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Cross-Sectional Dependence in Growth-at-Risk

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Cross-Sectional Dependence in Growth-at-Risk *

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Abstract

This paper explores the impact of cross-sectional dependence in panel data models that link Growth-at-Risk with macro-financial and uncertainty indicators. Using a long quarterly panel dataset for 24 countries, we find that including cross-sectional dependence enhances the model performance in both in-sample and out-of-sample evaluations. Aligning with our main objective of predicting GaR, we estimate a factor-augmented panel quantile regression set-up using the Common Correlated Effects technique. In a unique finding we note that in the presence of cross-sectional dependence, the indicators commonly associated with GDP catastrophes have limited significance on 5 per cent GaR. Encouraged by superior out-of-sample performance, we analyse predicted GaR and estimate a range of measures to quantify risks. We find several meaningful signals of risk and GDP slowdowns that are relatable to observed data at various points in time. We additionally find that the factors that are used to represent the cross-sectional dependence determine the direction of GaR. Also, these factors have a time-varying impact i.e., a positive role in normal times and exert further downward pull in times of distress.

JEL Codes C21, C23, C33, C53

Keywords Quantile Regressions, Cross-sectional Dependence, Growth-at-Risk

1 Introduction

After the Global Financial Crisis (GFC), to revive growth and restore the financial systems, monetary policy remained accommodative. Continuation of such policy support confronted policymakers with a key challenge

*The views in this paper are of the author only and not of any affiliated institution. All data are available in the public domain and sourced from the replication files of Brownlees & Souza (2021). I am grateful to Christian Brownlees for sharing the data and replication codes. I thank my PhD supervisor Jack Fosten for his guidance on this paper. I am grateful for the helpful comments and feedback from Filippo Pellegrino, Matei Demetrescu, C. Vladimir Rodríguez Caballero and other participants of the 8th Annual Conference of the International Association for Applied Econometrics (IAAE), June 2022. Thanks to Ahmet Benlialper and other participants of the RES Symposium of Junior Researchers, June 2022 for the interesting discussion.

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- the build-up of financial vulnerabilities and consequent worsening of the medium-term risks. Highlighting this inter-temporal trade-off, the International Monetary Fund (IMF), introduced the concept of Growth-at-Risk (GaR) as a surveillance tool (IMF 2017). GaR is used to quantify downside risks to GDP growth and is measured as the lower quantiles of the GDP growth distribution.

This paper re-examines the relationship of GaR for 24 countries with a wide range of financial indicators that are linked to growth vulnerability. A growing range of papers has contributed to the understanding of the relationship of financial conditions and the extreme quantiles of GDP growth, and two main perspectives emerge. One set of papers finds that financial conditions play a critical role in the future distribution of GDP growth and particularly influence the lower quantiles (Adrian et al. 2018, Adrian, Boyarchenko & Giannone 2019, Aikman et al. 2019, Carriero et al. 2020, Iseringhausen 2021). On the other hand, Plagborg-Moller et al. (2020) find that financial variables have no additional predictive information for the distributional forecasts of GDP growth. Brownlees & Souza (2021) find that models using vulnerability indicators rank low in terms of out-of-sample forecast performance. Reichlin et al. (2020) show that among financial condition indicators, price variables such as spreads have limited advanced information on growth vulnerability, while non-financial leverage provides leading signals for the left tail of the GDP distribution.

To analyse the relationship of GaR with the vulnerability indicators, we use a multi-country panel quantile regression framework. We differ in our method from the existing panel quantile models employed to study GaR (Aikman et al. 2019, Adrian et al. 2018, Iseringhausen 2021, Lloyd et al. 2021), as we incorporate the cross-sectionally dependent panel framework. The cross-sectional dependence in panel data is modelled by a residual multifactor error structure, which also parsimoniously proxies common shocks not explicitly modelled. Cross-sectional dependence (CSD) in panels is likely to be the rule, rather than the exception and it can arise from multiple sources of interaction among the cross-sectional units. Ignoring CSD makes panel data modelling incomplete and misleading Chudik & Pesaran (2015*a*). We estimate the cross-sectional dependence using common correlated effects (CCE) method of Harding et al. (2020), Chudik & Pesaran (2015*b*). A unique advantage of the CCE i.e. ability to estimate the factor-augmented regression in a single step without delving into details of the factors. This makes the CCE method particularly suitable for the main objective of our modelling exercise i.e. predict GaR in the presence of CSD.

In an interlinked global economy, increased global trade and financial integration with time and the strong co-movement of key macroeconomic indicators across countries are recognised as stylised facts (Zorzi et al. 2020). Foreign financial conditions have been found to have important contributions to domestic financial conditions over the last two decades and the speedy transmission of spillover impacts challenges timely policy action to control the domestic financial conditions (Arregui et al. 2018). While spillovers may arise from multiple sources, our framework allows natural data-driven spillovers in the form of CSD. So, we do not need to assume any specific source, channel or structure of the spillover effects. Among the GaR studies to date, Lloyd et al. (2021) explicitly include foreign variables and find significant impact and improved model performance.

1.1 Methods

In the empirical application, we model GaR, i.e., the lower tail quantiles of the GDP growth distribution, using a cross country dataset of 24 countries over the period 1973:Q1 to 2016:Q4. We use seven indicators as independent (predictor) variables. These broadly belong to two groups - macro-financial and uncertainty indicators. Of these, five are macro-financial indicators, used in modelling GDP catastrophes and could be further grouped into financial conditions and macro-financial imbalance indicators as per the practical guidance on GaR by Prasad et al. (2019). Representing financial conditions, we have the National Financial Conditions Index and term spreads indicating the price of risks embedded in asset prices; credit growth and gap represent macro-financial imbalances due to credit boom-bust cycles. We also include house prices representing both macro-financial imbalances through housing market imbalances and financial conditions as housing prices also reflect ease of obtaining finance. Additionally, we also model GaR on two indicators of uncertainty - Economic and Political Uncertainty and World Uncertainty Index. The literature examining the relationship of uncertainty and real economic activity has expanded rapidly after the GFC (see Jo & Sekkel 2019, and the references therein). While the first group of indicators has been already studied in the context of GaR, the uncertainty indicators have been only very recently studied by Brownlees & Souza (2021).

To construct the CSD panel quantile model for GaR, we adapt the model of Harding et al. (2020) to suit our framework. Harding et al. (2020) extend the Common Correlated Effects (CCE) technique of Pesaran (2006) to quantile regressions. The CCE approach has the unique advantage that it simplifies the entire estimation process and enables direct estimation of the factor-augmented panel model, without the requirement to explicitly estimate any additional quantities, for example, the number of factors, the factors or their loadings. The data set we use is large. However, with the highest frequency of GDP growth being quarterly, we still face data limitations. So, we allow heterogeneity through country-specific fixed-effects coefficients and assume homogeneity of slope coefficients and factor loadings. The homogeneous loadings lets us include 'time-effects' in addition to cross-sectional fixed effects, which has not so far been included in panel quantile models due to complications in estimation and asymptotics (Chernozhukov et al. 2020),

We also implement another important modification in the factor estimation technique, to perform our analysis from a forecasting perspective. Harding et al. (2020) estimate the factors using the Common Correlated Effects (CCE) method which is based on contemporaneous cross-sectional averages of the variables. We do not assume the knowledge of the contemporaneous GDP growth and estimate GaR in a forecasting set-up. So, we adopt the lagged CCE (LCCE) estimation technique, developed in the previous chapter. We estimate the model with lagged target variable and the vulnerability indicators. Thus, we arrive at our main panel quantile model with CSD (CSD panel). We benchmark the CSD panel model against a panel fixed-effects model not including the CSD component (non-CSD Panel) as in (as in Adrian et al. 2018, Aikman et al. 2019, Lloyd et al. 2021, Eguren-Martin & Sokol 2019) and unconditional quantiles (as in Brownlees & Souza 2021).

We estimate projected GaR up to 12 quarters using the local projections method of Jordà (2005). Subsequently, we evaluate the models in-sample and recursive out-of-sample set-ups for each vulnerability indicator. Further, we analyse a time series of predicted GaR from each model. We obtain a smoothed distribution of GDP by fitting the skew-t distribution of Azzalini & Capitanio (2003). A similar method has been also used by Adrian, Boyarchenko & Giannone (2019), Adrian et al. (2018), Plagborg-Moller et al. (2020), Lloyd et al. (2021). Using the fitted distribution, we derive four time-varying conditional moments and the entire predictive distribution. Finally, we decompose the predicted GaR from the CSD panel model into two components - the panel component consisting of the fixed-effects and the effect of the vulnerability indicator, and the combined effect of the factor and the loadings.

1.2 Findings

We emphasise four main findings. We first show that in the presence of the factors characterising CSD, all the seven indicators have a limited impact on the 5 per cent GaR. This is observed for almost all horizons up to 12 quarters. We however find significant impact and meaningful interpretation of term spreads, credit gap and EPU in the medium-term for higher GaR thresholds (10-25 per cent). The factors have dual interpretation as proxies for unobserved common shocks and international inter-linkages. We conclude that the commonly accepted vulnerability indicators associated with crisis, do not have any significant marginal predictive power for the lower quantiles of GDP growth. This relates to the findings of Plagborg-Moller et al. (2020). Alternatively, if we do not include the factors, all the vulnerability indicators turn out to be significant as documented in other GaR studies (such as Adrian et al. 2018).

Our second key finding is the superior performance of the CSD panel model in both in-sample and out-of-sample evaluations, using tick-loss also known as the quantile score function. Our findings are robust in different subsamples, including and excluding the global financial crisis of 2007-09.

In the third main finding, we note that out-of-sample GaR predictions from the CSD have interpretable economic patterns over time for most countries. The predicted higher moments especially variance and kurtosis provide important early warning signals for volatility and tail risks. From the moment analysis, we conclude that the risk emanates from a combination of a leftward shift of the entire distribution and rising tail risks. We complement the findings from the moments and the predictive density by expected shortfall - another well-accepted measure of tail-risk.

Finally, our results demonstrate that the unobserved factors have a strong influence and a mitigating role in normal economic times, whereas in times of economic distress the factors further worsen the situation. This may potentially justify the decision of policymakers to insulate individual economies from international spillovers.

1.3 Related Literature

This paper relates to three important strands of literature. Firstly, and most directly we relate to the GaR literature. Although the term GaR was originated by IMF (2017), the use of quantile regressions for GDP growth existed even before (Manzan 2015). GaR is studied in the context of individual countries or regions (Adrian, Boyarchenko & Giannone 2019, Ferrara et al. 2021) and multi-country frameworks (Aikman et al. 2019, Adrian et al. 2018, Lloyd et al. 2021, Iseringhausen 2021, Brownlees & Souza 2021). Our paper is closer to the later strand of literature. The closest to our paper is that of Lloyd et al. (2021), who in a panel framework, establish the significant impact of international inter-linkages and GDP tail risks. Plagborg-Moller et al. (2020), Carriero et al. (2020), Ferrara et al. (2021) estimate GaR in a Bayesian framework. The quantile regression framework to identify tail risks have also been applied to other important macro-financial variables, such as unemployment, inflation (Adams et al. 2021), exchange rates (Eguren-Martin & Sokol 2019), house prices (Alter & Mahoney 2020) and capital flows (Eguren-Martin et al. 2020, Gelos et al. 2022).

Secondly, we relate to the literature on CSD in panel quantile regressions. CSD has been established as an important characteristic of panels. It can be estimated with the CCE technique of Pesaran (2006), which was further developed for dynamic heterogeneous panels by Chudik & Pesaran (2015*c*). An alternative estimation technique is that of Bai (2009). Quantile regression was introduced by the seminal work of Koenker & Bassett (1978). The first panel quantile model was that with fixed-effects of Koenker (2004), and the literature expanded thereafter (Lamarche 2010, Canay 2011, Galvao & Wang 2015). Harding & Lamarche (2014) first introduced the interactive fixed-effects (CSD) in panel quantile models. This has been further developed for dynamic heterogeneous panels by Harding et al. (2020). Ando & Bai (2020) provide an alternative iterative estimation technique similar to Bai (2009).

Thirdly, we relate to GDP catastrophes and early warning literature, as we include four vulnerability indicators in addition to the aggregate financial conditions index which is commonly used in GaR literature. We relate papers that link various indicators to recession: credit boom (such as Krishnamurthy & Muir 2017, Jordà et al. 2016, 2015, Schularick & Taylor 2012, Jorda et al. 2013, and others); term spreads (for example Garcia Alvarado 2020, Rudebusch & Williams 2009, and others), credit to GDP gap (Drehmann & Juselius 2014) and uncertainty (Bloom 2014, Ahir et al. 2018).

The rest of the paper is organised as follows. Section 2 specifies the details of the main model used and the benchmarks. In particular, here we introduce the panel quantile model that we estimate and derive it from modifications of the existing panel quantile models. Section 3 describes the data. Section 4 evaluates the relevance of the vulnerability indicators in an in-sample framework. Section 5 presents the out-of-sample performance and empirical findings including the estimates of GaR, estimated higher moments and the contribution of the factors to the projected quantiles. Section 6 concludes.

2 Model Specification

In this section, we describe the quantile regressions used to model the distribution of real GDP growth and its relationship with different vulnerability indicators. With the quantile regression technique of (Koenker & Bassett 1978) we can analyse the impact of changes in a set of conditioning variables on the entire conditional distribution of the dependent variable i.e. GDP growth. Optimal estimates of a range of conditional quantiles are obtained instead of estimating only the mean.

We denote $Y_{i,t}$ as the quarterly growth rates of seasonally adjusted GDP and $x_{i,t}$ as the selected indicator from the set of the different vulnerability indicators detailed in section 3. Time is denoted by $t = 1, 2, \cdots, T$ and the countries for which we estimate the GaR i.e., the cross-sectional units are labelled with $i = 1, 2, \cdots, N$.

2.1 CCE Models

We develop our panel framework for the conditional quantiles of GDP growth following Harding et al. (2020) and adapt it to the specifics of our dataset. First, let us consider the following panel data model for the forecast horizon of h quarters:

$$y_{i,t+h} = \alpha_i + \beta^h x_{i,t} + \epsilon_{i,t} \tag{2.1a}$$

$$\epsilon_{i,t} = \lambda f_t + \zeta_{i,t} \tag{2.1b}$$

$$x_{i,t} = \alpha_{xi} + \gamma f_t + v_{i,t} \tag{2.1c}$$

The CSD represented by the factor error structure of equation 2.1b is estimated by the common correlated effects (CCE) method of Chudik & Pesaran (2015*c*) and adapted to quantile regression by Harding et al. (2020). Due to shorter panel dimensions, we assume homogenous factor loadings and allow heterogeneity through the country-specific fixed effect coefficients α_i. This way of assuming homogeneity in the factor loadings, lets us interpret the product of the factor and the loadings as common time effects.

The estimation procedure for the panel model in Pesaran (2006) or Chudik & Pesaran (2015*c*) or the panel quantile model of Harding et al. (2020), uses the cross-sectional averages of the dependent and the independent variable to estimate the factor augmented equation for the dependent variable obtained by combining equations 2.1a 2.1b i.e., equation 2.1d.

$$y_{i,t+h} = \alpha_i + \beta^h x_{i,t} + \lambda f_t + \zeta_{i,t} \tag{2.1d}$$

The corresponding conditional panel quantile model is given by:

$$Q_{y_{i,t+h}}(\tau|x_{i,t}) = \alpha_i(\tau) + \beta^h(\tau)x_{i,t} + \lambda(\tau)f_t \tag{2.2}$$

where τ is the quantile in the interval $(0, 1)$ and:

$$\theta_i(\tau) = \big(\alpha_i(\tau), \beta^h(\tau)\big)$$

is the set of parameters to be estimated and,

$$Q_{y_{i,t+h}}(\tau|x_{i,t}) = \inf\{y : P(Y_{i,t} \leq y|x_{i,t})\}$$

We use lagged Common Correlated Effects (LCCE) with lagged dependent variables in the cross-sectional averages as in the earlier chapter. LCCE is shown to be consistent and asymptotically unbiased in panel regressions previously. This is a necessary modification for a forward-looking analysis where we do not assume the knowledge of the target quarter GDP growth. Thus, we define our vector of cross-sectional averages as below:

$$\overline{z}_t = \begin{pmatrix} \overline{y}_{t-1} \\ \overline{x}_t \end{pmatrix} \tag{2.3}$$

where

$$\overline{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{i,t},\ \overline{x}_t = \frac{1}{N}\sum_{i=1}^{N} x_{i,t},$$

The estimation is based on the minimisation of the asymmetric quantile loss function given by :

$$\rho_\tau(u) = u\left[\tau - I\left(u \leq 0\right)\right] \tag{2.4}$$

where I(.) is the indicator function i.e.,

$$I(u \leq 0) = \begin{cases} 1, & \text{if } u \leq 0 \\ 0, & \text{otherwise} \end{cases}$$

So, the final equation to be estimated looks as below:

$$Q_{Y_{i,t+h}}(\tau|x_{i,t}) = \alpha(\tau) + x_{i,t}\beta^h(\tau) + \sum_{l=0}^{p_T} \overline{z}_{t-l}\Delta_l(\tau) \tag{2.5}$$

Harding et al. (2020) demonstrate the asymptotic equivalence of the two optimisation problems i.e., the one with unknown factors as in equation 2.2 and the one where the factors are substituted by cross-sectional averages as in equation 2.5. The estimation technique of Harding et al. (2020), thus can be easily modified to estimate 'time-effects' and 'fixed-effects' in panel quantile models. The existing panel quantile literature only include cross-sectional fixed effects as estimation of time-effects is not straight forward (Chernozhukov et al. 2020).

2.2 Benchmark Models

We benchmark the performance of the above CSD panel model against the following two models:

2.2.1 Panel without CSD

Our first benchmark is the panel model which does not incorporate CSD. This is similar to the model implemented in a number of GaR and other '*at-risk*' papers (for instance Adrian et al. 2018, Aikman et al. 2019, Lloyd et al. 2021, Eguren-Martin & Sokol 2019).

$$Q_{Y_{i,t+h}} = \alpha_i(\tau) + \beta^h(\tau)x_{i,t} \tag{2.6}$$

2.2.2 Unconditional Quantiles

As a second benchmark, we use the naive panel model, where the estimated GaRs are the unconditional quantiles of GDP growth as in Brownlees & Souza (2021):

$$Q_{Y_{i,t+h}} = \alpha_i(\tau) \tag{2.7}$$

2.3 Local Projections

All models are estimated for 1 to 12 quarters ahead using local projections of (Jordà 2005) which gives us the estimated quantile of GDP growth distribution for the specified horizon. This enables us to understand how the left tail of the GDP develops over the forecast horizons. For inference we use bootstrap. Various forms of block bootstrap and tapered block bootstrap (Gregory et al. 2018) were tried, but they failed to improve results. So, we keep to iid bootstrap. The coefficients $\beta^h(\tau)$ quantifies the association between the vulnerability indicator and the quantiles τ of the predicted GDP growth distribution at horizon h.

3 Data

We use the dataset from Brownlees & Souza (2021). Our target variable is the quarterly growth rates of seasonally adjusted GDP. We use seven of the eleven vulnerability indicators of Brownlees & Souza (2021). The global variables of Brownlees & Souza (2021) are excluded as these will be confounded with the unobserved global factors modelling the CSD. We will not be able to separately identify the impact of such global variables in our set-up, as this framework is already augmented with global factors estimated through the CCE. So, the final set of vulnerability indicators used consists of House Prices (HP), World Uncertainty Index (WUI), Term Spread (TS), Economic and Political Uncertainty (EPU), Credit Growth (CR), Credit to GDP Gap (CG) and National Financial Condition Index (NFCI). We have 24 OECD (Organisation of Economic Cooperation and Development) countries in the panel. Table 1 gives the details of the time series span for each of these indicators. As we see from table 1, the time dimension of the dataset is quite large. This covers many important events of economic distress in many of the countries[1].

	Data Series	Start Date	End Date
1	NFCI	Jan 1973	Sep 2016
2	Credit Growth	Jan 1973	Sep 2016
3	Credit Gap	Jan 1973	Sep 2016
4	EPU	Jan 1985	Sep 2016
5	Term Spread	Jan 1973	Sep 2016
6	WUI	Jan 1996	Sep 2016
7	House Prices	Jan 1973	Sep 2016

Table 1: Data and Time Span

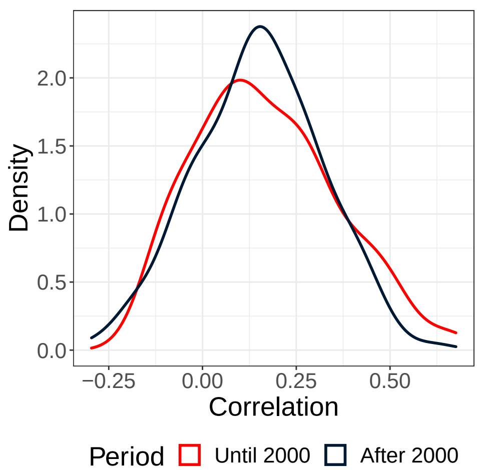
The importance of modelling CSD is already evident from the literature and stylised facts. Further from our data, figure 1 shows the results of a systematic examination of international macro-financial synchronisation using basic correlation statistic. We study the degree of comovement between the different indicators within countries using simple pair-wise correlations. We compare the distribution of the bilateral correlations for all possible country pairs for each indicator, over two different sub-periods, to identify the changes in the nature of association among countries. The first sub-period ends in 1999:Q4 and the second sub-period starts at 2000:Q1.

The plots reveal a general shift of the distribution towards the right. This is most striking for the NFCI (figure 1g) and is also very distinct for GDP growth (figure 1h). Especially from 2003 onwards, we see that the financial conditions indices of all the countries move remarkably along the same path, excepting a few countries. The credit variables do not show a rightward shift in distribution but show a higher peakedness of the density function around the positive modal values (figures 1a and 1b). Term spreads remain equally synchronised before and after 2000. Surprisingly, the pair-wise correlation for house prices seems to have declined indicating less synchronisation post-2000 (figures 1d and 1e). These initial confirmatory indications of increased synchronisation of macro-financial data in recent times suggest a greater impact of spillovers and common shocks in recent times. We now proceed to the actual estimation of the CSD panel models in the following sections.

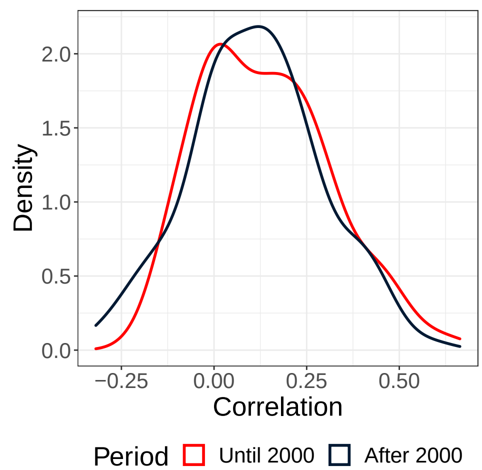
4 Empirical Analysis: In-Sample Results

The results of the in-sample analysis of the different models are presented in this section in two parts. Firstly, we assess the significance of the various vulnerability indicators and identify the determinants of GaR at

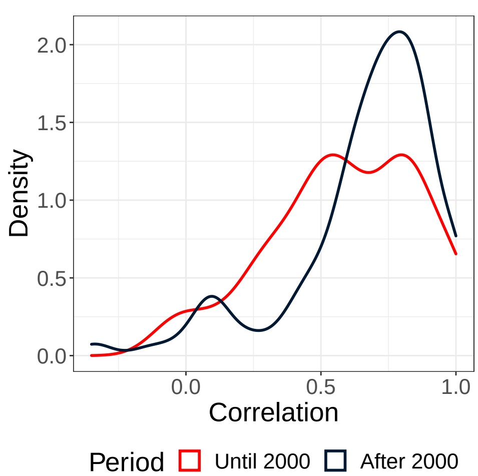
[1] (*Global Crises Data by Country* accessed 2021)



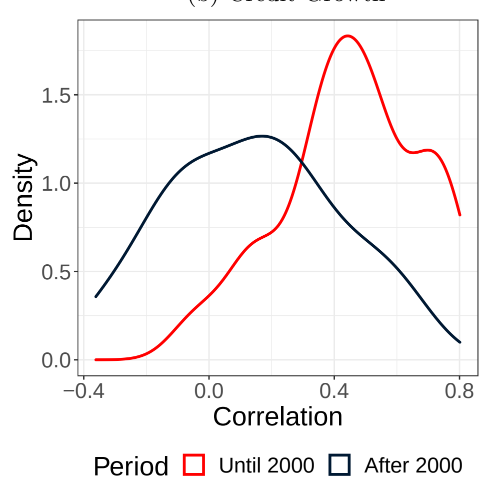
(a) Credit to GDP Gap



(b) Credit Growth



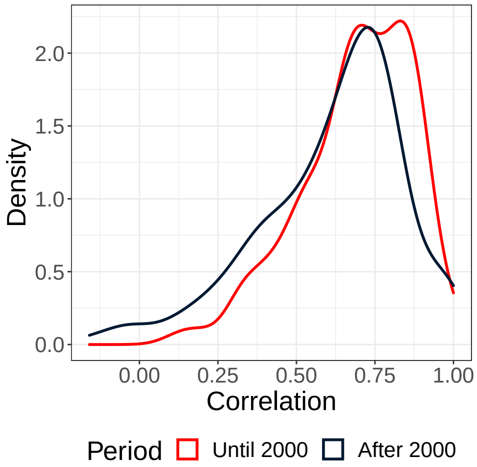
(c) EPU : Economic and Political Uncertainty



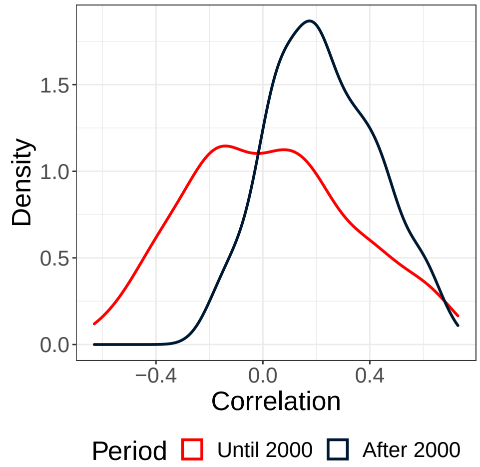
(d) House Prices[a]

[a]Based on 12 countries for which long time-series data was available

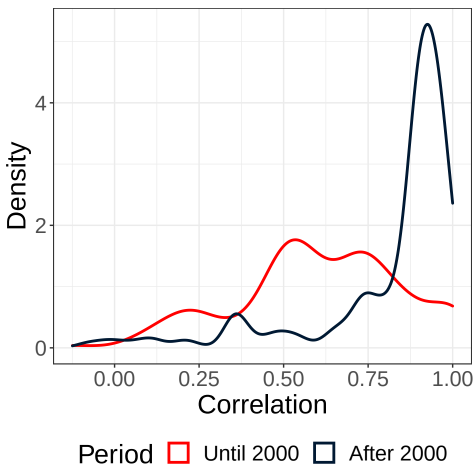
Figure 1: Distribution of Bilateral Correlations



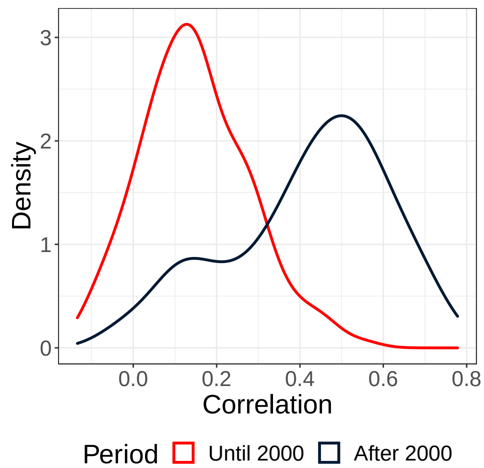
(e) Term Spread



(f) World Uncertainty Index



(g) National Financial Conditions Index



(h) GDP Growth

Figure 1: Distribution of Bilateral Correlations

Notes: The figures show the distribution of all possible pairwise correlations among countries for the selected indicator over time. We split the time series into two parts to identify the changing nature of synchronisation among the countries. Excluding Greece, Israel, Portugal, Ireland & Belgium.

different forecast horizons. Subsequently, we evaluate the quality of fit of the various alternative models described in section 2.

4.1 Determinants of Growth-at-risk

We begin by reporting the estimation results of a set of quantile regressions used to gauge the explanatory power of each predictor. For each country, forecast horizon $h = 1, 2, 3, \cdots, 12$ and predictor, we estimate the 5 per cent quantile regression for the equations 2.2[2] and 2.6 i.e., the panel with and without CSD respectively. We estimate the GaR up to 12 quarters ahead as this is the time range considered by Adrian et al. (2018)

[2]I am grateful to Dr. Carlos Lamarche for sharing the replication codes for Harding et al. (2020).

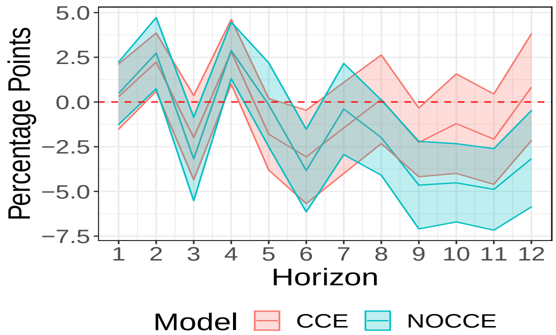
as it is commonly considered while framing policies. Models with and without CSD are placed in figure 2, where we show the relationship between the 5 per cent GaR and the different vulnerability indicators across different horizons.

We also use several additional GaR levels: 10, 15 and 25 per cent. Most of the GaR literature mentions a 5 per cent worst-case scenario. But 5 per cent GaR leaves very few actual occurrences of such events, even with advanced economies which have a large history of macroeconomic data. The size of the testing window must increase as we increase the severity of the GaR measure. With quarterly GDP being the dependent variable, there is limited scope to increase the number of observations. While it is important for policymakers to know and possibly influence the conditional response of the 5 per cent GaR, modelling higher levels of GaR can also provide useful signals. So, to ensure the dual objectives of the robust analysis and usefulness to policy, we use several levels of GaR. The in-sample results for the other GaR levels i.e., 10, 15 and 25 per cent are quite similar and are placed in Appendix A.1.

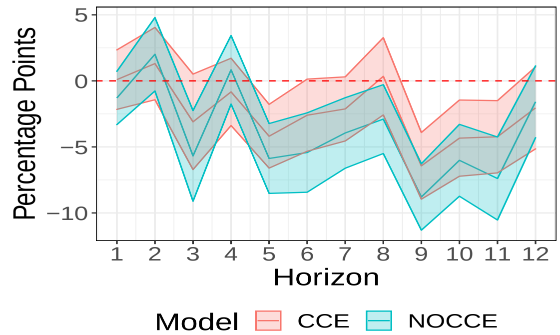
We focus on the impact of each vulnerability indicator on GaR estimated from the quantile regressions. We examine the relationship of one standard deviation change in the vulnerability indicator and the corresponding change in GaR at different horizons, as in (Adrian et al. 2018, Aikman et al. 2019, Lloyd et al. 2021, and others). The coefficients are interpreted as the impact on the estimated GaR, due to one standard deviation change in the vulnerability indicator. Since we directly model the quantiles of quarterly percentage changes in GDP, the numbers in the figures directly correspond to the quarterly changes in GaR for the respective horizon. We also look at the one standard deviation bootstrap confidence bands of the estimated coefficients.

Surprisingly, from the CSD panel model (figure 2g), we see very little impact of any of the seven vulnerability indicators on 5 per cent GaR. There is an initial negative impact of tightening financial conditions, which ease out and become insignificant as we increase the forecast horizon. This finding is contrary to the observations from cross-sectionally independent panels. The non-CSD panel corroborates the earlier findings of Adrian et al. (2018), who note that financial conditions have a negative impact on GaR in the near term and have a positive impact on the farther horizons. The 5 per cent GaR from the non-CSD panel seems to benefit from tighter financial conditions in the longer term. This effect disappears once we account for the CSD in the panels.

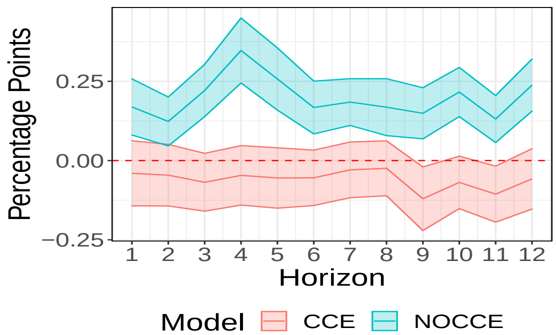
Turning to term spreads, it is significant for 10-25 per cent GaR, in the medium-term (4 - 8 quarters ahead) from the CSD panels as well. Term spreads have a positive relationship with the selected quantiles of real GDP growth. This implies an increase in the term spread is associated with higher values of GaR and vice-versa. The magnitude of the impact of term spreads on GaR in the CSD panel is, however, milder than that from the non-CSD panel. Brownlees & Souza (2021) also find term spreads to be the second



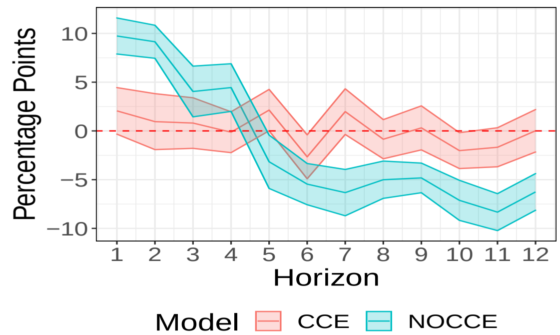
(a) Credit to GDP Growth



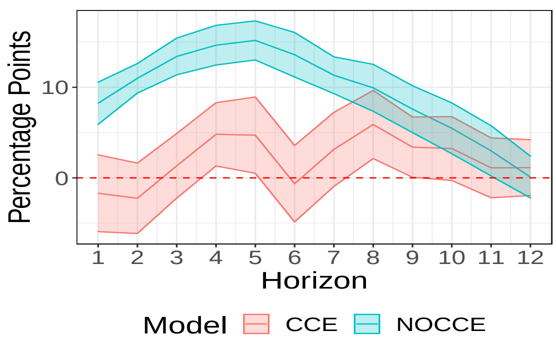
(b) Credit Gap



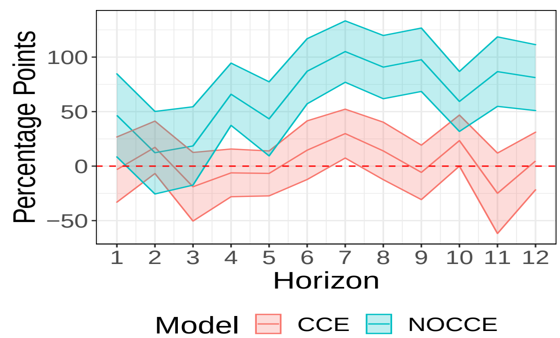
(c) Economic and Political Uncertainty



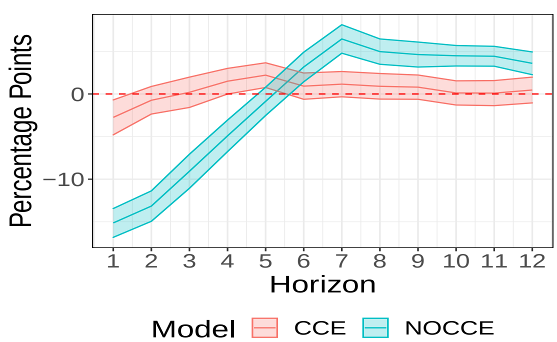
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 2: Impact of variables on 5 per cent GaR

most important variable in predicting GaR in the in-sample analysis up to 4 quarters prediction horizon for half of the sample of countries. The significance of term spreads is in line with the literature on early warning signals and the yield curve inversion phenomenon. The predictive content of term spreads for future growth and recession is known for a long time (Rudebusch & Williams 2009, Garcia Alvarado 2020, Parker & Schularick 2021, and others). The forecasting power of term spreads for future GDP is one of the most robust stylised facts in macroeconomics (Adrian, Estrella & Shin 2019).

Apart from term spreads, credit to GDP gap turns out to be weakly negatively significant at the medium-term (6-10 quarters horizon) for higher GaR thresholds. Measured by the deviation of credit to GDP ratio from its long-run trend, this is indicator is often associated with leverage and financial cycles. It measures the build-up of systemic leverage that poses risk to the banking sector (Drehmann et al. 2011). The Basel Committee of Banking Supervision (BCBS) recommends its use to track excess credit and vulnerability to the banking sector (BIS & BCBS 2010). Our finding of the inverse relationship suggests a larger credit to GDP gap indicates a worse GaR. Therefore, it is consistent with Drehmann & Juselius (2014) who establish credit to GDP gap as an important early warning indicator up to five years preceding crisis.

Figures 2c and 2f show the relationship of the uncertainty indices (WUI and EPU) with 5 per cent GaR. The WUI (World Uncertainty Index) is defined using the frequency of the word 'uncertainty' in the quarterly Economist Intelligence Unit country reports (Ahir et al. 2018). The index is seen to spike around the occurrences of major disruptions; not only economic but also those caused by political or health crises. The EPU (Economic and Political Uncertainty) index is another text-based indicator capturing general uncertainty (Baker et al. 2016) based on text analysis of newspapers. WUI and EPU are conceptually different yet have a lot in common and co-move over time (Ahir et al. 2018). The EPU is strongly counter-cyclical and is 51 per cent higher than its normal levels in the US, during recessions (Bloom 2014). Both WUI and EPU have been found to foreshadow declines in growth. Our results demonstrate that when we do not consider the CSD panel, both WUI and EPU are significant for all horizons up to 12 quarters. However, the relationship is insignificant, in the presence of CSD. At higher GAR thresholds i.e., 10, 15 or 25 per cent (Appendix A.1), EPU turns out to be significant with a negative sign, in the CSD panel models. The inverse relationship is agreed by previous studies associating uncertainty with GDP declines.

The remaining two vulnerability indicators, i.e., house prices and credit growth (CR) are not significantly related to the GaR, even at higher levels, once the presence of CSD is accounted for. A series of empirical studies document the link between housing prices and the real economy. Claessens et al. (2012) find that recessions following housing busts are weaker and recoveries associated with rapid growth in credit and housing tend to be stronger. Both house prices and credit growth are jointly noted to precede crisis and are important as early warning indicators (see Aikman et al. 2019, and the references therein). But, our results from the CSD panels do not support the link between housing and credit variables to risk in GDP.

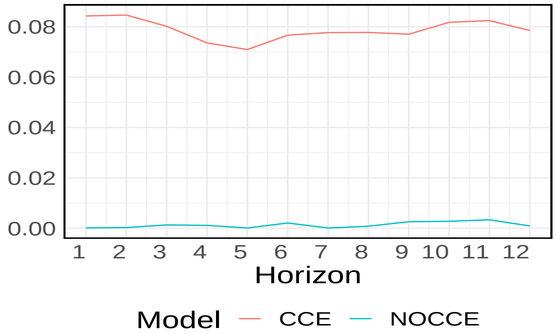
In this novel finding important early warning vulnerability indicators are rendered insignificant for the 5 per cent GaR in the presence of unobserved factors, except the negative impact of financial conditions at the one-quarter horizon. At higher GaR levels, we find term spreads, credit to GDP gap and EPU to be significant in the medium-term. Other variables we consider remain insignificant for all GaR levels. These results partially corroborate the findings of Aikman et al. (2019), who find financial conditions insignificant in the medium-term and in the presence of other determinants of GaR. The findings also resonate with those of Reichlin et al. (2020) who conclude that there is limited value in financial variables for detecting GDP risk in advance and that of Plagborg-Moller et al. (2020) who find no marginal power of financial variables to predict GaR, in addition to macroeconomic variables. In general, therefore, it seems that the strength of the relationship between GaR with the NFCI as revealed by a panel model without CSD is overstated. The reason for the difference in results may be inferred from the interpretation of the cross-sectional dependent factor error structure. The multi-factor error structure could be interpreted as natural data-dependent cross-country spillover impacts. These could also be regarded as proxies for common shocks not directly modelled. While each of the seven vulnerability indicators is known to forewarn crisis, our findings indicate that there are common unobserved factors that drive GaR and that these variables do not have any significant predictive power in addition to the factors.

4.2 Goodness-of-fit

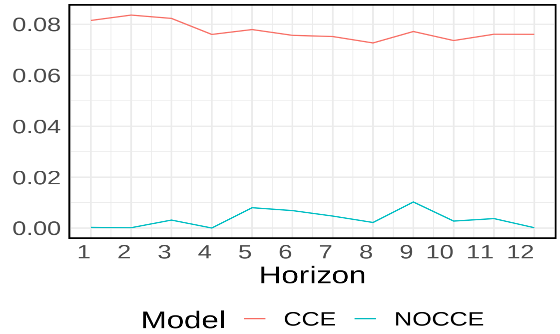
Now, we compare the in-sample goodness-of-fit measure for the panel models, one with the CSD and one without CSD. We use the metric developed by Koenker & Machado (1999), which is a quantile specific relative measure of the goodness-of-fit of two conditional quantile functions. This measure of in-sample fit has been recently used in 'at-risk' studies by Eguren-Martin & Sokol (2019) and Lloyd et al. (2021). It is also related to the out-of-sample tick-loss measure we use later. Going by the notations of Koenker & Machado (1999) we define the goodness-of-fit measure R^1 for GaR level τ and forecast horizon h as:

$$R^1_h(\tau) = 1 - \frac{\hat{V}(\tau)}{\tilde{V}(\tau)} \tag{4.1}$$

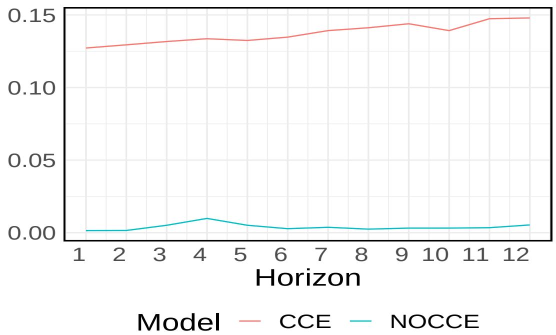
where $\hat{V}(\tau)$ denotes the sum of weighted absolute residuals from the respective model that we are trying to evaluate. $\tilde{V}(\tau)$ denotes the sum of weighted absolute residuals from the benchmark model as in equation 2.7 i.e., the unconditional quantiles. The interpretation is similar to the standard R^2 in linear regression. We can therefore attribute any difference in $R^1(\tau)$ estimated from the CSD and non-CSD panels as the incremental contribution of the multifactor error structure to the goodness-of-fit of the estimated τ^{th} quantile of the



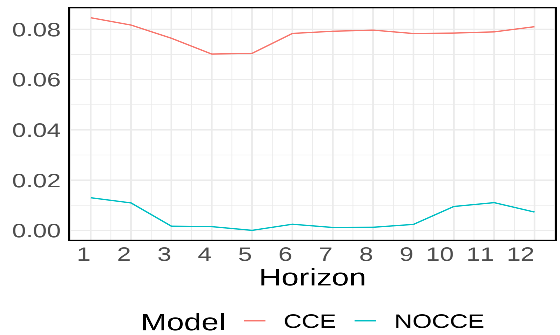
(a) Credit to GDP Growth



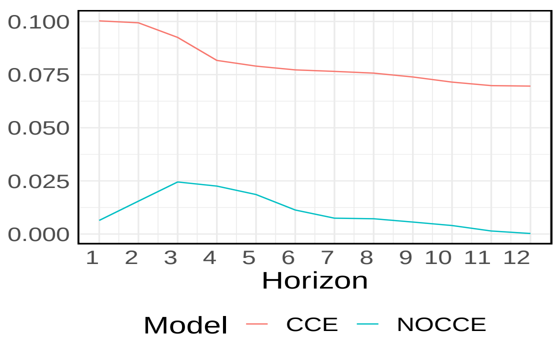
(b) Credit Gap



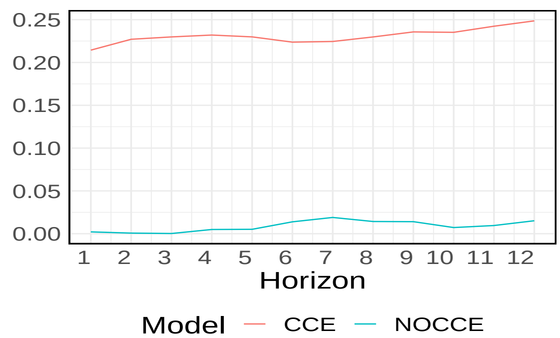
(c) Economic and Political Uncertainty



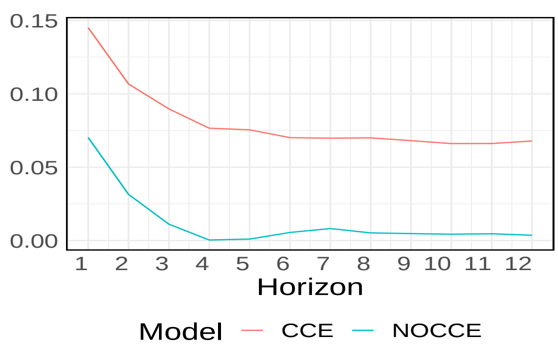
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 3: In-Sample Goodness-of-fit: 5 per cent GaR

h-quarter ahead real GDP growth.

The results in figure 3 reveal an improved in-sample fit from the CSD panel models as compared to the ones without CSD for 5 per cent GaR. Similar results for other GaR levels are placed in Appendix A.2. The measures are comparable to that of Lloyd et al. (2021). $R^1(\tau)$ nearly doubles due to the inclusion of the CSD. Also, $R^1(\tau)$ remains at similar levels across all horizons and is elevated in the CSD models for all the vulnerability indicators. The improvement in goodness-of-fit further strengthens the conclusions we draw in section 4.1.

5 Empirical Analysis: Out-of-Sample Results

This section consists of two parts. First, we present the out-of-sample accuracy assessment of the quantile projections. Thereafter, we estimate out-of-sample quantile forecasts, the predictive distribution, the moments and ES and draw inferences. The results for 5 per cent GaR are included in the section and other GaR levels are included in the appendices.

5.1 Accuracy Measures & Out-of-Sample Evaluation

We back-test the alternative panel models and evaluate them relative to each other. We generate out-of-sample GaR forecasts in an h-step-ahead recursive window scheme. The time dimensions of the panel are split up into estimation and evaluation windows. If we denote the total number of periods by T, then T is split as $T = R + P$ where we estimate the model using the first R periods and evaluate the model by computing the recursive predictions for the following P periods. For the out-of-sample analysis presented below, we consider $P = 0.25T$. Here we consider higher quantiles as well, namely, 50, and 90 per cent in addition to the ones considered for the in-sample analysis. This is because, later, we need the higher quantiles to estimate the entire predictive distribution.

We compare the model performances using several evaluation criteria prevalent in the literature on backtesting quantile forecasts. These measures are adapted from the Value-at-Risk literature and have been applied by recent studies to assess the accuracy of the out-of-sample GaR forecasts (Manzan 2015, Carriero et al. 2020, Brownlees & Souza 2021, Iseringhausen 2021, Gelos et al. 2022, and others). The measures are described below:

5.1.1 Coverage

We define the average empirical coverage for the predicted GaRs as the average (over time and cross-sections) number of realisations of GDP growth that are higher than the predicted GaR (equation 5.1a). Coverage of accurate GaR predictions is expected not to deviate very far from the nominal coverage. Here we try to assess graphically how close the estimated coverage is to the nominal coverage as in Brownlees & Souza (2021). The coverage for h quarter ahead $100 \times \tau$ per cent GaR is:

$$C_{\tau,h} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{T}\sum_{t=h+1}^{T} 1_{Y_{i,t} > GaR_{i,t|t-h}}\right] \tag{5.1a}$$

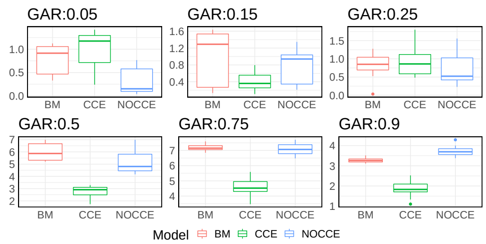
Figure 4 plots the absolute deviation of the average empirical coverage from the corresponding nominal coverage levels across the various quantile levels considered. Ideally, these differences should be as close as possible to zero. The box plots indicate the variation across the 12 quarter horizons. We find that the coverage is not the best for the CSD model at the lowest estimated tail levels (5 per cent) as compared with the benchmark or the non-CSD panel model. This can be attributed to the very low observed proportion of violation of the 5 per cent GaR. For the other GaR levels, we find that the CSD panel performs comparably to the alternatives. Overall, all three models are able to provide adequate coverage, although there is variation among the different vulnerability indicators considered. The performance deteriorates with EPU and WPI, due to the shorter time series (table 1). The CSD panel model in general has lesser variability among the 12 horizons. It is hard to arrive at the best performing model based on coverage alone. So, we consider additional out-of-sample performance indicators below.

5.1.2 Dynamic Quantile Test

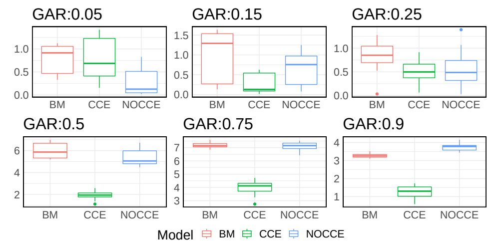
Dynamic quantile tests ascertain the optimality of the estimated conditional quantiles and hence the underlying model by testing the predictability of the hit sequence using specific regressors. Define the hit sequences as the series of binary variables equalling $1-p$, when we observe a violation of the p per cent GaR and $-p$ otherwise as:

$$H_{i,t} = 1_{Y_{i,t} < GaR_{i,t|t-h}} - p \tag{5.1b}$$

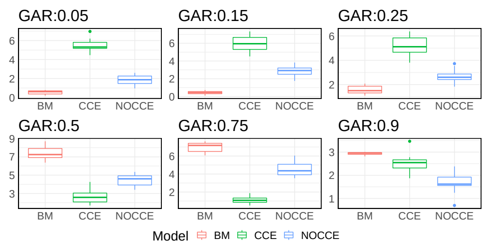
We report three versions of the dynamic quantile tests of Engle & Manganelli (2004). The first, DQ_{unc} tests the unconditional accuracy with no auxiliary predictors. The second one labelled DQ_{hits} tests optimality in the presence of lagged hit sequences as regressors. The third, DQ_{aug} tests optimality conditional on the lags of real GDP as a regressor. All auxiliary predictors are country-specific. We consider a suitably tailored



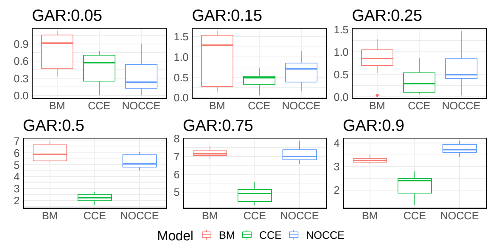
(a) Credit to GDP Growth



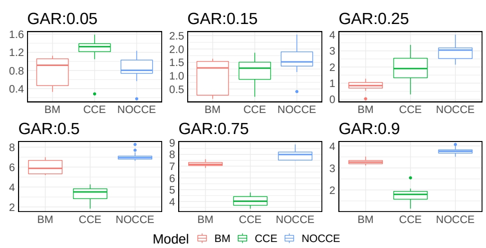
(b) Credit Gap



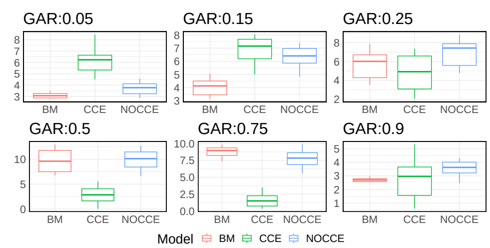
(c) Economic and Political Uncertainty



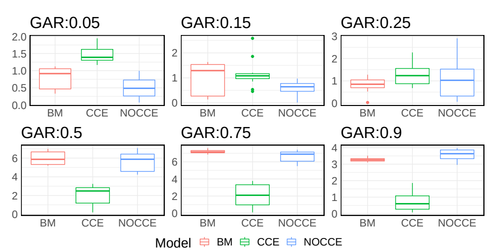
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 4: Coverage

Wald test statistic as in Brownlees & Souza (2021). Define the Dynamic Quantile Regressions as:

$$H_{t+h} = c_0 + \sum_{k=1}^{K} c_k W_{kt+} u_{t+h} \tag{5.1c}$$

W_{kt} is assumed to be constant, lagged hits and lagged real GDP respectively for DQ_{unc}, DQ_{hits} and DQ_{aug}. We test the below null hypothesis:

$$H_0 : c_0 = c_1 = \cdots = c_k = 0 \tag{5.1d}$$

Finally, we report the proportion (in per cent) of countries for which we fail to reject the null hypothesis at the five per cent level of significance, i.e., the countries for which the hit sequences of the violations of the predicted GaR are optimal. We consider the DQ tests for 12 horizons and six quantile levels. To summarise the results, we represent the variation across the horizons in the boxplots in figures 5, 6 and 7.

The panel models outperform the unconditional quantile benchmark. Moreover, all three versions of DQ tests indicate the same pattern, i.e., excluding the EPU and the WUI[3], the CSD panel model tends to be better relative to the non-CSD panel.

5.1.3 Tick-Loss

Next, we compare the performance of each model by tick-loss. Define the out-of-sample average tick-loss for a forecast horizon of h quarters as:

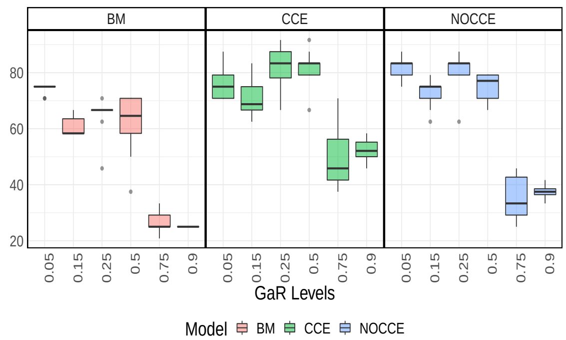
$$TL_{\tau,h} = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{1}{T} \sum_{t=h+1}^{T} \rho_\tau \left(Y_{i,t} - GaR_{i,t|t-h} \right) \right] \tag{5.1e}$$

$$\text{where } \rho_\tau(u) = u(\tau - 1_{u \leq 0}) \tag{5.1f}$$

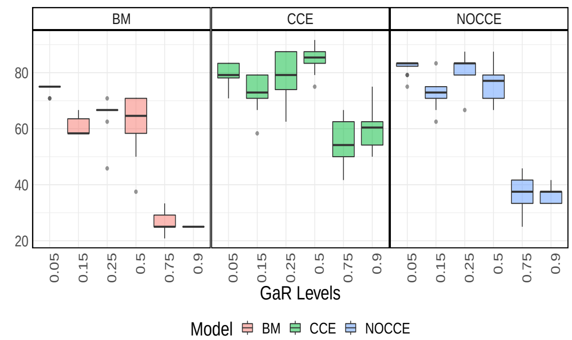
Tick-loss, also referred to as the quantile-score is a standard loss function to formally evaluate the conditional quantiles estimates and is used in several recent GaR and density prediction studies (see Manzan 2015, Carriero et al. 2020, Brownlees & Souza 2021, Iseringhausen 2021). It is the asymmetrically weighted average of the difference between the observed and the h-quarter ahead predicted quantile (the GaR). Equation 5.1e is the sample estimate of the expected h-step ahead loss defined as (see Clements et al. 2008):

$$TL_{\tau,h} = E \left[\rho_\tau \left(Y_{i,t} - GaR_{i,t\|t-h} \right) \right] \tag{5.1g}$$

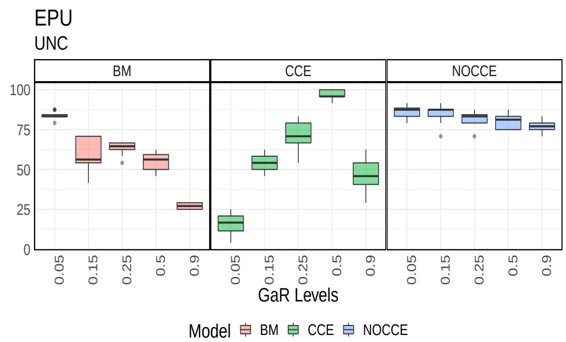
[3]The uncertainty indicators (EPU and WPI) are shorter in time-dimension.



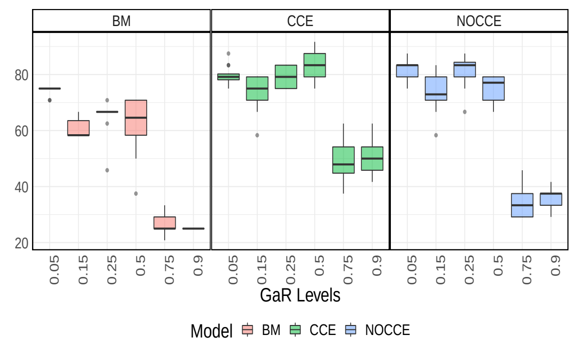
(a) Credit to GDP Growth



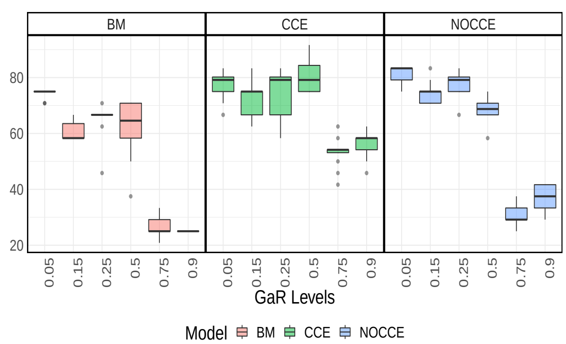
(b) Credit Gap



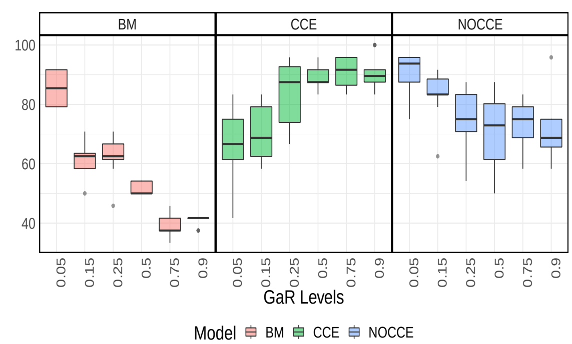
(c) Economic and Political Uncertainty



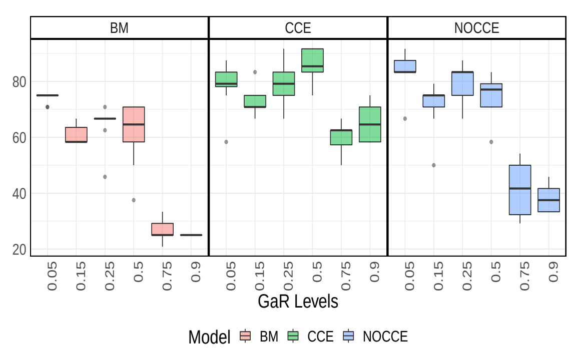
(d) House Prices



(e) Term Spread

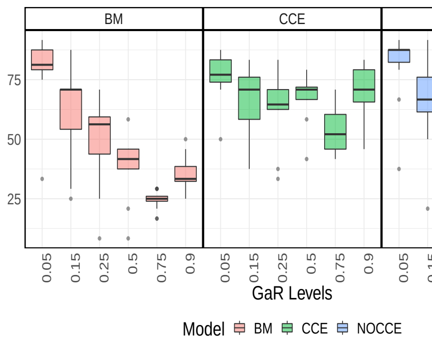


(f) World Uncertainty Index

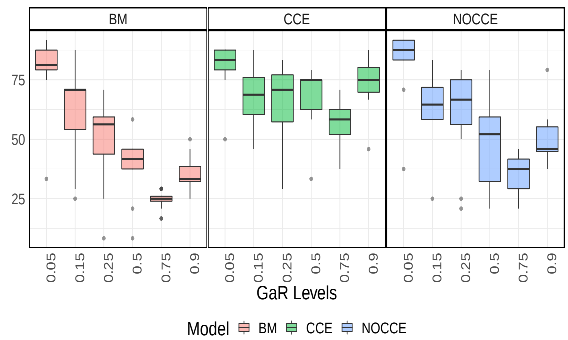


(g) National Financial Conditions Index

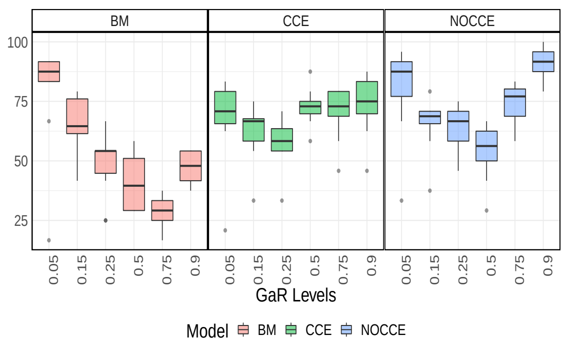
Figure 5: Dynamic Quantile Test - Unconditional



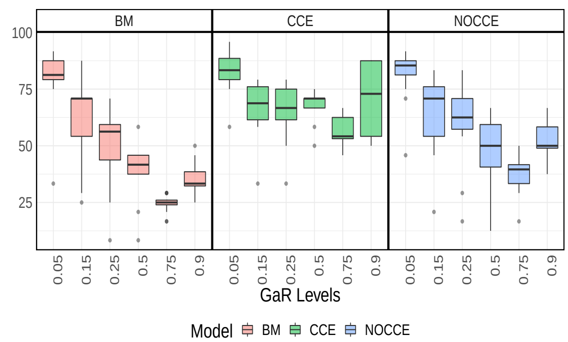
(a) Credit to GDP Growth



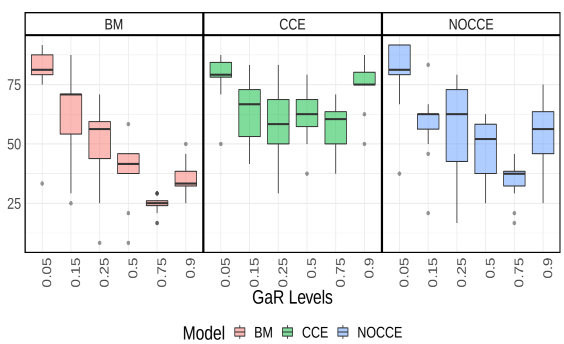
(b) Credit Gap



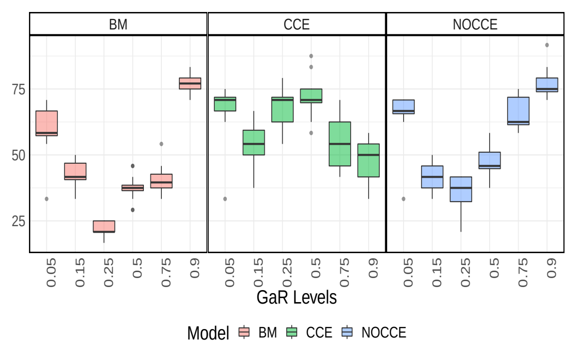
(c) Economic and Political Uncertainty



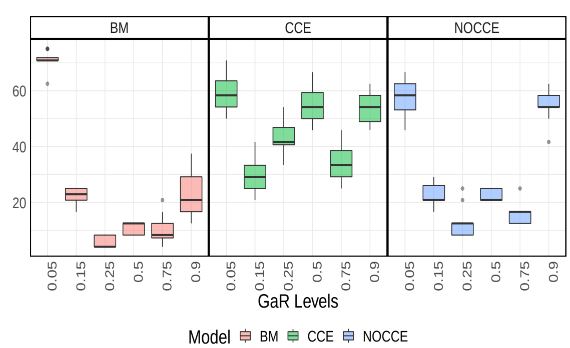
(d) House Prices



(e) Term Spread

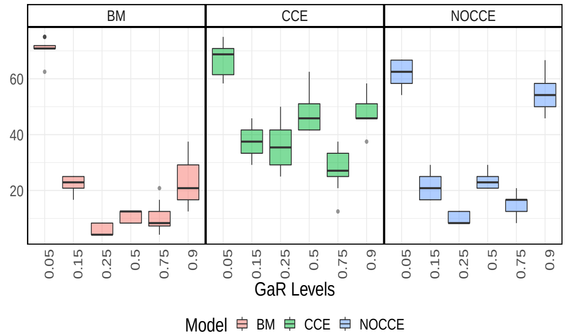


(f) World Uncertainty Index

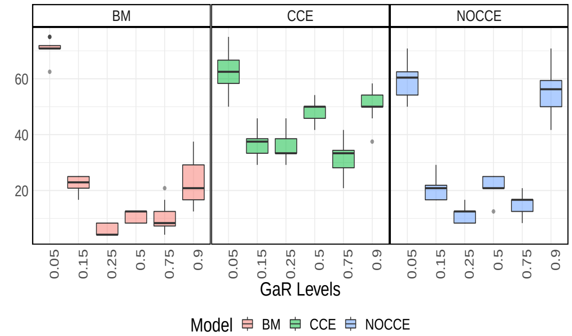


(g) National Financial Conditions Index

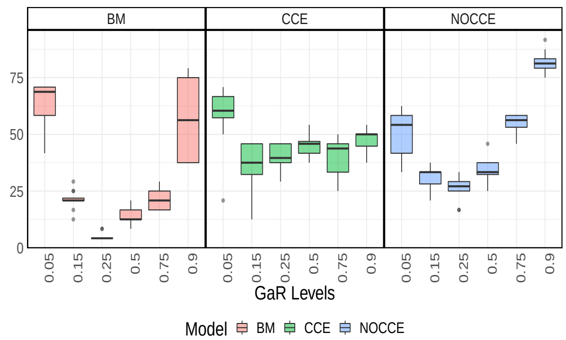
Figure 6: Dynamic Quantile Test - Augmented with Hits



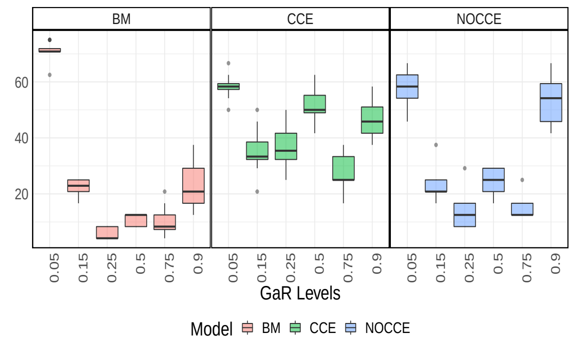
(a) Credit to GDP Growth



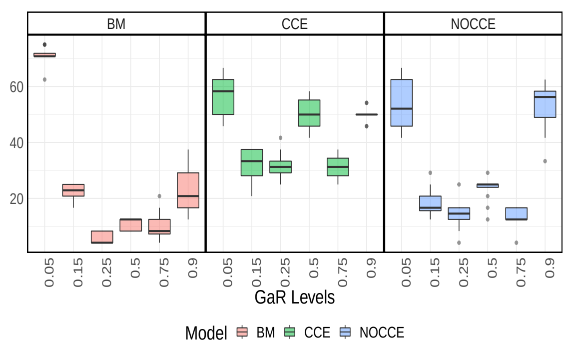
(b) Credit Gap



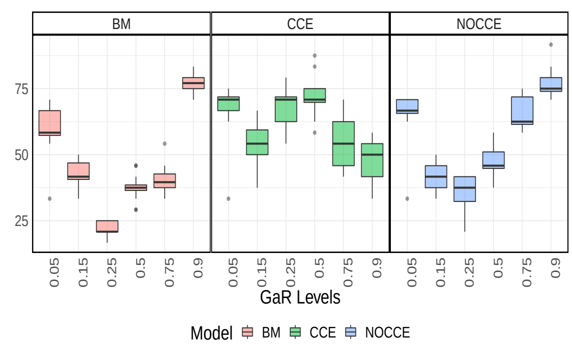
(c) Economic and Political Uncertainty



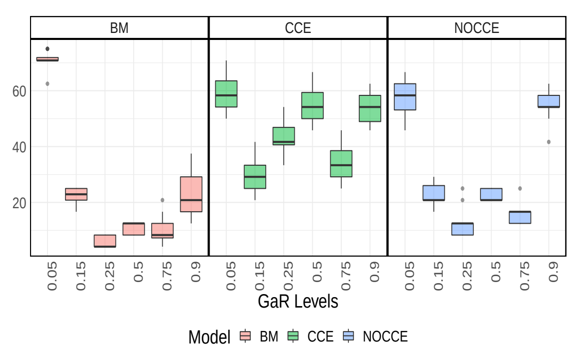
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 7: Dynamic Quantile Test - Augmented with lags of Real GDP

Figure 8 displays the gains in tick-loss of the panel models relative to the unconditional quantiles benchmark. The CSD panel model stands out in terms of larger gains in tick-loss against the benchmarks. Particularly for the lower quantiles (5, 15 and 25 per cents), which are considered as measures of GaR, the CSD panel model emerges as the best performing model, across all the 12 horizons under consideration. The CSD panel model also outperforms for the upper quantiles of 50 and 90 per cent for 5 of the seven indicators, while the non-CSD panel model performs better for the uncertainty indices i.e., EPU and WUI.

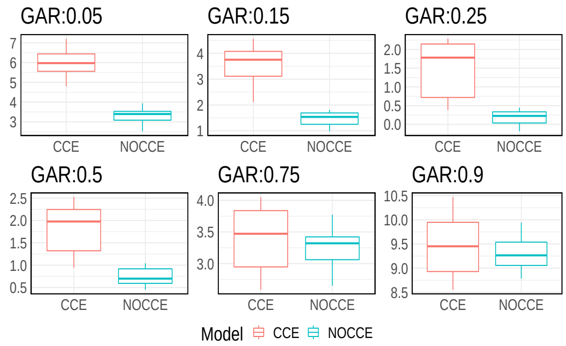
We ensure robust out-of-sample performance by repeating with different sub-sample, excluding the GFC around 2008 (see Appendix A.2). Our conclusions about the superior performance of the CSD panel model remains unchanged.

Combining the findings of the in-sample and out-of-sample performance, our results are in line with Brownlees & Souza (2021) that the models that generate superior out-of-sample forecast performance, are not able to establish a relationship of GaR with financial conditions, or other vulnerability indicators, at least for the 5 per cent GaR. We, however, see a relationship with term spreads, credit gap and EPU for higher GaR levels.

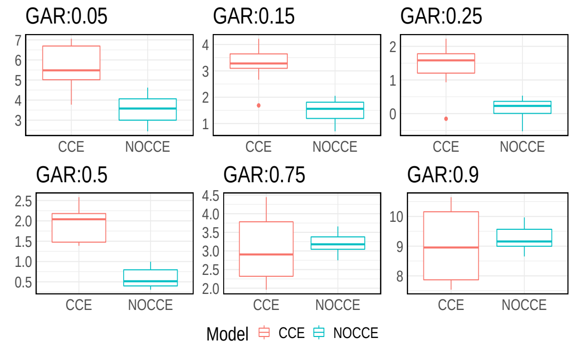
5.2 Estimated GaR

Having established the out-of-sample accuracy of the CSD panel model, in this sub-section we analyse the time series characteristics of projected GaR for individual countries in our panel. Figure 9 compares the estimated GaR at 12 quarter horizons for 6 major countries in our sample i.e., Australia, Japan, South Korea, Germany, the UK and the US. We illustrate the GaR with two vulnerability indicators as predictors namely NFCI and term spreads. We select the model with NFCI for the five per cent GaR (figure 9a) as it is the most studied vulnerability indicator in the GaR literature. However, we note that the choice of the vulnerability indicator is immaterial here as all the models for 5 per cent GaR have no significance for the indicator, although they have good in and out-of-sample fit. We also illustrate 25 per cent GaR with term spreads as it turns out to be significant for the higher GaR thresholds (figure 9b). Other forecast horizons are placed in Appendix C.

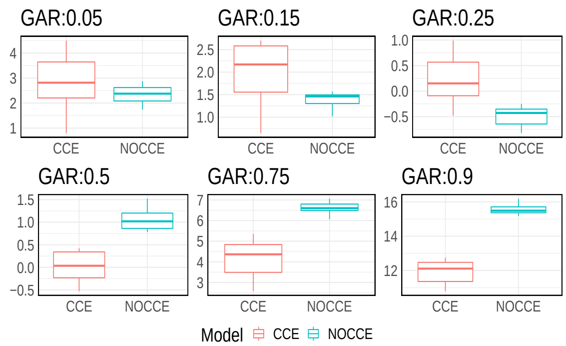
The GaR predicted from the three models are distinct. The GaR from the unconditional quantile benchmark is generally flat and does not track the fluctuations over time. Whereas the GaR from the panel models has better interpretability, the CSD panel model has sharper characteristics and is able to provide more distinct signals as compared to the non-CSD panel model. The non-CSD panel although is able to replicate most of the directions, however, is not able to capture the magnitude as well as the CSD panel model. This is due to the better explanatory power we saw in the in-sample analysis and improved out-of-



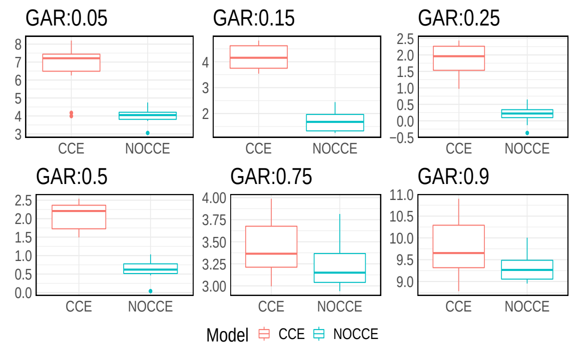
(a) Credit to GDP Growth



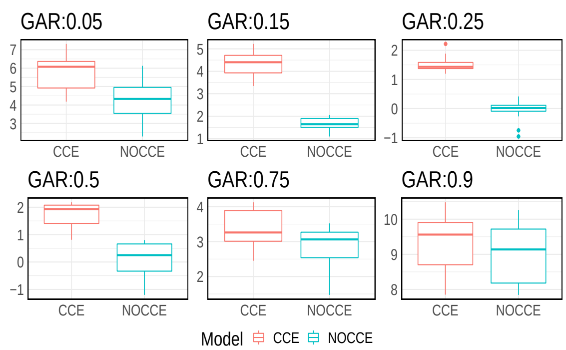
(b) Credit Gap



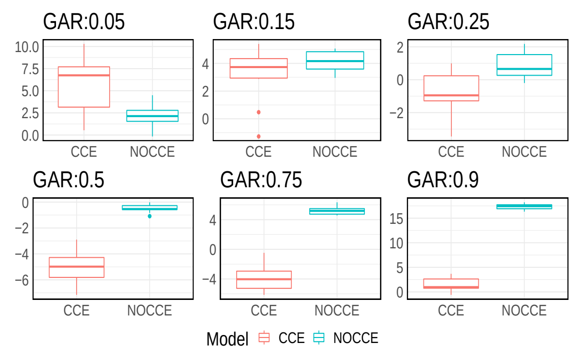
(c) Economic and Political Uncertainty



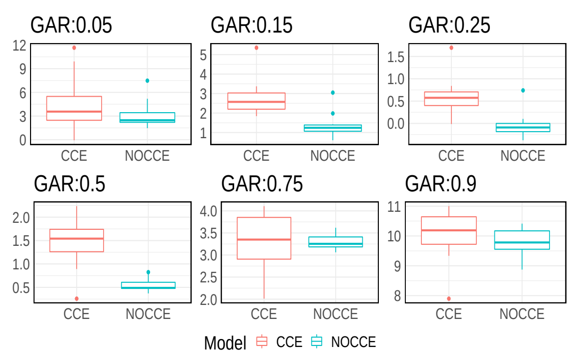
(d) House Prices



(e) Term Spread

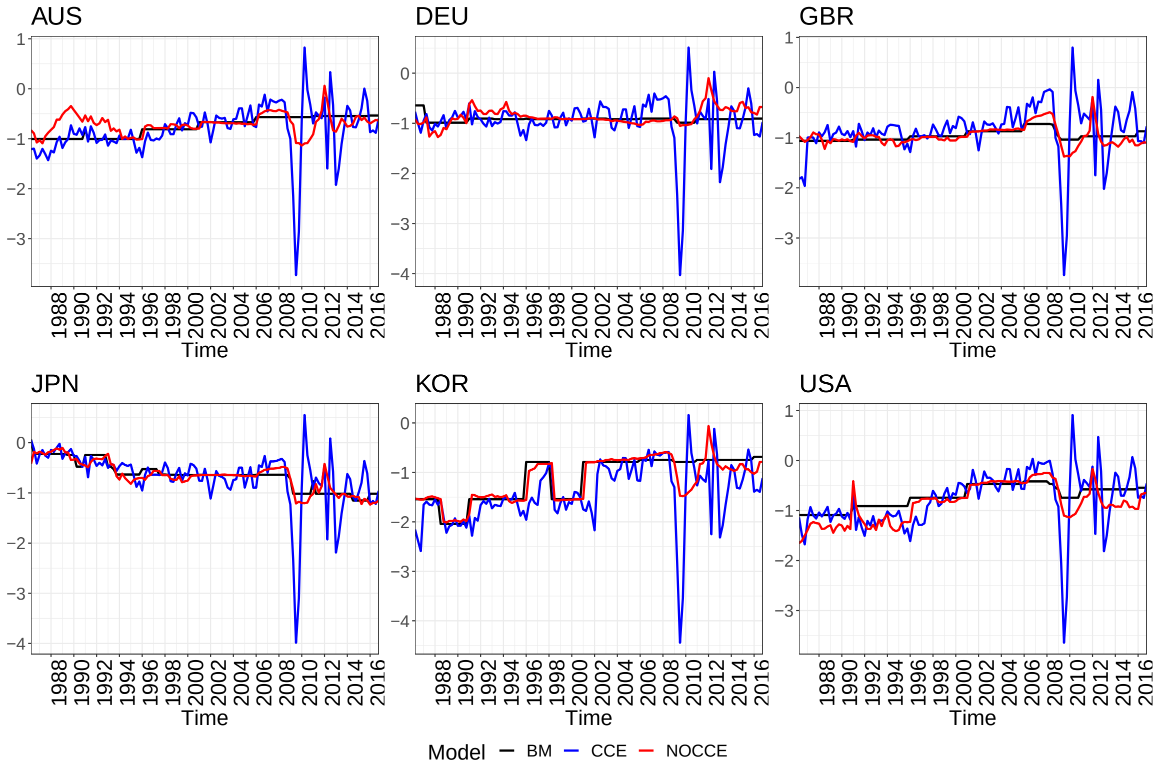


(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 8: Tick-Loss



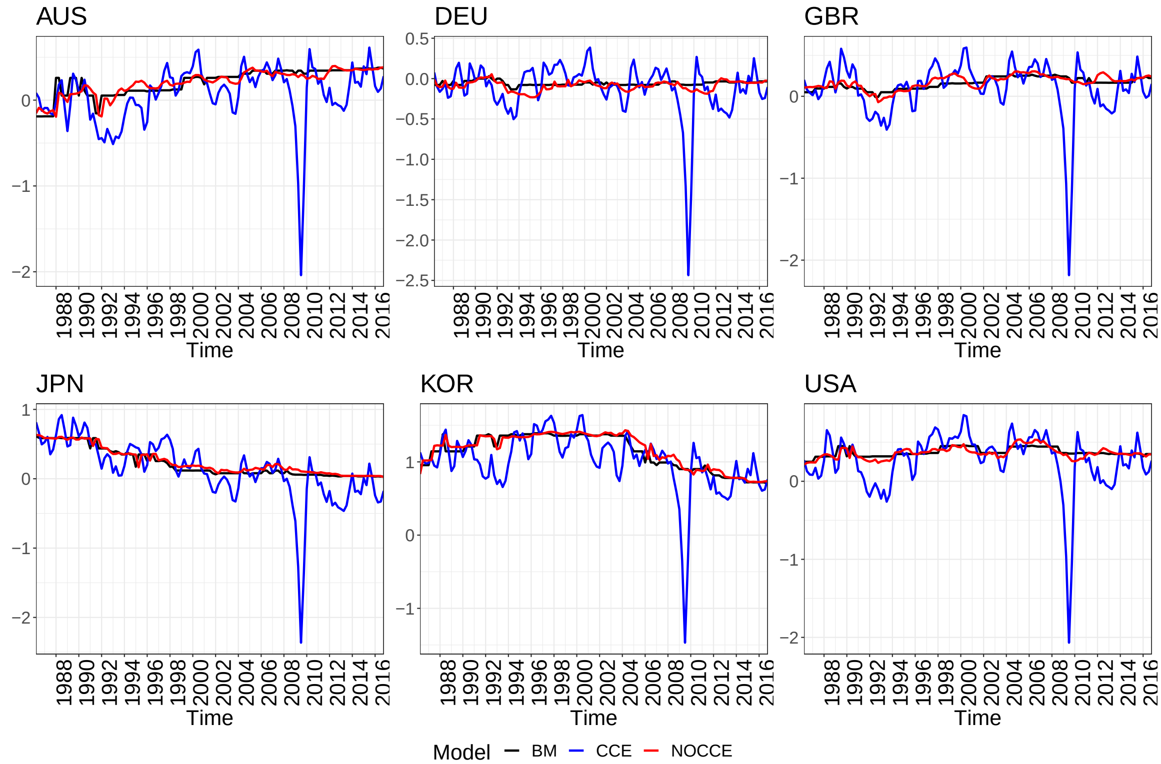
(a) Estimated GaR (5 per cent) at 12 quarter horizons, predictor - NFCI

sample predictive accuracy in terms of tick-loss. So, we see distinct and meaningful characteristics in the series of estimated GaR from the CSD panel. In the following subsections, we explore further the properties of the out-of-sample forecasts of the GaR.

With the CCE model, we are able to reproduce distinct patterns for the different countries. Among the six countries, at the two extremes, we see a declining pattern for Japan and an increasing pattern for Korea. The US, the UK and Germany also show an upward trend until the GFC. We see a sharp fall around the GFC and the predicted GaRs are Korea, Germany, Japan, the UK, Australia and the US respectively, in order starting from the minimum. Post GFC, both of the panel models signal more co-movement in GaR, with the CCE model indicating more synchrony.

5.3 Estimated Moments

The importance of quantile regressions in predicting higher moments of GDP is investigated in several studies (Adrian, Boyarchenko & Giannone 2019, Plagborg-Moller et al. 2020, Lloyd et al. 2021) and there is no consensus in the findings. While Plagborg-Moller et al. (2020) do not find any meaningful interpretation of moments other than the conditional mean, Lloyd et al. (2021) find that a quantile regression augmented with foreign variables is able to generate an interpretable pattern of time-varying higher-order moments.



(b) Estimated GaR (25 per cent) at 12 quarter horizons, predictor - Term Spreads

Figure 9: Estimated GaR

Adrian, Boyarchenko & Giannone (2019) find that higher moments of GDP growth are correlated with financial conditions. Delle-Monache et al. (2020) also find that conditional on large financial information sets, there is marked negative skewness and downside risk in the recovery path, in the past decade. In this section, we explore the conditional moments using the estimated panel quantile models considered in this paper.

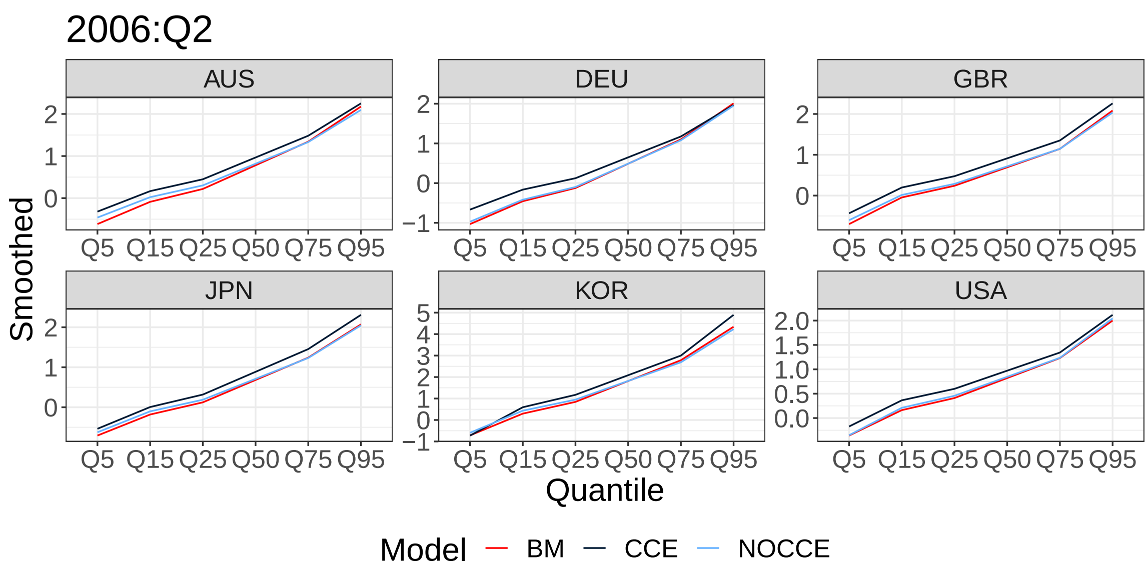
To arrive at the time-varying moments, we follow the method of Adrian, Boyarchenko & Giannone (2019), by smoothing the predicted quantiles using the skew-t distribution of Azzalini & Capitanio (2003). This flexible distribution is calibrated by four parameters and has been used in GaR studies to smoothen the quantiles and hence arrive at the entire the conditional distribution of future GDP growth. The skew-t probability density function takes the following functional form:

$$f(y;\mu,\sigma,\alpha,\nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};v\right) T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\left(\frac{y-\mu}{\sigma}\right)^2}};\nu+1\right) \tag{5.2}$$

where $t(.)$ and $T(.)$ respectively denote the pdf and cdf of the Student t-distribution. The four parameters of the distribution pin down the location μ, scale σ, fatness ν and shape α. For each quarter, we choose these parameters to minimise the squared distance between our estimated conditional quantiles (5,25,75 and 95th[4]) and the quantiles of the skewed t-distribution. This is a non-linear least-squares problem as below:

$$\{\hat{\mu}_{t=h}, \hat{\sigma}_{t=h}, \hat{\alpha}_{t=h}, \hat{\nu}_{t=h}\} = \underset{\mu,\sigma,\alpha,\nu}{\arg\min} \sum_{\tau} \left[\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) F^{-1}(\tau; \mu, \sigma, \alpha, \nu)\right] \tag{5.3}$$

The fitted smoothed quantiles are shown for three illustrative periods conditional on the NFCI for the 12-quarter ahead forecast horizon in figure 10. The estimated quantiles are smoothened, and the three models have distinct features.

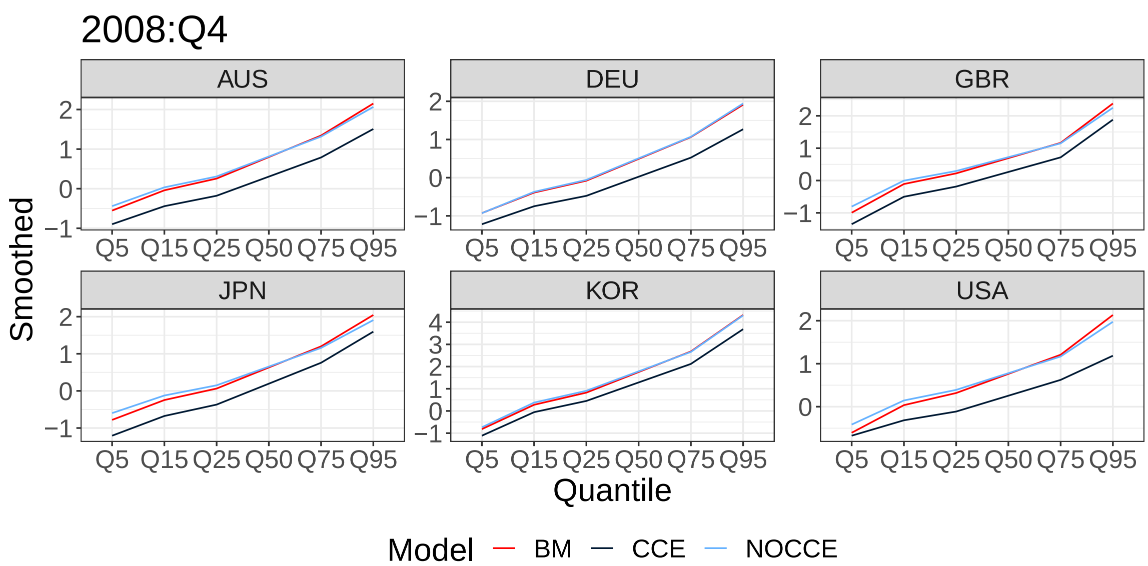


(a) Smoothed Conditional Quantiles

Figure 10: Smoothed Conditional Quantiles

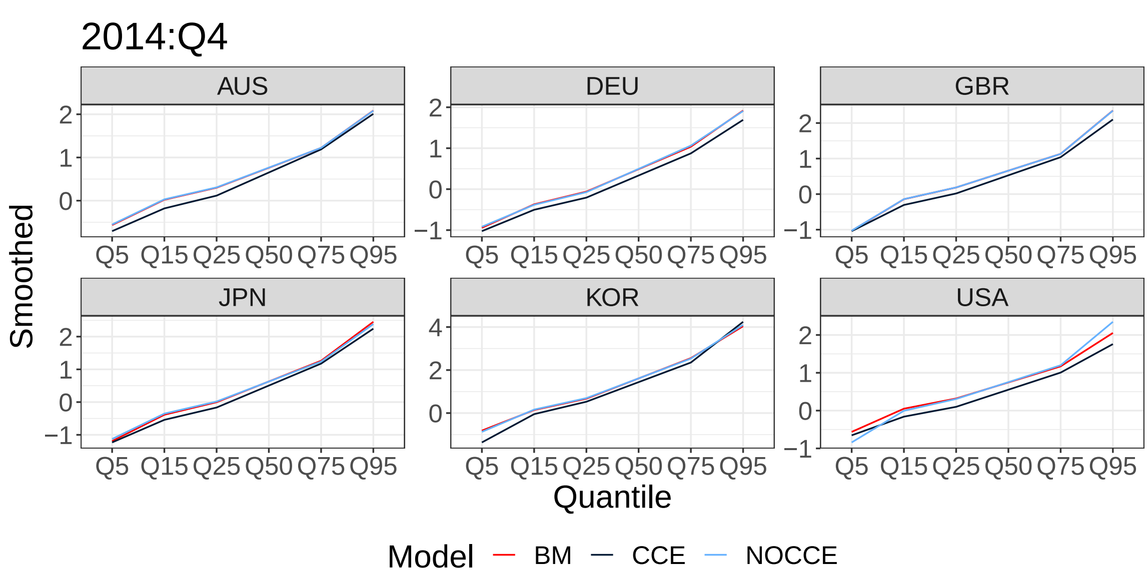
Figure 11 plots the three versions of the first four estimated time-varying moments (mean, variance, skewness and kurtosis) of the fitted skew-t distribution, corresponding to the unconditional benchmark model and the panel models with and without CSD. The horizon of prediction here is 12 quarters or three years. For brevity, we present the results for six major economies conditional on NFCI. We show additional estimated moments from other indicators and forecast horizons in Appendix B. The comparison indicates that the benchmark unconditional model is unable to replicate much of the variations in the moments. The panel models are better in representing the time-variation in the moments and we compare the moments estimated from the panel models in the following paragraphs.

[4]following Adrian, Boyarchenko & Giannone (2019)



(b) Smoothed Conditional Quantiles

Figure 10: Smoothed Conditional Quantiles



(c) Smoothed Conditional Quantiles

Figure 10: Smoothed Conditional Quantiles

5.3.1 Mean

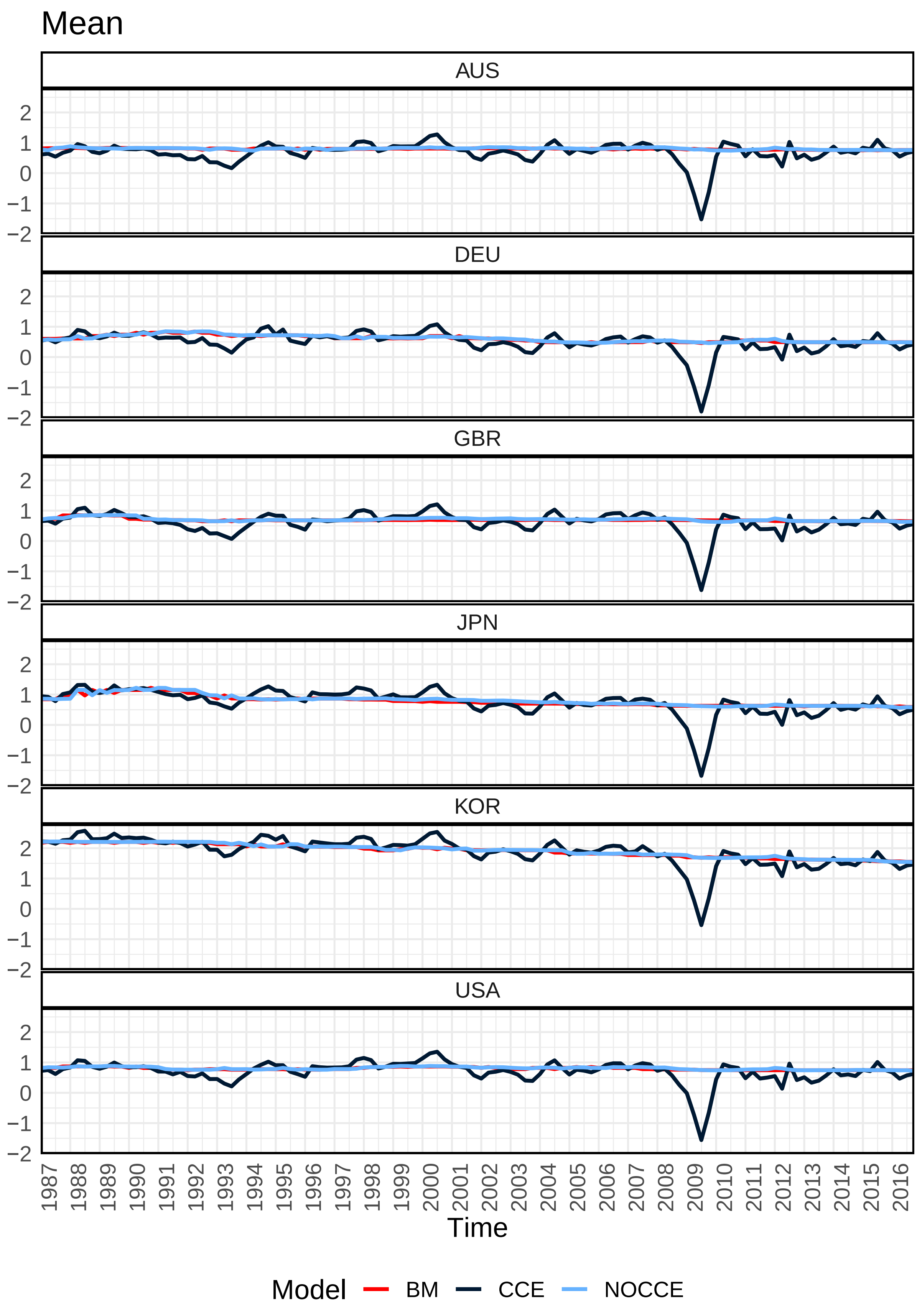
Except for the benchmark model, both the panel models are able to reflect interpretable economic patterns in the mean (figure 11a). However, the patterns are more prominent and distinguishable in the CSD panel model rather than the non-CSD panel. Out of the three distinguishable troughs in the US GDP growth series the most recent one i.e., the one due to the GFC, is well reflected by the estimated time-varying mean of the skew-t distribution. The other episodes of slowdowns in the US GDP i.e., in the early 1990s and 2000s decade has also been indicated in the estimated mean series. This holds for the other countries as well.

5.3.2 Variance

Variance spikes around dips in the estimated conditional mean which usually correspond to dips in real GDP growth. The pattern of variance is distinct for the six countries under consideration. We find more time-variability for Korea followed by the UK and US. Most of the known high-risk situations such as the GFC around 2008-2010 are reflected in the CSD-panel estimated variance (see figure 11b). The unpredictability and the surprise element of the GFC are seen in all countries in the CSD model, where the variance comes nearly to an all-time low early in 2008 and then suddenly start spiking sharply. Among the six countries in figure 11b, excepting Germany, we see that the non-CSD panel model is also largely able to signal the higher volatility around times of stress. For Australia and the UK, the non-CSD panel indicates a larger increase in variance around the GFC as compared to the CSD panel. However, the estimated volatility from the non-CSD panel is very flat and signals either remain elevated or indicate low volatility for significantly longer periods.

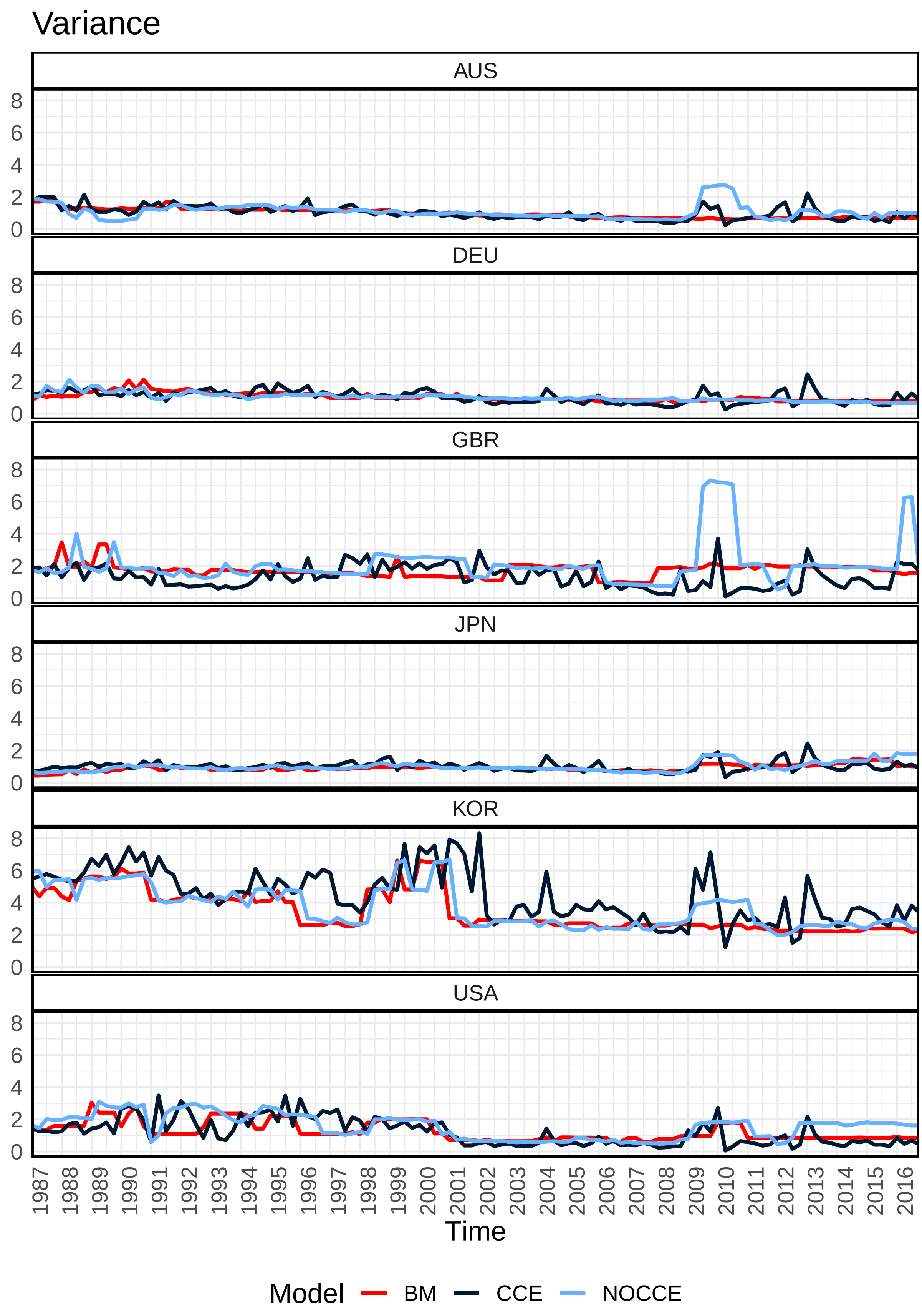
5.3.3 Skewness

Skewness is time-varying within the range of $(-1, 1)$. Skewness turns negative around the major episodes of economic disruption for example the early 2000s or 2008-09. Skewness is quite stable for Australia, Germany and Japan where there are only select episodes of negative skewness. The other countries namely US, UK and Korea show much more time-variation in skewness. For instance, in the UK, the recovery period after the dip in 1992, is accompanied by large negative skewness, which subsides around 2006 and then again spikes down during the GFC. The pattern is nearly similar for the US, along with an additional negative spike around 2004. The non-CSD panel indicates negative skewness at known periods of economic distress but is less responsive to time and prolongs the signal for an extended period. Also, there are differences in the magnitude of estimated skewness between the panel models.



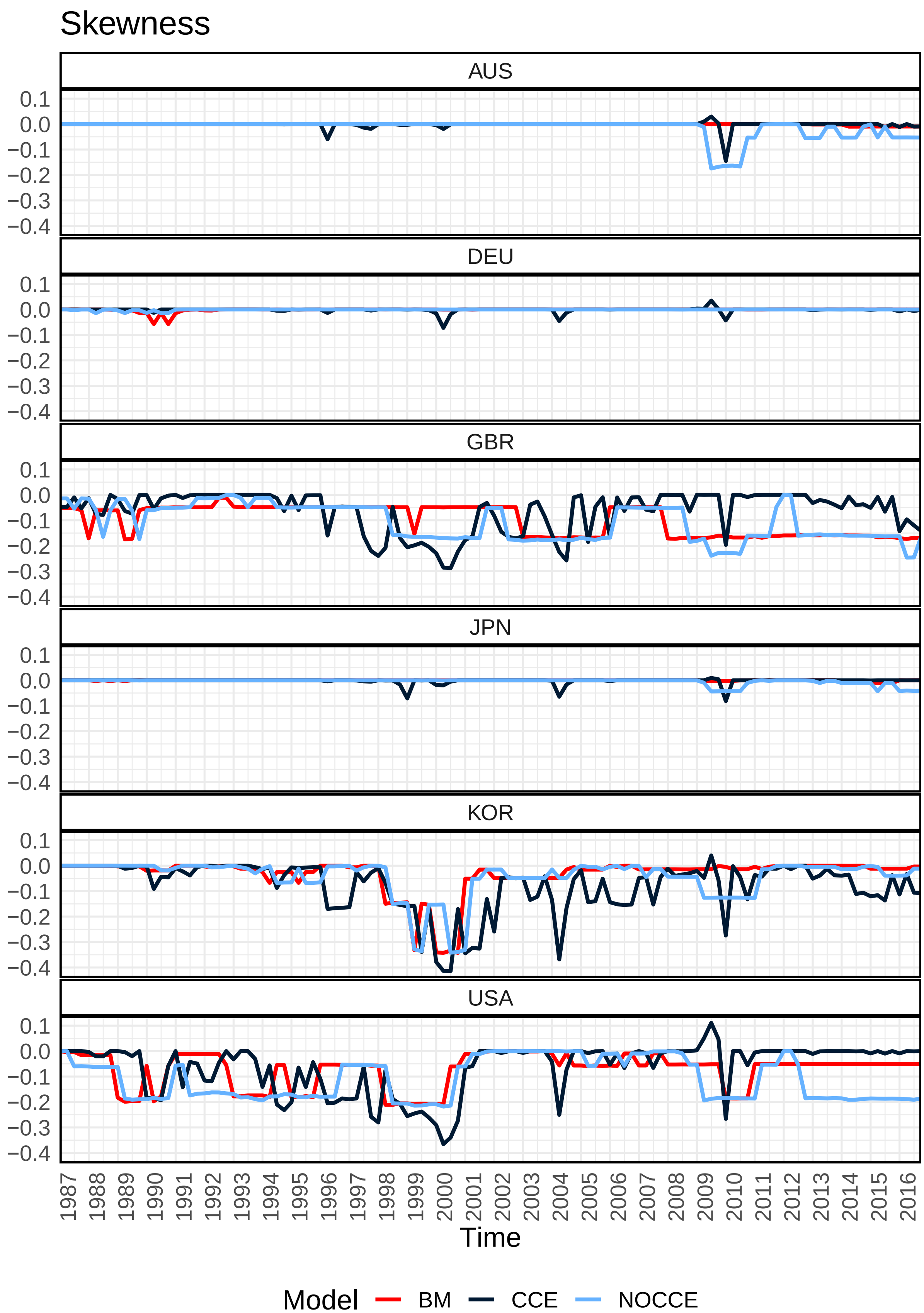
(a) Mean, conditional on NFCI

Figure 11: Moments, conditional on NFCI



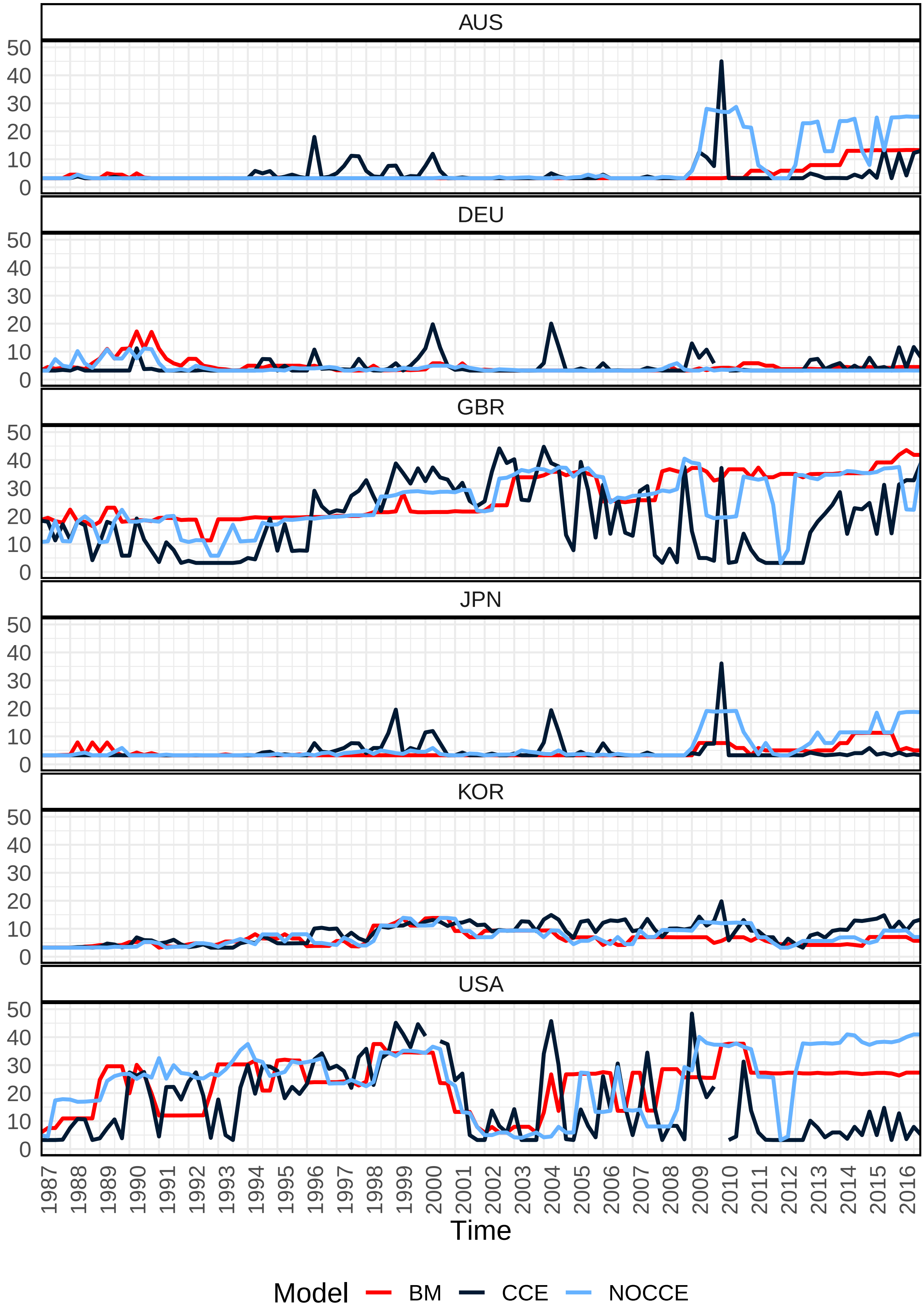
(b) Variance, conditional on NFCI

Figure 11: Moments, conditional on NFCI



(c) Skewness, conditional on NFCI

Figure 11: Moments, conditional on NFCI



(d) Kurtosis, conditional on NFCI

Figure 11: Moments, conditional on NFCI

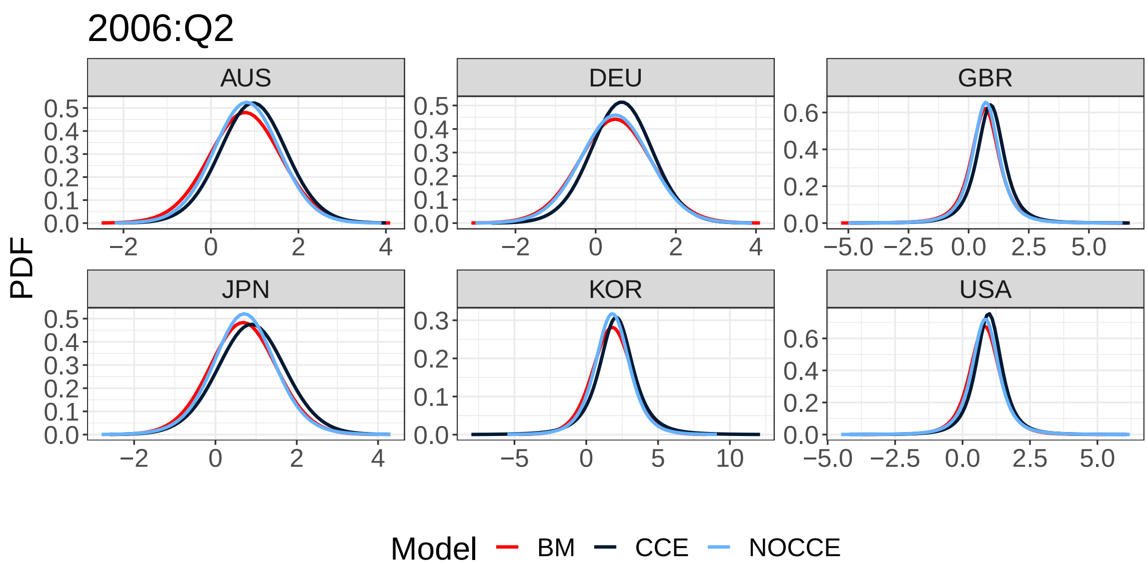
5.3.4 Kurtosis

Kurtosis is negatively correlated with skewness and positively with variance. So, an increase in kurtosis implies a corresponding tilt towards negative skew and higher variance of the growth distribution. We note the following key characteristics of time-varying kurtosis from the CSD-panel model. For the US we see elevated kurtosis, in the late 80s, which continues until the early years of the 90s and drops around 1993-94. The kurtosis remains low for a short term, reflecting the lowering of risks and once again starts rising in the mid-90s, reaching a peak around 2000-01. Kurtosis spikes up again in 2009 and 2010, signalling the GFC. It remains low thereafter until the end of our sample in 2016. The range of values of kurtosis, though broadly comparable to those of Plagborg-Moller et al. (2020), the specific values are quite distinct if compared at particular points in time and we differ from their finding of no meaningful pattern in kurtosis, over time. For the UK, we see the kurtosis slowly rising from lows in the late 90s and early 2000s. It continues to remain elevated, with temporary reliefs, until it reaches an extreme high in 2004. The common pattern across countries is the elevated level and indicate the building up of the GFC. At other times, kurtosis is relatively flat for Australia, Germany and Japan.

From the additional moment plots conditional on term spreads for forecast horizons 4 and 8 quarters (Appendix B), we also find the kurtosis from the non-CSD panel, and the unconditional benchmarks are either very flat or spike at times that could not be related to the economic conditions. For instance, in the US, the non-CSD panel demonstrates higher kurtosis around 2011-12 than in 2008-09. For the UK, kurtosis remains elevated since 2003-04 (figure 28d) until the end of our sample. The CSD panel generated moments are more meaningful and interpretable. The non-CSD panel is unable to capture the relatively low-risk period, after the GFC, until the end of our sample in 2016. It continues to show the same level of elevated risk in terms of higher variance and kurtosis for almost all the countries covered in the panel. This is probably due to the mitigating role played by the global factors of the CSD panel model. We will elaborate on this more in the subsequent section.

The moment analysis indicates the GFC 2008-09 in terms of a sharp dip in mean, higher variance, negative skewness and spiking kurtosis. Additionally, we are also able to identify from the moments other known episodes of macroeconomic risk. We can relate to the end of 80's decade and the early 90's recession, characterised by the then rapid growth in the US credit and house prices, accompanied by weak bank capital and further enhanced by monetary policy tightening in the late 80s (Aikman et al. 2019). We can identify the period in the late 90's decade, where the US experienced a series of macro-financial challenges i.e., the telecom-media-technology (TMT) bubble, the onset of a recession, worsened further by the terrorist attacks of September 2001 (IMF 2002). Amid the steep global slowdown, the UK around the same period witnessed a rapid growth in house prices, credit along with weakly capitalised banks (Aikman et al. 2019).

We conclude that although both panel models are able to indicate risk, signals from the CSD panel are sharper. The moments of the CSD panel model indicate that the risks emanate not from the negative skewness, but more from a shift of the entire distribution to the left and higher variance due to fatter tails. This is further reinforced in the select density plots and ES in the following sub-sections.



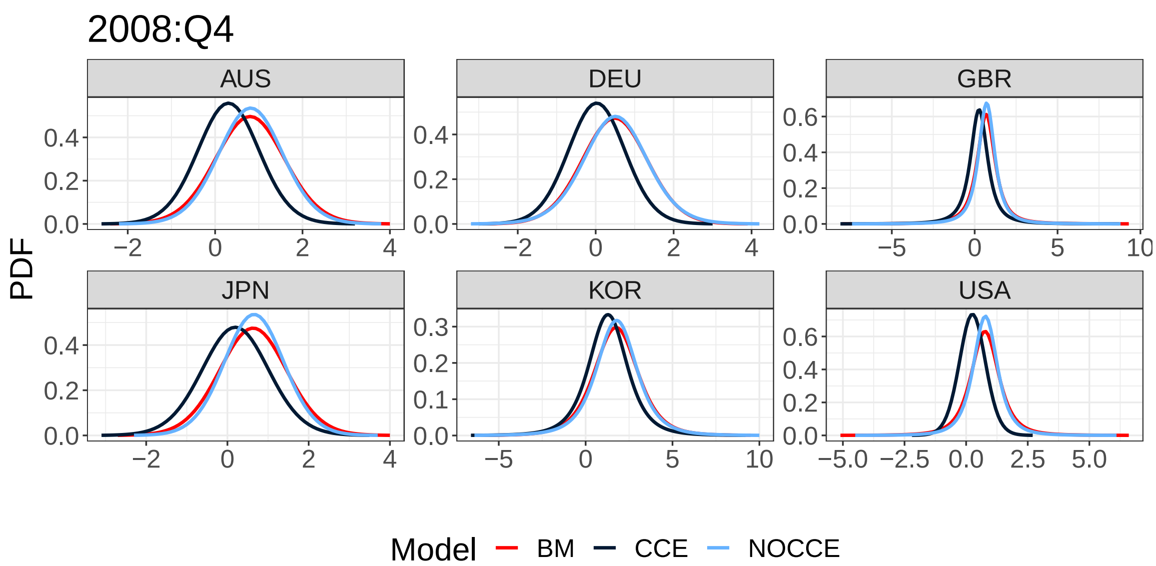
(a) Conditional Density - 2006:Q4

Figure 12: Conditional Density

5.4 Predictive Density

In this section, we analyse the entire conditional predicted distributions of GDP growth. These are directly derived from the fitted skew-t distributions. We focus on the three points in time, which are known to characterise normal, stressful and recovery times. The distributions are expected to substantiate the findings on the moments seen previously.

Figures 12 plot the fitted skew-t densities conditional on NFCI, for three quarters i.e., 2006:Q2, 2009:Q4 and 2014:Q4 (representing periods before the GFC, amid the GFC and after the GFC respectively). Of these 2006:Q2 and 2014:Q4 has been identified as periods of US business cycle upswings, while 2008:Q4 is a downturn (Adrian, Boyarchenko & Giannone 2019). The estimated densities based on the CCE panel is substantially different from the other two, specifically in 2008:Q2. We see that the estimated density from the CCE model is the most responsive. It shifts remarkably to the left, in 2008:Q4, while we do not notice such a shift in the densities estimated from the non-CSD panel or the benchmark. This corroborates findings from the time-varying mean in figure 11a.



(b) Conditional Density - 2008:Q4

Figure 12: Conditional Density

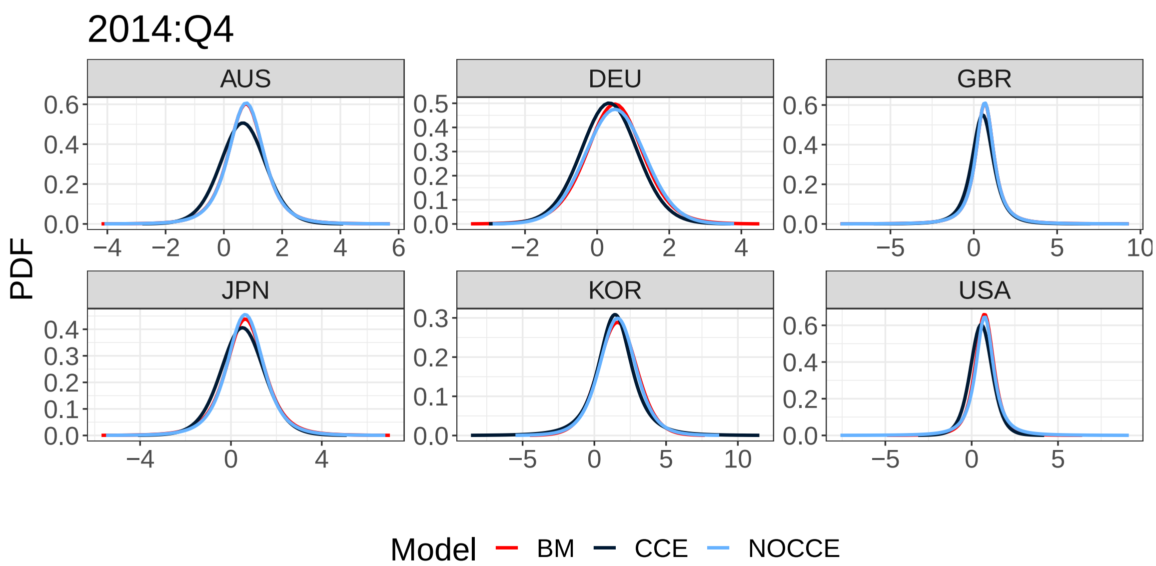
During the upswings, all three models produce nearly similar density functions. The CCE model produces a better scenario than the rest in 2006:Q2. Although 2014:Q4 is taken as a period of business cycle upswing, the CCE panel model still indicates a left-shifted distribution, relative to the other two models.

In a similar analysis, Reichlin et al. (2020), find that during times of stress, the spread of the entire conditional distribution increases, leading to a higher probability for a larger range of observations. Adrian, Boyarchenko & Giannone (2019) find that during the GFC, the conditional distribution has higher variance and is negatively skewed. We on the other hand note a leftwards shifting of the distribution along with higher kurtosis and variance observed previously, which causes lower values of growth to be more probable in the distress times.

5.5 Expected Shortfall

Expected shortfall (ES) is a classic quantification of tail-risk, measuring the expected value, conditional on violation of a threshold. It is the officially endorsed measure of risk by the Basel Committee and has renewed emphasis in the Third Basel Accord (Patton et al. 2019). GaR studies (Adrian, Boyarchenko & Giannone 2019, Iseringhausen 2021, Reichlin et al. 2020) have also computed and compared ES. In this context, ES is the expected GDP growth conditional on the violation of GaR. We compute ES as an additional measure of tail-risk quantification, to further validate the signals generated by the higher moments in the previous section.

For a chosen target probability π, ES is defined for the i^{th} cross-section as:



(c) Conditional Density - 2014:Q4

Figure 12: Conditional Density

Notes: The fitted skew-t distribution is conditional on the NFCI for the 12-quarter ahead forecast horizon. We show six major countries from the sample of 24 countries.

$$SF_{i,t+h} = E(y_{i,t+h}|y_{i,t+h} \leq GaR_{\pi}) = \frac{1}{\pi}\int_0^{\pi} \hat{F}_{y_{i,t+h|x_{i,t}}}(\tau|x_{i,t})d\tau, \tag{5.4}$$

where $\hat{F}_{y_{i,t+h|x_{i,t}}}(\tau|x_{i,t})$ is the estimated cumulative distribution function (CDF) of the skew-t density (equation 5.2).

In figure 13, we have the estimated ES measures from the different models using the NFCI as the vulnerability indicator. We note the flexibility of the ES measure constructed from the CCE panel models, in terms of the strength of the signals in times of distress. The lowest estimated ES for most countries is during the GFC and post GFC early 2013. In addition to the periods of risk we identified in the moment analysis, we see a low ES around 2013, when the growth outlook was bleak, with the recovery from the financial crisis slowing down. The important attributed reasons were weaker demand due to fiscal consolidation and weak financial systems. Apart from these, a general sentiment of uncertainty and the then ongoing European turmoil were some of the key factors that exerted a downward pull on the GDP growth of the major advanced economies (IMF 2012). As the outlook on growth gradually improved thereafter (IMF 2013*a*,*b*), we see a corresponding movement in ES too.

The estimated ES from the CCE panels has very meaningful correlations with the estimated moments in leads and lags (figure 14). The relationship with skewness is positive. From figure 11c, the distributions

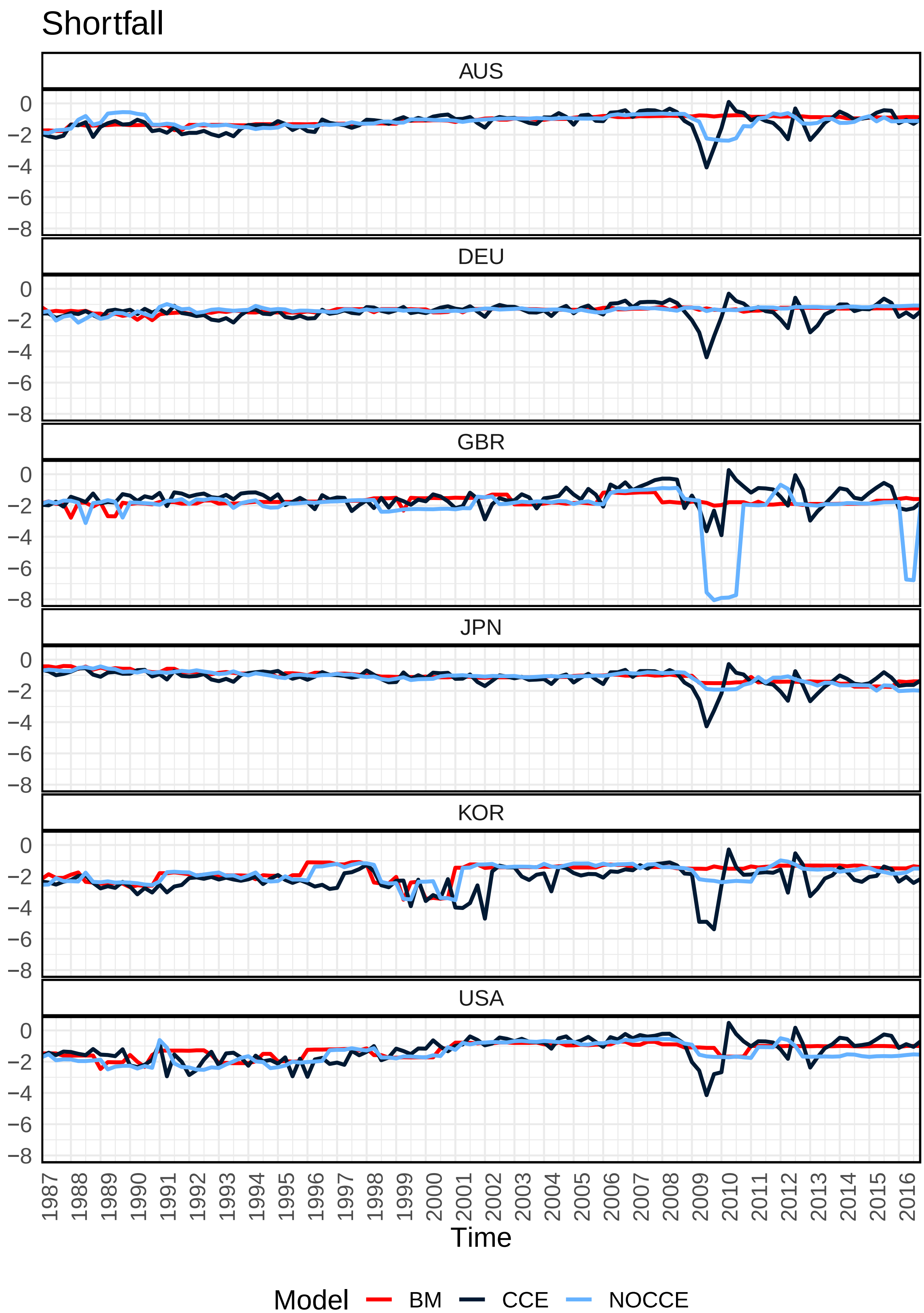
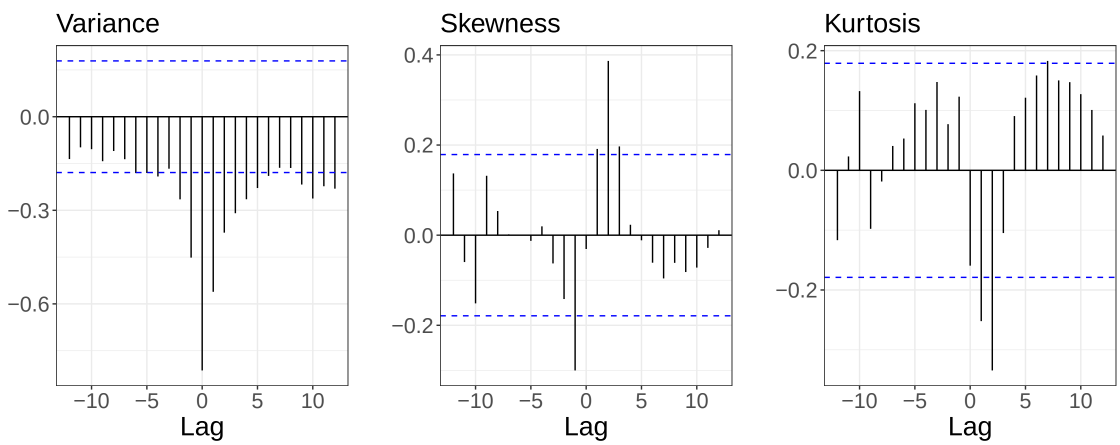
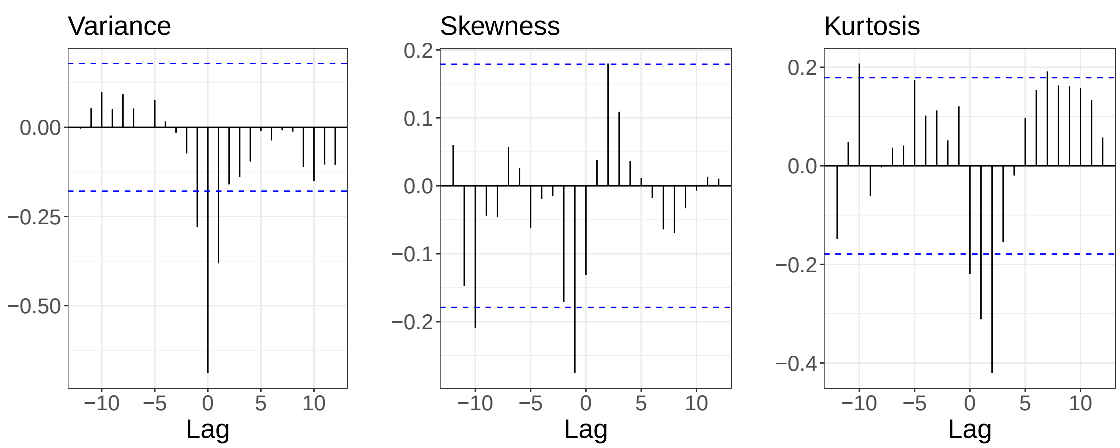


Figure 13: Expected Shortfall for 5 per cent GaR

are either moderately negatively skewed or symmetric, this implies a worsening of the ES is associated with a larger negative skewness. ES is negatively correlated with variance and kurtosis, which means higher volatility or fatter tails is associated with worse values for ES. There are differences in the relationship among the six countries.



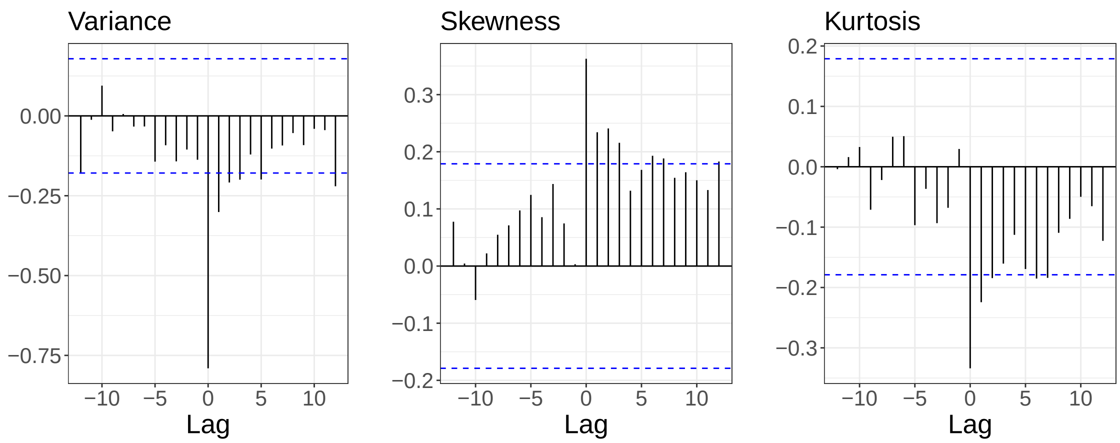
(a) Correlation of Expected Shortfall and Moments: AUS, model: CCE



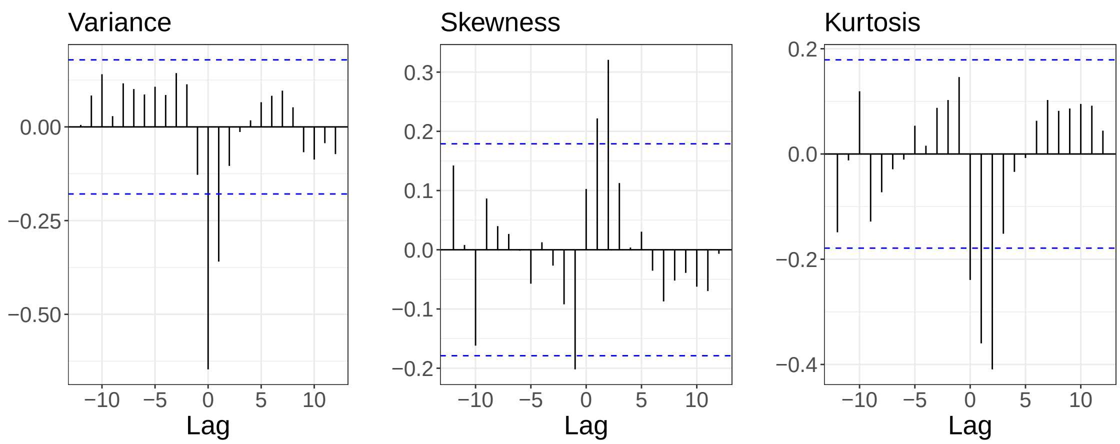
(b) Correlation of Expected Shortfall and Moments: DEU, model: CCE

5.6 Forecast Decomposition

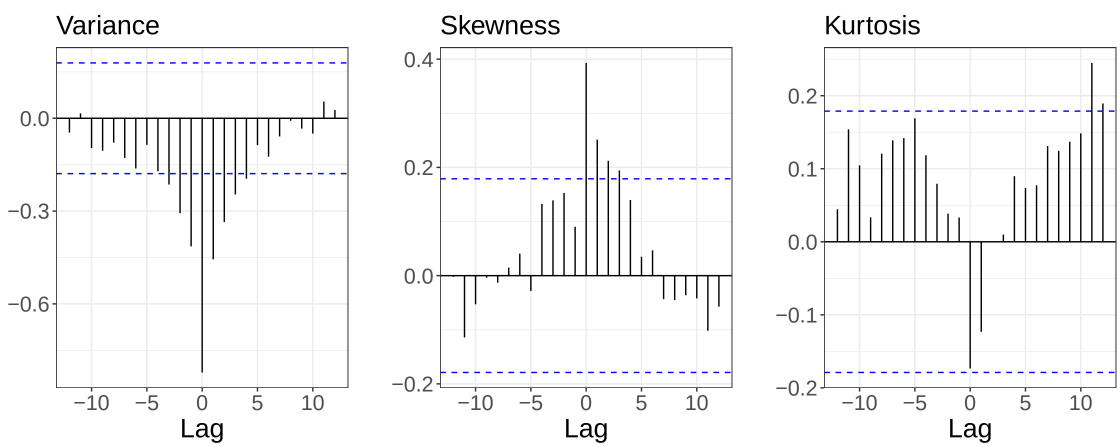
The results so far indicate superior in-sample and out-of-sample performance when we include the multifactor error structure in the panel model. In this section, we try to understand the contribution of the different components to the total predicted GaR by the CSD panel model only (we do not compare models in this section). We try decomposing the predicted GaR and segregate the role played by the global factors. A



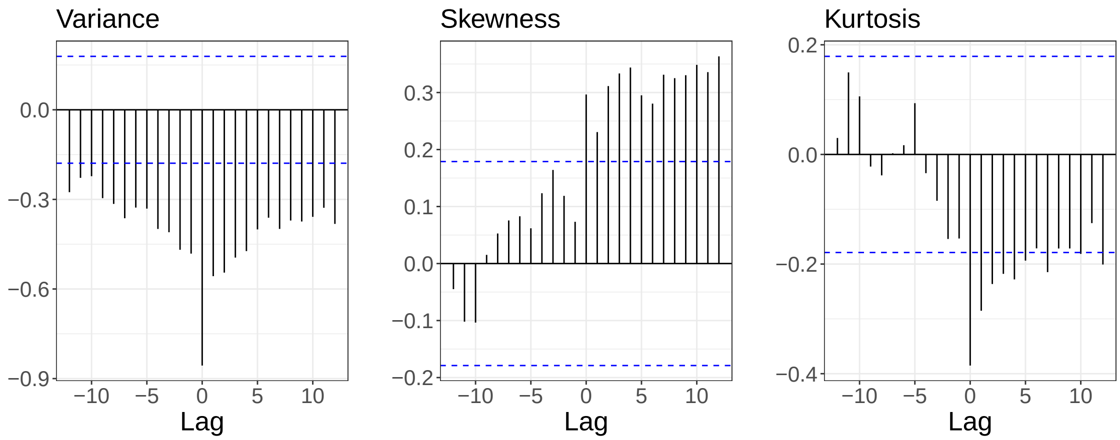
(c) Correlation of Expected Shortfall and Moments: GBR, model: CCE



(d) Correlation of Expected Shortfall and Moments: JPN, model: CCE



(e) Correlation of Expected Shortfall and Moments: KOR, model: CCE



(f) Correlation of Expected Shortfall and Moments: USA, model: CCE

Figure 14: Cross-Correlogram o- Expected Shortfall and Moments

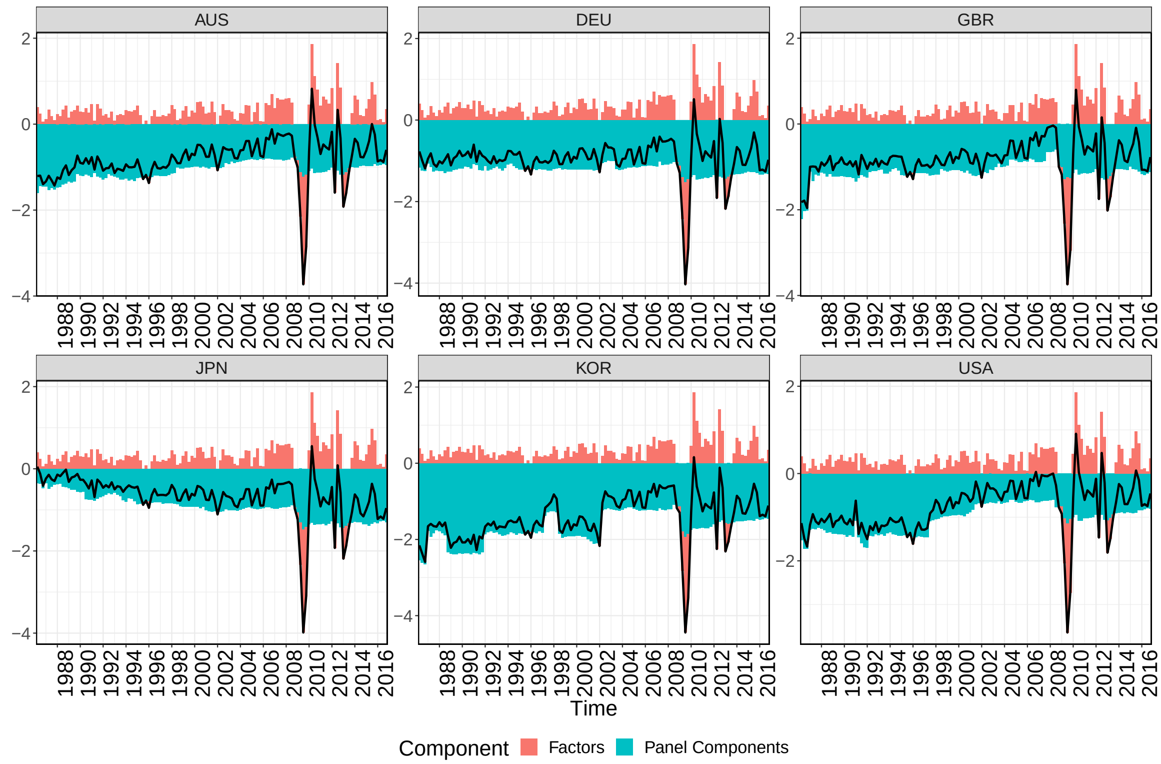
similar breakdown of estimated GaR into different sub-components has been done by Aikman et al. (2019) to identify the drivers of GaR and create a risk monitoring tool.

The black solid line in figure 15a represents the predicted GaR (5 per cent), 12 quarters ahead with NFCI as the vulnerability indicator. Although the magnitude of GaR is driven by the panel components, the direction is influenced by the CSD. The panel components (excluding the multi-factor error structure) have a negative impact and lower GaR. The common factors have a mitigating effect and generally pull up GaR. However, in times of extreme distress for example around the GFC, we see that both the panel components and the global factors together pull down GaR. It may be the case therefore that the non-inclusion of these mitigating global factors in the non-CSD panel, is the reason for signalling elevated risks in terms of higher kurtosis post-GFC in the period 2013-2016. The country-specific dynamics are quite distinct.

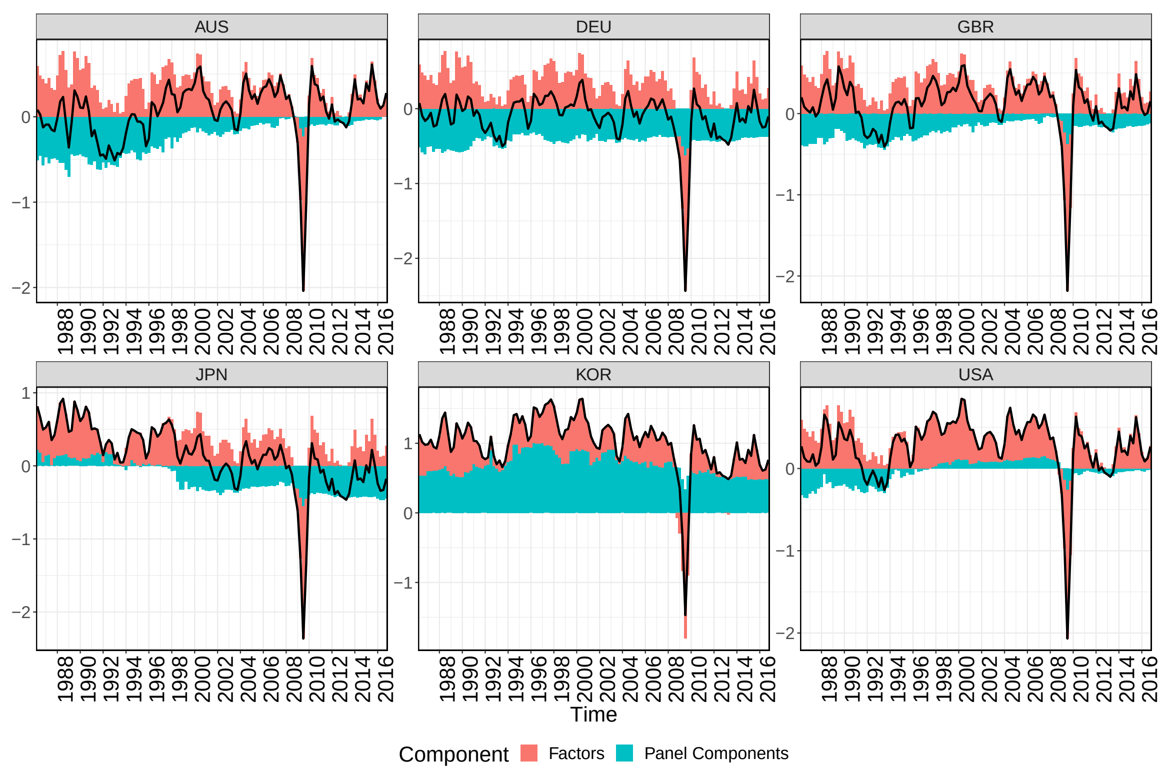
We find similar results when we use term spread as the independent variable for 25 per cent GaR in figure 15b i.e., the factors have a mitigating role in pulling up GaR, while the country-specific components pull the GaR projections down. The contribution of the factors here is much more prominent in 25 per cent GaR for all the 6 countries as compared to the 5 per cent GaR estimates. Findings are identical for other horizons in Appendix D.

6 Conclusions

In this paper, we provide evidence that modelling CSD is important and useful to forecast GaR in a multi-country panel quantile set-up. The factors used to model the cross-sectional dependence, have dual interpretations as common shocks or as international spillover impacts. When augmented with CSD, the results of



(a) Decomposition of Predicted GaR (5 per cent) - Predictor: NFCI



(b) Decomposition of Predicted GaR (25 per cent) - Predictor:Term Spreads

Figure 15: Decomposition of Predicted GaR

our panel quantile regressions suggest that important vulnerability indicators are rendered insignificant for 5 per cent GaR, up to a forecast horizon of 12 quarters. However, we find that three indicators namely credit gap, term spreads and EPU are significant in the medium-term for higher GaR levels i.e., 10-25 per cent. These conclusions were obtained using a large panel of 24 countries and consisting of quarterly data since 1973 for 5 of the vulnerability indicators. We had a slightly shorter sample for two additional uncertainty indicators - EPU and WUI. We also find that the CSD panel models have superior out-of-sample performance in terms of tick-loss. We show the practical relevance of CSD panel models by generating out-of-sample GaR, complete predictive distribution and its moments. We quantify tail-risk by ES. The analysis suggests signals obtained from these are able to replicate the state of the economy at various low points in time and is consistent with the published IMF outlooks around similar times. In addition, a breakdown of the forecasts into the panel components and the interactive fixed-effect terms indicate that the CSD part of the panel has a mitigating effect in normal times and exerts a further downward pull at crisis times.

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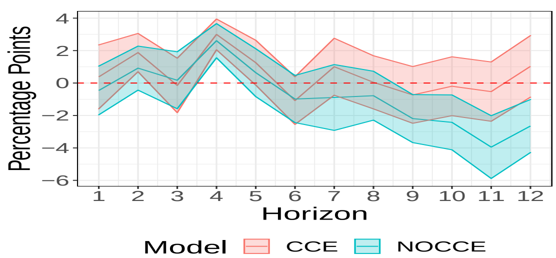
Appendices

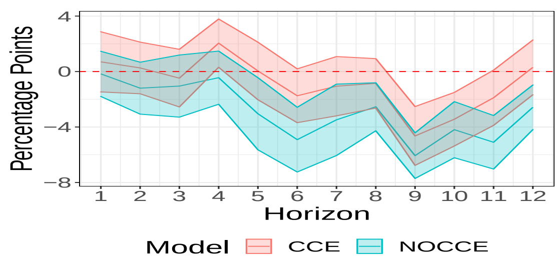
A In-sample Analysis

A.1 Explanatory Power of Vulnerability Indicators - Other GaR Levels

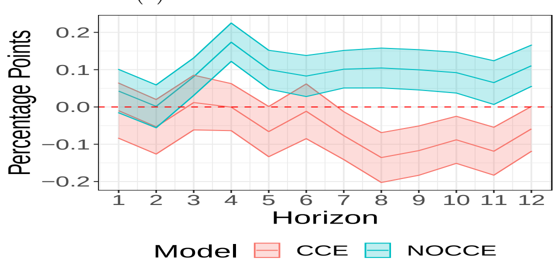
A.1.1 10 per cent GaR



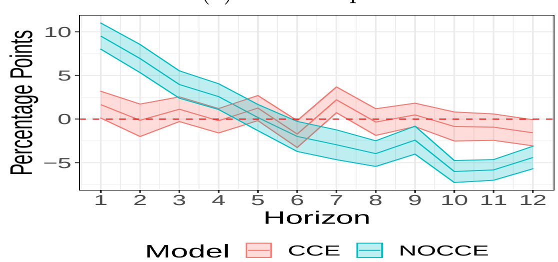
(a) Credit to GDP Growth



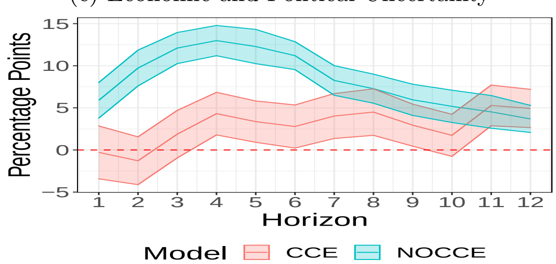
(b) Credit Gap



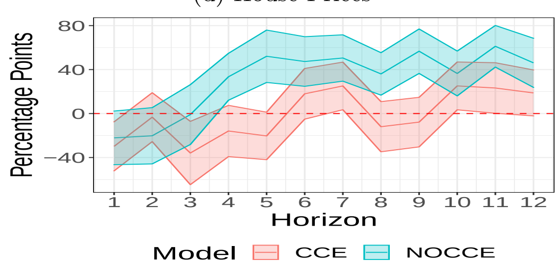
(c) Economic and Political Uncertainty



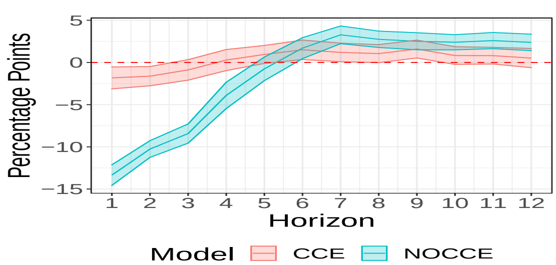
(d) House Prices



(e) Term Spread



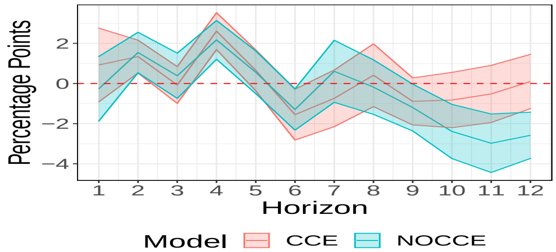
(f) World Uncertainty Index



(g) National Financial Conditions Index

Figure 16: Impact of variables on 10 per cent GaR

A.1.2 15 per cent GaR



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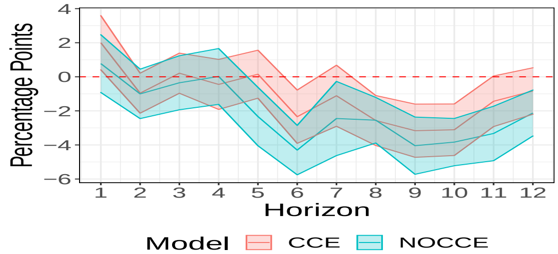

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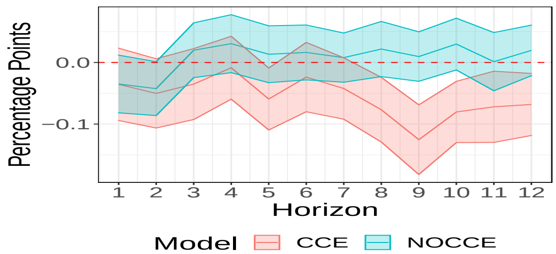
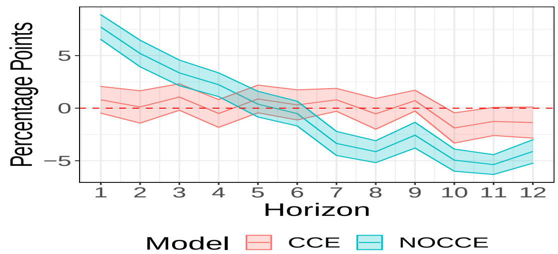
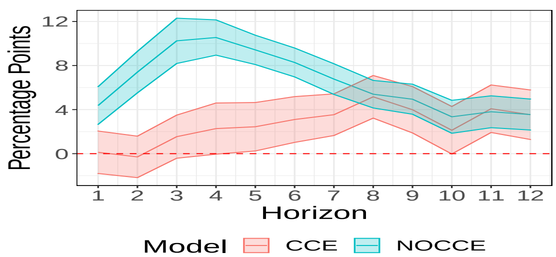


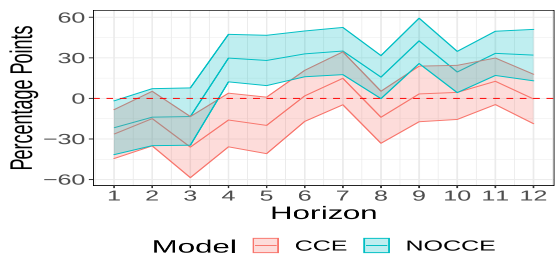
(c) Economic and Political Uncertainty



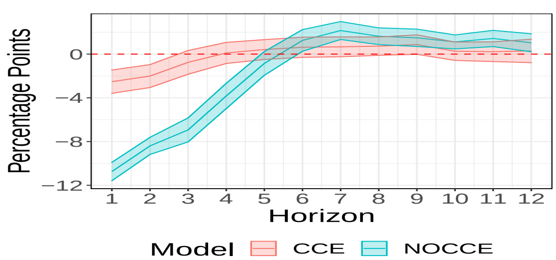
(d) House Prices



(e) Term Spread



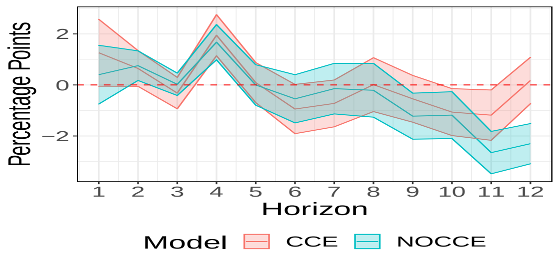
(f) World Uncertainty Index



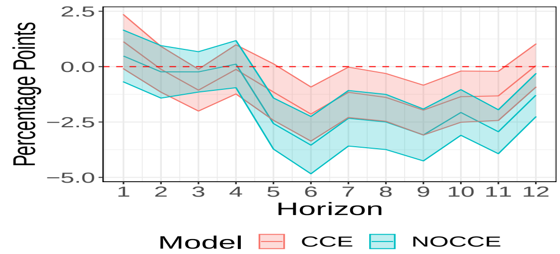
(g) National Financial Conditions Index

Figure 17: Impact of variables on 15 per cent GaR

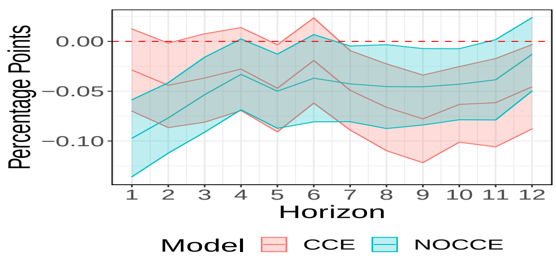
A.1.3 25 per cent GaR



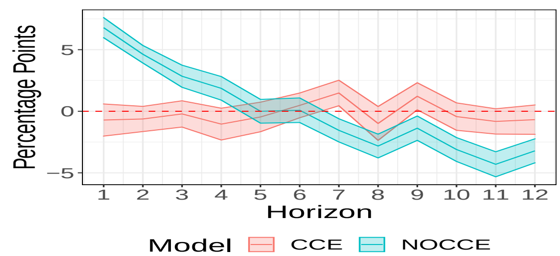
(a) Credit to GDP Growth



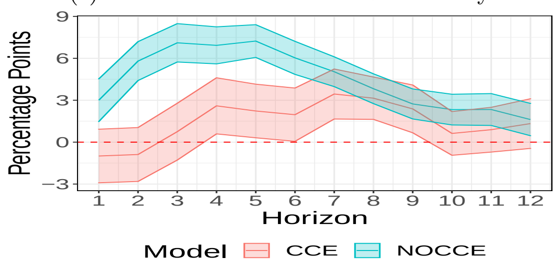
(b) Credit Gap



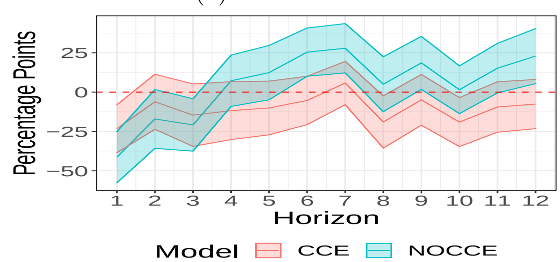
(c) Economic and Political Uncertainty



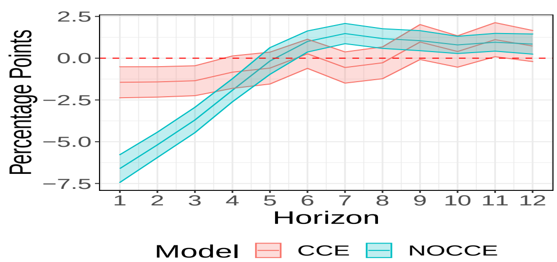
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index

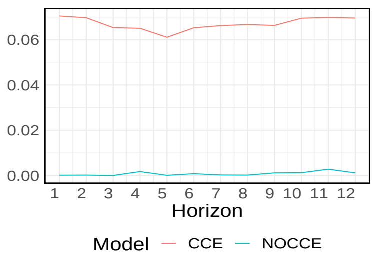


(g) National Financial Conditions Index

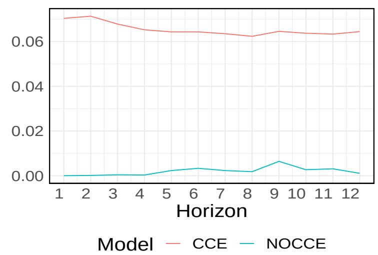
Figure 18: Impact of variables on 25 per cent GaR

A.2 Goodness-of-fit

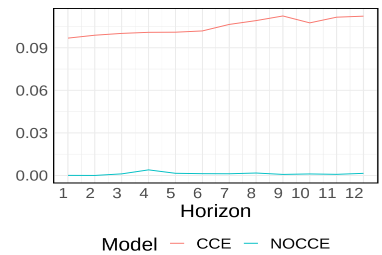
A.2.1 10 per cent GaR



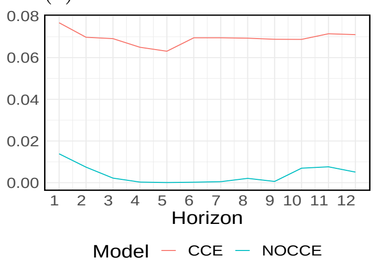
(a) Credit to GDP Growth



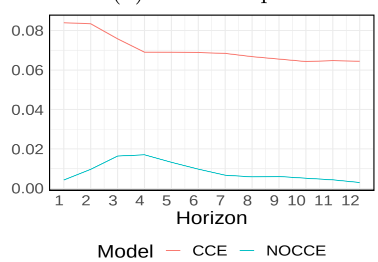
(b) Credit Gap



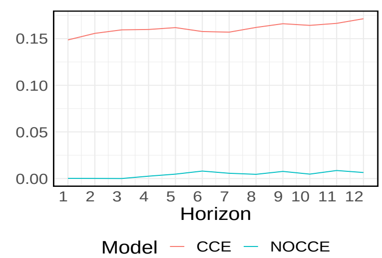
(c) Economic and Political Uncertainty



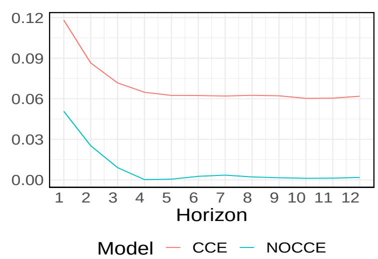
(d) House Prices



(e) Term Spread



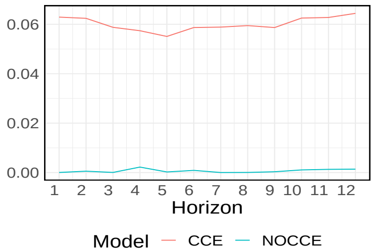
(f) World Uncertainty Index



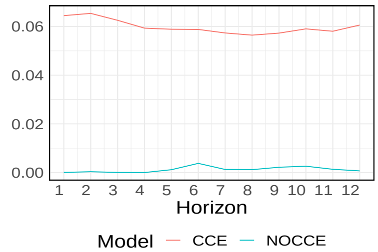
(g) National Financial Conditions Index

Figure 19: In-Sample Goodness-of-fit

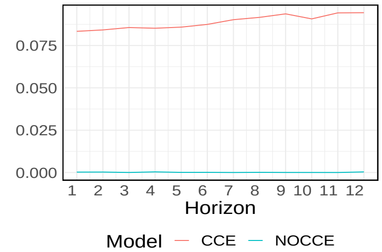
A.2.2 15 per cent GaR



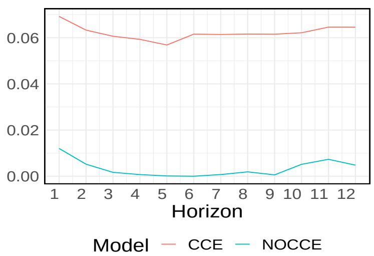
(a) Credit to GDP Growth



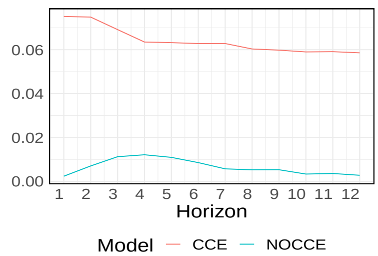
(b) Credit Gap



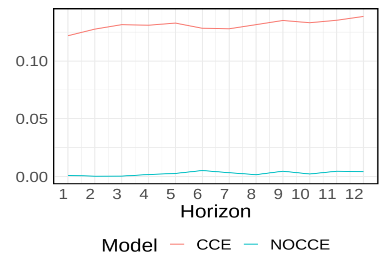
(c) Economic and Political Uncertainty



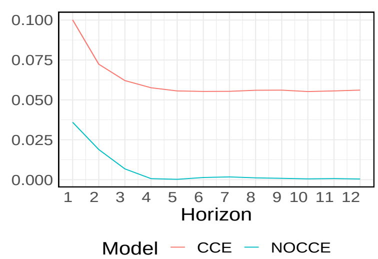
(d) House Prices



(e) Term Spread



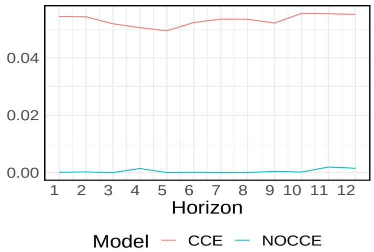
(f) World Uncertainty Index



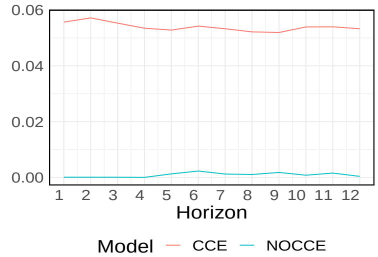
(g) National Financial Conditions Index

Figure 20: In-Sample Goodness-of-fit

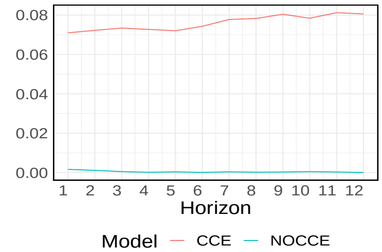
A.2.3 25 per cent GaR



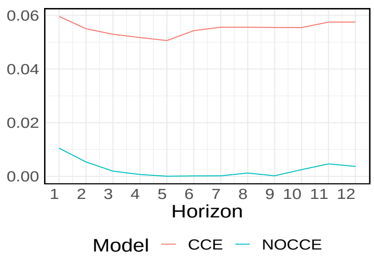
(a) Credit to GDP Growth



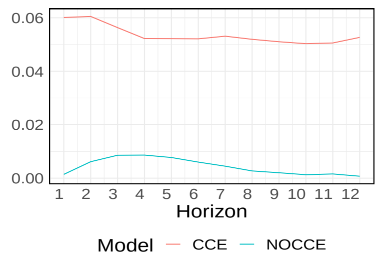
(b) Credit Gap



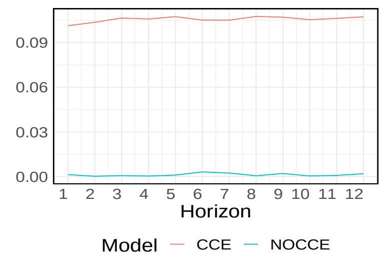
(c) Economic and Political Uncertainty



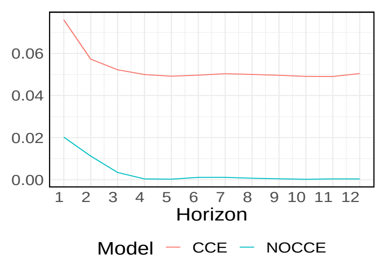
(d) House Prices



(e) Term Spread



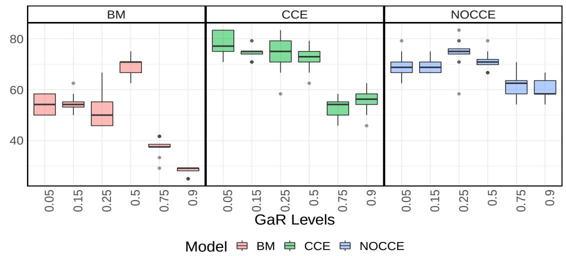
(f) World Uncertainty Index



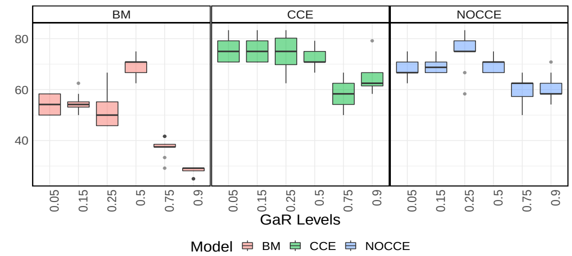
(g) National Financial Conditions Index

Figure 21: In-Sample Goodness-of-fit

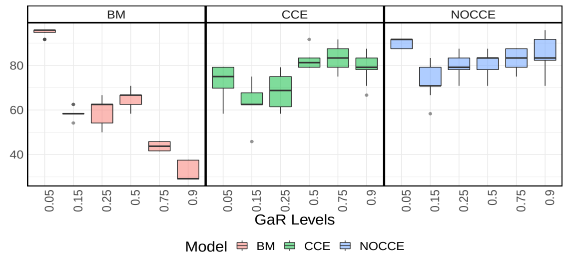
B Different Subsamples - 1986:Q2 - 2007:Q4



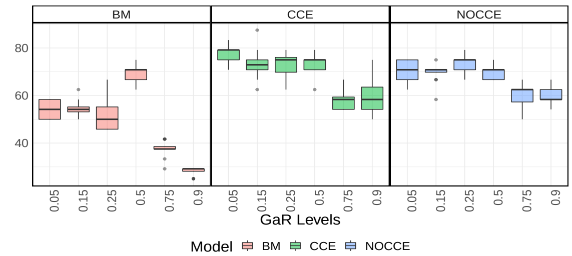
(a) Credit to GDP Growth



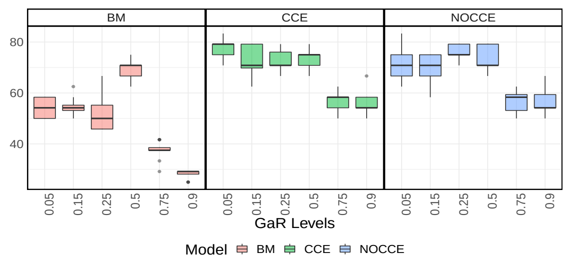
(b) Credit Gap



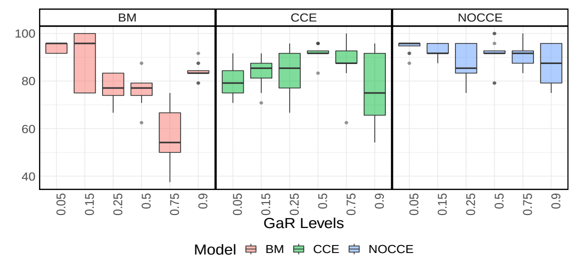
(c) Economic and Political Uncertainty



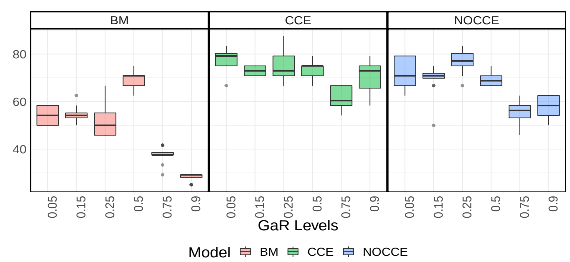
(d) House Prices



(e) Term Spread

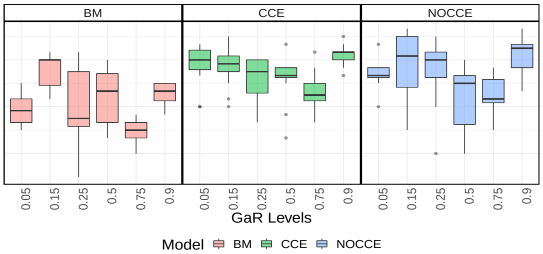


(f) World Uncertainty Index

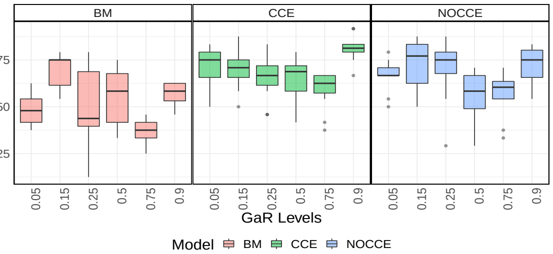


(g) National Financial Conditions Index

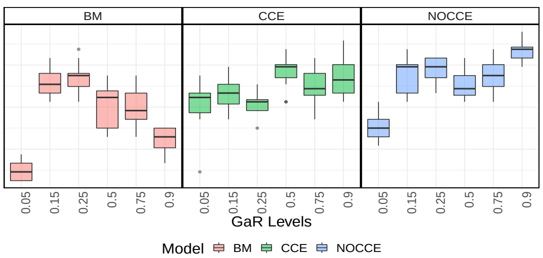
Figure 22: Dynamic Quantile Test - Unconditional



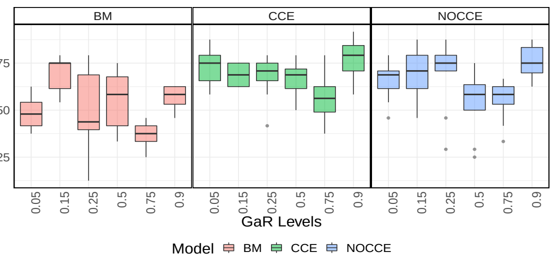
(a) Credit to GDP Growth



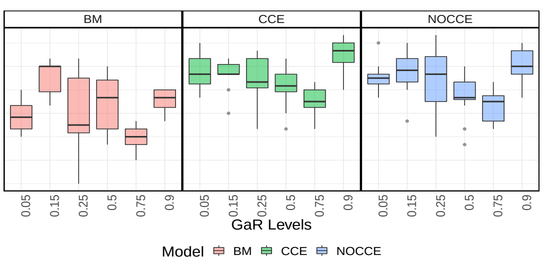
(b) Credit Gap



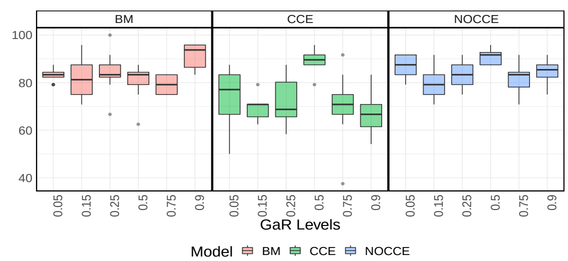
(c) Economic and Political Uncertainty



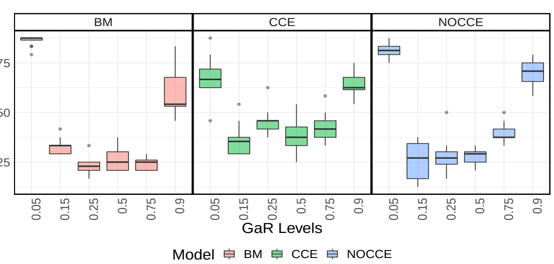
(d) House Prices



(e) Term Spread

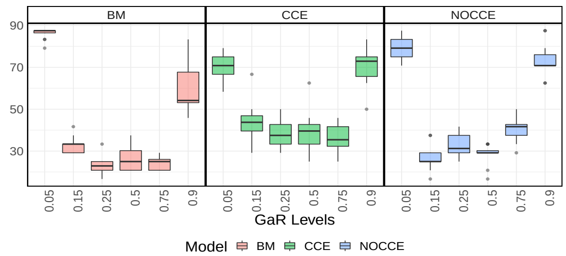


(f) World Uncertainty Index

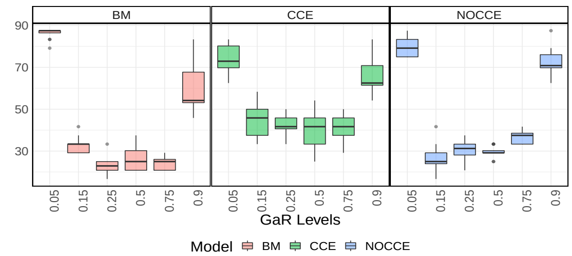


(g) National Financial Conditions Index

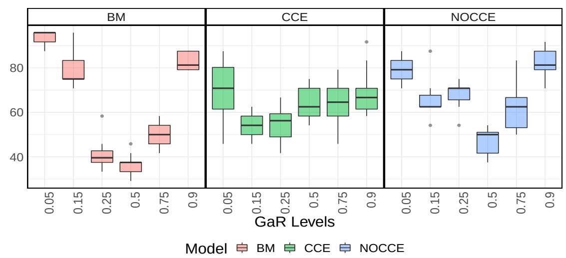
Figure 23: Dynamic Quantile Test - Augmented with Hits



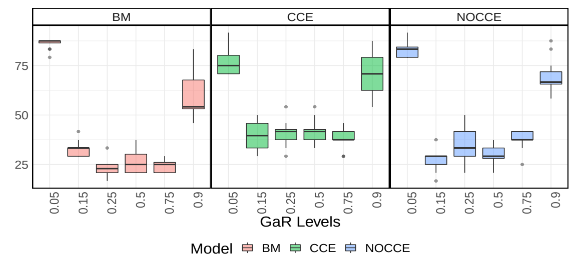
(a) Credit to GDP Growth



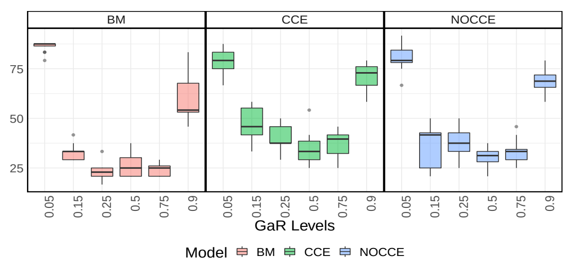
(b) Credit Gap



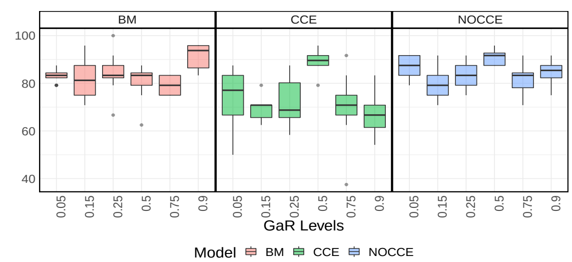
(c) Economic and Political Uncertainty



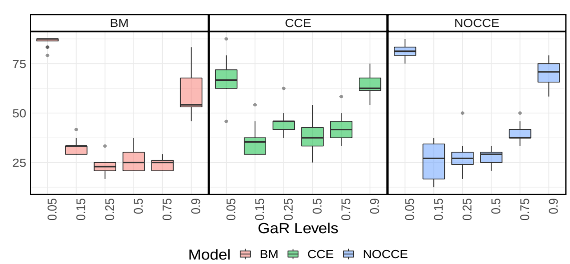
(d) House Prices



(e) Term Spread

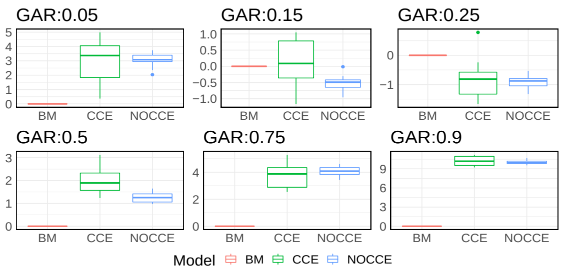


(f) World Uncertainty Index

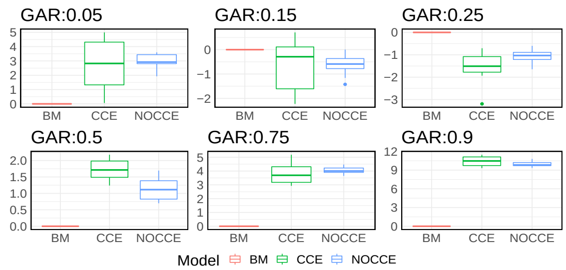


(g) National Financial Conditions Index

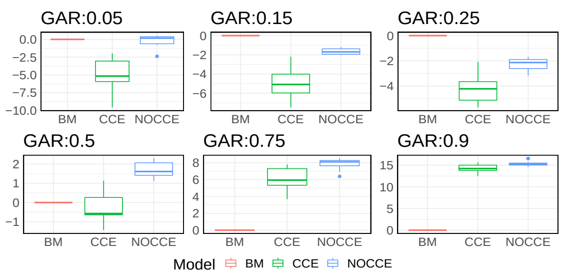
Figure 24: Dynamic Quantile Test - Augmented with lags of Real GDP



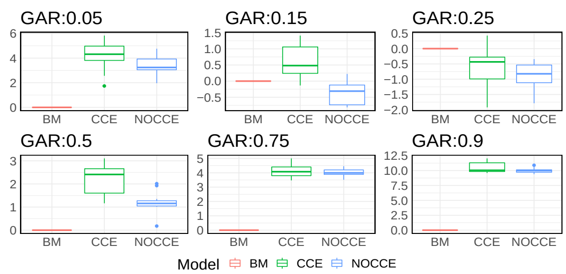
(a) Credit to GDP Growth



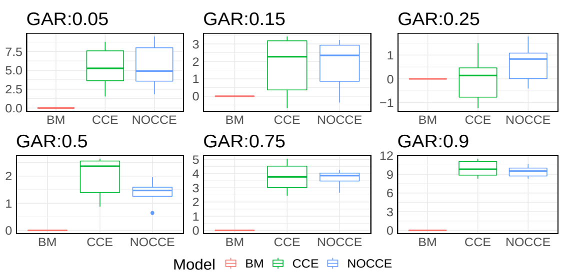
(b) Credit Gap



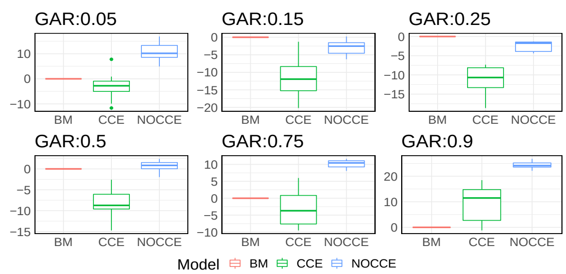
(c) Economic and Political Uncertainty



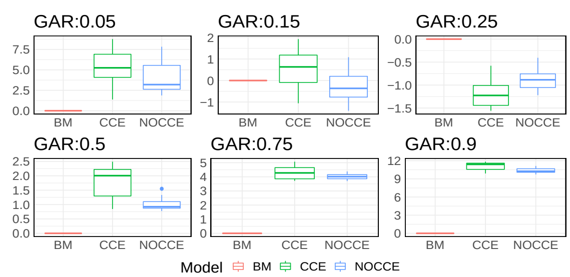
(d) House Prices



(e) Term Spread



(f) World Uncertainty Index

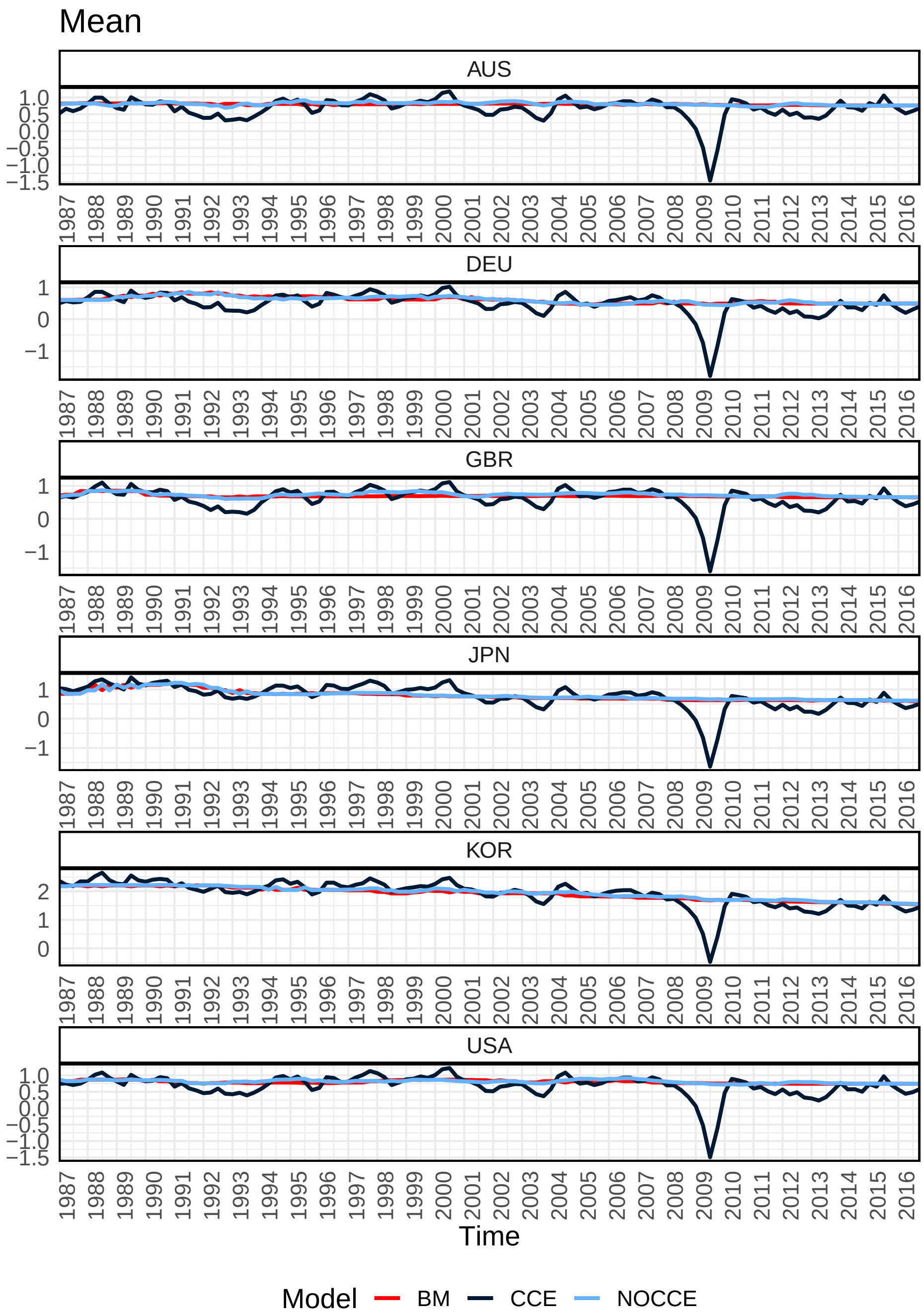


(g) National Financial Conditions Index

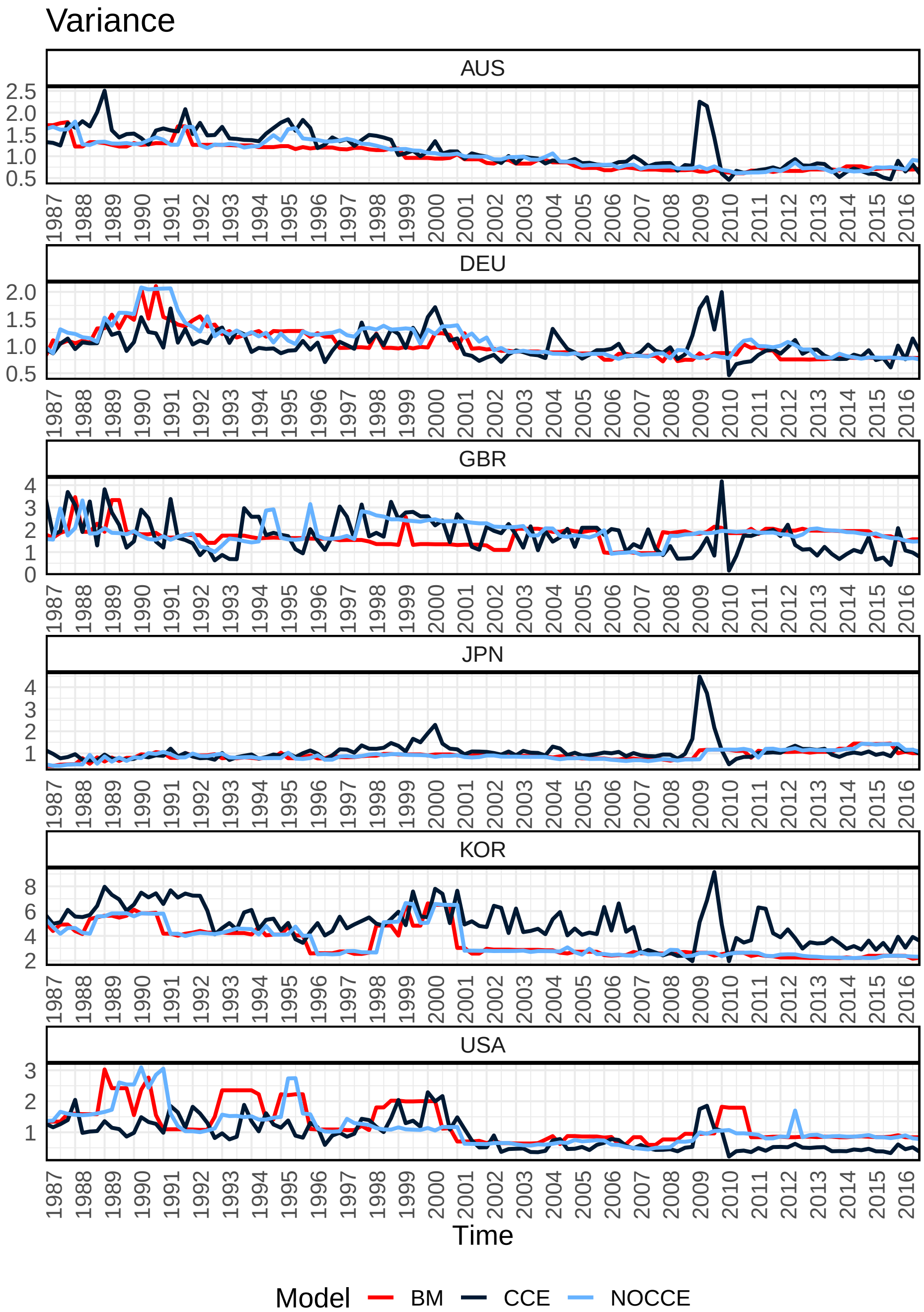
Figure 25: tick-loss

C Estimated Moments

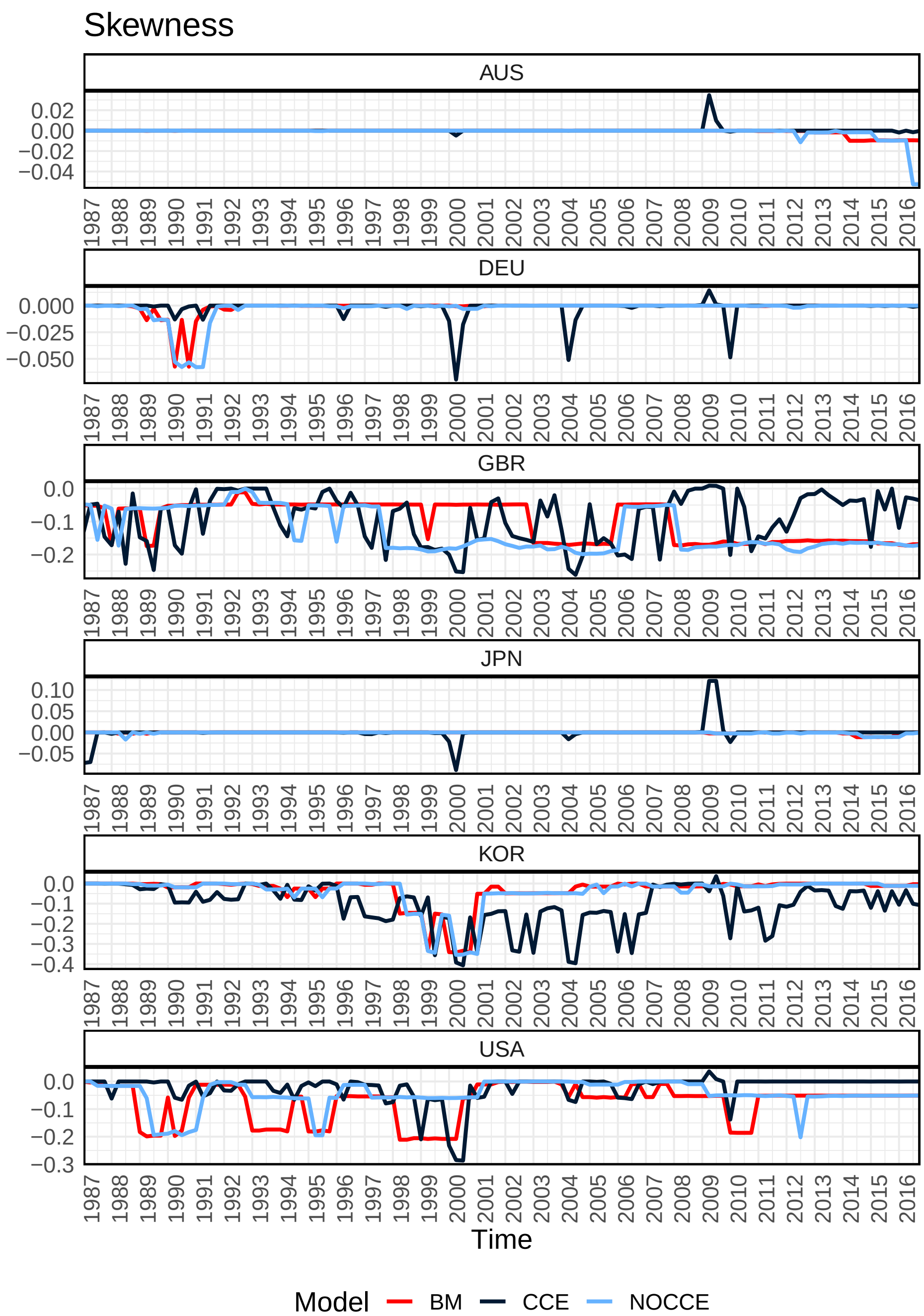
C.1 term Spreads; Forecast Horizon = 12 quarters



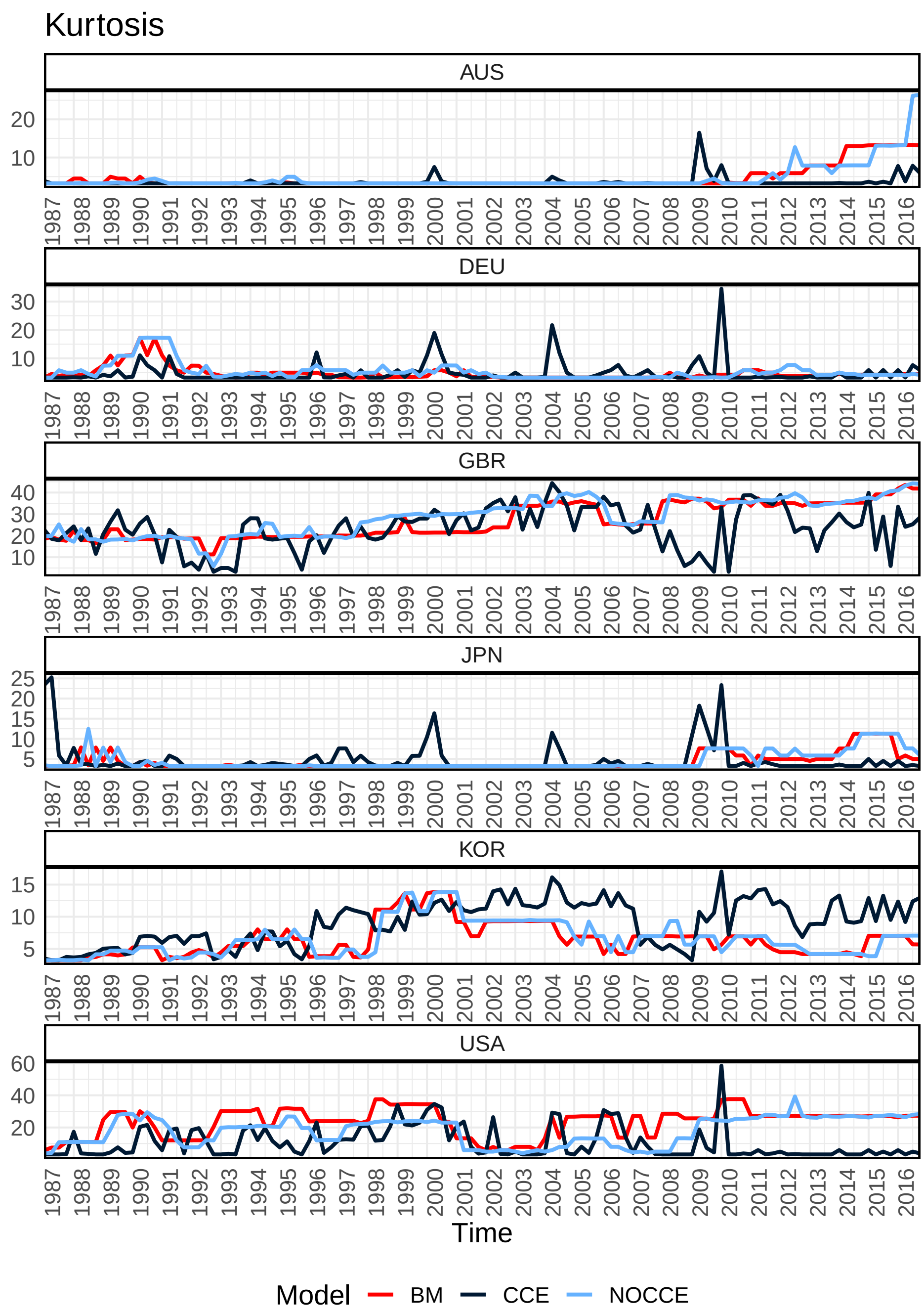
(a) Mean, conditional on term Spreads



(b) Variance, conditional on term Spreads

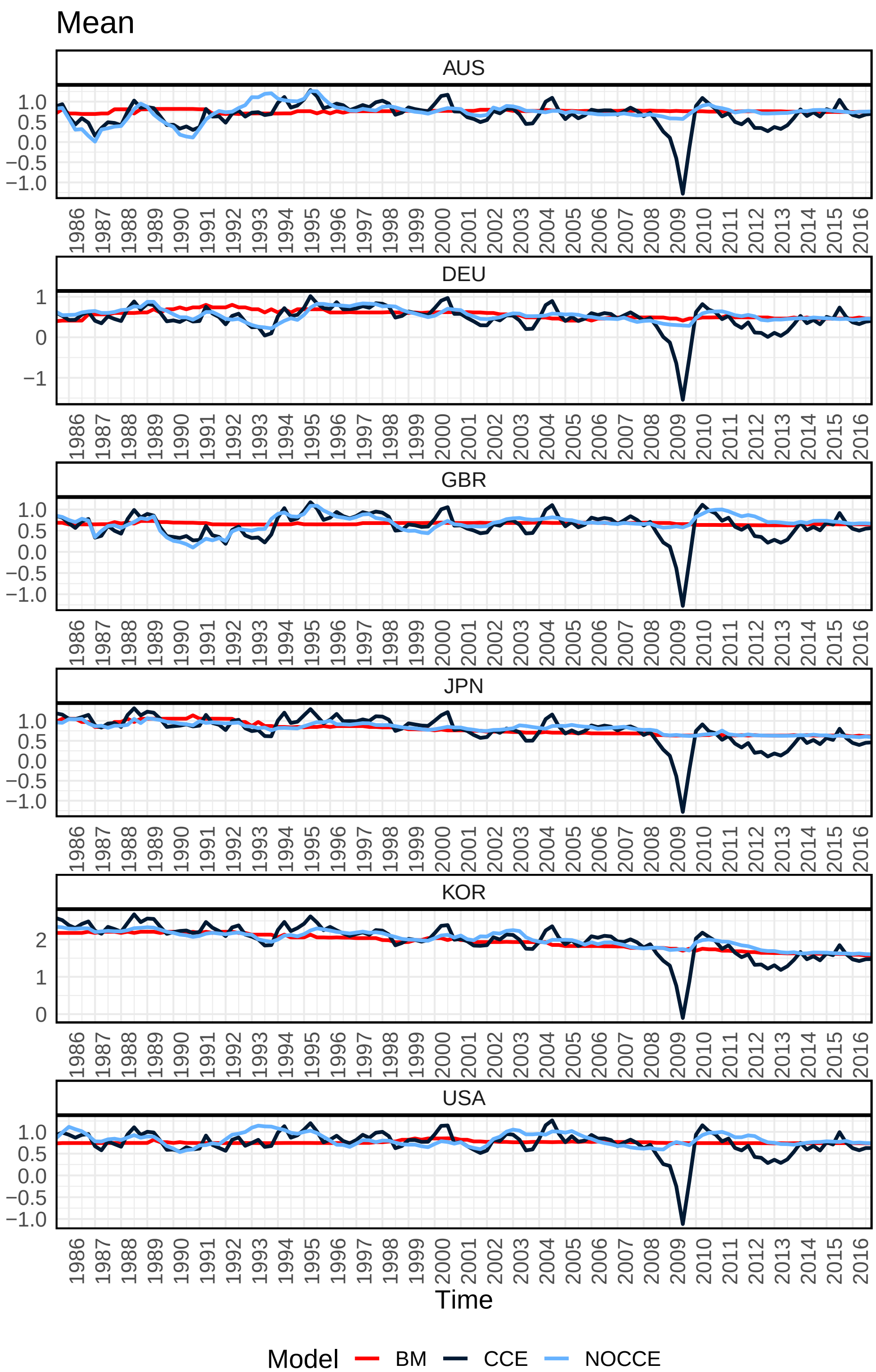


(c) Skewness, conditional on term Spreads

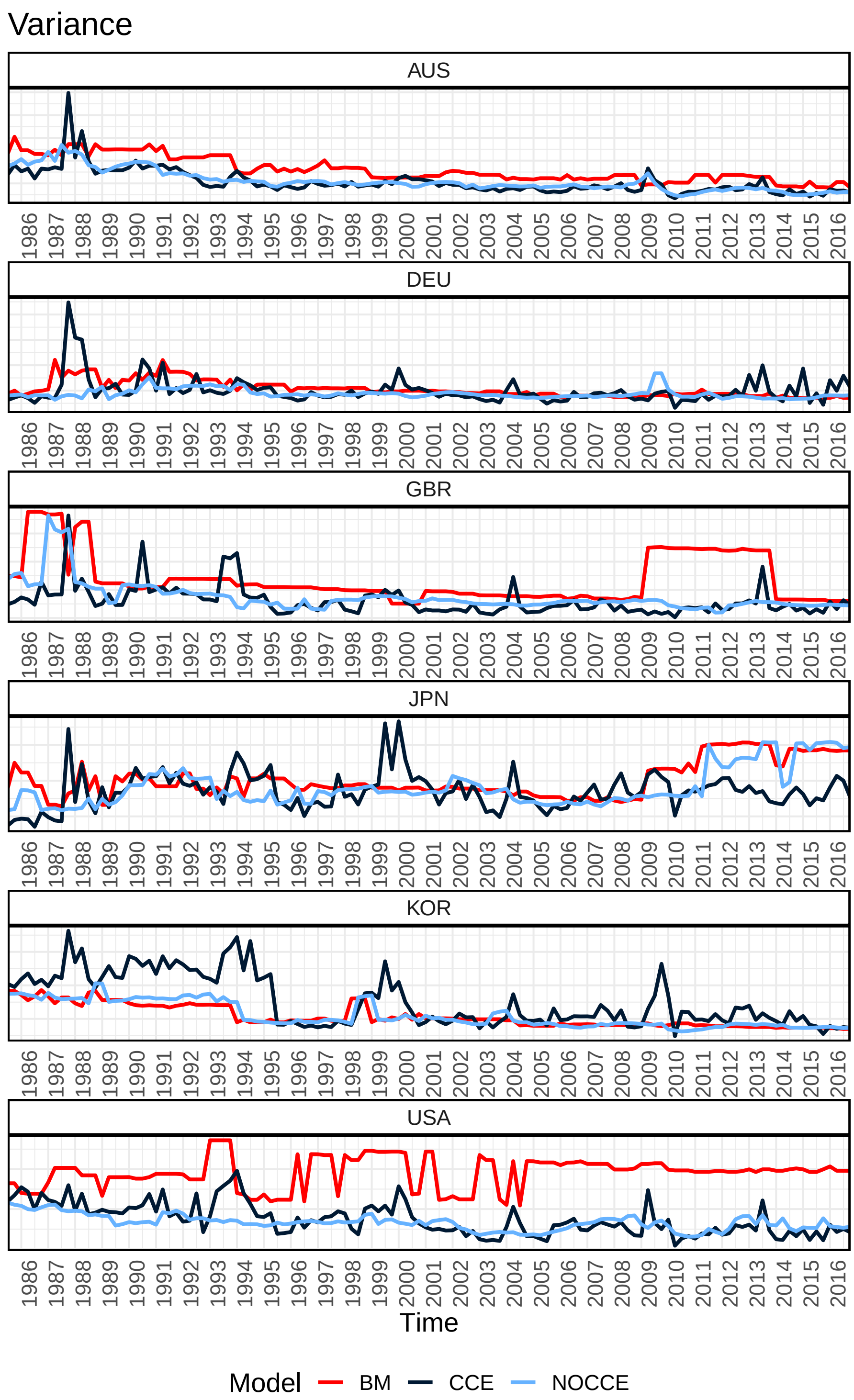


(d) Kurtosis, conditional on term Spreads

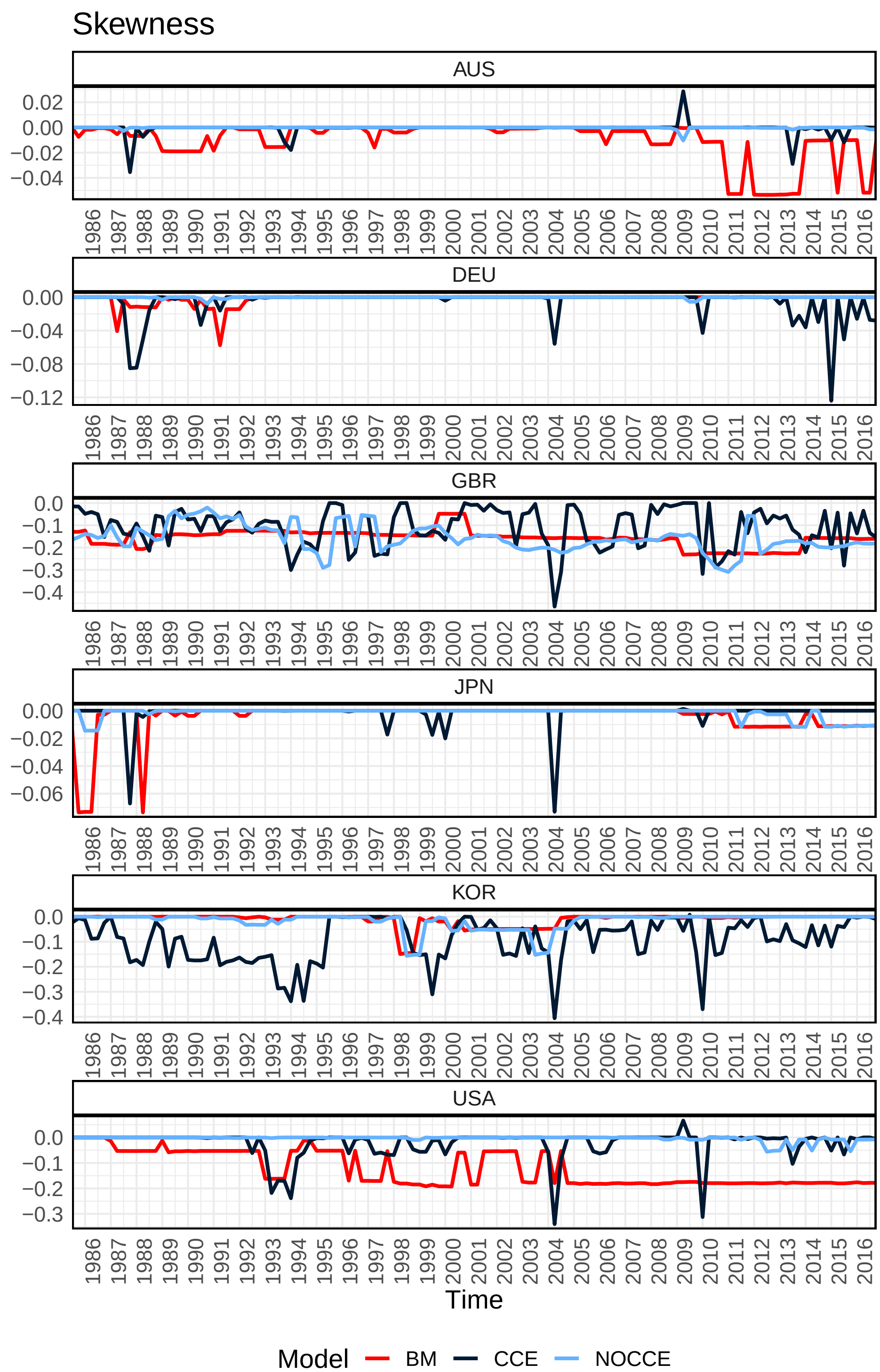
C.2 Term Spreads; Forecast Horizon = 4 quarters



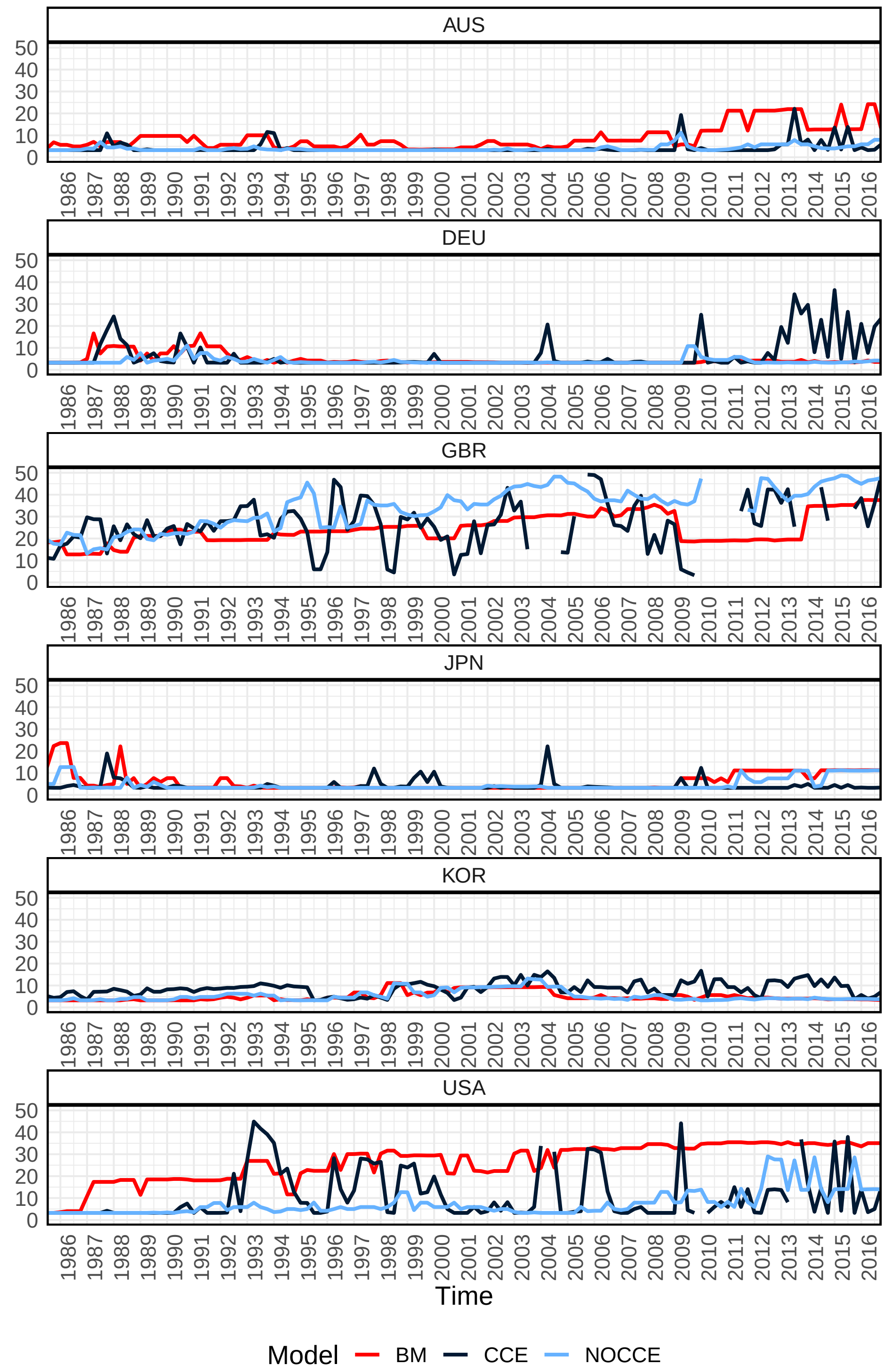
(a) Mean, conditional on term Spreads



(b) Variance, conditional on term Spreads

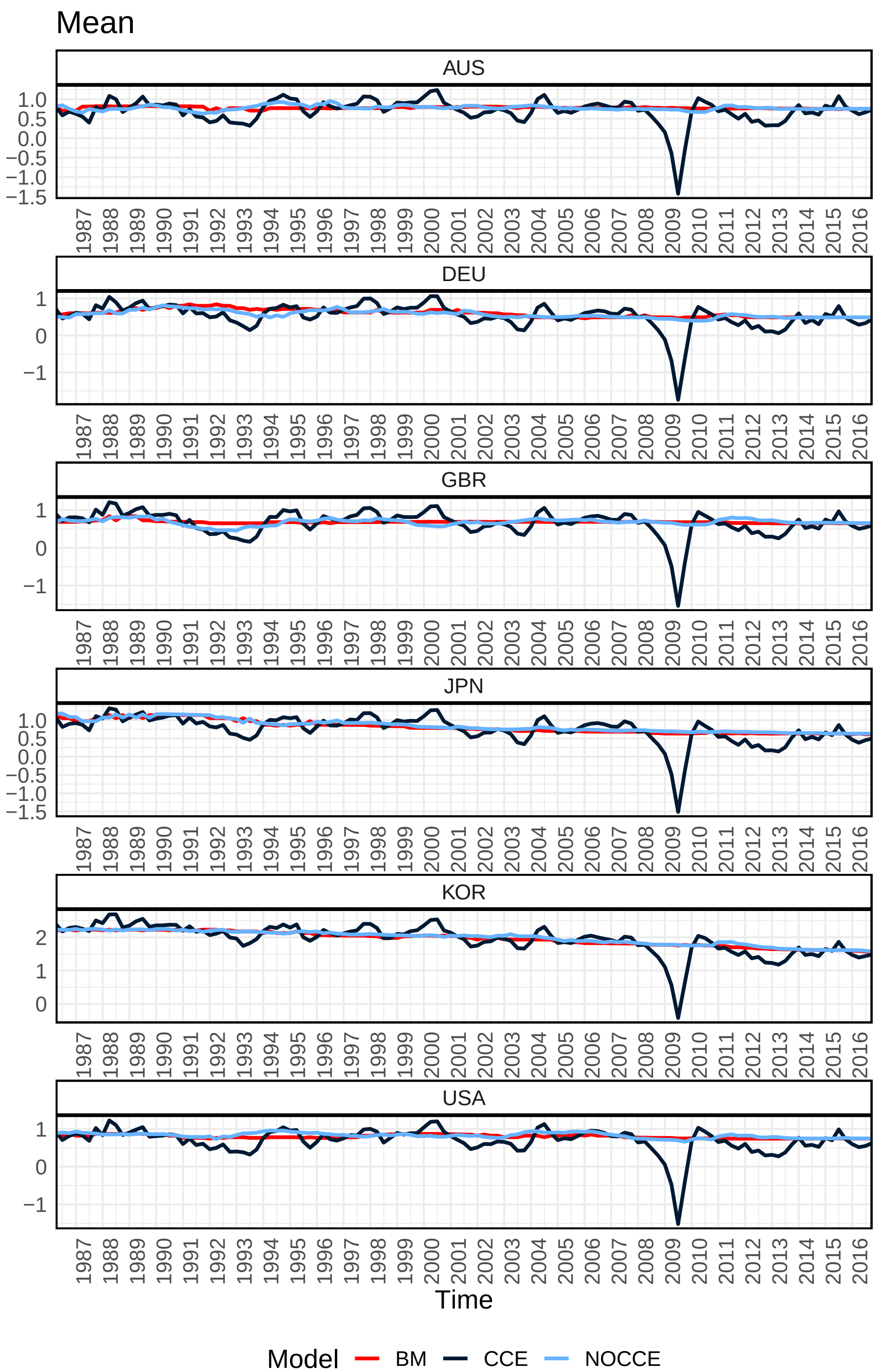


(c) Skewness, conditional on term Spreads

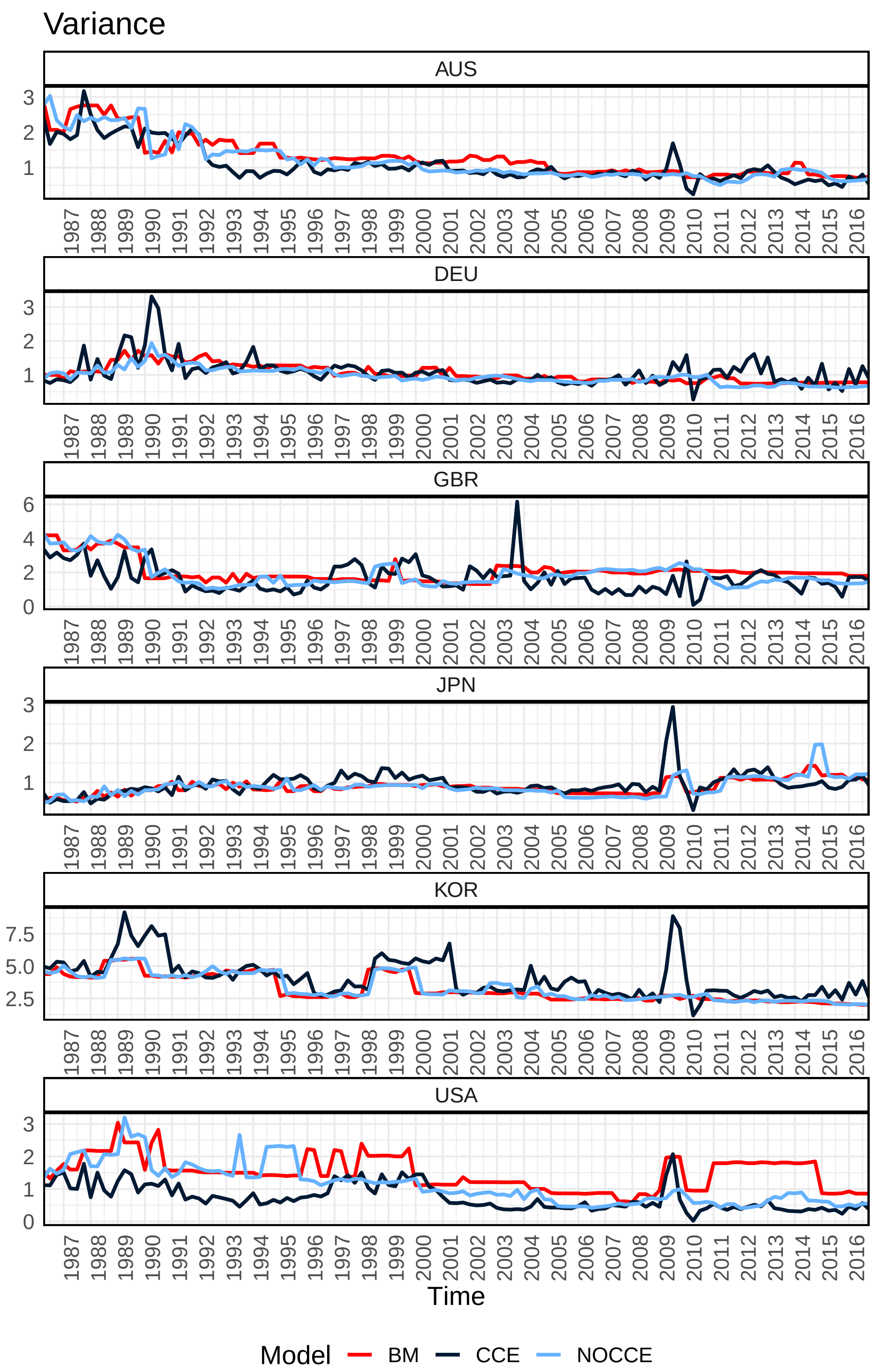


(d) Kurtosis, conditional on term Spreads

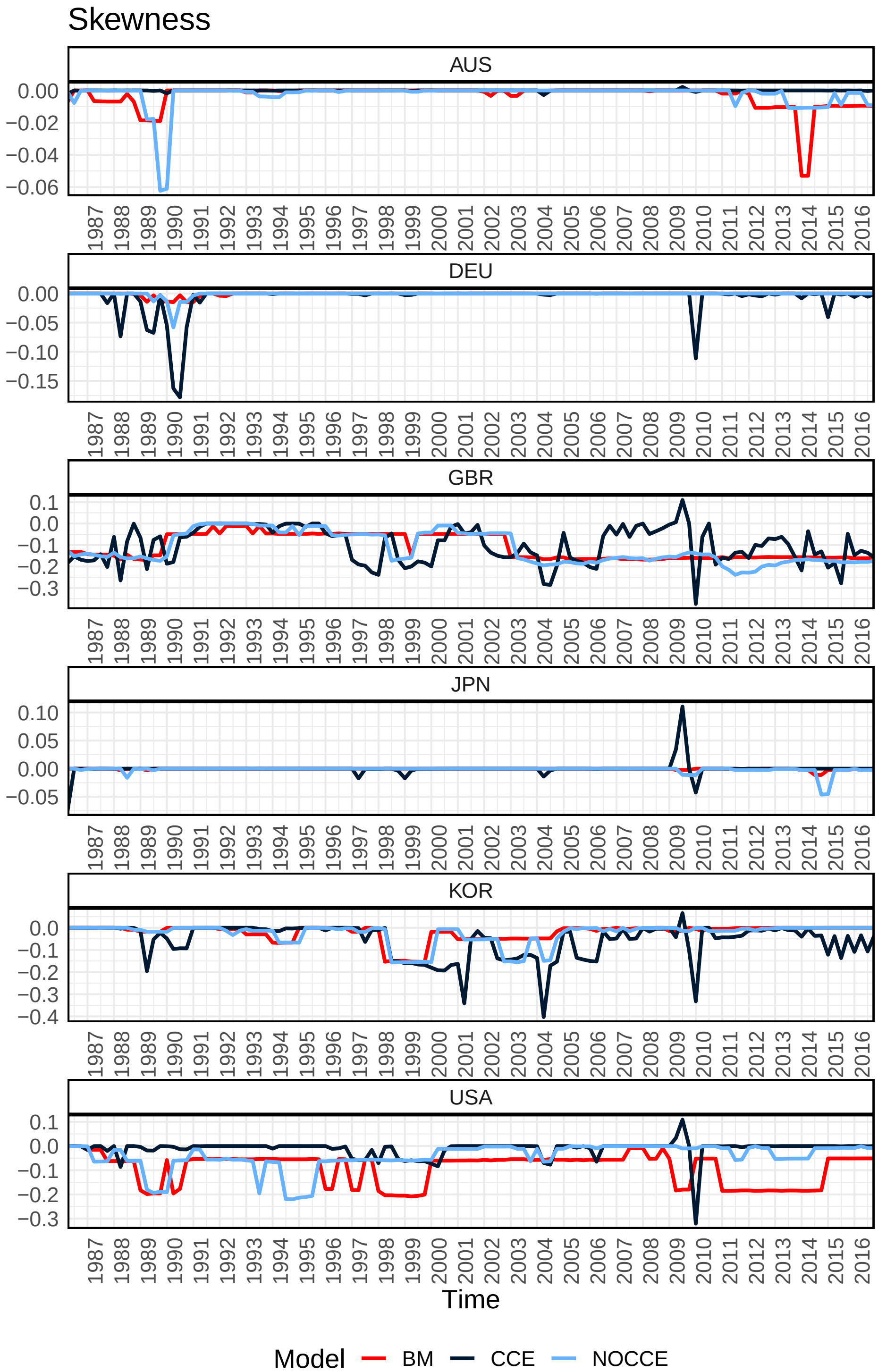
C.3 term Spreads; Forecast Horizon = 8 quarters



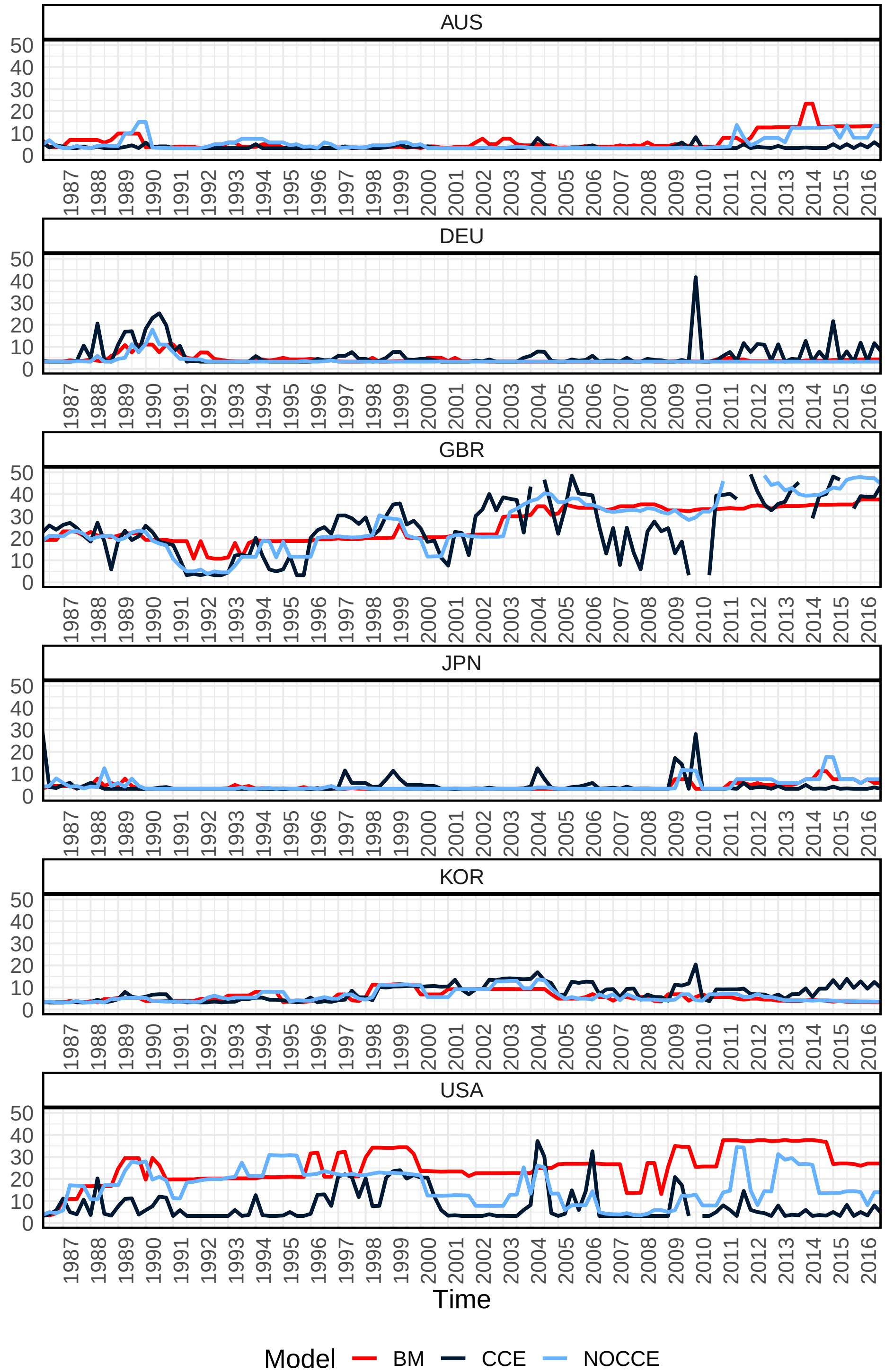
(a) Mean, conditional on term Spreads



(b) Variance, conditional on term Spreads

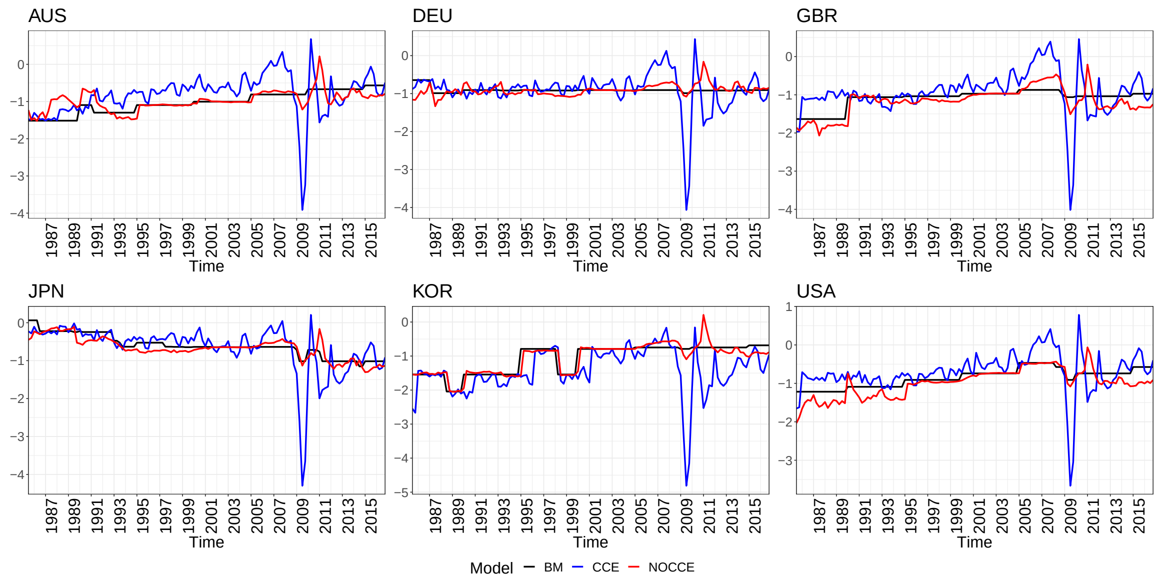


(c) Skewness, conditional on term Spreads

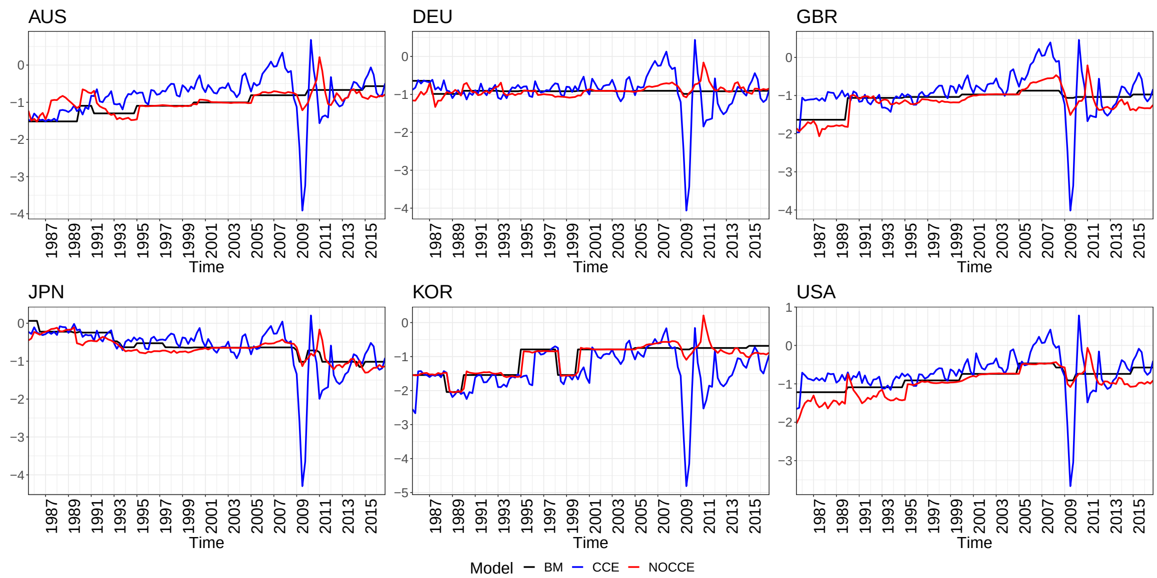


(d) Kurtosis, conditional on term Spreads

D Estimated GaR



(a) 4 quarter horizon

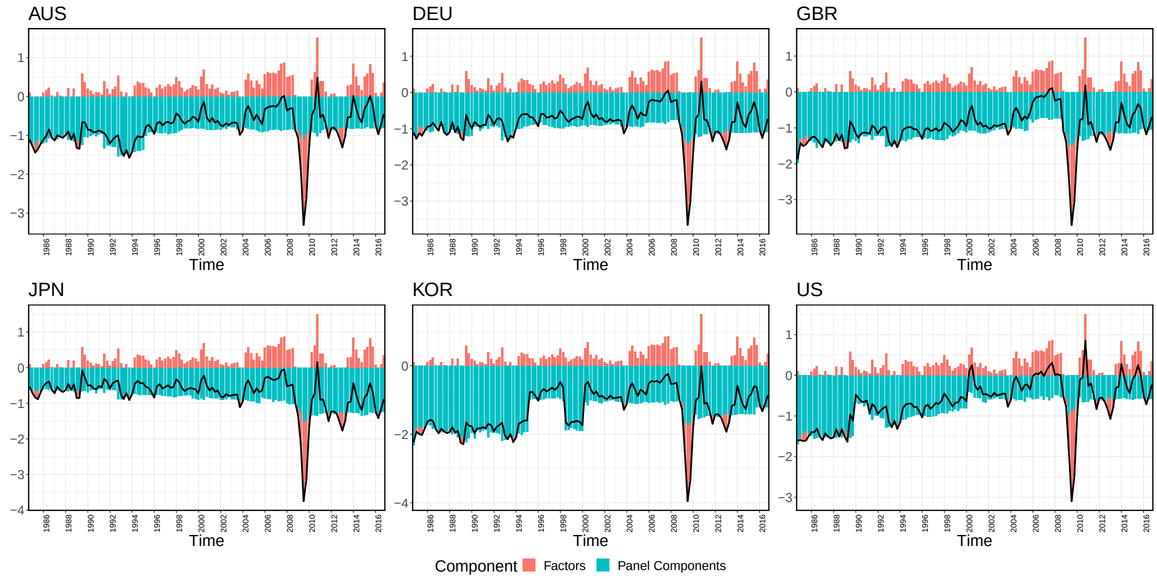


(b) 8 quarter horizon

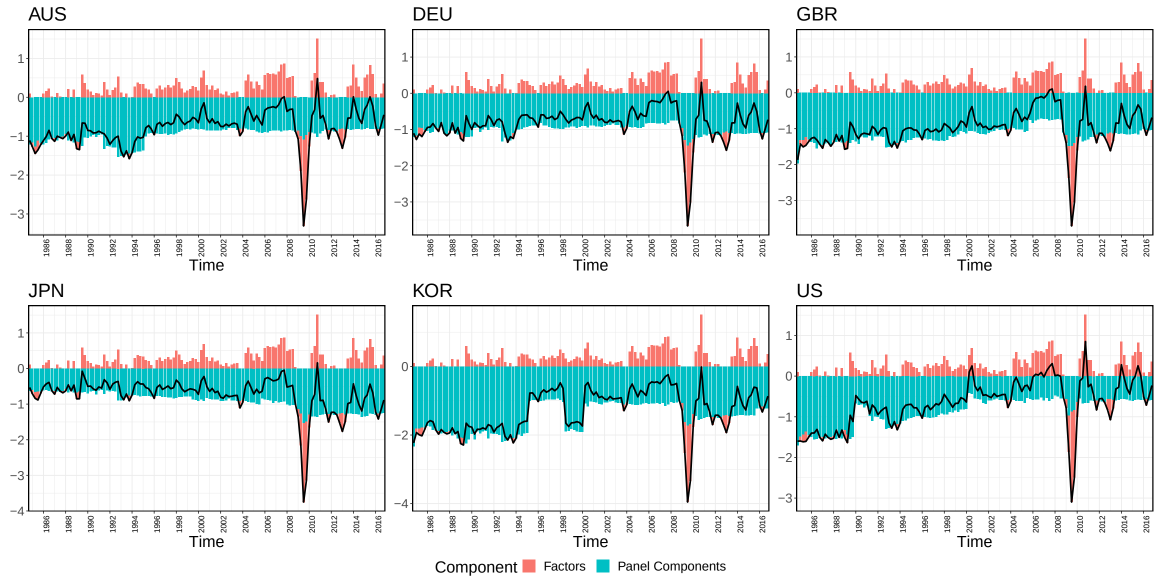
Figure 29: Estimated GaR (5 per cent) at different horizons, predictor - NFCI

Notes: Missing points indicate very high values. Forecast Horizon = 8 quarters

E Forecast Decomposition - Different Horizons



(a) Horizon = 4 Quarters



(b) Horizon = 8 Quarters

Figure 30: Decomposition of Predicted GaR (5 per cent) - Predictor: NFCI

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