Measuring Correlated Default Risk: A New Metric and Validity Tests [*] [†]

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Abstract. Extracting information from daily CDS spreads, we propose a measure of correlated default risk, which we show is a meaningful predictor of bankruptcy clusters. Focusing on U.S. corporate bonds, we also find that our measure of correlated default risk is more pronounced and commands a higher premium during periods of financial distress and for speculative issues. For instance, we find that after controlling for other known determinants of bond pricing, a 0.5 increase in aggregate correlated default risk is associated with a 13-bps increase in credit spreads, and elevates to a 22-bps premium for speculative issues and to a 17-bps premium during periods of financial distress. Overall, our paper provides compelling evidence as to the efficacy of our measure in capturing correlations in the likelihood of default over time, and has important implications for future work in asset allocation and fixed-income pricing.

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1. Introduction

Determining and predicting the time-varying correlation in default risk is of fundamental interest and importance to academics and practitioners alike. A clearer grasp of correlated default risk has direct implications for fixed-income pricing and portfolio risk management, particularly since correlated default risk undermines diversification efforts and results in a greater likelihood of extreme losses. Overall, a cleaner and more powerful measure of correlated default risk is crucial for properly calibrating fixed-income portfolios and ascertaining the Value-at-Risk (VaR), as well as for determining capital adequacy needs or setting leverage thresholds on investment portfolios.

However, empirical challenges lie in how to measure this unobservable risk that is inherently difficult, if not impossible, to capture directly through observed default intensities. For one, default events are uncommon, particularly for highly-rated investment grade issues. Thus, a sample correlation of default intensities provides an unreliable estimate of the actual time-varying correlation in the risk of default. Moreover, the time clustering in corporate defaults has empirically been significantly higher than what common firm-level and macroeconomic covariates imply (Das, Duffie, Kapadia, and Saita, 2007; Duffie, Eckner, Horel, and Saita, 2009), [1] suggesting the need for a more direct and powerful measure of correlated default risk across firms.

Our purpose is to introduce a well-specified yet broadly observable measure that better captures correlated default risk, and to organize evidence suggesting its efficacy in capturing correlated default risk. To this end, we leverage the important insight that the correlation in the realization of defaults mainly emanates from correlation in default probabilities (Das, Freed, Geng, and Kapadia 2006; Das, Duffie, Kapadia, and Saita, 2007). That is, if we can calculate a more accurate measure of correlations in the likelihood of default, this measure should also capture correlated default risk.

[1] See also Lando and Nielsen (2010) for additional discussion and potential pitfalls regarding tests of the doubly stochastic assumption under times to default (i.e., the assumption that default times are conditionally independent, given some structural determinants or underlying state process of default).

To do so, we propose a method to extract information contained in daily, single-name CDS spreads[2] to determine the correlation in the likelihood of default. In general, the CDS market is known to be far more liquid and efficient than the corporate bond market, with CDS spreads reflecting changes in credit quality of the reference entity in a more timely manner than the spreads of the corresponding bond issues (Blanco, Brennan, and Marsh, 2005; Ericsson, Jacobs, and Oviedo, 2009). Thus, to the extent that CDS spreads proxy for default probabilities (Friewald, Wagner, and Zechner, 2014), movements in CDS spreads provide us reliable and timely updates as the respective movements in the default probabilities of the corresponding reference entities.

As a result, rolling one-month correlations of daily, single-name CDS spreads provides us a measure of time-varying correlated default risk. That is, in capturing the correlation in the likelihood of default, our method ultimately captures the correlated default risk inherent in each issue, since the correlation in the realization of defaults predominately emanates from the correlation in default probabilities (Das, Freed, Geng, and Kapadia 2006; Das, Duffie, Kapadia, and Saita, 2007). Using CDS spreads in this way has the advantage of enabling us to avoid imposing any structural assumptions under the risk-neutral framework to infer default probabilities, and hence, allows us to avoid the joint hypotheses conundrum: i.e., the validity of the structural assumptions vis-à-vis the informative-ness of the data. This is mainly due to the fact that we are interested in the *correlation* in default probabilities and not the actual *levels* of default probabilities.

In our sample, which spans 63,377 bond-year-months from July 2002 to August 2013, the average correlation in default probabilities is 0.29, with a standard deviation of 0.24, suggesting substantial variation in correlated default risk across issues and across time. Notably, our comprehensive panel allows us to explore the cross-sectional and cross-temporal aspects of correlated default risk for the US corporate bond market as a whole, as well as various important segments and sub-periods throughout time.

[2] A credit default swap (CDS) is a financial swap agreement, whereby the contract writer agrees to compensate the CDS holder in the event that the reference entity defaults. In exchange for this guarantee, the CDS holder makes periodic payments, known as the CDS *spread* or *fee*, to the contract writer.

First, in examining how our *Aggregate Default Correlation* metric correlates with actual realizations of bankruptcies in the U.S., we find that after controlling for various other factors that predict the incidence of bankruptcies, a 0.50 increase in *Aggregate Default Correlation* approximates to an 8% increase in bankruptcy filings, as reported by United States Courts.[3] That is, our measure of correlated default risk is a meaningful predictor of bankruptcy clusters. Moreover, consistent with theory, *Aggregate Default Correlation* is positively associated with overall bond-market illiquidity,[4] and is more pronounced in the sub-period spanning the recent financial crisis, defined by December 2007 to June 2009.[5] We also find that *Aggregate Default Correlation* increases substantially following a market downturn, as measured by the S&P500 Composite Index. That is, there is an asymmetry in joint asset distributions, whereby correlations tighten considerably in downturns relative to normal conditions (a la Ang and Bekaert, 2002; Das and Uppal, 2004).

Thus, our measure of correlated default risk moves as expected with the clustering in bankruptcy filings, as well as with observable indicators of the correlation in default probabilities. In addition, the literature shows that observable covariates alone are inadequate in their ability to account for the empirical clustering/intensity of defaults (Das, Duffie, Kapadia, and Saita, 2007; Duffie, Eckner, Horel, and Saita, 2009). As such, to the extent that our default-correlation measure is an effective estimator of the correlation in the realization of defaults, we expect that our measure should contain additional information beyond that explained by the same observable covariates, which, among other factors include structural determinants such as leverage or volatility. Consistent with this idea, we find that the observable covariates account for less than 15% of the variation in our measure.

Furthermore, the pricing implications of our default-correlation metric further suggest its viability as an apt measure of correlated default risk. That is, controlling for pricing factors that are known to

[3] See http://www.uscourts.gov/statistics-reports/caseload-statistics-data-tables

[4] For instance, He and Xiong (2012) derive a model where debt-market illiquidity leads to greater credit risk by increasing the default boundary, and Ericsson and Renault (2006) derive a model where bond-market illiquidity affects the likelihood of debt renegotiation.

[5] We follow the period as defined by the Federal Reserve. See "The Great Recession of 2007-09" (Federal Reserve Bank of New York, 2013). See also peaks and troughs defined by the Federal Reserve Economic Data (FRED) site: https://research.stlouisfed.org/fred2/help-faq/#graph_recessions.

determine credit spreads, such as firm leverage, volatility, and bond-issue liquidity, we find that changes in credit spreads are substantially associated with the correlation in default probabilities. Specifically, a 0.50 increase in an individual issue's average pairwise default correlation (with other issues in the cross-section) is associated with a modest 6 basis-point (i.e., 3.0%) increase in the attendant credit spread, and is elevated to an 11 basis-point (i.e., 5.3%) increase for speculative issues and to a 13 basis-point (i.e., 6.2%) increase during the period spanning the subprime financial crisis.[6]

This association is markedly intensified when we examine the effects of aggregate economy-wide default correlation. That is, 0.50 increase in *Aggregate Default Correlation* is associated with a 13 basis-point (i.e., 6.4%) increase in credit spreads, and is elevated to a 22 basis-point (i.e., 10.5%) increase for speculative issues and to a 17 basis-point (i.e. 8.2%) increase in credit spreads during the period spanning the recent subprime financial crisis. Intuitively, the economy-wide tightening of correlations in default probabilities undermines diversification attempts and, thus, commands an even higher premium during times of financial distress. We find similar associations between our default correlation metric and changes in CDS spreads.

Overall, a timely and more powerful measure of the correlation in default probabilities is crucial for determining appropriate amounts of leverage for banks, shadow entities, and investment portfolios in general, and should also prove valuable to future work on asset allocation as well as fixed-income pricing with regime shifts, whereby correlations tighten considerably during bad times (a la Ang and Bekaert (2002), Gourieroux, Monfort, Pegoraro, and Renne (2014), and Elkamhi and Stefanova (2015)). Furthermore, the broadly observable metric of default correlation that we introduce should prove useful to future work concerning cross-sectional determinants of fixed-income and credit-derivatives pricing, and thus extends the work of Collin-Dufresne, Goldstein, and Martin (2001) and Friewald, Jankowitsch, and Subrahmanyam (2012), among others, who examine the determinants of credit spread and fixed-income pricing.

[6] The percentages reported here and in the following paragraph are based on a sample average credit spread of 2.08%.

Our study is also related to Anderson (2016), who decomposes the sources of increased co-movement in the CDS spreads on a group of liquid, investment grade reference entities during the recent 2007-2009 financial crisis. Whereas Anderson (2016) seeks to understand the fundamental and non-fundamental sources of the marked spike in correlations during the crisis, we seek to understand the uses of and information conveyed by cross-sectional and time-varying correlations in CDS spreads across reference entities spanning 1,901 distinct issues over an (unbalanced) panel of 11 years. That is, we seek to explore the important default-associated and pricing implications during both crisis and non-crisis years, as well as for a broader array of reference entities (both investment and non-investment grade).

This paper is organized as follows. In Section 2, we describe our method to measuring correlations in the likelihood of default using CDS data. In Section 3, we describe our data sources, define our main variables of interest, and provide key summary statistics. In Section 4, we explore the determinants of correlated default risk, and in Section 5, we examine how our measure of *Aggregate Default Correlation* relates to the incidence of bankruptcy filings. In Section 6, we examine how our measure of correlated default risk relates to corporate-bond spreads, and in Section 7 we provide additional analyses to test the robustness and validity of our measure. In Section 8 we discuss and conclude.

2. Measuring Correlation in Default Probabilities

Given the empirical challenges in directly measuring correlated default risk, we instead propose that the information contained in credit default swap (CDS) spreads be employed to extract the correlation in default risk between reference entities. Specifically, we propose that the time-varying correlation in default probabilities can be captured via correlations in daily single-name CDS spreads, which provides us a reliable metric of correlated default risk, since default correlation predominately emanates from the correlation in default probabilities (Das, Duffie, Kapadia, and Saita, 2007).

In general, CDS securities are known to be extremely liquid and efficient, with CDS spreads reflecting changes in the credit risk of the reference entity in a far more timely manner than the corresponding fixed-income issues (Blanco, Brennan, and Marsh, 2005; Ericsson, Jacobs, and Oviedo, 2009). Overall, the notional amount of CDS contracts grew from \$0.6 trillion in June 2001 to a peak of \$62.2 trillion by the second half of 2007,[7] and has rapidly become the most prominent and liquid credit derivative, encompassing approximately half of the entire credit-derivatives market (Blanco, Brennan, and Marsh, 2005).

Thus, correlated movements in CDS premia provide us reliable and timely updates as to the correlated movements in the respective reference entities' default probabilities. That is, the CDS spread is determined by: the *expected loss*, which captures the reference entity's likelihood of default times the loss given default, and the issuer's *counterparty risk*, which accounts for the joint likelihood that the contract writer is unable to pay the promised amount upon default of the reference entity. However, only the likelihood of default is of first-order importance, with the recovery rates and counterparty risk either being time-invariant over our one-month estimation horizon or exhibiting relatively little impact on the CDS spread itself.

That is, recovery rates are known to be extremely persistent, and the majority of work in this arena assume a constant recovery rate.[8] Furthermore, the impact of counterparty risk on CDS spreads is exceedingly small and economically negligible (Arora, Gandhi, and Longstaff, 2012).[9] [10] Specifically, "the credit spread of a CDS dealer would have to increase by nearly 645 basis points to result in a one-

[7] See ISDA Market Survey Summaries, 2010-1995 (http://www2.isda.org/functional-areas/research/surveys/market-surveys/)

[8] See, for example, page 2436 of Friewald, Wagner, and Zechner (2014). See also Bernt, Douglas, Duffie, Ferguson, and Schranz (2005) and Bharath and Shumway (2008), who also assume a constant recovery rate, and Hull, Predescu, and White (2004), who argue that the estimate of the CDS spread is fairly insensitive to the choice of recovery rate given such low probabilities of default. Other studies assuming a constant recovery rate include: Altman and Kishore (1996), Keenan, Shtogrin, and Soberhart (1999), and Eom, Helwege, and Huang (2004).

[9] Similarly, Junge and Trolle (2015) infer from the annual "Margin Surveys" by the International Swaps and Derivatives Associations (ISDA) that "the fraction of credit derivatives trades covered by collateral agreements averaged more than 80% over the sample period". Accordingly, they do not account for counterparty risk in their CDS pricing model.

[10] This empirical finding is distinct from prior theoretical work focusing on the impact of counterparty risk in the pricing of credit derivatives contracts in a model economy in which contracts liabilities are not collateralized (Jarrow and Yu, 2001; Hull and White, 2001; Kraft and Steffensen, 2007).

basis-point decline in the price of credit protection". Equivalently, counterparty risk has negligible impact on the covariance between CDS spreads.

Thus, the covariance between CDS spreads ultimately captures the covariance in default probabilities of the underlying reference entities:

$$Cov\left(CDS\ Sprd_{i,t}, CDS\ Sprd_{j,t}\right) = Cov\left(DefaultProb_{i,t}, DefaultProb_{j,t}\right) \quad \text{(Eq. 1)}$$

We emphasize that our method does not require us to impose structural assumptions under the risk-neutral framework to infer default probabilities, which allows us a more direct path to measuring correlated default risk. Our ability to do so is driven by the fact that we need only the *correlation* in default probabilities, and not the actual *level*s of the default probabilities themselves. To the extent that CDS spreads proxy for the risk-neutral default probabilities,[11] our measure captures the correlation in risk-neutral default probabilities, though we do not rule out that our measure may also be capturing the correlation in physical default probabilities (insofar as the general movements are similar under both the physical and risk-neutral measures).

To lend further support to the validity of our measure as a proxy for the correlation in default probabilities, in later analyses (which we present in Section 7), we explore the impact of recovery rates and CDS liquidity on the validity of our default correlation metric. Furthermore, since the correlation in CDS spreads could also reflect systematic movements in the price of default risk, we also explore the impact of time-varying credit-risk premia on our default correlation metric. Finally, in additional robustness tests, we orthogonalize the correlation in CDS spreads to correlations in CDS liquidity and recovery rates as well as to the excess bond premium (*ebp*). We now proceed to describe our data sources and key variables.

3. Data Sources and Description of Variables

In this section, we describe our data sources, and we present key summary statistics.

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[11] See, for instance, page 2436 (footnote 19) of Friewald, Wagner, and Zechner (2014).

3.1. Sources

Our sample period spans July 2002 to August 2013 and consists of the US corporate bond issues that lie at the intersection of the Trade Reporting and Compliance Engine (TRACE), Markit, Mergent Fixed Income Securities Database (FISD), OptionMetrics, Federal Reserve Economic Data (FRED), CRSP, and COMPUSTAT datasets. In the following section, we describe our filtering process and we provide a discussion of variables alongside dataset references. Ultimately, our final sample consists of a panel dataset of 63,337 monthly observations of 1,901 bond issues.

3.2. Key Definitions and Discussion of Variables

We calculate the pairwise correlation in default probabilities between issues *i* and *j* as the Pearson's rho correlation in the corresponding daily CDS spreads over the 30 days prior, which we obtain from Markit. *Default Correlation*$_{i,t}$ is then defined as the average pairwise correlation in daily CDS spreads of issue *i* with all other issues in year-month *t*. We also define a macro-level measure, *Aggregate Default Correlation*$_t$, calculated as the average *Default Correlation*$_{i,t}$ across all issues at time *t*.[12]

In our calculations, we focus on the five-year, single-name CDS contracts, as these are the most common and most liquid format (Hull, Presdescu, and White, 2004). Moreover, to be included in our sample, the number of reported CDS premia for a given reference entity during any given month must be at least equal to the average number of reported CDS premia for that month, which is calculated by scaling the total number of reported CDS premia for that month by the total number of observed reference entities in that month. This additional filter is applied to ensure that we include only those reference entities that are traded frequently enough to calculate meaningful correlations in CDS premia with other sample reference entities.

In Appendix A, we provide a brief summary sheet of all variables, and in Appendix B, we provide a more detailed outline of variable descriptions and calculations, along with the corresponding data source(s).

[12] Our results are robust to the use of medians versus means in defining our correlation metrics.

3.3. Summary Statistics

In Table 1, we present summary statistics on basic bond, CDS, and firm characteristics. The average default correlation in our sample is 0.29, with a standard deviation of 0.24. Furthermore, the average credit spread is 2.08%, with an average time to maturity of 9.20 years, and 66% of issues are investment grade (i.e., rated at least BBB or higher). We now proceed to explore our default correlation metric in greater detail.

4. The Determinants of Correlated Default Risk

To explore the observable covariates explaining the correlation in default probabilities across bond issues, we estimate the following OLS regression:[13]

$$Aggregate\ Default\ Correlation_{i,t} = \alpha + X_{i,t-1}\gamma + \varepsilon_{i,t} \qquad \text{(Eq. 2)}$$

Aggregate Default Correlation$_t$, the dependent variable, represents the average *Default Correlation*$_{i,t}$ across all bond issues in year-month t. X_{t-1} is a vector of the following macro-level variables: *r10*$_{t-1}$, *Yield Slope*$_{t-1}$, *S&P Return*$_{t-1}$, *VIX*$_{t-1}$, *Aggregate Amihud Illiquidity*$_{t-1}$, *Aggregate Leverage*$_{t-1}$, *ebp* $_{t-1}$, and *Crisis*$_{t-1}$ which are as defined in Appendix A. We employ a lagged regression specification, because *Default Correlation*$_{i,t}$ is calculated based on information from the month prior. *Aggregate Amihud Illiquidity*$_{t-1}$ and *Aggregate Leverage*$_{t-1}$ represent the average *Amihud Liquidity* and average *Leverage*, respectively, across all issues in our sample at time *t-1*. *T*-statistics are calculated using Newey-West standard errors with four lags,[14] to account for heteroscedasticity and serial correlation in *Aggregate Default Correlation*$_t$.

The results, presented in Table 2, show that *Aggregate Default Correlation* moves as expected with observable structural covariates that we expect to drive the correlation in default probabilities. First,

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[13] We choose OLS estimation for ease of exposition. A double-censored Tobit model produces almost identical results, and our results are robust to alternative specifications.

[14] We employ the formulas $0.75 \times N^{(1/3)} = 3.84$ and $4 \times (N/100)^{(2/9)} = 4.26$ to arrive at our four-lag specification (e.g., see Newey and West (1994); Adkins and Hill (2011)). Our results are robust to calculating Newey-West standard errors with five lags.

we observe that *Aggregate Default Correlation* increases substantially with overall bond-market illiquidity, consistent with the theory that bond-market illiquidity adversely impacts debt renegotiation (Ericsson and Renault, 2006) as well as rollover losses (He and Xiong, 2012) and thereby raises the default boundary. Specifically, a 0.40 increase in *Aggregate Amihud Illiquity* translates to an increase in *Aggregate Default Correlation* of 0.40 (*t*-statistic = 2.89). For reference, 0.40 represents a one standard-deviation change in the *Amihud Illiquidity* measure. We note that this illiquidity coefficient estimate is substantially abated with the inclusion of the $Crisis_t$ indicator variable, due to the fact that liquidity effects and flight-to-quality risk are particularly pronounced in times of financial crisis (Dick-Nielsen, Feldhutter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012).

Furthermore, our aggregate correlation measure increases considerably following negative realizations of the S&P500 Composite Index (coefficient estimate = -0.432, *t*-statistic = -1.72), which comports with the widely recognized principle that asset correlations tighten considerably following market downturns (Ang and Bekaert, 2002; Das and Uppal, 2004). Similarly, we observe that aggregate default correlation is elevated during the period spanning the recent financial crisis (coefficient estimate = 0.121, *t*-statistic = 3.02).

One possible concern is that, by dint of our method of calculation, our default-correlation metric may also be capturing the variation in the risk premium of default over time. That is, if CDS spread correlations increase during times when investors demand a greater price for bearing credit risk, our measure of aggregate default correlation would also pick up this time-varying excess credit-risk premia in addition to the time-varying correlated default risk. However, in contrast to the *Crisis* indicator and the *S&P Composite Index*, the excess bond premium (i.e., *ebp,* as calculated by Gilchrist and Zakrajsek (2012)), has quite a modest association with *Aggregate Default Correlation*, whereby a one standard-deviation (i.e., 0.79%) increase in *ebp* is associated with a 0.006 decrease in aggregate default correlation (coefficient estimate = -0.077, *t*-statistic = -2.80). That is, our default correlation metric is not simply capturing the time variation in excess credit-risk premia.

In addition, consistent with earlier findings that empirical covariates have very limited power to explain the empirical intensity or clustering of defaults (Das, Duffie, Kapadia, and Saita, 2007; Duffie, Eckner, Horel, and Saita, 2009), we observe that these standard structural determinants of default probabilities and credit spreads explain less than 15% of the variation in *Aggregate Default Correlation*, further suggesting its viability and validity as a proxy for the correlated risk that causes firms to fail together and drives up credit spreads. We now proceed to examine this idea in greater detail.

5. Aggregate Default Correlation and Bankruptcy Clusters

In this section, we explore whether our measure of correlated default risk behaves in the way that we expect as economy-wide correlations tighten and relax over time. Specifically, to bolster confidence in our measure, we begin by examining whether our measure of aggregate default correlation is meaningfully associated with the intensity of bankruptcy filings. To start, we estimate the following OLS regression:

$$\log(Bankruptcy\ Filings_t) = \alpha + \beta \cdot Agg.DefaultCorrelation_t + X_t\gamma + \varepsilon_t \qquad \text{(Eq. 3)}$$

log(*Bankruptcy Filings*$_t$), the dependent variable, represents the log of the sum of new Chapter 7, 11, 12, and 13 business filings at time *t*, as reported by United States Courts.[15] *Aggregate Default Correlation*$_t$ represents the average *Default Correlation*$_{i,t}$ across all bond issues in year-month *t*. X_t is a vector of the following macro-level variables: *r10*$_t$, which is the yield on the 10-year Treasury note; *Yield Slope*$_t$, which is the difference between the 10-year and the 2-year Treasury yields; *S&P Return*$_t$, which is the monthly return on the S&P500 composite index; *LogGDP*$_t$, which we obtain from the Federal Reserve Economic Data (FRED) database; *Industrial Production*$_t$, which measures the real output of all relevant establishments located in the United States (also obtained from FRED); *Inflation*$_t$, which we also obtain from FRED; and *Unemployment*$_t$, as reported by the Bureau of Labor Statistics.

In our regressions, we employ a contemporaneous specification as well as a lagged-variables specification, whereby we regress *log(Bankruptcy Filings*$_t$*)* against lagged values of our explanatory

[15] See http://www.uscourts.gov/statistics-reports/caseload-statistics-data-tables.

variables. Thus, in the contemporaneous specification, we are regressing time *t* bankruptcy filings on aggregate default correlation measured over the prior 30-day lookback period. Similarly, in the lagged specification, we are regressing time *t* bankruptcy filings on aggregate default correlation measure over the 30-day look-back period beginning 60 days prior. *T*-statistics are calculated using Newey-West standard errors with four lags,[16] to account for potential heteroscedasticity and serial correlation in $Bankruptcy\ Filings_t$.

The results, presented in Table 3, show a substantial clustering of bankruptcy filings when *Aggregate Default Correlation* is high. Specifically, in the contemporaneous specification (Column 1), we see a coefficient estimate of 0.166 (*t*-statistic = 2.41) on *Aggregate Default Correlation*, which translates to an approximate 0.166 × 0.5 = 8.3% increase in the incidence of bankruptcy filings for a 0.50 increase in aggregate default correlation.[17] Similarly, the coefficient estimate on *Aggregate Default Correlation* in the lagged specification (Column 2) is 0.163 (*t*-statistic = 2.14).[18] Figure 1 demonstrates this relation graphically, whereby we interlay bankruptcy filings with aggregate default correlation throughout our sample period. Consistent with our findings in Table 3, we observe that our measure of aggregate default correlation moves jointly with the incidence of bankruptcy filings, with both experiencing a marked spike during the crisis period.

These results suggest that a spike in our measure of aggregate default correlation subsequently translates to a clustering of realized bankruptcies, as we would expect to see in situations where economy-wide correlations tighten. We now proceed to explore additional implications and validity tests of our measure, namely as it relates to fixed-income and credit-derivatives pricing.

[16] We employ the formulas $0.75 \times N^{(1/3)} = 3.84$ and $4 \times (N/100)^{(2/9)} = 4.26$ to arrive at our four-lag specification (e.g., see Newey and West, 1994; Adkins and Hill, 2011). Our results are robust to calculating Newey-West standard errors with five lags.

[17] Recall: $ln(y) = x$ implies $dy/y = dx$. Similarly, when we employ a levels specification (untabulated), we observe a coefficient estimate on *Aggregate Default Correlation* of 1,489 (*t*-statistic = 2.59), which suggests an increase in bankruptcy filings of 744 and represents 7.5% of the mean. For reference, the average number of bankruptcy filings is 9,966 (untabulated).

[18] In untabulated analyses, we find that greater lags of *Aggregate Default Correlation* continue to have strong explanatory power in predicting subsequent bankruptcy clusters.

6. Implications and Uses of Our Measure

In this section, we examine the association between credit spreads and the correlation in default probabilities, after accounting for other factors known to determine credit spreads.

We begin, in Table 4, by presenting a comparison of basic summary statistics between crisis and non-crisis periods, as well as a comparison between investment and non-investment grade issues. As expected, we observe that average *Default Correlation* is higher in crisis periods (0.38) than in non-crisis periods (0.27). We also observe that average credit spreads are much higher in crisis years (3.98%) than in non-crisis years (1.64%). We do not observe a material difference in average *Default Correlation* within investment grade issues (0.29) versus non-investment grade issues (0.29); though, we do note that average credit spreads are substantially higher among non-investment grade issues (3.61%) than among investment grade issues (1.31%).

6.1. Credit Spreads and Correlated Default Risk

To further explore the efficacy and validity of our measure, we examine its changes in association with changes in the level of credit spreads via the following pooled OLS regressions:

$$\Delta CreditSpread_{i,t} = \alpha + \beta \times \Delta DefaultCorrelation_{i,t} + X_{i,t}\gamma + \varepsilon_{i,t} \quad \text{(Eq. 4)}$$

$$\Delta CreditSpread_{i,t} = \alpha + \beta \times \Delta AggregateDefaultCorrelation_{t} + X_{i,t}\gamma + \varepsilon_{i,t} \quad \text{(Eq. 5)}$$

Credit Spread$_{i,t}$, the dependent variable, is the difference between the yield on bond *i* and the yield on the associated Treasury at the same maturity in year-month *t*. *Default Correlation*$_{i,t}$ represents the average pairwise correlation in default probability of bond *i* with all other bonds at time *t*, as described earlier in Section 2 as well as in Appendix A, and *Aggregate Default Correlation*$_t$ represents the average *Default Correlation* across all issues at time *t*. $X_{i,t}$ represents a vector of control variables guided by prior literature studying this specification, and involves changes in firm-level characteristics (Δ*Amihud Illiquidity*$_{i,t}$, Δ*Investment Grade*$_{i,t}$, Δ*Leverage*$_{i,t}$, Δ*Volatility*$_{i,t}$) as well as changes in macro-level characteristics (Δ*r10*$_t$, Δ*Yield Slope*$_t$, Δ*ebp*$_t$, and *S&P Return*$_t$), which are also described earlier in

Appendix A. *T*-statistics are calculated using White-robust standard errors adjusted for firm-level clustering, which account for heteroscedasticity and serial correlation (Peterson, 2009).

The results, presented in Table 5, suggest that a 0.50 increase in *Default Correlation* (Panel A, Column 1) is associated with a 6 basis-point increase (*t*-statistic = 6.97) in the attendant credit spread, and the same increase in *Aggregate Default Correlation* (Panel B, Column 1) is associated with a 13 basis-point increase (*t*-statistic = 8.64) in the attendant credit spread. That is, accounting for other known structural determinants of credit spread changes, such as leverage and volatility, the correlation in default probabilities remains a substantial explanatory factor in fixed-income pricing.

The results also suggest that the correlation in default probabilities commands a far higher premium in crisis years (Column 3) and among non-investment grade issues (Column 5). Specifically, a 0.50 increase in an individual issue's average pairwise default correlation (with other issues in the cross-section) is associated with a modest 2 basis-point increase in credit spreads in non-crisis periods (*t*-statistic = 4.41), but is elevated to a 13 basis-point increase in credit spreads during the crisis period (*t*-statistic = 4.63).

Similarly, a 0.50 increase in *Aggregate Default Correlation* is associated with a 7 basis-point increase in credit spreads during non-crisis times (*t*-statistic = 7.50), and is elevated to a 17 basis-point increase during the crisis period (*t*-statistic = 5.03). Moreover, we observe that the aggregate correlation in default probabilities commands a substantially higher premium among non-investment grades issues. For instance, a 0.50 increase in *Aggregate Default Correlation* is associated with an 8 basis-point increase in credit spreads of investment grade issues (*t*-statistic = 10.02), but is associated with a 22 basis-point increase in credit spreads of non-investment grade issues (*t*-statistic = 5.66).

The results suggest that the correlation in default probabilities are meaningfully associated with credit spreads, even after controlling for other observable firm and macro characteristics, including the time-varying excess bond premium (as in Gilchrist andn Zajrajsek, 2012). Furthermore, we note that in measuring correlated default risk via correlations in CDS spreads, our analyses encompass those firms that are actively CDS traded, which tend to be larger, safer, more profitable, and have more working capital (Subrahmanyam, Tang, and Wang, 2014). Since correlated default risk likely commands a lower premium among such firms, we posit that any relation we observe between default-risk correlation and credit spreads within our sample likely understates the overall population impact.

6.2. CDS Spreads and Correlated Default Risk

Furthermore, we make similar observations within the context of credit-derivatives pricing, wherein we estimate a pooled OLS regressions of changes in CDS spreads against changes in default correlations:

$$\Delta\, CDS\ Spread_{i,t} = \alpha + \beta \times \Delta DefaultCorrelation_{i,t} + X_{i,t}\gamma + \varepsilon_{i,t} \qquad \text{(Eq. 6)}$$

$$\Delta\, CDS\ Spread_{i,t} = \alpha + \beta \times \Delta AggregateDefaultCorrelation_{t} + X_{i,t}\gamma + \varepsilon_{i,t} \qquad \text{(Eq. 7)}$$

where $CDS\ Spread_{i,t}$ is the average five-year, single-name CDS spread on reference entity *i* for month *t*, and all other regression variables are as specified above in equations (4) and (5).

The results, which we present in Table 6, show a similar pattern as in the previous set of analyses which studied changes in credit spreads. That is, the change in *Default Correlation* is also a significant determinant of the change in *CDS Spreads* (Panel A, Column 1: coefficient estimate = 0.077; *t*-statistic = 3.44), as is the change in *Aggregate Default Correlation* (Panel B, Column 1: coefficient estimate = 0.182, *t*-statistic = 3.32). Moreover, similar to the credit-spread specification, we continue to observe that the change in correlation in default probabilities is associated with a substantially higher change in CDS spreads during the crisis period (Column 3) and among non-investment grade reference entities (Column 5).

Finally, to be clear, we do not purport to solve the credit-spread puzzle or to identify the latent variable driving credit spreads (a la Collin-Dufresne, Goldstein, and Martin, 2001). In fact, when we conduct a principal component analysis (PCA) of the residuals from our credit-spread regression, the first principal component explains approximately 75% of the residual variation, which is similar in magnitude to that found by Collin-Dufresne et al. (2001). Instead, our purpose is to introduce a valid and easily quantifiable metric of correlated default risk, and to organize evidence along this regard. To this end, we now proceed to additional analyses to further test the validity of our proposed metric.

7. Additional Analyses

The results thus far point to the validity of our measure in capturing the correlated default risk, and suggest the importance of our measure in fixed-income and credit-derivatives pricing as well as in portfolio risk management. However, a question remains as to whether our measure, *Default Correlation*, is truly reflecting correlated default risk itself, as opposed to time-varying excess bond premia or correlations in CDS liquidity or recovery rates. Thus, we now proceed to empirically examine the extent to which CDS spreads – and more importantly, *correlations* in CDS spreads – may be affected by these factors. As an additional robustness check, we then proceed to examine the predictive power of our measure in bankruptcy clusters as well as the incremental pricing information it contains when we orthogonalize our measure of default correlation to the correlation in CDS liquidity and the correlation in recovery rates as well as to the excess bond premium (*ebp*).

7.1. A Further Look at the Role of Recovery Rates and CDS Liquidity

7.1.1. CDS Liquidity

A growing body of evidence suggests that liquidity risk in the bond market is a significant priced factor in fixed-income credit spreads (Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhutter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012). However, the substantial differences between credit default swaps and their underlying fixed income securities make it unclear as to whether liquidity risk in the CDS market is a priced factor in CDS spreads. For one, as mentioned previously, the single-name CDS market is far more liquid than the bond market, and represents the most liquid credit derivative, accounting for approximately half of the overall credit-derivatives market (Blanco, Brennan, and Marsh, 2005). Furthermore, the notional amount of CDS contracts is technically unlimited, making it unlikely that supply/demand imbalances affect the CDS market as they do the bond market, and since new CDS contracts can be written at any time, the CDS market is less susceptible to "cornering" or "squeezing" (Longstaff, Mithal, and Neis, 2005).[19]

More recent evidence suggests a strong liquidity component in intermediary asset pricing in general (Brunnermeir and Pedersen, 2009; He and Krishnamurthy, 2009; and Kondor and Vayanos, 2014), and in CDS spreads in particular (Tang and Yan, 2007; Bongaerts, De Jong, and Driessen, 2011; Junge and Trolle, 2015). Specifically, the capital and funding restrictions along with the risk-bearing capacity of the contributors and market-making intermediaries create frictions and illiquidity that would impact the pricing of CDS contracts. However, aside from the issue of whether liquidity is a significant, priced factor in CDS spreads, Junge and Trolle (2015) find that CDS market liquidity is highly persistent, with a first-order autocorrelation of 0.93.

Ultimately whether CDS liquidity is a concern in the implementation and interpretation of our default correlation measure, as operationalized by the correlation in CDS spreads, is an empirical issue. To explore this possibility, we begin by examining the impact of CDS liquidity, which we measure using Markit's number of contributors. In doing so, we follow a long line of studies that have used this variable to examine or to control for CDS market liquidity. For instance, Ashcraft and Santos (2009) provide evidence that CDS trading has increased the cost of debt financing, controlling for CDS liquidity via the number of contributors. Similarly, Friewald, Wagner, and Zechner (2014) study the cross-sectional relation between equity returns and credit risk, also controlling for Markit's number of contributors as a proxy for CDS liquidity. Furthermore, Qui and Yu (2012) study CDS liquidity itself, examining the determinants of liquidity provision in the CDS market, as measured by the number of contributors.[20]

The results, which we present in Table 7, show a significant association between the number of contributors and CDS spreads, with each additional contributor decreasing the corresponding CDS spread by 10.6 basis points (see Table 7, Panel A). For reference, the average CDS spread is 2.0%

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[19] In particular, see pages 2219-2220 of Longstaff, Mithal, and Neis (2005) for a discussion regarding the distinguishing features of credit default swaps making them less susceptible to liquidity risk premia.

[20] See Qui and Yu (2012) for an extensive discussion as to the validity of using Markit's number of contributors as a proxy for CDS liquidity.

(untabulated),[21] and the average number of contributors per contract is 6.5, with a minimum of 2 contributors and a maximum of 31 contributors per contract (untabulated).

However, when we explore the relation between the number of contributors and *correlations* between CDS spreads, we observe a statistically significant but economically negligible association. Specifically, each additional contributor to CDS *i* is associated with a 0.002 decline (*t*-statistic = -2.65) in the average pairwise correlation, measured over the preceding 30-day period, of CDS spread *i* with all other CDS spreads (see Table 7, Panel B.1).

Similarly, we also observe an economically negligible association in the relation between the *correlations* in the number of contributors and *correlations* between CDS spreads. Specifically, a one-standard deviation increase in the correlation in contributors (i.e., 0.06) is associated with an increase of 0.0207 (*t*-statistic = 8.50) in the correlation in CDS spreads (see Table 7, Panel B.2), which represents a move of less than 9% of one standard deviation in CDS spread correlation. For reference, the average correlation in contributors is 0.03, with a standard deviation of 0.06 (untabulated), and the average correlation in CDS spreads is 0.29, with a standard deviation of 0.24, which we presented earlier in Table 1.

7.1.2. Recovery Rate

We also examine the impact of reported recovery rates on the levels of CDS spreads, and ultimately, on the correlation between CDS spreads. We obtain recovery rates from the Markit database, which provides the recovery rate corresponding to each credit curve as reported to Markit by institutions (i.e., market makers) contributing daily CDS pricing data. As expected, we observe that the recovery rate plays a significant role in the pricing of CDS contracts (see Table 7, Panel A).

Upon further examination, the recovery rate itself is not a statistically significant factor in the *correlation* between CDS spreads (Table 7, Panel B.1). The *correlation* in recovery rates, though, does meaningfully associate with CDS spread correlation (Table 7, Panel B.2). That is, a one standard-

[21] As distinct from the 1.54% reported average CDS spread in our final sample (see Panel B of Table 1).

deviation (i.e., 0.36) increase in the correlation in recovery rates is associated with a 0.025 increase in correlation in CDS spreads. Nonetheless, the total adjusted R-squared, when accounting for both the *Correlation in Contributors* and the *Correlation in Recovery Rate* amounts to only 2.4% of the total variation in the correlation in CDS spreads. That is, these factors, though statistically significant, have very limited explanatory power due to the persistence in the number of contributors and the recovery rate over our 30-day estimation horizon.

7.1.3. Excess Bond Premium (ebp)

An earlier possible concern that we broached is that our default-correlation metric may be capturing the time-varying excess credit-risk premia. To further explore this possibility, we also include the excess bond premium, *ebp*, as an additional regressor (Table 7, Panel B.3), and we observe that the excess bond premium is not a significant contributor to the monthly spread correlation once the *Crisis* indicator is accounted for. That is, *ebp* explains only an additional 0.2% of the variation in the monthly spread correlation (coefficient estimate = -0.001, *t*-statistic = -0.47), once accounting for: (i) the *Correlation in Contributors*, (2) the *Correlation in Recovery Rate*, and (iii) the *Crisis* indicator.

7.2. Residual Aggregate Default Correlation and Bankruptcy Filings

We now re-estimate Equation 3 (i.e., Table 3), this time taking *Residual Aggregate Default Correlation*$_t$ as our main variable of interest to ensure that it is the correlation in default probabilities itself that is associated with bankruptcy clusters, rather than the correlation in expected recovery rates or correlation in CDS liquidity.

Specifically, we calculate *Residual Default Correlation*$_{i,t}$ as the residual from regressing *Default Correlation*$_{i,t}$ on (i) the average pairwise correlation of the recovery rate on firm i with the recovery rate of all other firms at time t, and (ii) the average pairwise correlation of the number of contributors/market-makers for firm i with the number of contributors/market-makers for all other firms at time t. We then define *Residual Aggregate Default Correlation*$_t$ as the average *Residual Default Correlation*$_{i,t}$ across all firms at time *t*. The results, which we present in Table 8, show that *Aggregate Default Correlation* remains a significant predictor of bankruptcy clusters even after removing the portion, if any, that is attributable to correlations in recovery rates or CDS liquidity.

7.3. Residual Default Correlation and Credit Spreads

As an additional robustness check of our measure, we also re-estimate our credit-spread regressions (Equations 4 and 5) and our CDS-spread regressions (Equations 6 and 7), now using *Residual Default Correlation*$_{i,t}$ and *Residual Aggregate Default Correlation*$_t$ as our main variables of interest. The results, which we present in Tables 9 and 10,[22] show that both individual default correlation as well as aggregate default correlation remain significant factors in credit spreads (Table 9) as well as in CDS spreads (Table 10), even after removing the portion, if any, that is attributable to correlations in recovery rates or CDS liquidity. Furthermore, we note that in including the excess bond premium (ebp_t) as an explanatory variable, these results also indicate that both individual default correlation as well as aggregate default correlation remain significant factors in credit spreads and CDS spreads even after removing the portion, if any, that is attributable to time-varying premia demanded by investors.

8. Conclusion

This paper proposes a novel method to measuring time-varying correlations in default probabilities, and organizes useful and compelling evidence as to its efficacy and validity in capturing the correlation in the realization of default. In particular, we find that our proposed measure is substantially associated with the incidence of bankruptcy filings. We also provide evidence that our measure is a meaningful determinant of changes in credit spreads and CDS premia, and we provide evidence that default correlation is more

[22] For ease of exposition, Tables 9and 10 report only the coefficient estimates on our main variables of interest, *Residual Default Correlation* and *Residual Aggregate Default Correlation*. The full array of coefficient estimates is reported in Appendix C (for Table 9) and Appendix D (for Table 10).

pronounced and commands an even higher premium during periods of financial distress and for non-investment grade issues.

Overall, the broadly observable metric of correlated default risk that we introduce should prove useful to future work concerning cross-sectional determinants of fixed-income pricing and returns, as well as to future work concerning optimal asset allocation in the face of time-varying correlations. Furthermore, as a timely and more powerful measure of the correlation in default probabilities, our measure should prove useful in active risk management and determination of capital adequacy needs in banks, shadow entities, and investment portfolios in general.

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Appendix A. List of Variables

Presented below is an alphabetized list of variables with corresponding definitions. Firm-level variables are identified by subscript *{i,t}* and macro-level variables are identified by subscript *{t}*. A more detailed outline of descriptions and calculations is presented in Appendix B.

Amihud Illiquidity$_{i,t}$	A proxy for the bond's liquidity, measured as the bond's average absolute return for time *t* scaled by its trading volume.
CDS Spread$_{i,t}$	The premium for a five-year, single-name credit default swap (CDS) on reference entity *i* at time *t*. For regression specifications on a daily frequency, this represents the CDS spread for entity *i* on day *t*, and for regression specifications on a monthly frequency, this represents the average CDS spread for entity *i* over month *t*.
Credit Spread$_{i,t}$	The difference between the bond's yield and the yield on the associated Treasury at the same maturity.
Crisis$_t$	An indicator variable that equals one in the year-months spanning December 2007 to June 2009,[23] and zero otherwise.
Default Correlation$_{i,t}$	The average pairwise correlation in default probability of bond *i* with all other bonds at time *t*, which we measure via rolling 30-day correlations of CDS premia. We also construct an economy-wide measure, *Aggregate Default Correlation*$_t$, calculated as the average *Default Correlation* across all bond issues in each year-month *t*.
ebp$_t$	*ebp* stands for *excess bond premium*, which represents the risk premium or average price of bearing exposure to credit risk in excess of the compensation for expected defaults, as estimated by Gilchrist and Zakrajsek (2012).[24]
Investment Grade$_{i,t}$	A dummy variable that equals one if the bond issue's rating is at least BBB (or its equivalent depending on the rating agency, as reported by Mergent FISD), and zero otherwise.
Leverage$_{i,t}$	The firm's leverage ratio, calculated as the book value of debt divided by the sum of the market value of equity and the book value of debt
r10$_t$	The riskless rate, represented by the yield on the 10-year Treasury note.
S&P Return$_t$	The monthly return on the S&P500 composite index.
Yield Slope$_t$	The difference between the 10-year and 2-year Treasury yields.
Volatility$_{i,t}$	The firm's 30-day implied volatility as reported by OptionMetrics.
VIX$_t$	The CBOE Volatility Index, which measures the implied volatility of options on the S&P500 index.

[23] We define the period as specified by the Federal Reserve. See "The Great Recession of 2007-09" (Federal Reserve Bank of New York, 2013).

[24] We use the *ebp* data provided at: http://people.bu.edu/sgilchri/Data/data.htm

Appendix B. Descriptions, Data Sources, and Discussion of Variables

In this section, we describe our filtering process, and we describe our regression variables along with the corresponding data source(s).

Firm Leverage

For each firm, we calculate leverage each month as the ratio of the firm's book value of debt to the sum of its market value of equity and book value of debt:

$$Leverage_{i,t} = \frac{Book\ Value\ of\ Debt_{i,t}}{Market\ Value\ of\ Equity_{i,t} + Book\ Value\ of Debt_{i,t}} \qquad \text{(Eq. B.1)}$$

Following Collin-Dufresne, Goldstein, and Martin (2001), we obtain equity valuation from CRSP, which we match to the most recent quarterly book value of debt obtained from COMPUSTAT.

Volatility

We use 30-day implied volatilities, obtained from OptionMetrics, to capture a forward-looking measure of the firm's volatility. We collect this information on the first day of each month in our sample.

Market Uncertainty

VIX, the CBOE Volatility Index which we obtain from OptionMetrics, is designed to capture overall market volatility, as measured by the implied volatility of options on the S&P500 composite index.

Overall Market Condition

Following Collin-Dufresne, Goldstein, and Martin (2001), we use monthly returns on the S&P500 composite index, which we obtain from CRSP, to capture the overall state of the economy.

Excess Bond Premium (ebp)

Following Gilchrist and Zakrajsek (2012), *ebp*, the excess bond premium, represents the average price of bearing exposure to credit risk in excess of the compensation for expected defaults over time. We obtain *ebp* data from http://people.bu.edu/sgilchri/Data/data.htm

Riskless Rate (r10)

Following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009), among others, we use the yield on the 10-year Treasury note, which we obtain from FRED.

Yield Curve Slope

Following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009), among others, we calculate the slope of the yield curve at the difference between the 10-year and 2-year Treasury yields, which are also obtained from FRED. Based on the expectations hypothesis of the term structure of interest rates, we interpret this measure as the market perception regarding the expectation of future short-term rates.

Bond Illiquidity

Following recent literature studying the impact of bond-market illiquidity on fixed-income pricing (Dick-Nielson, Feldhütter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012), we construct the Amihud (2002)-based measure of illiquidity as the bond's average absolute return scaled by trading volume for trades executed during time *t*:

$$Amihud\ Illiquidity_{i,t} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_j|}{v_j} \qquad \text{(Eq. B.2)}$$

Intuitively, greater price impact indicates less liquidity in the market. We obtain trading activity and returns data from TRACE. Although we employ the *Amihud Illiquidity* measure throughout our tabulated analyses, we check the robustness of our results using alternative liquidity proxies, such as trading volume and trading interval, which we also obtain from TRACE.

Credit Spread

Following Bessembinder, Kahle, Maxwell, and Wu (2009) and Friewald, Jankowitsch, and Subrahmanyam (2012), among others, we employ the newly available bond-pricing data from the Trade Reporting and Compliance Engine (TRACE), which provides intra-day price and yield information on individual bond transactions along with associated execution times. Specifically, to calculate daily bond yields, we begin by eliminating trades below \$100,000. We then calculate a trade-weighted average of the remaining transaction yields, thereby minimizing the effect of the relatively large bid-ask bounce associated with smaller trades (Bessembinder et al., 2009). Using these daily-yield calculations, we derive monthly bond yields by taking the trade-weighted average of daily yields.

Next, we merge our monthly-yield data with Mergent FISD to obtain various bond characteristics, such as credit rating and time to maturity. We then proceed to remove bond issues from our sample that (i) have embedded options, (ii) have defaulted, (iii) belong to issuers in the financial sector or utilities, (iv) have a convertibility feature, (v) are denominated in a foreign currency, or (vi) are an asset-backed issue. That is, we keep only the plain-vanilla, single-name corporate bond issues.

Finally, we calculate the credit spread for each issue *i* at year-month *t* as the difference between the bond's yield and the yield on the associated Treasury at the same maturity, which we obtain from the Federal Reserve Economic Data (FRED):

$$CreditSpread_{i,t} = Yield_{i,t} - TreasuryRate_{i,t} \qquad \text{(Eq. B.3)}$$

Specifically, we use the rates obtained from FRED to construct the term structure for each year-month *t*, interpolating between provided rates in the term structure to match the time to maturity of bond issue *i* at time *t*.

Appendix C. Changes in Residual Default Correlation and Credit Spreads (Table 9)

This table presents all coefficient estimates from pooled OLS regressions of *ΔCredit Spread*$_{i,t}$ on various explanatory factors, whereas Table 9 presents only our variables of interest. As before, *t*-statistics are calculated using White-robust standard errors adjusted for firm-level clustering. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel A. Changes in Credit Spreads and Bond-Level Residual Default Correlation					
Δ *Residual Default Correlation*$_{i,t}$	0.118***	0.039***	0.252***	0.062***	0.203***
	(6.75)	(3.86)	(4.50)	(6.35)	(5.01)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.206***	0.193***	0.178***	0.129***	0.250***
	(7.72)	(4.26)	(6.55)	(5.22)	(4.39)
Δ *Inv. Grade Dummy*$_{i,t}$	0.002	0.018	-0.128	-0.169***	0.117***
	(0.06)	(0.59)	(-0.43)	(-4.42)	(2.90)
Δ *Leverage*$_{i,t}$	3.910***	2.413***	7.404***	2.008***	4.026***
	(8.49)	(6.22)	(6.67)	(3.54)	(6.28)
Δ *Volatility*$_{i,t}$	0.587***	0.192***	1.022***	0.478***	0.633***
	(7.68)	(3.41)	(5.32)	(7.38)	(4.80)
Macro Characteristics:					
Δ *r10*$_t$	-0.609***	-0.383***	-0.844***	-0.357***	-1.264***
	(-10.68)	(-8.41)	(-8.49)	(-13.79)	(-11.39)
Δ *Yield Slope*$_t$	0.495***	0.247***	0.480***	0.323***	1.058***
	(9.27)	(4.77)	(5.39)	(10.87)	(8.13)
Δ *ebp*$_t$	0.480***	0.126***	1.028***	0.389***	0.758***
	(10.44)	(9.88)	(11.56)	(13.76)	(6.06)
S&P Return$_t$	-0.003	-0.007***	0.023***	0.000	-0.017**
	(-1.50)	(-5.90)	(5.72)	(0.23)	(-2.55)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.162	0.087	0.263	0.173	0.202

Appendix C. Table continued.

Variable	Coefficient Estimate (t-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel B. Changes in Credit Spreads and Aggregate Residual Default Correlation					
Δ *Aggregate Residual Default Correlation*$_{i,t}$	0.250***	0.108***	0.372***	0.156***	0.397***
	(8.97)	(7.06)	(5.68)	(10.36)	(5.65)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.205***	0.192***	0.178***	0.128***	0.248***
	(7.65)	(4.24)	(6.56)	(5.21)	(4.32)
Δ *Inv. Grade Dummy*$_{i,t}$	0.019	0.027	-0.107	-0.152***	0.138***
	(0.65)	(0.88)	(-0.37)	(-4.13)	(3.55)
Δ *Leverage*$_{i,t}$	3.940***	2.419***	7.521***	2.066***	4.037***
	(8.53)	(6.24)	(6.79)	(3.63)	(6.24)
Δ *Volatility*$_{i,t}$	0.591***	0.201***	1.004***	0.479***	0.643***
	(7.49)	(3.61)	(5.00)	(7.35)	(4.53)
Macro Characteristics:					
Δ $r10_t$	-0.603***	-0.381***	-0.842***	-0.354***	-1.247***
	(-10.53)	(-8.38)	(-8.26)	(-13.75)	(-10.83)
Δ *Yield Slope*$_t$	0.480***	0.246***	0.448***	0.311***	1.036***
	(8.99)	(4.75)	(4.38)	(10.62)	(7.76)
Δ ebp_t	0.494***	0.137***	1.030***	0.398***	0.779***
	(10.52)	(10.31)	(11.62)	(13.84)	(6.12)
S&P Return$_t$	-0.002	-0.007***	0.023***	0.001	-0.015**
	(-1.21)	(-5.69)	(5.66)	(0.55)	(-2.46)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.164	0.088	0.264	0.177	0.205

Appendix D. Changes in Residual Default Correlation and CDS Spreads (Table 10)

This table presents all coefficient estimates from pooled OLS regressions of *Δ CDS Spread$_{i,t}$* on various explanatory factors, whereas Table 10 presents only our variables of interest. As before, *t*-statistics are calculated using White-robust standard errors adjusted for firm-level clustering. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel A. Changes in CDS Spreads and Bond-Level Residual Default Correlation					
Δ *Residual Default Correlation$_{i,t}$*	0.073***	0.024***	0.209***	0.016**	0.165***
	(3.52)	(2.87)	(3.04)	(2.16)	(3.38)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity$_{i,t}$*	0.089***	0.034**	0.119***	0.020***	0.124***
	(3.19)	(2.52)	(4.08)	(3.18)	(5.33)
Δ *Inv. Grade Dummy$_{i,t}$*	-0.015	-0.020	0.095	-0.088	0.082**
	(-0.35)	(-0.41)	(0.66)	(-0.98)	(2.31)
Δ *Leverage$_{i,t}$*	3.440***	2.255***	6.050***	1.860***	3.186***
	(6.99)	(5.63)	(5.13)	(4.13)	(5.04)
Δ *Volatility$_{i,t}$*	0.347***	0.163**	0.572**	0.175***	0.442**
	(2.90)	(2.57)	(2.02)	(5.57)	(2.07)
Macro Characteristics:					
Δ *r10$_t$*	-0.427***	-0.239***	-0.782***	-0.210***	-0.982***
	(-7.00)	(-5.44)	(-5.99)	(-11.49)	(-6.80)
Δ *Yield Slope$_t$*	0.294***	0.141***	0.187**	0.115***	0.838***
	(4.68)	(2.71)	(2.38)	(5.84)	(5.17)
Δ *ebp$_t$*	0.296***	0.122***	0.361***	0.130***	0.749***
	(3.83)	(6.59)	(3.08)	(7.08)	(3.07)
S&P Return$_t$	-0.005	-0.002**	-0.011	-0.001	-0.023*
	(-1.44)	(-2.22)	(-1.25)	(-0.64)	(-1.80)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.075	0.072	0.101	0.168	0.117

Appendix D. Table continued.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel B. Changes in CDS Spreads and Aggregate Residual Default Correlation					
Δ *Aggregate Residual Default Correlation*$_{i,t}$	0.169***	0.094***	0.306**	0.056***	0.367***
	(3.39)	(5.63)	(2.51)	(4.21)	(2.92)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.088***	0.033**	0.119***	0.020***	0.122***
	(3.20)	(2.48)	(4.17)	(3.15)	(5.30)
Δ *Inv. Grade Dummy*$_{i,t}$	-0.003	-0.011	0.112	-0.081	0.103***
	(-0.07)	(-0.24)	(0.82)	(-0.91)	(2.68)
Δ *Leverage*$_{i,t}$	3.463***	2.265***	6.146***	1.886***	3.204***
	(7.00)	(5.68)	(5.16)	(4.18)	(5.07)
Δ *Volatility*$_{i,t}$	0.350***	0.173***	0.557*	0.176***	0.454**
	(2.88)	(2.72)	(1.95)	(5.55)	(2.03)
Macro Characteristics:					
Δ *r10*$_t$	-0.423***	-0.237***	-0.781***	-0.208***	-0.965***
	(-6.95)	(-5.41)	(-5.92)	(-11.48)	(-6.56)
Δ *Yield Slope*$_t$	0.283***	0.140***	0.162	0.110***	0.816***
	(4.66)	(2.69)	(1.62)	(5.65)	(5.10)
Δ *ebp*$_t$	0.306***	0.132***	0.363***	0.134***	0.771***
	(3.80)	(6.68)	(3.09)	(7.06)	(3.05)
S&P Return$_t$	-0.004	-0.002*	-0.011	-0.000	-0.021*
	(-1.37)	(-1.82)	(-1.24)	(-0.42)	(-1.79)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.076	0.076	0.102	0.170	0.119

Table 1. Bond/Firm-Specific and Macroeconomic Characteristics

This table presents descriptive statistics of various bond, firm, and macroeconomic characteristics for our sample of 1,901 US corporate bonds from July 2002 to August 2013. Panel A presents our main variable of interest: *Default Correlation*, which is the average pairwise correlation in default probability of a given bond with all other bond issues at a given point in time, which we measure via rolling 30-day correlations of CDS premia. Panel B presents other bond/firm characteristics, where: *Amihud Illiquidity* is measured as the bond's average absolute return at each point in time, scaled by its trading volume; *Credit Spread* is the difference between a bond's yield and the yield on the associated Treasury at the same maturity; *CDS Spread* is the average % premium for a five-year, single-name credit default swap (CDS) on reference entity *i* for month *t*; *Investment Grade Dummy* is a dummy variable that equals one if the bond issue's rating is at least BBB (or its equivalent depending on the rating agency), and zero otherwise; *Leverage* is measured as the book value of debt divided by the sum of the market value of equity and the book value of debt; *Time to* Maturity is the remaining time to maturity on the issue in question; and *Volatility* is the firm's 30-day implied volatility as reported by OptionMetrics. Panel C presents macroeconomic characteristics, where *r10* is the % yield on the10-year Treasury note; *S&P Return* is the % monthly return on the S&P500 composite index; *Yield Slope* is the difference between the 10-year and 2-year Treasury yields; *VIX* is the CBOE Volatility Index; *ebp* is the % excess bond premium, which represents the risk premium or average price of bearing exposure to credit risk in excess of the compensation for expected defaults, as estimated by Gilchrist and Zakrajsek(2012).

Variable	N	Mean	Median	(Stdev.)
		Panel A. Default Correlation		
Default Correlation	63,377	0.29	0.29	(0.24)
		Panel B. Other Bond/Firm Characteristics		
Amihud Illiquidity	63,377	0.18	0.09	(0.38)
Credit Spread (%)	63,377	2.08	1.33	(2.33)
CDS Spread (%)	63,377	1.54	0.70	(2.54)
Investment Grade Dummy	63,377	0.66	1.00	(0.47)
Leverage	63,377	0.29	0.25	(0.18)
Time to Maturity	63,377	9.20	6.38	(8.56)
Volatility	63,377	0.30	0.24	(0.20)
		Panel C. Macroeconomic Characteristics		
r10 (%)	134	3.60	3.84	(0.98)
S&P Return (%)	134	0.473	1.106	(4.40)
Yield Slope	134	1.57	1.77	(0.92)
VIX	134	0.21	0.18	(0.09)
ebp (%)	134	-0.011	-0.255	(0.79)

Table 2. Determinants of Correlated Default Risk

This table presents estimates from the following time-series OLS regression:

$$AggregateDefaultCorrelation_t = \alpha + X_{t-1}\,\gamma + \varepsilon_t$$

Aggregate Default Correlation$_t$, the dependent variable, is the average *Default Correlation* across all bond issues in month/year *t*. The vector of explanatory variables, X_{t-1}, consists of: *r10$_{t-1}$*, *Yield Slope$_{t-1}$*, *S&P Return$_{t-1}$*, *VIX$_{t-1}$*, *Aggregate Amihud Illiquidity$_{t-1}$*, *Aggregate Leverage$_{t-1}$*, *ebp$_{t-1}$*, and *Crisis$_{t-1}$*, which are described in Appendix A. Our sample consists of 1,901 US corporate bonds from July 2002 to August 2013. *T*-statistics are calculated using Newey-West standard errors with 4 lags. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)			
	(1)	(2)	(3)	(4)
Macro Characteristics:				
r10$_{t-1}$	-0.027**	-0.032**	-0.026**	-0.031***
	(-2.13)	(-2.44)	(-2.16)	(-2.71)
Yield Slope$_{t-1}$	0.019	0.017	0.019	0.016
	(1.10)	(0.99)	(1.14)	(0.99)
S&P Return$_{t-1}$	-0.438*	-0.467*	-0.432*	-0.469*
	(-1.77)	(-1.86)	(-1.72)	(-1.82)
VIX$_{t-1}$	-0.506*	-0.413	-0.346	-0.026
	(-1.70)	(-1.30)	(-1.05)	(-0.08)
Aggregate Amihud Illiquidity$_{t-1}$	0.900**	0.496	0.995***	0.482
	(2.49)	(1.23)	(2.89)	(1.28)
Aggregate Leverage$_{t-1}$	0.364	0.166	0.562	0.475
	(0.90)	(0.40)	(1.46)	(1.40)
ebp$_{t-1}$			-0.037	-0.077***
			(-1.03)	(-2.80)
Crisis$_{t-1}$		0.079**		0.121***
		(2.04)		(3.02)
No. of observations	133	133	133	133
Adjusted R-squared	0.099	0.116	0.100	0.141

Table 3. Correlated Default Risk and the Incidence of Bankruptcy Filings

This table presents estimates from the following time-series OLS regression:

$$\log(Bankruptcy\ Filings_t) = \alpha + \beta \times AggregateDefaultCorrelation_t + X_t\,\gamma + \varepsilon_t$$

log(*BankruptcyFilings*$_t$), is the log of the number of new business bankruptcy filings, as reported by United States Courts, in month/year *t*. *Aggregate Default Correlation*$_t$ is the average *Default Correlation* across all bond issues in month/year *t*, and $X_{i,t}$ is a vector of the following control variables: *r10*$_t$, which is the yield on the 10-year Treasury note; *Yield Slope*$_t$, which is the difference between the 10-year and the 2-year Treasury yields; *S&P Return*$_t$, which is the monthly return on the S&P500 composite index; *LogGDP*$_t$, which we obtain from the Federal Reserve Economic Data (FRED) database; *Industrial Production*$_t$, which measures the real output of all relevant establishments located in the United States (also obtained from FRED); *Inflation*$_t$, which we also obtain from FRED; and *Unemployment*$_t$, as reported by the Bureau of Labor Statistics. Column 1 presents the contemporaneous specification, whereby the dependent and independent variables are from time *t*, and Column 2 presents the lagged specification, whereby the independent variables are from time *t-1*. Our sample consists of 1,901 US corporate bonds from July 2002 to August 2013. *T*-statistics are calculated using Newey-West standard errors with 4 lags. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)	
	(1) Contemporaneous	(2) Lagged
Aggregate Default Correlation$_t$	0.166**	0.163**
	(2.41)	(2.14)
Other Macro Characteristics:		
r10$_t$	-0.044	-0.041
	(-1.46)	(-1.360)
Yield Slope$_t$	0.049	0.076
	(0.87)	(1.21)
S&P Return$_t$	-0.293**	-0.298**
	(-1.98)	(-2.03)
Log GDP$_t$	0.805**	1.189***
	(2.53)	(3.25)
Industrial Production$_t$	-0.047***	-0.053***
	(-5.32)	(-4.88)
Inflation$_t$	0.035*	0.033
	(1.83)	(1.50)
Unemployment$_t$	0.028	-0.004
	(0.98)	(-0.11)
No. of observations	134	133
Adjusted R-squared	0.77	0.75

Table 4. Bond/Firm-Specific and Macro Characteristics: A Subsample Analysis

This table presents the means of various bond, firm, and macroeconomic characteristics within various sub-segments of our sample of 1,901 US corporate bonds from July 2002 to August 2013. Panel A presents our main variable of interest: *Default Correlation*, which is the mean pairwise correlation in default probability of a given bond with all other bond issues at a given point in time, which we measure via rolling 30-day correlations of CDS premia. Panel B presents other bond/firm characteristics: *Amihud Illiquidity*, *Credit Spread*, *CDS Spread*, *Investment Grade Dummy*, *Leverage*, *Time to* Maturity, and *Volatility*, which are described in Appendix A. Panel C presents macroeconomic characteristics: *r10*, *S&P Return*, *Yield Slope*, *VIX*, and *ebp*, which are also described in Appendix A.

Variable	Mean				
	Entire Sample	Non-Crisis	Crisis (12/07-6/09)	Investment Grade	Non-Inv. Grade
			Panel A. Default Correlation		
Default Correlation	0.29	0.27	0.38	0.28	0.29
			Panel B. Other Bond/Firm Characteristics		
Amihud Illiquidity	0.18	0.15	0.31	0.16	0.21
Credit Spread (%)	2.08	1.64	3.98	1.31	3.61
CDS Spread (%)	1.54	1.30	2.54	0.67	3.24
Investment Grade Dummy	0.66	0.64	0.75	1.00	0.00
Leverage	0.29	0.28	0.34	0.22	0.43
Time to Maturity	9.20	9.16	9.39	9.57	8.48
Volatility	0.30	0.26	0.48	0.26	0.37
No. of Observations	63,377	51,312	12,065	41,951	21,426
			Panel C. Macroeconomic Characteristics		
r10 (%)	3.60	3.63	3.49	---	---
S&P Return (%)	0.473	0.84	-1.32	---	---
Yield Slope	1.57	1.51	1.88	---	---
VIX	0.21	0.18	0.32	---	---
ebp (%)	-0.011	-0.25	1.16	---	---
No. of Observations	134	111	23	---	---

Table 5. Changes in Credit Spreads and Correlated Default Risk: A Subsample Analysis

This table presents estimates from the following pooled OLS regression:

$$\Delta CreditSpread_{i,t} = \alpha + \beta \times \Delta\, DefaultCorrelation_{i,t} + X_{i,t}\,\gamma + \varepsilon_{i,t}$$

Δ*Credit Spread*$_{i,t}$, the dependent variable, is the change in the credit spread of bond *i* from time *t-1* to time *t*. Panel A features Δ*Default Correlation*$_{i,t}$, and Panel B *features* Δ*Aggregate Default Correlation*$_t$. The vector of explanatory variables, $X_{i,t}$, consists of: Δ*Amihud Illiquidity*$_{i,t}$, Δ*Investment Grade Dummy*$_{i,t}$, Δ*Leverage*$_{i,t}$, Δ*Volatility*$_{i,t}$, $\Delta r10_t$, Δ*Yield Slope*$_t$, Δebp_t, and *S&P Return*$_t$, which are described in Appendix A. Our sample consists of 1,901 US corporate bonds from July 2002 to August 2013. *T*-statistics are calculated using White-robust standard errors adjusted for firm-level clustering. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel A. Changes in Credit Spreads and Bond-Level Default Correlation					
Δ *Default Correlation*$_{i,t}$	0.124***	0.044***	0.257***	0.064***	0.222***
	(6.97)	(4.41)	(4.63)	(6.67)	(5.36)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.206***	0.193***	0.178***	0.129***	0.249***
	(7.71)	(4.26)	(6.55)	(5.21)	(4.38)
Δ *Inv. Grade Dummy*$_{i,t}$	0.003	0.019	-0.126	-0.168***	0.118***
	(0.10)	(0.62)	(-0.43)	(-4.39)	(2.90)
Δ *Leverage*$_{i,t}$	3.913***	2.416***	7.411***	2.008***	4.032***
	(8.50)	(6.23)	(6.68)	(3.54)	(6.31)
Δ *Volatility*$_{i,t}$	0.587***	0.192***	1.023***	0.478***	0.636***
	(7.67)	(3.42)	(5.31)	(7.37)	(4.80)
Macro Characteristics:					
$\Delta\, r10_t$	-0.608***	-0.382***	-0.843***	-0.356***	-1.264***
	(-10.67)	(-8.40)	(-8.49)	(-13.77)	(-11.37)
Δ *Yield Slope*$_t$	0.494***	0.247***	0.478***	0.322***	1.055***
	(9.26)	(4.77)	(5.35)	(10.86)	(8.10)

Table 5 continued.

Δ *ebp*$_t$	0.481***	0.127***	1.027***	0.389***	0.760***
	(10.42)	(9.92)	(11.55)	(13.77)	(6.06)
S&P Return$_t$	-0.003	-0.007***	0.023***	0.000	-0.016**
	(-1.49)	(-5.89)	(5.72)	(0.23)	(-2.54)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.162	0.087	0.264	0.174	0.203

Panel B. Changes in Credit Spreads and Aggregate Default Correlation

Δ *Aggregate Default Correlation*$_t$	0.266***	0.143***	0.341***	0.161***	0.435***
	(8.64)	(7.50)	(5.03)	(10.02)	(5.66)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.205***	0.192***	0.179***	0.128***	0.248***
	(7.66)	(4.22)	(6.57)	(5.21)	(4.33)
Δ *Inv. Grade Dummy*$_{i,t}$	0.013	0.026	-0.108	-0.152***	0.121***
	(0.44)	(0.88)	(-0.37)	(-4.17)	(3.14)
Δ *Leverage*$_{i,t}$	3.933***	2.418***	7.509***	2.054***	4.028***
	(8.52)	(6.24)	(6.77)	(3.61)	(6.24)
Δ *Volatility*$_{i,t}$	0.592***	0.204***	1.009***	0.480***	0.645***
	(7.49)	(3.65)	(5.03)	(7.36)	(4.52)
Macro Characteristics:					
Δ *r10*$_t$	-0.601***	-0.379***	-0.840***	-0.353***	-1.246***
	(-10.52)	(-8.36)	(-8.21)	(-13.73)	(-10.80)
Δ *Yield Slope*$_t$	0.482***	0.246***	0.469***	0.314***	1.035***
	(9.00)	(4.74)	(4.56)	(10.68)	(7.73)
Δ *ebp*$_t$	0.493***	0.139***	1.036***	0.397***	0.778***
	(10.52)	(10.41)	(11.61)	(13.83)	(6.13)
S&P Return$_t$	-0.002	-0.007***	0.024***	0.001	-0.016**
	(-1.25)	(-5.61)	(5.80)	(0.51)	(-2.48)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.164	0.090	0.263	0.176	0.204

Table 6. Changes in CDS Spreads and Correlated Default Risk: A Subsample Analysis

This table presents estimates from the following pooled OLS regression:

$$\Delta\, CDS\ Spread_{i,t} = \alpha + \beta \times \Delta\, DefaultCorrelation_{i,t} + X_{i,t}\,\gamma + \varepsilon_{i,t}$$

Δ*CDS Spread*$_{i,t}$, the dependent variable, is the change in the average five-year, single-name credit default swap (CDS) spread on reference entity *i* from month *t-1* to month *t*. Panel A features Δ*Default Correlation*$_{i,t}$, and Panel B *features* Δ*Aggregate Default Correlation*$_t$. The vector of explanatory variables, $X_{i,t}$, consists of: Δ*Amihud Illiquidity*$_{i,t}$, Δ*Investment Grade Dummy*$_{i,t}$, Δ*Leverage*$_{i,t}$, Δ*Volatility*$_{i,t}$, $\Delta r10_t$, Δ*Yield Slope*$_t$, Δebp_t, and *S&P Return*$_t$, which are described in Appendix A. Our sample consists of 1,901 US corporate bonds from July 2002 to August 2013. *T*-statistics are calculated using White-robust standard errors adjusted for firm-level clustering. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel B.1 Changes in CDS Spreads and Bond-Level Default Correlation					
Δ *Default Correlation*$_{i,t}$	0.077***	0.027***	0.213***	0.018**	0.179***
	(3.44)	(3.10)	(2.96)	(2.37)	(3.33)
Other Bond/Firm Characteristics:					
Δ *Amihud Illiquidity*$_{i,t}$	0.089***	0.034**	0.119***	0.020***	0.123***
	(3.19)	(2.51)	(4.09)	(3.18)	(5.34)
Δ *Inv. Grade Dummy*$_{i,t}$	-0.015	-0.019	0.096	-0.087	0.083**
	(-0.33)	(-0.40)	(0.67)	(-0.97)	(2.31)
Δ *Leverage*$_{i,t}$	3.442***	2.256***	6.056***	1.861***	3.191***
	(6.99)	(5.63)	(5.13)	(4.14)	(5.05)
Δ *Volatility*$_{i,t}$	0.347***	0.163**	0.573**	0.175***	0.444**
	(2.89)	(2.58)	(2.02)	(5.57)	(2.08)
Macro Characteristics:					
Δ *r10*$_t$	-0.427***	-0.239***	-0.781***	-0.209***	-0.982***
	(-7.00)	(-5.44)	(-5.99)	(-11.48)	(-6.79)
Δ *Yield Slope*$_t$	0.293***	0.141***	0.186**	0.115***	0.836***
	(4.69)	(2.71)	(2.33)	(5.84)	(5.17)

Table 6 continued.

Δ ebp_t	0.296***	0.122***	0.360***	0.130***	0.750***
	(3.82)	(6.56)	(3.08)	(7.09)	(3.06)
$S\&P\ Return_t$	-0.005	-0.002**	-0.011	-0.001	-0.023*
	(-1.44)	(-2.21)	(-1.25)	(-0.64)	(-1.80)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.075	0.072	0.101	0.168	0.117
Panel B.2 Changes in CDS Spreads and Aggregate Default Correlation					
Δ $Aggregate\ Default\ Correlation_t$	0.182***	0.117***	0.291**	0.059***	0.400***
	(3.32)	(5.39)	(2.37)	(3.95)	(2.94)
Other Bond/Firm Characteristics:					
Δ $Amihud\ Illiquidity_{i,t}$	0.088***	0.033**	0.120***	0.020***	0.122***
	(3.20)	(2.47)	(4.16)	(3.15)	(5.30)
Δ $Inv.\ Grade\ Dummy_{i,t}$	-0.007	-0.012	0.112	-0.080	0.088**
	(-0.17)	(-0.26)	(0.82)	(-0.91)	(2.46)
Δ $Leverage_{i,t}$	3.459***	2.263***	6.142***	1.883***	3.195***
	(7.00)	(5.68)	(5.15)	(4.17)	(5.07)
Δ $Volatility_{i,t}$	0.351***	0.174***	0.561*	0.176***	0.455**
	(2.88)	(2.73)	(1.96)	(5.56)	(2.04)
Macro Characteristics:					
Δ $r10_t$	-0.421***	-0.236***	-0.778***	-0.208***	-0.964***
	(-6.95)	(-5.40)	(-5.91)	(-11.48)	(-6.55)
Δ $Yield\ Slope_t$	0.284***	0.140***	0.176*	0.111***	0.815***
	(4.66)	(2.69)	(1.79)	(5.70)	(5.08)
Δ ebp_t	0.306***	0.133***	0.368***	0.133***	0.770***
	(3.80)	(6.60)	(3.09)	(7.03)	(3.06)
$S\&P\ Return_t$	-0.004	-0.002*	-0.010	-0.000	-0.022*
	(-1.38)	(-1.77)	(-1.21)	(-0.43)	(-1.79)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.076	0.076	0.101	0.170	0.119

Table 7. CDS Spreads, CDS Liquidity, and Recovery Rates

Presented below are estimates from the following pooled OLS regressions:

1. $Daily\ CDS\ Spread_{i,t} = \alpha + X_{i,t}\beta + \varepsilon_{i,t}$ (Panel A)
2. $Monthly\ Spread\ Correlation_{i,t} = \alpha + X_{i,t}\beta + \varepsilon_{i,t}$ (Panel B.1)
3. $Monthly\ Spread\ Correlation_{i,t} = \alpha + \gamma_{i,t}\beta + \varepsilon_{i,t}$ (Panel B.2 & Panel B.3.)

CDS Spread$_{i,t}$, the dependent variable in Panel A, is the daily, single-name CDS premium on a five-y contract on reference entity i at time t. *Monthly Spread Correlation$_{i,t}$*, the dependent variable in Pane is the average pairwise correlation of CDS spread i with all other CDS spreads measured over preceding 30-day period. $X_{i,t}$ is a vector consisting of the following explanatory variables: *Contributo* which represents the total number of institutions (i.e., market makers) contributing CDS pricing data CDS i on a daily basis, as reported by Markit; *RecoveryRate$_{i,t}$*, which represents the recovery corresponding to each credit curve, which is also reported to Markit by these institutions; and *Cri* which is an indicator variable that equals one during the time spanning December 2007 to June 2009, zero otherwise. For Panel B.2., $\gamma_{i,t}$ is a vector consisting of the following explanatory variab *Correlation-in-Contributors$_{i,t}$*, which is calculated as the average pairwise correlation of the numbe market makers for CDS contract i with the number of market makers for all other CDS contracts over preceding 30-day period; *Correlation-in-RecoveryRate$_{i,t}$*, which is calculated as the average pairv correlation of *RecoveryRate$_i$* with all other *Recovery Rates* over the preceding 30-day period; and indicator variable *Crisis$_t$*. For Panel B.3., $\gamma_{i,t}$ also includes *ebp$_t$*, the excess bond premium at time addition to the aforementioned regressors. Our sample consists of 864 reference entities from July 200 August 2013. *T*-statistics are calculated using White-robust standard errors adjusted for firm-l clustering. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and respectively.

Variable	Coefficient Estimate (*t*-statistic)	
	(1)	(2)
	Panel A. Dependent Variable = Daily CDS Spread$_{i,t}$ (%)	
Contributors$_{i,t}$	-0.106***	-0.122***
	(-4.90)	(-5.36)
Recovery Rate$_{i,t}$	-47.774***	-47.643***
	(-4.23)	(-4.30)
Crisis$_t$		1.761***
		(7.64)
No. of observations	1,212,630	1,212,630
Adjusted R-squared	0.128	0.156

Table 7. CDS Spreads, CDS Liquidity, and Recovery Rates-- Continued

Panel B.1. Dependent Variable = Monthly Spread Correlation$_{i,t}$

Contributors$_{i,t}$	-0.002***	-0.002***
	(-2.65)	(-3.20)
Recovery Rate$_{i,t}$	-0.140	-0.109
	(-1.14)	(-1.09)
Crisis$_t$		0.106***
		(24.19)
No. of observations	71,853	71,853
Adjusted R-squared	0.001	0.030

Panel B.2. Dependent Variable = Monthly Spread Correlation$_{i,t}$

Correlation in Contributors$_{i,t}$	0.345***	0.353***
	(8.50)	(9.14)
Correlation in Recovery Rate$_{i,t}$	0.096***	0.070***
	(11.82)	(9.30)
Crisis$_t$		0.094***
		(22.05)
No. of observations	71,853	71,853
Adjusted R-squared	0.024	0.045

Panel B.3. Dependent Variable = Monthly Spread Correlation$_{i,t}$

Correlation in Contributors$_{i,t}$	0.350***	0.353***
	(9.06)	(9.13)
Correlation in Recovery Rate$_{i,t}$	0.080***	0.070***
	(10.20)	(9.23)
ebp$_t$	0.034***	-0.001
	(13.88)	(-0.47)
Crisis$_t$		0.095***
		(19.27)
No. of observations	71,853	71,853
Adjusted R-squared	0.0342	0.0452

Table 8. Residual Default Correlation and the Incidence of Bankruptcy Filings

This table presents estimates from the following time-series OLS regression:

$$\log(Bankruptcy\ Filings_t) = \alpha + \beta \times Aggregate\ Residual\ DefaultCorr_t + X_t\,\gamma + \varepsilon_t$$

This table replicates Table 3, with the exception that our variable-of-interest is now *Aggregate Residual Default Correlation*$_t$, which is the average *Residual Default Correlation* across all issues *i* at time *t*. *Residual Default Correlation*$_{i,t}$ represents the residual from regressing *Default Correlation*$_{i,t}$ on *Correlation in Contributors*$_{i,t}$ and *Correlation in Recovery Rate*$_{i,t}$. All other specifications are identical to those in Table 3.

Variable	Coefficient Estimate (*t*-statistic)	
	(1) Contemporaneous	(2) Lagged
Aggregate Residual Default Correlation$_t$	0.209***	0.216***
	(3.10)	(3.14)
Other Macro Characteristics:		
r10$_t$	-0.048	-0.045
	(-1.59)	(-1.51)
Yield Slope$_t$	0.049	0.075
	(0.88)	(1.21)
S&P Return$_t$	-0.263*	-0.263*
	(-1.79)	(-1.81)
Log GDP$_t$	0.771**	1.144***
	(2.56)	(3.32)
Industrial Production$_t$	-0.046***	-0.053***
	(-5.54)	(-5.06)
Inflation$_t$	0.035*	0.034
	(1.88)	(1.57)
Unemployment$_t$	0.027	-0.004
	(0.99)	(-0.13)
No. of observations	134	133
Adjusted R-squared	0.77	0.76

Table 9. Changes in Residual Default Correlation and Credit Spreads

This table presents estimates from the following pooled OLS regression:

$$\Delta CreditSpread_{i,t} = \alpha + \beta \times \Delta Residual\ Default\ Correlation_{i,t} + X_{i,t}\,\gamma + \varepsilon_{i,t}$$

Residual Default Correlation$_{i,t}$ represents the residuals from regressing *DefaultCorrelation*$_{i,t}$ on (i) the average pairwise correlation of the recovery rate on firm *i* with the recovery rate of all other firms at time *t*, and (ii) the average pairwise correlation of the number of contributors/market-makers for firm *i* with the number of contributors/market-makers for all other firms at time *t* (intercept included). *Aggregate Residual Default Correlation*$_t$ is then the average *Residual Default Correlation*$_{i,t}$ across all firms at time *t*. All other specifications are identical to those in Table 5. The full array of coefficient estimates is available in Appendix C.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel A. Changes in Credit Spreads and Bond-Level Residual Default Correlation					
Δ Residual Default Correlation$_{i,t}$	0.118***	0.039***	0.252***	0.062***	0.203***
	(6.75)	(3.86)	(4.50)	(6.35)	(5.01)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.162	0.087	0.263	0.173	0.202
Panel B. Changes in Credit Spreads and Aggregate Residual Default Correlation					
Δ Aggregate Residual Default Correlation$_t$	0.250***	0.108***	0.372***	0.156***	0.397***
	(8.97)	(7.06)	(5.68)	(10.36)	(5.65)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.164	0.088	0.264	0.177	0.205

Table 10. Changes in Residual Default Correlation and CDS Spreads

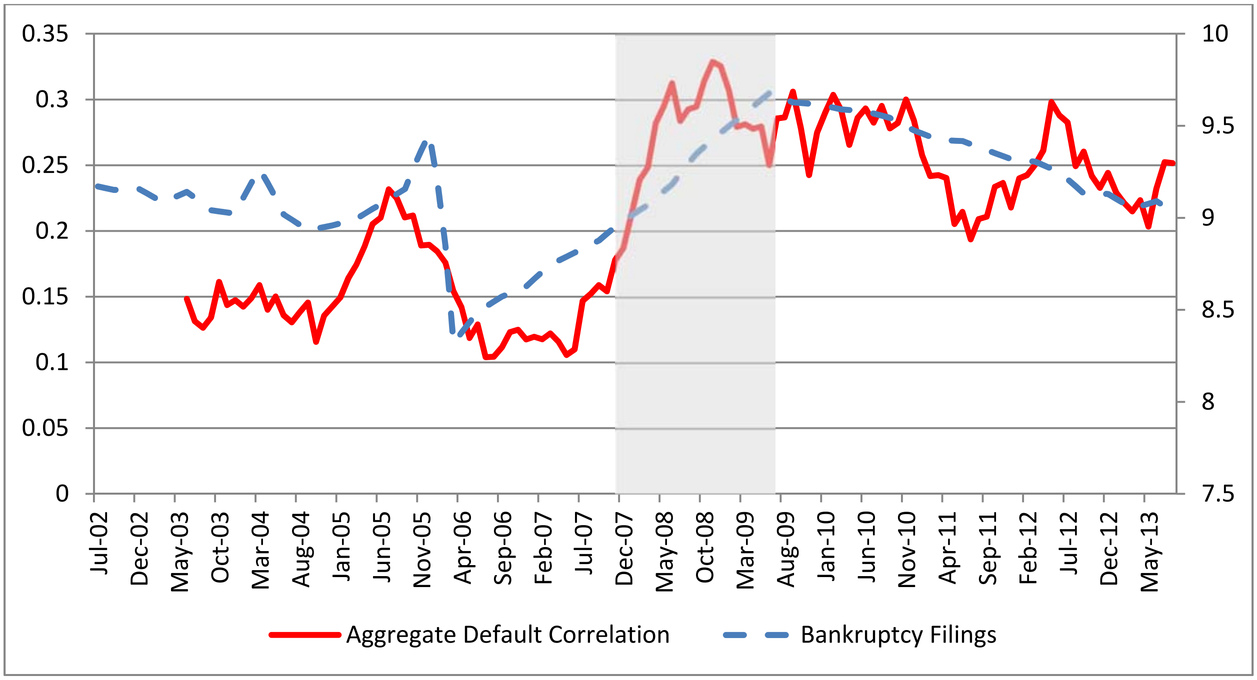
This table presents estimates from the following pooled OLS regression:

$$\Delta\, CDS\ Spread_{i,t} = \alpha + \beta \times \Delta Residual\ Default\ Correlation_{i,t} + X_{i,t}\,\gamma + \varepsilon_{i,t}$$

Residual Default Correlation$_{i,t}$ represents the residuals from regressing *DefaultCorrelation*$_{i,t}$ on (i) the average pairwise correlation of the recovery rate on firm *i* with the recovery rate of all other firms at time *t*, and (ii) the average pairwise correlation of the number of contributors/market-makers for firm *i* with the number of contributors/market-makers for all other firms at time *t* (intercept included). *Aggregate Residual Default Correlation*$_t$ is then the average *Residual Default Correlation*$_{i,t}$ across all firms at time *t*. All other specifications are identical to those in Table 6. The full array of coefficient estimates is available in Appendix D.

Variable	Coefficient Estimate (*t*-statistic)				
	(1) Entire Sample	(2) Non-Crisis	(3) Crisis (Dec 07 – June 09)	(4) Investment Grade	(5) Non-Investment Grade
Panel A. Changes in CDS Spreads and Bond-Level Residual Default Correlation					
Δ Residual Default Correlation$_{i,t}$	0.073***	0.024***	0.209***	0.016**	0.165***
	(3.52)	(2.87)	(3.04)	(2.16)	(3.38)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.075	0.072	0.101	0.168	0.117
Panel B. Changes in CDS Spreads and Aggregate Residual Default Correlation					
Δ Aggregate Residual Default Correlation$_t$	0.169***	0.094***	0.306**	0.056***	0.367***
	(3.39)	(5.63)	(2.51)	(4.21)	(2.92)
No. of observations	63,377	51,312	12,065	41,951	21,426
Adjusted R-squared	0.076	0.076	0.102	0.170	0.119

Figure 1. Aggregate Default Correlation and Bankruptcies over Time



This figure presents the twelve-month moving average of *Aggregate Default Correlation* and (the log of) bankruptcy filings over our sample period. The shaded area spanning December 2007 to June 2009 represents the recent subprime financial crisis. The left-hand axis pertains to aggregate default risk correlation, and the right-hand axis pertains to logged bankruptcies.