The macroeconomic impact of uncertainty

The question as to the consequences of heightened uncertainty has been increasingly pushed to centre stage in economic policy discourse in connection with the global recession of 2008-09 and the European sovereign debt crisis. Yet with regard to other events, too, such as the referendum on the United Kingdom remaining in the EU or parliamentary elections followed by difficulties in the formation of new governments, political uncertainty is regularly diagnosed as potentially being capable of impairing economic activity. Similar outcomes are also attributed to financial market turmoil and heightened uncertainty concerning the economic outlook. Against this background, this raises the question as to whether uncertainty is having a systematic impact on macroeconomic developments. Despite numerous explanatory approaches, it has proved challenging to demonstrate the existence of such an effect.

One reason is that there is no generally accepted measure of uncertainty. While some approaches focus on the political environment and evaluate the relevant information, others look at the volatility of financial market variables, the dispersion of survey results or the forecastability of key economic variables. Depending on the underlying approach, conventional measures of uncertainty can produce different findings. A comparison of selected measures of uncertainty in the euro area shows, in some cases, considerable discrepancies. These differences carry over to the estimated relationship between uncertainty and macroeconomic developments.

Details of econometric modelling likewise play a meaningful role in adequately capturing the macroeconomic consequences of uncertainty shocks. Different findings can be reached depending on how the estimation approach is specified. In addition, it is often very difficult to tell uncertainty shocks apart from other shocks that operate in a similar manner, such as financial shocks, for instance.

Over the observation period, even despite the aforementioned difficulties, the existence of statistically significant relationships between uncertainty shocks and the euro-area real economy can be proven. During the global financial and economic crisis of 2008-09, in particular, uncertainty weighed perceptibly on output. In the more recent past, however, there has been no evidence that uncertainty shocks have dampened macroeconomic activity.

Background

Heightened interest in the economic consequences of uncertainty

Over the past ten years, the question as to the consequences of heightened uncertainty for macroeconomic developments has been shifted increasingly towards centre stage in economic policy discourse. The global financial and economic crisis and the subsequent sovereign debt crisis in the euro area were key reasons for this. In particular, the considerable economic turmoil during the crisis years and the sluggish economic recovery – compared with earlier cycles – were regarded as a consequence of heightened uncertainty. The tensions visible in the financial markets in the aftermath of the Brexit referendum and the concerns aired prior to a number of significant parliamentary elections in Europe about their outcome have stoked interest in the aggregate costs of heightened uncertainty.

Possible transmission channels for uncertainty

In principle, there are many conceivable transmission channels through which uncertainty can impact adversely on output.[1] One of these channels, for instance, is sluggish investment or consumption patterns. Investment is often very difficult to reverse or is even irreversible. This can prompt firms to delay investment expenditures amidst heightened uncertainty in order to make better-informed decisions at a later date.[2] Households may behave similarly with regard to the purchase of durable consumer goods.[3] Increased precautionary saving on the part of households can also exert a negative macroeconomic impact owing to the attendant cutback in consumer spending.[4] Moreover, specific forms of performance-based executive compensation can lead to increased caution and thus hesitancy regarding investment decisions in times of heightened uncertainty.[5] Uncertainty-induced financial market responses such as rising risk premiums and a credit crunch can also dampen real economic growth.[6] Against this background, the question presents itself as to how much uncertainty shocks have weighed on output growth in the euro area over the past few years.

Approaches to capturing uncertainty

No clear-cut measure of uncertainty

An assessment of the macroeconomic impact of uncertainty is predicated on properly capturing this factor. Although theory goes some way towards defining the concept of uncertainty, especially setting it apart from risk, where probabilities can be assigned to a set of potential outcomes,[7] and surprises as forecast errors,[8] there is no unique, clear-cut measure. Conventional uncertainty indicators therefore generally do not follow such a strict separation, but are often a combination of uncertainty, risk, and in particular cases, surprise.[9] In addition, the individual meas-

1 An overview of the potential channels of uncertainty can be found, inter alia, in N. Bloom (2014), Fluctuations in uncertainty, Journal of Economic Perspectives 28 (2), pp. 153-176.
2 See B.S. Bernanke (1983), Irreversibility, uncertainty and cyclical investment, The Quarterly Journal of Economics, 98 (1), pp. 85-106; R.S. Pindyck (1991), Irreversibility, uncertainty and investment, Journal of Economic Literature 29(3), pp. 1110-1148; and Deutsche Bundesbank, Uncertainty, freedom of action and investment behaviour – empirical findings for Germany, Monthly Report, September 2001, pp. 71-86. Uncertainty-induced reluctance to invest can also manifest itself in hesitation to enter a given market. See also A. Dixit (1989), Entry and exit decisions under uncertainty, Journal of Political Economy 97 (3), pp. 620-638.
3 See J.C. Eberly (1994), Adjustment of consumers' durables stocks: Evidence from automobile purchases, Journal of Political Economy 102 (3), pp. 403-436; G. Bertola, L. Guiso and L. Pistaferri (2005), Uncertainty and consumer durables adjustment, Review of Economic Studies 72 (4), pp. 973-1007.
4 For more on the topic see, inter alia, S. Basu and B. Bundick (2017), Uncertainty shocks in a model of effective demand, Econometrica 85 (3), pp. 937-958.
5 See B. Glover and O. Levine (2015), Uncertainty, investment, and managerial incentives, Journal of Monetary Economics 69 (C), pp. 121-137.
6 See L.J. Christiano, R. Motto and M. Rostagno (2014), Risk shocks, American Economic Review 104 (1), pp. 27-65; S. Gilchrist, J.W. Sim and E. Zakrajšek (2014), Uncertainty, financial frictions, and investment dynamics, NBER Working Paper No 20038; I. Alfaro, N. Bloom and X. Lin (2018), The finance uncertainty multiplier, NBER Working Paper No 24571.
7 Knight (1921) makes a distinction between uncertainty and risk, which can be captured by probability theory. See F.H. Knight (1921), Risk, uncertainty and profit, Boston, Houghton Mifflin Company.
8 See C. Scotti (2016), Surprise and uncertainty indexes: Real-time aggregation of real-activity macro surprises, Journal of Monetary Economics 82 (C), pp. 1-19.
9 Exceptions may be found in G. Bekaert, M. Hoerova and M. Lo Duca (2013), Risk, uncertainty and monetary policy, Journal of Monetary Economics, 60 (7), pp. 771-788; B. Rossi, T. Sekhposyan and M. Soupre (2016), Understanding the sources of macroeconomic uncertainty, CEPR Discussion Papers No 11415; and C. Scotti (2016), op. cit.

ures are, in some cases, conceptually considerably different, in terms of both the method of calculating the indicators and also the data used.

Conventional uncertainty indicators based on volatility of financial market data, …

The time-varying volatility of financial market data is a conventional measure for approximating uncertainty. Examples include the volatility of stock market indices derived from options prices and the implied volatility of exchange rates calculated from foreign exchange options.[10] This rests on the assumption that option prices contain meaningful information about market participants' perception of risk.

… the dispersion of future expectations, …

The dispersion of future expectations represents an additional frequently used measure of uncertainty. This approach rests on the assumption that the dispersion of market agents' or analysts' forecasts increases with rising uncertainty, whereas a low degree of uncertainty leads to a more uniform picture of expectations.[11] Standard reference variables include growth of real gross domestic product (GDP), consumer price inflation and the change in manufacturing output.[12]

… media coverage analysis …

Another widespread approach is to use media coverage analysis to capture uncertainty tendencies.[13] For example, a popular indicator of economic policy uncertainty measures the frequency with which major daily newspapers report on it. Newspaper articles are searched at fixed intervals for keywords or combinations of terms referring to this type of uncertainty. A measure of uncertainty is then derived from the intensity of reporting.

… and the volatility of forecast errors

One general criticism of the uncertainty measures listed above is that the underlying data set is usually small, which calls their suitability into question. Another is that these measures do not always make a clear distinction between forecastable developments and developments that actually have to be regarded as unexpected. As a case in point, the dispersion of future expectations might reflect different, albeit certain (e.g. sector or firm-specific) expectations. The volatility of financial market variables – owing, for example, to changes in risk aversion or market participants' sentiment – can also increase without being attributable to uncertainty surrounding the possible realisation of macroeconomic fundamentals. Such indicators therefore run counter to a widely held opinion that uncertainty is linked to the limited ability to forecast future events.[14] Against the background of these two criticisms, more recent studies recommend deriving uncertainty indicators from the volatility of estimation errors resulting from the forecasting of a broad selection of business cycle-relevant time series and financial market data.[15] The fluctuation intensity of forecast errors determines the degree of uncertainty here.[16]

10 See N. Bloom (2009), The impact of uncertainty shocks, Econometrica 77 (3), pp. 623-685; and A. Haddow, C. Hare, J. Hooley and T. Shakir (2013), Macroeconomic uncertainty: What is it, how can we measure it and why does it matter? Bank of England Quarterly Bulletin 53 (2), pp. 100-109.
11 See A. Girardi and A. Reuter (2017), New uncertainty measures for the euro area using survey data, Oxford Economic Papers 69 (1), pp. 278-300.
12 See N. Bloom (2009), op. cit.; J.H. Wright (2011), Term premiums and inflation uncertainty: Empirical evidence from an international panel dataset, American Economic Review 101 (4), pp. 1514-1534; R. Bachman, S. Elstner and E. Sims (2013), Uncertainty and economic activity: Evidence from business survey data, American Economic Journal: Macroeconomics 5 (2), pp. 217-249.
13 See S.R. Baker, N. Bloom and S.J. Davis (2016), Measuring economic policy uncertainty, The Quarterly Journal of Economics 131 (4), pp. 1593-1636; D. Caldara and M. Iacoviello (2018), Measuring geopolitical risk, International Finance Discussion Papers No 1222, Board of Governors of the Federal Reserve System.
14 See K. Jurado, S.C. Ludvigson and S. Ng (2015), Measuring uncertainty, American Economic Review 105 (3), pp. 1177-1216; and S.C. Ludvigson, S. Ma and S. Ng (2015), Uncertainty and business cycles: Exogenous impulse or endogenous response? NBER Working Paper No 21803.
15 This measure of uncertainty is calculated in three steps. The first step is, using a factor model approach, to estimate the forecastable components of the underlying macroeconomic time series. Given the resultant forecast errors, a stochastic volatility model is employed in a second step to derive the individual uncertainty attributable to the respective macroeconomic time series, being captured by the conditional volatility of the forecast error. In the final step, the measure for macroeconomic uncertainty is determined by aggregating time-series-specific uncertainty. For a detailed description of the methodology, see K. Jurado, S.C. Ludvigson and S. Ng (2015), op. cit.
16 Analyses based on this indicator for selected euro area countries may be found in Deutsche Bundesbank (2016), Investment in the euro area, Monthly Report, January 2016, pp. 31ff.

Uncertainty measures for the euro area*

Monthly data

Sources: Bundesbank calculations based on data from Eurostat, Haver Analytics, Global Insight and www.policyuncertainty.com * A rise (fall) in the standardised indicators suggests a rise (fall) in uncertainty. The period from January 1999 to June 2018 forms the underlying dataset. **1** Based on the volatility of forecast errors derived from a comprehensive dataset. **2** Based on the dispersion of output expectations in manufacturing. **3** VSTOXX Volatility Index. Calculated from options on the EURO STOXX 50. **4** Calculated as the arithmetic mean of the Economic Policy Uncertainty Indexes for France, Germany, Italy and Spain.

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Development of uncertainty indicators for the euro area over time

A descriptive comparison of common uncertainty indicators for the euro area, …

Further analysis is based on four uncertainty indicators for the euro area. These comprise an indicator for economic policy uncertainty,[17] measures referring to the volatility of the stock market,[18] the dispersion of production expectations in manufacturing[19] and a proxy of macroeconomic uncertainty based on the volatility of the non-forecastable component of cyclically relevant indicators.[20]

… despite some similarities, …

Over the period under review, it becomes apparent that, except for the economic policy uncertainty indicator, all of the measures of uncertainty reached their peak during the global financial crisis of 2008-09. Although the economic policy uncertainty indicator rose during the crisis, it hit its peak in 2016 during the month in which the United Kingdom voted on whether to remain in the European Union.[21] In the months that followed, too, movements in the economic policy uncertainty index deviated from developments in the other measures of uncertainty. While economic policy uncertainty tended to hover at well above average levels, uncertainty in the euro area as indicated by the other measures remained relatively low on the whole as the economic recovery proceeded.[22]

17 The index of economic policy uncertainty is derived from the evaluation of newspaper articles and measures how often the words “uncertainty”, “economy” and specific policy-relevant keywords occur together. For a detailed description of the measurement concept, see S. R. Baker, N. Bloom and S. J. Davis (2016), op. cit. The indicator for the euro area was calculated as the simple arithmetic mean of the indicators for Germany, France, Spain and Italy (available at www.policyuncertainty.com).
18 Stock market volatility is calculated using the implied volatility of the EURO STOXX 50 derived from stock options (with a maturity of 30 days).
19 The dispersion of output expectations for the next three months in manufacturing is calculated on the basis of monthly opinion surveys conducted by the European Commission. See also R. Bachmann, S. Elstner and E. R. Sims (2013), op. cit.; P. Meinen and O. Röhe (2017), On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area, European Economic Review 92 (C), pp. 161-179; and European Commission, European Business Cycle Indicators: 4th Quarter 2016, Special topic: Measuring uncertainty using survey data – What do we measure?, European Economy Technical Paper No 13, January 2017, pp. 24-28.
20 The index of macroeconomic uncertainty for the euro area is calculated as the arithmetic mean of the measures for Germany, France, Spain and Italy. Depending on the country in question, the calculation comprises between 122 and 139 time series, including cyclical indicators, survey data, financial market series as well as prices and exchange rates. For a detailed description of the index concept, see K. Jurado, S. C. Ludvigson and S. Ng (2015), op. cit.; for a detailed description of the calculation method for the euro area, see P. Meinen and O. Röhe (2017), op. cit.
21 The indicators show further periods of heightened uncertainty in the euro area following the terrorist attacks in the United States on 11 September 2001, the Iraq war in 2003 (predominantly stock market volatility, economic policy and macroeconomic uncertainty), the European sovereign debt crisis and the recent US presidential election (the indicator of economic policy uncertainty only).
22 This is particularly true of the indicator for macroeconomic uncertainty, which has remained below its long-term average since October 2012.

Contemporaneous correlations of various measures of uncertainty and their interaction with real GDP growth in the euro area*

Variable	Macroeconomic uncertainty[1]	Dispersion of expectations[2]	Implied stock market volatility[3]	Economic policy uncertainty[4]
Real GDP growth	– 0.525***	– 0.682***	– 0.513***	– 0.311***
Macroeconomic uncertainty[1]	1.000	.	.	.
Dispersion of expectations[2]	0.593***	1.000	.	.
Implied stock market volatility[3]	0.721***	0.529***	1.000	.
Economic policy uncertainty[4]	– 0.170	0.135	0.232**	1.000

Sources: Bundesbank calculations based on quarterly data from Eurostat, Haver Analytics, Global Insight and www.policyuncertainty.com * The statistical significance of the estimated correlation coefficients is denoted by */**/*** at the usual levels. The period from Q1 1999 to Q2 2018 forms the underlying dataset. **1** Based on the conditional volatility of forecast errors derived from a comprehensive dataset. **2** Based on the dispersion of output expectations in manufacturing. **3** VSTOXX Volatility Index. Calculated from options on the EURO STOXX 50. **4** Calculated as the arithmetic mean of Economic Policy Uncertainty Indexes for France, Germany, Italy and Spain.

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… sometimes shows marked differences in terms of time pattern …

The unique behaviour of the indicator for economic policy uncertainty can also be seen in a simple correlation analysis. While implied stock market volatility, the dispersion of expectations and macroeconomic uncertainty as measured by forecast error volatility are fairly closely correlated, the same can only be said of economic policy uncertainty to a limited extent. In combination with the macroeconomic uncertainty indicator, it even gives rise to a negative correlation coefficient, albeit a statistically insignificant one. Stock market volatility and the macroeconomic uncertainty indicator exhibit an especially pronounced positive relationship.

… and interaction with output

All of the uncertainty indicators nevertheless display a negative relationship with respect to aggregate growth. The simple correlation coefficient with the quarterly GDP growth rate proves to be statistically significant for each of the indicators. The negative correlation measured using this method is particularly noticeable for the dispersion of expectations, while it is relatively weak for economic policy uncertainty.

Quantification of uncertainty effects for the euro area

The measurement of macroeconomic uncertainty effects …

Simple correlations can provide broad indications of relationships between economic time series. To analyse the macroeconomic effects of uncertainty in greater depth, two classes of models are commonly used in applied economic research. In addition to microfounded dynamic stochastic general equilibrium models (see also the box on pp. 54 ff.), structural vector autoregression models (SVAR models) are frequently employed. In these multi-equation models, a vector of selected endogenous variables is first regressed on its own lags. An estimated multi-dimensional linear equation system such as this can capture the dynamic relationships between a large number of key macroeconomic variables. The residual values of the various individual equations are then used to identify the drivers of the model – the structural shocks. The aim is to observe the impact of these disturbances on the system in isolation and to estimate their relative importance.

… can be carried out using econometric estimation methods

Identifying these shocks requires additional assumptions derived, inter alia, from economic theory. The recursive identification method assumes, for example, that certain shocks initially have a delayed impact on selected variables

Macroeconomic effects of uncertainty in the context of DSGE models

Microfounded dynamic stochastic general equilibrium models (DSGE models) have become a standard tool in quantitative macroeconomics. This type of model typically attempts to explain macroeconomic developments based on individual optimal decision rules of rational economic agents.[1] In these models, the cyclical dynamics of the economy are induced by a variety of unexpected disturbances (referred to as shocks).

The first generation of DSGE models was kept relatively simple, but methodological refinements and greater computing power have expanded their modelling possibilities.[2] As a result of these developments, it is also possible to explore the macroeconomic effects of uncertainty using DSGE models. One of the advantages here over other modelling strategies (such as structural vector autoregressive models) is the ability to map specific transmission channels in detail.

In DSGE models, uncertainty shocks are often captured as unexpected changes in the variance of selected disturbances[3], whereby frictions are of key importance to the macroeconomic effects of uncertainty shocks. Besides nominal and real rigidities, these include financial market imperfections, in particular.[4]

Depending on which frictions are taken into account, there can sometimes be clear differences in the quantification of uncertainty effects. This also applies to key macroeconomic variables such as output and price developments, which are of special interest from a monetary policy perspective.

It is true that the direction of the impact on aggregate output is largely undisputed – an increase in uncertainty generally has a dampening effect.[5] That said, the effects of the adverse uncertainty shocks on output

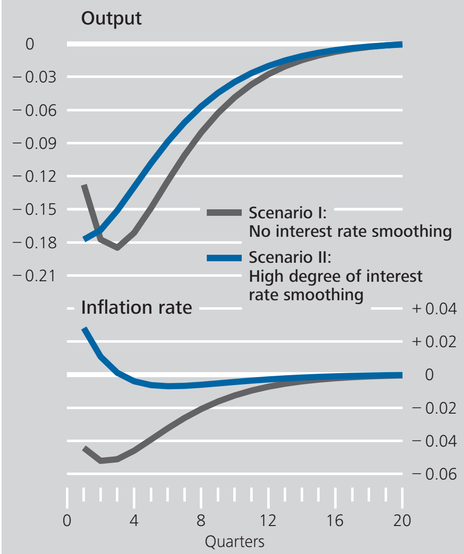
1 DSGE models typically assume that economic agents do not make any systematic errors when forming their expectations and that they make optimum use of all the information that is available to them. See also Deutsche Bundesbank, Lower bound, inflation target and the anchoring of inflation expectations, Monthly Report, June 2018, pp. 31-50.
2 See L.J. Christiano, M.S. Eichenbaum and M. Trabandt (2018), On DSGE models, Journal of Economic Perspectives 32 (3), pp. 113-140.
3 See J. Fernández-Villaverde, P. Guerrón-Quintana, J.F. Rubio-Ramírez and M. Uribe (2011), Risk matters: The real effects of volatility shocks, American Economic Review 101 (6), pp. 2530-2561. Alternative approaches to modelling uncertainty in DSGE models can be found, inter alia, in P.D. Fajgelbaum, E. Schaal and M. Taschereau-Dumouchel (2017), Uncertainty traps, The Quarterly Journal of Economics 132 (4), pp. 1641-1692 and T. Nakata (2017) Uncertainty at the zero lower bound, American Economic Journal: Macroeconomics, 9 (3), pp. 186-221.
4 An example of the interaction of uncertainty shocks and real rigidities in the form of (non-convex) adjustment costs for investment and employment can be found in Bloom et al. (2018). In their paper, Basu and Bundick (2017) focus on the interplay between price rigidities and uncertainty shocks. For information about the role of financial market imperfections in the transmission of uncertainty, see, inter alia, Arellano et al. (2018), Christiano et al. (2014) and Gilchrist et al. (2014). See L.J. Christiano, R. Motto and M. Rostagno (2014), Risk shocks, American Economic Review, 104 (1), pp. 27-65; S. Gilchrist, J.W. Sim and E. Zakrajšek (2014), Uncertainty, financial frictions, and investment dynamics, NBER Working Paper No 20038; S. Basu and B. Bundick (2017), Uncertainty shocks in a model of effective demand, Econometrica 85 (3), pp. 937-958; N. Bloom, M. Floetotto, N. Jaimovich, I. Saporta-Eksten and S.J. Terry (2018), Really uncertain business cycles, Econometrica, 86 (3), pp. 1031-1065; C. Arellano, Y. Bai and P.J. Kehoe (2018), Financial frictions and fluctuations in volatility, Journal of Political Economy, forthcoming.
5 In this context, several studies point to the increased impact of uncertainty shocks in periods with a binding zero lower bound on the nominal interest rate. Moreover, a binding zero lower bound in combination with conventional macroeconomic shocks, too, can lead to heightened uncertainty about macroeconomic developments. See also S. Basu and B. Bundick (2017), op. cit. and M. Plante, A.W. Richter and N.A. Throckmorton (2018), The zero lower bound and endogenous uncertainty, The Economic Journal 128 (611), pp. 1730-1757.

shown in the DSGE simulations range from relatively small[6] to clearly contractionary.[7]

When it comes to price developments, the direction of the impact is less clear cut. A number of analyses find that output and prices demonstrate unidirectional responses, as can also be observed for macroeconomic demand shocks.[8] Other studies point to the possibility of opposite movements as a result of heightened uncertainty.[9] In this context, the result sometimes depends significantly on the assumptions about the conduct of monetary policy.[10] In DSGE models, central bank policy is often described by a simple reaction function. The central bank adjusts the policy rate to movements in output measures and deviations of the inflation rate from the target. The strength of the response usually also depends on a smoothing parameter which is supposed to portray the preferences of the central bank in terms of interest rate stability.

Effects of an uncertainty shock under different degrees of interest rate smoothing*

Percentage deviation from the (stochastic) steady state



Source: Bundesbank calculations based on S. Basu and B. Bundick (2017), Uncertainty shocks in a model of effective demand, Econometrica 85 (3) pp. 937-958. * Impulse-responses of output and inflation rate to an uncertainty shock using a DSGE model for the United States.
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Simulations using a prototypical DSGE model with imperfect competition and nominal rigidities confirm that the assumed degree of interest rate smoothing can play a key role in determining the direction of the impact of uncertainty shocks on the inflation rate.[11] If the central bank decides not to smooth interest rate fluctuations, aggregate output and inflation respond to an unexpected increase in uncertainty in the same direction, as is typical for demand shocks.[12] In actual fact, however, empirical estimations usually point to comparatively

6 See B. Born and J. Pfeifer (2014), Policy risk and the business cycle, Journal of Monetary Economics 68, pp. 68-85.
7 See S. Leduc and Z. Liu (2016), Uncertainty shocks are aggregate demand shocks, Journal of Monetary Economics 82, pp. 20-35 and S. Basu and B. Bundick (2017), op. cit.
8 See S. Leduc and Z. Liu (2016), op. cit. and S. Basu and B. Bundick (2017), op. cit.
9 See also B. Born and J. Pfeifer (2014), op. cit. and J. Fernández-Villaverde, P. Guerrón-Quintana, K. Kuester and J. Rubio-Ramírez (2015), Fiscal volatility shocks and economic activity, American Economic Review 105 (11), pp. 3352-3384.
10 See S. Fasani and L. Rossi (2018), Are uncertainty shocks aggregate demand shocks?, Economics Letters 167, pp. 142-146. For an overview of the significance of heightened uncertainty for monetary policy, see also R. Mendes, S. Murchison and C.A. Wilkins (2017), Monetary policy under uncertainty: Practice versus theory, Bank of Canada Staff Discussion Paper No 2017-13.
11 The underlying model is based on Basu and Bundick (2017) and calibrated for the United States of America. See S. Basu and B. Bundick (2017), op. cit.
12 The direction in which the inflation rate moves following an uncertainty shock is the result of a combination of different forces. The decline in demand triggered by an uncertainty shock puts downward pressure on prices. This may be countered by the fact that firms which are subject to heightened uncertainty can also have an incentive to increase prices. Although the expected variability of future shocks increases when uncertainty is greater, the direction of impact is unclear. If price adjustment costs go up in line with the strength of the price change and if a price that is set too low in comparison to competitors causes a greater loss of profits than a price that is too high (convex price adjustment costs in combination with a concave profit function), prices may rise after an uncertainty shock. If the central bank reacts comparatively strongly to an uncertainty shock (no interest rate smoothing), the likelihood of high, cost-intensive future price adjustments decreases. In this case, the price dampening effect of uncertainty shocks therefore predominates.

high degrees of interest smoothing.[13] It is then also possible that output and prices move in opposite directions following uncertainty shocks. However, especially in periods of severe macroeconomic distortions, which are sometimes also characterised by a high degree of uncertainty, interest rate smoothing can be far less pronounced.[14] In these circumstances, it would also be conceivable that output and prices would respond in the same direction. This contradictory finding is consistent with the inconclusive empirical evidence on the price effects of uncertainty shocks (for details, see the box on pp. 60 ff.).

13 See R. Clarida, J. Gali and M. Gertler (1999), The science of monetary policy: A New Keynesian perspective, Journal of Economic Literature, 37 (4), pp. 1661-1707; and E. Castelnuovo (2007), Taylor Rules and interest rate smoothing in the euro area, The Manchester School; 75 (1), pp. 1-16.
14 See F. S. Mishkin (2009), Is monetary policy effective during financial crises?, American Economic Review: Papers and Proceedings, 99 (2), pp. 573-577; and F. S. Mishkin (2010), Monetary policy flexibility, risk management, and financial disruptions, Journal of Asian Economics, 21 (3), pp. 242-246.

and do not cause any direct effects within that same period.[23] In this identification strategy, it is not only the selected data frequency but also the order of the variables within the estimation model that determines how rapidly individual indicators react to certain disturbances over time.[24]

Structural vector autoregression models …

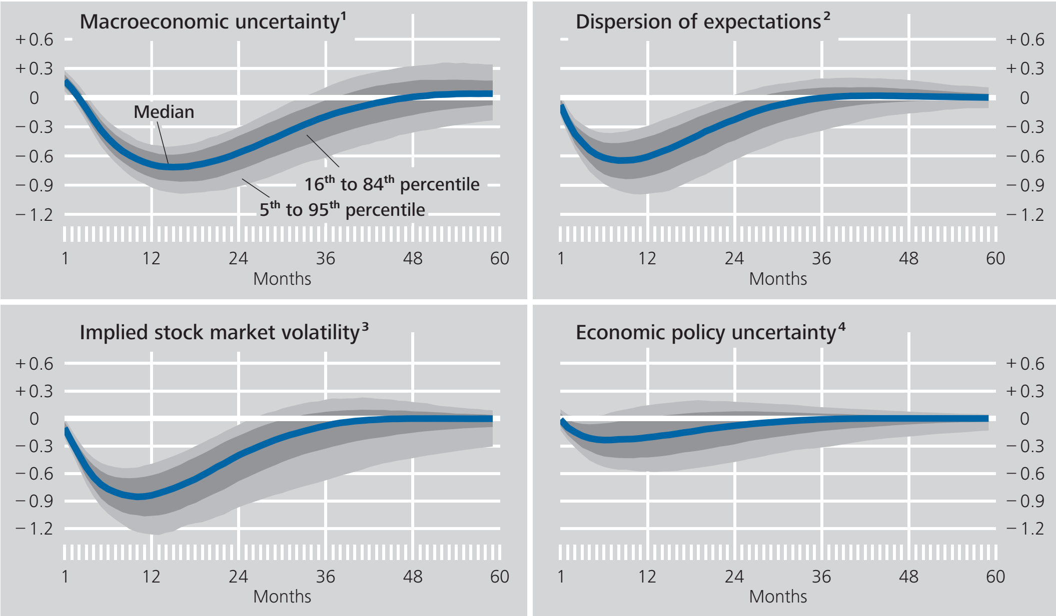
To obtain initial findings on the macroeconomic effects of uncertainty in the euro area, a recursive SVAR model is estimated using two variables – one of the uncertainty indicators presented and industrial production (excluding the construction sector) as an indicator of real economic activity.[25] Here it is assumed that uncertainty shocks can directly influence the level of uncertainty as well as the real economy. Output also responds immediately to shocks in the real economy. These, however, only affect uncertainty after a lag of one period. The assumption of a lag of one period in the impact of real economic shocks on uncertainty can be justified for at least some of the measures of uncertainty employed on account of their backward-looking orientation when using monthly data.[26] The use of lower-frequency data series such as quarterly GDP would be more problematic under this assumption.[27]

The relevance of the identified shocks can be determined using impulse-response functions and a variance decomposition of the model's

23 See C. A. Sims (1980), Macroeconomics and reality, Econometrica 48 (1), pp. 1-48.
24 A Cholesky decomposition of the variance-covariance matrix of the VAR residuals is generally used to carry out the recursive identification.
25 See C. Scotti (2016), op. cit.; and R. Bachmann, S. Elstner and E. R. Sims (2013), op. cit.
26 This is true, for instance, for the dispersion of output expectations based on surveys. See also S. Leduc and Z. Liu (2016), Uncertainty shocks are aggregate demand shocks, Journal of Monetary Economics 82, pp. 20-35; and K. Istrefi and S. Mouabbi (2018), Subjective interest rate uncertainty and the macroeconomy: A cross-country analysis, Journal of International Money and Finance 88, pp. 296-313.
27 See also B. Born, S. Breuer and S. Elstner (2018), Uncertainty and the Great Recession, Oxford Bulletin of Economics and Statistics 80 (5), pp. 951-971.

Effects of an adverse uncertainty shock on industrial production in the euro area using various measures of uncertainty*

in %



Sources: Bundesbank calculations based on data from Eurostat, Haver Analytics, Global Insight and www.policyuncertainty.com * Impulse responses resulting from uncertainty shocks of one standard deviation derived from Bayesian two-variable SVAR models. The structural shocks are obtained by recursive identification. The period from January 1999 to December 2017 forms the underlying dataset. **1** Based on the volatility of forecast errors derived from a comprehensive dataset. **2** Based on the dispersion of output expectations in manufacturing. **3** VSTOXX Volatility Index. Calculated from options on the EURO STOXX 50. **4** Calculated as the arithmetic mean of the Economic Policy Uncertainty Indexes for France, Germany, Italy and Spain.

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… as a common standard tool for analysing uncertainty shocks

forecast errors.[28] The impulse-response functions depict the responses of the model variables to each of the shocks over time. The variance decomposition sheds light on the relative importance of the shocks to the fluctuations in the variables observed.[29]

Estimation results generally show a negative …

For all four measures of uncertainty, the impulse-response functions derived from the two-variable model indicate a decline in industrial production resulting from an unexpected increase in uncertainty. However, the selected credible intervals are only able to identify a statistically highly significant effect for three of the uncertainty indicators presented (stock market volatility, dispersion of output expectations and macroeconomic uncertainty), but

28 The impulse-response analysis and variance decomposition are based on models estimated with Bayesian techniques. A normal-inverse-Wishart prior with a Minnesota structure is used as the prior distribution of the model parameters, while the hyperparameters are set on the basis of standard assumptions (see, inter alia, Canova, 2007). The impulse-response analysis and variance decomposition are depicted via the median and selected credible intervals calculated from the posterior distribution of the SVAR parameters using 2,000 draws. The period from January 1999 to December 2017 forms the underlying dataset. The maximum time lag for the endogenous variables to be included in the SVAR model (lag order) is 12 periods. The individual model equations also contain deterministic components in the form of a constant. See F. Canova (2007), Methods for applied macroeconomic research, Princeton University Press.

29 Forecast error variance decomposition specifically shows what share of the forecast error variance for a specific forecast horizon of the model's variables can be explained by the respective structural shock in the SVAR model. In the context of the impulse-response analysis, the SVAR system – assuming a state where all fundamental disturbances in the model take on the value zero – is hit once with a structural shock amounting to one standard deviation. The impulse-response function depicts the response of the model variables to this unexpected impulse over time. For a detailed description of the methodology, see, inter alia, H. Lütkepohl (2005), New Introduction to multiple time series analysis, Springer-Verlag; and L. Kilian and H. Lütkepohl (2017), Structural vector autoregressive analysis, Cambridge University Press.

Relative contribution of uncertainty shocks to the fluctuation in industrial production in the euro area using various measures of uncertainty*

%

Measure of uncertainty/model	Forecast horizon in months 1	12	36	60
Macroeconomic uncertainty[1]				
Two-variable SVAR	3	29	55	53
Multiple variable SVAR I[2]	1	47	39	37
Multiple variable SVAR II[3]	0	33	30	26
Dispersion of expectations[4]				
Two-variable SVAR	1	28	35	35
Multiple variable SVAR I[2]	0	16	13	12
Multiple variable SVAR II[3]	0	8	7	6
Implied stock market volatility[5]				
Two-variable SVAR	1	44	59	59
Multiple variable SVAR I[2]	1	34	33	33
Multiple variable SVAR II[3]	0	6	8	7
Economic policy uncertainty[6]				
Two-variable SVAR	0	4	6	6
Multiple variable SVAR I[2]	0	6	7	7
Multiple variable SVAR II[3]	0	1	2	2

Sources: Bundesbank calculations based on data from Eurostat, Haver Analytics, Global Insight and www.policyuncertainty.com * Forecast error variance decomposition for selected forecast horizons based on recursively identified SVAR models for industrial production in the euro area. The period from Q1 1999 to Q4 2017 forms the underlying dataset. **1** Based on the conditional volatility of forecast errors derived from a comprehensive dataset. **2** Multiple variable SVAR I: uncertainty shocks have an immediate impact on all model variables. **3** Multiple variable SVAR II: uncertainty shocks have an immediate impact on uncertainty and affect the remaining model variables with a lag of one period. **4** Based on the dispersion of output expectations in manufacturing. **5** VSTOXX Volatility Index. Calculated from options on the EURO STOXX 50. **6** Calculated as the arithmetic mean of the Economic Policy Uncertainty Indexes for France, Germany, Italy and Spain.

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not for economic policy uncertainty.[30] There are also noticeable differences in terms of the magnitudes of the uncertainty shocks. According to the estimated impulse-response functions, the decline in industrial production is much lower when the indicator for economic policy uncertainty is used compared to the other measures.

… and, in some cases, significant impact of shocks on the real economy

A similar picture emerges from a variance decomposition of the forecast errors. While uncertainty shocks do go a substantial way towards explaining the fluctuations in industrial production in the euro area for three of the indicators, i.e. stock market volatility, the dispersion of expectations and macroeconomic uncertainty, this is not the case for economic policy uncertainty.

The impact intensity of heightened uncertainty nevertheless depends on …

Though a two-variable model can provide initial insights into the macroeconomic significance of uncertainty shocks, a more precise quantification requires an expanded set of variables given the diverse ways in which economic variables interact. Therefore, a second econometric model takes into account a stock index, a shadow short rate, the Harmonised Index of Consumer Prices, the standardised unemployment rate and industrial production in the euro area in addition to one of the four measures of uncertainty.[31]

… the model size, …

As in the two-variable model, it is assumed that uncertainty shocks have an immediate impact on all other variables.[32] The variance decomposition shows that including additional macroeconomic relationships typically reduces the estimated extent to which uncertainty shocks account for fluctuations in output.[33] This decrease is particularly noticeable when measuring uncertainty based on the dispersion of output expectations. By contrast, the results for the macroeconomic uncertainty indicator prove relatively robust. Though the importance of uncertainty shocks declines significantly when the

30 Credible intervals are the Bayesian counterpart to confidence intervals used in frequentist statistics. They define the region that contains a specific, pre-defined share of the probability mass of the posterior distribution. See F. Canova (2007), op. cit.; and L. Kilian and H. Lütkepohl (2017), op. cit.
31 The EURO STOXX 50 price index was chosen as the stock index for the euro area. The shadow short rate is intended to measure the degree of monetary policy accommodation when the policy rate is at the zero lower bound. In "normal" periods, the shadow short rate matches the short-term interest rate. See L. Krippner (2013), Measuring the stance of monetary policy in zero lower bound environments, Economics Letters, 118 (1), pp. 135-138; and Deutsche Bundesbank, The influence of credit supply shocks on the development of real GDP and lending to euro-area non-financial corporations, Monthly Report, September 2015, pp. 36 ff.
32 Lag order, variable frequency and estimation periods are kept in accordance with the two-variable SVAR model. The specification and ordering of variables in the model are based on Bloom (2009). See N. Bloom (2009), op. cit.
33 While this is not the case for economic policy uncertainty, its explanatory contributions are approximately as low as in the two-variable model.

indicator for stock market volatility is employed, they still have a relatively high level of explanatory power.

… the model specification …

In a further review of the results, it is assumed that uncertainty shocks only have an effect on the remaining variables with a lag of one period.[34] On balance, the explanations provided by uncertainty shocks across the entire forecast horizon are once again much lower than before. This is especially true when uncertainty indicators geared towards stock market volatility and the dispersion of expectations are used. That said, uncertainty shocks do still explain a relatively large share of the fluctuations in industrial production when the indicator for macroeconomic uncertainty is deployed.

… and the chosen uncertainty indicator

It is therefore evident that estimations of the macroeconomic impact of uncertainty shocks can produce very different results depending on the measure of uncertainty selected and the specification of the econometric model. Only the measure for macroeconomic uncertainty based on the volatility of forecast errors yields relatively robust results. These suggest a clear temporary impact of uncertainty on aggregate activity.

Isolating uncertainty shocks

Need to identify uncertainty shocks precisely

When determining the macroeconomic impact of uncertainty shocks, it is particularly important to carefully separate these disturbances from other relevant shocks. In some cases, for instance, quantitative analyses point to markedly similar real economic effects arising from an unexpected increase in uncertainty and from other typical negative macroeconomic shocks – such as adverse financial shocks.[35] In this context, a precise identification is also important from a monetary policy perspective. This is demonstrated by a number of studies which indicate that an unexpected increase in uncertainty can impair the impact of conventional monetary policy measures.[36] For example, any changes in firms' price-setting behaviour[37] and in financial sector leverage[38] triggered by uncertainty can water down the effects of monetary policy on macroeconomic activity. Moreover, clearly identifying uncertainty shocks may be relevant when assessing price dynamics (see the box on pp. 60 ff.).

Uncertainty shocks difficult to isolate

With regard to the econometric framework used up until now, it is rather difficult to separate uncertainty shocks from financial shocks as they have a similar impact on macroeconomic variables and identifying assumptions regarding their lagged impact sometimes seem to be arbitrary. Such models may therefore cause the macroeconomic consequences of heightened uncertainty to be misinterpreted.

Use of sign restrictions to identify uncertainty shocks

Bearing all this in mind, identifying shocks on the basis of sign restrictions represents an alternative method of jointly capturing uncertainty and financial shocks in SVAR models.[39] Under this approach, the signs derived from economic theory are imposed on the impulse response

34 Uncertainty therefore now occupies the last position in the variable vector of the SVAR model. The lag in the impact of uncertainty shocks specified in this model is justified, amongst other things, by the desire to achieve the most conservative possible quantification of uncertainty effects on the real economy. Similar approaches can be found in K. Jurado, S.C. Ludvigson and S. Ng (2015), op. cit.; and P. Meinen and O. Röhe (2017), op. cit.
35 See also F. Furlanetto, F. Ravazzolo and S. Sarferaz (2018), Identification of financial factors in economic fluctuations, The Economic Journal, forthcoming.
36 See N. Bloom (2009), op. cit.
37 See J. Vavra (2014), Inflation dynamics and time-varying volatility: New evidence and an Ss interpretation, The Quarterly Journal of Economics 129 (1), pp. 215-258; K.A. Aastveit, G.J. Natvik and S. Sola (2017), Economic uncertainty and the influence of monetary policy, Journal of International Money and Finance 76, pp. 50-67; G. Pellegrino (2018), Uncertainty and the real effects of monetary policy shocks in the euro area, Economics Letters 162, pp. 177-181; and E. Castelnuovo and G. Pellegrino (2018), Uncertainty-dependent effects of monetary policy shocks: A New Keynesian Interpretation, Journal of Economic Dynamics and Control 93, pp. 277-296.
38 See S. Eickmeier, N. Metiu and E. Prieto, Time-varying volatility, financial intermediation and monetary policy, Deutsche Bundesbank Discussion Paper No 46/2016.
39 See D. Caldara, C. Fuentes-Albero, S. Gilchrist and E. Zakrajšek (2016), op. cit. as well as F. Furlanetto, F. Ravazzolo and S. Sarferaz (2018), op. cit.

The effects of uncertainty shocks on prices

Although the macroeconomic effects of uncertainty shocks have been examined intensively in the past few years, there are only a few empirical studies which deal with their price effects in more detail. Analyses based on micro-founded dynamic stochastic general equilibrium models (DSGE models) show distinct effects of these shocks on macroeconomic economic activity for the most part, but the direction of impact on prices is less clear. While part of the DSGE literature emphasises a co-movement of prices and real economic activity following unexpected changes in uncertainty,[1] there are also arguments suggesting that firms might increase their prices in response to adverse uncertainty shocks.[2] In this context, it must also be taken into account that assumptions made with regard to the monetary policy reaction function can be crucial for the price effects (see comments on page 54 ff.).

An investigation of the effects of uncertainty shocks on prices requires that these disturbances be isolated from other relevant structural shocks. A distinction is particularly challenging for the type of shocks that originate from the financial market, as these often turn out to have very similar macroeconomic effects. Moreover, the direction in which financial shocks move prices is likewise unclear.[3]

An empirical analysis of the price effects of uncertainty shocks is carried out here with the help of a structural vector autoregressive (SVAR) model. A setup with six variables is estimated each for the United States and the euro area. It contains the log real gross domestic product (GDP), the log Harmonised Index of Consumer Prices (HICP), a shadow short rate as a measure of the monetary policy stance,[4] a bank credit spread[5] and a stress indicator for the financial system[6] – in order to capture the situation in the financial markets – as well as a macroeconomic uncertainty measure.[7] For availability reasons, the estimates for the euro area are based on data for the period from the first quarter of 1999 to the fourth quarter of 2017 and for the United

1 See S. Leduc and Z. Liu (2016), Uncertainty shocks are aggregate demand shocks, Journal of Monetary Economics 82, pp. 20-35.
2 See B. Born and J. Pfeifer (2014), Policy risk and the business cycle, Journal of Monetary Economics, 68, pp. 68-85; J. Fernández-Villaverde, P. Guerrón-Quintana, K. Kuester and J. Rubio-Ramírez (2015), Fiscal volatility shocks and economic activity, American Economic Review 105 (11), pp. 3352-3384; and the comments on pp. 54 ff.
3 The analysis conducted by Abbate et al. (2016) is one of the few empirical studies to examine this issue. Along with empirical evidence for the United States, it also contains an overview of the literature on the price effects of financial market shocks in DSGE models. See A. Abbate, S. Eickmeier and E. Prieto (2016), Financial shocks and inflation dynamics, Deutsche Bundesbank Discussion Paper, No. 41/2016.
4 Krippner (2013) provides shadow short rate data for both economic areas. The indicator measures the degree of monetary policy accommodation when the policy rate is at the zero lower bound. Otherwise the shadow rate corresponds to the short-term interest rate. See L. Krippner (2013), Measuring the stance of monetary policy in zero lower bound environments, Economics Letters 118 (1), pp. 135-138. Updated data are available at https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures
5 The variable measures the interest rate spread between an average interest rate for bank loans to non-financial corporations and yields on ten-year German government bonds and ten-year US Treasuries.
6 The stress indicator for the euro area measures the yield spread between selected debt securities (bonds) issued by euro area non-financial corporations and German government bonds (zero-coupon bonds) with a corresponding maturity (Gilchrist and Mojon, 2018). Gilchrist and Zakrajšek (2012) provide a comparable indicator for the United States. See S. Gilchrist and B. Mojon (2018), Credit risk in the euro area, The Economic Journal 128 (608), pp. 118-158; and S. Gilchrist and E. Zakrajšek (2012), Credit spreads and business cycle fluctuations, American Economic Review 102 (4), pp. 1692-1720.
7 For the USA, the indicator developed by Jurado et al. (2015) is used and, for the euro area, that developed by Meinen and Röhe (2017). See K. Jurado, S.C. Ludvigson and S. Ng (2015), Measuring uncertainty, American Economic Review 105 (3), pp. 1177-1216 and P. Meinen and O. Röhe (2017), On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area, European Economic Review 92 (C), pp. 161-179.

Sign restrictions to identify contractionary structural shocks in a vector autoregressive model*

Variables/shocks	Aggregate supply shock	Aggregate demand shock	Monetary policy shock	Financial shock	Uncertainty shock
Gross domestic product	–	–	–	–	–
Consumer prices	+	–	–	.	.
Short-term shadow rate	+	–	+	–	–
Bank credit spread	.	–	.	+	+
Financial market stress	.	.	.	+	+
Financial market stress/ uncertainty 1	.	.	.	+	–

* A positive (negative) sign implies a contemporaneous rise (decline) in the variable as a result of the shock. A point means that there is no restriction. **1** The indicators for financial market stress and uncertainty are standardised; they therefore each have the same first and second moment. Although the relative response of both indicators is restricted, both series are entered into the model separately.

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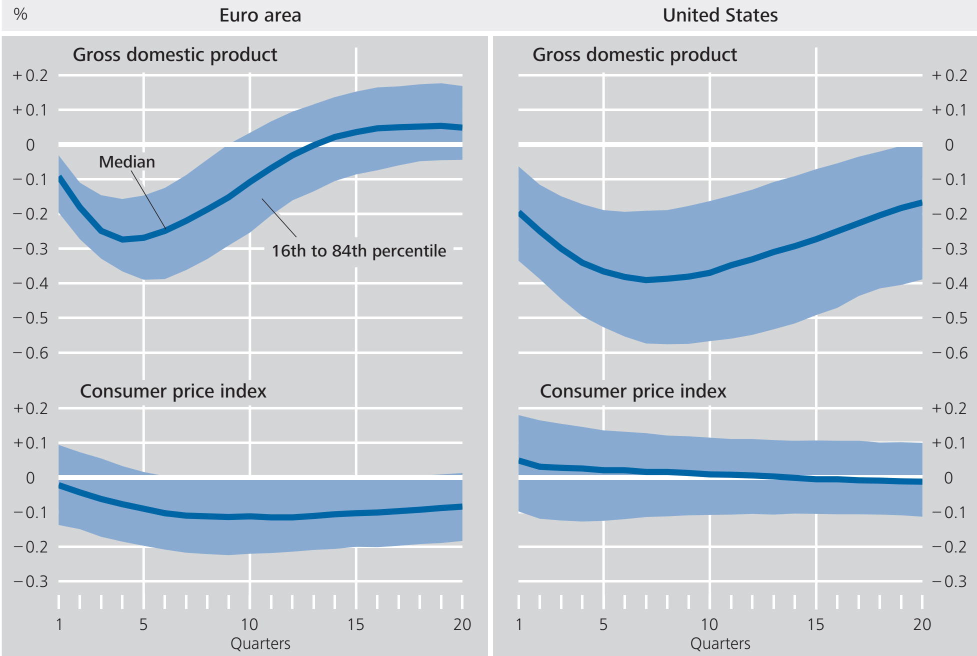
States from the third quarter of 1986 to the fourth quarter of 2017.[8]

In addition to the uncertainty shock, a financial shock, an aggregate supply shock, an aggregate demand shock and a monetary policy shock are identified in the model using sign restrictions. This identification approach is based on assumptions about the contemporaneous direction of the reaction of the variables to the shock in question, which generally stem from theoretical considerations. In this context, the structural shock must satisfy the following restrictions: A negative supply shock leads to a decline in GDP and an increase in the price level and short-term interest rate. By contrast, a negative demand shock leads to a reduction in GDP and a similar response by the consumer price index and shadow rate. Furthermore, an unexpected decline in aggregate demand results in a contraction of the bank credit spread. A negative monetary policy shock implies that interest rates will go up and GDP and consumer prices will go down.[9]

Financial shocks and uncertainty shocks are assumed to heighten uncertainty and financial market stress and increase the gap between bank lending rates and long-term government bond yields. At the same time, they have a dampening effect on macroeconomic activity and monetary policy becomes more accommodative.[10] Owing to the ambiguity of theoretical results, the direction of impact on prices is not specified.[11] The distinction between an

8 In addition to the contemporaneous and lagged variables, the individual model equations of the SVAR system each contain a constant. The lag order of the SVAR model is 5. The estimation is carried out using Bayesian methods. A normal-inverse Wishart prior with Minnesota structure is used, with the specification of hyperparameters in line with standard assumptions in the literature (see, inter alia, Canova, 2007). The implementation of sign restrictions is based on the algorithm developed by Rubio-Ramírez et al. (2010). See F. Canova (2007), Methods for Applied Macroeconomic Research, Princeton University Press; J. F. Rubio-Ramírez, D. F. Waggoner and T. Zha (2010), Structural vector autoregressions: Theory of identification and algorithms for inference, The Review of Economic Studies 77 (2), pp. 665-696.
9 Sign restrictions are used to ensure that the residual shock of the six-variable model is differentiated from the structural disturbances. For a detailed description of the identification strategy, see P. Meinen and O. Röhe (2018), To sign or not to sign? On the response of prices to financial and uncertainty shocks, Economics Letters 171, pp. 189-192.
10 See L. Gambetti and A. Musso (2017), Loan supply shocks and the business cycle, Journal of Applied Econometrics 32 (4), pp. 764-782; and D. Bonciani and B. van Roye (2016), Uncertainty shocks, banking frictions and economic activity, Journal of Economic Dynamics and Control, 73 (C), pp. 200-219.
11 For another study which does not restrict the price response to financial shocks, see Deutsche Bundesbank, The influence of credit supply shocks on the development of real GDP and lending to euro-area non-financial corporations, Monthly Report, September 2015, pp. 36-38. Based on these assumptions, uncertainty shocks and financial market shocks could result in a monetary policy response without this necessarily being required in terms of maintaining price stability. Such behaviour can be explained with a broader approach to monetary policy which incorporates the goal of financial market stability. The fact that a recent empirical study stressed the importance of financial market stress levels for monetary policy is consistent with this picture. See D. Caldara and E. Herbst (2018), Monetary policy, real activity, and credit spreads: evidence from Bayesian proxy SVARs. American Economic Journal: Macroeconomics, forthcoming.

Impact of an adverse uncertainty shock on macroeconomic activity and consumer prices in the euro area and in the United States*



* Impulse responses to uncertainty shocks of one standard deviation, derived from SVAR models estimated using Bayesian techniques. The models are estimated separately for the euro area and the United States and contain six variables each. Sign restrictions are used to identify the shock. The period from Q1 1999 to Q4 2017 forms the underlying data set.

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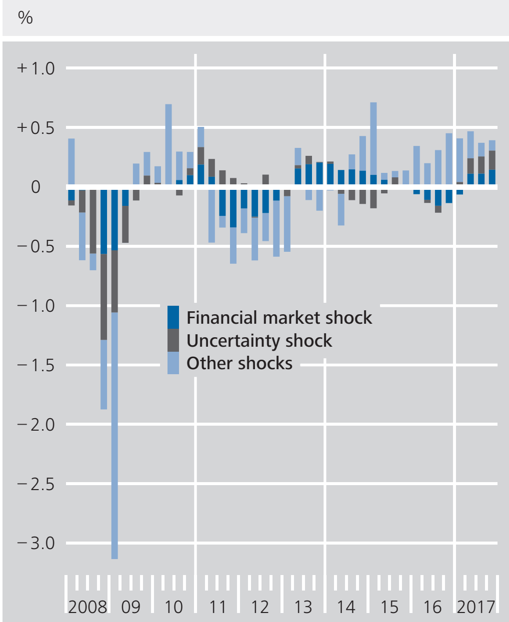
uncertainty shock and a financial shock is ultimately based on an assumption about the relative change in uncertainty and financial market stress. Here, an uncertainty shock is assumed to result in a stronger response by uncertainty relative to the stress indicator, whilst a financial market shock has a relatively stronger influence on stress levels in the financial market.[12]

The impulse response functions derived from the model first of all confirm that uncertainty shocks negatively impact macroeconomic activity in both economic areas. In addition, output responds in a fairly similar way to financial market shocks. By contrast, the response of prices is less clear. For the euro area, the median of the estimated impulse response functions tends to suggest a co-movement of both shocks with GDP, but the wide dispersion of the results – as shown by the credible intervals[13] – illustrates the high estimation uncertainty associated with the price effects. In the case of the United States, the median price reaction even runs counter to the GDP response following an unexpected increase in uncertainty. Estimation inaccuracy is even more pronounced here, however, which means that in this scenario, too, the response is indistinguishable from zero. Overall, the results therefore suggest that the response of prices to uncertainty shocks is ambiguous in empirical terms.[14]

12 This separation of financial and uncertainty shocks follows the approach devised by Furlanetto et al. (2018) See F. Furlanetto, F. Ravazzolo and S. Sarferaz (2018), Identification of financial factors in economic fluctuations, The Economic Journal, forthcoming.
13 Credible intervals are the Bayesian counterpart to confidence intervals used in frequentist statistics.
14 Further estimates indicate that if, as often occurs in empirical applications, a co-movement of GDP and prices is restricted in response to financial and uncertainty shocks, this can weaken the estimated role these disturbances play for real economic activity.

functions.[40] To this end, an SVAR model is estimated, in this instance at quarterly intervals, employing the indicator of macroeconomic uncertainty, real GDP, the Harmonised Index of Consumer Prices, a shadow short rate, a bank credit spread[41] and a stress indicator for the financial system.[42] The estimations are based on the period from the first quarter of 1999 to the fourth quarter of 2017.[43] Alongside a financial shock and an uncertainty shock, an aggregate supply shock, an aggregate demand shock, and a monetary policy shock are specified. All the above shocks are identified using contemporaneous sign restrictions, i.e. on the basis of assumptions regarding the direction of the response of the model variables during the period when the shock occurs. The uncertainty shock is distinguished from a financial shock by means of the relative change in uncertainty and financial market stress.[44] A detailed description of the identification strategy can be found in the box on pp. 60 ff.

Historical decomposition of the effects of economic shocks on the quarterly growth rate of real GDP in the euro area*



* Contributions of contemporaneous and past realisations of economic shocks to the deviation of the observed variable from its unconditional mean, as derived from a structural VAR model with sign restrictions. For each shock, the median of the posterior distribution of its contribution is shown. The period from Q1 1999 to Q4 2017 forms the underlying dataset.

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Uncertainty shocks have dampened euro area GDP, notably during the financial crisis

The macroeconomic impact of uncertainty and financial shocks in the euro area in specific periods is gauged by undertaking a historical shock decomposition of quarterly real GDP growth rates.[45] There is evidence that both uncertainty shocks and financial shocks have influenced macroeconomic developments in the euro area during different periods. This is especially true of the global financial and economic crisis of 2008-09. In addition, the analysis suggests that financial shocks also slowed GDP growth in the wake of the European sovereign debt crisis. Conversely, during this phase, uncertainty shocks had no discernible macroeconomic impact. Similarly, at the end of the period under review, in 2017, uncertainty was not observed to have had any detrimental effect on overall output in the euro area. In fact, GDP growth was noticeably boosted when the

40 See J. Faust (1998), The robustness of identified VAR conclusions about money, Carnegie-Rochester Series on Public Policy 49, pp. 207-244; F. Canova and G. De Nicoló (2002), Monetary disturbances matter for business fluctuations in the G-7, Journal of Monetary Economics 49 (6), pp. 1131-1159; H. Uhlig (2005), What are the effects of monetary policy on output? Results from an agnostic identification procedure, Journal of Monetary Economics 52 (2), pp. 381-419.
41 The interest rate spread between an average interest rate for bank loans to non-financial corporations and yields on ten-year German government bonds is captured.
42 The stress indicator for the euro area measures the yield spread between selected debt securities of non-financial corporations in the euro area and German government bonds with corresponding maturities (see the comments on p. 60).
43 Since the identification strategy using sign restrictions basically allows the structural shocks to have a contemporaneous impact on all the model variables, the choice of variable frequency is of secondary importance, unlike in the case of a recursive approach.
44 Uncertainty shocks and financial shocks are set apart from one another following the approach by Furlanetto et al. (2018), which does not rest on any one specific theoretical foundation. The other shocks are identified by deriving robust sign restrictions on the basis of standard New Keynesian DSGE models. See F. Furlanetto, F. Ravazzolo and S. Sarferaz (2018), op. cit.
45 The contributions of contemporaneous and past realisations of economic shocks to the deviation of the respective model variables from their unconditional mean are determined using a historical shock decomposition. This decomposition thus provides insights into the impact of the identified shocks on the evolution of the key variables under observation. For a detailed description of the methodology, see, inter alia, L. Kilian and H. Lütkepohl (2017), op. cit.

level of uncertainty unexpectedly decreased.[46] This finding is consistent with the observation of a favourable macroeconomic environment in the euro area.

Conclusion

Challenges faced when analysing uncertainty shocks

The importance of uncertainty shocks for macroeconomic developments has attracted greater attention on the back of the financial and sovereign debt crisis. However, the task of assessing these effects has proved far from simple. One reason for this is the lack of a clear-cut measure of uncertainty, making it necessary to rely on approximations when performing empirical analyses. What is more, the commonly used quantification methods have sometimes been known to respond sensitively to the selected model specification. These points should be taken into account when analysing uncertainty effects.

Not all uncertainty indicators have a demonstrable impact on GDP

In the context of econometric studies, for example, it has not been possible to identify any systematic impact on output in conjunction with a commonly used indicator of economic policy uncertainty – at least not for the euro area. Given the high degree of media interest in the indicator in question, this finding is remarkable. This is not the case for the indicator used to gauge macroeconomic uncertainty, which is derived from the volatility of the forecast errors of a plethora of macroeconomic time series. In the period under review, this indicator reveals that uncertainty has a relatively robust negative impact on output.

No indications of dampening effects due to uncertainty in the recent past

Applying this indicator for the euro area, uncertainty is shown to have had a pronounced impact on the real economy over the period under review, especially during the financial and economic crisis. During the sovereign debt crisis, by contrast, financial shocks were of greater relevance. In the past few years, a period encompassing not just an array of important general election results, but also the Brexit referendum, the economic development in the euro area does not appear to have suffered from any significant adverse uncertainty effects.

46 A historical decomposition of consumer price inflation shows that uncertainty shocks have had a dampening effect, especially in the wake of the financial and economic crisis, but no notable impact on price increases at the end of the observation horizon.