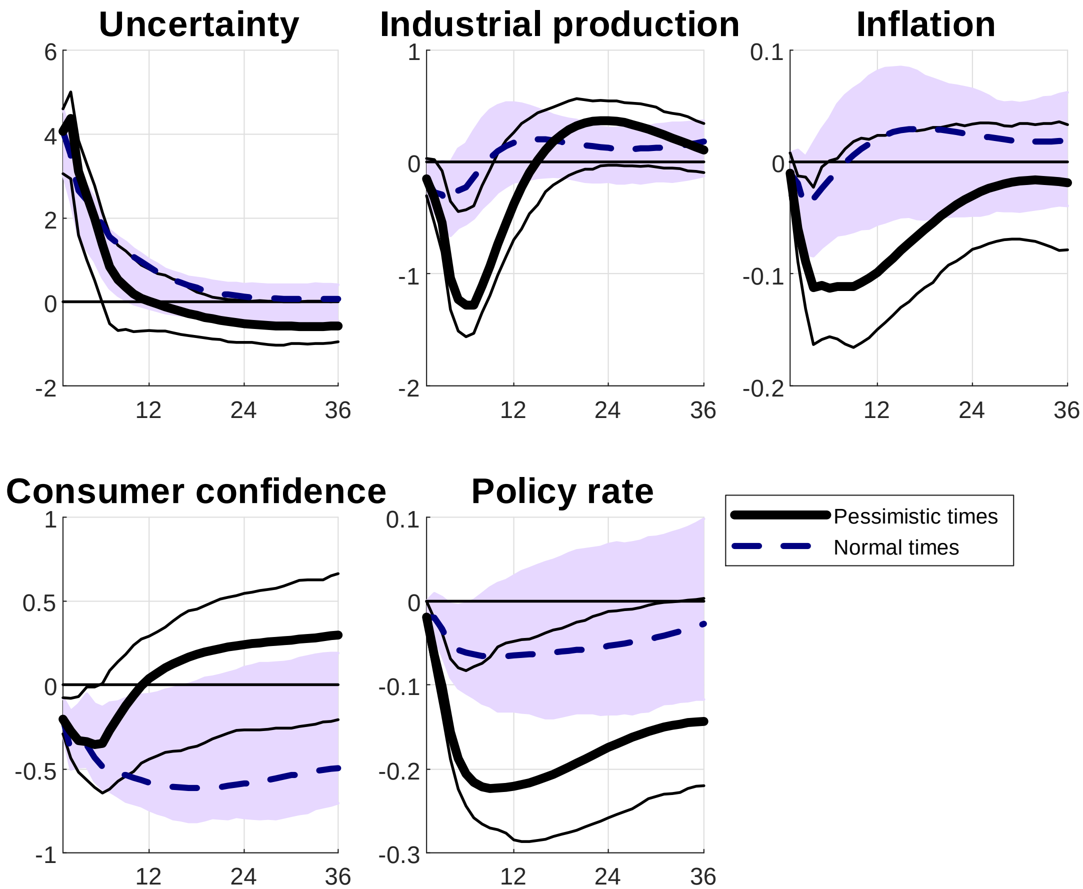

Figure 2: **Pessimistic vs. normal times state-conditional GIRFs**. Black solid lines: point estimates (bold lines) and 90% bootstrapped confidence bands for the GIRFs conditional to pessimistic times. Blue dashed lines and light blue areas: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional to normal times. Monthly data.

Figure 3: **Difference of state-conditional GIRFs between pessimistic and normal times**. Interior dark grey areas: 68 percent confidence bands for the difference between the pessimistic times conditional GIRF minus the normal times conditional GIRF. Confidence bands built with 500 bootstrap draws. Exterior light grey areas: 90 percent confidence bands. Monthly data.

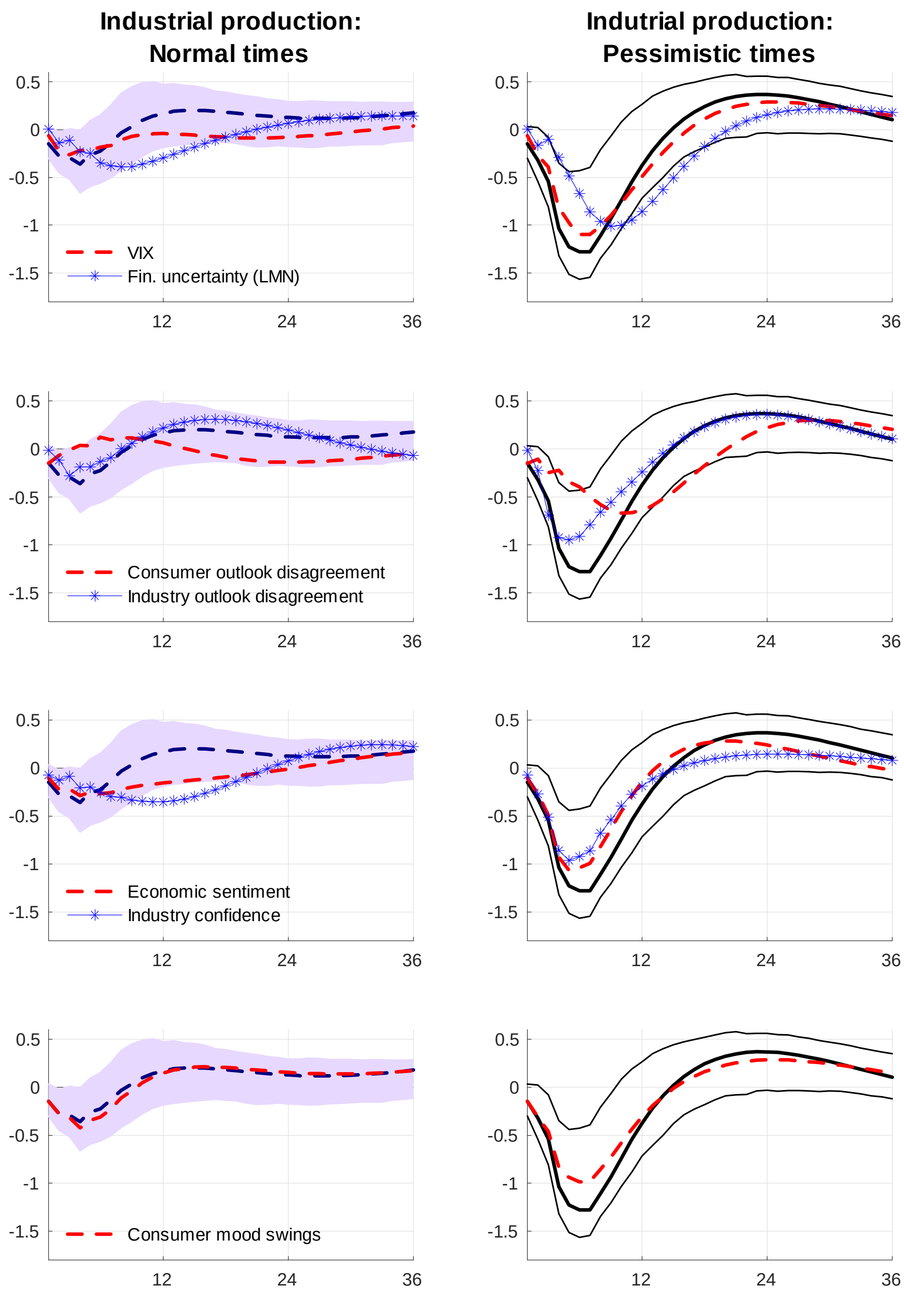

Figure 4: **IVAR models for alternative hypotheses: Industrial Production GIRF.** Left-hand-side panels: Blue dashed lines and light blue areas represent the point estimates and 90% bootstrapped confidence bands for the baseline industrial production GIRFs conditional on normal times. Right-hand-side panels: Black solid lines represent the point estimates (bold lines) and 90% bootstrapped confidence bands for the baseline industrial production GIRFs conditional on pessimistic times. For the other lines refer to the legend and the main text. Monthly data.

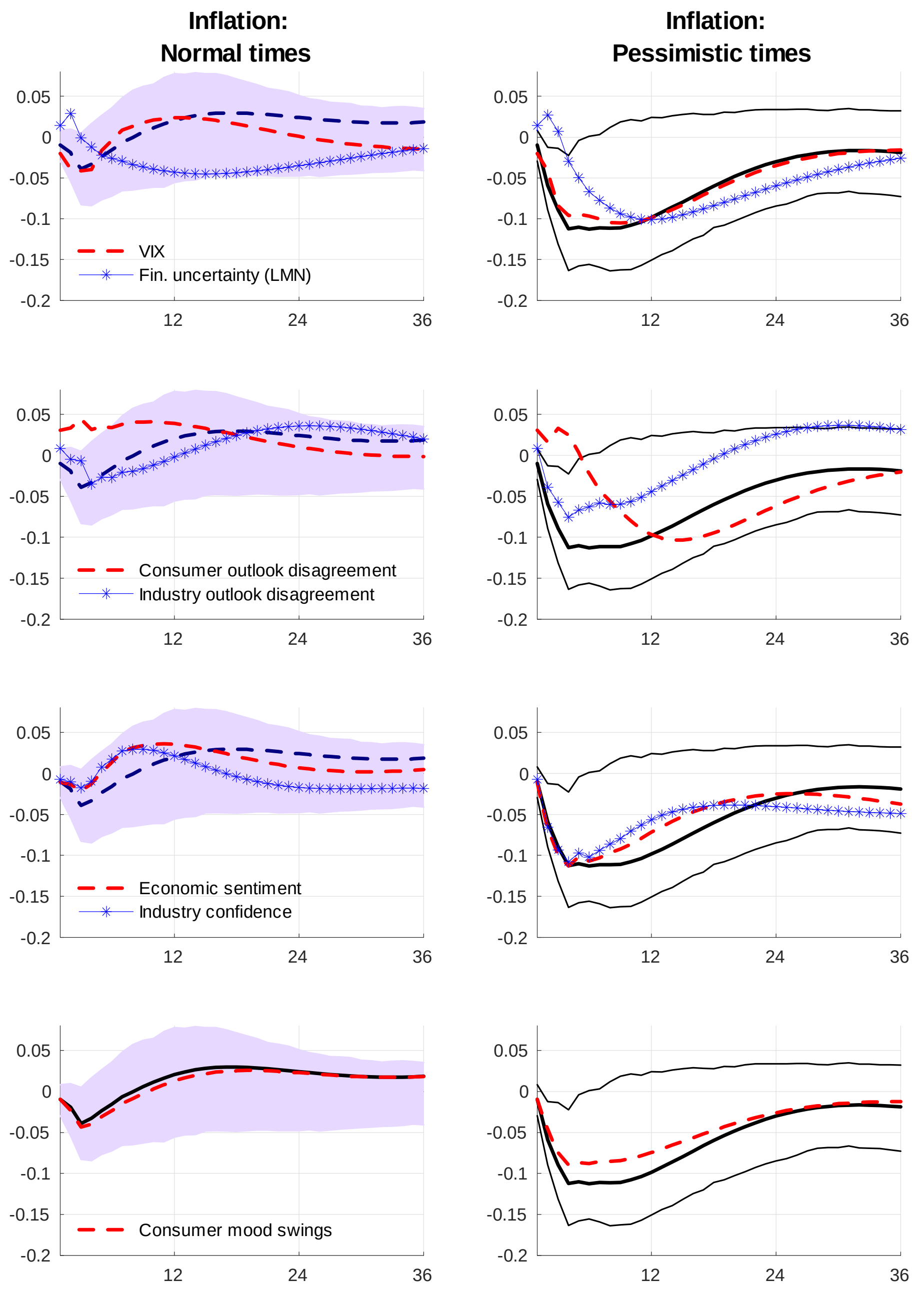

Figure 5: **IVAR models for alternative hypotheses: Inflation GIRF.** Left-hand-side panels: Blue dashed lines and light blue areas represent the point estimates and 90% bootstrapped confidence bands for the baseline inflation GIRFs conditional on normal times. Right-hand-side panels: Black solid lines represent the point estimates (bold lines) and 90% bootstrapped confidence bands for the baseline inflation GIRFs conditional to pessimistic times. For the other lines refer to the legend and the main text. Monthly data

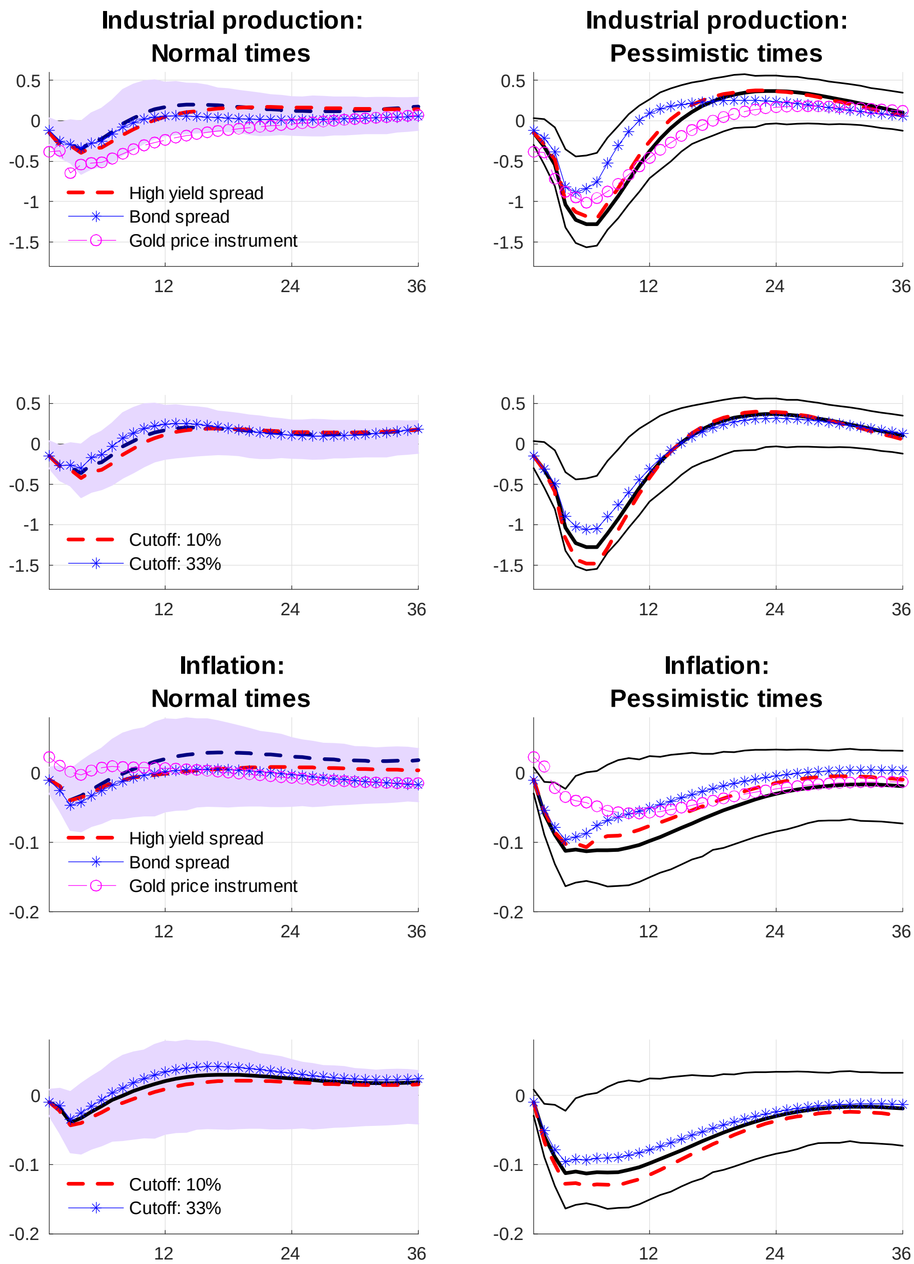

Figure 6: **Robustness to alternative IVAR specifications.** Top panels: Industrial Production GIRFs. Bottom Panels: Inflation GIRFs. Left-hand-side panels: Blue dashed lines and light blue areas represent the point estimates and 90% bootstrapped confidence bands for the baseline industrial production GIRFs conditional on normal times. Right-hand-side panels: Black solid lines represent the point estimates (bold lines) and 90% bootstrapped confidence bands for the baseline industrial production GIRFs conditional on pessimistic times. For the other lines refer to the legend and the main text. Monthly data.

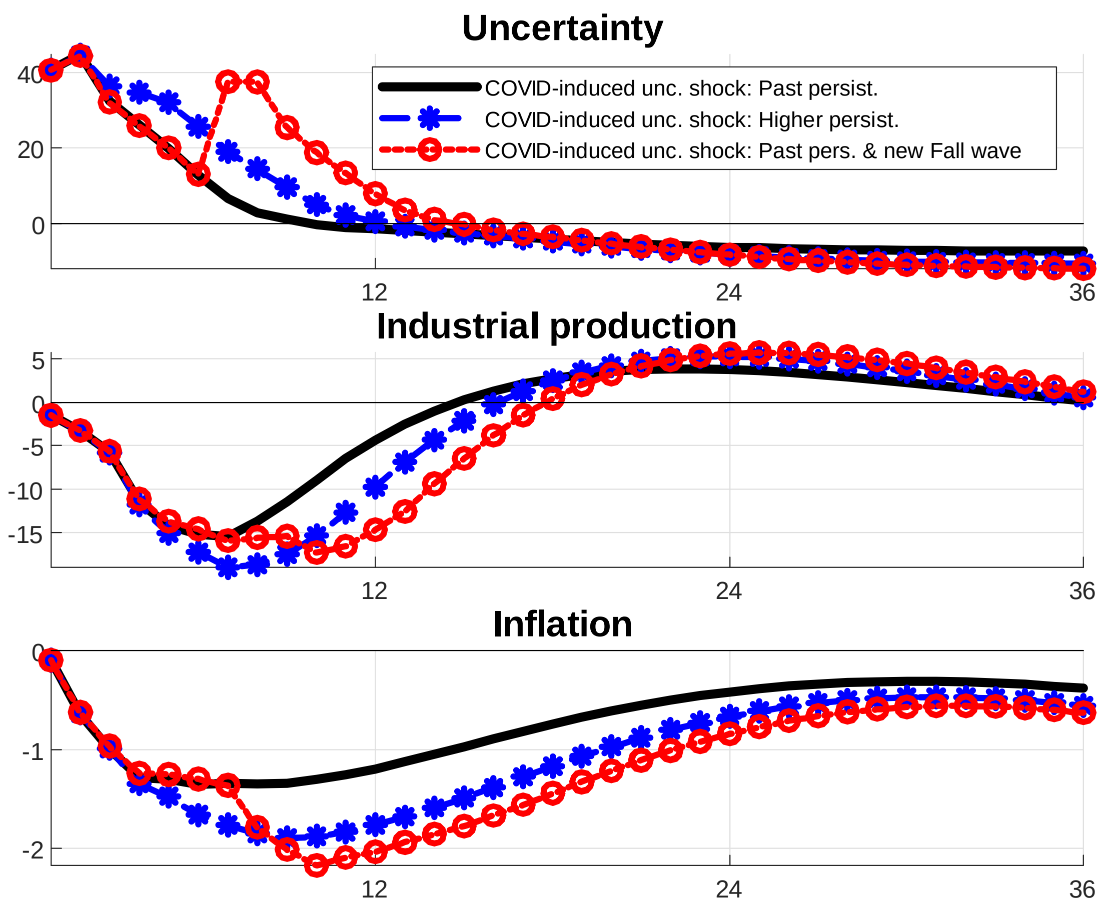

Figure 7: **The uncertainty-channel of the COVID-19 shock during pessimistic times: Alternative scenarios.** Solid black line: GIRF to a 10 standard deviation uncertainty shock hitting the economy during pessimistic times. Starred blue line: GIRF to the sequence of shocks $\boldsymbol{\delta} = [\delta_t, \delta_{t+2}, \delta_{t+3}, \delta_{t+4}, \delta_{t+5}, \delta_{t+6}, \delta_{t+7}] = [10, 1, 1, 1, 0.5, 0.5, 0.5]$ hitting the economy during pessimistic times (see equation 3). Circled red line: GIRF to the sequence of shocks $\boldsymbol{\delta} = [\delta_t, \delta_{t+6}] = [10, 7.5]$ hitting the economy during pessimistic times (see equation 3). The initial shock is assumed to hit in March 2020. Monthly data.

Online Appendix

"The Impact of Pessimistic Expectations on the Effects of COVID-19-Induced Uncertainty in the Euro Area" by Giovanni Pellegrino, Federico Ravenna and Gabriel Züllig

Computation of the Generalized Impulse Response Functions

This Section documents the algorithm employed to compute the state-dependent GIRFs and their confidence intervals. The algorithm follows Koop, Pesaran, and Potter (1996), with the modification of considering an orthogonal structural shock, as in Kilian and Vigfusson (2011). The algorithm is the same used in Pellegrino (2017).

The theoretical GIRF of the vector of endogenous variables $\mathbf{Y}$, h periods ahead, for a starting condition $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, and a structural shock in date t, δ_t, can be expressed – following Koop, Pesaran, and Potter (1996) – as:

$$GIRF_{\mathbf{Y},t}(h, \delta_t, \boldsymbol{\varpi}_{t-1}) = \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \boldsymbol{\varpi}_{t-1}\right] - \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right], \quad h = 0, 1, \ldots, H$$

where $\mathbb{E}[\cdot]$ represents the expectation operator. We are interested in the state-dependent GIRFs for pessimistic and normal times, which can be defined as:

$$GIRF_{\mathbf{Y},t}\left(h, \delta_t, \boldsymbol{\Omega}_{t-1}^{pessimistic\ times}\right) = \mathbb{E}\left[GIRF_{\mathbf{Y},t}\left(h, \delta_t, \left\{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{pessimistic\ times}\right\}\right)\right]$$

$$GIRF_{\mathbf{Y},t}\left(h, \delta_t, \boldsymbol{\Omega}_{t-1}^{normal\ times}\right) = \mathbb{E}\left[GIRF_{\mathbf{Y},t}\left(h, \delta_t, \left\{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{normal\ times}\right\}\right)\right]$$

where $\boldsymbol{\Omega}_{t-1}^{i}$ denotes the set of histories characterizing the state $i = \{pessimistic\ times, \quad normal\ times\}$.

The algorithm to estimate our state-conditional GIRF reads as follows:

1. pick an initial condition $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, i.e., the historical values for the lagged endogenous variables at a particular date $t = L+1, \ldots, T$. Notice that this set includes the values for the interaction terms;

2. draw randomly (with repetition) a sequence of (n-dimensional) residuals $\{\mathbf{u}_{t+h}\}^s$, $h = 0, 1, ..H = 19$, from the empirical distribution $d(\mathbf{0}, \widehat{\boldsymbol{\Omega}})$, where $\widehat{\boldsymbol{\Omega}}$ is the estimated VCV matrix. In order to preserve the contemporaneous structural relationships among variables, residuals are as-

sumed to be jointly distributed, so that if date t' s residual is drawn, all n residuals for date t are collected;

3. conditional on $\boldsymbol{\varpi}_{t-1}$ and on the estimated model (1), use the sequence of residuals $\{\mathbf{u}_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods to obtain the path $\mathbf{Y}^s_{t+h}$ for $h = 0, 1 \ldots H$. s denotes the dependence of the path on the particular sequence of residuals used;

4. conditional on $\boldsymbol{\varpi}_{t-1}$ and on the estimated model (1), use the sequence of residuals $\{\mathbf{u}_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods when a structural shock δ_t is imposed to $\mathbf{u}^s_t$. In particular, we Cholesky-decompose $\widehat{\boldsymbol{\Omega}}= \mathbf{CC}'$, where $\mathbf{C}$ is a lower-triangular matrix. Then, we recover the structural innovation associated to $\mathbf{u}^s_t$ by $\boldsymbol{\varepsilon}^s_t = \mathbf{C}^{-1}\mathbf{u}^s_t$ and add a quantity $\delta < 0$ to the scalar element of $\boldsymbol{\varepsilon}^s_t$ that refers to the uncertainty measure, i.e. $\varepsilon^s_{t,unc}$. We then move again to the residual associated with the structural shock $\mathbf{u}^{s,\delta}_t = \mathbf{C}\boldsymbol{\varepsilon}^{s,\delta}_t$ to proceed with simulations as in point 3. Call the resulting path $\mathbf{Y}^{s,\delta}_{t+h}$;

5. compute the difference between the previous two paths for each horizon and for each variable, i.e. $\mathbf{Y}^{s,\delta}_{t+h} - \mathbf{Y}^s_{t+h}$ for $h = 0, 1 \ldots, H$;

6. repeat steps 2-5 for a number of $S = 500$ different extractions for the residuals and then take the average across s. Notice that in this computation the starting month $t-1$ does not change. In this way we obtain a consistent point estimate of the GIRF for each given starting month in our sample , i.e. $\widehat{GIRF}_{\mathbf{Y},t}(\delta_t, \boldsymbol{\varpi}_{t-1}) = \left\{\widehat{\mathbb{E}}\left[\mathbf{Y}_{t+h} \mid \delta_t, \boldsymbol{\varpi}_{t-1}\right] - \widehat{\mathbb{E}}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right]\right\}_{h=0}^{19}$. If a given initial condition $\boldsymbol{\varpi}_{t-1}$ brings an explosive response (namely if this is explosive for most of the sequences of residuals drawn $\{\mathbf{u}_{t+h}\}^s$, in the sense that the response of the variable shocked diverges instead than reverting to zero), it is discarded and not considered for the computation of state-conditional responses at the next step;[21]

7. repeat steps 2-6 to obtain an history-conditional GIRF for each initial condition $\boldsymbol{\varpi}_{t-1}$ of interest. In particular, we select two particular subsets of initial conditions related to the

[21] While we allow this to happen for bootstrapped simulated responses, we make sure that this does not happen for point-estimated responses (i.e. our responses estimated on actual data) so that to back up the stability of the estimated IVAR . The nonlinear DSGE literature has developed the pruning method in order to preserve stability (see Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2017)) but this is not currently available for nonlinear VARs.

historical level of consumer confidence to define two states. An initial condition $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$ is classified to belong to the "pessimistic times" state if $conf_{t-1}$ is in the bottom 20% of the consumer confidence empirical distribution and to the "normal times" state if $conf_{t-1}$ is in not in its bottom 20%;

8. history-dependent GIRFs obtained in step 7 are then averaged over the state they belong to produce our estimate of the state-dependent GIRFs, i.e., our $\widehat{GIRF}_{\mathbf{Y},t}\left(\delta_t, \boldsymbol{\Omega}_{t-1}^{pessimistic\ \ times}\right)$ and $\widehat{GIRF}_{\mathbf{Y},t}\left(\delta_t, \boldsymbol{\Omega}_{t-1}^{normal\ times}\right)$;

9. confidence bands around the point estimates obtained in point 8 are computed through bootstrap[22]. In particular, we simulate $R = 500$ datasets statistically equivalent to the actual sample and for each of them interaction terms are constructed coherently with the simulated series. Then, for each dataset, (i) we estimate our Interacted VAR model and (ii) implement steps 1-8. In implementing this procedure this time we have that the starting conditions and the VCV matrix used in the computation depend on the particular dataset r used, i.e. $\boldsymbol{\varpi}_{t-1}^{r}$ and $\widehat{\boldsymbol{\Omega}}^{r}$. Of the resulting distribution of state-conditional GIRFs, we take the 5th and 95th percentiles to construct the 90% confidence bands.

Computation of the Generalized Forecast Error Variance Decomposition

The algorithm for the computation of the state-dependent Generalized Forecast Error Variance Decomposition (GFEVD) for our nonlinear VAR model follows Caggiano, Castelnuovo, and Pellegrino (2017). In particular, the innovations to the algorithm proposed in Lanne and Nyberg (2016) are: i) it is designed to simulate the importance of an orthogonal structural shock, and ii) it considers a one standard deviation shock in each variable. The expression at the basis of our computation of the GFEVD is the same proposed by Lanne and Nyberg (2016, equation 9).

In particular, conditional on a specific initial history $\boldsymbol{\varpi}_{t-1}$ and a forecast horizon of interest z, the $GFEVD_{ij}$ that refers to a variable i and a shock j whose size is δ_t^j is given by:

$$GFEVD_{ij}(z, \boldsymbol{\varpi}_{t-1}) = \frac{\sum_{h=0}^{z} GIRF_{Y_i}(h, \delta_t^j, \boldsymbol{\varpi}_{t-1})^2}{\sum_{j=1}^{n}\sum_{h=0}^{z} GIRF_{Y_i}(h, \delta_t^j, \boldsymbol{\varpi}_{t-1})^2} \qquad i, j = 1, ..., n, \tag{A1}$$

[22] The bootstrap used is similar to the one used by Christiano, Eichenbaum and Evans (1999, footnote 23). Our code repeats the explosive artificial draws to be sure that exactly 500 draws are used.

where h is an indicator keeping track of the forecast ahead, and n denotes the number of variables in the vector $\mathbf{Y}$.[23] Differently from Lanne and Nyberg (2016), in our case the object $GIRF_{Y_i}(\cdot)$ in the formula refers to GIRFs à la Koop, Pesaran, and Potter (1996) computed by considering an orthogonal shock as in Kilian and Vigfusson (2011).[24] In our application we are interested in the contribution of an identified uncertainty shock to the GFEVD of all the variables in the vector $\mathbf{Y}$. Further, while formula (A1) defines the GFEVD for a given history, we are interested in computing a state-conditional GFEVD referring to a set of histories.

Given our model (1), we compute our state-dependent GFEVD for Normal times and Pessimistic times by following the steps indicated below. In particular, we:

1. consider an orthogonal shock equal to a standard deviation in each variable of the estimated I-VAR model. This is equivalent, for a Cholesky decomposition, to taking a vector of shocks equal to $\left(\delta_t^1, \delta_t^2, ..., \delta_t^n\right) = (1, 1, ..., 1)$ in our algorithm in the previous Section;[25]

2. pick a history $\boldsymbol{\varpi}_{t-1}$ from the set of all histories;

3. compute the $GIRF_{\mathbf{Y}}(\cdot, \cdot, \boldsymbol{\varpi}_{t-1})$ for each δ_t^j $(j = 1, ..., n)$ and for each $h \leq z$ according to points 2-6 of the algorithm in the previous Section;

4. plug the GIRFs computed in step 3 into equation (A1) to obtain $GFEVD_{ij}(z, \boldsymbol{\varpi}_{t-1})$ for the particular forecast horizon z and history $\boldsymbol{\varpi}_{t-1}$ considered;

5. repeat steps 2–4 for all the histories, distinguishing between the histories belonging to the "Normal times" state and the "Pessimistic times" one (see the definition at point 7 of the GIRFs algorithm);

6. compute the state-dependent GFEVD for the "Normal times" state and the "Pessimistic times" one by computing the average of the $GFEVD_{ij}(z, \boldsymbol{\varpi}_{t-1})$ across all the histories relevant for the two states.

[23] Expression (A1) gives a GFEVD that by construction lies between 0 and 1, and for which the contribution of all the shocks on a given variable sum to 1.

[24] The object $GIRF_{Y_i}(\cdot)$ in Lanne and Nyberg's (2016) expression refers to the GIRFs à la Pesaran and Shin (1998). This definition of the GIRF refers to a non-orthogonalized shock and it can be applied both to linear and to nonlinear VAR models. Details can be found in Pesaran and Shin (1998) and Lanne and Nyberg (2016).

[25] The size of the shock matters in a nonlinear model. The use of a one standard deviation shock in all variables allows our GFEVD algorithm to return the usual Forecast Error Variance (FEV) and Forecast Error Variance Decomposition (FEVD) quantities referred to an orthogonal shock when the algorithm is applied to a standard linear VAR model.

Proxy Structural Interacted VAR models

Our reduced-form Interacted VAR model can be written as:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \cdot conf_{t-j} \right] + \mathbf{u}_t,$$

from where the corresponding Structural IVAR model can be obtained as:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \cdot conf_{t-j} \right] + \mathbf{B}_0^{-1} \boldsymbol{\nu}_t,$$

where $\mathbf{Y}_t$ is a vector of variables of interest, $\mathbf{A}_j$ and $\mathbf{c}_j$, $j = 1, ..., L$, are coefficient matrices and coefficient vectors, respectively, and $\boldsymbol{\nu}_t$ is a vector of economically meaningful structural shocks that are a linear combination of the reduced-form IVAR residuals, i.e., $\boldsymbol{\varepsilon}_t = \mathbf{B}_0^{-1} \boldsymbol{\nu}_t$. Suppose we are interested in partial identification and, in particular, in the impulse response of a shock $\nu_{it} \in \boldsymbol{\nu}_t$. This means that we only need to identify the i-th column of the matrix $\mathbf{B}_0^{-1}$, $\mathbf{b}_{0,i}^{-1}$. Call the other columns as $\mathbf{B}_{0,\bar{\imath}}^{-1}$. Hence we can rewrite $\boldsymbol{\varepsilon}_t = \mathbf{B}_0^{-1} \boldsymbol{\nu}_t$ as:

$$\boldsymbol{\varepsilon}_t = \mathbf{b}_{0,i}^{-1} \nu_{it} + \mathbf{B}_{0,\bar{\imath}}^{-1} \boldsymbol{\nu}_{\bar{\imath}t}$$

A Proxy Structural IVAR model allows us to identify the impact vector $\mathbf{b}_{0,i}^{-1}$ by means of an instrument m_t that satisfies the following conditions:

$$\begin{array}{cc} \mathbb{E}\left[m_t \nu_{it}\right] = \phi \neq 0 & (\textit{Relevance condition}) \\ \mathbb{E}\left[m_t \boldsymbol{\nu}_{\bar{\imath}t}\right] = \mathbf{0} & (\textit{Exogeneity condition}) \end{array} .$$

The previous conditions imply:

$$\mathbb{E}\left[m_t \boldsymbol{\varepsilon}_t\right] = \mathbf{b}_{0,i}^{-1} \phi,$$

or:

$$\begin{pmatrix} \mathbb{E}\left[m_t \varepsilon_{1t}\right] \\ \mathbb{E}\left[m_t \varepsilon_{2t}\right] \\ . \\ \mathbb{E}\left[m_t \varepsilon_{Nt}\right] \end{pmatrix} = \begin{pmatrix} \mathbf{b}_{0,i}^{-1}(1)\phi \\ \mathbf{b}_{0,i}^{-1}(2)\phi \\ . \\ \mathbf{b}_{0,i}^{-1}(N)\phi \end{pmatrix},$$

where $\mathbf{b}_{0,i}^{-1}(z),\ z = 1, ..., N$, denotes z-th element of the vector $\mathbf{b}_{0,i}^{-1}$. Without loss of generality, assume that we are interested in the effects of the first shock, or $i = 1$. Hence with $\mathbb{E}\left[m_t \boldsymbol{\varepsilon}_t\right]$ in hand we can recover the normalized impact vector as:

$$\begin{pmatrix} 1 \\ \frac{\mathbb{E}[m_t \varepsilon_{2t}]}{\mathbb{E}[m_t \varepsilon_{1t}]} \\ . \\ \frac{\mathbb{E}[m_t \varepsilon_{Nt}]}{\mathbb{E}[m_t \varepsilon_{1t}]} \end{pmatrix} = \begin{pmatrix} 1 \\ \frac{\mathbf{b}_{0,1}^{-1}(2)}{\mathbf{b}_{0,1}^{-1}(1)} \\ . \\ \frac{\mathbf{b}_{0,1}^{-1}(N)}{\mathbf{b}_{0,1}^{-1}(1)} \end{pmatrix},$$

which corresponds to the impact vector for an unitary shock, $\left[1; \mathbf{b}_{0,1}^{-1}(\bar{1})/\mathbf{b}_{0,1}^{-1}(1)\right]$. An estimate of $\mathbf{b}_{0,1}^{-1}(\bar{1})/\mathbf{b}_{0,1}^{-1}(1)$ can be obtained from the two stage least square regression of $\boldsymbol{\varepsilon}_{\bar{1}t}$ on ε_{1t} using the instrument m_t. The first stage regression:

$$\varepsilon_{1t} = \beta m_t + \xi_t$$

gives the fitted values $\hat{\varepsilon}_{1t}$, that are then used in the second stage regression to recover the true normalized impact vector:

$$\begin{aligned} \boldsymbol{\varepsilon}_{\bar{1}t} &= \boldsymbol{\gamma} \hat{\varepsilon}_{it} + \boldsymbol{\varsigma}_t. \\ &= \frac{\mathbf{b}_{0,1}^{-1}(\bar{1})}{\mathbf{b}_{0,1}^{-1}(1)} \hat{\varepsilon}_{it} + \boldsymbol{\varsigma}_t, \end{aligned}$$

where the recoverability of $\mathbf{b}_{0,1}^{-1}(\bar{1})/\mathbf{b}_{0,1}^{-1}(1)$ depends from the fact that $\mathbb{E}\left[m_t \boldsymbol{\varepsilon}_t\right] = \mathbf{b}_{0,1}^{-1}\phi$.[26]

The (absolute) impact vector $\mathbf{b}_{0,1}^{-1}$ can then be derived from the estimated reduced form variance-covariance matrix, $\Sigma = \mathbb{E}\left[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'\right]$, as explained, e.g., in Gertler and Karadi (2015).[27] At this point we can compute the impulse response function to a one standard deviation shock in date t, $\delta_t = 1$,

[26] Indeed, we have: $\gamma = \frac{\mathbb{E}\left[\boldsymbol{\varepsilon}_{\bar{1}t} \hat{\varepsilon}_{it}\right]}{\mathbb{E}\left[\hat{\varepsilon}_{it}^2\right]} = \frac{\mathbb{E}\left[\boldsymbol{\varepsilon}_{\bar{1}t} \beta m_t\right]}{\mathbb{E}\left[\beta^2 m_t^2\right]} = \frac{\beta \mathbb{E}\left[\boldsymbol{\varepsilon}_{\bar{1}t} m_t\right]}{\beta^2 \mathbb{E}\left[m_t^2\right]} = \frac{\frac{\mathbb{E}[\varepsilon_{1t} m_t]}{\mathbb{E}\left[m_t^2\right]} \mathbb{E}\left[\boldsymbol{\varepsilon}_{\bar{1}t} m_t\right]}{\left(\frac{\mathbb{E}[\varepsilon_{1t} m_t]}{\mathbb{E}\left[m_t^2\right]}\right)^2 \cdot \mathbb{E}\left[m_t^2\right]} = \frac{\mathbb{E}\left[\boldsymbol{\varepsilon}_{\bar{1}t} m_t\right]}{\mathbb{E}[\varepsilon_{1t} m_t]} = \frac{\phi \mathbf{b}_{0,1}^{-1}(\bar{1})}{\phi \mathbf{b}_{0,1}^{-1}(1)}$.

[27] Specifically, to recover the absoulte impact vector we follow Piffer's notes on the identification of VARs using external instruments available at https://sites.google.com/site/michelepiffereconomics/ .

to ν_{1t}, according to the usual Generalized IRF à la Koop, Pesaran, and Potter (1996):

$$\begin{aligned} GIRF_{Y,t}(h,1,\boldsymbol{\varpi}_{t-1}) &= \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \delta_t = 1, \boldsymbol{\varpi}_{t-1}\right] - \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right], \text{ for } h = 0,1,...,H \\ &= \begin{cases} \mathbf{b}_{0,1}^{-1} & \text{, for } h = 0 \\ \mathbb{E}[\mathbf{Y}_{t+h} \,| \delta_t = 1, \boldsymbol{\varpi}_{t-1}] - \mathbb{E}[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}] & \text{, for } h = 1,...,H \end{cases}, \end{aligned}$$

where $\boldsymbol{\varpi}_{t-1}$ denotes the initial condition, or $\{\mathbf{Y}_{t-1},...,\mathbf{Y}_{t-L}\}$. In computing the GIRF we follow the same algorithm outlined earlier.

Supplementary results

Figure A1 plots the time series that enter our baseline IVAR.

Figure A2 plots the daily VSTOXX index, our proxy for Euro area financial uncertainty, against its monthly average.

Figure A3 in its upper panel plots the consumer confidence indicator released by the European Commission in April – a leading indicator of future economic activity –, which signaled a confidence level approaching the number reached during the 2008-2009 financial crisis. The bottom panel of Figure A3 plots the monthly VSTOXX, our baseline measure of financial uncertainty, which in March 2020 reached levels comparable to the Global Financial Crisis.

Figure A4 plots all the uncertainty indicators we use in our analysis, as described in the robustness checks Section of the paper.

Figure A5 plots all the indices of survey-based confidence we use in our analysis, as described in the robustness checks Section of the paper.

Figure A6 plots the pessimistic-times state under the alternative interpretation of pessimism based on "mood swings", i.e., sudden negative changes in the consumer confidence series. We classify an initial month to the pessimistic-times state whenever the cumulative change in the last six months of the Consumer Confidence Index is in its bottom 20%.[28] In such a way, pessimistic times only include phases of negative mood swings.

Figure A7 and Table A1 complement the findings in Figure 7 and Table 2 of the paper. They show that, in a situation in which consumer confidence is not allowed to mean revert for the first 6 months after the shock, the same shocks considered in Section 3.2 imply larger peak losses and

[28] This threshold corresponds to a cumulative change of -2.5.

more time to rebound in the case of a new fall wave.[29] This means that in our findings in Section 3.2 we are conservative on the possible losses implied by the COVID-19-induced uncertainty shock.

[29] We compute the GIRF for a counterfactual where the consumer confidence level (for each of the shocked paths behind the average shocked path in equation 2 of the main paper, $\mathbb{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \boldsymbol{\varpi}_{t-1}\right]$) is not allowed to increase if not after 6 months. If the consumer confidence would increase, a counterfactual shock keeps its level constant to the last value.

Table A1: **Euro area predicted response to the COVID-19-induced uncertainty shock: Alternative case without a fast recovery in consumer confidence** 'Time to trough': number of months for the peak impact on industrial production to occur. 'Time to rebound': number of months for year-over-year growth in industrial production to go back to zero.

	March 2020 shock (historical shock persistence)	
	Industrial Production	Inflation
Peak y-o-y loss	−15.41%	−1.35%
Time to trough	7 months (September 2020)	6 months (August 2020)
Time to rebound	15 months (May 2021)	–
	March 2020 shock (increased shock persistence and lower confidence)	
Peak y-o-y loss	−19.53%	−1.96%
Time to trough	7 months (September 2020)	9 months (November 2020)
Time to rebound	17 months (July 2021)	–
	March 2020 shock (hist. persist. and lower conf.) and fall 2020 shock	
Peak y-o-y loss	−18.80%	−2.29%
Time to trough	10 months (December 2020)	10 months (December 2020)
Time to rebound	19 months (September 2021)	–

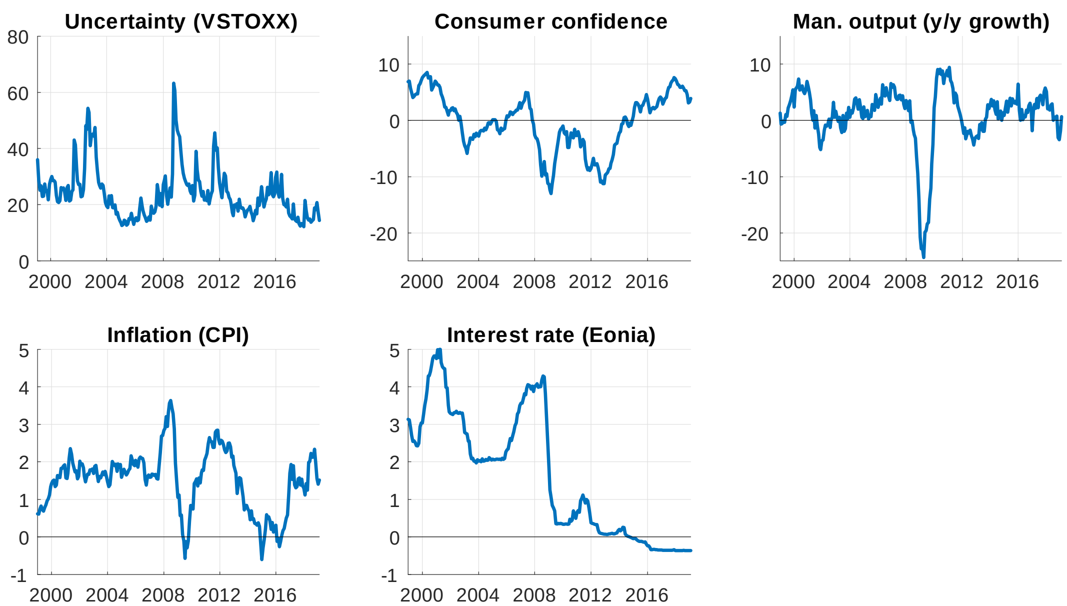

Figure A1: **Time series modeled in our baseline IVAR model.** *Note*: the series and their sources are given in Section 2 of the main paper. The sample period modeled is 1999m1-2020m1.

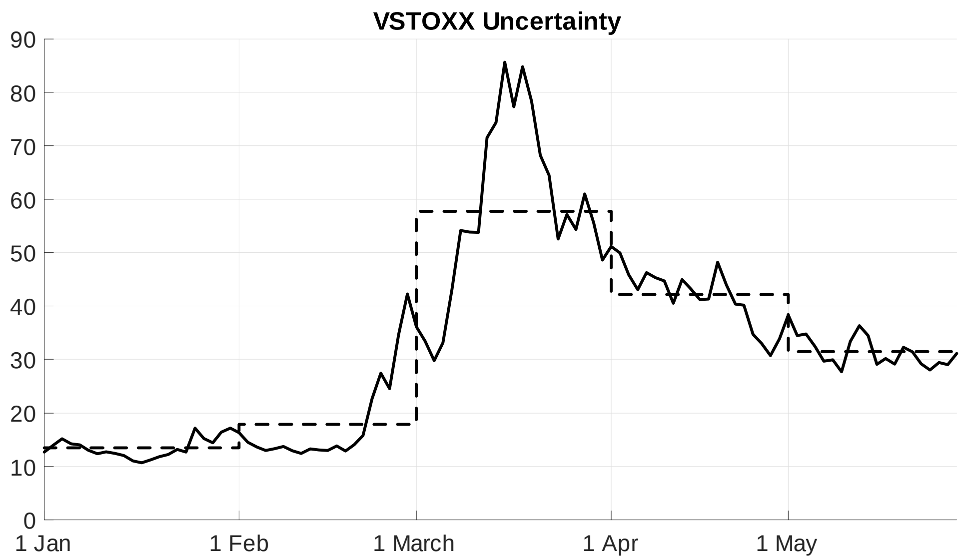

Figure A2: **VSTOXX index since January 2020.** Black solid line: daily index. Black dashed line: monthly average.

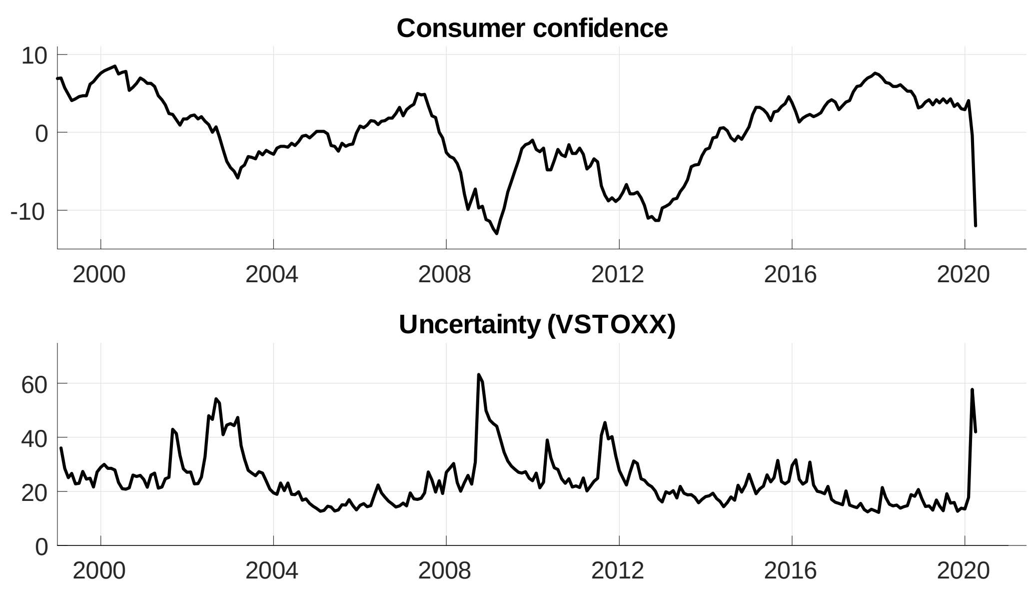

Figure A3: **Consumer Confidence and Uncertainty.** Top panel: European Commission Consumer Confidence Index**.** Bottom panel: VSTOXX. *Note*: 1999m1-2020m4.

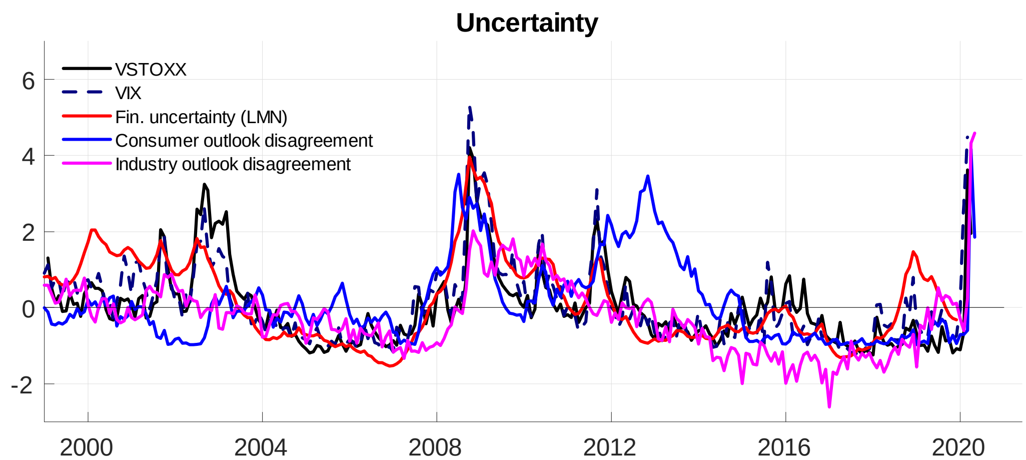

Figure A4: **Uncertainty indicators**. *Note*: 1999m1-2020m4. Each series is standardized to have 0 mean and unit variance to make the series comparable.

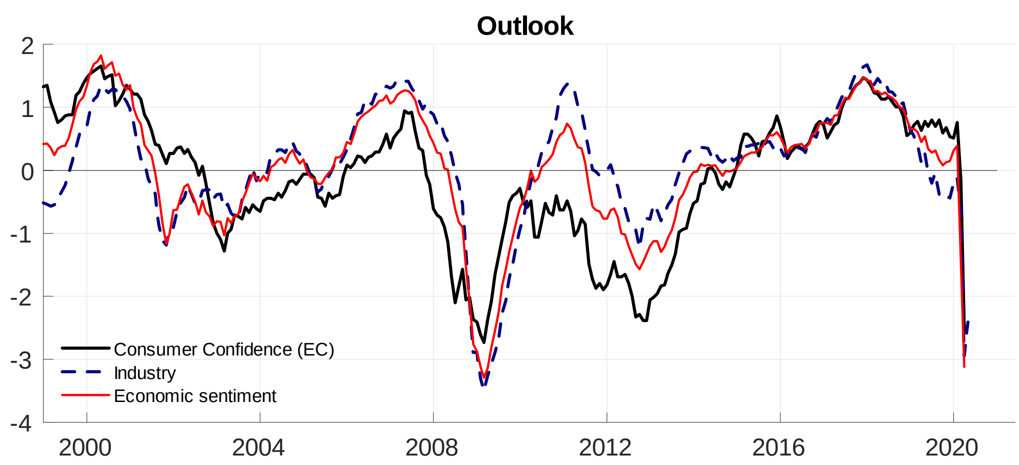

Figure A5: **Survey-derived measures of confidence**. *Note*: 1999m1-2020m4. Each series is standardized to have 0 mean and unit variance to make the series comparable.

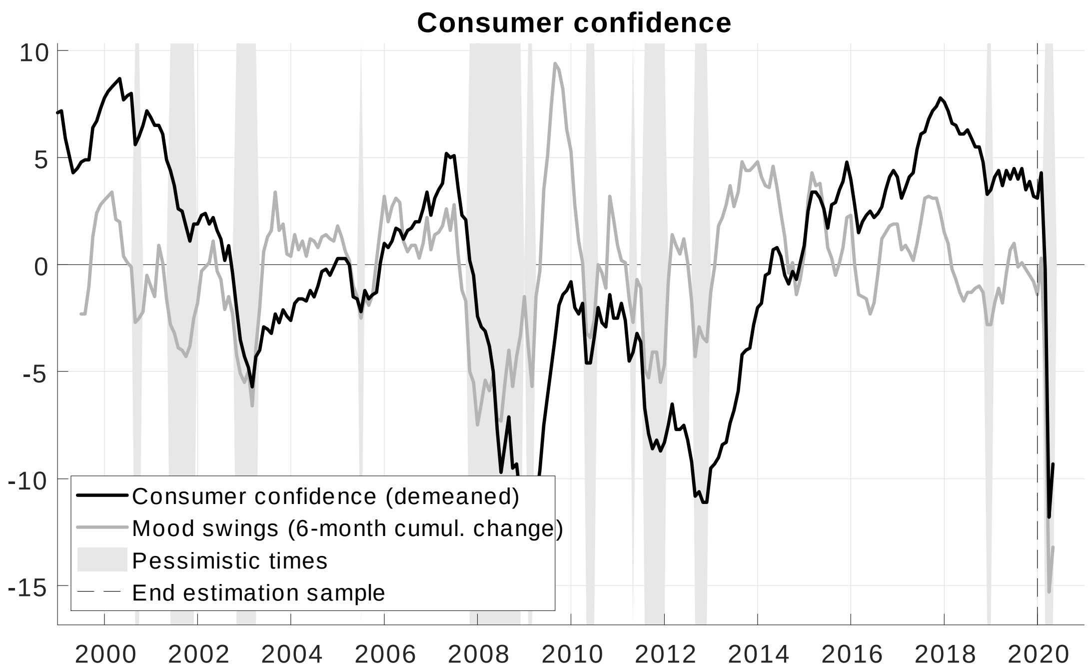

Figure A6: **Alternative definition of pessimistic times based on "mood swings"**. Black solid line: EC Consumer Confidence Index. Grey line: cumulative change in the last six months of the Consumer Confidence Index. Grey vertical bars: initial quarters with the bottom 20% cumulative change in the last six months of the confidence series defining the Pessimistic times state. Vertical black dashed line: of the estimation sample.

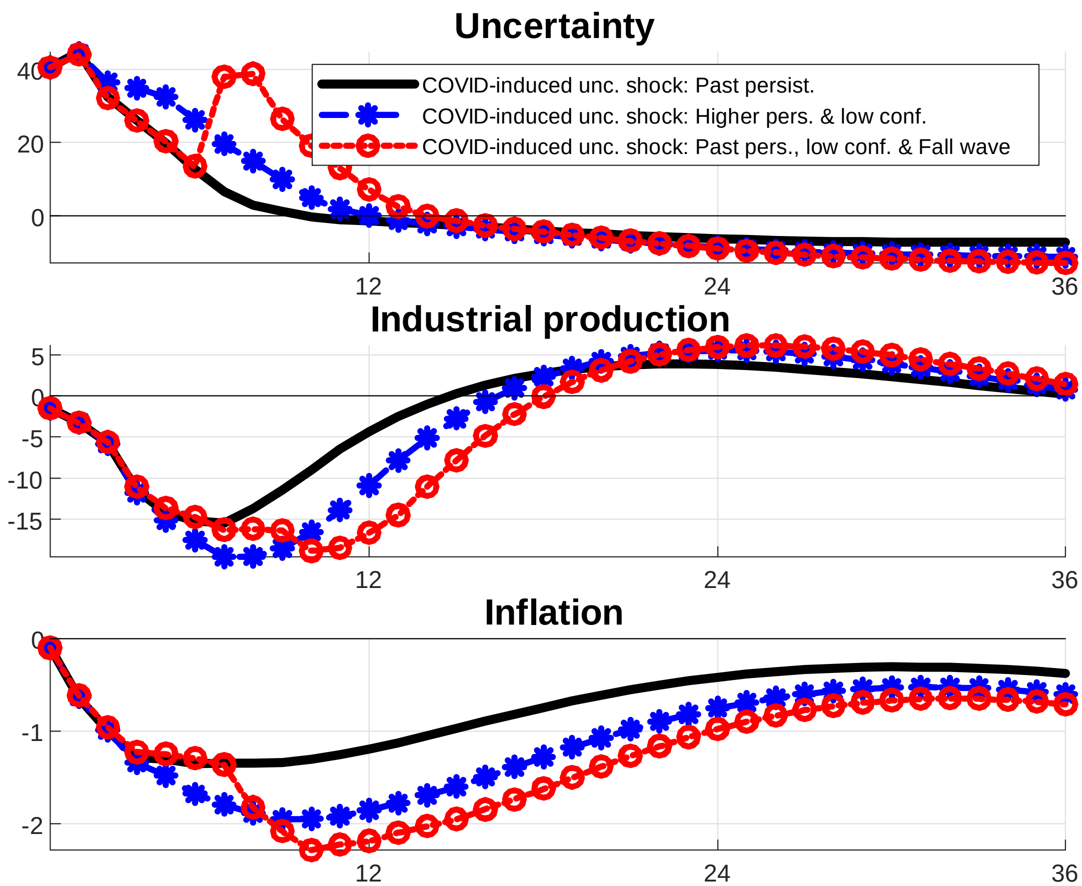

Figure A7: **The uncertainty-channel of the COVID-19 shock during pessimistic times: Alternative scenarios (case without a fast recovery in consumer confidence).** Solid black line: GIRF to a 10 standard deviation uncertainty shock hitting the economy during pessimistic times. Starred blue line: GIRF to the sequence of shocks $\boldsymbol{\delta} = [\delta_t, \delta_{t+2}, \delta_{t+3}, \delta_{t+4}, \delta_{t+5}, \delta_{t+6}, \delta_{t+7}] = [10, 1, 1, 1, 0.5, 0.5, 0.5]$ hitting the economy during pessimistic times (see equation 3 in the main paper). Circled red line: GIRF to the sequence of shocks $\boldsymbol{\delta} = [\delta_t, \delta_{t+6}] = [10, 7.5]$ hitting the economy during pessimistic times (see equation 3). *Note*: x-axis in months. The initial shock is assumed to hit in March 2020. The subsequent shocks are the same considered for the exercise at the basis of Figure 7 in the main paper. For the computation of the counterfactual GIRF please see foonote 29.

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