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

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Abstract

This paper proposes the volatility of sovereign credit default swaps (CDS) as a measurement of economic uncertainty. Sovereign CDS provide protection against losses from sovereign defaults and are traded for almost all countries by the world's largest financial institutions. The premium for protection, the so-called CDS spread, depends on a country's economic and political conditions and provides an *outside* view of global financial institutions. The empirical results show that the volatility of sovereign CDS spreads contains information about economic uncertainty. For a broad panel of 16 countries we find that sovereign CDS volatility shares directional information with popular news-based economic policy uncertainty (EPU) indices. Using Bayesian panel vector autoregressions, we also find similar responses of output and unemployment to shocks in CDS volatility, equity volatility, and EPU. Sovereign CDS volatility can therefore be used either as an additional indicator of uncertainty or as a general indicator of economic uncertainty when EPU indices are not available or other indicators are considered unreliable.

Keywords: Credit Default Swap; Directional Forecasts; Economic Policy Uncertainty; Financial Market Volatility.

JEL Codes: D80, E66, G18.

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1. Introduction

Economic activity and uncertainty regarding key political, financial, and economic issues appear to be negatively related. As economic uncertainty increases, firms and consumers tend to postpone consumption and investment decisions and become more risk averse. Consequently, firms tend to reduce hiring and investment (Bloom, 2009; Caggiano, Castelnuovo and Groshenny, 2014; Kang, Lee and Ratti, 2014; Baker, Bloom and Davis, 2016; Caldara et al., 2016; Basu and Bundick, 2017; Bloom et al., 2018), banks tend to reduce lending (Bordo, Duca and Koch, 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.[2]

The recent global financial crisis and the 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. However, economic uncertainty is a fuzzy concept as different economic agents can have different levels of knowledge and very different views about the future. As a result, there is no single "true" measure of economic uncertainty. Rather, economic uncertainty can be measured from different angles.

Various indicators of economic uncertainty have been proposed in the literature. News-based economic policy uncertainty (EPU) indices are based on text searches in newspapers for key-words that reflect economic and political uncertainty (Baker, Bloom and Davis, 2016). Survey-based indicators of uncertainty measure the amount of disagreement about the evolution of key economic variables (Bachmann, Elstner and Sims, 2013). Further measures of economic uncertainty include indicators extracted from a large set of economic time series (Jurado, Ludvigson and Ng, 2015; Scotti, 2016), distribution-based measures (Rossi and Sekhposyan, 2015), and measures of stock market volatility (Datta et al., 2017). A common factor of these indicators is that they are based on complex and data-intensive methods, are often only available for a few large economies, or that they depend on well developed stock markets.

Against this background, we empirically investigate whether the volatility of sovereign credit default swap (CDS) spreads contains information about economic uncertainty. A sovereign CDS is a credit derivative that

[1] See, Bloom (2014), Castelnuovo (2022), or Cascaldi-Garcia et al. (2023) for a survey of this literature.

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

provides protection against financial losses from government defaults or sovereign debt restructuring. The CDS spread is thus the periodic premium that must be paid for protection, which ultimately depends on the economic and political conditions in a country.[3] In addition, sovereign CDS contracts are mainly traded by the world's largest banks in the derivative business - the so-called G16 traders. The volatility of sovereign CDS spreads therefore reflects uncertainty of these global banks regarding the prevailing economic conditions and prospects in a country. As a result, sovereign CDS volatility could provide another potentially complementary angle to gauge economic uncertainty. We refer to this as an *outside view* on economic uncertainty. Since CDS contracts are traded for almost all countries, the availability of this uncertainty indicator does not depend on country-specific data issues (e.g. availability of news- or survey-based indicators) or well developed equity markets. Sovereign CDS volatility thus provide policymakers and researchers with an outside view on economic uncertainty that is 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). For that purpose, we examine the empirical relationship between CDS volatility and the news-based EPU indices of Baker, Bloom and Davis (2016), as these indices have been widely used by practitioners as a measure of uncertainty. Furthermore, the EPU index is the only monthly uncertainty index available for a larger set of countries. As our country selection indicates, the coverage of the EPU indices is currently still limited. Nevertheless, we emphasize that CDS spreads are in principle available for a larger set of countries.

We proceed in two steps: First, we investigate whether the volatility of sovereign CDS spreads and EPU indices share directional information. We focus on directional predictions because EPU indices and CDS volatility are indicators that cannot be directly compared numerically. The volatility of CDS spreads is measured in basis points. In contrast, EPU indices are dimensionless (arbitrarily normalized to an average level of 100). Thus, direct numerical comparisons of CDS volatility and EPU indices are not meaningful. We therefore examine how often we can successfully predict an upward (downward) movement in the EPU index using the upward (downward) movement in CDS volatility as a predictor. As discussed later in section

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

3, CDS volatility and EPU indices capture the uncertainty of different economic agents. Nevertheless, we expect the directional movements of both indicators to coincide to some extent.

Second, we compare macroeconomic responses to an economic uncertainty shock when uncertainty is induced through different indicators. First, we provide a comparison of CDS volatility induced uncertainty shocks to ones measured with the EPU index but also through equity volatility. Both EPU and equity volatility is available for a panel of countries. For the US only, we can also compare the macroeconomic consequences to uncertainty shocks induced by the financial uncertainty index of Jurado, Ludvigson and Ng (2015). To do so, we estimate a Bayesian (panel) vector autoregression (VAR) and identify an uncertainty shock following Bloom (2009). This allows us to compute impulse response functions (IRFs) across the different country groups we consider. Specifically, we investigate the impulse responses of output and unemployment to uncertainty shocks.

Our main results can be summarized as follows: The directional predictions for EPU indices based on directional changes in CDS volatility are in almost all cases better than random predictions. Hence, directional changes in sovereign CDS volatility contain some information about directional changes in the corresponding EPU country index. 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 empirical results from the PVAR reveal that the responses of output and unemployment to shocks to sovereign CDS volatility and EPU indices are qualitatively similar in all three groups of countries. Output declines and unemployment rises after an uncertainty shock, no matter whether uncertainty is measured by CDS volatility or by an EPU index. Results indicate that responses to CDS volatility shocks offer a much more distinct pattern than EPU index shocks. We argue that this is due to the EPU index being a more noisy measure. On the contrary, uncertainty shocks induced by CDS volatility or by equity volatility are remarkably similar in shape and size. In a last exercise, we find that the US-specific responses to shocks in CDS volatility and responses to financial uncertainty shocks are also similar.

The rest of the paper is structured as follows. In the next section, we describe the data. In section 3, we outline the computation of sovereign CDS volatility, discuss why sovereign CDS volatility captures economic uncertainty, and explain similarities and differences with other measures of economic uncertainty. Section 4 deals with the evaluation of directional predictions for EPU indices based on CDS volatility. In section 5 we outline the panel VAR methodology, present the results for the macroeconomic responses to uncertainty shocks, and report some additional robustness analysis. Section 6 provides conclusions.

2. Data

Our data consists of the standard macroeconomic variables output (as measured by industrial production), unemployment, short-term interest rates, equity prices, and daily data on sovereign CDS spreads and monthly data on 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 Baker, Bloom and Davis (2016).[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 started already around the year 2000, but CDS contracts were initially traded only 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.

2.1 Computation of 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 frequently traded in the market (Vogel, Bannier and Heidorn, 2013). For each country, we compute CDS volatility in three steps. First, we calculate daily CDS spread changes $\Delta s_t = s_t - s_{t-1}$, $(t = 1, \ldots, T)$. We use changes because the spreads s_t themselves are not stationary. Only unpredictable movements in CDS spreads thus contribute to CDS volatility. Therefore, we then regress the daily CDS spread changes on their first five lags

$$\Delta s_t = \alpha_0 + \alpha_1 \Delta s_{t-1} + \ldots + \alpha_4 \Delta s_{t-5} + e_t \tag{2.1}$$

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

to remove any predictable mean dynamics. The resulting residuals 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 in month m 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 $\sqrt{\pi/2}$ in equation (2.2) 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.

Table A1 and Table A2 in Appendix A summarize the main statistical properties of the daily CDS spreads and the resulting monthly CDS volatility series. There it can be seen that Spain, Italy, Ireland, Brazil, Croatia, Mexico, and Russia – the countries with higher CDS spreads – are also the countries that display higher CDS volatility.

3. Sovereign CDS Volatility and Economic Uncertainty

In this section, we explain why sovereign CDS volatility captures economic uncertainty, discuss differences and similarities with other measures of uncertainty, and relate it to EPU indices.

3.1 CDS Volatility and Economic Uncertainty

As already mentioned, sovereign CDS volatility reflects the uncertainty of traders in global banks about the prevailing economic conditions and prospects in a country. We now discuss in more detail why and which facets of economic uncertainty sovereign CDS volatility might capture.

The pricing of CDS contracts provides some insights. The CDS spread s_t is approximately equal to

$$s_t \approx lgd \cdot pd_t^Q = lgd \cdot pd_t + rp_t\ , \tag{3.1}$$

where lgd is the loss given default and pd_t^Q is the risk neutral default probability. Substituting the objective default probability pd_t (which is typically smaller than pd_t^Q) for the risk neutral default probability yields the second expression, which defines the CDS spread as the sum of the objective expected loss $lgd \cdot pd_t$ and a risk premium rp_t. See Amato (2005), Berg (2010) and Das, Hanouna and Sarin (2009) for further details.[6] A CDS is priced assuming a constant loss given default over the life of the contract.[7] Changes in the CDS spread Δs_t therefore essentially reflect changes in the objective probability of default and the degree of risk aversion of investors. Consequently, the volatility of CDS spread changes σ_m reflects uncertainty about the evolution of the determinants of a country's default probability and fluctuations in risk aversion.

Empirical work suggests that a country's default probability depends mainly on the government's effectiveness in collecting taxes and using them efficiently (Jeanneret, 2018), fiscal space (i.e., debt and deficit relative to tax revenues), inflation, trade openness, external debt (Aizenman, Hutchison and Jinjarak, 2013), the size and state of the economy, and the size and health of the financial system (Dieckmann and Plank, 2012). In addition to these country-specific variables, the literature finds that global risk factors reflecting exposure to US business cycle risk (Longstaff et al., 2011) and global risk aversion (Remolona, Scatigna and Wu, 2008) also help to explain CDS spreads. It seems that global risk factors tend to be more important in normal times, while country-specific variables become more important in times of crisis (Augustin, 2018). As a result, sovereign CDS volatility captures uncertainty about country-specific economic conditions, especially during economic downturn, while in normal times sovereign CDS volatility may also partly reflect changes in global economic risk and risk aversion.

3.2 Sovereign CDS Volatility and Other Uncertainty Measures

We now briefly compare sovereign CDS volatility with other measures of economic uncertainty that have been proposed in the literature. As mentioned in the introduction, these measures fall into four broad groups: model-based measures using large sets of economic indicators, market-based measures, survey-based measures, and measures based on text searches.

Model-based measures of uncertainty (Jurado, Ludvigson and Ng, 2015; Scotti, 2016; Ludvigson, Ma and Ng, 2020) and sovereign CDS volatility are similar in that both use forecast errors from econometric models to obtain an uncertainty measure. They differ in that the former approaches use information from many economic series and computationally intensive methods, while we use quoted CDS spreads and the computationally simple equations (2.1) and (2.2) to construct our CDS-based measure of economic uncertainty.

[6] Under the simplifying assumptions of a constant hazard rate of default and a constant risk free rate, equation (3.1) becomes an exact expression for the CDS spread (Chaplin, 2005).
[7] The loss given default is often assumed to be 60%.

Market-based uncertainty measures such as realized stock market volatility are conceptually similar to sovereign CDS volatility and differ mainly in the underlying variable. Another notable difference is that stock market volatility is often computed from raw stock index returns (Ederington and Guan, 2006; Poon and Granger, 2003), whereas we first remove the predictable variation in CDS spread changes to avoid mixing the predictable variation with the unpredictable variation in computing sovereign CDS volatility.

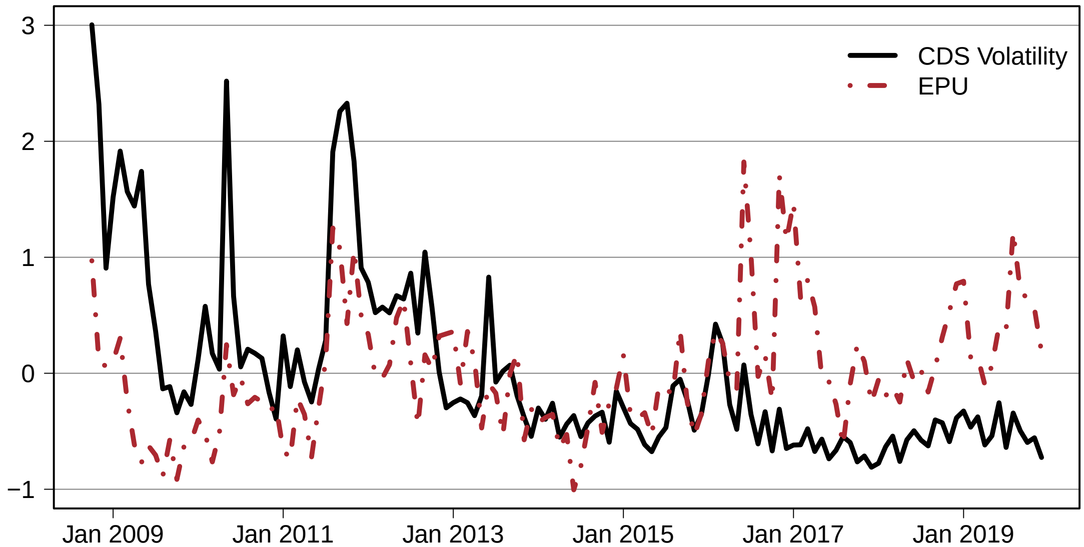
Survey-based uncertainty measures (Altig et al., 2022; Leduc and Liu, 2016; Bachmann, Elstner and Sims, 2013) use disagreement of households, professional forecasters, or firms about future business, expenditures, and future economic activity. A similarity between survey-based measures and our CDS-based uncertainty measure is that both use information generated by specific economic agents. Survey methods use discrepancies of forecasts from professional forecasters, firms and households, while sovereign CDS volatility uses fluctuations in CDS spreads to capture CDS traders uncertainty about a country's economic health.

Text-based uncertainty measures are constructed from searches for key-words related to uncertainty in newspapers (Baker, Bloom and Davis, 2016; Husted, Rogers and Sun, 2020; Caldara et al., 2020), other publications (Ahir, Bloom and Furceri, 2022), or the internet (Bontempi et al., 2021). The monthly available EPU indices from Baker, Bloom and Davis (2016) are the most popular, but unlike sovereign CDS volatility, the indices are only available for a limited number of countries. The World Uncertainty Index (WUI) is based on key-word searches in Economist Intelligence Unit country reports and available for more than 140 countries (Ahir, Bloom and Furceri, 2022). Unfortunately, WUI indices are only available on a quarterly basis. As with survey-based approaches, sovereign CDS volatility and EPU indices have in common that the information about uncertainty comes from specific agents. In the case of CDS volatility, the information comes from CDS traders, while EPU indices use information from journalists. In the next section, we discuss EPU indices in more detail, as they are very popular and have also been found to help explain CDS spreads (Wisniewski and Lambe, 2015).

3.3 Sovereign CDS Volatility and Economic Policy Uncertainty Indices

For the reasons just mentioned, the news-based EPU index introduced in Baker, Bloom and Davis (2016) is the benchmark measure of economic uncertainty in our analysis. Country-specific EPU indices are constructed from keyword searches in the electronic archives of a country's major newspapers. For instance, the EPU index for the US is based on searches in the archives of the ten most important US newspapers. Articles are

Figure 1: CDS Volatility and EPU.



Notes: Bold black line denotes the cross-sectional average of CDS volatility while the red dashed line denotes the cross-sectional average of EPU. Both series are standardized.

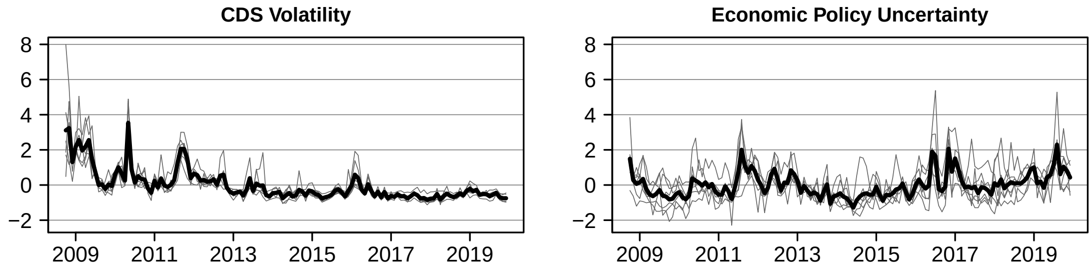
counted that contain triples of the words "economic" or "economy", "uncertain" or "uncertainty", and one or more of the words "Congress", "deficit", "Federal Reserve", "legislation", "regulation", or "White House". The monthly counts are then scaled and normalized to a mean of 100. The EPU indices for the other countries in the sample are constructed in a similar manner.[8]

Figure 1 shows how sovereign CDS volatility (black, solid line) and EPU (red, dashed line) averaged over all countries in the sample evolved over time. For better comparability both series are standardized. Figure 1 indicates that the cross-sectional averages of the EPU indices and the CDS volatility series show co-movement over time. As can bee seen, average CDS volatility already peaked at the beginning of the sample period due to the crisis in 2009. In 2010 and 2012 two more spikes occurred because of the European debt crisis. From 2017 onward, average CDS volatility was relatively low. However, some of the individual volatility series remained quite high and sometimes reached levels of more than 200 basis points.

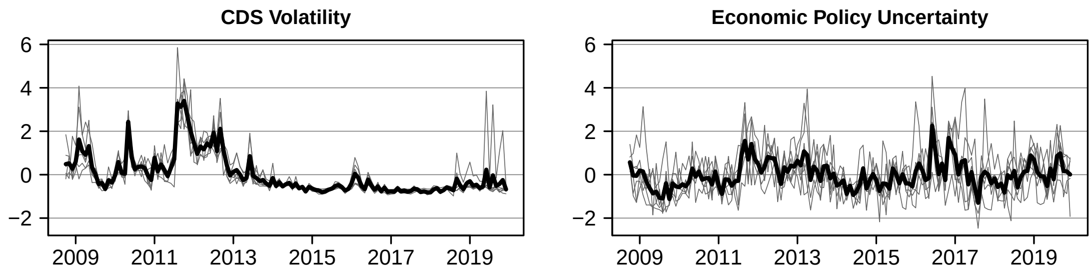
The summary statistics in Table A3 in Appendix A show that average EPU was particularly high for Brazil, Canada, China, France, and Great Britain. In all these countries, the unusually high index values occurred mainly in the last few years of the sample period. Recent political scandals provide an explanation 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

[8] Baker, Bloom and Davis (2016) provide all the details.

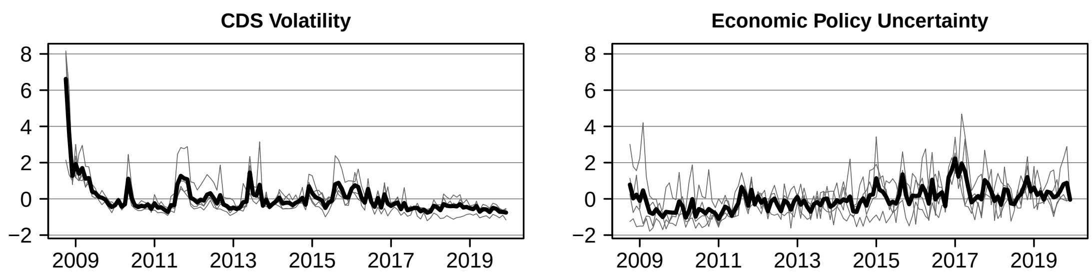
Figure 2: CDS Volatility and EPU Across Country Groups.



(a) Advanced Economies



(b) Euro Area Economies



(c) Emerging Market Economies

Notes: Grey thin lines denote country-specific standardized CDS volatility and EPU series, while the bold black line denotes the cross-sectional average. The country groups are defined as follows: advanced economies (CA, GB, JP, KR, SE, US), euro area economies (DE, ES, FR, IE, IT, NL), and emerging market economies (BR, HR, MX, RU).

Great Britain and a series of ISIS terror attacks is responsible for the high index values for France. The peaks in the standardized average EPU reflect these episodes of high EPU (Figure 1).

Figure 2 shows the evolution of the individual and average series for CDS volatility (left column) and EPU (right column) for our three country groups. The following observations stand out. Standardized CDS volatility is on average slightly lower than standardized EPU towards the end of the sample period. The individual EPU series tend to fluctuate more than the CDS volatility series. The peaks in the average CDS volatility series are more pronounced than in the EPU series in the crisis years 2009, 2010, and 2012. In contrast, EPU is peaking around 2016–2017 when Trump was elected, the UK held the Brexit referendum, and several countries including Brazil, France, and South Korea faced political turmoils. The patterns for the EPU indices and CDS volatility thus suggest that EPU tends to react more strongly to political uncertainty and sovereign CDS volatility tends to react more sharply to financial uncertainty.

4. Common Directional Information in Sovereign CDS Volatility and EPU Indices

In this section, we examine whether sovereign CDS volatility and EPU indices share directional information about economic uncertainty. More precisely, we ask whether the directional change of sovereign CDS volatility in month m 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.[9] We evaluate the directional predictions by computing performance statistics and regression based statistical tests.

4.1 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 Table 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}

Notes: N_{uu} denote the number of correct up predictions, N_{dd} the number of correct down predictions, N_{ud} the number of incorrect up predictions, and N_{du} the number of incorrect down predictions.

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

$$AC = \frac{N_{uu} + N_{dd}}{N_{uu} + N_{du} + N_{ud} + N_{dd}}. \tag{4.1}$$

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

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" is defined as

$$HI = \frac{N_{uu}}{N_{uu} + N_{du}}, \tag{4.2}$$

and also has 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

$$F = \frac{N_{ud}}{N_{ud} + N_{dd}}, \tag{4.3}$$

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

The difference between the hit rate and the false alarm rate is known as the Kuiper score:

$$KS = 100 \cdot (HI - F). \tag{4.4}$$

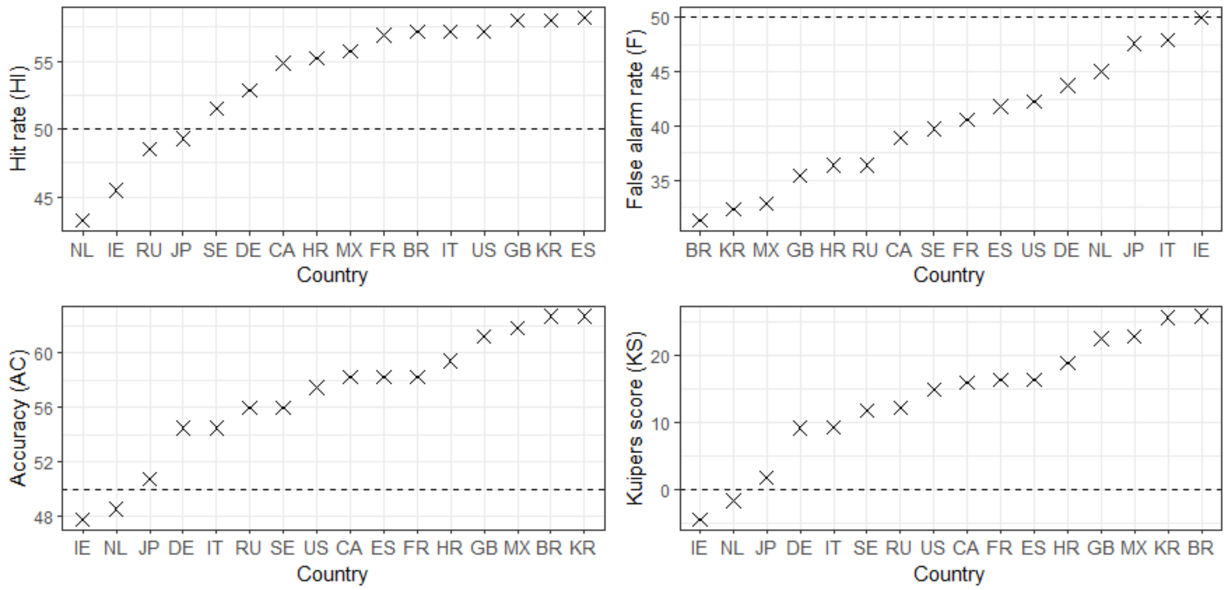
The KS statistic has a range of [-100, 100] and indicates how well CDS volatility discriminates between up and down movements in the EPU index over time. The KS statistic is around zero if the directional predictions are essentially random. A positive KS statistic indicates that CDS volatility helps 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

$$y_t = \alpha + \beta x_t + u_t \tag{4.5}$$

Figure 3: Directional Forecast Statistics.



and test for $\beta = 0$. This test assumes that the error u_t in (4.5) has zero mean, a constant variance and is serially uncorrelated (i.e., $E(u_t^2|x_t, x_{t-1}, \ldots) = \sigma^2 > 0$ and $E(u_t u_s|x_t, x_{t-1}, \ldots) = 0$ 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

$$y_t = \alpha + \beta x_t + \sum_{j=1}^{m} \gamma_j x_{t-j} + \sum_{j=1}^{n} \delta_j y_{t-j} + u_t \tag{4.6}$$

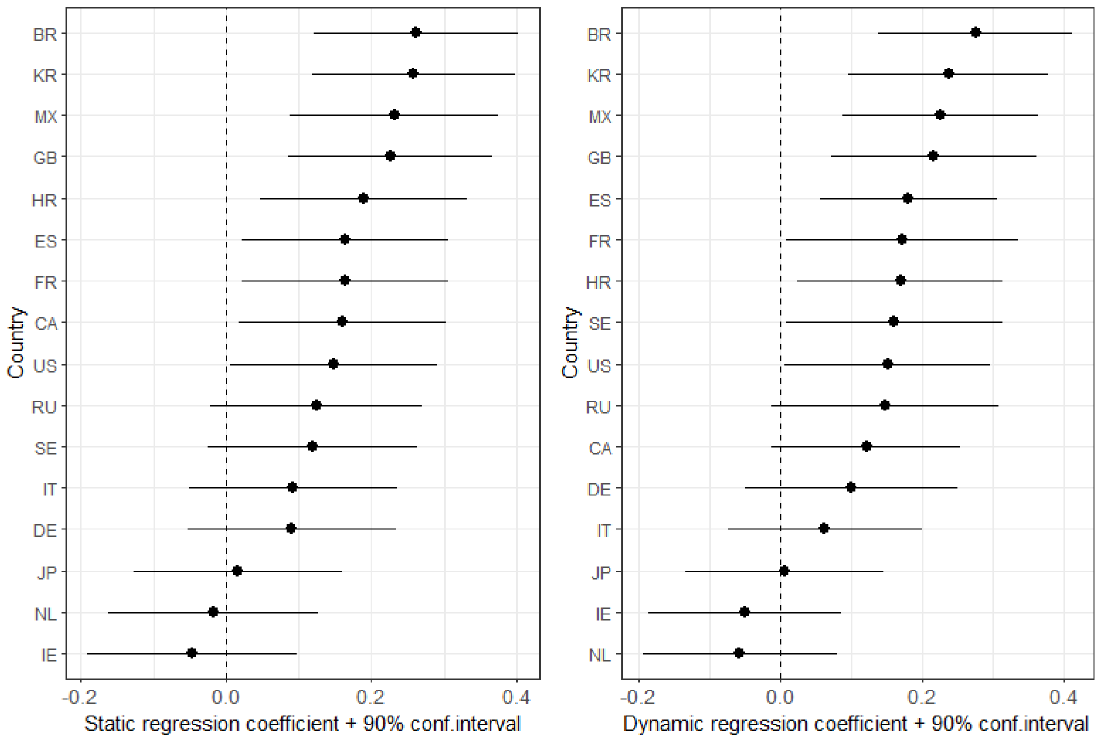
that corrects for the effects of lagged dependent and explanatory variables. The hypothesis to be tested is again $\beta = 0$. To account for any remaining autocorrelation in the residuals we compute the t-test statistic with robust Newey-West standard errors (Newey and West, 1987).

4.2 Results of 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 in Figure 3.

The upper left plot in Figure 3 shows the results for the hit rate, defined as the proportion of correct upward predictions. As can be seen, twelve out of sixteen hit rates exceed 50%. The hit rates reach about 57.5% for France, Brazil, Italy, the US, Great Britain, South Korea, and Spain. The hit rates for Canada, Croatia and

Figure 4: Regression Tests of Directional Forecast Accuracy.



Mexico 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 from 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 Figure 3 shows the country-specific Kuiper scores that indicate 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 produce more correct than incorrect directional forecasts of the corresponding EPU index movements. The familiar exceptions are again Ireland and the Netherlands.

Let us now 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 directional movements in CDS volatility. Figure 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.

Taken together, the results from the regression tests and the descriptive statistics tell the same story, namely that in most cases sovereign CDS volatility does contain some information about directional 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.[10]

5. Macroeconomic Responses to Uncertainty Shocks

Now, we turn to the impulse response analysis. We resort to a Bayesian panel VAR approach to compare the macroeconomic effects of shocks to economic uncertainty, proxied either by sovereign CDS volatility, the EPU index, or equity volatility.

5.1 Econometric Model

The use of a panel VAR can be motivated from various angles. First, the sample length of the time series is rather short, so pooling information across countries is advantageous. Second, to also account for a degree of cross-country heterogeneity, we estimate the panel for the respective country groups separately. Last, we are interested in the *average* (within a country group) effects of macroeconomic quantities to economic uncertainty shocks. This renders a Bayesian panel VAR without cross-sectional heterogeneity and no static or dynamic interdependence attractive (Canova and Ciccarelli, 2009; Canova and Ciccarelli, 2013).

[10] 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 in predicting changes in EPU indices.

We assume that an $M \times 1$-dimensional multivariate time series process $\{\boldsymbol{y}_{it}\}_{t=1}^{T}$ of each country $i = 1, \ldots, N$ follows

$$\boldsymbol{y}_{it} = \boldsymbol{c}_i + \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{y}_{it-j} + \boldsymbol{\varepsilon}_{it}, \qquad \boldsymbol{\varepsilon}_{it} \sim \mathcal{N}_M(\mathbf{0}, \boldsymbol{\Sigma}), \tag{5.1}$$

where the $M \times 1$ vector $\boldsymbol{c}_i$ is a country-specific fixed effect, while the $M \times M$ coefficient matrix $\boldsymbol{A}_j$ is fixed across countries (*no dynamic cross-sectional heterogeneity*). The reduced-form error term $\boldsymbol{\varepsilon}_{it}$ follows a multivariate Gaussian distribution with zero mean and covariance matrix $\boldsymbol{\Sigma}$, which is also fixed across countries (*no static cross-sectional heterogeneity*). Cross-sectional heterogeneity is captured by the three country-groups: advanced economies, Euro area economies, and emerging market economies. Further note that this structure neither allows for static nor for dynamic interdependence across countries (i.e., $Var(\boldsymbol{y}_{it}, \boldsymbol{y}_{jt}) = 0$ and $Var(\boldsymbol{y}_{it}, \boldsymbol{y}_{jt-1}) = 0\ \forall i \neq j$). In our application this assumption is appropriate because we are not interested in measuring spillovers between countries. Instead, we want to empirically compare the transmission of economic uncertainty shocks measured with different measures of economic uncertainty across the three different groups of countries.

We estimate the model with Bayesian methods. The proposed model is similar to a standard linear VAR except for the country-fixed effects. We implement the widely used Minnesota prior (Doan, Litterman and Sims, 1984; Litterman, 1986). In this framework, we assume a Gaussian prior distribution on the coefficients and inverse-Wishart prior distribution on the covariance matrix. The Minnesota prior specifies the prior belief that macroeconomic time series follow a unit root. Furthermore, it imposes the belief that higher-order lags are less important and thus closer linked to a value of zero. Practically, this means that the variance is smaller for coefficients on further lags. Finally, we impose that little is known about exogenous variables (i.e., fixed effects), so that the variance on these terms may be large. We follow standard practices as outlined in Kilian and Lütkepohl (2017). We draw 10,000 posterior draws from the full posterior distribution in the Markov Chain Monte Carlo sampler and discard the first 5,000 draws as burn-ins.

5.2 Data and Identification

The panel VAR model contains the following six variables: the respective uncertainty indicator x_{it} under consideration, the leading stock index of a country eq_{it}, the short-term interest rate i_{it}, the price level p_{it}, the unemployment rate u_{it}, and industrial production ip_{it}. All variables except the unemployment rate and interest rates enter in log-levels and we use the lag-length specification recommended by the Bayesian information criterion (BIC). In particular, we check the BIC up to twelve lags in each model.[11] It points to a low number of lags (either one or two lags), and thus we consistently use $p = 2$ lags for all estimated models.[12] In the baseline VAR the sample period ranges from October 2008 to December 2019. 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 January 2003 and provide results for both sample periods. This results in four country groups, which we label as follows: advanced economies, Euro area economies, emerging market economies (short sample), and emerging market economies (long sample).

To identify the macroeconomic impact of an uncertainty shock, we rely on a standard Cholesky decomposition where the variables appear in the following ordering: $\boldsymbol{y}_{it} = \{x_{it}, eq_{it}, i_{it}, p_{it}, u_{it}, ip_{it}\}$. Thus, as in Baker, Bloom and Davis (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.[13] Results with this alternative ordering are available upon request but leave our main findings unchanged.

5.3 Results of the Impulse Response Analysis

This section presents the results of the impulse response analysis. For comparability, we normalize the responses to both shocks to yield a 10% decrease in the stock index. In the following, we present the impulse responses for output and unemployment to uncertainty shocks as measured by sovereign CDS volatility and the EPU country indices, respectively. We compute impulse responses for a horizon of two years (i.e., 24 months). The responses for all variables in the PVAR can be found in Appendix B.

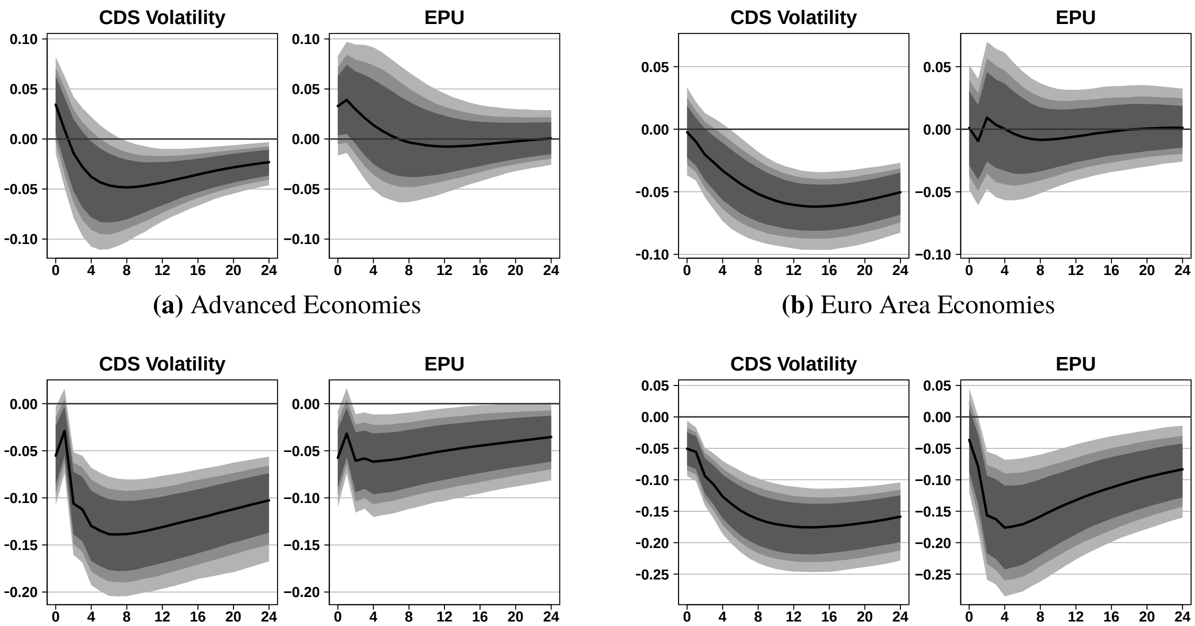
Figure 5 and Figure 6 present the impulse responses of output and unemployment to both types of uncertainty shocks, respectively. Both plots offer in four panels (one for each country group) a direct comparison between the impulse response of the model featuring CDS volatility and EPU to induce the uncertainty shock. For both indicators, we observe a decrease of economic activity after an uncertainty shock. This is consistent with findings for the US (Bloom, 2009; Fernández-Villaverde et al., 2015; Baker, Bloom and Davis, 2016; Basu and Bundick, 2017).

[11] Other model selection criteria point, such as the Deviance information criterion, the Akaike information criterion, or the Hannan-Quinn information criterion are in line with these results, albeit pointing to a somewhat higher number of lags. Nevertheless, results remain qualitatively similar when changing the number of lags, see also the robustness check later.

[12] In some instances, the BIC pointed to only using one lag. To ensure consistency across the models, we decided to use $p = 2$ across all estimated models.

[13] In his seminal contribution, Bloom (2009) orders equity prices first, while in a more recent study, Baker, Bloom and Davis (2016) order equity prices second.

Figure 5: Impulse Responses of Output to Uncertainty Shocks (Comparison to EPU).



(a) Advanced Economies

(b) Euro Area Economies

(c) Emerging Market Economies (Short Sample)

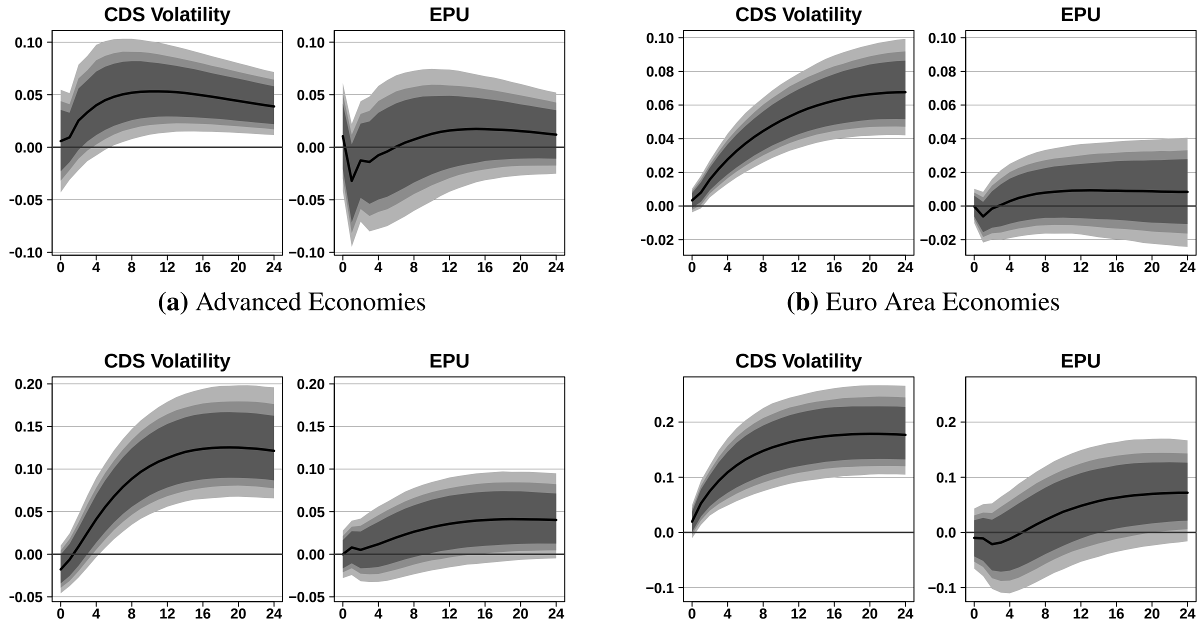
(d) Emerging Market Economies (Long Sample)

Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. The reaction of output is in percent. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

The reduction of economic activity could be triggered by either the the real options or the risk aversion channel. The real options channel is associated with a wait-and-see attitude of households and firms in response to heightened uncertainty, which results in a delay of consumption and investment. Following the risk aversion channel, risk-averse (domestic and international) investors demand a higher risk premium in the face of higher uncertainty, which raises the cost of finance. Furthermore, higher uncertainty leads to an expansion of left-tail events, thereby increasing the probability of default. This leads to a higher default premium. Higher economic uncertainty is thus strongly linked to increasing borrowing costs, which leads to a dampening of macro aggregates (Christiano, Motto and Rostagno, 2014).

The medium term response to output is clearly negative for CDS volatility across the country groups. For EPU, we observe negative effects for the emerging market sample but less clear-cut effects for advanced economies or the Euro area economies. Shocks are economically and statistically significant and sizable. Effect sizes range from a 6% (Euro area) to a 16% (emerging markets) output contraction for uncertainty shocks induced by CDS volatility. Lastly, our results are also in line with the more recent literature on the macroeconomic effects of uncertainty (Bachmann, Elstner and Sims, 2013; Jurado, Ludvigson and Ng, 2015), that finds no evidence for any overshooting effects in output. The same pattern holds also when

Figure 6: Impulse Responses of Unemployment to Uncertainty Shocks (Comparison to EPU).



(a) Advanced Economies

(b) Euro Area Economies

(c) Emerging Market Economies (Short Sample)

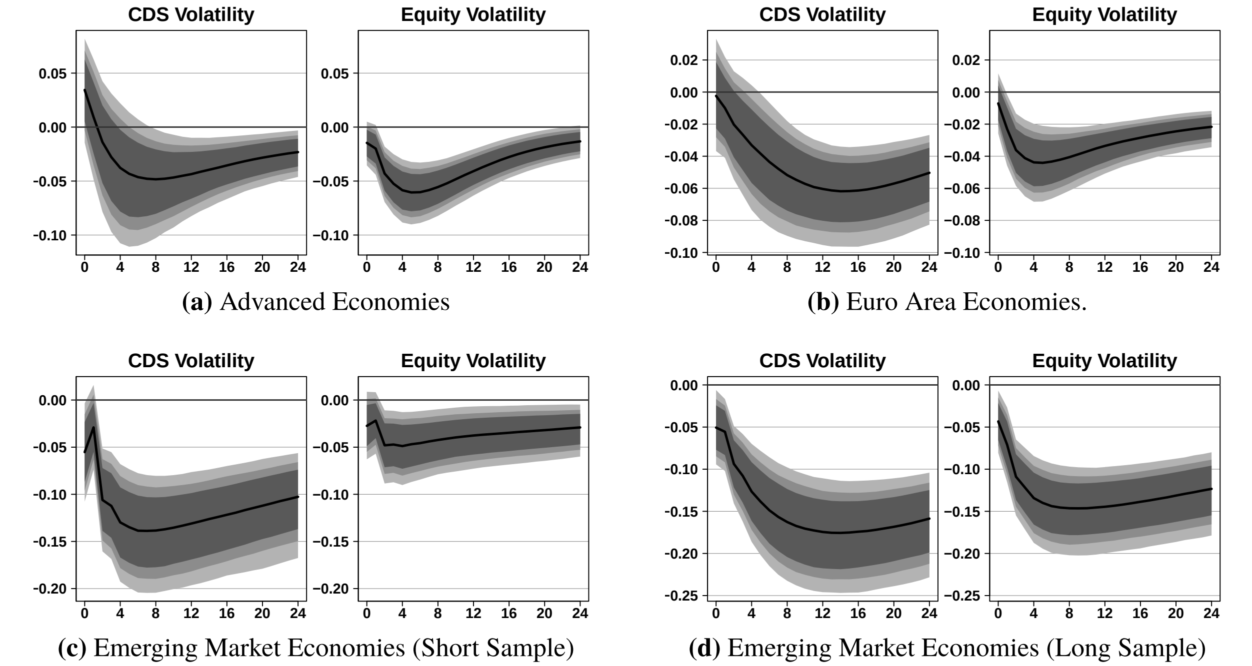
(d) Emerging Market Economies (Long Sample)

Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. The reaction of unemployment is in percent. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

inspecting the impulse responses of unemployment. While CDS volatility leads to a surge in unemployment, we see only significant effects for EPU in the emerging market samples. CDS shocks lead to a significant rise in unemployment throughout all regions with peak effects ranging from 5% (advanced economies) to 15% (emerging markets).

Overall, our results point to similar effects when comparing these uncertainty shocks. Nevertheless, the results of EPU are less precisely estimated and do not induce economic contractions in two out of three country groups. We argue that these differences arise because both measures proxy different information sets. CDS volatility is informative on how global banks reflect on the prevailing economic conditions in a country and is thus a market-based measure of uncertainty. EPU, however, is a news-based measure and thus captures not only financial but also other facets of uncertainty. Most importantly, a news-based measure also comprises uncertainty with respect to political processes and economic policy, which is not per se detrimental for economic outcomes. Therefore, the measure is more noisy than CDS volatility.

Figure 7: Impulse Responses of Output to Uncertainty Shocks (Comparison to Equity Volatility).



(a) Advanced Economies

(b) Euro Area Economies.

(c) Emerging Market Economies (Short Sample)

(d) Emerging Market Economies (Long Sample)

Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. The reaction of output is in percent. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

5.4 Comparisons with Further Measures of Economic Uncertainty

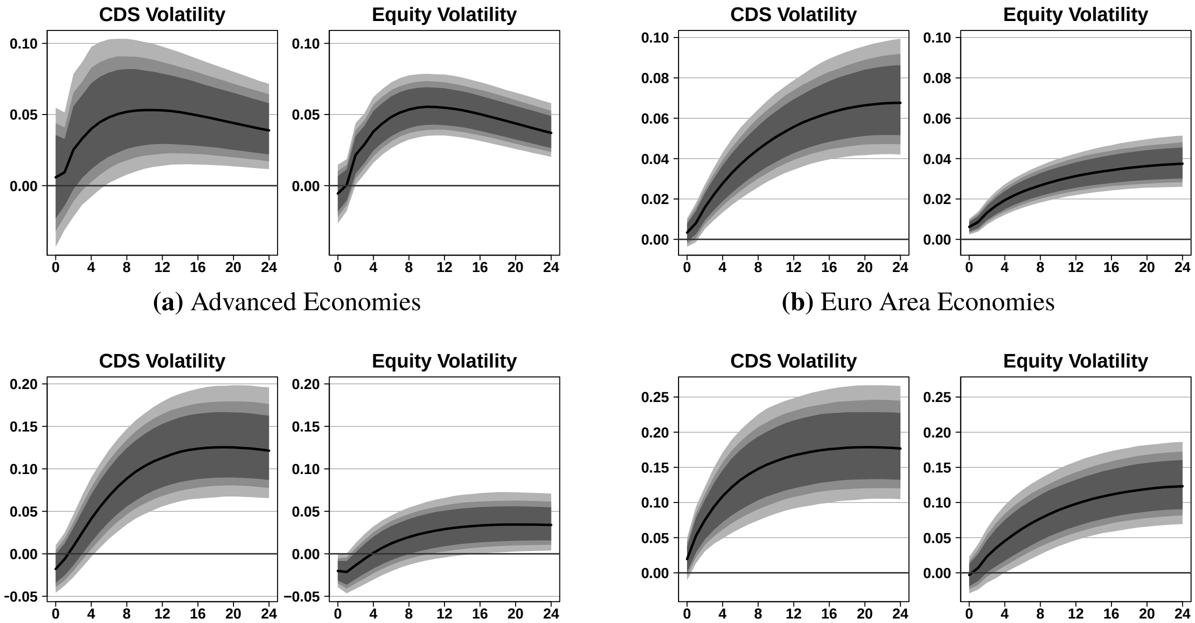
As already mentioned, the literature on economic uncertainty effects has proposed several uncertainty measures. Therefore, we cross-check our results with further alternatives.[14] More specifically, we use the volatility of stock index returns as an alternative measure of economic uncertainty (see also Datta et al., 2017). Stock market/equity volatility is a widely used measure of uncertainty that can be computed for all countries in the sample. For each country, we compute monthly stock market volatility from the daily returns on the leading stock index of the country.[15]

Furthermore, we also compare our proposed measure of uncertainty, the CDS volatility, to the financial uncertainty indicator introduced by Jurado, Ludvigson and Ng (2015). The financial uncertainty index of Jurado, Ludvigson and Ng (2015) is an econometrically quite sophisticated measure of uncertainty that is only available for the USA. It exploits a data-rich environment to generate the conditional volatility of an

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

[15] We first remove the mean dynamics in the daily returns with an AR(1) model. Then we compute monthly volatility in the same way as CDS volatility from the absolute values of the residuals of the AR(1) model.

Figure 8: Impulse Responses of Unemployment to Uncertainty Shocks (Comparison to Equity Volatility).



(a) Advanced Economies

(b) Euro Area Economies

(c) Emerging Market Economies (Short Sample)

(d) Emerging Market Economies (Long Sample)

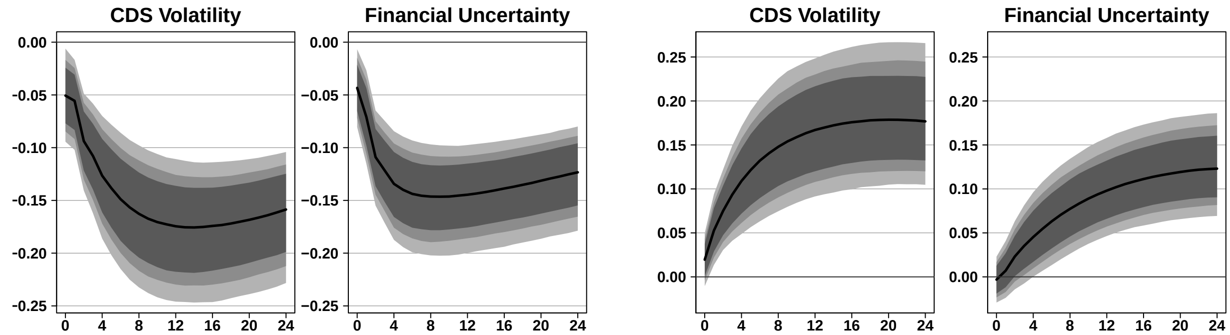
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. The reaction of unemployment is in percent. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

unforecastable disturbance to measure (financial) uncertainty.[16] Specifically, we utilize the volatility of the one-step ahead forecast error of the financial uncertainty index. It thus serves as an ideal robustness check whether CDS volatility captures similar information to a measure based on a high-dimensional dataset from the real and financial economy of the US. To ensure comparability, the model specification and the ordering of the variables in the VAR is the same as in the other VAR models.

We start by discussing the results with the comparison to equity volatility as an alternative measure of economic uncertainty. Figure 7 and Figure 8 present the impulse responses of output and unemployment to both types of uncertainty shocks, respectively. Both plots offer in four panels a direct comparison between the impulse response of the model featuring CDS volatility and equity volatility to induce the uncertainty shock. Again, we have normalized the shock to a 10% decrease in equity prices and the responses of all variables in the PVAR can be found in Appendix B. Overall, results demonstrate a strong similarity between CDS volatility and stock market volatility. In all country groups, economic activity in terms of output and unemployment unequivocally declines. This means that output contracts and unemployment rises. Shocks

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

Figure 9: Impulse Responses to an Uncertainty Shock (Comparison with Financial Uncertainty).



(a) Output **(b)** Unemployment

Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. The reaction of output and unemployment is in percent. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

are economically and statistically significant. In the model with equity volatility, effect sizes range from a 4% (Euro area) to 15% (emerging markets) decline and are thus comparable with the outcomes of CDS volatility. In some instances, CDS volatility even points to more detrimental effects than stock market volatility. We interpret this as the difference between an *inward* and *outward* (financial) market-based view on uncertainty.

To compare sovereign CDS volatility with the financial uncertainty index for the US we estimate a single-country Bayesian VAR.[17] Then, we use the same recursive identification scheme as before to compute the impulse responses. The scaling of the shocks is again normalized to a 10% drop of equity prices on impact.

We present the impulses responses of output and unemployment in Figure 9 and the full set of impulse responses in Appendix B. It turns out that the responses to both shocks are again qualitatively similar. Again, and in line with the literature on economic uncertainty, US economic activity strongly contracts. A few remarks are in order. First, peak effects are even stronger for the US than in a panel of countries. Second, the financial uncertainty indicator seems to trigger slightly weaker responses. Third, although the indicators are rather differently constructed, the correlation between them is 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.

[17] We use the same model setup as in the PVAR but featuring only one intercept (fixed effect) instead. This is convenient because we can utilize exactly the same prior setup.

5.5 Robustness

We conduct a number of robustness exercises to the results. First, we check for different lag lengths and re-estimate the model with different lag lengths. Figures B6 to B9 show the impulse response functions to an uncertainty shock proxied by either CDS volatility, the EPU index, or equity volatility when using $p = 4$ lags. Results are stable when accounting for more lags. Specifically, the responses to unemployment and output are insensitive to the baseline results.

Second, we also test for subsample stability by starting the sample only after the great financial crisis in 2010M1. Again, we provide the impulse responses to the uncertainty shocks of all proxies in the appendix. Figures B10 to B12 show the results. Now, the responses to output and unemployment are not as pronounced as before but they still point to the fact that uncertainty shocks reduce economic activity. This is expected since the last financial crisis was a major event and influential for the results.

6. Conclusions

The world's largest financial institutions are the biggest traders of sovereign CDS contracts and sovereign CDS spreads depend on a country's solvency. Based on these two observations, we argue that the volatility of sovereign CDS spreads provides information about country-specific economic uncertainty from the viewpoint of global financial institutions.

For a panel of 16 countries which we divided into major advanced economies, euro area countries, and emerging market economies, we found that sovereign CDS volatility shares directional information with EPU country indices – a benchmark measure of economic uncertainty. We also found that the mean impulse responses of output and unemployment after an unexpected uncertainty shock are similar for all three groups of countries, regardless of whether economic uncertainty is measured by sovereign CDS volatility, an EPU index, stock market volatility, or as in case of the USA, the financial uncertainty index of Jurado, Ludvigson and Ng (2015). The CDS volatility shock tends to lead to more precise inference though. Taken together, our empirical findings therefore show that sovereign CDS volatility captures economic uncertainty.

As noted earlier, there is no single true measure of economic uncertainty, and we want to emphasize that we are not claiming that sovereign CDS volatility is a *better* indicator of economic uncertainty than others. We argue, however, that sovereign CDS volatility is a valuable indicator of economic uncertainty for at least three reasons. Sovereign CDS volatility provides information about economic uncertainty from the perspective of the world's largest financial institutions and thus it can be used as a supplementary indicator of economic uncertainty. In addition, sovereign CDS volatility is easy to compute and CDS spreads for almost all countries are readily available in all major financial and economic databases. Finally, sovereign CDS volatility can be used as a general indicator of economic uncertainty for countries for which no EPU index is available and other indicators are considered unreliable or difficult to obtain. Sovereign CDS volatility thus provide policymakers and researchers with an outside view on economic uncertainty that is widely available across countries.

Declaration of Interest

The authors declares to have no conflict of interest.

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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.

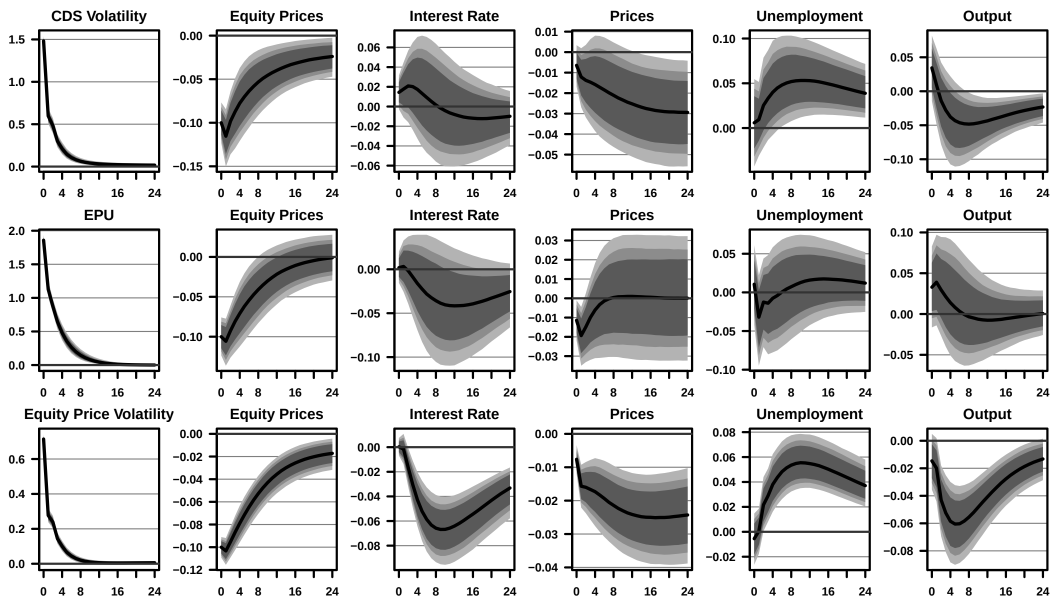
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BR	135	103.3	91.2	19.5	52.5	127.4	839.4
CA	135	5.7	5.1	0.04	2.6	7.4	29.9
DE	135	15.9	17.9	1.0	4.3	21.5	94.9
ES	135	72.4	81.3	2.7	15.6	102.3	390.7
FR	135	28.8	30.9	1.7	8.8	40.8	147.8
GB	135	21.5	26.2	1.1	5.1	26.9	143.7
HR	135	90.2	68.7	7.3	35.3	122.2	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

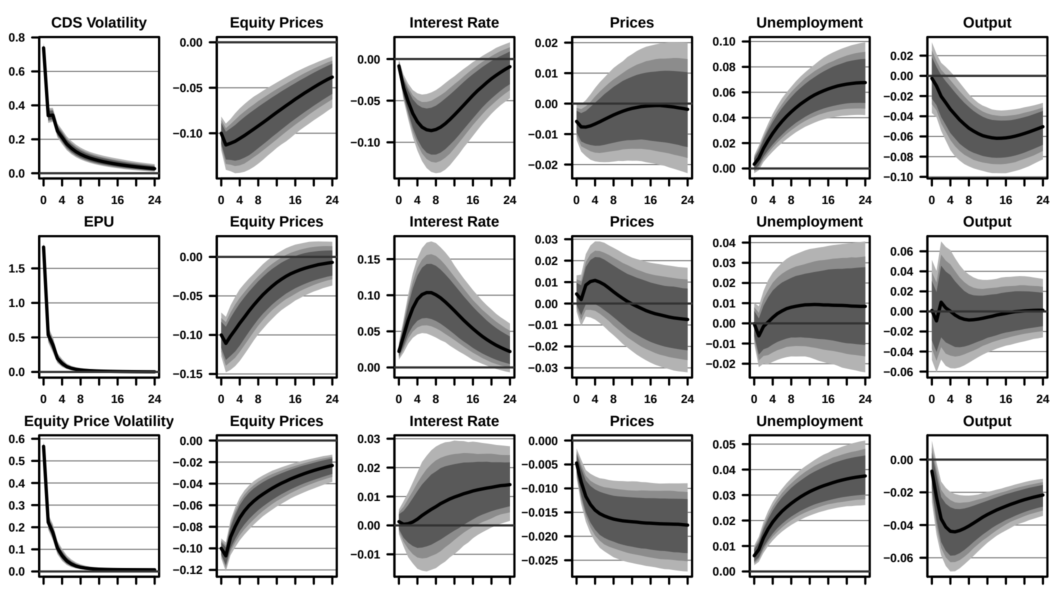
B. Additional Results

Figure B1: Impulse Responses to Uncertainty Shocks in Advanced Economies.



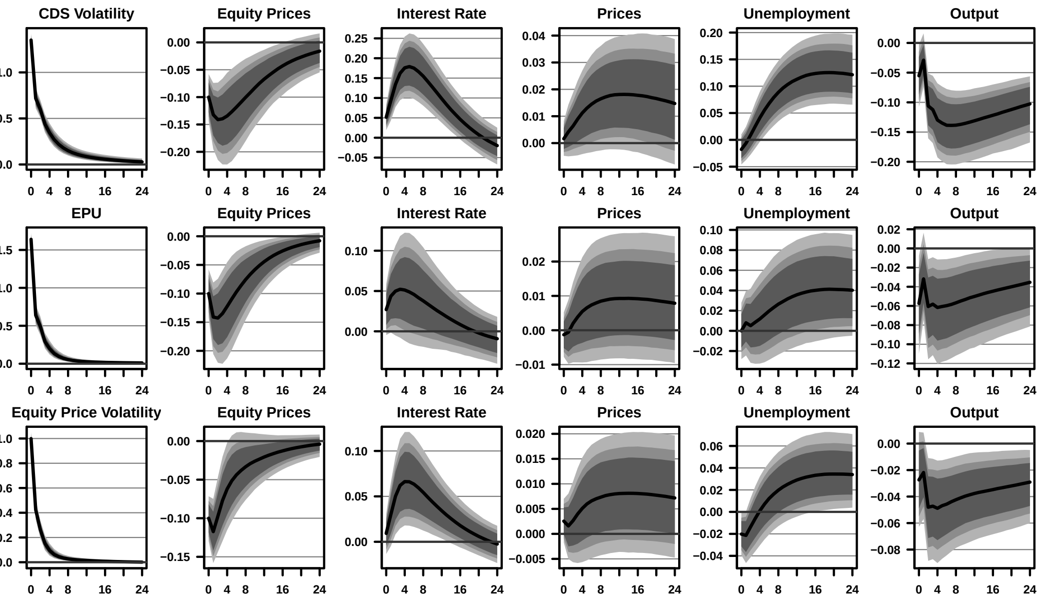
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B2: Impulse Responses to Uncertainty Shocks in Euro Area Economies.



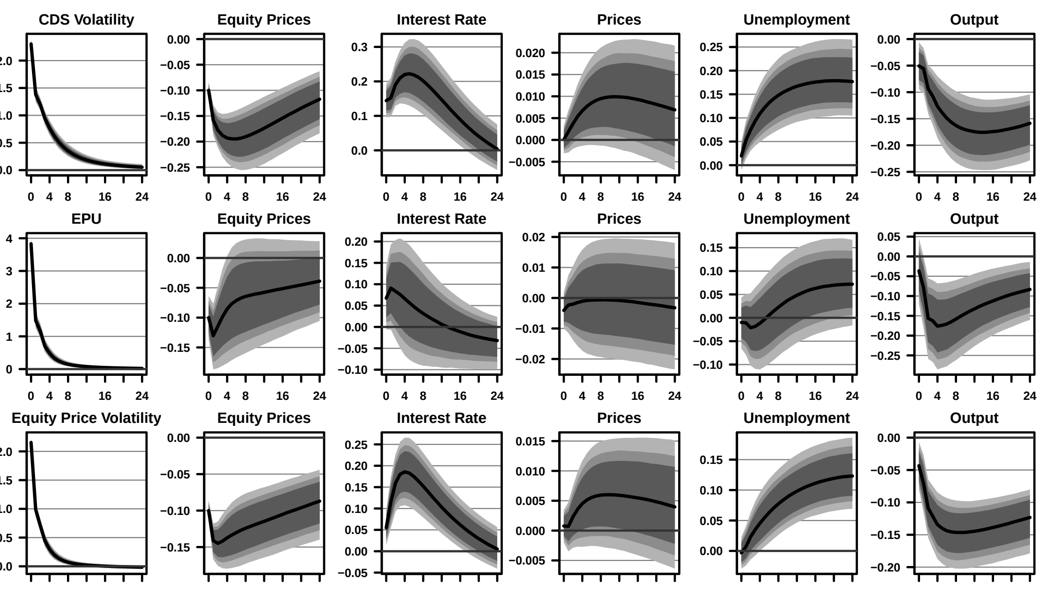
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B3: Impulse Responses to Uncertainty Shocks in Emerging Market Economies (Short Sample).



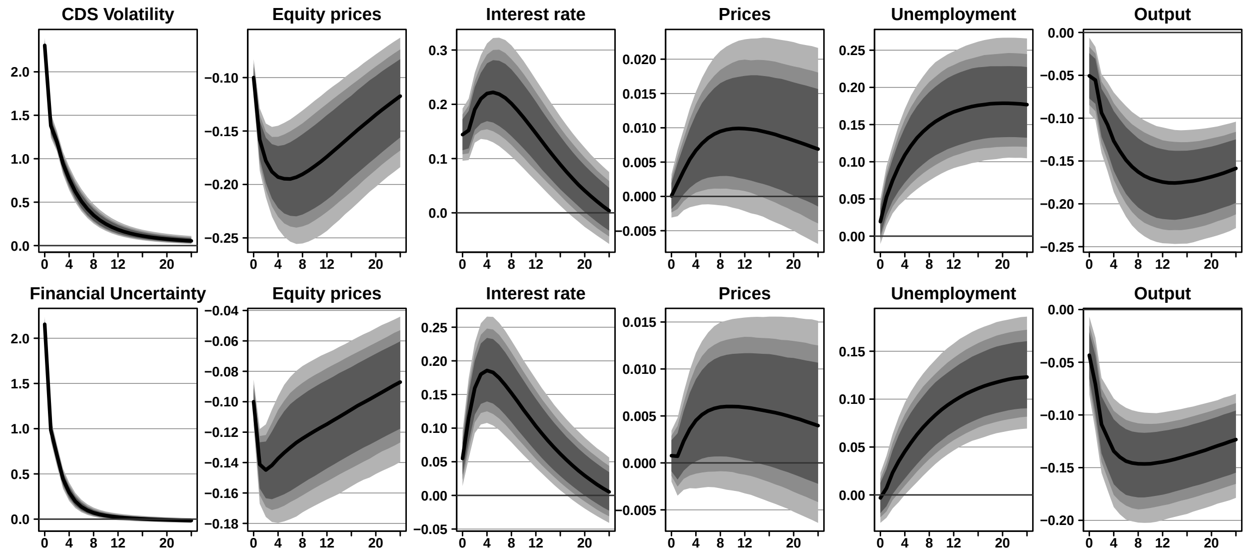
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B4: Impulse Responses to Uncertainty Shocks in Emerging Market Economies (Long Sample).



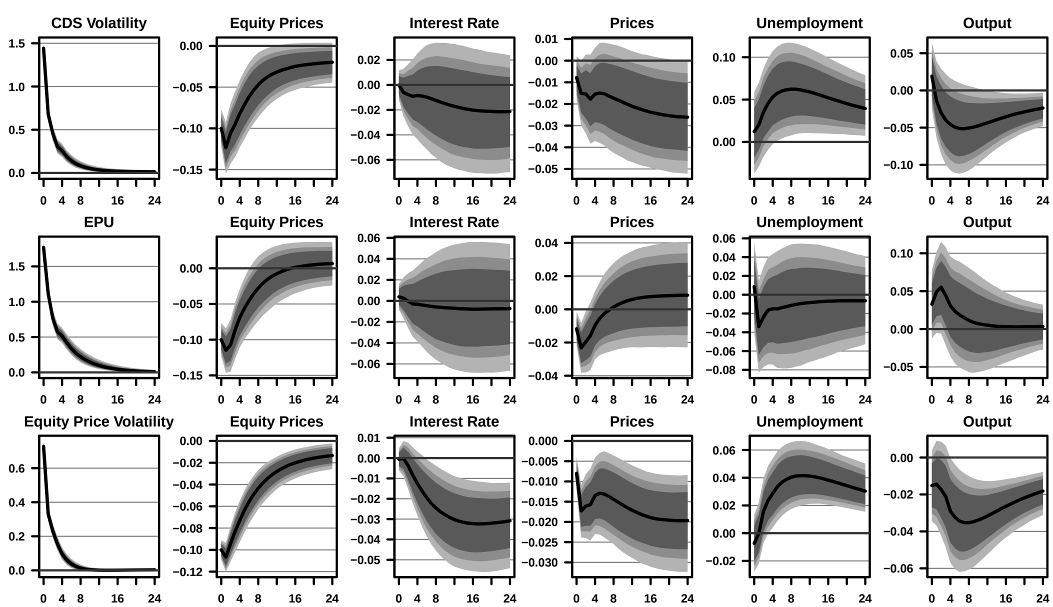
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B5: Comparison with Financial Uncertainty Shocks.



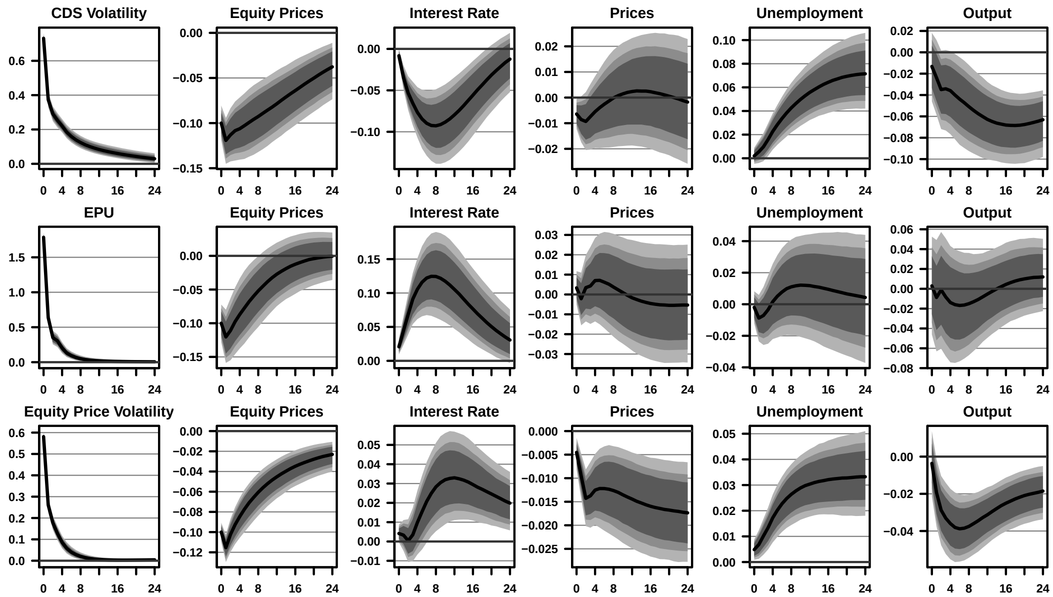
Notes: Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B6: Impulse Responses to Uncertainty Shocks in Advanced Economies ($p = 4$).



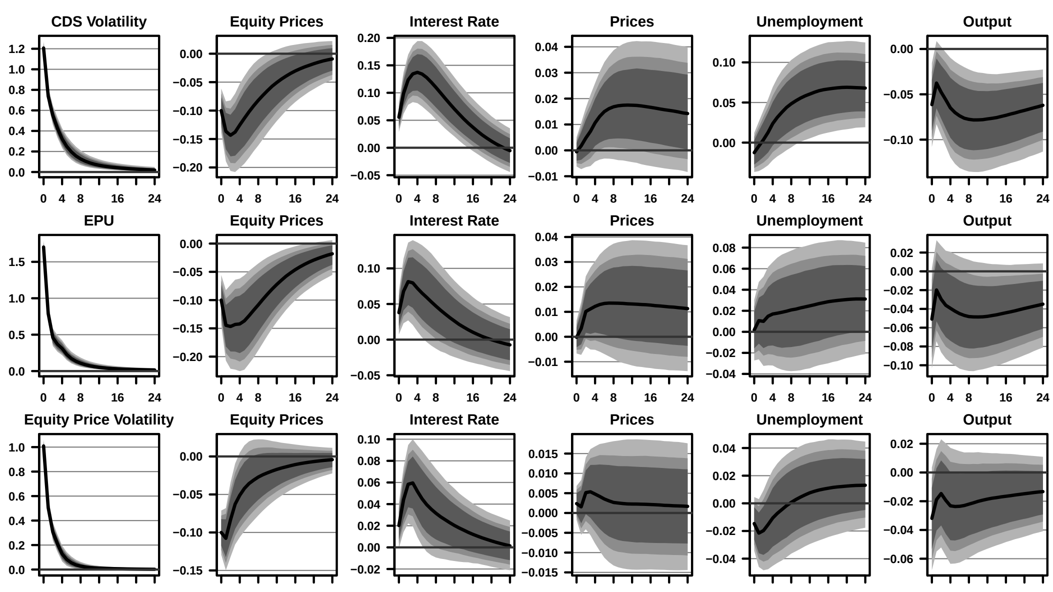
Notes: Robustness exercise with $p = 4$. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B7: Impulse Responses to Uncertainty Shocks in Euro Area Economies (p = 4).



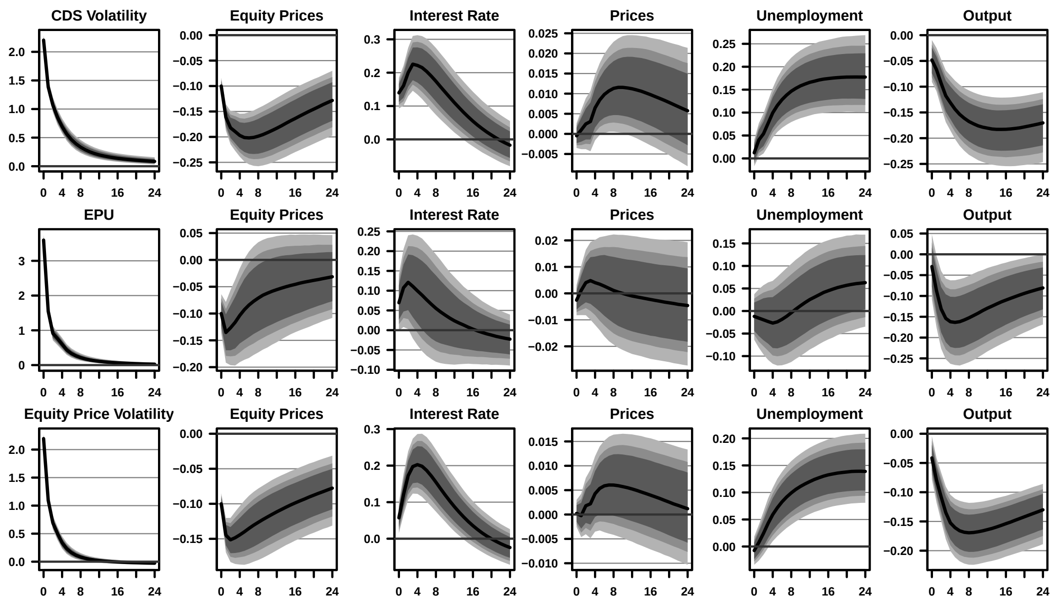
Notes: Robustness exercise with $p = 4$. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B8: Impulse Responses to Uncertainty Shocks in Emerging Market Economies (Short Sample) (p = 4).



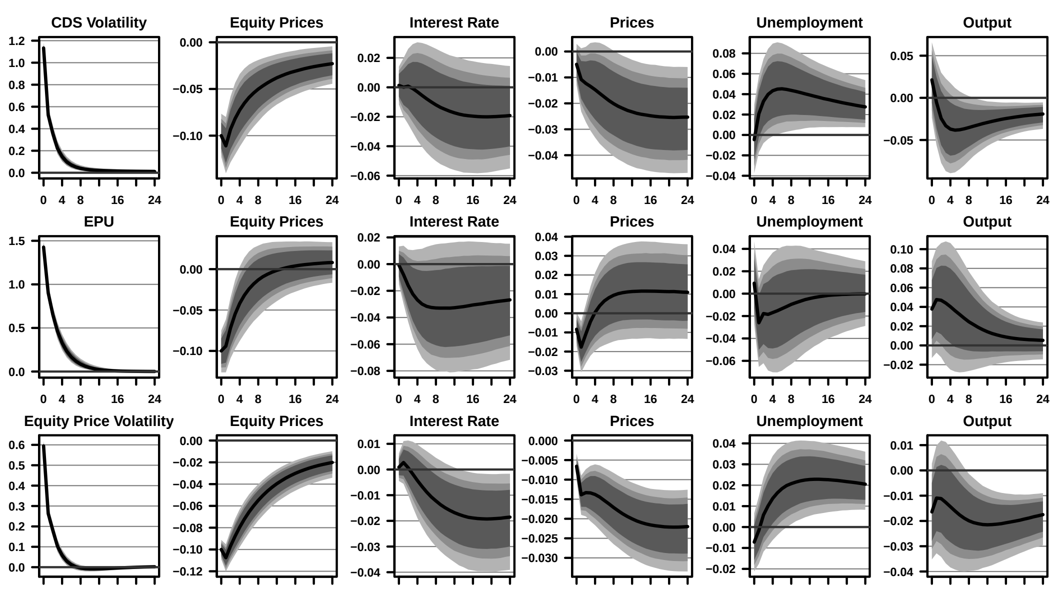
Notes: Robustness exercise with $p = 4$. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B9: Impulse Responses to Uncertainty Shocks in Emerging Market Economies (Long Sample) (p = 4).



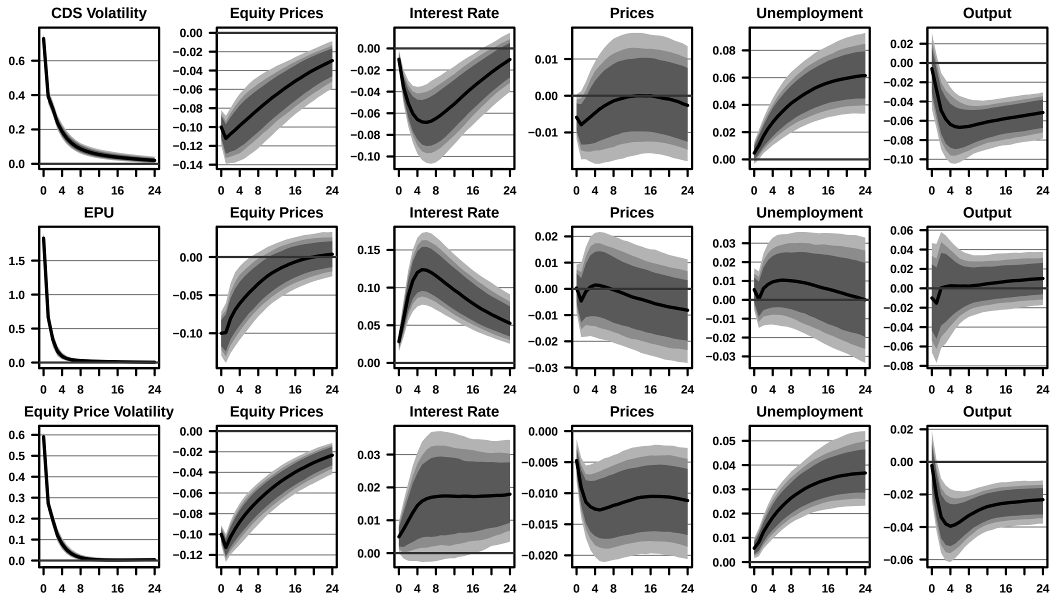
Notes: Robustness exercise with p = 4. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B10: Impulse Responses to Uncertainty Shocks in Advanced Economies (Short Sample).



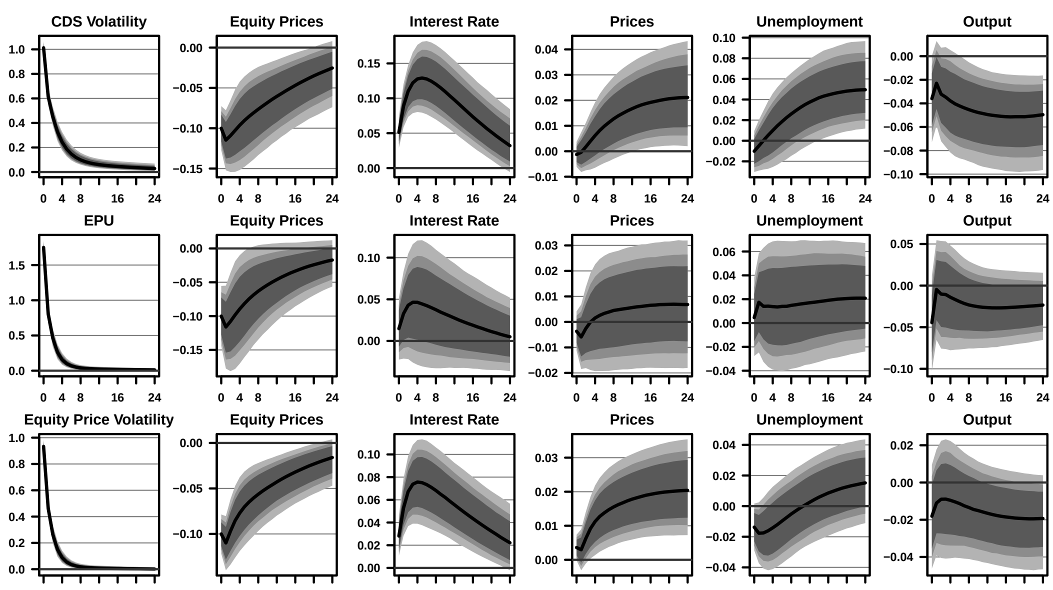
Notes: Robustness exercise with sample starting in 2010M1. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B11: Impulse Responses to Uncertainty Shocks in Euro Area Economies (Short Sample).



Notes: Robustness exercise with sample starting in 2010M1. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.

Figure B12: Impulse Responses to Uncertainty Shocks in Emerging Market Economies (Short Sample).



Notes: Robustness exercise with sample starting in 2010M1. Responses to an uncertainty shock scaled to a 10% decrease in equity prices. Black solid lines denote the median effect along with 68% (dark gray), 80% (gray) and 90 % (light gray) credible intervals.