Measuring and Modeling Default Dependence: Evidence from CDO, CDS and Equity Data*

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Abstract

Characterizing the dependence between companies' defaults is a central problem in the credit risk literature. This dependence structure is a first order determinant of the relative values of structured credit products such as collateralized debt obligations (CDO). We present a number of stylized facts useful in guiding the modeling of default dependence. We systematically compare correlation measures implied from three different markets: base correlations implied by CDO prices, correlations implied by equity returns, and correlations estimated from default intensities implied by CDS prices. We use flexible dynamic equicorrelation techniques introduced by Engle and Kelly (2007) to capture time variation in CDS-implied and equity return-implied correlations while base correlations are obtained using the Gaussian copula. We perform this analysis using North American data, the components of the CDX index, as well as European data, the components of the iTraxx index. For each index, there is substantial co-movement between the three correlation time-series. All correlations are highly time-varying and persistent. European and North American correlation series display considerable co-movement. Correlations across both markets increased significantly during the turbulent second half of 2007.

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1 Introduction

The measurement and modeling of the dependence between default probabilities, firm asset value, and equity returns is a problem of great importance in the credit risk literature. Not only is this dependence a key determinant for the value of portfolios of credit risky instruments, but the reliability of dependence metrics has become exceedingly important in recent years as a result of the growth in the market for Collateralized Debt Obligations (CDOs) and other structured credit products. Investors hold long or short positions in CDO tranches with varying degrees of seniority, and default dependence is a first order determinant of the values of these tranches.

Conceptually, the most straightforward approach is to estimate default correlations using historical default data, but it is widely accepted that the available time series of default data are not sufficiently long. Several methods have therefore been developed that estimate and model correlations implied by the prices of traded securities. These methods differ across three dimensions. First, they are applied to different types of securities data; second, security prices can be filtered through different models to generate default probabilities or asset returns before correlation techniques are applied; and third, different statistical techniques can be used to model correlations after extracting default probabilities and/or asset returns from security data.

Several methods are commonly used in the academic literature and finance practice to estimate default probabilities. Structural credit risk models can be used to extract the default dependence for two companies by estimating and correlating their asset returns from underlying equity returns or credit-risky securities written on the companies, such as CDS contracts or corporate bonds.[1] An alternative approach is to use a reduced-form framework to model default dependence. This approach directly models default intensities without reference to deeper structural variables such as firm assets, and attempts to capture realistic dependence structures by allowing default intensities to be driven by latent common factors, or by letting default probabilities depend on observables, such as macroeconomic variables or interest rates. Intensity-based models are typically calibrated using the market prices of credit-risky securities such as corporate bonds or credit default swaps (CDS).[2]

After using the structural or reduced-form approach to model default probabilities, a number of techniques can be used for modeling the correlation between these. Factor models are often used to model correlations for large portfolios, regardless of whether default probabilities are extracted

[1]The structural approach goes back to Merton (1974). See Black and Cox (1976), Leland (1994) and Leland and Toft (1996) for extensions. For recent applications of the structural approach see Ericsson and Renault (2006), Garlappi, Shu and Yan (2008), Schaefer and Strebulaev (2006), and Tarashev and Zhu (2007).

[2]See Jarrow and Turnbull (1995) and Duffie and Singleton (1999) for early examples of the reduced form approach. See Lando (2004) and Duffie and Singleton (2003) for surveys. Duffie and Garleanu (2001) use intensity-based models to value CDOs.

using structural or reduced-form models. In many cases simple rolling correlations or exponential smoothers are used. Multivariate GARCH techniques have been developed over the past two decades, and it is well-recognized that the explicit modeling of the second moment in GARCH models may provide benefits for correlation modeling, but it has proven difficult to estimate multivariate GARCH models for large numbers of underlying securities.[3]

When valuing CDOs, academics as well as practitioners often use copulas to model the multivariate distribution of credit-risky securities underlying the CDO. The most frequently used model is the Gaussian copula, and calibration of the correlation structure is mostly performed using CDO data.[4] For our purpose, it is important to remember that for most applications of the copula approach to CDO pricing, the parameterization of the correlation structure is low dimensional, thus facilitating calibration. The Gaussian copula is typically implemented with a pairwise correlation which is held constant across time and firms.

In summary, correlation and dependence measures can be obtained from equity returns, historical default data, CDO data, and CDS data, any other default-risky security, or any combination of the above. The statistical and economic frameworks used vary from simple historical averages to the use of structural and intensity-based models, as well as more complex copula models. Moreover, due to the differences in calibration methods, some correlation measures are obtained under the physical measure, whereas others are obtained under the risk-neutral measure.

A systematic analysis of default correlation estimates from different sources seems therefore of substantial interest. Unfortunatel, this issue has received little attention in the literature.[5] A number of papers estimate default correlation from credit risky securities or default data and use these estimates to price CDOs. For example, Azizpour and Giesecke (2008) use a model with default contagion to value CDO tranches using estimates from default data. Akhavein, Kocagil and Neugebauer (2005) consider default correlation estimated using default data, rating transitions and equity based methodologies. Among other things they document an upward bias when using equity data to estimate asset correlations. Tarashev and Zhu (2007) extract correlations from CDS data and subsequently analyze the price of correlation risk by comparing CDO tranche market prices with prices computed using CDS-implied correlations. Das, Duffie, Kapadia and Saita (2007) investigate

[3]The GARCH approach goes back to Engle (1982) and Bollerslev (1986). For early examples of multivariate GARCH models see Bollerslev, Engle and Kroner (1988) and Engle and Kroner (1995). Recently, a new and more flexible generation of multivariate models has been developed by Engle (2002), Tse and Tsui (2002), and Franses and Hafner (2003) as well as by Ledoit, Santa-Clara and Wolf (2003), and Ledoit and Wolf (2003). For overviews see Andersen, Bollerslev, Christoffersen, and Diebold (2006) and Bauwens, Laurent and Rombouts (2006).

[4]On copulas see for example Li (2000), Andersen and Sidenius (2004), and Hull and White (2004). Schonbucher and Schubert (2001) incorporate copulas in an intensity-based model of default.

[5]McGinty, Beinstein, Ahluwalia and Watts (2004) provide an interesting practitioner-oriented and case-based discussion of using default data, equity prices and credit spreads to compute default correlation. They also provide a primer on CDO implied default correlation.

whether a doubly stochastic default intensity model based on four observable covariates (trailing firm level and market wide equity returns, distance-to-default and the short term government rate) can explain the amount of default clustering observed in firm level data. They conclude that this model specification generates insufficient default clustering and can thus be statistically rejected.

This paper provides a comparison of correlation measures obtained from three different data sources: CDOs, CDS spreads, and equity returns. Our emphasis is on the time variation in the correlation measures. In our opinion this analysis is very timely. While our understanding of default correlation in general and of CDO valuation in particular has improved in recent years, the turmoil in structured credit markets starting in the summer of 2007 certainly suggests that an improved understanding of default correlation and more sophisticated modeling techniques are highly desirable. The similarities and differences between correlation measures from different sources are simply not yet well understood.

We analyze the differences between correlations implied by CDO tranche spreads on the one hand, and from CDS spreads and equity returns on the other hand. To extract correlation measures from CDO data, we apply the standard Gaussian copula to the CDX and iTraxx indexes. To characterize correlation between default intensities, we proceed in two steps. The first stage is strictly univariate: we fit a simple intensity based model to the time series of CDS spreads for each of the underlying names in the CDX and iTraxx indexes. This step yields a time series of fitted default probabilities for each of the underlying companies. In the second stage, we use the dynamic equicorrelation (DECO) framework of Engle and Kelly (2008) in order to model the default dependence structure between the index constituents. As the name suggests, DECO allows for correlation dynamics but assumes that the cross-sectional correlations are equal across all pairs of assets. We also apply DECO techniques to a sample of equity returns for the CDX and iTraxx index constituents.

Figures 1 and 2 summarize our main findings. Figure 1 presents results for CDX data, and Figure 2 for iTraxx data. Consider first the CDX data in Figure 1, which contains the time series for the correlations implied by the equity tranche (top-left panel) and a mezzanine tranche (top-right panel), as well as the CDS-based (bottom-left) and equity-based (bottom-right) DECO correlations. These concepts will of course all be defined in detail later. The correlation between the CDS-based DECO correlation with the base correlation for the mezzanine tranche is very high at 68%, as indicated by Table 4. The correlation with the equity tranche is lower at 37%. The correlations between the equity-based time series and the two base correlations are 44% and 68% respectively. Figure 2 shows that for the iTraxx, the CDS-based and CDO-implied correlations move together even more strongly, but the equity-based correlations are less in line than in the case of the CDX in Figure 1.

The overall conclusion from Figures 1 and 2 will of course depend on one's prior, but in our opinion the evidence in favor of co-movement between these different correlation measures is arguably unexpectedly strong. The Gaussian copula is widely acknowledged to be overly simplistic, as evidenced for instance by the different correlation levels implied by different tranches. In light of this, the correlations in Table 4 are perhaps surprisingly high. *This high degree of similarity in the time series between CDO based correlations and their CDS counterparts is surprising not only as the implied correlation acts as a catch all for obvious misspecifications in the modeling of default risk, but also because it will capture any CDO market specific risk premia, illiqiuidity premia and demand / supply effects.*

The other important conclusion from Figures 1 and 2 is that regardless of the data source, default intensity correlations are highly time-varying. This suggests that neglecting the time variation in correlations may induce substantial errors in the pricing of structured credit products. The DECOs, which can usefully be thought of as average pairwise correlations, can easily change by 30% over short periods of time and, as exemplified by the performance of hedge funds long in CDO equity products in May 2005 (following the Ford and GM downgrades) and in the second half of 2007, such a change can have a dramatic impact on the valuation of different tranches.

The paper proceeds as follows. In Section 2 we discuss the importance of correlation for the valuation of credit risky securities such as CDSs and CDOs, and we also summarize existing methods for measuring default correlation. In Section 3 we discuss several methodological issues: we explain how we extract default intensities from CDS contracts, and we discuss the class of multivariate GARCH models known as dynamic equicorrelation (DECO) models. Section 4 discusses the different data sources, and Section 5 discusses empirical results. Section 6 concludes.

2 Credit Markets

In this section we discuss a number of recent developments in credit markets, with an emphasis on Credit Default Swap (CDS) markets and Collateralized Debt Obligations (CDOs). We also discuss existing methods for computing default probability correlations, and the relevance of default correlation for the valuation of CDOs.

2.1 CDS and CDO Markets

The last decade has seen the emergence of a large variety of new portfolio credit products. In this paper we focus on collateralized debt obligations (CDOs). In essence, a CDO is a portfolio of credit risky exposures, acquired in cash markets (e.g. bonds or loans) or synthetically in derivative markets (using credit derivatives). These credit risky securities may or may not trade independently in separate markets. The underlying securities' payoffs are allocated to issued notes that differ in their seniority. These notes are typically referred to as the tranches of the CDO, and their riskiness differs because of the differences in seniority. The most risky tranche of the CDO absorbs the first x% of portfolio losses. It is usually referred to as the equity or first-loss tranche. The safest tranche only absorbs losses if they can no longer be covered by the more risky tranches. It is usually referred to as a senior or super-senior tranche. The intermediate tranches are often known as mezzanine tranches. For a more thorough discussion of CDOs, including some stylized examples, see Duffie and Garleanu (2001) and Longstaff and Rajan (2006).

The CDO market has experienced very rapid growth. Early on, the market consisted exclusively of cash CDOs. In a cash CDO, the underlying securities are assets such as bank loans, investment-grade and high-yield bonds, and commercial mortgages. In many cases, the motivation for the CDO was securitization. For instance, banks were interested in securitizing illiquid loan portfolios. Gradually, interest in the CDO market has shifted away from securitization and synthetic CDOs have become highly popular. A typical synthetic CDO consists of a portfolio of credit default swaps (CDS) rather than cash securities.

Synthetic CDOs include index products as well as "bespoke" or "single-tranche" CDOs. An index tranche is not backed by actual exposures but is referenced by an index of key names. The two most important examples are the CDX family, lead by the NA.IG grouping of the 125 most actively traded North-American investment grade reference entities, and the iTraxx family. A bespoke CDO is created when a dealer sells a tailor-made tranche demanded by an investor. This tranche is not backed by the cash flows of existing assets or synthetic exposures. Instead the position is dynamically hedged by the CDO dealer who relies on the market for index tranches as well as single-name default swap contracts to manage his exposure.

Since a thorough understanding of CDSs is important for our empirical work, we discuss this security now in more detail. A CDS is essentially an insurance contract where the insurance event is defined as default by an underlying entity such as a corporation or a sovereign country. Which events constitute default is a matter of some debate, but for the purpose of this paper it is not of great importance. The insurance buyer pays the insurance provider a fixed periodical amount, expressed as a "spread" which is converted into dollar payments using the notional principal - the size of the contract. In case of default, the insurance provider compensates the buyer for his loss. Synthetic CDOs collect these CDS contracts in portfolios. While the nature of the contracts is somewhat different than in a cash CDO, it can be easily seen that defaults in the underlying securities affect the value of the CDO and the value of the CDOs tranches in a similar way. In particular, changes in default dependence affect the value of the CDO tranches in a similar way, as a function of their respective seniorities.

The CDS market has exploded in recent years. One element of its success has been the creation of market indexes consisting of CDSs, the CDX index in North America and the iTraxx index in Europe. In our empirical work, we will use the constituents of both indices, which consist of 125 underlying investment grade actively traded corporate reference entities.

According to the International Swaps and Derivatives Association 2007 mid-year survey, the size of the credit derivatives market as a whole has reached a staggering 45 Trillions $US in notional principal. Based on this size metric, the market is now four times larger than equity derivatives markets. In 1998 the credit derivatives market size stood at 350 billion $US. The share of single-name credit default swaps in this market has been relatively stable for some time at around a third of the overall market. Over the last three years, the market for index credit derivatives has grown to approximately one third of the market, while synthetic CDO tranches now constitute more than one fifth of the market. This implies that multi-name credit derivatives, which traded in very low volumes before 2004, now constitute the largest market segment.

Starting in the summer of 2007, the market for CDOs has experienced severe problems, and in this paper we document a number of stylized facts in both CDS and CDO markets during this period. Interestingly, while the market's appetite for complex CDO products is virtually nonexistent for the time being as a result of these market fluctuations, the CDS market is still very strong, underlining the importance of credit markets. The purpose of our paper is to better understand correlation between credit names, either underlying a CDO product or as part of any other portfolio.

2.2 Methods for Measuring and Modeling Default Dependence

Measuring default dependence has always been a problem of interest in the credit risk literature. For instance, a bank that manages a portfolio of loans is interested in how the borrowers' creditworthiness fluctuates with the business cycle. While the change in the probability of default for an individual borrower is of interest, the most important question is how the business cycle affects the value of the overall portfolio, and this depends on default dependence. An investment company or hedge fund that invests in a portfolio of corporate bonds faces a similar problem. Over the last decade, the measurement of default dependence has taken on added significance because of the emergence of new portfolio credit products, and as a result new methods to measure correlation have been developed.

We now discuss different available techniques for estimating default correlation. First, default correlation can be computed using historical data. Second, the Merton (1974) model - or any of its offspring - can be used in conjunction with a factor model to model default dependence using equity prices. Third, there are different ways to estimate and model default correlation in the context of intensity-based credit risk models. Finally, we discuss the modeling of default correlation using copula-based models.

The oldest and most obvious way to estimate default correlation is the use of historical default data. This can simply be thought of as an application of the CreditMetrics methodology to estimate ratings transitions, where default is one particular rating. The analogy with CreditMetrics also immediately clarifies the weakness of this approach for the purpose of estimation default correlations. In order to reliably estimate ratings transitions or default probabilities for an individual firm, typically a large number of historical observations are needed. This problem is obviously compounded when using historical data to estimate default correlations. Nevertheless, historical data on default are a rich and indispensable source of information. See for instance deServigny and Renault (2002).

For publicly traded corporates, a second source of data on default correlation is the use of the Merton (1974) model that links equity returns or the prices of credit-risky securities to the underlying asset returns.[6] This approach is used for instance by KMV corporation. The use of a factor model for the underlying equity return implies a factor model for the value of the credit risky securities, and it also determines the default dependence. Clearly the reliability of the default dependence estimate is determined by the quality of the factor model.

A third way to estimate default dependence is in the context of intensity-based models, which have become very popular in the academic credit risk literature over the last decade. This approach typically models the default intensity using a jump diffusion, and is also sometimes referred to as the reduced-form approach. Within this class of models, there are different approaches to model default dependence. One class of models, referred to as conditionally independent models or doubly stochastic models, assumes that cross-firm default dependence associated with observable factors determining conditional default probabilities is sufficient for characterizing the clustering in defaults. See Duffee (1999) for an example of this approach. Das, Duffie, Kapadia and Saita (2007) provide a test of this approach and find that this assumption is violated. Other intensity-based models consider joint credit events that can cause multiple issuers to defaults simultaneously, or they model contagion or learning effects, whereby default of one entity affects the defaults of others. See for example Davis and Lo (2001) and Jarrow and Yu (2001). Jorion and Zhang (2006) investigate contagion using CDS data.

Finally, modeling default correlation using Copula methods has become extremely popular, especially among practitioners and for the purpose of CDO modeling. The advantage of the copula approach is its flexibility, because the parameters characterizing the multivariate default distribution, and hence the correlation between the default probabilities, can be modeled in a second

[6]See Zhou (2001) for a discussion of default correlation in the context of the Merton model.

stage, after the univariate distributions have been calibrated. In many cases the copulas are also relatively parsimoniously parameterized, which facilitates calibration. The most often used model is the Gaussian copula, and calibration of the correlation structure is mostly performed using CDO data.

Copula modeling is sometimes interpreted as an alternative to the structural and reduced-form approaches. Strictly speaking, this is not the case. Copulas are in fact more usefully interpreted in a narrow sense as a tool for modeling correlation. Their role is rather similar to the role played by GARCH models or rolling correlations in the last step of the procedure outlined above for modeling default dependence in structural or reduced-form models. Of course, within the context of a given copula model, assumptions about default are usually made in order to price CDOs. For example, the popular Gaussian copula can be thought of as a multivariate structural Merton (1974) model because of the normality assumption (see Hull, Predescu and White (2006)). For our purpose, it is important to remember that for most applications of the copula approach to CDO pricing, the parameterization of the correlation structure is low dimensional, thus facilitating calibration. The Gaussian copula is typically implemented with constant correlations.

3 Methodology

In this section, we discuss the methodological and statistical approaches we use to study correlation. First, we outline the methodology we use to extract default intensities from CDS data. Second, we provide a discussion of dynamic equicorrelation (DECO) techniques. Third, we briefly discuss methods to extract implied correlations from CDO data.

3.1 Extracting Default Intensities from CDS Data

The valuation of CDS contracts, and the estimation of default intensities that relies on this valuation, has been studied in several papers.[7] Consider a given risk-neutral survival probability $q(t, T)$. The premium on an CDS is the spread paid by the protection buyer that equates the expected present value of default costs to be borne by the protection seller ("floating leg") to the expected present value of investing in the CDS ("fixed leg"). The value of the fixed leg is the present value of the spread payments the protection seller receives from the protection buyer, while the unknown floating leg comprises the potential payment by the protection seller to the buyer.

[7] The literature on CDS contracts has expanded rapidly. For theoretical work, see Das (1995), Das and Sundaram (1998) and Hull and White (2000). For empirical studies, see Berndt, Douglas, Duffie, Ferguson, and Schranz (2004), Blanco, Brennan, and Marsh (2003), Ericsson, Jacobs and Oviedo (2007), Houweling and Vorst (2005), Hull, Predescu and White (2004), Longstaff, Mithal and Neiss (2004), and Zhang, Zhou and Zhu (2006).

Consider now a CDS contract with payment dates $T = (T_1, ..., T_N)$, maturity T_N, premium P and notional 1. Denote the value of the fixed leg by $V_{Fixed}(t, T, P)$, the value of the floating leg by $V_{Floating}(t)$, and the discount factors by $D(t, T_i)$. At each payment date T_i, the buyer has to pay $a(T_{i-1}, T_i)P$ to the seller, where $a(T_{i-1}, T_i)$ represents the time period between T_{i-1} and T_i (T_0 is equal to t). If the reference entity does not default during the life of the contract, the buyer makes all payments. However, if default occurs at time $s \leq T_N$, the buyer has made $I(s)$ payments, where $I(s) = \max(i = 0, ..., N : T_i < s)$, and has to pay an accrual payment of $\alpha(T_I(s), s)P$ at time s. Denote the probability density function associated with the default intensity process λ_t by $f(t)$, such that $f(t) = \frac{dq(t)}{dt}$, and let the recovery rate be δ, then

$$V_{Fixed}(t, T, P) = P_t \left[\sum_{i=1}^{N} D(t, T_i)\alpha(T_{i-1}, T_i)q(t, T_i) + \int_t^{T_N} D(t, s)\alpha(T_{I(s)}, s)f(s)ds \right]$$

$$V_{Floating}(t) = \int_t^{T_N} D(t, s)(1 - \delta)f(s)ds.$$

At initiation of the contract, the premium P_0 is chosen in such a way that the value of the default swap is equal to zero. Since the value of the fixed leg is homogeneous of degree one in P, the premium should be chosen as $P_0 = V_{Floating}(0)/V_{Fixed}(0, T, 1)$.

In our empirical application, we replace the integrals by numerical approximations. We define a monthly grid of maturities $s_0, ..., s_m$, where $s_0 = t$ and $s_m = T_N$ and set

$$\int_t^{T_N} D(t, s)(1 - \delta)f(s)ds \approx \sum_{i=1}^{m} D(t, s_i)(1 - \delta)(q(t, s_{i-1}) - q(t, s_i))$$

$$\int_t^{T_N} D(t, s)\alpha(T_{I(s)}, s)f(s)ds \approx \sum_{i=1}^{m} D(t, s_i)\alpha(T_{I(s_i)}, s_i)(q(t, s_{i-1}) - q(t, s_i)$$

We use this valuation framework to back out time paths of default intensities that are subsequently used as inputs in an econometric analysis of the correlation of default intensities across companies. Besides a concern regarding the consistency of the default intensities with a valuation model, we therefore need the resulting time paths of intensities to have appropriate statistical properties.

To reliably use the DECO correlation technique that we detail below, the inputs need to be standardized white noise residuals. Conceptually this can be addressed by backing out the residuals from an intensity-based model that specifies a white noise residual. At first, we took a standard approach: we specified a simple square root (CIR) model for the default intensity λ_t. The results for the CIR model were subject to two types of problems. First, the estimated residuals often exhibited substantial serial correlation and heteroskedasticity. This invalidates the subsequent correlation analysis, which assumes that these residuals are white noise. A second problem with the CIR model is that in approximately 5% of the cases, we obtained local optima that were economically unrealistic, for instance because they implied implausible average default intensities. Attempts to address these deficiencies with multifactor models were not successful.

We therefore proceeded with a simpler approach. Instead of assuming a CIR dynamic within the pricing framework, we backed out a time path of default intensities assuming that the default intensity is constant at every time t. Then, the link between the risk-neutral survival probability $q(t,T)$ and the default intensity is then simply

$$q(t,T) = \exp(-\lambda_t(T-t))$$

The time-subscript on the λ now signifies that a new value for λ in the constant-intensity model is extracted on each day. This gives economically very plausible results for all companies, but the other problem associated with the CIR model remains, in that statistical tests indicate that the resulting constant intensity time series are non-stationary and contain short-run dynamics as well. In order to obtain white-noise innovations from these intensities, we therefore fit univariate $ARIMA(p,1,q) - GARCH(1,1)$ models to the intensity time series.

To be specific, we estimate the following model

$$\Delta\lambda_t = \mu_{\lambda,t} + z_t$$

$$\mu_{\lambda,t} = \mu_\lambda + \sum_{i=1}^{p} \phi_i \Delta\lambda_{t-i} + \sum_{j=1}^{q} \theta_j z_{t-j}$$

$$z_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega_\sigma + \alpha_\sigma z_{t-1}^2 + \beta_\sigma \sigma_{t-1}^2$$

$$\varepsilon_t \sim i.i.d.(0,1)$$

where $\omega_\sigma > 0$, $\alpha_\sigma \geq 0$, $\beta_\sigma \geq 0$, and ε_t is independent of $(\Delta\lambda_s)$ for $s < t$. We proceed in two steps. First, we fit all $ARMA$ models with $p \leq 4, q \leq 4$, with and without intercepts, and choose the model with the lowest $AICC$ value

$$AICC = -2LLF + 2(p+q+c+1)T/(T-p-q-c-2)$$

where LLF is the log likelihood value, $c = 0$ if the $ARMA$ model does not have an intercept, and $c = 1$ if the $ARMA$ model has an intercept, and T is the number of observations available after differencing. Second, we fit a $GARCH(1,1)$ on the $ARMA$ filtered residuals z_t.

3.2 Modeling Dynamic Equicorrelation

Engle (2002) proposes a new class of models, named Dynamic Conditional Correlation Multivariate GARCH (DCC), which preserves the convenience of Bollerslev's (1990) constant correlation model, while allowing correlations to change over time. The DCC approach allows each of the companies in the analysis to have its separate dynamic for the marginal distribution. The DCC approach puts a dynamic multivariate distribution on top of the dynamic marginal distributions and can therefore be viewed as a dynamic copula approach.

The dynamic equicorrelation (DECO) model in Engle and Kelly (2008) is essentially an extreme case of a DCC model in which the correlations are equal across all pairs of companies but where this common equicorrelation is changing over time. The resulting dynamic correlation can be thought of as an average dynamic correlation between the companies included in the analysis.

In the standard DCC analysis, the correlation matrix R_t must be inverted for each iteration required in the numerical optimization procedure. This is costly for small cross-sections, and potentially infeasible for larger ones. In the DECO approach with has compact forms for the determinant and inverse of the correlation matrix, the problem is reduced to the optimization of a function whose arguments are all scalars with no matrix inversion or determinant computation required. It is therefore relatively straightforward to generate results for arbitrarily large cross sections of companies. We will rely solely on the DECO approach in the empirical analysis below.

Following Engle and Kelly (2008), we parameterize the dynamic equicorrelation matrix as

$$R_t = (1 - \rho_t) I_n + \rho_t J_{n \times n}$$

where I_n denotes the n-dimensional identity matrix and $J_{n \times n}$ is an $n \times n$ matrix of ones. The inverse and determinants of the equicorrelation matrix, R_t, are given by

$$R_t^{-1} = \frac{1}{(1 - \rho_t)} [I_n - \frac{\rho_t}{1 + (n-1)\rho_t} J_{n \times n}] \text{ and}$$

$$\det(R_t) = (1 - \rho_t)^{n-1} [1 + (n-1)\rho_t]$$

Note that R_t^{-1} exists if and only if $\rho_t \neq 1$ and $\rho_t \neq \frac{-1}{n-1}$, and R_t is positive definite if and only if $\rho_t \in \left(\frac{-1}{n-1}, 1\right)$. The time-varying equicorrelation parameter, ρ_t is assumed to follow the simple dynamic

$$\rho_{t+1} = \omega + \alpha u_t + \beta \rho_t$$

where u_t represents the equicorrelation update. We considered the following three updating rules adopted from Engle and Kelly (2008): u_t^{SS1}, u_t^{SS1R}, and u_t^{SS2}. The first updating rule u_t^{SS1} is of interest because its expectation is the time t equicorrelation parameter, and it requires only two simple inputs at time t: the sum of squares of the realizations and the squared sum of realizations. It is given by

$$u_t^{SS1} = \frac{1}{n(n-1)} \sum_{i \neq j} \varepsilon_{i,t} \varepsilon_{j,t} = \frac{1}{n(n-1)} \left[\left(\sum_i \varepsilon_{i,t} \right)^2 - \sum_i \varepsilon_{i,t}^2 \right]$$

It does have some disadvantages, however. It is not restricted to the range $(\frac{-1}{n-1}, 1)$, and estimates can exceed one when the true correlations are near one. In the empirical analysis below we therefore truncate it as follows

$$u_t^{SS1R} = \min(u_t^{SS1}, 1 - \delta)$$

where is δ a small positive number. Engle and Kelly (2008) report that u_t^{SS1R} may yield biased estimates of the equicorrelation parameter, especially for high levels of correlation.

The second updating rule u_t^{SS2} is given by

$$u_t^{SS2} = \frac{\sum_{i \neq j} \varepsilon_{i,t} \varepsilon_{j,t}}{(n-1) \sum_i \varepsilon_{i,t}^2} = \frac{\left(\sum_i \varepsilon_{i,t}\right)^2 - \sum_i \varepsilon_{i,t}^2}{(n-1) \sum_i \varepsilon_{i,t}^2}$$

Note that u_t^{SS2} lies within the positive definite range $\left(\frac{-1}{n-1}, 1\right)$. However, Engle and Kelly (2008) find that u_t^{SS2} may yield biased estimates of the equicorrelation parameter in small samples, because the numerator and denominator are correlated. In the empirical analysis we will estimate correlation models using both the u_t^{SS1R} and the u_t^{SS2} updating rules.

The correlation matrices R_t are guaranteed to be positive definite if the parameters satisfy $\omega/(1-\alpha-\beta) \in (-1/(n-1), 1)$, $u_t \in (-1/(n-1), 1)$, and $\alpha + \beta < 1$, $\alpha > 0$, $\beta > 0$. Engle and Kelly (2008) report that the u^{SS2} form will be the least sensitive to residual volatility dynamics and extreme realizations, due to the use of a normalization that uses the mean cross sectional variance. However it can be subject to downward bias because it is a ratio of correlated random variables. One way to address this bias is to alter the implementation to ensure that the fitted equicorrelation process obeys the bounds $\left(\frac{-1}{n-1}, 1\right)$ without imposing $\alpha + \beta < 1$. We will investigate this in the empirical analysis below.

3.3 Extracting Implied Correlations from CDO Data

Motivated by the volatility modeling literature which has found it fruitful to consider option implied volatilities, we want to assess credit correlations implied from multi-name credit derivatives. Fortunately, there is an interesting analogy between the correlation parameter in the market standard Gaussian Copula model for valuing structured credit products such as CDOs and the volatility parameter in the more traditional equity option pricing models. First of all, the correlation can loosely be thought of as the volatility of the distribution of portfolio losses for a CDO: the stronger the dependence, the more likely are scenarios with either very few or with many aggregate losses; for lower levels of dependence the distribution of potential losses is narrower. Second, it is used in very much the same way for both asset classes. It is common in both equity option and structured credit markets to imply parameters from market prices of benchmark instruments - option implied volatilities and tranche implied correlations. A correlation implied from CDO prices can best be understood by analogy to implied Black-Scholes volatilities: it is the correlation between the CDS names underlying the CDO that makes the price of the CDO tranche equal to the observed market price, conditional on the Gaussian copula method being the correct pricing method.

A typical CDO tranche consists of a stream of coupon payments which are made in exchange of payments that compensate for losses as they accrue to that tranche. To be more precise, let $L_{a,d}$ denote the risk-adjusted present value of the "loss leg" for a tranche with attachment and detachment points a and d respectively. As an example, consider the loss leg of a 5 year 0-3% first-loss or equity tranche with quarterly payments

$$L_{0,3} = \sum_{t=1}^{20} \Delta EL_t D(t),$$

where $\Delta EL_t = EL_t - EL_{t-1}$ denotes the incremental expected loss during the time interval $[t-1, t]$ and $D(t)$ is a discount factor with maturity t. Now consider the present value of an annuity that pays 1 dollar per dollar of remaining notional on each payment date. The original notional principal is denoted N. When defaults arrive the size of the payment is scaled down by the proportional total losses. Hence

$$A_{0,3} = \sum_{t=1}^{20} (N - EL_t)\, D(t)$$

can be thought of as the present value of a stream of payments equal to the expected remaining notional over the lifetime of the tranche. For a given spread $S_{0,3}$, the value of the tranche to the insurance seller is then[8]

$$\frac{S_{0,3}}{4} A_{0,3} - L_{0,3} \tag{3.1}$$

The par spread for a newly struck tranche is such that both parties view the transaction as a zero NPV deal. Given an observed market par spread $S_{0,3}^{mkt}$, one can solve for the correlation parameter such that the model value (3.1) of the tranche is zero - that is the implied correlation $\widehat{\rho}_{0,3}$ solves

$$\frac{S_{0,3}^{mkt}}{4} = \frac{L_{0,3}\left(\widehat{\rho}_{0,3}\right)}{A_{0,3}\left(\widehat{\rho}_{0,3}\right)}$$

In the early days of the CDO market it was common to extract an implied correlation parameter for each tranche of a CDO. Since, the standard that has evolved to what is known as an implied base correlation. These are defined for hypothetical equity or first-loss tranches and have the desirable feature of avoiding multiple solutions in the inversion of tranche values for the correlation parameter. So instead of extracting correlations from e.g. 0-3%, 3-7% or 7-10% tranches, base correlations will be associated with 0-3%, 0-7% and 0-10% equity tranches, although only the 0-3% tranche will

[8] For convenience we assume that all tranches are quoted without upfront payment.

actually be traded in CDO markets. The remaining hypothetical tranches are constructed using a bootstrapping procedure similar to that used to compute implied zero-coupon bond prices from coupon bonds.[9]

To see how this works in practice, consider the on-the-run 3-7% tranche for which we know

$$L_{3,7} = \frac{S_{3,7}^{mkt}}{4} A_{3,7}$$

Losses and payment streams are additive so that

$$L_{3,7} = L_{0,7} - L_{0,3}$$

and

$$A_{3,7} = A_{0,7} - A_{0,3}$$

Then, given a value for $\widehat{\rho}_{0,3}$ extracted from the trade 0-3% tranche, we can let $\widehat{\rho}_{0,7}$ solve

$$L_{0,7}\left(\widehat{\rho}_{0,7}\right) - L_{0,3}\left(\widehat{\rho}_{0,3}\right) = \frac{S_{3,7}^{mkt}}{4} A_{0,7}\left(\widehat{\rho}_{0,7}\right) - A_{0,3}\left(\widehat{\rho}_{0,3}\right)$$

Now, given the base correlations $\widehat{\rho}_{0,3}$ and $\widehat{\rho}_{0,7}$ we can together with the market spread for the traded 7-10% tranche compute $\widehat{\rho}_{0,10}$, the implied base correlation for the hypothetical 0-10% equity tranche and so on.

We extract base correlations from CDO data using the Gaussian copula framework to estimate values for the loss and premium legs L and A in the above. This method is discussed in more detail in Li (2000), Andersen and Sidenius (2004) and Hull and White (2004), and we refer the interested reader to those papers for a more detailed discussion.

4 Data

4.1 CDS Spreads

We conduct our empirical investigation using daily CDS premia on American corporates provided by CDX, and on European corporates provided by iTraxx. At any point in time, the CDX and iTraxx indexes consists of 125 components. The composition of the index is changed every six months. We use CDS data from October 14, 2004 to December 31, 2007. From the 125 corporates

[9] See McGinty, Beinstein, Ahluwalia and Watts (2004) for a detailed discussion.

that constitute the CDX index on October 14, 2004, 61 corporates stay in the index over the whole sample period. For the iTraxx index, this number is 64. Our empirical analysis uses these 61 respectively 64 corporates. Descriptive statistics for the CDS premia of the 61 CDX components are provided in Table 1, and descriptive statistics for the CDS premia of the 64 iTraxx components are provided in Table 2. Panel A of Figure 3 depicts the cross-sectional average of the spreads for the 61 CDX components, and Panel B does the same for the iTraxx components. Figure 3 indicates that the average premia are highly persistent over time. The same is true for the spreads for individual companies, which are omitted because of space constraints. They also contain occasional large shifts, as evidenced by the skewness and excess kurtosis statistics reported in Table 1. Most of the companies display positive skewness, and for some of the lower rated companies we occasionally observe substantial excess kurtosis.

The time series of spreads for individual companies (not reported) also suggest significant commonality in CDS premia across companies: For example, the spike in the CDS premia in early May 2005, which is associated with the General Motors and Ford downgrades, is shared by many (but not all) of the companies. Even more importantly, the spreads significantly increase in the second half of 2007 for almost all companies. Tables 1 and 2 and Figure 3 do not indicate dramatic differences between the European and American names.

4.2 CDO Data

We use the time series for the on-the-run investment grade CDX and Itraxx index spread with 5 years to maturity, from October 14, 2004 to December 31, 2007, to coincide with the CDS samples. For each index, we have five time series. For the CDX index depicted in Figure 4, we have tranche spreads for attachment and detachment points 0%-3%, 3%-7%, 7%-10%, 10%-15% and 15%-30%. For the iTraxx index depicted in Figure 5, we have tranche spreads for attachment and detachment points 0%-3%, 3%-6%, 6%-9%, 9%-12% and 12%-22%.

Figures 4 and 5 depict tranche spreads, and Table 3 presents descriptive statistics. The patterns are very similar for the CDX and the iTraxx tranche spreads. As a function of the tranches' attachment points, the spread and the spread volatility decrease, but the kurtosis and the (positive) skewness increase.

4.3 Equity Returns

We use two samples of equity returns in our empirical analysis. We obtain time series of equity returns for the period October 14, 2004 to December 31, 2007, which coincides with the CDS sample period. We also perform an analysis using equity returns for the same companies for the time period January 1, 2000 to December 31, 2007. We use all of the 61 CDX constituents and 64 iTraxx constituents used in the analysis of the CDS data for which we are able to obtain equity returns over these samples. This amounts to 54 CDX constituents and 58 iTraxx constituents. Because of space constraints, we do not present descriptive statistics for these equity return samples. They are entirely standard and are available from the authors on request.

5 Empirical Results

We now discuss our empirical results. We first separately discuss the results for different securities: CDOs, CDSs and equity. We then discuss similarities and differences between the time series of correlations extracted from these different securities. We pay particular attention to the robustness of our results by discussing alternative techniques and sample periods whenever possible.

5.1 Implied Correlations Extracted from CDO Index Spreads

Figures 4 and 5 plot the time series of implied base correlations extracted from iTraxx index spreads, one for each combination of available attachment-detachment points. The implied base correlations are significantly higher for higher attachment points. This is well known among practitioners. It could be argued that this finding in itself is evidence of the inadequacy of the Gaussian copula model used to extract the correlations, and that this indicates that the implied base correlations should not be interpreted as correlations, but rather as a rest category that captures the model's inadequacies. However, we also note that while the levels of the implied correlations strongly depend on the attachment points, the five CDX time series in Figure 5 seem highly correlated. The correlation matrix in Table 4 indicates that many series have correlations of over 85%. The base correlation for the equity tranche is the least related to the four others, but even the lowest of the correlations, between the equity tranche and the most senior tranche, is 40%. Figure 5 and Table 4 clearly indicate that the same is true, a fortiori, for the iTraxx base correlations. The lowest correlation between any of these two time series is 83%.

The time horizon of our sample is very limited, because of the fact that credit derivatives markets are a relatively new phenomenon. However, because of the very nature of these markets, the data contain a lot of variation. Most interestingly, our sample contains two periods of significant stress in credit markets. The first stress period occurs in April-May 2005 after the GM and Ford downgrades. Interestingly, while Figure 3 indicates that CDS spreads on average increase in this period for the CDX and iTraxx constituents (and inspection of the time series for individual spreads indicates that most of them increase in this period), Figures 4 and 5 indicate that base correlations decrease, significantly so for the equity tranche. We also note that the co-movements between the different time series of base correlations for the CDX decrease during this period. The second period of market stress begins in the summer of 2007. In this episode, CDS spreads as well as correlations go up, and the variations in base correlations are very significant across the different tranches.

Interestingly, while there is substantial time variation in the base correlations, this variability is very similar across tranches, as can be seen from the standard deviations in Table 3. The standard deviations for iTraxx tranches are also very similar to those of CDX tranches. Moreover, the third and fourth moments for the iTraxx tranches are also not dramatically different from those of the CDX tranches. Finally, we note that whereas skewness and kurtosis of the spreads monotonically increase as a function of the attachment points, this is not the case for the skewness and kurtosis of the base correlation time series.

We must of course be careful when comparing CDX and iTraxx base correlations directly. As mentioned before, it is a robust finding that base correlations increase as a function of the attachment point. It is therefore not very instructive to compare the base correlation for the CDX senior tranche with that of the iTraxx senior tranche, because the attachment points are very different. The most obvious comparison is between the equity tranches for both indexes, which are both 0-3% tranches. For these tranches, the average iTraxx base correlation is 17%, compared to 14% for the CDX. It can be seen from Figures 1 and 2 though that these differences are small. Also, Table 4 indicates that the correlation between both time series is 90%.

5.2 Correlations Between CDS-Implied Default Intensities

5.2.1 Extracting Standardized Intensity Residuals

Our empirical strategy based on CDS data proceeds in two steps. In the first step, we use an intensity model to extract standardized residuals from CDS spreads. In the second stage, we perform a DECO analysis on the standardized residuals from the first stage in order to determine their co-variation across time.

As explained in Section 3, we eventually settled on a constant intensity model for the first step, because it proved necessary to use a GARCH model for standardizing the residuals even after applying more complex intensity models. Furthermore, the simple constant intensity model yields the most economically sensible estimates. Tables 5 and 6 report on the standardized ARIMA-GARCH residuals for the CDX and iTraxx companies used in the analysis. The test statistics indicate that there are no significant remaining heteroskedasticity and autocorrelation patterns.

Panels A and B of Figure 6 plot the time path of the average (annualized) implied risk-neutral default intensities for the CDX and iTraxx respectively. Clearly these probabilities are closely related to the average CDS premia in Figure 3. This is also the case for default intensities for individual companies and individual spreads, which are not depicted because of space constraints. However, Tables 7 and 8 report descriptive statistics for the annualized default intensities. The results indicate substantial cross-sectional heterogeneity in default probabilities. For the CDX, the highest average annualized default probability is 1.97% and the lowest one is 0.27%. For the iTraxx companies, those numbers are 1.18% and 0.22%. Moreover, there are substantial differences between companies in the second, third and fourth moments. Many of these cross-sectional averages can be directly related to the spread data in Tables 1 and 2. For example, for the CDX components, high average default intensities are obtained for homebuilders and mortgage lenders such as Pulte or Countrywide. Table 1 indicates that these spread series also exhibit high kurtosis, and this carries over to Table 7.

5.2.2 CDS-Based Dynamic Conditional Equicorrelation Estimation

We perform a dynamic equicorrelation (DECO) analysis on the 61 components of the CDX index that are part of the index for the entire sample period, and for the 64 components of the iTraxx index that are part of the index for the entire sample period. The results of the DECO analysis are reported in Figures 1 and 2, and the parameter estimates are reported in Table 9.

The main conclusions were already given in the introduction, but we repeat them here for convenience. First, there is a large amount of covariation between the DECO-implied correlations and the base correlations from CDOs, for the CDX as well as the iTraxx. The correlation matrix in Table 4 confirms this. Second, there is a substantial amount of time variation in these DECO correlations. The intensity-based correlations vary more than the base correlations, as confirmed by the second moments in Table 3.

A number of other conclusions obtain. Interestingly, there is a large common component to the intensity-based correlations for the CDX and the iTraxx. Table 4 indicates that the correlation between the two time series is 85%. However, the levels are dramatically different, as confirmed by the averages in Table 3: the average CDX intensity DECO is 17%, and the average iTraxx intensity DECO is 33%. Standard deviation, skewness and kurtosis are not dramatically different. The co-movements as well as the level differences can clearly be seen from Figures 1 and 2.

5.3 Correlations from Equity Returns

We also apply DECO techniques to simple equity returns, to verify whether this source of information on correlation yields results that are comparable to the base correlations from CDOs. Figures 1 and 2 report results for the October 14, 2004 to December 31, 2007 sample which was also used for the intensity data. The DECO estimates underlying this time series are obtained using equity returns data for the time period January 1, 2000 through December 31, 2007. These estimates are reported in Table 9. We will comment on this choice of estimation period in Section 5.5.4 below.

For the CDX in Figure 1, there is a substantial amount of co-movement between the equity-based DECO correlations and the base correlations. Table 4 indicates that the correlations are between 65% and 73%. For the iTraxx in Figure 2, this is not the case: Table 4 indicates that the correlations are between 15% and 19%. The correlation between the equity DECO correlation and the CDS-implied DECO correlation is 61% in the case of the CDX, and 45% for the iTraxx. Interestingly however, when we look at the average correlations in Table 3, the average equity-based correlation is much closer to the average intensity-based correlation for the iTraxx than for the CDX. In fact, the iTraxx and CDX equity-based correlations are very similar on average (29% and 28% respectively) and the correlation between the two series is 50%.

5.4 Discussion

The main purpose of this paper is to provide a description of a set of stylized facts regarding default dependence. Although correlation between different companies can be measured using a variety of different securities, the literature does not contain a great deal of systematic comparisons between these different correlation measures. This is perhaps not surprising: the comparison between different correlation measures is fraught with difficulties because the correlations are obtained using different models, and the choice of model is often motivated by the complexity of the credit risky security. For example, when extracting correlations from CDOs, most often a Gaussian copula with constant correlation is used because of the complexity of the CDO valuation problem.

We use the Gaussian copula to extract a time series of correlations based on CDO tranche spreads. Even though the time variation in this time series is somewhat hard to interpret, because each estimate is obtained assuming constant correlation, we compare this somewhat ad hoc time variation in implied correlation with time varying correlations from CDS spreads and equity returns which are captured using an explicitly time-varying DECO correlation model.

It is instructive to keep these limitations in mind when comparing the correlation measures. However, to some extent the value of our results depends on how strongly the resulting time series of correlations move together. If the correlations implied by equity returns, CDS premia, and CDO tranche spreads are very different, this might be due to differences in the underlying correlation and default intensity models. Because we find that the resulting correlation series move together in many instances, we are able to draw a fairly strong conclusion; presumably if we could correct for the differences in the underlying models, the correlation time series would co-vary even more.

Besides the strong co-movements between the different correlation series, our most important finding is probably the significant amount of time-variation in the three correlation time series. This has important implications for the valuation of portfolio credit products.

Our empirical findings can be interpreted in various alternative ways. Most importantly, following the reasoning in Tarashev and Zhu (2007), we could compare the correlations based on CDS data with the correlations based on CDO tranche spreads to draw conclusions about correlation risk. The underlying logic is that while the default probabilities implied by CDS data are risk neutral default probabilities, the default dependences are physical because the underlying securities are univariate and therefore do not incorporate a risk premium for correlation risk. This contrast with CDO tranche spreads, which do incorporate such a risk premium. A comparison of these two correlation time series is therefore thought to be instructive about correlation risk.

There are two potential problems with this reasoning. First, as can be clearly seen from Figures 4 and 5, while the base correlations for different tranches are highly correlated, the levels of the correlation time series increase with the attachment points. Any inference regarding the risk premium will therefore depend on which tranche spread one chooses as a reference point. In Tarashev and Zhu (2007), this point is somewhat obscured because the comparison is made using tranche spreads rather than implied correlations, but the exercise is similarly constrained by the fact that the CDO valuation models are not rich enough. A second, more subtle, limitation of this type of analysis is that while credit default swaps are univariate credit products, they are priced in equilibrium, and therefore it is not clear that they do not contain a correlation risk premium. By analogy, we do not need portfolio equity products to unearth market risk: it is priced in the equity returns of individual companies. Therefore, while we could interpret the ratio between the CDS and CDO-implied correlations in Figures 1 and 2, or similar ratios using the base correlations in Figures 4 and 5, as correlation risk premia, in our opinion this type of conclusions are better addressed within the context of an explicit general equilibrium model. We prefer to focus on the similarities and differences in the correlations, without necessarily interpreting the differences as risk premia, and we prefer to focus on co-movements rather than level differences.

While overall we emphasize the similarities between the three types of correlations, there are some interesting differences. The overall level of the CDX intensity correlations is low in comparison with the iTraxx intensity correlations and the equity correlations. The most interesting difference is the behavior of implied correlations in the credit crisis of May 2005, following the downgrade of Ford and GM. While credit spreads increase in this period, implied correlations decrease significantly for the equity tranche, and much less for the more senior tranches, while equity-based and CDS-based correlations do not decrease. It may be possible that this finding is due to market mispricing, with the prices of equity tranches overreacting to expectations of higher default rates.

5.5 Robustness

5.5.1 Modeling Dynamic Equicorrelation

As explained in Section 3.2, Engle and Kelly (2008) propose different updating rules for estimating dynamic equicorrelations. The DECO correlations in Figures 1 and 2 are obtained using the u_t^{SS2} updating rule, a choice that is motivated by the analysis in Engle and Kelly (2008). Figure 7 presents a robustness analysis for one particular dataset, namely iTraxx default intensities. Robustness analyses yield similar results for the CDX and for equity returns. Our results confirm those in Engle and Kelly (2008). The updating rules u_t^{SS1R} and u_t^{SS2} yield very similar correlation paths that are much smoother than some of the other updating rules suggested in Engle and Kelly (2008) and not reported here.

Another issue is that Engle and Kelly (2008) show that u_t^{SS2} may yield downward biased estimates of the equicorrelation parameter in small samples. Engle and Kelly (2008) suggest that one way to remedy this is to remove the restriction that $\alpha + \beta < 1$. Figure 8 demonstrates that the intensity DECO for the CDX companies is indeed somewhat higher when removing this restriction, significantly so towards the end of the sample. For the iTraxx companies, removing this restriction did not change the estimates. The estimates for equity returns are also not affected by this constraint.

5.5.2 Asset Return Correlations

We directly model the correlation between default intensities, and compare this with correlations based on equity returns. Equity correlations are commonly used as proxies for asset returns and have been extensively studied.[10] Less is known about CDS-implied correlations. In order to verify whether our results are robust to this modeling choice, we estimate correlations implied by asset returns. We assume that the asset value process of entity i is given by

$$\frac{dV_{i,t}}{V_{i,t}} = \mu_i dt + \sigma_i dW_{i,t}$$

where μ_i is the expected return, σ_i is the asset's instantaneous volatility, and $W_{i,t}$ is a standard Wiener process. Company i defaults whenever the value of its assets falls below a barrier D_i. This

[10] It has been shown that correlations derived from market prices of equities tend to be more reliable than correlations estimated from rating transitions or actual defaults. There is some debate in the literature as to whether correlations between equity returns are sufficiently similar to correlations between equity return implied asset correlations.

corresponds to the Black and Cox (1976) extension of Merton's (1974) model. As a consequence, the probability at time $t < T$ of the firm defaulting at T is given by

$$PD_{i,t,T} = P[V_{i,T} < D_i | V_{i,t}]$$

By Ito's lemma, the asset value at time T can be expressed as a function of the current asset value $V_{i,t}$ as follows

$$V_{i,T} = V_{i,t} \exp\left\{ \left(\mu_i - \tfrac{1}{2}\sigma_i^2\right)(T-t) + \sigma_i \sqrt{T-t} X_{i,t,T} \right\}$$

where $X_{i,t,T}$ is given by $X_{i,t,T} = \frac{W_{i,T} - W_{i,t}}{\sqrt{T-t}}$, and follows a standard normal distribution with zero mean and variance one. We can express the condition for firm i defaulting at time T in terms of the random variable $X_{i,t,T}$:

$$V_{i,T} < D_i \Longleftrightarrow X_{i,t,T} < K_{i,t,T}$$

where

$$K_{i,t,T} = \frac{\ln D_i - \ln A_{i,t} - \left(\mu_i - \frac{1}{2}\sigma_i^2\right)(T-t)}{\sigma_i \sqrt{T-t}}$$

Defining $K_{i,t,T}$ as the default threshold process, the probability at time $t < T$ of the firm defaulting at T is given by

$$PD_{i,t,T} = \Phi(K_{i,t,T})$$

and $K_{i,t,T}$ can be derived by

$$K_{i,t,T} = \Phi^{-1}(PD_{i,t})$$

Tarashev and Zhu (2007) discuss several ways to estimate the physical asset-return correlation in this type of framework, for example by assuming that the default barrier D_i, the asset volatility σ_i and the drift μ_i remain constant over time, which means that asset return correlations are closely related to $K_{i,t,T}$. In CDO pricing, as in Vasicek (1987, 1991, 2002) for example, the random variables $X_{i,t,T}$ are usually modeled as factor models, and the input correlations are actually the correlation coefficients between each pair of random variables $X_{i,t,T}$ and $X_{j,t,T}$. We therefore directly examine correlations between the $X_{i,t,T}$, which are non-linear transformations of the firms' asset values, which itself are unobserved and hard to estimate. We assume that the correlation between the $X_{i,t,T}$ is approximated by the corresponding correlation among default threshold processes $K_{i,t,T}$ derived from the known probability of default determined by the constant intensities, where the $PD_{i,t}$ is taken to be the one-year risk-neutral probability of default. We filter $K_{i,t,T}$ using $ARIMA-GARCH$ models and subsequently apply DECO techniques.

Figure 9 compares asset return-implied correlations with intensity-implied correlations. Differences are relatively small, though it is noteworthy that for the CDX the asset return implied correlation is consistently higher than the intensity implied correlation.

5.5.3 Rolling Correlations

Dynamic equicorrelation methods are meant to yield more reliable estimates than simple rolling correlations. First and foremost, with rolling correlations a choice has to be made about window size, with shorter windows leading to more variable correlations. These results are not reported because of space constraints. However, some other differences between DECO correlations and rolling correlations are more subtle. We report on these in Figures 10 and 11 using intensity data and three-month correlations, but the conclusions are robust to using different windows.

The first and most important conclusion is that one has to carefully check the intensities' statistical properties when constructing rolling correlations. The top panels in Figures 10 and 11 depict three-month rolling correlations constructed using the raw default intensities extracted from the CDS data. These correlations vary widely over time, despite the fact that they are relatively persistent, and they are very different from the intensity-based correlations reported in Figures 1 and 2. The reason for this is that the intensity time series are highly persistent, as indicated by Tables 7 and 8.

The bottom panels of Figures 10 and 11 indicate that by simply differencing the intensity time series, the resulting correlation time series are much closer to the DECO correlations. We also illustrate that by standardizing the rolling correlations, we again get closer to the DECO correlations. The conditional variances used in the standardization are the ones used in the DECO approach. However, even after differencing and standardizing, substantial differences still exist between DECO correlations and rolling correlations, with the DECO correlations being substantially smoother.

5.5.4 Sample Size

An important concern with any analysis that uses CDS data is the limited time horizon of existing samples. While it is impossible to investigate the impact of sample size using the CDS data, we can get some indication of the importance of sample size by investigating equity return data. The equity-return implied correlations in Figures 1 and 2 are based on DECO estimates for the January 1, 2000 to December 31, 2007 sample. We use all of the 61 CDX constituents and 64 iTraxx constituents used in the analysis of the CDS data for which we are able to obtain equity returns over these samples. This amounts to 54 CDX constituents and 58 iTraxx constituents.

Figure 12 compares the resulting correlation series with another correlation estimate obtained using equity returns for the period October 14, 2004 to December 31, 2007, which coincides with the CDS sample period. We again use all companies available for this sample period, which amounts to 55 CDX constituents and 60 iTraxx constituents. The correlation time series obtained using the shorter sample displays much more variability, and is much less persistent. This may suggest that when longer sample periods become available for estimating default intensities from CDS data, the resulting correlation estimates will be less variable over time. However, one has to keep in mind that the equity return and default intensity data have different properties, and therefore these results may not directly carry over. In fact, it is surprising that the correlations obtained using the shorter CDS sample display persistence similar to those obtained using the longer equity sample, as evidenced by Figures 1 and 2.

6 Conclusion

This paper systematically compares correlation measures implied by three different types of securities. We compare base correlations implied by CDOs with correlations implied by equity returns and correlations implied by default intensities. We perform this analysis using both North American data, using the CDX index, and European data, using the iTraxx index. Our results are largely complementary to existing findings in the intensity-based literature. Existing studies attempt to characterize observable macro variables that induce realistic correlation patterns in default probabilities (see Duffee (1999) and Duffie, Saita and Wang (2007)). Our approach does not attempt to characterize the dependence of the default intensities on the observables. Instead, we keep the common component in the default intensities in the first stage, and subsequently characterize it in the second stage.

We obtain base correlations from CDO data using the standard Gaussian copula. To characterize the correlation of default intensities, we use a two-step procedure, where we first extract default intensities from CDS data using a pricing model. To characterize time variation in equity return and default dependences, we use flexible dynamic equicorrelation techniques. The empirical results for intensity-based correlations provide valuable information regarding default dependence from market prices that is different from existing estimates of default dependence, which typically use either historical default rates or equity returns.

Our main finding is that default intensity correlations are substantially time-varying. Neglecting the time variation in correlations may induce substantial errors in the pricing of structured credit products, in particular the relative pricing of CDO tranches with different seniority levels. Correlations can easily drop or increase by 30% over short periods of time. This can have a dramatic impact on the pricing of junior CDO tranches, as exemplified by the performance of hedge funds long in CDO equity tranches following the recent downgrades of Ford and GM. Another important finding is that the correlation measures obtained from different data sources are in most cases highly correlated. It is very interesting that base correlations obtained using the Gaussian copula are strongly related to default intensity correlations estimated from CDS data. We find this result surprising given that CDO market implied base correlations will include structured credit market specific effects as well as being a catch-all for any consequences of model misspecification.

Our results suggest a number of extensions. First, given the richness and complexity of the estimated correlation structures, it will prove interesting to explore the implications of equity-based and intensity-based correlation dynamics for CDO valuation. See Berd, Engle and Voronov (2007) for such an approach. A second potentially interesting extension is to extract correlation risk premia from estimates such as the ones in this paper, but this will necessitate richer models for CDO valuation. Third, a more extensive exploration of the cross-section of correlation dynamics seems warranted.

In this paper, we use very straightforward approaches to modeling default dependence in each asset class - a basic intensity model for CDS prices, raw equity returns for stock based correlations and the market workhorse Gaussian Copula for CDO base correlations. We chose to do this with a view to keeping our methodology as simple and transparent as possible. Another criterion for model choice which could be used instead would be to require that the models for each asset class nest each other - for example we could use Merton's model to extract asset values from stock prices as well as CDS prices and also interpret the Gaussian Copula model in the Merton context. Clearly, this would be an interesting exercise but in carrying it out a number of additional complexities would emerge. First, book data would be required to estimate such a structural model. Second the approach becomes sensitive to the choice of model which in turn is limited by the requirement for cross asset class consistency.

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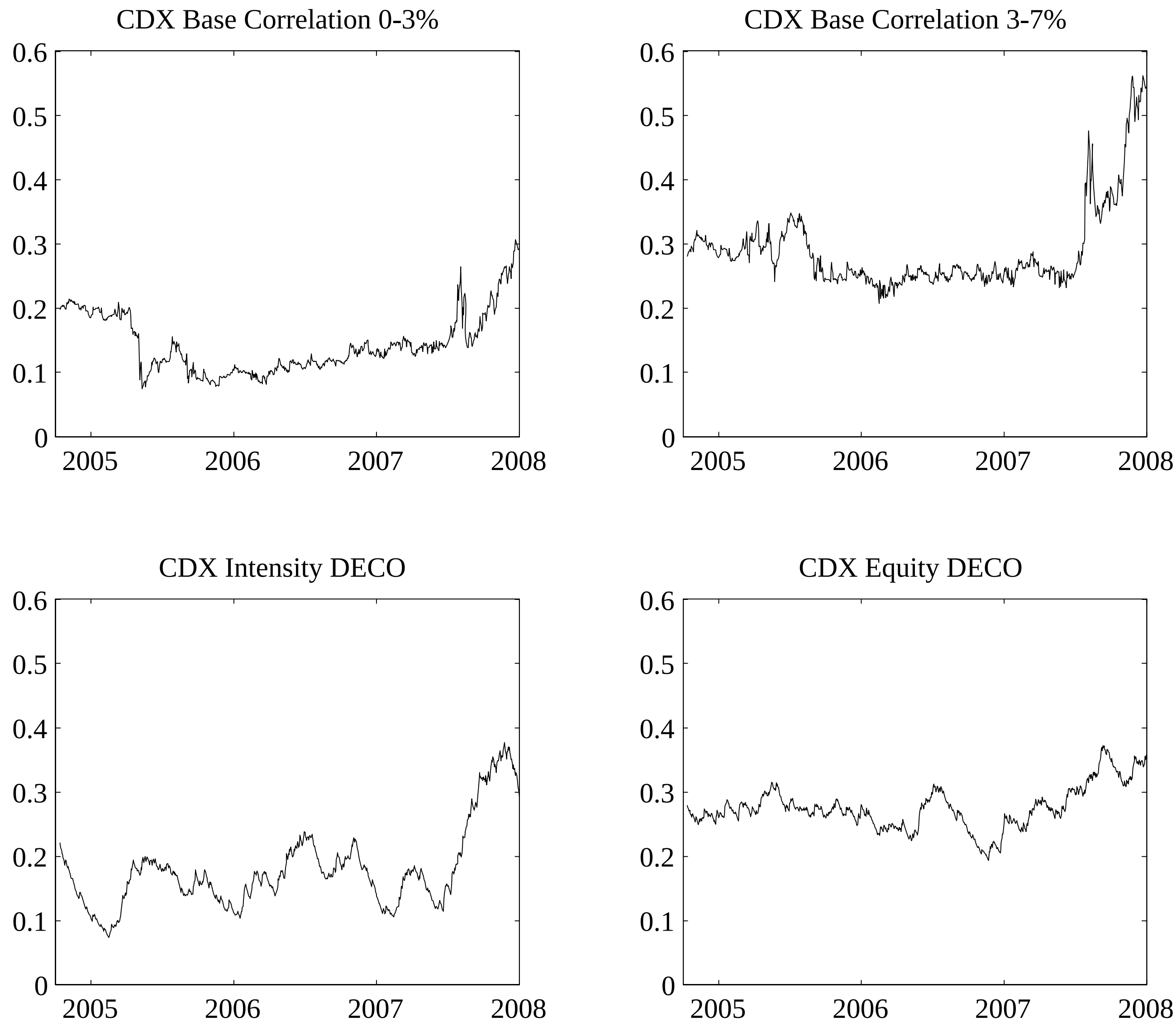
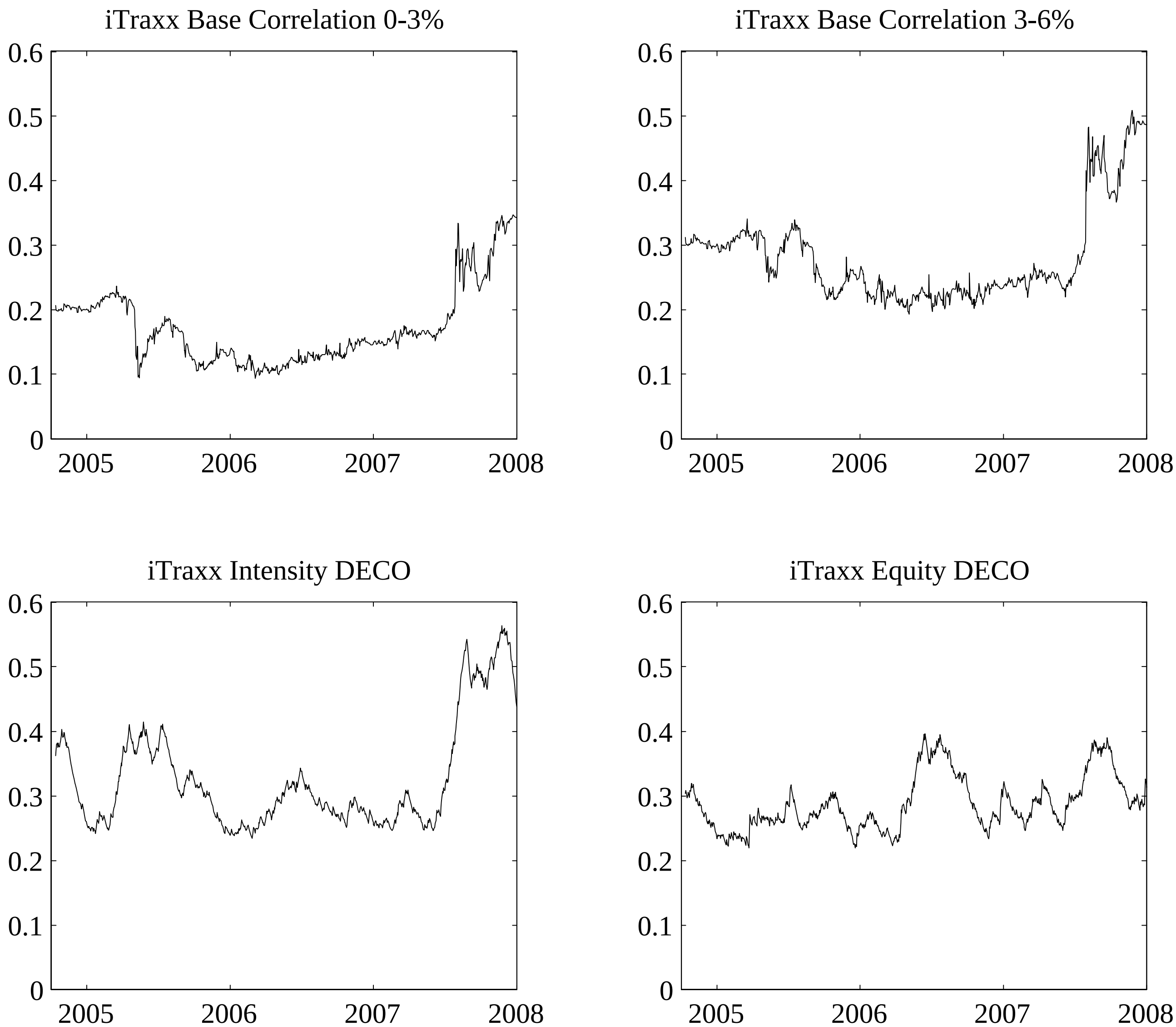
Figure 1: DECOs and Base Correlations for CDX Companies
October 14, 2004 - December 31, 2007



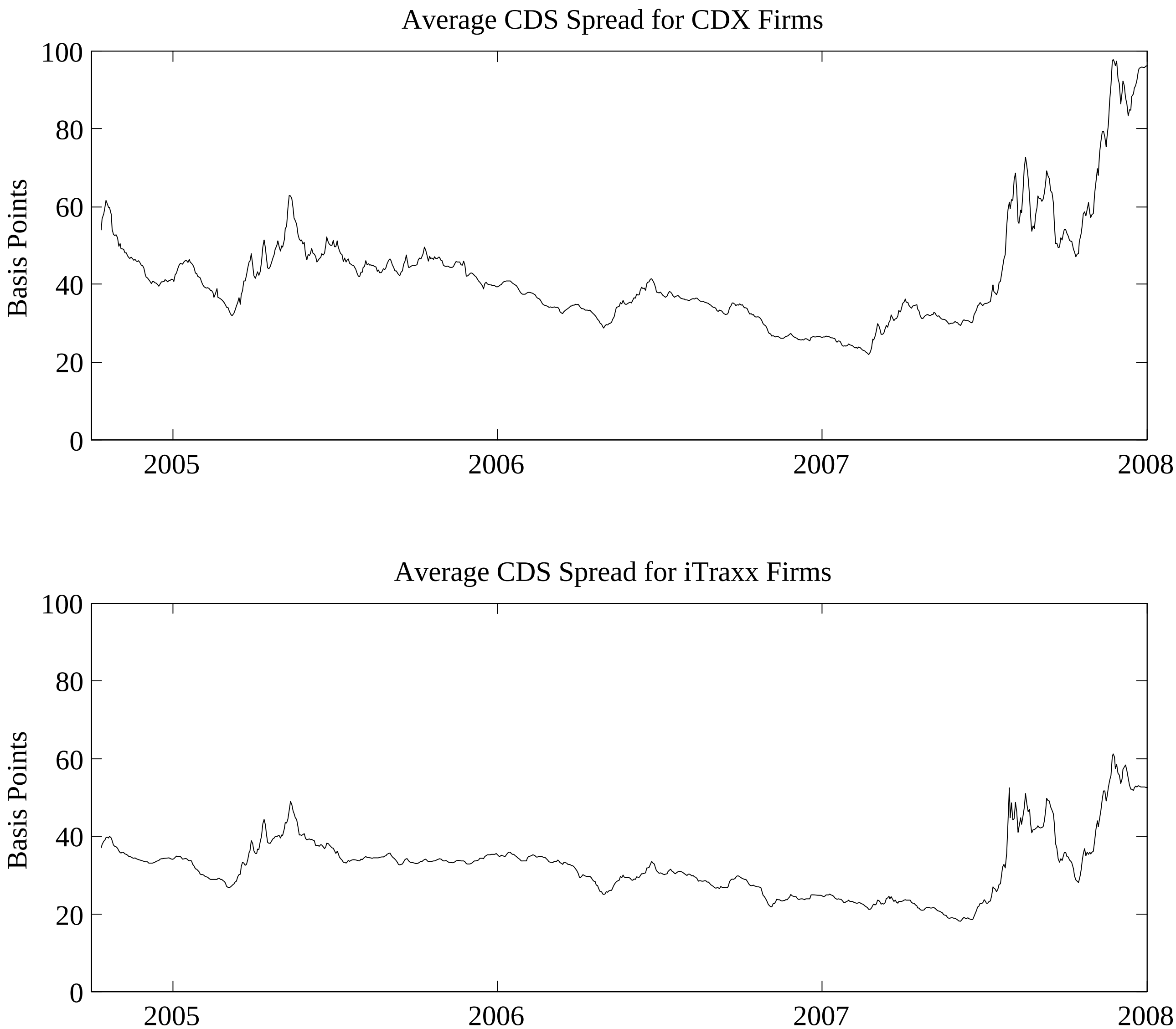
Notes to Figure: We plot equity and intensity dynamic equicorrelations for CDX companies, and base correlations for the 0-3% and 3-7% CDX tranches, using data from October 14, 2004 through December 31, 2007.

Figure 2: DECOs and Base Correlations for iTraxx Companies
October 14, 2004 - December 31, 2007



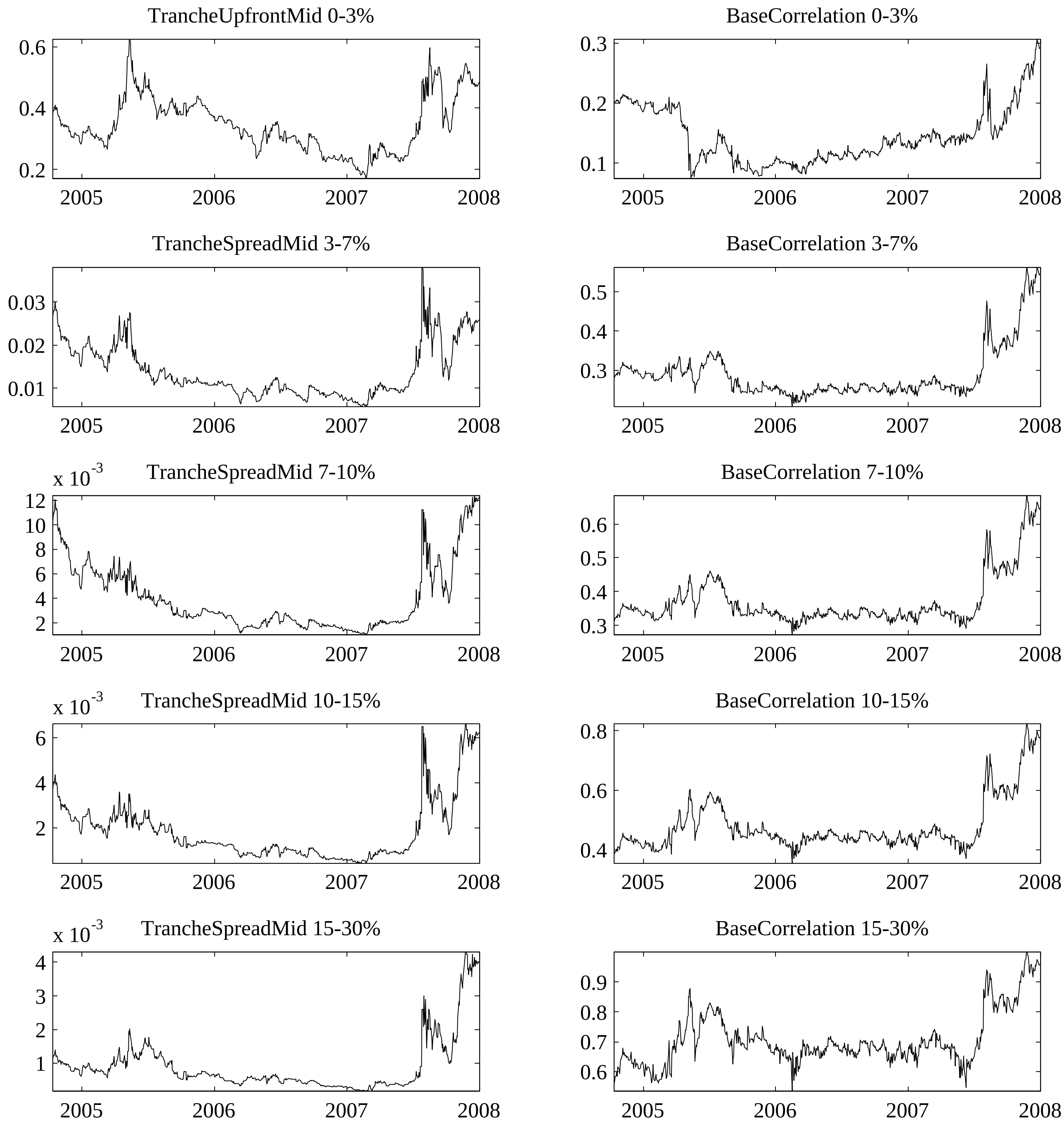
Notes to Figure: We plot equity and intensity dynamic equicorrelations for iTraxx companies, and base correlations for the 0-3% and 3-6% iTraxx tranches, using data from October 14, 2004 through December 31, 2007.

Figure 3: Cross Sectional Averages of CDS Premia.
October 14, 2004 - December 31, 2007.



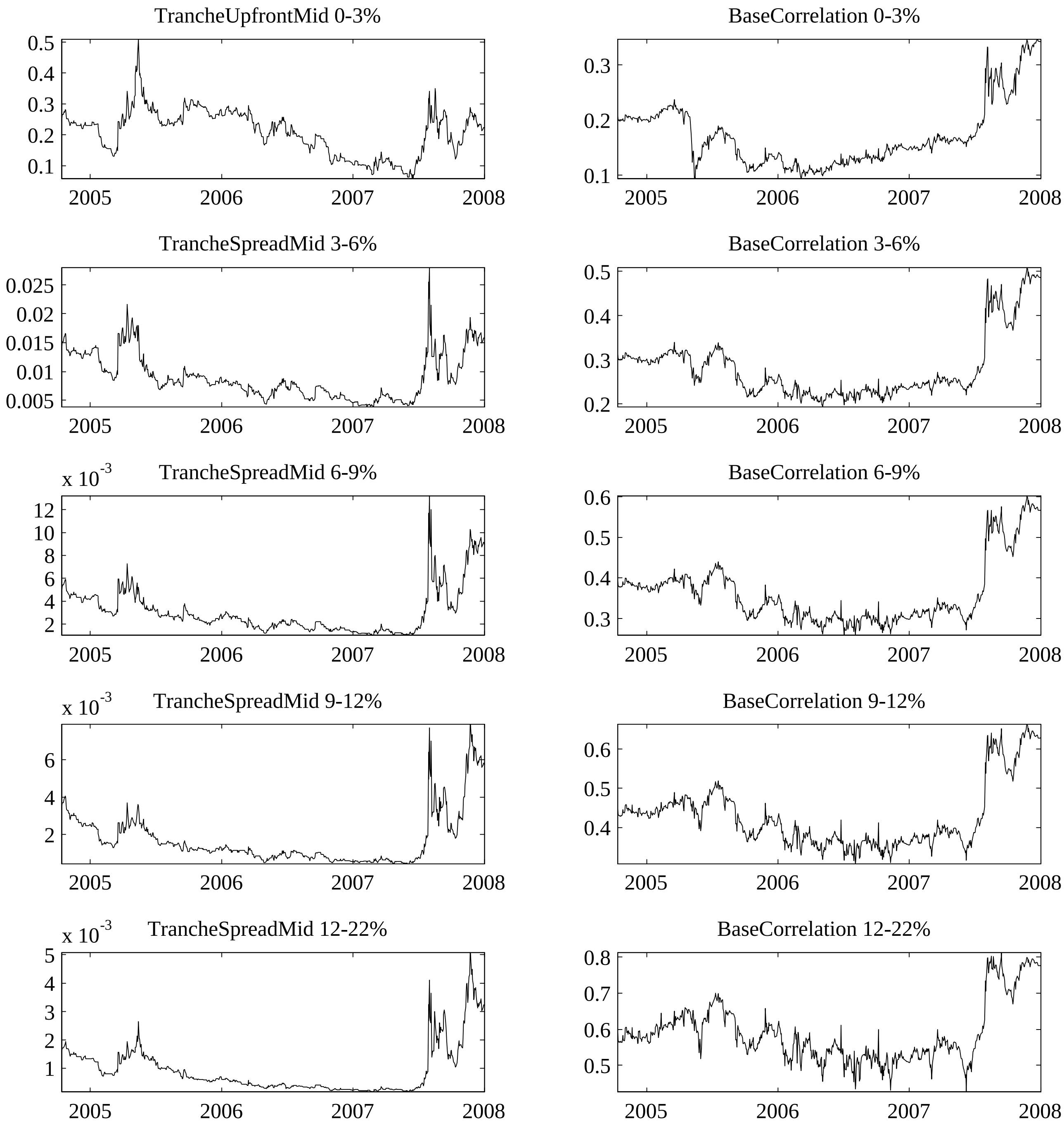
Notes to Figure: We plot cross sectional averages of CDS premia for CDX and iTraxx companies using October 14, 2004 through December 31, 2007 data.

Figure 4: CDX Tranche Spreads and Base Correlations. October 14, 2004 - December 31, 2007.



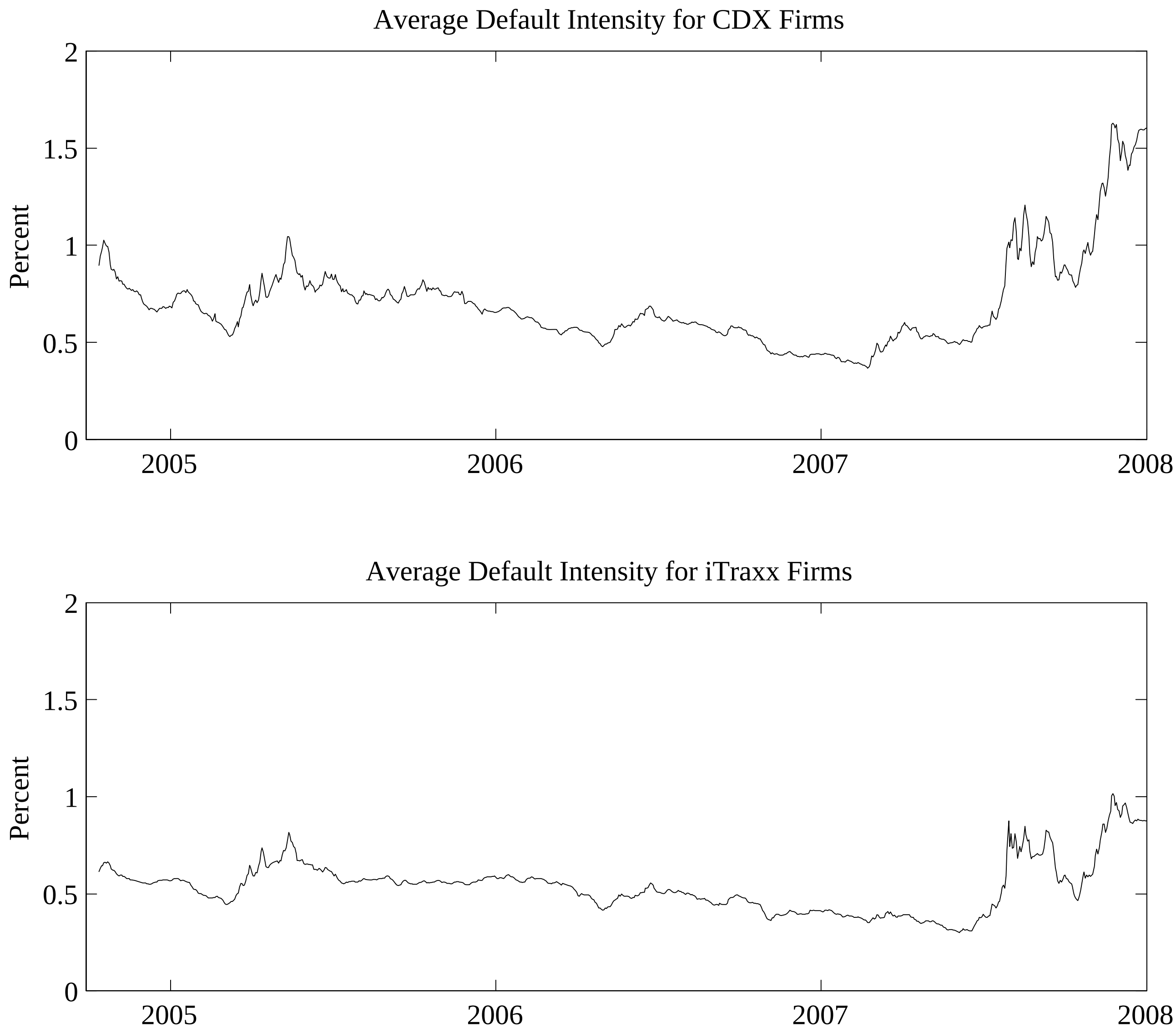
Notes to Figure: We plot tranche spreads and base correlations for all CDX tranches using data from October 14, 2004 through December 31, 2007.

Figure 5: iTraxx Tranche Spreads and Base Correlations. October 14, 2004 - December 31, 2007.



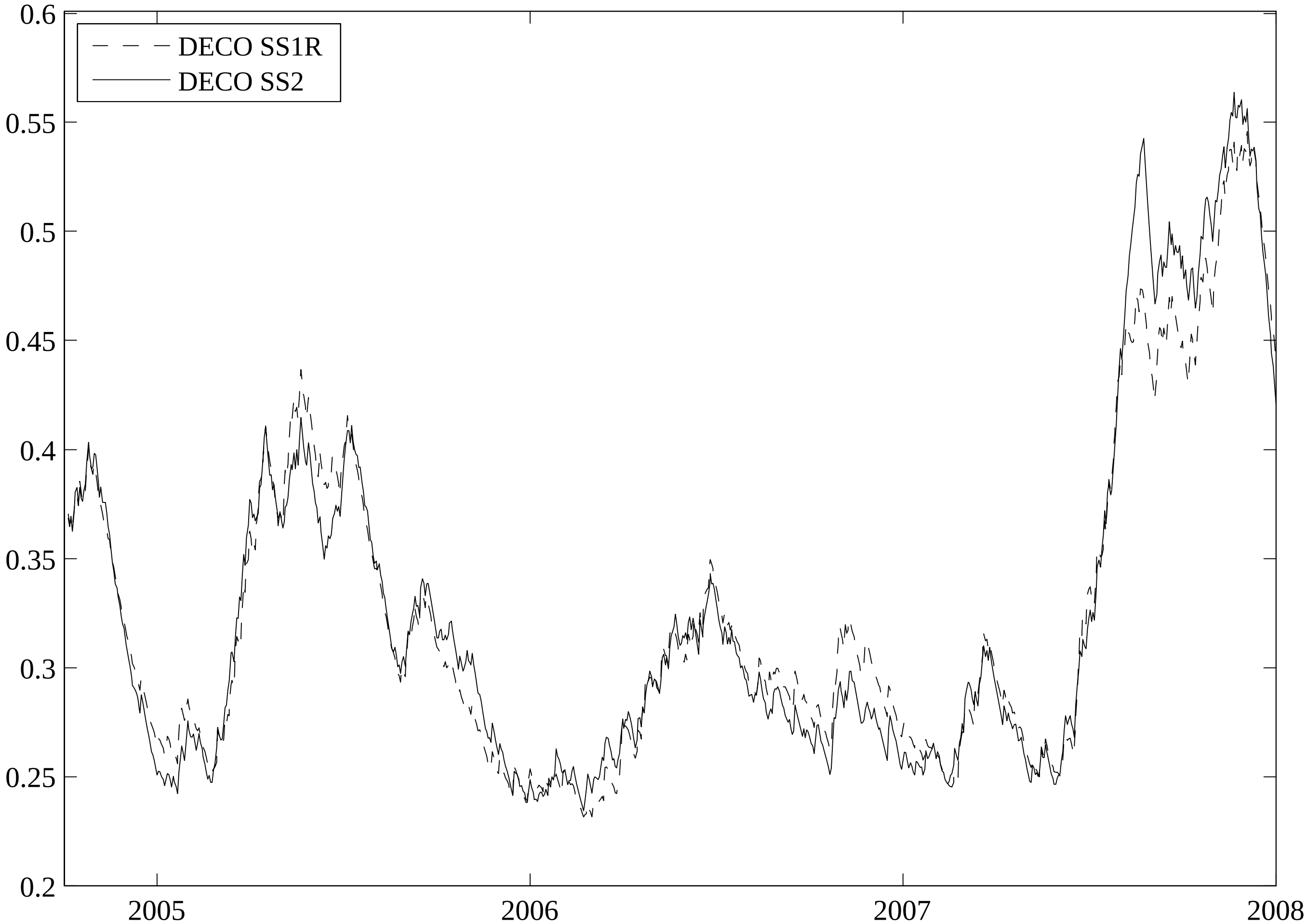
Notes to Figure: We plot tranche spreads and base correlation for all iTraxx tranches using data from October 14, 2004 through December 31 2007.

Figure 6: Cross Sectional Average Default Intensities.
October 14, 2004 - December 31, 2007.



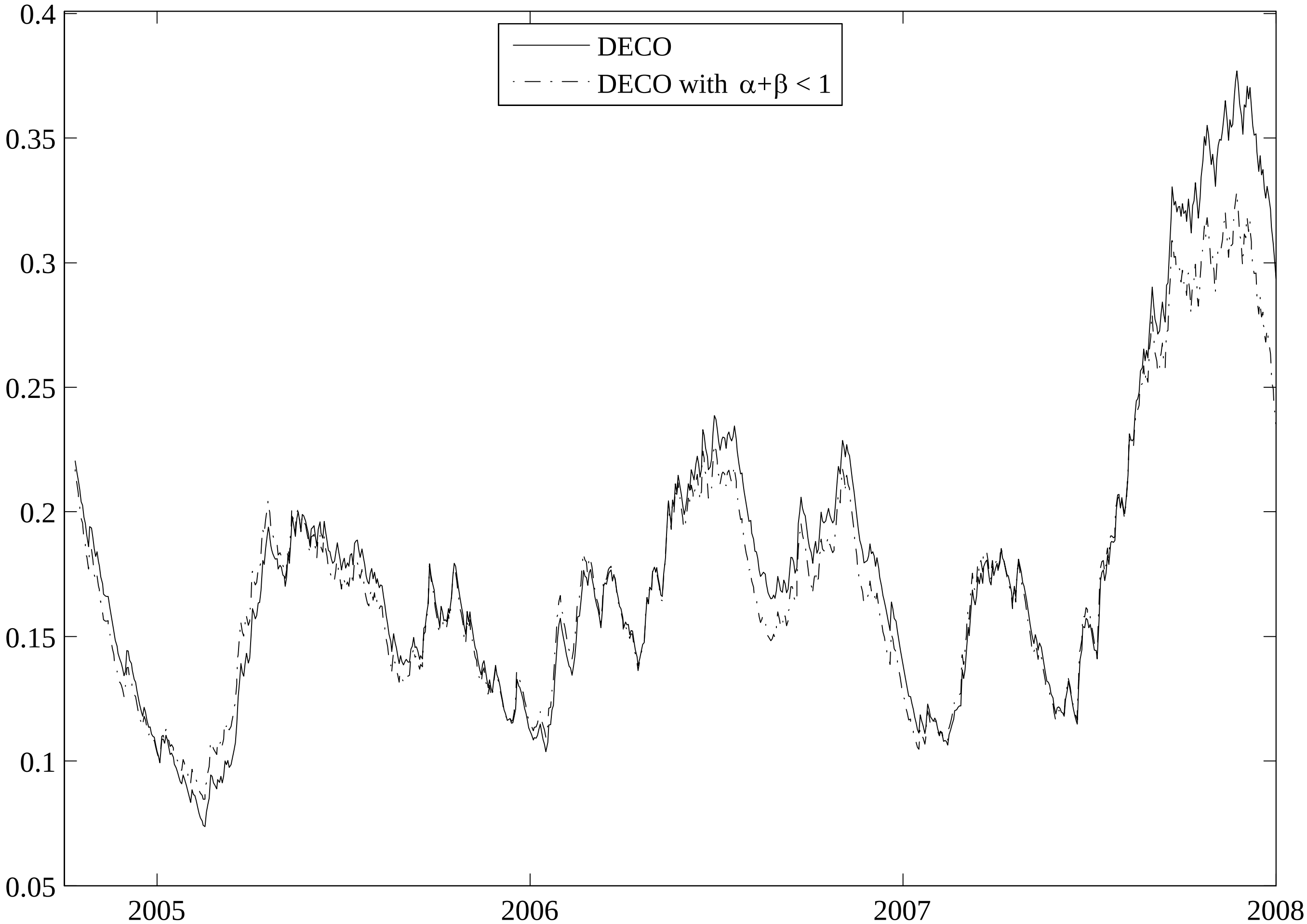
Notes to Figure: We plot cross sectional average default intensities for CDX and iTraxx companies using October 14, 2004 through December 31, 2007 data.

Figure 7: Intensity DECOs for iTraxx Companies.
October 14, 2004 - December 31, 2007.



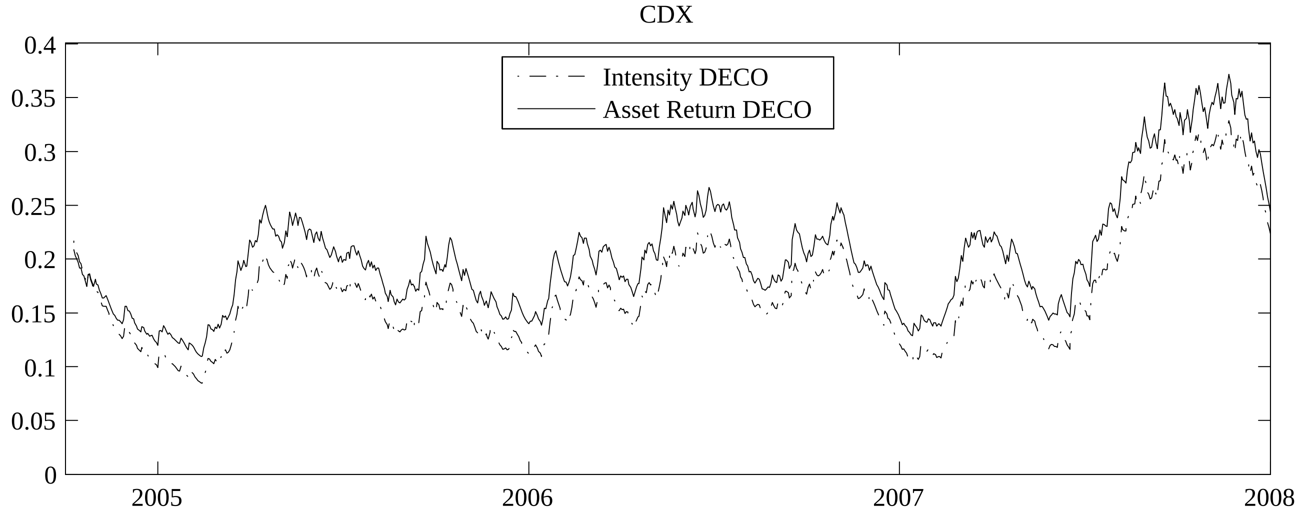
Notes to Figure: We plot dynamic equicorrelations based on default intensities for iTraxx companies. We plot two different equicorrelation measures: DECO $SS1R$, and DECO $SS2$ as defined in the text. We use data from October 14, 2004 through December 31, 2007.

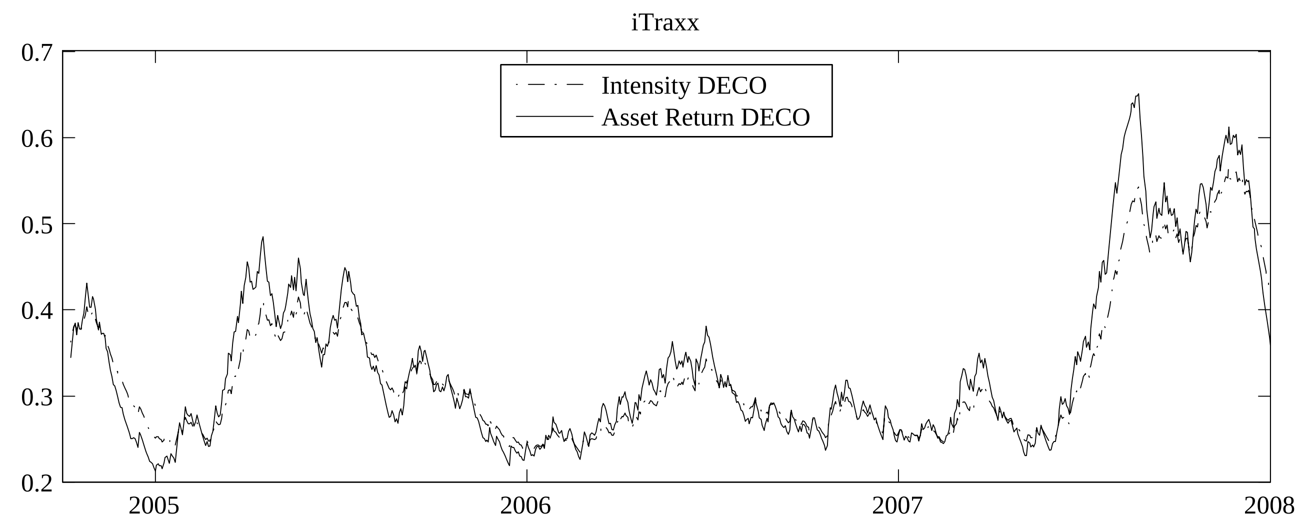
Figure 8: Intensity DECO with and without Restricting $\alpha + \beta < 1$ for CDX Companies. October 14, 2004 - December 31, 2007



Notes to Figure: We plot intensity DECO SS2 with and without the restriction that $\alpha + \beta < 1$ for the CDX companies, from October 14, 2004 through December 31.

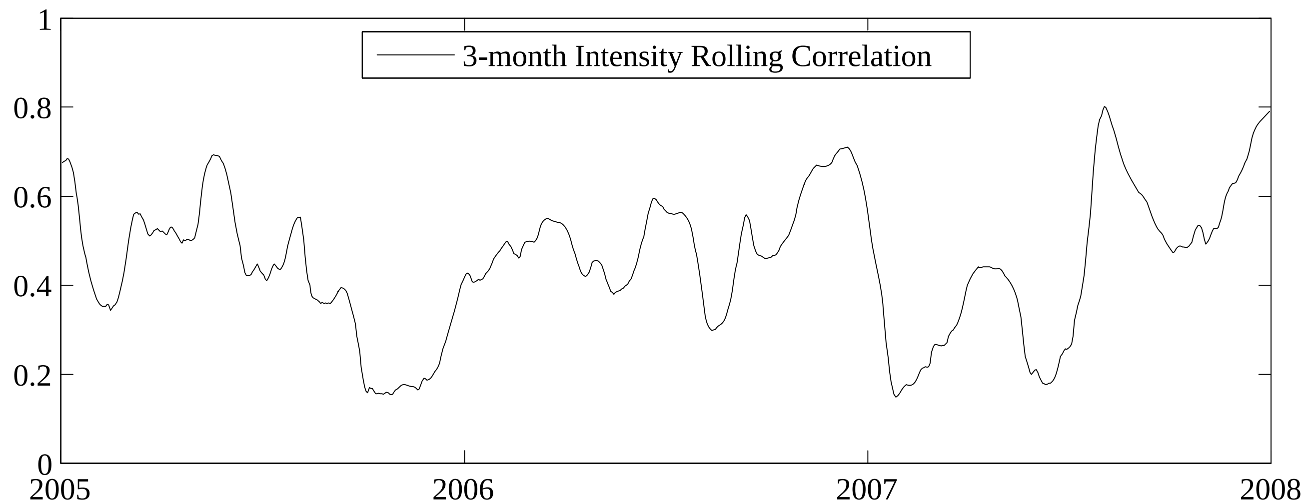
Figure 9: Intensity DECOs vs. Asset Return DECOs.
October 14, 2004 - December 31, 2007.

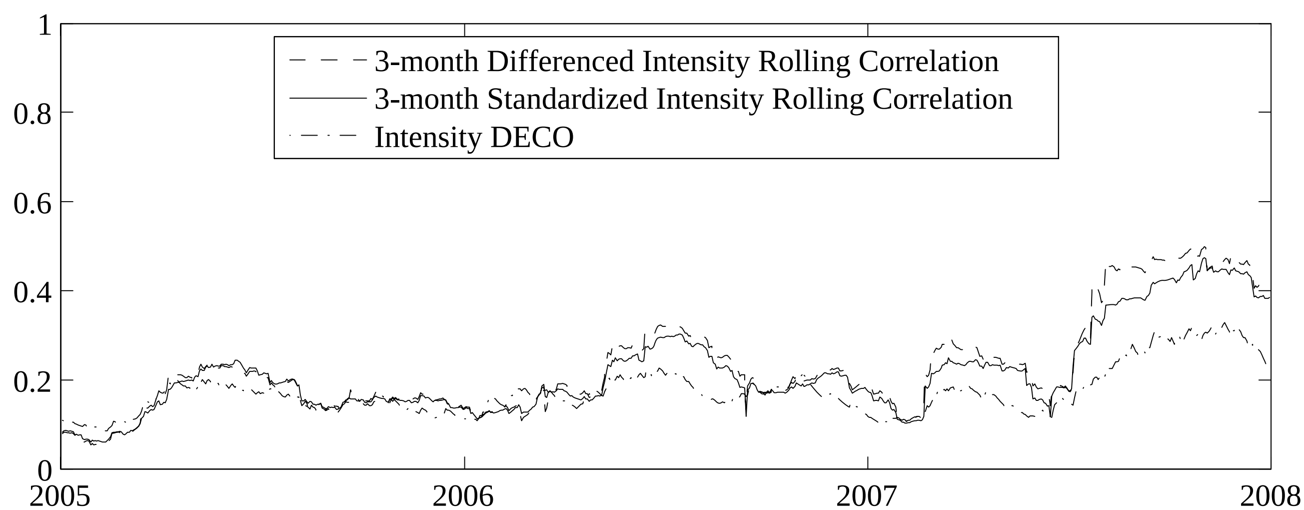




Notes to Figure: We plot intensity and asset return dynamic equicorrelations for CDX and iTraxx companies, using data from October 14, 2004 through December 31, 2007. We assume that correlations between asset returns are approximated by correlations between default thresholds derived from default probabilities.

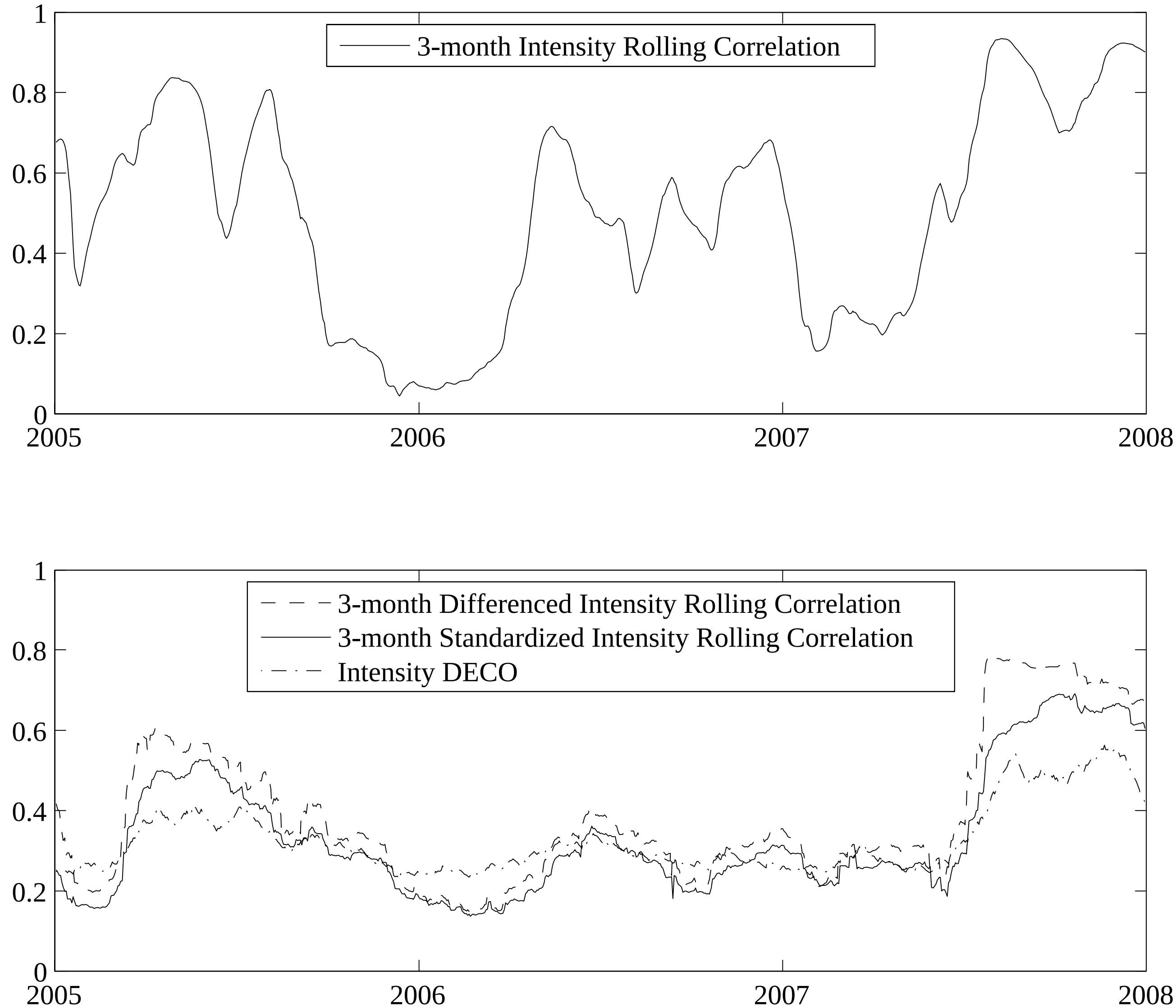
Figure 10: Three-Month Rolling Correlations and DECOs for CDX Companies.
January 6, 2005 - December 31, 2007.





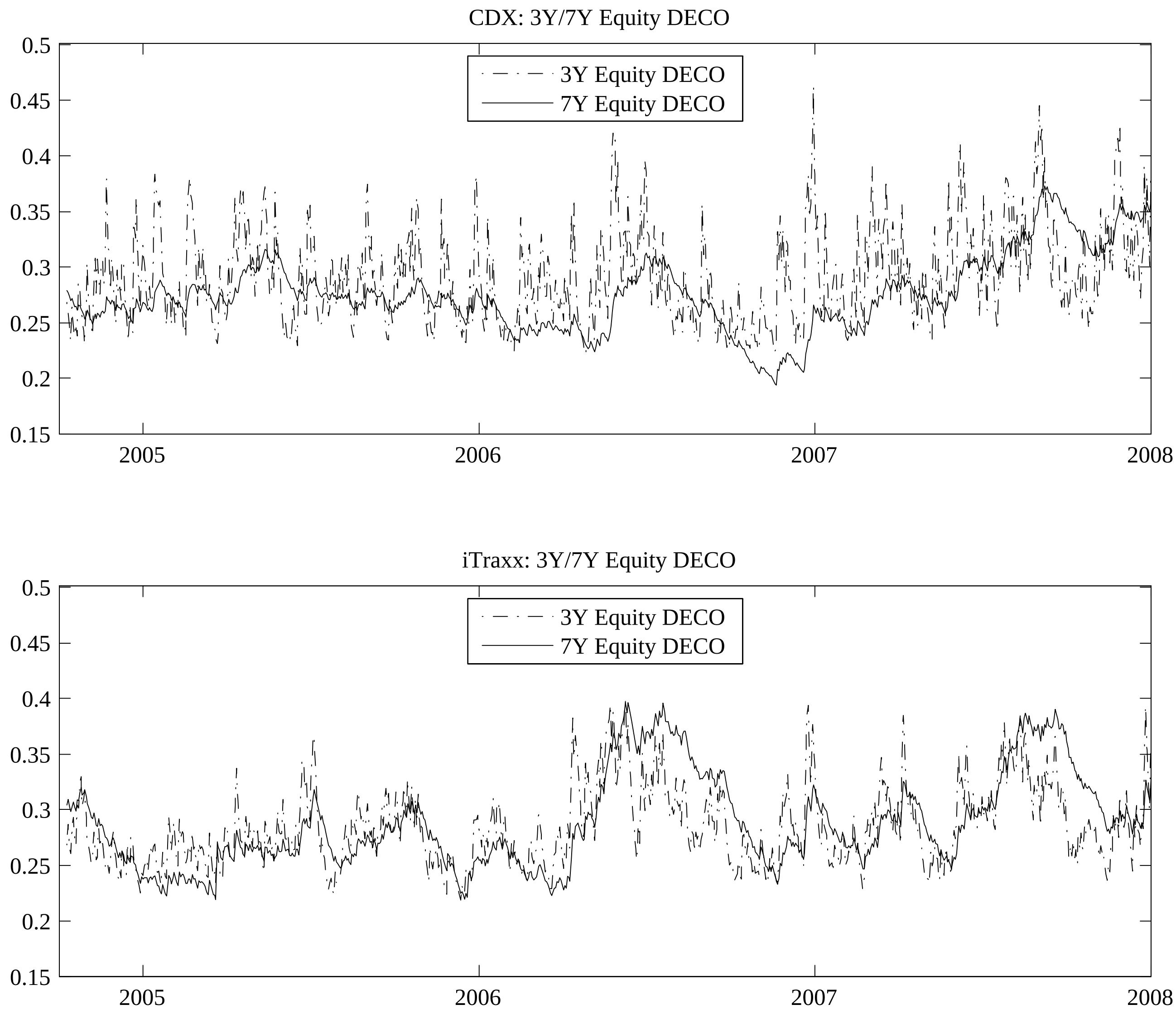
Notes to Figure: We plot three month rolling correlations for intensities (top panel), as well as three-month rolling correlations for the first difference of intensities, three-month rolling correlations for standardized intensities, and DECOs for CDX firms (bottom panel), using data from October 14, 2004 through December 31, 2007.

Figure 11: Three-Month Rolling Correlations and DECOs for iTraxx Companies.
January 6, 2005 - December 31, 2007.



Notes to Figure: We plot three month rolling correlations for intensities (top panel), as well as three-month rolling correlations for the first difference of intensities, three-month rolling correlations for standardized intensities, and DECOs for iTraxx firms (bottom panel), using data from October 14, 2004 through December 31, 2007.

Figure 12: Dynamic Equicorrelations Based on Equity Returns.
October 14, 2004 - December 31, 2007.



Notes to Figure: We plot dynamic equicorrelations based on equity returns for CDX and iTraxx companies, for the period October 14, 2004 through December 31, 2007. The first set of DECO correlations (3Y Equity DECO) is obtained using data from October 14, 2004 through December 31, 2007, the second (7Y Equity DECO) using data from October 11, 2000 through December 31, 2007.

Table 1: Descriptive Statistics for CDX Spreads (in Basis Points)

Firm Name	Ticker	Average	Std Dev	Skewness	Kurtosis
Ace Limited	ACE	37.14	14.05	0.59	2.73
Alcan Inc.	AL	29.50	8.32	1.45	5.33
Alcoa Inc.	AA	27.88	10.55	0.85	2.56
Altria Group, Inc.	MO	63.49	39.18	1.06	3.57
American Express Company	AXP	24.19	15.13	2.28	8.34
American International Group, Inc.	AIG	24.47	16.13	1.88	6.81
Anadarko Petroleum Corporation	APC	35.95	9.38	0.94	3.42
Arrow Electronics, Inc.	ARW	60.24	13.72	0.12	2.62
AT&T Inc.	ATTINC	38.01	35.82	2.49	9.45
AutoZone, Inc.	AZO	63.58	22.84	0.07	1.88
Baxter International Inc.	BAX	21.28	7.45	-0.15	2.50
Boeing Capital Corporation	BA-CapCorp	16.78	7.00	0.43	2.33
Bristol-Myers Squibb Company	BMY	18.02	5.62	-0.09	1.92
Burlington Northern Santa Fe Corporation	BNI	26.56	6.70	1.13	4.51
Campbell Soup Company	CPB	20.83	6.45	0.37	2.37
Cardinal Health, Inc.	CAH	42.04	22.83	2.92	16.17
Carnival Corporation	CCL	28.41	8.40	1.46	5.98
CenturyTel, Inc.	CTL	64.72	11.54	-0.01	2.55
Cigna Corporation	CI	33.59	9.47	0.00	2.43
CIT Group Inc.	CIT	65.09	87.58	2.71	9.36
Comcast Cable Communications, LLC	CMCSA-CableLLC	38.77	12.32	0.04	2.23
ConocoPhillips	COP	21.70	6.05	0.32	3.41
Constellation Energy Group, Inc.	CEG	35.98	12.33	0.85	3.71
Countrywide Home Loans, Inc.	CCR-HomeLoans	108.36	187.52	3.56	15.37
Cox Communications, Inc.	COX-CommInc	55.79	18.04	0.05	4.04
CSX Corporation	CSX	38.27	12.59	0.73	2.99
Devon Energy Corporation	DVN	30.86	8.72	0.98	6.16
Dominion Resources, Inc.	D	35.47	9.71	-0.66	2.41
The Dow Chemical Company	DOW	26.94	7.15	0.74	3.58
Eastman Chemical Company	EMN	46.45	8.59	0.60	2.82
General Electric Capital Corporation	GE-CapCorp	21.99	11.09	2.12	8.06
Honeywell International Inc.	HON	17.71	4.26	-0.01	3.21
IAC/InterActiveCorp	IACI	99.11	23.21	0.72	4.24
International Lease Finance Corporation	AIG-IntLeaseFin	30.41	13.13	0.77	2.75
Lennar Corporation	LEN	115.32	124.14	2.82	10.38
Loews Corporation	LTR	24.61	9.04	0.28	2.53
Marsh & McLennan, Inc.	MMC	59.29	27.83	3.38	20.73
National Rural Utilities Cooperative Finance Corporation	NRUC	21.95	9.75	1.10	5.47
News America Incorporated	NWS-AmInc	39.55	13.91	-0.06	1.88
Omnicom Group Inc.	OMC	26.30	7.64	-0.25	2.01
Progress Energy, Inc.	PGN	34.79	15.15	0.13	3.01
Pulte Homes, Inc.	PHM	119.33	108.01	1.94	5.13
Rohm and Haas Company	ROH	26.59	6.66	0.61	3.71
Safeway Inc.	SWY	54.16	16.75	0.74	2.88
Sempra Energy	SRE	34.19	12.69	0.07	2.52
Simon Property Group, L.P.	SPG-LP	37.20	21.30	2.19	8.73
Southwest Airlines Co.	LUV	39.29	10.30	0.18	3.11
Sprint Nextel Corporation	S	50.01	22.11	2.54	10.20
Starwood Hotels & Resorts Worldwide, Inc.	HOT	112.96	25.79	0.46	2.84
Textron Financial Corporation	TXT-FinCorp	24.42	8.68	0.62	3.69
Time Warner Inc.	TW	44.53	12.47	0.40	2.68
Transocean Inc.	RIG	31.00	8.70	3.00	15.35
Union Pacific Corporation	UNP	33.46	8.49	0.79	4.47
Valero Energy Corporation	VLOC	40.84	11.97	1.88	9.46
The Walt Disney Company	DIS	24.33	9.54	0.27	2.32
Washington Mutual, Inc.	WM	60.27	78.24	3.60	15.42
Wells Fargo & Company	WFC	16.50	11.89	2.56	9.58
Weyerhaeuser Company	WY	53.80	17.74	1.00	4.76
Whirlpool Corporation	WHR	50.79	12.23	0.55	2.52
Wyeth	WYE	21.52	11.44	2.20	9.38
XL Capital Ltd.	XL	44.27	20.52	2.22	9.63

Notes to Table: We present the ticker and the first four moments for 61 of the 125 components of the CDX industrials series 9 version 1. The sample consists of daily CDS premia for the period October 14, 2004, through December 31, 2007. The sample exclusively consists of firms who were part of the CDX industrials index over the entire sample period.

Table 2: Descriptive Statistics for iTraxx Spreads (in Basis Points)

Firm Name	Ticker	Average	Std Dev	Skewness	Kurtosis
Aktiebolaget Volvo	VLVY	32.43	9.30	1.09	3.96
Bayerische Motoren Werke Aktiengesellschaft	BMW	20.32	8.43	1.05	4.92
Compagnie Financiere Michelin	MICH-CoFinMich	36.89	10.70	1.14	4.55
Continental Aktiengesellschaft	CONTI	45.70	11.76	0.97	3.28
GKN Holdings PLC	GKNLN-Hldgs	68.51	19.65	1.18	6.37
Peugeot SA	PEUGOT	30.56	9.71	2.07	7.38
Renault	RENAUL	36.32	9.89	1.16	5.29
Valeo	VLOF	71.28	17.95	-0.14	3.31
Volkswagen Aktiengesellschaft	VW	39.57	16.87	0.50	2.26
Accor	ACCOR	49.52	12.94	0.46	3.44
British American Tobacco PLC	BATSLN	38.68	11.97	0.64	3.21
Carrefour	CARR	20.99	5.78	0.82	4.12
Deutsche Lufthansa Aktiengesellschaft	LUFTHA	52.63	10.22	0.27	3.21
Koninklijke Philips Electronics N.V.	PHG	28.23	8.01	0.16	2.41
LVMH Moet Hennessy Louis Vuitton	MOET	29.39	7.90	0.37	3.06
Marks and Spencer PLC	MKS-M+SPlc	63.98	35.67	0.76	2.06
Metro AG	METFNL	38.90	8.36	0.40	2.74
PPR	PPR	61.06	17.56	0.58	2.33
Sodexho Alliance	EXHO	36.47	13.69	1.04	3.70
Unilever N.V.	ULVR	18.06	3.96	0.84	3.16
E.ON AG	EON	19.03	6.66	2.16	9.23
Edison SPA	FERRUZ	26.83	9.68	0.42	3.04
EDP - Energias de Portugal, SA	EDP	22.65	9.55	1.35	5.29
Electricite de France	EDF	16.40	6.31	0.64	3.58
EnBW Energie Baden-Wuerttemberg AG	BAD	19.24	6.76	0.66	3.61
Endesa, SA	ELESM	27.28	12.81	1.62	5.86
Enel SPA	ENEL	22.39	12.86	2.47	9.07
Fortum Oyj	FORTUM	23.42	8.72	0.28	2.94
Iberdrola, SA	IBERDU	24.09	9.66	2.47	9.48
Repsol YPF SA	REP	36.01	12.14	1.73	5.99
RWE Aktiengesellschaft	RWE	18.05	5.67	1.36	6.87
Suez	LYOE	24.11	9.01	0.72	3.77
Union Fenosa SA	UNFSM	31.33	10.38	0.48	2.97
Vattenfall Aktiebolag	VATFAL	20.60	7.45	0.74	3.79
Veolia Environnement	VEOLIA	31.53	8.53	1.34	4.89
ABN AMRO Bank NV	AAB-Bank	13.11	12.80	2.48	8.08
Aegon NV	AEGON	23.24	13.05	1.57	5.63
AXA	AXAF	22.82	11.81	1.38	5.27
Banca Monte Dei Paschi Di Siena Spa	MONTE	17.55	10.37	1.60	5.12
Barclays Bank PLC	BACR-Bank	13.15	12.65	2.58	8.84
Commerzbank Aktiengesellschaft	CMZB	19.48	13.46	1.95	5.95
Deutsche Bank Aktiengesellschaft	DB	17.95	11.22	2.23	6.97
Hannover Rueckversicherung AG	HANRUE	22.11	9.43	0.60	3.21
Muenchener Rueckversicherungs-Gesellschaft	MUNRE	19.18	9.48	0.80	3.69
Swiss Reinsurance Company	SCHREI	20.80	10.82	1.72	6.12
Zurich Insurance Company	VERSIC-InsCo	26.00	12.62	0.38	2.16
Adecco S.A.	ADO	54.25	15.54	0.22	3.06
AKZO Nobel N.V.	AKZO	28.32	5.88	1.34	4.87
Bayer Aktiengesellschaft	BYIF	28.00	6.62	0.66	3.69
Compagnie de Saint-Gobain	STGOBN	34.64	12.82	2.46	9.59
European Aeronautic Defence and Space Company EADS N.V.	EAD	25.12	7.97	2.18	8.74
Lafarge	LAFCP	41.52	13.24	1.67	6.86
Siemens Aktiengesellschaft	SIEM	17.95	6.26	1.82	7.33
UPM-Kymmene Oyj	UPMKYM	50.93	20.50	1.95	6.38
Bertelsmann AG	BERTEL	33.96	7.92	-0.03	3.20
Deutsche Telekom AG	DT	38.04	7.60	0.17	3.25
France Telecom	FRTEL	36.48	8.84	-0.32	2.23
Hellenic Telecommunications Organisation SA	OTE	43.54	8.77	-0.15	2.51
Koninklijke KPN N.V.	KPN	52.59	16.37	0.83	2.68
Reuters Group PLC	RTRGRP	25.21	4.39	-0.44	2.42
Telecom Italia SPA	TIIMN	53.47	8.61	0.06	3.53
Telefonica, SA	TELEFO	38.83	9.63	0.50	2.46
Vodafone Group PLC	VOD	30.44	8.07	1.45	4.88
Wolters Kluwer NV	WOLKLU	45.05	14.13	1.11	4.23

Notes to Table: We present the ticker and the first four moments for 64 of the 125 components of the iTraxx Europe series 8 version 1. The sample consists of daily CDS premia for the period October 14, 2004, through December 31, 2007. The sample exclusively consists of firms who are part of the iTraxx Europe index over the entire sample period.

Table 3: Descriptive Statistics for CDO Tranche Spreads, Base Correlations and DECO Correlations

Panel A: CDX Tranche Spreads, Base Correlations and DECO Correlations

Tranche Spread (in Basis Points) or Base Correlation	Average	Std Dev	Skewness	Kurtosis
TrancheUpfrontMid 0-3%	3446.73	894.47	0.49	2.63
TrancheSpreadMid 3-7%	139.52	61.93	0.98	3.15
TrancheSpreadMid 7-10%	40.29	27.89	1.31	3.92
TrancheSpreadMid 10-15%	18.58	13.71	1.70	5.70
TrancheSpreadMid 15-30%	9.19	8.30	2.40	8.76
Base Correlation 0-3%	0.14	0.05	1.00	3.58
Base Correlation 3-7%	0.29	0.07	2.23	7.92
Base Correlation 7-10%	0.37	0.08	2.15	7.26
Base Correlation 10-15%	0.48	0.09	1.91	6.25
Base Correlation 15-30%	0.71	0.09	1.21	4.16
Intensity DECO Correlation	0.17	0.05	1.05	3.81
Equity DECO Correlation	0.28	0.03	0.50	3.40

Panel B: iTraxx Tranche Spreads, Base Correlations and DECO Correlations

Tranche Spread (in Basis Points) or Base Correlation	Average	Std Dev	Skewness	Kurtosis
TrancheUpfrontMid 0-3%	2087.69	725.68	0.01	2.98
TrancheSpreadMid 3-6%	90.64	39.17	0.98	3.60
TrancheSpreadMid 6-9%	31.00	19.98	1.72	6.15
TrancheSpreadMid 9-12%	17.24	14.20	1.94	6.81
TrancheSpreadMid 12-22%	9.38	8.70	1.91	6.85
Base Correlation 0-3%	0.17	0.06	1.22	3.99
Base Correlation 3-6%	0.28	0.07	1.48	4.46
Base Correlation 6-9%	0.36	0.08	1.34	4.04
Base Correlation 9-12%	0.43	0.08	1.22	3.72
Base Correlation 12-22%	0.59	0.08	0.97	3.28
Intensity DECO Correlation	0.33	0.08	1.27	3.66
Equity DECO Correlation	0.29	0.04	0.76	2.77

Notes to Table: We present the first four moments for the tranche spreads and base correlations based on the CDX Industrials and the iTraxx Europe indexes, as well as the CDX and iTraxx DECO correlations. The sample is October 14, 2004, through December 31, 2007.

Table 4: Correlations Between Base Correlations and Dynamic Equicorrelations (in Percent)

	CDX Equity DECO	CDX Intensity DECO	CDX BaseCorrelation 0-3%	CDX BaseCorrelation 3-7%	CDX BaseCorrelation 7-10%	CDX BaseCorrelation 10-15%	CDX BaseCorrelation 15-30%	iTraxx Equity DECO	iTraxx Intensity DECO	iTraxx BaseCorrelation 0-3%	iTraxx BaseCorrelation 3-6%	iTraxx BaseCorrelation 6-9%	iTraxx BaseCorrelation 9-12%	iTraxx BaseCorrelation 12-22%
CDX Equity DECO	100.00	61.47	44.33	67.58	69.51	68.68	65.77	49.71	76.04	65.38	71.92	73.09	73.09	71.77
CDX Intensity DECO	61.47	100.00	37.26	67.79	72.93	75.05	75.37	56.42	85.08	54.42	62.38	62.49	61.71	59.74
CDX BaseCorrelation 0-3%	44.33	37.26	100.00	78.91	65.13	54.87	40.08	4.80	56.21	89.96	78.41	72.52	68.15	59.03
CDX BaseCorrelation 3-7%	67.58	67.79	78.91	100.00	97.67	93.88	84.86	20.68	84.80	89.23	93.32	92.04	90.39	86.02
CDX BaseCorrelation 7-10%	69.51	72.93	65.13	97.67	100.00	98.99	93.60	26.26	86.81	81.42	89.62	89.77	89.16	86.94
CDX BaseCorrelation 10-15%	68.68	75.05	54.87	93.88	98.99	100.00	97.31	29.76	86.43	74.16	84.77	85.86	85.92	85.11
CDX BaseCorrelation 15-30%	65.77	75.37	40.08	84.86	93.60	97.31	100.00	35.76	82.87	61.68	74.47	76.72	77.70	79.07
iTraxx Equity DECO	49.71	56.42	4.80	20.68	26.26	29.76	35.76	100.00	44.53	15.32	18.60	17.88	17.00	16.60
iTraxx Intensity DECO	76.04	85.08	56.21	84.80	86.81	86.43	82.87	44.53	100.00	76.13	85.35	86.59	86.26	83.33
iTraxx BaseCorrelation 0-3%	65.38	54.42	89.96	89.23	81.42	74.16	61.68	15.32	76.13	100.00	96.02	92.56	89.87	83.50
iTraxx BaseCorrelation 3-6%	71.92	62.38	78.41	93.32	89.62	84.77	74.47	18.60	85.35	96.02	100.00	99.32	98.18	94.31
iTraxx BaseCorrelation 6-9%	73.09	62.49	72.52	92.04	89.77	85.86	76.72	17.88	86.59	92.56	99.32	100.00	99.68	97.15
iTraxx BaseCorrelation 9-12%	73.09	61.71	68.15	90.39	89.16	85.92	77.70	17.00	86.26	89.87	98.18	99.68	100.00	98.62
iTraxx BaseCorrelation 12-22%	71.77	59.74	59.03	86.02	86.94	85.11	79.07	16.60	83.33	83.50	94.31	97.15	98.62	100.00

Notes to Table: We compute unconditional correlations for the base correlations for iTraxx and CDX indexes, as well as intensity and equity dynamic equicorrelations. The sample period is from October, 14, 2004, through December 31, 2007.

Table 5: Descriptive Statistics for CDX Standardized ARIMA-GARCH Intensity Residuals

Ticker	Mean	Std Dev	Skewness	Kurtosis	AutoCorr (1st)	LB(20) P-Value	LB(20) P-Val on Abs Residuals
ACE	0.04	1.22	5.14	74.68	0.13	0.00	0.66
AL	-0.01	1.00	3.37	55.15	0.02	0.36	0.14
AA	0.03	1.02	7.76	141.86	0.02	1.00	0.25
MO	-0.09	1.07	-2.87	38.25	0.08	0.46	0.57
AXP	0.02	1.10	2.15	24.64	-0.06	0.00	0.00
AIG	0.02	1.11	1.70	15.56	-0.01	0.04	0.63
APC	0.03	1.06	4.26	58.17	0.01	0.33	0.19
AZO	-0.02	1.04	1.24	8.89	0.11	0.13	0.69
BAX	-0.01	1.03	2.74	28.58	0.05	0.72	0.43
BA-CapCorp	-0.04	1.03	0.49	6.49	0.14	0.01	0.00
BMY	0.00	1.05	1.36	20.24	0.09	0.21	0.82
BNI	0.04	1.03	1.90	15.57	0.07	0.12	0.08
CPB	0.00	1.02	2.48	21.78	0.09	0.33	0.15
CAH	-0.01	1.08	2.62	29.02	0.08	0.00	0.28
CCL	0.03	1.07	0.78	9.62	0.06	0.81	0.39
CTL	0.00	1.00	0.77	7.07	0.09	0.14	0.25
CMCSA-CableLLC	-0.01	1.00	-2.71	45.09	0.01	0.34	0.00
COP	0.01	1.05	1.39	9.39	0.11	0.00	0.61
CEG	0.02	1.01	0.58	28.83	0.05	0.61	0.01
CCR-HomeLoans	0.04	1.08	0.31	15.52	0.02	0.46	0.00
COX-CommInc	-0.06	1.00	0.68	9.75	0.06	0.00	0.12
CSX	0.02	1.07	1.63	17.59	0.05	0.70	0.04
DVN	0.01	1.06	2.57	25.42	0.08	0.02	0.91
D	-0.02	1.03	-0.10	15.45	0.11	0.23	0.00
DOW	0.03	1.02	8.21	139.96	-0.01	0.82	0.84
HON	0.01	1.01	1.68	19.24	0.10	0.18	0.61
IACI	0.01	1.04	0.78	57.27	0.05	0.91	0.61
AIG-IntLeaseFin	0.00	1.07	1.61	13.66	0.03	0.60	0.01
LEN	0.06	1.04	0.74	6.11	-0.08	0.02	0.23
LTR	-0.01	1.06	1.35	11.10	0.19	0.00	0.01
MMC	0.04	1.14	5.19	69.62	0.00	0.37	0.35
NRUC	-0.01	1.02	1.78	29.36	-0.09	0.07	0.36
NWS-AmInc	-0.05	1.00	0.52	9.54	0.07	0.02	0.65
OMC	-0.02	1.04	0.31	7.34	0.10	0.00	0.66
ROH	0.02	1.00	0.56	5.91	0.06	0.71	0.69
SWY	-0.02	0.99	3.03	36.29	0.14	0.00	0.21
SRE	0.00	1.12	3.51	40.31	0.06	0.41	0.43
SPG-LP	0.02	1.15	3.10	30.71	-0.03	0.03	0.00
LUV	0.03	1.02	2.15	19.48	0.08	0.60	0.01
S	0.05	1.05	1.23	11.96	-0.04	0.67	0.01
HOT	0.02	1.00	1.86	20.09	0.07	0.41	0.00
TXT-FinCorp	0.03	1.11	3.28	40.62	0.08	0.05	0.00
TW	0.01	1.01	0.90	9.73	0.02	0.80	0.79
RIG	0.04	1.00	4.28	53.78	0.01	0.53	0.19
UNP	0.02	1.07	0.89	8.86	0.08	0.12	0.12
VLOC	0.01	1.00	1.45	14.60	-0.06	0.00	0.16
DIS	-0.02	1.04	0.77	10.42	0.15	0.00	0.01
WM	0.04	1.07	-0.27	20.55	-0.08	0.00	0.00
WFC	0.03	1.14	1.82	24.42	-0.09	0.00	0.19
WY	0.04	1.00	1.30	10.68	-0.04	0.00	0.35
WHR	0.01	1.00	0.44	5.67	0.12	0.05	0.99
WYE	-0.01	1.05	3.60	41.90	-0.02	0.65	0.95
XL	0.05	1.06	1.25	11.20	-0.05	0.02	0.05

Notes to Table: We report the first four sample moments and the first order autocorrelation of the standardized ARIMA-GARCH residuals for each company. We also report the p-value from a Ljung-Box test that the first 20 autocorrelations are zero for residuals and absolute residuals. The sample period is from October, 14, 2004, through December 31, 2007.

Table 6: Descriptive Statistics for iTraxx Standardized ARIMA-GARCH Intensity Residuals.

Ticker	Mean	Std Dev	Skewness	Kurtosis	AutoCorr (1st)	LB(20) P-Value	LB(20) P-Val on abs residuals
VLVY	0.02	1.04	3.28	34.95	0.06	0.58	0.06
BMW	-0.02	1.00	0.09	8.23	0.02	0.02	0.05
MICH-CoFinMich	0.01	1.01	0.92	8.00	0.13	0.00	0.60
CONTI	0.02	1.10	1.97	20.88	0.10	0.00	0.85
GKNLN-Hldgs	0.00	1.08	2.67	33.40	0.01	0.13	0.24
PEUGOT	0.00	1.00	0.93	7.80	0.10	0.01	0.08
RENAUL	-0.02	1.05	1.53	17.47	0.09	0.00	0.40
VLOF	0.03	1.00	2.15	29.55	0.07	0.46	0.02
BATSLN	-0.06	1.00	-1.12	19.11	0.10	0.00	0.18
CARR	-0.02	1.06	1.89	17.85	0.19	0.00	0.00
LUFTHA	0.00	1.01	1.30	11.89	0.14	0.00	0.34
PHG	-0.01	1.01	1.48	24.55	0.00	0.23	0.22
MOET	0.01	1.04	1.41	11.17	0.07	0.13	0.05
MKS-M+SPlc	-0.01	1.03	0.37	6.61	0.09	0.05	0.00
METFNL	0.00	1.00	0.90	6.87	0.16	0.00	0.75
PPR	-0.02	1.02	0.10	16.21	0.16	0.00	0.01
EXHO	-0.04	1.01	0.68	26.73	0.06	0.04	0.03
FERRUZ	-0.03	1.00	0.59	9.64	0.11	0.00	0.55
EDP	0.00	1.01	0.96	9.29	0.07	0.15	0.07
EDF	-0.02	1.00	0.50	10.83	0.09	0.00	0.87
BAD	-0.04	1.00	0.44	6.76	0.17	0.00	0.88
ELESM	0.02	1.00	0.73	12.80	-0.01	0.00	0.07
ENEL	0.01	1.00	0.74	9.20	0.02	0.00	0.31
FORTUM	-0.01	1.01	-0.13	10.56	-0.05	0.00	0.17
IBERDU	0.02	1.02	1.55	17.02	0.02	0.02	0.26
REP	0.03	1.00	6.60	107.73	0.02	0.59	0.00
UNFSM	0.01	1.06	1.72	15.33	0.02	0.25	0.00
VATFAL	-0.02	1.02	-0.16	10.65	0.09	0.48	0.90
VEOLIA	0.02	1.05	1.39	14.48	0.08	0.13	0.01
AAB-Bank	0.01	1.04	0.43	8.83	0.12	0.00	0.02
AEGON	0.00	1.03	0.38	9.84	0.19	0.00	0.68
AXAF	-0.01	1.04	0.08	12.15	0.01	0.00	0.88
MONTE	-0.02	1.06	-0.22	11.68	-0.04	0.00	0.31
BACR-Bank	0.02	1.05	0.97	11.46	0.02	0.00	0.51
CMZB	-0.03	1.03	0.61	11.05	0.27	0.00	0.30
DB	0.03	1.08	5.09	68.44	0.15	0.00	0.00
HANRUE	0.00	1.13	3.95	59.28	0.04	0.00	0.00
MUNRE	0.00	1.05	1.21	15.93	0.13	0.00	0.06
SCHREI	0.02	1.02	0.19	8.07	0.12	0.00	0.08
VERSIC-InsCo	-0.02	1.06	-0.14	10.00	0.07	0.00	0.66
ADO	-0.02	1.00	0.31	7.04	0.15	0.00	0.18
AKZO	0.04	1.00	3.00	33.69	0.12	0.08	0.10
BYIF	0.02	1.04	1.49	16.35	0.10	0.03	0.32
STGOBN	0.03	1.00	1.57	11.82	0.18	0.00	0.18
EAD	0.01	1.00	6.13	98.30	0.10	0.64	0.15
LAFCP	0.05	1.05	0.84	8.60	0.16	0.03	0.36
SIEM	0.01	1.02	0.60	8.29	0.04	0.01	0.23
UPMKYM	0.02	1.00	1.08	8.70	0.13	0.01	0.85
BERTEL	0.01	1.00	1.08	8.98	0.11	0.18	0.38
DT	0.01	1.00	0.51	7.49	0.12	0.02	0.30
FRTEL	-0.02	1.00	0.10	6.56	0.14	0.00	0.69
OTE	0.01	1.00	2.78	33.54	0.11	0.24	0.92
KPN	0.03	1.00	1.43	14.36	0.09	0.46	0.42
RTRGRP	0.00	1.06	8.38	154.39	0.06	0.49	0.81
TIIMN	0.02	1.00	6.21	107.05	0.10	0.53	0.35
TELEFO	0.04	1.00	2.12	18.48	0.13	0.16	0.13
VOD	0.02	1.00	0.20	9.21	0.09	0.11	0.58
WOLKLU	0.02	1.00	3.83	55.88	0.06	0.67	0.00

Notes to Table: We report the first four sample moments and the first order autocorrelation of the standardized ARIMA-GARCH residuals for each company. We also report the p-value from a Ljung-Box test that the first 20 autocorrelations are zero for residuals and absolute residuals. The sample period is from October, 14, 2004, through December 31, 2007.

Table 7: Descriptive Statistics for CDX Default Intensities (in Percent)

Firm	Ticker	Mean	Std Dev	Skewness	Kurtosis	AutoCorr
1	ACE	0.62	0.23	0.60	2.73	0.99
2	AL	0.49	0.14	1.46	5.36	0.98
3	AA	0.46	0.17	0.86	2.58	0.98
4	MO	1.06	0.65	1.06	3.57	1.00
5	AXP	0.40	0.25	2.28	8.46	1.00
6	AIG	0.40	0.27	1.90	6.96	0.99
7	APC	0.60	0.16	0.95	3.45	0.99
8	ARW	1.00	0.23	0.12	2.62	0.99
9	ATTINC	0.63	0.60	2.49	9.44	1.00
10	AZO	1.06	0.38	0.06	1.89	0.99
11	BAX	0.35	0.12	-0.15	2.50	0.99
12	BA-CapCorp	0.28	0.12	0.43	2.33	0.98
13	BMY	0.30	0.09	-0.08	1.92	0.99
14	BNI	0.44	0.11	1.14	4.55	0.97
15	CPB	0.35	0.11	0.37	2.37	0.98
16	CAH	0.70	0.38	2.92	16.17	0.98
17	CCL	0.47	0.14	1.46	6.06	0.99
18	CTL	1.07	0.19	-0.01	2.55	0.98
19	CI	0.56	0.16	0.00	2.44	0.99
20	CIT	1.07	1.44	2.75	9.62	0.99
21	CMCSA-CableLLC	0.64	0.20	0.05	2.24	0.99
22	COP	0.36	0.10	0.30	3.39	0.98
23	CEG	0.60	0.20	0.84	3.73	0.99
24	CCR-HomeLoans	1.77	3.05	3.63	15.96	1.00
25	COX-CommInc	0.93	0.30	0.06	4.04	0.99
26	CSX	0.63	0.21	0.72	2.99	0.99
27	DVN	0.51	0.15	0.98	6.16	0.98
28	D	0.59	0.16	-0.66	2.41	0.99
29	DOW	0.45	0.12	0.74	3.61	0.96
30	EMN	0.77	0.14	0.60	2.83	0.98
31	GE-CapCorp	0.36	0.18	2.12	8.14	1.00
32	HON	0.29	0.07	-0.01	3.23	0.97
33	IACI	1.65	0.39	0.72	4.24	0.97
34	AIG-IntLeaseFin	0.50	0.22	0.78	2.77	0.99
35	LEN	1.90	2.03	2.85	10.62	1.00
36	LTR	0.41	0.15	0.29	2.52	0.99
37	MMC	0.98	0.46	3.38	20.75	0.98
38	NRUC	0.36	0.16	1.10	5.48	0.99
39	NWS-AmInc	0.66	0.23	-0.06	1.88	0.99
40	OMC	0.44	0.13	-0.24	2.01	0.98
41	PGN	0.58	0.25	0.14	3.00	0.99
42	PHM	1.97	1.79	1.96	5.23	1.00
43	ROH	0.44	0.11	0.59	3.68	0.98
44	SWY	0.90	0.28	0.74	2.88	0.99
45	SRE	0.57	0.21	0.08	2.52	0.99
46	SPG-LP	0.61	0.35	2.19	8.87	0.99
47	LUV	0.65	0.17	0.12	2.96	0.99
48	S	0.83	0.36	2.58	10.52	1.00
49	HOT	1.88	0.43	0.46	2.85	0.98
50	TXT-FinCorp	0.40	0.14	0.61	3.70	0.99
51	TW	0.74	0.21	0.39	2.66	0.99
52	RIG	0.51	0.14	2.90	15.03	0.98
53	UNP	0.56	0.14	0.80	4.48	0.98
54	VLOC	0.68	0.20	1.91	9.66	0.99
55	DIS	0.40	0.16	0.27	2.32	0.99
56	WM	0.99	1.27	3.67	16.09	1.00
57	WFC	0.27	0.19	2.59	9.82	0.99
58	WY	0.89	0.29	1.00	4.82	0.98
59	WHR	0.84	0.20	0.55	2.54	0.98
60	WYE	0.36	0.19	2.21	9.40	1.00
61	XL	0.73	0.33	2.17	9.47	0.99

Notes to Table: We report the first four sample moments of the default intensity for each company. We also report the first order autocorrelation.The sample period is from October, 14, 2004, through December 31, 2007.

Table 8: Descriptive Statistics for iTraxx Default Intensities (in Percent)

Firm	Ticker	Mean	Standard Dev	Skewness	Kurtosis	AutoCorr
1	VLVY	0.54	0.15	1.10	4.00	0.99
2	BMW	0.34	0.14	1.04	4.95	1.00
3	MICH-CoFinMich	0.61	0.18	1.14	4.60	0.99
4	CONTI	0.76	0.19	0.97	3.29	0.98
5	GKNLN-Hldgs	1.14	0.33	1.18	6.36	0.99
6	PEUGOT	0.51	0.16	2.09	7.54	0.99
7	RENAUL	0.60	0.16	1.15	5.33	0.99
8	VLOF	1.18	0.30	-0.13	3.31	0.99
9	VW	0.66	0.28	0.51	2.27	1.00
10	ACCOR	0.82	0.22	0.46	3.43	0.99
11	BATSLN	0.64	0.20	0.65	3.21	1.00
12	CARR	0.35	0.10	0.83	4.15	0.99
13	LUFTHA	0.87	0.17	0.28	3.21	0.99
14	PHG	0.47	0.13	0.15	2.38	1.00
15	MOET	0.49	0.13	0.36	3.07	0.99
16	MKS-M+SPlc	1.06	0.59	0.76	2.06	1.00
17	METFNL	0.65	0.14	0.40	2.76	0.99
18	PPR	1.01	0.29	0.58	2.34	0.99
19	EXHO	0.61	0.23	1.04	3.70	1.00
20	ULVR	0.30	0.07	0.84	3.18	0.99
21	EON	0.32	0.11	2.18	9.46	0.99
22	FERRUZ	0.45	0.16	0.41	3.05	1.00
23	EDP	0.38	0.16	1.35	5.36	1.00
24	EDF	0.27	0.10	0.64	3.60	0.99
25	BAD	0.32	0.11	0.65	3.63	0.99
26	ELESM	0.45	0.21	1.62	5.90	1.00
27	ENEL	0.37	0.21	2.49	9.24	1.00
28	FORTUM	0.39	0.14	0.28	2.95	0.99
29	IBERDU	0.40	0.16	2.48	9.68	1.00
30	REP	0.60	0.20	1.74	6.09	0.99
31	RWE	0.30	0.09	1.36	6.98	0.99
32	LYOE	0.40	0.15	0.71	3.78	1.00
33	UNFSM	0.52	0.17	0.48	2.99	1.00
34	VATFAL	0.34	0.12	0.73	3.81	1.00
35	VEOLIA	0.52	0.14	1.34	4.94	0.99
36	AAB-Bank	0.22	0.21	2.52	8.29	1.00
37	AEGON	0.38	0.21	1.57	5.71	0.99
38	AXAF	0.38	0.19	1.38	5.33	1.00
39	MONTE	0.29	0.17	1.61	5.20	1.00
40	BACR-Bank	0.22	0.21	2.62	9.06	1.00
41	CMZB	0.32	0.22	1.96	6.03	0.99
42	DB	0.30	0.19	2.25	7.09	0.99
43	HANRUE	0.37	0.16	0.60	3.22	0.99
44	MUNRE	0.32	0.16	0.80	3.72	0.99
45	SCHREI	0.34	0.18	1.73	6.22	0.99
46	VERSIC-InsCo	0.43	0.21	0.38	2.16	1.00
47	ADO	0.90	0.26	0.23	3.06	0.99
48	AKZO	0.47	0.10	1.35	4.91	0.98
49	BYIF	0.46	0.11	0.65	3.72	0.99
50	STGOBN	0.57	0.21	2.49	9.85	0.99
51	EAD	0.42	0.13	2.20	8.94	0.99
52	LAFCP	0.69	0.22	1.64	6.87	0.99
53	SIEM	0.30	0.10	1.83	7.47	1.00
54	UPMKYM	0.84	0.34	1.97	6.51	0.99
55	BERTEL	0.56	0.13	-0.05	3.21	0.99
56	DT	0.63	0.13	0.15	3.24	0.99
57	FRTEL	0.61	0.15	-0.31	2.23	0.99
58	OTE	0.72	0.15	-0.15	2.51	0.99
59	KPN	0.87	0.27	0.84	2.68	1.00
60	RTRGRP	0.42	0.07	-0.43	2.41	0.98
61	TIIMN	0.89	0.14	0.06	3.54	0.98
62	TELEFO	0.64	0.16	0.49	2.47	0.99
63	VOD	0.51	0.13	1.45	4.94	0.99
64	WOLKLU	0.75	0.24	1.11	4.22	0.99

Notes to Table: We report the first four sample moments of the default intensity for each company. We also report the first order autocorrelation.The sample period is from October, 14, 2004, through December 31, 2007.

Table 9: Parameter Estimates for DECO Model

Equity Returns

CDX Firms			iTraxx Firms		
ω	**α**	**β**	**ω**	**α**	**β**
0.0011	0.0165	0.9824	0.0026	0.0257	0.9717

Intensity Innovations

CDX Firms			iTraxx Firms		
ω	**α**	**β**	**ω**	**α**	**β**
0.0011	0.0308	0.9681	0.0043	0.0251	0.9706

Notes to Table: We report parameter estimates for the dynamic equicorrelation models. The sample period for equity returns is October 11, 2000 through December 31, 2007. The sample period for default intensities is October 14, 2004, through December 31, 2007.