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Uncertainty shocks and financial crisis indicators

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Non-technical summary

Research Question

Many empirical studies have shown that low levels of uncertainty tend to be beneficial in terms of investment or economic growth. However, theory suggests that prolonged periods of low levels of uncertainty might lead to overconfidence which potentially induces overindebtedness, overinvestment and excessive risk-taking. In this respect, the uncertainty may have negative effects on financial stability. We investigate the effect of an unexpected decline (exogenous shift) in uncertainty on variables, so called *early-warning indicators that* tend to precede financial crises. To this end we use an empirical model of the aggregate economy. The analysis ties on Hyman Minsky's conclusion that "stability is destabilizing".

Contribution

We contribute to the existing literature by investigating the effects of exogenous shifts in uncertainty on well-established predictors of financial crises in the four largest economies of the euro area. In particular, we (1) perform identification of uncertainty shocks which separates them from standard business cycle developments, (2) consider several measures of uncertainty instead of only one as done in most related studies and (3) estimate the model on a homogeneous panel of euro area countries, which improves precision and generates robust results.

Results

Estimates show that an unexpected drop in uncertainty induces crisis predictors to increase after about two years. Shocks to various uncertainty measures may thus signal potential build-ups of vulnerabilities in the financial sector. While the analysis does not claim to provide a causal link between uncertainty and financial crises, it determines a strong empirical relationship to a set of financial crisis predictors.

Nichttechnische Zusammenfassung

Forschungsfrage

Viele empirische Studien zeigen, dass geringe Unsicherheit Investitionen und Wirtschaftswachstum begünstigt. Allerdings deuten theoretische Überlegungen an, dass Perioden niedriger Unsicherheit zu übermäßigem Optimismus führen können, was potenziell Überschuldung und eine Unterschätzung von Risiken nach sich zieht. In diesem Zusammenhang könnte Unsicherheit einen negativen Effekt auf die Finanzstabilität haben. Wir untersuchen den Effekt eines unerwarteten Rückgangs von Unsicherheit auf *Frühwarnindikatoren* für Finanzkrisen. Beispiele für solche Frühwarnindikatoren sind die Kredit-BIP-Lücke sowie Maße, die auf der Entwicklung des aggregierten Schuldendienstes, auf Immobilienkrediten und Immobilienpreisen sowie auf Kreditrisikoaufschlägen basieren. Hierzu verwenden wir ein empirisches Modell der Volkswirtschaft. Die Analyse knüpft an Hyman Minskys Wort an, dass „Stabilität destabilisierend" sei.

Beitrag

Unser Beitrag zur Literatur besteht in der Analyse der Effekte von unerwarteten Schwankungen der Unsicherheit auf etablierte Finanzkrisenindikatoren. Dabei (1) identifizieren wir Unsicherheitsschocks und trennen sie von gewöhnlichen Konjunkturentwicklungen, (2) betrachten unterschiedliche Unsicherheitsmaße und (3) schätzen unser Modell für eine homogene Gruppe von Ländern der Eurozone, was die Präzision verbessert und robuste Ergebnisse erzeugt.

Ergebnisse

Unsere Ergebnisse zeigen, dass etwa zwei Jahre nach einem unerwarteten Rückgang der Unsicherheit die Krisenindikatoren signifikant ansteigen. Somit signalisieren Schocks der verschiedenen Unsicherheitsmaße potenziell einen Aufbau von Verwundbarkeiten im Finanzsektor. Wir stellen einen starken empirischen Zusammenhang zu einer Reihe von Frühwarnindikatoren fest, allerdings können wir über mögliche Ursachen für Finanzkrisen keine Aussage treffen.

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Uncertainty Shocks and Financial Crisis Indicators*

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Abstract

The current paper broadens the understanding for the role of uncertainty in the context of a macroeconomic environment. It focuses on the implications of uncertainty shocks on indicators that tend to precede financial crises. In an empirical analysis we show for a set of four euro area countries that negative uncertainty shocks, while accompanied by favorable effects to economic activity, are followed by unfavorable reactions of financial crisis indicators. We conclude that uncertainty indicators contain some useful information on the potential buildup of vulnerabilities in the financial system.

JEL classifications: D89, C32, E44, G01

Key words: uncertainty, crisis indicators, structural macroeconomic shocks, sign restrictions

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1 Introduction

Periods of low levels of various kinds of uncertainty – e.g. regarding the future macroeconomic situation, financial market developments, or the economic policy stance – tend to be beneficial for near term economic growth.(Bloom 2009, Baker & Bloom 2013, Bachmann, Elstner & Sims 2013, Gilchrist, Sim & Zakrajsek 2014, Jurado, Ludvigson & Ng 2015, Baker, Bloom & Davis 2016, Meinen & Roehe 2017, See for example). In particular, a muted level of uncertainty is usually associated with easier financial conditions, an acceleration in capital accumulation as well as a higher willingness to hire labor and invest in riskier projects. However, as suggested by economic theory and repeatedly stressed by policymakers, periods characterized by low levels of uncertainty might lead to overconfidence among private agents and make them prone to overindebtedness, overinvestment and excessive risk taking. The resulting inefficient allocation of capital might increase the vulnerability of the financial system and lead to a higher likelihood of financial crises.[1] Based on theoretical considerations Minsky (1977) even concludes, *"stability is destabilizing"*.

However, the bulk of the literature exploring the link between uncertainty and the emergence of financial vulnerabilities and financial crises is theoretical in nature. It concentrates on spelling out the channels that might give rise to such a link. In contrast, the empirical literature focusing on whether and how low uncertainty might make the economy less resilient and increase systemic risk is still scarce. This is where the current paper steps in. We empirically investigate the relationship between exogenous shifts in uncertainty and different indicators of the probability of financial crises in the four largest euro-area countries, Germany, France, Italy and Spain. To this end we employ structural vectorautoregressive models (SVAR) and resort to several alternative schemes for the identification of uncertainty shocks. At this point, three important qualifications are warranted. First, we do not estimate the direct link between uncertainty shocks and financial crisis. The reason is that our data set, comprising a cross section of four advanced economies, does not contain enough tail events that can be characterized as financial crises. Instead, we rather quantify whether uncertainty shocks tend to push important crisis indicators upwards. Clearly, a higher value of such an indicator merely signals that the financial system *might* have become more vulnerable and thus, *more prone to* turmoil. Second, the crisis indicators we focus on have been shown to be good predictors of domestic financial crises – most of which reflect tensions in the banking sector – while being less well correlated with exchange rate crises. Third, a sequence of such shocks leading to a (prolonged) spell of low uncertainty would imply an even stronger and more persistent change in the crisis indicators.

[1] See Minsky (1977), Geanakoplos (2010), Brunnermeier & Sannikov (2014), Bhattacharya, Goodhart, Tsomocos & Vardoulakis (2015), Bordalo, Gennaioli & Shleifer (2018), IMF (2017, 2018), BIS (2018).

Since uncertainty is not directly observable and a unique definite way to measure it has not been developed yet, we consider four commonly used proxies - a broad indicator of macroeconomic uncertainty as proposed by Jurado et al. (2015), implied stock market volatility, a survey-based measure of disagreement and the economic policy uncertainty index provided by Baker et al. (2016). Similarly, we also consider several indicators shown to have significant power in predicting financial crises well in advance. These indicators typically signal the build up of sizable misallocations of capital, potentially making the domestic financial system more vulnerable. In particular, we resort to the credit-to-GDP gap, the private sector's debt-service ratio, measures of households indebtedness and property price developments as well as the credit spread. Finally, we also employ the crisis indicator produced by an early-warning model which aggregates the information from various variables with forecasting power regarding financial crises.

We contribute to the existing literature by being the first to investigate the dynamic effects of uncertainty shocks on the well-established predictors of financial crises in the largest economies of the euro area. In contrast to a small number of related studies, we do not concentrate on one uncertainty proxy only, but rather cover a broad set of alternative measures.

Our main findings are as follows. Innovations to three of the four major uncertainty proxies – i.e. leading to a sudden decline in macroeconomic uncertainty, implied stock market volatility or survey-based expectational dispersion – induce significant and persistent increases in the indebtedness related crisis indicators. In contrast, shocks to the index of economic policy uncertainty do not seem to induce significant changes in any of the early-warning indicators. Furthermore, there is a dichotomy between the indebtedness related crisis predictors and those derived from relative prices. In particular, the gaps of the credit-to-GDP, the debt-service or the mortgage-debt-to-GDP ratios respond significantly to uncertainty shocks, while the relative-price related indicators, i.e. the real residential property price and the credit spread – do not. In sum, sudden shifts in important uncertainty measure might indeed contribute to an increase in the likelihood of financial crises, namely by putting upward pressure on overindebtedness indicators like the credit-to-GDP gap.

Our paper mainly relates to three strands of literature. The study closest to our work is that by Danielsson, Valenzuela & Zer (2018). They analyze the effects of stock market volatility on risk-taking and banking crises based on a historical panel covering 60 countries and up to 211 years and by using logit regressions. They find that prolonged periods of low stock market volatility, increase the probability of crises. While our results broadly support the findings by Danielsson et al. (2018), our approach differs in several ways from theirs. First, we do not treat uncertainty as an exogenous variable but rather allow its dynamics to be endogenously driven by various exogenous shocks and other macroeconomic aggregates. This allows us to filter out exogenous and unexpected shifts in uncertainty which are most likely not a pure reflection of standard business cycle shocks such as disturbances to aggregate supply, aggregate demand, monetary policy, or credit supply. Second, we study the effects of several proxies of uncertainty instead of focusing on stock market volatility only. Finally, in contrast to a sample covering several hundreds of years and potentially heterogeneous countries, in our analysis we make use of a relatively homogeneous group of advanced euro area economies over a sample period in which substantial structural shifts like changes in the political system, the judiciary, the monetary or fiscal framework are less of an issue. Our paper also relates to the huge and steadily growing empirical SVAR literature seeking to quantify the macroeconomic effects of uncertainty shocks.[2] However, these papers focus on how unexpected movements in uncertainty affect investment, GDP or employment while leaving aside the probability of financial crises or respective indicators. Our work also relates to the early-warning literature concerned with identifying good crisis predictors.[3] However, we do not conduct an early-warning exercise but rather ask whether and how uncertainty shocks affect the crisis indicators identified by that literature.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the empirical model and the identifying assumptions of the structural shocks, we describe the underlying data in Section 3, results with respect to our baseline model specification as well as several robustness exercises are discussed in Section 4. Section 5 concludes.

2 VAR Model

2.1 Panel VAR model

We employ a panel VAR model in order to investigate the impact of uncertainty shocks on a set of crisis indicators. The reduced form representation of the model reads

$$\boldsymbol{y}_{c,t} = \boldsymbol{b}_c + \sum_{j=1}^{p} \boldsymbol{B}_j \boldsymbol{y}_{c,t-j} + \boldsymbol{e}_{c,t}, \quad \text{for } t = 1, \dots, T_c$$

where $\boldsymbol{y}_{c,t}$ denotes an $n \times 1$ vector of endogenous variables, $\boldsymbol{b}_c$ is an $n \times 1$ country specific intercept vector, $\boldsymbol{B}_j$ are $n \times n$ matrices with slope coefficients, and $\boldsymbol{e}_{c,t} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$ denotes an $n \times 1$ vector of reduced form residuals. The panel dimension

[2] A by no means exhaustive list of papers includes: Bloom (2009), Baker & Bloom (2013), Bachmann et al. (2013), Gilchrist et al. (2014), Jurado et al. (2015), Ludvigson, Ma & Ng (2015), Baker et al. (2016), Born, Breuer & Elstner (2018), Meinen & Roehe (2017), Castelnuovo & Tran (2017).

[3] See e.g. Alessi & Detken (2011), Gourinchas & Obstfeld (2012), Lo Duca & Peltonen (2013), Drehmann & Juselius (2014), and Beutel, List & von Schweinitz (2018)

improves upon the limited sample size and helps us to sharpen precision of the estimates. We estimate the model on cross-country data incorporating observations of 4 countries indicated by subscript $c \in \{DE, ES, FR, IT\}$. We assume cross-country homogeneity with respect to the underlying model such that pooling of observations over the cross-section yields unbiased results.

We set $n = 5$ where the vector $\boldsymbol{y}_{c,t}$ includes the following five variables: *(i)* the log of the stock market price index, *(ii)* an uncertainty proxy , *(iii)* a crisis indicator, *(iv)* the log of real GDP and *(v)* the log of the GDP deflator. Each uncertainty proxy used is standardized at the country level by transforming it in the corresponding Z-score. This is done for the sake of better comparability across countries and across different uncertainty measures. In Section 4.3.4 we show that our results are qualitatively robust to alternative types of normalization. In our baseline panel VAR specification, we proxy uncertainty by the measure of macroeconomic uncertainty derived by Meinen & Roehe (2017) based on the approach proposed by Jurado et al. (2015) while the credit-to-GDP gap serves as the crisis indicator.

The reduced form representation does not offer a suitable environment for meaningful analyses. We impose economically motivated identifying assumption which recover the structural representation of the model

$$\boldsymbol{A}_0\boldsymbol{y}_{c,t} = \boldsymbol{a}_c + \sum_{j=1}^{p} \boldsymbol{A}_j\boldsymbol{y}_{c,t-j} + \boldsymbol{u}_{c,t},$$

where $\boldsymbol{u}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\mathcal{I}}_n)$. The structural coefficients are contained in the $n \times n$ matrices $\boldsymbol{A}_j$ and the $n \times 1$ vector $\boldsymbol{a}_c$ respectively. The matrix $\boldsymbol{A}_0$ captures the contemporaneous effect of the structural shocks $\boldsymbol{u}_{c,t} = \boldsymbol{A}_0\boldsymbol{e}_{c,t}$ and fulfills $(\boldsymbol{A}_0\boldsymbol{A}_0')^{-1} = \boldsymbol{\Sigma}$.

We assume a Bayesian perspective, in other words inference is based on draws from the posterior distribution of the structural model. While the prior distribution is of a conjugate normal-inverse-Wishart form, a diffuse specification seems sufficient for our purposes. In the context of our analysis, tight prior distributions are not necessary since the panel dataset offers a relatively large sample which ensures the parameters to be properly estimated. Sampling from the posterior distribution is standard as $\text{vec}(\boldsymbol{B}), \boldsymbol{\Sigma}$ follow the normal-inverse-Wishart distribution, where $\boldsymbol{B} = [\boldsymbol{B}_1, \boldsymbol{B}_2, \cdots, \boldsymbol{B}_p]'$.

2.2 Identification of structural shocks

So far there is no definite consensus regarding the most appropriate way to identify uncertainty shocks within SVARs. The literature has rather suggested several alternative strategies each of them based on a different rationale. In most cases however, identification relies on particular recursive orderings of the variables in the VAR. In the current paper, we do not take a stand on the appropriateness of each approach but accompany our baseline identification with several commonly used alternative specifications.

In our baseline set-up we identify the structural uncertainty shock by the following recursive Choleski–type scheme:

$$\begin{pmatrix} \text{Crisis Indicator} \\ \text{log of GDP} \\ \text{log of GDP Deflator} \\ \text{log of Stock Market Index} \\ \text{Uncertainty Measure} \end{pmatrix}$$

In particular, we follow Jurado et al. (2015) and place the stock market and the uncertainty measure last. This reflects the notion that they are fast moving variables typically very sensitive to any type of news as well as sudden sentiment shifts.[4] In contrast, the remaining macro aggregates are assumed to only respond with a lag of at least one quarter to unexpected movements in stock markets and uncertainty. This reflects the theoretically motivated notion of sluggish reactions due to various types of real, nominal and informational frictions. In order to disentangle the uncertainty shock from a pure stock market innovation, we proceed similarly to Bloom (2009) and Jurado et al. (2015) and impose that the stock market shock, unlike its counterpart in the uncertainty equation, may affect the uncertainty indicator on impact. Accordingly, the uncertainty shock captures exogenous shifts in the uncertainty proxy after having controlled for the effects of sudden movements in the stock market.[5] In fact, our baseline identification strategy constitutes a conservative choice where the uncertainty shock is the residual innovation left after having controlled for all other shocks. Similar approaches are found in Jurado et al. (2015) and Charles et al. (2018) or are used in robustness exercises in e.g. Bloom (2009), Bachmann et al. (2013), or Meinen & Roehe (2017).[6]

To test the sensitivity of our results with regard to the identification scheme, in Section 4.3 we experiment with several alternative sets of short-run restrictions. In particular, we consider different Choleski orderings and relax the assumption that the stock market index does not react to uncertainty shocks on impact. We find that

[4]Benati (2019) also places the stock market and the uncertainty proxy first in his VAR. Additionally to the zero restrictions, he also imposes a sign restriction assuming that a non-negative policy uncertainty shock induces, within the month, a non-positive response in stock prices. He motivates the restriction by arguing that, on the contrary, uncertainty shocks should never be associated with stock-price increases.

[5]Bachmann et al. (2013), Meinen & Roehe (2017) and Charles, Darné & Tripier (2018) employ similar assumptions to separate both shocks.

[6]Gilchrist et al. (2014) identify uncertainty shocks by allowing them to have an immediate effect on credit spreads and interest rates but not on prices and real activity.

our results remain qualitatively unchanged. In Section 4.5, we further identify two conventional business cycle drivers – an aggregate demand and an aggregate supply disturbance – by means of zero and sign restrictions. We show that our recursive identification scheme ensures that the uncertainty shock is sufficiently different from the two standard business cycle drivers.

3 Data

We resort to quarterly data consisting of uncertainty proxies, indicators of financial crisis probability, the stock market price index, GDP and the corresponding GDP deflator for a panel comprising the four largest economies of the euro area – i.e. Germany, France, Spain and Italy. Whenever the original data has a monthly or a higher frequency, it is transformed to a quarterly average. Depending on the availability of the series involved, the estimation sample starts between 1995:Q1 and 2001:Q1 and goes through 2018:Q3. We next provide a detailed description of the non-standard variables used.

3.1 Crisis indicators

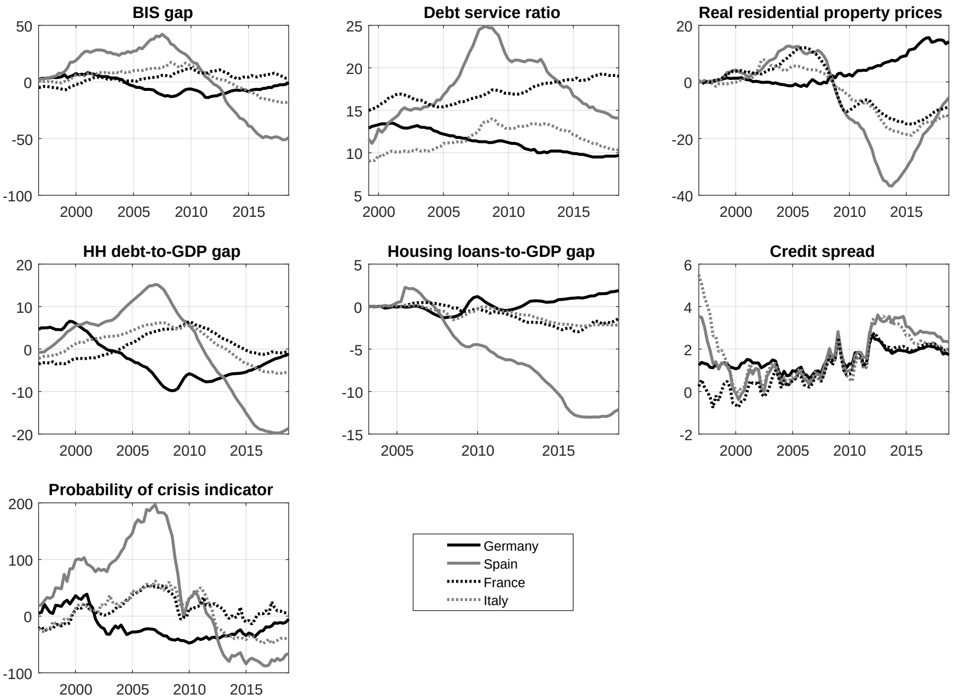
The literature has suggested several indicators with desirable early-warning properties which outperform other potential predictors of financial crises. However, we still lack the decisive evidence indicating which of those indicators should be preferred. For this reason, we conduct analyses with the most popular and frequently used predictors of financial crises. In particular, these are the gaps – i.e. deviations from a one-sided HP filter long-run trend of the following ratios: total credit relative to GDP, households' debt to GDP, mortgage loans to GDP and the debt-service ratio (DSR). In addition, we consider the gap of the real residential property price and the credit spread. Finally, we consider a crisis indicator produced by the empirical early-warning model of Beutel et al. (2018). The latter is a summary statistic combining the information from the aforementioned indicators as well as other variables. The crisis indicators are illustrated in Figure 1.

The credit-to-GDP gap is the deviation of the ratio of total credit to the private non-financial sector to GDP from its long-run trend. Positive values of the gap can be interpreted as indicating an excessive, potentially unsustainable, credit expansion which is a frequent precursor of crises. Drehmann, Borio & Tsatsaronis (2011), Gourinchas & Obstfeld (2012), Jorda, Schularick & Taylor (2013), Drehmann & Tsatsaronis (2014), and Drehmann & Juselius (2014) provide a discussion of the quite satisfactory properties of the credit-to-GDP gap as a crisis predictor. In addition, according to the Basel Committee on banking Supervision (2010), the gap is an integral part of discussions among policy makers about adjusting the countercyclical capital buffer. An elevated debt-service ratio (DSR) also signals overindebtedness, however, with a stronger emphasis on possible liquidity shortages. Regarding the early-warning properties of the DSR Drehmann, Borio & Tsatsaronis (2012), Drehmann & Juselius (2012), and Drehmann & Juselius (2014) find that it performs better than most other indicators and similarly well as the credit-to-GDP gap. As discussed by Drehmann & Juselius (2012), under the special condition of constant lending rates as well as maturities the DSR and the credit-to-GDP provide the same information. However, the authors show that this condition is not satisfied, so that the DSR reflects the burden imposed by debt better than the credit-to-GDP gap.

Several studies argue that in advanced economies the component of total credit corresponding to household or mortgage debt is the primary driving force behind the dynamics of the credit-to-GDP ratio and its good early-warning properties. The importance and predictive power of the debt-to-income ratio is discussed for example by Jorda, Schularick & Taylor (2016) or Mian, Sufi & Verner (2017). A rise in any of these indebtedness ratios tends to reduce the scope for consumption and income smoothing. In the case of adverse shocks it increases the default likelihood and may lead to sharper aggregate demand contractions. We view both, total household debt as well as mortgage loans to private households as proxies for the overall mortgage credit granted to the household sector. As shown by Zabai (2017), mortgage debt constitutes the lion's share of total household debt. In 2017 it amounted to 86% in France, 92% in Italy and close to 97% in Germany and Spain. Mortgage loans granted by banks are lower than the total amount of mortgage borrowing by households. Nevertheless, the gap of household debt relative to GDP displays a strong comovement with the gap of the mortgage-loans-to-GDP ratio. The correlation amounts to 0.60 in Germany and France and 0.89 and 0.97 in Italy and Spain respectively.

The gap between the real residential property price and its long run trend is usually a sign of a boom or an overvaluation in an important asset market which might lead to overborrowing by households as well as excessive risk taking and lax credit standards in the banking sector. Reinhart & Rogoff (2008), Mian & Sufi (2009), DellAriccia, Igan & Laeven (2012) or Bhutta & Keys (2016). Drehmann & Juselius (2014) and Borio & McGuire (2004) discuss that property prices peak around 2-3 years before a crisis but start to decrease in the actual run-up. Accordingly, a muted property price growth becomes a significant crisis predictor only around 2 quarters ahead of the crisis. Low credit spreads might indicate excessive risk appetite which in turn, might bring about misallocations of credit and thus, higher financial fragility. Krishnamurthy & Muir (2017) show that normalized credit spreads – defined as the difference between high-yield and low-yield corporate bonds – have significant predictive power regarding financial crises. Lopez-Salido, Stein & Zakrajek (2017)

Figure 1: Crisis Indicators



discuss the predictive power of spreads regarding economic downturns.

Finally, early-warning models attempt to directly estimate the probability for the occurrence of a financial crisis in the near future and develop thresholds above which the model delivers a timely signal about that occurrence.[7] We resort to the model estimated by Beutel et al. (2018) based on a country-panel model. In particular, the authors use the ECB/ESRB crises database of Lo Duca, Koban, Basten, Bengtsson, Klaus, Kusmierczyk, Lang, Detken & Peltonen (2017) and for each point in time estimate the likelihood of a financial crisis occurring within the following 5 to 12 quarters. The indicator we use is the one derived from the linear version of their best performing specification.

The credit-to-GDP gap is the deviation of the ratio of nominal total credit to nominal GDP from a specific long-run trend. The measure is backward looking and computed by means of a one-sided Hodrick-Prescott filter with a smoothing parameter set to 400 000. The credit-to-GDP gap series are provided by the BIS for various countries. The ratios of overall household debt and mortgage loans to GDP are transformed into gaps via the same methodology. The DSR is provided by the BIS and corresponds to the flow of interest payments and mandatory repayments of principals relative to nominal income and covers the private non-financial sector. The denominator of the DSR corresponds to nominal gross domestic income

[7] See Alessi & Detken (2011), Gourinchas & Obstfeld (2012), Drehmann & Juselius (2014), Halopainen & Sarlin (2017) among others.

augmented by interest payments and dividends for the non-financial corporations. In the case of real residential property prices, the gap is defined as the absolute deviation from the long run trend. The latter is extracted by the one sided HP-filter with the same smoothing parameter as for the indebtedness ratios.

Our definition of the credit spread deviates from that of Krishnamurthy & Muir (2017) who compute it as the difference between the yield of risky and safe corporate bonds. In contrast, we define the credit spread as the distance between the interest rate on bank loans to non-financial corporations on the one hand and the yield of German government bonds with a three year maturity on the other. Since Germany, France, Italy and Spain rather have a banking based financial system, the relevant refinancing costs are likely much better reflected in loan rates.

3.2 Uncertainty proxies

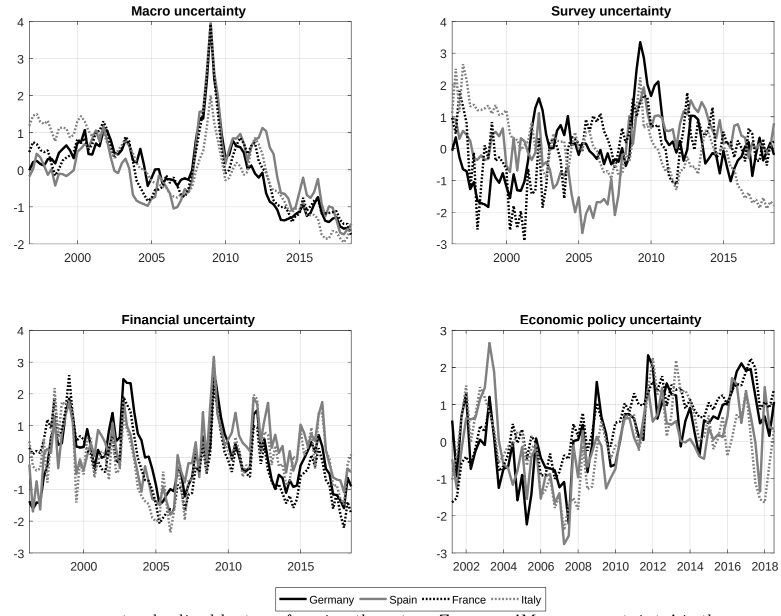
There is a range of uncertainty proxies in the literature. Measures differ with respect to their main focus – i.e. the economy as a whole or particular sectors of it – as well as regarding the data base they are derived from. We do not take a stand about which of them should be preferred under which circumstances. We rather remain agnostic and explore the effects of four commonly accepted and frequently used measures of uncertainty. They are based on *(i)* the forecast errors with respect of a large set of macroeconomic series, *(ii)* the implied volatility of stock market returns, *(iii)* the disagreement in the expectations component of business surveys and *(iv)* the number of newspaper articles discussing economic policy uncertainty. The series used in the estimation are shown in Figure 2.

3.2.1 Macroeconomic uncertainty

Jurado et al. (2015) construct a novel measure for uncertainty attempting to cover a wide range of economic aspects. It relies on the unpredictable part of numerous time series reflecting different dimensions of the macroeconomic development, i.e. real activity, prices, labor markets, financial markets, foreign trade, fiscal and monetary policy, etc. In particular, for each period t and each time series, Jurado et al. (2015) compute the conditional volatility of the h-step-ahead forecast error obtained given information as of t. Then, the time varying macroeconomic uncertainty index (MUI) is obtained as a weighted average over the individual conditional volatilities. Meinen & Roehe (2017) follow the approach proposed by Jurado et al. (2015) and construct a MUI for the four largest euro area countries, Germany, Spain, France, and Italy.[8] The index starts in 1996:M6 and is regularly updated by the authors.

[8] Grimme & Stoeckli (2018) construct a similar macroeconomic uncertainty index for Germany.

Figure 2: Uncertainty Indicators



Notes: All uncertainty measures are standardized by transforming them to a Z-score. 'Macro uncertainty' is the measure of macroeconomic uncertainty provided by Meinen & Roehe (2017). 'Survey uncertainty' corresponds to the expectational dispersion derived from business surveys. It is computed as a weighted average over the manufacturing and the construction sector. 'Financial uncertainty' is the implied or - if the latter is unavailable - the realized stock market volatility. 'Economic policy uncertainty' is the newspaper-based measure provided by Baker et al. (2016).

3.2.2 Survey-based dispersion in expectations

Following Bachmann et al. (2013) and Meinen & Roehe (2017) we construct a survey-based proxy of uncertainty capturing the the cross-sectional dispersion in individual firms' output/employment expectations. The measure closely resembles the concept of cross-sectional forecast disagreement frequently used in numerous empirical studies.[9] As emphasized by Bachmann et al. (2013), a survey-based proxy of uncertainty has the advantage of *'capturing the mood of actual decision makers'*, being available at a relatively high frequency and relying on a narrowly defined segments of the economy which reduces the likelihood that, instead of reflecting uncertainty, the dispersion measure simply reflects certain but heterogeneous expectations.[10] Here we resort to the business and consumer surveys data provided by the European Commission. In order to achieve a better coverage of the supply side of the economy, we resort to information from both, the manufacturing sector as well as the construction/building sector survey. Unfortunately, a broader dispersion measure which also incorporates the retail-trade sector is only feasible for Germany, France

[9]See for example Giordani & Soderlind (2003), Clements (2008), Lahiri & Sheng (2010), Baker et al. (2016)

[10]A well-known weakness of cross-sectional measures of expectation dispersion or forecast disagreement is that they might potentially reflect heterogeneous reactions to aggregate shocks at constant uncertainty or even under certainty. However, for German manufacturing, Bachmann et al. (2013) show that these problems are very likely of limited importance.

and Italy due to the limited data availability in the case of Spain whose retail-trade survey starts in 2008.[11] In particular, each month firms in the manufacturing sector are asked whether they expect their production to *'increase'*, *'remain unchanged'* or *'decrease'* over the next three months. In the construction/building sector the corresponding question is about a firm's employment expectations. Following Bachmann et al. (2013) and Meinen & Roehe (2017), we define the dispersion measure in sector $j = \{manuf, build\}$ as follows

$$EDISP_{j,t} = \sqrt{Frac^{+}_{j,t} + Frac^{-}_{j,t} - (Frac^{+}_{j,t} - Frac^{-}_{j,t})^2}, \tag{1}$$

where $Frac^{+}_{j,t}$ corresponds to the fraction of firms expecting an 'increase' while $Frac^{-}_{j,t}$ is the fraction of 'decrease' responses in the survey. Then we construct the weighted average over the two sectors as $EDISP_t = \sum_j \omega_{j,t} EDISP_{j,t}$, where the weights $\omega_{j,t}$ correspond to the sector's fraction in nominal value added in the previous year, e.g. $\omega_{manuf,t} = VA_{manuf,t}/(VA_{manuf,t} + VA_{build,t})$, with VA denoting nominal value added.

3.2.3 Financial Uncertainty

The stock market volatility is another frequently used uncertainty proxy (Bloom 2009). It corresponds to the volatility implied by index options or the realized volatility of stock market returns. Similar to Meinen & Roehe (2017) we employ the following country specific volatility series. For Germany and France we use the implied volatility indexes VDAX and the VCAC respectively. Since the VCAC is only available from the beginning of 2000 on, we extend the series backwards by the monthly volatility of the CAC 40. For Spain and Italy we also compute a measure of realized volatility derived form daily returns based on a corresponding national stock price index, the Madrid SE General (IGBM) and the FTSE Italia MIB Storico respectively.

3.2.4 Economic Policy Uncertainty

Baker et al. (2016) develop a novel proxy reflecting economic policy uncertainty (EPU). It quantifies newspaper coverage of policy-related economic uncertainty. Data for the countries considered in our analysis is available from the first quarter of 2001 on.

[11] Nevertheless, in a robustness exercise we perform estimations based on survey data covering all three sectors for Germany, France and Italy while comprising only the manufacturing and the construction sector for Spain. We experiment with two dispersion measures for the retail sector, one based on firms' expectations regarding their business activity and the second regarding their future employment. In both cases the results are barely distinguishable from those presented in the main text.

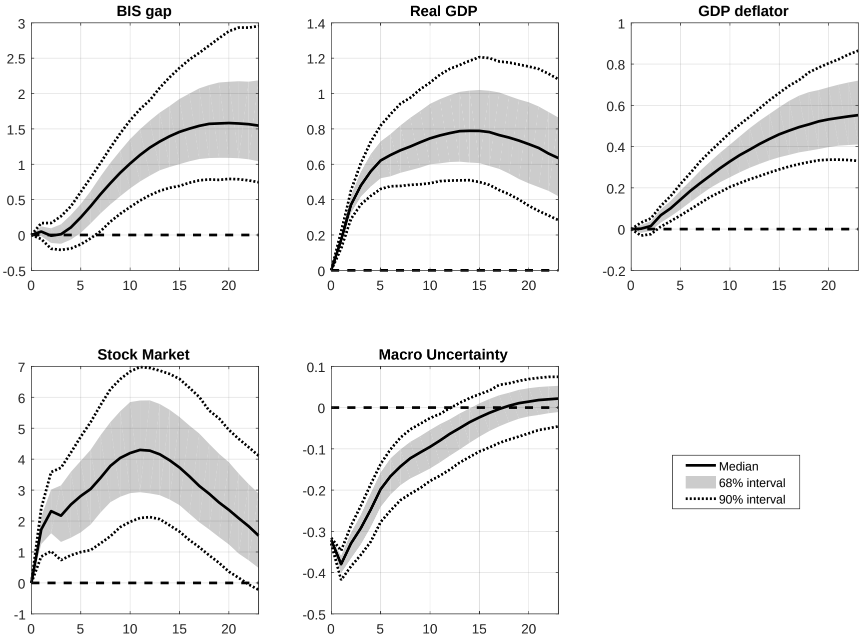
4 Empirical results

4.1 Main findings

In our baseline estimation, we use the credit-to-GDP gap (BIS gap) as the crisis indicator and proxy uncertainty by the index of macroeconomic uncertainty constructed by Meinen & Roehe (2017) for Germany, France, Italy and Spain. Figure 3 depicts our main result based on the identification scheme described in Section 2. As can be seen, a sudden decline in macroeconomic uncertainty triggers the expected boom in GDP, prices and stock markets. However, in this cyclical pick-up aggregate output and the activity in credit markets do not seem to expand at a similar pace. About 2 years after the shock, aggregate lending rather starts to grow faster than GDP with the consequence of a significant and sizable positive response of the credit-to-GDP gap. The latter stays above average for quite a while.

As discussed in the introduction, the credit-to-GDP gap is not the sole early predictor of financial crises. The literature has rather suggested several alternative indicators with a similar forecasting properties. For this reason, we estimate a series of alternative VAR models which are identical to our baseline specification described in Section 2, except that we replace the credit-to-GDP gap by one of the other indicators of financial crises discussed in Section 3.1. The reactions of the alternative indicators to an exogenous drop in the macroeconomic uncertainty is depicted in Figure 4 and reveal a qualitatively similar message as that provided by the model including the credit-to-GDP gap. As can be seen, the gaps of the ratios of debt-service to income, of household debt to GDP, of mortgage loans to GDP and of real estate prices to the consumer price index increase significantly and persistently, even though with some delay. The crisis indicator derived from the early-warning model by Beutel et al. (2018), which aggregates information over several potential crisis predictors, also exhibits a significant and persistent increase as a reaction to an unexpected decline in macroeconomic uncertainty. Solely in the case of the credit spread we do not observe a clear-cut tendency. If anything, the spread displays a rather short lived positive reaction to the uncertainty shock.

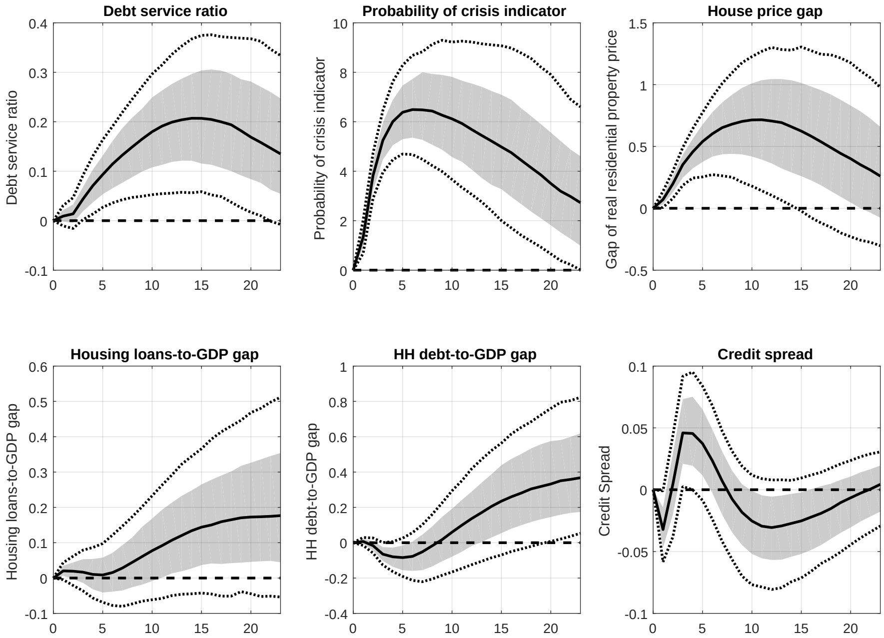
Figure 3: Baseline specification. Impulse responses to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points. All other variables are measured in percent.

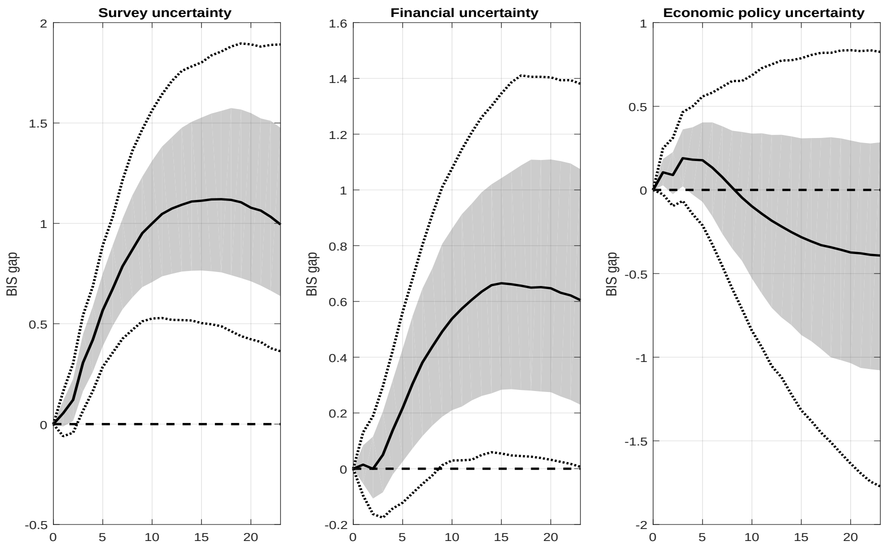
Similarly, macroeconomic uncertainty coexists with several other proxies of uncertainty (see Section 3.2). To investigate their effects on the credit-to-GDP gap, we modify our baseline VAR specification from Section 2 by replacing macroeconomic uncertainty by stock market volatility, survey-based expectational disagreement, or the index of economic policy uncertainty. The resulting responses to a sudden drop in the respective uncertainty proxy are shown in Figure 5. Shocks to both, stock market volatility and the dispersion of non-financial firms' expectations induce qualitatively the same reaction of the credit-to-GDP gap as innovations to macroeconomic uncertainty. Table 1 summarizes the sign and significance of the reactions of the various indicators of financial crises to each individual uncertainty proxy. As can be seen, unexpected declines in macroeconomic uncertainty, stock market volatility and the survey-based expectational dispersion lead to significant and persistent increases in the majority of the gaps considered to be good crisis predictors. The only exception is the index of economic policy uncertainty. The latter does not seem to induce significant changes in important measures of overborrowing or excessive house price development. Solely the credit spread seems to respond systematically to sudden shifts in economic policy uncertainty.

Figure 4: Alternative crisis indicators. Impulse responses to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Debt-Service-Ratio Gap', 'Household-Debt-to-GDP Gap', 'Mortgage-Loans-to-GDP Gap', 'House-Price Gap', 'Spread' and 'Early-Warning Indicator'. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The gap in house prices is measured in percent. The indicator derived from the Early-Warning model is unit free. All other variables are measured in percentage points.

Figure 5: Alternative uncertainty proxies. Impulse responses to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Survey uncertainty', 'Financial uncertainty', 'Economic policy uncertainty'; crisis probability = 'Debt-Service-Ratio Gap'. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points.

4.2 Discussion

While our results do not directly indicate that uncertainty shocks increase the probability of financial crises, nevertheless, exogenous shifts in three of the most important proxies of uncertainty are associated with systematic increases in measures of excessive credit developments or unsustainable debt-service burden. These measures have been shown to have remarkably good early-warning power with respect to financial – especially banking – crises in the near future. Our evidence thus suggest that exogenous shifts in important uncertainty proxies might be an early sign of a beginning misallocation of credit and thus, the build-up of vulnerabilities. The latter in turn, might translate into an adverse tail event. Accordingly, policy makers responsible for financial stability should closely monitor the development of the three uncertainty measures in general, and the reasons for their fluctuations in particular.

Table 1 also indicates that favorable uncertainty shocks mainly affect the crisis indicators related to the quantity of overborrowing, i.e. the credit-to-GDP gap, the debt service ratio and the gaps of the ratios of household debt and mortgage loans to GDP. In contrast, crisis predictors derived from relative price developments like the gap of real residential property prices and the credit spread seem to be much less responsive to the various types of uncertainty. In particular, the trend deviation of real house prices reacts significantly only in the case of shocks to macroeconomic uncertainty while the spread robustly declines only in the case of innovations to stock market volatility. What might be the reason for the weak responsiveness of the two crisis indicators derived from relative prices? Our agnostic empirical approach does not permit the development of a theoretical explanation going beyond a mere speculation. Nevertheless, one possible explanation could be that declines in uncertainty nearly symmetrically affect the mood on the demand and the supply side of the housing market and important segments of the credit market. For example, if sentiment and thus loan demand among potential borrowers increases by roughly the same amount as the corresponding sentiment and loan-supply willingness among banks, the credit spread would not change much. A similar reasoning can be applied to the housing market. In addition, the weak responsiveness of the gap of real residential property prices to uncertainty shocks might be the reflection of nominal house prices and consumer good prices increasing by very similar amounts in the case of such shocks. Figure 6 provides some suggestive evidence in favor of such an interpretation. It shows the effects of macroeconomic uncertainty shocks on several confidence indicators, as well as commercial banks' assessment of credit standards and credit demand.[12] Each graph presents the regression coefficients (and

[12]The macro uncertainty shocks are the means of the estimated structural shocks based on our baseline specification (see Figure 3). 'Construction Confidence', 'Manufacturing Confidence' and 'Consumer Confidence' are taken from the EU Commission's database and correspond to the balances of the confidence indicators for the respective sector. The 'Loan Rate' is an average over

the corresponding credibility bounds) derived from a country-level panel regression of the respective variable on the means of the uncertainty shocks estimated in our baseline VAR specification. Figure 6 indicates that both, credit demand and credit standards are pushed in a favourable direction by uncertainty shocks. This tendency is especially pronounced for mortgage credit while credit demand by non financial firms tend to rise only after a sizable delay. Consistent with this pattern, the average loan rate barely reacts to uncertainty shocks. Similarly, the mood in the construction and the manufacturing sector - as reflected by the corresponding confidence indicators - tends to improve significantly which might provide a supply-side driven reduction of the upward pressure on house prices.

Table 1: Alternative crisis indicators and uncertainty proxies. Significance of responses.

	credit to GDP	debt-service ratio	household debt to GDP	mortgage loans to GDP	Early-Warning model	real residential property price	credit spread
macro uncertainty	+	+	+	+	+	+	?
survey-based disagreement	+	+	+	+	+	0	0
stock market volatility	+	+	+	+	+	0	-
economic policy uncertainty	0	0	0	0	0	0	-

Notes: '+' - response is positive, significant, and robust over alternative specifications (identification strategies, lag orders, detrending); '-' - response is negative, significant, and robust over alternative specifications; '0' - response is insignificant; '?' - sign and significance not robust across alternative specifications.

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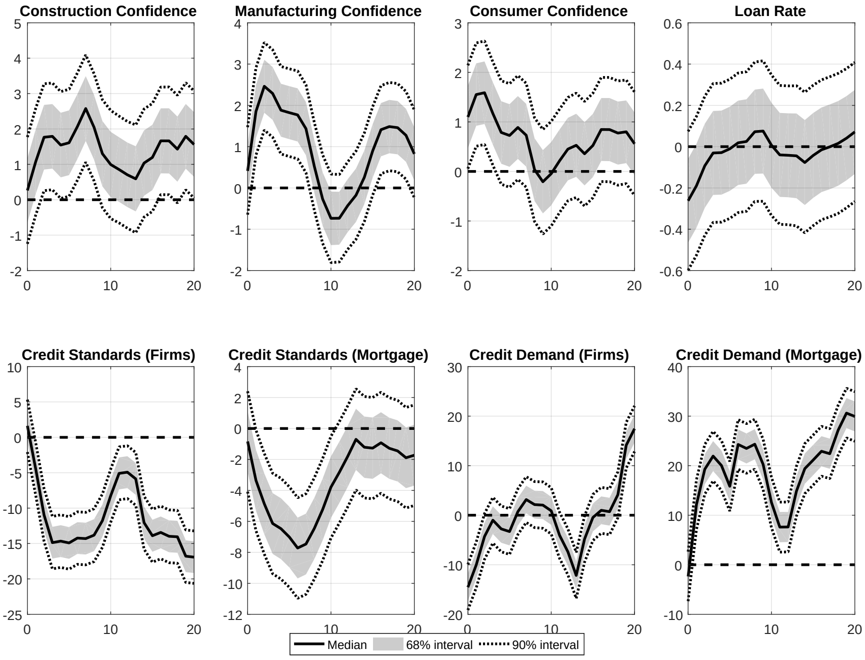
loans to non-financial corporations and loans to households for house purchase, both related to new business only (source ECB: Statistical Data Warehouse (SDW)). 'Credit Standards (Firms)', 'Credit Standards (Mortgage)', 'Credit Demand (Firms)' and 'Credit Demand (Mortgage)' are from the *Bank Lending Survey* of the ECB. The series are country-level aggregates, measured as cumulative net percentages, and reflect commercial banks' assessment of changes in the overall credit standards they applied to firms or to households for mortgage loans and changes in the loan demand they face.

Figure 6: Reactions of various variables to the innovations to macroeconomic uncertainty.



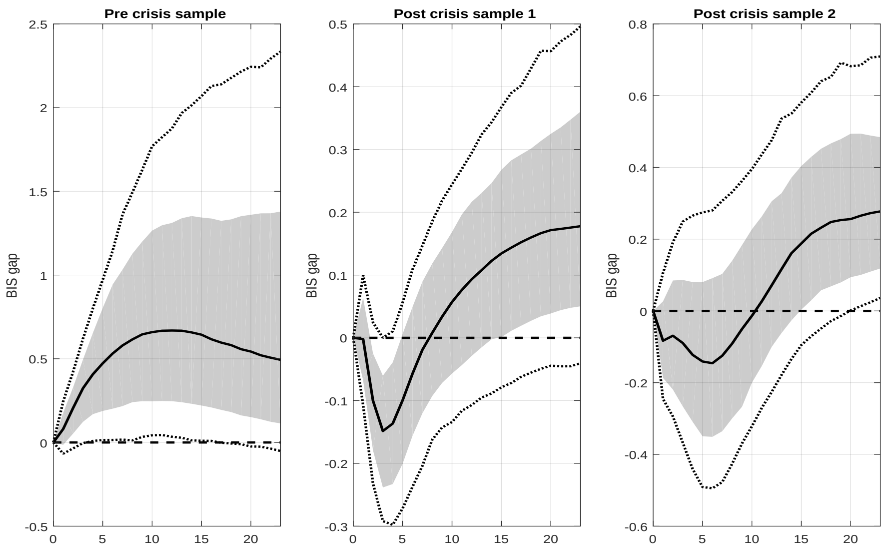
Notes: Each panel shows the reactions of the corresponding variable based on regressing the latter on the current and 20 lagged values of the macro uncertainty shock. Each panel shows the resulting regression coefficients with the corresponding credibility bounds. The macro uncertainty shocks are the means of the estimated structural shocks based on our baseline specification (see Figure 3). 'Construction Confidence', 'Manufacturing Confidence' and 'Consumer Confidence' are taken from the EU Commission's database and correspond to the balances of the confidence indicators for the respective sector. The 'Loan Rate' is an average over loans to non-financial corporations and loans to households for house purchase, both related to new business only (source ECB: Statistical Data Warehouse (SDW)). 'Credit Standards (Firms)', 'Credit Standards (Mortgage)', 'Credit Demand (Firms)' and 'Credit Demand (Mortgage)' are from the Bank Lending Survey of the ECB. The series are country-level aggregates, measured as cumulative net percentages, and reflect commercial banks' assessment of changes in the overall credit standards they applied to firms or to households for mortgage loans and changes in the loan demand they face.

4.3 Robustness

4.3.1 The Global Financial Crisis

The Global Financial Crisis, especially the first year after its outbreak in the fall of 2008 is a very special episode associated with a historical decline in aggregate economic activity and an extraordinary jump in several uncertainty indicators. The latter remained elevated for several years even after the initial shock had abated and a slow recovery had set in (see Figure 2). In addition, the financial crisis triggered various economic reactions which are potentially structural in nature with presumably persistent consequences, e.g. the adoption of unconventional monetary policy measures for an extended period of time, substantial and persistent shifts in the fiscal policy stance, structural reforms in labor and product markets, and potentially far-reaching adjustments of macroprudential oversight and policy. Accordingly we want to check the stability of our findings across relevant subsamples. In particular, we repeat our baseline estimations over the following periods: *(i)* the *pre-crisis sample*, i.e. ending in 2007/Q4, *(ii)* a *post crisis sample 1* beginning in 2008/Q1 and *(iii) post crisis sample 2* starting one year later in 2009/Q1. The reactions of the credit-to-GDP gap to a shock to macroeconomic uncertainty are shown in Figure 7. As can be seen, they are qualitatively similar to our baseline results shown in Figure 3. However, the post crisis period seem to be associated with a weaker, albeit equally significant and persistent, reaction of the crisis indicator to sudden declines in macroeconomic uncertainty.

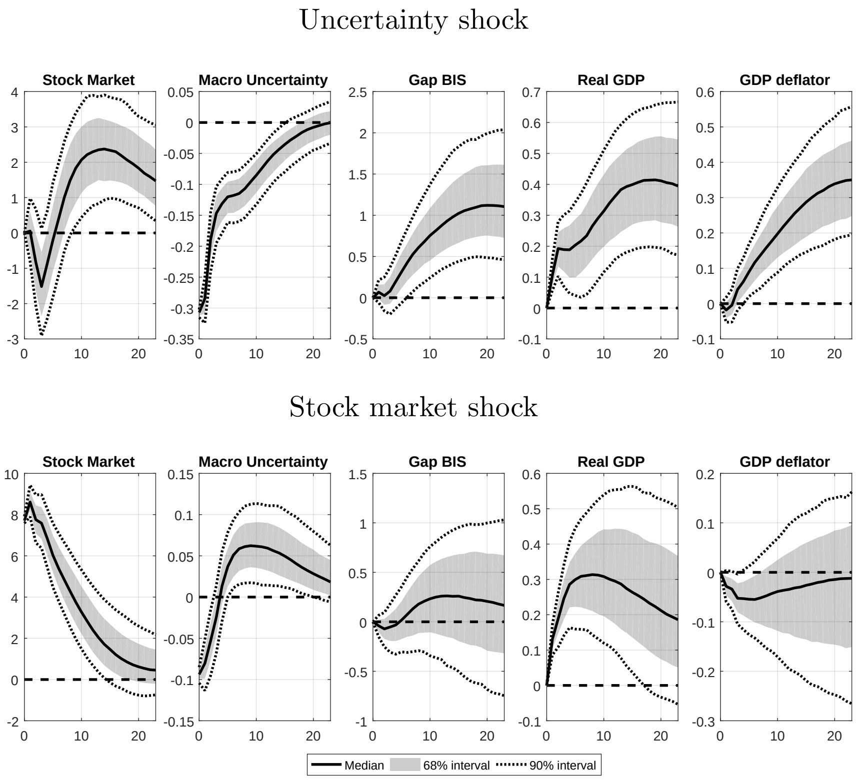
Figure 7: Subsamples. Baseline specification. Impulse responses to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. Pre crisis sample refers to 2000/Q1 - 2007/Q4, Post crisis sample 1 refers to 2008/Q1 - 2018/Q3, Post crisis sample 2 refers to 2009/Q1 - 2018/Q3. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points.

An alternative way to gauge the potential bias due to the marked spike in macroeconomic uncertainty in the second half of 2008 (see Figure 2) is by including a dummy variable in our model. In particular, we extend our baseline specification, covering the full sample, by a level shifter equal to one between 2008/Q3 and 2009/Q4 and zero otherwise. The responses to a macro-uncertainty shock and a stock market innovation are shown in Figure 8 and reveal the same qualitative picture as our main results. Finally, it should be noted that the extraordinary episode 2008 - 2009 in fact works against our baseline results. The reason is that the large jump in uncertainty was associated with an almost simultaneous, sizable decline in GDP. In contrast, the adjustment of the aggregate stock of credit started later and proceeded at a slower pace, since a substantial fraction of the credit stock is fixed through contracts signed in the past. Accordingly, the credit-to-GDP increased during and immediately after the outbreak of the Global Financial Crisis. As a consequence, the episode around 2008 - 2009, if anything, tends to weaken the link between *downward* shifts in uncertainty and *upward* shifts in the credit-to-GDP gap.

Figure 8: Crisis dummy. Impulse responses to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Baseline specification extended by including a crisis dummy. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points.

4.3.2 Identification scheme

We check the robustness of our results along several dimensions. First, as described in Section 2, to test the sensitivity of our results with respect to the identification scheme, we replace our baseline specification by alternative Choleski orderings.

First, similarly to Bloom (2009) we order the variables as follows:[13]

$$\begin{pmatrix} \textbf{log of Stock Market Index} \\ \textbf{Uncertainty Measure} \\ \text{Crisis Indicator} \\ \text{log of GDP} \\ \text{log of GDP Deflator} \end{pmatrix}$$

We term this specification *'Alternative Choleski 1'.* Second, we assume that the uncertainty proxy only reacts to its own shock on impact while the stock market index is immediately affected by both the uncertainty and the the stock market innovation. This amounts to the following recursive ordering:

$$\begin{pmatrix} \text{Crisis Indicator} \\ \text{log of GDP} \\ \text{log of GDP Deflator} \\ \textbf{Uncertainty Measure} \\ \textbf{log of Stock Market Index} \end{pmatrix}$$

This specification is termed *'Alternative Choleski 2'.* Baker et al. (2016) and Born et al. (2018) also order the uncertainty measure before the stock market index.[14]

The results are shown in Figure 9 and reveal that our results remain qualitatively unchanged. This also holds for the models proxing uncertainty by stock-market volatility or survey based disagreement as well as for the models resorting to alternative crisis indicators – i.e. the gap of the debt-service ratio, the ratios of household debt or mortgage loans to GDP and the indicator derived form an Early-Warning model (see also Table 1).[15]

[13]Bachmann et al. (2013), Bonciani & van Roye (2016) and Meinen & Roehe (2017) resort to a similar ordering in their baseline specifications. Castelnuovo & Tran (2017) even places the uncertainty measure first.

[14]Caggiano, Castelnuovo & Pellegrino (2017) use an interacted VAR (I-VAR) to disentangle uncertainty in normal times from uncertainty at the zero lower bound. Ludvigson et al. (2015) adopt a novel *shock-restricted* identification strategy which combines a set of event constraints with a set of correlation constraints. The former require the identified financial uncertainty shocks to have defensible properties during the 1987 stock market crash and the 2007-09 financial crisis. The latter requires the identified uncertainty shocks to exhibit a minimum absolute correlation with certain variables external to the VAR.

[15]Results available upon request.

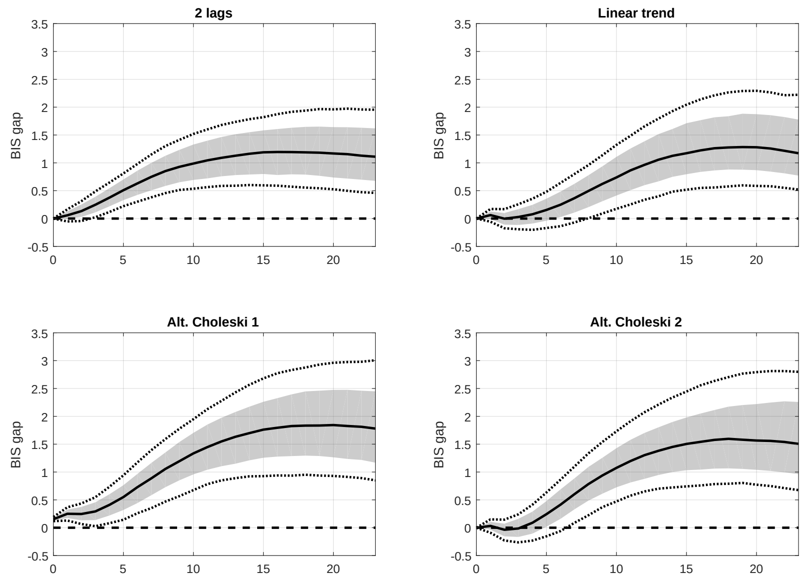
4.3.3 Linear trend and lag length

Further, we deviate form the baseline specification of our panel VAR by including a country-specific linear trend in each equation, or by reducing the lag length from 4 to 2. The latter is suggested by the BIC information criterion. The corresponding results are also shown in Figure 9.

4.3.4 Standardization of variables

Finally we turn to the issue of standardization of the uncertainty proxies. As explained in Section 2, they are transformed into Z-scores at the country level. This normalization appears reasonable since each individual uncertainty proxy is measured in different units with the consequence that the average level and volatility can differ by an order of magnitude across proxies or countries. To check the robustness to the standardization, we run two alternative estimations of our VARs – one with non-standardized uncertainty measures and one in which each endogenous variable is standardized at the country level. The results are qualitatively the same as shown in Figure 3 for the baseline case and in Table 1 for alternative uncertainty proxies and crisis indicators.

Figure 9: Robustness checks. Impulse responses of the credit-to-GDP gap to a macro-uncertainty shock.



Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro uncertainty'; crisis probability = 'Credit-to-GDP Gap'. '2 lags' - model with 2 lags; 'Linear trend' - model with a country specific linear trend in each equation; 'Choleski 1' - recursive ordering, uncertainty proxy is ordered second after the stock market index : 'Cholesky 2' - recursive ordering, uncertainty proxy is ordered last; 'Alternative sign restriction' - as baseline but stock market is allowed to react on impact. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points.

4.4 Exogenous and endogenous movements in stock markets

As explained in Section 2.2 and as suggested in the literature cited there, we design our identification scheme such that innovations to uncertainty and stock market shocks are most likely disentangled. Nevertheless, both types of shocks trigger a significant endogenous response in the respective other variable. Thus it is interesting to quantify the extent to which the reaction of the credit-to-GDP gap to uncertainty shocks results from stock market movements. Similarly we want to gauge on the importance of endogenous shifts in uncertainty for the response of the credit-to-GDP gap to stock market innovations as well as shocks to aggregate demand or aggregate supply.

To this end we compute counterfactual compute counterfactual impulse responses in which the stock market index or the uncertainty measure are held constant. To implement these experiments we resort to the Kalman filter approach described in Camba-Mendez (2012) which extracts the most likely combination of structural shocks consistent with the restriction on one (or more) endogenous variables. The first row in Figure 10 replicates the impulse responses to an uncertainty innovation according to our baseline specification. The second row shows the *counterfactual* reactions to the same shock, however under the restriction that the stock market index remains unchanged. For the sake of a better comparison between the the actual and counterfactual responses, the medians of the latter are shown as blue lines in the upper row of Figure 10. As can be seen, shutting-off the endogenous movements in stock markets slightly dampens the responses of the other variables. However, the qualitative picture remains the same. Notably, the Credit-to-GDP gap still exhibits a delayed but significant and persistent increase as a consequence of the exogenous shift in macroeconomic uncertainty. Accordingly, our results suggest that the stock market is of secondary importance for the transmission of uncertainty shocks to the crisis indicator.

Next we reverse the counterfactual exercise by computing the counterfactual responses to a stock market shock under the condition that the uncertainty measure remains unchanged. The results are shown in Figure 11 alongside the actual reactions to the same shock. As can be seen, the unrestricted effect of innovation to the stock market index on the Credit-to-GDP gap is barely significant. However, preventing macroeconomic uncertainty from responding to the shock leads to a delayed but significant increase of the crisis indicator (second row in Figure 11). This is mainly due to reversing the strong endogenous increase in uncertainty above its mean between the 5th and 20th quarter (see first row and second column in Figure 11). We conclude that the response of the Credit-to-GDP gap to stock market innovations is strongly affected by the endogenous movement in uncertainty induced by the shock.

4.5 Shocks to aggregate demand and aggregate supply

Finally, we turn to the case of aggregate demand and aggregate supply shocks and investigate to what extent their effects on the credit–to–GDP gap are driven by the associated endogenous response of uncertainty. We identify these two standard drivers of the business cycle as well as shocks to uncertainty and the stock market, by means of a combination of zero and sign restrictions.[16] Table 2 summarizes these restrictions. In particular, we assume that innovations to economy-wide demand shift GDP and the corresponding deflator in the same direction while these variables move in opposite directions in the case of shocks to aggregate supply. Innovations to uncertainty and the stock market are identified by the same recursive scheme as in

[16]To impose simultaneously zero and sign restrictions, we resort to the approach proposed by Arias, Rubio-Ramrez & Waggoner (2018).

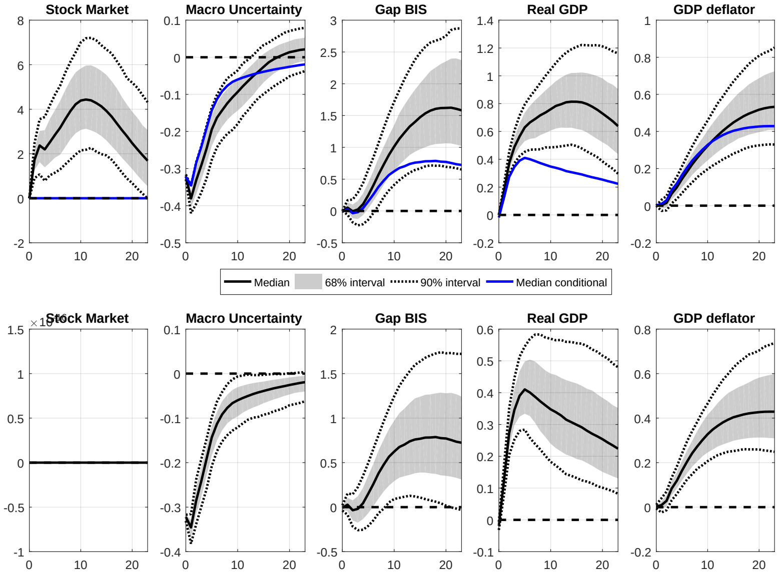
Table 2: Baseline identification scheme: sign and zero restrictions

Variable: / Shock:	Stock market index	Macroeconomic uncertainty	Credit-to-GDP gap	Real GDP	GDP deflator
Stock market	↑	0	0	0	0
Uncertainty		↓	0	0	0
Aggregate demand				↑ (2Q)	↑ (2Q)
Aggregate supply				↑ (2Q)	↓ (2Q)

Notes: Restrictions are generally imposed on impact, while '2Q' indicates restrictions imposed on the first two quarters. '0' indicates a zero restriction on impact

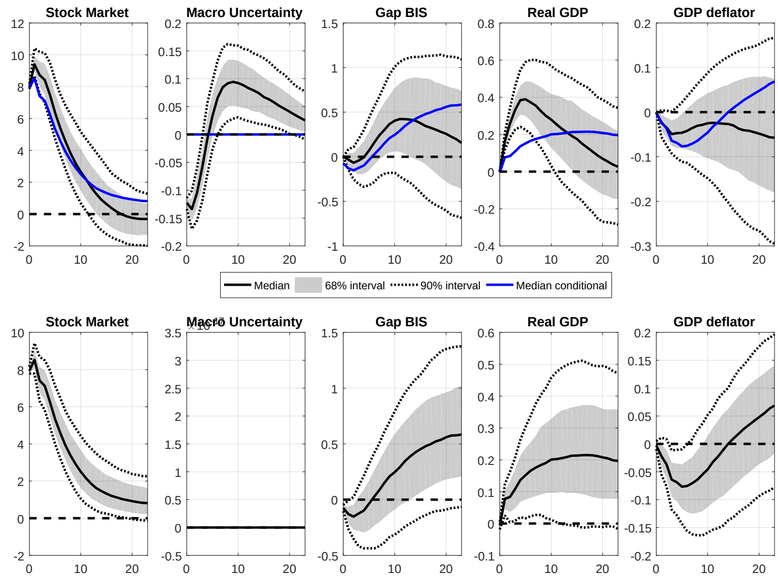
our baseline specification (see Section 2.2). I.e. on impact, uncertainty shocks only affect the uncertainty measure while stock market shocks can affect both, the stock market index itself as well as the uncertainty measure. The remaining variables react only with a one-period lag to innovations in uncertainty and the stock market. The impulse responses to aggregate demand and aggregate supply disturbances are shown in Figures 12 and 13. It turns out that positive aggregate demand shocks barely affect the Credit-to-GDP gap (first row in Figure 12). This implication is robust to preventing macroeconomic uncertainty from responding to the aggregate demand disturbance (second row in Figure 12). As shown in Figure 13, aggregate supply shocks trigger a significant decline in the Credit-to-GDP gap. However, this reaction seems to be partly due to the endogenous response of macroeconomic uncertainty. In particular, the latter rises significantly when an aggregate supply shock hits the economy. If this increase is removed, the initial decline in the Credit-to-GDP gap becomes weaker, and is followed by significantly above average values of the crisis indicator about 20 quarters after the shock (second row and third column in Figure 13).

Figure 10: Actual and counterfactual responses to an uncertainty shock.



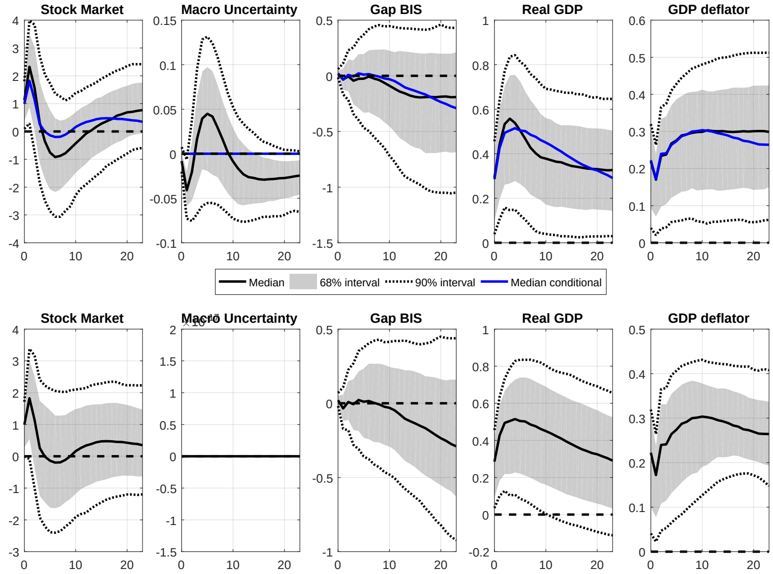
Notes: Uncertainty shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. First row - actual IRFs. Second row - counterfactual IRFs under the restriction that 'Stock Market' = 0. The blue lines in the first row correspond to the medians of the counterfactual IRFs. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points. All other variables are measured in percent.

Figure 11: Actual and counterfactual responses to a stock market shock.



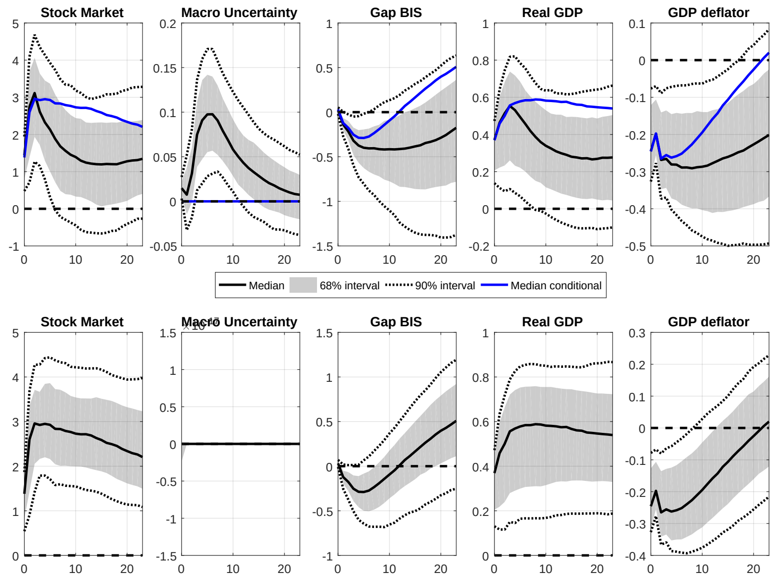
Notes: Stock market shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. First row - actual IRFs. Second row - counterfactual IRFs under the restriction that 'Macro Uncertainty' = 0. The blue lines in the first row correspond to the medians of the counterfactual IRFs. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points. All other variables are measured in percent.

Figure 12: Actual and counterfactual responses to an aggregate demand shock.



Notes: Aggregate demand shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. First row - actual IRFs. Second row - counterfactual IRFs under the restriction that 'Macro Uncertainty' = 0. The blue lines in the first row correspond to the medians of the counterfactual IRFs. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points. All other variables are measured in percent.

Figure 13: Actual and counterfactual responses to an aggregate supply shock.



Notes: Aggregate supply shock identified based on the restrictions shown in Table 2. Indicators used: uncertainty = 'Macro Uncertainty'; crisis probability = 'Credit-to-GDP Gap'. First row - actual IRFs. Second row - counterfactual IRFs under the restriction that 'Macro Uncertainty' = 0. The blue lines in the first row correspond to the medians of the counterfactual IRFs. Shaded areas and dotted lines correspond to the 68% and the 90% credibility bounds respectively. Time is in quarters. The credit-to-GDP gap is measured in percentage points. All other variables are measured in percent.

5 Conclusion

While the role of uncertainty with respect to macroeconomic activity measures has been well-explored by the empirical literature, evidence with respect to indicators that tend to precede financial crises is scarce. The current paper seeks to fill this gap and estimates a structural vector autoregression model for a set of four euro area countries in order to investigate the dynamic responses of shocks to uncertainty. We show that a drop in uncertainty, while driving up real economic activity, prices, and stock market indices, induces crisis indicators to increase after about two years.

Even though, our results should not be interpreted as direct or causal evidence for uncertainty to increase the likelihood of financial crises, they hint that uncertainty measures may serve as useful indicators for potential buildups of vulnerabilities. Qualitatively, our findings are robust through a set of uncertainty measures like macroeconomic uncertainty, survey uncertainty, and financial uncertainty and a set of crisis indicators like the Basel credit-to-GDP gap, a housing loans-to-GDP gap, a household debt-to-GDP gap, a debt service ratio, or a house price gap. Effects with respect to a measure of the credit spread as a crisis indicator uncertainty yield inconclusive results. A speculative explanation is that uncertainty shocks shift both, the demand and the supply side of the respective asset markets, by a similar amount. As a consequence, shocks impact on quantities but let prices rather unaffected.

We emphasize the purely positive nature of our analysis, where the explicit and detailed transmission mechanism of uncertainty shocks is still left to be explored by future empirical or theoretical research. Still our results contain valuable information with respect to one source financial system vulnerabilities.

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Appendix

- **Credit-to-GDP gap:** Source: BIS `https://www.bis.org/statistics/c_gaps.htm`.
- **The household-debt-to-GDP ratio:** "Total credit to households (as % of GDP)", source: BIS `https://www.bis.org/statistics/totcredit.htm`
- **Mortgage loans to households and NPISH:** "Lending for house purchase", source: ECB Statistical Data Warehouse `https://sdw.escb.eu/browse.do?node=9691311`. In particular, for each country we sum up the stocks corresponding to the maturities
'Up to 1 year': BSI.M.**XX**.N.A.A22.F.1.U6.2250.EUR.E; 'Over 1 and up to 5 years': BSI.M.**XX**.N.A.A22.I.1.U6.2250.EUR.E; 'Over 5 years': BSI.M.**XX**.N.A.A22.J.1.U6.2250.EUR.E, where **XX** is the placeholder for the country code. The resulting overall stock of mortgage credit is seasonally adjusted with X12-ARIMA and divided by seasonally adjusted nominal GDP provided by Eurorstat.
- **Debt-service-ratio:** Source: BIS `https://www.bis.org/statistics/dsr.htm`.
- **Real residential property prices:** Ratio of its nominal counterpart to the corresponding national consumer price index, source: BIS, `https://www.bis.org/statistics/pp_selected.htm`
- **Loans to non-financial corporations:** New business, average over all maturities, source: ECB Statistical Data Warehouse `https://sdw.escb.eu/browse.do?node=9691393`, coded as MIR.M.**XX**.B.A2A.A.R.A.2240.EUR.N, where **XX** denotes the country code.
- **German government bond yield:** Source: Thomson Reuters, Datastream, code: GBBD03Y.

- **Early-warning indicator:** Based on the crises database, Beutel et al. (2018) define a binary variable equal to 1 within a time window between 5 and 12 quarters prior to the occurrence of a financial crisis. The resulting binary variable is then regressed – within linear as well as logit models – on several explanatory variables. Given the regression results one can compute an estimate of the crisis probability or – in the case of a linear model – a linear indicator for this probability.

- **Survey-based dispersion in expectations:** Source: Economic database of the European Commission `https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en`. The corresponding survey question in the questionnaire for firms in the manufacturing sector reads: *How do you expect your production to develop over the next 3 months? It will: (+) increase; (=) remain unchanged; (-) decrease;*. See `https://ec.europa.eu/info/sites/info/files/bcs_user_guide_en_0.pdf` for further details. In the construction/building sector the precise question is: *How do you expect your firms total employment to change over the next 3 months? It will: (+) increase; (=) remain unchanged; (-) decrease.*

- **Economic policy uncertainty:** In particular, the construction of the EPU index for the euro-area economies considered in our analysis is based on two newspapers per country: Le Monde and Le Figaro for France, Handelsblatt and Frankfurter Allgemeine Zeitung for Germany, Corriere Della Sera and La Repubblica for Italy, El Mundo and El Pais for Spain. See `http://www.policyuncertainty.com/index.html` for data and methodological details.