Christian Grimme and Marc Stöckli

## Measuring Macroeconomic Uncertainty in Germany<sup>1</sup>



Christian Grimme ifo Institute



Marc Stöckli ifo Institute

### INTRODUCTION

As a result of the financial crisis in 2008/09, academic research on economic uncertainty has experienced a surge in interest. A large body of this literature finds that uncertainty has a negative impact on economic activity and that it was partly responsible for the slow recovery after the crisis.<sup>2</sup> Uncertain times are associated with the growing difficulty of predicting the future accurately. When the future becomes less predictable, firms are more reluctant to make new investments and postpone decisions into the future. Similarly, consumers' demand for durable goods decreases. However, economic uncertainty is not observable and has to be inferred. The literature on this topic to date predominantly relies on proxies based on stock market volatility, forecaster disagreement and newspaper coverage. This article presents a novel measurement method based on Jurado et al. (2015), which is adopted for Germany. Comparing the new measure to the existing proxies, we find that our measure is significantly less volatile and tended to fall over the course of the euro crisis. Furthermore, we show that macroeconomic uncertainty can explain up to 11 percent of the fluctuations in investment activity in Germany.

### MEASURING MACROECONOMIC UNCERTAINTY

Jurado *et al.* (2015), JLN thereafter, propose a measure of macroeconomic uncertainty for the United States. We adopt their method and construct a corresponding index for Germany.<sup>3</sup> JLN start from the premise that

what matters to economic decision-making is whether the economy has become more or less predictable. Their aim is to estimate an indicator that is as free as possible from theoretical models and from dependence on a single observable economic indicator. In the spirit of JLN, we employ a macroeconomic forecasting model and define economic uncertainty as the volatility of the expected forecast errors. The intuition behind this is that uncertainty is high when decision-makers believe that they are worse at predicting the future. It is worth noting that the emphasis is on the expected volatility of the forecast errors, which does not necessarily imply that the realised volatility changes due to uncertainty. In practice, this poses an empirical issue, since ex-ante expected errors are not observable in historic data. We follow JLN and estimate the ex-ante errors from observable ex-post errors with a stochastic volatility model.4

Our estimation is conducted in two steps: firstly, the respective uncertainty is estimated for a large number of variables. In this context, large means around 100 variables. We consider indicators that are typically of interest for macroeconomic forecasters, such as industrial production, the unemployment rate, or stock market indices. More formally, the uncertainty of a variable  $y_t$  over the forecast horizon h is defined as the conditional volatility of the purely unforecastable component of the future value of that variable:

(1) 
$$U_{jt}^{y}(h) = \sqrt{E\left[\left(y_{jt+h} - E\left[y_{jt+h}|I_{t}\right]\right)^{2}|I_{t}\right]}$$

where  $y_{it+h}$  denotes the realised value of variable jat time t+h, and  $E[y_{it+h}|I_t]$  is the expectation of the future value of that variable at time  $t. I_t$  denotes the information set at time t, that is, all available information about the economy at a given point in time. The difference between the realised and expected value,  $y_{jt+h} - E[y_{jt+h}|I_t]$ , represents the 'purely unforecastable component'. The equation captures the intuition that decision-makers form an expectation about how precisely they will forecast an indicator variable. When they expect forecasting error to be more volatile, or forecasting to be less precise, uncertainty increases. In a second step, these individual estimates are aggregated to a single index to reflect uncertainty at the macro level. This step ensures that the index only measures economy-wide uncertainty instead of uncertainty specific to an individual variable, which may not have an impact on the economy as a whole.

To construct the index, we rely on a set of 102 monthly indicator variables.<sup>5</sup> The time period

While we use a different set of input variables, our results are surprisingly similar (correlation = 0.88).

 $<sup>^{\</sup>rm 1}$   $\,$  This article is an updated and shortened version of Grimme and Stöckli (2017).

<sup>&</sup>lt;sup>2</sup> See, for example, Baker et al. (2016), Born et al. (forthcoming), Bloom (2009), Bloom et al. (2012), Henzel and Rengel (2017), and Jurado et al. (2015). There is also a series of studies which estimates the effects of uncertainty on Germany, e.g. the impact on production and investment (von Kalckreuth 2003; Popescu and Smets 2010; Bachmann et al. 2013; Grimme et al. 2015; Buchholz et al. 2016; Klepsch 2016; Grimme and Henzel 2018), on interest rates (Grimme 2017), on prices and the effectiveness of monetary policy (Bachmann et al. 2013), and on the effectiveness of fiscal policy (Berg 2015 and forthcoming).

<sup>&</sup>lt;sup>3</sup> Meinen and Röhe (2017) also adopt the method by JLN and construct a measure of macroeconomic uncertainty for Germany.

<sup>&</sup>lt;sup>4</sup> Stochastic volatility models are also used to measure inflation uncertainty (see Dovern *et al.* 2012; Grimme *et al.* 2014).

JLN additionally use a set of financial variables that go beyond stock market indices. We omit the inclusion of corresponding variables for two reasons. Firstly, there are no comparable variables available for Germany, and we would have to use data on the

ranges from January 1991 to November 2017. The variables can be clustered into nine groups: (i) production and business situation; (ii) employment and wages; (iii) real estate; (iv) consumption, orders and inventory; (v) money supply; (vi) bonds and exchange rates; (vii) prices; (viii) stock market indices; and (ix) international trade. All variables are seasonally adjusted and, if necessary, transformed to stationarity.

### MACROECONOMIC UNCERTAINTY IN GERMANY 1991 - 2017

Figure 1 shows the macroeconomic uncertainty index for Germany. The horizontal red line represents values that are 1.65 standard deviations above the sample mean, indicating exceptionally high values of the index. The shaded grey areas denote recessions in Germany.8 It is clearly visible that the highest level of the index occurs during the financial crisis in 2008/09, and peaks in December 2008. Beginning with the liquidity problems of the British bank Northern Rock and fuelled by the collapse of Lehman Brothers in September 2008, there is an unprecedented surge in uncertainty. Other periods that are associated with an exceptionally high level of uncertainty include Black Wednesday in 1992 and the German parliamentary elections in 1994. Further increases in the indicator, albeit to a lesser extent, can be attributed to the Russian financial crisis in 1998, the burst of the dotcom bubble in 2000, the September 11 attacks in 2001, and the Baghdad bombings in 2003.

These findings are largely in line with previous results in the literature on this topic to date. However, we also find that there is a general downward trend

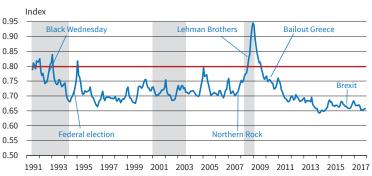
Continued FN 5:

European level instead. Secondly, we have re-estimated JLN without the financial variables and find that their impact on macroeconomic uncertainty is negligibly small.

- <sup>6</sup> A list of all the variables can be found on the webpage: https://sites.google.com/site/econgrimme.
- $^7$  We present estimates of macro uncertainty for the one-month horizon, that is of  $\textit{\textit{U}}^{\nu}_{\mu}(\iota).$
- 8 Recessions are dated by the Economic Cycle Research Institute (ECRI).

Figure 1

Macroeconomic Uncertainty in Germany
1991–2017



Notes: The shaded grey areas denote recessions in Germany. The horizontal red line represents values that are 1.65 standard deviations above the sample mean, indicating exceptionally high values of the index. The series is standardized.

Source: Datastreaming; own calcultions.

© ifo Institute

in macroeconomic uncertainty in the aftermath of the financial crisis and until the end of 2013, despite the Eurozone crisis and Greece potentially leaving the Eurozone. Afterwards, uncertainty moves more or less laterally, despite the Britain's decision to leave the European Union in June 2016 and the election of Donald Trump as US President in December 2016. Currently, macroeconomic uncertainty is nearly at an all-time low.

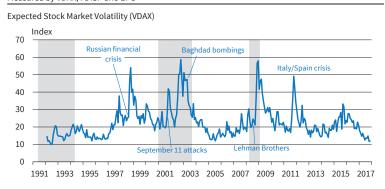
In the following, we compare our uncertainty indicator to the most commonly used alternatives. Panel 1 in Figure 2 shows the VDAX, a measure of expected volatility of the DAX stock market index. Bloom(2009) popularised the use of stock market indices as a proxy for uncertainty. The VDAX is calculated on the basis of traded options on the DAX, where option prices are used to infer expected volatility. An increase in the VDAX indicates that the market expects the DAY to be more volatile. Stock market indices are a viable choice of proxy due to data availability for most countries. In accordance with the results of our measure, there are sharp increases in expected stock market volatility after the Russian financial crisis, the September 11 attacks, and the 2008 financial crisis. There is an additional increase in 2011, which might be related to the debt crisis in Italy and Spain during the Eurozone crisis. The VDAX is clearly countercyclical; two of the three recessions in our sample are associated with high index values. In contrast to our measure, the VDAX is more volatile and reacts quicker to bad news events. For example, the Russian financial crisis and the September 11 attacks are associated with an immediate increase, whereas macroeconomic uncertainty rises more slowly and to a lesser degree in terms of magnitude. It is worth noting that proxies based on stock market volatility do not remove the 'forecastable component' of the time series, as the index by JLN does. This suggests that some of the variation in stock market volatility is, in fact, forecastable, and we erroneously attribute this variation to increases in uncertainty. An additional issue is that higher uncertainty in the financial market

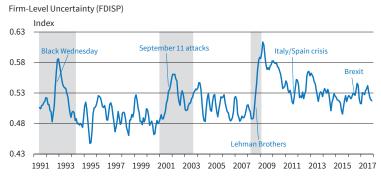
may not have an impact on the real economy. This is especially important for Germany, where many firms are not publicly listed.

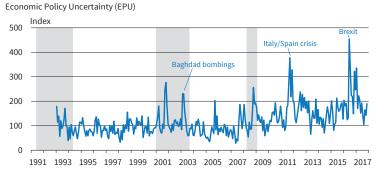
A measure of firm-level uncertainty, *FDISP*, is proposed by Bachmann *et al.* (2013). They use micro data from the ifo Business Climate Survey, a monthly German business confidence survey. Firm-level uncertainty is identified as the cross-sectional variation of individual survey participants' responses to a question on expected domestic production.<sup>9</sup>

<sup>&</sup>lt;sup>9</sup> The question is: "Expectations for the next three months: our domestic production activities with respect to product X will (with-

Figure 2
Economic Uncertainty in Germany
Measured by VDAX, FDISP and EPU







Note: The shaded grey areas denote recessions in Germany.
Sources: Deutsche Börse; Economic Policy Uncertainty; own calculations.

© ifo Institute

The higher the dispersion of expected production, the higher is uncertainty. Thus, the measure implies that uncertainty is associated with heterogeneous expectations. However, this link does not necessarily always hold. Imagine a situation in which a larger share of firms lowers their expectations due to an increase in unobserved uncertainty. Firms' expectations become less dispersed and *FDISP* falls, despite the fact that firms are actually more uncertain. <sup>10</sup> The advantage of this indicator is that it is generated from survey data and is therefore based on the expectations of real decision-makers. Panel 2 in Figure 2 shows that uncertainty as measured by *FDISP* is high after Black Wednesday in 1992, the September 11 attacks and the 2008 financial crisis. The Eurozone crisis and the Brexit

Continued FN 9:

out taking into account differences in the length of months or seasonal fluctuations) increase, roughly stay the same, or decrease".

<sup>10</sup> Bachmann *et al.* (2013) show that the dispersion of the expectations is highly correlated with alternative uncertainty measures at the firm-level and conclude that FDISP reliably measures firm-level uncertainty.

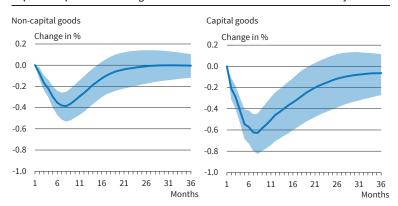
vote are also marked by visible surges in uncertainty.

Panel 3 finally shows a measure for economic policy uncertainty, EPU, proposed by Baker et al. (2016). EPU measures the frequency of articles in daily newspapers in which keywords related to economic uncertainty are used. The index increases when there are more reports on economic policy uncertainty. By construction, EPU strongly reacts to news events. The Brexit vote and the debt crisis in Italy and in Spain are the two periods with the highest policy uncertainty. A drawback of the EPU index is that it is not immediately obvious whether the choice of newspapers, which are used to construct the index, is representative for the German media market. In fact, the index only considers two newspapers for Germany (Frankfurter Allgemeine Zeitung and Handelsblatt). It is also unclear whether the index. with its focus on media coverage, has an impact on firm activity. EPU is typically based on a wide range of (national) economic policies, whereas firms are mostly concerned with policy measures that have a direct effect on their activity.

# IMPACT OF MACROECONOMIC UNCERTAINTY ON THE GERMAN ECONOMY

Ultimately, we are interested in the impact of uncertainty on economic activity. Empirically, we have an identification problem: uncertainty can have an impact on the business cycle, but uncertainty can also be influenced by the business cycle. If, for example, an increase in our measure is observed and we want to measure the effect of this change on economic activity, we must control for the fact that part of this increase may have resulted from changes in production. Therefore, we have to identify changes in uncertainty, which are independent of activity. This can be achieved by using a vector autoregressive (VAR) model. The model contains six variables: our measure for macroeconomic uncertainty, the DAX stock market index, the EONIA interest rate as a measure for monetary policy, an index for consumer prices (CPI), and two variables for economic activity. These two variables are industrial production of

Figure 3
Impulse Responses of an Exogenous Increase in Macroeconomic Uncertainty



The thick line represents the median response to an uncertainty shock of one standard deviation, while the shaded area shows the 68% error band. The impulse responses are generated from 5,000 draws.

Source: Calculations of the ifo Institute.

© ifo Institute

capital goods, a measure of investment activity, and industrial production of non-capital goods; the latter is included to investigate whether other industrial sectors react differently to uncertainty.<sup>11</sup>

In the following, we analyse the impact of an exogenous increase of macroeconomic uncertainty on the two activity variables. Figure 3 demonstrates the results. The thick line indicates the median response, while the shaded area shows the 68-percent error band. Our results show that the production of both capital and non-capital goods declines steadily for seven months. The return to the previous path is completed after about two years, respectively. Quantitatively, the maximum reduction in the production of capital goods (0.6 percent) is stronger than that of non-capital goods (0.4 percent).

To further show the quantitative importance of macroeconomic uncertainty, we perform a forecast error variance decomposition of investment activity

Table 1

Contribution of Macroeconomic Uncertainty to Fluctuations in Investment (in %)

Forecast horizons				
1 month	3 months	6 months	12 months	36 months
0	2.0	7.2	11.0	11.2

Note: The table presents the share of the total forecast error variance of the production of capital goods that are explained by exogenous changes in macroeconomic uncertainty. We show the median contribution for different forecast horizons.

Source: Calculation of the ifo Institute.

for various forecast horizons. The results are shown in Table 1. Macro uncertainty explains 7 percent of the fluctuations in investment within the first six months. At larger horizons it contributes to 11 percent of the variance in investment activity. Uncertainty therefore has a nonnegligible effect on the German business cycle.

### CONCLUSION

In this study, we present a new measure of macroeconomic uncertainty in Germany, based on the method by Jurado *et al.* (2015).

We show that there was a strong increase in uncertainty during the 2008 financial crisis. In contrast to alternative measures, we find a declining trend during the Eurozone crisis. In addition, we demonstrate that macroeconomic uncertainty can explain part of the volatility in German investment activity. Overall, our measure extends the number of uncertainty measures that are available for Germany.

#### REFERENCES

Bachmann, R., B. Born, S. Elstner and C. Grimme (2013), *Time-Varying Business Volatility and the Price Setting of Firms*, NBER Working Paper

Bachmann, R., S. Elstner and E.R. Sims (2013), "Uncertainty and Economic Activity: Evidence from Business Survey", *American Economic Journal:*Macroeconomics 5, 217–249.

Baker, S., N. Bloom and S. Davis (2016), "Measuring Economic Policy Uncertainty", *Quarterly Journal of Economics* 131, 1593–1636.

Banbura, M., D. Giannone and L. Reichlin (2010), "Large Bayesian Vector Auto Regressions", *Journal of Applied Econometrics* 25, 71–92.

Berg, T. (2015), "Time Varying Fiscal Multipliers in Germany", *Review of Economics* 66, 13–46.

Berg, T. (forthcoming), "Business Uncertainty and the Effectiveness of Fiscal Policy in Germany", *Macroeconomic Dynamics*.

Bloom, N. (2009), "The Impact of Uncertainty Shocks", Econometrica 77, 623–685.

Bloom N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten and S.J. Terry (2012), *Really Uncertain Business Cycles*, NBER Working Paper 18245.

Born, B., S. Breuer and S. Elstner (forthcoming), "Uncertainty and the Great Recession", Oxford Bulletin of Economics and Statistics.

Buchholz, M., L. Tonzer and J. Berner (2016), Asymmetric Investment Responses to Firm-specific Uncertainty, IWH Discussion Papers 7/2016.

Dovern, J., U. Fritsche and J. Slacalek (2012), "Disagreement among Forecasters in G7 Countries", *Review of Economics and Statistics* 94, 1081–1096.

European Commission (2013), "Highlight: Using Survey Data for Measuring Uncertainty", European Business Cycle Indicators – 3rd Quarter 2013, 7–18, http://ec.europa.eu/economy\_finance/publications/cycle\_indicators/2013/pdf/3\_en.pdf.

Grimme, C. (2017), Uncertainty and the Cost of Bank vs. Bond Finance, MPRA Working Paper 79852

All of the variables, except for uncertainty and EONIA, enter in logarithms. The model is estimated with twelve lags for the period June 1991 to November 2017 with Bayesian methods. The prior for uncertainty is white noise, the prior for the rest of the variables is a random walk. The uncertainty shock is identified recursively (Cholesky-Decomposition). The order of the variables is: production of non-capital goods, production of capital goods, consumer prices, EONIA, DAX, and uncertainty. This implies that all of the variables do not react contemporaneously to an uncertainty shock.

<sup>&</sup>lt;sup>12</sup> The size of this shock is equal to an increase of 1.6 percent compared to the mean value of the uncertainty series. By comparison, macroeconomic uncertainty increased between its trough just before the start of the financial crisis in July 2007 and its peak in December 2008 by over 30 percent. However, it is worth noting that a considerable part of this rise can be explained by other factors, which are unrelated to uncertainty (see Born et al. forthcoming).

Grimme, C. and S. Henzel (2018), *The Macroeconomic Effects of Uncertainty in Times of Low and High Uncertainty*, ifo Institute, mimeo.

Grimme, C., S. Henzel and S. Bonakdar (2015), "Zum Einfluss von Unsicherheit auf die deutsche und österreichische Konjunktur", Wirtschaftspolitische Blätter 62, 655–667.

Grimme, C., S. Henzel and E. Wieland (2014), "Inflation Uncertainty Revisited: A Proposal for Robust Measurement", *Empirical Economics* 47, 1497–1523.

Grimme, C. and M. Stöckli (2017), "Makroökonomische Unsicherheit in Deutschland", *ifo Schnelldienst* 70(6), 41–50.

Henzel, S. and M. Rengel (2017), "Dimensions of Macroeconomic Uncertainty: A Common Factor Analysis", *Economic Inquiry* 55, 843–877.

Jurado, K., S.C. Ludvigson and S. Ng (2015), "Measuring Uncertainty", *American Economic Review* 105, 1177–1216.

Klepsch, C. (2016), How Asset Irreversibility Influences the Investment-Uncertainty Relationship, Working Paper LMU Munich.

Meinen, P. and O. Röhe (2017), "On Measuring Uncertainty and Its Impact on Investment: Cross-country Evidence from the Euro Area", *European Economic Review* 92, 161–179.

Popescu, A. and F. Smets (2010), "Uncertainty, Risk-taking, and the Business Cycle in Germany", CESifo Economic Studies 56, 596–626.

Von Kalckreuth, U. (2003), "Exploring the Role of Uncertainty for Corporate Investment Decisions in Germany", *Swiss Journal of Economics* 139, 173–206.