Limited Arbitrage between Equity and Credit Markets

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Abstract

We document that short-horizon pricing discrepancies across firms' equity and credit markets are common and that an economically significant proportion of these are anomalous, indicating a lack of integration between the two markets. Proposing a statistical measure of market integration, we investigate whether equity–credit market integration is related to impediments to arbitrage. We find that time variation in integration across a firm's equity and credit markets is related to firm-specific impediments to arbitrage such as liquidity in equity and credit markets and idiosyncratic risk. Our evidence provides a potential resolution to the puzzle of why Merton model hedge ratios match empirically observed stock–bond elasticities (Schaefer and Strebulaev, 2008) and yet the model is limited in its ability to explain the integration between equity and credit markets (Collin-Dufresne, Goldstein, and Martin, 2001).

Keywords: limited arbitrage, market integration, Merton model, capital structure arbitrage

JEL classification: G14, G12, C31

1 Introduction

Merton's (1974) structural model of credit risk implies that changes in stock price and credit spread must be precisely related to prevent arbitrage. Moreover, hedge funds and private equity firms are active in a variety of trading strategies—popularly known as capital structure arbitrage—that attempt to arbitrage across equity and credit markets. Given active arbitrageurs and integrated equity and credit markets, stock returns and changes in credit spreads should be closely related. However, recent research finds the contrary. In a regression of monthly changes in credit spreads on stock returns and other variables, Collin-Dufresne, Goldstein, and Martin (2001) find adjusted R^2 values of the order of 17% to 34%. The authors conclude,

> "Given that structural framework models risky debt as a derivative security which in theory can be perfectly hedged, this adjusted R^2 seems extremely low."

Blanco, Brennan, and Marsh (2005) conduct a similar analysis using weekly changes in credit default swap (CDS) spreads and find that three-quarters of the variation remains unexplained.

This low correlation poses a puzzle for two reasons.[1] First, compared to changes in spreads, Merton model factors do a much better job in explaining the variation in the level of credit spreads (Cremers, Driessen, Maenhout, and Weinbaum, 2008; Ericsson, Jacobs, and Oviedo, 2009; Zhang, Zhou, and Zhu, 2009). With our data, a cross-sectional regression of the average five-year CDS spread over 2001–2009 on the firms' average debt ratio and stock return volatility results in an adjusted R^2 of 56%. Second, Schaefer and Strebulaev (2008) document that the empirical sensitivity of bond returns to stock returns is roughly of the order of magnitude predicted by the Merton model.

How can the Merton model provide reasonable hedge ratios and yet not explain the integration of equity–credit markets? The existing literature provides two hypotheses regarding why equity–credit market correlations may be low. First, a low correlation can result from wealth transfers across shareholders and bondholders, as, for example, when there are unexpected changes in a firm's volatility and debt.[2] Indeed, changes in equity volatility are an explanation

[1] Collin-Dufresne, Goldstein, and Martin (2001) document the existence of a single large principal component in the residuals of the regression, and therefore suggest that the low correlation is explained by an unobserved factor. Recent work by Cremers, Driessen, Maenhout, and Weinbaum (2008) and Ericsson, Jacobs, and Oviedo (2009) indicates that, after including option-based information, there is little evidence of a single large principal component. These papers do not provide any alternative explanation for the low R-square.

[2] Merton's (1974) model assumes constant firm volatility and debt. Initial attempts to make the model more realistic focused on specifications for the default boundary, recovery, and the stochastic process determining the

for pricing discrepancies in the equity option market (Bakshi, Cao, and Chen, 2000). Second, the low correlation may be explained by a non-structural pricing model where the credit market prices a factor that is not priced in the equity market. For example, the credit market may price a credit market-specific systematic liquidity factor. Longstaff, Mithal, and Neis (2005) and Chen, Lesmond, and Wei (2007) document liquidity components in corporate bond spreads. By the first hypothesis, wealth transfers between shareholders and bondholders falsely signal a lack of integration. By the second hypothesis, the low correlation between equity and credit markets is to be expected because, when markets price different factors, by definition, the two markets are not integrated. The common implication of both these hypotheses is that Merton model pricing discrepancies are *not* anomalies when evaluated against the true credit pricing model.

This paper proposes and investigates a third hypothesis, that short-term Merton model pricing discrepancies are, at least in part, anomalies, and the lack of integration of the two markets is related to impediments to arbitrage. Impediments and other limits to arbitrage can prevent arbitrageurs such as hedge funds from investing the capital required to eliminate pricing anomalies, thereby limiting equity–credit market integration. Our study is the first to investigate the possibility that limited arbitrage explains integration across firms' equity and credit markets.[3] The CDS–equity market setting is a singularly useful laboratory to test the hypothesis, not only because of its size but also because of the participation of active and sophisticated arbitrageurs.

Limited arbitrage is a natural hypothesis to explore, because convergence trades across equity and credit markets are, in practice, not a zero-capital riskless arbitrage as modeled in structural models. When faced with mispricing, arbitrageurs will limit the capital deployed because of existing or potential funding constraints (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009) and liquidity and other costs associated with undertaking the arbitrage (e.g., Pontiff, 1996, 2006). In addition to institutional constraints (Merton, 1987), mispricing will persist over time because arbitrage capital can accumulate slowly for a number of reasons such as limited trader attentiveness (Duffie, 2010). Arbitrage activity may be expected to

underlying firm value or leverage (see, e.g., Black and Cox, 1976; Leland, 1994; Leland and Toft, 1996; Longstaff and Schwartz, 1995; Anderson and Sundaresan, 1996; Collin-Dufresne and Goldstein, 2001). More recently, there has been an attempt to incorporate macroeconomic and business cycle effects, as in Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), and Bhamra, Keuhn, and Strebulaev (2010a, 2010b).

[3] Limits to arbitrage have been invoked for a wide range of anomalies, including the closed-end fund discount (Pontiff, 1996), violations of put–call parity (Ofek, Richardson, and Whitelaw, 2004), negative stub values (Mitchell, Pulvino, and Stafford, 2002; Lamont and Thaler, 2003), and the observation of a negative basis across CDS and bond spreads (see also related work by Ali, Hwang, and Trombley, 2003; Mitchell, Pedersen, and Pulvino, 2007; Gabaix, Krishnamurthy, and Vigneron, 2007).

reduce pricing discrepancies, on average, but not necessarily completely or always (Xiong, 2001; Kondor, 2009).

We begin by proposing a statistical measure of market integration that is robust but sufficiently sensitive to mispricing over short horizons. When pricing in two related markets is determined by a single factor, as stocks and bonds in the Merton model, pricing discrepancies can be identified by the concordance of price changes in the two markets. Therefore, a measure of the concordance can serve as a measure of market integration without requiring a parametric setup. Because the concordance is directly linked to pricing discrepancies, there is no ambiguity in its interpretation, unlike alternative measures such as the coefficient of determination. Importantly, we demonstrate the measure is sensitive to mispricing over short horizons.

We relate market integration to arbitrageur costs using a panel of 214 firms over 2001–2009. The econometric specification allows us to relate variation in integration to firm-specific impediments to arbitrage after controlling for wealth transfers that may result in relative price movements in a firm's equity and credit securities.[4]

Our primary findings can be summarized as follows. First, short-horizon Merton model pricing discrepancies are common across firms, frequent and economically large. Over an interval of five business days, 41% of all relative stock and CDS spread movements are classified as discrepancies. Pricing discrepancies decline with horizon length: Over 50 business days, pricing discrepancies are lower by about 9%. Discrepancies are coincident with economically large changes in the underlying spread and stock returns. For example, pricing discrepancies over 50 business days are associated with a 9.23% mean absolute stock return, and the mean absolute change in CDS spread is about 40 basis points (bps) in the *wrong* direction.

Pricing discrepancies cannot be explained away by changes in equity option-implied volatility or firms' debt levels. Indeed, more discrepancies occur when increases (decreases) in implied volatility coincide with decreases (increases) in stock prices. Over short horizons of a quarter, the book value of debt changes by less than 2%, on average. Not surprisingly, changes in the book value of debt do not explain pricing discrepancies.

[4]Having an econometric specification that is robust to wealth transfers is important, because the relation between equity prices and credit spreads can be impacted through many channels, ranging from firm-specific events such as merger offers and takeover threats to macroeconomic and systematic factors in the pricing kernel. There is a longstanding literature that has investigated the wealth impacts of mergers and takeovers (e.g., Asquith and Kim, 1982). There is considerable empirical evidence on the impact of systematic factors such as index returns and volatility on credit spreads (see Collin-Dufresne, Goldstein, and Martin, 2001). For a discussion of the impact of macroeconomic risk on equity and credit markets, see Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010b).

An economically significant proportion of pricing discrepancies are anomalous. Capital structure arbitrage trades—betting on the convergence of equity and credit markets after observation of short-term pricing discrepancies—earned average excess returns over 2001–2009 of between 5% and 6% per annum, with a Sharpe ratio of 0.5. The convergence of the two markets is evidence against any hypotheses that argue pricing discrepancies are not real anomalies. In the absence of arbitrage risks or costs, these commonly observed discrepancies would constitute profitable, and therefore unlikely, opportunities.

Equity–credit market integration can be explained by firm-level variables associated with impediments to arbitrage. For a firm, a decline in the liquidity of the CDS markets and an increase in idiosyncratic risk result in lower equity–credit market integration. For investment–grade firms, higher liquidity in equity markets is associated with greater integration. During the financial crisis, illiquidity resulted in lower market integration for riskier more volatile firms. Of our control variables, equity volatility is significant with an increase in volatility resulting in more integrated equity–credit markets.

Illiquidity in the credit market has a significant economic impact, with a change of one standard deviation in liquidity explaining 9.5% of variability in equity–credit market integration for a typical firm. Together with idiosyncratic risk and equity volatility, the three variables explain about 29% of the variability. In summary, we find extensive support for the hypothesis that impediments to arbitrage explain variation in equity–credit market integration for a firm.

Our finding that it is possible to identify mispricing using the simplest implication of the Merton model complements the finding of Schaefer and Strebulaev (2008), that the Merton model also matches the sensitivity of bond returns to stock returns. Our finding also helps reconcile their results with those of Collin-Dufresne, Goldstein, and Martin (2001). Even though it is possible to identify economically significant mispricings based on the Merton model, integration of equity and credit markets depends on costs associated with convergence trades.

In related work, Duarte, Longstaff, and Yu (2007) and Yu (2006) study the profitability of capital structure arbitrage and show, as we do, that the returns are positive, positively skewed, and have high Sharpe ratios. Duarte, Longstaff, and Yu (2007) suggest that positive returns may be a result of the deployment of intellectual capital. However, we demonstrate that if no costs are associated with arbitrage, then even simple trading rules that require the trader only to pay attention to relative price movements in equity–credit markets lead to significant positive returns.

Other papers have also indicated that limited arbitrage capital may explain anomalous movements in the CDS market in times of market stress. Mitchell and Pulvino (2011) document the violation of the arbitrage relation between bond yield spreads and CDS spreads during the financial crisis. As Duffie (2010) notes, this is likely to be the result of the depletion of dealer capital because of the crisis. We complement their analysis by focusing on impediments to arbitrage that impact markets not only during crises but also in "normal" times.

We proceed as follows. Section 2 reviews the relevant literature. Section 3 proposes a statistical measure of market integration. Section 4 describes the data. Section 5 documents Merton model pricing discrepancies across the market. Section 6 empirically tests whether variation in integration between a firm's equity and credit markets can be explained by variables impacting arbitrage activity. The last section concludes the paper.

2 Overview of the Literature and Empirical Implications

We review the existing literature and derive implications for market integration based on differences in arbitrage costs.

2.1 Funding Liquidity

Arbitrage activity is impacted by an arbitrageur's ability to fund positions, or funding liquidity. Gromb and Vayanos (2002) observe that the inability to cross-margin is a significant constraint on funding liquidity. The margin must be posted separately on each leg of the convergence trade: The long position on one leg of the trade cannot be posted as collateral for the short position on the other leg. Besides preventing an arbitrageur from taking every potentially profitable opportunity, the risk of tightening a financial constraint and forced liquidation also reduces the arbitrage capital allocated to a convergence trade. Brunnermeier and Pedersen (2009) provide a comprehensive discussion of the importance of funding constraints. The literature does not indicate, however, how funding liquidity is expected to vary with firm characteristics.

Let the arbitrageur's available equity be W. Let the equity and debt of the firm of asset value A be $P(A)$ and $B(A)$, respectively. Let $|n_P|$ and $|n_B|$ designate the arbitrageur position in stocks and bonds as a fraction of the firm's equity and debt, P and B, respectively. The size of the bond position, $|n_B|B$, for a given stock position, $|n_P|P$, in the convergence trade will be determined by the elasticity, $(B/P)(\partial P/\partial A)/(\partial B/\partial A)$. If a change in firm value results in stock and bond returns of 80 bps and 20 bps, respectively, then for every $1 stock position, the arbitrageur will take a $4 bond position. Let m_P and m_B be the margin requirements ("haircut") on the stocks and bonds, respectively, defined as a fraction of the dollar value of the position. Then, the total margin, W, is

$$\begin{aligned} W &= m_P|n_P|P + m_B|n_B|B \\ &= |n_P|P\left(m_P + m_B\frac{\partial P/\partial A}{\partial B/\partial A}\frac{B}{P}\right). \end{aligned} \tag{1}$$

For a given stock position, $|n_P|P$, the total margin required to fund the convergence trade is determined by (i) the margin requirement for the stock, m_P, (ii) the margin requirement for the bond or CDS, m_B, and (iii) the elasticity, $(B/P)(\partial P/\partial A)/(\partial B/\partial A)$.

Regulation T of the Federal Reserve Board does not require the margin for equity m_P to vary across the cross section of stocks. Margin requirements for selling protection with five-year CDSs recently proposed by the Financial Industry Regulatory Authority (FINRA) depend on credit riskiness as follows.[5]

Spread (bps)	Margin
0–100	4%
100–300	7%
300–500	15%
500–700	20%
> 700	25%

The margin requirement for below–investment–grade CDSs is about three to six times that for investment–grade CDS.

Finally, to understand how the elasticity varies in the cross section, consider Table 5 of Schaefer and Strebulaev (2008). The authors report the sensitivity of the bond return for a given stock return, that is, the reciprocal of $(B/P)(\partial P/\partial A)/(\partial B/\partial A)$. The sensitivity of the bond return decreases rapidly as the bond gets safer. For an investment–grade firm with quasi-leverage of 0.20 and asset volatility of 20%,[6] the authors report a sensitivity of 0.70, compared with 24.17 for a firm with quasi-leverage of 0.50 and asset volatility of 40%. That is, the bond position required to hedge a given stock position, $(B/P)(\partial P/\partial A)/(\partial B/\partial A)$, changes

[5]See FINRA Rule 4240, "Margin Requirements for Credit Default Swaps." The margin requirements for buying protection are half the margin requirements for selling protection and therefore have similar cross-sectional implications.

[6]Quasi-leverage is defined as the ratio of the face value of debt discounted at the risk-free rate to asset value.

rapidly as the bond gets safer.[7]

Thus, cross-sectional differences in margin requirements are more impacted by cross-sectional differences in elasticity than by cross-sectional differences in margins. Because the elasticity is related to the firm's credit risk, the equity required to fund trades will vary with credit riskiness. The firm's credit riskiness is an indirect proxy for the funding cost associated with the equity required to fund trades.

2.2 Market Liquidity

Convergence traders may not be able to enter or unwind their position in a timely manner without impacting the price. The liquidity of underlying markets is especially important, because convergence trading requires coordinated trades across equity and credit markets. Thus, the illiquidity of either market can constrain an arbitrageur. In addition, liquidity risk may be related to funding illiquidity, since it is likely that arbitrageurs get funding from prime brokers, who also make markets. The natural hypothesis that follows is that lower liquidity in either the equity or credit markets will reduce arbitrage activity and the level of integration between the two markets.

A number of measures using stock daily return data have been proposed for measuring the different aspects of equity market liquidity, including those in Roll (1984), Lesmond, Ogden, and Trzcinka (1999), and Amihud (2002). Compared with the equity liquidity literature, the literature documenting liquidity in the credit markets is more recent (e.g., Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007). Das and Hanouna (2009) study cross-market liquidity across a firm's equity and credit markets.

2.3 Idiosyncratic Risk

Despite having a long and a short position, the arbitrageur is unlikely to be perfectly hedged. For example, the arbitrageur may not have the correct hedge ratio, or it may be stale if it is not possible to continuously adjust the hedge. If so, the arbitrageur will have a net long or short position in the underlying firm, resulting in the arbitrageur being exposed to the total risk of the firm. Exposure to the systematic component of the firm's risk may not be a cost to the arbitrageur, since the arbitrageur is compensated for this exposure. However, the arbitrageur

[7] Alternatively, we can also characterize the margin in terms of the stock position required for a given CDS position. From equation (1), as $W = |n_B| B \left(m_B + m_S \frac{\partial B/\partial A}{\partial P/\partial A} \frac{P}{B} \right)$, the equity position changes rapidly as the bond gets riskier. The direction of change is, however, different.

is not compensated for non-priced idiosyncratic risk. Pontiff (2006) argues that exposure to idiosyncratic risk imposes a significant constraint on arbitrageurs. Shleifer and Vishny (1997) also argue that idiosyncratic risk deters arbitrage.

Empirical evidence also relates pricing discrepancies in the equity markets to idiosyncratic risk. Wurgler and Zhuravskaya (2002) demonstrate that stocks with higher idiosyncratic risk have higher abnormal stock returns when they are included in the Standard & Poor's 500 index. Ali, Hwang, and Trombley (2003) and Mashruwala, Rajgopal, and Shevlin (2006) relate idiosyncratic risk to the book-to-market anomaly and accrual anomaly, respectively.

If unhedged idiosyncratic risk is costly, arbitrageurs will be less active when the firm has greater idiosyncratic risk. The level of integration between a firm's equity and credit markets will then be negatively correlated to the magnitude of the firm's idiosyncratic risk.

2.4 Slow-Moving Capital and Horizon

Duffie (2010) points to many channels that can result in slow-moving capital, as, for example, the limited attentiveness of market participants. A number of papers present evidence consistent with slow-moving capital, for example, Mitchell, Pulvino, and Stafford (2002), Mitchell, Pedersen, and Pulvino (2007), Coval and Stafford (2007), and Mitchell and Pulvino (2011). An implication of slow-moving capital is that pricing discrepancies will decline over longer horizons.

3 Methodological Framework

We begin by proposing a measure of market integration that is robust and also sufficiently powerful to detect mispricing over datasets of short time series length.

3.1 Statistical Measure of Market Integration

When the underlying asset return follows a one-dimensional diffusion, the "delta" of a call option is bounded between zero and one. Thus, in the Merton (1974) model, an increase (decrease) in firm value results in an increase (decrease) in *both* stock prices and credit spreads. We propose a statistical measure of market integration based on the theory.

Let P_i and CDS_i be the stock price and CDS spread, respectively, for firm i. Assume that on a given date we have $k = 1, ..., M$ observations of CDS spreads and stock prices, where the spread is the cost of insurance on the firm's zero coupon debt of face value F and time to maturity T. Define $\Delta CDS^{\tau}_{i,k} = CDS_i(k+\tau) - CDS_i(k)$ and $\Delta P^{\tau}_{i,k} = P_i(k+\tau) - P_i(k)$, $k \leq M-\tau$, $1 \leq \tau \leq M-1$. Then, a pair of stock prices and CDS spreads presents an arbitrage if $\Delta CDS^{\tau}_{i,k}\Delta P^{\tau}_{i,k} > 0$. We define market integration for a stock i based on the frequency of observations of such arbitrage opportunities. Specifically, define $\hat{\kappa}_i$ as

$$\hat{\kappa}_i = \sum_{\tau=1}^{M-1} \sum_{k=1}^{M-\tau} \mathbb{1}_{[\Delta CDS^{\tau}_{i,k}\Delta P^{\tau}_{i,k} > 0]}. \tag{2}$$

For a given M, firm i's stock and CDS markets are more integrated than those of firm j if $\hat{\kappa}_i < \hat{\kappa}_j$.

The measure takes into account all pairs of CDS and stock prices. As an illustration, suppose stock prices are $P(1) = 100$, $P(2) = 80$, and $P(3) = 90$. The markets are more integrated if the corresponding CDS spreads are $CDS(1) = 50$ bps, $CDS(2) = 30$ bps, and $CDS(3) = 60$ bps than if they are $CDS(1) = 50$ bps, $CDS(2) = 30$ bps, and $CDS(3) = 40$ bps. In the latter case, there is an (Merton model) arbitrage across every pair of observations $[1, 2]$, $[2, 3]$, and $[1, 3]$.

This definition of market integration is appealing for several reasons. First, the measure is robust because (i) it is nonparametric and (ii) not impacted by nonlinearities. Second, the measure accounts for all possible pairs formed from M observations and is therefore independent of the horizon over which prices are observed. This is useful, since there may be variations in the length of the periods over which pricing discrepancies develop and disappear. Third, because the measure relies only on the concordance of stock and CDS prices, there is a one-to-one correspondence between $\hat{\kappa}$ and the Kendall correlation (Kendall, 1938). Defining κ as the Kendall correlation,

$$\kappa = \frac{4\hat{\kappa}}{M(M-1)} - 1. \tag{3}$$

The advantage of this correspondence is that we can use standard statistical theory to interpret κ. In particular, using κ as a measure of market integration provides a simple null hypothesis. In the absence of mispricing, $\kappa = -1$. A more positive κ corresponds to a less integrated market.[8] Finally, as we document in simulations below, the measure is sensitive to mispricing

[8] In contrast, the coefficient of determination from a linear regression used in Collin-Dufresne, Goldstein, and Martin (2001) and Blanco, Brennan, and Marsh (2005) is impacted by the nonlinear relation between credit spreads and equity prices. Even in the absence of mispricing, the coefficient of determination is less than one. Moreover, since the nonlinearity varies with the spread, it is difficult to use R^2 to make inferences about time variation in market integration for a firm. The use of residuals from the linear regression is subject to the identical limitation.

in short time series, potentially allowing for a powerful statistical test.[9]

3.2 Simulation Evidence

We use simulation to investigate the robustness of κ as a measure of integration. Because our empirical tests consider the variation of κ to determinants of mispricing, we specifically investigate sources of bias in the sensitivity of κ to mispricing. Related to this objective is the question of whether violation of the assumption that multiple pairs of stock and CDS prices are observed on a single date results in a bias in the magnitude or sensitivity. To understand why there is a bias, suppose we observe CDS spreads on five-year debt on two different dates, t_1 and t_2, $t_2 > t_1$. The firm can have debts of identical maturity on two different dates only if it refinances existing debt on t_2. But if the firm refinances to keep debt maturity constant, the magnitude of κ is biased and, even in the absence of mispricing, it will not be equal to -1.[10] We first investigate the impact of this source of bias on the sensitivity of κ to mispricing.

For dates $t = (k-1)\tau$, $k = 1, 2, ..., M$, let $B(t; F(t), T)$ be the price for the zero-coupon bond of face value $F(t)$ and time to maturity T. On each date, the firm refinances its existing debt of face value $F(t-\tau)$ and remaining time to maturity $T-\tau$ with new debt of face value $F(t)$ and maturity T of identical value, that is, $F(t)$ is chosen so that $B(t; F(t), T) = B(t; F(t-\tau), T-\tau)$. Replacing existing debt of remaining time to maturity $T - \tau$ by debt of maturity T in this manner has no impact on firm value or stock price, and there are no wealth transfers across bondholders and stockholders. We allow for mispricing by assuming that at any time t there is a constant probability of mispricing. Mispricings are independent; a mispricing on date t has no bearing on mispricing on another date t'. We simulate one quarter (12 weeks) of data at a weekly frequency and compute κ. For comparison, we also compute κ under the assumption that all stock prices and credit spread values are observed at an instant in time (the "unbiased" κ). Parameters are chosen to be representative of our sample. More details on the simulation procedure are given in Appendix A.

Figure 1 plots the two estimates of κ against the probability of mispricing for a weekly

[9] Although taking into account all pairs of CDS and stock prices allows mispricing to be detected over small samples, this benefit comes with a tradeoff. The power to detect mispricing deteriorates rapidly with the horizon. From our simulations, the measure is sensitive to levels of mispricing when the time period is less than a year, and thus is especially suitable here, given our objective of investigating short-horizon mispricing.

[10] The bias arises because a firm cannot replace existing debt of shorter maturity with debt of longer maturity while keeping both leverage and spread constant. If the firm refinances to keep the market value of debt (and thus leverage) constant, then the spread at which it issues the longer maturity debt will be different from that of the refinanced debt. If, on the other hand, the firm changes its leverage to keep the spread of the new debt at the same level as the refinanced debt, then there will be wealth transfers between stockholders and bondholders. Either way, κ will be biased away from -1.

frequency. As noted, when M pairs of stock prices and credit spreads are observed on M different dates, κ is biased in its magnitude. The bias is small relative to the impact of the probability of mispricing. The maximum bias is about 0.03 when there is no mispricing, and is lower for higher levels of mispricing. Moreover, as can be observed from Figure 1, the impact of the bias on the sensitivity of κ to mispricing—the slope of the plot—is negligible.

We verify the robustness of these conclusions by computing κ over longer horizons of up to one year. The bias on the magnitude, and therefore slope, remains small. For instance, the bias when the probability of mispricing is 40% is about 0.02 for a one-year horizon, versus less than 0.01 when κ is computed over three months.

3.3 Robustness to Stochastic Volatility and Interest Rates

Asset volatility and the risk-free interest rate are assumed to be constant in the Merton (1974) model. For a given firm value, V_t, a change in asset volatility causes wealth transfers across stockholders and bondholders. Changes in the risk-free rate impacts the risk-neutral drift of the firm, with an increase (decrease) making the firm less (more) likely to default.

How is the relation of κ to mispricing impacted by the stochasticity of interest rates or volatility? We extend the simulation of the previous section by letting asset volatility and the risk-free interest rate be stochastic. As in the previous section, we simulate 12 weeks of data at a weekly frequency to estimate κ. For comparison, we also provide the Merton model estimate of κ. The Merton model is nested in the model with stochastic volatility (SV), which in turn is nested in the model with both stochastic volatility and interest rates (SIV). Details of the simulation are provided in Appendix A. The results of the simulation are reported in Table 1. The simulation exercise demonstrates that there is a positive bias in the magnitude of κ because of stochastic volatility and interest rates. This bias, ranging from 0.01 to 0.03, is relatively stable for different levels of mispricing.

Our primary concern is how the sensitivity of κ to mispricing is impacted. A linear regression of κ on the frequency of mispricing provides the following estimates:

$$\begin{aligned}
\kappa &= -1.03 + 1.35 \text{ MISPRICING } + e \qquad \text{Merton,} \\
\kappa &= -1.02 + 1.33 \text{ MISPRICING } + e \qquad \text{SV,} \\
\kappa &= -1.01 + 1.31 \text{ MISPRICING } + e \qquad \text{SIV.}
\end{aligned}$$

The sensitivity of κ to mispricing reduces from 1.35 to 1.31 when both volatility and interest rates are stochastic. For the parameters considered, the impact is small, and κ is still sensitive to the frequency of mispricing.

The impact depends on the parameters used in the simulation. When the mean reversion of volatility increases, the impact of SV on five-year debt decreases as volatility reverts more rapidly to its long-term mean. The parameters we use in the base case simulation generate a half-life of about 1.4 months for a volatility shock. However, some firms may have more persistent volatility shocks. To investigate, we reduce the mean reversion to make volatility a near unit-root process by increasing the half-life to six months (see Appendix A for details). The sensitivity of κ to mispricing decreases with the slope coefficient now equal to 1.29 instead of 1.35 for the Merton model. More persistent volatility shocks make it more difficult to detect the impact of mispricing. Increasing the variability of volatility has a similar effect; it also decreases the sensitivity of κ to mispricing. For instance, doubling the volatility of the variance process results in a slope coefficient of 1.30. Thus, reducing the mean reversion of volatility or increasing the variability of volatility reduces the power of our regression tests to detect mispricing, but the impact is limited.

The more critical impact on the power of our tests involves the length of the time series over which κ is estimated. By design, κ is sensitive to mispricing over short histories, and its sensitivity to mispricing deteriorates rapidly with longer horizons. Estimating κ using a 52-week history instead of a 12-week history reduces the sensitivity from 1.35 to 0.82. Our empirical implementation focuses on the shorter horizon of a calendar quarter for all tests.

In summary, our measure is sensitive to mispricing over short horizons. In addition, it is robust, since any alternative determinant (e.g., time-varying volatility and interest rates) of relative equity–credit market movements *reduces* the power of our regression tests, making our empirical results conservative.

4 Data

4.1 CDSs

Our dataset consists of CDS spreads, equity prices, and relevant accounting information for U.S. non-financial firms over the period from January 2, 2001, to March 31, 2009. We restrict the data to the first quarter of 2009 because contractual terms in the market were changed on April 8, 2009 (the CDS Big Bang). We obtain daily price data for five-year CDSs on senior, unsecured debt of non-financial and non-government firms from Markit Group, the leading industry source for credit pricing data. Markit Group collects CDS quotes from a large number of contributing banks and then cleans them to remove outliers and stale prices. The obligors that enter our sample are components of the Dow Jones CDX North American indices (investment grade as well as high yield). We specifically choose firms that are included in the index to ensure continuity in price quotes. The Big Bang standardizes CDSs for U.S. firms to include a no-restructuring ("XR") clause for all firms. We follow this convention in our sample choice.

We manually match the data from Markit to data from the Center for Research in Security Prices (CRSP) and Compustat to construct an initial sample of 268 North American non-financial and non-government firms. From these, we eliminate firms that (i) were delisted or had a credit event during this period or (ii) had less than one year of data. Our final sample set consists of 214 firms, with 115 obligors with an average rating of investment grade (AAA, AA, A, and BBB) and the remaining 99 obligors below investment grade (BB, B, and CCC).[11]

We obtain daily equity prices, returns, outstanding numbers of shares, and other equity information from the CRSP. Accounting data are obtained from the Compustat quarterly database. We construct three firm-level variables: size, leverage, and equity return volatility. The market capitalization (size) of the firm is calculated as the product of stock prices and the outstanding number of shares. Leverage is computed as the ratio of the book debt value to the sum of the book debt value and market capitalization. The book value of debt is defined as the sum of long-term debt (data51) and debt in current liabilities (data45). Equity volatility is the annualized standard deviation of daily stock returns over the sample period.

Table 2 reports summary statistics of CDS spreads and firm characteristics. In computing these statistics, we first average over our sample period for each obligor and then take a second average across all firms. The mean CDS spread across the entire sample is 237 bps. The mean spread across investment–grade firms is 60 bps, while that across below–investment–grade firms is much larger, at 439 bps. The average size of investment–grade firms is $23 billion, versus $4.7 billion for non–investment–grade firms. As might be expected, below–investment–grade firms have higher equity volatility and leverage than investment–grade firms.

Figure 2 plots the mean CDS spread over the sample period for each firm against the firm's average leverage and equity volatility. Consistent with the basic Merton (1974) model, the spread is related to volatility and leverage. In fact, a linear regression of the mean CDS spread

[11]Markit provides information on both the average agency rating and an implied rating. We use the agency rating averaged over our sample period when available. When the agency rating is unavailable, we use the implied rating.

on these variables gives an adjusted R^2 of 56%:

$$\text{CDS}_i = \underset{[-15.6]}{-0.03945} + \underset{[25.2]}{0.11625}\ \text{EQVOL}_i + \underset{[8.4]}{0.05489}\ \text{LEV}_i + e, \quad R^2\text{=56\%}.$$

4.2 Liquidity and Idiosyncratic Risk

We construct liquidity measures for each firm–quarter. Equity market liquidity measures are estimated from daily stock price data from the CRSP. Our primary measures are (i) the Amihud (2002) measure (*amihud*) and (ii) the proportion of zero stock returns (*zprop*). Goyenko, Holden, and Trzcinka (2009) demonstrate that the Amihud measure is a good measure of price impact. To construct the Amihud measure, we first compute $10^6 * |\text{return}|/|\text{price} * \text{sharevolume}|$ from the daily data for each firm and then take the time series mean of the daily estimate over the quarter. We only compute the measure if we have at least 15 days of non-zero volume. The higher the price response associated with a given dollar of trading volume, the lower the liquidity of the stock. The zero return proportion is calculated as the ratio of the number of days with zero returns to the total number of days with non-missing observations (Lesmond, Ogden, and Trzcinka, 1999). The higher the proportion of zeros, the more illiquid the stock.

We consider two credit market liquidity measures. Our first measure is based on the number of contributors that provide quotes to Markit on any given date. Since contributors are required by Markit to have firm tradable quotes, the greater the number of contributors, the greater should be the depth and liquidity of the CDS. Thus, our first measure (*depth*) is computed as the mean of the daily number of contributors for each firm. Gala, Qiu, and Yu (2010) also use the number of contributors as a measure of liquidity. Second, analogous to the equity liquidity measure, we use the proportion of zero spread changes (*spreadzero*), defined as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the quarter. As with the equity market measure, a larger proportion of zero spread changes indicates lower liquidity. Markit does not provide bid–ask spreads, and therefore we cannot use liquidity measures based on bid–ask spreads.

We construct the measure of idiosyncratic risk from the Fama–French three-factor model (Fama and French, 1992). We first obtain the coefficient of determination R_i^2 from a regression of excess returns for stock i on the factors using daily returns. Next, following Ferreira and Laux (2007), we compute the ratio of the idiosyncratic volatility to the total volatility for each stock as

$$\frac{\sigma_{i,\epsilon}^2}{\sigma_i^2} = \frac{\sigma_i^2 - \frac{\sigma_{im}^2}{\sigma_m^2}}{\sigma_i^2} = 1 - R_i^2.$$

The idiosyncratic measure *idiosyn* is then defined as the logistic transformation $\ln\left(\frac{1-R_i^2}{R_i^2}\right)$. The corresponding measure computed using the standard market model had a correlation of 0.85 with the measure of idiosyncratic risk from the Fama–French model. We only report results for the latter model.

To ensure that our results are not impacted by outliers, we winsorize all the liquidity variables at the 1% level. Panel A of Table 3 presents the descriptive statistics. Each variable exhibits considerable variation. For example, the average number of contributors to the CDS quote is about seven, with a (within) standard deviation of 2.6. The mean of the proportion of zero spread changes (8.5%) is much larger than the mean of the proportion of zero returns (1.3%), consistent with the expectation that the equity market is more liquid than the CDS market. Panel B reports pairwise correlations between the variables. The liquidity in the credit market (*depth*) is negatively correlated with the illiquidity measure (*spreadzero*). Firms with higher leverage and equity volatility have lower equity liquidity. The price impact Amihud measure has low correlations with the credit liquidity measures. Interestingly, equity volatility is negatively correlated with credit market liquidity (*depth*), indicating that the number of dealers contributing to CDS quotes declines with equity volatility.

5 Pricing Discrepancies and Mispricing

5.1 Existence of Pricing Discrepancies

Table 4 reports the frequency of pricing discrepancies defined by $\Delta CDS_{i,k}^{\tau}\Delta P_{i,k}^{\tau} > 0$, for different horizons, $\tau \in \{5, 10, 25, 50\}$, corresponding to weekly, biweekly, monthly, and bimonthly horizons, respectively. We also report the frequency of "zeros," corresponding to $\Delta CDS_{i,k}^{\tau}\Delta P_{i,k}^{\tau} = 0$. Similar exercises in other markets are conducted in Bakshi, Cao, and Chen (2000), Buraschi and Jiltsov (2007), and Buraschi, Trojani, and Vedolin (2009).

Pricing discrepancies over short horizons are common across firms and occur frequently. Over the entire sample, with a frequency of every five business days, stock prices and CDS spreads co-move as expected ($\Delta CDS_{i,k}^{\tau}\Delta P_{i,k}^{\tau} < 0$) only 57% of the time. This is not explained away by lead–lag relations across the equity and CDS markets, since there are significant pricing discrepancies over all horizons. Even at a horizon of 50 business days, 32% of co-movements represent arbitrage opportunities for the Merton model. These pricing discrepancies are associated with large and economically significant movements in the underlying markets. Discrepancies over 50 business days occur with an average (absolute) stock return of 9.2% and an average (absolute) change in CDS spread of 40 bps in the *wrong* direction.

Pricing discrepancies decline over longer horizons. Including zeros, the fraction of discrepancies for intervals of 5, 10, 25, and 50 business days are 43%, 40%, 37%, and 32%, respectively. The identical pattern holds if we consider sub-samples of investment–grade or speculative-grade firms. This observation is consistent with the implication of slow-moving capital, that if arbitrage capital takes time to be deployed, pricing discrepancies should decline with time. Some of the anomalous observations at the weekly frequency, 1.9% of all observations, are related to cases where CDS spreads or stock prices do not change. Such zero changes decrease as the horizon increases; at a frequency of 50 days, zeros constitute only 0.3% of the observations. Since zero changes are associated with higher trading costs (Lesmond, Ogden, and Trzinka, 1999), this observation is also consistent with the hypothesis that the level of discrepancies is related to arbitrage costs.

There are substantial cross-sectional differences. First, for every time interval, investment–grade firms have more frequent pricing discrepancies. For example, 10- (25-) business-day pricing discrepancies for investment–grade firms are 41.5% versus 37.4% (39.8% versus 34.1%). The magnitude of the price changes associated with the discrepancy for investment–grade firms is about half that of high-yield firms; the mean absolute stock returns associated with the 10-day (25-day) pricing discrepancy are 3.3% versus 6.0% (4.9% vs. 8.6%), respectively. Figure 3 illustrates the relation between the CDS spread and stock price for three firms—Alcoa (AA), GATX (GMT), and Goodyear (GT)—using available data up to the end of 2007. It is evident that there is wide variation in the stock–CDS relation. There is a clearly discernible relation between GT's stock price and CDS spread, while, at the other extreme, AA's stock price and CDS spread appear unrelated, with GMT being in between. When we compare the frequency of pricing discrepancies at a five-business-day frequency, pricing discrepancies are 41.92% for Alcoa, but much fewer, at 31.20%, for Goodyear.

5.2 Pricing Discrepancies and Changes in Volatility and Leverage

Before we examine whether pricing discrepancies are anomalous, we first check whether they can be explained away by unexpected changes in volatility or leverage. To do so, we construct a contingency table, dividing pricing discrepancies according to whether they coincide with increases or decreases in stock prices and implied volatility/debt. Pricing discrepancies would be explained by changes in volatility or leverage if mispricing occurs in periods where increases (declines) in stock prices coincide with increases (declines) in volatility or debt.

We use changes in the Black–Scholes implied volatility of the at-the-money near-month option to proxy for unexpected changes in volatility.[12] The change in implied volatility is measured as the change in implied volatility from the first date of the interval to the last date of the interval. We use a horizon of exactly one month to avoid overlapping intervals.

Panel A of Table 5 reports the results. To explain pricing discrepancies, we should observe more pricing discrepancies in periods when an increase (decrease) in stock price is coincident with an increase (decrease) in volatility (the right diagonal of the contingency table, $\Delta\text{P}\Delta\text{Vol} > 0$). Instead, a slightly greater proportion of discrepancies, 51%, are in periods when an increase (decrease) in stock price coincides with a decrease (increase) in volatility ($\Delta\text{P}\Delta\text{Vol} < 0$). In fact, changes in implied volatility make about over half of the discrepancies appear even more anomalous. Even if we attribute all of the remaining 49% of pricing discrepancies to coincident changes in volatility, about half of the observed pricing discrepancies remain to be explained.[13]

Do unexpected changes in debt levels cause wealth transfers across equityholders and bondholders? Panel B of Table 5 reports pricing discrepancies conditioned on stock price changes and changes in the book value of debt. The book value of debt is taken from quarterly financial statements, and we also compute pricing discrepancies over a quarter so as to match the horizon with the financial statements. To explain pricing discrepancies, we should observe more pricing discrepancies in periods when an increase (decrease) in stock price is coincident with an increase (decrease) in debt (the right diagonal of the contingency table).

We find no evidence to indicate that pricing discrepancies are related to changes in the face value of debt. The proportion of pricing discrepancies when stock price increases (decreases) coincides with increases (decreases) in debt is 49.6%. Clearly, changes in the book value of debt cannot explain pricing anomalies. This is not entirely surprising. Unlike volatility, firm debt levels do not change much over short horizons; the median quarterly change in the debt

[12] Cremers, Driessen, Maenhout, and Weinbaum (2008) document that increases in equity implied volatility increases credit spreads.

[13] Even though the bulk of the pricing discrepancies cannot be explained by volatility changes, a fraction are likely to be explained by them. Although roughly half of the pricing discrepancies are associated with each of the two scenarios $\Delta P\Delta\text{Vol} > 0$ and $\Delta P\Delta\text{Vol} < 0$, the former scenario occurs less frequently than the latter (41% versus 59%, respectively). Therefore, conditioning on the scenario, it is far more likely to observe a pricing discrepancy when $\Delta P\Delta\text{Vol} > 0$. Indeed, across our entire sample, pricing discrepancies constitute 37.8% of the 7,548 observations, but of the 1,391 observations when $\Delta P\Delta\text{Vol} > 0$, pricing discrepancies comprise 44.7% of the sample. The higher proportion indicates that even though coincident changes in volatility cannot explain away all pricing discrepancies, volatility innovations, not surprisingly, do play a role in explaining some of them.

ratio for firms in our sample is only 2%.

5.3 Are Pricing Discrepancies Mispricing?

Merton model pricing discrepancies are not anomalous if they are the result of wealth transfers or if pricing kernels in the equity and bond markets are distinct (e.g., if a systematic liquidity factor is priced in the bond market but not priced in the equity market). If Merton model pricing discrepancies are not anomalous, arbitrageurs are unlikely to make excess returns trading on perceived pricing discrepancies. On the other hand, significant excess returns serve as evidence against either of these hypotheses.

We investigate the magnitude of excess returns using the following trading rules based on Table 4. We initiate a trade across a firm's stock and CDS markets if there is a pricing discrepancy over the previous τ business days coincident with a large change in stock prices, and if there is no existing open trade. Specifically, the trade is initiated at time t if $\Delta CDS_{i,t}^{\tau}\Delta P_{i,t}^{\tau} > 0$ and if $|\Delta P_{i,t}^{\tau}/P_{i,t}| > 3\%$ (long on both stocks and CDSs if stock returns are negative, and short if stock returns are positive). We maintain consistency with Table 4 by choosing τ to be either five or 10 business days. The 3% threshold is chosen to be roughly consistent with the average absolute stock return for $\tau = 5$ in Table 4. To avoid overlapping intervals, each firm has only one open trade at any point in time (i.e., a trade is not initiated if a previous trade is open). Each position is initiated with a total equity of $W = \$1,000,000$, where $W = m_P|n_P|P + m_{CDS}|n_{CDS}|S$, and n_P and n_{CDS} are the number of shares and CDS contracts, respectively, that form the two legs of the (hedged) convergence trade. The margins for equity and CDS, m_P and m_{CDS}, respectively, are given in Section 2.1. The hedge ratio is determined empirically by running a regression of changes in monthly CDS spreads on stock returns, as in Schaefer and Strebulaev (2008), and does not make any model assumptions. Details are provided in Appendix B. Once the trade is initiated, the hedge ratio is not adjusted dynamically. The position is closed at the end of a predetermined trading horizon, T, or if the cumulative loss in the position exceeds 10% of the original equity (i.e., \$100,000), whichever occurs first. Trading horizons are one or two months. Using the trading rule, we implement convergence trades for each firm in our sample and compute the average cumulative excess return for each firm. Excess return is defined as total gains less interest costs for the trade divided by the initial equity position. The CDS is marked to market using the International Swaps and Derivatives Association (ISDA) standard model that has been adopted by the industry for this purpose.[14]

[14]The ISDA standard model is maintained at http://www.cdsmodel.com/cdsmodel/ by Markit Partners. Note

Summary statistics are reported in Table 6 for the mean excess return across our cross section of firms: Panel A reports results for the first trading rule with $\tau = 5$ and a horizon of one month, and Panel B for the second rule with $\tau = 10$ and a horizon of two months. Because the financial crisis had a significant impact on the CDS market, we split our sample period into two sub-periods corresponding to the pre-crisis period of January 2001 to December 2007 and the financial crisis period of January 2008 to March 2009. Given the high frequency of pricing discrepancies, there are ample opportunities to execute a convergence trade. When the maximum trading horizon is one month (two months), the mean number of trades for each firm was 32.1(20.8) trades per firm over the 2001–2007 period. In the crisis period of 2008–2009, the mean numbers of trades per firm were 10.7 and 6.9, respectively, for the two horizons.

Convergence trading, on average, across firms earns statistically significant positive excess returns. In Panel A of Table 6, in the pre-crisis period, a convergence trade for the average firm earns an excess return of 0.14% over the one-month horizon. In Panel B, over the longer horizon of two months, the convergence trade earns only a little more, 0.17%, suggesting that most of the profits in the pre-crisis period accrue over the first month. The excess returns are an order of magnitude higher during the crisis period, with average excess returns over the one- and two-month horizons of 1.18% and 2.22%, respectively. To understand the economic significance from the viewpoint of a capital structure arbitrageur, we consider the cumulative portfolio returns over our sample period. Figure 4 plots the cumulative profits on an equity investment of $1 million by compounding the mean daily return over all open positions. The two strategies earned cumulative excess returns between 5% and 6% per year on equity over the entire sample period. In comparison, the annualized daily volatility for both strategies is about 10%. An alpha over 5% and a Sharpe ratio greater than 0.5 compare handsomely with alternative hedge fund strategies.

Significant excess returns indicate at least partial convergence of CDS and equity markets after the onset of a pricing anomaly. It is unlikely that divergence is solely a result of wealth transfers or differing pricing kernels. Moreover, the magnitude of excess profits supports the notion of limited arbitrage. Why do hedge funds leave these gains on the table? Markets would have to be exceptionally inefficient to explain the magnitude and persistence of these profits from trading strategies based on the simplest implication of the Merton model. Moreover, implementing the convergence trades requires no information apart from attentiveness to relative price movements in equity and credit markets.[15] The presence of significant arbitrage

that although the ISDA pricing model is based on a reduced-form model, it should be viewed simply as a market convention to mark to market. This is analogous to the currency derivative market using the Black–Scholes formula to mark a currency option to market based on an implied volatility quote.

[15]Observe that both the trading rule and the hedge ratio used in the convergence trade are determined by

costs and risks constitutes perhaps the simplest explanation of these profits.

At the very least, it is evident that convergence trades are risky. If traders had a stop-loss criterion of 10% of initial capital, a significant proportion of trades would be closed early. For example, in Panel A of Table 6, about eight of the average 32 trades were closed prematurely in the pre-crisis period. In the crisis period, premature closures increased to over half of all trades (5.72 out of an average of 10.7 trades per firm).

The recent financial crisis demonstrates the risk. Figure 4 plots the cumulative gains over our sample period. Through the latter half of 2007 and 2008, capital structure arbitrage trades lost considerable money. It would require both fortitude and capital for a trading group to last through this hemorrhaging to make the exceptional returns that were possible in the tail end of the recession. Indeed, the capital structure arbitrage group of Deutsche Bank under Boaz Weinstein, one of the most profitable in the period before the crisis, was shut down after losses incurred in 2008.[16]

6 Impediments to Arbitrage and the Integration of Equity and Credit Markets

The existence of significant mispricing supports the interpretation of κ as a measure of integration. Table 7 provides summary statistics for $\bar{\kappa}$ across the cross section of firms, which is the transformed variable $\bar{\kappa} = \frac{1}{2}\ln\frac{(1+\kappa)}{(1-\kappa)}$ used in the regressions. For each firm, κ is estimated from stock prices and CDS spreads at weekly ($\tau = 5$) and biweekly ($\tau = 10$) intervals for each quarter in our dataset. The mean cross-sectional estimates of κ for both weekly and biweekly horizons are very different from -1. Firms with high-yield debt have a more negative κ, consistent with the lower frequency of mispricing documented in Table 4.

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relative price movements in equity and CDS markets by running a regression of CDS spread changes on stock returns. Thus, the implementation of the strategy requires the trader to do nothing more than be an attentive observer of the markets. The strategy is *completely* model free.

[16] *The Wall Street Journal* (February 6, 2009) reported that the capital structure arbitrage group at Deutsche Bank made an estimated $900 million in 2006 and $600 million in 2007 but lost it all in 2008. According to *The Wall Street Journal*, the group undertook trades across equity and CDS markets, as well as across corporate bonds and CDS markets. Arbitrage trades across corporate bonds and CDS markets are typically undertaken when there is a "negative basis," that is, when the cost of protection is less than the income produced by the bond. A significant proportion of the 2008 loss at Deutsche Bank appears to be related to the widening of the basis coinciding with lower funding liquidity.

6.1 Panel Regression Specification

To investigate whether the integration of firms' equity and credit markets is related to arbitrage costs, we use a panel specification after applying Fisher's z transformation (David, 1949) to κ, defining the transformed variable as $\bar{\kappa} = \frac{1}{2} \ln \frac{(1+\kappa)}{(1-\kappa)}$. The panel specification is

$$\bar{\kappa}_{i,t} = \alpha_i + \gamma_t + \beta_1 \text{lev}_{i,t} + \beta_2 \text{eqvol}_{i,t} + \beta_3 \text{lnmcap}_{i,t} + \beta_4 \text{variable}_{i,t} + \epsilon_{i,t}, \tag{4}$$

where $variable_{i,t}$ refers to each of the variables of interest, namely, measures of liquidity in the CDS market (*depth* and *spreadzero*) and equity markets (*amihud* and *zprop*) and idiosyncratic risk (*idiosyn*). We include the log of the size of the firm (*lnmcap*) and proxies for the firm's credit risk, equity volatility (*eqvol*), and leverage (*lev*) as control variables. The hypothesis that equity–credit market integration is related to arbitrage costs is examined by the significance and sign of the variables of interest. As already discussed, the impact of an impediment to arbitrage should be to make $\bar{\kappa}$ less negative.

We account for both time and firm fixed effects. It is important to control for unobserved firm fixed effects. For example, Goldstein, Ju, and Leland (2001) note that firms that are close to financial distress may behave differently from other firms because good news for the firm may not translate into good news for bondholders if bondholders anticipate the firm using the opportunity to issue more debt. In addition to a fixed effect, there may be transient firm-specific events that impact a firm's equity and credit securities differently. Although our sample does not include firms that were delisted because of defaults and mergers, there may be other pertinent firm events. Kerkorian's bid for GM stock in 2005 benefited stockholders, but bondholders reacted negatively. Petersen (2009) provides simulation evidence to indicate that using robust standard errors clustered by firm (Rogers standard errors) helps control for transient firm effects. Therefore, in addition to including firm fixed effects, we also cluster standard errors by firm. Finally, macroeconomic and other systematic factors can impact equity–credit markets systematically across all firms (e.g., Hackbarth, Miao, and Morellec, 2006; Bhamra, Kuehn, and Strebulaev, 2010b; Chen, Collin-Dufresne, and Goldstein, 2009; Chen, 2010). Therefore, we include a time fixed effect. The econometric specification allows us to isolate the impact of arbitrage costs on market integration *after* accounting for unobserved firm-specific and macroeconomic fixed effects.

In univariate regressions (not reported here), size, equity volatility, and leverage are all significant. The sign for size is positive and the sign for both equity volatility and leverage is negative, indicating that smaller, riskier firms have more integrated markets. When fixed effects are not included, the standard errors when adjusted for clusters are larger by 14% (for equity volatility), to 58% (for size), than White standard errors. As noted in Petersen (2009), this is evidence of an unobserved firm effect. Thus, our inclusion of a firm dummy is justified.[17]

When all three variables size, equity volatility, and leverage are combined in a multivariate regression, the impact of leverage is subsumed by size and equity volatility. The adjusted R^2 values for the regression are 12% and 9.2% for $\tau = 5$ and $\tau = 10$, respectively.

6.2 Determinants of Market Integration

Table 8 reports the results for the entire sample of 214 firms over 2001–2009 for 14 specifications. In the first 10 specifications, we consider each of our proxies for arbitrage costs individually, in addition to leverage, equity volatility, and size.

6.2.1 Credit Market Liquidity

In specifications (1) to (4), we consider the impact of the two measures of credit market liquidity. Both measures indicate that an increase (decrease) in credit market liquidity increases (decreases) equity–credit market integration. The credit market illiquidity measure *spreadzero* is significant at the 99% level for both $\tau = 5$ and $\tau = 10$. The sign of the coefficient is positive, indicating that when firms have less liquid credit markets (having a larger fraction of zero spread changes), they have less integrated equity–credit markets. The second measure of credit market liquidity, the log of *depth*, is also significant with a negative sign. Because *depth* measures the average number of dealers who provide CDS quotes, the negative sign indicates that equity–credit market integration increases with more dealers in the CDS market. Although both measures appear to be good proxies for credit market liquidity, significance levels for *depth* are slightly lower than those for *spreadzero*. Including either of the credit market liquidity measures does not change the significance or sign of leverage, equity volatility, or size. In particular, equity volatility remains highly significant for all specifications.

[17] After including firm fixed effects, there is little difference between White standard errors and robust standard errors clustered by firm, suggesting that it may not be necessary to also cluster by firm (perhaps because our sample selection criteria eliminate most firms with transient firm effects). That is, it appears more important to account for firm fixed effects than for transient effects.

6.2.2 Equity Market Liquidity

In the next four sets of regressions, we consider the impact of equity market liquidity on equity–credit market integration. Specifications [5] and [6] consider the Amihud measure of price impact. It is not significant for either $\tau = 5$ or $\tau = 10$. Next, we consider *zprop*, the proportion of zeros in the quarter as a measure of the illiquidity of the market. It is insignificant in both specifications. In addition, we also try variants of the Amihud measure, specifically, the square root of the Amihud measure and the square root of the Amivest measure. Neither of these measures is significant. Overall, for the entire sample, equity liquidity does not help explain variation in market integration.

6.2.3 Idiosyncratic Risk

Specifications [9] and [10] consider the impact of idiosyncratic risk as estimated from the regression of the three-factor Fama–French model. The coefficient is positive for both specifications, indicating that an increase in idiosyncratic risk is coincident with a decrease in equity–credit market integration. For both $\tau = 5$ and $\tau = 10$, the coefficient is highly significant, with t-statistics of 2.90 and 2.76, respectively. If we replace the idiosyncratic risk from the three-factor Fama–French model with idiosyncratic risk computed from the market model, the coefficient has the same sign and significance levels. In summary, as with the results for credit and equity market liquidity, the results for idiosyncratic risk also indicate that an increase in an impediment to arbitrage results in a less integrated market.

6.2.4 Encompassing Regression

The last four specifications, [11] to [14], estimate an encompassing regression, including a proxy each for equity and credit market liquidity, respectively, along with idiosyncratic risk. Because both measures of credit market liquidity are significant, we report results for the encompassing regression, including either *spreadzero* or *depth*. The results are consistent with the earlier specifications that considered each variable individually. With the exception of *amihud*, the t-statistics for both measures of credit market liquidity and idiosyncratic risk exceed 2.0. The signs of all coefficients remain the same as noted earlier, indicating that a decline in credit market liquidity or an increase in idiosyncratic risk is associated with lower equity–credit market integration. The adjusted R^2 values are a little higher for *spreadzero* (12.6% and 10.1%) than for *depth* (12.4% and 9.5%). The coefficients and signs for the size, equity volatility, and leverage also remain consistent with those previously reported.

Although credit market liquidity and idiosyncratic risk are both statistically significant, they may be of different economic significance. To investigate, we consider the impact of a change in each variable of interest in the cross section. For this exercise, we use the coefficients from specification [11] for $\tau = 5$, since this specification has the highest adjusted R^2. A change of one standard deviation in the measure of credit market liquidity and idiosyncratic risk changes the absolute value of $\bar{\kappa}$ by 0.04 and 0.025, respectively. Given the (within) standard deviation of $\bar{\kappa}$ of 0.42, credit market liquidity and idiosyncratic risk explain 9.5% and 5.8%, respectively, of the variability in market integration for a firm. Although both credit market liquidity and idiosyncratic risk are statistically significant, credit market liquidity has the larger economic impact on market integration.

Finally, equity volatility is both statistically and economically significant, with a change of one standard deviation in equity volatility explaining 13.3% of the variability in market integration. The sign indicates that an increase in the riskiness of a firm results in greater integration between its equity and credit markets.[18]

6.2.5 Robustness

Our first two robustness checks focus on the CDS data. First, we consider the impact of the restructuring clause in the CDS contract. Our analysis uses CDS contracts that exclude restructuring events from triggering a settlement. Prior to the Big Bang, it was common for investment–grade firms to trade on a modified restructuring (MR) clause. Indeed, previous literature focused solely on CDS spreads with the MR clause (e.g., Blanco, Brennan, and Marsh, 2005; Jorion and Zhang, 2007). Therefore, we redo our analysis using a sample of CDSs with an MR clause. Our conclusions remain the same, with the significance and signs of the variables being close to those previously discussed. Second, we consider whether our results are driven by the evolution of the CDS market. Arbitrage activity may have been limited when CDS contracts were introduced into the market, and, if so, our results may be driven primarily by the (lack of) early trading in the CDS market. To examine this, we exclude all observations in the first three years of our sample period, 2001–2003. Both credit market liquidity measures remain significant. Thus, the results are not driven by the initial conditions

[18] We can speculate why this is so. One explanation may be that arbitrageurs decide the size of their trade by first determining the size of the equity leg; then the capital required to fund trades will increase rapidly as the firm becomes safer. For a given mispricing in the equity market, arbitrageurs may then prefer to trade in markets of firms with higher equity volatility. An alternative explanation may be the limited attentiveness of market participants (Duffie, 2010). Higher volatility may attract equity capital simply because traders tend to focus their attention on more volatile markets. Although we cannot distinguish between these or other explanations within our present framework, it would be interesting for future research to do so.

in the CDS market.

Our next robustness check considers interaction terms in our regression specification. In particular, volatility in the equity markets can interact with both equity and credit market liquidity. The relation between trading activity, volatility, and liquidity is well documented in the equity market (Chordia, Roll, and Subrahmanyam, 2001). Equity volatility can also interact with credit market liquidity through its impact on credit risk. As a firm gets riskier, market makers in the CDS market may be less inclined to provide liquidity. Therefore, we estimate the panel regression over our entire sample period, including interaction terms. We find no evidence of interaction effects. It is possible that the interaction of equity volatility and liquidity only matters when market conditions are severe. We revisit this issue when we examine the financial crisis in more detail below.

6.3 Investment–Grade versus Speculative–Grade Firms

We next consider sub-samples of investment–grade versus below–investment–grade firms. The panel regression imposes a common coefficient across all firms, and this restriction may ignore differences across the markets of investment–grade versus below–investment–grade firms. For example, Bhamra, Keuhn, and Strebulaev (2010b) note that, given the endogeneity of the capital structure decision, financially constrained firms react differently to the business cycle.

Table 9 presents the results for the encompassing regressions for these sub-samples. First, consider investment–grade firms in Panel A of Table 9. Interestingly, credit market liquidity and idiosyncratic risk, despite their overall economic importance in the complete sample, are not significant for investment–grade firms. Instead, time variation in market integration is related to equity market liquidity (as measured by the *amihud* measure), which was not significant for the overall sample. The *amihud* measure is significant at the 5% level in three of the four specifications, with a positive sign, indicating that a decline in the liquidity of the equity market results in a less integrated equity–credit market.

Next, consider the sample of below–investment–grade firms. As with the overall sample, both measures of credit market liquidity are significant, indicating that when firms have less liquid credit markets, their equity and credit markets are less integrated. In addition, idiosyncratic risk is significant with p-values close to zero. Overall, when below–investment–grade firms have more illiquid credit markets and higher idiosyncratic risk, they also have lower levels of market integration.

Overall, the results indicate that there are significant differences in the variation of market integration for investment–grade compared with below–investment–grade firms. The results are intuitive. Compared with below–investment–grade firms, investment–grade firms have credit markets that are less susceptible to liquidity shocks. investment–grade firms, being larger, also have less idiosyncratic risk. Thus, the results are consistent with prior literature on how the impact of impediments to arbitrage should differ across firms with investment and speculative ratings.

6.4 Financial Crisis of 2008–2009

How do impediments to arbitrage impact market integration in the period corresponding to the financial crisis? Panel A of Table 10 reports the regression results for the relation between market integration and the impediments to arbitrage over two sub-periods of 2001–2007 and 2008–2009, respectively. The results for 2001–2007 mirror those discussed earlier, with both measures of credit market liquidity and idiosyncratic risk being statistically significant. The results for the crisis period of 2008–2009 are very different. Surprisingly, none of the variables (apart from size in two specifications) are significant.

As a diagnostic, observe that equity volatility is not significant. Given the economic significance of equity volatility in the rest of the sample, it is surprising that equity volatility does not explain variation in market integration over the period 2008–2009. A possible reason may be that, during the crisis period, liquidity in a firm's markets is closely associated with the credit risk of the firm, since flight to safety has a greater impact on the liquidity of the riskier securities. Given that the base specification does not include interaction variables, this relation of equity volatility and liquidity is not captured. To look into this possibility, we add interaction variables to the regression. Panel B of Table 10 reports the results.

In the first two specifications, we consider the impact of the interaction between equity volatility and credit market liquidity. The coefficient to the interaction variable is significant, with p-values close to zero. We also consider interaction between equity volatility and equity liquidity, as well as interaction with equity volatility and idiosyncratic risk. Neither of these coefficients are significant. Thus, the primary interaction that is relevant for understanding market integration during the crisis period is the one between equity volatility and the liquidity of the credit markets.

The sign of the coefficient of interaction between equity volatility and credit market liquidity is positive, indicating that illiquidity in the credit market has a larger impact on riskier firms. While before the crisis an increase in equity volatility resulted in greater integration, during the crisis period volatility interacts with credit market liquidity to *lower* integration. The riskier the firm, the greater the impact of credit market liquidity on market integration. Our finding suggests that arbitrageurs selectively reduced activity in the markets of the riskiest firms, perhaps (correctly) concerned that these markets were more likely to have heightened liquidity risk during the crisis.

7 Conclusion

Why are firms' equity and credit markets not highly correlated on average? What explains variation in equity–credit market integration? Frequent pricing discrepancies over short horizons (of days and weeks) are unlikely to be completely explained by changes in the pricing kernel or firm-specific events. Indeed, we find that if there were no arbitrageur costs and risks, pricing discrepancies would constitute profitable trading opportunities, especially in the last half of 2007 and 2008, when arbitrage capital exited the market. We find empirical support for the hypothesis that pricing discrepancies are related to impediments to arbitrage. Greater liquidity of a firm's equity and credit markets results in greater equity–credit market integration. Idiosyncratic risk deters market integration. Below–investment–grade firms are more sensitive to liquidity in the credit market than investment–grade firms. During the financial crisis, illiquidity of the credit market had a larger impact on market integration for riskier firms. Overall, our findings indicate that equity and credit markets of firms are more integrated when they have lower impediments to arbitrage.

Our findings suggest that some of the pricing discrepancies across equity and credit markets are anomalies that, in time, will be corrected. If so, empirical tests of structural models of credit risk need to be implemented over horizons that are sufficiently long to ensure integration. It is not entirely surprising that empirical studies using weekly or monthly frequencies find it difficult to explain co-movements in the equity and credit markets.

Our findings also provide some of the strongest empirical support for recent literature on the determinants of arbitrage activity, because the CDS market is precisely a market dominated by sophisticated arbitrageurs such as hedge funds. In particular, our findings indicate that the variables posited in the literature as impediments to arbitrage activity are both statistically and economically significant. Limited arbitrage activity is important not just in times of crises but also in times of relative tranquility.

Our findings raise additional questions. First, our results indicate that short-horizon mispricing are common. What determines both cross-sectional and time series variation in pricing discrepancies? One possible avenue to pursue here is whether differences of opinion across market participants (Basak and Croitoru, 2000, 2006) impact the prevalence of mispricings. There may be other channels. Second, because we focus on firm-level determinants of arbitrage activity, we do not examine the role of systematic factors. It would be useful to understand the relative roles of systematic and firm-specific impediments to market integration. We leave this for future research.

Appendix A Simulation Design

A.1 Simulation of Section 3.2

We simulate stock and bond prices using the Merton (1974) model. Let $A(t)$ and $P(t)$ be the time t value of the (non–dividend–paying) firm's assets and equity, respectively. Assume that at each instant in time t the firm has debt of face value $F(t)$ and remaining time to maturity T. Let $B(t; F(t), T)$ be the price of the bond. The Merton model value of the equity $P(t)$ is

$$P(t) = A(t)\,\Pi_1 - e^{-r\tau}F(t)\,\Pi_2, \tag{5}$$

where

$$\begin{aligned}\Pi_1 &= \frac{\ln(A(t)/F(t)) + (r_f + \frac{1}{2}V)T}{\sqrt{V}\sqrt{T}} \\ \Pi_2 &= \Pi_1 - \sqrt{VT},\end{aligned} \tag{6}$$

with r_f the risk-free rate and $\sqrt{V}$ asset volatility. The value of the bond is

$$B(t) = A(t) - P(t), \tag{7}$$

and the credit spread is defined as $CDS = \frac{1}{T}\ln(F(t)/B(t)) - r_f$.

The simulation is implemented as follows. For dates $t = (k-1)\tau$, $k = 1, 2, ..., M$, we simulate asset values with

$$A_{k\tau} = A_{(k-1)\tau}\exp\left((r_f + \mu - \frac{1}{2}V)\tau + \sqrt{V\tau}\tilde{z}_1\right), \tag{8}$$

where $r_f + \mu$ is the expected return on the firm and $\tilde{z}_1$ is a standard normal variate. At each date, the firm refinances its existing debt of face value $F(t-\tau)$ and maturity $T-\tau$ with new debt of face value $F(t)$ and maturity T of identical value, that is, $F(t)$ is chosen such that $B(t; F(t), T) = B(t; F(t-\tau), T-\tau)$. In the absence of mispricing, stock and bond prices are given by (5) and (7), respectively.

We assume there is a fixed probability of observing mispricing in the equity market. When there is mispricing, the observed stock price is

$$P(t) = \begin{cases} P(t-\tau) * 1.03 & \text{if } A(t) < A(t-\tau) \\ P(t-\tau) * 0.97 & \text{if } A(t) > A(t-\tau) \end{cases}$$

instead of the true stock price given by equation (5). The magnitude of mispricing is chosen to roughly match the average mispricing observed in our Table 3. The bond is correctly priced from equations (5) and (7), and therefore the mispricing results in $\Delta CDS^{\tau}_{i,k}\Delta P^{\tau}_{i,k} > 0$. The variable κ is estimated using these simulated stock and bond (spread) prices. We vary the probability of mispricing to estimate κ as a function of the probability.

The parameters for the simulation are as follows: $A(0) = 100$, $F(0) = 50$, $T = 5$, $\mu = 0.10$, $r_f = 0.03$, $\sqrt{V} = 0.40$, $\tau = 1/52$, and $M = 16$. For a given probability of mispricing, κ is estimated from $N = 1,000$ simulations.

A.2 Simulation of Section 3.3

We extend the simulation described above by allowing asset volatility and interest rates to be stochastic:

$$V_{k\tau} = V_{(k-1)\tau} + \kappa_v(\theta_v - V_{(k-1)\tau})\tau + \sigma_v\sqrt{V}_{(k-1)\tau}(\rho\tilde{z}_1 + \sqrt{1-\rho^2}\tilde{z}_2), \tag{9}$$

$$r_{k\tau} = r_{(k-1)\tau} + \kappa_r(\theta_r - r_{(k-1)\tau})\tau + \sigma_r\sqrt{r}_{(k-1)\tau}\tilde{z}_3, \tag{10}$$

where $\tilde{z}_1$, $\tilde{z}_2$, and $\tilde{z}_3$ are independent standard normal variates. Under the assumption that both asset volatility and interest rates follow a square-root diffusion, the value of equity is

$$P(t) = A(t)\,\mathcal{P}_1 - F(t)\,\mathcal{P}_2, \tag{11}$$

where $\mathcal{P}_1$ and $\mathcal{P}_2$ are provided, for example, in Pan (2003, p. 35). Given the value of the equity, B_t is computed from equation (7).

The parameters for the volatility process are taken from Pan (2003): $\kappa_v = 5.3$, $\sigma_v = 0.38$, and $\rho = -0.57$. The parameters for the interest rate process are those used in Chapman and Pearson (2000): $\kappa_r = 0.21459$ and $\sigma_r = 0.07830$. The initial values for both volatility and interest rates are equated to their long-term means, $V(0) = \theta_v = 0.16$ and $r(0) = \theta_r = 0.03$. For robustness, we also make the volatility process more persistent by reducing the rate of reversion to $\kappa_v = 1.38$ (half-life of six months).

The rest of the procedure follows the simulation procedure described in Section A.1. On each date, the firm refinances its existing debt of face value $F(t-\tau)$ with new debt of face value $F(t)$ of identical value. Mispricings are generated in the same manner as previously described.

Appendix B Capital Structure Arbitrage Hedge Ratio

To determine the relation between changes in CDS spreads and stock returns, we run a regression of the change in CDS spreads on the stock returns. Denote $\Delta CDS_{i,t}^{j} = CDS_{i,t}^{j} - CDS_{i,t-1}^{j}$ and $\Delta P_{i,t}^{j} = P_{i,t}^{j} - P_{i,t-1}^{j}$ as the change in CDS spreads and stock prices, respectively, for firm i and rating j. Then, following Schaefer and Strebulaev (2008), we first run the following regression for each firm i:

$$\Delta CDS_{i,t}^{j} = \alpha_i + \beta_i^j \frac{\Delta P_{i,t}^{j}}{P_{i,t-1}^{j}} + e_{i,t}. \tag{12}$$

We then average the coefficient over the N^j firms within the rating class to obtain $b^j = \frac{1}{N^j}\sum_i^{N^j} \beta_i^j$.

To determine the hedge ratio, we need to determine the value of the CDS at a given spread. We use the market standard model recommended and maintained by ISDA and Markit (http://cdsmodel.com) to determine the cash settlement value, $S_{i,t}^{j}$, of the spread. For small changes in the spread, we approximate the relation between the change in the value of the spread, $\Delta S_{i,t}^{j} = S_{i,t}^{j} - S_{i,t-1}^{j}$ and $\Delta CDS_{i,t}^{j}$ by

$$\Delta S_{i,t}^{j} = \Delta CDS_{i,t}^{j}\, D_{i,t}^{j}, \tag{13}$$

where we define $D_{i,t}^{j}$ as the duration of the spread. The duration of the spread depends on the level of the spread and is determined by the pricing model. For example, when the spread is 50 bps, the duration is about 4,300, that is, the value of the CDS changes by $4,300 for a 1-bps change in spread.

The hedge ratio, $\delta_{i,t}^{j}(P_{i,t}^{j})$, defined as the dollar amount of equity required to hedge one CDS contract, is then given by

$$\delta_{i,t}^{j}\left(P_{i,t}^{j}\right) = b^j D_{i,t}^{j}. \tag{14}$$

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Table 1: Simulation-Based Estimates of κ

This table reports the simulation-based estimates of κ as a function of the probability of mispricing. The second column reports the Merton model κ when asset volatility and interest rates are constant. The third and fourth columns report κ when asset volatility (SV) and both volatility and interest rates are stochastic (SIVs), respectively.

P(mispricing)	Merton	SV	SVI
0.00	-0.97	-0.95	-0.94
0.10	-0.87	-0.86	-0.84
0.20	-0.76	-0.75	-0.75
0.30	-0.66	-0.65	-0.63
0.40	-0.54	-0.54	-0.54
0.50	-0.42	-0.42	-0.42
0.60	-0.28	-0.27	-0.28
0.70	-0.13	-0.13	-0.13
0.80	0.05	0.05	0.05
0.90	0.33	0.30	0.30

Table 2: Descriptive Statistics

The sample consists of 214 non-financial U.S. firms over the period January 2, 2001, to March 31, 2009, with 115 firms of average rating above investment grade and 99 firms with average ratings of speculative grade. Volatility is the annualized standard deviation of the stock return over the sample period. Size is the market capitalization measured in billions of dollars. Leverage is the ratio of the book value of debt to the sum of the book value of debt and market capitalization. For each obligor, we first compute the time series mean of its (daily) five-year CDS spreads, (daily) market capitalization, and (quarterly) leverage, and then compute the statistics in the cross section. The equity volatility is computed as the annualized standard deviation of daily returns across the sample period.

	Five-Year CDS Spread (bps)				
	Mean	Median	Min	Max	Std
All	237.49	115.26	13.37	3991.72	394.69
Investment Grade	60.45	43.44	13.37	233.58	44.48
High Yield	439.31	286.33	81.51	3991.72	505.64
	Size (billions of dollars)				
	Mean	Median	Min	Max	Std
All	14.51	7.32	0.08	217.87	24.06
Investment Grade	23.14	14.09	1.65	217.87	30.18
High Yield	4.67	3.12	0.08	24.47	4.70
	Equity Volatility				
	Mean	Median	Min	Max	Std
All	0.46	0.43	0.20	0.96	0.16
Investment Grade	0.36	0.35	0.20	0.74	0.09
High Yield	0.58	0.55	0.31	0.96	0.15
	Leverage				
	Mean	Median	Min	Max	Std
All	0.36	0.34	0.02	0.98	0.19
Investment Grade	0.28	0.26	0.02	0.80	0.13
High Yield	0.47	0.48	0.03	0.98	0.20

Table 3: Summary Statistics

Panel A reports summary statistics for equity and credit market liquidity measures and idiosyncratic risk for 214 firms over the period January 2001 to March 2009. Here *depth* is the number of dealers who contribute to the composite CDS quote. The average of daily values is computed as the measure for each firm. The variable *spreadzero* is the proportion of zero daily CDS spread changes among all the non-missing daily changes in the sample period. The variable *amihud* is constructed as $10^6 * |\text{return}|/|\text{price} * \text{sharevolume}|$ from daily data. Here *zprop* is the proportion of zero daily returns among all non-missing returns in the sample period, and *idiosyn* is the idiosyncratic risk computed as the logistic transformation of the coefficient of determination from a regression of daily excess returns on the Fama–French three-factor model (Fama and French, 1992), $\ln\left(\frac{1-R^2}{R^2}\right)$. The first row presents the overall statistics, and the second and third rows present the between and within results for the standard deviation. Liquidity variables are winsorized at 1%.

Panel B of the table reports the correlations between the variables.

Panel A: Descriptive Statistics

	Mean	Median	Min	Max	Std
depth	7.36	7.15	2.15	15.15	2.63
(between)					1.42
(within)					2.30
spreadzero (%)	8.47	4.92	0.00	83.33	16.88
(between)					10.09
(within)					13.92
amihud (%)	0.17	0.03	0.00	4.18	0.54
(between)					0.44
(within)					0.38
zprop (%)	1.30	1.07	0.00	7.94	1.70
(between)					0.82
(within)					1.48
idiosyn	0.87	0.74	-1.99	6.96	1.00
(between)					0.46
(within)					0.89

Panel B: Correlation Matrix

	depth	spreadzero	amihud	zprop	idiosyn	lev	eqvol
depth	1.00						
spreadzero	-0.54	1.00					
amihud	-0.13	0.05	1.00				
zprop	-0.01	0.04	0.21	1.00			
idiosyn	0.01	0.13	0.00	0.19	1.00		
lev	-0.07	0.08	0.43	0.26	0.01	1.00	
eqvol	-0.14	0.06	0.46	0.05	-0.20	0.46	1.00

Table 4: Pricing Discrepancies

This table reports the co-movements between CDS spreads and stock prices, $\Delta CDS^\tau \Delta P^\tau > 0$, $\Delta CDS^\tau \Delta P^\tau < 0$, and $\Delta CDS^\tau \Delta P^\tau = 0$, as a proportion of total observations measured over non-overlapping time intervals $\tau \in \{5, 10, 25, 50\}$. Here $|\Delta CDS|$ is the mean of absolute spread changes, $|\Delta P/P|$ is the mean of absolute stock returns, and Obs. is the total number of non-missing pairs of spread and price changes in the sample. Co-movements are pricing discrepancies if $\Delta CDS^\tau \Delta P^\tau > 0$.

			$\Delta CDS\,\Delta P < 0$			$\Delta CDS\,\Delta P > 0$			$\Delta CDS\,\Delta P = 0$
Sample	Interval (days)	Obs.	Fraction (%)	$\lvert\Delta CDS\rvert$ (bps)	$\lvert\Delta P/P\rvert$ (%)	Fraction (%)	$\lvert\Delta CDS\rvert$ (bps)	$\lvert\Delta P/P\rvert$ (%)	Fraction (%)
	5	44,772	57.28	21.03	4.74	40.85	11.51	3.51	1.87
All	10	22,312	59.69	30.34	6.39	39.27	17.21	4.65	1.04
	25	8,777	62.72	55.71	10.10	36.77	25.85	6.75	0.51
	50	4,307	67.84	89.40	14.90	31.86	39.93	9.23	0.30
	5	20,859	55.80	3.88	2.96	43.19	3.03	2.37	1.01
Invt.	10	10,408	57.98	5.83	4.07	41.47	4.79	3.27	0.55
Grade	25	4,082	60.00	10.75	6.48	39.78	7.78	4.88	0.22
	50	1,988	65.59	17.25	9.55	34.21	12.38	6.76	0.20
	5	23,913	58.56	35.28	6.22	38.82	19.73	4.63	2.62
High	10	11,904	61.17	50.66	8.31	37.35	29.27	5.99	1.48
Yield	25	4,695	65.09	91.74	13.00	34.14	44.15	8.64	0.77
	50	2,319	69.77	147.54	19.22	29.84	67.00	11.65	0.39

Table 5: Discrepancies Conditioned on Changes in Volatility and Debt

Panel A reports the fraction of total pricing discrepancies conditioned on the direction of changes in stock price and implied volatility on a monthly frequency. The implied volatility is the average of the nearest to the money call and put for a maturity of 30 days. The total number of pricing discrepancies at the monthly frequency is 2,856 (37.8% of the total observations, $N = 7,548$). Panel B reports the fraction of total pricing discrepancies between CDS spreads and stock prices conditioned on the direction of changes in stock price and the book value of debt on a quarterly frequency. The book value of debt is defined as sum of long-term and short-term debt. The total number of pricing discrepancies at the quarterly frequency is 1,166.

Panel A: Volatility

Sample	$\Delta P_i > 0$	$\Delta P_i < 0$
Increase in Vol	0.253	0.260
Decrease in Vol	0.253	0.234

Panel B: Debt

Sample	$\Delta P_i > 0$	$\Delta P_i < 0$
Increase in Debt	0.234	0.197
Decrease in Debt	0.307	0.262

Table 6: Capital Structure Arbitrage Excess Returns

For each firm, using the trading strategy documented in the text, we compute the average excess return per trade over 2001–2009. This table reports descriptive statistics for the mean excess return over the cross section of 214 firms. Panel A reports results when the trading rule is based on price changes over the previous five business days and the position is held for a maximum period of one month. Panel B reports results when the trading rule is based on price changes over the previous 10 business days and the position is held open for a maximum period of two months.

Panel A

Sample	Period	# of Firms	# of Trades	Excess Return	Median	Std. Dev.	Skew	Kurtosis	Min.	Max.	# of Premature Closures
All	Jan2001–Dec2007	205	32.1	0.14%	0.19%	2.58%	-0.04	4.33	-10.46%	11.36%	7.92
	Jan2008–Mar2009	198	10.7	1.18%	-0.12%	6.20%	0.78	0.95	-14.55%	22.68%	5.72
Invt. Grade	Jan2001–Dec2007	109	34.9	0.24%	0.16%	2.47%	0.03	4.07	-10.46%	8.63%	7.63
	Jan2008–Mar2009	109	10.4	2.01%	0.15%	5.71%	0.62	0.66	-12.65%	22.03%	4.90
High Yield	Jan2001–Dec2007	96	29.1	0.04%	0.16%	2.84%	-0.33	4.38	-10.16%	11.36%	8.25
	Jan2008–Mar2009	89	11.0	0.15%	-1.18%	6.74%	1.00	1.52	-14.55%	22.68%	6.79

Panel B

Sample	Period	# of Firms	# of Trades	Excess Return	Median	Std. Dev.	Skew	Kurtosis	Min.	Max.	# of Premature Closures
All	Jan2001–Dec2007	205	20.8	0.17%	0.07%	3.78%	0.18	1.76	-11.88%	15.28%	7.77
	Jan2008–Mar2009	198	6.9	2.22%	0.57%	10.15%	1.91	6.83	-16.31%	55.98%	4.64
Invt. Grade	Jan2001–Dec2007	109	20.9	0.23%	-0.02%	3.79%	0.38	2.67	-10.86%	15.28%	6.49
	Jan2008–Mar2009	108	7.0	1.34%	-0.75%	9.47%	2.21	9.74	-15.22%	55.98%	4.43
High Yield	Jan2001–Dec2007	96	20.8	0.10%	0.34%	3.80%	-0.06	0.80	-11.88%	10.40%	9.30
	Jan2008–Mar2009	89	6.8	3.28%	2.03%	10.87%	1.65	4.99	-16.31%	52.16%	4.92

Table 7: Descriptive Statistics for $\bar{\kappa}$

This table reports descriptive statistics for the log-transformed variable $\bar{\kappa} = \frac{1}{2}\ln(\frac{1+\kappa}{1-\kappa})$ across the cross section of 214 firm for $\tau \in \{5, 10\}$ over 2001.1–2009.3. We also present the between and within results for the standard deviation.

Panel A: Whole Sample

τ	Mean	Median	Min.	Max.	Std.
5	-0.29	-0.29	-2.09	1.40	0.44
(between)					0.16
(within)					0.42
10	-0.28	-0.35	-2.20	2.03	0.53
(between)					0.17
(within)					0.51

Panel B: Investment Grade

τ	Mean	Median	Max.	Min.	Std.
5	-0.25	-0.25	-2.09	1.40	0.43
(between)					0.12
(within)					0.42
10	-0.24	-0.20	-2.20	1.49	0.53
(between)					0.13
(within)					0.52

Panel C: Below Investment Grade

τ	Mean	Median	Max.	Min.	Std.
5	-0.34	-0.35	-2.09	1.10	0.45
(between)					0.18
(within)					0.43
10	-0.34	-0.35	-2.03	2.03	0.53
(between)					0.20
(within)					0.50

Table 8: Panel Regression for the Whole Sample

This table reports the results of the panel regression,

$$\bar{\kappa}_{i,t} = \alpha_i + \gamma_t + \beta_1 \text{eqvol}_{i,t} + \beta_2 \text{lnmcap}_{i,t} + \beta_3 \text{lev}_{i,t} + \beta_4 \text{variable}_{i,t} + \epsilon_{i,t},$$

where $\bar{\kappa}$ is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+\kappa}{1-\kappa})$, where κ is the Kendall correlation. The set of *variable* includes credit market illiquidity (*spreadzero*), credit market liquidity (*depth*), stock market illiquidity (*amihud*), stock market illiquidity (*zprop*), and idiosyncratic risk (*idiosyn*). The regressions are conducted quarterly. The leverage *lev* is calculated as the ratio of the book value of debt to the sum of the book debt value and market capitalization. Here *eqvol* is the annualized equity volatility in every quarter and *lnmcap* is the log of the market capitalization. Standard errors are robust and clustered by firm. We do not report the intercepts due to space limitations. The t-values are reported in parentheses. Here ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$
lev	-0.0376	-0.0932	-0.0762	-0.0078	-0.1225	-0.0442	-0.1305	-0.0489	-0.1173	-0.0387	-0.0321	-0.0872	-0.0685	-0.0027
	(-0.31)	(-0.60)	(-0.72)	(-0.06)	(-1.17)	(-0.35)	(-1.25)	(-0.38)	(-1.13)	(-0.31)	(-0.27)	(-0.56)	(-0.64)	(-0.02)
eqvol	-0.2207***	-0.2677***	-0.2121***	-0.2800***	-0.2204***	-0.2804***	-0.2058***	-0.2751***	-0.2151***	-0.2858***	-0.2306***	-0.2739***	-0.2301***	-0.2916***
	(-3.90)	(-3.91)	(-4.28)	(-4.77)	(-4.24)	(-4.41)	(-4.18)	(-4.66)	(-4.32)	(-4.78)	(-3.84)	(-3.66)	(-4.32)	(-4.48)
lnmcap	0.0733***	0.0361	0.0769***	0.0541*	0.0716***	0.0478	0.0697***	0.0485	0.0759***	0.0556*	0.0810***	0.0416	0.0889***	0.0635*
	(2.44)	(0.97)	(2.81)	(1.65)	(2.47)	(1.38)	(2.50)	(1.45)	(2.72)	(1.66)	(2.60)	(1.08)	(3.11)	(1.84)
spreadzero	0.2968***	0.3050***									0.2894***	0.2995***		
	(4.31)	(3.49)									(4.26)	(3.46)		
lndepth			-0.0822***	-0.0691**									-0.0801***	-0.0670**
			(-3.33)	(-2.18)									(-3.26)	(-2.12)
amihud					1.8466	0.4642					-0.0705	-0.9475	1.7300	0.4637
					(0.80)	(0.15)					(-0.03)	(-0.29)	(0.75)	(0.15)
zprop							0.4394	0.3136						
							(0.98)	(0.55)						
idiosyn									0.0302***	0.0343***	0.0277**	0.0290**	0.0297***	0.0338***
									(2.90)	(2.76)	(2.32)	(2.18)	(2.86)	(2.72)
N	3,632	3,518	4,643	4,500	4,643	4,500	4,643	4,500	4,643	4,500	3,632	3,518	4,643	4,500
$Adj.R^2$	12.4%	10.0%	12.2%	9.3%	12.0%	9.2%	12.0%	9.3%	12.3%	9.4%	12.6%	10.1%	12.4%	9.5%
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Panel Regression for the Investment–Grade and Below–Investment–Grade Samples

This table reports the results of the regressions for each rating class,

$$\bar{\kappa}_{i,t} = \alpha_i + \gamma_t + \beta_1 \text{lev}_{i,t} + \beta_2 \text{eqvol}_{i,t} + \beta_3 \text{lnmcap}_{i,t} + \beta_4 \text{CDSliq}_{i,t} + \beta_5 \text{amihud}_{i,t} + \beta_6 \text{idiosyn}_{i,t} + \epsilon_{i,t},$$

where $\bar{\kappa}$ is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+\kappa}{1-\kappa})$. The set of *CDSliq* includes either credit market illiquidity (*spreadzero*) or credit market liquidity (*depth*). We also include stock market illiquidity (*amihud*) and idiosyncratic risk (*idiosyn*). The leverage *lev* is calculated as the ratio of the book value of debt to the sum of the book debt value and market capitalization. Here *eqvol* is the annualized equity volatility in every quarter and *lnmcap* is the log of the market capitalization. The regressions are conducted quarterly. Standard errors are robust and clustered by firm. We do not report the intercepts due to space limitations. The t-values are reported in parentheses. Here ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Investment Grade				High Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$
lev	0.2225	-0.1085	0.0664	0.1933	-0.1073	-0.0800	-0.1053	-0.0845
	(0.95)	(-0.42)	(0.43)	(1.13)	(-0.77)	(-0.44)	(-0.78)	(-0.47)
eqvol	-0.2685	-0.1622	-0.3685***	-0.4274***	-0.2426***	-0.2991***	-0.2480***	-0.3058***
	(-1.27)	(-0.69)	(-3.64)	(-3.64)	(-3.95)	(-3.68)	(-3.99)	(-3.72)
lnmcap	0.1872***	0.1310*	0.1691***	0.1499***	0.0623*	0.0381	0.0710**	0.0465
	(2.92)	(1.67)	(4.10)	(2.88)	(1.71)	(0.84)	(2.00)	(1.07)
spreadzero	0.1506	-0.0600			0.3123***	0.3585***		
	(1.09)	(-0.31)			(3.68)	(3.56)		
lndepth			-0.0395	-0.0038			-0.1142***	-0.1189***
			(-1.07)	(-0.08)			(-3.31)	(-2.84)
amihud	65.8077	197.1617**	48.6939**	52.0679***	-0.4433	-1.1685	-0.5707	-1.3414
	(0.77)	(2.11)	(2.07)	(3.17)	(-0.17)	(-0.34)	(-0.22)	(-0.39)
idiosyn	0.0149	0.0149	0.0232	0.0282	0.0385***	0.0455***	0.0389***	0.0455***
	(0.73)	(0.64)	(1.62)	(1.53)	(2.63)	(2.90)	(2.64)	(2.88)
N	1,674	1,631	2,685	2,613	1,958	1,887	1,958	1,887
$Adj.R^2$	9.4%	8.4%	11.0%	8.5%	13.2%	10.3%	13.0%	10.2%
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Panel Regression for the Periods Before and During the Crisis

This table reports the results of the regressions for the periods before and during the financial crisis,

$$\bar{\kappa}_{i,t} = \alpha_i + \gamma_t + \beta_1 \text{lev}_{i,t} + \beta_2 \text{eqvol}_{i,t} + \beta_3 \text{lnmcap}_{i,t} + \beta_4 \text{CDSliq}_{i,t} + \beta_5 \text{amihud}_{i,t} + \beta_6 \text{idiosyn}_{i,t} + \epsilon_{i,t},$$

where $\bar{\kappa}$ is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+\kappa}{1-\kappa})$. *CDSliq* is either credit market illiquidity (*spreadzero*) or credit market liquidity (*depth*). We also include stock market illiquidity (*amihud*) and idiosyncratic risk (*idiosyn*). The leverage *lev* is calculated as the ratio of the book value of debt to the sum of the book debt value and market capitalization. *eqvol* is the annualized equity volatility in every quarter and *lnmcap* is the log of the market capitalization. The regressions are conducted quarterly. Standard errors are robust and clustered by firm. We do not report the intercepts due to space limitations. The t-values are reported in parentheses. Here ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Results Before and During the Crisis

	2001–2007				2008–2009			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$	$\bar{\kappa}(\tau = 5)$	$\bar{\kappa}(\tau = 10)$
lev	-0.1063	-0.1530	-0.0700	-0.0288	0.2216	0.2918	-0.0695	-0.2580
	(-0.74)	(-0.78)	(-0.55)	(-0.17)	(0.40)	(0.41)	(-0.15)	(-0.43)
eqvol	-0.2929***	-0.2801***	-0.3514***	-0.3926***	-0.1437	- 0.2370	-0.1492	-0.2567*
	(-3.77)	(-2.68)	(-4.92)	(-4.13)	(-1.18)	(-1.61)	(-1.15)	(-1.66)
lnmcap	0.0528	0.0281	0.0448	0.0168	0.2538**	0.2544	0.2700***	0.2473
	(1.62)	(0.65)	(1.50)	(0.44)	(2.22)	(1.52)	(2.39)	(1.64)
spreadzero	0.2450***	0.2893***			1.6708	2.2112		
	(3.48)	(3.00)			(0.82)	(0.97)		
lndepth			-0.0866***	-0.0651*			-0.0294	-0.1544
			(-3.25)	(-1.84)			(-0.25)	(-0.97)
amihud	2.6214	6.4601	2.5876	4.9948	- 0.2645	0.4808	1.7917	2.4057
	(0.42)	(0.92)	(0.44)	(0.70)	(-0.06)	(0.09)	(0.38)	(0.43)
idiosyn	0.0294**	0.0340**	0.0287***	0.0410***	0.0298	0.0263	0.0370	0.0185
	(2.20)	(2.27)	(2.43)	(2.98)	(0.89)	(0.64)	(1.43)	(0.54)
N	3,171	3,065	3,756	3,627	461	453	887	873
$Adj.R^2$	11.7%	10.2%	11.9%	9.8%	28.2%	21.0%	21.9%	16.7%
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Results with Interaction Terms during the Crisis (2008–2009)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$	$\bar{\kappa}(\tau=5)$	$\bar{\kappa}(\tau=10)$
lev	0.1842	0.2171	-0.0351	-0.1446	0.1582	0.1882
	(0.33)	(0.30)	(-0.06)	(-0.18)	(0.26)	(0.23)
eqvol	-0.2114*	-0.3151**	-0.0684**	-0.1080	-0.1323	-0.2221
	(-1.78)	(-2.13)	(-0.51)	(-0.69)	(-1.05)	(-1.44)
lnmcap	0.2329*	0.2229	0.2261	0.2101	0.2396*	0.2319
	(1.89)	(1.35)	(1.61)	(1.12)	(1.84)	(1.29)
spreadzero	-1.9366	-1.7086	1.6617	2.1889	1.6773	2.2177
	(-0.84)	(-0.62)	(0.83)	(0.98)	(0.82)	(0.97)
amihud	-0.2670	0.3550	6.8473	13.3488	- 0.4403	0.2522
	(-0.06)	(0.07)	(0.63)	(1.37	(-0.09)	(0.05)
idiosyn	0.0413	0.0383	0.0352	0.0356	0.0463	0.0486
	(1.22)	(0.92)	(1.01)	(0.84)	(0.90)	(0.77)
eqvol*spreadzero	4.1600***	4.5508***				
	(4.02)	(2.56)				
eqvol*amihud			-4.7761	-8.6040		
			(-0.76)	(-1.35)		
eqvol*idiosyn					-0.0197	-0.0273
					(-0.41)	(-0.48)
N	461	453	461	453	461	453
$Adj.R^2$	29.6%	22.1%	28.3%	21.3%	28.1%	20.9%
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes

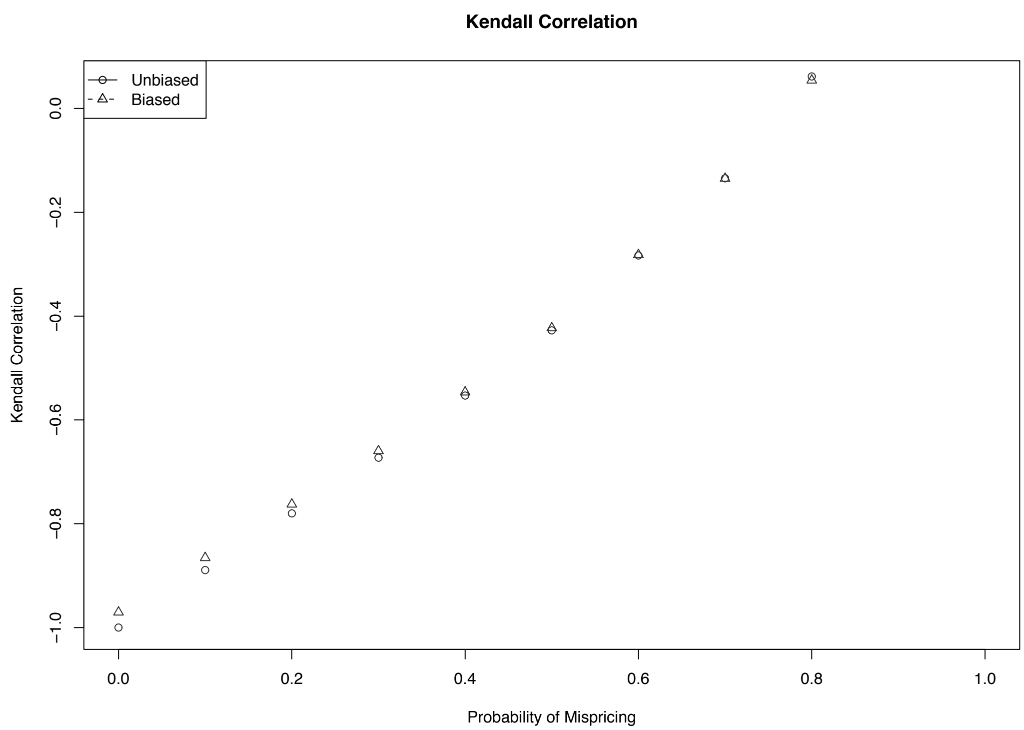
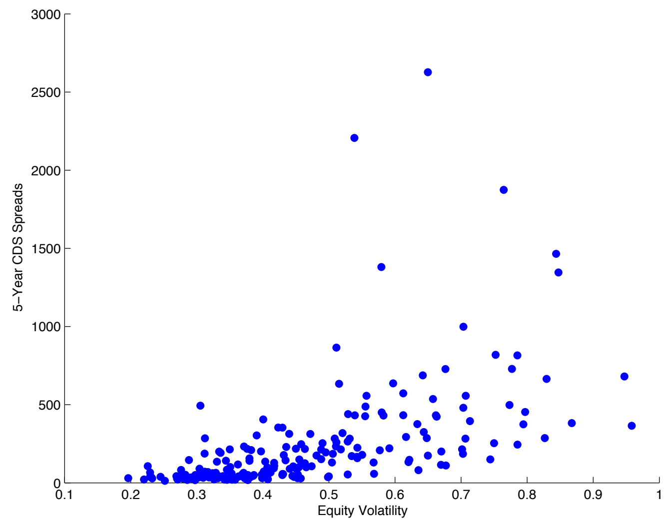


Figure 1:
κ_i versus the probability of mispricing.



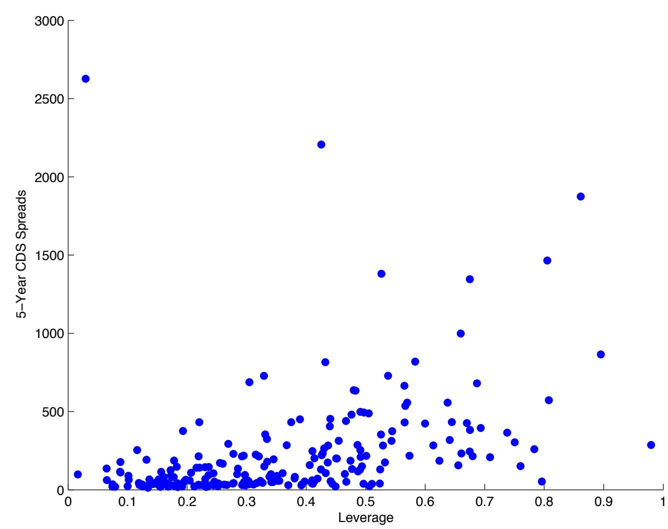


Figure 2: CDS spread versus volatility and leverage.

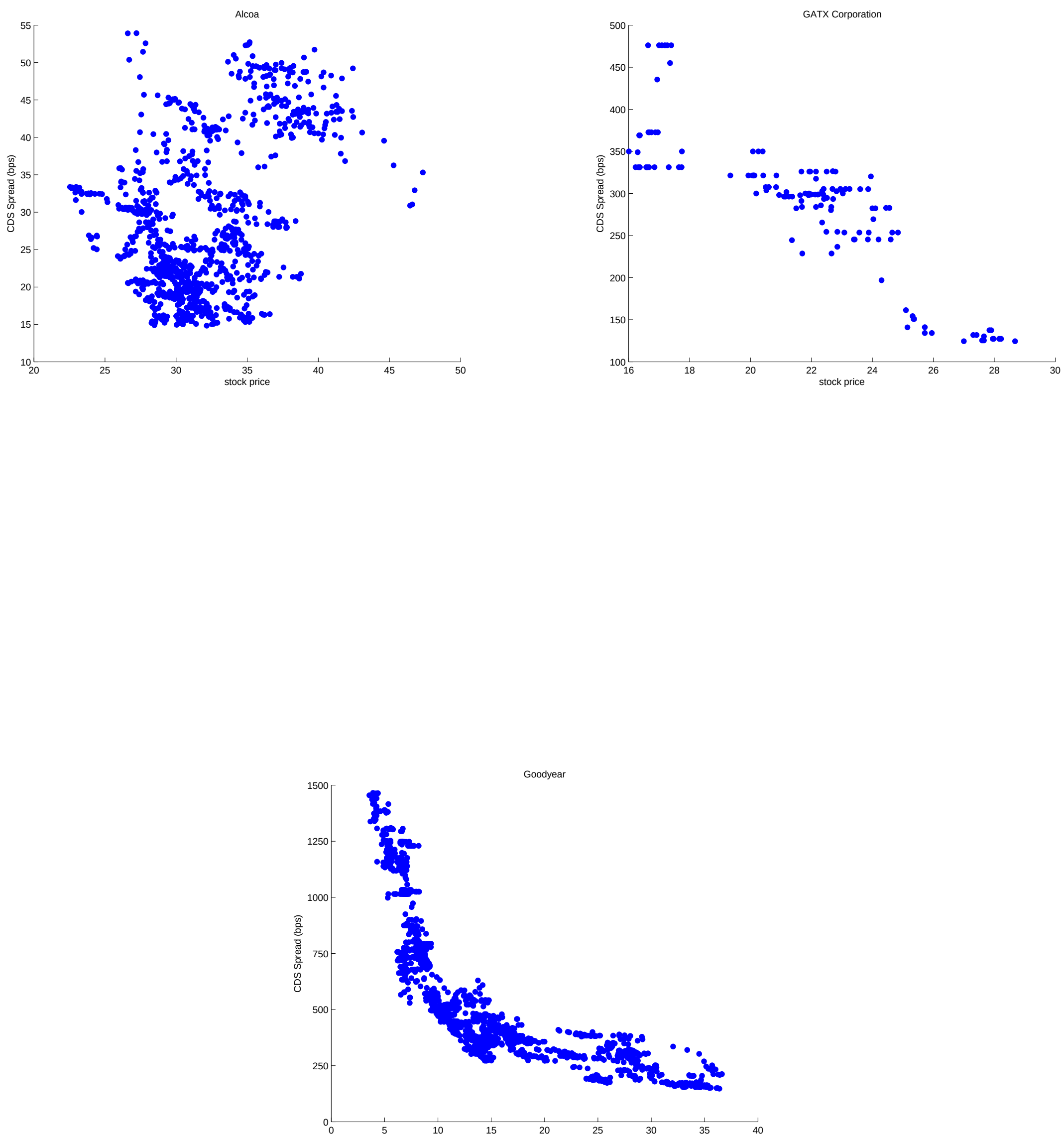


Figure 3: CDS spread versus stock price (2001–2007).

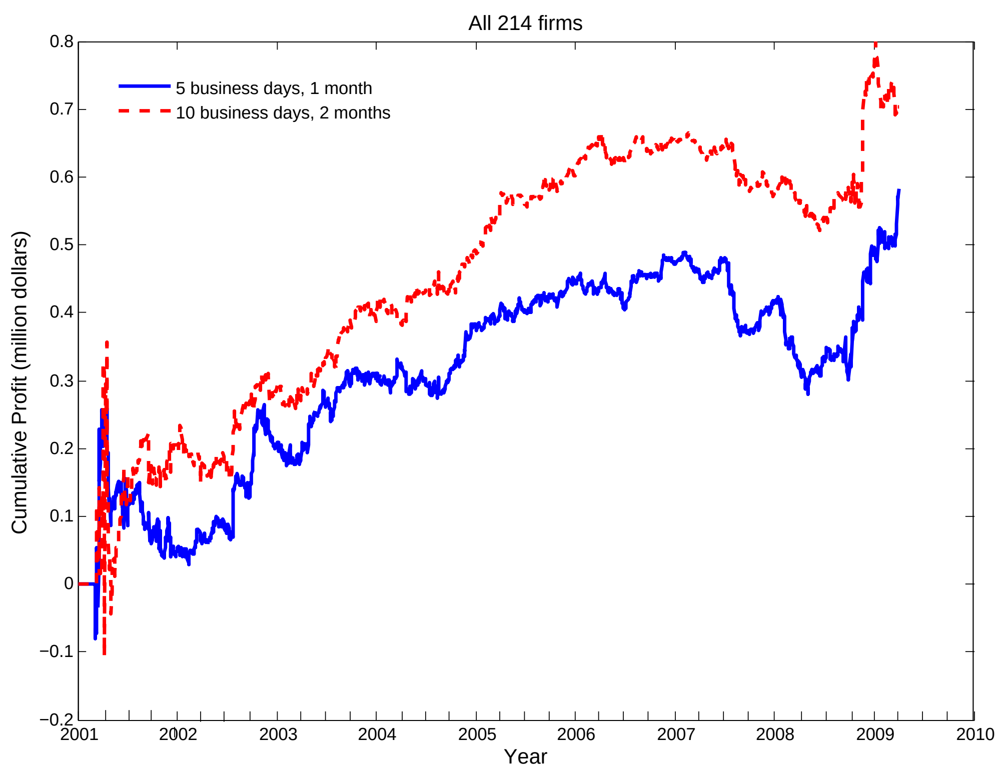


Figure 4: Cumulative profits from capital structure arbitrage. Cumulative profits are computed by compounding the mean daily return over all open positions. The annualized daily volatility values for the one- and two-month horizons are 10.18% and 10.22%, respectively.