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The determinants of CDS spreads: evidence from the model space

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Non-technical summary

Research Question

The CDS market plays an important role in understanding the dynamics of financial markets and financial stability and consequently has received growing attention in the recent literature. Despite the rich literature there is still no consensus about which factors mainly drive CDS spreads. Instead we observe an increasingly large number of potential determinants being suggested. We aim to provide a transparent and robust analysis for the determinants of CDS spreads by focusing on the information provided by a large number of models (the “model space”) instead of focusing on one or few “hand-picked” specifications. Our model space covers most of the specifications used elsewhere in the literature and includes several variables measuring the sensitivity of firms to extreme market movements (tail dependence).

Contribution

We show that the model space includes models which allow backing many different theories by significant coefficients and good fit to the data. Thus, the information content from single model specifications is rather restricted. In contrast to previous studies, we use information from the entire model space instead of restricting ourselves to some “hand-picked” models. Doing so, we provide a transparent and robust analysis for the determinants of CDS spreads. Besides covering the informational content of most previous studies in our analysis we also give clear evidence on the impact of using different estimation procedures to measure tail dependence in CDS markets.

Results

Using a large data-set, we find that CDS price dynamics can be mainly explained by factors describing firms’ sensitivity to extreme market movements. More precisely, our results suggest that variables measuring tail dependence – based on so-called dynamic copula models – incorporate almost all essential pricing information making other potential determinants such as default risk (Merton-type) factors or variables capturing the systematic market evolutions negligible.

Nichttechnische Zusammenfassung

Fragestellung

Aufgrund seiner Bedeutung für das Verständnis von Finanzmärkten und wichtigen Implikationen für die Finanzstabilität erfährt der CDS-Markt in der Literatur ein umfangreiches und zunehmendes Interesse. Trotz der großen Literatur gibt es bisher keine Einigkeit darüber, durch welche Faktoren die Dynamik von CDS-Spreads erklärt werden kann. Stattdessen beobachten wir, dass in der Literatur immer mehr verschiedene Einflussfaktoren vorgeschlagen werden, die in gewissen Kombinationen Erklärungsgehalt aufweisen. In diesem Papier untersuchen wir die Einflussfaktoren, indem wir uns nicht auf einzelne Modellspezifikationen, sondern auf Information aus vielen verschiedenen Modellen (dem “Modellraum”) stützen. Unser Modellraum enthält nahezu alle Spezifikationen, die sonst in der Literatur vorgeschlagen werden, und berücksichtigt verschiedene Variablen, welche die Sensitivität einer Firma gegenüber extremen Marktbewegungen messen (Randabhängigkeit), als erklärende Faktoren.

Beitrag

Wir zeigen zunächst, dass es im Modellraum Modelle gibt, die verschiedenste Theorien durch signifikante Koeffizienten und guten Erklärungsgehalt für die Daten stützen können. Somit ist der Informationsgehalt in einem einzelnen Modell sehr beschränkt. Im Vergleich zu anderen Studien verwenden wir daher Information aus dem gesamten Modellraum und können so eine transparente und robuste Analyse für die treibenden Faktoren von CDS-Spreads durchführen. Unsere Analyse enthält den überwiegenden Teil an Spezifikationen, die bisher in der Literatur vorgeschlagen wurden, und liefert klare Evidenz dafür, dass es von zentraler Bedeutung ist, mit welcher Methodik man Randabhängigkeit auf CDS-Märkten schätzt.

Ergebnisse

Basierend auf Analysen für einen großen Datensatz, zeigen wir, dass die Dynamik von CDS-Spreads vorwiegend durch die Sensitivität einer Firma gegenüber extremen Marktbewegungen erklärt werden kann. Unsere Ergebnisse zeigen, dass Maße für die Randabhängigkeit – so wie sie von sog. dynamischen Copula-Modellen gemessen wird – nahezu alle verfügbare Information zur Bepreisung von CDS enthalten. Der Informationsgehalt von anderen potentiellen Einflussgrößen, wie z.B. Faktoren für das Ausfallrisiko oder Indikatoren für die allgemeine Marktbewegung scheint in den Maßen für die Randabhängigkeit enthalten.

The determinants of CDS spreads: evidence from the model space*

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Abstract

We apply Bayesian Model Averaging and a frequentistic model space analysis to assess the pricing-determinants of credit default swaps (CDS). Our study focuses on the complete model space of plausible models covering most of the variables and specifications used elsewhere in the literature, including different copula models. The approach followed supports ultimate transparency and robustness for the empirical study at hand. Using a large data-set of CDS contracts we find that CDS price dynamics can be mainly explained by factors describing firms' sensitivity to extreme market movements. More precisely, our results suggest that dynamic copula based measures of tail dependence incorporate almost all essential pricing information making other potential determinants such as Merton-type factors or variables measuring the systematic market evolution - based on simple means or principal component analysis - negligible.

Keywords: CDS; bayesian model averaging; crash aversion; tail risk; tail dependence; time-varying copulas.

JEL classification: G12, C11, G01.

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1 Introduction

By now literature provides a substantial body of empirical studies on the determinants of CDS spreads¹ (see, amongst others, [Collin-Dufresne et al., 2001](#); [Benkert, 2004](#); [Ericsson et al., 2009](#); [Alexander and Kaeck, 2008](#); [Benkert, 2004](#)). The theoretical foundation for most of these studies is provided by [Merton \(1974\)](#). He shows theoretically that a firm's default probability is influenced by the firm's leverage, its equity volatility, and the level of the risk-free interest rate. Consequently, these characteristics should function as main drivers of the corresponding CDS as well. Additionally, there are many other studies presenting a variety of additional factors that seemingly explain CDS spreads: examples are commonality-factors, liquidity, investor sentiment, financial distress indicators and various macroeconomic variables such as GDP or inflation. Recently, [Meine et al. \(2015b\)](#) extend evidence from option pricing that investors protect themselves against extreme downside risk (see [Rubinstein, 1994](#); [Gârleanu et al., 2009](#)) to the CDS market for banking firms and show – using a copula approach – that CDS protection sellers of contracts on banks require a premium for bearing the risk of a joint tail event in the financial market.

There is increasing evidence that investors demand compensation to redeem their fear of extreme tail events in financial markets and reward their risk-taking (see, e.g., [Bollerslev and Todorov, 2011](#); [Chabi-Yo et al., 2014](#); [Meine et al., 2015b](#); [Bollerslev et al., 2015](#); [Ait-Sahalia and Lo, 2000](#); [Jackwerth and Rubinstein, 1996](#)). First evidence of investors being crash-averse was provided by [Rubinstein \(1994\)](#), but especially the recent literature studies the impact of crash aversion on the pricing of individual financial instruments. In times of financial turmoil assets that are crash sensitive are highly unattractive for investors that show signs of crash-o-phobia. Instead, these investors would prefer assets that are crash-insensitive. In line with these arguments, [Chabi-Yo et al. \(2014\)](#) provide evidence that crash-sensitive stocks bear a premium, while [Meine et al. \(2015b\)](#) show that CDS spreads of banks bear a premium for tail risk during the financial crisis. This pricing of downside risk can be interpreted as a non-linear addendum to the CAPM asset pricing theory in which the sensitivity of asset prices to market movements is modeled linearly ([Chabi-Yo et al., 2014](#)).

Despite of the comprehensive empirical literature there is still no consensus about which factors mainly drive CDS spreads and whether there is a superior model setup which one should follow. In this sense, we do not observe any convergence in literature, but rather an increasingly large number of factors that have some influence. Importantly, the related pricing theory is not explicit about an ultimate setup such that creative theorizing gives

¹A credit default swap (CDS) is a financial agreement that provides insurance against default risk of a reference entity. The seller of the CDS will compensate the buyer in the event of a loan default or some other predefined credit event. In exchange, the buyer of the CDS makes a series of payments (the CDS spread or premium, usually measured in basis points) to the seller.

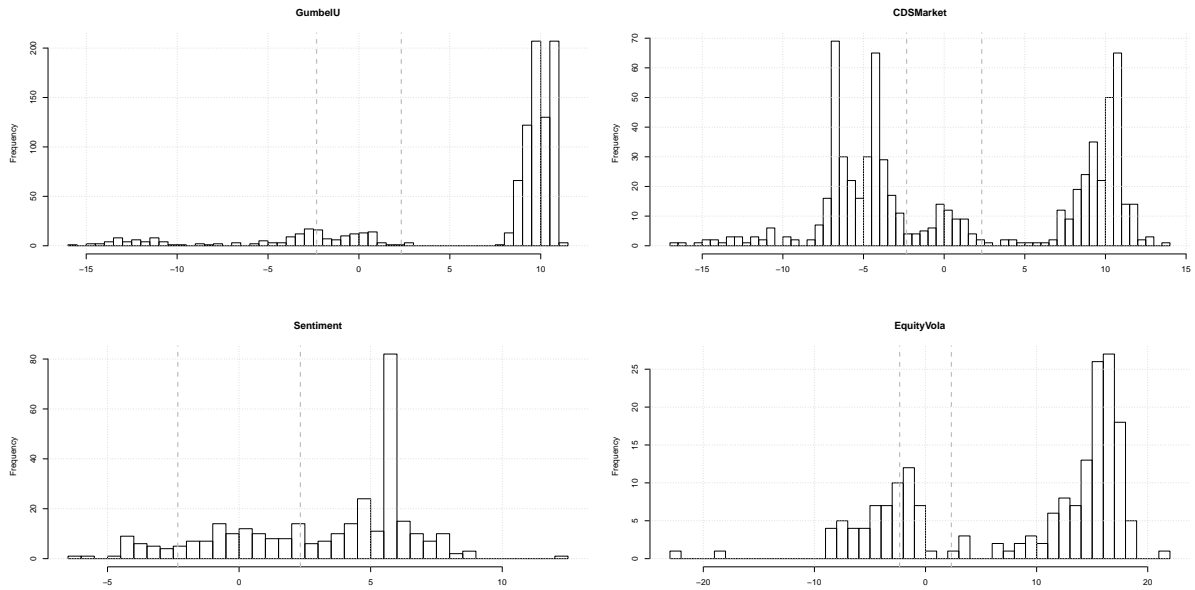


Figure 1: t -statistics for long-run-multipliers of regressors in the model space.

The figure shows t -statistics for long-run-multiplier (lrm) of different regressors in the model space. The first histogram (top left) represents the coefficients for the upper tail dependence measure estimated with the dynamic Gumbel copula, the histogram at the top right shows the CDS Market coefficients, the lower panel shows the investor sentiment measure provided by the American Association of Individual Investors on the left, and the equity volatility measure on the right hand side. Dotted vertical lines indicate the 99% confidence interval for a significance test. LRM were estimated using the so-called delta method (see [Greene, 2003](#)). For the definition of the regressor variables see [Table 2](#).

rise to different setups in the literature. As we will emphasize throughout the paper, in many empirical settings the data at hand provides the possibility to back many theories by significant parameter findings if the number of *plausible* models in the model space is large enough. [Figure 1](#) illustrates this problem for our empirical setup. Exemplary, the t -statistics for the Long-Run-Multiplier (LRM) of four different potential regressors in a fixed effect panel regression with CDS returns as the dependent variable are shown. The different t -statistics stem from different models where all of the considered models exhibit values between 50% and 54% of adjusted (in-between) R^2 .

Obviously various stories can be told based on the models in the model space, e.g. ranging from a non-significant impact of (upper) tail dependence to a highly positive or even negative impact. The variety of results is driven by high collinearity between the regressors used in the CDS literature making the presented models sensitive to the choice of control variables and the exact model setup (compare [Table 6](#)). Importantly, the model setup is also driven by the concrete specification of variables, i.e. how researchers transform, specify or estimate their regressor variables. Of particular interest in this context is the sensitivity of results to differing copula specifications used to measure the effect of tail dependence on CDS-pricing.

Copula models to capture dependence structures of financial time series have become very popular as, e.g., demonstrated by [Patton \(2009\)](#); [Genest et al. \(2009\)](#); [Christoffersen et al. \(2012\)](#); [Meine et al. \(2015b\)](#) or [Weiß and Scheffer \(2015\)](#). While early models such as [Li \(2000\)](#) focused on the use of the Normal or Gauß copula, nowadays the use of the t copula has become the popular choice (see, e.g., [Demarta and McNeil, 2005](#); [Christoffersen et al., 2012](#); [Meine et al., 2015b](#)). In contrast to the Gauß copula, the t copula exhibits heavy tails and non-zero tail dependence. Additionally, the recent research relies on dynamic copula models to take evidence that conditional volatility of economic time series changes through time ([Andersen et al., 2006](#)) into consideration. Consequently, any analysis focusing on the dependence structure between financial time series should rely on dynamic copula models to capture the time-variation (see also [Meine et al., 2015b](#)).

To illustrate the effect of differing copula specifications in our empirical setup, [Table 1](#) presents the coefficients of simple panel regressions that measure the influence of tail dependence on returns of CDS spreads. We run four simple regressions, where the tail dependence measure is estimated using different copula models. As we see, the dimension of the influence of the tail dependence measure differs in size as well as in significance depending on the copula model chosen.

	(1)	(2)	(3)	(4)
	CDS Spread	CDS Spread	CDS Spread	CDS Spread
t copula	0.848*** (0.152)			
SJC copula		0.0841 (0.106)		
Rotated Clayton copula			0.219** (0.0737)	
Gumbel copula				0.222*** (0.0631)
Constant	-0.0638*** (0.0139)	-0.00649 (0.0254)	-0.0341* (0.0153)	-0.0522** (0.0188)
F	30.95	0.634	8.781	12.35

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Regressions of tail dependence measured with different copula models.

The regressions estimate the relation between the single name CDS Spreads and differently estimated tail dependence measures over the period January 1, 2001 to September 18, 2014. Tail dependence measures are lagged by one period. The sample consists of 336 publicly traded firms. CDS data are retrieved from *Markit* database. Estimation procedures of copula models are given in [Section A](#). The regressions include all firms from our sample. We apply a quarterly panel regression with firm-fixed effects using clustered robust standard errors at the firm level. P-values are in parentheses, *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

In response to the problems sketched above, this paper intends to provide a robust and transparent analysis for the determinants of CDS spreads by focusing on the model space instead of just one specific model.² We intend to include most of the variables suggested elsewhere in the literature as regressors and we include tail dependence measures derived from four different dynamic copula models. Using model search algorithms, we identify the best 10,000 models according to adjusted R^2 and a pre-defined maximum of regressor variables. By doing so, most specifications suggested elsewhere in the literature will be part of the model space that we assess. We then analyze the model space by looking first at the number of significant LRM of the different variables in the model space followed by so-called Bayesian Model Averaging (BMA) which summarizes the model space by weighting the different models proportional to their informational content. For more in-depth analyses, we apply BMA also to subsets of the model space, which include only models satisfying imposed plausibility and collinearity conditions. Finally, we perform out-of-sample hypothesis tests for predictive ability to back-up and clarify the results obtained from BMA. Our CDS data-set set comprises 227 firms from different industries. We analyze both investment grade and high volatility contracts to consider the possible (large) differentness between the investment vehicles. Similarly, we distinguish between pre-, during, and post-crisis periods to account for differences in pricing between bullish and bearish periods.

Our methodological approach to analyze the CDS-determinants is inspired by the growing literature focusing on the model space (or a subset of it) rather than single models (see, e.g., [Sala-I-Martin et al., 2004](#); [Hansen, 2007](#); [Hansen et al., 2011](#); [Elliott et al., 2013](#)). The growing popularity of these approaches can mainly be attributed to the availability of computational capacities that allow analyses of large subsets of models and the recognition that in many empirical settings there exists no single model that dominates competing setups in a statistically significant way.

Our findings suggest that the tendency of an individual CDS to jointly experience extreme movements with the market is the major determinant of CDS premia: The measure for tail dependence, estimated using a t copula, has the highest explanatory power - measured by so-called posterior inclusion probabilities - among all regressors. Also, a model including only tail dependence measures significantly outperforms the out-of-sample forecast quality of any other model. Importantly, the choice of the copula to estimate tail dependence is crucial for the explanatory power, and the t copula dominates all other copula model specifications. In contrast, Merton-type and macroeconomic factors can be considered as negligible since their informational content seems to be covered by the tail dependence measures. This also holds for variables measuring the systematic market evolution based

²For an excellent paper on model risk and the consequences of model risk for the risk exposure of option writers the reader is referred to [Green and Figlewski \(1999\)](#). For more literature on model risk, see, e.g., [Derman \(1996\)](#); [Hull and Suo \(2002\)](#); [Danielsson \(2008\)](#); [Buoche et al. \(2014\)](#).

on simple means or principal component analysis (pca).

The main contribution of our paper is the following: We provide a transparent and robust study for the determinants of CDS spreads. In contrast to previous studies, we do not restrict our analysis to some selected models but rather analyze the information content of the entire model space. The CDS market has received growing attention in the recent literature and plays an important role in understanding the dynamics of financial markets and also financial stability (see, amongst others, [Meine et al., 2015b](#); [Christoffersen et al., 2014](#); [Oh and Patton, 2013](#)). However, previous studies rely on the assumption of a/several specific model(s) and thus face - as we show in our analyses - a substantial degree of model risk. Our analyses of the model space are able to provide clear evidence on the main determinants of CDS prices.

The paper proceeds as follows. First, we introduce the related literature in Section 2. In Section 3, the data is described and the expected influence of the included variables is discussed. Section 4 presents our dynamic copula models and the estimation procedure. In Section 5, we document the main findings of the analysis on CDS spreads. Section 6 concludes.

2 Related literature

This section present related literature from two different strands. First, we present notable contributions from the literature on CDS determinants (Section 2.1). Then, we turn to the literature on model averaging in Section 2.2.

2.1 Determinants of CDS

The empirical work of our study is related to several recent papers on the determinants of credit default swaps (using regression analysis) inspired by [Collin-Dufresne et al. \(2001\)](#). For example, our work is related to the studies by [Benkert \(2004\)](#), [Ericsson et al. \(2009\)](#) and [Alexander and Kaeck \(2008\)](#). [Ericsson et al. \(2009\)](#) are concerned with the drivers of credit default swap premia and investigate the relationship between theoretical Merton determinants of default risk and CDS spreads, while [Benkert \(2004\)](#) studies the influence of volatility on CDS premia (see also [Zhang et al., 2009](#)). The studies find that only volatility and leverage have substantial explanatory power.³ [Alexander and Kaeck \(2008\)](#) are interested in regime dependent determinants of CDS spreads. They show that CDS spreads are extremely sensitive to stock volatility during periods of CDS market turbulence while they are more sensitive to stock returns in ordinary market circumstances.

³Moreover, [Chen et al. \(2006\)](#) and [Arora et al. \(2005\)](#) provide evidence that the Merton model underestimates the corporate bond spreads.

Moreover, several studies (e.g. [Aunon-Nerin et al. \(2002\)](#), [Hull et al. \(2004\)](#), [Norden and Weber \(2004\)](#) and [Tang and Yan \(2013\)](#)) are concerned with the effect of rating events on CDS spreads. These studies find evidence that CDS spreads predict negative rating events. More recently, [Pires et al. \(2015\)](#) use a quantile regression approach to study the determinants of CDS spreads. The authors find evidence that implied volatility, historical stock returns, leverage, profitability but also illiquidity costs determine CDS premiums. Also, the authors find that high-risk firms are more sensitive to changes in the explanatory variables than low-risk firms and that the goodness-of-fit of the model increases with CDS premiums, which is consistent with the credit spread puzzle. The credit spread puzzle states that structural models are not able to explain yield spreads and default rates simultaneously ([Huang and Huang, 2012](#)). [Huang and Huang \(2012\)](#) find that credit risk only accounts for a small fraction of the corporate-Treasury yield spreads for investment grade bonds while it accounts for a much higher fraction of yield spreads for high yield bonds. Thus, structural models are not able to explain yield spreads and default rates simultaneously. One possible implication is that the unexplained portion of the yield spread might be due to non-credit factors such as commonality, tail-dependence or liquidity. More evidence on the influence of liquidity on CDS spreads is provided by [Meine et al. \(2015a\)](#); [Arakelyan et al. \(2015\)](#); [Tang and Yan \(2008\)](#); [Bongaerts et al. \(2011\)](#); [Longstaff et al. \(2005\)](#); [Qiu and Yu \(2012\)](#). Following the Lehman Brothers default, [Arora et al. \(2012\)](#) identify counterparty risk as another factor affecting CDS spreads, but to an economically small magnitude.

[Heinz and Sun \(2014\)](#) focus on sovereign CDS spreads and find that European countries' CDS spreads are mainly driven by investor sentiment, macroeconomic fundamentals and liquidity conditions in the market. [Dieckmann and Plank \(2012\)](#) analyze CDS spreads of advanced European economies during the financial crisis and document that the state of a country's financial system and the state of the world financial system have strong explanatory power for the behavior of sovereign CDS spreads.

The literature on CDS spreads and its determinants is rich, and covering all contributions would exceed the scope of this paper. For a more thorough review of the literature on CDS spreads the reader is referred to [Augustin et al. \(2014\)](#) for a recent survey.

More closely related to our paper, is the study of [Berndt and Obreja \(2010\)](#) who show that economic catastrophe risk has become more important to explain the variation in European CDS returns (see also [Coval et al., 2009](#); [Gourio, 2011](#), on catastrophe risk). The authors find evidence of sizable commonality on European CDS returns using principal component analysis and study the drivers of the commonality. The authors show that about half of the variation in European CDS returns can be explained by a common factor that mimics economic catastrophe risk and that the importance of this factor increased during the financial crisis, relative to other risk factors. This concurs with [Han and Zhou \(2015\)](#) who find that the explanatory factor of structural models is very limited and a

significant common component is missing that affects the term structure of CDS spreads. [Augustin and Tédongap \(2011\)](#) develop a consumption-based equilibrium pricing model and find that spreads are mostly driven by compensation for losses in bad states. The authors find that the first two principal components capture about 75% of the variation and interpret these two factors as level and slope of the yield curve.

Most closely related to our article are the recent works by [Meine et al. \(2015b\)](#); [Christoffersen et al. \(2014\)](#); [Koziol et al. \(2015\)](#) and [Keiler and Eder \(2013\)](#). The paper by [Meine et al. \(2015b\)](#) provides evidence that the propensity of a bank to experience extreme co-movements in its own credit default swap together with the market is priced in the CDS during the financial crisis. The authors find that the effect is limited to the recent financial crisis. However, their study is limited to a sample of banks and their model is restricted to the skewed t -copula, while our paper studies the effect of different copulas and we do not restrict our study to a sample of banks. Going in the same direction is the study of [Keiler and Eder \(2013\)](#). They address the question of how the CDS spread of one financial company is influenced by the CDS spreads of other financial companies within the system. They find significant contagion due to the interconnectedness of financial institution in their sample. [Christoffersen et al. \(2014\)](#) study a sample of CDS spreads for 215 firms and find that copula correlations are highly time varying and persistent. Also, the authors provide evidence that tail dependence in credit spreads increases during the financial crisis. However, their study is restricted to the use of a skewed t -copula and some selected models. Also, the sample in this study is restricted to the North America Investment Grade Index of CDS contracts while we consider a broader sample and a wider array of methods to verify the robustness of the findings. Also concerned with correlation amongst CDS contracts is the work by [Koziol et al. \(2015\)](#). The authors study whether correlated defaults are priced in the CDS market. They find that correlated default factors did not matter prior to the financial crisis, but the importance increased during and after the crisis. Moreover, the authors find evidence that especially CDS prices of firms with an overall low CDS level are affected and that idiosyncratic risk factors are more important when CDS premia are high. Again, our study relies on a larger sample and a wider array of methods. Thus, we are able to provide more robust results and additional insights.

2.2 Model Averaging

From a methodological standpoint, our work is related to the literature of model combination and model averaging, in particular the BMA method, and more general to the literature focussing on ensembles of models rather than single models (e.g. [Hansen et al., 2011](#)). The key idea of model averaging is to consider and estimate all possible models (the *model space*) and to focus on summarized statistics based on weighted averages of

the models in the model space. Madigan and Raftery (1994), Kass and Raftery (1995) and Raftery et al. (1997) provide a sound statistical derivation for a model combination procedure, called BMA, where the model weights are derived as additional statistical parameters in a bayesian estimation setup. Since then many authors have applied BMA on economic topics, especially on empirical growth. The seminal papers on model averaging and growth are Fernandez et al. (2001) and Sala-I-Martin et al. (2004). Following Raftery et al. (1997), Sala-I-Martin et al. (2004) combine ordinary least squares (OLS) estimates with the Bayesian Information Criterion (BIC) approximation as the weight for averaging and denominated it Bayesian Averaging of Classical Estimates (BACE). To apply BMA on classical OLS estimates Sala-I-Martin et al. (2004) assume a diffuse prior distribution for the parameters. Aside from empirical growth, model averaging techniques are also applied in forecasting financial variables such as stock returns (e.g. Avramov, 2002; Cremers, 2002) or exchange rates (e.g. Wright, 2008). In the macro forecasting, Garratt et al. (2003) employ BMA to predict inflation and output growth in the UK and Wright (2009) forecasts US inflation by BMA.

The papers mentioned above have one thing in common. They restrict the analysis to cross-country data or time series data which are often constrained by the limited number of observations. Moral-Benito (2012) extends the BMA approach to panel data models with fixed effects. The author stresses that his BMA approach solves the problem of inconsistent estimates with dynamic panel estimators. Eicher et al. (2009) propose a two-step BMA procedure that first averages across the first-stage models. Then, the authors take the averaged fitted values for the endogenous regressors from the first stage and estimate the desired model, again taking averages, in the second stage.

While most of the applications of BMA apply weights based on BIC as originally suggested in Kass and Raftery (1995), Burnham and Anderson (2002) strongly suggest to replace BIC by the (smoothed) Akaike Information Criterion (S-AIC) since BIC aims to identify the models with the highest probability of being the true model for the data assuming a true model exists. Since a *true model* in reality does not exist, BIC tends to assign too much weight to the *best* model. AIC, on the contrary, tries to select the model that most adequately fits the unknown model, and can be interpreted as being the probability that a model is the expected best model in repeated samples. Hansen (2007) report rather poor performance of BIC weights compared to S-AIC weights, particularly if the sample size is large.⁴

Many authors also attend to gauge the efficiency of BMA. Magnus et al. (2010) introduce a method called Weighted-Average Least Square (WALS) in which the WALS estimator

⁴Note, that model averaging using smoothed AIC weights instead of BIC in the literature is often referred to as smoothed AIC estimator (S-AIC), see e.g. Hansen (2007). We however, use the term BMA more generally, covering also the AIC weight variation.

employs a non-informative prior and compared to BMA is able to reduce the computational burden. But when both methods are applied on growth theory the authors do not find evidence that WALS outperforms BMA. Regarding the analysis of U.S. stock return, [Elliott et al. \(2013\)](#) assess that Complete Subset Regressions (CSR) perform better than non-equal-weighted methods like BMA. The authors use CSR which is a shrinkage technique for linear regression to run predictive regression for all models with the same number of predictors.

BMA and other model averaging frameworks have the great advantage in providing frameworks to analyze and take into account the information from the entire model space. But they also increase forecast accuracy in comparison with OLS. [Baele et al. \(2015\)](#) examine the systemic risk in US banking and show that BMA reduces the root mean square error and therefore leads to a better-out-of-sample performance.

To apply BMA in practice one has to obtain a reasonable approximation of the posterior model probabilities (pmp) of all models in the model space. This requires taking into account all models that have a non-negligible pmp. [Raftery et al. \(1997\)](#) describe two approaches. First, one can use a Markov Chain Monte Carlo Model Composition (MC3) as suggested by [Madigan and York \(1995\)](#), which moves through the model space and focusses on models with high posterior model probability. Second, [Madigan and Raftery \(1994\)](#) introduce Occam's window which focusses on a subset of models for which strong evidence exists that they are superior to the models outside of the subset. The objective is to exclude models that predict the data far less well than model with the best prediction. As a rule for the choice of the threshold which defines the relative superiority of the best model, [Hoeting et al. \(1999\)](#) and [Madigan and Raftery \(1994\)](#) recommend numbers between 20 and 100.

Using this strategy the number of models to be estimated is drastically reduced, i.e. the model space is *trimmed*. However, a search strategy is required to identify the models in Occam's window. [Volinsky et al. \(1997\)](#) use the *leaps and bounds* algorithm suggested by [Furnival and Wilson \(1974\)](#), which provides an efficient method for identifying the models in the window. The algorithm provides the top q models for each model size based on (e.g.) the adjusted R^2 . If q is chosen large enough, this procedure will return the models in Occam's window plus many additional models.

A related strand of the model uncertainty literature suggests to analyze a Model Confident Set (MCS) ([Hansen et al. \(2011\)](#)) which also intends to overcome the problem of selecting one *best* model. The advantage of the MCS is that conditional on the limits to the information of the data, MCS seeks to find a group of models that are equally likely to be superior. A hypothesis test for equal predictive ability (EPA) is performed on the set of initial models M using an equivalence confidence level $1 - \alpha$. If the null hypothesis is rejected, an elimination rule is employed to remove an inferior model. The process is then

repeated until the null hypothesis is not rejected and the remaining set of models is the MCS. Recently, authors like [Samuels and Sekkel \(2011\)](#) apply MCS to create a set of best predictors by trimming the worst models. Applying three different trimming techniques (fixed trimming, MCS trimming, Occam’s window) [Samuels and Sekkel \(2011\)](#) show that trimmed forecast combinations outperform BMA on an untrimmed model space due to the parameter estimation error in small sample sizes.

3 Data

This section describes the construction of our sample and presents the choice of our main independent variables as well as descriptive statistics of our data.

3.1 Sample construction

We retrieve our CDS data from *Markit* and consider the spread quoted on 5-year CDS contracts on all cross-industry single names that are included in one of the first 24 series of the North American investment grade index (CDX NA IG) or the North American high yield index (CDX NA HY). Thus, we include contracts with different investment qualities and are able to investigate possible differences between these. We consider 5-year CDS contracts as these contracts are the most liquid and constitute the majority of the CDS market (see also [Jorion and Zhang, 2007](#)). We restrict our study to senior unsecured contracts with no restructuring (XR) denoted in US-Dollar as they constitute the convention for the U.S.⁵ The CDX NA IG index consists of 125 most liquid North American entities with investment grade credit ratings that trade in the CDS market, while the CDX NA HY consists of 100 most liquid North American entities with high yield credit ratings. Markit is the provider of the included indexes. All indexes are updated twice a year, based on a liquidity list. E.g., the CDX NA IG is updated in March and September of each year. The updated index is labeled as on-the-run index. After each update, the previous version of the index continues trading as an off-the-run index which now does not necessarily consist of the most liquid contracts available. As a result, the on-the-run indexes comprise the single names with the highest liquidity in the credit derivatives market (see also [Koziol et al., 2015](#)). Thus, using only the most liquid CDS contracts circumvents a possible illiquidity-pricing effect in our study. We start with the longest possible sample available from Markit which starts on January 1, 2001 and ends September 18, 2014. Initially, we have 455 time series of CDS data. However, some of these belong to the same entity, but have changed names or tickers symbols over

⁵With the CDS Big Bang on April 8, 2009 a move towards more standardized CDS contracts took place. Since then, contracts with no restructuring (XR) became the convention for North America.

the course of time. Moreover, we drop all firms that do not have at least one year of consecutive data available. Overall, we lose 119 firms due to our thorough filtering which leaves us with 336 unique firms with CDS data.

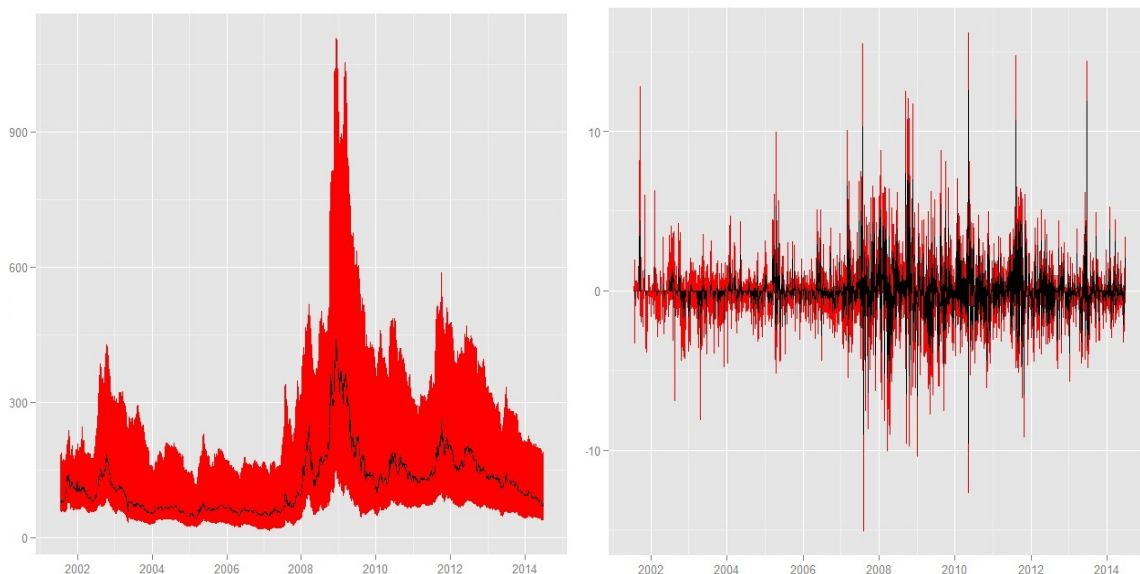


Figure 2: Time evolution of CDS spreads and CDS spread returns

The figure shows the evolution of CDS spreads and the log differences of CDS spreads (CDS spread returns) over the sample period from January 2001 to Sept. 2014. For both panels, we show the mean across all single name contracts (black line) and the inter-quartile range in the shaded area. CDS spreads are denominated in basis points whereas CDS spread returns are measured in %.

Figure 2 shows the time evolution of CDS spreads and CDS spread returns across our sample period together with the inter-quartile range. Figure 3 shows the distribution and the quantile-quantile plot of our CDS market returns. Note, that the returns seem to exhibit excess kurtosis and skewness. Initial tests on our CDS data confirm that the spread returns exhibit excess kurtosis (market kurtosis of 155.7) and non positive skewness (market skewness of -0.165).

We supplement the CDS data with daily share price retrieved from *Thomson Reuters Financial Datastream* and financial accounting data from the *Worldscope* database. From our initial sample we loose some observations because no accounting or share price data is available from Datastream or because the data is not available for the same time period. In total, we loose 59 firms during our matching process of Markit data and Datastream data which leaves us with a sample consisting of 277 unique firms.

Moreover, we complement our data with proxies for the overall business climate retrieved from the *Federal Reserve Bank of St. Louis* and the *American Association of Individual Investors* databases.

We use daily CDS data to analyze the dependence structure and focus of log-differences to ensure econometrical tractability. We then average the daily data on a quarterly basis

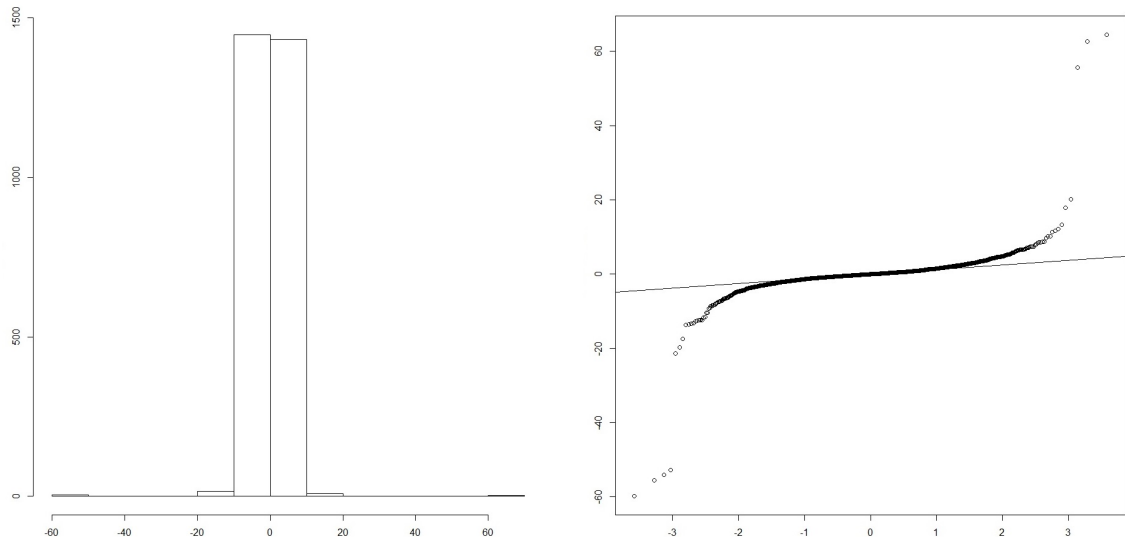


Figure 3: Histogram and Quantile-Quantile Plot of CDS market returns

The figure shows the distribution and the quantile-quantile plot with respect to the normal distribution of our CDS market returns.

to run our regression analysis using quarterly data. This approach allows us to include a wide array of control variables that are not available on a daily or weekly basis while at the same time maintaining some granularity.⁶

3.2 Variables

Our study intends to provide robust information on the determinants of CDS spreads by analyzing the entire model space of possible specifications. Hence, we include a large array of potential explanatory variables with the objective to cover most of the specifications suggested elsewhere in the literature in our model space. A particular focus of our analyses lies in the influence of tail risk on CDS premia, which is why we include tail-dependence measures based on various dynamic copula specifications. As the dependent variable we use log-differences of CDS premia. The estimation procedures for the tail dependence are presented in section A. Our expectation is that CDS contracts of firms that show a tendency to jointly surge with the market are traded at a premium which would be in line with the findings of [Meine et al. \(2015b\)](#) and [Christoffersen et al. \(2014\)](#). We include the lower tail dependence (LTD) and upper tail dependence (UTD) of single name CDS contracts with the market in our sample. Contrary to the UTD, the LTD dependence captures the propensity of the single name CDS to jointly depreciate with the market. Hence, pronounced LTD characterizes single name contracts that are

⁶In comparison, [Meine et al. \(2015b\)](#) also rely on quarterly CDS spreads for their study, while [Christoffersen et al. \(2014\)](#) use weekly data.

especially *safe* during booms. Our expectation is that CDS contracts with a high lower tail dependence are traded at a discount.

Next, we include the return of an CDS market index to control for general market movements. As an alternative for the market index we consider *commonality*. To measure the commonality between CDS spread returns, we follow [Berndt and Obreja \(2010\)](#) and estimate the first principal component of the standardized CDS returns. We estimate the principal component for four distinct intervals. We split our sample period into four subperiods for two reasons. First, we believe the common underlying factors change over the cause of time. This is underlined by the finding that the variation explained by the first principal component increases over time. While the first principal component is able to explain only 13% of the variation for the first subperiod, the number increases to 40.2% for the fourth subperiod. This is consistent with the findings of [Berndt and Obreja \(2010\)](#). Secondly, splitting our sample period into subperiods allows us to include more entities into each subperiod analysis. Note, that our sample is unbalanced. Hence, some firms drop out over the sample period and others enter the sample. Only 35 firms are in our sample over almost the entire sample period.⁷ By dividing the sample into subsamples, we are able to estimate the commonality for up to 202 firms for each subperiod. [Figure 4](#) presents the evolution of the commonality of CDS spreads across our sample together with CDS spreads and CDS spread returns. During times of financial distress we observe increased commonality.

Further, we include a number of idiosyncratic regressors. First, we include CDS volatility (see also [Kita, 2015](#)) using our GARCH estimates as a proxy, and liquidity on the CDS market (see, e.g., [Meine et al., 2015a](#); [Arakelyan et al., 2015](#); [Tang and Yan, 2008](#); [Bongaerts et al., 2011](#); [Qiu and Yu, 2012](#)). Note, that we only include our measure for liquidity using a subsample from 2011 to 2014 as Markit does not provide information on liquidity prior to 2011. We employ the converted bid-ask spread provided by Markit as liquidity measure. However, we find that our main results hold regardless of the liquidity control variable (see [Section 5.5](#)).

Moreover, we include equity returns, stock price volatility, and leverage following the theory of [Merton \(1974\)](#). Further variables to control for firm risk are the stock price beta and the firm value.⁸ We calculate the stock price beta on the basis of daily log differences of stock prices from rolling windows of 100 data points. We rely on the definition $\beta = \frac{\text{cov}(R_{i,t}, R_{m,t})}{\text{var}(R_{m,t})}$. As discussed by [Merton \(1974\)](#) the market price of risk must be the same for all contingent claims on a firm's assets. Consequently, risk premia in credit and equity markets should be related.⁹

⁷Estimating a principal component using only these 35 firms gives us a first principal component that is able to explain about 35% of the entire variation over the full sample period.

⁸To control for firm value we multiply the number of shares outstanding with the current share price.

⁹Note however the *distress puzzle* pointed out by several studies. The distress puzzle terms the finding

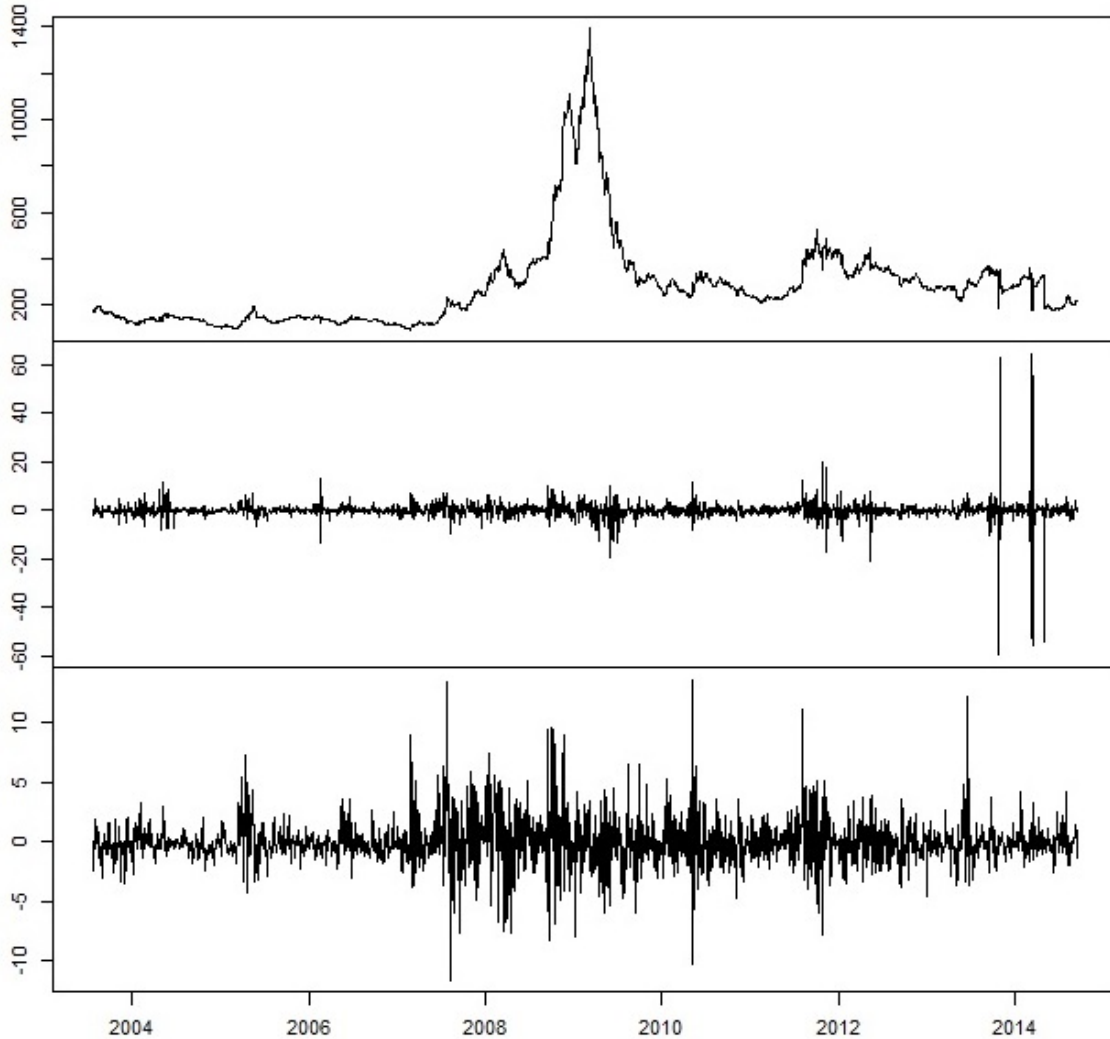


Figure 4: Evolution of the commonality of CDS spread returns

The figure shows the commonality of CDS spread returns across our sample (bottom panel) together with CDS spreads (top panel) and log returns of CDS spreads (second panel). The commonality is measured using the first principal component of our data as described in Section 3.2.

Finally, we calculate variables for *coskewness* and *tail beta* for the CDS spreads and include them in our study. The rationale behind this is that the effect captured by the tail dependence might also be captured by these variables. Hence, we show that the effect we measure is not captured by other variables. The coskewness is defined as the realized coskewness based on daily log differences of CDS spreads. We compute the coskewness on the basis of rolling windows of 100 data points according to $\text{Coskewness} = \frac{\mathbb{E}[(R_{i,t} - \mathbb{E}[R_{i,t}])(R_{m,t} - \mathbb{E}[R_{m,t}])^3]}{\sqrt{\text{var}(R_{i,t}) \text{var}(R_{m,t})^{3/2}}}$. The tail beta is the realized beta defined as regular beta conditional on the log differences of the CDS index being in its 90% quantile. The

that high credit risk premia square with abnormally low equity risk premia. For example, [Friewald et al. \(2013\)](#) provide evidence that firms' stock returns increase with credit risk premia obtained from CDS spreads.

computation is again based on daily log differences of CDS spreads for rolling windows of 100 data points. Formally, $\beta_{90\%} = \frac{\text{cov}(R_{i,t}, R_{m,t} | R_{m,t} > R_{m,t}^q)}{\text{var}(R_{m,t} | R_{m,t} > R_{m,t}^q)}$, where $R_{m,t}^q$ denotes the 90% quantile of the log differences of CDS spreads.

Turning to non-idiosyncratic control variables, we use several indicators to control for the overall state of the economy. First, we include the level of the risk-free interest rate based on the theory of [Merton \(1974\)](#). We include the TED Spread as a measure of banking liquidity, and the Federal Funds rate. Also transformations, such as year on year changes (YoY) and Quarter on Quarter changes (QoQ) of these variables are included.

Furthermore, we control for the business climate with the industrial production (YoY, QoQ), include an applicable national equity index (Russel 3000, QoQ and YoY), and national GDP (YoY, QoQ). We also include information on the Crude Oil price (YoY, QoQ), and Inflation (YoY, QoQ). Next, to control for investor sentiment (see, e.g., [Kumar and Lee, 2006](#); [Heinz and Sun, 2014](#)) we use information from the *American Association of Individual Investors* and also include investor risk aversion or fear using the VIX. We include a financial stress index (level, YoY, QoQ) in our analysis to proxy for the state of the financial system. All variables are listed in [Table 2](#). Note, that in the BMA analyses we also control for collinear variables, i.e. we do not include different variables measuring similar effects in the same models but apply exclusion restrictions on the model space (these will be discussed in greater detail in [Section 4.1](#)). In addition, plausibility conditions in form of economic sign restrictions are imposed on the model space (see also [Section 4.1](#)).

4 Methodology

This section describes our BMA regression setup. A detailed discussion of the univariate and multivariate modeling of the CDS spread time series using different time-varying copula models can be found in the appendix ([Section A](#)). We employ a symmetric t copula, a Gumbel copula with its rotated counterpart, a Clayton copula with its rotated counterpart, and a SJC copula. All copula models are dynamic.

4.1 Regression setup

To explain the determinants of (log) CDS returns we consider in total $K = 53$ different explanatory variables (see [Table 3](#)).

For the estimation, we apply fixed effect panel regressions and restrict our specifications

Table 2: Variable definitions and data sources.

This table presents both, definitions and data sources for all dependent and independent variables that are used in the empirical study. CDS data from *Markit*, stock market data and firm characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

<i>Variable name</i>	<i>Definition</i>	<i>Data source</i>
CDS	Daily CDS spread log returns, denoted in basis points and obtained from <i>Markit</i> .	Markit
CDSMarket	Daily CDS market spread log returns, denoted in basis points and obtained from <i>Markit</i> .	Markit, own calc.
Comm	First principal component of standardized CDS returns, following Berndt and Obreja (2010) .	Markit, own calc.
UTD and LTD	Upper and lower tail dependence of daily CDS spread returns with CDS market returns, estimated using a dynamic copula approach described in Section A.	Markit, own calc.
CDSVola	Volatility of daily CDS spreads; estimated with GARCH model.	Markit, own calc.
Liquidity	Liquidity of individual CDS spreads obtained from <i>Markit</i> .	Markit
Equity	Daily stock market returns, denoted in U.S. Dollar and obtained from <i>Thomson Reuters Datastream</i> .	Datastream, own calc.
EquityVola	Volatility of daily stock market prices; estimated with GARCH model.	Datastream, own calc.
StockBeta	Stock price beta on the basis of daily log differences of stock prices from rolling windows of 100 data points according to the definition $\beta = \frac{\text{cov}(R_{i,t}, R_{m,t})}{\text{var}(R_{m,t})}$.	Datastream, own calc.
FirmVal	Current share price multiplied by the number of ordinary shares in issue.	Datastream, own calc.
Leverage	Ratio between Total Debt and Total Capital	Datastream
CoSkew	Realized coskewness based on daily log differences of CDS spreads; we compute the coskewness on the basis of rolling windows of 100 data points according to $\text{Coskewness} = \frac{\text{E}[(R_{i,t} - \text{E}[R_{i,t}])(R_{m,t} - \text{E}[R_{m,t}])^3]}{\sqrt{\text{var}(R_{i,t}) \text{var}(R_{m,t})^3/2}}$.	Markit, own calc.
UpBeta	Realized beta defined as regular beta conditional on the log differences of the CDS index being above its 90% quantile; computation is based on daily log differences of CDS spreads for rolling windows of 100 data points; Formally, $\beta_{90\%} = \frac{\text{cov}(R_{i,t}, R_{m,t} R_{m,t} > R_{m,t}^q)}{\text{var}(R_{m,t} R_{m,t} > R_{m,t}^q)}$, where $R_{m,t}^q$ denotes the 90% quantile of the log differences of CDS spreads.	Markit, own calc.

to the model class of Autoregressive Distributed Lag (ADL) models, i.e.:

$$Y_{i,t} = \sum_{l=1}^L a_l Y_{i,t-l} + \sum_{j=0}^J \beta_j \mathbf{X}_{i,t-j} + f_i + \epsilon_{i,t} \quad (1)$$

with \mathbf{X} as matrix containing the exogenous regressors (including an intercept), Y as vector including the CDS returns for the different firms i and quarters t , and f_i as time-invariant firm fixed effect. In our basic setup we allow for up to two time lags, i.e. $L = 2$ and $J = 2$, which implies a total of $N = 161$ potential regressors. Further, in the basic setup we restrict the maximum number of regressors in a model *nvmax* to four variables, such

Table 2: Variable definitions and data sources (II).

<i>Variable name</i>	<i>Definition</i>	<i>Data source</i>
Sentiment	Weekly Bull-Bear-Spread, measured as the difference between the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next six month.	American Association of Individual Investors
VIX	CBOE Volatility index (VIX); measures expectation of near term volatility.	Federal Reserve Bank of St. Louis
Risk-free interest rate	Ten year Treasury Bill rate.	Federal Reserve Bank of St. Louis
Fed	Effective Federal Funds rate is the rate at which depository institutions trade federal funds with each other over night.	Federal Reserve Bank of St. Louis
Ted	TED spread, calculated as the spread between 3-month LIBOR and 3-month Treasury Bill.	Federal Reserve Bank of St. Louis
Russel	National equity index Russel 3000 which measure the performance of the largest 3,000 U.S. companies.	Federal Reserve Bank of St. Louis
GDP	Real national GDP growth rate (in %).	Federal Reserve Bank of St. Louis
IP	Industrial production Index (INDPRO) that measures real output for all facilities located in the U.S.	Federal Reserve Bank of St. Louis
Oil	Crude oil prices, West Texas Intermediate.	Federal Reserve Bank of St. Louis
I10	GDP deflator.	Federal Reserve Bank of St. Louis
FDI	The Financial stress indicator (STLFSI) measures the degree of financial stress in the markets.	Federal Reserve Bank of St. Louis
Crisis	Dummy variable that equals one if a financial crisis is identified by Laeven and Valencia (2012) in a country for a given year, and zero otherwise.	Laeven and Valencia (2012)

that our model space consists of $\sum_{j=1}^{nvmax} \frac{N!}{j!(N-j)!} = 28,355,643$ different model setups. The number of observations for each variable are 6,521.

To eliminate the fixed effect, we demean Equation (1) on both sides, yielding:

$$\ddot{Y}_{i,t} = \sum_{l=1}^L a_l \ddot{Y}_{i,t-l} + \sum_{j=0}^J \beta_j \ddot{X}_{i,t-j} + \ddot{\epsilon}_{i,t}, \quad (2)$$

where $\ddot{Y}_{i,t}$, $\ddot{Y}_{i,t-l}$, $\ddot{X}_{i,t-j}$ and $\ddot{\epsilon}_{i,t}$ are variables which were demeaned by their respective firm-specific means. This specification is known to suffer from the so-called Nickell-Bias, however the bias is inversely related to the panel time dimension T . Since we have on average $T = 24$ observations per firm in the time dimension, we assume that the bias will be rather small (see, e.g., [Nickell, 1981](#)). A potential influence on the outcomes is ruled out by robustness checks (see Section B in the Appendix).

Instead of choosing one specific panel regression setup for Equation (2), we consider the entire model space and employ a model averaging approach. In the model averaging we

Copula Based	Idiosyncratic	Macro-Factors I	Macro-Factors II
ClaytonL −	Liquidity	CDSMarket +	IPQoQ −
ClaytonU +	Equity −	CPIQoQ	IPYoY −
GumbelU +	dFirmVal −	CPIYoY	OilQoQ +
GumbelL −	dLeverage +	I10	OilYoY +
SJCU +	FirmVal −	I10QoQ	Ted
SJCL −	Leverage +	I10YoY	TedQoQ
tCop	EquityVola +	GDPQoQ −	TedYoY 0
dClaytonL −	CDSVola +	GDPYoY −	RusselQoQ −
dClaytonU +	CoSkew +	Fed	RusselYoY −
dGumbelU +	StockBeta	FedQoQ	Comm
dGumbelL −	UpBeta +	FedYoY	Sentiment −
dSJCU +	dCoSkew +	FDI +	VIX +
dSJCL −	dUpBeta +	FDIQoQ +	
dtCop		FDIYoY +	

Table 3: List of variables included in BMA regressions and respective sign restriction

The table lists all variables included in the BMA regression setup. The + or − behind each variable shows the sign of the effect that we expect from the variable based on economic reasoning; no sign means that the sign can either be positive or negative. A detailed list of all variables included in our study can be found in Table 2. The use of sign restrictions is explained in Section 4.1.

combine several ADL specifications to one *large* model using a weighting scheme for the different models in the model space. While there are several weighting schemes suggested in the literature (see, e.g., [Moral-Benito \(2015\)](#) for a good overview), we follow a modified BMA approach which uses (approximations of) posterior model probabilities as model weights based on smoothed AIC (S-AIC).

4.1.1 Bayesian Model Averaging (BMA)

The rationale behind model averaging is the need to account for model uncertainty in statistical analyses. Within a bayesian estimation setup model uncertainty can be treated as an additional parameter. Given a model space M that describes our data D , we intend to estimate the model parameters β in a linear regression context. The output of a bayesian estimation is the posterior probability distribution:

$$Pr(\beta|D) = \frac{Pr(D|\beta) \cdot Pr(\beta)}{Pr(D)}, \quad (3)$$

with $Pr(\beta)$ as a prior distribution for the parameters, $Pr(D|\beta)$ as the likelihood function and a scalar $Pr(D)$ as the density of the data. If we introduce model uncertainty we

yield the following posterior distribution:

$$Pr(\beta|D, M) = \sum_{i=1}^I Pr(\beta|M_i, D) \cdot Pr(M_i|D). \quad (4)$$

This is a weighted average over the posterior distributions for the different specific models M_i , where weights are defined by the models' posterior model probabilities $Pr(M_i|D)$ and the subscript i identifies the individual model. The posterior model probabilities express our belief for M_i being the *true* model given the data.

Assuming a diffuse prior for $Pr(\beta|M_i)$ in the context of a linear regression model leads to an equivalence between the posterior distribution (3) and the traditional sampling distribution of OLS (see, e.g., [Sala-I-Martin et al., 2004](#)). Hence, the mean of the posterior distribution in (4) can be written as:

$$\hat{\beta}_{BMA} = E(\beta|D) = \sum_{i=1}^I Pr(M_i|D) \cdot \hat{\beta}_i, \quad (5)$$

where $\hat{\beta}_i$ is the OLS estimate for β with the regressor set of model i .

The posterior model probabilities can be expressed as follows:

$$Pr(M_i|D) = \frac{Pr(D|M_i) \cdot Pr(M_i)}{\sum_{i=1}^I Pr(D|M_i) \cdot Pr(M_i)}, \quad (6)$$

with $Pr(M_i)$ as the prior model probabilities, which we will assume in the following to be uniform for all models such that the prior cancels out in (7).¹⁰ Hence, we are left to determine $Pr(D|M_i)$, which is given by the following marginal likelihood $Pr(D|M_i) = \int Pr(D|\beta, M_i) \cdot Pr(\beta|M_i) d\beta$. Making specific assumptions about the prior of the parameters $Pr(\beta|M_i)$ and using ratios of the marginal likelihood of different models (Bayes Factors) one can directly derive the following BIC based weights (given uniform $Pr(M_i)$):

$$\omega_i = \frac{Pr(D|M_i)}{\sum_{i=1}^N Pr(D|M_i)} = Pr(M_i|D) = \frac{\exp(-0.5 \cdot BIC_i)}{\sum_{j=1}^M \exp(-0.5 \cdot BIC_j)} \quad (7)$$

with - if we assume for the errors of the regression $\epsilon_t \sim N(\mu, \sigma_\epsilon^2)$ - $BIC_i = n \cdot \ln(\hat{\sigma}_\epsilon^2) + k \cdot \ln(n)$. These weights, however, were criticized in the literature, and some authors show that the use of S-AIC based weights improves the performance of model averaging (see Section 2).

¹⁰While this assumption is often made in the literature some authors like [Sala-I-Martin et al. \(2004\)](#) actually define a prior for the model probabilities and suggest that there is usually a prior belief of researchers that the *true* model is rather parsimonious specified. Since we restrict our model space to a maximum of four regressors we do not face the problem of very large models.

We follow the suggestions of [Burnham and Anderson \(2002\)](#) and replace the BIC weights (7) by the following expression:

$$\omega_i = \frac{\exp(-0.5 \cdot \Delta_i)}{\sum_{i=1}^N \exp(-0.5 \cdot \Delta_i)}, \quad (8)$$

with $\Delta_i = AIC_i - AIC_{\min}$ and - if we assume $\epsilon_t \sim N(\mu, \sigma_\epsilon^2)$ - $AIC = n \cdot \log(\sigma^2) + 2 \cdot k$. Expression (8) - while not directly derived from the marginal likelihood above - can be interpreted as an approximation or frequentistic analogue of the posterior model probabilities (6) (see [Kapetanios et al., 2008](#)). According to [Burnham and Anderson \(2002\)](#), the difference between the AIC of two models (Δ_i) can be interpreted as the difference between the Kullback-Leibler (KL) distance for the two models ([Kullback and Leibler, 1951](#)) and hence has an attractive information theoretic interpretation.¹¹ Hence, ω_i can be regarded as the probability for model i to be the KL best model in repeated samples.

To make BMA feasible, i.e. not having to estimate the 28,355,643 possible models in our model space, we apply Occam's window as described by [Madigan and Raftery \(1994\)](#). Our objective is to obtain a subset O of the entire model space for which strong evidence exists that these are superior to the models outside of the subset. To identify O , we apply the *leaps and bounds* algorithm suggested by [Furnival and Wilson \(1974\)](#) which provides us - for each specified model size - in an computationally efficient manner with the q best models in the model space according to the adjusted R^2 . We then obtain (preliminary) weights ω_i^{pre} for the 10,000 best models according to adjusted R^2 , given the model contains less than five regressors. For given ω_i^{pre} we determine the model with the maximum weight, m_{opt} and calculate relative risk weights according to $\omega_i^{rel} = \frac{\omega_{m_{opt}}^{pre}}{\omega_i^{pre}}$. Then we drop all models with $\omega_i^{rel} > 100$ from our set to arrive at the Occam's window subset O . The threshold value 100 implies that we drop all models from the subset for which we have 100 times less evidence to be the KL best model than for the model with the highest evidence. Finally, we calculate ω_i for all models in O and the BMA parameter estimates are obtained as the weighted averages of the models in this subset.

4.1.2 Long-Run-Multiplier and Posterior Inclusion Probabilities

To analyze the model space we calculate long-run-multiplier (LRM) of the different regressors and the posterior inclusion probabilities (PIP) for the estimated BMA model. Further, for a general and purely frequentistic view of the model space we calculate significance tests for the LRM for the 10,000 best models as obtained by the *leaps and bounds* algorithm.

¹¹The use of S-AIC weights is in the literature sometimes referred to as S-AIC estimator ([Hansen, 2007](#)) or information theoretic model averaging ([Kapetanios et al., 2008](#)).

The LRM for regressor i is given by:

$$\theta_i = \sum_{k=0}^{\infty} \frac{\partial EY_{t+k}}{\partial X_{i,t}} = \frac{\sum_{j=0}^J \beta_{i,j}}{1 - \sum_{l=1}^L \alpha_l}, \quad (9)$$

with J as the number of lags of the exogenous regressors and L as the number of endogenous lags. The LRM describe the effect of the regressor i on Y if the regressor is permanently increased by one unit. To test for significance of the LRM we apply the delta method (see, e.g., [Greene, 2003](#)) to approximate the standard error for θ_i . The corresponding test-statistic is asymptotically $N(0, 1)$ distributed.

For BMA, the LRM are derived on basis of $\hat{\beta}_{BMA}$. We normalize θ_i according to $\theta_i^{norm} = \frac{\sigma(X_i)}{\sigma(Y_i)} \cdot \theta_i$ which makes the LRM directly comparable by size. θ_i^{norm} describes the effect of a permanent shock of one standard deviation on regressor i on Y (in terms of standard deviations of Y).

The posterior inclusion probabilities (PIP) for regressor i is defined as:

$$\text{PIP}_i = \sum_{j=1}^N \mathbf{1}_{i \neq 0} \cdot \omega_i, \quad (10)$$

i.e. it corresponds to the sum over the posterior model probabilities of all models in which the regressor takes a non-zero value. Hence, the PIP summarizes the aggregated evidence for regressor i in the model space. A regressor is said to be significant in the bayesian sense if the PIP exceeds the prior inclusion probability (PriorIP), which - assuming uniform prior model probabilities - is obtained by calculating the ratio of average model size over the number of potential regressors K , i.e.:

$$\text{PriorIP}_i = \frac{\sum_{j=1}^{nvmax} j \cdot \frac{K!}{j! \cdot (K-j)!}}{\sum_{j=1}^{nvmax} \frac{K!}{j! \cdot (K-j)!}}. \quad (11)$$

PriorIP can be interpreted as the share of models in which regressor i will be part of if we randomly assign variables to the different models. In our basic setup with $K = 53$ and $nvmax = 4$, PriorIP equals 7.1% for all regressors.

4.1.3 Clustering of Standard Errors and Model Space Restrictions

To allow for (conditional) heteroscedasticity and serial correlation of unknown form in the regressions (2) - which otherwise can bias our t -tests for the LRM coefficients - we use cluster-robust estimators for the covariance matrix treating each individual firm as a cluster (see, e.g., [Wooldridge, 2003](#)). However, since clustering does not prevent to obtain inconsistent parameter estimates in the presence of endogenous regressors and

serially correlated errors, we exclude all models with endogenous variables for which tests indicate serial correlation from the Occam’s window subset O . To test for serially correlated errors we apply the Breusch-Godfrey Test (see [Breusch, 1978](#); [Godfrey, 1978](#)).

In addition to the serial correlation constraints, we also impose some plausibility restrictions on the model space. In general, researchers deem some models as more plausible than others, usually based on the sign of the effect of the regressors. Further, one aims to minimize collinearity issues in the models and hence avoids putting highly correlated regressors in the models.

To account for these considerations we filter the model space such that all models in the subset O satisfy (i) all imposed sign restrictions on the LRM of each model, and (ii) exclusion restrictions that guarantee that no regressors with correlations of above 70% will be in the same model. Further, we do not allow that a regressor can be present in different specifications, i.e. level, QoQ or YoY, in the same model. Note, that any other plausibility criterion that researchers want to apply can be implemented in the BMA framework by filtering the model space accordingly.

Table 6 shows the correlation matrix of the regressors, where correlations above 70% leading to exclusion restrictions are highlighted. The imposed sign restrictions - based on economic reasoning - can be found in Table 3.

Importantly, in Section 5 we will look at the restricted and the unrestricted model space, such that the effect of the restrictions on the outcomes is transparent. Moreover, we present several robustness checks in the appendix (Section B).

4.1.4 Out-of-Sample Hypothesis Testing

Finally, building upon the outcomes of the BMA analyses, we will carry out some hypothesis tests with respect to the forecast accuracy of differing model specifications to back up and clarify some of the results obtained in the model space analysis. These analyses will show if the dominating identified model setups in the BMA setting do translate in increased forecast performance.

To do so, we follow suggestions of [Clark and McCracken \(2001\)](#) to test hypotheses of predictive ability by focusing on the out-of-sample model errors produced by competing model setups. For this, we split the sample into a training and holdout sample. The training sample is used to estimate the parameters of the models while the holdout sample is used for prediction. To define the two different samples we randomly draw observations from the full sample, where we restrict the size of the training sample to 10% of the full sample. The relative small training sample compared to the holdout sample is chosen since we observe that results in terms of the models mean-squared-errors (MSE) converge quickly with increasing sample size in our setup. The splitting of the sample ensures that

the risk of model overfitting is minimized. Based on the model errors from the predictions we carry out Diebold-Mariano (DM) tests for relative predictive accuracy (Diebold and Mariano, 1995). The two-sided DM provides a test of the hypothesis of equal expected loss, e.g. MSE, valid under quite general conditions. We apply the one-sided version of the test, i.e. we explore the hypothesis that among two competing forecast models one has superior predictive ability.

5 Tail Dependence and CDS premia

This section presents and discusses the main findings of our study. First, we estimate each time-varying copula model for every single name CDS in our dataset together with the market and report the results of several goodness of fit tests in Section 5.1. Then, we take a look at simple correlations of the regressors with CDS spreads and CDS returns (Section 5.2). In Section 5.3, we present results from our frequentistic model space analysis, before we turn to the BMA estimates in Section 5.4. In Section 5.5, we discuss the analysis of several sub-samples to identify possible differences in the determinants of CDS spreads for bullish and bearish markets, respectively, or for different investment quality classes, investment grade and high yield, respectively. Section 5.6 presents several hypothesis tests based on the forecast performance of different model specifications. In the appendix we provide results from several robustness checks with respect to our BMA setup.

5.1 Copula model estimates, tail dependence and goodness-of-fit

Figure 5 shows the time evolution of the upper tail dependence measured with the t copula over our sample period. The figure shows the average daily tail dependence across all single name contracts in our sample together with the inter-quartile range (shaded area). The second panel shows the average quarterly tail dependences across all single name contracts over our sample period.

Similarly, Figure 6 shows the evolution of upper tail dependence when estimated with the Gumbel copula. Clearly, the estimates using the two different copula models show some similarities but also differ in other aspects. This raises the question which model provides the better fit.

The results of our goodness of fit tests are presented in Table 4. The table shows the proportion of each individual copula being the superior model for a single-name CDS contract joint with the market based on several gof-tests for our dataset of CDS contracts. The presented results highlight one aspect of the motivation of our study. Depending on

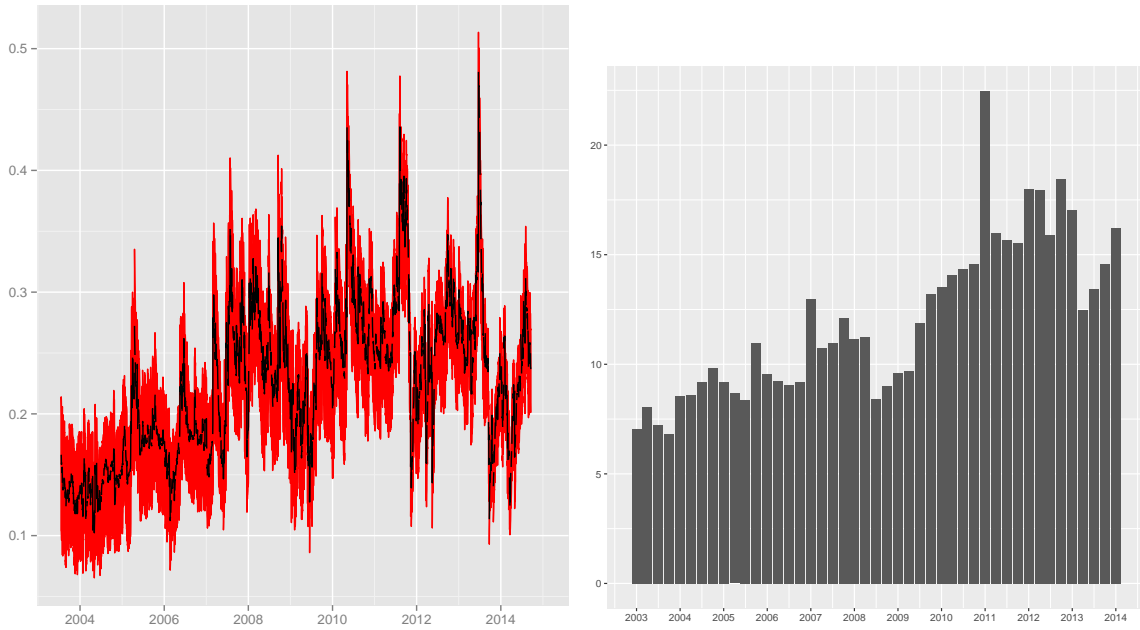


Figure 5: Time evolution of daily and quarterly tail dependence: t copula

The figure shows the evolution of daily (panel I) and quarterly (panel II) average tail dependence for the sample period from 2003 to 2014, respectively. Tail dependence is measured with the dynamic t copula. For the daily tail dependence, we additionally show the inter-quartile range in the shaded area.

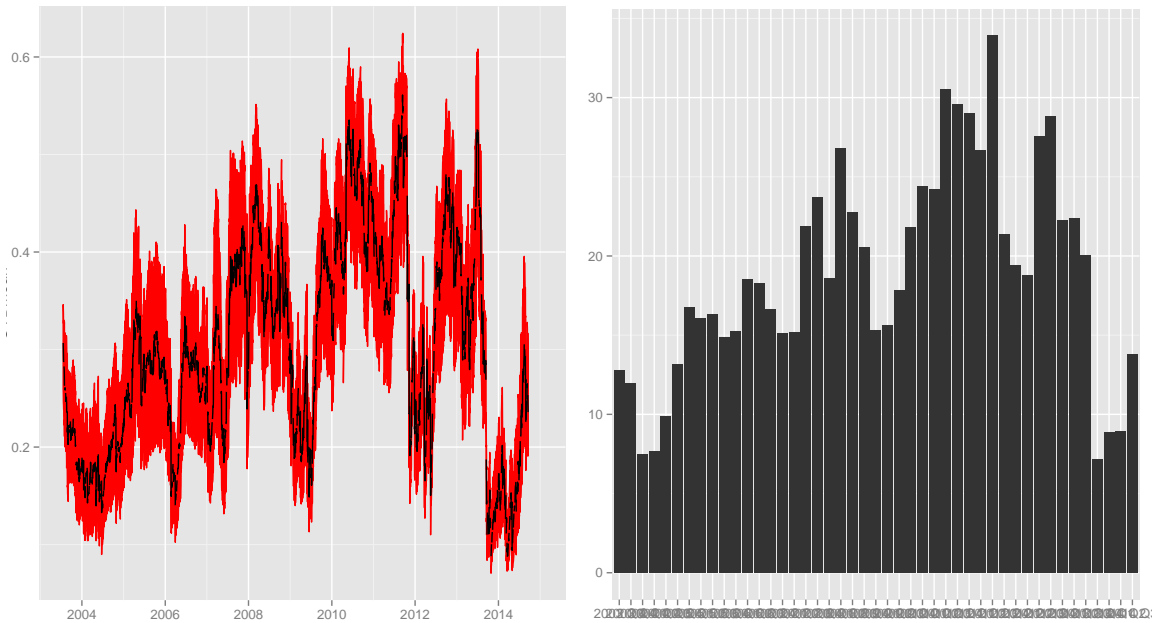


Figure 6: Time evolution of daily and quarterly tail dependence: Gumbel copula

The figure shows the evolution of daily (panel I) and quarterly (panel II) average upper tail dependence for the sample period from 2003 to 2014, respectively. Upper tail dependence is measured with the dynamic Gumbel copula. For the daily tail dependence, we additionally show the inter-quartile range in the shaded area.

the selected test to quantify the fit of each model, different models are selected. Also, our results show that a copula model with a good fit over the entire domain does not necessarily provide good fit in the tails and vice versa. Hence, we find first evidence that justifies our approach to take several copula models into account. In the following, we include all estimated copula models in the BMA regressions and rely on the BMA approach to *select* the copula model with the best fit. Note however, that we impose exclusion restrictions at this point.

Note, that the presented gof-tests show the in-sample goodness-of-fit of the models. We do not include goodness-of-fit tests based on the out-of-sample performance (see, e.g., [Diks et al., 2010](#)) as we test the out-of-sample performance of each model with our BMA approach. We can rely on the BMA approach to select the *best* copula model, that is, the copula model with the best out-of-sample forecast performance.¹²

Copula	Cramer-von Misses	Kolmogorov-Smirnov	Anderson-Darling	Pickands
t	0.13	0.55	0.31	0.02
SJC	0.48	0.18	0.11	0.07
Rotated Clayton	0	0.04	0.1	0.9
Gumbel	0.39	0.23	0.49	0

Table 4: Goodness-of-fit tests of individual copulas

This table presents the proportion of each individual copula model being the superior model to capture the dependency structure for a single name CDS contract joint with the market based on Cramer-von Misses, the Kolmogorov-Smirnov, and the Anderson-Darling goodness-of-fit tests. All goodness-of-fit tests are applied to Rosenblatt transformed data, then the copula with the best goodness-of-fit statistic is selected. Empirical tail dependence is estimated according to [Frahm et al. \(2005\)](#). The last column presents the selection based on the Anderson-Darling distance between the empirical tail dependence and the parametric tail dependence measured with Pickand’s dependency function computed from the fitted copula models.

5.2 Correlation analysis

Next, we examine simple correlations of the regressors with CDS spreads and CDS returns. Table 5 presents the largest correlations of regressors with CDS spreads, while Table 6 presents pairwise correlations between all variables included in the BMA regression setup. We observe the highest correlations between the first principal component, which is a weighted average of the individual CDS spreads measuring commonality, and the spreads, followed by the market and the spread. The higher correlation between Comm and CDS spreads can be attributed to the Commonality extracted by the pca. Thus, CDS spreads that experience less commonality with the other are attributed a

¹²Note, that [Diks et al. \(2010\)](#) find that the t copula is superior to the Clayton, Gumbel, or Gauss copula in comparisons based on the out-of-sample performance.

lower weight. Also, correlations with overall market movements (Russell) and financial stress are high. Moreover, we observe high correlations between the CDS spreads and the tail dependence measured with the t copula (0.52). We attribute this high correlation at least in part to the correlation being part of the tail dependence estimate.

Further correlations can be seen from Table 6. Most strikingly are high correlations between the tail dependence measures estimated with different copula models. Note, that the t -copula measure is least correlated with other copulas, but most correlated with market and commonality. Moreover, the other copula measures are not highly correlated with any of the other variables, which can be interpreted as a sign of uniqueness of the copula measures. The commonality factor is highly correlated with the financial distress indicator. Also, equity returns do not show any large correlations with other variables. Notable correlations are only with equity volatility and, not surprisingly, the change in firm value.

We run additional correlation analysis for our liquidity subsample period. We find that the liquidity measure is very unique as we do not observe any correlations above .3 (in absolute values). Consequently, we do not impose any exclusion restrictions on the liquidity measure.

Variable	Correlation with CDS Spread
CDSMarket	0.60
Comm	0.67
t copula tail dependence	0.52
Russell	-0.48
FDI	0.48

Table 5: Largest correlations with CDS Spreads

The table presents the largest correlations of independent variables with CDS spreads from our sample.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
1 CDSMarket	1.0	0.2	0.2	0.3	0.2	0.2	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.4	-0.1	0.2	0.1	0.1	-0.3	0.4	0.1	-0.4	-0.1	-0.3	-0.1	0.2	-0.5	-0.2	0.3	0.7	0.3	-0.3	0.1	-0.5	0.3	0.5	0.4	0.5	-0.7	0.0	0.9	-0.4	0.3	
2 ClaytonL	0.2	1.0	1.0	0.9	0.8	0.8	0.4	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.1	0.1	0.0	0.0	0.1	-0.2	-0.2	-0.3	-0.1	-0.1	-0.2	-0.2	0.1	0.1	-0.1	0.0	0.1	0.0	0.2	0.1	0.1	0.0	-0.1	0.1	0.2	-0.2	0.2			
3 ClaytonU	0.2	1.0	1.0	0.9	0.8	0.8	0.4	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.1	0.1	0.0	0.0	0.1	-0.2	-0.2	-0.3	-0.1	-0.1	-0.2	-0.2	0.1	0.1	-0.1	0.0	0.2	0.1	0.1	0.0	-0.1	0.1	0.2	-0.2	0.2					
4 GumbelU	0.3	0.9	0.9	1.0	0.9	0.9	0.5	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.1	0.2	0.2	0.1	-0.1	0.1	-0.2	-0.2	-0.3	-0.1	-0.1	-0.2	-0.3	-0.2	0.1	0.2	-0.1	0.0	0.1	-0.1	0.2	0.1	0.1	0.0	0.2	0.1	0.3	-0.3	0.2		
5 GumbelL	0.2	0.8	0.8	1.0	0.9	0.9	0.4	0.0	0.0	0.1	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.1	0.1	0.2	0.0	0.0	0.1	-0.2	-0.2	-0.3	-0.1	-0.1	-0.2	-0.2	0.1	0.1	-0.2	0.0	0.1	0.0	0.2	0.0	0.1	-0.1	0.0	0.1	0.2	-0.2	0.2		
6 SJCU	0.2	0.8	0.8	0.9	0.9	0.9	0.4	0.2	0.2	0.2	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.1	0.2	0.1	0.0	0.1	-0.2	-0.2	-0.2	0.0	0.0	-0.2	-0.2	-0.1	0.0	0.1	-0.2	0.1	0.2	0.0	0.2	0.0	0.1	-0.1	-0.1	0.1	0.2	-0.2	0.1		
7 SJCL	0.2	0.8	0.8	0.9	0.9	0.9	1.0	0.4	0.2	0.2	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.1	0.2	0.1	0.0	0.1	-0.2	-0.2	-0.2	0.0	0.0	-0.2	-0.2	-0.1	0.0	0.1	-0.2	0.1	0.2	0.0	0.2	0.0	0.1	-0.1	-0.1	0.1	0.2	-0.2	0.1		
8 tCop	0.7	0.4	0.4	0.5	0.4	0.4	1.0	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.4	0.0	0.2	0.1	0.1	-0.3	0.2	0.0	-0.4	-0.3	-0.2	-0.2	0.0	-0.6	-0.4	0.3	0.5	0.2	-0.3	0.0	-0.2	0.2	0.5	0.3	0.3	-0.6	-0.1	0.8	-0.5	0.4
9 dClaytonL	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.1	1.0	1.0	0.7	0.7	0.6	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	-0.1	0.1	0.1	0.0	0.1	-0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	-0.1	0.0	0.0			
10 dClaytonU	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.1	1.0	1.0	0.7	0.7	0.6	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	-0.1	0.1	0.1	0.0	0.1	-0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	-0.1	0.0	0.0		
11 dGumbelU	0.0	0.0	0.0	0.0	0.1	0.2	0.2	0.1	0.7	0.7	1.0	0.9	0.7	0.7	0.3	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	-0.2	-0.1	-0.1	0.3	0.1	0.1	0.0	0.1	-0.1	0.0	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.1	0.1	-0.2	-0.1	
12 dGumbelL	0.0	0.0	0.0	0.0	0.2	0.2	0.1	0.7	0.7	0.9	1.0	0.7	0.7	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-0.1	-0.1	0.2	0.1	0.0	-0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	-0.1	0.0	
13 dSJCU	0.0	-0.1	-0.1	-0.1	-0.1	0.1	0.1	0.0	0.6	0.6	0.7	0.7	1.0	0.8	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	0.0	-0.1	0.1	0.1	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	-0.1	0.0		
14 dSJCL	0.0	-0.1	-0.1	-0.1	-0.1	0.0	0.1	0.0	0.6	0.6	0.7	0.8	1.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	0.0	-0.1	0.1	0.1	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	-0.1	0.0	
15 dtCop	-0.1	0.0	0.0	-0.1	0.0	0.0	0.0	-0.2	0.2	0.2	0.2	0.2	0.2	0.2	1.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	0.0	0.4	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.1	-0.1	-0.2	-0.1	0.1	0.2	0.1	-0.2	-0.2	0.1	0.2	0.1	-0.1	-0.1	-0.2			
16 Equity	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.2	0.0	0.1	0.0	-0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
17 dFirmVal	-0.3	0.0	0.0	-0.1	0.0	-0.1	-0.1	-0.2	0.0	0.0	-0.1	0.0	0.0	0.0	0.0	0.2	1.0	0.0	0.1	0.0	-0.1	-0.1	-0.1	-0.1	0.0	0.1	-0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.2	0.2	-0.2	-0.2	-0.1	0.2	0.1	0.2	0.0	-0.2	-0.1	0.3	0.1	-0.3	0.2	-0.2		
18 dLeverage	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
19 FirmVal	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.1	-0.2	0.0	0.0	0.1	0.2	0.1	0.1	-0.1	0.1	0.1	0.2	0.0	0.1	-0.2	
20 Leverage	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
21 EquityVola	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.4	-0.1	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	-0.1	-0.1	0.1	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.1			
22 CDSVola	0.2	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	0.0	-0.1	0.0	0.0	1.0	0.1	0.0	0.0	-0.1	0.1	0.0	-0.1	-0.1	0.1	-0.1	-0.2	-0.2	-0.3	0.1	-0.3	-0.3	0.3	0.2	0.2	-0.2	-0.2	-0.2	-0.1	0.3	0.1	-0.3	-0.3	0.2	-0.2			
23 CoSkew	0.4	0.4	0.4	0.5	0.4	0.3	0.3	0.4	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.1	0.0	-0.1	0.0	0.0	0.1	1.0	-0.1	0.3	0.1	0.0	0.0	0.1	-0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
24 StockBeta	-0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.0	0.0	-0.1	1.0	0.0	-0.1	-0.1	-0.3	-0.5	-0.1	-0.2	-0.1	-0.2	-0.3	-0.1	-0.2	0.1	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.2	-0.1	0.2		
25 UpBeta	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.2	-0.1	-0.1	-0.1	-0.1	0.0	0.0	-0.1	0.0	0.0	0.0	0.0	0.1	0.3	0.0	1.0	-0.1	0.1	0.0	0.1	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	-0.1	0.1	0.2	0.1	-0.1	0.0	0.1	0.2	0.1	0.2	0.2	-0.2	0.1			
26 dCoSkew	0.1	0.1	0.1	0.2	0.2	0.2	0.																																													

5.3 Frequentistic Model Space Analysis

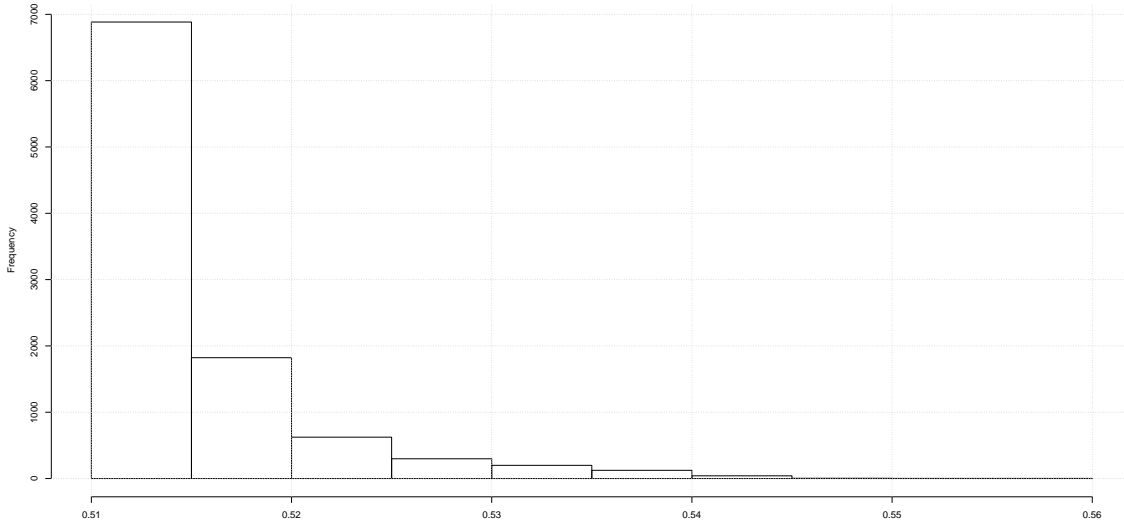


Figure 7: Histogram of adjusted R^2 for the considered model space.

The figure presents the distribution of adjusted R^2 of models in our considered model space.

For our regression analysis we consider all models in the model space as described in section 4.1. The *leaps and bound* algorithm provides us with 40,158 models from which we consider in our analysis (before applying Occam’s window) the best 10,000 models according to the adjusted R^2 . Figure 7 shows the histogram of the adjusted R^2 for our model space. All of the models exhibit values between 50% and 54% of adjusted R^2 which are each on the upper bound of what is reported elsewhere in the literature. To analyze the model space from a purely frequentistic point of view, we carry out t -tests on the long-run parameters (LRM) of the estimated models. Table 7 shows the results from these tests in terms of significance of the parameters on the 1% level. It shows the relative frequency of test-outcomes (negatively, positively or not significant) for a given regressor in the model space as well as the relative share of models in which the respective regressor is present.

Highlighted are variables which are included in more than 10% of the models. It is obvious that for most of the regressors significant effects can be found in at least some models. For example, for only five variables from our model space we cannot find any model with a statistically significant positive influence (GumbelL, Leverage, StockBeta, dUpbeta, FDIYoY). For many regressors, e.g. for CDSMarket, GDPQoQ or FDIQoQ, there is a large share of positively, negatively, and non-significant specifications in the model space. This shows the major problems of empirical studies focusing on single or a small set of *hand-picked* specifications. Given some creative theoretic rationale many

stories can be backed by the data, and often with a model providing great fit to the data. Choosing one model, e.g. based on the highest adjusted R^2 , cannot be justified from a statistical point of view since picking one model simply means discarding the information from all the other models. Put another way, the information of all models for which we do not have clear statistical evidence that they are outweighed by other models should be taken into account.

By looking at Table 7 we see that using all information from the model space we can get much stronger evidence with respect to the importance of specific regressors than one specific model can provide. Strikingly, the lower tail coefficient of the Gumbel copula, the tail dependence estimated using the t -copula, and the commonality factor are present in the major part of the model space, with mostly unambiguous significant effects. Also there seems to be quite strong evidence for effects of the delta of the t -copula tail coefficient and of the CDS volatility.

At this stage of the analysis our conclusions are based on the assumption that all models provide the same level of information. However, it seems intuitive that if some regressor is contained in a model which provides a better approximation to the data or the *true model* than others, then this regressor should obtain larger weight than a regressor in a model with a *poor* approximation. In the next step we will therefore weight the different models proportional to the statistical evidence to be the Kullback Leibler (KL) best model.

	Negative Significance	No Significance	Positive Significance	Times Included
CDSMarket	50.07%	9.50%	40.43%	6.95%
ClaytonL	37.03%	25.24%	37.74%	4.24%
ClaytonU	37.26%	25.00%	37.74%	4.24%
GumbelU	11.93%	7.99%	80.09%	9.39%
GumbelL	99.98%	0.02%	0.00%	94.19%
SJCU	31.18%	14.92%	53.90%	4.49%
SJCL	21.90%	22.96%	55.15%	3.79%
tCop	0.00%	0.00%	100.00%	99.99%
dClaytonL	0.00%	40.74%	59.26%	2.43%
dClaytonU	0.00%	40.74%	59.26%	2.43%
dGumbelU	0.00%	24.85%	75.15%	3.26%
dGumbelL	7.42%	52.40%	40.17%	2.29%
dSJCU	0.00%	44.26%	55.74%	2.96%
dSJCL	0.00%	66.35%	33.65%	2.11%
dtCop	9.04%	0.05%	90.91%	19.69%
Equity	51.83%	45.03%	3.14%	1.91%
dFirmVal	72.79%	5.10%	22.11%	5.88%
dLeverage	0.00%	67.38%	32.62%	1.87%
FirmVal	0.00%	26.44%	73.56%	2.61%
Leverage	0.00%	100.00%	0.00%	1.83%
EquityVola	21.81%	11.70%	66.49%	1.88%
CDSVola	0.00%	21.99%	78.01%	10.23%
CoSkew	63.90%	29.60%	6.50%	2.77%
StockBeta	77.98%	22.02%	0.00%	2.77%
UpBeta	0.00%	92.75%	7.25%	1.93%
dCoSkew	0.45%	40.27%	59.28%	2.21%
dUpBeta	0.00%	100.00%	0.00%	1.89%
CPIQoQ	49.90%	11.53%	38.57%	4.77%
CPIYoY	13.45%	56.72%	29.83%	2.38%
I10	0.00%	68.42%	31.58%	2.28%
I10QoQ	14.15%	67.32%	18.54%	2.05%
I10YoY	1.11%	34.69%	64.21%	2.71%
GDPQoQ	24.50%	29.63%	45.87%	3.51%
GDPYoY	1.10%	10.97%	87.93%	5.47%
Fed	0.00%	61.97%	38.03%	2.34%
FedQoQ	1.50%	11.99%	86.51%	4.67%
FedYoY	0.19%	4.44%	95.37%	5.40%
FDI	82.82%	14.54%	2.64%	4.54%
FDIQoQ	31.77%	10.29%	57.94%	6.61%
FDIYoY	98.87%	1.13%	0.00%	7.96%
IPQoQ	1.11%	9.83%	89.05%	5.39%
IPYoY	0.46%	10.98%	88.56%	4.37%
OilQoQ	56.90%	12.48%	30.62%	5.29%
OilYoY	2.65%	29.71%	67.65%	3.40%
Ted	82.50%	12.08%	5.42%	4.80%
TedQoQ	4.38%	26.04%	69.58%	4.57%
TedYoY	83.37%	11.31%	5.32%	4.51%
RusselQoQ	9.89%	32.20%	57.91%	3.54%
RusselYoY	1.29%	9.25%	89.46%	4.65%
Common	0.53%	0.02%	99.44%	82.74%
Sentiment	8.33%	27.47%	64.20%	3.24%
VIX	75.12%	21.98%	2.90%	4.14%

Table 7: Results t -tests for LRM of regressor variables based on model space.

The table shows the results from t -tests for long-run multipliers of regressors variables for the entire model space in terms of significance of the parameters on the 1% level. It shows the relative frequency of test-outcomes (negatively, positively or not significant) for a given regressor in the model space as well as the relative share of models in which the respective regressor is present. Highlighted are variables which are included in more than 10% of the models.

5.4 BMA Estimates

The BMA methodology provides us with a statistically consistent framework to deal with model uncertainty by weighting the different models in the model space proportional to their *informational content*. Based on the model space used above (without further restrictions) we first calculate Occam’s window which discards all models for which we have weak statistical evidence that they are the best approximation to the unknown *true* model. Occam’s window leaves us with 51 models (see Table 9), which we combine according to the BMA weighting scheme. Figure 8 shows graphically the results for the BMA model: the posterior inclusion probabilities (PIP) and the normalized long-run-multiplier (LRM). Comparing the PIP to the prior inclusion probabilities (indicated by the horizontal dotted line), we find that the Gumbel copula (UTD and LTD), the t -copula (delta and level), CDS volatility, commonality and the financial distress indicator are significant. From the LRM, however, we learn that the Gumbel copula and the t -copula (level) have by far the strongest impact, while the other factors - taking delta t -cop aside - have rather negligible effects. These results suggest that firms’ CDS-returns are largely dominated by their sensitivity to extreme market movements as measured by the different copula measures. Further, it seems that - instead of one copula based measure - one should take into account information provided by differing copula measures. Table 8 summarizes the PIP and LRM for the significant regressors.

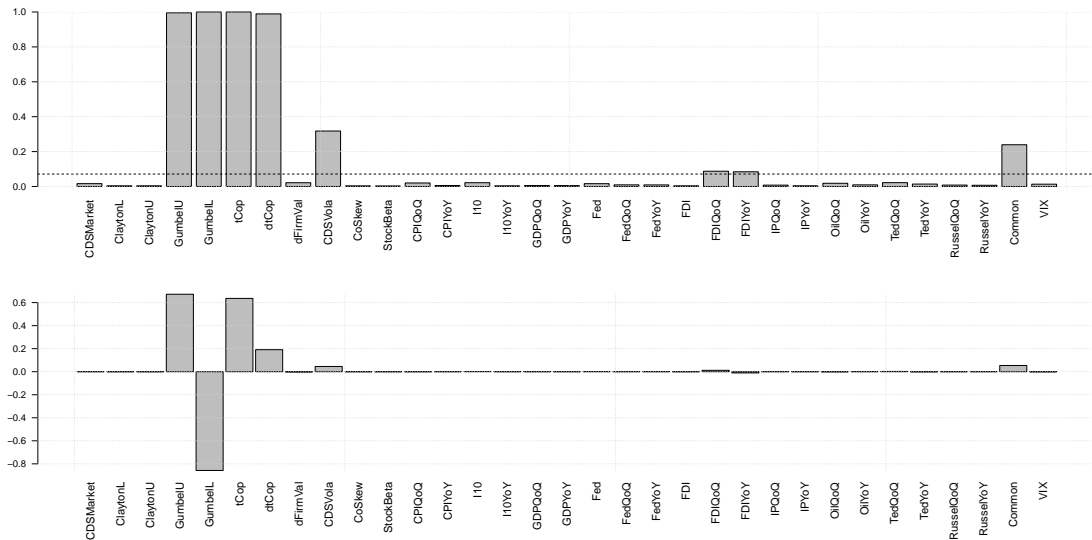


Figure 8: PIP (upper panel) and LRM (lower panel) of all regressors in the unrestricted BMA model.

The figure shows PIP (upper panel) and LRM (lower panel) of all regressors in the unrestricted BMA model. A detailed list of all variables included in the models and their description can be found in Tables `tab:bmvvariables` and 2. The horizontal dotted line in the upper panel indicates the prior inclusion probabilities. A variable is significant if the PIP is larger than the prior inclusion probability.

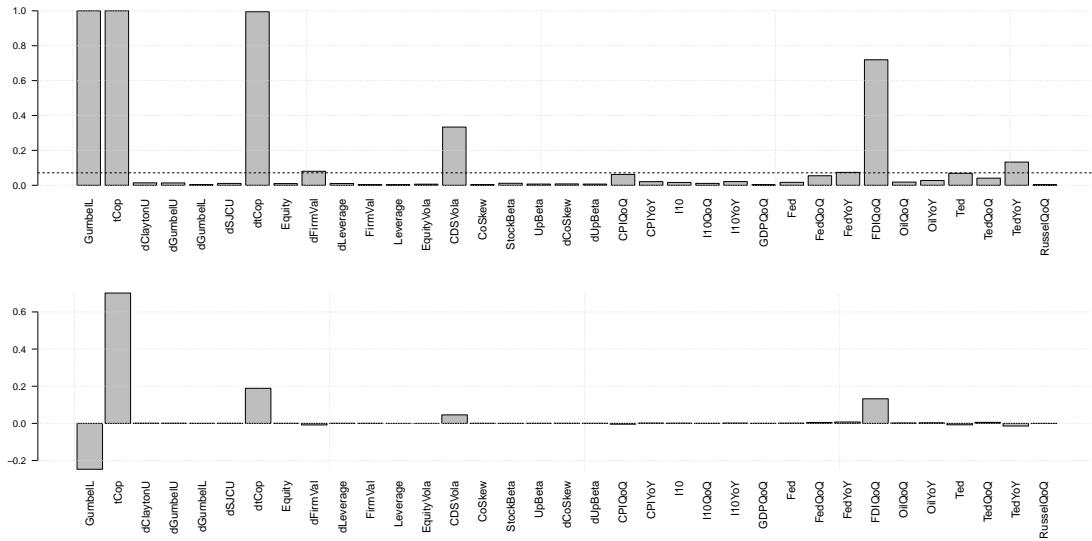


Figure 9: PIP (upper panel) and LRM (lower panel) of all regressors in the restricted BMA model.

The figure shows PIP (upper panel) and LRM (lower panel) of all regressors in the restricted BMA model. A detailed list of all variables included in the models and their description can be found in Tables `tab:bmavariab` and 2. The horizontal dotted line in the upper panel indicates the prior inclusion probabilities. A variable is significant if the PIP is larger than the prior inclusion probability.

Since model selection is often also based on assessments of *plausibility*, we filter the model space in the next step such that only models satisfying our reasoning will be considered. We apply sign-restrictions on the coefficients of the LRM and discard models that suffer from highly collinear variables. In Table 9 an overview for the filtering process is given. Figure 9 shows the results for the restricted BMA model. We see that, analogue to the analysis in Section 5.3, the Gumbel copula (LTD), the *t*-copula (delta and level) and CDS volatility are the most significant variables. In addition, the financial distress indicator, the Ted-rate and the firm-value (delta) are significant. The normalized LRM indicate that the effect of the *t*-copula dominates the Gumbel copula, the delta *t*-copula and the financial distress indicator by more than factor three, while the CDS volatility and the firm value (delta) have rather negligible effects. Table 8 again summarizes the PIP and LRM for the significant regressors.

These findings support the studies by [Meine et al. \(2015b\)](#) or [Christoffersen et al. \(2014\)](#) that find evidence for the relationship between CDS spreads and tail dependence. Note however, that up to this point, our study confirms this relationship for the entire sample period which includes crisis and non-crisis periods, and not only for crisis periods. A more detailed analysis for bullish and bearish markets will be performed in Section 5.5. In contrast to the study by [Meine et al. \(2015b\)](#), we analyze the influence of level values of tail dependence as well as deltas. As anticipated, the level values of the tail

dependence measures provide a much better fit for our overall model than the deltas of the tail dependence measures. A high level of tail dependence captures a high cross-sectional probability of single name contracts to jointly surge with the market without the tail dependence necessarily increasing during these surges. Hence, in a cross-section comparison, single name contracts with a high level of tail dependence indicate a high probability of joint surges. The tendency to surge with the overall market is persistent. It does change over time, but not rapidly enough to explain joint surges as good as the level values do.

Compared to unrestricted BMA the upper Gumbel tail coefficient has dropped from the model space. The reason is the high correlation between upper and lower tail coefficient of the Gumbel copula which leads to models being dropped in which both are present. Importantly, the aggregated LRM effect from the Gumbel copula (upper and lower) in unrestricted BMA is close to the effect of the Gumbel (lower) in restricted BMA. In addition, the effects of the t -copula (level) and the financial distress indicator increase.

The basic results from unrestricted BMA, however, remain valid when moving to restricted BMA. Still results are largely dominated from the tail coefficients as measured by different copula specifications. For example, our results provide some evidence that commonality indeed is related to CDS returns as argued by, e.g. [Berndt and Obreja \(2010\)](#). However, this effect seems to be dominated by other factors. We will return to this observation in Section 5.6.

Variable	Unrestricted		Restricted	
	PIP	LRM	PIP	LRM
GumbelU	100%	0.673	-	-
GumbelL	100%	-0.858	100%	-0.247
tCop	100%	0.636	100%	0.702
dtCop	99%	0.191	99%	0.189
dFirmVal	-	-	8%	-0.008
CDSVola	32%	0.045	33%	0.046
FedYoY	-	-	7%	0.007
FDIQoQ	9%	0.012	72%	0.132
FDIYoY	8%	-0.011	-	-
TedYoY	-	-	13%	-0.014
Common	24%	0.054	-	-

Table 8: PIP and LRM of significant regressors in the unrestricted and restricted BMA model.

The table shows PIP and LRM of all significant regressors in the unrestricted (left panel) and restricted (right panel) BMA model. A detailed list of all variables included in the models and their description can be found in Tables 3 and 2. A variable is significant if the PIP is larger than the prior inclusion probability.

Unfiltered Model Space	10,000
Occam's Window Unrestricted	51
Models satisfying Exclusion Restrictions	1,510
Model satisfying Sign Restrictions	3,610
Models satisfying Exclusion & Sign Restrictions	282
Occam's Window Restricted	127
R^2 Range Model Space	50%-54%

Table 9: Overview of the model space filtering process

The table presents an overview of our model space as a results to thorough filtering. Each line shows the size of our entire model space as a result of applying the described filter.

5.5 Analyses based on sub-samples

As the BMA approach provides very robust results, we do not present slightly adjusted model setups here. Instead, we focus on different subsamples to provide evidence whether our results are driven by specific samples, e.g. by crisis periods, or CDS of a specific investment quality class, and to determine whether pricing determinants change during bullish or bearish times, or differ across investment quality classes. Moreover, we use the analysis of subsamples to follow up on literature that provides evidence that the sensitivity of CDS spreads towards a specific pricing factor increases during certain market circumstances (see, e.g., [Alexander and Kaeck, 2008](#)). Table 10 shows the results of t -tests for LRM of regressor variables of the model space, based on different subsamples, while Table 11 presents PIP and LRM for both, the unrestricted and the restricted BMA model for our six subsamples. Table 12 shows the overview of the model space filtering process for different subsamples. We loose many models due to our exclusion and sign restrictions, but are left with at least 299 models for all subsamples.

The first panel of the tables focuses on an additional liquidity measure. Several studies highlight the importance of liquidity in the context of asset pricing (see, e.g., [Meine et al., 2015a](#); [Arakelyan et al., 2015](#); [Tang and Yan, 2008](#); [Bongaerts et al., 2011](#); [Longstaff et al., 2005](#); [Qiu and Yu, 2012](#)) and argue that many effects can be explained by liquidity. As the Markit dataset only provides a measure of liquidity starting in 2011, and we find it hard to argue that stock liquidity can serve as a reasonable proxy for CDS spread liquidity, we rely on a sub-sample analysis covering the period from 2011 to 2015 to check the influence of liquidity. Our results show that indeed we do find models with a significant influence of the liquidity measure on CDS spreads. However, we notice that the liquidity measure is only included in 1.23% of models of the model space, and that the measure is not included in the BMA models. Thus, our results show that indeed, we are able to find some models with a significant relationship between liquidity and CDS spreads, which is in line with [Meine et al. \(2015a\)](#); [Arakelyan et al. \(2015\)](#); [Tang and Yan \(2008\)](#); [Bongaerts et al. \(2011\)](#); [Longstaff et al. \(2005\)](#); [Qiu and Yu \(2012\)](#), but we cannot confirm their hypothesis that liquidity can explain many puzzles. Moreover, the results show that

the influence tail dependence measures, especially measures with the t copula, still have the highest inclusion rates. Apart from the t copula, the Gumbel copula is included in many models with a significant sign, and the lower tail dependence estimated with the SJC copula is included in most of the remaining models. Also, several non-idiosyncratic measures are included in addition to the copula measures for the liquidity sub-sample.

Next, we run one analysis focusing on single name CDS contracts that are part of the CDX North America Investment Grade Index and one analysis focusing on CDS contracts that are part of the High Volatility Index. The results are presented in panels two and three of Tables 10 and 11. We observe several differences between the determinants of CDS spreads with regard to the investment quality class. Notably, the delta of the firm value enters the models of the HV sub-sample in 76.59% of the model space, and in 86% of the restricted models, while this factor is not considered for investment grade CDS spreads. Similarly, the overall market development seems to be more important for the HV sample, but this does not hold for the restricted BMA models. On the other hand, CDS volatility, lower tail dependence measured with the Gumbel copula, and the delta of the t copula tail dependence are more important for the IG sample. However, for both samples the tail dependence measures estimated using the t copula and the Gumbel copula have the highest inclusion probability. Thus, the connection between tail dependence and CDS spread returns is not a particular feature for certain investment quality classes.

Finally, we control for the crisis period as, e.g., Alexander and Kaeck (2008) show that CDS spreads are more sensitive to volatility in the stock market during periods of market turbulence, and more sensitive to stock returns otherwise. Thus, one could argue reasonably well that the pricing of CDS contracts changed during the crisis period. Consequently, we run sub-sample regressions focusing on pre-crisis, during-crisis, and post-crisis periods. According to Laeven and Valencia (2012), the crisis period in the U.S. ranges from 2007 to 2011. Indeed, less factors are included in the unrestricted and restricted BMA models during the crisis period. For example, $dFirmVal$ is included in several models pre- and post-crisis, but not during the crisis period. Also notably, our volatility measure is included in several models pre- and during the crisis period, but not post-crisis. Again, the tail dependence measures estimated with the t and the Gumbel copula are the factor with the highest inclusion probability for all sub-samples. Thus, we expand the evidence of Meine et al. (2015b) who find a statistically significant relationship between the delta of a tail dependence measure and CDS returns for a sample of banks during the crisis period. In contrast to their study, we find that this relationship also holds pre- and post-crisis.

Note, that for all sub-samples we obtain reasonably high R^2 . The only exception is the pre-crisis period with R^2 values around 40%. For all other periods, we obtain R^2 higher than 50%, which is about the size that is reported in other studies in the literature. For

the investment grade sub-sample we even obtain R^2 values close to 60%.

		Negative Significance	Non Significance	Positive Significance	Times Included
Liquidity	Liquidity	16.26%	83.74%	0.00%	1.23%
	tCop	0.00%	0.00%	100.00%	99.99%
	dtCop	3.60%	3.41%	92.99%	31.97%
	GumbelL	99.91%	0.08%	0.01%	86.48%
	Fed	8.00%	2.29%	89.71%	24.49%
	FedQoQ	1.89%	1.51%	96.60%	35.00%
	FedYoY	3.55%	4.61%	91.84%	14.09%
	OilYoY	81.42%	1.84%	16.74%	24.97%
IG	GumbelL	99.88%	0.12%	0.00%	69.10%
	tCop	0.00%	0.00%	100.00%	99.66%
	dtCop	20.47%	1.95%	77.58%	17.93%
	CDSVola	3.23%	3.07%	93.69%	61.53%
	FDIYoY	98.84%	1.07%	0.09%	21.57%
	Common	5.93%	0.23%	93.84%	48.23%
	Sentiment	2.02%	4.81%	93.17%	10.39%
	HV	CDSMarket	0.46%	0.67%	98.87%
GumbelU		66.20%	3.33%	30.47%	11.42%
GumbelL		98.31%	1.69%	0.00%	18.92%
tCop		0.00%	0.00%	100.00%	99.31%
dtCop		2.01%	1.45%	96.54%	31.78%
Equity		94.64%	5.36%	0.00%	23.13%
dFirmVal		99.71%	0.27%	0.01%	76.59%
OilQoQ		89.94%	9.10%	0.97%	12.42%
Common		4.48%	4.39%	91.13%	22.54%
PreCrisis		CDSMarket	51.33%	2.81%	45.87%
	GumbelU	1.59%	2.80%	95.61%	20.75%
	GumbelL	99.99%	0.01%	0.00%	93.79%
	tCop	0.00%	0.00%	100.00%	99.70%
	dtCop	0.62%	0.20%	99.18%	56.41%
	CDSVola	7.58%	2.77%	89.65%	19.52%
	dCoSkew	0.57%	6.40%	93.02%	12.18%
	Crisis	GumbelU	9.18%	6.64%	84.18%
GumbelL		99.79%	0.21%	0.00%	72.04%
tCop		0.00%	0.00%	100.00%	99.60%
dtCop		6.97%	0.34%	92.69%	70.75%
CDSVola		0.00%	6.27%	93.73%	15.14%
dCoSkew		67.96%	2.02%	30.02%	26.28%
Common		77.21%	5.17%	17.61%	10.05%
PostCrisis		GumbelL	99.63%	0.34%	0.03%
	tCop	0.00%	0.00%	100.00%	99.53%
	dtCop	9.88%	1.52%	88.60%	20.44%
	CPIQoQ	88.47%	6.32%	5.21%	11.71%
	Fed	14.57%	3.99%	81.44%	13.04%
	FedQoQ	0.87%	2.24%	96.89%	13.84%
	FDIYoY	96.34%	3.44%	0.22%	13.65%
	Common	0.36%	0.09%	99.55%	75.69%

Table 10: Results t -tests for LRM of regressor variables of model space based on different sub-samples.

The table shows the results from t -tests for long-run multipliers of regressors variables for the entire model space for our sub-sample analysis in terms of significance of the parameters on the 1% level. It shows the relative frequency of test-outcomes (negatively, positively or not significant) for a given regressor in the model space as well as the relative share of models in which the respective regressor is present. The table only includes variables which are included in more than 10% of the models.

Subsample	Variable	Unrestricted		Restricted	
		PIP	LRM	PIP	LRM
Liquidity	GumbelL	87%	-0.337	89%	-0.334
	SJCL	-	-	7%	-0.018
	tCop	100%	0.661	100%	0.667
	dtcop	35%	0.069	48%	0.09
	CPIQoQ	12%	0.001	10%	0
	I10YoY	-	-	9%	0.003
	Fed	23%	0.063	31%	0.1
	FedQoQ	36%	0.099	31%	0.093
	FedYoY	15%	0.039	16%	0.047
	FDIQoQ	9%	-0.013	-	-
	OilYoY	27%	-0.060	8%	0.009
	TedQoQ	-	-	9%	-0.012
	TedYoY	-	-	13%	-0.005
IG	GumbelU	24%	0.147	-	-
	GumbelL	100%	-0.412	98%	-0.233
	tCop	100%	0.720	100%	0.739
	dtCop	62%	0.102	83%	0.137
	CDSVola	88%	0.165	93%	0.16
	FedQoQ	-	-	10%	0.014
	FedYoY	-	-	13%	0.016
	FDIYoY	68%	-0.142	-	-
	Ted	-	-	19%	-0.028
	TedYoY	-	-	16%	-0.017
Common	9%	0.020	-	-	
HV	CDSMarket	51%	0.153	-	-
	ClaytonL	8%	-0.008	-	-
	ClaytonU	8%	-0.008	-	-
	GumbelU	12%	0.030	-	-
	GumbelL	22%	-0.070	23%	-0.041
	SJCU	8%	-0.009	-	-
	tCop	100%	0.429	100%	0.550
	dtCop	41%	0.079	97%	0.199
	Equity	23%	-0.041	22%	-0.038
	dFirmVal	78%	-0.173	86%	-0.195
	CPIQoQ	-	-	13%	-0.016
	CPIYoY	-	-	11%	0.015
	FDIQoQ	-	-	30%	0.065
	OilQoQ	15%	-0.028	-	-
	OilYoY	-	-	13%	0.018
	RusselQoQ	-	-	18%	-0.039
	Common	20%	0.055	-	-

Table 11: PIP and LRM for unrestricted and restricted BMA model for different subsamples (Panels 1-3).

The table shows PIP and LRM of all significant regressors in the unrestricted (left panel) and restricted (right panel) BMA model. A detailed list of all variables included in the models and their description can be found in Tables 3 and 2. A variable is significant if the PIP is larger than the prior inclusion probability.

Subsample	Variable	Unrestricted		Restricted	
		PIP	LRM	PIP	LRM
PreCrisis	CDSMarket	8%	-0.005	-	-
	GumbelU	42%	0.173	-	-
	GumbelL	99%	-0.384	95%	-0.234
	tCop	100%	0.607	100%	0.640
	dtCop	67%	0.145	80%	0.166
	dFirmVal	-	-	7%	-0.008
	CDSVola	19%	0.029	27%	0.044
	dCoSkew	12%	0.018	16%	0.024
	CPIYoY	-	-	7%	-0.008
	I10	-	-	8%	0.007
	GDPYoY	9%	-0.013	13%	-0.018
	Fed	8%	0.010	11%	0.013
	FedQoQ	-	-	10%	-0.013
	OilYoY	10%	-0.015	-	-
	TedQoQ	-	-	8%	-0.009
Crisis	GumbelU	13.28%	0.056	-	-
	GumbelL	83.24%	-0.269	88%	-0.243
	tCop	100.00%	0.795	100%	0.820
	dtCop	82.89%	0.189	94%	0.220
	CDSVola	14.27%	0.019	15%	0.020
	dCoSkew	20.02%	-0.007	12%	0.017
	CPIQoQ	7.25%	-0.006	10%	-0.006
	FDIQoQ	12.64%	0.024	15%	0.034
	Ted	-	-	8%	0.004
	TedQoQ	11.70%	0.018	17%	0.030
	TedYoY	-	-	7%	-0.006
	Common	7.11%	-0.010	-	-
	PostCrisis	GumbelU	14%	0.069	-
GumbelL		95%	-0.308	98%	-0.295
tCop		100%	0.560	100%	0.738
dtCop		30%	0.042	71%	0.119
dFirmVal		-	-	11%	-0.014
CPIQoQ		14%	-0.016	24%	-0.029
GDPQoQ		8%	-0.007	14%	-0.02
Fed		32%	0.059	59%	0.123
FedQoQ		11%	0.014	15%	0.024
FedYoY		9%	0.020	-	-
FDIQoQ		10%	-0.024	9%	0.013
FDIYoY		18%	-0.032	-	-
OilYoY		-	-	17%	0.026
Ted		-	-	13%	-0.011
TedQoQ		-	-	10%	-0.001
TedYoY		-	-	9%	-0.013
Common	71%	0.215	-	-	

Table 11: PIP and LRM for unrestricted and restricted BMA model for different subsamples (Panels 4-6).

The table shows PIP and LRM of all significant regressors in the unrestricted (left panel) and restricted (right panel) BMA model. A detailed list of all variables included in the models and their description can be found in Tables 3 and 2. A variable is significant if the PIP is larger than the prior inclusion probability.

	Liquidity	IG	HV	PreCrisis	Crisis	PostCrisis
Unfiltered Model Space	10,000	10,000	10,000	10,000	10,000	10,000
Occam's Window Unrestricted Models satisfying	10,000	122	10,000	4,221	9,890	2,295
Exclusion Restrictions Models satisfying	6,410	3,430	2,090	5,290	6,520	1,450
Sign Restrictions Models satisfying	3,670	2,520	4,150	5,320	4,170	3,140
Exclusion & Sign Restrictions Occam's Window	2,192	570	771	2,961	2,728	299
Restricted R^2 Range	2,192	209	771	2,961	2,728	299
Model Space	49%-53%	55%-59%	49%-55%	38%-44%	58%-63%	50%-54%

Table 12: Overview of the model space filtering process for different sub-samples.

The table presents an overview of our model space as a results to thorough filtering for our sub-sample analysis. Each line shows the size of our entire model space as a result of applying the described filter.

5.6 Hypothesis tests based on forecast performance

Finally, we use want to back up and clarify some of the results obtained in Section 5.4 by comparing the predictive ability of different model setups. To do so, we carry out a sequence of Diebold-Mariano (DM) tests for different model setups based on out-of-sample forecasts as described in Section 4.1.4. The setups are BMA models in which we restrict the possible regressors to a smaller subset. The different specifications take into account all regressors that were found to be significant in the unrestricted BMA setup for the full sample. Importantly, even in the case a setup contains only one regressor, BMA will ensure that different dynamic specifications are considered. Further, we apply sign restrictions but no exclusion restrictions to the model space to ensure that not some regressors are *crowded out* due to collinearity issues. The main purpose of the sequence of tests is to clarify the working hypothesis obtained from Section 5.4 that focusing on copula based regressors is sufficient for modeling CDS returns. This would imply that all pricing information is covered by a combination of different tail dependence measures.

As a benchmark forecasting model we use a simple $AR(2)$ process. In Table 13 the results from the tests are summarized. In addition the respective root-mean-squared (forecast) errors (RMSE) for each setup are reported. The test sequence works as follows. In each test, we test for the superior predictive ability of the respective setup compared to the best setup obtained from the precedent tests. The tests have three main blocks. First, we test different specifications based on copula and market based measures. We find that, confirming the results obtained in Section 5.4, a combination of several copula measures (setup 1(i)) significantly outperforms all other setups including those in which market based measures are present. Also note the high explanatory power of the commonality (pca) even though this is an non-idiosyncratic factor. Thus, we find a high explanatory

power of the commonality factor, confirming the results of [Berndt and Obreja \(2010\)](#), but at the same time provide evidence that this effect is dominated by other factors - namely the tail dependence measures of our copula models.

In the second block of the tests, we recursively add idiosyncratic factors which were found to be significant in some of the setups of previous sections. We find that only CDS volatility significantly improves the forecast performance. The gain in RMSE, however is rather low. The third testing block checks for the contribution of different macro factors. Here we find that the financial distress indicator (QoQ) can improve the forecasts. But also here the gain in RMSE is very small.

We conclude, that the hypothesis, indicated by the results from previous sections, is strongly confirmed that close to all relevant pricing information can be obtained by a combination of copula based measures of tail dependence.

Overall, these results provide evidence that the tail dependence, when estimated with the t copula, is significantly superior in explaining CDS spreads to other factors. Moreover, adding additional different tail dependence measures estimated using different copula models decreases the RMSE. First, the tail dependence measure of the t copula significantly outperforms the measure estimated with the Gumbel copula, the market, and the commonality measure. We argue that commonality is an important factor when pricing CDS contracts. However, additional to the linear dependence measured with the simple means (CDS Market) or weighted averages (Commonality), non-linear dependence (tail dependence) has significant explanatory power which decreases RMSE. Moreover, we argue that the specific construction of the t copula, consisting of the correlation, and the degrees of freedom parameter, allows to capture both, linear and tail dependence at the same time. Thus, the tail dependence measure estimated using the t copula outperforms all other tail dependence measures as well as the linear dependence measures. Note, that the t copula may converge against the Gauss copula, and thus only capture linear dependence for large degrees of freedom parameter. However, in our sample, the estimate for the parameter capturing the degrees of freedom is never larger than 21. Hence, we do not observe convergence to linear dependence in our sample. Additionally, adding a different tail dependence measure to the t copula, the Gumbel copula in our case, increases forecasting ability due to the increased modeling flexibility in the tails of the distribution. Hence, we can state that these measures do not capture the same dynamics, but instead the Gumbel copula is able to pick up on additional dependence structures that the t copula cannot capture.

		RMSE	t-stat. of DM test	p-value of DM test
	AR(2) Model	0.516	-	-
1 Copula/Market	(a) GumbelU + GumbellL	0.460	14.160	2.20E-16***
	(b) CDSMarket	0.417	8.570	2.20E-16***
	(c) Common	0.396	8.764	2.20E-16***
	(d) tCop	0.390	1.550	0.0605*
	(e) tCop+Common	0.390	-1.550	0.9395
	(f) Common+tCop+CDSMarket	0.390	-1.523	0.9361
	(g) tCop+dtCop	0.383	8.944	2.20E-16***
	(i) GumbelU+GumbellL+tCop+dtCop	0.355	10.874	2.20E-16***
	2 Idiosyn.	(a) 1(i) + dCoSkew	0.355	-0.388
(b) 1(i) + CDSVola		0.353	3.701	0.0001086***
(c) 2(b) + dFirmVal		0.353	-3.041	0.9988
(d) 2(b) + Equity		0.353	-3.298	0.995
3 Macro	(a) 2(b) + FDIQoQ	0.351	4.071	2.37E-5***
	b. 3(a) + TedQoQ	0.351	-4.920	1
	c. 3(a) + RusselQoQ	0.351	-4.370	1
	d. 3(a) + OilQoQ	0.351	-4.650	1
	e. 3(a) + CPIQoQ	0.351	-4.950	1

Table 13: RMSEs and Diebold Mariano (DM) tests for different setups.

The table shows RMSE calculated on basis of holdout sample. In the DM tests the model setup in each row is tested against the alternative that it has superior predictive ability than the respective best setup found previous to the checked setup. The respective best setup against which is tested is the setup - standing above of the checked setup - showing significant superior predictive ability (i.e. is denoted by *, ** or ***). The concrete dynamic specification of each model setup is calculated via BMA. Each setup uses the same observations in the training and holdout sample respectively.

6 Conclusion

This paper contributes to the literature on the determinants of CDS spreads and to the literature on the pricing of downside risk. Even though the literature on CDS determinants is rich, there is still no consensus about which factors mainly drive CDS spreads and whether there is a superior model setup which one should follow. We do not observe convergence to some factors in the literature. The recent literature on the impact of crash aversion on the pricing of individual financial instruments, including CDS, shows that crash-sensitive financial instruments bear a premium (Chabi-Yo et al., 2014; Meine et al., 2015b) which can be interpreted as a non-linear addendum to the CAPM asset pricing theory.

Our paper provides a robust and transparent analysis for the determinants of CDS spreads by focusing on the model space instead of just one specific model. We include many of the variables suggested elsewhere in the literature as regressors, including tail dependence measures derived from four different dynamic copula models. Using a CDS data-set set of 227 firms from different industries we analyze both investment grade and high volatility contracts and distinguish between pre-, during, and post-crisis periods.

Our results suggest, that the tendency of an individual CDS contract to jointly experience extreme movements with the market is the major determinant of CDS premia. The

estimated tail dependence of a symmetric t copula has the highest explanatory power among all regressors. Moreover, we show that a model including only tail dependence measures significantly outperforms the out-of-sample forecast quality of any other model. On the other hand, our results suggest that Merton-type and macroeconomic factors can be considered as negligible. This also holds for variables measuring the systematic market evolution based on simple means or principal component analysis. While a systemic risk measure based on simple means is just able to capture linear dependencies, our tail dependence measure incorporates both linear and non-linear dependencies as the tail dependence critically depends on the correlation between time series, but also on the degrees of freedom of the estimated t copula model. The pca provides a more precise measurement of common factors than a simple means model; however, the tail dependence measure is superior. Adding an additional measure to allow for non-symmetric tail dependence increases out-of-sample forecast quality. Hence, our study suggests that CDS spreads are mainly determined by investors' fear of joint turbulences with the market.

Additionally, we show that the choice of the copula to estimate tail dependence is crucial for the explanatory power. With respect to different copula models, we find that the symmetric t copula dominates all other copula specifications. We attribute this finding to the fact, that the tail dependence estimate of the symmetric t copula captures time-varying correlations with one parameter, but also depends on the degrees of freedom parameter estimate. However, adding a different tail dependence measure in addition to the t copula, the Gumbel copula in our case, increases the explanatory power of our models. Thus, we provide evidence that these different copula measures do not capture the same dynamics, but instead the Gumbel copula is able to pick up on additional dependence structures that the t copula cannot capture, i.e. non-symmetric attributes.

Our results have implications for understanding the dynamics of financial markets and financial stability as we highlight the importance of tail risk and common factors in asset pricing.

A Time-varying copula models

This section describes the time-varying copula models employed in our study, as well as the estimation of tail dependence measures, and goodness-of-fit tests.

A.1 Modeling extreme comovements

To capture the extreme comovement between financial time series, we rely on Copula-GARCH models (see [Jondeau and Rockinger, 2006](#)) in our study. These models allow for some in an autoregressive manner time-varying parameters, conditional on the set of past information. To consider conditional distributions of some random variable X_t given an information set \mathcal{F} an extension of Sklar's theorem (see [Sklar, 1959](#)) is necessary. This extension to the conditional case is due to [Patton \(2006\)](#) who defines the *conditional copula*:

$$\mathbf{F}_t(x \mid \mathcal{F}_{t-1}) = \mathbf{C}_t(F_{1,t}(x_1 \mid \mathcal{F}_{t-1}), F_{2,t}(x_2 \mid \mathcal{F}_{t-1}), \dots, F_{n,t}(x_n \mid \mathcal{F}_{t-1}) \mid \mathcal{F}_{t-1}), \quad \forall x \in \mathbb{R}^n.$$

Here, $X_i \mid \mathcal{F}_{t-1} \sim F_{i,t}$ and \mathbf{C}_t denotes the conditional copula of \mathbf{X}_t given \mathcal{F}_{t-1} .

A.1.1 Univariate modeling of returns

As noted by [Sklar \(1959\)](#), the use of copulas allows to define multivariate models where the marginal distributions are not of the same type as the copula model. Thus, we can combine non-parametric estimation for the marginal distributions with parametric estimation of the copula (see [Chen and Fan, 2006](#); [Chen et al., 2006](#)). As our study focuses on the dependence structures between CDS spreads, we are not interested in the estimation of the marginals and only estimate the copula. Estimation methods for the copula assume identical independent distributed data (see [Genest et al., 1995](#)). However, stylized facts of financial time series state that model residuals are often skewed and fat tailed in addition to a leverage effect (see [Cont, 2001](#); [Joe, 2015](#)). Focusing on CDS spread time series, [Cont and Kan \(2011\)](#) provide evidence that CDS spread returns are stationary and exhibit positive autocorrelation. Moreover, the authors find that the returns are described by conditional heteroscedasticity, two-sided heavy tails, serial dependence in extreme values, and sizable co-movements that are not necessarily linked to credit events. Hence, as returns of financial data in general and specifically CDS data are usually not i.i.d. and we can confirm the stylized facts for our dataset (see section [3.1](#)), we have to filter the data first.

Thus, we first apply our data to an AR(m)-GARCH(p,q) model, before we standardize the i.i.d. residuals from the filtration to uniform. We use a probability integral transform of the following form. Due to the filtration, ϵ_t , $t = 1, \dots, T$ is a time series of i.i.d. variables. Under the assumption $\epsilon_t \sim F_i$, $t = 1, \dots, T$, $u_{i,t} = F_i(\epsilon_t)$ is the probability integral transform of ϵ_t with $u_{i,t} \sim U[0, 1]$, $t = 1, \dots, T$. Specifically, we employ the empirical cumulative distribution function (CDF) for the transformation:

$$\hat{F}_i(x) = \frac{1}{T+1} \sum_{t=1}^T \mathbf{1}_{X_{i,t} \leq x}$$

where $\mathbf{1}$ denotes the indicator function. Finally, we can estimate the copula parameters using the uniform residuals with maximum likelihood estimation.

We do not summarize the estimation results for the univariate $AR(m)$ -GARCH(p,q) model and copula model estimations to preserve space. The results are available from the authors upon request. We choose the AR lag m for each time series and the GARCH model according to the AIC value.

Figure A.1 presents representative plots of autocorrelation functions of the market returns prior to applying the AR-GARCH model and after filtering. Note, that the residuals do not exhibit significant autocorrelations.

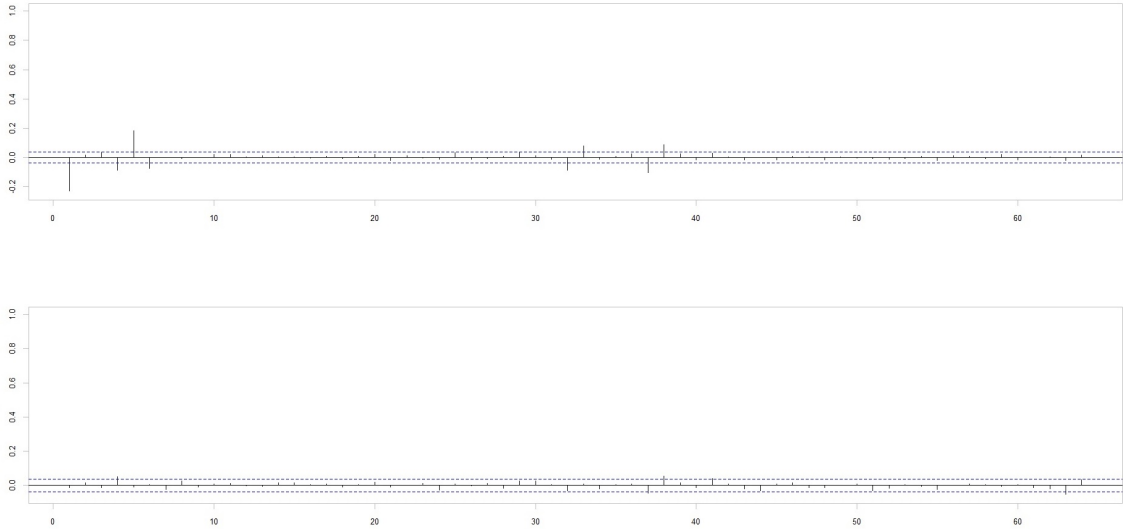


Figure A.1: Autocorrelation functions before and after applying the AR-GARCH filter

The figure shows representative plots of autocorrelation functions of the market returns prior to applying the AR-GARCH model and after filtering.

A.1.2 Time-varying copulas

In this section, we present the different copula models that we utilize to model tail dependence. To allow for possibly time-varying dependency structures (see, e.g. Andersen et al., 2006; Bauwens et al., 2006) between assets we utilize several time-varying copulas in our study. We include copula models with different characteristics. To be specific, we employ copulas that allow for pronounced tail dependence in their upper or lower tail, respectively.

In our study, we include the time-varying symmetric t copula given by

$$C(u_1, u_2 | \eta, P) = \int_{-\infty}^{t_{\eta}^{-1}(u_1)} \int_{-\infty}^{t_{\eta}^{-1}(u_2)} \frac{\Gamma(\frac{\eta+n}{2})}{\Gamma(\frac{\eta}{2})\sqrt{(\pi\eta)^n |P|}} \left(1 + \frac{x'P^{-1}x}{\eta}\right)^{-\frac{\eta+n}{2}} dx,$$

where t_{η}^{-1} denotes the quantile function of the univariate t distribution with degrees of freedom parameter η . P denotes the covariance matrix with off-diagonal element ρ . Our t copula allows for variation in the correlation and in the degrees of freedom parameter.

With $\tau^U \in (0, 1)$ and $\tau^L \in (0, 1)$, the Joe-Clayton copula (see [Joe, 1997](#)) is given by

$$C_{JC}(u_1, u_2 | \tau^U, \tau^L) = 1 - \left(1 - \frac{1}{\left(\frac{1}{(1-(1-u_1)^\kappa)^\gamma} + \frac{1}{(1-(1-u_2)^\kappa)^\gamma} - 1 \right)^{1/\gamma}} \right)^{1/\kappa},$$

where $\kappa = \frac{1}{\log_2(2-\tau^U)}$ and $\gamma = -\frac{1}{\log_2(\tau^L)}$. Here, τ^U and τ^L capture the dependence in the upper and lower tail, respectively. As noted by [Patton \(2006\)](#), the Joe-Clayton copula exhibits asymmetry even for $\tau^U = \tau^L$. Thus, he suggests the *symmetrized Joe-Clayton copula*

$$C_{SJC}(u_1, u_2 | \tau^U, \tau^L) = 0.5 \cdot C_{JC}(u_1, u_2 | \tau^U, \tau^L) + (1 - u_1, 1 - u_2 | \tau^U, \tau^L) + u_1 + u_2 - 1)$$

which is symmetric by construction for $\tau^U = \tau^L$ (see also [Han et al., 2015](#)).

The Clayton copula (see [Clayton, 1978](#); [Genest and Rivest, 1993](#)) is given by

$$C_C(u_1, u_2 | \theta) = (\max\{u_1^{-\theta} + u_2^{-\theta} - 1, 0\})^{-1/\theta}$$

for $\theta > 0$.

Finally, the Gumbel copula (see [Gumbel, 1960](#)) is given by

$$C_G(u_1, u_2 | \theta) = \exp(-((-\log u_1)^\theta + (-\log u_2)^\theta)^{1/\theta}).$$

For both, the Clayton and the Gumbel copula, we also include the rotated version to capture upper and lower tail dependence, respectively.

We follow [Patton \(2006\)](#) and [Creal et al. \(2013\)](#) to specify the time dynamics of the copulas. Time-varying copula models can be characterized by their time varying parameters. As noted by [Patton \(2006\)](#) it is "difficult to know what might (or should) influence" the copula parameter to change unless the parameter has some kind of interpretation. Hence, we limit our study to copulas characterized by such a parameter. For example, for the time-varying t copula, the correlation among the risk factors and the degrees of freedom are time-varying while for the Symmetrized Joe-Clayton Copula the upper and lower tail dependence parameter is time-varying and for the Clayton copula Kendall's tau is the time-varying parameter.

[Patton \(2006\)](#) defines the updating equation for the time varying parameter of a bivariate model by

$$f_{t+1} = \omega - \frac{1}{m} A_1 \cdot \sum_{i=1}^m |u_{1,t-i+1} u_{2,t-i+1}| + B_1 f_t,$$

where m is a positive integer that characterizes the smoothness of the function and $u_{1,t}$ and $u_{2,t}$ are the probability integral transforms of the univariate marginals. Let $\omega < 0$, $A_1 > 0$, and $1 > B_1 > 0$. If the most recent values of $u_{1,t}$ and $u_{2,t}$ are close together, hinting at a stronger dependence, f_{t+1} is likely to increase, while for recent values that are far apart f_{t+1} more likely decreases. We employ the approach by Patton for the symmetric t and the SJC copula. For the symmetric t copula time dynamics are captured by a time varying correlation parameter ρ_t that follows the transformation $\rho_t = \frac{1-e^{-f_t}}{1+e^{-f_t}} = \tanh(\frac{f_t}{2})$. The modified logistic transformation is used to keep ρ_t in $(-1, 1)$ at all times.

Additionally, we allow for trends in the degrees of freedom (see also [Christoffersen et al., 2014](#)). We assume that the degree of freedom at time t is given by the exponential

quadratic spline

$$\eta_{C,t} = \underline{\eta}_C + \delta_{C,0} \exp \left(\delta_{C,1} t + \sum_{j=1}^k \delta_{C,j+1} \max(t - t_{j-1}, 0)^2 \right).$$

$\underline{\eta}_C$ marks the lower bound for the degrees of freedom and $\delta_{C,0}, \dots, \delta_{C,k+1}$ are scalar parameters that have to be estimated. We split the sample in k segments of equal length to obtain $\{t_0 = 0, t_1, t_2, \dots, t_k = T\}$. For our estimations, we set $k = 3$ which allows us to capture times of positive and times of negative trends.

By introducing time dependence in correlations and degrees of freedom, [Christoffersen et al. \(2014\)](#) allow for time-variation in tail dependence that is distinct from time-variation in correlations as tail dependence for the t copula is characterized by both, correlation and degrees of freedom.

For the SJC copula we use $\Lambda(x) \equiv \frac{1}{1+e^{-x}}$ as logistic transformation which is used to keep the parameters τ^U and τ^L in $(0, 1)$ at all times (see [Patton, 2006](#)).

For the Clayton and the Gumbel copula we rely on the generalized autoregressive score (GAS) model, GAS (1, 1), introduced by [Creal et al. \(2013\)](#), which is similar to the model of [Patton \(2006\)](#) for $m = 1$. [Creal et al. \(2013\)](#) provide a dynamic version of following their GAS specification. The density regarding to [Creal et al. \(2013\)](#) reads

$$c_C(u_1, u_2, \theta) = 1 - 2 + u_1^{-\theta} + u_2^{-\theta}.$$

For the Clayton copula the time-varying factor following the GAS equation reads

$$f_t = \frac{1}{\theta_t^2} \ln c_t(\theta_t) - \left(\frac{1}{1 - \theta_t} - \ln(u_{1,t}) + \frac{1}{1 - 2\theta_t} - \ln(u_{2,t}) \right) + \left(\frac{1}{\theta_t} + 2 \right) c_t(\theta_t)^{-1} \left(u_{1,t}^{-\theta_t} \ln(u_{1,t}) + u_{2,t}^{-\theta_t} \ln(u_{2,t}) \right).$$

For the Gumbel copula, the updating equation for the dynamic parameter is given by

$$f_{t+1} = \omega + \beta f_t + \alpha \cdot \frac{\frac{\partial}{\partial \theta} \log c_G(u_1, u_2 | \theta)}{\sqrt{\mathbb{E}_{t-1} \left[\left(\frac{\partial}{\partial \theta} \log c_G(u_1, u_2 | \theta) \right)^2 \right]}}$$

and the density reads

$$c_G(u_1, u_2 | \theta) = C_G(u_1, u_2, \theta) \frac{((-\log u_1)(-\log u_2))^{\theta-1}}{((-\log u_1)^\theta + (-\log u_2)^\theta)^{2-1/\theta}} \left(((-\log u_1)^\theta + (-\log u_2)^\theta) + \theta - 1 \right).$$

The copula parameter of the Gumbel copula is required to be greater than one. Thus, we use the function $\theta_t = 1 + \exp f_t$ to ensure this.

A.2 Measures of tail dependence

The main focus of our study is on the influence of tail dependence on CDS returns. A convenient way to measure for the upper tail dependence at time t is via the probability

limit:

$$\tau_{i,j,t}^U = \lim_{\zeta \rightarrow 1} \mathbb{P}[u_{i,t} \geq \zeta \mid u_{j,t} \geq \zeta] = \lim_{\zeta \rightarrow 1} \frac{1 - 2\zeta + C_t(\zeta, \zeta)}{1 - \zeta}.$$

Similarly, for the lower tail dependence

$$\tau_{i,j,t}^L = \lim_{\zeta \rightarrow 0} \mathbb{P}[u_{i,t} \leq \zeta \mid u_{j,t} \leq \zeta] = \lim_{\zeta \rightarrow 0} \frac{C_t(\zeta, \zeta)}{\zeta}.$$

As far as our copula models are concerned, the Gumbel and the Clayton copula possess upper and lower tail dependence that is not equal to zero, while dependence in the opposite tail is zero for both cases. For the rotated versions of both copula models, dependence in the tails is opposite. For both (or all four, together with the rotated versions) copula models, the tail dependence depends on the dynamic copula parameter. The SJC copula is characterized by positive tail dependence in the lower and the upper tail, and these measures may be different. The tail dependence is given by the (time-varying) copula parameters. Lastly, the (symmetric) t copula has the property of non-negative tail dependence for both tails. However, the lower and the upper tail dependence is identical for the symmetric t copula. For all copulas included in our study, closed form equations for the tail dependence are known.

A.3 Tests of goodness of fit

This section briefly presents several goodness of fit tests that we employ to estimate the fit of each copula model and identify one model as the model with the best fit. Relying on the works of [Genest et al. \(2009\)](#); [Kole et al. \(2006\)](#) and [Berg \(2009\)](#) we first use the *Kolmogorov-Smirnov test* and the *Cramer-von Mises test* to test the goodness of fit of our copula models. Both of these tests rely on the empirical copula serving as a nonparametric estimate of the true conditional copula. However, as our estimated copula is time-varying, we cannot rely on the two tests directly. Instead, we follow [Diebold et al. \(1999\)](#); [Genest et al. \(2009\)](#) and [Rémillard \(2010\)](#) and employ the *Rosenblatt transformation* ([Rosenblatt, 1952](#)) before using the Kolmogorov-Smirnov and the Cramer-von Mises tests.

The Rosenblatt transformation of the original data produces a vector of identical independent uniform distributed variables on the interval $[0, 1]$. In the bivariate case, the transform is given by

$$\begin{aligned} v_{1,t} &= u_1, \quad \forall t, \\ v_{2,t} &= \mathbf{C}_{2|1,t}(u_{2,t} \mid u_{1,t}, \theta). \end{aligned}$$

Note, that the ordering of the variables affects the transformation. Employing the Rosenblatt transformation, the Kolmogorov-Smirnov and the Cramer-von Mises tests are as

follows:

$$\begin{aligned}\hat{\mathbf{C}}_T(\mathbf{v}) &= \frac{1}{T} \sum_{t=1}^T \prod_{i=1}^n \mathbf{1}_{V_{i,t} \leq v_i}, \\ \mathbf{C}(\mathbf{V}_t, \hat{\theta}_T) &= V_{1,t} \cdot V_{2,t}, \\ \text{KS} &= \max_t | \mathbf{C}(\mathbf{V}_t, \hat{\theta}_T) - \hat{\mathbf{C}}_T(\mathbf{V}_t) |, \\ \text{CvM} &= \sum_{t=1}^T \left(\mathbf{C}(\mathbf{V}_t, \hat{\theta}_T) - \hat{\mathbf{C}}_T(\mathbf{V}_t) \right)^2.\end{aligned}$$

Note, that these gof-tests are designed to test the fit of the copula model over the entire domain. For example, the Kolmogorov-Smirnov distances are sensitive to deviations in the center of the distribution. However, as our study focuses on the tail dependence, we additionally estimate a non-parametric dynamic estimator of upper tail dependence. More precisely, we estimate the *log estimator* proposed by [Frahm et al. \(2005\)](#) using rolling window estimation. Note, that we again perform the Rosenblatt transformation before estimating the log estimator of tail dependence. We then calculate the *Integrated Anderson-Darling* distances between the non-parametric tail dependence coefficients and the tail dependence coefficients we infer from the fitted copula models via

$$D_{j,AD} = \sum_{t_i=1}^T \sum_{t_k=1}^T \frac{\left(\hat{\lambda}^U\left(\frac{t_i}{T}, \frac{t_k}{T}\right) - \lambda_j^U\left(\frac{t_i}{T}, \frac{t_k}{T}, \hat{\theta}\right) \right)^2}{\lambda_j^U\left(\frac{t_i}{T}, \frac{t_k}{T}, \hat{\theta}\right) \cdot \left(1 - \lambda_j^U\left(\frac{t_i}{T}, \frac{t_k}{T}, \hat{\theta}\right)\right)},$$

where λ^U denotes the upper tail dependence coefficient, $\hat{\lambda}^U$ denotes the empirical tail dependence coefficient, $\hat{\theta}$ the estimated copula parameter(s), and the copula models are evaluated at every point on the lattice

$$L = \left[\left(\frac{t_i}{T}, \frac{t_k}{T} \right), t_i = 1, \dots, T, t_k = 1, \dots, T \right].$$

Lastly, we estimate the fit of each copula model based on the AD-distance to Pickands dependency function evaluated at 0.5.

B Robustness Checks

Our basic BMA setup resides on some ad hoc assumptions such as to restrict the maximum number of regressors to four and using the 10,000 *best models* from the *leaps and bounds* algorithm. Further, there might be concerns that models exhibiting serial correlation are dynamically misspecified and this should be cured by additional lags of the endogenous variable. However, since lagged endogenous infer the so-called Nickell-Bias in fixed effect regressions, we also check robustness with respect to purely exogenous specifications, i.e. where no lagged endogenous are present. To ensure that the assumptions made do not influence our results, we carry out the following robustness checks:

1. We increase the number of models provided by the *leaps and bounds* algorithm from 10,000 to 40,000.

2. We consider only models which exhibit no serial correlation. To ensure that the model space provided by the *leaps and bounds* algorithm is large enough only models with two lagged endogenous variables are considered in the search algorithm.
3. We consider only models without lagged endogenous variables to control for the effect of the Nickell Bias.
4. We set *nvmax*, the maximum number of regressors in a model, to six instead of four.

Table [A.1](#) shows the results from our robustness checks regarding the BMA setup (unrestricted and restricted). Each of the four robustness checks confirms our findings, i.e. the model space is dominated by the *t*-copula followed by other copula based variables by a large difference. Notably, the BMA specification (Setup D) where we allow for up to six variables instead of four, shows that the inclusion of more variables leads to a model space where no model satisfies the imposed model space conditions. As can be seen from Table [A.2](#), the exclusion restrictions "kill" almost all models. From this we conclude that the inclusion of more variables in the regressions simply supports models where redundant information is present (i.e. variables with correlation of more than 70% in absolute value).

		Unrestricted		Restricted	
Variable		PIP	LRM	PIP	LRM
Setup A	GumbelU	100%	0.673	-	-
	GumbelL	100%	-0.858	100%	-0.247
	tCop	100%	0.636	100%	0.702
	dtCop	99%	0.191	99%	0.189
	dFirmVal	-	-	8%	-0.008
	CDSVola	32%	0.045	33%	0.046
	FedYoY	-	-	7%	0.007
	FDIQoQ	9%	0.012	72%	0.132
	FDIYoY	8%	-0.011	-	-
	TedYoY	-	-	13%	-0.014
	Common	24%	0.054	-	-
Setup B	GumbelU	15%	0.073	-	-
	GumbelL	87%	-0.225	100%	-0.217
	tCop	100%	0.471	100%	0.660
	dtCop	-	-	58%	0.081
	CDSVola	-	-	15%	0.020
	FDIQoQ	-	-	8%	0.011
	Common	75%	0.208	-	-
Setup C	GumbelU	100%	0.673	-	-
	GumbelL	100%	-0.858	100%	-0.248
	tCop	100%	0.636	100%	0.704
	dtCop	99%	0.191	99%	0.190
	dFirmVal	-	-	8%	-0.009
	CDSVola	32%	0.046	34%	0.047
	FedYoY	-	-	8%	0.008
	FDIQoQ	9%	0.012	72%	0.132
	FDIYoY	9%	-0.011	-	-
	Ted	-	-	7%	-0.008
	TedYoY	-	-	14%	-0.015
Common	24%	0.055	-	-	
Setup D	GumbelU	100%	0.64	-	-
	GumbelL	100%	-0.85	-	-
	tCop	100%	0.64	-	-
	dtCop	100%	0.20	-	-
	CDSVola	95%	0.14	-	-
	GDPQoQ	12%	-0.02	-	-
	FDIYoY	67%	-0.11	-	-
	Common	15%	0.03	-	-

Table A.1: Robustness Tests: Estimated PIP and LRM for different BMA setups.

The table shows PIP and LRM of all significant regressors in the unrestricted (left panel) and restricted (right panel) model space for different BMA setups. A detailed list of all variables included in the models and their description can be found in Tables 3 and 2. A variable is significant if the PIP is larger than the prior inclusion probability. Setup A: Number of models obtained from the *leaps and bounds* algorithm is increased from 10,000 to 40,000. Setup B: Model space restricted to models without serial correlation. Setup C: Model space restricted to models without lagged endogenous variables to control for the effect of the Nickell bias. Setup D: Maximum number of regressors allowed in a model is increased from four to six.

	Setup A	Setup B	Setup C	Setup D
Unfiltered Model Space	40,000	10,000	10,000	10,000
Occam's Window Unrestricted	51	13	49	453
Models satisfying Exclusion Restrictions	1,510	8,360	1,490	53
Model satisfying Sign Restrictions	3,610	5,170	3,510	3,364
Models satisfying Exclusion & Sign Restrictions	282	2,187	510	0
Occam's Window Restricted	127	14	123	0
R2 Range Model Space	50%-56%	44%-52%	51%-56%	55%-58%

Table A.2: Overview of the model space filtering process in the different robustness checks.

The table presents an overview of our model space as a results to thorough filtering for our robustness checks. Each line shows the size of our entire model space as a result of applying the described filter.

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