Check for updates

OXFORD BULLETIN OF ECONOMICS AND STATISTICS, 83, 4 (2021) 0305-9049
doi: 10.1111/obes.12431

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

GIOVANNI PELLEGRINO†, FEDERICO RAVENNA‡,¶,§,‡‡ and GABRIEL ZÜLLIG†,¶

†*Aarhus University, Aarhus, Denmark (e-mail: gpellegrino@econ.au.dk)*
‡*Danmarks Nationalbank, Copenhagen, Denmark (e-mail: fera@nationalbanken.dk)*
¶*University of Copenhagen, Copenhagen, Denmark (e-mail: gz@econ.ku.dk)*
§*HEC Montreal, Montreal, Canada*
‡‡*CEPR, London, UK*

Abstract

We estimate a monthly interacted-VAR model for euro area macroeconomic aggregates allowing for the impact of uncertainty shocks to depend on the state of the average outlook for the economy measured by survey data. We find that, in response to an uncertainty shock, the peak decrease in industrial production and inflation is around three and a half times larger during pessimistic times. We build an assessment of the role of uncertainty for a path of innovations consistent with the increase in the observed VSTOXX measure of uncertainty since the outset of the COVID-19 epidemics in February and March 2020. Industrial production is predicted to experience a year-over-year peak loss of around 9.2% in the fourth quarter of 2020, and subsequently to recover with a rebound to pre-crisis levels roughly in June 2021. The large impact is the result of an extreme shock to uncertainty occurring at a time of very negative expectations for the economic outlook. We conduct simulations that quantify the potential benefit of recovered confidence in reducing the uncertainty-induced losses associated with a possible third wave of the pandemic.

JEL Classification numbers: C32. E32.
*We thank Henrik Yde Andersen, Efrem Castelnuovo, Menzie Chinn, Alessia Paccagnini, Michele Piffer, Carl Walsh and participants to the 21st IWH-CIREQ-GW Macroeconometric Workshop: Forecasting and Uncertainty (Halle Institute for Economic Research) for providing comments, and Roberta Friz for providing the granular data at the basis of the European Commission consumer and business surveys. Contacts: Giovanni Pellegrino: gpellegrino@econ.au.dk; Gabriel Züllig: gz@econ.ku.dk. Federico Ravenna: fera@nationalbanken.dk. The viewpoints and conclusions stated are the responsibility of the individual contributors, and do not necessarily reflect the views of Danmarks Nationalbank. The authors alone are responsible for any remaining errors.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

I. Introduction

The social distancing measures imposed worldwide in response to the outbreak of 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 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]

What is the role of agents' expectations about the future outlook for the transmission of uncertainty shocks? This paper assesses through a state-dependent VAR model the impact of an increase in uncertainty conditional on optimistic and pessimistic expectations for the euro-area economic outlook, and estimates the macroeconomic impact of the COVID-19-induced uncertainty.

A large body of empirical evidence supports the hypothesis that unexpected surges or 'shocks' in uncertainty have a negative effect on real activity (see, e.g. Bloom, 2009; Bachmann, Elstner and Sims, 2013; Mumtaz and Zanetti, 2013; Jurado, Ludvigson and Ng, 2015; Fernández-Villaverde *et al*., 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' behaviour (see, e.g. Bernanke 1983; Caballero, 1990 respectively). At the same time, 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).

Our findings show that the impact of uncertainty shocks is dependent on future expectations, and greatly increased at times of pessimistic expectations. This result has important implications for the assessment of the economic impact of the COVID-19 pandemic. The observed increase in uncertainty measured during the COVID-19 pandemic can be interpreted as a perceived increase in the probability of very negative outcomes – for example, future pandemic waves 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. Given an

[1] By the second half of April 2020, the eurozone-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, 2020a,b).

[2] The German ZEW sentiment index and the consumer confidence indicator released by the European Commission in April 2020 signalled a confidence level approaching the number reached during the 2008–09 financial crisis.

[3] Baker *et al*. (2020) document the recent enormous increase in economic uncertainty as measured by several US indicators: the VIX index; the US Economic Policy Uncertainty Index; several survey-based measures reporting uncertainty about the outlook among firms.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

average outlook, higher uncertainty increases the risks in the outlook: it implies a higher chance of more extreme outcomes. The impact of heightened upside or downside 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 or smaller impact on the distribution of economic outcomes. Several economists, including contributions by Fajgelbaum, Schaal and Taschereau-Dumouchel (2014) and Cacciatore and Ravenna (2020) have suggested models able to explain the state-dependent impact of uncertainty shocks.

The empirical analysis proceeds as follows. We measure expectations for the economic outlook with consumer confidence and interpret plummeting consumer confidence as capturing pessimism about the future. We empirically test whether pessimism amplifies the impact of uncertainty shocks by modelling a vector of euro area macroeconomic data with an interacted VAR (IVAR) model for the period 1999m1–2020m1. The IVAR augments a standard 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.[4]

Following the seminal work by Bloom (2009), we focus on financial uncertainty, which we measure by the VSTOXX index, a high-frequency measure of the implied volatility of the euro STOXX 50 stock market index (the European analogue of the VIX index for the United States). This is important since – as shown in Ludvigson *et al*. (2019) and Angelini *et al*. (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 −0.35% (−0.04%) in normal times. Consistently with these findings, uncertainty shocks are found to be about three times more important in explaining business cycle fluctuations in industrial production and inflation during pessimistic times than during normal times, respectively, explaining 42% and 26% 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

[4]See Caggiano, Castelnuovo and Pellegrino (2017) and Pellegrino (2021) for details on the IVAR model.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

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. To account for both the first and second wave-induced uncertainty shock, we simulate the IVAR model conditional on uncertainty shocks determined by the evolution of the VSTOXX since the COVID-19 outbreak. The impact of uncertainty shocks alone is predicted to lower euro-area industrial production with a year-over-year peak loss of 9.21% peaking after 7 months from the shock, in September 2020, and subsequently recovering with a rebound to pre-crisis levels in June 2021. In terms of GDP, a back-of-the-envelope calculation suggests uncertainty shocks account for a corresponding fall in year-over-year GDP of roughly 3.3% at peak.

We also build alternative scenarios for a hypothetical third wave of the pandemic in 2021. We find that what mostly matters for the economic impact of a third wave-induced uncertainty shock is the level of confidence when the shock hits rather than the size of the shock. An uncertainty shock twice the size of the second wave shock occurring in a situation of recovered confidence implies a year-over-year peak loss in industrial production of 2.17%, which is smaller than the corresponding peak loss of 2.94% associated to an uncertainty shock half its size but occurring in pessimistic times.

Related Literature. 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. Caggiano, Castelnuovo and Groshenny (2014), Chatterjee (2018), Caggiano, Castelnuovo and Figueres (2020), and Paccagnini and Colombo (2020), among others, employ non-linear Structural VAR techniques to enquire whether contractionary vs. expansionary phases are important in determining the impact of uncertainty shocks. Alessandri and Mumtaz (2019), Angelini *et al.* (2019), and Lhuissier and Tripier (2019) investigate whether financial or volatility regimes are important for the real effects of uncertainty shocks. Jackson, Kliesen and Owyang (2020) study whether periods of low vs. high uncertainty have a role in the propagation of uncertainty shocks as well. Our work 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 results are also related to the recent efforts to estimate with VAR models the impact of COVID-19 uncertainty in the United States. Baker *et al.* (2020) estimate a peak impact on year-over-year US GDP growth of about 5.5%, while Leduc and Liu (2020) estimates an impact on US unemployment peaking at % points after 12 months. As regards the global effects of the COVID-19 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-19 pandemic. Further, none of the aforementioned papers study the consequences of the

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

COVID-19 uncertainty shock for the euro area economy, the economy most hit in per capita terms at the time of writing.

Our value-added to the literature is twofold. First, we make use of a nonlinear VAR model to empirically study the role of pessimistic expectations for future outcomes for the historical propagation of uncertainty shocks in the euro area. Second, we make use of this novel finding on the role of pessimism to predict the expected propagation of the COVID-19-induced uncertainty shock.

The paper is structured as follows. Section II presents the empirical model and the data, while section III documents our empirical findings. Section IV concludes the paper.

II. 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, that is, 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 modelled 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 the implied volatility of the euro STOXX 50 stock market index. The VSTOXX index is the European analogue of the VXO index for the United States, 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 in households' consumption and savings, based on answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment and savings capability.[5] To capture the stance of monetary policy, we use the overnight interest rate (EONIA), while industrial production

[5]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)

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

(measured by the manufacturing sector) and inflation (measured by the CPI index) are aggregates for the euro area.[6] The Appendix reports plots of all the data series used in the model.

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 – high or low consumer confidence – hence making the responses less sensitive to outliers in a particular regime.

Although non-linear in variables, the IVAR is linear in parameters and does not depend on unobservable variables or nuisance parameters. Hence the IVAR model can be estimated by OLS over the full sample. The two economic states of interest – consisting of two sets of initial histories – only come to play after estimation, allowing initial conditions to affect the dynamics of the system after a shock (Koop *et al.*, 1996), or in other words, to recover initial conditions-dependent impulse responses.

An alternative approach for estimating the macroeconomic effects of uncertainty shocks would be to use a VAR with stochastic volatility in mean (VARSVM) model such as in Carriero, Clark and Marcellino (2018). Their VARSVM allows the estimation of macroeconomic and financial uncertainty – the common factors driving the volatility in either macroeconomic or financial variables – within the model, hence without recurring to an external uncertainty proxy. However, differently from the IVAR specification adopted, the VARSVM implies a linear effect of uncertainty shocks and hence is not well suited to answer our research question. To address the concern raised from relying on an externally-constructed uncertainty proxy, which can potentially suffer from measurement errors, in section III we conduct a robustness check in the context of a Proxy Structural IVAR model along the lines of Carriero *et al*. (2015).

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 risky steady state (Andreasen *et al*., 2021). See Caggiano *et al*. (2017) and Pellegrino (2021) for further details on the IVAR model. 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 end date is chosen to avoid the extreme observations recorded during the COVID-19 pandemic. This choice is consistent with

[6]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.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

results in Lenza and Primiceri (2020), who find that explicitly modelling the change in shock volatility to account for the exceptionally large macroeconomic innovations during the pandemic period gives results similar to a simpler strategy consisting of dropping the extreme observations – a strategy which they find justifiable for the purpose of parameter estimation. Importantly, the values of consumer confidence and uncertainty associated to the pandemic do not represent outliers with respect to our sample values, providing confidence in the information carried by the estimated IVAR for the assessment of the uncertainty-channel of the COVID-19 shock.

The model is estimated by OLS. We use four lags as suggested by the AIC statistic. A multivariate LR test rejects the null of linearity against our IVAR model ($P = 0.00$).

GIRFs for normal and pessimistic times. We compute GIRFs à la Koop *et al.* (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, $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, \ldots, \mathbf{Y}_{t-L}\}$, is given by the following difference of conditional expectations:

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

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 vector $\mathbf{Y}$ corresponding to observations in 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

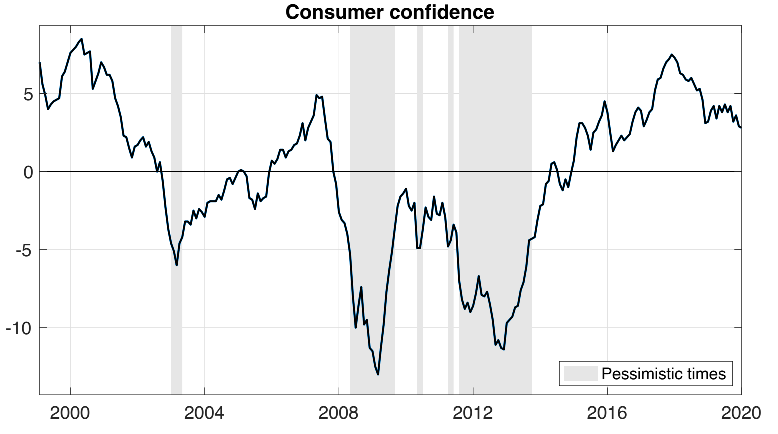

Figure 1. European commission consumer confidence index (rescaled)
Notes: Solid line: European Commission Consumer Confidence Index. The series is obtained by subtracting the long-run average of the original series. Grey vertical bars: Initial quarters in the bottom 20% of the consumer confidence distribution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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

representation of the two states. Pessimistic times mostly capture the period of the great financial crisis of 2008–09 and the sovereign debt crisis of 2011–13 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 **Y** above, that is, $[unc, \Delta_{12}\ln IP, \pi, conf, i]'$. 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 *et al*., 2014; Fernández-Villaverde *et al*., 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 *et al*. (2019) and Angelini *et al*. (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.

III. Empirical results

The effects of uncertainty shocks in the euro area: The role of pessimism

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. 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.

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 −0.35% in normal times, that is, around three and a half times larger. 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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

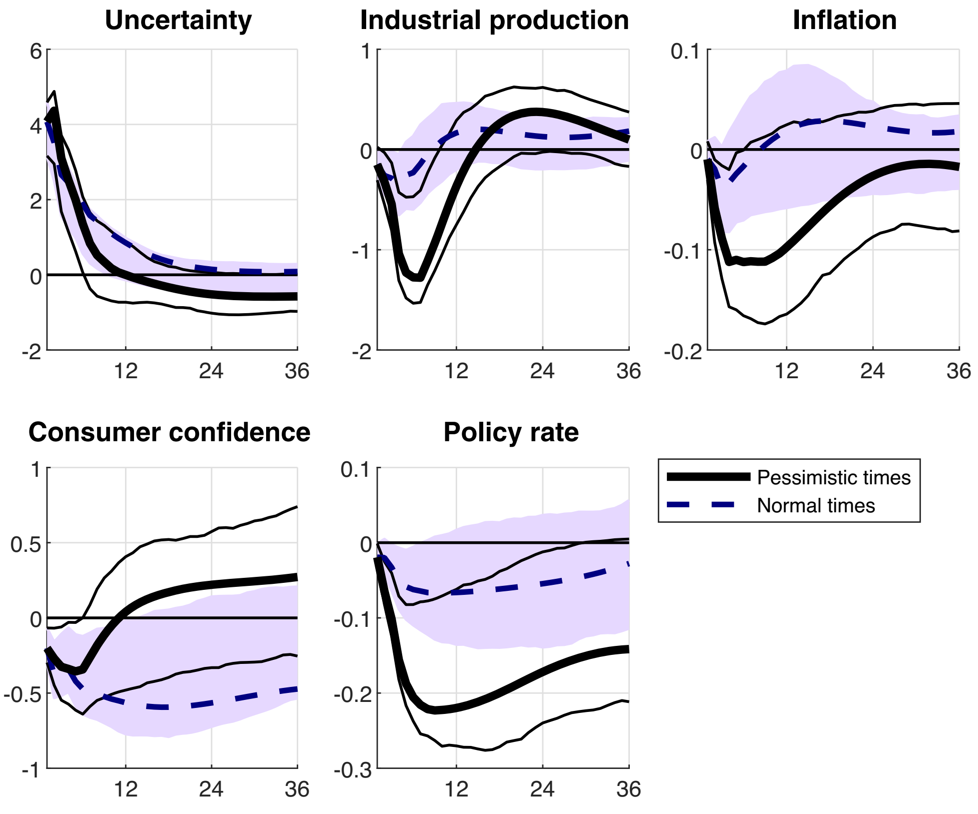

Figure 2. Impact of a one-standard deviation uncertainty shock. Pessimistic vs. normal times state-conditional GIRFs
Notes: Black solid lines: point estimates (bold lines) and 90% bootstrapped confidence bands for the GIRFs conditional to pessimistic times. Blue dashed lines and light blue areas: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional on normal times. Monthly data

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 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 8 months after 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 2 years computed by adopting the

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

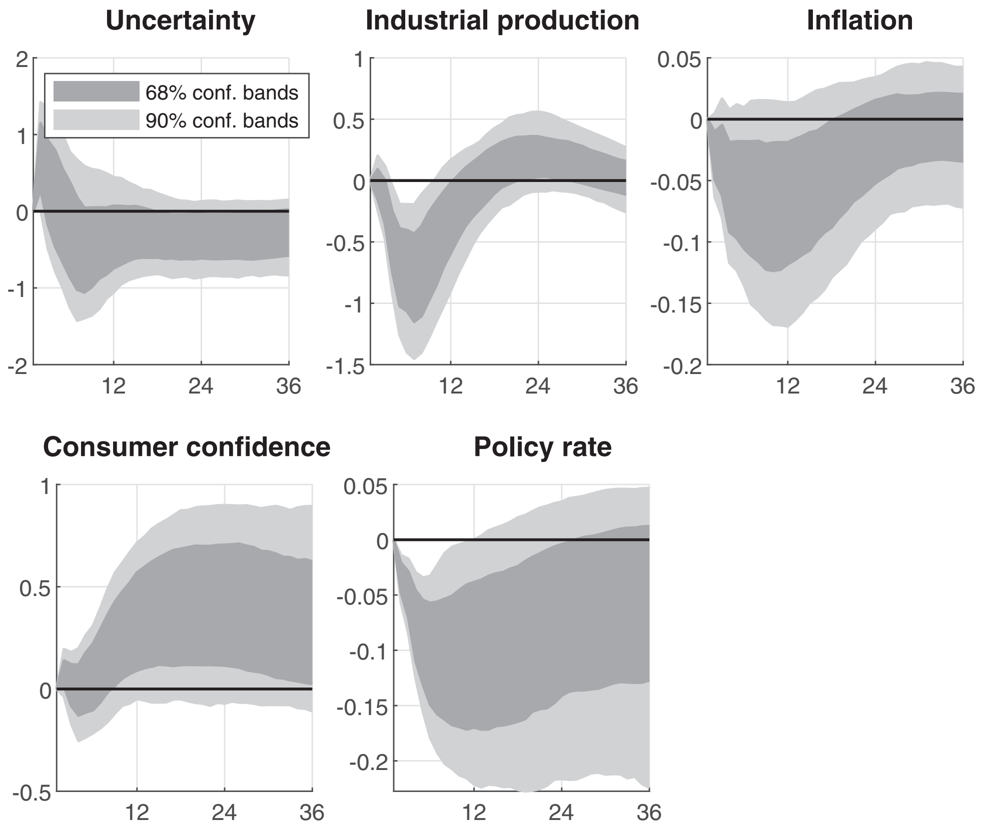

Figure 3. Difference of state-conditional GIRFs between pessimistic and normal times
Notes: Interior dark gray areas: 68% confidence bands for the difference between the pessimistic times conditional GIRF minus the normal times conditional GIRF. Confidence bands built with 500 bootstrap draws. Exterior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

algorithm proposed by Lanne and Nyberg (2016).[7] 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%, 26% and 57% for the volatility of industrial production, inflation and the policy rate respectively. In normal times, these shares drop to 17%, 10% and 20%, that is, roughly one-third of those in pessimistic times. Our results are in line with both euro area and United States analyses. According to the ECB Economic Bulletin (2016), uncertainty on average explains 20% of real GDP fluctuations in the euro area. Jurado *et al*. (2015) find that uncertainty shocks account for up to 29% of the variation in United States industrial production at business cycle frequencies, and

[7]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 *et al*. (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.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

Caldara *et al*. (2016) find that uncertainty shocks explain between 20% to 40% of the same. All these studies adopt linear VAR models. Our results imply that most 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 index is mainly explained by its own shock in both states (88% in normal times and 91% in pessimistic times). This is consistent with the findings by Ludvigson *et al*. (2019) and Angelini *et al*. (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 9% 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 in 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

TABLE 1

Generalized forecast error variance decomposition: Contribution of uncertainty shocks in the two states

Variable	*Normal times*	*Pessimistic times*
VSTOXX	0.88	0.91
Industrial production	0.17	0.42
Inflation	0.10	0.26
Consumer confidence	0.26	0.9
Policy rate	0.20	0.57

Notes: GFEVD computed according to Lanne and Nyberg’s (2016) algorithm for a one-standard deviation shock to all variables. Forecast horizon: 2 years.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

stream completely, and may optimally choose to change their behaviour 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 behaviour than what would be observed in normal times with a less extreme outlook (this intuition is formalized in Fajgelbaum *et al*., 2014 and Cacciatore and Ravenna, 2020, among others).

Alternative hypotheses on the impact of uncertainty shocks

In this section, we study alternative specifications to discuss further findings on the role of pessimism in 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 United States financial scandals in 2002, Gulf War II in 2003, and the Global Financial Crisis. 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 *et al*. (2015), that is, 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. The 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. 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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

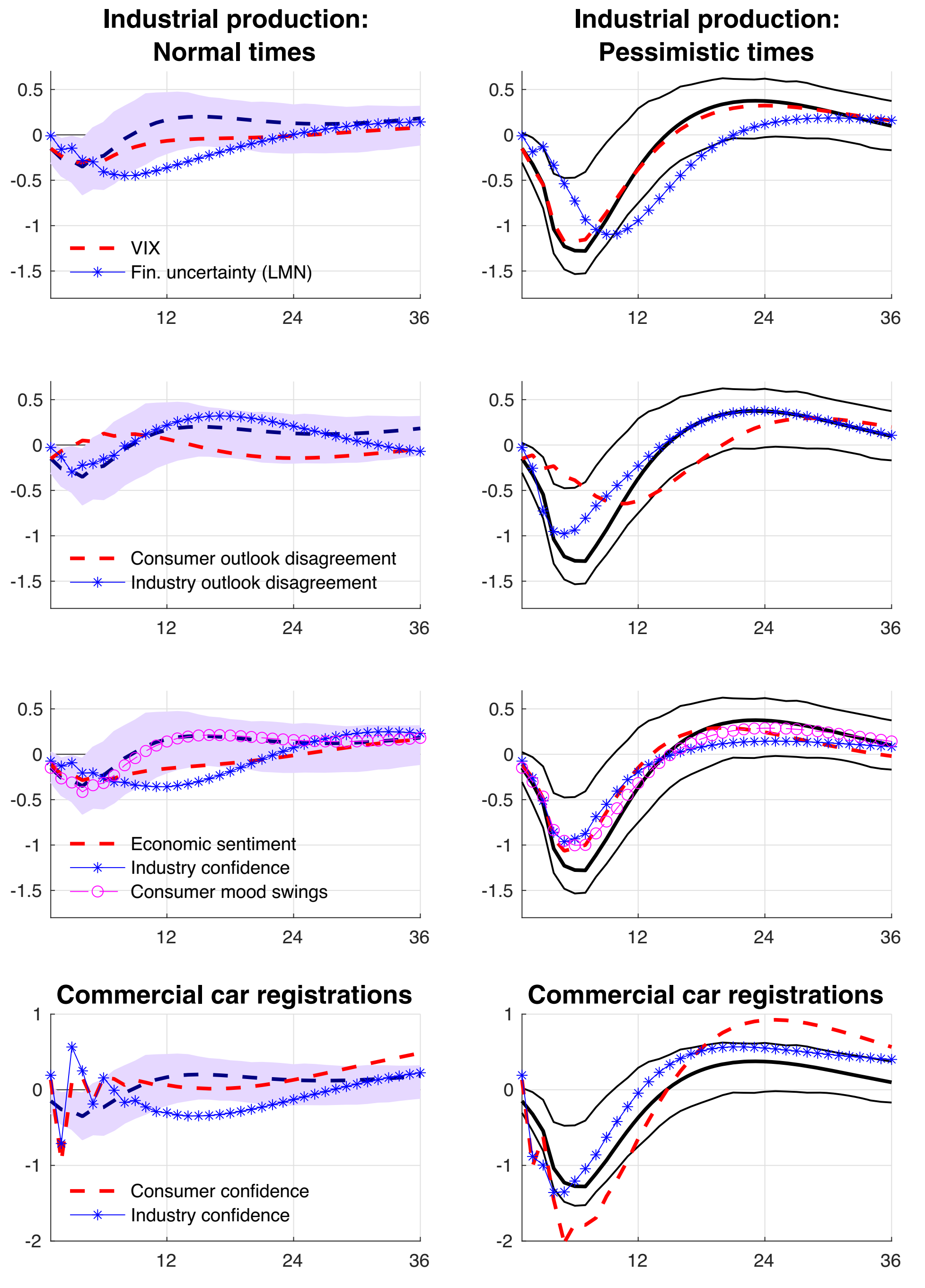

Figure 4. IVAR models for alternative hypotheses: Impact of a one-standard deviation uncertainty shock, Industrial Production GIRF

Notes: 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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

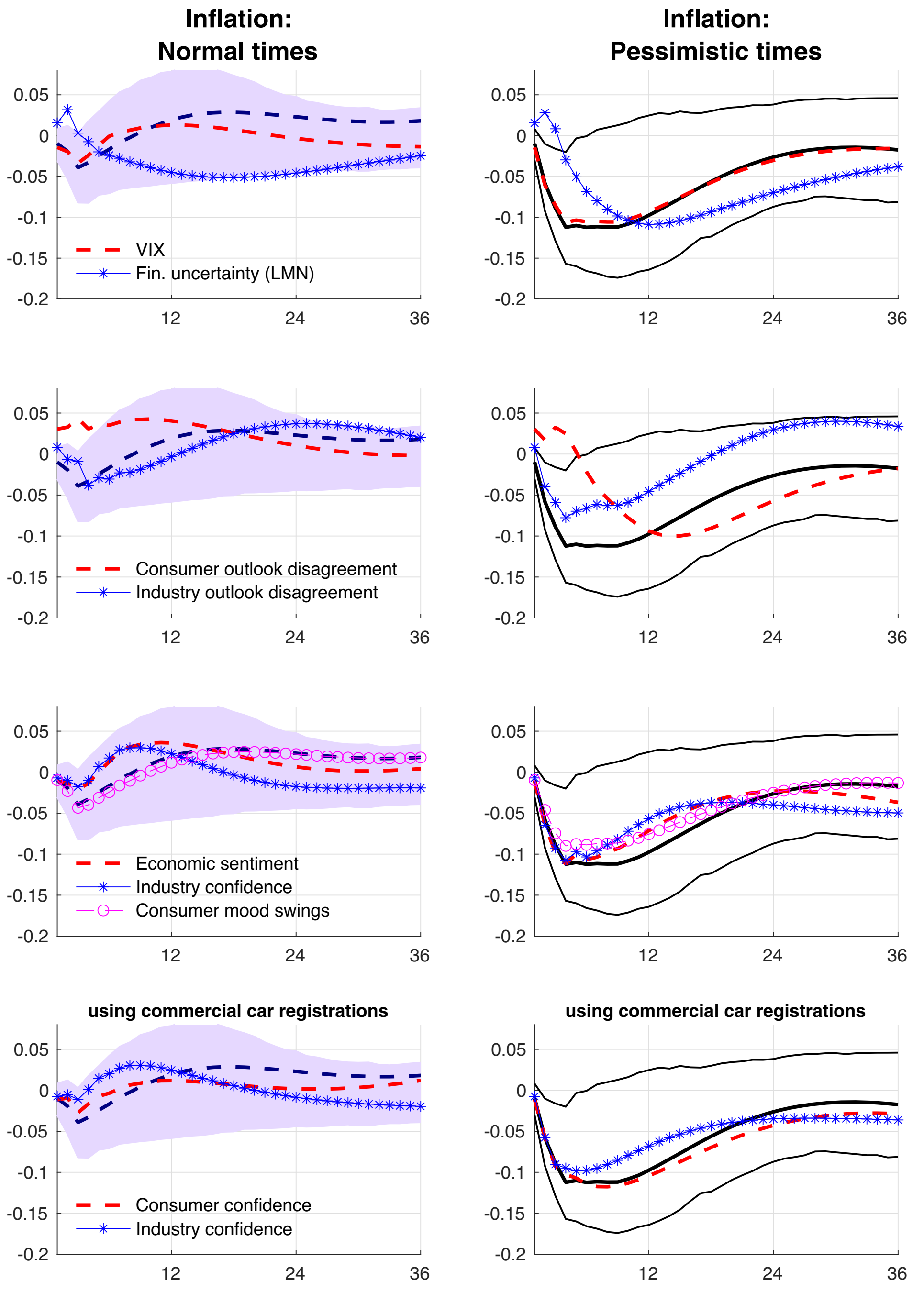

Figure 5. IVAR models for alternative hypotheses: Impact of a one-standard deviation uncertainty shock, Inflation GIRF

Notes: 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 on pessimistic times. For the other lines refer to the legend and the main text. Monthly data

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

ARCH model is positively related to the disagreement among forecasters at the time of the forecast.

To construct a consumer disagreement index, we exploit the dispersion of responses to the following forward-looking survey question:[8]

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 (2020a,b) 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, that is:

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

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:/*
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):

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

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

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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

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 an 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 survey-based indices across consumers and producers in 5 sectors, with the following weights: industry 40%; services 30%; consumers 20%; construction 5%; retail trade 5%.[9] Our baseline Consumer Confidence Index is the consumers' component of the Economic Sentiment Indicator. It is of interest to also consider its industry component alone. The latter covers firms in the manufacturing sector (2-digit NACE codes 10–33), 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. This suggests that consumer confidence is a more important driver of state-dependency in the responses to uncertainty shocks in pessimistic times vs. normal times than industry confidence.

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 in the index reflects pessimism, that is, a negative outlook for the future of the economy. However, one can 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 third row of panels of Figures 4 and 5 – are very similar to baseline ones, the only difference being that now uncertainty shocks have milder effects under this alternative interpretation of pessimistic times.

Commercial vehicles registrations as a proxy for business investment. Our baseline IVAR does not include a measure of business investment as an endogenous

[9]More details can be found in the European Commission's (2020a,b) user guide for the harmonized business and consumer surveys available at https://ec.europa.eu/info/sites/info/files/bcs_user_guide_2020_02_en.pdf.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

variable since it is not available at monthly frequencies. Jackson *et al.* (2020) and Paccagnini and Colombo (2020) investigate the transmission mechanism of uncertainty shocks in uncertain times vs. tranquil times and in booms vs. busts, respectively, and find that the response of investment is an important driver of the state-dependent response of output to uncertainty shocks. To infer how uncertainty affects firms' investment decisions in pessimistic vs. normal times, we consider an alternative IVAR where we replace industrial production with a variable which proxies for business investment and is available at the monthly frequency, that is, euro area commercial vehicle registrations.[10] On top of considering our baseline consumer confidence index, we also run an IVAR specification where we this indicator is replaced with the industry confidence index used in previous specifications. As documented in the fourth row of panels of Figures 4 and 5, results for commercial vehicle registrations are similar to our baseline ones for the industrial production response, also in terms of magnitude. Results are consistent with the real-option effects of heightened uncertainty suggesting that firms postpone partially-irreversible investment to the future and adopt a 'wait and see' behaviour. According to our results, such a behaviour is more widely adopted during times of pessimistic outlook.

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.

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.

Controlling for financial variables. Our baseline VAR does not model any financial variable. However, financial stress indicators – such as credit spreads – can be relevant to the econometric specification for at least three reasons. First, it is well known that credit spreads have large predictive power for both United States 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 (Gilchrist, Sim and Zakrajšek 2014; Alfaro, Bloom and Lin, 2018; Arellano, Bai and Kehoe 2019). 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 end of the yield curve.

[10]Data on commercial vehicle registrations for each country is available at the website of the European Automobile Manufacturers Association (https://www.acea.be/statistics/tag/category/by-country-registrations). We build the euro area series by compositionally-adjusting the individual countries series by also taking into account that the composition of the euro area changes over time. Consistently with our baseline IVAR, we consider year-over-year growth rates of the series.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

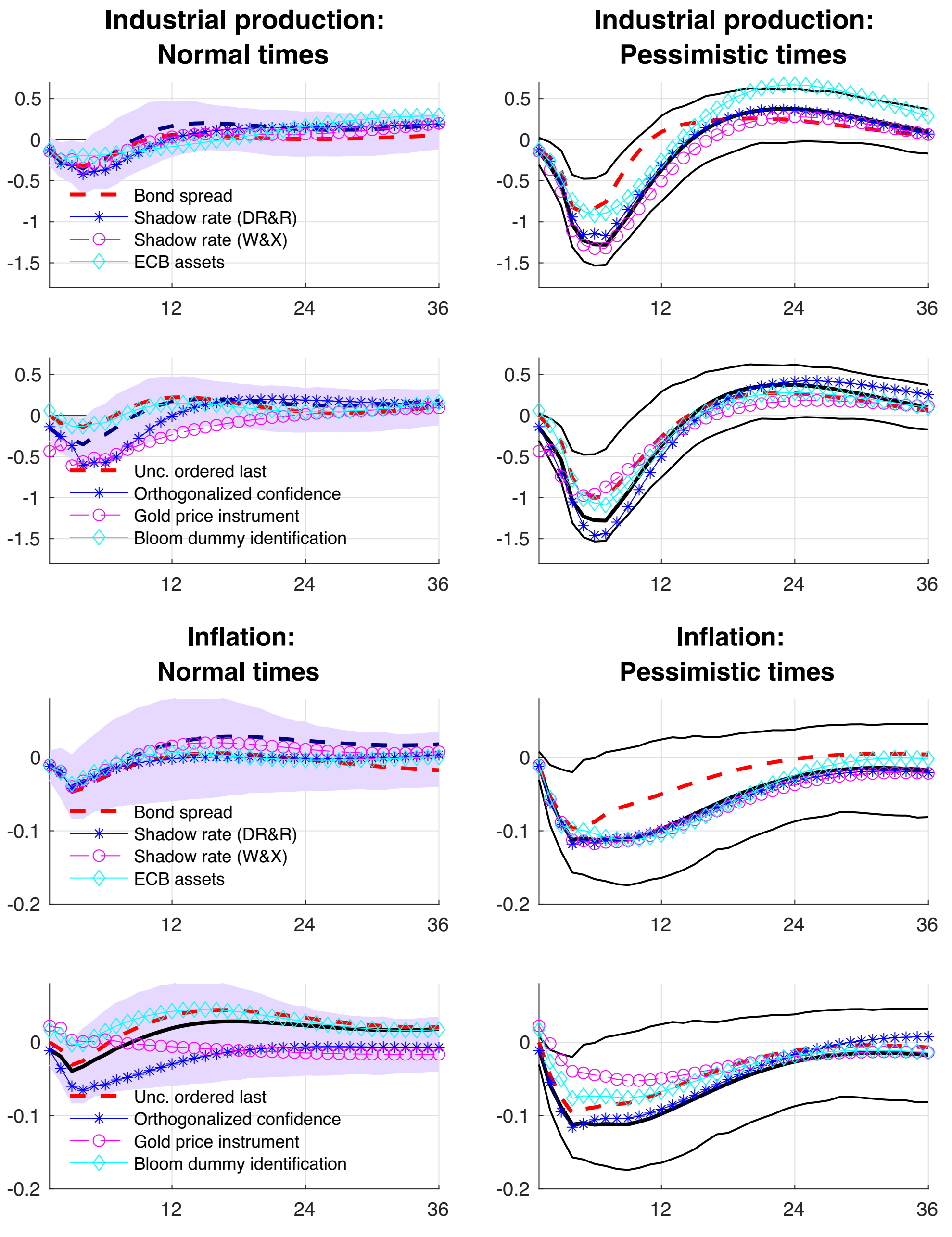

Figure 6. Robustness to alternative IVAR specifications. Impact of a one-standard deviation uncertainty shock

Notes: 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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

We add a bond spread indicator to our baseline IVAR and order it immediately after the VSTOXX uncertainty measure.[11] We use the Gilchrist and Mojon's (2018) credit spread measure for 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.[12] As Figure 6 documents, controlling for financial variables does not affect our main results: the impulse responses under this alternative specification of our IVAR are within the baseline results confidence bands. Unreported results confirm robustness of our main findings also to the use of another credit spread measure, that is the ICE/BofA Euro High Yield Index Spread, which 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 (source: Federal Reserve Bank of St. Louis).

Controlling for unconventional monetary policy. We investigate the robustness of our results to alternative monetary policy measures accounting for unconventional monetary policy. ECB unconventional policies include quantitative easing policies, monetary policy measures targeted at financing specific sectors in the economy, changes in the composition of the ECB balance sheet, and ECB announcements about future policy initiatives providing forward guidance. How to account for all of these policies is still not a settled issue. We estimate an IVAR replacing in our baseline specification the policy rate with a shadow rate measuring the implied level of the conventional monetary policy instruments, built from sovereign-bond yield curves and meant to account for the market assessment of each of the different unconventional monetary policy tools. We first use two different euro area shadow rates, which display differences of hundreds of basis points between them. The first shadow rate measure adopts the recent estimates by De Rezende and Ristiniemi (2020).[13] The second shadow rate is computed using the method of Wu and Xia (2017).[14] As an alternative check that more closely accounts for quantitative easing, or large-scale asset purchases, we instead include a measure of ECB assets in our baseline IVAR model, following Gambacorta, Hofmann and Peersman (2014) and Paccagnini and Colombo (2020).[15]

[11]The use of a Cholesky decomposition does not allow us to easily disentangle uncertainty shocks from financial shocks provided that both variables are fast-moving and are contemporaneously correlated (see Caldara *et al*., 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.

[12]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.

[13]The series we use is taken from the website of Rafael B. De Rezende (https://rafaelbderezende.wixsite.com/rafaelbderezende/shadow-rates).

[14]The series is available on the webpage of Jing Cynthia Wu (https://sites.google.com/view/jingcynthiawu/shadow-rates).

[15]The series is available in the Federal Reserve Bank of St. Louis's dataset (mnemonic: ECBASSETSW).

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

Figure 6 shows that the impulse responses from these alternative IVAR specifications are very similar to our baseline responses and are within the confidence bands for the baseline specification. These findings suggest that our baseline specification is robust to several alternative measures of ECB policy.

The introduction of unconventional monetary policy measures after 2009 may have had an important impact on the inflation expectations' formation process. We checked whether our results are robust to the use of inflation expectations in the specification, in lieu of current inflation, since these measures could very well be different from the IVAR-implied forecast of inflation conditional on the current state of the economy. The only index that satisfies our criteria of being available for the entire time span of our estimation sample (1999m1–2020m1) at the monthly frequency is a qualitative index of inflation expectations that is computed based on the European Commission surveys used widely within the paper (mnemonic: CONS.EU.TOT.6.B.M.). When we replaced realized inflation with this measure, all our results hold true.

Disentangling uncertainty and confidence. A reasonable concern throughout the uncertainty literature is how much measures of uncertainty contain additional information relative to measures of the average economic outlook. Nowzohour and Stracca (2020), find that the common variation of uncertainty and expectations measures for the economic outlook explains around 50% of the total variation of each indicator across a sample of countries. However, they also find that monthly consumer confidence and business confidence indicators have low correlation with a variety of uncertainty indicators at the country level, across a panel of 27 advanced economies.

In our baseline, we order the uncertainty indicator as first in our recursive identification. Two implications of this choice deserve to be assessed, in relation to the interaction between confidence and uncertainty measures. First, our baseline identification choice is equivalent to assuming that the one-month-ahead forecast error in the VSTOXX index is explained only by uncertainty shocks. Consumer confidence is already included among the IVAR variables, rather than only affecting the conditioning to measure state-dependence of the impact of identified uncertainty shocks. This is also the approach followed in Baker *et al*. (2016), which includes the Michigan Consumer Sentiment in their estimated VAR. However, VSTOXX movements may also be *contemporaneously* explained by other shocks, among which confidence shocks. To address this concern, we purge the identified uncertainty shocks from contemporaneous movements in other variables including confidence, by using an alternative Cholesky-ordering that places uncertainty last.[16]

A second concern with our baseline Cholesky identification is that confidence reacts on impact to uncertainty shocks and hence it will be partly explained by uncertainty. However, since we use the confidence variable's distribution to define the two economic states, it is important to check that the two states do not proxy for different levels of uncertainty. We conduct an exercise where we replace the measure of confidence in our IVAR with its orthogonalized component to uncertainty, by using

[16]We also experimented with another check that replaces the VSTOXX index in our IVAR with the orthogonalized innovation to the VSTOXX index, using a projection on the confidence index and a constant. The baseline results in the paper are unaffected.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

the residual from a projection of confidence on uncertainty and a constant. In such a way we 'clean' consumer confidence from any information it might carry about uncertainty. As Figure 6 documents, both alternative econometric specifications return results similar to the baseline IVAR exercise.

Identification via external instrument: A Proxy Structural 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 use an alternative identification scheme, via external instruments, adopted in Proxy Structural VARs (see Stock and Watson, 2012; Mertens and Ravn, 2013, 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).[17] Figure 6 shows that our main 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.

We also estimate an additional Proxy Structural IVAR to check the robustness of our results against the possibility of measurement errors in the uncertainty proxy we use, that is, the VSTOXX index. In particular, following Carriero *et al*. (2015), we use a dummy variable capturing all the major VSTOXX spikes as an instrument for uncertainty shocks. Similarly to Bloom (2009), this dummy takes a value of 1 for all the months when the peak of the Hodrick–Prescott detrended financial volatility level rose more than 1.65 standard deviations above the mean. Figure 6 documents that baseline results are robust to this alternative identification strategy less prone to measurement errors in the uncertainty proxy.

In the Appendix, we also check that our main results are robust to the use of alternative cutoffs on the historical distribution of consumer confidence for the definition of our pessimistic-times state (bottom decile, bottom tertile and median). Our main results are also robust to the use of alternative lag orders (3 and 6).

[17]The instrument is available on Michele Piffer's webpage (https://sites.google.com/site/michelepifferec onomics/). For our sample period, the instrument is associated with an F statistic equal to 8.17. Our first-stage regression coefficient is 155.82 which is close to Piffer and Podstawski's (2018 table 2) one of 166.40, notwithstanding the different sample considered. Unlike 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 with 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.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

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 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 VSTOXX index saw its largest 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, the euro area's countries have been relaxing their restrictions.

The April release of the European Commission Consumer Confidence Indicator signalled a confidence level approaching the level reached during the 2008–09 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 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 has been facing in terms of both uncertainty and consumer confidence. Moreover, the values of consumer confidence and uncertainty experienced since the outbreak of the pandemic 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.

In our first simulation, we make use of the latest crop of data to extract the model's assessment of the role played by uncertainty shocks during the first and second waves of the pandemic. This is achieved by using the IVAR to simulate the industrial production and inflation outcomes conditional only on the identified uncertainty shocks consistent with the historical VSTOXX outcomes for the March to November 2020 period. We simulate the statistical model under the assumption that the IVAR impulse response of the VSTOXX index tracks perfectly the post-COVID-19 outbreak evolution of the VSTOXX in the data. The latter evolution is obtained by rescaling the VSTOXX index to be zero in February 2020. Such an approach allows us to credibly recover the role of uncertainty in the recession that followed the pandemic outbreak.

We believe such an approach to be optimal for two main reasons. First, we can sensibly calibrate our uncertainty shocks even without updating the IVAR sample, something which would be problematic (Lenza and Primiceri, 2020) and not even possible (as, e.g. the industrial production index is released with a few months delay and at the time we are writing is only available up to September 2020). Second, to the extent that the VSTOXX index is mitigated by expansionary monetary policy shocks (as suggested by Bekaert, Hoerova and Lo Duca, 2013; Lutz, 2017; Pellegrino, 2021;

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

Mumtaz and Theodoridis, 2019), our approach allows us to also indirectly capture the role of monetary policies in mitigating the uncertainty-channel of the Covid-19 pandemic.

Because of the pandemic-induced uncertainty shock, the VSTOXX surged by about 40 points in March 2020. This gives us the initial uncertainty shock, which according to our estimated IVAR corresponds to roughly a ten standard deviation shock. We then compute GIRFs by feeding a sequence of shocks. We generalize the GIRF definition in equation (2) with the following:

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

where now $\boldsymbol{\delta}$ is a vector including several unexpected shocks hitting at different times, or $\boldsymbol{\delta} = [\delta_t, \delta_{t+1}, \ldots, \delta_{t+H}]$. The shocks are implied by the evolution of the monthly averages of the VSTOXX in the data between March and November 2020. Uncertainty between May and November 2020 remained at levels twice or thrice the level of 2019. The Appendix reports a plot with the evolution of the VSTOXX since the pandemic outbreak. On Friday (29 October 2020), the VSTOXX index peaked at its highest level since June 2020 (at about four times its lowest level in 2019), when France announced entering a second lockdown due to the second wave. On an end-of-month basis, the second wave-induced VSTOXX surge in October 2020 with respect to September 2020 amounts to roughly a 2.2 standard deviation shock according to our IVAR.

The black solid line in Figure 7 plots the effects of the first and second wave-induced uncertainty shocks during the average pessimistic state according to our estimated IVAR. The green starred line plots the actual VSTOXX, industrial production and inflation, rescaled to be zero in February 2020 so that to capture their evolution since the COVID-19 outbreak. The pandemic has caused these variables to deviate vigorously from trend values. By comparing the implied economic outcomes with the data it is clear that the initial massive drop in industrial production of around 36% is mainly due to the lockdowns effects. As for the implied impact of the uncertainty-channel of the pandemic – taken on its own, and net of other shocks occurring over the sample – industrial production experiences a year-over-year peak loss of 9.21% 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 June 2021 (Table 2). 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 3.3% at peak. Inflation's year-over-year peak decrease is predicted to be −0.94% in November 2020.

Our analysis is conditional on the COVID-19-induced uncertainty shocks only whereas the observed data is a result of all shocks hitting the economy, including rescue stimulus policies implemented by the ECB and by both national and European fiscal authorities which we do not consider (if not limited to the extent they are successful in mitigating uncertainty as proxied by the VSTOXX index). This consideration can explain why observed industrial production overshoots our prediction conditional on uncertainty shocks only, something which suggests that the policies supporting the economy have worked well.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

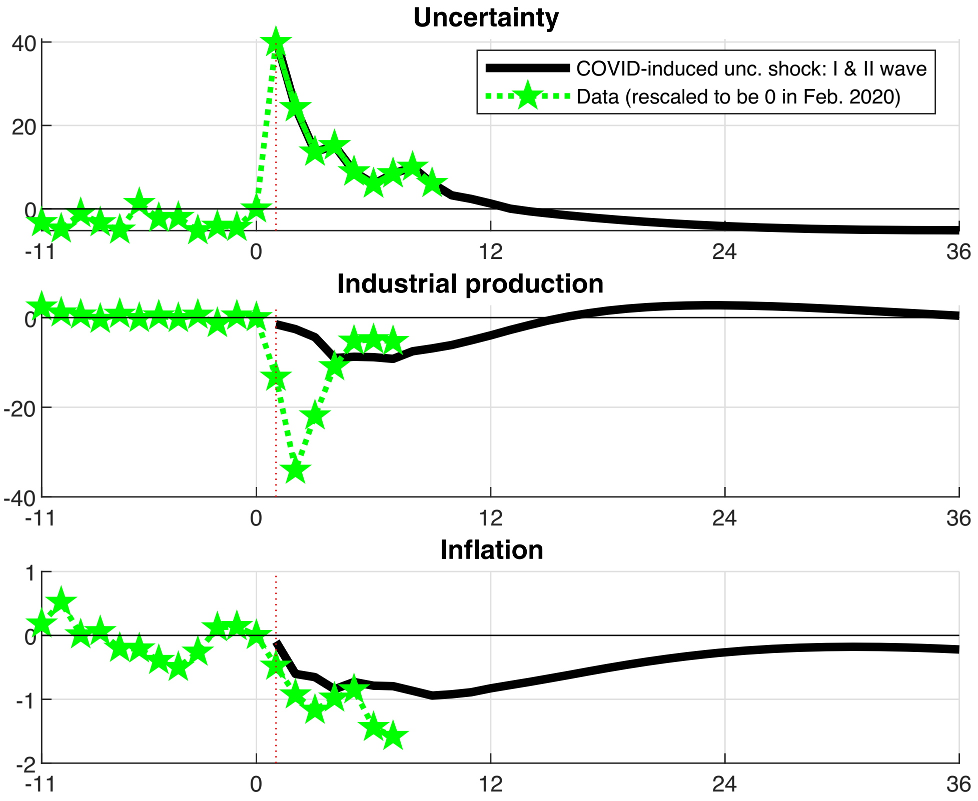

Figure 7. The uncertainty-channel of the COVID-19 shock during pessimistic times: An assessment of the first and second waves

Notes: Solid black line: GIRF to a sequence of shocks hitting the economy during pessimistic times (see equation (3)). The sequence of shocks from March to November 2020, $\boldsymbol{\delta} = [\delta_t, \delta_{t+1}, \delta_{t+2}, \delta_{t+3}, \delta_{t+4}, \delta_{t+5}, \delta_{t+6}, \delta_{t+7}, \delta_{t+8}]$, is implied by the evolution of the VSTOXX in the data since the COVID-19 outbreak to make sure that the IVAR impulse response of the VSTOXX index tracks perfectly its data counterpart. Starred green line: actual data rescaled to be zero in February 2020. The initial shock is assumed to hit in March 2020 (corresponding to the vertical red line). Monthly data

TABLE 2

Euro area predicted response to the COVID-19-induced uncertainty shock: first and second waves

	Industrial production	*Inflation*
Peak y-o-y loss	−9.21%	−0.94%
Time to trough	7 months (September 2020)	9 months (November 2020)
Time to rebound	16 months (June 2021)	–

Notes: ‘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 return to zero.

The economic relevance of the predicted impact of the COVID-19-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-19 pandemic (including lockdowns and falling foreign demand, among other

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

factors). According to their analysis, real GDP will plummet by around 12% in 2020 in their assumed severe scenario, reaching a trough of around −15% in the second quarter of 2020. In our case, the previous back-of-the-envelope calculation suggests a year-over-year fall in GDP of roughly 3.3% at its trough, hence around one fifth of the large contraction predicted to happen in 2020 due to the COVID-19 disaster.

What should we expect for the uncertainty effects of a hypothetical third wave of the pandemic in 2021 and what would the role of confidence be? To answer this question, we combine three alternative scenarios for the size of the unexpected uncertainty shock with two alternative scenarios for the level of confidence in place when the third wave hits. In particular, provided the difficulty in predicting the size of the shock, we consider the following three scenarios: (i) one in which the uncertainty shock size is equal to the surge realized between September and October 2020 on an end-of-month basis (i.e. 2.2 standard deviation shock), (ii) one in which the uncertainty shock size is twice the previous one, and (iii) one in which the shock size is half the October 2020 one. A shock larger than the one observed in the second wave can be supported by the assumption that, given the availability of a COVID-19 vaccine and the possibility that the policy response observed during the first and second wave may change, uncertainty about the possibility of national or selective lock-downs and fiscal and monetary policy implemented to support firms and households will be high. Another possibility of (potentially very) high future uncertainty regards the case that a new unknown mutation of the virus spreads out.

As for the level of confidence at the time of the hypothetical third wave, we consider two scenarios: i) one where the economy is in pessimistic times (as previously defined by the set of initial conditions where confidence is in the lowest quintile of its historical distribution), and ii) one where confidence is around average (or in the middle quintile of its distribution). The first confidence scenario considers the case in which confidence does not recover. Up to November 2020 the level of consumer confidence remained low - at a level comparable with the 2012–13 trough. The latter scenario accounts for the possibility that the start of the vaccination campaign in 2021 will boost confidence. In performing the simulations, we assume that the persistence of the uncertainty shock is equal to the one implied by our baseline IVAR estimated on historical data. Our results do not depend on the exact timing when the third wave-induced uncertainty shock will occur in 2021.

Figure 8 documents the implied outcomes for the considered scenarios. One result is striking: what mostly matters for the economic impact of a third wave-induced uncertainty shock is the level of confidence when the shock hits rather than the size of the shock. In particular, an uncertainty shock twice the size of the second wave shock occurring in a situation of recovered confidence implies a year-over-year peak loss in industrial production of 2.17%, which is smaller than the corresponding peak loss of 2.94% associated to an uncertainty shock half its size but occurring in pessimistic times. Instead, in case the uncertainty shock twice the size of the second wave shock occurs in pessimistic times, the predicted peak loss in industrial production is as big as 6.22%, around three times stronger than if it occurred in a situation of recovered confidence. Similar considerations can be done for the response of inflation. Overall, these results stress the key role of confidence in the forecast for the effects of uncertainty shocks.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

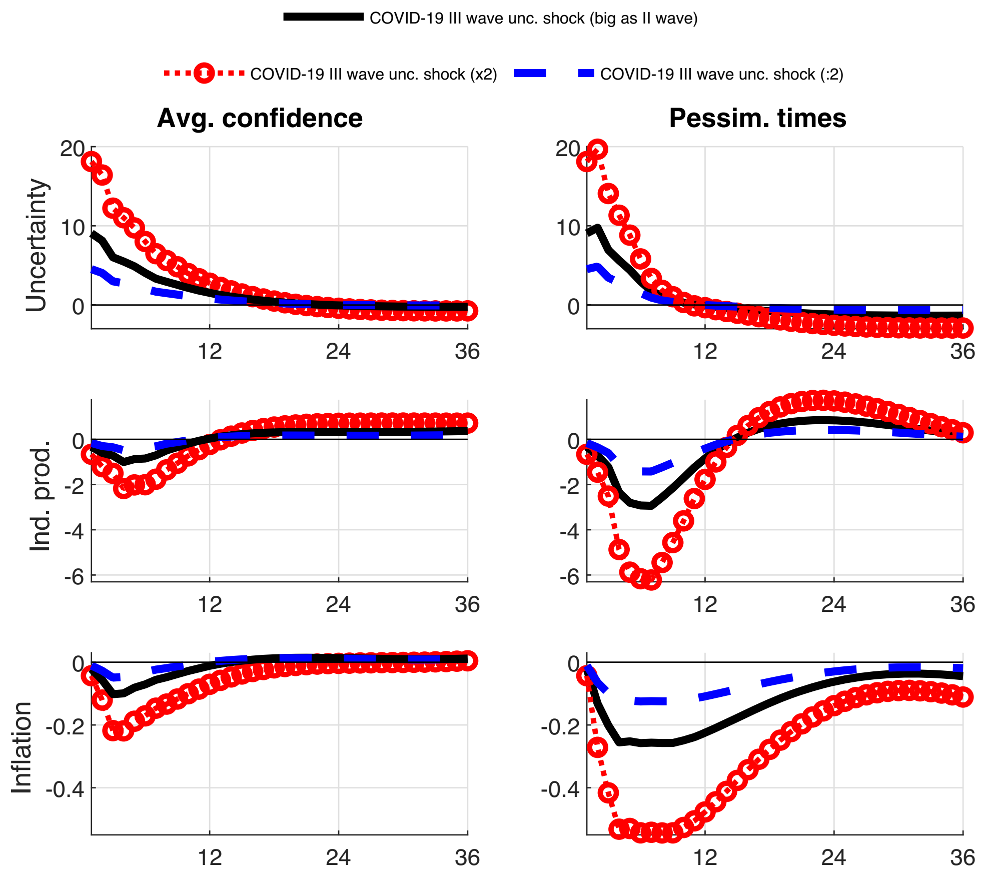

Figure 8. The uncertainty-channel of the COVID-19 shock: Alternative scenarios for the third wave in 2021

Notes: Left column: shock hitting during times of average confidence (middle quantile of its historical distribution). Right column: shock hitting during pessimistic times (bottom quantile of confidence historical distribution). Solid black line: GIRF to a 2.2 standard deviation uncertainty shock hitting the economy during pessimistic times. Circled red line: GIRF to a 4.4 standard deviation uncertainty shock. Dashed blue line: GIRF to a 1.1 standard deviation uncertainty shock. Monthly data

IV. Conclusion

We analyse the impact of uncertainty shocks using an IVAR model for the euro area. The IVAR model allows the shocks to depend on the state of expectations for the economic outlook. Our results suggest that the impact of an uncertainty shock in the euro area is highly state-dependent, and varies according to the expectations as measured by several confidence survey-measures.

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 *et al*. (2020). Like 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

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

analysis. To address these concerns, we calibrated the uncertainty shock process to imply a VSTOXX impulse response that exactly match the actual data evolution of the VSTOXX since the COVID-19 outbreak.

Using the estimated IVAR model, we assess that the rebound after the COVID-19 epidemics will be slow and painful – even if the 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 recent experience is unique, in that measures of uncertainty registered surges in both the United States and the euro area equal to several standard deviations, and measures of economic sentiment simultaneously hit their record bottom. 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 aimed specifically at resolving the uncertainty by providing to the public contingent scenarios and policies ready to be adopted if the worst-case outcomes materialize.

Final Manuscript Received: February 2021

References

Alessandri, P. and Mumtaz, H. (2019). ‘Financial regimes and uncertainty shocks’, *Journal of Monetary Economics*, Vol. 101, pp. 31–46.

Alfaro, I., Bloom, N. and Lin, X. (2018). The Finance Uncertainty Multiplier, NBER Working Paper No. 24571.

Andreasen, M., Caggiano, G., Castelnuovo, E. and Pellegrino, G. (2021). Why Does Risk Matter More in Recessions than in Expansions? mimeo, Aarhus University, Monash University, and University of Melbourne.

Angelini, G., Bacchiocchi, E., Caggiano, G. and Fanelli, L. (2019). ‘Uncertainty across volatility regimes’, *Journal of Applied Econometrics*, Vol. 34, pp. 437–455.

Arellano, C., Bai, Y. and Kehoe, P. J. (2019). ‘Financial frictions and fluctuations in volatility’, *Journal of Political Economy*, Vol. 127, pp. 2049–2103.

Bachmann, R., Elstner, S. and Sims, E. (2013). ‘Uncertainty and economic activity: evidence from business survey data’, *American Economic Journal: Macroeconomics*, Vol. 5, pp. 217–249.

Baker, S., Bloom, N. and Davis, S. J. (2016). ‘Measuring economic policy uncertainty’, *Quarterly Journal of Economics*, Vol. 131, pp. 1539–1636.

Baker, S. R., Bloom, N., Davis, S. J. and Terry, S. J. (2020). Covid-induced Economic Uncertainty, Discussion Paper, National Bureau of Economic Research. Working Paper No. 26983.

Barsky, R. B. and Sims, E. R. (2012). ‘Information, animal spirits, and the meaning of innovations in consumer confidence’, *American Economic Review*, Vol. 102, pp. 1343–1377.

Basu, S. and Bundick, B. (2017). ‘Uncertainty shocks in a model of effective demand’, *Econometrica*, Vol. 85, pp. 937–958.

Bekaert, G., Hoerova, M. and Lo Duca, M. (2013). ‘Risk, uncertainty and monetary policy’, *Journal of Monetary Economics*, Vol. 60, pp. 771–788.

Bernanke, B. S. (1983). ‘Irreversibility, uncertainty, and cyclical investment’, *Quarterly Journal of Economics*, Vol. 98, pp. 85–106.

Bloom, N. (2009). ‘The impact of uncertainty shocks’, *Econometrica*, Vol. 77, pp. 623–685.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

Bomberger, W. A. (1996). ‘Disagreement as a measure of uncertainty’, *Journal of Money, Credit and Banking*, Vol. 28, pp. 381–392.

Caballero, R. (1990). ‘Consumption puzzles and precautionary savings’, *Journal of Monetary Economics*, Vol. 25, pp. 113–136.

Cacciatore, M. and Ravenna, F. (2021). ‘Uncertainty, wages, and the business cycle’, *The Economic Journal*, Forthcoming.

Caggiano, G., Castelnuovo, E. and Figueres, J. M. (2020). ‘Economic policy uncertainty spillovers in booms and busts’, *Oxford Bulletin of Economics and Statistics*, Vol. 82, pp. 125–155.

Caggiano, G., Castelnuovo, E. and Groshenny, N. (2014). ‘Uncertainty shocks and unemployment dynamics: an analysis of Post-WWII U.S. recessions’, *Journal of Monetary Economics*, Vol. 67, pp. 78–92.

Caggiano, G., Castelnuovo, E. and Kima, R. (2020). The Global Effects of Covid-19-Induced Uncertainty, mimeo, Monash University and University of Melbourne.

Caggiano, G., Castelnuovo, E. and Pellegrino, G. (2017). ‘Estimating the real effects of uncertainty shocks at the zero lower bound’, *European Economic Review*, Vol. 100, pp. 257–272.

Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajšek, E. (2016). ‘The macroeconomic impact of financial and uncertainty shocks’, *European Economic Review*, Vol. 88, pp. 185–207.

Carriero, A., Clark, T. E. and Marcellino, M. (2018). ‘Measuring uncertainty and its impact on the economy’, *Review of Economics and Statistics*, Vol. 100, pp. 799–815.

Carriero, A., Mumtaz, H., Theodoridis, K. and Theophilopoulou, A. (2015). ‘The impact of uncertainty shocks under measurement error: a proxy SVAR approach’, *Journal of Money, Credit and Banking*, Vol. 47, pp. 1223–1238.

Castelnuovo, E. (2016). ‘Modest macroeconomic effects of monetary policy shocks during the great moderation: an alternative interpretation’, *Journal of Macroeconomics*, Vol. 47, pp. 300–314.

Chatterjee, P. (2018). ‘Asymmetric impact of uncertainty in recessions - are emerging countries more vulnerable?’, *Studies in Nonlinear Dynamics and Econometrics*, forthcoming.

De Rezende, R. B. and Ristiniemi, A. (2020). A Shadow Rate without a Lower Bound Constraint, Staff Working Paper No. 864, Bank of England.

ECB (2016). ‘The impact of uncertainty on activity in the euro area’, *Economic Bulletin*, Issue 8.

ECB (2020). ‘Alternative scenarios for the impact of the COVID-19 pandemic on economic activity in the euro area’, *Economic Bulletin*, Issue 3. May 14. Study prepared by Niccolò Battistini and Grigor Stoevsky.

European Commission (2020a). Flash Consumer Confidence Indicator for EU and Euro Area, Press Release, 23 April 2020, Discussion Paper.

European Commission (2020b). The Joint Harmonised EU Programme of Business and Consumer Surveys: User Guide, February 2020, Discussion Paper, Directorate-General for Economic and Financial Affairs, available at https://ec.europa.eu/info/.les/user-guide-joint-harmonised-eu-programme-business-and-consumer-surveys_en.

Fajgelbaum, P., Schaal, E. and Taschereau-Dumouchel, M. (2014). Uncertainty Traps, Working Paper 19973, National Bureau of Economic Research.

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K. and Rubio-Ramírez, J. (2015). ‘Fiscal volatility shocks and economic activity’, *American Economic Review*, Vol. 105, pp. 3352–3384.

Gambacorta, L., Hofmann, B. and Peersman, G. (2014). ‘The effectiveness of unconventional monetary policy at the zero lower bound: a cross-country analysis’, *Journal of Money, Credit and Banking*, Vol. 46, pp. 615–642.

Gertler, M. and Karadi, P. (2015). ‘Monetary policy surprises, credit costs, and economic activity’, *American Economic Journal: Macroeconomics*, Vol. 7, pp. 44–76.

Gilchrist, S. and Mojon, B. (2018). ‘Credit risk in the euro area’, *The Economic Journal*, Vol. 128, pp. 118–158.

Gilchrist, S., Sim, J. W. and Zakrajšek, E. (2014). Uncertainty, Financial Frictions, and Investment Dynamics, Discussion Paper, National Bureau of Economic Research, No. 20038.

Gilchrist, S. and Zakrajšek, E. (2012). ‘Credit spreads and business cycle fluctuations’, *American Economic Review*, Vol. 102, pp. 1692–1720.

Görtz, C., Tsoukalas, J. D. and Zanetti, F. (2016). News Shocks under Financial Frictions, Working Paper 2016 15, Business School - Economics, University of Glasgow.

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd

Jackson, L. E., Kliesen, K. L. and Owyang, M. T. (2020). 'The nonlinear effects of uncertainty shocks', *Studies in Nonlinear Dynamics & Econometrics*, Vol. 24, pp. 1–19.

Jurado, K., Ludvigson, S. C. and Ng, S. (2015). 'Measuring uncertainty', *American Economic Review*, Vol. 105, pp. 1177–1216.

Koop, G., Pesaran, M. and Potter, S. (1996). 'Impulse response analysis in nonlinear multivariate models', *Journal of Econometrics*, Vol. 74, pp. 119–147.

Lanne, M. and Nyberg, H. (2016). 'Generalised forecast error variance decomposition for linear and nonlinear multivariate models', *Oxford Bulletin of Economics and Statistics*, Vol. 78, pp. 595–603.

Leduc, S. and Liu, Z. (2016). 'Uncertainty shocks are aggregate demand shocks', *Journal of Monetary Economics*, Vol. 82, pp. 20–35.

Leduc, S. and Liu, Z. (2020). 'The uncertainty channel of the coronavirus', *FRBSF Economic Letter*, Vol. 2020, pp. 1–05.

Lenza, M. and Primiceri, G. E. (2020). How to Estimate a VAR after March 2020, NBER Working Paper 27771, National Bureau of Economic Research.

Lhuissier, S. and Tripier, F. (2019). Regime-Dependent Effects of Uncertainty Shocks: a Structural Interpretation, Banque de France Working Paper No. 714.

Ludvigson, S. C., Ma, S. and Ng, S. (2019). 'Uncertainty and business cycles: exogenous impulse or endogenous response?', *American Economic Journal: Macroeconomics*, forthcoming.

Ludvigson, S. C., Ma, S. and Ng, S. (2020). Covid19 and the Macroeconomic Effects of Costly Disasters, Working Paper 26987, National Bureau of Economic Research.

Lutz, C. (2017). Unconventional Monetary Policy and Uncertainty, Copenhagen Business School, mimeo.

Meinen, P. and Röhe, O. (2017). 'On measuring uncertainty and its impact on investment: cross-country evidence from the euro area', *European Economic Review*, Vol. 92, pp. 161–179.

Mertens, K. and Ravn, M. O. (2013). 'The dynamic effecs of personal and corporate income tax changes in the United States', *American Economic Review*, Vol. 103, pp. 1212–1247.

Mertens, K. and Ravn, M. O. (2014). 'A reconciliation of SVAR and narrative estimates of tax multipliers', *Journal of Monetary Economics*, Vol. 68, pp. S1–S19.

Mumtaz, H. and Theodoridis, K. (2019). 'Dynamic effects of monetary policy shocks on macro-economic volatility', *Journal of Monetary Economics*, forthcoming.

Mumtaz, H. and Zanetti, F. (2013). 'The impact of the volatility of monetary policy shocks', *Journal of Money, Credit and Banking*, Vol. 45, pp. 535–558.

Nowzohour, L. and Stracca, L. (2020). 'More than a feeling: confidence, uncertainty, and macroeconomic fluctuations', *Journal of Economic Surveys*, Vol. 34, pp. 691–726.

Paccagnini, A. and Colombo, V. (2020). 'The asymmetric effects of uncertainty shocks', Centre for Applied Macroeconomic Analysis, Working Paper 72.

Pellegrino, G. (2021). Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory, Economic Inquiry, Forthcoming.

Piffer, M. and Podstawski, M. (2018). 'Identifying uncertainty shocks using the price of gold', *Economic Journal*, Vol. 128, pp. 3266–3284.

Smets, F. and Wouters, R. (2003). 'An estimated dynamic stochastic general equilibrium model of the euro area', *Journal of the European Economic Association*, Vol. 1, pp. 1123–1175.

Stock, J. H. and Watson, M. W. (2012). 'Disentangling the channels of the 2007–2009 recession', *Brookings Papers on Economic Activity*, Spring, 81–135.

Wu, J. C. and Xia, F. D. (2017). 'Time-Varying Lower Bound of Interest Rates in Europe', *Chicago Booth Research Paper*, (17-06).

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Online Appendix

© 2021 The Department of Economics, University of Oxford and John Wiley & Sons Ltd