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New uncertainty measures for the euro area using survey data

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Abstract

This paper presents three survey-based uncertainty indicators, which constitute further developments of similar, already existing measures. Their main merits are that they can be computed on the basis of publicly available time series, rather than hard-to-acquire micro data, and are derived from the assessments of actors in a multitude of economic sectors, rather than just a single one, which makes them particularly suitable to assess more comprehensively the impact of uncertainty on economic activity. Empirical analysis shows the indicators to be counter-cyclical with major uncertainty peaks coinciding with low growth. Moreover, shocks to our uncertainty measures are found to be a quantitatively important driver of economic fluctuations, leading to a temporary reduction in real activity without any signs of overshooting. A comparison with other commonly used uncertainty proxies shows that the new indicators account for a much larger fraction of real GDP variability.

JEL classifications: C83, D81, E32.

1. Introduction

Starting with the outbreak of the financial crisis in 2008 and propagated by the ensuing sovereign debt crunch in Europe, an extensive body of literature has been dedicated to the impact of uncertainty on economic output. A number of contributions on the subject have shown that uncertainty surrounding fiscal or monetary policies exerts a significant effect on macroeconomic activity (Fernández-Villaverde *et al.*, 2011; Mumtaz and Zanetti, 2013; Fernández-Villaverde *et al.*, 2015). At the same time, a raft of articles has dedicated particular attention to the question of how best to measure uncertainty (e.g. Bachmann *et al.*, 2013; Jurado *et al.*, 2015). Since uncertainty is not directly observable, its measurement proves particularly challenging and a number of different strategies have been proposed in the economic literature.

A popular approach is to operationalize uncertainty as dispersion in the guesses of economic actors or analysts about the future. The underlying assumption is that, in times of high uncertainty, ideas about the future (e.g. future levels of economic growth) should be more diverse than in times of low uncertainty, where most actors will agree on roughly the same outlook. The operationalization of uncertainty as dispersion can be applied to a number of different variables. Bloom (2009) and Bekaert *et al.* (2013), for example, focus on the prices of options with identical times to maturity. Their dispersion, commonly referred to as stock market volatility, is interpreted as a gauge of economic uncertainty. Another group of researchers (Rich and Tracy, 2010; Rossi and Sekhposyan, 2015) champions the dispersion in professional forecasts of economic aggregates. Bachmann *et al.* (2013), by contrast, tap the richness of data gathered in business tendency surveys, deriving uncertainty from the dispersion of businesses' expectations for the future. In spite of their popularity, there is a downside to all dispersion-based uncertainty measures, notably that they are not solely driven by changes in the level of uncertainty. An important additional factor determining their evolvement is, for instance, the degree of genuine disagreement among the actors inquired. Professional forecasters might have very different forecasts about future economic growth, but, based on their models, be completely sure about them. In such a case, the dispersion of forecasts seems to signal a high level of uncertainty, while, actually, the indicator only reports elevated disagreement levels. It is important to keep these limitations in mind when interpreting dispersion-based uncertainty indicators.

An alternative approach to the measurement of uncertainty is to track the magnitude of errors in forecasting macro-economic series over time (Glass and Fritsche, 2014; Jurado *et al.*, 2015). Assuming that wrong forecasts reflect uncertainty, a rise in the forecasting error is interpreted as an indication of increased uncertainty at the time the forecast was prepared. The obvious shortcoming of the approach is its *ex post* nature, with uncertainty levels only measureable with hindsight.

Yet another strategy is to purposefully collect new data for the explicit aim of measuring uncertainty, rather than deriving it from existing datasets (Alexopoulos and Cohen, 2009; Baker *et al.*, 2015). Baker *et al.* (2015) arguably the spearheads of this approach, for example, construct an economic policy uncertainty indicator based on the number of newspaper articles which feature a combination of search terms which suggest the presence of economic policy uncertainty. The downside of such an approach is obviously the non-negligible degree of subjectivity involved in its execution (e.g. the choice of newspapers, the search terms).

This paper presents three new uncertainty indicators for the measurement of economic uncertainty, which adhere to the first of the above-described construction methods (i.e. they operationalize uncertainty as dispersion). Given the particular richness of available data, which, in the authors' opinion, is still far from being fully exploited, all three indicators are based on data from business and consumer surveys. The new indicators allow complementing the existing body of literature in two major respects:

First of all, their construction method pays particular attention to the practical needs of a broad target group of applied economists. To this end, the indicators are the first ones to be based on publicly available survey data, rather than hard-to-acquire micro survey data (i.e. non-aggregated data displaying the responses of individual firms/consumers). Furthermore, deviating from survey indicators presented so far and in line with Jurado *et al.*'s (2015), as well as Glass and Fritsche's (2014) approach of deriving uncertainty from developments in many, rather than a few, variables, the proposed indicators are based on the assessments of actors in a multitude of economic sectors. This reliance on several sectors arguably decreases the probability of the indicator signalling false positives (i.e. signalling high uncertainty where there is none) or negatives (i.e. failure to detect mounting uncertainty). Moreover, it will undoubtedly provide a more nuanced picture of the prevalence of uncertainty, as the degree of uncertainty is not just determined by the dispersion of respondents' answers to given questions (as in Bachmann *et al.*, 2013), but also by the share of economic sectors to which uncertainty has spread. Finally, two of the three indicators are available in real time, rather than *ex post*, allowing their use for timely analyses on topical issues.

The second major contribution of the paper relates to the strand of research focussing on the impact of uncertainty on economic output, rather than the intricacies involved in its measurement. Adding to the findings reported in Fernández-Villaverde *et al.* (2011), Mumtaz and Zanetti (2013), as well as Fernández-Villaverde *et al.* (2015), our novel measures of uncertainty, which are based on a multitude of economic sectors and agents rather than just a single source of uncertainty, provide an alternative, comprehensive assessment of the impact of uncertainty on economic activity. Furthermore, the indicators are constructed and assessed on the basis of euro area data, closing an important gap in the literature, which has hitherto focussed on the US case.[1] Finally, assuming that uncertainty is a human condition with potential effects across all branches of the economy, rather than only a few, the indicators are assessed in terms of their bearing on overall GDP (as in Rossi and Sekhposyan, 2015), rather than more indirect proxies for the level of economic activity, like industrial production (Bloom, 2009; Bachmann *et al.*, 2013; Jurado *et al.*, 2015).

We provide evidence that the proposed survey-based measures detect high uncertainty during recessions: they are thus counter-cyclical, with major uncertainty peaks occurring in the presence of important uncertainty-enhancing events. We also find shocks to the proposed indicators being quantitatively important drivers of economic fluctuations, leading to a temporary reduction in real activity, which is absorbed gradually over time without any signs of overshooting, even when controlling for a number of potentially relevant variables. Moreover, a comparison with the effect of shocks to other types of commonly used uncertainty gauges (e.g. stock market volatility) shows that survey-based uncertainty indicators account for a much larger fraction of real GDP variability.

The paper is organized as follows: Section 2 starts off with a presentation of the three proposed indicators, followed by an inspection of their ability to capture major uncertainty-enhancing economic/political events (Section 3). Sections 4 and 5 go one step further, analysing the role of the uncertainty measures in shaping economic fluctuations in the euro area by estimating and simulating multivariate time-series models. Conclusions follow.

2. The proposed uncertainty measures

2.1. The dataset

Our analysis uses data provided by the Joint Harmonised EU Programme of Business and Consumer Surveys (EU BCS), which inquires every month some 120,000 enterprises, as well as 40,000 consumers, across Europe (see European Commission, 2014). While enterprises are asked to assess the development of concepts like production, order books, or employment, consumers give insights into their personal financial situation and their views on

1 There are few exceptions, notably: Bachmann *et al.* (2013), who compare evidence from the USA and Germany; Arslan *et al.* (2015), who focus on the case of Turkey; and Glass and Fritsche (2014), who do consider the case of the euro-area aggregate, but focus on factor-, rather than survey-based uncertainty indicators.

macro-economic developments. The survey questions refer to the present situation, developments over the past three, or expectations for the next three months.[2] A number of questions feature twice on the questionnaire, so as to capture their assessments in terms of past and future developments. Once collected, the replies to each question are summarized in the form of so-called balances, i.e. the share of respondents giving positive answers *minus* the share of those responding negatively.

2.2. A note of caution: the limitations of the proposed uncertainty indicators

All three uncertainty measures proposed in this paper derive uncertainty from the level of dispersion in the underlying survey data. As already mentioned in the Introduction, dispersion-based uncertainty measures suffer from a major weakness, notably that their evolvement does not solely reflect changes in underlying uncertainty levels, but also in other forces. They should thus correctly be called uncertainty 'proxies', rather than indicators. Arguably, there are three major forces impacting on survey data dispersion:

(a) *Heterogeneity*: depending on characteristics like the economic sector in which firms operate, the level of export orientation, the degree of dependency on external funding, etc., participants in business surveys can (legitimately) have different views on their prospects, as well as current and recent developments. The same goes for consumers, with income and education levels, as well as the sector of employment, etc., having a likely impact on their answering behaviour. The way in which respondent heterogeneity influences dispersion in survey data can be illustrated by imagining a booming economy faced with a strongly appreciating currency. In such a scenario, export-oriented enterprises, as well as their employees, are likely to switch from largely positive to negative assessments, driving up the level of dispersion in business and consumer surveys. The surge, however, does not *per se* indicate higher uncertainty levels.

(b) *Disagreement*: enterprises, as well as consumers, might come up with different answers to the survey questions, because they use different information sets. Their assessments of the different concepts inquired in the surveys (e.g. the business or income situation) might thus vastly differ and translate into high survey data dispersion, without this necessarily indicating that respondents are uncertain about their assessments. Respondents actually disagree, rather than sensing elevated uncertainty.

(c) *Uncertainty*: firms or consumers having the same background characteristics (i.e. heterogeneity being largely absent) and resorting to the same information set to inform their assessments (i.e. not displaying genuine disagreement) in practice still give different answers to the same survey questions. Their assessments are thus noisy. If the variance of this noise rises, i.e. similar respondents using comparable information sets give unusually divergent answers, the corresponding increase in the dispersion of survey data reflects genuine uncertainty.

In the following sections, for each of the proposed indicators, we highlight which of the above sources of dispersion going beyond uncertainty (source (c)) they actually encapsulate.

2.3. Uncertainty indicator 'FW-DISP'

The first measure is an extension of Bachmann *et al.*'s (2013) dispersion-based uncertainty indicator. Contrary to the original set-up, though, we do not construct it on the basis of

2 In the case of the consumer survey, the inquired time horizon is 12 months, rather than three.

responses to a single forward-looking survey question, but to all 22 (monthly and quarterly) forward-looking questions contained in the EU BCS programme. An overview of the questions, which cover the programme's business (industry, services, retail trade, construction), as well as consumer survey, is provided in the online Appendix.

Turning to the construction method of the indicator, the first step consists of calculating the cross-sectional standard deviation of the share of positive and negative responses for every survey question q and month t as follows:

$$DISP_{qt} = \sqrt{fraction^{+}_{qt} + fraction^{-}_{qt} - \left(fraction^{+}_{qt} - fraction^{-}_{qt}\right)^{2}} \qquad (1)$$

Subsequently, the question-specific dispersion measures are standardized so as to have zero mean and unit standard deviation. This step helps avoiding that the average dispersion across all questions ($\bar{DISP}_t$), which is calculated in a next step, is dominated by survey questions with a particularly pronounced degree of volatility and/or an incomparably high absolute mean.[3] To enable an easier interpretation of the indicator, $\bar{DISP}_t$ is rescaled such that its mean is 100 and its standard deviation 10.[4] Values above 110 or below 90 thus indicate extremely positive/negative values, when compared to the indicators' usual readings. The resulting measure will henceforth be referred to as FW-DISP, hinting at its construction on the basis of the dispersion (DISP) of responses to forward-looking (FW) survey questions. Given that FW-DISP measures the current level of uncertainty prevailing at the time when the indicator is constructed, it delivers a real-time assessment of uncertainty in the economy.

In terms of the possible sources of dispersion identified in the preceding section, FW-DISP is arguably a mixture, not only reflecting changes in the level of (c) genuine uncertainty, but also of (a) (legitimate) heterogeneity reflecting respondents' background characteristics, as well as (b) disagreement following the use of different information sets. The nature of FW-DISP as a proxy, rather than a precise measure of uncertainty, should thus be sufficiently plain.

2.4. Uncertainty indicator 'BW-DISP'

The second indicator is an extension of FW-DISP. Inspired by Bachmann *et al.*'s (2013) measure of *ex post* forecast errors, it capitalizes on the fact that several of the forward-looking questions used for the construction of FW-DISP are also available with a backward-looking time horizon (e.g. there is not just a question inquiring developments in production over the next three months, but also over the *past* three months). The corollary

3 The dispersions of business and consumer questions can be combined in a single indicator, although they refer to different time periods (next three vs. next 12 months). After all, the reason for the longer time horizon inquired in consumer surveys is that consumers tend to update their beliefs less frequently than businesses. Descriptive evidence (available on request) suggests that versions of FW-DISP (as well as BW-DISP and IQ-DISP) which rely only on business or only on consumer data show patterns broadly in line with the versions of the indicators combining the two types of data. Still, a deeper investigation of the 'term structure' of uncertainty depending on the time horizon of the underlying survey questions might represent an interesting extension of the present analysis. See on this Jurado *et al.* (2015).

4 This is achieved by (i) subtracting from $\bar{DISP}_t$ its mean, (ii) dividing the resulting amount by its standard deviation, and then (iii) multiplying the measure by 10 and (iv) adding 100.

is that a given three-month period (e.g. January to March) is in fact assessed twice, once in terms of expected developments, as communicated by respondents in January, and, additionally, in the form of an *ex post* assessment, submitted in the April survey. The interesting feature about the existence of forward- and backward-looking assessments of the same variable and over the same time period is that the possible drivers of dispersion differ. While dispersion in the answers to forward-looking questions is influenced by (a) heterogeneity, (b) disagreement, and (c) uncertainty (see previous section), answers to backward-looking questions should only have one source of dispersion, namely heterogeneity (source (a)). After all, uncertainty (factor (c)) should, by definition, be absent from an assessment of past developments. Furthermore, disagreement due to the use of different information sets (factor (b)) should not occur, since, deviating from assessments about future developments, there should be broad agreement among respondents on the selection of variables to consult when assessing past developments (e.g. looking at past sales, when asked to assess past production) and all these variables should be equally available to the respondents. The proposed new indicator takes advantage of the difference between the drivers of dispersion in forward- and backward-looking questions, by scaling the dispersion of answers to the forward-looking questions, as inquired in month t, by the dispersion of answers to the corresponding backward-looking questions, as inquired in month $t+3$.[5] Since the dispersion of answers to backward-looking questions represents only the heterogeneity of respondents, the scaling operation in fact neutralizes the impact of respondent heterogeneity on the dispersion in responses to forward-looking questions. What remains is the dispersion in forward-looking questions, which is attributable to disagreement and uncertainty, rather than all three components. These time series can subsequently be aggregated into a new uncertainty indicator, which should, at least in theory, be closer to actual uncertainty than FW-DISP. Reflecting its use of the dispersion (DISP) of answers to backward-looking (BW) survey questions (in addition to the commonly deployed forward-looking ones), the indicator will subsequently be referred to as BW-DISP.

In concrete terms, the ingredients for the calculation of BW-DISP are all forward-looking questions used for the construction of FW-DISP, which are also asked in respect of developments over the past 3/12 months (see the online Appendix for the full list). In a first step of the construction, the question-specific dispersions for the forward- and backward-looking versions of the questions are calculated in line with condition (1). Subsequently, the uncertainty-induced change in dispersion is calculated as

$$DISP_{ct} = \ln\left(\frac{DISP^{fw}_{c,t-x}}{DISP^{bw}_{c,t}}\right), \tag{2}$$

where c is the economic concept the question refers to (e.g. production or demand), fw and bw indicate whether the concept is assessed from a forward- or backward-looking perspective, and $x = 3$ in the case of questions referring to business surveys, while $x = 12$ for consumer surveys. All resulting time series are subsequently standardized to equalize their means and their degree of volatility, before the average across all series is calculated. The latter is, in a final step, standardized once more and rescaled to have a mean of 100 and a standard deviation of 10.

5 In the case of consumer survey questions, which inquire developments over a 12-month horizon, $t+12$ is applied.

In spite of its potential, there are two major downsides of BW-DISP, which should not go unnoticed: First of all, the indicator construction rests on the assumption that the economic conditions remain (broadly) stable between the time the ex-ante and the *ex post* assessments are communicated. Should the conditions, by contrast, change, the level of heterogeneity-induced dispersion of the ex-ante and the *ex post* question cannot be reasonably assumed to be similar anymore. For example, if the currency sees a drastic appreciation between the time of the two assessments, the *ex post* assessment will see additional heterogeneity-induced dispersion stemming from export-oriented firms posting more negative assessments than the other firms. The scaling procedure would inadvertently 'neutralize' a large chunk of the dispersion in the forward-looking questions and thus artificially lower the level of presumed uncertainty. A second downside is that, due to its construction on the basis of respondents' retrospective assessments of past developments, the indicator is only available with a significant time lag.[6] The indicator thus does not lend itself to analyses conducted in real time.

2.5. Uncertainty indicator 'IQ-DISP'

Both uncertainty indicators discussed so far have in common that the ingredients used to construct them are question-specific dispersions, i.e. the standard deviation of positive and negative answers to a given survey question. Our third measure reflects the fact that a high degree of uncertainty might not only manifest itself in respondents giving very diverse answers to a given question (question-specific perspective), but also in the resulting balance scores developing into very different directions across questions (inter-question perspective). The inter-question perspective operationalizes uncertainty as the dispersion of changes in balance scores at time t across a number of survey questions.

The rationale of the approach rests on the assumption that uncertainty is naturally intertwined with change. Imagining a given economic situation (e.g. a boom) which persists from one period to another, one can assume that the changes in the balances of the different survey questions will be relatively limited. If, however, one imagines the same scenario again, but with a heightened degree of uncertainty about future developments, one would likely see changes in respondents' assessments: While questions relating to the past and the current situation (which were/are characterized by a boom) would change little, uncertainty about the future would induce at least a fraction of the respondents to change the optimistic expectations they usually communicated during the boom to neutral or negative ones. The result would be negative changes in questions about the future, coupled with stable readings for questions about the current and past situation. Compared to the scenario where the boom continued without any uncertainty, the addition of uncertainty to the scenario thus drives up the inter-question dispersion of the changes. Other than putting the forward-looking questions on a different trajectory than those having a focus on the past or present, uncertainty about the future might also induce respondents to provide seemingly illogical assessments. In the field of consumer surveys, for instance, uncertainty about the future course of the economy might induce respondents to expect an increase in unemployment in the country. However, since the assessment of expected unemployment reflects mainly uncertainty and cannot be bolstered by hard facts, the same respondents are unlikely to perceive their own jobs as acutely endangered. Accordingly, they are likely to report no

6 For instance, to be able to measure uncertainty in January, one must wait for the *ex post* assessments, as inquired in April.

changes to the outlook of their personal financial situation. The different developments of the two questions (unemployment expectations on the rise; assessments of personal finances largely stable) would drive up cross-question dispersion. Since its focus on the level of inter-question (IQ) dispersion (DISP) is the major difference to the other uncertainty measures proposed in this article, the new uncertainty indicator presented here will be referred to as IQ-DISP.

To calculate IQ-DISP in practice, all qualitative, monthly survey questions of the EU BCS programme are used (see the online appendix), in a way consistent with the idea put forward by Glass and Fritsche (2014) and Jurado *et al.* (2015) according to which uncertainty indicators have to be based on a broad information set. Each survey question is transformed from levels into changes compared to three months ago.[7] Following standardization of the resulting time series, the dispersion (standard deviation) across all question-specific change series is calculated for each point in time. In a last step, the final indicator (IQ-DISP) is obtained by standardizing the time series and rescaling it to have a mean of 100 and a standard deviation of 10. As for the case of FW-DISP, also the third uncertainty indicator reflects the current level of uncertainty at a given point in time t, so that it constitutes a true real-time measure of uncertainty.

While the cross-question perspective captures elements of uncertainty, one should be aware that, as FW-DISP and BW-DISP, it is also influenced by other forces. In terms of the classification introduced in Section 2.2, force (b) (disagreement among respondents) is arguably of little concern. However, heterogeneity does play an important role. Deviating from FW-DISP and BW-DISP, though, heterogeneity does not refer to the characteristics of the individual respondents, but of the questions. In fact, the concepts inquired by the different survey questions are heterogeneous in terms of the degree to which they typically lead or lag the business cycle (e.g. employment plans, structurally, tend to lag production expectations). Consequently, normal business cycle fluctuations (e.g. the emergence of a recession) can produce increases in the cross-question dispersion of month-on-month changes (the recession first drives down production and, later on, employment), which are not strictly related to uncertainty. Similarly, the different concepts inquired also behave differently in the face of typical economic shocks. A supply shock, for instance, is characterized by increasing prices and lower production. The assessments of these concepts (prices, production) in the aftermath of a supply shock will thus be characterized by a higher level of cross-question dispersion. While clearly a downside of IQ-DISP, the observation can be relativized, keeping in mind that changes of the economic regime (e.g. from boom to recession), as well as most types of economic shocks, can safely be assumed to be associated with higher uncertainty levels. Against this backdrop, the heterogeneity-induced part of IQ-DISP might, in many cases, move in the same direction as—and thus reinforce the signal of—uncertainty.

3. A snapshot of the proposed uncertainty indicators

This section presents an overview of the indicators, as well as some descriptive statistics. Graphs in Panel A of Fig. 1 plot the uncertainty measures over the period from 1999q1 to 2014q4 (in terms of quarterly averages).

7 In the case of industry Q4, retail trade Q2, and consumer Q7, the sign of the balance is inverted to ensure that an uptick is associated with positive economic developments and vice versa, as is the case for the other questions.

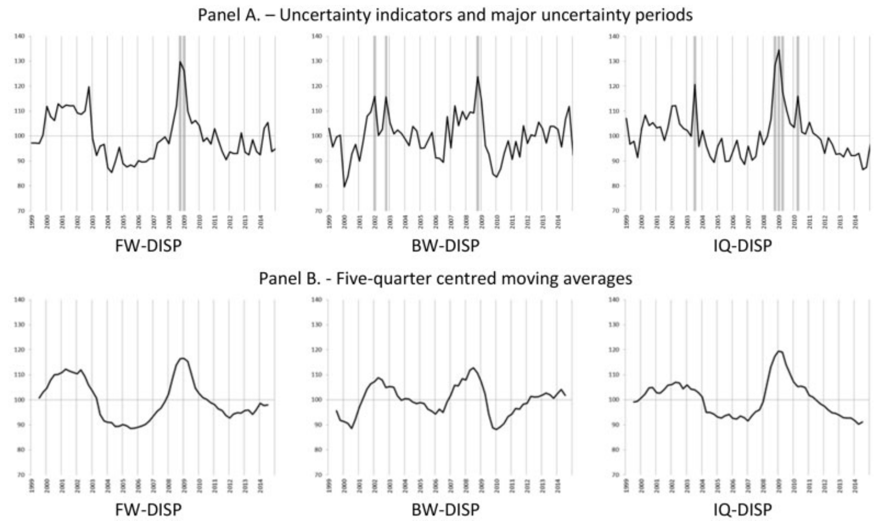

Fig. 1. Survey-based uncertainty measures (quarterly data)
Note: FW-DISP, BW-DISP and IQ-DISP are defined in Sections 2.3–2.5. Grey bars in graphs of Panel A identify extreme uncertainty periods defined as the quarters in which a given uncertainty indicator rises by at least 1.65 standard deviations above its mean.

Given the latent character of the concept of uncertainty, there is no track record of 'known' uncertainty levels in the past (see Bloom, 2014). We can therefore only inquire whether the indicators' evolvement is plausible. To this end, we focus on increases in the uncertainty indicators of at least 1.65 standard deviations (i.e. statistically significant ones at the 10% level, in line with Bloom, 2009) and verify whether they coincide with potentially relevant political/economic events.

The first graph on the left, which plots FW-DISP, shows that there are only two striking deviations from the mean, notably in 2008q4 and 2009q1 (highlighted by grey bars). These are clearly in line with a commonly held belief that the financial crisis (2008q3–2009q2) was one of the major uncertainty-generating events of the last decades. Also BW-DISP and IQ-DISP show a clear reaction to the financial crisis, with the former peaking in 2008q4, while the latter also signals exceptionally high uncertainty levels in the following two quarters.

Turning to BW-DISP in more detail, it also flags 2002q1 and 2002q4 as exceptionally uncertain periods. The former arguably reflects the terrorist attacks of 11 September 2001 (and the subsequent Afghanistan war), since it results from a series of three rises in uncertainty which took their onset with a particularly sharp one in 2001q3. The 2002q4 peak in uncertainty is likely to reflect the beginning discussions about a US invasion in Iraq, which eventually materialized in March 2003.

IQ-DISP does not only differ by flagging three (rather than one/two) quarters of the financial crisis as characterized by high uncertainty, but also by introducing two new high-uncertainty periods. The 2010q2 spike, most probably, captures fears of a Greek default, which climaxed with EU Member States adopting a first rescue package in May 2010. The surge in 2003q3 can be argued to owe to the three largest EU economies (Germany,

Table 1. Correlation analysis

	GDP (qoq)	GDP (yoy)	ESI	FW-DISP	BW-DISP	IQ-DISP
GDP (qoq)	–	0.72	0.67	–0.46	–0.53	–0.46
GDP (yoy)		–	0.95	–0.31	–0.27	–0.44
ESI			–	–0.20	–0.29	–0.40
FW-DISP				–	0.27	0.66
BW-DISP						0.08

Note: GDP (qoq) and GDP (yoy) indicate quarter-on-quarter and year-on-year quarterly growth rates. See Fig. 1.

France, Italy) entering recession. The bad news was released in August 2003,[8] which registered the highest-ever uncertainty level outside the financial crisis period of 2008/09.

Given that the uncertainty indicators are, by construction, rather volatile, Panel B of Fig. 1 displays them in terms of five-quarter centred moving averages. Indeed, the real-time uncertainty measures (FW-DISP, IQ-DISP) have much variation in common. Although not identical, the distribution of quarters into those characterized by above- and below-average uncertainty levels has a large overlap. Both uncertainty indicators identify the years 2000–2002 and 2008–2009 as periods of high uncertainty, while the opposite holds for 2004–2007 and 2012–2014. The *ex post* uncertainty indicator (BW-DISP) shows clear deviations, the most striking ones being above-average uncertainty during the sovereign debt crisis of 2012–2014, as well as below-average uncertainty in the second half of 2009 and throughout 2010.

A look into Table 1 formalises the assessment. The correlation between the two (quarterly) real-time measures (FW-DISP and IQ-DISP) is at 0.66 and thus suggests that the two measures gauge, to a certain extent, the same uncertainty, while BW-DISP correlates at less than 0.30 points with the other two uncertainty measures.

Another important finding is that all indicators display a solid, negative, correlation with GDP growth. Furthermore, the indicators tend to move in opposite directions with respect to current economic sentiment, suggesting that uncertainty is higher when agents' appraisal of the economic stance worsens, and vice versa. These insights are important preconditions for the next section, which introduces the proposed uncertainty indicators in VAR models to assess what impact on GDP they would exert in the case of an uncertainty shock and whether this effect persists when controlling for the level of economic sentiment. Obviously, significant uncertainty effects on GDP are only conceivable, if uncertainty has a clearly dominant direction of impact on real activity (in this case, a negative one, the higher uncertainty gets).

4. Empirical results

4.1. Baseline specifications

In keeping with the relevant empirical literature on the subject (Bloom, 2009; Bachmann *et al.*, 2013; Jurado *et al.*, 2015, Baker *et al.*, 2015), the quantitative assessment of the role exerted by a given uncertainty measure in explaining macroeconomic dynamics is carried

8 See, for example, http://news.bbc.co.uk/2/hi/business/3165999.stm, last accessed on 10 May 2016.

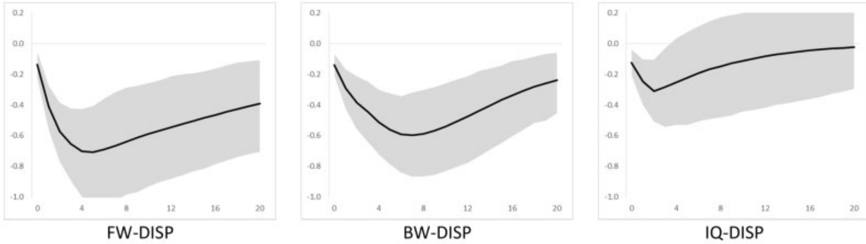

Fig. 2. GDP response to an uncertainty shock, bivariate models

Note: The vertical axis indicates percentage deviations of real GDP from the baseline path. The horizontal axis denotes simulation quarters. All models are estimated with four lags and include a constant as deterministic component. Variables enter the systems in levels. The identification scheme is a recursive one, where the uncertainty series is ordered first. The shaded areas represent the 90% bias-corrected bootstrap confidence intervals computed as suggested by Kilian (1998). See also Fig. 1.

out within a Vector Autoregressive (VAR) framework. Given that unrestricted VAR models can represent only reduced form shocks and, thus, provide little or no guidance on causality, further assumptions on the relationship between the variables are required. We opt for the Choleski decomposition, which delivers orthogonal shocks in a recursive structure that is determined by the order in which the variables are listed in the VAR, in a way consistent with the above-quoted works. All models are estimated with four lags over the period from 1999q1 to 2014q4 and include a constant term as deterministic component. The frequency of the series is quarterly, while the simulation horizon is set equal to 20 quarters (five years).

In order to provide some preliminary evidence on the dynamic effects of uncertainty shocks on the economy, our baseline systems include, separately, one of the three unfiltered (quarterly) measures of uncertainty defined in Section 2 (*unc*) and (the log-level of) GDP as a measure of overall economic activity (*gdp*), by ordering the uncertainty series first in the recursive identification scheme.

Figure 2 shows the response of GDP to shocks to the different uncertainty measures. To ensure comparability across models, the size of the uncertainty impulses is fixed at 5 points (corresponding roughly to one standard deviation of the identified error in the VAR models). The shaded areas represent the 90% bias-corrected bootstrap confidence intervals computed as suggested by Kilian (1998).

The leftmost graph shows that a shock in the dispersion of real-time expectations (FW-DISP) reduces the level of aggregate activity by about 0.1% on impact. The contraction peaks one year after the shock (at –0.7%) and then is gradually absorbed. After five years, the level of activity is still below its pre-shock level of 0.5 percentage points. The response of GDP to an innovation in the *ex post* uncertainty measure (BW-DISP) reveals similar dynamics, with a decrease in output peaking six quarters after the shock (at –0.6%) followed by a subsequent rebound. Also the third dispersion measure (IQ-DISP) confirms the hitherto observed pattern, albeit with some deviations. While GDP responds negatively to the uncertainty spike, the negative effect reaches its peak already after two quarters and the subsequent fading-out happens quicker. Furthermore, the magnitude of the effect is less pronounced (minimum at –0.3% after two quarters).

Overall, our findings appear in line with the evidence reported in Bloom (2009) for the USA and Bachmann *et al.* (2013) for the German economy. Contrasting with Bloom

(2009), though, our results do not corroborate the existence of an over-shooting phenomenon, where a rise in uncertainty at first depresses real activity and then lifts it above the pre-shock level. At the level of theoretical literature, our results are consistent with the commonly held view of a detrimental effect of uncertainty on consumption and investment decisions which may induce a (temporary) decline of the level of demand for goods and services in the economy. As for consumers, Romer (1990) and Carroll (1997) show that under the assumption of convex marginal utility higher uncertainty can induce households to build up a 'buffer stock' of savings to draw on in periods of relatively low income, thereby reducing their *current* consumption levels (especially for durable goods, since they are costly to reverse). However, this effect is likely to be transitory since it lasts until households have saved the amount they require as insurance against future fluctuations in their income. The irreversibility effect is also at the heart of the expected negative relationship between uncertainty levels and (private) investments (Bernanke, 1983; Pindyck, 1993; Bloom *et al.*, 2007): with greater uncertainty the value of the option to postpone investment (in order to wait for new information) increases, so that the decision to invest is delayed (the 'perpetual call option' value of an investment plan), thus temporarily depressing investment spending.

4.2. Extending the baseline model

Though instructive, the results from a bivariate system are prone to misspecification. Accordingly, we test whether the documented temporary negative effect of uncertainty shocks on real activity remains robust when extending the baseline setup by including a number of additional series in the estimated models.

In a first step, we augment the benchmark specification by an overall measure of confidence (the level of the economic sentiment indicator, *esi*). This is warranted against the backdrop of Section 3 above, which shows all uncertainty measures peaking during the 2008–2009 crisis, a period coinciding with a major blow to confidence. It thus seems that uncertainty shocks may coincide with shocks to the first moment of the distribution (that is, changes in the level of 'confidence').[9] To address the question of whether the proposed uncertainty indicators can really be interpreted as measures of uncertainty, or whether, instead, they simply pick up the effect of changes in confidence regarding future outcomes (Haddow *et al.*, 2013), we extend the baseline setup to control for possible 'first moment' effects. Concretely, we include *esi* in a three-variable VAR system, ordering, first, our measure of confidence under a recursive identification scheme where *unc* is ordered before *gdp*, as in the baseline specification (extension 1).

Panel A of Figure 3 reports the impulse–response functions of GDP to an unexpected uncertainty shock from the three-variable models. Compared to the results in Fig. 2, the drop in GDP loses a bit of its magnitude (ca. 0.1 percentage points), but remains unequivocal, with a trough of about –0.5% in the cases FW-DISP and BW-DISP and –0.3% for IQ-DISP. The shape of the response changes somewhat, in that the maximum contraction is reached

9 The clearly negative correlation between confidence (as measured by the ESI) and the three uncertainty measures (see Table 1) suggests that, in times of crisis, households and firms tend to (i) revise down their central expectation of the economic outlook, while, at the same time, (ii) attaching a higher probability to extreme events occurring to either side of the (more pessimistic) central tendency. Bachmann *et al.* (2013) reacted to this phenomenon with the 'by product' hypothesis, according to which high uncertainty might be a consequence of poor economic performance, rather than its driving force.

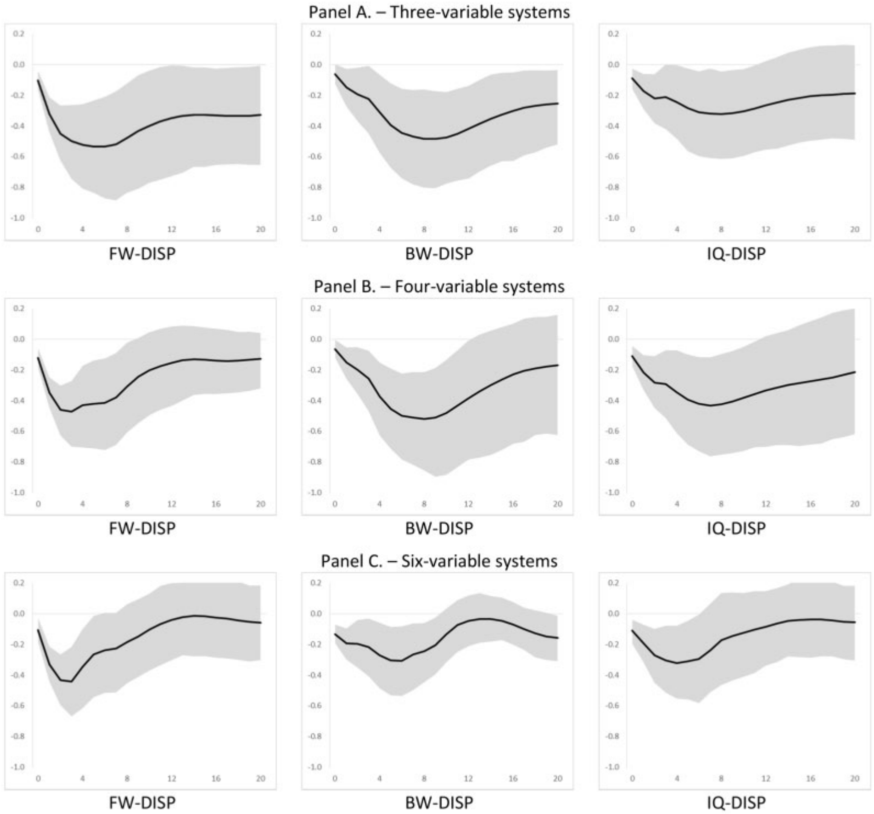

Fig. 3. GDP response to an uncertainty shock, extensions of the baseline system
Note: The identification scheme is a recursive one, where the uncertainty series is ordered second. See also Fig. 2.

later. This observation holds true in particular for IQ-DISP, where the trough occurs some six quarters later than in the previous exercise and now broadly aligns with the other two uncertainty measures. Following the contraction, GDP embarks on a gradual recovery path.

With the main findings of the baseline setup confirmed, our analysis proceeds to a second extension of the benchmark specification, aiming to take into account the role of labour input. The underlying rationale is twofold. First, besides taking its toll on demand, uncertainty can also impinge on the potential output level of the economy: uncertainty may make workers less willing to seek new jobs, which in turn could lessen productivity growth through less efficient matching of skills to jobs (Lazear and Spletzer, 2012), and/or cause companies to postpone hiring (and firing) decisions (Bloom, 2009). Second, the irreversibility of investments, which makes their level particularly sensitive to uncertainty, may be somewhat alleviated/counteracted by the reversibility of production factors, like labour inputs (Eberly and van Mieghem, 1997; Bontempi *et al.*, 2010). In operational terms, the VAR system is extended so as to include the (log of) euro-area employment levels (*emp*) in a recursive VAR specification with ordering *esi*, *unc*, *emp*, *gdp*, in a way similar to Bloom (2009) and Jurado *et al.* (2015) (extension 2). Finally, the tetra-variate VAR system is

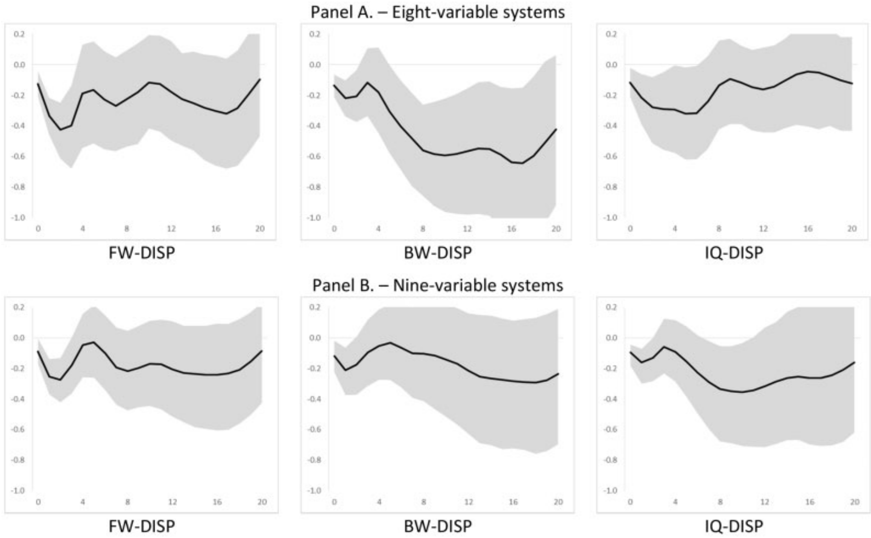

Fig. 4. GDP response to an uncertainty shock, larger systems
Note: See Fig. 3. Panel B refers to eight-variable specifications augmented by credit costs.

altered through the addition of a measure of the intensiveness of labour input – (log of) hours worked (*hrs*), as well as the (logs of) the wage levels (*wge*), resulting in a six-variable specification which resembles the one discussed in Bachmann *et al.* (2013), where the recursive scheme is based on the following variable ordering: *esi*, *unc*, *wge*, *hrs*, *emp*, *gdp* (extension 3).

The results of extensions 2 and 3 of the benchmark model are reported in Panels B and C of Fig. 3, respectively. In line with the previous results, both extensions show, in the short run, a contractionary effect of uncertainty on aggregate activity, which subsequently attenuates and, towards the end of the simulation horizon, tends to be fully absorbed. Also the level of the trough in output seems to remain broadly stable compared to the previous results. The only exception is BW-DISP, where the inclusion of hours and wages (extension 3) restricts the drop to some –0.3 percentage points.

4.3. Evidence from larger systems

This section reports the dynamic responses of GDP to an uncertainty shock from a specification which mirrors the modelling framework in Bloom (2009) and is replicated by Bachman *et al.* (2013) and Jurado *et al.* (2015). The step means to augment our six-variable system with two additional variables: the harmonized index of consumer prices (*cpi*) and the nominal short-term interest rate (*str*), resulting in a recursive eight-variable VAR system with the following ordering: *esi, unc, str, wge, cpi, hrs, emp, gdp*.

In line with previous findings, an unexpected shock in uncertainty leads to a contraction in real GDP (Panel A of Fig. 4): in the case of FW-DISP, the drop in real activity is clearly short-lived, with GDP forming a trough already two/three quarters after the impulse and, subsequently, following a more or less horizontal path, which is statistically not significantly different from 0. As for BW-DISP, we observe a more pronounced (negative) deviation from the pre-shock level, both in terms of size and persistence, with the (relatively wide) confidence region approaching the horizontal axis only towards the end of the simulation span. Finally, also the specification based on the second real-time measure (IQ-DISP) results in a negative effect of an uncertainty hike on real GDP. The effect is similar to the one of FW-DISP in so far as it is rather short-lived. Deviating from the latter, though, the specification suggests a somewhat smaller drop in GDP due to uncertainty.

To further assess the role of uncertainty shocks for macroeconomic developments, we also control for credit costs. As pointed out by Christiano *et al.* (2014) and Gilchrist *et al.* (2014), credit costs are likely to co-move with uncertainty measures and exert a negative effect on economic activity, which does not stem from uncertainty, but harsher conditions faced by economic agents when seeking for external financing. In view of that, a modelling framework which omits credit variables is likely to overestimate the impact and importance of uncertainty shocks (Caldara *et al.*, 2016). Following Gilchrist and Mojon (2015), our measure of credit costs (*cre*) is constructed by subtracting the Eonia swap rate from the retail bank interest rate for new business.[10]

Panel B of Fig. 4 displays the responses of GDP to an innovation in uncertainty from a nine-variable VAR specification where the recursive ordering is given by the sequence: *esi, cre, unc, str, wge, cpi, hrs, emp, gdp*.[11] Comparing the impulse responses to those in Panel A suggests that including credit costs has little effect on the dynamic response of real GDP: we continue observing that a spike in any of the three uncertainty indicators leads to a statistically significant short-run decline in real GDP, followed by a slow and gradual recovery. In terms of magnitude, the response of GDP to an uncertainty shock gets somewhat lower than in the case of the graphs of Panel A., confirming the conclusions in Gilchrist *et al.* (2014) and Caldara *et al.* (2016) according to which the effect of uncertainty on economic activity is reduced when the underlying empirical setup includes proxies for credit conditions.

4.4. Forecast error variance decomposition

Table 2 shows the contribution of shocks to the three uncertainty measures in terms of the error variance of forecasts of real GDP for the case of the baseline bivariate system, as well as the extensions (three-, four-, six-, and eight-variable models). Panels A, B, and C of Table 2 summarize the results for the FW-DISP, BW-DISP and IQ-DISP variants, respectively. The rows refer to the different extensions of the baseline model, while the columns refer to selected simulation quarters.

A first observation is that, across all indicators and time horizons, uncertainty accounts for a non-negligible share of GDP variation. When looking at the evolvement of the contribution over time (i.e. focussing on a given row of a model), two main tendencies can be discerned: (i) In the case of the real-time measures (FW-DISP and, in particular, IQ-DISP), we

10 The resulting spread displays peaks occurring in accordance with major uncertainty events (like those referring to 2008q4 and 2011q3).

11 As pointed out by Caldara *et al.* (2016), the separation of the underlying structural shocks when both uncertainty and credit costs are included in a VAR framework poses serious difficulties. While not presenting a genuine solution to this intricacy (in fact, further discussion of the identification issue would go beyond the scope of this paper), we have examined an alternative ordering scheme where *unc* comes first, followed by *cre* (while maintaining the same recursive structure for the other variables). Overall, the results (available upon request) are qualitatively similar to those reported in Fig. 4.

Table 2. Forecast variance decomposition

Panel A	FW-DISP			
	Horizon			
	0	4	8	20
Two-variable model	0.14	0.43	0.48	0.51
Three-variable model	0.06	0.27	0.33	0.29
Four-variable model	0.08	0.34	0.40	0.37
Six-variable model	0.05	0.23	0.17	0.10
Eight-variable model	0.11	0.22	0.17	0.14
Panel B	**BW-DISP**			
	Horizon			
	0	4	8	20
Two-variable model	0.17	0.30	0.38	0.48
Three-variable model	0.03	0.10	0.24	0.36
Four-variable model	0.03	0.15	0.30	0.33
Six-variable model	0.11	0.17	0.33	0.33
Eight-variable model	0.11	0.10	0.28	0.41
Panel C	**IQ-DISP**			
	Horizon			
	0	4	8	20
Two-variable model	0.14	0.17	0.15	0.13
Three-variable model	0.07	0.10	0.15	0.13
Four-variable model	0.10	0.15	0.20	0.14
Six-variable model	0.09	0.23	0.22	0.12
Eight-variable model	0.06	0.17	0.19	0.11

Note: Columns identify selected simulation quarters. See also Figs 1–3.

observe a concave development, with the contribution to GDP variability rising to a peak in quarters 4 or 8 and subsequently receding; (ii) As for BW-DISP (Panel B), there is evidence of a somewhat increasing role of uncertainty shocks over the simulation horizon with a remarkable degree of stability across specifications (i.e. across rows).

Turning to the magnitude of the observed uncertainty effects, in the case of IQ-DISP, the share of the contribution to GDP variability appears broadly robust to the model specification (i.e. no major differences between the rows). The evidence from specifications based on FW-DISP suggests that the importance of uncertainty for GDP variability varies somewhat, depending on the number of variables included in the model. The six- and eight-variable models, though, yield results completely in line with those of the IQ-DISP models. At the five-year horizon, uncertainty shocks account for some 10–15% of GDP variability. Compared to the real-time measures, the contribution of BW-DISP appears similar at the beginning of the simulation exercise (up to the fourth quarter), while, at later stages, the share attributable to uncertainty tends to leapfrog that of the real-time

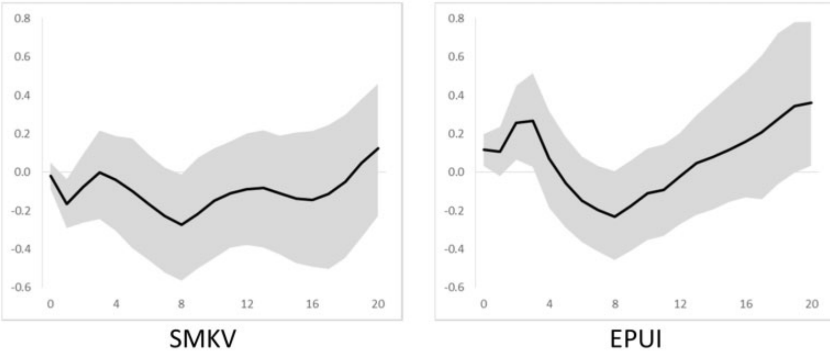

Fig. 5. GDP response to an uncertainty shock, eight-variable systems (alternative uncertainty measures)

Note: SMKV and EPUI are defined in Section 5.1. See also Fig. 4.

measures (to around 30–40%). This goes, in particular, for the six- and eight-variable specifications.

Overall, the results for all three indicators are broadly in line with the observations of Bachmann *et al.* (2013), as well as Jurado *et al.* (2015), who report, for the cases of Germany and the USA, a concave shape of the impact of uncertainty shocks on GDP variability, as well as magnitudes of the effect in the range of 10 to 40% of the variability in economic output (in their cases represented by industrial production).

5. Extensions and robustness

5.1. Comparison with other uncertainty measures

To put the above results into perspective, we re-do part of the analysis, substituting the proposed uncertainty indicators by popular alternative indicators, namely stock market volatility (SMKV), as in Bloom (2009) and, alternatively, the economic policy uncertainty index (EPUI), designed by Baker *et al.* (2015). Figure 5 presents the results from an eight-variable specification, with the ordering of the other variables being the same as that applied in the eight-variable system reported in the previous section. The left and right panels of Fig. 5 refer to an unexpected shock to SMKV and EPUI, respectively.

In response to a positive innovation to SMKV, real GDP drops and remains below zero before exhibiting a mild upward tendency starting around the eighth quarter of the simulation. The deviations from the baseline path are, however, only on the brink of statistical significance. The results from the simulation of a shock in EPUI are rather inconclusive. The immediate aftermath of the shock is characterized by a positive (and statistically significant) deviation from the baseline path, followed by a temporary drop below the pre-shock level and, ultimately, a steep upward movement. While this pattern is partially consistent with the overshooting effect found in Bloom (2009), it differs from the evidence reported in Section 4 above.

Table 3 presents the contribution of SMKV/EPUI shocks (first two lines) to GDP variability at selected simulation horizons, alongside the share explained by the three survey-based measures presented in Section 2 above (see the last three rows in each column of Table 2). We observe that the effect of SMKV/EPUI shocks tends to be considerably smaller

Table 3. Forecast variance decomposition: comparison with alternative uncertainty measures (eight-variable systems)

	Horizon			
	0	4	8	20
SMKV	0.01	0.04	0.11	0.12
EPUI	0.08	0.12	0.08	0.06
FW-DISP	0.11	0.22	0.17	0.14
BW-DISP	0.11	0.10	0.28	0.41
IQ-DISP	0.06	0.17	0.19	0.11

Note: See Table 2 and Figs 4 and 5.

than in the case of shocks to the survey-based measures. In fact, whatever time horizon looked at (i.e. in every column), the smallest contribution to GDP variability is always associated with one of the two standard measures. These results are broadly consistent with the evidence documented for the US economy: As pointed out by Bachmann *et al.* (2013), a possible rationale for the difference between the two groups of indicators in respect of the magnitude of their effect on GDP variability is that SMKV (and EPUI) developments capture uncertainty-related aspects different from the ones covered by survey-based metrics. Especially in respect of the SMKV indicator, one should bear in mind the remark in Jurado *et al.* (2015), according to which SMKV is likely to be driven by factors hardly related to genuine macroeconomic uncertainty.

5.2. Considering alternatives to the standard deviation

While the proposed indicators operationalize dispersion as standard deviation, *sd*, there is a variety of possible alternatives. To test for the robustness of our indicators, we model dispersion, in the case of FW-DISP and BW-DISP, as the index of qualitative variation (*iqv* – Mueller and Schussler, 1961, pp. 177–179) and entropy (*ent* – Senders, 1958, p. 79), rather than condition (1). Regarding IQ-DISP, where the standard deviation is applied when computing the cross-sectional dispersion among survey questions at a given point in time, we check for robustness by using the interquartile range (*iqr*) and the median absolute deviation (*mad*), since they are measures more robust to possible outliers (Leys *et al.*, 2013).[12]

Figure 6 plots impulse responses of euro-area real GDP to innovations in the newly generated uncertainty measures. Continuous black lines as well as the confidence region identified by the grey areas refer to the baseline case (*sd*). In the cases of FW-DISP and BW-DISP, dashed (dotted) lines indicate the responses from models where uncertainty is measured on the basis of *i qv* (*ent*), while, in the case of IQ-DISP, they refer to specifications based on *iqr* (*mad*).

A bird's-eye view of the graphs of Fig. 6 suggests a remarkable stability of the results: in almost all cases the responses from alternative specifications fall in the grey region, closely

12 Our main findings are also robust to further modifications of the baseline setup, notably: (i) the inclusion of a deterministic trend in the deterministic part of the models; (ii) the use of a recursive structure where uncertainty is placed last in the ordering scheme; (iii) the computation of generalized impulse–response functions in place of those based on a recursive scheme; (iv) the extension of the estimation sample over the period 1985–2014. The results of these additional robustness checks can be found in the online Appendix.

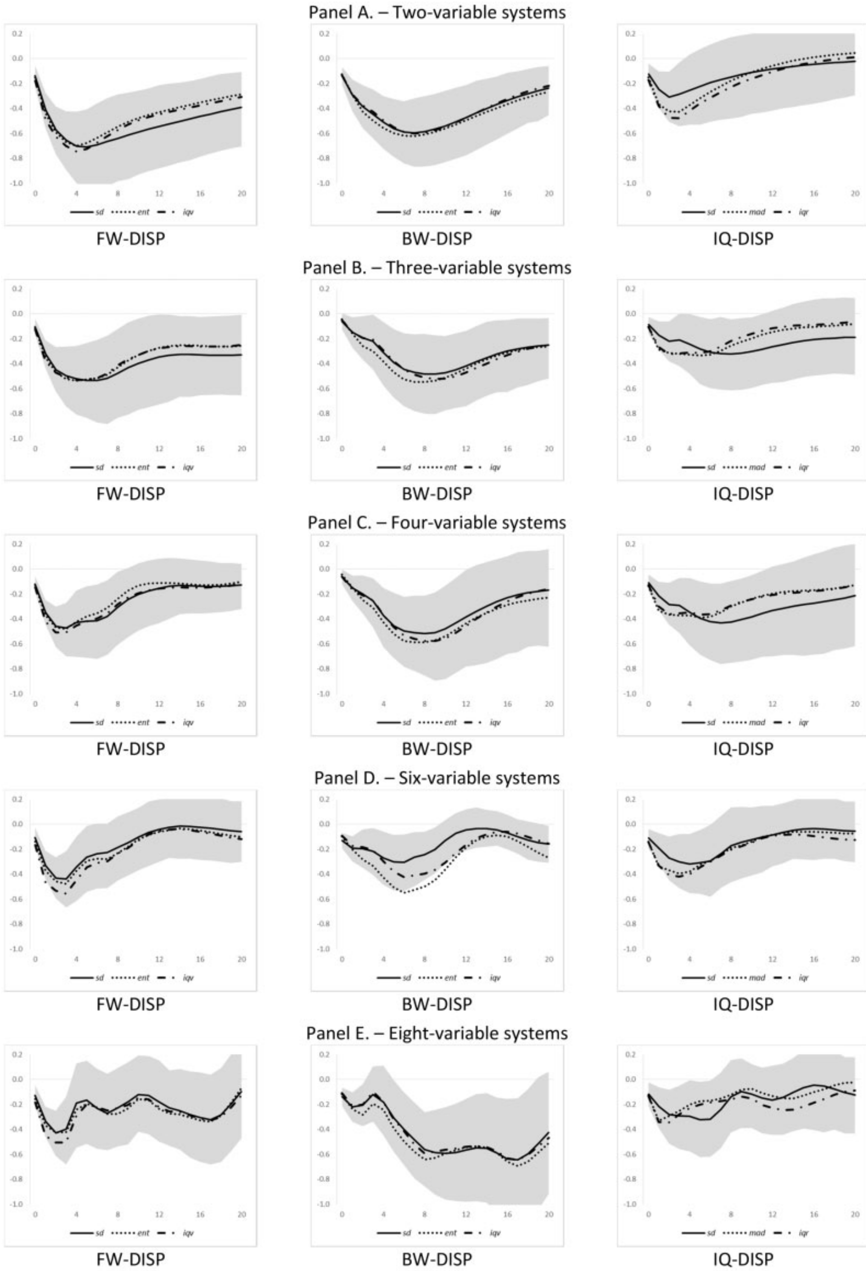

Fig. 6. GDP response to an uncertainty shock, specifications based on uncertainty indicators constructed by using alternative measures of dispersion

Note: Continuous lines refer to FW-DISP, BW-DISP, and IQ-DISP based on the standard deviation (*sd*), as defined in Sections 2.3–2.5. As for FW-DISP and BW-DISP, dashed and dotted lines indicate the responses from models where uncertainty is measured on the basis of the index of qualitative variation (*iqv*) and the entropy formula (*ent*), respectively, while in the case of IQ-DISP, they refer to specifications based on the interquartile range (*iqr*) and the median absolute deviation from the median (*mad*), respectively. See also Figs. 2–4.

Table 4. Forecast variance decomposition (comparison with uncertainty indicators constructed by using alternative measures of dispersion)

Panel A	FW-DISP							
	ent				*iqv*			
	Horizon							
	0	4	8	20	0	4	8	20
Two-variable model	0.18	0.47	0.48	0.46	0.24	0.50	0.51	0.48
Three-variable model	0.08	0.30	0.34	0.26	0.10	0.28	0.33	0.28
Four-variable model	0.10	0.38	0.42	0.32	0.11	0.37	0.40	0.32
Six-variable model	0.09	0.26	0.22	0.14	0.13	0.32	0.27	0.16
Eight-variable model	0.14	0.23	0.18	0.16	0.18	0.32	0.22	0.16
Panel B	**BW-DISP**							
	ent				*iqv*			
	Horizon							
	0	4	8	20	0	4	8	20
Two-variable model	0.13	0.31	0.38	0.46	0.14	0.26	0.34	0.45
Three-variable model	0.02	0.15	0.31	0.40	0.02	0.09	0.22	0.38
Four-variable model	0.01	0.21	0.37	0.40	0.03	0.14	0.32	0.43
Six-variable model	0.06	0.27	0.51	0.40	0.05	0.12	0.30	0.31
Eight-variable model	0.08	0.16	0.37	0.43	0.05	0.07	0.24	0.43
Panel C	**IQ-DISP**							
	mad				*iqr*			
	Horizon							
	0	4	8	20	0	4	8	20
Two-variable model	0.17	0.27	0.23	0.16	0.19	0.31	0.28	0.20
Three-variable model	0.09	0.18	0.20	0.14	0.08	0.17	0.18	0.14
Four-variable model	0.13	0.23	0.25	0.17	0.11	0.21	0.22	0.16
Six-variable model	0.13	0.29	0.28	0.20	0.12	0.30	0.29	0.23
Eight-variable model	0.07	0.11	0.09	0.07	0.08	0.16	0.13	0.13

Note: See Table 2 and Fig. 6.

mirroring the shape of the baseline models. We take this robustness as an encouraging sign adding confidence to the validity of the proposed measures in gauging uncertainty. There are two exceptions to this conclusion: (i) in the case of the six-variable model based on BW-DISP, we observe a much stronger reaction of real GDP to an uncertainty shock when measured using the entropy formula; (ii) as for IQ-DISP, the use of robust measures of dispersion (*iqv* and *mad*) leads to sharper and more temporary drops in real activity compared to the corresponding outcomes of the baselines. Also the results from the forecast error variance decomposition exercise of Table 4 point to a greater role of uncertainty shocks in explaining real GDP volatility compared to the corresponding figures in Table 2. This conclusion holds true for the two real-time uncertainty measures in almost all models and/or simulation quarters; in the case of the variants to BW-DISP, we observe that using iqv in place of *sd* leads to marginal differences, while specifications based on ent tend to magnify the relevance of uncertainty shock for business cycle variability especially in the six-variable model. All in all, the evidence reported in Sections 4 and 5 can be viewed as 'conservative' in the sense that specifications based on *sd* provide a sort of lower bound in comparison to the alternatives considered.

6. Concluding remarks

This paper has presented three survey-based uncertainty indicators for the euro-area economy which can complement existing gauges due to a number of useful properties. First, all proposed measures are based on publicly available data (rather than micro data). Second, the uncertainty indicators resort to broad information sets based on a number of questions inquired from firms operating in several sectors (industry, services, retail trade, and construction) and across consumers.

We have documented that the proposed uncertainty indicators appear to adequately capture major uncertainty-inducing events. The measures are shown to be counter-cyclical with major uncertainty peaks coinciding with periods of low growth. Our evidence shows that shocks to the proposed indicators are quantitatively important drivers of economic fluctuations. Generally, the immediate aftermath of the shocks is associated with (statistically significant) drops in GDP, which gradually fade out over time. Worth highlighting, we do not find any indications of an overshooting effect as reported by Bloom (2009). All conclusions are robust across a large number of alternative specifications of the empirical models. Moreover, survey-based uncertainty indicators are shown to account for a much larger fraction of real GDP variability than popular alternatives (like stock market volatility indices).

Though the empirical evidence suggests the three indicators have a broadly similar behaviour, the practical usefulness of the real-time uncertainty measures (FW-DISP and IQ-DISP) for the purpose of policy-making is arguably higher than that of the *ex post* alternative (BW-DISP). After all, real-time indicators measure the degree of uncertainty prevailing at the point in time, where the indicator is constructed (rather than three months ago) and are thus genuine real-time uncertainty measures. As pointed out by Arslan *et al.* (2015) and Rossi and Sekhposyan (2015), the availability of timely (and reliable) uncertainty indicators could help policy-makers have a clearer picture of the real-time stance of the economy.

It is also worth noting that the proposed uncertainty measures have the particular advantage of not including any variables which are highly country-specific. They can thus easily be applied to measure the level of uncertainty in other economies. Given the status of the EU BCS programme as international best practice, the same or similar survey questions can also be found in a number of extra-EU survey programmes, rendering the extension to other countries/regions straightforward.

Supplementary material

Supplementary material—the Appendix—is available online at the OUP website.

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