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Impact of uncertainty measures on the Portuguese economy

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Abstract
The purpose of this paper is to review developments in a number of uncertainty measures for Portugal and gauge their impact on macroeconomic developments in recent years, particularly on GDP, private consumption and GFCF. Our analysis shows that elevated uncertainty had a significant negative impact on economic activity during the financial and sovereign debt crises, while the unwindinding of uncertainty associated with the conclusion of the economic and financial assistance programme in 2014 boosted the subsequent recovery.

JEL: C32, E27, E32

Keywords: Uncertainty shocks, business cycles, structural VAR.

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1. Introduction

Uncertainty has often been considered a driver of weak developments in advanced economies since the 2008 financial crisis. As a result, the literature on the measurement of uncertainty and the evaluation of the macroeconomic effects of uncertainty has grown in recent years.

Economic uncertainty refers to a situation involving imperfect and/or unknown information about the future of the economy.[1] When deciding on consumption or investment, economic agents must form expectations on relevant future events on the basis of available data. These expectations are affected by uncertainty, to the extent that the likelihood of alternative events is unknown or impossible to gauge with precision. It should be noted that there is always some level of uncertainty in an economy, being an intrinsic feature of the economic cycle. It is the change in uncertainty levels over time that impacts on the decisions of economic agents.

Economic theory suggests that there are three main transmission channels of uncertainty to economic activity.[2] The first channel is through possible wait-and-see effects. Firms and consumers might decide to postpone spending decisions in order to avoid costly mistakes. Firms may also cut back on hiring when faced with higher uncertainty. A high level of uncertainty gives agents an incentive to delay or cancel decisions involving considerable irreversible costs until uncertainty is reduced and more information becomes available, restraining economic activity. This channel is usually referred to as the real option theory to uncertainty, because the option value of waiting in the face of uncertainty increases. Precautionary savings might also be a channel of transmission. Heightened uncertainty about future income may induce households to reduce current consumption in order to increase savings for the future. Finally, uncertainty may also have an impact on economic activity via higher risk premia. In the presence of heightened uncertainty, agents are likely to demand a higher risk premium, which reduces asset prices and pushes up borrowing costs. A potential reduction in the volume of credit may also occur in periods of high and prolonged uncertainty, as banks have less incentive to provide loans.

The empirical literature on the impact of uncertainty suggests that it tends to be detrimental to short-term growth.[3] For the Portuguese economy, there

1. Economists tend to distinguish between uncertainty and risk. Knight (1921) was probably the first to drew the distinction between risk – possible outcomes to which one can assign probabilities (measured or learned) - and uncertainty – outcomes with unknow probabilities or not knowing all the possible outcomes. While anything is possible (which is the essence of uncertainty) everything is not equally probable (which is the essence of risk). In this article, as in much of the empirical literature, we do not distinguish between the two concepts given that in practice they are difficult to disentangle.

2. See Haddow *et al.* (2013) and references herein, and IMF (2012).

3. For a overview, see Bloom (2014).

is little evidence on this link between uncertainty and economic activity.[4] Therefore, the purpose of this article is to present a set of uncertainty measures specific to the Portuguese economy and to assess how uncertainty matters for economic developments in Portugal.

The article is organised as follows. The next section presents and analyses some commonly used proxies of uncertainty applied to the Portuguese economy. In the methodology section we describe the structural Bayesian vector auto regression (BVAR) models used to quantify the impact of shocks to these uncertainty measures on economic activity, investment and private consumption in Portugal. The main results are discussed in the results section. The last section summarizes the main findings of the article.

2. Uncertainty indicators

An empirical assessment of the relationship between uncertainty and economic activity requires a quantification of uncertainty. Uncertainty cannot be directly observed but a number of measures have been proposed in the empirical literature, based on different methods and data. These measures can be classified into three main groups, which emphasize distinct aspects of uncertainty. A first group of measures is finance-based, relating mainly to volatility in financial markets. Financial market participants' expectations about the outlook of the economy are reflected in equity prices, bond yields and exchange rates. Thus, low volatility in these markets should be an indication of stable expectations, while high volatility should indicate that financial market participants are more uncertain about future economic developments. Some other measures take into account the prevalence of certain terms related to economic uncertainty in news publications. Alexopoulos and Cohen (2009) consider this newspaper based approach to identify uncertainty shocks as similar methodologically to the use of narrative to identify monetary policy shocks or the reliance on magazines and newspapers to pinpoint fiscal policy shocks. Finally, a third group of measures focuses on the disagreement of professional analysts' forecasts for selected macroeconomic aggregates or among survey participants' expectations regarding firm sales or sectoral output. The rationale is that expectations about the future should be more diverse in times of high uncertainty than in times of low uncertainty, when agents should broadly share the same outlook.

4. Schneider and Giorno (2014) present a comparative analysis of the impact of uncertainty in Greece, Portugal and Ireland using as uncertainty measure stock market volatilities, which limits its comprehensiveness. Gunnemann (2014) develops national economic policy uncertainty indices, based on newspaper news, for nine European countries, including Portugal, and studies their impact on industrial production and unemployment.

Each group of measure has its own pros and cons, they are imperfect and partial ways of assessing economic uncertainty. Measures based on financial markets volatility have the advantage of being timely. However, they can move regardless of changes in uncertainty, including as a result of increasing risk aversion of economic agents, and might be a narrow indicator, failing to capture uncertainty shocks relevant to the broader economy. News-based uncertainty indexes have the advantage of better representing the degree of uncertainty felt by the general population. As phrased by Alexopoulos and Cohen (2009), press coverage is likely to be more important for perceptions of uncertainty on "Main Street", rather than financial volatility which primarily is directly observed on "Wall Street". Caveats to newspaper-based measures relate to accuracy and potential bias. Finally, measures based on the dispersion of forecasts or survey responses can also have a more direct link with the real economy but the problem is that they may not capture only uncertainty but also disagreement. Each forecaster/survey respondent could be extremely certain, but there could still be a high degree of disagreement (and vice versa). In spite of these caveats, the uncertainty proxies proposed are expected to provide a useful guide to the true degree of uncertainty in the economy. In this article we atempt to use uncertainty measures for Portugal from these three groups.

In the first group, we consider two measures for Portugal. Both are built on the methodological concept of the Composite Indicator of Systemic Stress (CISS-EA) from Holló *et al.* (2012) who apply basic portfolio theory to the aggregation of market-specific stress indicators into a composite index.[5] One of the indicators considered is the composite indicator of financial stress for Portugal (acronym **ICSF**) from Braga *et al.* (2014). The ICSF takes into account individual indicators of financial stress such as realised asset return volatilities and risk spreads in several relevant domestic financial markets (stock, bond, money, exchange rate and financial intermediaries markets) as well as the correlation between them. The other indicator is narrower in scope, measuring only stress in sovereign bond markets in Portugal (**SovCISS-PT**). It integrates measures of credit risk, volatility and liquidity into an overall measure of sovereign systemic stress indicator.[6] The SovCISS-PT is compiled by the ECB.[7]

In the second group of measures, which rely on the frequency of press references to terms relating to economic uncertainty, we tested the relevance

5. The indicators represent a correlation-weighted average of individual stress indicators, with correlation-weights which vary over time. The basic idea is that the overall level of systemic stress increases with a stronger correlation between various stress symptoms, all else being equal.

6. See Garcia-de Andoain and Kremer (2016) for methodological details.

7. Monthly updates of the SovCISS for the euro area as a whole (SovCISS-EA) and individual euro area countries can be obtained from the ECB´s Statistical Data Warehouse: http://sdw.ecb.europa.eu/browse.do?node=9551138.

of three indicators. The first is the well-known index of economic policy uncertainty for Europe (**EPU**) from Baker *et al.* (2016), which is based on searches for keywords in the press, counting each month the number of newspaper articles which simultaneously contain terms having to do with economy, economic policy and uncertainty.[8] While the indicator is for Europe, we will test its relevance for Portugal, which can be expected to be high given Portugal's small open economy characteristics, its degree of integration (euro area and EU) and its exposure to economic and political developments at the European level. Gunnemann (2014) has compiled a comparable indicator for the Portuguese economy (**EPU-PT**), but information for recent years is not available. Finally, it is possible to build an alternative indicator for Portugal by computing an EPU trade-weighted indicator (**EPU-TW**), by taking the weighted average of national EPU indices for six European countries (France, Germany, Italy, Spain, the United Kingdom and Ireland), where weights correspond to the share of these countries in Portuguese exports.

Finally, in the third group, we constructed three uncertainty survey-based indicators for Portugal in line with the approach of Girardi and Reuter (2017) by exploiting the information of the European Commission Business and Consumer surveys (European Commission (2017)).[9] These indicators rely on the idea that divergence in respondents' expectations may be interpreted as an indication of uncertainty, which is thus measured directly at the level of economic agents making decisions on investment and consumption expenditures. The first measure (**UNC1**) is based on the dispersion of positive and negative answers to forward-looking survey questions. The rationale is that consumers (or enterprises) can be expected to have broadly similar expectations about future developments in times of low uncertainty, while an increasing dispersion of expectations indicates rising uncertainty. In a first step, as in

8. Some authors have proposed the use of measures of policy-related uncertainty based on the volume of Google searches (see Donadelli (2015) and Bontempi *et al.* (2016)). The idea behind these measures is that internet users manifest their uncertainty by searching for specific words with greater frequency. However, the evidence suggests that these Google-search-based uncertainty metrics are closely related to the standard indexes of economic policy uncertainty developed by Baker *et al.* (2016).

9. The European Commision Business and Consumer Surveys include questions to companies about their assessment of developments in production, order books, employment, etc., while consumers are asked about their views on their personal financial situation (e.g. their intentions to save or consume), as well as about macroeconomic developments (unemployment, prices, etc.). The survey questions the present situation, developments over the past three, or expectations for the next three months. In the case of the consumer survey, the time horizon covered by the questions referring to the past and the future is twelve months. Once collected, the replies to each question are summarised in the form of balances. The answers to the questions in the business surveys fall into three main qualitative categories: "positive", "negative" and "neutral". If $Fraction^{+}$, $Fraction^{=}$ and $Fraction^{-}$ (with $Fraction^{+} + Fraction^{=} + Fraction^{-} = 100$) denote the percentages of respondents having chosen respectively the option positive, neutral, and negative, the balance is calculated as $Balance = Fraction^{+} - Fraction^{-}$.

Bachmann *et al.* (2013) and Girardi and Reuter (2017) we calculate the cross-sectional standard deviation of the share of positive and negative responses for every survey question q and month t as follows:

$$DISP_{q,t} = \sqrt{Fraction^{+}_{q,t} + Fraction^{-}_{q,t} - (Fraction^{+}_{q,t} - Fraction^{-}_{q,t})^2} \quad (1)$$

where Fraction^{+} is the fraction of respondents with positive responses to question q at time t and Fraction^{-} is the equivalent for negative responses.[10] The question-specific dispersions are standardized so as to have zero mean and unit standard deviation. This standardisation is essential to make the individual component series comparable in terms of both their mean level and volatility before aggregation. Girardi and Reuter (2017) compute an aggregate measure by simply taking the average of all standardized series. We refer to this measure as **UNC1A**. Alternatively, we computed first an uncertainty index for each sector (manufacturing, services, retail trade and construction) and for consumers, by averaging the standard deviations series in each survey.[11] We then aggregated these sectoral and consumer uncertainty indexes into an economy-wide uncertainty indicator (**UNC1B**), by taking a weighted mean which uses the weights of the Economic Sentiment Indicator. The second measure (**UNC2**) takes advantage of the fact that the surveys contain a number of questions inquiring about expectations and retrospective assessment of some variables. The proposed indicator takes advantage of the difference between drivers of dispersion in the answers to these pairs of forward and backward-looking questions. While dispersion in answers to forward-looking questions can be influenced by uncertainty and other factors (namely, heterogeneity and disagreement), dispersion in answers to backward-looking questions should not reflect uncertainty. In practice, the indicator involves scaling the dispersion of answers to the forward-looking questions, as inquired in a given month, by the dispersion of answers to the corresponding backward-looking questions, as inquired some months latter, which can be interpreted as a measure of the extent of uncertainty, expressed as a share of the "natural" dispersion across the economy. The construction of the UNC2 indicator requires, in a first step, the computation of dispersions for the forward- and backward looking versions of each question as in equation (1) and, subsequently, the calculation of the change in dispersion according to:

$$DISP_{c,t} = ln \frac{DISP^{fw}_{c,t}}{DISP^{bw}_{c,t+x}} \quad (2)$$

10. In the consumer survey, there are five main categories of response: "very positive", "positive", "very negative", "negative" and "neutral". In this case, Fraction^{+} is computed by summing the fraction of very positive answers with the fraction of positive responses (similarly for Fraction^{-}).

11. We only included in each aggregated index the question-specific standard deviations that were negatively correlated to GDP growth.

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 is the number of months in the case of questions referring to business surveys and x=12 for consumer surveys. All resulting time series are standardized to equalize their means and degree of volatility and, in a second step, the indicator UNC2 results from averaging across all these series. The main downside to uncertainty proxy UNC2 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. The third measure of uncertainty (**UNC3**) proposed by Girardi and Reuter (2017) is based on the idea that a high degree of uncertainty might not only manifest itself in respondents giving very diverse answers to a given question, but also in the resulting balance scores diverging across different questions (increased dispersion across questions rather than within questions). In times of certainty, we can expect that the assessment of most variables should be more or less commonly shared, i.e. businesses should have a favourable assessment of output, orders, stocks etc. ("everything gets better"), while the opposite should be true in times of uncertainty, when the dispersion of balance scores regarding these questions can be expected to increase. This UNC3 measure is derived, first, by computing the changes in balance scores in a given month compared to the previous three months across all questions in the surveys, second, by standardizing all resulting time-series and, finally, by calculating the standard deviation across all questions' changes.

The individual measures can also be combined in a synthetic indicator, better able to capture the underlying uncertainty process in the economy by smoothing away the noise inherent to any particular measure. The synthetic index of uncertainty for Portugal (**SIU-PT**) aggregates four of the above listed proxies, namely the ICSF, EPU, UNC1B and UNC3, which were chosen because of their timeliness and to cover the three categories of uncertainty measures. The index is a weighted average of the standardized components, where the weights are 1/3 for the ICSF, 1/3 for the EPU and 1/3 for a simple average of the two survey-based measures UNC1B and UNC3.

Figures 1-5 present all the above described uncertainty proxies for Portugal.[12] As there is no track record of "known" uncertainty levels for the Portuguese economy, with which to compare the evolution of the uncertainty indicators, a graphical inspection can therefore only assess whether that evolution is plausible. Thus, we start by checking whether the peaks in the uncertainty indicators coincide with potentially relevant political/economic events, both domestic and international. The shaded areas in the charts identify

12. Standardised variables were used, i.e. net of the average and divided by the standard deviation computed over the sample period.

Uncertainty measures for Portugal

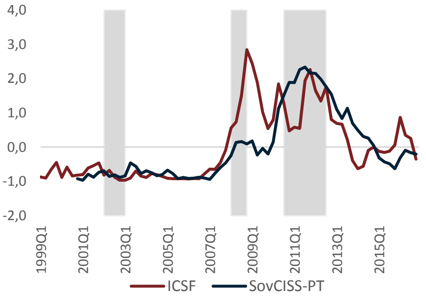


FIGURE 1: Based on financial markets data

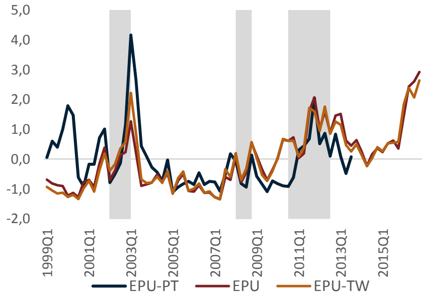


FIGURE 2: Based on newspaper data

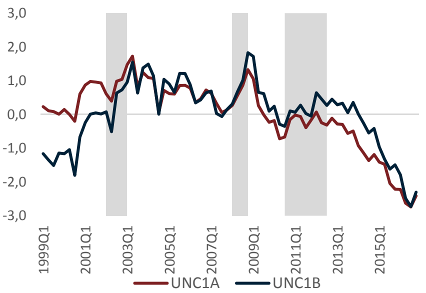


FIGURE 3: Based on survey data

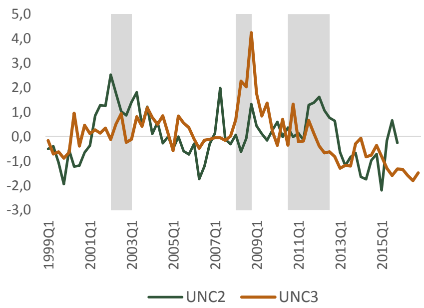


FIGURE 4: Based on survey data

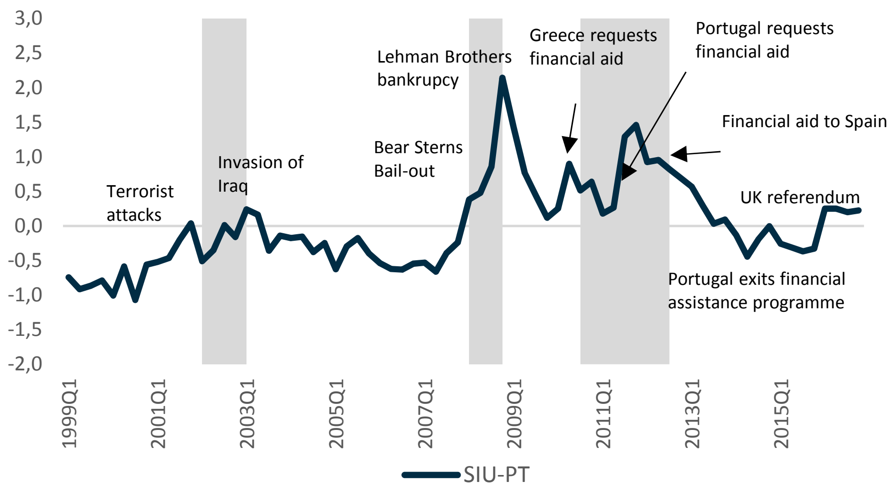


FIGURE 5: Synthetic indicator of uncertainty

the last three recessions in Portugal, with the last two being also observed in the euro area.

At a first glance, the measures look reasonale. They appear to capture the major uncertainty-enhancing events of the past fairly well, although to varying degrees. The ICSF and the SovCISS-PT remained at a low level for a prolonged period (from 1999 until 2007), but reacted rather strongly during the global financial crisis in 2008 and the euro area sovereign debt crisis (starting in 2010), hinting at the systemic nature of these crises (Figure 1). The SovCISS-PT points to a bigger and more lasting effect of the sovereign crisis. EPU, EPU-PT and EPU-TW exhibited some spikes at the occasion of shocks such as the 9/11 terrorist attacks and the Gulf war in 2003 (Figure 2). These news-based measures rose only moderately during the global financial crisis, but reacted more significantly during the euro area sovereign debt crisis. It is sensible that economic policy uncertainty indicators are better able to capture the rise in uncertainty in this period, as the sovereign debt crisis gave rise to questions as regards the euro area institutional framework. Measures of economic uncertainty based on the dispersion of survey responses show a somewhat different pattern than other sub-indices (Figures 3 and 4). They reacted relatively strong to the global financial crisis but much more moderately to the euro area sovereign crisis (except UNC2). Finally, the synthetic indicator of uncertainty, while spiking in all major uncertainty shocks, registered the largest peaks during the global financial crisis and the euro area sovereign crisis. The SIU-PT rose by more than two standard deviations from its mean in late 2008 and by one and a half standard deviations in the last quarter of 2011 (Figure 5).

The different nature of the indicators might help explain their diverging performances in the most recent period. The EPU and the EPU-TW started rising in 2015, in the context of the Greek crisis, and spiked strongly in early 2016, likely reflecting first a relatively negative review of the European banking sector as well as the European immigration crisis and, subsequently, the consequences of the UK's referendum. It has remained elevated since, which can be associated to uncertainties regarding Brexit as well latent political risks in view of recent and upcoming elections in several countries. The indicators stood at maximum levels in the end of 2016. Uncertainty, measured by financial stress indicators (ICSF and SovCISS-PT), also rose in the begginning of 2016, but comparatively less, and has since subsided. Regarding the survey-based uncertainty proxies (UNC1 and UNC3), they point to a persistent reduction of uncertainty in mid-2014, an effect that may have been potentiated by the conclusion of the Economic and Financial Assistance Programme. At the end of 2016, both measures were substantially below their historical average levels. The synthetic indicator SIU-PT points to some elevation in economic uncertainty in early 2016 and subsequent stabilization in the remaining of the year, at slightly above average levels.

Uncertainty measures for Portugal - Comparison with euro area

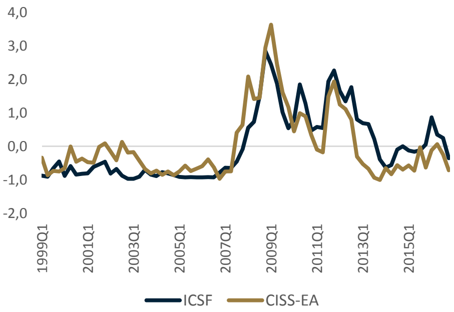


Figure 6: ICSF/CISS

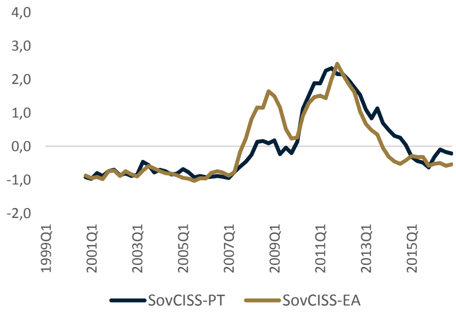


Figure 7: SovCISS

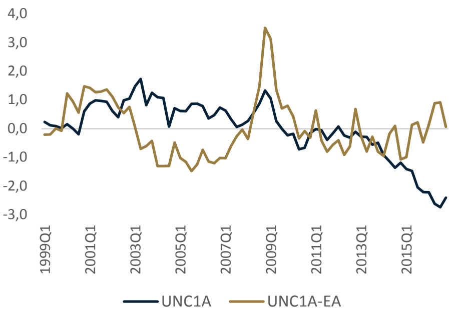


Figure 8: UNC1A

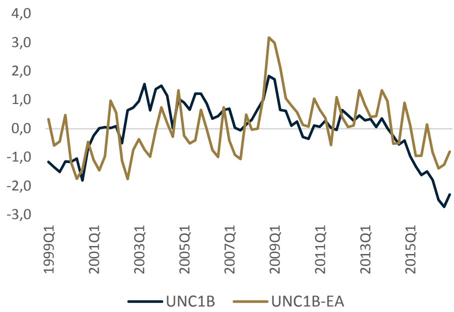


Figure 9: UNC1B

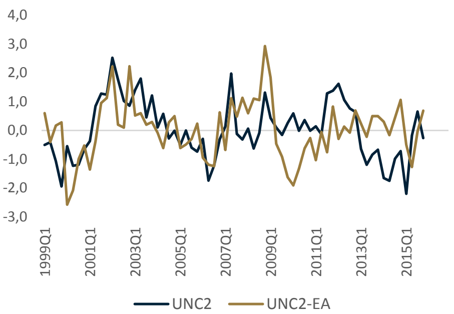


Figure 10: UNC2

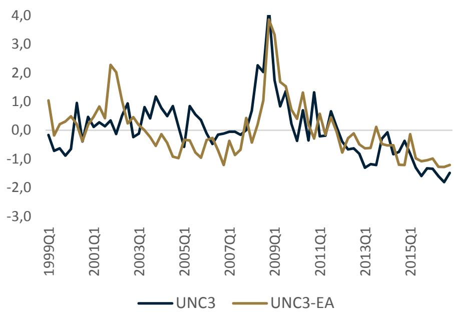


Figure 11: UNC3

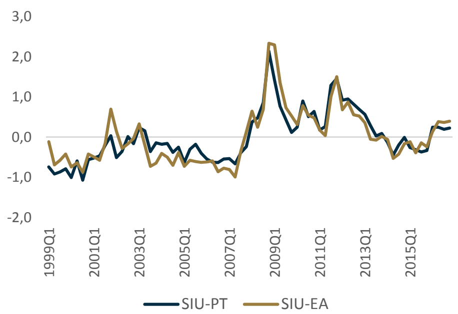


Figure 12: Synthetic indicator of uncertainty

Uncertainty appears to have a countercyclical association with real gross domestic product (GDP). Figures 1-5 show that uncertainty, proxied by the various measures, tends to increase during recession periods and to fall in periods of stable growth. Table 1 shows that all indicators of uncertainty for Portugal display a negative correlation with GDP growth as well as with gross fixed capital formation (GFCF) and private consumption, either expressed in quarter-on-quarter or year-on-year rates.

Figures 6-9 compare the uncertainty measures constructed for Portugal with similar measures for the euro area, revealing that the recent evolution of uncertainty in Portugal has been strikingly similar to that in the euro area. The main exceptions concern measures UNC1A and UNC2. The later appears as the only survey-based indicator pointing to higher uncertainty levels in Portugal than in the euro area during the period of the sovereign crisis. The SovCISS measure for Portugal shows a much bigger rise during the sovereign crisis than during the financial crisis, while the two episodes generated comparable increases in the euro area measure. The deeper and longer impact of the debt crisis in Portugal, as in other vulnerable sovereigns in the euro area, likely explains the much bigger rise in uncertainty (as measured by SovCISS) during this period. The high correlations of the indicators with similar measures for the euro area suggest that global common factors have been the important drivers of uncertainty in Portugal.

	GDP		GFCF		Private Consumption	
	yoy rate	qoq rate	yoy rate	qoq rate	yoy rate	qoq rate
ICSF	-0,63	-0,51	-0,53	-0,33	-0,60	-0,50
SovCISS-PT	-0,56	-0,46	-0,56	-0,34	-0,64	-0,53
EPU	-0,47	-0,36	-0,45	-0,20	-0,44	-0,32
EPU-TW	-0,49	-0,39	-0,48	-0,23	-0,45	-0,34
EPU-PT	-0,22	-0,19	-0,30	-0,17	-0,23	-0,21
UNC1A	-0,08	-0,12	-0,15	-0,12	-0,11	-0,11
UNC1B	-0,46	-0,35	-0,39	-0,20	-0,41	-0,28
UNC2	-0,33	-0,34	-0,44	-0,32	-0,39	-0,44
UNC3	-0,14	-0,32	-0,07	-0,12	-0,08	-0,18
SIU-PT	-0,74	-0,64	-0,64	-0,36	-0,68	-0,56

Table 1. Correlations between measures of uncertainty and macroeconomic aggregates

3. Methodology

The connection between the uncertainty indicators presented and economic activity can be best described with models that explore the mutual interdependence between these variables, without imposing *a priori* a causal relationship. Vector Autoregression (VAR) models are a common used tool for this purpose, in particular when estimated using Bayesian techniques that reduce the overfitting problems of traditional VAR models. Therefore, the importance of uncertainty to macroeconomic developments was estimated on the basis of structural Bayesian Vector Autoregression (BVAR) models,[13] along the lines of Meinen and Röhe (2016) and European Commission (2015). The structural decomposition of shocks was based on the Cholesky method, which is standard in the literature (ECB (2016)). The macroeconomic variables considered were those for which the channels of uncertainty transmission are better and more often identified in the literature, namely GDP, GFCF and private consumption (see Haddow *et al.* (2013) and references herein).

The models for each macroeconomic variable were initially estimated in a baseline version that includes a number of regressors that are typically considered in the literature. This version was then re-estimated by adding one uncertainty measure at a time, which was placed firstly in the Cholesky ordering, i.e., uncertainty is assumed to affect contemporaneously all other variables in the model. This assumption is also in line with the most common option in the literature. Finally, a third version was estimated including, along with each uncertainty variable, a measure of private sector leveraging, proxied by the relevant stock of credit.

Thus, the first baseline model includes as covariates[14] GDP, inflation, employment, the stock of loans to households and non-financial corporations (as proxy for indebtedness levels) and the short-term nominal interest rate. In the case of GFCF, the set of covariates in the model is similar, with the inclusion of GDP and the exclusion of employment and the proxy for household indebtedness as determinants. Finally, the last baseline model includes private consumption, inflation, disposable income, the short-term interest rate and a measure of the stock of total wealth (composed of housing and financial wealth) and the stock of credit to households.[15]

13. Models were estimated using the MATLAB-based toolbox presented in Dieppe *et al.* (2016).

14. The order according to which the variables are presented here describes the Cholesky ordering of the variables in the model.

15. Some authors, like Girardi and Reuter (2017) or Haddow *et al.* (2013), also include in their estimated VARs a confidence measure given the observation that rises in uncertainty measures tend to coincide with reductions in confidence. Thus, there is the possibility that these measures may be capturing the effect of changes in confidence and not uncertainty shocks. However, the authors report that controlling for changes in confidence does not change results significantly, and therefore this avenue was not pursued.

In order to enrich and increase the robustness of the analysis, a set of variants of the models were estimated. Namely, all the models were estimated both in levels and in differences, whereas in the latter case a standard BVAR and a mean-adjusted VAR model were considered. The mean-adjusted VAR allows the determination of priors on the steady state of the model (in this case determined by the constants in the equations), avoiding unreasonable results.[16] In addition, all models are estimated with one up to four lags. Results, available upon request, show that on the basis of the loglikelihood of the model (a criteria which actually tends to favour more lags (StataCorp. (2015)) the optimal choice of lags is overwhelmingly one and never more than two, possibly due to the short sample size. Therefore, for simplicity, all the results presented refer to models with one lag. Another robustness check involved estimation for two subsamples. The first ranges from 1999Q1 to 2007Q4, thus excluding both the great recession and the euro area sovereign debt crises, while the second ranges from 1999Q1 to 2010Q4, therefore excluding just the euro area sovereign debt crisis.[17] This robustness test is relevant given that the estimated impact of uncertainty depends crucially on the presence on the estimation sample of large changes in uncertainty levels, which for the majority of the indicators considered are precisely those associated with the last two recessions mentioned. Therefore, in some cases, estimation on the basis of a sample up to 2008 only will imply a response of macroeconomic variables to uncertainty without the expected sign or strongly non significant. In the case of SovCISS-PT and the UNC2 this holds also when the sample is extended to 2010, given that they generate responses to the uncertainty shocks which are positive on impact. Therefore results for these indicators are not presented, being available upon request.

Following Banbura *et al.* (2015), the majority of variables are expressed in logs (with the exception of the interest rate, which is in levels), and for the model in differences, the variables are expressed as annualized quarter-on-quarter rates of change. Uncertainty indicators are expressed in levels in both types of models, also as in Banbura *et al.* (2015) and following a preliminary analysis that shows that the correlations with the year-on-year rates of change of macroeconomic variables are maximized when uncertainty indicators are expressed in levels.[18]

16. For more details on the methodology, see Jarocinski and Smets (2008) and Dieppe *et al.* (2016). The necessary priors on the constants of the model were defined in a naïve way as an the interval centered on the sample average with length given by twice the sample standard deviation.

17. There are exceptions to these estimation samples, and to the samples available for conditional forecasts evaluation, namely for the models which include the SovCISS-PT (available only from 2000Q4 onwards) and the EPU_PT and UNC2 (available only up to 2013Q3 and 2015Q4, respectively).

18. Although the models were estimated in levels and in first differences of the variables, the focus of result presentation will be year-on-year rates of change, given the volatility of the some of the variables, namely GFCF.

Formally, the estimated model is given by:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + C x_t + \varepsilon_t \quad \text{where t = 1, 2,... T} \tag{3}$$

Where $y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})$ is a $n \times 1$ vector of endogenous variables at time t, $B_1, B_2, ..., B_p$ are $n \times n$ matrices, C is a $n \times m$ matrix and x_t is a vector of exogenous variables, that in this case only includes the constant.

$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{nt})$ is a vector of residuals that follows a multivariate normal distribution: $\varepsilon \sim N(0, \Sigma)$.

Following the BVAR methodology, and a choice of priors relatively standard in the literature (see for example Meinen and Röhe (2016)) it is assumed that the vector of parameters β and the residual variance covariance matrix Σ follow a Normal multivariate distribution and a Normal Inverse Whishart distribution respectively:

$$\begin{aligned} \beta &\sim N(\beta_0, \Omega_0) \\ \Sigma &\sim IW(S_0, \alpha_0) \end{aligned} \tag{4}$$

The hyperparameters that characterize the distributions above are chosen according to standard values in the literature.[19]

4. Results

4.1. Conditional forecasts

In order to access how uncertainty could have helped explain the path of GDP, GFCF and consumption in the recent past, a conditional forecast analysis was performed with the BVAR. The conditional forecasts are obtained by constraining the path of all the variables to the observed one, with the exception of the macroeconomic aggregate of interest in each case. This allows for an assessment of the counterfactual path for these variables given by the model and to what extent the inclusion of uncertainty and leveraging indicators in the model would aproximate this path from the actual one. This exercise was performed in Ciccarelli and Osbat (2017) to analyse inflation developments and is applied to the impact of uncertainty in European Commission (2015). Therefore, models are estimated for a subsample and an

19. In particular, the overall shrinkage parameter, $\lambda_1 = 0.1$; the cross-variable specific variance parameter, $\lambda_2 = 1$; the scaling coefficient for convergence speed of lags greater than 1, $\lambda_3 = 1$ and the variance parameter for exogenous variables, $\lambda_2 = 100$. The autoregressive coefficient in the expected value for β is set to 0.8. The cross-variable variance of parameters is estimated with the results of OLS regressions of an univariate AR(1). For more details, see Dieppe *et al.* (2016).

out-of-sample forecasted path for each macroeconomic variable in question is computed on the assumption that the path of all other variables is known. The relative performance of all models is evaluated on the basis of their ability to improve the root-mean squared error (RMSE) of the conditional forecasts for the year-on-year rate of change of the macro variable vis-à-vis the baseline model during the financial and sovereign debt crises and the ensuing recovery.

Tables (A.1) and (A.2) in the Appendix show the relative (vis-à-vis the baseline) RMSE of the estimated models for the forecasts of year-on-year rates of change, in the case of the subsamples ending in 2007 and 2010, respectively. Results for RMSE levels, available upon request, give rise to some preliminary conclusions.

For models in first differences, the use of mean-adjusted VARs gives rise in general to lower RMSE, particularly for the post sovereign crisis period. Therefore only these results will be presented. However, models in levels are clearly preferred to models in differences, except for the GFCF in the post sovereign crisis period. Therefore the remaining analysis will be focused on results for models in levels, although the models in differences confirm that uncertainty indicators (at least in some cases) improve conditional forecasts for all macroeconomic aggregates considered.

In addition, a longer estimation sample originates in general lower RMSE for conditional forecasts of the sovereign crisis and posterior period, reinforcing the theory that a major uncertainty event in the estimation sample is necessary to identify the impact of these indicators on the macroeconomic variables. There is however an exception in the case of GFCF, for which models estimated only up to 2008 perform better.

Results in tables (A.1) and (A.2) are rather consistent for both estimation samples used and show that the inclusion of uncertainty variables in the models improves the conditional forecasts in some cases (highlighted with shading), specially in the post-sovereign crisis period. In the case of consumption, however, improvements in forecasts take place mostly over the 2008-2010 period. Gains in forecasting performance happen with the addition of uncertainty indicators to the baseline model in the case of GDP and consumption, while in the case of GFCF relative gains are smaller and are mostly present when leveraging indicators are also included in the model. This conclusion, identical to the one in European Commission (2015), does not mean that uncertainty is not a driver of GFCF, but that it does not appear to have been a major factor accounting for the insufficiency of GDP and the other variables in the model in explaining the drop in investment over the two recessions under analysis. Another possibility is that the relevant uncertainty factors for GFCF decisions are more idiosyncratic than the ones captured by most of the indicators in this article, which appear to capture essentially supranational phenomena.

This hypothesis is strengthened by the choice of the "best" uncertainty indicators, i.e., those that generate lower RMSE. In the case GDP it appears to be the ICFS for both estimation subsamples, in the model version that does not include leveraging variables. The trade weighted EPU is the second best indicator for the 1999-2010 subsample. Figures (A.1) and (A.2) show the median conditional forecast for the model versions that include the ICFS indicator. The base model forecasts tend to overestimate GDP growth in 2012-2014, and the presence of the uncertainty indicator partly explains the weaker recovery than in the baseline. In the case of the EPU_TW, the RMSE gain of the model with uncertainty is very marginal and concentrated in 2012-2013. In both cases the model version with leveraging indicators would imply a much lower GDP over the sovereign debt crisis period and therefore this type of model does not lead to an improvement in conditional forecasts vis-à-vis the baseline.

For GFCF, and focusing on the 1999-2007 subsample, given that it gives rise to lower RMSE, the best indicator in relative terms is EPU_PT, when credit variables are included in the model. However, because this indicator is only available up until 2013Q3, the second best indicator, UNC1A, is also presented.[20] However, most survey based indicators provide similar results. Charts (A.3) and (A.4) show conditional forecasts for the models that include these two indicators. In the case of the EPU_PT, the inclusion of uncertainty and leverage variables approximate conditional forecasts from actual outturns over 2011, while worsening the performance of the model over the great recession. The evolution of the model including the UNC1A is virtually the same as EPU_PT over the sovereign crisis period.

Finally, in the case of consumption, the greatest improvement in conditional forecasts takes place for the great recession period when credit and uncertainty indicators are included in the model. For the sovereign crisis period, in contrast, improvements in conditional forecasts, which are much more modest, take place when only uncertainty indicators are added to the model. For both estimation samples, a common feature is that the uncertainty indicators that improve the conditional forecasts for the sovereign crisis period are derived from surveys or correspond to the synthetic indicator. In particular, UNC3 stands out as the indicator that improves the RMSE of the model in relative terms more significantly, although all survey based indicators provide approximately the same results. Therefore, figures (A.5) and (A.6) show the results for the conditional forecasts obtained with the models that include UNC3 and SIU. Both figures show that the contracfatual path for consumption obtained with the uncertainty plus leverage model substantially approximates the decline of consumption in 2008-2009, while for the sovereign debt crisis credit variables do not appear to help explain the fall. For this subperiod, the inclusion of uncertainty in the model slightly accentuates the reduction in consumption

20. Over 2011Q1-2013Q3, the conditional forecast errors for EPU_PT and UNC1 are identical.

over 2011-2012 and the following recovery when compared to the base model, but this gain is very marginal.

In summary, the financial-based and media-based uncertainty indicators appear to be the most helpful for explaining GDP developments, while in the case of the GFCF and private consumption the prefered indicators are survey-based (in the case of GFCF, the media-based indicator EPU_PT seems promising, but the available sample is limited). This possibly results from the fact that GFCF and private consumption require more specific information that is contained in the survey indicators, which reflect directly the opinion of managers and consumers.

Results in terms of additional gains in explaining the GDP decline over the last two recessions by including uncertainty indicators (and in some case leverage measures) seem to be relatively limited, which suggests that there is still a large part of economic developments over this period that can not be explained with this set of models/variables. Actually, uncertainty and leverage indicators appear to be more useful in explaining the slow recovery than the large decline in macroeconomic aggregates. One possibility for these relatively limited gains in RMSE is that more uncertainty episodes of large scale are necessary for the model to estimate accurately the impact of uncertainty in the economy. This result is observationally equivalent to the possibility that the impact of uncertainty for macroeconomic developments has increased since the great recession (an hypothesis supported by European Commission (2013)). To assess this possibility, conditional forecasts were recalculated for the case in which the model coefficients were estimated with the full available sample. Results, summarized in Table (A.3), show that gains in relative RMSE for all macroeconomic aggregates are larger and more broad based across uncertainty indicators. Another relevant feature is that although the addition of uncertainty indicators to the models increases in general their performance, results are further enhanced when leverage indicators are also included. This suggests that indebtness issues where determinant during the sovereign debt crisis and subsequent recovery.

As regards indicator selection, conclusions to do not change significantly when compared to those obtained with the out-of-sample conditional forecasts, given that the best performing indicators are the same for GDP, and for GFCF and private consumption these are still survey-based indicators, and, in the latter case, also the SIU.

4.2. Impulse response functions

This subsection focuses on the quantification of the impact of uncertainty indicators through impulse response functions (IRF) and historical decompositions, obtained with models estimated with the full sample. Results are presented for models that include both uncertainty and leverage indicators, but are very similar for the models that include only uncertainty indicators.

Figures (B.1) to (B.3) display the IRF of the level of each macroeconomic aggregate (in percentage points) to a standard deviation structural shock associated with uncertainty. These are statistically significant for the majority of indicators, specially over the first half of the impulse response function.

In the case of GDP, the impact of the shocks is similar across most indicators, and also not very different in magnitude from the results obtained by Girardi and Reuter (2017) for the euro area, Meinen and Röhe (2016) for the largest four euro area countries and Gil *et al.* (2017) for Spain. The magnitude of the maximum response to an uncertainty shock is also similar to the one obtained for Portugal by Gunnemann (2014), although in that case economic activity is proxied by industrial production and results are not significant. As regards Schneider and Giorno (2014) results for Portugal, information on the exact size of the shock considered is unavailable, but the cumulative impact on the level of GDP over the financial crisis seems to be much smaller than the one described in the next subsection, possibly because the scope of the uncertainty measure considered is too limited. In the case of GFCF and private consumption, while the ICFS and the media-based indicators generate similar IRF, these are in general much weaker for the survey-based indicators, and in some cases (UNC3) even positive on impact. This feature is also found in Meinen and Röhe (2016) for the response of the GFCF to a dispersion measure of the type of UNC1A.

A feature that is common to the three macroeconomic indicators is that the SovCiss-PT stands out as an outlier, in the sense that the IRF is larger in magnitude and much more persistent (in the case of GDP reaching a through only 30 quarters after the shock). Notice that this indicator, given its restricted nature, has only one significant change (more than two standard deviations) in the sovereign debt crisis period, which may be insufficient to identify the impact of uncertainty. Another common feature to the three macroeconomic variables is the fact that SIU is the lower envelope of the IRF (excluding the SovCiss-PT). This possibly stems from the fact that being an average of indicators with a different nature, the SIU covers a broader range of uncertainty episodes, capturing more accurately the impact of uncertainty on the business cycle. The use of a composite of uncertainty indicators to evaluate macroeconomic effects is a common approach in the literature (ECB (2016), Gil *et al.* (2017)).

4.3. Historical decomposition

Another way to analyse the impact of uncertainty on business cycle developments is to assess its impact over time trough a historical decomposition exercise. Figures (C.1) to (C.6) in the Appendix show results for the indicators and models suggested by the out-of-sample conditional forecast analysis, a choice which is not substantially altered when the model is estimated full sample, as mentioned above. Given the disparity of IRF results between survey-based indicators and the rest in the case of GFCF and private consumption, the composite measure SIU is also reported.

The time profile of uncertainty contributions measured by the SIU is quite similar across macroeconomic aggregates and also to the ICSF in the case of GDP. Uncertainty had a negative impact of between 1 and 2 percentage points (p.p.) on GDP growth from late 2008 up to mid 2012, starting to abate from then onwards. The largest impact of uncertainty in this period is however positive, over 2014, possibility associated with the end of the economic and financial assistance program for Portugal. Over 2016, the positive impact of uncertainty on GDP started to fade away, turning negative over the second half of year. Several events may have contributed to this path, including the immigration crisis in Europe, a relatively negative review of its banking sector and the period leading to and in the aftermath of the UK referendum on EU participation (so called Brexit). The contributions of uncertainty to GFCF developments where in general larger in magnitude, which is not surprising given the stronger volatility of this component. The maximum impacts over the post 2008 period took place in mid 2009 and 2012, standing above 3 p.p. in magnitude. For private consumption, the time profile and magnitude of uncertainty contributions to the year-on-year rate of change is similar to the one for GDP, with the maximum impact being reached in 2012.

However, results for GFCF and private consumption are substantially different when assessed with survey-based indicators, which show a much more marginal role for uncertainty. In the case of GFCF, the impact of uncertainty is always lower than 1 p.p. and concentrated on the financial and sovereign crisis recoveries. In the case of consumption, uncertainty, evaluated with the UNC3 indicator, has the largest impact during the financial crisis, with virtually no effect during the sovereign debt crisis. This result is hard to reconcile with the Economic and Financial Assistance Programme measures that had an impact on disposable income and with the increase in unemployment over this period, which is a proxy for uncertainty used in models for consumption (Gil *et al.* (2017)).

This analysis suggests that results are more consistent for GDP than for its subcomponents, possibly because these are more susceptible to idiosyncratic shocks not captured by the majority of uncertainty indicators. In fact, these appear to reflect essentially supranational events, as suggested by the similarity between the Portuguese and euro area composite indicators.

5. Conclusions

This paper presented a set of uncertainty indicators for the Portuguese economy, covering several types of approaches to the measurement of this variable. Among these measures, the survey-based indicators were computed for Portugal for the first time. A composite indicator of these measures shows striking similarities to a comparable measure for the euro area. An analysis based on BVAR models for GDP, GFCF and private consumption reinforce previous results in the literature that report a negative impact of uncertainty increases on economic developments. Results suggest that these indicators, either by themselves or along with leverage indicators, help explain the decline in macroeconomic aggregates over the financial and sovereign debt crises and the weakness of the ensuing recovery. However, the magnitude of that impact is very dependent on the type of uncertainty indicator considered. Results for GDP are however very consistent across indicators and indicate a relevant negative impact of uncertainty in the last two recessions and positive impact after the end of the financial assistance programme.

This topic offers several avenues for further research, from the analysis of additional uncertainty measures to further robustness checks in the models considered. Possibly the most interesting one would be the estimation of a threshold VAR. That would allow for asymmetrical responses to uncertainty shocks and for these only to be active above a certain degree, features that the estimation results of this article hint to be relevant.

Appendix A: Conditional Forecast Results

		Var in levels						Var in differences					
		GDP		GFCF		CONS		GDP		GFCF		CONS	
Uncertainty indicator	Model	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4
CIFS	Base												
	Base+Uncert	0.93	0.90	1.49	1.18	1.19	1.11	1.33	1.34	0.76	1.44	0.95	1.13
	Base+Uncert+Loans	1.38	1.39	2.01	1.11	0.83	1.70	1.31	0.98	0.98	1.53	0.93	0.96
EPU	Base												
	Base+Uncert	1.03	0.97	1.01	1.02	1.07	1.15	0.97	1.25	1.10	1.16	1.03	1.29
	Base+Uncert+Loans	1.28	1.50	1.06	0.99	0.68	1.65	1.00	1.18	0.85	1.19	1.16	1.25
EPU_PT	Base												
	Base+Uncert	0.98	1.01	1.01	1.02	1.04	0.89	1.19	0.95	1.12	1.01	1.10	0.97
	Base+Uncert+Loans	1.24	1.83	1.06	0.92	0.62	2.64	1.22	0.79	0.86	0.86	1.24	0.92
UNC1A	Base												
	Base+Uncert	1.01	1.06	1.04	1.01	0.99	0.89	1.09	1.93	1.07	1.24	1.10	1.39
	Base+Uncert+Loans	1.32	1.60	1.20	0.93	0.58	1.58	1.10	1.58	0.71	1.21	1.21	1.41
UNC3	Base												
	Base+Uncert	1.01	1.02	1.11	1.02	0.92	0.87	0.43	1.58	0.97	1.04	0.79	1.08
	Base+Uncert+Loans	1.12	1.35	1.24	0.96	0.51	1.48	0.55	1.20	0.71	1.23	0.84	1.05
UNC1B	Base												
	Base+Uncert	1.01	0.95	1.00	1.01	1.04	0.82	0.94	1.44	0.98	1.19	0.96	0.99
	Base+Uncert+Loans	1.28	1.59	1.06	0.93	0.63	1.47	1.02	1.07	0.70	1.34	1.03	1.08
EPU_Europe_TW	Base												
	Base+Uncert	1.08	1.01	1.02	1.00	1.09	1.01	1.10	0.84	1.11	1.13	1.09	0.97
	Base+Uncert+Loans	1.32	1.55	1.06	0.95	0.67	1.54	1.15	0.84	0.80	1.08	1.22	0.92
SIU	Base												
	Base+Uncert	1.08	1.06	1.00	0.99	0.90	0.88	0.55	0.73	0.91	1.48	0.56	0.57
	Base+Uncert+Loans	1.27	1.48	1.17	0.95	0.58	1.59	0.54	0.63	0.85	1.56	0.60	0.53

TABLE A.1. Relative Root mean squared errors for the 1999Q1-2007Q4 estimation subsample

Notes: Values refer to the RMSE computed on the yoy rates of change projection errors. Results are not completely comparable between the EPU_PT and the rest because the RMSE are computed with errors up until 2013Q3.

		Var in levels			Var in differences		
		GDP	GFCF	CONS	GDP	GFCF	CONS
Uncertainty indicator	Model	2011Q1-2016Q4	2011Q1-2016Q4	2011Q1-2016Q4	2011Q1-2016Q4	2011Q1-2016Q4	2011Q1-2016Q4
CIFS	Base						
	Base+Uncert	0.88	1.01	1.08	0.93	1.12	0.75
	Base+Uncert+Loans	1.60	0.95	1.91	0.81	0.90	0.75
EPU	Base						
	Base+Uncert	1.00	1.02	1.09	0.91	1.10	0.96
	Base+Uncert+Loans	1.64	0.99	1.97	0.86	0.97	0.98
EPU_PT	Base						
	Base+Uncert	1.04	1.02	1.03	0.89	1.04	0.97
	Base+Uncert+Loans	2.54	0.98	4.04	0.85	0.76	1.01
UNC1A	Base						
	Base+Uncert	1.08	1.00	1.12	1.31	1.02	1.00
	Base+Uncert+Loans	1.25	0.94	1.92	1.18	0.87	1.02
UNC3	Base						
	Base+Uncert	1.08	0.95	0.86	1.61	0.90	1.02
	Base+Uncert+Loans	1.50	0.93	1.85	1.65	0.92	1.03
UNC1B	Base						
	Base+Uncert	0.96	1.01	0.91	1.19	1.02	0.91
	Base+Uncert+Loans	1.36	0.95	1.88	0.98	0.94	1.00
EPU_Europe_TW	Base						
	Base+Uncert	0.94	1.01	1.02	0.81	1.09	0.92
	Base+Uncert+Loans	1.64	1.00	1.94	0.83	0.97	0.94
SIU	Base						
	Base+Uncert	1.00	1.02	0.90	0.85	1.14	0.87
	Base+Uncert+Loans	1.69	1.00	1.92	0.85	1.00	0.89

TABLE A.2. Relative Root mean squared errors for the 1999Q1-2010Q4 estimation subsample

Notes: Values refer to the RMSE computed on the yoy rates of change projection errors. Results are not completely comparable between the EPU_PT and the rest because the RMSE are computed with errors up until 2013Q3.

Conditional forecast results for GDP

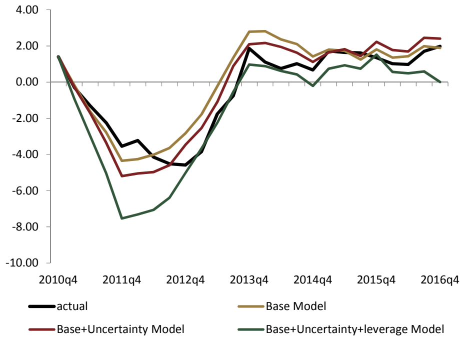


Figure A.1: ICFS as uncertainty indicator

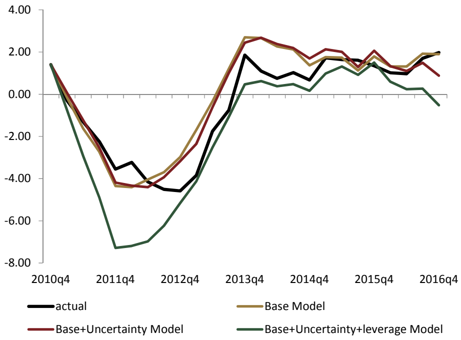


Figure A.2: EPU_TW as uncertainty indicator

Conditional forecast results for GFCF

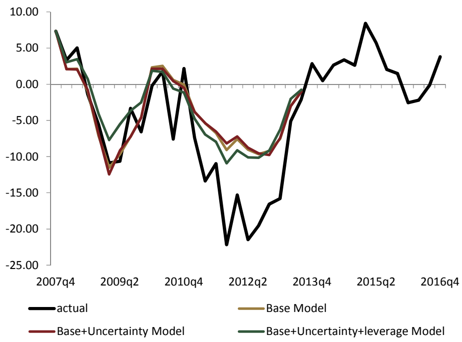


Figure A.3: EPU_PT as uncertainty indicator

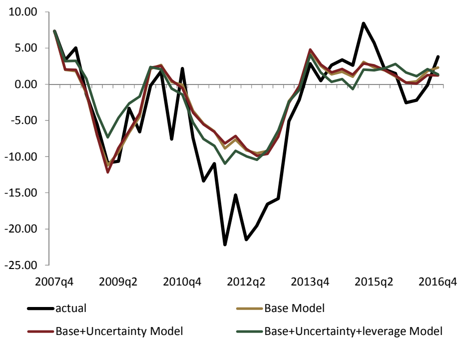


Figure A.4: UNC1A as uncertainty indicator

Conditional forecast results for Private Consumption

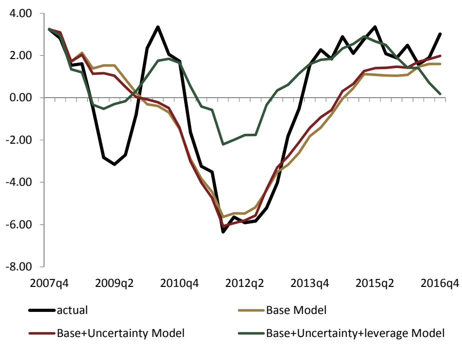


Figure A.5: UNC3 as uncertainty indicator

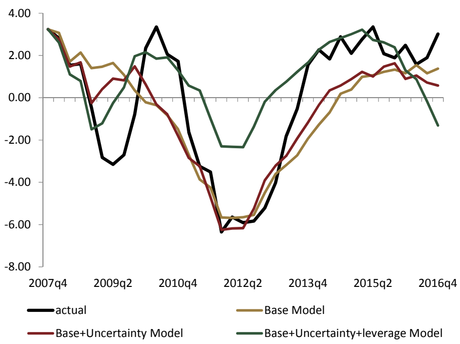


Figure A.6: SIU as uncertainty indicator

		Var in levels					
		GDP		GFCF		CONS	
Uncertainty indicator	Model	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4	2008Q1-2010Q4	2011Q1-2016Q4
CIFS	Base						
	Base+Uncert	1.11	0.80	1.09	0.93	0.95	0.87
	Base+Uncert+Loans	1.11	0.89	0.90	0.79	0.93	0.70
EPU	Base						
	Base+Uncert	0.91	0.96	1.00	0.98	0.90	0.89
	Base+Uncert+Loans	1.13	0.85	0.85	0.85	0.93	0.68
EPU_PT	Base						
	Base+Uncert	0.99	0.87	0.99	0.95	0.94	0.98
	Base+Uncert+Loans	1.08	0.79	0.87	0.58	0.85	0.93
UNC1A	Base						
	Base+Uncert	1.03	1.05	1.12	1.03	0.91	0.88
	Base+Uncert+Loans	1.12	0.99	0.82	0.90	0.77	0.80
UNC3	Base						
	Base+Uncert	1.11	1.11	0.85	0.83	0.87	0.89
	Base+Uncert+Loans	1.05	0.98	0.66	0.76	0.89	0.65
UNC1B	Base						
	Base+Uncert	0.98	1.04	1.12	1.06	0.85	0.88
	Base+Uncert+Loans	1.09	0.96	0.80	0.95	0.78	0.81
EPU_Europe_TW	Base						
	Base+Uncert	0.84	0.96	0.97	1.03	0.97	0.91
	Base+Uncert+Loans	1.04	0.83	0.85	0.91	0.99	0.72
SIU	Base						
	Base+Uncert	1.02	0.93	1.03	1.01	0.79	0.84
	Base+Uncert+Loans	1.01	0.94	0.85	0.89	0.81	0.70

TABLE A.3. Relative Root mean squared errors for the full estimation sample

Notes: Values refer to the RMSE computed on the yoy rates of change projection errors. Results are not completely comparable between the EPU_PT and the rest because the RMSE are computed with errors up until 2013Q3.

Appendix B: Impulse response function results

Figure B.1: Impulse response functions to an uncertainty shock for GDP

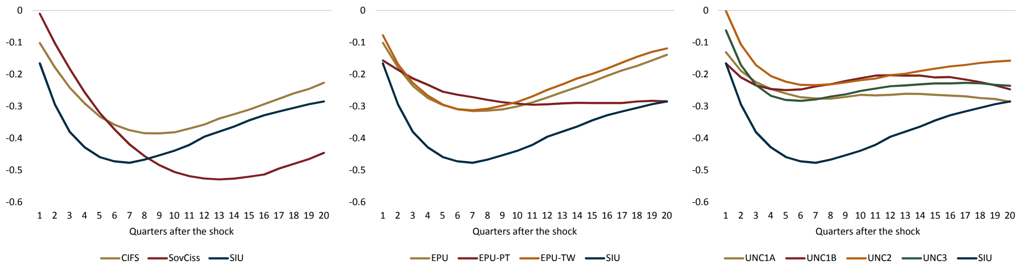


Figure B.2: Impulse response functions to an uncertainty shock for GFCF

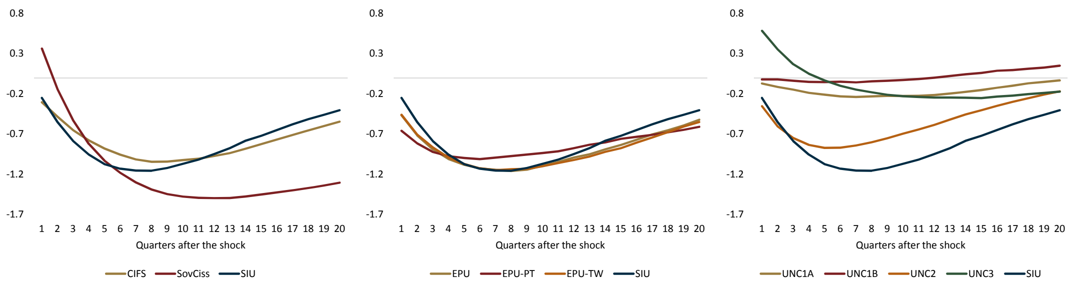
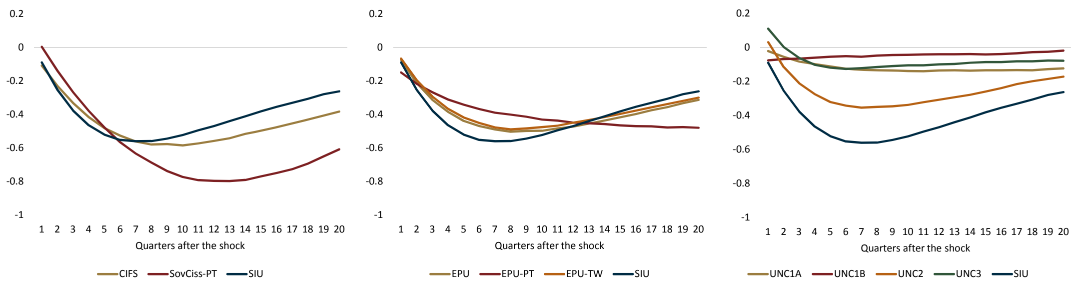


Figure B.3: Impulse response functions to an uncertainty shock for Private Consumption



Appendix C: Historical decomposition results

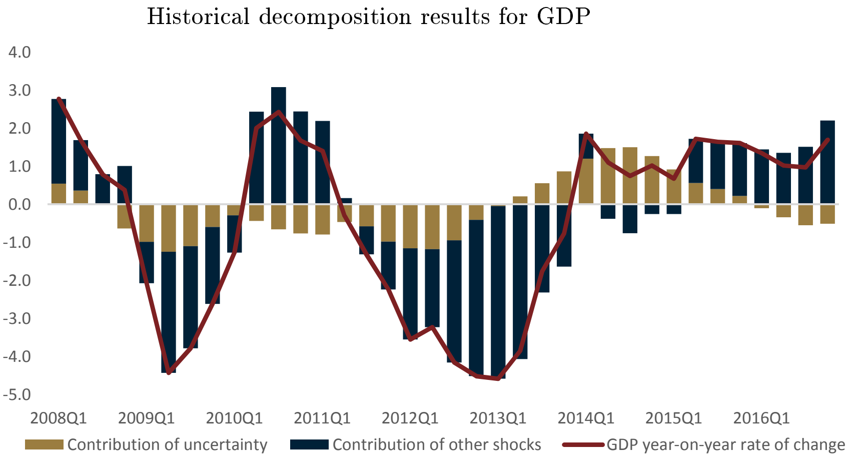


FIGURE C.1: ICFS as uncertainty indicator

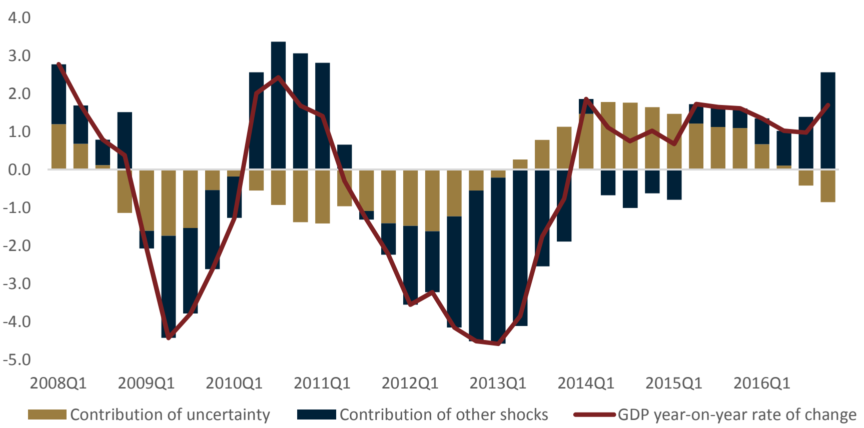


FIGURE C.2: SIU as uncertainty indicator

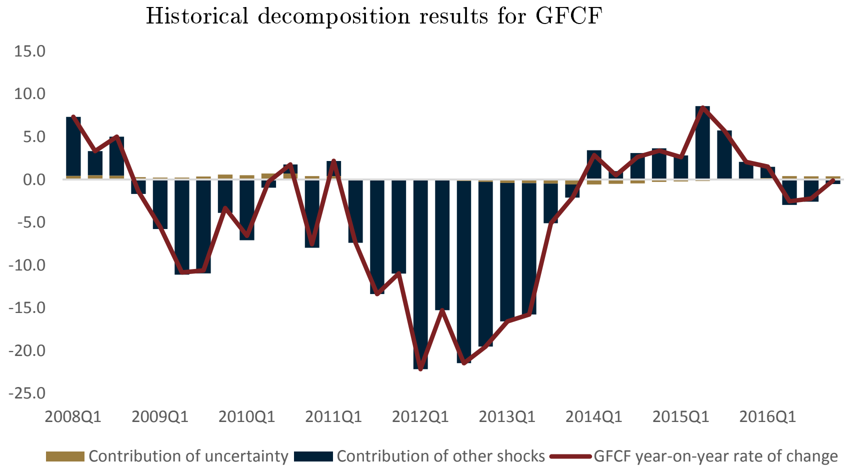


FIGURE C.3: UNC1 as uncertainty indicator

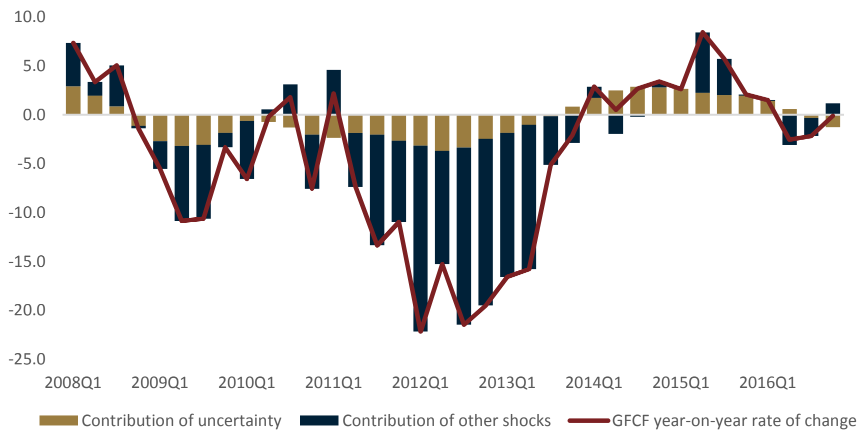


FIGURE C.4: SIU as uncertainty indicator

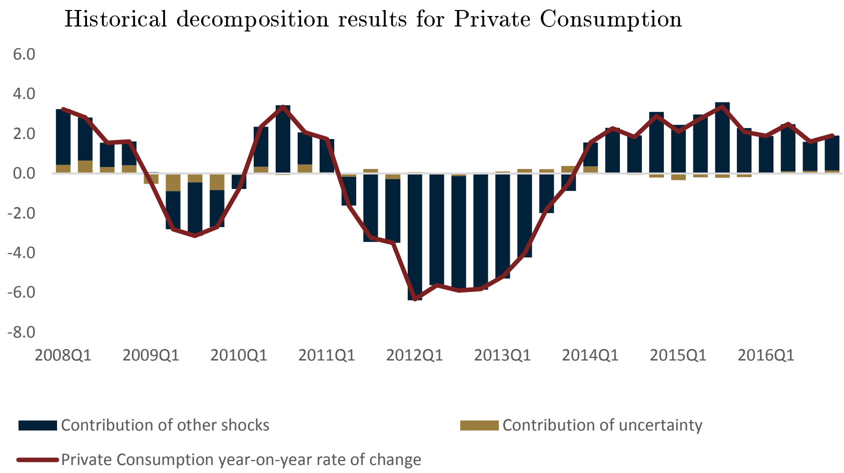


FIGURE C.5: UNC3 as uncertainty indicator

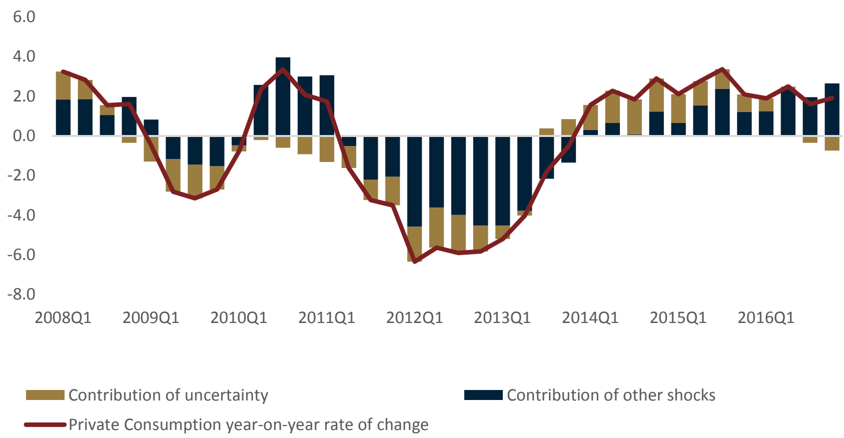


FIGURE C.6: SIU as uncertainty indicator

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