OESTERREICHISCHE NATIONALBANK
EUROSYSTEM

WORKING PAPER 233

A View from Outside: Sovereign CDS Volatility as an Indicator of Economic Uncertainty

Maximilian Böck, Martin Feldkircher, Burkhard Raunig

The *Working Paper series of the Oesterreichische Nationalbank* is designed to disseminate and to provide a platform for discussion of either work of the staff of the OeNB economists or outside contributors on topics which are of special interest to the OeNB. To ensure the high quality of their content, the contributions are subjected to an international refereeing process. The opinions are strictly those of the authors and do in no way commit the OeNB.

The Working Papers are also available on our website (http://www.oenb.at) and they are indexed in RePEc (http://repec.org/).

Publisher and editor *Oesterreichische Nationalbank*
Otto-Wagner-Platz 3, 1090 Vienna, Austria
PO Box 61, 1011 Vienna, Austria
www.oenb.at
oenb.info@oenb.at
Phone (+43-1) 40420-6666
Fax (+43-1) 40420-046698

DVR 0031577

ISSN 2310-5321 (Print)
ISSN 2310-533X (Online)

A View from Outside: Sovereign CDS Volatility as an Indicator of Economic Uncertainty

MAXIMILIAN BÖCK*, MARTIN FELDKIRCHER† and BURKHARD RAUNIG‡

Abstract

A sovereign credit default swap (CDS) compensates for losses when a country defaults on its debt. The periodic premium payment for such default protection is the so called CDS spread. The volatility of sovereign CDS spreads reflects the amount of uncertainty of CDS traders about the level the spreads. As sovereign CDS contracts are mainly written by leading global financial institutions, sovereign CDS volatility captures the uncertainty of these institutions about the economic conditions in a country. In this paper, we investigate the merits of sovereign CDS volatility as an indicator of economic uncertainty for a broad panel of 16 countries. Using directional forecast evaluation methods, we find that sovereign CDS volatility does contain information about economic policy uncertainty (EPU) as measured by popular news-based EPU indices. Furthermore, using Bayesian panel VARs, we estimate the responses of output and unemployment after an unexpected increase in economic uncertainty measured with CDS volatility and compare them with responses obtained with EPU indices and other measures of economic uncertainty. Our results indicate that the responses to CDS volatility shocks are qualitatively similar to the responses to EPU index shocks. However, the responses to shocks to CDS volatility can be estimated more precisely.

Keywords: Credit default swap; Directional forecasts; Economic policy uncertainty; Financial market volatility
JEL codes: D80, E66, G18

*Vienna University of Economics and Business, Welthandelsplatz 1, A-1020 Vienna, Austria, e-mail: maximilian.boeck@wu.ac.at

†Vienna School of International Studies, Favoritenstraße 15a, A-1040 Vienna, Austria, e-mail: martin.feldkircher@da-vienna.ac.at

‡Oesterreichische Nationalbank, Economic Studies Division, Otto-Wagner-Platz 3, A-1090 Vienna, Austria, e-mail: burkhard.raunig@oenb.at.

The views expressed in this paper do not necessarily reflect those of the Oesterreichische Nationalbank or the Eurosystem.

Non-Technical Summary

Since economic uncertainty can have serious negative effects on financial markets and real economic activity, policy makers and economic analysts need meaningful measures of economic uncertainty. Currently available measures of economic uncertainty are, however, based on complex and data-intensive methods and are often only available for a few large economies. This paper investigates whether the volatility of sovereign credit default swap (CDS) spreads can be used to measure economic uncertainty. Sovereign CDS volatility could be an attractive measure of economic uncertainty because sovereign CDS volatility reflects the uncertainty of global financial institutions about the economic conditions in a country. In addition, CDS volatility can be easily computed and CDS contracts are available for almost all countries.

We examine the usefulness of CDS volatility as an indicator of economic uncertainty for three groups of economies: euro area countries (France, Germany, Ireland, Italy, Netherlands, Spain), major advanced economies (Canada, Great Britain, Japan, South Korea, Sweden, USA) and emerging market economies (Brazil, Croatia, Mexico, Russia). Currently very popular measures of economic uncertainty are news-based economic policy uncertainty (EPU) indices. We therefore first investigate whether the CDS volatility for a country is helpful in predicting directional movements in the EPU index for the country. We then examine the macroeconomic responses to shocks to economic uncertainty when uncertainty is measured in terms of sovereign CDS volatility and compare them to responses to a shock to the news-based EPU index.

We find that sovereign CDS volatility does contain information about changes in EPU country indices. Furthermore, the responses of output and unemployment to shocks to sovereign CDS volatility and EPU indices are qualitatively similar, but both macroeconomic variables tend to respond more strongly to shocks in sovereign CDS volatility than to shocks in the EPU country index. It also turns out that responses to CDS volatility shocks can often be estimated more accurately than responses to shocks to EPU indices. Sovereign CDS volatility could thus either serve as a primary measure of economic uncertainty or as an additional measure of uncertainty if other indicators of economic uncertainty are already available

1 Introduction

Economic activity and uncertainty regarding key political, financial, and economic issues appear to be negatively related. As economic uncertainty increases, firms tend to reduce hiring and investment (Bloom, 2009; Bloom et al., 2018; Baker et al., 2016; Caldara et al., 2016; Caggiano et al., 2014; Kang et al., 2014), banks tend to reduce lending (Bordo et al., 2016) and financial markets tend to become more volatile (Boutchkova et al., 2012; Liu and Zhang, 2015; Pástor and Veronesi, 2013).[1] As a result, economic uncertainty can cause severe output fluctuations (Ludvigson et al., 2020).[2] The recent global financial crisis and the ongoing COVID-19 pandemic are current examples of extraordinary high economic uncertainty. These experiences and the potentially severe negative effects of economic uncertainty on financial markets and real economic activity therefore greatly increase the demand for indicators of economic uncertainty.

A key question is how to properly measure economic uncertainty? To that end, the literature has proposed news-based indices (Baker et al., 2016), survey-based measures (Bachmann et al., 2013), indicators extracted from large sets of economic time series (Jurado et al., 2015; Scotti, 2016) and distribution-based measures (Rossi and Sekhposyan, 2015). What all these indicators have in common is that they are based on complex and data-intensive methods and that they are often only available for a few large economies.

In this paper, we investigate whether the volatility of sovereign credit default swap (CDS) spreads is a useful measure of economic uncertainty. A sovereign CDS is a credit derivative that provides protection against default or restructuring of government debt, and the CDS "spread" is the periodic premium that must be paid for such protection.[3] Using the volatility of sovereign CDS spreads as a measure of economic uncertainty is attractive for several reasons. CDS contracts are traded for almost all countries, and CDS volatility can be compared directly between countries. More importantly, most of sovereign CDS trading is done by leading global financial institutions. Sovereign CDS volatility thus captures the uncertainty in the assessment of global financial institutions about the macroeconomic health of a particular country. Sovereign CDS volatility thus offers a more global view about the economic uncertainty in a country, while other measures of economic uncertainty tend to reflect more local perspectives on economic uncertainty.

We examine the usefulness of CDS volatility as an indicator of economic uncertainty for three groups of economies: euro area countries (France, Germany, Ireland, Italy, Netherlands, Spain), major advanced economies (Canada, Great Britain, Japan, South Korea, Sweden, USA) and emerging market economies (Brazil, Croatia, Mexico, Russia). For that purpose, we examine the empirical relationship between CDS volatility and the news-based economic policy uncertainty (EPU) indices of Baker et al. (2016), as these indices have been widely used by practitioners as a measure of uncertainty. Furthermore, these are the only uncertainty indices available for a larger set of countries. As our country selection indicates, the coverage of the EPU indices is currently still limited.

We proceed in two steps: First, we investigate whether the volatility of sovereign CDS spreads can be used to predict movements in the corresponding EPU index. Since EPU indices are dimensionless measures of uncertainty, we focus on directional predictions, i.e., how often can we successfully predict an upward (downward) movement in the EPU index when we use the upward (downward) movement in CDS volatility as a predictor? If the directional predictions are reasonably good, then CDS volatility could be used as a timely indicator for the development of economic uncertainty in countries where an EPU country index is unavailable or only available with a time lag. Second, we examine the macroeconomic responses to shocks to economic uncertainty when uncertainty is measured by sovereign CDS volatility. To this end, we calculate output and

[1] See, Castelnuovo (2019) for a survey of this literature.

[2] Ludvigson et al. (2020) argues that financial uncertainty causes output fluctuations, while macroeconomic uncertainty is likely to be the endogenous response to output shocks.

[3] The term "spread" is somewhat misleading but common market language. The underlying of a sovereign CDS contract are government bonds. The CDS spread is the cost of insurance against the credit risk in these bonds. See, Lando (2004) for details about CDS pricing.

unemployment responses to shocks in sovereign CDS volatility and compare them to those from a shock to the news-based EPU index. We estimate the impulse responses with a Bayesian panel vector-autoregressive (VAR) model that allows us to compare responses across and within each of the three regions we consider.

Our main results can be summarized as follows: Changes in sovereign CDS volatility do contain information about changes in the corresponding EPU country index. The directional predictions for EPU indices based on directional changes in CDS volatility are in almost all cases better than random predictions. For most countries the fraction of correct directional predictions is between 55% and 60%. For some countries (i.e., Great Britain, Mexico, Brazil, and South Korea) this fraction exceeds 60%. The results from the panel VAR reveal that the responses of output and unemployment to shocks to sovereign CDS volatility and EPU indices are qualitatively similar. However, both variables tend to respond more strongly to a shock in sovereign CDS volatility than to a shock in the corresponding EPU country index. The difference in the reactions is strongest for the euro member states. The impulse responses for CDS volatility shocks and EPU index shocks are more similar in emerging market economies. Furthermore, it turns out that responses to CDS volatility shocks can often be estimated more accurately than responses to shocks to EPU indices.

The rest of the paper is structured as follows. In the next section, we describe the data and the computation of CDS volatility. Sec. 3 deals with the the evaluation of directional predictions of EPU indices based on CDS volatility. In Sec. 4 we outline the panel VAR methodology, present the results for the macroeconomic responses to uncertainty shocks, and report some additional robustness analysis. Sec. 5 provides conclusions.

2 Data

Our data consists of the standard macroeconomic variables output as measured by industrial production (ip_t), unemployment (ur_t), short-term interest rates (i_t) and equity prices (eq_t), daily data on sovereign CDS spreads (s_t), and monthly news-based EPU country indices. The macroeconomic data are obtained from Eurostat, the IMF and the OECD. The CDS spreads come from the Macrobond database.[4] The EPU indices come from the Economic Policy Uncertainty homepage maintained by Scott Baker, Nick Bloom and Steven Davis.[5] We were able to collect complete data on all variables for 16 countries. We divide these countries into three groups: the euro area (France, Germany, Ireland, Italy, Netherlands, Spain), major advanced economies (Canada, Great Britain, Japan, South Korea, Sweden, USA) and emerging market economies (Brazil, Croatia, Mexico, Russia).

The sample period in our baseline analysis ranges from 2008m10 to 2019m12. We do not start earlier because the CDS market was essentially illiquid for most countries until the US investment bank Lehman Brothers went bankrupt in September 2008. CDS trading on government debt did start around the year 2000, but CDS contracts were initially traded mainly for Brazil, Japan, Mexico, the Philippines and South Africa - all countries with serious economic problems at that time (Packer and Suthiphongchai, 2003). Only after the Lehman collapse, CDS contracts were traded on a large scale for all countries in our sample. For the emerging market economies where the CDS market was liquid earlier, we also consider the larger sample period from 2003m1 to 2019m12 when we compute responses to economic uncertainty shocks.

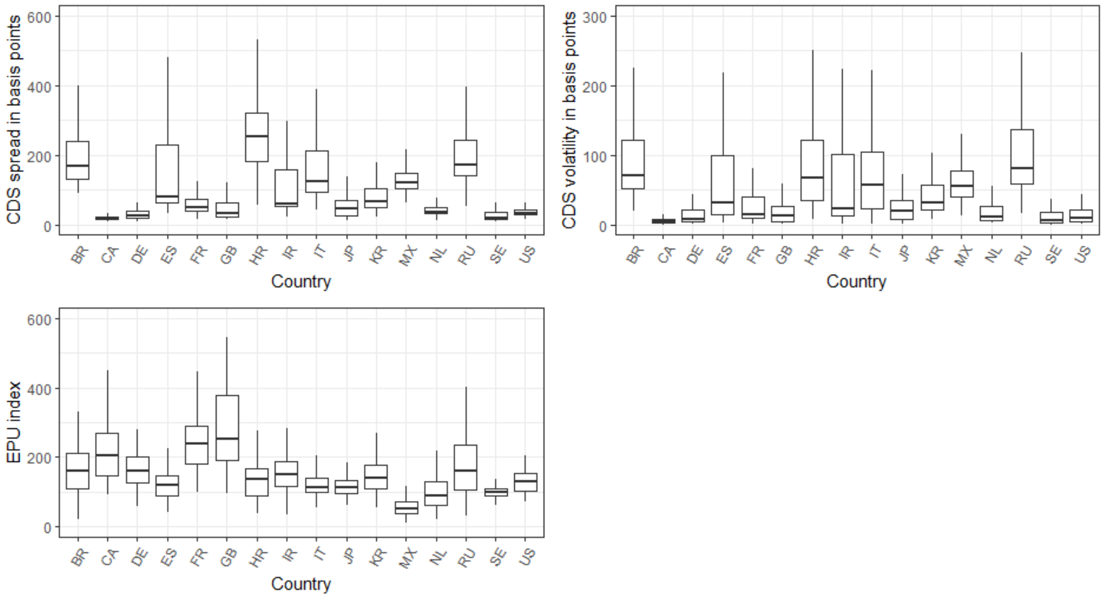
The paper is about the volatility of CDS spreads, but for completeness we also show box plots for the level of daily CDS spreads (upper left diagram in Fig. 1).[6] The box plots show that the daily CDS spreads were particularly high for Spain, Italy, Ireland, Brazil, Croatia, Mexico, and Russia. The former three countries were involved in the European Debt Crisis in 2010. The latter four countries also had serious economic and political problems during the sample period.

[4] For more information about the Macrobond database see, https://www.macrobond.com/

[5] See, http:/www.policyuncertainty.com/

[6] Tab. A1 in the appendix provides additional summary statistics.

Figure 1: Box plots for daily CDS spreads, annualized monthly CDS volatility and monthly EPU indices



2.1 CDS volatility

We calculate CDS volatility at a monthly frequency from the daily CDS spread quotes for five year sovereign CDS contracts denoted in US dollars because this type of contract is most commonly traded in the market (Vogel et al., 2013). For each country we compute CDS volatility in three steps. First, we calculate daily CDS spread changes $\Delta s_t = s_t - s_{t-1}, t = 1, ..., T$. We use changes because the spreads s_t themselves are not stationary. Only unpredictable movements in CDS spreads contribute to CDS volatility. Therefore, we then regress the daily CDS spread changes on their first four lags

$$\Delta s_t = \alpha_0 + \alpha_1 \Delta s_{t-1} + \ldots + \alpha_4 \Delta s_{t-4} + e_t \tag{2.1}$$

to remove any predictable mean dynamics. The resulting residuals in in equation (2.1) are the unpredictable movements in CDS spreads. In the final step, we compute CDS volatility at monthly frequency from the absolute values $|e_i|$ of the residuals as

$$\sigma_m = a\sqrt{\frac{\pi}{2}} \sum_{i=1}^{D_m} \frac{|e_t|}{D_m}. \tag{2.2}$$

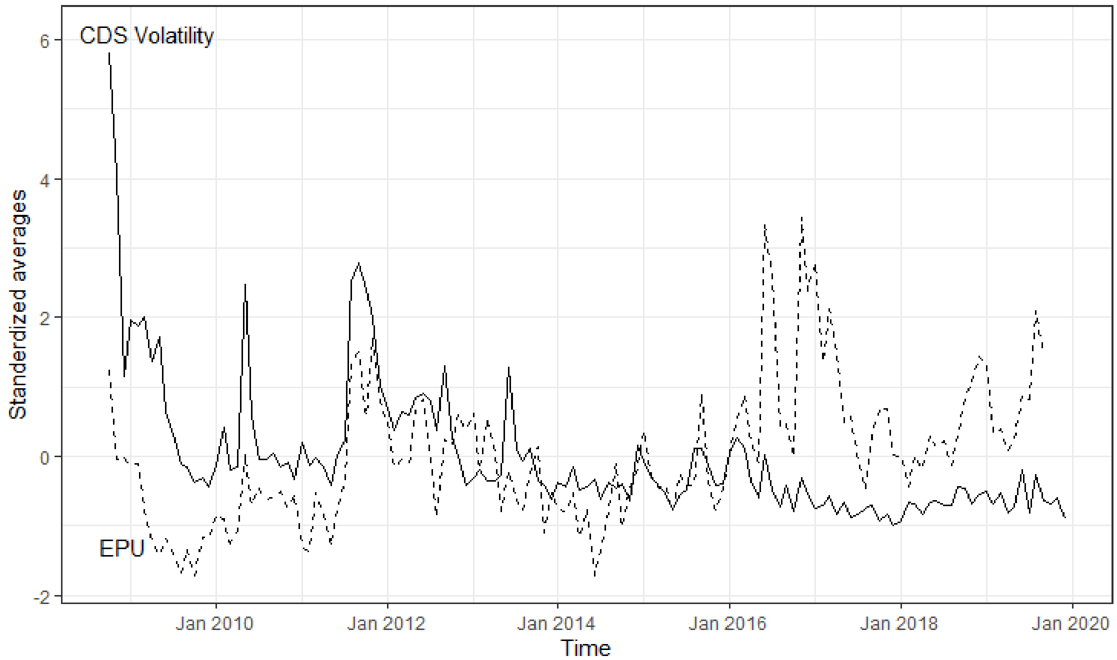
where D_m is the number of trading days in month m, and $a = \sqrt{252}$ is a scaling factor that converts the average daily volatility into annualized volatility.

We use the absolute values of the residuals to obtain a measure of CDS volatility that is robust against extreme observations. The term $\sqrt{\pi/2}$ results from the fact that the expectation of the absolute value of a random variable $R = \sigma \cdot u$ is $E(|R|) = \sigma\sqrt{2/\pi}$ when σ is a positive constant and u is standard normally distributed.

The box plots in the upper right diagram in Fig. 1 summarize the main statistical properties of the CDS volatility series. As can be seen, Spain, Italy, Ireland, Brazil, Croatia, Mexico, and Russia – the countries with higher CDS spreads – are also the countries that display higher CDS volatility.

Fig. 2 shows how the average levels of CDS volatility and EPU over all countries in the sample evolved over time. For better comparability both series are standardized. As can bee seen, the average level of CDS volatility across all countries already peaked at the beginning of the sample period due to the crisis in 2009.

Figure 2: Standardized cross-sectional averages of CDS volatility and EPU indices over time.



In 2010 and 2012 two more spikes occurred because of the European debt crisis. Afterwards, average CDS volatility went down and approached its lowest level towards the end of the sample period. However, some of the individual volatility series remained quite high after 2012 and sometimes reached levels of more than 200 basis points.

2.2 Economic policy uncertainty

The popular news-based EPU indices introduced in Baker et al. (2016) are the benchmark measure of economic uncertainty in our analysis. The EPU indices are constructed from keyword searches in the electronic archives of a country's most important newspapers. For example, the US EPU index is based on searches in the archives of the ten most important US newspapers. Counted are articles that contain triples of the words "economic" or "economy", "uncertain" or "uncertainty", and one or more of the words "Congress", "deficit", "Federal Reserve", "legislation", "regulation", or "White House". The monthly article counts are then scaled and normalized to a mean of one-hundred. The EPU indices for the other countries in the sample are constructed in a similar way. Baker et al. (2016) provide all the details.

How did the EPU indices for the countries in the sample evolve over time? Fig. 2 shows that the cross-sectional averages of EPU indices and CDS volatility show co-movement over time. In addition, the lower left panel in Fig. 1 indicates that average EPU was particularly high for Brazil, Canada, China, France, and Great Britain (Tab. A3 in the appendix provides additional summary statistics). In all these countries the unusually high index values occurred mainly in the last few years of the sample period. Recent political scandals provide an explanation for Brazil. The rough US trade policy is likely to be responsible for this pattern in Canada and China. Uncertainty surrounding the planned exit from the European Union explains the high EPU index values for Great Britain and a series of ISIS terror attacks is responsible for the high index values for France. The peaks in the standardized cross-sectional average EPU over the countries in the sample reflect these episodes of high EPU (Fig. 2).

3 Predicting directional changes of EPU indices

Analysts may require a timely indication of an upward or downward movement in economic uncertainty, but prominent measures of economic uncertainty such as the EPU index are only available with a time lag and for particular countries. In this section, we examine whether the directional changes in CDS volatility are useful in predicting directional changes in the corresponding EPU indices. More precisely, we ask whether the directional change of sovereign CDS volatility in month m correctly predicts (i.e., nowcasts) the directional change of the corresponding EPU country index in month m? We use directional forecast evaluation methods to answer this question[7] and evaluate the directional predictions in three different ways: First, we compute performance statistics, second, we run regression based statistical tests, and third, we assess the economic value of the directional predictions based on sovereign CDS volatility.

3.1 Methods for evaluating directional predictions

To assess the predictive ability of sovereign CDS volatility we compute four performance statistics based on the contingency matrix in Tab. 1. In this matrix the indicator variable x_t takes on the value of one when the volatility of CDS spreads has increased from time $t-1$ to time t, and is zero otherwise. Analogously, the indicator variable y_t takes on a value of one when the EPU index has increased from $t-1$ to t and is zero otherwise. The entries N_{uu} and N_{dd} denote the number of correct up and down predictions, and the entries N_{ud} and N_{du} denote the number of incorrect up predictions and incorrect down predictions.

Table 1: Contingency matrix for directional predictions

		EPU	
		Up($y_t = 1$)	Down($y_t = 0$)
CDS volatility	Up($x_t = 1$)	N_{uu}	N_{ud}
	Down($x_t = 0$)	N_{du}	N_{dd}

The first statistic that we compute summarizes the overall accuracy of the directional predictions. Accuracy is defined as

$$AC = \frac{N_{uu} + N_{dd}}{N_{uu} + N_{du} + N_{ud} + N_{dd}}. \tag{3.1}$$

The value of the AC statistic is between zero and one and shows the proportion of correct predictions. The statistic is intuitive, but can be misleading if upward or downward movements are rare.

The next statistic, the so called "hit rate"

$$HI = \frac{N_{uu}}{N_{uu} + N_{du}}, \tag{3.2}$$

has also a value between zero and one. The hit rate HI is the proportion of correct up predictions and can be recognized as a sample estimate of the conditional probability that CDS volatility will increase when EPU rises. The statistic is sensitive to upward movements but ignores false upward predictions.

The "false alarm rate" defined as

$$F = \frac{N_{ud}}{N_{ud} + N_{dd}}, \tag{3.3}$$

looks at the the proportion of incorrect upward predictions. The statistic provides an estimate of the conditional probability of an incorrect upward prediction when the EPU index goes in fact down. The related

[7] Since we use use directional forecast evaluation methods we stick with the term "predicting" rather than "nowcasting". Both terms can of course be used interchangeably.

quantity $1 - F$ is an estimate of the conditional probability that CDS volatility provides of a correct downward prediction when EPU actually did go down.

The difference between the hit rate and the false alarm rate,

$$KS = HI - F, \tag{3.4}$$

is known as the Kuiper score. The KS statistic has a range from minus one to plus one and indicates how well CDS volatility discriminates between up and down movements in the EPU index over time. The KS statistic is around zero if the directional predictions are essentially random. A positive KS statistic indicates that CDS volatility helps to predict the directional movements of an EPU index.

The statistics just described examine the ability of movements in CDS volatility to correctly capture movements in EPU indices, but they are not formal statistical tests. We therefore also perform two regression-based statistical tests suggested in Blaskowitz and Herwartz (2014). Both tests use the indicator variables x_t and y_t for up and down movements in CDS volatility and the corresponding EPU index. In both tests the null hypotheses of zero covariance between x_t and y_t implies that the directional predictions based on CDS volatility are purely random.

In the first test we run the linear regression

$$y_t = \alpha + \beta x_t + u_t \tag{3.5}$$

and test for $\beta = 0$. This test assumes that the error u_t in (3.5) has zero mean, a constant variance and is serially uncorrelated (i.e., $E(u_t^2|x_t, x_{t-1}, ...) = \sigma^2 > 0$ and $E(u_t u_s|x_t, x_{t-1}, ...) = 0$ for all $t \neq s$). Under these assumptions the hypotheses $\beta = 0$ can be tested with a standard t-test.

In the second test these assumptions can be relaxed by running an augmented regression of the type

$$y_t = \alpha + \beta x_t + \sum_{j=1}^{m} \gamma_j x_{t-j} + \sum_{j=1}^{n} \delta_j y_{t-j} + u_t \tag{3.6}$$

that corrects for the effects of lagged dependent and explanatory variables. The hypothesis to be tested is again $\beta = 0$. To account for any remaining autocorrelation in the residuals we compute the t-test statistic with robust Newey-West standard errors (Newey and West, 1987).

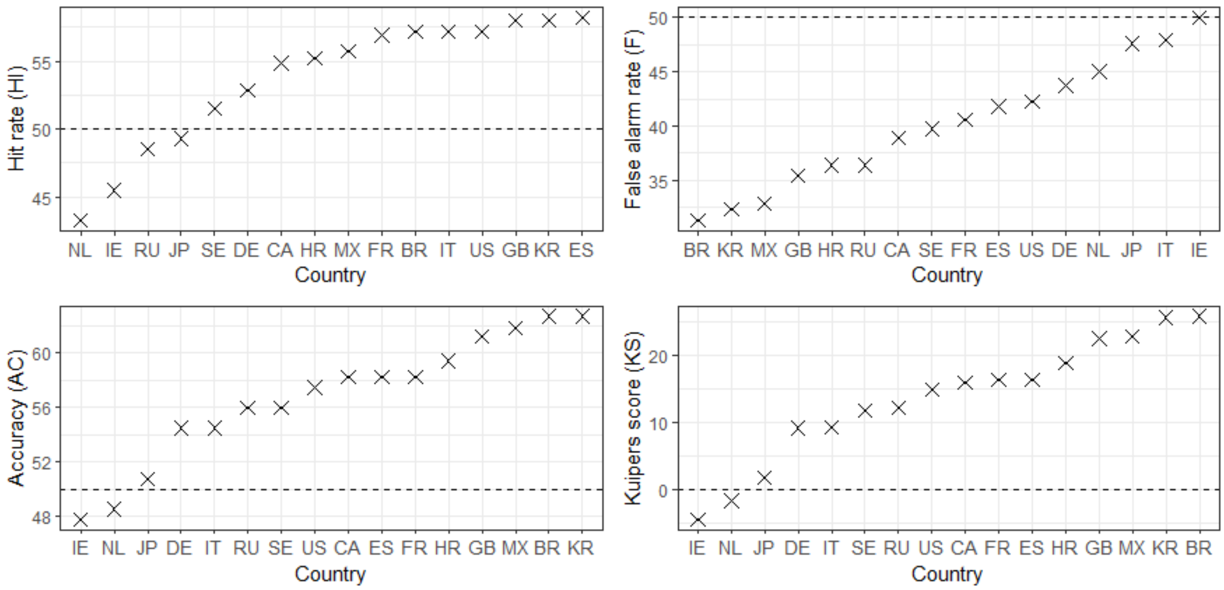
In order to illustrate the economic value of the directional predictions, we consider a simple betting game that penalizes incorrect directional predictions and rewards correct predictions in proportion to the size of EPU changes. In the betting game the player cannot observe the EPU index and uses the directional change in CDS volatility to predict the directional change in the EPU index. A correct directional prediction at time t yields a monetary gain equal to the absolute value of the change of the EPU index between t and $t - 1$. An incorrect prediction yields a loss equal to the absolute value of the movement of the index between $t - 1$ and t. The game is played over the sample period. During the entire period the player cannot observe the EPU index and does not know any intermediate outcomes of the game. The net gain/loss is payed out at the end of the game. A positive net gain shows that the predictions based on sovereign CDS volatility have economic value in this game.

3.2 Results for directional predictions

In this section we present the empirical findings about the ability of monthly sovereign CDS volatility to predict the directional change of the corresponding EPU country index in the same month. We begin with the performance statistics (Fig. 3).

The upper left plot in Fig. 3 shows the results for the hit rate - the proportion of correct up predictions. As can be seen, twelve out of sixteen hit rates exceed 50%. The hit rates reach about 57.5% for France, Brazil,

Figure 3: Directional forecast statistics



Italy, the US, Great Britain, South Korea, and Spain. The hit rates for Canada, Croatia and Mexico are not much lower and are around 55%. However, CDS volatility does not always help predict upward movements in EPU. The hit rates for the Netherlands, Ireland, Russia, and Japan are below 50%.

The upper right diagram shows that the directional predictions form CDS volatility do not produce excessively high false alarm rates. The proportion of incorrect upward predictions is for almost all countries well below 50%. With values close to 32%, the false alarm rates are particularly low for Brazil, South Korea, and Mexico. Most other false alarm rates are between 35% and 45%. An exception is Ireland, where the false alarm rate reaches 50%.

Accuracy - the proportion of correct predictions - is for fourteen out of sixteen countries above 50%. For eleven countries accuracy is 56% or higher. Due to the high hit rates and low false alarm rates the accuracy of the directional predictions for Brazil and South Korea is particularly high and exceeds 62%. Exceptions are the Netherlands and again Ireland where accuracy is only about 48%.

The lower right diagram in Fig. 3 shows the Kuiper scores that indicates how well changes in CDS volatility predict the directional changes in EPU over time. The Kuiper score is positive for fourteen out of sixteen countries. Thus over time, changes in CDS volatility do produce more correct than incorrect directional forecasts of the corresponding EPU index movements. The now familiar exceptions are again Ireland and the Netherlands.

Let us turn to the results of the regression based tests of the predictive ability of changes in CDS volatility. Recall that in the test regressions the β coefficient measures the correlation between the directional movements in the EPU index and the changes in CDS volatility. Fig. 4 displays the estimated β coefficient in the static and the dynamic test regressions together with 90% confidence intervals. As can be seen, the results from the static regression, shown in the left plot, and the results from the dynamic regression in the right plot are very similar. In particular, with the exception of Ireland and the Netherlands, the estimated β coefficients are always positive in both test regressions. Most of the β coefficients are between 0.1 and 0.3. The 90% confidence intervals imply that many β coefficients are also statistically significant at the 10% significance level.

Figure 4: Regression tests of directional forecast accuracy

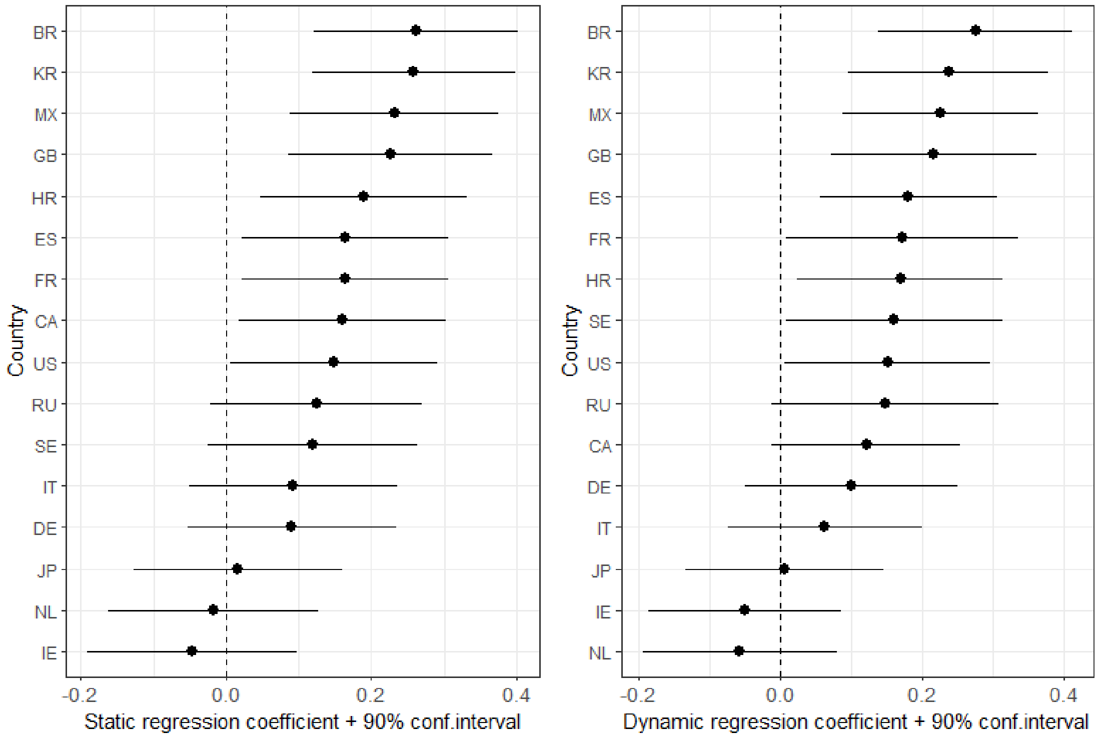
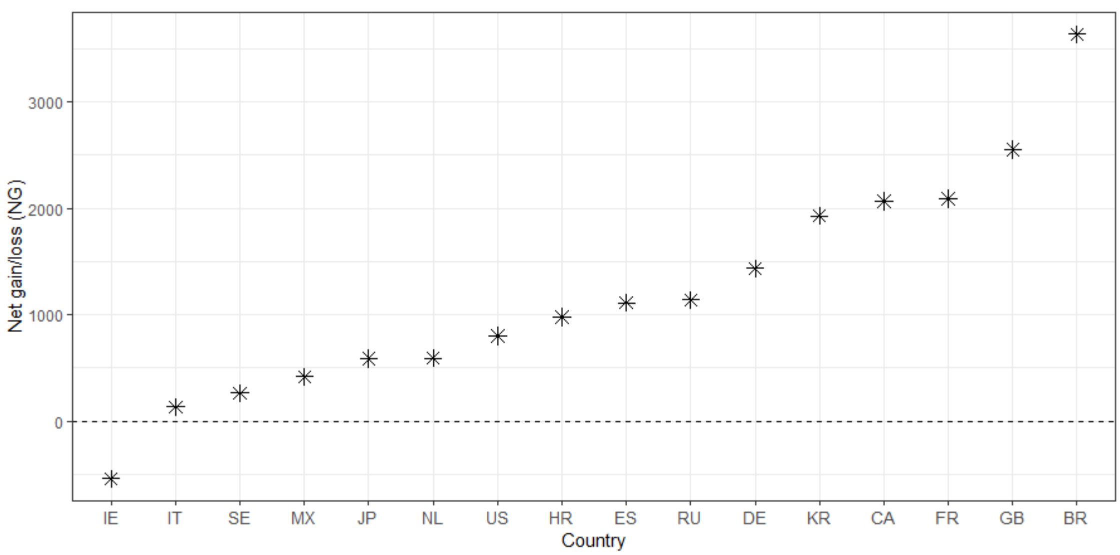


Figure 5: Net gains in terms of EPU index points



The results presented so far suggest that CDS volatility helps to predict changes in EPU indices. But do these predictions have economic value? The game that we described in section 3.1 considers the economic value of the directional predictions. Recall that in the game correct (incorrect) directional predictions generate gains (losses) proportional to the size of the movements of the EPU index. Fig. 5 shows the results of the game expressed in terms of EPU index points. It turns out that the directional predictions of the EPU index movements based on CDS volatility have economic value. The directional predictions would, except for Ireland, in all cases produce net economic gains.

Taken together, the results from the regression tests, the descriptive statistics, and the economic value of the directional forecasts tell the same story, namely that in almost all cases sovereign CDS volatility does contain useful information about movements in EPU indices. Nevertheless, we observe some heterogeneity in the information content across countries, and we find that for Ireland and the Netherlands CDS volatility does not perform well in predicting movements in the news-based country EPU indices.[8]

4 Macroeconomic responses to uncertainty shocks

In the impulse response analysis we estimate a Bayesian panel VAR model in the spirit of Jarociński (2010) to quantify the macroeconomic effects of shocks to economic uncertainty as measured by sovereign CDS volatility. Using this model we also examine the qualitative differences of unemployment and output responses to shocks to CDS volatility and shocks to EPU indices. In addition, we can use the model to compare the mean response a of group of countries to an uncertainty shock with the country-specific deviations from the mean response.

For each country $i = 1, \dots, N$ we assume an M-dimensional time series process

$$\boldsymbol{y}_{it} = \boldsymbol{c}_i + \sum_{j=1}^{p} \boldsymbol{A}_{ij} \boldsymbol{y}_{it-j} + \boldsymbol{\varepsilon}_{it}, \qquad \boldsymbol{\varepsilon}_{it} \sim \mathcal{N}_M(\boldsymbol{0}, \boldsymbol{\Sigma}_i), \tag{4.1}$$

where $\boldsymbol{A}_{ij}$ is a $M \times M$ coefficient matrix and $\boldsymbol{\Sigma}_{it}$ denotes the country-specific variance-covariance matrix. Note that this structure neither allows for static nor for dynamic interdependencies across countries (i.e., $Var(\boldsymbol{y}_{it}, \boldsymbol{y}_{jt}) = 0$ and $Var(\boldsymbol{y}_{it}, \boldsymbol{y}_{jt-1}) = 0$). In our application this assumption is appropriate because we are not interested in measuring spillovers between countries. Instead, we want to empirically compare different measures of economic uncertainty at the country level and across the three different groups of countries that we consider in this paper. In the model, we thus allow for cross-country heterogeneity of first and second moment coefficients, but we additionally apply a pooling prior to find commonalities in the data.

We put additional structure on the coefficients to avoid overfitting and to shrink each country model to the common mean model (Jarociński, 2010). Therefore, we assume that the $K = M(Mp + 1)$ vectorized regression coefficients $\boldsymbol{a}_i = \text{vec}[(\boldsymbol{c}_i, \boldsymbol{A}_{i1}, \dots, \boldsymbol{A}_{ip})']$ for each country i arise from a common distribution,

$$\boldsymbol{a}_i \sim \mathcal{N}_K(\boldsymbol{\mu}, \boldsymbol{V}), \tag{4.2}$$

where $\boldsymbol{\mu}$ denotes a common mean and $\boldsymbol{V} = (\lambda_1 \otimes \boldsymbol{I}_K)\boldsymbol{\Omega}$ is a variance-covariance matrix of the coefficients and λ_1 is a parameter to be estimated that measures the degree of cross-country heterogeneity. $\boldsymbol{\Omega} = \text{diag}(\omega_1, \dots, \omega_K)$ is defined in the spirit of the Minnesota prior (Doan et al., 1984) where we choose typical values found in the literature for the remaining hyperparamters set by the researcher.[9] The exact prior specifications and an outline of the Bayesian estimation algorithm can be found in App. B.

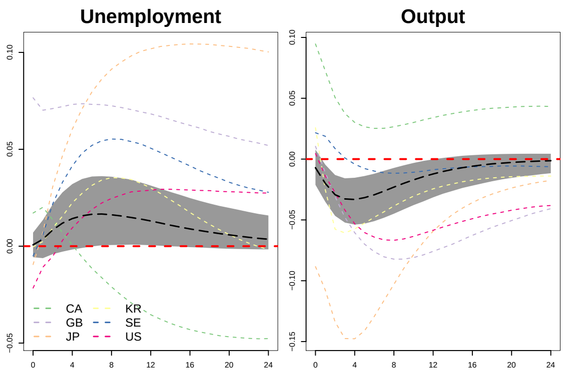
4.1 Results for impulse responses

In this section we present the results of our impulse response analysis. Our VAR model contains the following six variables: the uncertainty indicator x_t under consideration, the leading stock index of a country eq_t, the

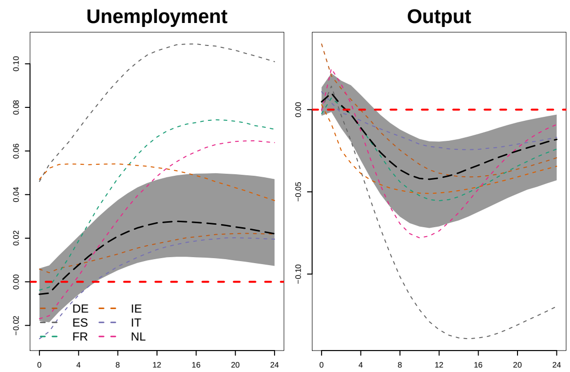
[8] We have repeated the entire directional forecasting exercise with CDS volatility computed from squared residuals instead of the absolute value of the residuals from equation (2.1). The results are very similar, but overall CDS volatility based on absolute residuals performs slightly better.

[9] In particular we use $\lambda_2 = 0.5$ for cross-equation coefficients, $\lambda_3 = 1$ denoting the penalty term for higher lags and $\lambda_4 = 100$ for deterministics along the lines of Dieppe et al. (2016).

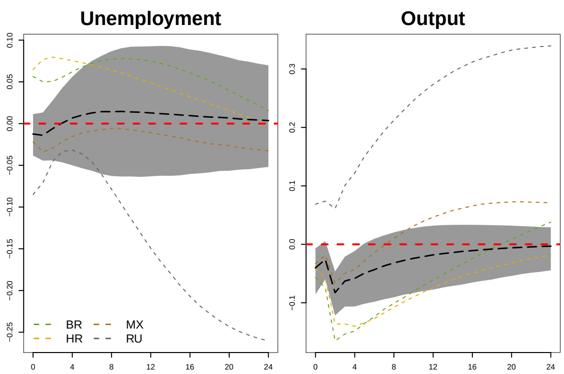
Figure 6: Impulse responses after an unexpected CDS volatility shock. The plot shows the common mean effect (dashed, black line) along with 68% credible intervals (gray, shaded area) and country-specific responses (dashed, colored lines).



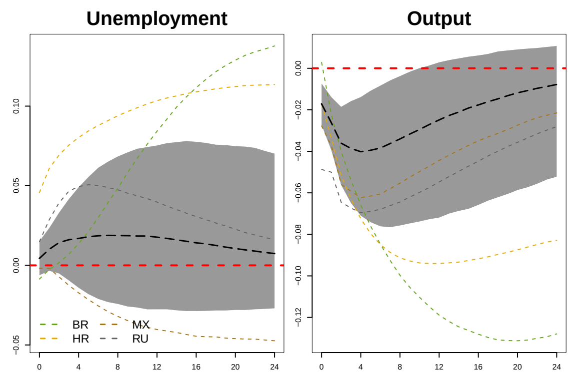
(a) Advanced economies



(b) Euro Area economies



(c) Emerging market economies (short sample)



(d) Emerging market economies (long sample)

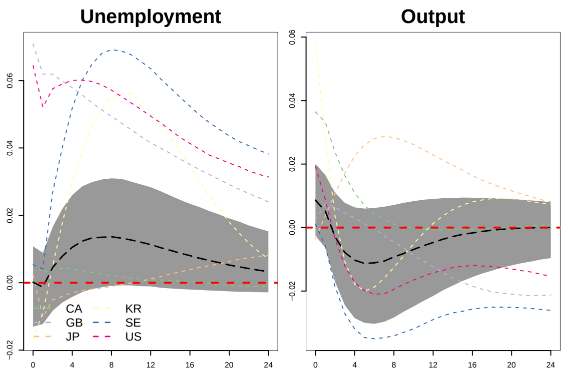
short-term interest rate i_t , the price level p_t, the unemployment rate u_t, and industrial production ip_t. All variables except the unemployment rate and interest rates enter in log-levels and we use $p = 2$ lags for all variables[10] . In our baseline VAR the sample period ranges from 2008m10 to 2019m12. As already mentioned, for the emerging market economies in our sample the CDS market was already liquid before the global financial crisis. For these countries we therefore extend the sample back to 2003m01 and provide results for both sample periods.

To identify the macroeconomic impact of an uncertainty shock, we rely on a standard Cholesky decomposition where the variables appear in the ordering $\boldsymbol{y}_t = \{x_t, eq_t, i_t, p_t, u_t, ip_t\}$. Thus, as in Baker et al. (2016), the economic uncertainty indicator is the first variable in the system. Since uncertainty measures and stock market indices are both fast moving variables, an alternative ordering would be to put the stock index first.[11] Our results are, however, qualitatively unaffected when we put stock market returns first. We normalize the responses to yield a 10% decrease in the stock index.

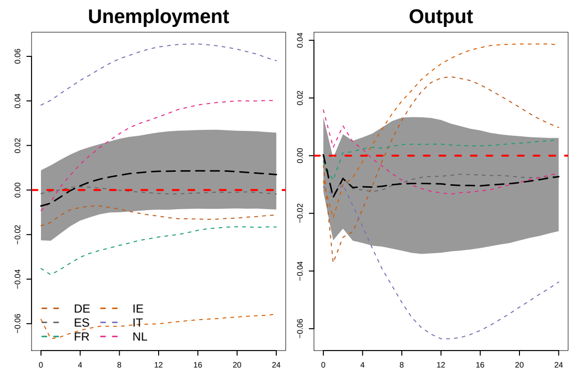
[10]Model selection criteria point to a low number of lags with a maximum of four. While the Bayesian information criterion point almost consistently to only one lag, the deviance information criterion points to two to four lags. To be consistent across all models and to mitigate possible autocorrelation of the residuals, we use consistently $p = 2$ lags across all models. Nevertheless, results remain qualitatively similar when changing the number of lags.

[11]In his seminal contribution, Bloom (2009) orders equity prices first, while in the more recent study, Baker et al. (2016) decide to order equity prices second.

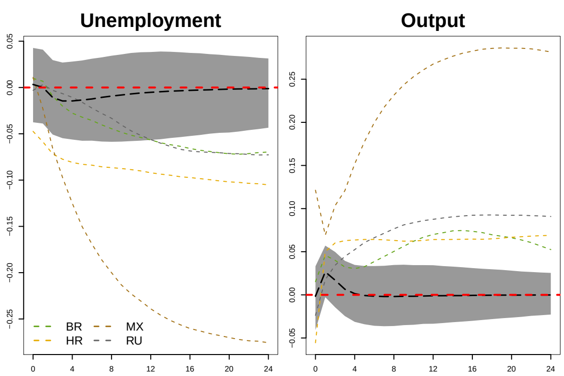
Figure 7: Impulse responses of unemployment and oitput after an unexpected EPU shock. The plot shows the common mean effect (dashed, black line) along with 68% credible intervals (grey, shaded area) and country-specific responses (dashed, coloured lines).



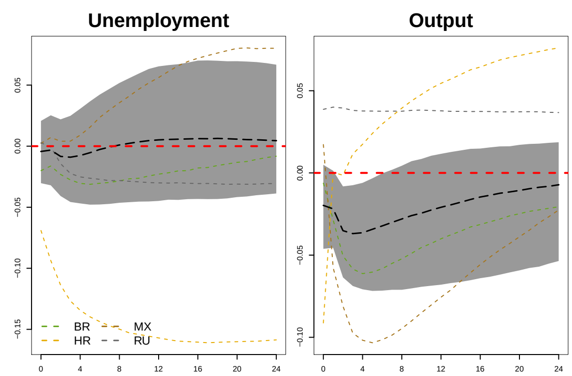
(a) Advanced economies



(b) Euro Area economies



(c) Emerging market economies (short sample)



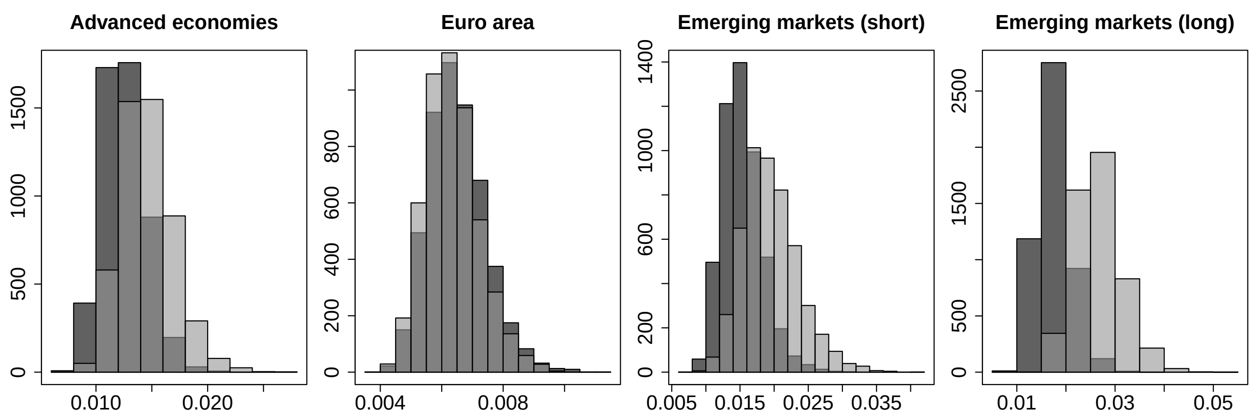
(d) Emerging market economies (long sample)

Figures 6 and 7 show the estimated responses of unemployment and output to uncertainty shocks as measured by sovereign CDS volatility and the EPU country indices, respectively. In the plots the black dashed line is the estimated common mean of the responses and the gray shaded area is the associated 68% credible interval. The colored dashed lines are the posterior median responses for the individual countries. The responses for the other variables in the VAR can be found in App. C.

We start discussing the responses to a shock in CDS volatility (Fig. 6), which are normalized to yield a 10% decrease in equity prices. The estimated mean responses show a rise in unemployment and a decline in output in all three groups of countries. In emerging market economies, responses of unemployment are not very precisely estimated, while output responses are significantly negative in all country groups. As demonstrated in the more recent literature on the macroeconomic effects of uncertainty (Bachmann et al., 2013; Jurado et al., 2015), we do not find an overshooting effect in output. On average, output responses are most pronounced in emerging market economies. Considering advanced economies, Japan reacts most strongly to an uncertainty shock, while in the euro area unemployment and production in Spain are hardest hit by an uncertainty shock. One explanation could be the comparably high indebtedness and external vulnerability of these countries. In the same vein, emerging market economies show stronger output responses relative to their peers from other regions.

Next, we turn to responses to an uncertainty shock measured by the EPU country index. The shock is again normalized to yield a 10% decrease in equity prices. As with CDS volatility, the estimated common mean responses decline for output and rise for unemployment in all three regions (Fig. 7). However, there

Figure 8: Posterior distribution of λ_1 indicating heterogeneity of responses across countries in each subgroup. Dark grey bars indicate the posterior distribution for the model that includes the EPU index, light grey bars indicate the posterior distribution for the model that includes the CDS volatility.



is one striking difference. For some countries (e.g., Sweden, the US, Great Britain, and Italy) the responses to the EPU shock are quite pronounced, but with the exception of output in emerging market economies in the longer sample, the zero mean responses fall always inside the 68% credible intervals. The finding in Bloom (2009) of a significant decline in output and employment for the USA after an uncertainty shock does therefore not generalize to all of the countries in our sample when we use EPU indices as an uncertainty measure.

In the panel VAR, the parameter λ_1 indicates the overall heterogeneity of the country models with respect to the common mean. The posterior distribution of λ_1 therefore provides systematic information about the degree of heterogeneity within the country groups. It turns out that the posterior distributions for λ_1 for both measures of uncertainty largely overlap (Fig. 8). The cross-country heterogeneity in the country groups is therefore not related to the choice of the uncertainty measure. The euro area countries show the most homogeneous responses, while the responses in the emerging market economies group are most heterogeneous. This pattern is consistent with the fact that the euro area countries operate in a common economic environment, while the emerging market economies group is much more heterogeneous from an economic point of view.

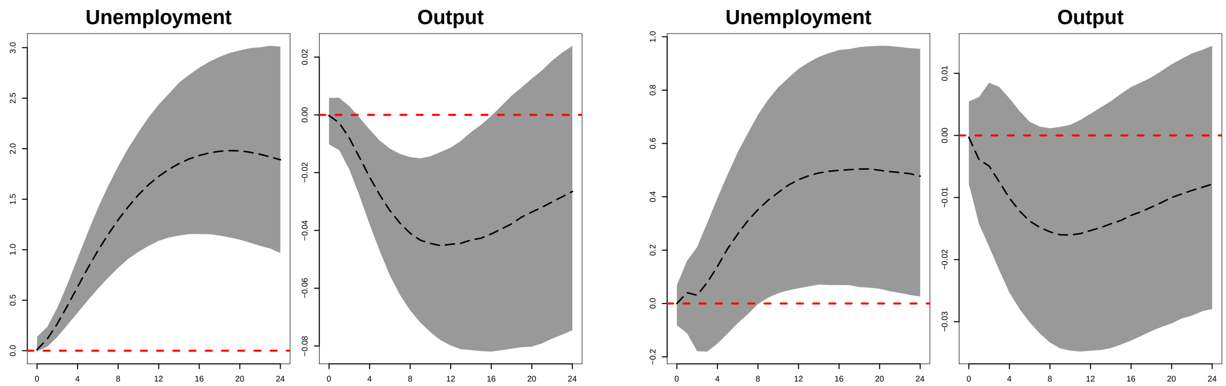
Overall, the responses to shocks to CDS volatility and news-based EPU indices are qualitatively similar. One important difference is, however, the higher precision in inference: Responses to CDS volatility show smaller credible intervals compared to responses from an EPU shock. The reasons for preciser inference might be two-fold: First, sovereign CDS spreads summarize the believes of international investors about the macroeconomic health of an economy. CDS spreads thus provide a broad outside view on the current economic state of an economy. In contrast, EPU indices are based on news that emerge mainly from within a country. Second, CDS trading involves large sums of money and this provides strong incentives to accurately assess the state of an economy. Large discrepancies about the health of an economy – as measured by sovereign CDS volatility – should therefore be a rather strong signal of economic uncertainty.

4.2 Robustness checks: Other measures of economic uncertainty

The previous section has highlighted the usefulness of CDS volatility as a proxy for EPU. Since the literature on uncertainty effects has proposed several uncertainty measures, we cross-check our results with further alternatives.[12] More specifically, we use the financial uncertainty index of Jurado et al. (2015) and the

[12] For an excellent survey of different kind of uncertainty measures see for instance (Nowzohour and Stracca, 2020).

Figure 9: Impulse responses of unemployment and output in the US after an unexpected financial uncertainty shock and an unexpected CDS volatility shock. The dashed, black lines are the median response. Grey, shaded areas are 68% credible intervals.



(a) Financial uncertainty **(b)** CDS volatility

volatility of stock index returns as alternative measures of economic uncertainty. Stock market volatility can be computed for all countries in the sample. The financial uncertainty index of Jurado et al. (2015) is only available for the USA.[13] We argue for robustness with the two additional measures due to the following. First, the financial uncertainty measure captures probably most of the information of a single stock market, i.e., the US stock market and hence provides an econometrically sophisticated measure of uncertainty. Stock market volatility, however, is a widely used measure of uncertainty (see also Datta et al., 2017.

In our comparison of CDS volatility with the financial uncertainty index for the US we estimate a single-country, Bayesian VAR as outlined in Huber and Feldkircher (2019)[14] and compute the impulse responses after structurally identifying the model via the same recursive ordering as in the panel VAR model. The scaling of the shocks is comparable due to the normalization of 10% impact on equity prices. It turns out that the responses to both shocks (Fig. 9) are remarkably similar (the full set of responses are available in App. C), but two remarks are in order. First, financial uncertainty seems to trigger stronger responses. Second, although the indicators are rather differently constructed, the correlation between them is still quite high ($\rho = 0.52$). Overall, sovereign CDS volatility and the financial uncertainty index seem to contain similar information about economic uncertainty in the USA. Simple regression analysis reveals that CDS volatility has also predictive power for financial uncertainty[15].

We also consider stock market volatility as an alternative measure of economic uncertainty. For each country, monthly stock market volatility is computed from the daily returns on the leading stock index of the country.[16] To ensure comparability, the model specification and the ordering of the variables in the VAR is the same as in the other VAR models. A rise in unemployment and a fall in output after a unit unit shock in stock market volatility is again visible (Fig. 10). This applies not only to the common mean response, but also to many individual country responses. In particular, the responses in the advanced economies and the euro area economies are pronounced and show only small deviations from the corresponding common mean. In emerging market economies the country responses are considerably more heterogeneous. Two reasons

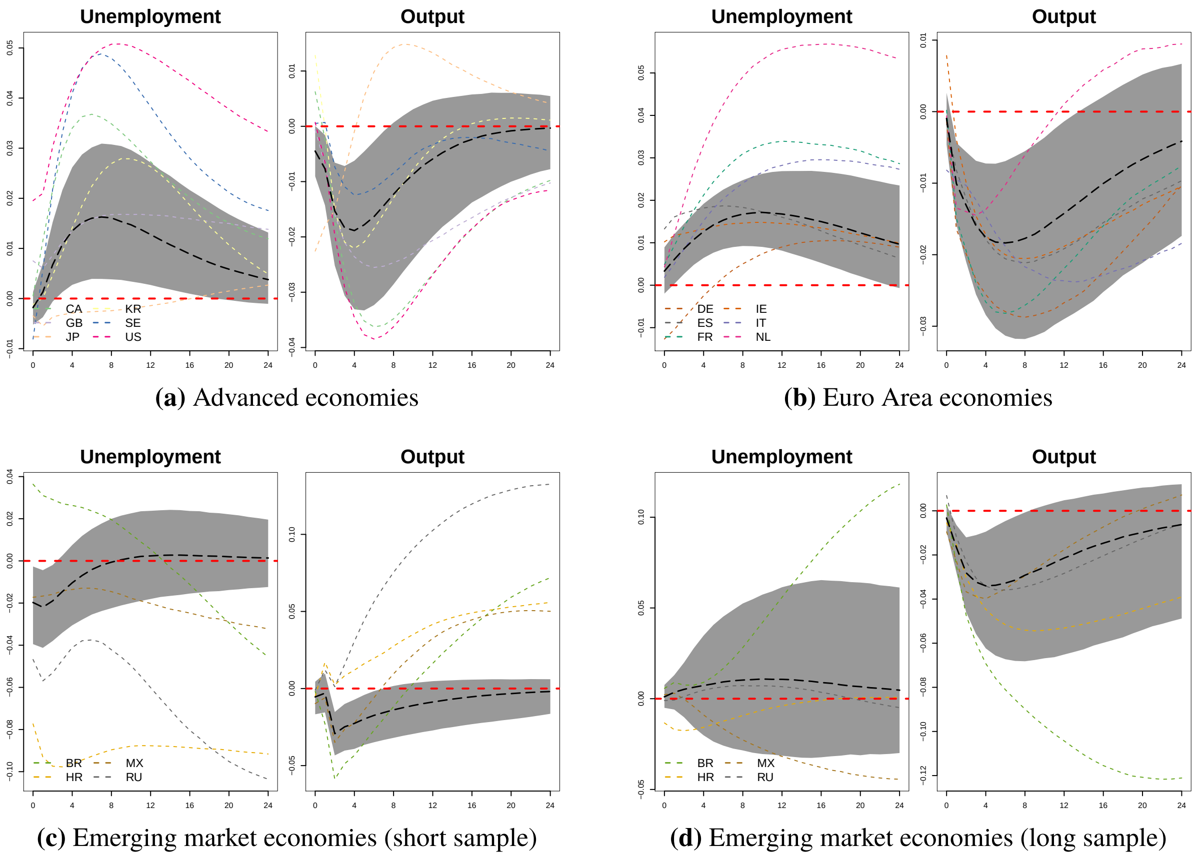
[13] This index is regularly updated and available on the website of Sydney Ludvigson: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

[14] We use the same model setup as in the Panel VAR, just without the cross-country dimension for both uncertainty measures. This translates into a Bayesian VAR with Normal-Gamma shrinkage prior, but without stochastic volatility.

[15] We support this hypothesis with linear regression techniques, but also with an (autoregressive) distributed lag model of order one.

[16] The mean dynamics in the daily returns is first removed with an AR(1) model. Then monthly volatility is computed in the same way as CDS volatility from the absolute values of the residuals of the AR(1) model.

Figure 10: Impulse responses unemployment and output after an unexpected shock to stock market volatility. The plot shows the common mean effect (dashed, black line) with 68% credible intervals (grey, shaded area) and country-specific responses (dashed, coloured lines).



(a) Advanced economies

(b) Euro Area economies

(c) Emerging market economies (short sample)

(d) Emerging market economies (long sample)

for this heterogeneity could be less developed financial markets or a looser connection between stock market volatility and economic uncertainty in these countries.

5 Conclusions

The volatility of sovereign CDS spreads reflects the uncertainty of large international financial institutions and investors about a country's economic condition. Using evaluation methods for directional predictions and Bayesian VAR models, we examined whether the volatility of sovereign CDS spreads is a useful measure for economic uncertainty and how it relates to other prominent uncertainty indices such as the ones proposed by Bloom (2009) or Jurado et al. (2015).

We find that the directional changes in sovereign CDS volatility help in predicting the directional changes in the corresponding news-based EPU country indices. Hence, sovereign CDS volatility and EPU indices contain overlapping information about economic uncertainty. Furthermore, our VAR models produces qualitatively similar responses of unemployment and output to EPU index shocks and CDS volatility shocks. The responses to shocks to sovereign CDS volatility are, however, often more pronounced and more precisely estimated. We think that both findings are related to the strong incentives in sovereign CDS trading to accurately judge the economic health of a country. These results are robust to other measures of uncertainty, such as the financial uncertainty index of Jurado et al. (2015) or stock market volatility.

Our results reveal sovereign CDS volatility as a powerful indicator of economic uncertainty that could either serve as a primary measure of economic uncertainty or as an additional measure of uncertainty if other indicators of economic uncertainty are already available. For the practitioner, using CDS volatilty as a measure of uncertainty has several advantages: It can be easily computed, is readily available for a broad set of countries and allows to assess uncertainty at high frequency. The latter is especially important given the demonstrated and detrimental effects of uncertainty on the macroeconomy (e.g., Bloom, 2009; Baker et al., 2016).

References

Bachmann, R., Elstner, S., Sims, E. R., 2013. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics 5 (2), 217–249. [1, 11]

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics 131 (4), 1593–1636. [1, 4, 10, 15]

Blaskowitz, O., Herwartz, H., 2014. Testing the value of directional forecasts in the presence of serial correlation. International Journal of Forecasting 30 (1), 30 – 42. [6]

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685. [1, 10, 12, 14, 15]

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S. J., 2018. Really uncertain business cycles. Econometrica 86 (3), 1031–1065. [1]

Bordo, M. D., Duca, J. V., Koch, C., 2016. Economic policy uncertainty and the credit channel: Aggregate and bank level u.s. evidence over several decades. Journal of Financial Stability 26, 90 –106. [1]

Boutchkova, M., Doshi, H., Durnev, A., Molchanov, A., 2012. Precarious politics and return volatility. The Review of Financial Studies 25 (4), 1111–1154. [1]

Caggiano, G., Castelnuovo, E., Groshenny, N., 2014. Uncertainty shocks and unemployment dynamics in u.s. recessions. Journal of Monetary Economics 67, 78 – 92. [1]

Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajšek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. European Economic Review 88, 185 – 207. [1]

Carriero, A., Clark, T. E., Marcellino, M., 2019. Large bayesian vector autoregressions with stochastic volatility and non-conjugate priors. Journal of Econometrics . [19]

Castelnuovo, E., 2019. Domestic and global uncertainty: A survey and some new results. CAMA Working Paper 75, Crawford School of Public Policy, Centre for Applied Macroeconomic Analysis, Australian National University. [1]

Datta, D., Londono, J. M., Sun, B., Beltran, D. O., RT Ferreira, T., Iacoviello, M. M., Jahan-Parvar, M. R., Li, C., Rodriguez, M., Rogers, J. H., 2017. Taxonomy of global risk, uncertainty, and volatility measures. FRB International Finance Discussion Paper (1216). [13]

Dieppe, A., Legrand, R., Van Roye, B., 2016. The BEAR toolbox. Working Papers 1934, European Central Bank. [9]

Doan, T., Litterman, R., Sims, C., 1984. Forecasting and conditional projection using realistic prior distributions. Econometric reviews 3 (1), 1–100. [9]

Huber, F., Feldkircher, M., 2019. Adaptive shrinkage in bayesian vector autoregressive models. Journal of Business & Economic Statistics 37 (1), 27–39. [13, 19]

Jarociński, M., 2010. Responses to monetary policy shocks in the east and the west of europe: a comparison. Journal of Applied Econometrics 25 (5), 833–868. [9, 19]

Jurado, K., Ludvigson, S. C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105 (3), 1177–1216. [1, 11, 12, 13, 14]

Kang, W., Lee, K., Ratti, R. A., 2014. Economic policy uncertainty and firm-level investment. Journal of Macroeconomics 39, 42 – 53. [1]

Lando, D., 2004. Credit Risk Modelling. Princeton University Press. [1]

Liu, L., Zhang, T., 2015. Economic policy uncertainty and stock market volatility. Finance Research Letters 15, 99 – 105. [1]

Ludvigson, S. C., Ma, S., Ng, S., 2020. Uncertainty and business cycles: Exogenous impulse or endogenous response. American Economic Journal: Macroeconomics . [1]

Newey, Whitney, K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708. [6]

Nowzohour, L., Stracca, L., 2020. More than a feeling: Confidence, uncertainty, and macroeconomic fluctuations. Journal of Economic Surveys 34 (4), 691–726. [12]

Packer, F., Suthiphongchai, C., 2003. Sovereign credit default swaps. BIS Quarterly Review , 79–88. [2]

Pástor, Ľ., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110 (3), 520–545. [1]

Rossi, B., Sekhposyan, T., May 2015. Macroeconomic uncertainty indices based on nowcast and forecast error distributions. American Economic Review 105 (5), 650–55. [1]

Scotti, C., 2016. Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. Journal of Monetary Economics 82, 1 – 19. [1]

Vogel, H.-D., Bannier, C., Heidorn, T., 2013. Functions and characteristics of corporate and sovereign cds. Frankfurt School - Working Paper Series 203, Frankfurt School of Finance and Management. [3]

A Summary statistics

Table A1: Summary statistics of daily CDS spreads

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BR	2,935	198.6	91.6	89	130	238.2	610
CA	2,935	18.1	4.8	8	14.5	21.5	36
DE	2,935	33.1	21.9	8	20.5	38	122
ES	2,935	151.0	129.3	34.0	63.0	230.2	596.0
FR	2,935	65.3	44.7	15.0	40.5	74.5	247.0
GB	2,935	44.5	26.9	15.0	23.0	62.0	169.0
HR	2,935	249.6	106.4	55	180.2	322.2	558
IR	2,935	191.5	219.1	22	54	202.5	968
IT	2,935	174.6	115.1	43.5	95.0	212.5	651.5
JP	2,935	53.6	29.5	13.0	26.5	71.5	154.5
KR	2,935	89.4	74.0	22	50	102.5	685
MX	2,935	137.3	61.6	64	105	149	600
NL	2,935	46.1	23.7	13.5	32.5	50.0	138.0
RU	2,935	224.0	138.2	53	143	255	1,300
SE	2,935	29.0	21.9	8	15.5	34.5	154
US	2,935	35.3	9.7	15.5	28.0	42.0	69.0

Table A2: Summary statistics of annualized monthly CDS volatility

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BR	135	103.3	91.2	19.5	52.5	127.4	839.4
CA	135	5.7	5.1	0.04	2.6	7.4	29.9
DE	135	15.9	17.9	1.0	4.3	21.5	94.9
ES	135	72.4	81.3	2.7	15.6	102.3	390.7
FR	135	28.8	30.9	1.7	8.8	40.8	147.8
GB	135	21.5	26.2	1.1	5.1	26.9	143.7
HR	135	90.2	68.7	7.3	35.3	122.2	306.5
IR	135	92.5	132.8	1.6	12.6	138.9	870.0
IT	135	86.9	87.6	0.8	24.3	117.5	424.0
JP	135	26.7	25.3	1.2	8.2	35.6	154.6
KR	135	63.4	105.7	7.7	21.4	58.7	907.6
MX	135	80.4	86.8	13.1	40.3	84.5	789.2
NL	135	19.3	19.7	1.9	6.4	26.3	106.1
RU	135	142.8	202.6	16.1	58.9	159.8	1,785.3
SE	135	14.5	20.0	0.03	3.2	17.3	109.7
US	135	13.5	11.8	1.0	4.8	20.6	71.3

Table A3: Summary statistics of monthly EPU indices

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BR	135	183.1	105.4	22.3	110.1	213.5	677.0
CA	135	220.0	85.9	91.3	146.2	270.4	495.9
DE	135	168.1	63.1	59.6	125.3	199.9	454.0
ES	135	123.5	45.5	42.3	89.3	146.8	282.2
FR	135	242.4	83.5	98.0	181.6	288.0	574.6
GB	135	300.2	156.6	95.4	192.2	398.2	1,141.8
HR	134	132.0	53.4	36.5	88.3	168.1	315.0
IR	135	150.1	53.4	34.0	116.0	186.5	282.1
IT	135	121.4	36.4	31.7	98.6	141.1	241.0
JP	135	117.5	31.6	62.6	96.6	132.1	239.0
KR	135	157.1	72.1	55.9	111.1	176.0	538.2
MX	132	58.6	30.2	12.1	37.7	70.8	185.6
NL	135	101.3	50.9	22.7	62.8	131.2	302.2
RU	135	177.8	87.7	32.4	106.0	235.4	431.2
SE	135	100.7	16.9	62.2	90.0	110.3	156.7
US	135	131.5	33.8	71.3	103.5	152.5	245.1

B Bayesian estimation of the Panel VAR

The estimation of the panel VAR is carried out in a Bayesian fashion. Therefore we have to specify a prior distribution for each model parameter. The choice of the priors is rather standard and details can be found in Jarociński (2010). We only put a shrinkage prior on the common mean and use the algorithm suggested in Carriero et al. (2019) to speed up computation.

The parameters of the model come from a hyperprior constituting the common mean $\boldsymbol{a}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{V})$. Following Carriero et al. (2019) we triangularize the country variance-covariance matrix $\boldsymbol{\Sigma}_i = \boldsymbol{H}_i^{-1}\boldsymbol{D}_i\boldsymbol{H}_i^{-1\prime}$ to speed up the computation. $\boldsymbol{H}^{-1}$ denotes a lower triangular matrix and $\boldsymbol{D}_i = \text{diag}(d_{i1}, \ldots, d_{iM})$ is a diagonal matrix where each element $d_i \sim IG(a_i, b_i)$ follows an Inverse-Gamma distribution. We chose the hyperparameters such that the prior does not introduce much information to the model, i.e., $a_i = b_i = 0.01$. For the elements in $\boldsymbol{H}_i^{-1}$ and in $\boldsymbol{\mu}$ we specify a Normal-Gamma shrinkage prior (Huber and Feldkircher, 2019) where a typical element is denoted by θ_{ij} following

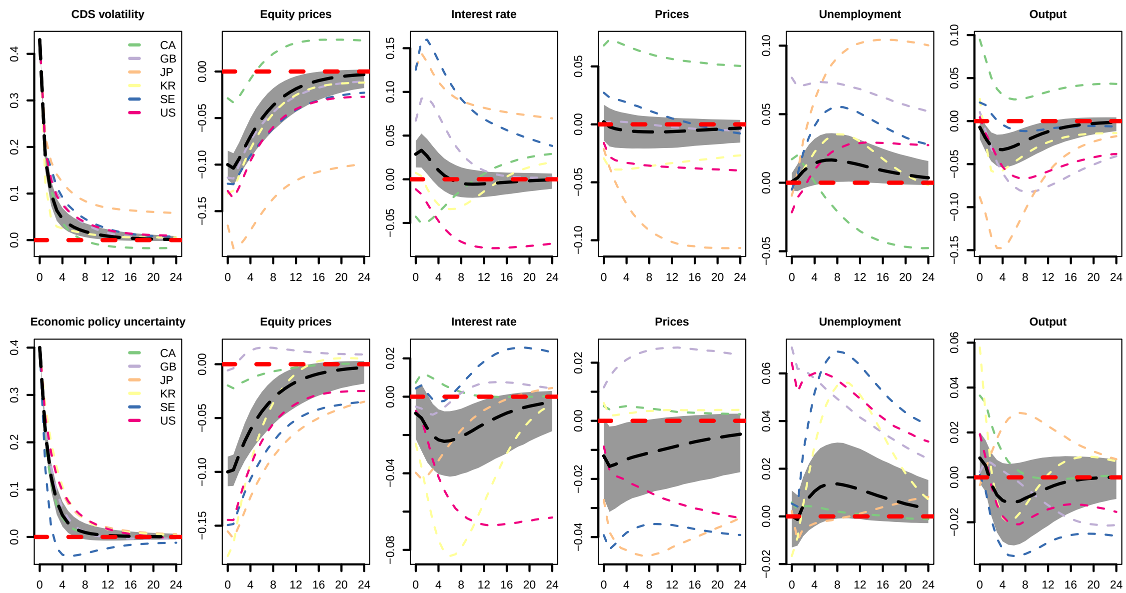
$$\theta_{ij} \sim \mathcal{N}(0, 2\xi_i^{-2}\tau_{ij}), \quad \xi_i^2 \sim G(c_0, d_0), \quad \tau_{ij} \sim G(\vartheta, \vartheta), \tag{B.1}$$

where i refers to the local shrinkage component (like each element of a matrix or a coefficient matrix) and j to the global shrinkage component (like each lag in the VAR system). Both are controlling for the tightness of the prior. We set $c_0 = d_0 = 0.01$ uninformative and estimate ϑ, which is distributed as $\vartheta \sim Exp(1)$ to have a priori unity as mean corresponding to the Bayesian Lasso. For V, the variance of the common mean, we specify an Inverse Wishart distribution, $\boldsymbol{V} \sim iW(v_W, \boldsymbol{V_W})$ with $v_w = Mp$ and $V_W = I_K * 1000$. Finally, we use an Inverse-Gamma prior on $\lambda_1 \sim IG(s_0/2, v_0/2)$, where $s_0 = v_0 = 0.5$ to be uninformative.

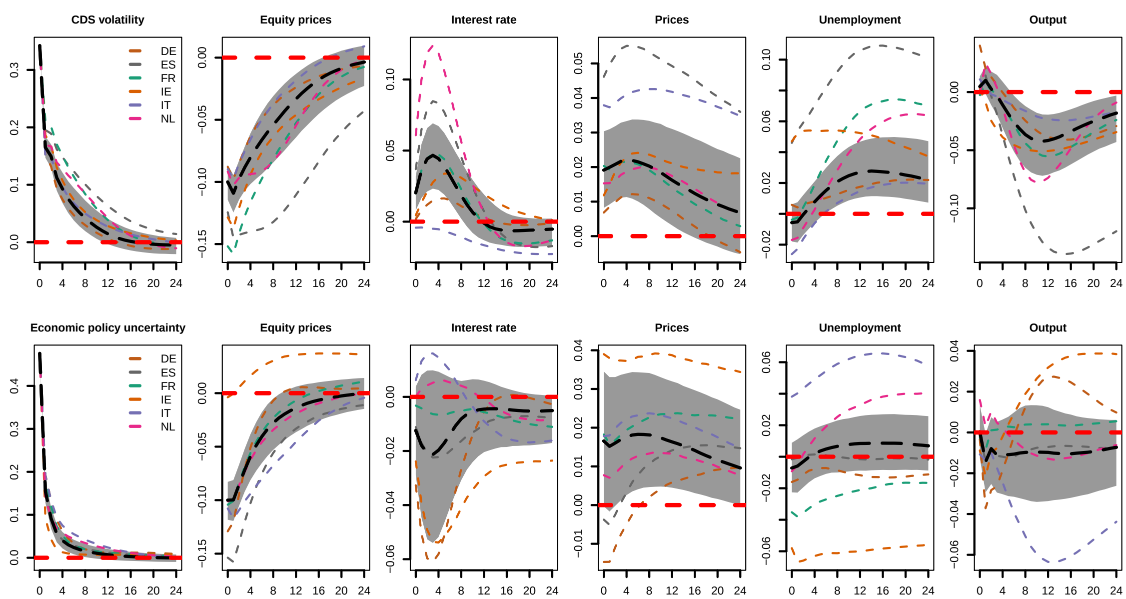
Our econometric specification leads to a fairly standard Gibbs sampler, where we iteratively draw from the respective conditional posterior distributions. We only have one MH-in-Gibbs step to sample ϑ which is outlined in Huber and Feldkircher (2019). Therefore, and due to the linear structure, the model converges relatively quickly to its posterior distribution. We use 5.000 iterations as burn-in and save 5.000 draws afterwards.

C Impulse Responses

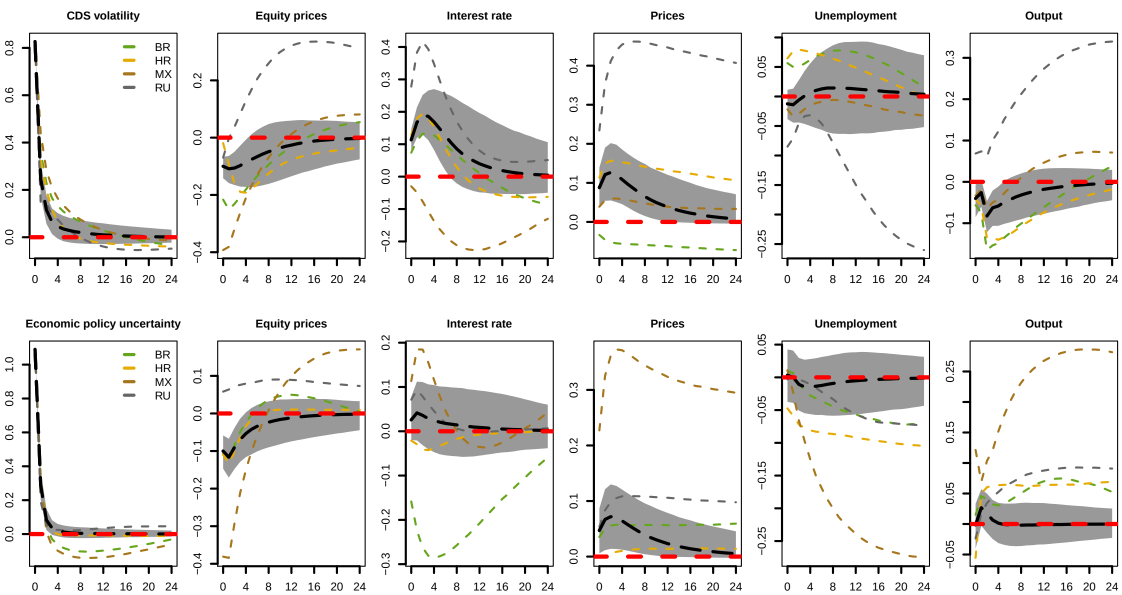
Figure 11: Impulse responses after an unexpected CDS volatility shock (upper panel) or EPU shock (lower panel). The plot shows the common mean effect (black, dashed line) along with 68% credible intervals (grey, shaded area) and country-specific responses (dashed, coloured lines).



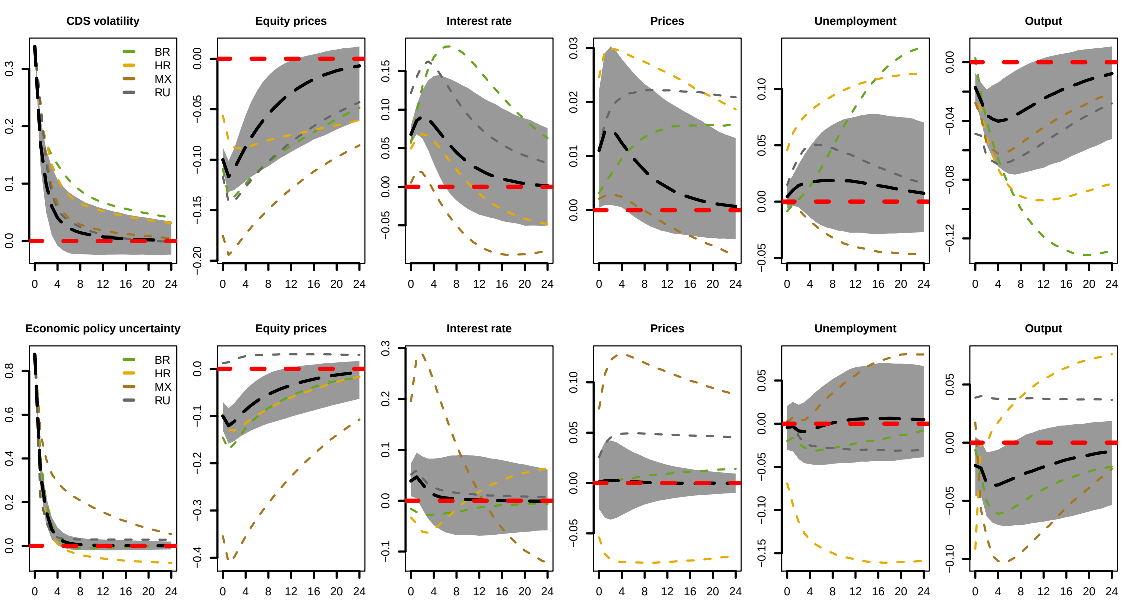
(a) Advanced economies



(b) Euro area economies

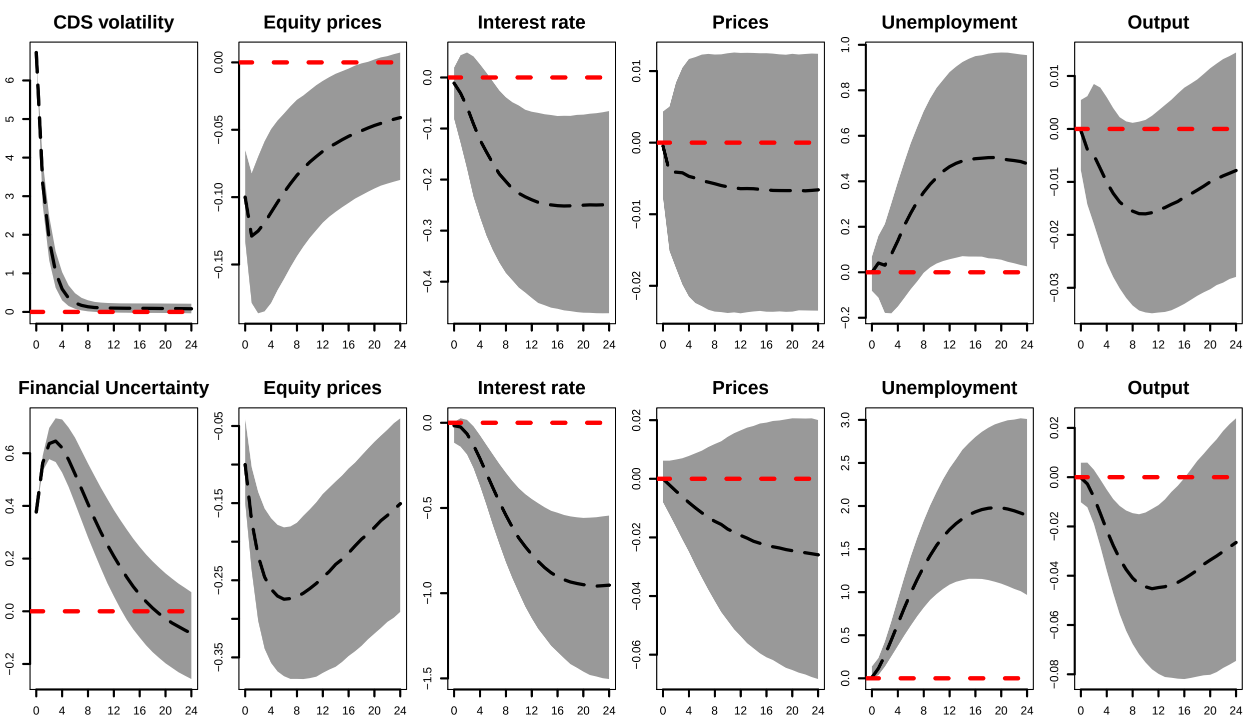


(c) Emerging market economies (short sample)



(d) Emerging market economies (long sample)

Figure 12: Impulse responses after an unexpected CDS volatility shock (upper panel) or financial uncertainty shock (lower panel). The plot shows the median response (black, dashed line) along with 68% credible intervals (grey, shaded area).



Index of Working Papers:

June 15, 2015	Anil Ari	202	Sovereign Risk and Bank Risk-Taking
June 15, 2015	Matteo Crosignani	203	Why Are Banks Not Recapitalized During Crises?
February 19, 2016	Burkhard Raunig	204	Background Indicators
February 22, 2016	Jesús Crespo Cuaresma, Gernot Doppelhofer, Martin Feldkircher, Florian Huber	205	US Monetary Policy in a Globalized World
March 4, 2016	Helmut Elsinger, Philipp Schmidt-Dengler, Christine Zulehner	206	Competition in Treasury Auctions
May 14, 2016	Apostolos Thomadakis	207	Determinants of Credit Constrained Firms: Evidence from Central and Eastern Europe Region
July 1, 2016	Martin Feldkircher, Florian Huber	208	Unconventional US Monetary Policy: New Tools Same Channels?
November 24, 2016	François de Soyres	209	Value Added and Productivity Linkages Across Countries
November 25, 2016	Maria Coelho	210	Fiscal Stimulus in a Monetary Union: Evidence from Eurozone Regions
January 9, 2017	Markus Knell, Helmut Stix	211	Inequality, Perception Biases and Trust
January 31, 2017	Steve Ambler, Fabio Rumler	212	The Effectiveness of Unconventional Monetary Policy Announcements in the Euro Area: An Event and Econometric Study
May 29, 2017	Filippo De Marco	213	Bank Lending and the European Sovereign Debt Crisis
June 1, 2017	Jean-Marie Meier	214	Regulatory Integration of International Capital Markets

October 13, 2017	Markus Knell	215	Actuarial Deductions for Early Retirement
October 16, 2017	Markus Knell, Helmut Stix	216	Perceptions of Inequality
November 17, 2017	Engelbert J. Dockner, Manuel Mayer, Josef Zechner	217	Sovereign Bond Risk Premiums
December 1, 2017	Stefan Niemann, Paul Pichler	218	Optimal fiscal policy and sovereign debt crises
January 17, 2018	Burkhard Raunig	219	Economic Policy Uncertainty and the Volatility of Sovereign CDS Spreads
February 21, 2018	Andrej Cupak, Pirmin Fessler, Maria Silgoner, Elisabeth Ulbrich	220	Exploring differences in financial literacy across countries: the role of individual characteristics and institutions
May 15, 2018	Peter Lindner, Axel Loeffler, Esther Segalla, Guzel Valitova, Ursula Vogel	221	International monetary policy spillovers through the bank funding channel
May 23, 2018	Christian A. Belabed, Mariya Hake	222	Income inequality and trust in national governments in Central, Eastern and Southeastern Europe
October 16, 2018	Pirmin Fessler, Martin Schürz	223	The functions of wealth: renters, owners and capitalists across Europe and the United States
October 24, 2018	Philipp Poyntner, Thomas Reininger	224	Bail-in and Legacy Assets: Harmonized rules for targeted partial compensation to strengthen the bail-in regime
Dezember 14, 2018	Thomas Breuer, Martin Summer	225	Systematic Systemic Stress Tests
May 20, 2019	Helmut Stix	226	Ownership and purchase intention of crypto-assets – survey results
October 17, 2019	Markus Knell, Helmut Stix	227	How Peer Groups Influence Economic Perceptions

February 26, 2020	Helmut Elsinger	228	Serial Correlation in Contingency Tables
March 2, 2020	Mariarosaria Comunale, Markus Eller, Mathias Lahnsteiner	229	Assessing Credit Gaps in CESEE Based on Levels Justified by Fundamentals –A Comparison Across Different Estimation Approaches
April 30, 2020	Martin Brown, Nicole Hentschel, Hannes Mettler, Helmut Stix	230	Financial Innovation, Payment Choice and Cash Demand – Causal Evidence from the Staggered Introduction of Contactless Debit Cards
July 30, 2020	Katharina Drescher, Pirmin Fessler, Peter Lindner	231	Helicopter Money in Europe: New Evidence on the Marginal Propensity to Consume across European Households
November 20, 2020	Michael Sigmund	232	The Capital Buffer Calibration for Other Systemically Important Institutions – Is the Country Heterogeneity in the EU caused by Regulatory Capture?
January 13, 2021	Maximilian Böck, Martin Feldkircher, Burkhard Raunig	233	A View from Outside: Sovereign CDS Volatility as an Indicator of Economic Uncertainty