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Measuring Forecast Uncertainty of Corporate Bond Spreads by Bonferroni-Type Prediction Bands

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Abstract

The recent financial crisis has seen huge swings in corporate bond spreads. It is analyzed what quality VAR-based forecasts would have had prior and during the crisis period. Given that forecasts of the mean of interest rates or financial market prices are subject to large uncertainty independent of the class of models used, major emphasis is put on the quality of measures of forecast uncertainty. The VAR considered is based on a model first suggested in the literature in 2005. In a rolling window analysis, both the model's forecasts and joint prediction bands are calculated making use of recently proposed methods. Besides a traditional analysis of the forecast quality, the performance of the proposed prediction bands is assessed. It is shown that the actual coverage of joint prediction bands is superior to the coverage of naïve prediction bands constructed pointwise.

Keywords: forecasts, corporate bond spreads, prediction bands

JEL Classification: C32, C53, G12

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1 Introduction

Corporate bond spreads are considered as a relevant indicator of financing conditions of firms and, consequently, both as an indicator of financial market stress and as a leading indicator of economic activity. Thus, it is not surprising that a substantial literature was developed with regard to modeling and forecasting corporate bond spreads. A recent survey of this literature can be found in Fischer (2014). It has been found that approaches based on classical option pricing theory are not able to provide a satisfactory explanation of corporate bond spreads, giving rise to the so-called "corporate bond spread puzzle". Therefore, additional factors including macroeconomic indicators have been considered in a reduced-form modeling approach in order to improve fit and forecast performance of univariate models for corporate bond spreads. Multivariate approaches, in particular VAR models, however, have not been used often in this context.

Nevertheless, in Bundesbank (2005, pp. 141–150) a VAR model was introduced to study determinants of corporate bond spreads, which are considered to be a relevant indicator of financial market conditions. The analysis concentrated mainly on impulse response functions indicating which factors influence corporate bond spreads with a specific focus on the effect of changes in short-run money market rates. However, as any other VAR-model, this model can also be used in a straightforward way to forecast corporate bond spreads. Estimating the model with vintage data up to 2007, we found in previous research that the predicted corporate bond spreads increased substantially just before the financial crisis. Thus, it might be of interest to study the forecast performance of this model in more detail. To this end, we conduct a rolling-window multi-step forecasting exercise over a period of ten years and present the results.

Given that forecasts of corporate bond spreads, like many other financial market indicators, are subject to a large amount of uncertainty, we put special emphasis on the assessment of the uncertainty surrounding the forecast paths generated from the model for several months ahead. To this end, we apply bootstrapped prediction bands. Besides classical point-wise prediction bands, we also consider some of the alternative bands recently suggested by Staszewska-Bystrova and Winker (2013) and Lütkepohl *et al.* (2014a) in order to assess which of the methods provides the most accurate information about the prediction uncertainty. An alternative approach to the forecasting exercise performed in this paper would be to use Bayesian methods described, e.g., by Carriero *et al.* (2013) or Waggoner and Zha (1999), and the corresponding measures of path forecast uncertainty (see, e.g., Demetrescu and Wang (2014)).

The paper is organized as follows. First, in Section 2 we present the original model, some adjustments made, and the relevant data. Section 3 describes the construction of joint prediction bands as a measure of the uncertainty of the model-based forecasts. The results of a rolling window forecast analysis covering the period from 2004 to

January 2014 are provided in Section 4. A summary and an outlook for future research are given in Section 5.

2 VAR model and data

The analysis is based on the VAR model introduced in Bundesbank (2005, pp. 141ff). We will shortly present the model and the motivation for the variables included in the reduced-form VAR. Furthermore, some modifications of the original model are described which are partially due to data availability. The data used for the empirical analysis are also introduced.

Although the theoretical background of models for corporate bond spreads is discussed in some detail in Bundesbank (2005, pp. 141ff), the empirical modeling follows a more agnostic procedure. Such a procedure appears adequate given the conflicting results both with regard to theoretical modeling and empirical results. Taking into account arguments from both option price theory and macroeconomic portfolio theory, the authors suggest to include further variables besides the corporate bond spreads and a short-run money market rate as a monetary policy related indicator. In particular, factors such as the sustainability of corporate debt, growth prospects, the volatility of firm value, and the relative volume of corporate bonds to total bond emissions should be taken into account.

Table 4 in the appendix provides an overview of the variables used in the analysis. While the original paper considered option adjusted spreads for Euro area corporate bonds with AAA and BBB rating and a time to maturity of 7 to 10 years, our analysis focuses on bonds with a time to maturity of 5 to 7 years only. This is due to the fact that for the most recent period after the financial crisis, a shrinking number of long-run corporate bond spreads outstanding no longer allows the calculation of an index of option-adjusted spreads with maturities longer than 7 years. Data are obtained from the Bank of America/Merrill Lynch global index system (see `http://www.mlindex.ml.com/gispublic/default.asp`). These series will be denoted by `aaa` and `bbb`, respectively.

All other series used for the analysis are obtained from Datastream. The short-term interest rate is given by the 3-month Euribor. It is considered both as a measure of monetary policy and of conditions on the interbank market in the short run and will be denoted as `r3m`. Expectations about business cycle conditions and asset prices, which are considered to be alternatives to corporate bonds, are reflected by the growth rate of the Dow Jones Stoxx 50. The original paper used the annual growth rate of this indicator. Given that this might result in the underestimation of standard errors due to the overlap of the monthly values in a VAR setting, we prefer to use the monthly growth rate instead, which is labeled as `d_dj50`. Uncertainty about the firms' value might have a positive impact on the corporate bond spreads. It is approximated by the logarithm of the implied volatility of the Dow Jones Stoxx 50, which is denoted by `lvola`. A measure of the medium to long term financial market conditions is provided by the spread between interest rates on 2- and 10-year government bonds, denoted by `slope`, which is based on German government bonds to exclude the effects of the Euro crisis after 2010.

We do not consider two further variables proposed in Bundesbank (2005, pp. 141ff), namely the relation of gross emissions of European non-financial corporate bonds to those of government bonds and the relation between the sum of credits and bonds outstanding for the corporate sector to its average profit growth. These exclusions are due both to a limited availability of these data and to the intention to reduce the dimension of our VAR-model. In fact, adding variables with only small impact on the corporate bond spreads might help to improve the forecasting performance of the model, but at the same time increases the estimated standard errors. As our main goal is to assess the uncertainty of such forecasts with the use of joint prediction bands, we select a VAR-model with only the six variables indicated. We also do not include dummy variables as has been done in the original paper for the time period 2001 to 2002. While this might be beneficial for the approximation quality and explanatory power of the model in sample, it might be less adequate for the kind of out of sample forecasting analysis we conduct.

The analysis will be done at monthly frequency using the end of month observations of all indicators. The data are available from January 1999 to January 2014. Figure 1 exhibits the data used for the further analysis.

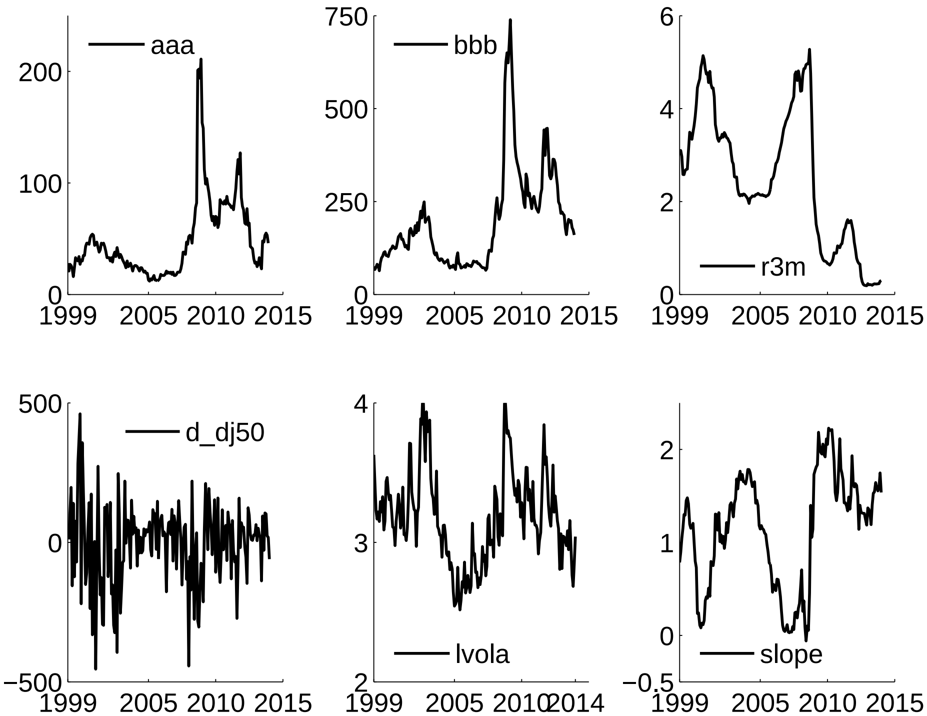
For $\mathbf{y}_t$ denoting the vector of the six variables `aaa`, `bbb`, `r3m`, `d_dj5`, `lvola`, and `slope` at time t, the VAR-model is given by

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + \ldots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t\,, \tag{1}$$

where $\mathbf{c}$ stands for a vector of equation specific constants, $\mathbf{A}_1, \ldots, \mathbf{A}_p$ are the coefficient matrices for the lagged endogenous variables and $\mathbf{u}_t$ represents the vector of error terms at time t. While the quality of the estimation by means of ordinary least squares depends on whether certain assumptions about the (joint) distribution of the error terms (including also the issues of stationarity of the variables or co-integration) are satisfied, the evaluation of the model's forecasting performance based on these estimates does not. In fact, it might be expected that deviations from the assumptions worsen the properties of the estimators and, consequently, also forecasts. Thus, the forecast analysis might be considered as the test of joint hypotheses regarding the underlying reduced form economic model and the quality of the estimation of the reduced form econometric model.

A final step of the model specification, which might be important for the forecasting performance, is the choice of the lag length p. Using longer lag orders, allows the model to better adjust to complex higher order dynamics. However, at the same time, the number of irrelevant coefficients might increase, resulting in higher standard errors. Typically, this trade-off is dealt with by using information criteria for the lag length selection. We follow Staszewska-Bystrova and Winker (2013) and Lütkepohl *et al.* (2014a) by using an information criterion for lag length selection in each step of

Figure 1: Time series from January 1999 to January 2014



the forecasting analysis. A more refined lag length selection procedure, allowing for alternative lag orders for different equations or even for imposing zero constraints on all elements of the **A** matrices separately, might result in improved forecasts (Savin and Winker 2013), but is not considered here due to its high computational complexity and the difficulty to deal with the zero constraints in the calculation of prediction bands.

3 Joint prediction bands

To measure uncertainty associated with paths of forecasts joint prediction bands based on bootstrap predictive distributions are employed. The inference is done with respect to forecast paths of individual variables and so "joint" refers to the combined treatment of forecasts derived for a given variable for a number of consecutive periods. It would be also possible to construct prediction bands, which enable joint inference with respect to forecast paths of a number of variables (see e.g. Lütkepohl *et al.* (2014b)), but this approach is not used here as the focus is on the corporate bond spreads. The bands are expected to cover the actual trajectory with probability given by or not smaller than the nominal coverage rate, denoted by $1-\gamma$ for a predefined value of γ. The bands are referred to as conservative if their actual coverage exceeds the nominal level.

Several types of bands which can be used for making joint inferences have been proposed in the literature and applied in the areas of forecasting and impulse response analysis based on VARs (see e.g. Inoue and Kilian (2014), Lütkepohl *et al.* (2014b), Staszewska-Bystrova (2013), Wolf and Wunderli (2012)). Given the relative performance of alternative methods found in simulation studies, two methods of constructing joint bands described by Lütkepohl *et al.* (2014a) are selected for the application in this paper: the Bonferroni method and an adjusted Bonferroni method. The assessment of the measure of forecast uncertainty provided by these bands is compared to that provided by the so-called naïve band which does not make use of the joint predictive distribution. The naïve band is given by the collection of $(1-\gamma)\times 100\%$ bootstrap prediction intervals for each individual forecast horizon. In effect, not much is known about the coverage probability of this commonly used band, apart from that it can be substantially smaller than $1-\gamma$ (see e.g. Staszewska-Bystrova (2011)).

All bands are obtained using the residual-based bootstrap procedure implemented as in Staszewska-Bystrova (2011) with the bias-correction of the predictors based on the formula provided by Nicholls and Pope (1988). In the procedure $B = 5\,000$ bootstrap replicates of future trajectories with H elements are generated.

Then, the $(1-\gamma)\times 100\%$ Bonferroni band is given by a set of individual prediction intervals for each horizon i with nominal coverage rates of $(1-\gamma/H)\times 100\%$:

$$[s(1)_{\gamma/2H}, s(1)_{1-\gamma/2H}] \times \ldots \times [s(H)_{\gamma/2H}, s(H)_{1-\gamma/2H}]\,,$$

where $s(i)_{\gamma/2H}$ and $s(i)_{1-\gamma/2H}$ for $i = 1,\ldots,H$ are respectively $\gamma/2H$ and $1-\gamma/2H$ quantiles of the bootstrap predictive distribution at horizon i. By construction, the band contains at least $(1-\gamma)B$ bootstrap replicates of future trajectories and has an expected coverage probability greater or equal to $1-\gamma$.

The idea behind an adjusted Bonferroni method is to modify the Bonferroni band in such a way that it would cover exactly $(1-\gamma)B$ bootstrap replicates of future trajectories. The motivation is to adjust the coverage probability of the band towards the nominal value of $1-\gamma$. The width of the band is also reduced in the process rendering it less conservative than the original Bonferroni band.

As a benchmark, the naïve band is computed as:

$$[s(1)_{\gamma/2}, s(1)_{1-\gamma/2}] \times \ldots \times [s(H)_{\gamma/2}, s(H)_{1-\gamma/2}]\,,$$

where $s(i)_{\gamma/2}$ and $s(i)_{1-\gamma/2}$ for $i = 1,\ldots,H$ are end points of the $(1-\gamma)\times 100\%$ percentile prediction intervals.

While previous studies have analyzed the relative performance of these methods in Monte Carlo simulations, the focus of the present study is on their merits in a real application. In this settings, several properties of the model, cannot be easily controlled for. Nevertheless, the performance of forecast bands is crucial for an appropriate assessment of financial risks related to corporate bond spreads. Thus, our main focus in the following rolling window analysis is on the coverage rates of the bands with respect to the actual trajectories.

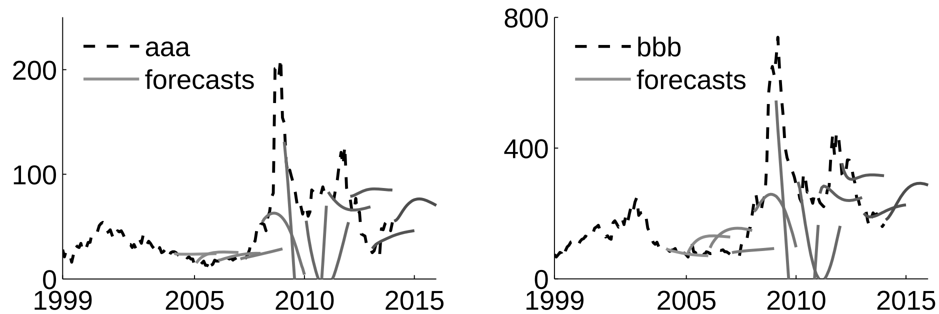
4 Results of rolling window analysis

The performance of alternative measures of prediction uncertainty for forecast paths is analyzed using a rolling window analysis. We consider a fixed window length of 48 monthly observations starting with the sample January 2000 to December 2003. For a given sample, the lag length of the VAR is identified using the Bayesian information criterion (Schwarz 1978) and the model is estimated for this lag order. We impose a maximum lag order of 4 resulting in VAR models with one lag for all but three subsamples falling in the crisis period 2008 – 2010. Applying the AIC results in including more lags for some subsamples, but otherwise provides qualitatively similar results which are not reported but available on request. Based on the resulting estimates, iterative forecasts conditional only on observations up to December 2003 are calculated for the next 12 and 24 months, respectively. Next, the sample is shifted in each step of the recursive analysis by one month until it covers the observations from February 2010 to January 2014. Obviously, the forecasts made employing the last windows cannot be compared with actual data (yet). Therefore, the last forecast path constructed for the horizon of 12 months used in the evaluations is the one for the period from February 2013 to January 2014 based on observations up to January 2013. The last path for 24 months contains forecasts for the period from February 2012 to January 2014, based on observations up to January 2012.

Figure 2 shows the forecast paths for the spreads `aaa` and `bbb` resulting from this exercise for the 24 months horizon starting always in January of a year, i.e. based on observations up to December of the previous year. Of course, all other prediction paths are also calculated and will be considered in the evaluation, but are not included in the graph in order not to overload it. The dashed lines represent the actual values of the spreads.

It becomes obvious from the plots that the quality of the path forecasts is quite heterogenous. While those forecasts starting up to 2007 and again from 2011 exhibit at least some qualitative resemblance to the actual development of the corporate bond spreads, the forecast paths calculated for the phase of exploding corporate bond spreads during the financial crisis deviate drastically from the actual values. Before evaluating the performance of these forecasts in some more detail, it should be stressed that the central focus of our study is the construction and evaluation of prediction bands constructed for a given forecast horizon. Hence, independently of the actual forecasting performance of the models, we are mainly interested in the measures of forecast uncertainty, i.e., to see to what extent the increasing uncertainty

Figure 2: Actual spreads and forecast paths for `aaa` and `bbb`



about the actual development of corporate bond spreads during the crisis period is reflected in prediction bands obtained by different methods.

Forecast Evaluation

Nevertheless, before coming back to prediction bands and their evaluation, we start with a more traditional analysis of the forecast performance. We consider both forecasts made for individual horizons and full forecast paths as depicted in Figure 2. As measures of forecasting performance, we consider the root mean squared error (RMSE) and Theils' U, i.e., the relative RMSE as compared to that of a naïve benchmark, namely the random walk forecast assuming that the corporate bond spreads stay constant over the forecast horizon. Given the obvious impact of the financial market crisis, we perform this analysis separately for three subsamples: 2004.1–2007.12, 2008.1–2010.12 and 2011.1–2014.1.

Table 1 summarizes some results for different fixed forecast horizons and both corporate bond spreads. It has to be kept in mind that the forecasts are based on an estimation window of length 48 months. Thus, e.g., a forecast with a horizon of 24 months for January 2010 is based on data up to January 2008. Consequently, splitting up of the evaluation period does not completely eliminate the subsample heterogeneity. Furthermore, given that the first forecasts are made based on the data up to December 2003, 48 forecast errors are observed for the first subsample and a horizon of 1 month, while this number decreases to 25 for the 24 months forecast horizon.

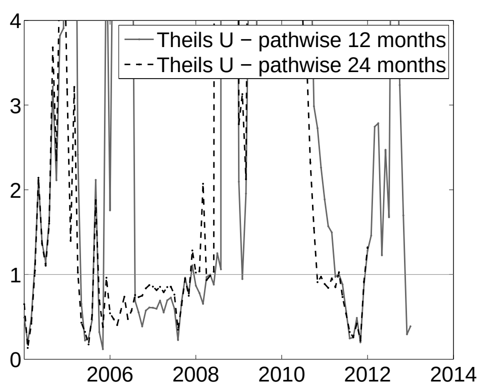
First, values of Theils' U smaller than one indicate that the simple VAR models seem to exhibit some forecasting power for `aaa` and longer horizons for the period prior to the financial market crisis, and both for `aaa` and `bbb` for some horizons after 2011. This is rather surprising given that spread forecasts might be used for financial market arbitrage. Furthermore, it becomes obvious that the forecasting errors are always larger for the high risk spread `bbb`. This applies not only to the RMSE of the VAR model, but also to the RMSE of the random walk benchmark. Finally, the

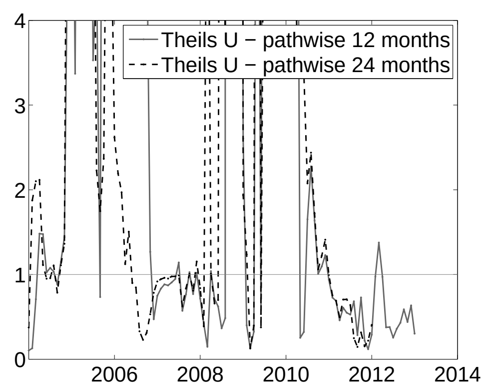
Table 1: Forecast evaluation for aaa and bbb

Forecasts for aaa						
	2004.1 – 2007.12		2008.1 – 2010.12		2011.1 – 2014.1	
Horizon	RMSE	Theils' U	RMSE	Theils' U	RMSE	Theils' U
1 month	3.29	1.113	44.28	1.835	11.36	1.003
2 months	4.63	1.099	112.60	3.262	14.11	0.968
3 months	5.46	1.066	258.04	5.786	18.46	0.987
6 months	8.69	1.050	$2.78 \cdot 10^3$	42.327	28.32	1.048
12 months	9.90	0.952	$2.86 \cdot 10^5$	$3.53 \cdot 10^3$	45.68	1.260
18 months	7.77	0.690	$2.94 \cdot 10^7$	$3.37 \cdot 10^5$	54.17	1.295
24 months	12.43	0.933	$3.01 \cdot 10^9$	$3.41 \cdot 10^7$	110.68	2.518
Forecasts for bbb						
	2004.1 – 2007.12		2008.1 – 2010.12		2011.1 – 2014.1	
Horizon	RMSE	Theils' U	RMSE	Theils' U	RMSE	Theils' U
1 month	14.69	1.348	53.42	0.937	33.13	0.971
2 months	23.18	1.416	138.35	1.408	47.42	0.906
3 months	29.38	1.599	329.23	2.526	53.86	0.826
6 months	47.41	1.797	$3.81 \cdot 10^3$	18.263	64.47	0.702
12 months	58.42	2.473	$3.99 \cdot 10^5$	$1.38 \cdot 10^3$	120.15	0.973
18 months	43.02	1.738	$4.10 \cdot 10^7$	$1.24 \cdot 10^5$	182.04	1.297
24 months	38.19	1.270	$4.20 \cdot 10^9$	$1.31 \cdot 10^7$	487.19	2.526

exploding values both of RMSE and Theils' U for the crisis period clearly indicate that the model did perform disastrously for this period. Possibly, relevant variables, in particular linked to market liquidity, are missing.

Figure 3: Theils' U for 12 and 24 months forecast pathes for aaa (left) and bbb (right)





Given that our focus is on forecast paths, we switch to the performance analysis of dynamic forecasts for 12 and 24 months, respectively. In this case, the measures of (relative) forecast error can be calculated independently for each individual forecast made. Therefore, we report the results for the two spreads in form of time series in Figure 3. The figures show for each time period, the relative measure of forecast error of the VAR model as compared to the random walk for the following 12 and 24 months. All observations are censored for a value of Theils' U larger than 4. Again, the results indicate some predictability of the corporate bond spreads in the period just before the financial crisis, i.e., 2006 and 2007, and again after 2011. In this context, predictability means that the forecasts produced by the VAR models for the next 12 and 24 months, respectively, result in smaller prediction errors than relying on the random walk assumption of constant bond spreads.

4.1 Coverage of prediction bands

For each of the forecast paths with horizon 12 and 24 months, we also calculated the prediction bands according to the methods presented in Section 3 for 5 000 bootstrap replications. Table 2 shows the coverage rates for all forecast bands, i.e., the frequency that the actual path is fully contained in the prediction band calculated for a specific nominal coverage rate.

Table 2: Actual coverage of different prediction bands over the period 2004.1 – 2014.1

nominal coverage: 0.68						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
aaa	0.246	0.736	0.664	0.153	0.694	0.561
bbb	0.355	0.718	0.609	0.296	0.735	0.663
nominal coverage: 0.90						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
aaa	0.627	0.791	0.745	0.520	0.755	0.674
bbb	0.609	0.836	0.746	0.561	0.806	0.725
nominal coverage: 0.95						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
aaa	0.700	0.818	0.773	0.622	0.755	0.694
bbb	0.682	0.864	0.809	0.622	0.806	0.755

For all nominal coverage levels, the naïve method of constructing prediction bands results in a substantial underestimation of the actual uncertainty of the forecast paths. For the most extreme setting with a nominal coverage level of 0.68, only 15.3% of the actual paths of aaa over a horizon of 24 months are contained fully in the prediction band. Both Bonferroni and the adjusted Bonferroni method preform reasonably well for a nominal level of 0.68. However, the performance for higher nominal coverage rates such as 0.90 or 0.95 worsens also for these joint prediction bands. A closer look at the subperiods is provided in Table 3 for $1-\gamma = 0.95$. It is used to evaluate to what extent this weaker performance is linked to the period of the onset of the financial market crisis.

Table 3: Actual coverage for subperiods for a nominal level of 0.95

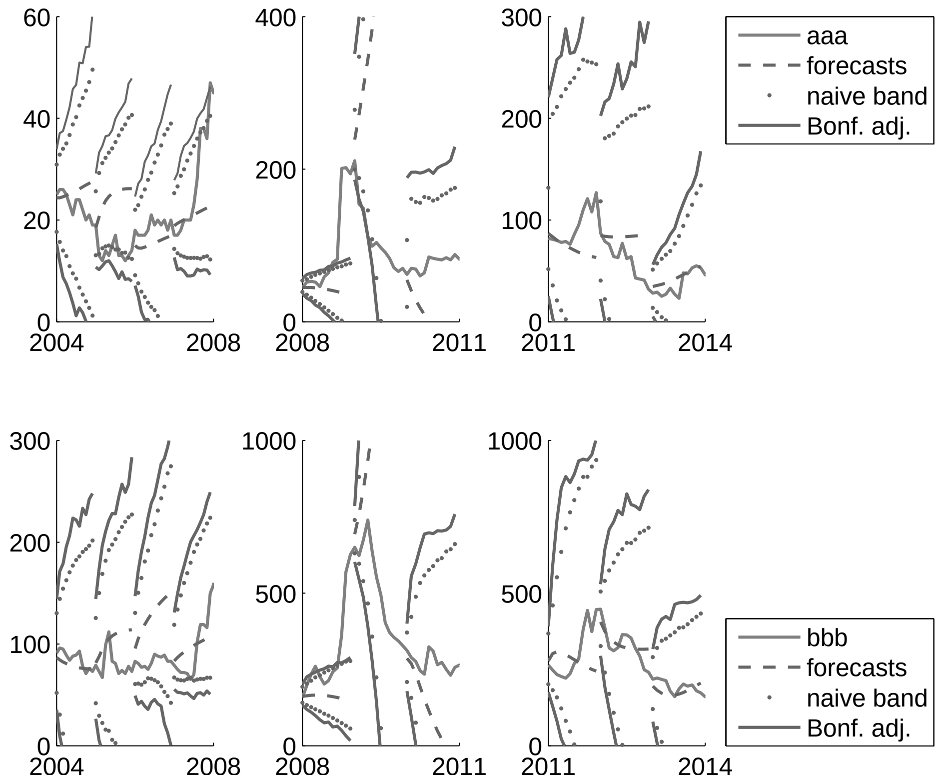
Forecast horizon: 12 months									
	naïve			Bonferroni			Bonferroni adj.		
	04–07	08–10	11-14	04–07	08–10	11-14	04–07	08–10	11-14
aaa	0.757	0.361	0.973	0.919	0.528	1	0.892	0.417	1
bbb	0.730	0.333	0.973	1	0.583	1	0.919	0.500	1
Forecast horizon: 24 months									
	naïve			Bonferroni			Bonferroni adj.		
	04–07	08–10	11-14	04–07	08–10	11-14	04–07	08–10	11-14
aaa	0.640	0.222	1	0.920	0.389	1	0.880	0.250	1
bbb	0.920	0.139	0.892	1	0.50	0.973	1	0.361	0.973

From Table 3 one might conclude that all methods perform poorly for the crisis period. However, also for this period, the Bonferroni and adjusted Bonferroni bands provide substantially better coverage of the actual paths. For the "normal" periods prior and after the crisis, the coverage of the joint bands might be considered to be satisfactory, while the naïve method underachieves also in these subintervals. Obviously, the improved performance of the joint prediction bands comes at the cost of wider bands. Tables 5 and 6 in the appendix provide the corresponding numbers. Here, the width of a band is measured by the mean of the sum of spreads between upper and lower bound divided by the forecast horizon. While the width of the Bonferroni bands is always substantially larger than that of the naïve bands, the difference becomes much less pronounced for the adjusted version. In fact, in particular during the crisis period, the adjusted Bonferroni bands become even smaller than the naïve bands, still exhibiting better coverage of actual paths. Thus, one might conclude that making use of the joint prediction bands is recommended in order to obtain a more reliable assessment of the uncertainty linked to the forecasts. In particular, the adjusted Bonferroni method seems to provide a good tradeoff between the bands' coverage and width.

Figure 4 shows exemplarily the forecasts starting in January of each year for a horizon of 12 months. It also exhibits the actual values of `aaa` and `bbb` as well as the naïve and adjusted Bonferroni prediction bands.

The figure illustrates the findings concerning the forecast performance presented in the previous subsection. In particular, for the first subperiod and – to a smaller extent – for the third, the forecasts generated by the model contain some, but only quite limited amount of information regarding the actual development. However, the uncertainty linked to these forecasts is huge as exhibited by the prediction bands. The difference between the naïve and the adjusted Bonferroni prediction bands is not very impressive. However, the example of the forecast path starting in January 2007

Figure 4: Forecasts starting in January with corresponding prediction bands (horizon: 12 months) for aaa (top) and bbb (bottom)



for aaa (upper panel, leftmost graph) shows that even a relatively small increase of band width might result in a more accurate coverage of actual realizations. And this holds true also for the crisis period when the uncertainty became extreme, but still the adjusted Bonferroni bands provide a better approximation to this uncertainty.

5 Conclusion and outlook

The analysis of a simple VAR model of corporate bond spreads led to the surprising result that for some subperiods the random walk forecast can be improved. However, it also became apparent that the forecast paths generated from VAR models are associated with a large amount of uncertainty which became striking in the financial crisis period. It is found that the construction of joint prediction bands making use of recent proposals helps to assess this uncertainty much better than the traditional

method relying on naïve prediction bands which are constructed pointwise.
The drastic failure of the model's approximation during the financial crisis period hints at possible extensions of the analysis in future research. In particular, following the suggestion by Fischer (2014), one might consider using heuristic optimization to select appropriate lag structures for the VARs estimated at each step of the rolling window analysis. It might also be a sensible idea to consider non-linear VAR models such as smooth transition VARs to take into account the non-linear reactions in a crisis period. Obviously, the methods for constructing joint prediction bands would have to be adjusted to these more flexible models. Finally, the model might be extended by factors related to the non-linear behavior in crisis periods, e.g., market liquidity or systemic market risk. The aim of a separate future analysis would be to compare measures of uncertainty of forecast paths generated along the lines presented in this contribution with those obtained by Bayesian methods.

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A Data

The definitions of the variables used in the analysis are summarized in Table 4.

Table 4: Definition and source of variables used

Variable	Description	Source	Label
`aaa`	OAS for EMU Corp. AAA Rated 5-7 Yr	BoA/ML GIS	ER 13
`bbb`	OAS for EMU Corp. BBB Rated 5-7 Yr	BoA/ML GIS	ER 43
`r3m`	3-month Euribor	Datastream	EIBOR3M
`dj50`	Dow Jones Stoxx 50	Datastream	DJSTO50
`d_dj50`	Month to month growth rate of dj50		
`vola`	implied volatility of Dow Jones Stoxx 50	Datastream	VSTOXXI
`lvola`	logarithm of `vola`		
`slope`	difference between returns on	Datastream	GBBD02Y
	2 and 10 years German government bonds		GBBD10Y

Notes:

- OAS – option-adjusted spreads
- BoA/ML GIS – Bank of America/Merrill Lynch Global Indicator System

B Width of prediction bands

Table 5: Mean width (mean sum of spreads divided by the forecast horizon) of different prediction bands over the period 2004.1 – 2014.1

nominal coverage: 0.68						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
`aaa`	932	3673	618	$2.16{\cdot}10^6$	$5.23{\cdot}10^7$	$5.35{\cdot}10^5$
`bbb`	1231	4207	971	$2.56{\cdot}10^6$	$5.38{\cdot}10^7$	$6.66{\cdot}10^5$
nominal coverage: 0.90						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
`aaa`	2080	5312	1566	$1.04{\cdot}10^7$	$1.12{\cdot}10^8$	$5.18{\cdot}10^6$
`bbb`	2559	6111	2154	$1.14{\cdot}10^7$	$1.10{\cdot}10^8$	$5.59{\cdot}10^6$
nominal coverage: 0.95						
	forecast horizon: 12			forecast horizon: 24		
	naïve	Bonferroni	Bonferroni adj.	naïve	Bonferroni	Bonferroni adj.
`aaa`	2880	6386	2303	$2.11{\cdot}10^7$	$1.52{\cdot}10^8$	$1.15{\cdot}10^7$
`bbb`	3429	7143	2975	$2.22{\cdot}10^7$	$1.36{\cdot}10^8$	$1.21{\cdot}10^7$

Table 6: Mean width (mean sum of spreads divided by the forecast horizon) for subperiods for a nominal level of 0.95

Forecast horizon: 12 months									
	naïve			Bonferroni			Bonferroni adj.		
	04–07	08–10	11–14	04–07	08–10	11–14	04–07	08–10	11–14
aaa	25	$8.56 \cdot 10^3$	206	40	$1.91 \cdot 10^4$	342	33	$6.72 \cdot 10^3$	277
bbb	179	$9.63 \cdot 10^3$	643	295	$2.04 \cdot 10^4$	$1.07 \cdot 10^3$	230	$8.00 \cdot 10^3$	829
Forecast horizon: 24 months									
	naïve			Bonferroni			Bonferroni adj.		
	04–07	08–10	11–14	04–07	08–10	11–14	04–07	08–10	11–14
aaa	38	$5.75 \cdot 10^7$	373	76	$4.13 \cdot 10^8$	$1.45 \cdot 10^3$	51	$3.16 \cdot 10^7$	527
bbb	277	$6.06 \cdot 10^7$	$1.22 \cdot 10^3$	591	$3.71 \cdot 10^8$	$3.96 \cdot 10^3$	367	$3.28 \cdot 10^7$	$1.65 \cdot 10^3$