Dynamic Implied Correlation Modeling and Forecasting in Structured Finance

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Abstract

Correlations are the main drivers for credit portfolio risk and constitute a major element in pricing credit derivatives such as synthetic single-tranche collateralized debt obligation swaps. This paper suggests a dynamic panel regression approach to model and forecast implied correlations. Random effects are introduced to account for unobservable time-specific effects on implied tranche correlations. The implied-correlation forecasts of tranche spreads are compared to forecasts using historical correlations from asset returns. The empirical findings support our proposed dynamic mixed-effects regression correlation model.

Key words:
Base Correlations, Dynamic Panel Regression, Implied Correlations,
Single-tranche Collateralized Debt Obligations, Spread Forecast.

JEL classification: C 23; C 51; C 53; G 21; G 24;
1 Introduction

The market volume of credit derivatives increased rapidly from $180 billion in 1996 to over $57 trillion in 2008 (BBA, 2006; BIS, 2010). This growth rate highlights the importance of these new instruments in financial markets. Consequences of the global financial crisis (GFC), e.g., the Lehman Brothers’ bankruptcy in 2008, underline the challenge to aggregate individual risk contributions in the presence of correlations, which is essential for pricing credit derivatives such as collateralized debt obligations (CDOs). The GFC has shown that pooling and tranching within CDO structures amplify errors in the assessment of underlying asset default risks and correlations (compare Coval et al., 2009).

In general, credit risks and their correlations determine the loss distributions of credit portfolios related to credit derivatives (Longstaff and Rajan, 2008). However, ‘true’ correlations are not observable and thus they are unknown parameters. This underlines the need for appropriate correlation models in order to estimate expected tranche losses, which in turn determine tranche spreads. Accordingly, appropriate correlation forecasts are important parameters in pricing models of structured financial instruments.

In practice, several standard approaches are used to estimate implied correlations matching observable market spreads of credit derivatives (Hull and White, 2006). Analogous to the Black-Scholes methodology to extract implied volatilities from option market prices, implied correlations can be extracted from CDO tranche prices (compare Ncube, 1996; Finger, 2009). Similar to implied volatilities, the spread-dependent implied correlations may also differ widely in asset securitizations (compare Hull and White, 2006).
This paper provides an econometric framework which extends existing literature on pricing credit derivatives. Three correlation estimation approaches are examined within this empirical spread analysis and evaluated with regard to their forecast performance. Firstly, we derive base correlations from quoted *iTraxx Europe* index tranche spreads.\(^1\) The 5-year (5Y) *iTraxx Europe* is one of the most popular credit default swap (CDS) indices representing a portfolio of 125 most liquid as well as equally weighted single-name CDS contracts. Secondly, base correlations are modeled with two different dynamic regression correlation models: i) a dynamic fixed effects regression correlation model (FERM) and ii) a dynamic mixed effects regression correlation model (MERM). By implementing dummy variables and error components, we account for fixed tranche effects as well as random time effects in the dynamic MERM. In addition, dynamic historical asset correlations are derived from corresponding asset returns. Thirdly, daily spreads are forecasted based on these correlation approaches and root mean square forecast errors are calculated.

Eventually, we compare the forecast performances of the provided models. We show that the implied correlation models are superior to the dynamic historical asset correlation approach in terms of prediction errors. Thus, the results correspond to findings related to option markets, where implied volatility regression models outperform forecasts based on standard deviations of log-returns (compare Ncube, 1996). We find that the accuracy of daily spread forecasts strongly depends on both correlation type and estimation approach. Overall, the forecast quality of our dynamic panel regression correlation models out-

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\(^1\) Offered tranches are standardized with attachment points \( A \in \{0\%, 3\%, 6\%, 9\%, 12\%\} \) and detachment points \( D \in \{3\%, 6\%, 9\%, 12\%, 22\%\} \) respectively. The composition of the basket is fixed until maturity. For a detailed description of the *iTraxx Europe* family refer to www.iTraxx.com.
performs forecasts based on standard correlation approaches. Especially, the
dynamic MERM accounting for random time effects as well as fixed tranche
effects seems to be highly relevant for pricing. Last but not least, our empiri-
cal study provides useful implications for both hedging credit risk and pricing
several kinds of credit derivatives, e.g., non-standardized CDO tranches and
bespoke portfolios.

The remainder of the paper is organized as follows. In Section 2, we develop the
theoretical pricing framework and demonstrate how to calculate the correla-
tion types applied. We then introduce our dynamic panel regression correlation
models MERM and FERM. In Section 3, our empirical results are presented.
Section 4 concludes.

2 Correlation Approaches and Dynamic Panel Regression Models

2.1 Valuation of Single-tranche CDO Swaps

Synthetic single-tranche collateralized default obligation swaps (STCDO) refer
to a basket of single-name CDS contracts. A well known credit index of single-
name CDS is the 5Y iTraxx Europe credit index. The valuation of STCDOs
implies calculating the fair spreads of each tranche.\footnote{Tranche spreads reflect the compensated credit risk and are thus determined by the tranche-specific risk profile in terms of default risk and related losses.} By definition, a fair tranche spread equals the mark-to-market value of a STCDO contract to zero using risk-neutral valuation. Risk-neutral valuation is based on a risk-neutral martingale measure $\mathbb{Q}$ which is taken into consideration for all expectations in the following.
The determination of fair tranche spreads decisively relies on the cumulative loss distribution of the underlying credit portfolio. The industry-standard model for the valuation of STCDO swaps is the single-factor Gaussian copula model (Hull and White, 2008; Finger, 2009), which was firstly applied by Vasicek (1987) and combined with default intensity models by Li (2000), Schönbucher (2003), Laurent and Gregory (2005) and Longstaff and Rajan (2008).

Tranche investors suffer losses at time $t$ if the total portfolio loss $L_P^t$ in percent of its notional exceeds the lower attachment point $A \in [0, 1)$ of the respective tranche $T_{[A,D)}$. Occurring tranche losses $L_{T_{[A,D)}}^t$ at time $t$ are restricted to the difference of the upper attachment point $D \in (0, 1]$, and the lower attachment point $A$ of tranche $T_{[A,D)}$. In terms of the total portfolio loss $L_P^t$, it follows for the tranche-specific losses:

$$L_{T_{[A,D)}}^t = \min \left( \max \left( 0, L_P^t - A \right), D - A \right)$$

(1)

In order to calculate the present value $PV$ of both the premium leg and the protection leg of a STCDO referring to tranche $T_{[A,D)}$ with a maturity of five years ($M = 5$), we proceed as follows: Firstly, we define the fair STCDO

---

3 The *premium leg* contains all premium payments over the product’s maturity, which are paid to tranche investors for providing default protection. The premium payments depend on i) the tranche-specific spread varying by seniority and ii) the outstanding notional amount. The higher the tranche’s seniority within a securitization, the lower the default risk and thus the related credit spread (and vice versa).

4 The *protection leg* refers to cash flows paid out to the protection buyer in cases of default events causing losses within the underlying CDS basket and affecting purchased tranches.
premium

\[ S_{T(A,D)}^* (0, M) = s_{T(A,D)}. \]  

(2)

This premium is paid to investors at discrete payment dates \( t_j, j \in \{1, ..., \kappa\}, \)
with respect to the remaining face value of tranche \( T_{(A,D)}^{(0,M)} = s_{T_{(A,D)}}^{(2)} \).

Therefore, the present value of the \textit{premium leg} \( PV_{PV_{\text{prim}}} \) is defined by

\[
PV_{PV_{\text{prim}}} = s_{T_{(A,D)}} \cdot \eta \cdot \mathbb{E} \left[ \sum_{j=1}^{\kappa} \Delta_j \cdot Q_{t_j} \left( 1 - L_{T_{(A,D)}}^{(t_j)} \right) \right].
\]  

(3)

where \( \eta \) denotes the face value (notional), \( Q_{t_j} \) describes the time-specific discount factor, and \( \mathbb{E}(\cdot) \) corresponding expectations. \( \Delta_j \) describes the constant distance between fixed payment dates. Tranche-specific losses at time \( t_j \) are denoted by \( L_{T_{(A,D)}}^{(t_j)} \).

Secondly, we calculate the present value of the \textit{protection leg} \( PV_{PV_{\text{prot}}} \) with regard to discrete payment dates \( t_j, j \in \{1, ..., \kappa\} \)

\[
PV_{PV_{\text{prot}}} = \eta \sum_{j=1}^{\kappa} Q_{t_j} \left[ \mathbb{E} \left( L_{T_{(A,D)}}^{(t_j)} \right) - \mathbb{E} \left( L_{T_{(A,D)}}^{(t_{j-1})} \right) \right].
\]  

(4)

Finally, we infer fair tranche spreads \( s_{T_{(A,D)}} \) by equalizing Equation (3) and Equation (4):

\[
s_{T_{(A,D)}} = \frac{\sum_{j=1}^{\kappa} Q_{t_j} \left[ \mathbb{E} \left( L_{T_{(A,D)}}^{(t_j)} \right) - \mathbb{E} \left( L_{T_{(A,D)}}^{(t_{j-1})} \right) \right]}{\sum_{j=1}^{\kappa} \Delta_j \cdot Q_{t_j} \cdot \left[ 1 - \mathbb{E} \left( L_{T_{(A,D)}}^{(t_j)} \right) \right]}.
\]  

(5)

The valuation process shows that in cases of spread calculation a precise knowledge of expected tranche losses is essential. These expected tranche losses are
determined by the cumulative loss distribution of the underlying credit risky portfolio. Approaches to estimate portfolio loss distributions are provided, for example, by Li (2000) and Duffie and Gârleanu (2001).

Within the framework of the single-factor Gaussian copula model, we can use asymptotic analytical approximation procedures to calculate expected tranche losses (compare Vasicek, 1987):

The expected loss of tranche $T_{[A,D]}$ with $D \in (0,1]$ is analytically given by

$$
E\left(L_{T_{[A,D]}}\right) = \frac{1}{D-A} \left[ \Phi_2\left(\omega(A), c; -\sqrt{1-\rho}\right) - \Phi_2\left(\omega(D), c; -\sqrt{1-\rho}\right) \right]
$$

(6)

with $\omega(\chi) := -\Phi^{-1}\left(\frac{\chi}{1-R}\right)$ for $\chi \in \{A, D\}$ and $R \in [0,1)$ describing the recovery rate of the underlying credit portfolio (compare Kalemanova et al., 2007). $\Phi_2(\cdot)$ denotes the cumulative distribution function of the bivariate normal distribution and $\rho \in [0,1]$ its correlation parameter. Additionally, we define the time-dependent default threshold $c$ by

$$
c = c(t_j) = \Phi^{-1}\left(1 - \exp\left(-\lambda \cdot t_j^4\right)\right).
$$

(7)

Note that cash flows are paid in quarterly time intervals. Following O’Kane (2008), we approximate $\lambda$ by

$$
\lambda = \frac{s_{Trax}}{1 - R_{Trax}}
$$

(8)

with $\lambda$ as time-constant default intensity of the 5Y iTraxx Europe (Trax)

\footnote{A recovery rate of $R = 40\%$, for example, indicates that 40% of the contract’s face value will be recovered in case of a default event. For a general analysis of basket default swaps, we refer to Laurent and Gregory (2005).}
derived from the daily index spread $s^{\text{Trax}}$ and the related index recovery rate $R^{\text{Trax}} = R$.  

### 2.2 Correlation Approaches

From Equation (6) follows that the correlation parameter $\rho$ affects decisively the expected tranche loss $L_{T^{(A,D)}}$ and thus the tranche spread $s_{T^{(A,D)}}$ (see Equation (5)). We conclude that fair tranche spreads $s_{T^{(A,D)}}$ are highly sensitive to variations of the correlation $\rho$. Thus, $\rho$ is a decisive factor in pricing STCDO swaps.

According to Longstaff and Rajan (2008), observable market quotes for STCDO swaps reflect a market-specific view of correlations. In the following, we introduce the applied correlation approaches for extracting different correlation types from given market information.

This practice was inspired by the implied volatility approach from Black-Scholes in which implied volatilities are derived from option market prices. The implied correlation approach can therefore be termed as a direct adaption of Black-Scholes implied volatilities to the STCDO swap market (Hull and White, 2004). We obtain the corresponding implied correlations by inverting the introduced Gaussian copula model and matching model generated prices to market quoted spreads. In detail, we use a numeric inversion procedure referring to Equation (5) to infer the correlation parameter which produces a model spread equal to the market quoted spread. Generally speaking, the

---

6 Note that on each day the default intensity of the 5Y iTraxx Europe is derived from its index spread notation. Thus, the implied default intensity may vary by day, but nevertheless it is assumed to be constant over the 5-year maturity of the index.  

7 Implied volatilities provide a common benchmark for a comparison of options across maturities and strikes (see Ncube, 1996).
time-varying implied correlation differs across tranches.\(^8\)

One of the main shortcomings with compound correlations is related to the applied quadratic optimizing techniques whose solutions are not unique.\(^9\) The observable ambiguity of compound correlations is mentioned critically in the recent literature: according to the spread function in Equation (5) two different - but still plausible - compound correlations may lead to the same observable tranche spread. Such a lack of uniqueness makes interpretations of compound correlations much more difficult, even more so in CDO hedging (see Finger, 2009). Non-monotonic correlations, especially for mezzanine tranches, have a weakening effect on the applicability of this concept.\(^10\)

In 2004, the base correlation approach was proposed by McGinty et al. (2004) to overcome limitations of compound correlations. In contrast to compound correlations, they are defined as implied correlations of virtual equity tranches.\(^11\) These virtual equity tranches \(T_{[0\%,D]}\) have the same lower attachment point as standard equity tranches, but differ in their detachment level \(D\).\(^12\) The correlations of tranches \(T_{[0\%,D]}\) are received in line with the procedure introduced in the latter paragraphs for compound correlations. A methodical modification within the base correlation approach is a bootstrap process presented by JP Morgan (compare McGinty et al., 2004; Parcell and Wood, 2007).

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\(^8\) In the same way that a \textit{volatility smile} is a function of the option’s strike, the \textit{correlation smile} is a function of the tranche-specific subordination level. Hence, different tranches on the same underlying credit portfolio trade at various correlations (compound correlations). This implies that for valuing STCDOs, a flat correlation is not sufficient to model market spreads (Andersen and Sidenius, 2005b).

\(^9\) Solving for the correlation \(\rho\) means to minimize the sum of square errors of quoted market and model spreads which leads to the stated quadratic optimization problem.

\(^10\) For more details compare McGinty et al. (2004).

\(^11\) The equity tranche \(T_{[0\%,3\%]}\) is also called first loss tranche.

\(^12\) Note that base correlations can be used to value non-standardized CDOs with specific interpolation methods as provided by Parcell and Wood (2007).
ditionally, base correlations increase monotonically with subordination level which is known as base correlation skew. We also conclude that the concept of base correlation exploits the monotonicity of equity tranches to overcome the problem of non-uniqueness of compound correlations, which leads to a more meaningful skew.

The presented base correlation approach provides market participants with a simple measure of implied correlation inherent in quoted tranches. This measure leads to unique solutions and offers a reasonable valuation framework for non-standardized CDOs (Andersen and Sidenius, 2005a; Hull and White, 2006; Finger, 2009).

In the basic single-factor Gaussian copula framework, only a single correlation parameter $\rho$ is needed to describe the overall dependency structure of borrowers in the underlying credit portfolio. After estimating the correlation parameter $\rho$ and based on a specified default threshold $c$, the bivariate Gaussian copula model can be applied to calculate fair tranche spreads $s_{T}^{[A,D]}$ as denoted in Equations (5) and (6). $\text{13}$

One standard approach to directly approximate the dependency parameter $\rho$ is inspired by fundamental assumptions in the Merton model. Within this framework, the default event of a firm is endogenously modeled by assessing the firm’s capital structure (compare Merton, 1974). This idea can be extended to a credit portfolio. In order to derive joint default correlations of firms in the credit portfolio, the firms’ asset returns and their dependency structures are taken into consideration. Hence, current market information is included in

$\text{13}$ In the market standard model for pricing STCDOs, a single correlation parameter is sufficient for pricing securitized tranches. However, such a single correlation parameter implies a flat correlation structure, which is in contrast with observable implied correlation smiles and skews.
modeling dependency structures across borrowers. Other authors who address this kind of direct modeling are, for example, Lucas (1995), Gupton et al. (1997) and Zhou (2001).

For our empirical analysis, we modify this standard approach as follows: firstly, we define several sample periods of our empirical study to account for different states of the global economy, as described in Section 3. Secondly, we investigate the log-asset returns of the firms which are included in the ‘on the run’ series of the 5Y iTraxx Europe in order to calculate average asset correlations.\footnote{Using DataStream provided by Thomson Reuters.}

The daily average asset correlations – also called \textit{historical asset correlations} – are dynamically calculated for every trading day $t$ in the specified sample period, with $t \in \{1, \ldots, T\}$ and then used for forecasting tranche spreads (one day ahead).\footnote{The specific length of different forecast periods is denoted in Table II of Section 3.2.} The calculation of a historical asset correlation is based on the assets’ last 250 trading days, which are approximately representing an one-year time horizon (250-day time window).\footnote{Note that the first window ends one day before the first spread forecast. In the following, the 250-day time window dynamically rolls through the specified forecast periods in daily increments.} Eventually, we approximate the asset correlation $\rho$ applied in Equation (6) by the average historical asset correlations among the index entities of ‘on the run’ series.

In contrast with forecasts based on implied correlations, forecasts with various types of \textit{historical asset correlations} assume an identical correlation for each tranche $T_{(A,D)}$. Consequently, daily spread forecasts based on implied correlations consider tranche-specific correlation values, while the dynamic asset correlation model (ACM) does not. Despite these general limitations of single-correlation models, the dynamic ACM is used as a benchmark model due to
its pricing popularity in the past.

2.3 Dynamic Panel Regression Approach for Base Correlations

Implied correlations are not constant, but change over time and between tranches. By inverting the spread formula in Equation (5) numerically, we get daily implied correlation parameters for each tranche $T_{[A,D]}$.\(^{17}\) Thus, our panel data consists of 5 cross-sectional units (tranches $T_{[A,D]}$) which are observed over time $t \in \{1, ..., T\}$. Hence, panel data models can be estimated for the implied correlation parameter in order to reflect both cross-sectional and time characteristics. According to our model assumptions, the correlations range between 0 and 1, $\rho_{it} \in [0,1]$. Due to this restriction, a probit transformation is commonly applied in order to create a variable ranging between $[-\infty, +\infty]$ which matches the assumptions of the regression models.\(^{18}\) We use the following abbreviation:

\[
i = T_{(0\%,D_i)}.
\] (9)

Since we regard tranches $T_{(0\%,D_i)}$ of five different levels $i$, it follows that $i \in \{1, ..., 5\}$. Additionally, we include the lagged correlation parameter $\rho_{i,t-1}$ of tranche $i$ as explanatory variable in the model to account for autocorrelation. $\tilde{\beta}_i = \tilde{\beta}_0 + \alpha^i$ is the intercept for the $i$-th base correlation, $\tilde{\beta}_0$ represents the ‘mean’ intercept (Ncube, 1996). $\alpha^i$ is the difference between the individual intercept and the ‘mean’ intercept and thus accounting for time-constant differences between tranches in both of our proposed dynamic panel regression models (fixed effect). Therefore, fixed effects vary across tranches $i$ depending

\(^{17}\)In order to obtain implied correlations, we used the Quasi-Newton Method.

\(^{18}\)In this context, a logit transformation is also commonly accepted.
on their seniority. We assume that \( \rho_{i-1} \) is a convenient predictor for the base correlation \( \rho_i \). For the \( i \)-th tranche the model is given by

\[
\Phi^{-1}(\rho_i) = (\bar{\beta}_0 + \alpha^i) + \beta_1 \cdot \Phi^{-1}(\rho_{i-1}) + e_i^t,
\]

(10)

with \( t \in \{1, ..., T\} \). \( \Phi^{-1}(\cdot) \) denotes the inverse of the standard normal distribution function and \( T \) describes the amount of days. \( \beta_1 \) describes the sensitivity with respect to the lagged correlation which is identical for all tranches \( i \). \( e_i^t \) denotes the residual.

Firstly, we propose a fixed effects regression model (FERM) allowing for fixed effects only. In this manner, we assume that \( \alpha^i \) is a fixed tranche-specific effect and the residual \( e_i^t \) consists only of a single component

\[
e_i^t = u_t^i,
\]

(11)

where \( u_t^i \sim \mathcal{N}(0, \sigma_u^2) \) i.i.d.. This leads to the following dummy-variable model for the \( i \)-th tranche

\[
\Phi^{-1}(\rho_i) = (\bar{\beta}_0 + \alpha^i) + \beta_1 \cdot \Phi^{-1}(\rho_{i-1}) + u_t^i
\]

(12)

with \( t \in \{1, ..., T\} \). By expanding our FERM, it is easily possible to additionally account for fixed time-specific effects. However, when fixed time-specific effects are estimated ex post, they are estimated for time \( t \). The fixed effects model does not produce forecasts for time \( t + 1 \). As our focus is on forecasting, we favor random time-specific effects as the model produces a distribution for this effect, which can be used for correlation forecasts. We apply such models in the next paragraphs.
In a next step, we extend the FERM specification by a time-specific systematic random effect to allow for cross-section dependence. We propose such a mixed effects regression correlation model (MERM) allowing for fixed effects and random time effects. In this manner, we assume that the parameter \( v_t \) describes an unobservable random effect accounting for any time-specific effect that is not included in the regression.

The residual \( e_t^i \) consists of two components:

\[
e_t^i = v_t + u_t^i, \tag{13}
\]

where \( v_t \sim \mathcal{N}(0, \sigma_v^2) \) i.i.d., \( u_t^i \sim \mathcal{N}(0, \sigma_u^2) \) i.i.d. and \( \sigma_e^2 = \sigma_v^2 + \sigma_u^2 \). While \( v_t \) describes an unobservable time effect, \( u_t^i \) is the remainder stochastic disturbance term varying in time and with tranche seniority. The resulting model is

\[
\Phi^{-1}(\rho_t^i) = (\bar{\beta}_0 + \alpha^i) + \beta_1 \cdot \Phi^{-1}(\rho_{t-1}^i) + v_t + u_t^i \tag{14}
\]

Equation (14) implies that the forecast correlations are tranche- and time-specific. The tranche-specific heterogeneity is modeled by tranche intercepts \( \bar{\beta}_0 + \alpha^i \). The time-varying information is decomposed into a time-lagged component modeled by the transformed correlation of the prior period \( \beta_1 \cdot \Phi^{-1}(\rho_{t-1}^i) \) and a contemporary random effect \( v_t \). The analysis of base correlations over time indicates that the impact of time-lagged correlations is homogeneous.

We have therefore assumed a tranche-independent specification for \( \beta_1 \). The

\[\text{For a discussion of dummy-variable and error-component models refer to Hsiao (1986) and Baltagi (1995). Time-series and cross-section studies not controlling for heterogenous individuals run the risk of obtaining biased results, see, e.g., Baltagi (1995).}\]
interaction between tranche and time effects is captured by the contemporary and tranche specific error term \( u_i^t \). These assumptions reflect the information available to financial markets.

We assume the following residual covariance structure:

\[
\text{cov}(e_i^t, e_j^s) = \begin{cases} 
\sigma_v^2 & \text{if } i \neq j, t = s \\
\sigma_e^2 & \text{if } i = j, t = s \\
0 & \text{otherwise.}
\end{cases}
\]  

(15)

The correlation structure is given by

\[
\psi = \text{corr}(e_i^t, e_j^s) = \begin{cases} 
\frac{\sigma_v^2}{\sigma_e^2} & \text{if } i \neq j, t = s \\
1 & \text{if } i = j, t = s \\
0 & \text{otherwise},
\end{cases}
\]  

(16)

and shows that the correlation between base correlations \( \rho_i^t \) is determined by the variance \( \sigma_v^2 \) of the random time effect \( v_t \) for a given time period. This intra-class correlation \( \psi \)

\[
\psi = \frac{\sigma_v^2}{\sigma_u^2 + \sigma_v^2}
\]  

(17)

measures the extent of unobserved latent time-invariant variation relative to the total unobserved variation. The intra-class correlation provides an indication of systematic risk influences on the correlation parameter \( \rho_i^t \) since i) all tranches are affected by the time-specific effect \( v_t \) in the same way, and ii) the intra-class correlation measures the ratio of its variance \((\sigma_v^2)\) to the total

\[\text{cov}(e_i^t, e_j^s) = \mathbb{E}(e_i^t \cdot e_j^s) = \mathbb{E}(v_t^2) = \mathbb{E}(v_t) \cdot \mathbb{E}(v_t) + \text{cov}(v_t, v_t) = \sigma_v^2 \text{ due to the independence between } v_t \text{ and } u_i^t.\]
variance.

The FERM is subject to assumptions with regard to the random effect (i.e., normal distribution, mean zero, and time constant variance). To check the robustness, we have estimated a model with time-specific dummies which results in similar root mean square forecast errors. In a qualitatively similar approach, Pesaran (2006) uses cross-sectional averages of the observed data as a proxy for common shocks. The chosen random time-specific effects dominate contemporaneous fixed effects or cross-sectional averages as the model produces a forecast distribution for their realisations and reflects the information available at the point of forecast.

3 Empirical Analysis

3.1 Panel Data

Our database contains daily spreads of both the 5Y iTraxx Europe index and its standardized synthetic STCDOs from August 2005 to September 2008.\(^{21}\) Within our empirical study we focus on quoted market spreads referring to the ‘on the run’ series of the 5Y iTraxx Europe.\(^{22}\)

Figure 1 shows historical spreads of the 5Y iTraxx Europe index (red line) and the time series of several tranche spreads (black lines) from August 24\(^{th}\), 2005 to September 19\(^{th}\), 2008. The quoted spreads refer to several ‘on the run’ series. The runtime of each series is indicated by the dashed-dotted vertical lines and

\(^{21}\) All quoted market spreads are provided by Markit. For daily closing quotes we consider the mid of quoted bid/ask spreads.

\(^{22}\) A new ‘on the run’ series is issued every six months with a constant maturity of 5 years and a fixed basket of CDS.
marked by $iTraxx \, S\, 4$ to $iTraxx \, S\, 9$. The x-axis denotes the observation days. While the y-axis on the left hand side denotes the market upfront payment of the equity tranche $T_{[0\%,3\%]}$ in percent, the secondary y-axis on the right hand side denotes spreads in basis points (bps).\(^{23}\)

\begin{center}
[Insert Figure 1 here]
\end{center}

From August 24\(^{th}\), 2005 to June 18\(^{th}\), 2007 we observe slightly decreasing index spreads from 39 bps to almost 20 bps. In contrast to the remaining time series of the 5Y $iTraxx\, Europe$, the index spread movements are moderate and at a relatively low level during this period. For this reason, we define our first sample from August 24\(^{th}\), 2005 to June 18\(^{th}\), 2007 ($Sample\, 1$). On June 18\(^{th}\), 2007 it is reported for the first time, that Merrill Lynch seizes collateral from a Bear Stearns hedge fund invested heavily in subprime loans, which leads to strongly increasing credit spreads over the following days. Therefore, we define the 19\(^{th}\) of June as the beginning of our GFC sample ($Sample\, 2$). Several days after this announcement - at the end of July 2007 - the 5Y $iTraxx\, Europe$ reaches its first peak at 68 bps. Despite loan interventions through the Federal Reserve Bank (New York) in March 2008 attempting to avert a sudden collapse of Bear Stearns, the company can not be saved and is sold to JP Morgan Chase later on. Within these market turbulences, the 5Y $iTraxx\, Europe$ registers a new all time high of 160 bps on March 17\(^{th}\), 2008, when JP Morgan Chase offers to acquire Bear Stearns. This peak is at least 8 times higher than the last peak in June 2007. The time series of the $iTraxx\, Europe$ strongly reflects the chronology of the GFC.\(^{24}\) In comparison to $Sample\, 1$ (before the GFC),

\(^{23}\) Note that it is market standard that the premium for the equity tranche is paid upfront whereas the premiums of all other tranches are paid in periodic (quarterly) time intervals.

\(^{24}\) The chronology of the GFC is reported in more detail in BIS (2009).
the observed 5Y *iTraxx Europe* index spreads are much more volatile as well as higher quoted throughout Sample 2 (during the GFC). Lastly, we define our third sample as the entire observation period by combining Sample 1 and 2 into Sample 3, in which we are not accounting explicitly for the GFC.

Corresponding to the index chart in Figure 1, all 5Y *iTraxx Europe* tranche spreads are slightly decreasing in Sample 1 and strongly increasing after the 18th of June 2007. Throughout Sample 2 we observe i) relatively high spread volatilities and ii) an absolute increase in the tranche-specific spread levels. For example: while the standard deviation (STD) in bps of the mezzanine tranche $T_{[6\%,9\%]}$ is 18 times higher in Sample 2 than in Sample 1 ($STD_{1}^{T_{[6\%,9\%]}} = 5.78$ vs. $STD_{2}^{T_{[6\%,9\%]}} = 105.59$)\(^{25}\), the mean of tranche spreads $s_{T_{[6\%,9\%]}}$ increases from 18.81 bps to 164.38 bps. In fact, the most senior tranche (dotted line) seems to be much more affected by economic downturns like the GFC than other tranches. This may be indicated by the relation between average tranche spreads $[\bar{s}_{T_{[A,D]}}^{2}/\bar{s}_{T_{[A,D]}}^{1}]$. This relation is increasing with tranche seniority: we obtain a value of around 14 for the most senior tranche, which means that the average tranche spread $\bar{s}_{T_{[12\%,22\%]}}^{2}$ is 14 times higher in Sample 2 than in Sample 1. For the upfront payment of the equity tranche (dashed line) and the mezzanine tranche $T_{[6\%,9\%]}$ (continuous black line) this relation is 1.54 and 8.74 respectively.

Table I provides additional summary statistics for index and tranche data referring to Sample 3.

[Insert Table I here]

The entire sample contains 749 daily observations for i) the 5Y *iTraxx Eu-

\(^{25}\)Index 1 refers to Sample 1 and index 2 to Sample 2 respectively.
rope and ii) each of its securitized tranches. The mean spreads monotonically
decrease with increasing tranche seniority. Thus, the highest (lowest) default
risk is linked to the equity (senior) tranche which is indicated by the highest
(lowest) mean spread of 2,321.84 bps (25.93 bps). The senior tranche exhibits
the largest spread range: its maximum spread is 91 times higher than its
minimum spread. Additionally, considering the relation between standard de-
viation and average spread ($STD/\text{Mean}$), we conclude that the sensitivity to
systematic risk, e.g., in economic downturns, is increasing monotonically in
tranche seniority due to the increasing systematic risk exposures. Depending
on the systematic risk exposures, credit risk premia of tranches may increase
in economic downturns. This increase is higher for senior tranches.

Depending on the specified time periods (Sample 1, 2 and 3), the sample sizes
of our empirical analysis vary: while Sample 1 contains 431 daily observations
for the credit index and each of its tranches (total quotes: 2,586), Sample 2
includes 318 daily spreads for the $i\text{Traxx}$ index and 1,509 daily tranche spreads
(total quotes: 1,908). The entire period (Sample 3) refers to 749 trading days
with 4,494 quoted spreads in total (index and tranche spreads).

3.2 Panel Data Regression Analysis

In order to obtain tranche-specific base correlations $\rho_i$ with $i \in \{1, ..., 5\}$ –
using the Quasi-Newton Method – we make commonly applied parameter
assumptions in relation to

- the recovery rate $R^{Trax}$ of the 5Y $i\text{Traxx Europe}$ index,
- the default intensity $\lambda$ of the 5Y $i\text{Traxx Europe}$ index, and
- the risk-less rate $r$, which is used to calculate the time-dependent discount
factors $Q_{t,j}$.  

Following the literature, e.g., Andersen and Sidenius (2005b); Laurent and Gregory (2005); Hull and White (2006) and Markit, we assume a constant recovery rate of 40% for investment grade names of the 5Y iTraxx Europe index which leads to $R = \text{R}^{\text{Trax}} = 40\%$.  

Similar to Hull and White (2004) and analogous to Equation (7), we assume a time-constant default intensity $\lambda$. This approximates the risk-neutral default intensity of the 5Y iTraxx Europe, which is implicitly given by the daily index spread notations (compare Equation (8)). Thus, $\lambda$ is time-variant, but constant over the products’ maturity.

Further, we follow the recent literature by assuming a flat term structure of risk-less interest rates (compare Hull and White, 2004; Heitfield, 2009). Based on Sample 3, we set the risk-less interest rate $r$ at 2%, which is at the lower end of the related historical T-bill term-structure. Note that changes in recoveries or interest rates result in parallel shifts in the implied correlation level. Consequently, solving for observable market spreads makes parameter settings less important.

Next, we derive base correlations $\rho_i^t$ from market quotes of the standardized 5Y iTraxx Europe tranches. Figure 2 shows base correlation curves for each tranche $T_{[0\%, D_i]}$ from August 24th, 2005 to September 19th, 2008.

[Insert Figure 2 here]

\footnote{Compare Equations (5), (7), and (8).}

\footnote{The quoted market spreads are provided by Markit.}

\footnote{We have tested various settings with qualitatively similar results.}
Throughout Sample 3 (x-axis), the skewed curves indicate that base correlations $\rho_i$ (y-axis) are increasing monotonically with increasing detachment level $i$. This effect can be expected as long as spreads of index tranches are decreasing in line with increasing tranche seniority. In other words, the synthetic equity tranche $T_{[0\%,22\%]}$ exhibits the highest base correlation, while tranche $T_{[12\%,22\%]}$ with highest seniority exposes the lowest tranche spread $s_{T_{[12\%,22\%]}}$ (compare Figure 1). In contrast, the equity tranche $T_{[0\%,3\%]}$ with lowest seniority exhibits the lowest base correlation as well as the highest tranche spread $s_{T_{[0\%,3\%]}}$ across all other securitized tranches. The plotted base correlations correspond also to findings related to Figure 1: as the base correlations $\rho_i$ move moderately sideways in Sample 1 the correlation levels increase simultaneously at the beginning of the GFC. During the GFC, the tranche-specific base correlations are on average about 1.8 times higher than in Sample 1, while the average standard deviation of base correlations across all tranches is about 2.8 times higher than in Sample 1.

Our dynamic regression correlation models – Equations (12) and (14) – are compared in terms of accuracy in pricing STCDOs against a benchmark measure using historical asset correlations. In order to validate all our proposed models, we examine their accuracy in matching quoted market spreads. Eventually, we test which correlation measure prices STCDOs more accurately by comparing root mean square forecast errors (RMSFE) of our model-based spread forecasts. We compare the following three correlation models:

- the dynamic fixed effects regression correlation model (FERM) which accounts for fixed tranche effects,
- the dynamic mixed effects regression correlation model (MERM) which accounts for both random time-specific effects and fixed tranche effects, and
the dynamic asset correlation model (ACM).

In the following, the regression and forecast methodology is briefly explained: regression windows (respectively calibration windows) that are fixed in their size (40-, 50- and 60-days) dynamically roll through Sample 1, 2 and 3 in daily increments.

Based on each regression window, we calibrate both of our prediction models MERM and FERM to forecast base correlations $\rho^i_t$ one day ahead. Referring to the next day $t$ (forecasting day), we generate point predictions for $\rho^i_t$ and distributions of base correlations. In this respect, we use Monte Carlo simulations to compute daily samples of 1,000 observations for the time-specific effects $v_t$ and the residual $u^i_t$. Then, we compute 1,000 one day ahead forecasts for base correlations $\rho^i_t$. Before the estimation window is shifted forward one day, this set of out-of-sample correlation forecasts is used in Equation (5) to compute an average spread for each tranche $T_{[A,D]}$ denoting the respective spread forecast. This indirect spread forecasting technique allows us to derive useful descriptive statistics from the simulated spread distribution. Figure 3 displays such a spread distribution for a single forecast day in comparison to the real market upfront payment (UP). The x-axis denotes various spread classes and the y-axis the frequency.

The mean spread of these 1,000 spread realizations constitutes our UP forecast for the equity tranche $T_{[0\%,3\%]}$ (dashed line). The observed market UP is denoted by the black line. In this example, the difference between the market UP (2,590 bps) and the mean model spread (2,599 bps) is 9 bps which is less than 0.4 percent of the market UP. This result indicates the accuracy of our
model forecasts.

Analogously, we predict spreads $s_{T|A,D}$ one day ahead for all tranches. As we receive new spread information every day, we focus methodically only on one day ahead forecasts. Forecasted tranche spreads $s_{T|A,D}$ are then compared to those forecasted with the historical asset correlation parameter. Results of all three forecast models are compared to market spreads. Since all our spread forecasts refer to the first day after each calibration window, our forecasts are out of sample forecasts or out of window forecasts. After the regression window is incrementally rolled forward one day, we recalibrate our prediction models, forecast base correlations and finally derive model-specific spread forecasts. This estimation and forecast exercise is repeated until the end of each sample. For comparability, the forecast periods related to each window size (40-, 50- and 60-days) should correspond to each other. Therefore, they are identically defined across all window sizes within our samples. Table II summarizes the three forecast periods depending on the defined rolling regression windows.

[Insert Table II here]

Depending on our forecast period, we estimate between 258 and 688 regressions of Equation (12) and (14) to get the same number of predicted base correlations $\rho_i^t$ for each synthetic equity tranche $T_{(0\%-D_i)}$, which we also use to derive corresponding spread forecasts. Eventually, we forecast 1,850 model-specific tranche spreads in terms of Sample 1, 1,290 spreads in terms of Sample 2 and 3,440 spreads in terms of Sample 3.

An example: the first forecast day in Sample 1 is December 2nd, 2005. In case of a 40-days regression window, we estimate our models on daily data observed from October 5th, 2005 to December 1st, 2005 (40 observation days). We anal-
ogously proceed for the remaining two regression windows. As a result, *Sample 1* contains three different starting dates for the rolling windows depending on the window size (40-, 50- or 60-days), but the first forecast day is December 2\textsuperscript{nd}, 2005 for all windows. For re-estimating the dynamic correlation models the fix-sized regression windows are rolled forward in daily increments. Thus, the second forecast day is December 3\textsuperscript{rd}, 2005 and so on.

Our rolling regression analysis is applied to backtest all prediction models on historical data. In order to evaluate the model-specific forecast accuracy, we implement a root mean square forecast errors metric referring to the difference between market spreads and model spreads. Finally, our RMSFE metric is i) window-specific, ii) model-specific, and iii) sample-specific.

To ensure the comparability of our results, we calculate the RMSFEs according to

\[
RMSFE_p = \sqrt{\frac{\sum_{t=1}^{T} \left(1 - \frac{s_{t,p}}{\hat{s}_{t,p}}\right)^2}{T}}.
\]

Thereby, \( p \in \{1, 2, 3\} \) indicates the respective sample, \( \hat{s}_{t,p} \) denotes the predicted tranche spread on day \( t \), \( s_{t,p} \) describes the corresponding market spread and \( T \) denotes the amount of sample-specific daily forecasts.

The descriptive statistics provided in Section 3.1 underline differences in the behavior of tranche spreads within the entire observation period (*Sample 3*). By dividing this entire period in subsamples, we test the forecasting accuracy of our models i) under moderate market conditions (*Sample 1*), and ii) in times of market turbulence (*Sample 2*). In this way, we control for various calibration periods, market conditions as well as different prediction models.
to verify the robustness of our findings.

3.3 Results

Firstly, we estimate our dynamic fixed effects regression correlation model (FERM) as well as our dynamic mixed effects regression correlation model (MERM) for the three samples.\textsuperscript{29}

Figure 4 illustrates the parameter estimates for our dynamic regression model MERM (10) based on 40-days estimation windows. The various boxplots refer to estimation results of 688 regressions within Sample 3. While the upper four boxplots describe the parameter estimates, the lower boxplots summarize the corresponding p-values indicating the statistical significances of the estimates.

\begin{figure}[h]
[Insert Figure 4 here]
\end{figure}

Based on the reference intercept $\bar{\beta}_0^5$ composed of the ‘mean’ intercept $\bar{\beta}_0$ and $\alpha^5$ (the fixed effect related to the senior tranche), the mean of tranche-specific fixed effects $\alpha^i$ is monotonically decreasing with decreasing tranche seniority. The fixed-effect estimates are on average statistically significant at the 9%-level. Thus, considering tranche-specific fixed effects should generally amend the spread forecast performance.

According to the upper boxplots, lagged base correlations $\rho_{t-1}$ are highly influencing the endogenous variables which is also underlined by the corresponding p-values (boxplot below): each coefficient $\beta_1$ (min: 0.37, max: 1.14) exhibits a p-value $< 0.0001$ throughout Sample 3 indicating a high statistical significance.

\textsuperscript{29} The parameters of the regression models in Equations (12) and (14), several variance components and the random time effects were estimated using the Restricted Maximum Likelihood method.
of these estimates. Random time-specific effects $v_t$ significantly impact the endogenous variable with p-values below the 0.0035% quantile.

Note that the $\beta_1$ estimates are statistically different yet close to unity. In an additional unreported analysis, we compare the forecast models to a ‘naive’ lagged base correlation Model (NLBM), in which solely the lagged base correlation is used to provide tranche-specific spread forecasts. The MERM dominates in nine of 15 cases (i.e., three samples and five tranches), while the NLBM dominates in six of fifteen cases. In particular during the crisis period (Sample 2), MERM dominates for the four lower tranches, while NLBM dominates only for the 12%-22% tranche. Next to a better forecast accuracy, MERM allows for a decomposition of the residual error into a systematic and a tranche-specific component and an analysis of systematic risk which is presented in the following.

Secondly, we provide tranche spreads $s_{T[A,D]}$ for each index tranche in accordance to our forecasted base correlations $\rho^t_i$. Figure 5 shows the time series of market upfront payments (black line) in comparison to forecasted UPs of tranche $T_{[0\%,3\%]}$. The red area refers to the 5% and 95% quantiles of the simulated model spreads under the applied MERM for Sample 3 (x-axis). The y-axis denotes the UP in bps.

[Insert Figure 5 here]

According to the plotted quantiles the predicted UPs of tranche $T_{[0\%,3\%]}$ continuously surround observed market UPs, including the time of the GFC.

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30 Based on the $\beta_1$ estimates reported in Figure 4, a t-test is provided for $H_0 : \beta_1 = 1$ to check for the unit root. 63.23% of the $\beta_1$ estimates are different to one with statistical significance at the 1st percentile, 80.67% at the 5th percentile and 88.52% at the 10th percentile. These results support our forecast models.

31 We do not consider any other effects in this naive model setup.
In Figure 6, we also provide corresponding UPs (y-axis) using the dynamic historical asset correlation model (ACM) for Sample 3 (x-axis). The dashed line shows the performance of UP forecasts.

[Insert Figure 6 here]

In comparison to Figure 5, UP forecasts underestimate market spreads (black line) throughout Sample 1. Reasonable results are reached at the beginning of the GFC, but during the last months of Sample 3, the ACM forecasts are clearly overestimating quoted market spreads. This leads to higher RMSFE in Sample 3 (see Table III). For example: on the 5th of June 2007, the spread of tranche $T_{[0\%,3\%]}$ denotes 636 bp which is the lowest notation within the entire observation period (Sample 3). While the corresponding ACM forecast is 420 bp – about 34% below the market spread – the MERM forecast is only 6 bp above the observed market spread (compare Figures 5 and 6). Alternatively, we observe the highest spread of tranche $T_{[0\%,3\%]}$ on the 17th of March 2008 denoting 5,219 bp. On this date, the ACM overestimates the tranche spread by almost 15% (ACM: 5,994 bp). Our MERM spread forecast is 5,165 bp, which underestimates the tranche spread on this date by only 1%. Both examples support the accuracy of the spread forecasts.

Referring to both the equity tranche and most senior tranche of the 5Y iTraxx Europe, we provide model-specific scatter plots in Figure 7. The scatter plots indicate the forecast accuracy of our dynamic regression correlations models in comparison to our ACM benchmark model in terms of the coefficient of determination ($R^2$). More comprehensive results - also related to other tranches - as well as applied test statistics are provided in Appendix A. In each chart, the observed market spreads (x-axes) are plotted against the respective model spreads (y-axes). The three charts on the left hand side of Figure 7 refer to
the UPs of the equity tranche. The three charts on the right hand side provide results related to the senior tranche. Both upper charts focus on the ACM benchmark model, both charts in the middle refer to the FERM. The results of the two lower charts refer to the MERM.

[Insert Figure 7 here]

All charts indicate that the spread forecasts scatter more during the GFC (Sample 2) since the spread deviations are higher at higher spread levels. During Sample 1, where the spreads across all tranches are at the lowest level, the forecast error of each model is also lowest. Concerning the three left charts, the ACM provides the worst UP forecasts in terms of $R^2$ ($R^2_{ACM} = 91.28\%$). Therefore, both dynamic regression correlation models outperform our ACM: the $R^2$ is almost 98.12\% for FERM and 98.14\% for MERM.

In comparison to UP forecasts, we obtain a higher accuracy in forecasting senior tranche spreads with each of the three models (three charts on the right). Again, the forecast errors are highest in case of the benchmark model ($R^2_{ACM} = 94.14\%$). The lowest errors relate to the MERM ($R^2_{MERM} = 98.64\%$), closely followed by those of the FERM ($R^2_{FERM} = 98.6\%$).

In summary, the $R^2$ metric shows that we reach the highest explanatory power for all tranches of the 5Y iTraxx Europe by considering both random time effects and fixed tranche effects (MERM).

In order to obtain more detailed insight into the spread forecast accuracy, we compare all mentioned correlation models - FERM, MERM and ACM - by calculating the introduced RMSFE metric (compare Equation (18)). Table III shows an overview of the RMSFEs related to the three correlation models for the three samples and regression windows. s.
In *Sample 1*, the dynamic ACM shows the lowest accuracy across all tranches and regression windows. Additionally, the results confirm some theoretical findings related to our benchmark model: even though the ACM may provide accurate results for both the equity tranche and the senior tranche, its applicability seems to be strongly limited for the remaining tranches. Thus, our dynamic regression correlation models dominate the ACM clearly since we simultaneously obtain more accurate results for all securitized tranches. With respect to our main models, the dynamic MERM provides overall the highest performance accuracy across all tranches and all regression windows related to *Sample 1* in terms of our RMSFE metric.

During the GFC, the performance of our dynamic correlation models is slightly worse, but still dominates our benchmark model. In contrast to *Sample 1*, we observe a decrease of forecast accuracy for both models MERM and FERM: across all tranches and regression windows the RMSFE are on average 21% higher. Furthermore, the results show that the forecasted ACM spreads lead to lower RMSFEs during the GFC. Thus, the forecast accuracy of the ACM strongly increases under these volatile market conditions. Averaging the improvements across all tranches, we observe a RMSFE decrease of almost 80% in *Sample 2* related to the ACM. The results show that particularly in times of financial distress the effects considered by our MERM show the lowest RMSFEs in four of five tranches.

Referring to both dynamic correlation models, we further find that in contrast to rather moderate economic climates (*Sample 1*), the RMSFEs are monotonically as well as disproportionately strongly increasing with the tranche seniority during the GFC. Thus, particularly in times of financial distress,
the spread forecast performance seems to decrease with increasing tranche seniority. This may be due to the specific risk characteristics of senior tranches related to systematic risk.

Our empirical study shows similar results for the remaining sample. For the entire time interval \((Sample\ 3)\), the overall results show that the forecast performance of both dynamic regression correlation models is better than the respective forecasts with historical asset correlations. Across all tranches, base correlation estimates provide lower RMSFEs of spread forecasts. This underlines the superiority of our proposed dynamic regression correlation models, especially if we account for random time-specific and fixed tranche effects. \(^{32}\)

We conclude that both dynamic regression correlation models dominate the dynamic ACM in terms of RMSFEs. Thus, the inclusion of correlation parameters gained from corresponding log-returns leads to spread forecasts which may widely differ from quoted market spreads. We confirm that the consideration of dependency structures reflected by historical asset returns is not sufficient for pricing synthetic STCDOs. Consequently, we assume that historical asset correlations incompletely reflect relevant market information for pricing and forecasting structured financial instruments. As we show, base correlations are much more suitable for relatively accurate tranche spread forecasts than historical asset correlations. In consequence, we assume that base correlations contain more relevant market information for a reliable synthetic STCDO pricing. However, our dynamic regression correlation models also indicate an underestimation of systematic risk which is i) especially affecting securitized

\(^{32}\) Since \(Sample\ 3\) refers to the entire period, it accounts also for 60 unconsidered days between \(Sample\ 1\) and \(2\) which are the calibration days of \(Sample\ 2\) with respect to the 60-days regression window. During these 60 days, we observe extremely high RMSFEs. Thus, \(Sample\ 3\) reveals relative worse RMSFEs compared to \(Sample\ 2\).
tranches (compare Coval et al., 2009) and ii) potentially causing the dispro-
portionate strong increase of RMSFEs related to senior tranches during the
GFC.

Our empirical findings show that the dynamic MERM dominates the other
models considered in this paper in terms of one-day-ahead forecast accuracy
using a RMSFE metric. Our FERM outperforms the dynamic ACM as well and
underlines the general superiority of dynamic regression correlation models,
even during the GFC. In order to improve the forecast accuracy indicated by
decreasing RMSFEs, spread forecast models should account for both random
time-specific effects and fixed tranche-specific effects.

Figure 8 shows both the variance components and the intra-class correlation
curve for *Sample 3* (x-axis). The primary y-axis on the left hand side refers to
the variances, the secondary y-axis on the right hand side denotes the intra-
class correlation values.

![Insert Figure 8 here]

The intra-class correlation is high throughout the entire sample and varies
between 74% and 97%. This indicates that the variance of the time-specific
effect explains a high ratio to the total variance of base correlation forecasts.
This is also underlined by the remaining two curves in Figure 8: while the
dashed line denotes the unobservable time-specific component $\sigma_t$ of the total
variance, the dotted line denotes the residual disturbance $u_t$ of that variance
(compare section 2.3). We conclude that the time-specific component repre-
sents a main part of the total variance throughout *Sample 3*. This time effect
simultaneously affects all tranches of the 5Y *iTraxx Europe* index, especially
during the GFC, and also reaches statistical significance. Eventually, the time-
specific effect is particularly striking in times of financial distress and can not be considered by our FERM. Based on the intra-class correlation which exists across all tranches, we suspect the presence of systematic risk simultaneously affecting all tranches.

Prior to 2007, the intra-class correlation coefficient follows the trend of decreasing credit spreads. The correlation increases following negative financial news: early 2007, various mortgage lenders reported financial stresses. In March 2007, Ben Bernanke, quoting Alan Greenspan, warned that the Government Sponsored Enterprises, Fannie Mae and Freddie Mac, were a source of ‘systemic risk’ and suggested legislation to avoid a possible crisis. In July 2007, shareholder concerns on the financial stability of Bear Stearns, Sentinel Management Group and Countrywide Financial increased (compare Section 3.1). On September 15th, 2007, Lehman Brothers filed for bankruptcy.

In addition, the correlation temporarily decreases during these events as positive news, such as industry and government interventions (e.g., central bank lending to distressed institutions and interest rate cuts), are announced. For example, in mid-October, a consortium of U.S. banks backed by the U.S. government announced funding of $100 billion to purchase mortgage-backed securities with reduced market values.

Overall, these results suggest the existence of systematic risk which are indicated by our MERM but not considered explicitly. Thus, the intra-class

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33 For example, on 10 January 2007, Ownit Mortgage Solutions filed for Chapter 11 owing approximately $93 million to Merrill Lynch. On 29 January 2007, American Freedom Mortgage filed for Chapter 7. Other examples for bankruptcy filings at this time were ResMae Mortgage, People’s Choice and New Century Financial. In addition, other firms such as HSBC, New Century Financial, American Home Mortgage, Option One and Fremont Capital reported larger losses on the subprime mortgage books.
correlation may be interpreted as an indicator of unconsidered systematic risk varying over time and simultaneously influencing all tranches.

Finally, we conclude that the dynamic FERM dominates the dynamic ACM. This suggests that the spread forecast performance may be improved by accounting for both random time effects and fixed tranche effects. In addition, further systematic risk factors may be identified through our dynamic MERM.

4 Conclusion

We develop two dynamic regression correlation models in order to forecast various base correlations. Our proposed dynamic fixed effects regression correlation model (FERM) accounts only for fixed tranche-specific effects, whereas our proposed dynamic mixed effects regression correlation model (MERM) additionally assumes that the time effect is varying stochastically. Through Monte Carlo simulations, we forecast daily STCDO spreads. Within three samples, we measure the forecast accuracy of our models by calculating root mean square forecast errors of forecasted STCDO spreads. Analogously, we forecast daily STCDO spreads with a dynamic asset correlation model (ACM). A comparison of the forecast accuracy suggests the superiority of our proposed dynamic regression correlation models in terms of the suggested RMSFE metric. Applying the MERM, we can account for both cross-sectional and time-series information in quoted market spreads related to the securitized tranches. The consideration of both existing effects is important for more accurate correlation forecasts, even during the global financial crisis. The increased accuracy leads to an improvement of the overall spread forecast performance with several implications for financial institutions and regulatory authorities dealing
with structured finance instruments.

The intra-class correlation indicates the existence of unconsidered systematic risk varying over time. Furthermore, it underlines the importance of applying our proposed dynamic MERM in order to account for such systematic time effects. By expanding the MERM to other relevant systematic risk factors, useful information can be derived in order to develop appropriate stress-tests for structured finance products. It also may support the measurement of risk contributions of synthetic STCDOs to portfolio inherent credit risks, which is highly relevant for investors in securitized tranches.
A Forecast Accuracy

In this section, we examine the forecast accuracy of our three correlation models by comparing market spreads with our model-specific spread forecasts:

\[ s_{t,p} = \theta_{0,p} + \theta_{1,p} \cdot \hat{s}_{t,p} + \epsilon_{t,p} \]  

(A.1)

with \( \epsilon_{t,p} \sim \mathcal{N}(0, \sigma^2) \) i.i.d. The hypothesis \( H_0 : \theta_{q,p} = 0 \) is tested with \( q \in \{0, 1\} \).

Table IV summarizes the regression results as well as corresponding p-values of the second test statistic for Sample 3 and each of our three correlation models, each regression windows (40-, 50- and 60-days), and tranches.

[Insert Table IV here]

We find i) that the intercepts \( \theta_0 \) are not significantly different from zero and ii) the coefficients \( \theta_{1,p} \) of spread forecasts \( \hat{s}_{t,p} \) are significantly different from zero. These findings hold for all tranches and all regression windows. Since the estimates \( \theta_{1,p} \) are close to one across all tranches and regression windows as well, we apply a F-test for \( H_0 : \theta_{1,p} = 1 \). The p-values of the secondary test statistic (F-test) indicate that the estimated coefficients \( \theta_{1,p} \) are not significantly differing from one (compare the last column of Table IV). On the other hand, the estimation results related to the ACM show that the intercepts \( \theta_0 \) as well as the spread forecast coefficients \( \theta_{1,p} \) are different from zero with a statistical significance at the 10%-quantile across all tranches. Further, the secondary test statistic indicates that the coefficients \( \theta_{1,p} \) are different from one at the statistical significance level of 0.01%. These test statistics confirm that all three correlation models provide valuable forecast performance.
Bibliography


Figures

**Fig. 1.** Spreads of the Standardized 5Y iTraxx Europe, 2005 - 2008

*Notes:* The figure shows historical 5Y iTraxx Europe index spreads (red line) as well as several tranche spreads with regard to 'on the run' series S to S9 which are indicated by the dashed-dotted vertical lines. The sample period is August 24th, 2005 to September 19th, 2008. During series S7, all spreads strongly increase for the first time in line with increasing spread volatility due to the start of the GFC.

**Fig. 2.** Time-series of base correlations, 2005 - 2008

*Notes:* The figure shows time series of calculated base correlations $T_{[0\% , D_i]}$ from August 24th, 2005 to September 19th, 2008. The base correlations monotonically increase with increasing detachment level and are strongly linked to each other. Similar to Figure 1, the base correlations are also strongly increasing in the beginning of the GFC and exhibit a higher volatility in the aftermath.
**Fig. 3. Distribution of Spread Forecasts for Tranche T_{0\%,3\%} on December 2^{nd}, 2005**

*Notes:* The figure shows a histogram of 1,000 simulated model upfront payments (UPs) for tranche $T_{0\%,3\%}$ on December 2^{nd}, 2005 (MERM). The mean of the simulated model UPs is denoted by the dashed line and the real observed market UP by the black line. For forecast purposes, the mean of the model UPs is taken into consideration.

**Fig. 4. MERM Estimation Results**

*Notes:* The figure shows various boxplots for Sample 3 which summarize the estimation results of 688 regressions based on our MERM (40-days). The upper four boxplots refer to the distribution of tranche-specific fixed effects $\alpha_i$, the intercept ($\beta_0$) considering the reference group $\alpha^5$, the coefficient $\beta_1$ of the lagged base correlation $\rho_{t-1}$ and the random time effect $v_t$. The four lower boxplots show the distribution of the respective p-values.
Fig. 5. Forecast Performance with Base Correlations for Tranche $T_{[0\%,3\%]}$

Notes: This Figure shows the market upfront payment (UP) for tranche $T_{[0\%,3\%]}$, the red area describes the forecast interval related to the 5% to 95% quantile of forecasted UPs. All forecasts are calculated with estimated base correlations (MERM, 40-days window). The red area surrounds the market upfront payment throughout the forecast horizon, which is from December 2nd, 2005 to September 19th, 2008.

Fig. 6. Forecast Performance with Dynamic Asset Correlations for Tranche $T_{[0\%,3\%]}$

Notes: This figure shows upfront payment forecasts calculated with dynamic historical asset correlations versus real market upfront payments of tranche $T_{[0\%,3\%]}$. The forecasting horizon is December 2nd, 2005 to September 19th, 2008.
Notes: This figure shows several scatter plots to indicate the forecast performance of our dynamic regression correlation models MERM (lower charts) and FERM (middle charts) in comparison to our benchmark model ACM (upper charts). In each chart, the real market spread is plotted against the model-specific spread forecast. The three charts on the left hand side show the forecast results referring to the market upfront payments, the charts on the right hand side analogously show the results related to spreads of the senior tranche. The forecasting horizon is December 2nd, 2005 to September 19th, 2008.
Fig. 8. Variance Effects and Intra-class Correlation

Notes: This figure shows the time series (x-axis) of derived intra-class correlations (y-axis on the right) for Sample 3 and both parts of the estimated variance (y-axis on the left): i) the time-specific component $v_t$ and ii) the disturbance $u_{it}$. The results refer to the dynamic panel regression correlation model accounting for mixed effects (MERM) and a regression window of 40-days.
### Tables

#### Table I
**Summary Statistics for the 5Y *iTraxx Europe* Index and Index Tranche Spreads**

<table>
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<tr>
<th>Tranche</th>
<th>Mean</th>
<th>STD</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
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<td>953.41</td>
<td>636.07</td>
<td>5219.11</td>
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<td>3% - 6%</td>
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<td>145.09</td>
<td>39.70</td>
<td>685.93</td>
<td>749</td>
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<td>6% - 9%</td>
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<td>10.25</td>
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<td>749</td>
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<td>30.42</td>
<td>20.09</td>
<td>160.00</td>
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</table>

*Notes:* This table provides summary statistics of market spreads in basis points for *Sample 3*. The results refer to the combination of ‘on the run’ time series. The sample period is August 24th, 2005 to September 19th, 2008. *N* denotes the amount of observations. STD describes the respective standard deviation of market spreads.

#### Table II
**Forecast Periods of the Empirical Analysis by Sample**

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<th>Forecast period</th>
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<th>Sample 2</th>
<th>Sample 3</th>
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<td>12th of Oct 07</td>
<td>2nd of Dec 05</td>
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<td>End:</td>
<td>18th of Jun 07</td>
<td>19th of Sep 08</td>
<td>19th of Sep 08</td>
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<td>Spread forecasts</td>
<td>370 (1850)</td>
<td>258 (1290)</td>
<td>688 (3440)</td>
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*Notes:* The table shows an overview of three different forecast periods which are identically defined across all regression windows. Values in brackets describe the total amount of tranche spread forecasts related to all of the five index tranches.
Table III
Root Mean Square Forecast Errors by Sample

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<th>6% - 9%</th>
<th>9% - 12%</th>
<th>12% - 22%</th>
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Notes: This table shows RMSFEs of tranche spread forecasts for each correlation model. MERM denotes the dynamic mixed effects regression correlation model for the base correlation estimation. This model accounts for random time-specific effects and for fixed tranche-specific effects as well. The second base correlation model is the dynamic fixed effects regression correlation model (FERM) accounting only for fixed tranche effects. ACM denotes the dynamic historical asset correlation model and is independent of different regression windows. The RMSFEs vary with i) the window size, ii) the respective tranche and iii) the specific sample. The lowest RMSFEs are highlighted in bold.
Table IV
Forecast Test Statistics

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<th>Test Statistic (p-value)</th>
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<td>0.000</td>
<td>0.507***</td>
<td>0.004</td>
<td>0.973</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>9% − 12%</td>
<td>0.000**</td>
<td>0.000</td>
<td>0.606***</td>
<td>0.005</td>
<td>0.954</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>12% − 22%</td>
<td>0.000**</td>
<td>0.000</td>
<td>0.639***</td>
<td>0.006</td>
<td>0.941</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: The table provides test statistics related to tranche-specific spread forecasts for each correlation model (MERM, FERM, ACM) and window size (40-, 50-, 60-days). The results refer to the forecast period of Sample 3. While the parameter estimates are tested for $H_0: \theta_1 = 0$ with $q \in \{0, 1\}$, the test-statistic tests the coefficient $\theta_1$ of spread forecasts for $H_0: \theta_1 = 1$. STD denotes the standard deviation of parameter estimates. ***, ** and * are indicating statistical significance at the 0.1%, 5% and 10% level. $R^2$ denotes the coefficient of determination.