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The economic content of direct and indirect business uncertainty measures *

Christian Glocker and Werner Hölzl

Abstract

We introduce a novel measure of uncertainty that is based on a business survey, in which firms are asked *directly* how certain/uncertain they are. So far, the literature has tried to capture economic uncertainty *indirectly* by means of expectation errors or the extent of disagreement. Our direct measure of economic uncertainty has a decent contemporaneous correlation with various indirect measures, though its informational content is different. Across all uncertainty measures, shocks to uncertainty trigger effects in GDP of opposite sign, however, the indirect measures tend to significantly underestimate the effects on GDP and other macroeconomic aggregates. Moreover, the direct uncertainty measure outperforms the indirect ones in terms of the informational content relevant for forecasting economic activity.

Keywords: Uncertainty shocks, Aggregate fluctuations, Firm dispersion, Surveys of expectations

JEL Classification: E32, E37, E44, C80

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1 Introduction

The discussion on the role of uncertainty in economic decision-making has received renewed attention since the financial crisis. A number of contributions have shown that uncertainty affects firm and household behaviour. As uncertainty is not directly observable, its measurement poses a challenge (e.g. Jurado et al., 2015).

Various approaches have been proposed with which to measure uncertainty. One stream of the literature defines uncertainty as the dispersion of expectations about the future. The main idea is that in times of high uncertainty there should be more divergence in expectations than in times of low uncertainty. Uncertainty measured as dispersion can be applied to a number of different variables. Bloom (2009) used stock market volatility as a measure of economic uncertainty. Rich and Tracey (2010) or Rossi and Sekhposyan (2015) used the dispersion in professional forecasts of economic aggregates. Bachmann et al. (2013) and Arslan et al. (2015) used microdata of quarterly business surveys to construct measures of uncertainty based on the dispersion of idiosyncratic expectation errors at the firm level and derive an aggregate time series of business uncertainty from this. Girardi and Reuter (2017) used aggregate time series from business surveys to construct dispersion-based measures of business uncertainty. A drawback of measuring uncertainty as dispersion is that it may not only be driven by uncertainty but also by the degree of genuine disagreement on the future. A similar problem arises in business surveys: a time-varying cross-sectional dispersion in firm answers could be caused by different reactions of firms to aggregate shocks even when the overall level of uncertainty does not change.

A second stream of the literature focuses on forecast errors. Jurado et al. (2015) and Glass and Fritsche (2015) propose measuring uncertainty as the magnitude of errors in forecasting macroeconomic time series. If wrong forecasts reflect uncertainty, then an increase in forecast errors can

be interpreted as a rise in uncertainty. The approach of Bachmann et al. (2013) and Arslan et al. (2015) can also be considered as being associated with this line of measuring uncertainty. However, they do not measure uncertainty by looking at a large set of time series; instead, they consider the forecast errors across a large number of firms in the cross-section. A drawback of this approach is its ex-post nature, as forecast errors can only be measured retrospectively. This limits the practical use of this approach in real time, since uncertainty is being measured with a delay of one period.

A third way is to collect data with the explicit aim of measuring uncertainty. The best known example is Baker et al. (2016), who construct an economic policy measure based on newspaper articles that feature a combination of search items that suggest the presence of economic policy uncertainty. However, there are some concerns associated with this approach of measuring uncertainty, as choices regarding the selection of newspapers and keywords may affect the overall measure of uncertainty substantially. The approach of Guiso and Parigi (1999) and Bontempi et al. (2010) can be viewed as an extension of this and is more closely related to the direct uncertainty measure proposed in this paper. They use managers' subjective probability distributions of future events, that can be used to compute a measure of interpersonal uncertainty. However, as such probability distributions are not available repeatedly, Bontempi et al. (2010) constructed an uncertainty measure encompassing eight years only.

The contribution of this paper is threefold. First, we introduce a novel measure of business uncertainty. It is based on a question in a business survey asking companies directly how certain/uncertain they are. To that purpose, we rely on microdata – in particular, firm-level data – and use the subjective uncertainty of individual respondents directly to construct an aggregate measure of uncertainty. In addition, we assess the heterogeneity of uncertainty among firms, that is, we try to identify the extent to which

uncertainty is related to firm growth and firm size.

In a second step, we identify the relationship between our direct measure of business uncertainty and alternative indirect measures commonly used in the literature and by practitioners. The focus here is on evaluating the commonality across the various uncertainty measures. In this respect we also assess the extent to which the direct measure of uncertainty provides valuable information for forecasting.

Finally, we analyse the macroeconomic impact of business uncertainty by using the direct and indirect uncertainty measures. Emphasis is placed on examining the informational content of these measures and their ability to explain macroeconomic fluctuations. To this end, we estimate a Bayesian vector-autoregressive (BVAR) model with a block-exogenous structure. This allows identifying uncertainty shocks for the purpose of determining the transmission channel of uncertainty shocks and assessing their importance for business cycle fluctuations.

Our empirical analysis is based on a business survey carried out among firms of the Austrian economy. This survey – the so-called *WIFO Konjunkturtest* – has contained a question that asks firms to assess the certainty/uncertainty of their expectations regarding the state of their business over the next six months. We consider this question a direct approach for capturing and measuring economic uncertainty. As this question has been part of this survey since the end of the 1980s, we have a fairly long time series at our disposal, rendering feasible the application of sophisticated time series techniques. To the best of our knowledge, we are not aware of any other business survey featuring a question of this type.

We find that our direct uncertainty measure is positively correlated with various indirect alternatives. Evidently, they share one common component; this highlights the extent to which all of them capture the same phenomenon, which we refer to as *uncertainty*. Based on the direct uncertainty measure, we however find, differences in the perception of uncertainty across firm size. Smaller firms consistently exhibit the highest

level of uncertainty, while large firms always have the lowest level of uncertainty. We observe that this gap remains rather constant over time, suggesting that the variation firms experience in their perception of uncertainty over the business cycle is rather independent of firm size. In a similar context, we find that the perception of uncertainty is higher among firms whose employment is declining, while firms with growing employment are found to be less uncertain over the course of the business cycle.

As regards forecasting, we find that all uncertainty measures Granger cause economic activity with a statistical level of significance of at least 5%. Hence, the in-sample evaluation yields a high degree of commonality across all uncertainty measures. In contrast to that, the out-of-sample forecasting evaluation shows a more heterogeneous picture. Estimating an ARMAX model for industrial production with uncertainty measures as exogenous variables, we find that the indirect uncertainty measures do not add to the forecast performance if compared to a simple ARMA model. In contrast, the ARMAX model with the direct uncertainty measure leads to forecasts which are significantly better than those from a simple ARMA model. In other words our direct uncertainty measure outperforms the indirect uncertainty measures in terms of its informational content relevant for forecasting economic activity.

As regards the macroeconomic implications, we find that uncertainty shocks trigger statistically significant effects in GDP, industrial production and investment of opposite sign, while private household consumption remains unaffected. This pattern also prevails when considering alternative uncertainty measures, such as for instance, indirect business uncertainty measures or even financial market stress indicators, which are commonly used as proxies for business uncertainty. All uncertainty measures are found to be important for key macroeconomic aggregates, though our direct measure explains by far the largest share of the fluctuations in industrial production, investment and GDP. In other words, the

indirect uncertainty measures appear to significantly underestimate the effects of uncertainty shocks on macroeconomic aggregates. We interpret this as evidence in favour of a different informational content of our direct uncertainty measure relative to that of indirect alternatives.

Our results confirm that uncertainty shocks are important in shaping macroeconomic fluctuations. This is in line with the findings in Salamaiki and Venetis (2018), Caggiano et al. (2014), Caggiano et al. (2017) or Crespo Cuaresma et al. (2017), to name a few. Our work extends these studies by considering the novel direct uncertainty measure. Though confirming the findings in the literature qualitatively, we observe significant quantitative differences. Moreover, our results point towards a specific transmission channel of uncertainty shocks. The literature has stressed the importance of theories concerning the (i) *real-option* effect (see for instance Bernanke, 1983) and the (ii) *risk-aversion* effect (see for instance Carroll and Samwick, 1998) in transmitting uncertainty shocks. Our findings on the impact of business uncertainty are in line with the *real-option* effect in transmitting uncertainty shocks, while we find no evidence in favour of the *risk-aversion* theory. Our results are robust to various extensions.

The paper is structured as follows. Section 2 describes the business survey utilised in this paper, the construction of the direct uncertainty measure and the various indirect alternatives. Section 3 assesses the commonalities among the various business uncertainty measures. In addition to this, we analyse differences in the perception of uncertainty related to firm size and firm growth rates and evaluate the extent to which uncertainty can be considered useful for forecasting. We carry out the macroeconomic analysis in Section 4 where we assess the effects and the importance of uncertainty shocks; we consider various extensions and robustness checks. Finally, Section 5 concludes.

2 Measures of uncertainty based on business tendency surveys

Our analysis is based on microdata for the manufacturing sector from the “WIFO Konjunkturtest” (WIFO business survey). The WIFO Konjunkturtest is a business survey conducted among Austrian companies, which has been carried out by the Austrian Institute of Economic Research (WIFO) since 1954 on a quarterly basis. Since 1996, this survey has been part of the Joint Harmonized EU Programme of Business and Consumer Surveys. This came along with an adjustment of the frequency of the survey – from quarterly to monthly.

The aim of this business survey is to provide indicators that offer an accurate picture of current and near-term developments of the manufacturing sector and other industries.¹ The WIFO business survey contains a question on uncertainty, which we focus on in this paper. However, we can only use that part of the survey, which relates to the manufacturing sector as this particular question has only been surveyed among manufacturing firms. Moreover, in 2014 the wording of the question on uncertainty changed; against this background, we use data from the first quarter of 1996 (1996:Q1)² to the third quarter of 2013 (2013:Q3), as this time span is not interrupted by any change in the format and/or wording of the question on uncertainty.³

We use this dataset, first of all, to construct a *direct measure for business uncertainty*. The same dataset is then utilized to develop commonly used alternative measures for business uncertainty, which we refer to as *indirect uncertainty measures*. We do so for the purpose of comparing

¹see Hölzl and Schwarz (2014) for a recent description of the survey.

²The reason for using the first quarter of 1996 as the starting point of the sample is the fact that – according to current classification systems – most macroeconomic variables (GDP, investment, industrial production ...) for the Austrian economy are only available from 1996 onwards. Since we want to relate our uncertainty measures to macroeconomic aggregates, the limits from the National Account Statistics restrict the time span for the analysis as a whole.

³We assess the implications of the change in the wording of the question on uncertainty in Section C of the Appendix.

our direct uncertainty measure with alternatives. Additionally, we use the index of industrial production (*IPIdx*) as reference series. In what follows, we denote the direct uncertainty measure by *UNC-D*.

2.1 A direct measure of uncertainty

Since the mid-1980s the WIFO business survey has contained a question that asks firms directly about their certainty/uncertainty in their perception of the expected business situation in six months (“The business situation for our products six months from now will improve/not change/deteriorate”). Table 1 presents the question on uncertainty in German along with its translation.

Table 1: Question on uncertainty

Die zukünftige ENTWICKLUNG unserer Geschäftslage ist

- **in gewissem Maße abschätzbar**
- **sehr unsicher**
- **wenig abschätzbar**
- **unsicherer als je zuvor**

Translation: The future development of our business situation can be assessed to a certain degree/is difficult to assess/ is very uncertain/ is more uncertain than ever.

From the answers to this question we construct a measure that takes on the value of 0 if there is little uncertainty and a value of 1 if all firms report the highest level of uncertainty (more uncertain than ever) in the following way:

$$UNC-D = 0 \cdot \text{fraction}^{(1)} + \frac{1}{3} \cdot \text{fraction}^{(2)} + \frac{2}{3} \cdot \text{fraction}^{(3)} + 1 \cdot \text{fraction}^{(4)}$$

where *UNC-D* denotes the uncertainty index and $\text{fraction}^{(x)}$ refers to the fraction of firms that have chosen the x^{th} answer category. The index ranges from 0 (*low uncertainty* – the future business situation can be assessed to a certain degree) to 1 (*high uncertainty* – more uncertain than ever). We construct the index at the level of 2-digit industries and aggre-

gate it using value added weights so that it reflects the structure of the manufacturing industry. For the purpose of comparison to the alternative uncertainty measures discussed below, we standardise the index so that the resulting time-series is comprised by a mean of zero and a standard deviation of unity.

2.2 Indirect uncertainty measures

The following considers various alternative measures for business uncertainty commonly analysed and discussed in the literature. As these measures are constructed by means of the extent of disagreement, forecast errors, etc., we hence refer to them as *indirect uncertainty measures*. We use the same dataset in order to construct these measures for the Austrian manufacturing sector, so as to be able to compare uncertainty measures commonly used in the literature with our new direct measure.

2.2.1 Uncertainty as expectation errors

The idea of using expectation errors as a measure of uncertainty goes back to Bomberger (1996) and was taken up by Bachman et al. (2013) and Arslan et al. (2015). The microdata from the WIFO business survey allow us to construct a qualitative index of the ex-post forecast error standard deviations. The basic idea is that we compare firms' answers of production expectations with realized industrial production and construct a measure of firm-specific expectation errors. We use two pairs of questions to construct two different sets of measurements of forecast uncertainty. The questions are presented in Table 2 and refer to firms' production and the business climate.

Table 2: Survey questions for expectation error

	Question	Reply options
Climate:		
Expectation _{t-1} :	The business situation for our products six months from now will ...	improve / not change / deteriorate
Assessment _t :	The business situation for our products is ...	good / satisfactory / bad
Production:		
Expectation _{t-1} :	In the next three months our production will ...	increase / remain unchanged / decrease
Assessment _t :	Over the last three months our production ...	increased / stayed roughly the same / decreased

In order to construct forecast errors we weight the answers to quantify the survey responses. We use the expectations at time $t - 1$ and the assessments as of time t . This implies that, to assess the business climate, we only take into account a three-month horizon, rather than a six-month horizon. This is a first approximation. However, a closer look at the survey answers suggests that firms consider this question primarily as a forward-looking question, but do not take its time horizon literally. The weighting of the survey answers is outlined in Table 3. Given the weights, we then aggregate the survey responses to obtain an aggregate measure of expectation errors. This follows Bachmann et al. (2013) who motivate the following uncertainty measure:

$$UNC-F = \frac{\sum_{i=1}^N (W_{i,t} - \bar{W}_t)^2}{N}$$

where $W_{i,t}$ is the idiosyncratic uncertainty at the firm level at time t , defined as the expectation as of time $t - 1$, relative to the assessment as of time t , taking into account the weights of Table 3; and $\bar{W}_t = \frac{\sum_{i=1}^N W_{i,t}}{N}$.

This measure of uncertainty is thus a measure of idiosyncratic uncertainty at the firm, level since aggregate uncertainty (\overline{W}_t^2) is not considered.⁴ The construction of the uncertainty indicator shows that, due to a publication lag of the business situation assessment, it can only be observed with a lag of one period. This limits its use in real time. As before, we compute the individual uncertainty series at the level of 2-digit industries and aggregate them using value added weights to get time series for the aggregate forecast error. We derive two distinct times series: *UNC-F-CL* and *UNC-F-PR*; the first is based on questions regarding the business situation (business situation assessments and business situation expectations), the second on questions regarding production (production assessments and production expectations). Both time series are standardized in order to allow for a comparison with the direct measure.

Table 3: Weights of expectation errors

		Development over the last 3/6 months:		
		Increased	Remained Unchanged	Decreased
Expectations for the next 3/6 months:	Increase	0	-1/2	-1
	Remain Unchanged	1/2	0	-1/2
	Decrease	1	1/2	0

2.2.2 Uncertainty as dispersion

Two further indirect uncertainty measures are derived from Reuter and Girardi’s (2017) dispersion, which is based on responses to forward-looking survey questions (monthly and quarterly) in the WIFO business survey. To construct these measures, we first of all calculate the cross-sectional standard deviations of the share of positive and negative responses of

⁴Arslan et al. (2015) take into account aggregate uncertainty in the form of \overline{W}_t^2 . However, our results suggest that this measure of aggregate uncertainty is not informative for the Austrian manufacturing industry. Therefore, we do not present the results of aggregate forecast error uncertainty.

forward-looking survey questions for a particular quarter t as follows:

$$UNC-DISP = \sqrt{\text{fraction}_t^{(+)} + \text{fraction}_t^{(-)} - \left(\text{fraction}_t^{(+)} - \text{fraction}_t^{(-)}\right)^2}$$

where $\text{fraction}^{(+)}$ refers to the fraction of positive answers (e.g. production is expected to increase) and $\text{fraction}^{(-)}$ to the fraction of negative answers (e.g. production is expected to decrease). Based on these specific dispersion measures at the level of survey questions, we then determine the following two different uncertainty measures: The first measure is based on the expected business situation (“Geschäftslage”) in six months. As before, the measure is computed first at the 2-digit industry level and then aggregated using value added weights so that it reflects the structure of the manufacturing sector. This measure is standardised in order to allow for a better comparison and is referred to as *UNC-DISP-CL* from here on.

The second measure follows the idea of Reuter and Girardi (2017) and utilizes the average dispersion over four different survey questions on expectations (business situation, production, employment and order books). The dispersions are standardized in order to avoid the average dispersion being dominated by a single question. The uncertainty measure is again computed at the 2-digit industry level and aggregated using value added weights. In the following we refer to this uncertainty measure as *UNC-DISP*.

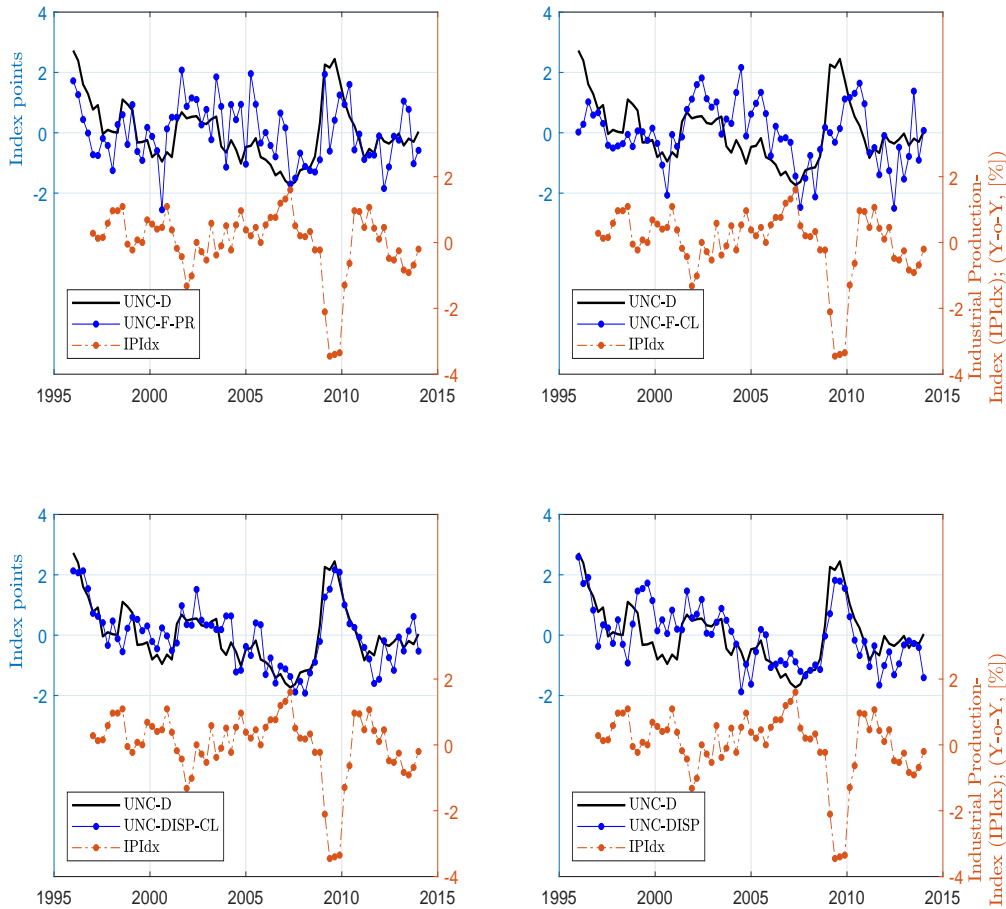
2.3 Descriptive analysis

Figure 1 displays the time series of the business uncertainty measures together with the year-over-year growth rate of industrial production (*IPIIdx*). In each subplot we compare our direct uncertainty measure (*UNC-D*) with an indirect alternative. We observe a close positive co-movement of the uncertainty measures to each other, and a negative one in relation to industrial production. The spikes in the uncertainty mea-

asures align with known episodes of economic turmoil.

Figure 1: The uncertainty measures – an overview

The figure plots the time series of the various uncertainty measures ($UNC-D$, $UNC-F-PR$, $UNC-F-CL$, $UNC-DISP-CL$ and $UNC-DISP$) motivated in the previous sections. All uncertainty measures shown are standardised. Additionally, each subplot shows the year-over-year growth rate of industrial production (IPI_{dx}).



The crisis of the European Monetary System (EMS) of the mid-1990s is reflected in most of the uncertainty measures by high values at the early stage of the sample. After several years of moderation, the Russian crisis marks a spike in the years 1997/1998, which however only triggered an intermediate increase in uncertainty followed by a quick attenuation. The

early 2000s in turn came along with a rise in uncertainty as a consequence of the increased global economic turmoil and the economic stagnation of the Austrian economy in the year 2002. The years prior to the global financial crisis are reflected in a comparably low level of uncertainty across all uncertainty measures. The spike due to the global financial crisis shows up very clearly in the direct uncertainty measure (*UNC-D*) though less so in the case of two of the indirect measures (*UNC-F-CL* and *UNC-F-PR*). Even worse, *UNC-F-CL* particularly points towards increased uncertainty at a point in time when the global financial crisis had already ended. The years following the global financial crisis show up in the uncertainty measures in rather heterogeneous patterns; some indicators point towards above-average levels of uncertainty (*UNC-F-PR*), while others point towards the opposite (*UNC-DISP*).

2.4 Uncertainty along firm size and firm growth distributions

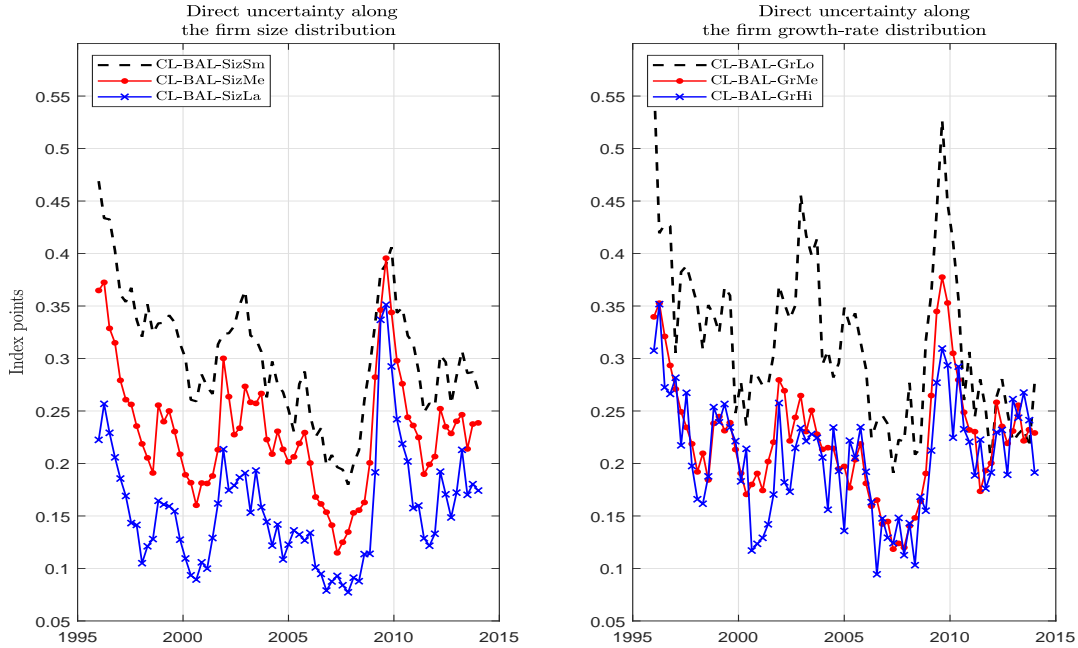
An appealing extension to the aggregate direct uncertainty measure of Section 2.1 is to consider the behaviour of the direct uncertainty measure along the cross-sectional dimension of firms. For this, we focus on two: firm size and firm growth rate.

As regards the first dimension, we distinguish between small firms (smaller than 25 employees, *CL-BAL-SizSm*), medium sized firms (larger than 25 but below 250 employees, *CL-BAL-SizMe*) and large firms (more than 250 employees, *CL-BAL-SizLa*). The time series of direct uncertainty for the three groups are in the left panel of Figure 2. We observe that small firms tend to have the highest level of uncertainty, while large firms always have the lowest level of uncertainty. However, the co-movement of the series is quite similar. The difference is mostly due to a level effect and not due to a different cyclical pattern.

As regards the second dimension, we consider the growth rate distri-

Figure 2: Direct uncertainty along firm size and firm growth rate distribution

The figure plots different measures for direct uncertainty based on firm size (left panel) and firm growth rates (right panel), where the growth rate considers employees. For the left panel, the acronyms refer to small firms (*CL-BAL-SizSm*), medium sized firms (*CL-BAL-SizMe*) and large firms (*CL-BAL-SizLa*). For the right panel, the acronyms refer to firms with a low growth rate (*CL-BAL-GrLo*), firms with a medium growth rate (*CL-BAL-GrMe*) and to firms with a high growth rate (*CL-BAL-GrHi*).



bution. For this we calculate year-over-year growth rates of the number of employees for each quarter for all firms. Firms are then allocated to three symmetric brackets of firm growth rates: firms with high growth rates (*CL-BAL-GrHi*), medium growth rates (*CL-BAL-GrMe*) and low growth rates (*CL-BAL-GrLo*). The firm growth rates are lagged two quarters in order to capture firms in the middle of their expansion process. The time series of the direct uncertainty measures according to the growth rate distribution are shown in the right panel of Figure 2. The pattern is not as similar across the groups, as in the case of the firm size distribution. The largest degree of uncertainty is recorded for firms with low growth rates, while firms with high growth rates tend to have a lower level of uncertainty throughout. The uncertainty measures of firms comprised by high and/or

medium growth rates are fairly similar to each other. The uncertainty behaviour of firms with low growth rates is however noticeably different. In fact, up to the year 2005 there is a stark difference in the behaviour of the direct uncertainty measure of firms with low growth rates compared to the other two groups. Since 2005 the behaviour is similar, especially during and in the aftermath of the global financial crisis.

3 The informational content of the various business uncertainty measures

In what follows, we assess the economic content of the business uncertainty measures by focusing on simple correlations, cross-correlations and principal component analysis and forecasting.

3.1 Correlation between uncertainty measures

Table 4 displays the (contemporaneous) correlation matrix of the uncertainty measures. All of the five uncertainty measures show a positive correlation with each other, with *UNC-D/UNC-DISP-CL* and *UNC-DISP/UNC-DISP-CL* having the highest pairwise correlation.

Table 4: Contemporaneous Correlations

	<i>UNC-D</i>	<i>UNC-F-PR</i>	<i>UNC-F-CL</i>	<i>UNC-DISP-CL</i>
<i>UNC-F-PR</i>	0.45	1		
<i>UNC-F-CL</i>	0.42	0.59	1	
<i>UNC-DISP-CL</i>	0.81	0.40	0.47	1
<i>UNC-DISP</i>	0.69	0.41	0.30	0.81

Figure 3 presents the cross correlations between the uncertainty measures and the reference series (industrial production) together with a 95% confidence interval. All uncertainty measures display a negative contemporaneous correlation with the reference series, though in some cases the correlation is comparably low. The direct uncertainty measure (*UNC-D*)

has the highest correlation (in absolute terms) with the reference series, followed by the uncertainty indicator related to business climate expectations (*UNC-DISP-CL*).

UNC-F-CL and *UNC-F-PR* have their highest correlation (in absolute terms) with the reference series at $\tau < 0$ implying that these uncertainty measures follow industrial production with a lag of at least one quarter. This circumstance weighs on the usefulness of these two uncertainty measures in assessing developments in industrial production in real time. The remaining three uncertainty measures have a high correlation with the reference series not only contemporaneously, but also at $\tau = 1$. This implies that these measures tend to lead industrial production to some extent rendering them useful in assessing changes in the reference series at least one quarter ahead.

3.2 Principal component analysis

Principal component analysis (PCA) allows to assess the extent to which the five uncertainty measures share one or more common component(s). For this, we consider the eigenvalues of the first five principal components. Figure 4 presents the scree plot of the eigenvalues of the five components together with a 95% confidence interval. The PCA shows that the various uncertainty measures share one common component which is indicated by an eigenvalue above unity. The remaining components do not explain much of the variation in the uncertainty measures. This strongly suggests that the five measures are (imperfectly) capturing an unobserved phenomenon that might be referred to as *uncertainty*.

Table 5 presents the correlations of the uncertainty measures with the first principal component. The correlation of each of the uncertainty measures with the first principal component exceeds a correlation coefficient of 0.65. The highest correlation coefficients are recorded for *UNC-DISP-CL*, *UNC-D* and *UNC-DISP*, while the correlation coefficients for the

Figure 3: Cross-correlations between the uncertainty measures and the reference series

The figure plots the cross-correlation coefficient between the various uncertainty measures ($UNC-D$, $UNC-F-PR$, $UNC-F-CL$, $UNC-DISP-CL$ and $UNC-DISP$) and the year-over-year growth rate of industrial production (IPI_{idx}), which is the reference series. A high correlation at $\tau > 0$ (*lead*) refers to a situation where the uncertainty indicator has a temporal lead relative to the reference series. The dotted lines display the 95% confidence interval.

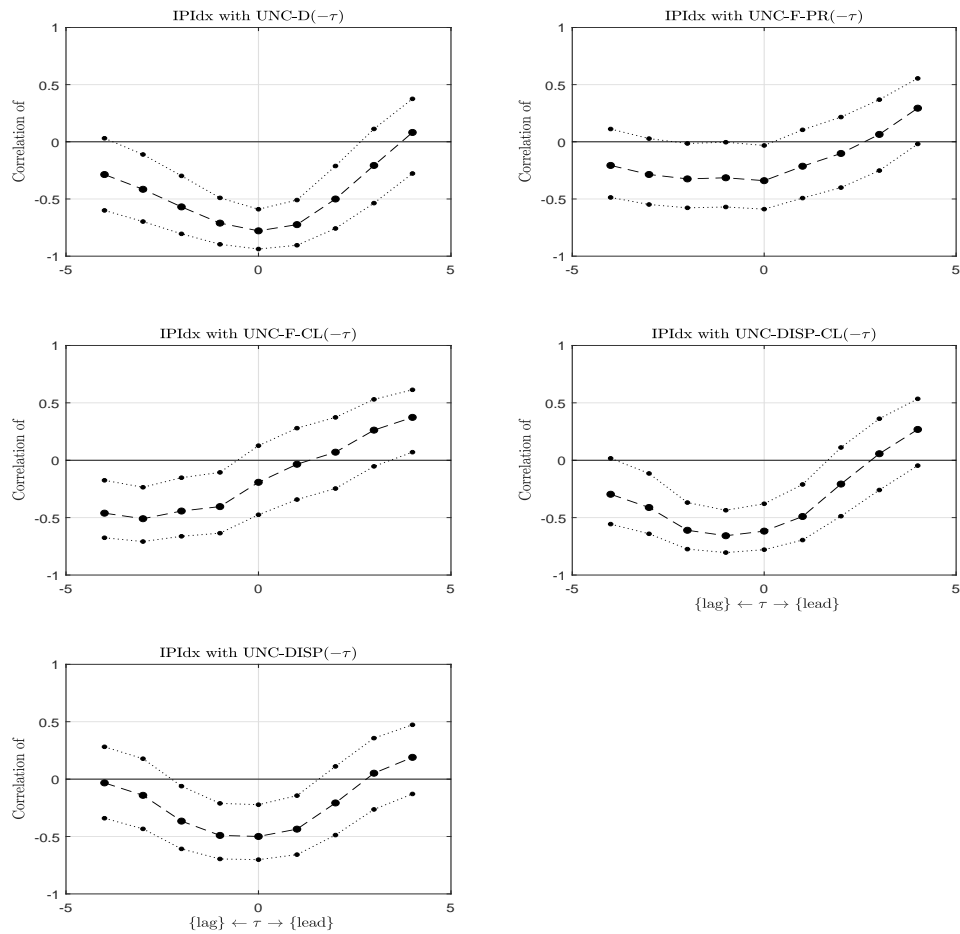
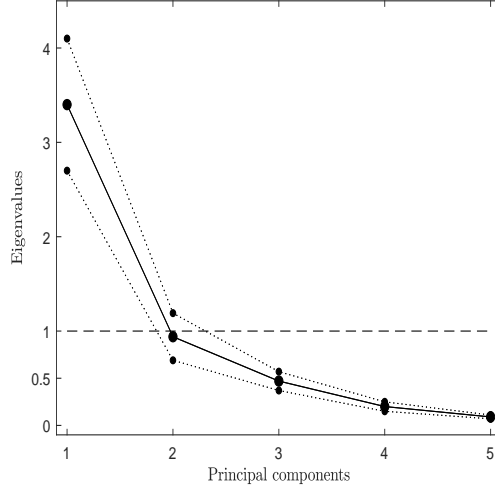


Figure 4: Scree plot of the five principal components

The figure plots the first 5 principal components of the various uncertainty measures ($UNC-D$, $UNC-F-PR$, $UNC-F-CL$, $UNC-DISP-CL$ and $UNC-DISP$) jointly with a 95% confidence interval (dotted lines).



two uncertainty measures based on expectation errors ($UNC-F-PR$ and $UNC-F-CL$) are weaker. The correlation pattern with the second principal component reflects the difference between the uncertainty measures based on expectation errors and the other uncertainty measures.

Table 5: Correlation of the uncertainty measures with the first two principal components

	Comp1	Comp2
$UNC-D$	0.88	-0.26
$UNC-F-PR$	0.67	0.58
$UNC-F-CL$	0.66	0.61
$UNC-DISP-CL$	0.92	-0.28
$UNC-DISP$	0.85	-0.36

Overall the principal component analysis confirms that the different uncertainty measures capture the same underlying phenomenon – we refer to that as *uncertainty* – as there is one important common component only. However, the analysis also indicates that the indicators show some degree of heterogeneity which is due to the different approach to measur-

ing uncertainty.

3.3 Uncertainty measures as predictors for economic activity

We explore the role of the uncertainty measures as predictors of the near-term course of economic activity. In particular, letting y_t denote the reference series, which is given by the year-over-year growth rate of industrial production (*IPI* dx) at a quarterly frequency, we estimate the following ARMAX model: $\Phi(L)y_t = \Xi(L)x_{t-\tau} + \Theta(L)\epsilon_t$, where $\Phi(L)$, $\Xi(L)$ and $\Theta(L)$ are lag-polynomials, L is the lag operator, τ is the lag delay between the input and output series, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, and x_t is an external input variable which will be used to introduce our uncertainty measures – one at a time – in the model. For each of the five uncertainty measures, we estimate an ARMAX model separately by OLS. We choose the lag-length of the lag-polynomials by relying on the Schwarz information criterion and the lag-delay τ between the input and output series equal to zero. We perform an in-sample forecast evaluation by using Granger causality tests and an out-of-sample forecast evaluation by relying on root mean squared errors (RMSE) of the forecast errors.

As regards the in-sample evaluation, we provide estimates of the possible bi-directionality of Granger causality, that is, causality running from the uncertainty measures (U) to the reference series (R), denoted by $U \rightarrow R$ and of the reverse direction, denoted by $R \rightarrow U$. Table 6 presents the results of the Granger causality tests depicting the corresponding the p-values. All uncertainty measures are Granger caused by the reference series (column headed by $R \rightarrow U$). The same applies also to the reference series – it is Granger caused by uncertainty. Hence there seems to be a bi-directional relationship between industrial production and uncertainty – at least as regards forecasting. This applies to all uncertainty measures. In contrast, the out-of-sample forecasting evaluation shows a clearer pic-

ture of heterogeneity across the uncertainty measures. The two right columns display the root mean squared error (RMSE) of the ARMAX model with a particular uncertainty measure compared to the RMSE of a simple ARMA model for the reference series only. We perform out-of-sample forecasts for (i) one-quarter ahead and (ii) two-quarter ahead forecasts. The results show that the two uncertainty measures based on expectation errors (*UNC-F-PR* and *UNC-F-CL*) produce out-of-sample forecasts that are worse than the simple ARMA forecasts. The uncertainty measures based on dispersion (*UNC-DISP-CL*, *UNC-DISP*) yield lower out-of-sample forecast errors than the simple ARMA model. And finally, the ARMAX model with the direct uncertainty measure (*UNC-D*) yields the lowest RMSE.

Table 6: Forecast evaluation

	Granger causality		Out-of-sample	
	<i>p-value</i>		<i>relative RMSE</i>	
	<i>U</i> → <i>R</i>	<i>R</i> → <i>U</i>	1 Quarter	2 Quarters
<i>UNC-D</i>	0.00	0.05	0.81**	0.85***
<i>UNC-F-PR</i>	0.01	0.05	1.02	1.04
<i>UNC-F-CL</i>	0.05	0.00	1.02	1.01
<i>UNC-DISP-CL</i>	0.00	0.03	0.91*	0.93*
<i>UNC-DISP</i>	0.00	0.00	0.95	0.95

Notes: The first two columns of the table report the p-values for Granger-causality tests. The third and fourth column are relative root mean squared errors (RMSE) defined as the RMSE of the ARMAX model with a particular uncertainty measure relative to the RMSE of a simple ARMA model for the reference series. Stars (**), (***) and (*) refer to the 1%, 5% and 10% level of significance of the modified Diebold-Mariano test of equal forecast accuracy according to Harvey, Leybourne, and Newbold (1997).

We employ the modified Mariano-Diebold test⁵ to assess whether the forecasts of the ARMAX models are different to those of the simple ARMA model for industrial production. The forecasts of the ARMAX

⁵Diebold and Mariano (1995) provide a pairwise test to analyse whether the differences between two or more competing models are statistically significant. As there is potentially a small-sample problem, we apply the modified version of the Diebold-Mariano test according to Harvey, Leybourne, and Newbold (1997).

model with the two uncertainty measures based on expectations errors (*UNC-F-PR* and *UNC-F-CL*) and *UNC-DISP* yield forecasts which are not significantly different to those of the simple ARMA model. We find some evidence for the ARMAX model in producing better forecasts when *UNC-DISP-CL* is used as uncertainty measure (10% level of significance). For the direct uncertainty measure, the forecasts of the ARMAX model are significantly more accurate than those of the ARMA model at both horizons and at comparably high levels of significance (5% for the one-quarter ahead horizon and 1% for the two-quarter horizon). In other words the direct uncertainty measure outperforms the other uncertainty indicators in terms of the informational content relevant for forecasting economic activity.

The results of this forecasting exercises are, however, completely silent on the causal relationship between uncertainty and economic activity, but they are instructive for two reasons. First, they highlight that different measures of uncertainty are informative about the economic outlook (this is also found in Caldara et al., 2016). Second, even though the forecasting performance and informational content of the uncertainty measures is mixed, the evidence suggests that some uncertainty measures have statistically significant and economically relevant predictive power for economic activity⁶. As episodes of economic turmoil are closely associated with periods of elevated economic uncertainty and economic downturns in turn promote uncertainty, this evidence raises the question how uncertainty and economic activity interact. To address this question empirically we use a structural model.

⁶This is also confirmed by other studies, for instance by Camacho and García-Serrador (2014) or by Glocker and Wegmueller (2017) to name a few.

4 Assessing the macroeconomic content of the uncertainty measures

The business uncertainty measures presented in the previous section capture business uncertainty rather differently. This raises the question of the extent to which these measures contain information relevant to explain macroeconomic fluctuations. Against this background, this section studies the various uncertainty measures from a macroeconomic perspective. To this purpose we use a structural framework to assess the impact of uncertainty shocks on key macroeconomic variables. We focus on (i) characterising the macroeconomic content captured in each individual uncertainty measure, and (ii) identifying the transmission channel of spikes in uncertainty.

4.1 The BVAR model

We consider the following block-exogenous Bayesian vector-autoregressive (BVAR) model:

$$\begin{bmatrix} I_G & 0 \\ A_{C,G}^0 & I_C \end{bmatrix} \begin{bmatrix} y_t^G \\ y_t^C \end{bmatrix} = \sum_{k=1}^K \begin{bmatrix} A_{G,G}^k & 0 \\ A_{C,G}^k & A_{C,C}^k \end{bmatrix} \begin{bmatrix} y_{t-k}^G \\ y_{t-k}^C \end{bmatrix} + \begin{bmatrix} \Xi_G \\ \Xi_C \end{bmatrix} x_t + \begin{bmatrix} e_t^G \\ e_t^C \end{bmatrix} \quad (1)$$

where y_t^G is a vector of global macroeconomic variables, y_t^C is a vector of domestic (country-specific) variables and x_t is a vector of exogenous variables. A_{ij}^k and Ξ_i are coefficient matrices and K is the number of lags in the model. I_C and I_G are conformable identity matrices. e_t^C is a Gaussian random vector of reduced form disturbances of domestic origin with mean zero and covariance matrix Σ_C and the vector e_t^G is the global counterpart with covariance matrix Σ_G . Due to the block exogenous structure of the BVAR model, e_t^C and e_t^G are mutually uncorrelated by construction

(Frisch–Waugh theorem) and the joint error vector $e_t = [(e_t^G)', (e_t^C)']'$ has a block-diagonal covariance matrix Σ with elements Σ_G and Σ_C .

The various uncertainty measures of Section 2 are derived from a business survey with the focal area being the manufacturing sector. Hence, we use the log of industrial production (*IPI**dx*) as our principal measure for real economic activity. In addition to that, the vector of domestic variables y_t^C contains investment (gross fixed capital formation, *GFCF*), GDP and private household consumption (*PHC*), all in real terms and in log-levels. Finally, y_t^C also contains the previously defined uncertainty measures where we use only one at a time; this implies that y_t^C is a five-dimensional vector.

We control for global economic uncertainty and global aggregate supply conditions by considering two variables in the vector of global variables y_t^G : the VIX index and global industrial production, both in log-levels. We use the VIX index in our baseline specification, as it is the most commonly used measure of global economic uncertainty. This index captures the implied volatility of S&P500 index options and represents a measure of financial markets' expectations of stock market volatility over the next 30 days.

The assumption of block-exogeneity implies that global economic shocks, captured by changes in the VIX index and industrial production, can have an impact on the domestic economy; however, in contrast to that, shocks arising from the domestic block leave the global block unaffected. This assumption seems reasonable in consideration of the interaction between a small open economy – Austria – and its global counterpart.

The vector of exogenous variables x_t includes a constant term and a deterministic time trend. It is important to note that the variables in x_t do not allow for a dynamic interaction; it is for this reason that we decided to include the VIX index and global industrial production in the form of a block-exogenous structure rather than as a further element in x_t , as otherwise their dynamics would not be adequately captured.

We choose a lag length of two⁷ and estimate the parameter matrices of the BVAR model as outlined in equation (1) with Bayesian techniques, using an uninformative Normal-Wishart prior density for the coefficient matrices and the covariance matrix.⁸ Since e_t^C and e_t^G are uncorrelated, the two blocks can be simulated separately. Our sample comprises quarterly data that cover the period from 1996:Q1 to 2013:Q3.

The block-exogeneity structure is a testable restriction. It implies that y_t^G is Granger causally prior with respect to y_t^C and Granger causal priority is a testable assumption. We assess the hypothesis that y_t^G is Granger causally prior with respect to y_t^C by means of the Schwarz information criterion. The test results indeed favour the assumption of the block-exogeneity structure in the BVAR model.

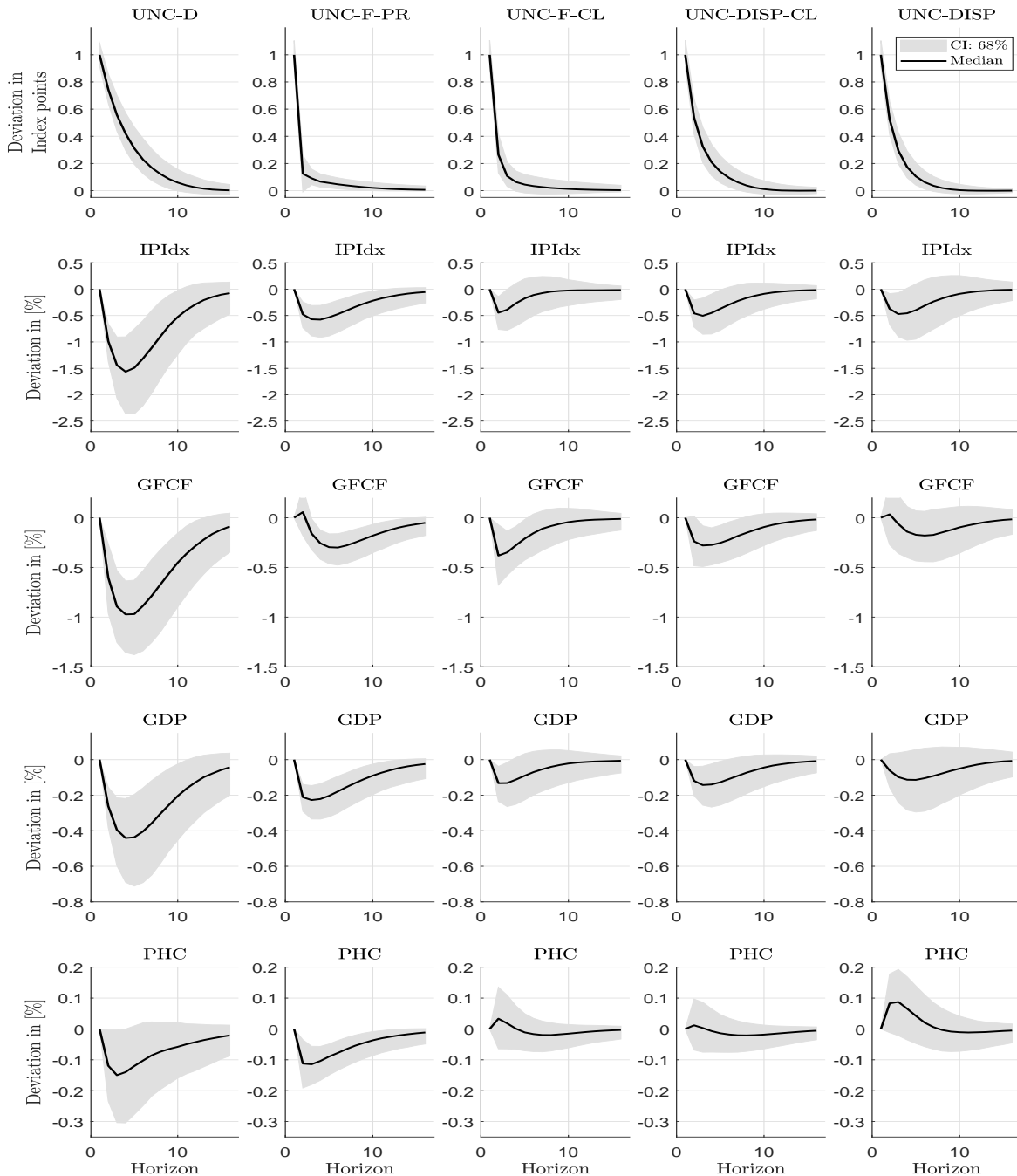
We pursue a recursive identification structure in order to produce structural impulse responses and hence to identify the BVAR model: a change in uncertainty is allowed to affect real activity with a one-quarter delay, changes in economic activity in turn are allowed to affect economic sentiment immediately. These assumptions are incorporated into the model explicitly by means of a Cholesky decomposition of the variance-covariance matrix Σ_C of the BVAR model and capture the speed with which uncertainty can adjust to incoming data, whereas the remaining variables respond more sluggishly to changing sentiment conditions.

⁷The lag length is chosen by means of the Schwarz information criterion. A Ljung-Box test cannot reject the null of no autocorrelation in the residuals.

⁸Some computational details: We sample the regression coefficients $A_{i,j}^k$ and covariance matrix blocks Σ_i with $i = G, C$ from the posterior distribution. Σ_i is drawn from an Inverted-Wishart Distribution $IW(\Sigma_{i,OLS}, T)$, and coefficient matrices $A_{i,j}^k$ and Ξ_i from a Normal Distribution $N(i_{OLS}, \Sigma_{i,OLS})$, where T is the number of observations, $i, j \in C, G$ is the respective coefficient matrix, $\Sigma_{i,OLS}$ is the corresponding covariance matrix of the coefficients, and subscript OLS refers to the ordinary-least squares estimates.

Figure 5: Impulse response functions to a domestic business uncertainty shock

The figure reports the impulse response functions to a domestic business uncertainty shock for industrial production (*IPIIdx*), investment (*GFCF* – gross fixed capital formation), GDP, private household consumption (*PHC*) and domestic uncertainty. Each column refers to a particular BVAR specification; across the various specifications, only the measure for domestic uncertainty changes (*UNC-D*, *UNC-F-PR*, *UNC-F-CL*, *UNC-DISP-CL* and *UNC-DISP*). The impulse response functions are shown for a horizon of 16 quarters (4 years).



4.2 The transmission channel of economic uncertainty

In what follows, we assess the various uncertainty measures as regards the transmission channel of uncertainty shocks to macroeconomic aggregates. We place an emphasis on examining the informational value of these uncertainty indicators and their ability to explain macroeconomic activity. The focus is on the implications of *domestic* uncertainty shocks. We show and discuss foreign uncertainty shocks in Section A of the Appendix.

In Figure 5 we show the impulse response functions of the various uncertainty measures jointly with their corresponding effects on industrial production (*IPI*), investment (*GFCF*), GDP and private household consumption (*PHC*). Each subplot displays the median of the posterior distribution for the impulse response functions together with the 68% confidence interval: the 16% and 84% percentile of the posterior distribution. Each column in Figure 5 refers to a particular BVAR specification where only the uncertainty measure changes across columns; the remaining variables are unchanged. Each column considers an uncertainty shock of size one. The figure shows the impulse response functions of the various uncertainty measures in the subplots of the first row; the subplots of the second row and below display the effects of the uncertainty shock on the macroeconomic variables.

The figure highlights several important aspects. First of all, across all five measures for uncertainty, their responses have a fairly similar shape and show a reaction which is significantly different from zero for at least three quarters. A direct implication of that is that the dynamic interaction between the uncertainty variable from which the shock originated, and the other variables in the BVAR model is limited. Hence, there appears to be no substantial evidence of feedback effects from real activity to macroeconomic uncertainty. This finding holds across all different uncertainty measures considered and is in line with the evidence found in

Salamaliki and Venetis (2018). We observe, though, that the uncertainty shock originating from the direct uncertainty measure (*UNC-D*) shows the highest degree of persistence, as the shock dies out only after around eight quarters. Hence, there is some evidence that indirect uncertainty measures are likely to underestimate the degree of inertia in business uncertainty.

Secondly, an uncertainty spike exerts downward pressure on real economic activity. This applies to all of the five different uncertainty measures when considering their effect on industrial production. When using the direct uncertainty measure, the downswing in industrial production and the persistence of the negative reaction are however highest. As concerns the indirect uncertainty measures, we find evidence that their shocks trigger statistically significant effects on industrial production with a probability of at least 68%, though noticeably smaller in size. Moreover, across all different measures considered, we observe a hump-shaped adjustment pattern of industrial production; a trough is reached with a delay of around four quarters. After that, the impulse response functions display a gradual trajectory back to the steady state, which is reached after around ten quarters. Hence, even though the shock as such is comprised by a comparably low degree of persistence, its effects on industrial production show a sizeable degree of inertia.

Thirdly, we find that uncertainty shocks originating from the direct uncertainty measure (*UNC-D*) trigger effects in industrial production largest in size – uncertainty shocks originating from the indirect uncertainty measures trigger noticeably smaller effects on industrial production. This confirms the previous finding that the direct measure of uncertainty (*UNC-D*) tends to outperform expectation-based measures of uncertainty as regards their informational content relevant for real economic activity.

Finally, the real effects of the uncertainty shocks are not limited to industrial production; indeed they trigger sizeable aggregate effects. As can be seen in the fourth row, GDP reacts negatively and in most cases also

significantly different from zero. The largest reaction is again observed once the direct measure of uncertainty (*UNC-D*) is used; a one-unit increase in uncertainty causes a trough of around -0.4%, which is reached after more or less four quarters after the shock originated. Evidently, the negative reaction of industrial production characterizes the supply side effect. As regards the demand side, we find evidence that the negative effects on GDP are triggered by a strong decline in investment. We find hardly any evidence for effects of uncertainty shocks on private household consumption across the various uncertainty measures.

4.3 The transmission channel – some theoretical considerations

The theoretical literature stresses the relevance of two distinct transmission channels for the effects of uncertainty on economic activity. The first channel focuses on the *real options* effect. From a firm's point of view, high uncertainty about the future induces them to be more cautious as regards their investment plans, especially when individual investment plans are irreversible (Bernanke, 1983; Bloom, 2009). As a consequence, firms are likely to wait and postpone or delay planned investment spending and hiring decisions until business conditions become clearer. The second channel addresses consumers. Their response to high uncertainty is similar to the reaction of firms, since it is more valuable to wait and postpone (reduce) consumption, particularly for durable goods, during more uncertain times. This channel is commonly referred to as the *risk aversion* effect. Risk averse consumers tend to increase precautionary savings in times of high uncertainty, which leads to a decrease in consumption spending (Carroll and Samwick, 1998).

Our results provide clear evidence as regards the relevance of these two theories in explaining the transmission channel of uncertainty shocks. As Figure 5 highlights, the effects of business uncertainty shocks on pri-

vate household consumption are both negligibly small in size and – in most cases – insignificantly different from zero. As a consequence, the transmission of business uncertainty shocks via the channel of private household consumption is of minor importance, rendering the theory on risk aversion less relevant as an explanation for the transmission of uncertainty shocks. This applies when using the direct and/or the indirect business uncertainty measures alike.

In contrast to that, uncertainty shocks leave a large and significant effect on production and investment. Obviously, the effect on investment is characterised by a large immediate negative effect; however, and even more importantly – the reaction of investment shows the highest degree of inertia in the adjustment process to uncertainty shocks. This suggests that firms react to heightened uncertainty by postponing investment. The drop in investment then triggers a decline in aggregate output.

This is broadly in line with the evidence found in the literature. Alexopoulos and Cohen (2009), for instance, use a VAR model and find negative responses of US economic activity – in particular, a negative response in investment – to positive stock market volatility shocks (i.e., unanticipated increases in volatility). Meinen and Röhe (2017) consider various indirect uncertainty measures and find evidence for a large and negative investment response to increases in uncertainty for the four biggest Euro-area countries (Germany, France, Italy, and Spain). Carriero et al. (2018) propose a framework representing aggregate macroeconomic and financial uncertainty, and document sizeable effects of uncertainty shocks on many macroeconomic and financial variables in an application to the US economy. Macroeconomic and financial uncertainty shocks lead to significant and persistent declines in economic activity.

4.4 The informational value of the business uncertainty measures

We assess the informational content of the various uncertainty measures by means of the forecast error variance decomposition (FEVD). This decomposition indicates the amount of information each variable's shock contributes to the other variables in the system. We in turn focus on the uncertainty shock only. In this context, the forecast error variance decomposition indicates the importance of uncertainty shocks in explaining fluctuations in the remaining variables in the BVAR model.

The block exogenous structure of the BVAR model allows to consider both domestic and foreign uncertainty shocks. We focus on domestic uncertainty shocks only and leave the discussion on foreign uncertainty shocks for the Appendix (Section A). Table 7 reports the forecast error variance decomposition for domestic uncertainty shocks – that is, the fraction of the variance of the k -step-ahead forecast error that can be explained by the uncertainty shock. The uncertainty shocks are based on different measures for economic uncertainty as outlined in Figure 5. We show the FEVD for different horizons. Considering the direct uncertainty measure (*UNC-D*) first, we find that uncertainty shocks explain around 23% of the fluctuations in industrial production within two quarters, and up to 30% percent for horizons of four up to eight quarters. The same holds more or less for GDP. As regards investment (*GFCF*) uncertainty shocks tend to trigger a delayed reaction; they explain only 7% of the fluctuations in investment at a 2-quarter horizon, but up to 25% for longer horizons (eight quarters). Finally, as concerns private household consumption, we find that the uncertainty shock explains a comparably small fraction of the fluctuations therein; this holds for both short and longer horizons. This also applies to the indirect uncertainty measures – the uncertainty shocks indirectly derived from business surveys tend to contain no relevant information for explaining fluctuations in private

household consumption.

Table 7: Forecast error variance decomposition – domestic uncertainty shock

		Horizon (in quarters)		
		2	4	8
Uncertainty measure:	UNC-D			
	IPIIdx	0.23	0.29	0.30
	GFCF	0.07	0.19	0.25
	GDP	0.21	0.27	0.27
	PHC	0.05	0.07	0.08
Uncertainty measure:	UNC-F-PR			
	IPIIdx	0.13	0.12	0.10
	GFCF	0.07	0.08	0.09
	GDP	0.12	0.13	0.11
	PHC	0.03	0.04	0.05
Uncertainty measure:	UNC-F-CL			
	IPIIdx	0.14	0.14	0.11
	GFCF	0.09	0.15	0.14
	GDP	0.08	0.07	0.06
	PHC	0.04	0.04	0.04
Uncertainty measure:	UNC-DISP-CL			
	IPIIdx	0.14	0.16	0.18
	GFCF	0.03	0.09	0.13
	GDP	0.14	0.16	0.15
	PHC	0.04	0.05	0.07
Uncertainty measure:	UNC-DISP			
	Manuf	0.04	0.08	0.10
	GFCF	0.02	0.04	0.07
	GDP	0.04	0.08	0.10
	PHC	0.03	0.04	0.05

Notes: The table reports the forecast error variance decomposition for uncertainty shocks – that is, the percentage of the variance of the k-step-ahead forecast error that can be explained by the shock. The uncertainty shocks are based on different measures for economic uncertainty. The variables are: industrial production (*IPIIdx*), investment (*GFCF* – gross fixed capital formation), GDP, private household consumption (*PHC*).

Table 7 highlights that business uncertainty shocks explain a comparably large fraction of the fluctuations in industrial production, investment and GDP when considering the direct uncertainty measure. Shocks from the indirect uncertainty measures tend to explain a noticeably smaller

amount of the fluctuations. This in turn implies that the informational content of the direct uncertainty measure relevant for explaining macroeconomic fluctuations outweighs that of the indirect measures. As highlighted in Section 4.2, the impulse response functions of industrial production, investment and GDP triggered by business uncertainty shocks are qualitatively the same across direct and indirect uncertainty measures. However, indirect uncertainty measures are likely to underestimate the importance of uncertainty shocks in triggering macroeconomic fluctuations.

4.5 Discussion

Kozeniauskas et al. (2018) have put forward the notion that different types of uncertainty and dispersion are theoretically distinct – neither are they mechanically linked, nor do they naturally fluctuate together. Against this background, the authors argue that it is erroneous to treat different types of uncertainty and dispersion as a single unified phenomenon, since the informational value contained in distinct uncertainty measures is different.

Our results in Section 3 show that, even though our measures for business uncertainty are statistically distinct, they share one important common component. Section 4.2 highlighted that this is not simply due to business cycle effects, as there is essentially no feedback from real variables to uncertainty. Our uncertainty measures co-move significantly above and beyond what the cycle alone can explain. This highlights that all of our uncertainty measures capture an underlying core phenomenon, though some do so more than others.

The difference in the informational content of the uncertainty measures becomes more apparent in the context of the forecast error variance decomposition. All of our indicators are based on microdata. In this context, Kozeniauskas et al. (2018) argue that, if there is more dispersion in

the signals agents receive, they will have more dispersed beliefs, which will result in higher micro-dispersion. When aggregating this introduces noise, rendering the resulting aggregate uncertainty indicator less informative. The fact that this arises more in the case of indirect uncertainty measures than for the direct uncertainty measure (compare Section 3), implies that the informational content across the five measures is distinct – some of the measures capture uncertainty with less precision, in particular the indirect measures. As the direct measure captures business uncertainty directly, the degree of dispersion in the signals agents receive and the resulting excessive dispersion of indicators are of lower importance. In other words, the direct uncertainty measure gives a clearer picture as regards the informational content on business uncertainty.

4.6 Robustness and extension

In this section we assess the extent to which the results of Section 4.2 are robust to the selection of different sets of firms in order to construct the direct uncertainty measure, as well as issues of sub-sample stability and omitted variables. In addition, in Section 4.6.4 we discuss the usefulness of financial market stress indicators as proxies for business uncertainty.

4.6.1 Direct uncertainty along the firm size and the firm growth rate distribution

Section 2.4 showed how our direct uncertainty measure varies across firm size and across firm growth rates. In what follows, we assess the extent to which these distributional effects in measuring direct uncertainty alter the implications outlined in the previous section. For this, we re-run the block-exogenous BVAR model using disaggregated measures of direct uncertainty which we vary along two dimensions: (i) along the size of firms (small, medium and large) and (ii) the growth rate of firms (fast, medium and slow). We use these disaggregated measures instead of the

baseline direct uncertainty measure in the model and report the impulse response functions to a domestic uncertainty shock in Figure 6. The left panels display the results for different firm sizes and the right panels those for firms' growth rates.

As regards the variation across the firm size, we find that the disaggregated uncertainty measures for small and medium sized firms trigger more pronounced effects in GDP than the baseline result. The opposite applies to large firms. Concerning the variation across firms' growth rates, we find that the negative effects of uncertainty spikes on GDP are comparably muted when considering fast-growing firms.

The results provide evidence in favour of differences in the informational content of the disaggregated measures; in this context, an excess sensitivity to uncertainty can be observed within small and medium sized firms. In turn, fast-growing firms seem to react less to changes in uncertainty.

4.6.2 Sub-sample instability

The short period which is covered by our sample does not leave much room for a sophisticated analysis regarding sub-sample instabilities. We proceed by splitting the sample in the middle: hence, one period spans from 1996:Q1 to 2005:Q2 and the other from 2005:Q3 to 2013:Q3. Each sub-sample is now characterised by one recessionary episode and by a period of normal economic fluctuations.

The results are depicted in Figure 7, where we only show the impulse response functions of the uncertainty measures used as well as those of GDP. The subplots display the baseline results of Section 4.2 by means of black solid lines surrounded by the 68% confidence interval. The impulse response functions for the two sub-samples are in green (pre-2005:Q2 period) and red (post-2005:Q3 period). For both sub-samples the structural impulse response functions to a surprise domestic uncertainty shock follow those in Figure 5 closely. Due to the small sample size, the precision of

Figure 6: Different measures for direct uncertainty

The figure reports the impulse response functions to a domestic uncertainty shock for the various direct uncertainty measures along two dimensions: (i) across firm size involving small firms (*CL-BAL-SizSm*), medium sized firms (*CL-BAL-SizMe*) and large firms (*CL-BAL-SizLa*); and (ii) across firms' growth rates involving firms with a low growth rate (*CL-BAL-GrLo*), firms with an intermediate growth rate (*CL-BAL-GrMe*) and firms with a high growth rate (*CL-BAL-GrHi*).

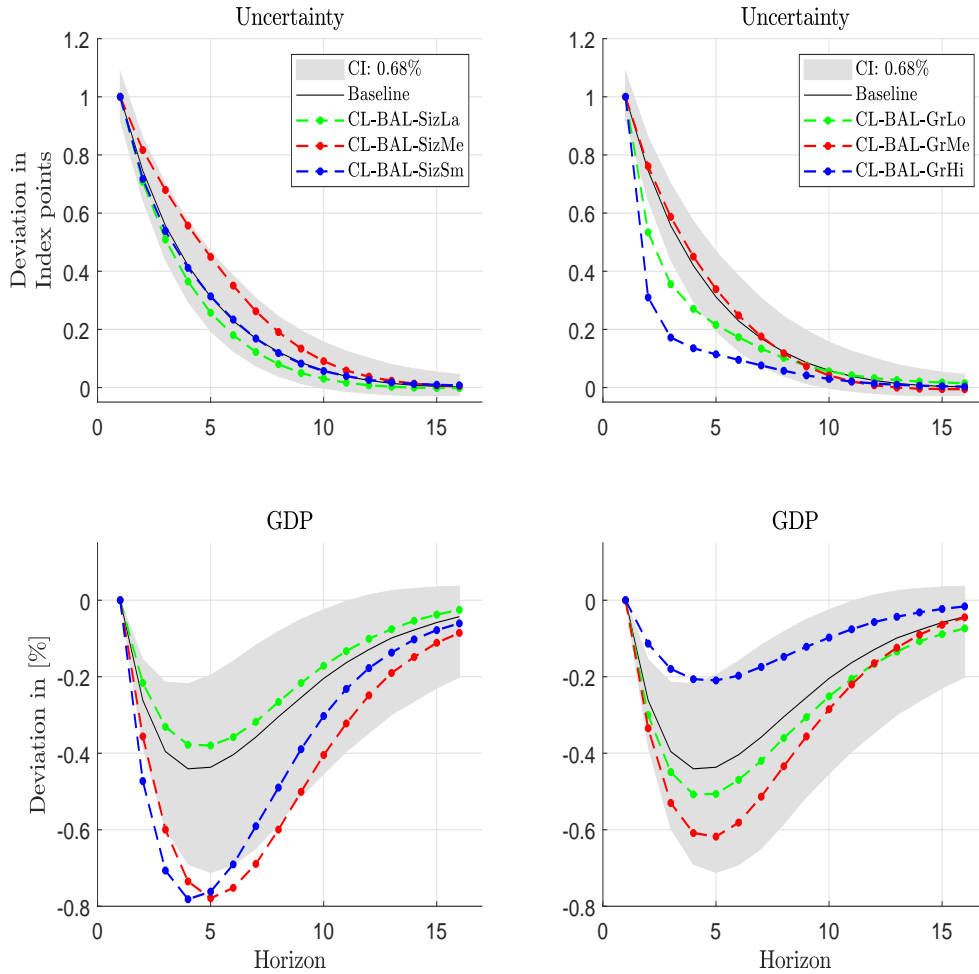
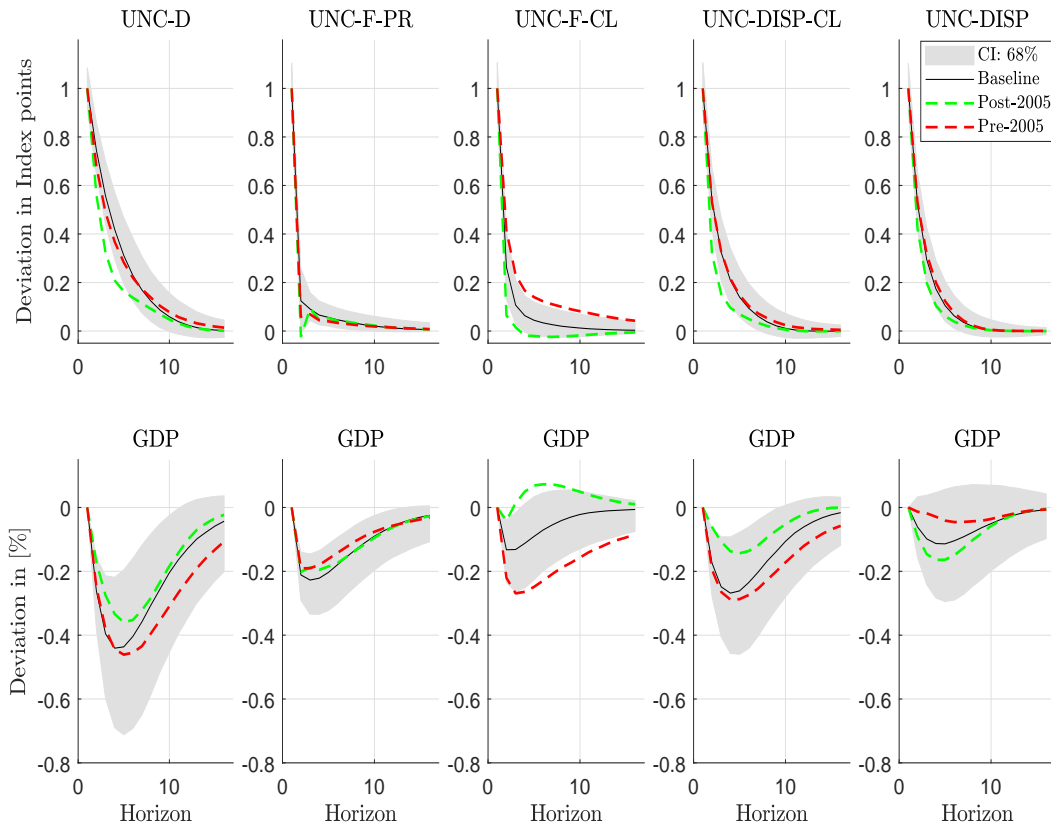


Figure 7: Sub-sample stability

The figure reports the impulse response functions to a domestic uncertainty shock for the various domestic uncertainty measures ($UNC-D$, $UNC-F-PR$, $UNC-F-CL$, $UNC-DISP-CL$ and $UNC-DISP$) and GDP. Each column refers to a particular BVAR specification, where one of the five uncertainty measures is used. The impulse response functions are shown for a horizon of 16 quarters (4 years) based on (i) the full sample, (ii) the pre-2005:Q2 sub-sample and (iii) the post-2005:Q3 period sub-sample.



the estimation of the impulse response functions for the two sub-samples is lower, i.e. their confidence interval is much wider (not shown), but their median responses remain mostly within the 68% confidence interval of the baseline results. We interpret these findings in favour of our results of Section 4.2 being robust across sub-samples.

4.6.3 Omitted Variables

Separate Ljung-Box tests on each residual time series cannot reject the null hypothesis that they follow a white noise process. However, it is still possible that omitted variables matter for the results. To check whether the identified uncertainty shocks are correlated with other variables we follow Glocker and Towbin (2015) and compute correlations of the estimated structural disturbances with variables that a large class of general equilibrium models suggests as being jointly generated by various shocks. Specifically, we compute correlations up to six leads and lags between the shocks and the growth rate of the Austrian stock market index (ATX), the stock index of the Euro-area (EURO STOXX 50), the implied volatility index of the EURO STOXX 50 (VSTOXX), the oil price⁹, the policy interest rates of the ECB and the US Fed.

The cross-correlations indicate that none of the omitted variables correlates significantly with the structural shocks' disturbances.¹⁰

4.6.4 Financial market stress indicators as proxies for economic uncertainty

Financial market stress indicators are commonly used as proxies for economic uncertainty. In their comprehensive empirical anatomy of the Great Recession, Stock and Watson (2012) explicitly single out the high degree

⁹We use the cyclical component of the oil price only to check for a possible correlation with the structural disturbances. For this, we apply the Christiano-Fitzgerald filter on the logarithm of the oil price.

¹⁰The statistical importance of the cross-correlations has been judged by means of the upper and lower limits of an asymptotic 68% confidence tunnel for the null hypothesis of no cross-correlation.

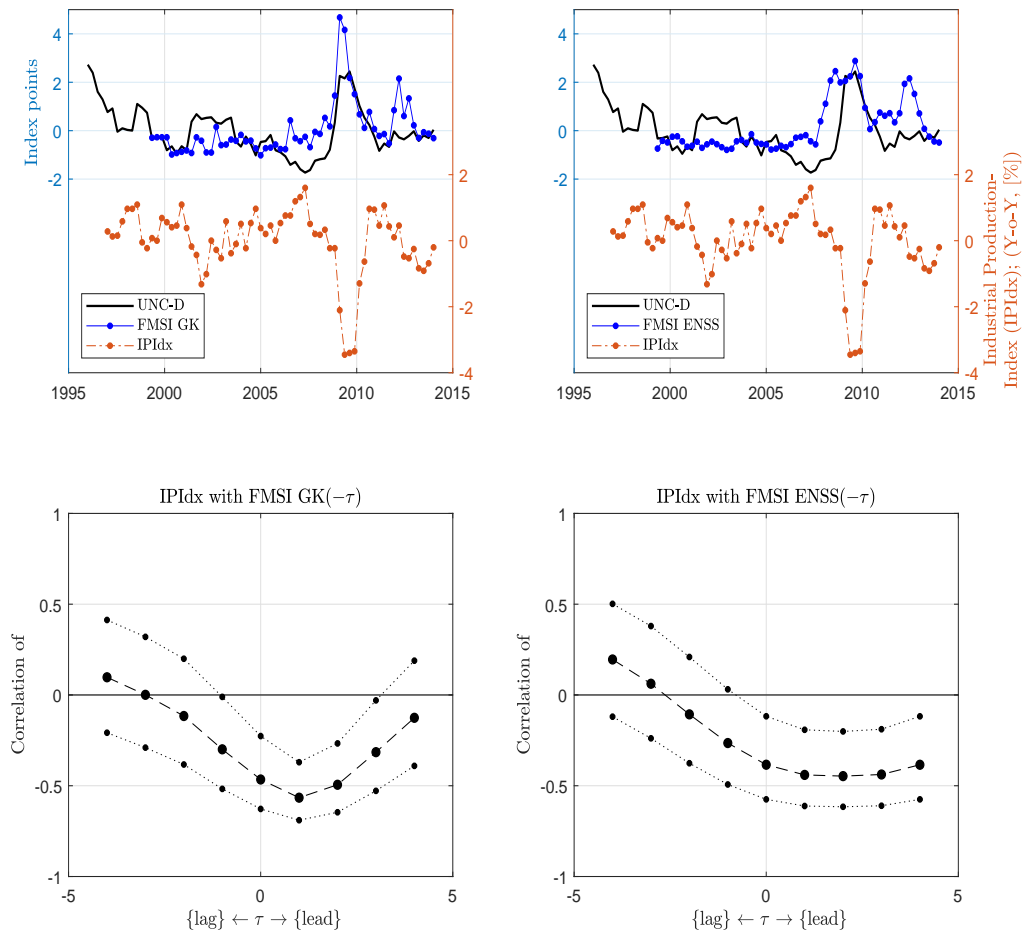
of similarity between financial shocks and proxies for economic uncertainty shocks (i.e. uncertainty shocks based on indirect measures of economic uncertainty) and conclude that “[t]hese two sets of instruments do not seem to be identifying distinct shocks”. In the following, we assess the degree of similarity of financial shocks in relation to the direct uncertainty measure. We have several financial stress indicators at our disposal, allowing us to compare and assess the differences in the informational content of financial market stress indicators relative to our direct business uncertainty measures. We proceed by considering two financial market stress indicator for the Austrian economy: We use the indicators developed in Eidenberger et al. (2013) (*FMSI ENSS*) and Glocker and Kaniovski (2014) (*FMSI GK*).

Figure 8 shows the time series of the two financial market stress indicators in the upper two subplots. Additionally, we show therein the reference series (industrial production, *IPI dx*) and the direct uncertainty measure (*UNC-D*). The lower two subplots display the cross-correlation of the two financial market stress indicators with the reference series. These two subplots are to be compared with Figure 3. As can be seen, both indicators tend to have their highest correlation with the reference series at a lead of around one quarter, rendering these two financial market stress indicators leading indicators with respect to economic activity. Nevertheless, throughout the dynamic structure considered for the cross-correlations, their correlation with the reference series is on average lower than the one of the direct business uncertainty measure (compare Figure 3).

We estimate the same model as outlined in Section 4.2, but now we substitute the business uncertainty measures with the financial market stress indicators. Figure 9 shows the results. The first column shows the baseline result of Section 4.2, i.e. the impulse response functions of an uncertainty shock based on the direct uncertainty measure (*UNC-D*). The impulse response functions are only shown for the uncertainty

Figure 8: Financial market stress indicators vs. economic uncertainty measures

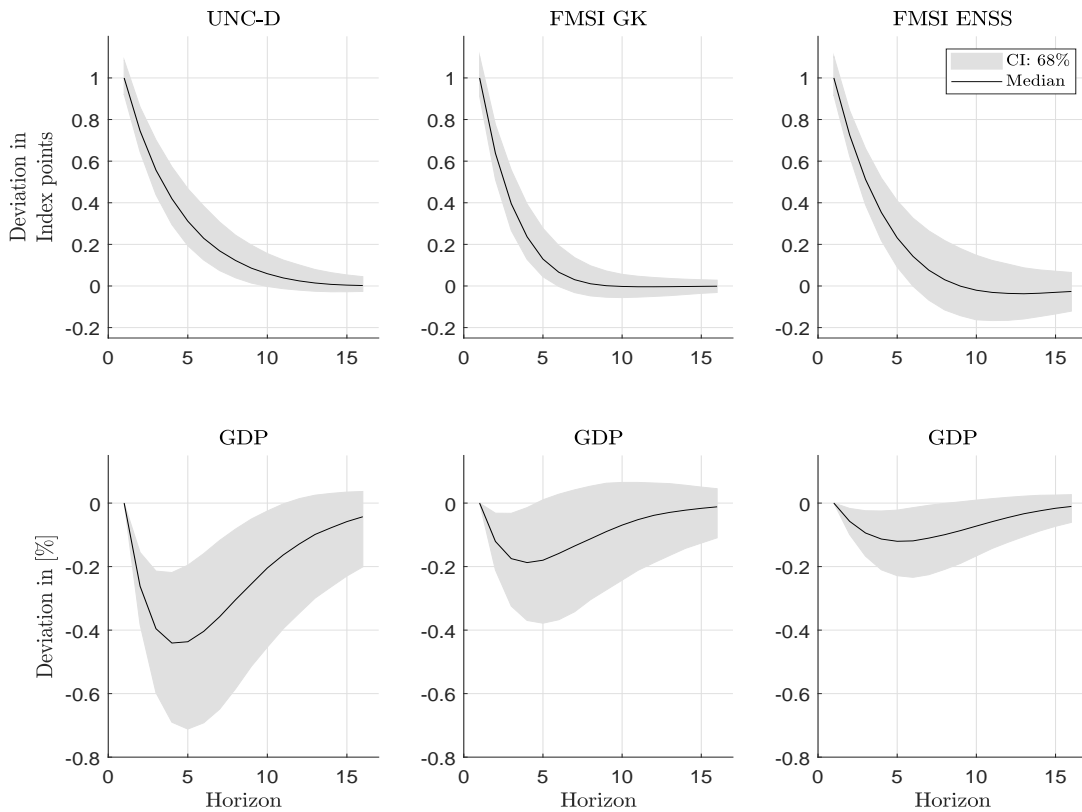
The figure reports the time series of two financial market stress indices (FMSI) shown in comparison to the direct uncertainty measure ($UNC-D$) and the reference series (industrial production ($IPIIdx$)). Additionally, the figure reports the cross-correlation of the FMSIs with the reference series (industrial production).



measure and GDP. In the second and third column we show the impulse response functions to shocks originating from the financial market stress indicators; they are based on a specification of the BVAR model in which the financial market stress indicators are used instead of the business uncertainty measure.

Figure 9: Financial market stress indicators as measures of economic uncertainty

The figure reports the impulse response functions to an uncertainty shock for the direct uncertainty measure (*UNC-D*), and GDP (first column). The second and third column display financial market shocks based on two distinct financial market stress indicators (*FMSI GK* and *FMSI ENSS*) for the financial indicators themselves and GDP. The impulse response functions are shown for a horizon of 16 quarters (4 years).



The results show that shocks to financial market stress trigger effects of opposite sign in GDP, as does business uncertainty. However, a shock to any of the two financial market stress indicators leads to an effect

on GDP that is considerably smaller than the effect observed for the direct uncertainty measure. Figure 5 shows that the effects of shocks to financial market stress trigger fluctuations in GDP which are similar in size to those of uncertainty shocks based on indirect uncertainty measures. This in turn implies that financial market stress indicators are likely to be characterised by a similar macroeconomic content as are the indirect uncertainty measures (see also Stock and Watson, 2012). In this respect, our results are qualitatively in line with those described in Caldara et al. (2016). According to their results, both financial and uncertainty shocks have robust negative effects on economic activity that are quite similar in magnitude. Quantitatively, however, our results are different. By using a direct measure of business uncertainty, we find a dominance of uncertainty shocks relative to financial shocks in terms of their effects on real economic activity. The analysis, however, ignores any potential interaction between financial shocks and business uncertainty shocks.

Figure 11 in Section B of the Appendix shows that the transmission mechanism of financial market shocks might be different. In contrast to uncertainty shocks, financial market shocks seem to trigger a significant decline in private household consumption. This applies to both financial market stress indicators considered. Hence, financial market stress indicators capture business uncertainty to some extent, but their informational content on uncertainty seems to go beyond pure business uncertainty.

5 Conclusion

This paper introduces a survey-based measure of business uncertainty. The novel measure is direct – that is, it is based on a survey question asking firms how certain/uncertain they are about their expectations of the business situation in the near future. We compare this measure with other (indirect) measures of business uncertainty that can be derived from business surveys. The results not only confirm that it is possible to con-

struct a measure of uncertainty from questions that elicit information on the subjective uncertainty of respondents directly, but that this measure also has a different, more precise informational content. While the direct measure of business uncertainty is correlated with indirect alternatives and even shares the same qualitative macroeconomic properties, we nevertheless find different informational content relevant for explaining macroeconomic fluctuations across the uncertainty measures. Common to all uncertainty measures, shocks to uncertainty trigger effects in real economic activity of opposite sign, but the indirect measures tend to significantly underestimate the effects on GDP and other macroeconomic aggregates, as compared to the direct measure of business uncertainty. We interpret this in favour of a higher informational content on macroeconomic activity being part of the direct uncertainty measure relative to that of indirect alternatives. In other words, the direct uncertainty measure contains more precise information on business uncertainty.

Our results confirm that business uncertainty shocks are relevant for macroeconomic fluctuations. In this context, we find no evidence for a transmission of uncertainty shocks through consumption. Our results suggest that the real option effect – uncertainty makes firms more cautious regarding investment plans – is the dominant macroeconomic transmission channel of business uncertainty, while the risk aversion effect seems to be irrelevant, at least as regards the Austrian economy.

Aside from the higher precision on uncertainty, the direct measure has two additional advantages for practitioners. First, it is available in a timely manner. Second, while indirect measures are built upon the dispersion of expectations or forecast errors, the direct business uncertainty measure is based on answers of firms. Thus, the results can be communicated as direct statements of the surveyed firms.

Overall, the results show that it is possible to construct direct measures of uncertainty by asking firms about their level of uncertainty and that the resulting aggregate indicator is a more precise measure of busi-

ness uncertainty than other survey-based alternatives. This suggests that direct questions on uncertainty should be included in business surveys if business uncertainty is needed to be measured in a timely manner. However, further research on other countries is clearly recommended, as the available evidence on business uncertainty measures suggests that there may be important differences across countries.

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A Foreign uncertainty shocks

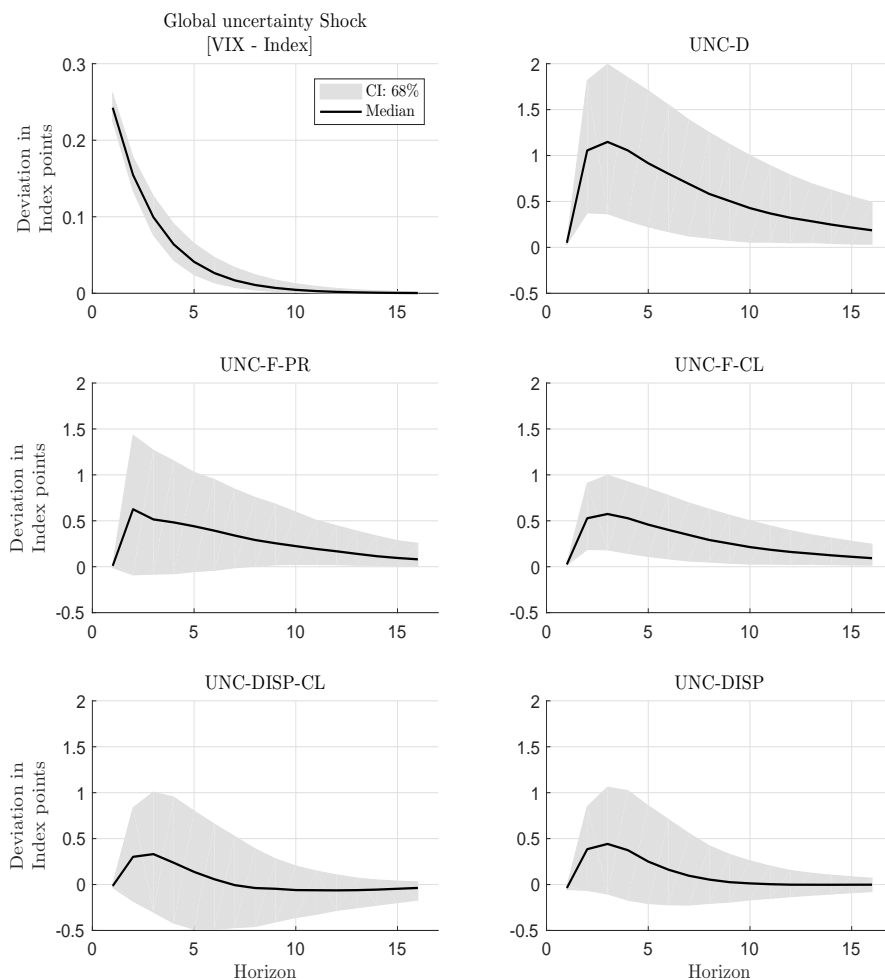
In Figure 10 we show the impulse response functions of the various uncertainty measures with respect to a global uncertainty shock, i.e. a shock in the VIX index. Figure 10 is based upon the same model structure as Figure 5 – that is, we estimate individual BVAR models for each of the five domestic uncertainty measures; across the different specifications, only the measure for domestic uncertainty changes. The first subplot in Figure 10 displays the global uncertainty shock. This shock shows exactly the same shape across all different BVAR specification, which is due to the block-exogenous structure of the model. The remaining subplots show the response of the various domestic uncertainty measures, where each of them corresponds to a particular BVAR specification.

Figure 10 highlights that an increase in global uncertainty also raises domestic business uncertainty. Across all of the five uncertainty measures, a peak is reached after around three quarters. The spike is statistically significant across four out of the five different uncertainty measures. As regards the indirect measures, the reaction is fairly similar across different uncertainty measures. The direct business uncertainty indicator tends to react stronger to a global uncertainty shock than the indirect measures.

Table 8 provides evidence for the importance of global uncertainty shocks in shaping domestic uncertainty. We do so by means of a forecast error variance decomposition, reporting results for three different horizons for the five domestic uncertainty measures. Each row in Table 8 refers to a particular BVAR specification where the uncertainty measure of a particular row is used as the domestic uncertainty variable. We observe that global uncertainty shocks trigger sizeable changes in domestic uncertainty when considering the direct domestic uncertainty measure (*UNC-D*); in this case global uncertainty shocks explain up to 31% of domestic business uncertainty. As regards the indirect uncertainty measures, the picture is again different; the global uncertainty shocks explain a comparably small

Figure 10: Implications of a foreign uncertainty shock on domestic economic uncertainty

The figure reports the impulse response functions to a foreign uncertainty shock captured by a surprise innovation in the VIX index. The measures for domestic uncertainty shown in the Figure ($UNC-D$, $UNC-F-PR$, $UNC-F-CL$, $UNC-DISP-CL$ and $UNC-DISP$) are used separately in the BVAR model. Across the different BVAR specifications, the global shock considered is always the same and shown in the first subplot; only the measure for domestic uncertainty changes across the BVAR specifications. The impulse response functions are shown for a horizon of 16 quarters (4 years).



amount of domestic business uncertainty.

Table 8: Forecast error variance decomposition – foreign uncertainty shock

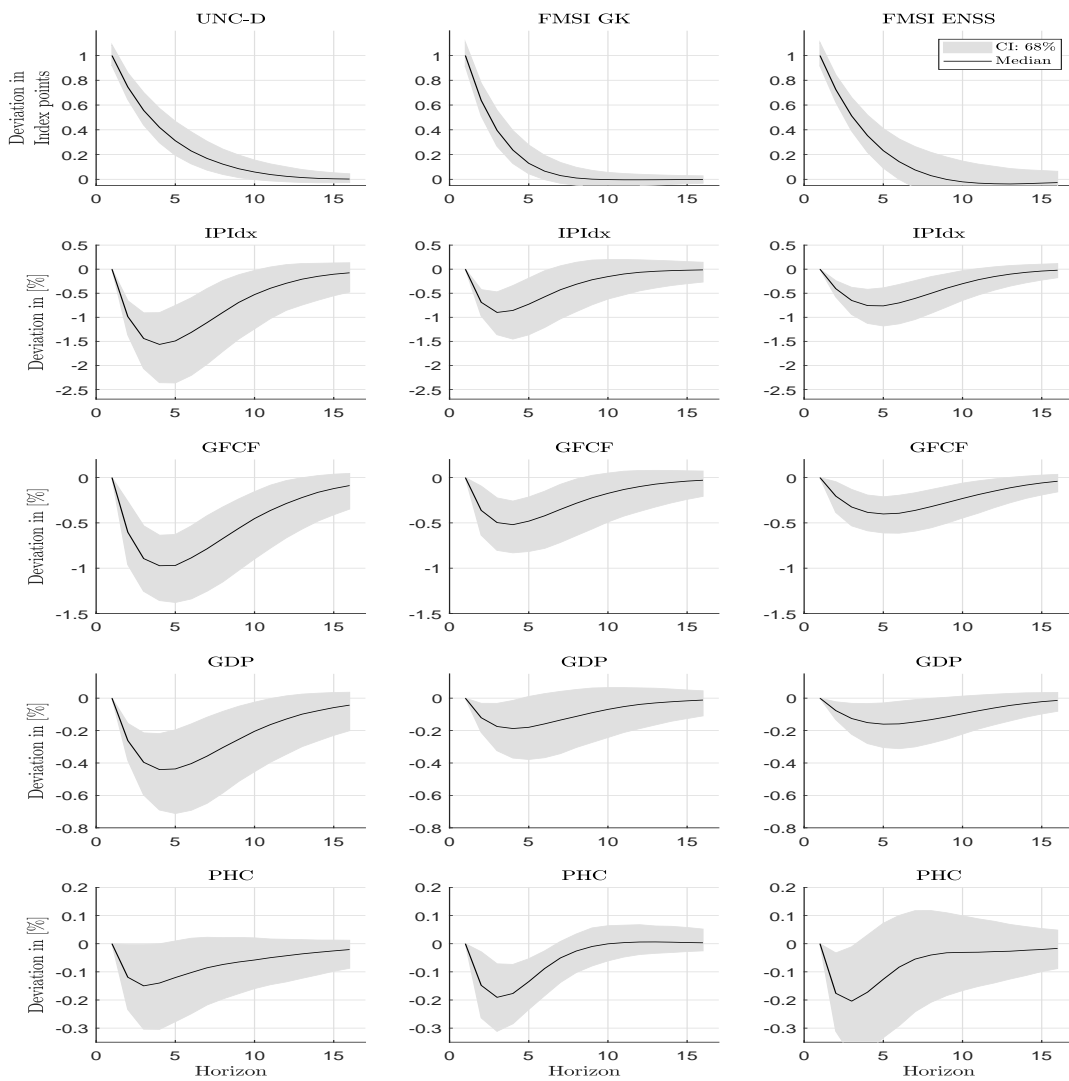
	Horizon (in quarters)		
	2	4	8
UNC-D	0.10	0.24	0.31
UNC-F-PR	0.01	0.02	0.04
UNC-F-CL	0.00	0.02	0.06
UNC-DISP-CL	0.03	0.10	0.13
UNC-DISP	0.04	0.10	0.14

Notes: The table reports the forecast error variance decomposition of foreign uncertainty shock on domestic economic uncertainty, that is, the percentage of the variance of the k-step-ahead forecast error of domestic uncertainty that can be explained by the foreign uncertainty shock. Foreign uncertainty is measured by the VIX index.

B Economic uncertainty shocks and financial market shocks

Figure 11: Financial market stress indices as measures for economic uncertainty

The figure reports the impulse response functions to an uncertainty shock for the direct uncertainty measure (*UNC-D*), industrial production (IPIIdx), investment (GFCF), GDP and private household consumption (PHC) in the first column of the subplots. The second and third column display financial shocks based on two distinct financial market stress indices (*FSMI GK* and *FSMI ENSS*) for the financial indicators themselves, IPIIdx, GFCF, GDP and PHC. The impulse response functions are shown for a horizon of 16 quarters (4 years).



C New wording of the question on uncertainty

Table 9: Question on uncertainty

Die zukünftige ENTWICKLUNG unserer Geschäftslage ist

- sehr gut abschätzbar
- kaum abschätzbar
- einigermaßen abschätzbar
- gar nicht abschätzbar

Translation: The future development of our business situation can be easily assessed / can be assessed to some extent / is difficult to assess / is not assessable.

The question on uncertainty which our direct uncertainty measure is based upon received a new wording in 2014. The short time span renders an econometric evaluation of the index based upon the new wording only unfeasible. Nevertheless, it is possible to calculate a new index based on the new question and then merge it with the index based on the old wording. We do so by standardizing the index for each sub-period separately, and then merge the indices of the two sub-periods to obtain one long time series capturing direct uncertainty from 1996:Q1 to 2018:Q2. The long time series for direct uncertainty is shown in Figure 12. We re-run the BVAR model and compare the impulse response functions to a domestic uncertainty shock of the extended time-span to the results of Section 4.2. Figure 13 shows the results.

We find hardly any evidence for a different degree of inertia of the shock itself. The impulse response function of the uncertainty measure based on the extended series (green dotted line) is always within the confidence interval of the baseline results. We find weak evidence for a more persistent adjustment path in GDP. As can be seen in the right panel of Figure 13, the impulse response function of GDP to a spike in uncertainty tends to be comprised by a slightly higher degree of inertia in case of the extended series (green dotted line). The impulse response function is still

within the confidence interval of the baseline results, however clearly at the lower bound of the confidence interval.

Figure 12: Extended time-series for direct uncertainty

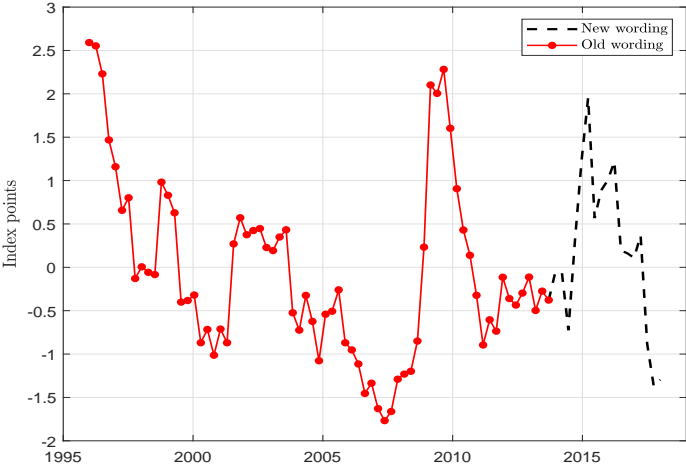


Figure 13: Implications of the discontinuation of the wording on uncertainty

The figure reports the impulse response functions to a domestic uncertainty shock for the direct domestic uncertainty measure (*UNC-D*) and GDP. The plots show the baseline results as of Section 4.2 and a new set of impulse response functions (green dotted line) based on the merged series of uncertainty (old and new wording of the question on uncertainty). The impulse response functions are shown for a horizon of 16 quarters (4 years).

