Limited Arbitrage between Equity and Credit Markets

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Abstract

We examine whether limits to arbitrage explain the level of integration of a firm's equity and credit market. Consistent with the hypothesis, we find that the cross-sectional variation in the correlation between firms' equity and credit markets is related to the heterogeneity of its investors, funding liquidity, market liquidity, and the idiosyncratic risk of the firm. This set of variables explain as much as 44for alternative hypotheses that pricing discrepancies are related to changes in a firm's volatility or debt, or related to systematic liquidity of the credit markets.

Keywords: limited arbitrage, structural models, credit default swaps,

1 Introduction

An important implication of Merton's (1974) structural model of credit risk is that stock price and credit spread changes must be precisely related to ensure the absence of arbitrage. Not surprisingly, 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. The popular press often writes of the relation between equity and credit markets as in this recent article from the *Wall Street Journal*:[1]

> Compare junk-bond yields to the earnings yields on stocks, and it seems like stocks are incredibly cheap. "Look at the valuations in the two markets and they're about as far apart as they've ever been," says M.S. Howells strategist Brian Reynolds. That creates a great arbitrage situation for deal makers, who get to issue expensive-looking bonds to buy cheap-looking stock.

Given the theoretical link between the equity and bond of a firm and active arbitrage activity, equity and credit markets should be closely integrated. Instead, recent research has found stock returns and changes in credit spreads to be weakly correlated. In a regression of monthly changes in credit spreads on stock returns and other variables consistent with a structural framework, Collin-Dufresne, Goldstein and Martin (2001) find adjusted R^2s of the order of 17% to 34%. They 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 exercise using weekly changes in spreads of credit default swaps (CDS), and find that three-quarters of the variation remains unexplained. This low correlation is especially surprising because the Merton (1974) model does an excellent job of fitting the cross-sectional dispersion of medium horizon credit spreads. In our dataset, a cross-sectional regression of the average five-year credit default swap over 2001-05 on the firm's average debt ratio and stock return volatility gives an adjusted R^2 of 61%. How then to explain low correlations between equity and credit markets?

The existing literature suggests two hypotheses. First, the low correlation may be explained by a structural model that relaxes, in particular, Merton (1974) assumptions

[1] Justin Lahart, *Wall Street Journal*, November 21, 2006.

of constant firm volatility and debt.[2] Changes in a firm's volatility and debt can cause wealth transfers between shareholders and bondholders and reduce the observed correlation between equity returns and credit spread changes. Changes in equity volatility are an explanation 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 give a false signal of 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 with the "true" credit pricing model.

In this paper, we propose and investigate a third hypothesis that Merton-model pricing discrepancies, at least in part, are anomalies, and the lack of integration of the two markets is a result of limited arbitrage activity. Limits to arbitrage that prevent arbitrageurs like hedge funds from investing the capital required to eliminate pricing anomalies have been actively explored in existing literature, but not been previously proposed as an explanation for the low correlation between equity and credit markets.[3]

We are motivated to examine the limits to arbitrage hypothesis because of striking empirical regularities that are inconsistent or difficult to explain with the other hypotheses. First, we document that Merton-model pricing discrepancies, defined as instances when increases in stock prices coincide with increases in CDS spreads, decline over longer horizons. Over 5-business day intervals, on average, 45% of all price movements are classified as anomalous, but over a 50-business day interval, these anomalies reduce by more than half to 21.5%. This observation is difficult to reconcile with the first two hypotheses. As firms' financial or investment policies are stable over short horizons, pricing discrepancies induced

[2] Attempts to make the Merton (1974) model more realistic have focused on specifications for the default boundary, recovery, and the stochastic process determining the underlying firm value or leverage. See Black and Cox (1976), Leland (1994), Leland and Toft (1996), Longstaff and Schwartz (1995), Anderson and Sunderesan (1996), Collin-Dufresne and Goldstein (2001).

[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)) and negative stub values (Mitchell, Pulvino and Stafford (2002), Lamont and Thaler (2003)). See also related work by Ali, Hwang and Trombley (2003) and Mitchell, Pedersen and Pulvino (2007).

by wealth transfers should be more frequent over longer horizons than shorter. The cumulative impact of a credit market specific pricing factor should lead to greater divergence between equity and credit markets and more pricing discrepancies over longer horizons, not fewer. Second, there is significant cross-sectional variation in pricing discrepancies; the relation between stock prices and CDS spreads is clearly discernible for many firms, but not for others. Figure 2 plots the CDS spread vs. the stock price over the five-year period of our sample for Alcoa, Hilton and GM. The long-term relation between the equity and the CDS spread for GM is clearly discernible, less so for Hilton, and not for Alcoa. The puzzle is not that the two markets have a low correlation on average, but that the level of integration varies significantly in the cross-section.

The limits to arbitrage literature provides a framework to understand these observations. As in Shleifer and Summers (1990) and Shleifer and Vishny (1997), consider convergence trades across equity and credit markets to be risk arbitrage trades instead of the zero-capital, riskless arbitrage modeled in structural models. Given mispricing (Basak and Croitoru (2000, 2006)), arbitrageurs will deploy capital if they are not funding constrained (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2008)); the amount of capital deployed will depend upon the costs associated undertaking the arbitrage (e.g., Pontiff (1996, 2006)), arbitrage capital will accumulate slowly (Abreu and Brunnermeier (2002), Mitchell, Pedersen and Pulvino (2007)) in part because of institutional constraints on the availability of risk capital (Merton (1987)), and reduce pricing discrepancies, on average, but not necessarily completely nor always (Xiong (2001), Kondor (2009)). The observation that anomalies decrease with horizon is consistent with the notion that arbitrage capital is slow moving. Moreover, the literature provides specific cross-sectional implications.

First, even in the absence of irrational noise traders, Basak and Croitoru (2000) note that mispricing can develop when market participants with portfolio constraints have differences in opinions. Basak and Croitoru (2006) formally demonstrate that in such a setup, an arbitrageur can profit by facilitating trades between the heterogeneous investors. To apply their setup to capital structure arbitrage, suppose stock holders are more optimistic about the prospects of the firm than bond holders but, in the short run, the firm is constrained from replacing the debt with relatively expensive equity. This market imperfection effectively creates a portfolio constraint on investors, preventing them from reaching their desired portfolio holding. The arbitrageur can facilitate trade between stock and bond holders by simultaneously selling credit default swaps to the bond holders and shorting stock to the stock holders. The profits of the arbitrager, and, therefore, should be related in the cross-section to the heterogeneity of opinions across investors.

In practice, an arbitrageur cannot take advantage of a mispricing if he cannot fund his position and, therefore, as Brunnermeier and Pedersen (2008) note, funding liquidity is an important determinant of arbitage activity. Gromb and Vayanos (2002) observe that the problem of funding a position arises because an arbitrageur cannot cross-margin, and instead has to post margin on each leg of his trade. The inability to cross-margin has a surprisingly strong and simple cross-sectional implication: The capital requirements for a convergence trade increases as the default risk of a firm decreases. This is because bonds of a firm with a low default risk also have a low sensitivity to changes in the firm value. For a given position on the equity leg, the arbitrageur thus requires a larger position on the credit leg. As the firm gets safer, the capital requirements for taking advantage of small mispricing increases rapidly, making it costly or even impossible to fund the convergence trade.

There are costs associated with implementing a convergence trade. First, we expect liquidity of the markets to impact costs associated with arbitrage. As the arbitrageur has to trade across markets, both equity and credit market liquidity may impact arbitrage activity. We should expect, however, that the less liquid market will have a more significant impact on arbitrage activity. Second, in practice, arbitrageurs are unlikely to perfectly hedge an equity position against the credit position. For example, an arbitrageur betting on a decline in stock prices or CDS spreads cannot hedge against the firm-specific risk that the firm might undertake a corporate action that, in fact, does the opposite as, for example, if the firm enters into a leveraged buyout transaction. An inability to construct a perfect hedge results in the arbitrageur being exposed to the idiosyncratic risk of the firm. Pontiff (2006) argues that idiosyncratic risk is the primary holding cost for an arbitrageur. Given cross-sectional differences in equity and credit market liquidity as well as idiosyncratic risk, costs of implementing a convergence trade will vary across the cross-section.

Finally, given slow moving arbitrage capital and synchronization risk, arbitrageurs will be more effective in integrating markets over longer horizons. This has two implications. First, as noted earlier, a firm's equity and credit market will be more integrated over longer horizons. Second, as the effectiveness of arbitrage activity increases, cross-sectional differences in integration will more closely reflect the variables that impact arbitrage activity. Therefore, these variables will explain a larger proportion of the cross-sectional variation in integration over longer horizons. That is, not only should the correlation between equity and credit markets increase with horizon, but the ability to explain cross-sectional variation should also increase.

We test these implications in a sample of 199 firms over 2001-05, and find extensive support for the hypothesis. First, we document that pricing discrepancies are frequent, persistent, and economically large. Over a 5 business day interval, 45.5% of all price changes are classified as discrepancies. Although these decrease with the sampling interval, they represent 28.5% of observations at a 50 business day interval. These discrepancies are coincident with large changes in the underlying spread and stock return: the average stock return is 10.1% and the average change in CDS spread is 52 basis points.

Next, we show that the cross-sectional variation in the degree of integration is consistent with the implications of limited arbitrage. First, firms with higher diversity of opinions, proxied by analysts' forecast dispersion, have more integrated equity and CDS markets, indicating that arbitrage activity is related to the disagreement amongst investors. Second, riskier firms - firms with higher equity volatility and lower rating - are more integrated, suggesting that funding liquidity is an important determinant of arbitrage activity. Third, liquidity in the credit markets is significant in determining cross-sectional variation in integration, but equity market liquidity, at least for the firms in our sample, plays no role. Fourth, firms with higher idiosyncratic risk have less integrated equity and credit markets, consistent with the hypothesis that idiosyncratic risk is an important holding cost for arbitrageurs. Fifth, these variables explain more of the cross-sectional variation in integration over longer horizons as one would expect if arbitrage activity is more effective over longer horizons. The coefficient of determination over a 1-week horizon is 25% as compared with 42% for a 50-day horizon. Our results are robust to sampling horizons from 5- to 50-business days and to sub-periods. They are robust to contractual differences across CDS contracts. The fact that the adjusted R^2 is as high as 42% indicates the importance of arbitrage activity in explaining the integration of the equity and credit markets.

To what extent do alternative hypotheses explain mispricing? For pricing discrepancies to be related to wealth transfers, they should be higher in periods when an increase (decrease) in stock price is coincident with an increase (decrease) in volatility. Instead, we find the opposite. There are significanly more discrepancies in the periods when an increase (decrease) in stock price coincides with a decrease in volatility. Next, we investigate whether pricing discrepancies are related to changes in the face value of debt, and find no evidence of a relation between pricing discrepancies and changes in the book value of debt. That is, the standard explanations of wealth transfer do not explain pricing discrepancies. If there are market-wide factors that impact pricing discrepancies, then these factors should explain the pricing discrepancies across the market in the time-series. First, we check whether a systematic credit-market specific liquidity factor impacts market-wide discrepancies. Second, we check whether the Treasury rate impacts pricing discrepancies. In both cases, we find that there is no significant relation. Finally, we test whether changes in an arbitrageur's cost of funding can explain the time-variation in pricing discrepancies across the market. In line with our cross-sectional evidence, we find that changes in the Eurodollar rate do explain the time-variation in pricing discrepancies across the market. Overall, in this battery of tests, we find no evidence in support of other explanations, but instead find additional support for the limits to arbitrage hypothesis.

In addition to the literature already cited, our paper is related to a number of other papers. Duarte, Longstaff and Yu (2005) and Yu (2005) study the profitability of capital structure arbitrage, and show that the returns are positive, positively skewed, and have high Sharpe ratios. In particular, Duarte, Longstaff and Yu (2005) suggest that the alpha to capital structure arbitrage are amongst the highest across fixed income arbitrage strategies.[4] Acharya, Schaefer and Zhang (2008) focus on an interesting episode where downgrades of Ford and GM debt in May 2005 results in a market-wide increases in correlation between firms' CDS spreads. They interpret these results as being consistent with funding constraints on market participants in crisis times resulting in temporary liquidity risk. We complement their analysis by observing that in addition to a short-lived impact in the time series, funding constraints on arbitrage activity also have cross-sectional effects.

We proceed as follows. Section 2 presents the theoretical literature, and the framework for our tests. Section 3 describes our data. Section 4 documents the Merton-model pricing discrepancies. Section 5 empirically tests whether the cross-sectional variation in integration between a firm's equity and credit markets may be explained by variables suggested in the litarature that models arbitrage activity. Section 6 investigates the extent to which alternative hypotheses explain pricing discrepancies. The last section concludes.

[4] The Wall Street Journal (February 6, 2009) estimated that the capital structure arbitrage group at Deutsche Bank made an estimated \$900 million in 2006 and \$600 million in 2007.

2 Framework and Overview of the Literature

As in Gromb and Vayanos (2002), assume that equity and credit markets are segmented in that at least some investors hold only the stock or the credit default swap, thus creating a role for the risk arbitrageur. Arbitrageurs engage in convergence trades across the equity and credit markets, taking into account the costs and risks associated with the trade. With limited arbitrage capital, arbitrage capital will vary across the cross-section of stocks. Arbitrageurs, on average, make the equity and credit markets more integrated in the sense that there are less (but not necessarily zero) pricing discrepancies.[5] Markets with more arbitrage capital will have fewer pricing discrepancies and be more integrated. If there are cross-sectional variations in the arbitrage capital, there will be cross-sectional differences in the level of integration. Below, we review the theoretical literature to derive specific hypotheses.

2.1 Diversity of Opinions

Basak and Croitoru (2000) and Hong and Stein (2003) are amongst the first to note that differences in opinions create opportunities for an arbitrageur.[6] Basak and Croitoru (2006) develop a formal model of a convergence trader. In their model, the convergence trader profits by facilitating trades between heterogeneous investors who are constrained from directly trading with each other.

To illustrate, suppose stock holders are more optimistic about the prospects of the firm and its value than bond holders. The firm could issue more stock to its shareholders and use the proceeds to reduce the holding of the pessimistic bond holders. However, if the firm is unwilling or unable to do so quickly, the convergence trader can step in to facilitate the trade. The convergence trader would simultaneously sell credit default swaps to the bond holders and short stock to the stock holders, and thus help to integrate the two markets.

If pricing discrepancies are not completely eliminated and arbitrage capital varies in the

[5]As in Xiong (2001) and Gromb and Vayanos (2002), arbitrageurs may at times exacerbate pricing discrepancies when they liquidate their positions in the face of widening spreads.

[6]In principle, it is also possible for convergence traders to profit from irrational noise traders until the latter run out of capital. However, a number of recent papers starting with De Long, Shleifer, Summers and Waldmann (1990) have suggested that noise traders also create risks for a convergence trader. In Xiong (2001), the presence of noise traders has an ambiguous impact on the capital invested by the risk arbitrageur. By pushing prices further away from fundamentals, noise traders can create a larger alpha, but the losses on an open position because of widening spreads can also make the convergence trader more risk averse.

cross-section, then there may exist a cross-sectional relation between investor heterogeneity and the level of integration. Much of the recent literature argues that arbitrageurs do not eliminate mispricing. In Liu and Longstaff (2004) and Kroner (2009), arbitrageurs choose to limit the amount of capital allocated to a convergence trade even when facing a fundamentally riskless arbitrage opportunity, and therefore not fully integrate the market. In Basak and Croitoru (2006), arbitrageurs do not eliminate pricing discrepancies because they are non-competitive. In addition, the literature suggests that arbitrage capital may vary in the cross-section. In Basak and Croitoru (2006), the amount of arbitrage capital increases with higher investor disagreement. Merton (1987) points out that information costs can make market participants specialize and focus on a subset of opportunities. If so, arbitrageurs may choose to specialize in markets that are more likely to have mispricing, leading to cross-sectional variation in the allocation of arbitrage capital. Although greater arbitrage capital reduces the magnitude of potential gains, it can also reduce risk by making convergence more likely.[7]

In summary, if mispricing are not fully eliminated and the allocation of capital varies cross-sectionally, it should be possible to empirically observe the relation between investor heterogeneity and the level of integration of firms' equity and credit markets.

2.2 Cross-margin, Funding Liquidity and Riskiness of Debt

The ability to take advantage of a profitable opportunity is limited by an arbitrageur's ability to fund the positions, or, his funding liquidity. Gromb and Vayanos (2002) argue that an important constraint on funding liquidity is the inability to cross-margin. Typically, an arbitrageur has to post margin 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. Brunnermeier and Pedersen (2008) provide a comprehensive discussion of the importance of funding constraints.[8] Besides preventing the arbitrageur from taking every potentially profitable opportunity, the risk of a tightening of a financial constraint and forced liquidation will also reduce the arbitrage capital allocated to any convergence

[7] Abreu and Brunnermeier (2002) observe that there are three risks to a convergence trade: fundamental risk, noise trader risk, and the risk that arbitrageurs may not coordinate their activities. Of these, the latter two are mitigated when more arbitrage capital enters the market. Noise traders are less likely to cause spreads to widen when the amount of arbitrage capital increases. And it is easier for arbitrageurs to synchronize their activity and make spreads converge when there is more arbitrage capital.

[8] Also, see Attari, Mello and Ruckes (2005).

trade.

The inability to cross-margin inhibits the capital-constrained arbitrageur from taking potentially profitable opportunities where the convergence trade requires a large position in one leg. To observe the cross-sectional implication of the risks associated with funding liquidity, consider the following illustration. Let the arbitrageur's available capital be W. Let the prices of the stock and bond on a firm V with 1 share outstanding be $S(V)$ and $B(V)$, respectively. Assume that the stock price is priced too high relative to the bond so that the arbitrageur engages in a convergence trade by shorting the stock and buying the bond. The relative amounts of stocks and bonds will be in the ratio of their respective deltas, i.e., $(\partial S/\partial V)/\ (\partial B/\partial V)$. That is, if the arbitrageur expects that a \$1 change in firm value will result in a 80 cent change in the stock price and a 20 cent change in the bond price, then for every \$1 in the stock position, the arbitrageur will have a \$4 bond position. Let m_S and m_B be the margin requirements on the stock and bond, respectively, defined as a fraction of the dollar value of the position. Then, the financial constraint of the arbitrageur is,

$$W \geq m_S S + m_B \frac{\partial S/\partial V}{\partial B/\partial V} B. \tag{1}$$

Equation (1) indicates that the financial constraint is more likely to be binding when the bond is *less* risky because the amount of capital required to implement the convergence trade increases as the bond gets safer and $\partial B/\partial V$ decreases. For a very safe bond, the sensitivity of the bond to small changes in the firm value is pretty close to zero, and it may be practically impossible for a funding constrained arbitrageur to integrate the market for small mispricing.

In summary, the inability to cross-margin imposes a cost to the arbitrageur that depends on the riskiness of the outstanding debt. All else equal, arbitrage capital will be deployed towards firms with riskier debt, leading to these firms have more integrated debt and equity markets.

2.3 Liquidity Risk

Convergence traders face liquidity risk. They may not be able to enter or unwind the position in a timely manner without impacting the price. The liquidity of the underlying markets is especially important for the arbitrageur because the convergence trade requires coordinated trades across the equity and credit markets. Thus, illiquidity of either market can impose a severe cost and constrain an arbitrageur. In addition, liquidity risk interacts with funding illiquidity as it is likely that arbitrageurs get funding from the same investment banks that also make markets.

Cross-sectional differences across liquidity have been extensively documented in the literature. In particular, a number of measures using stock daily return data have been proposed for measuring the different aspects of equity market liquidity. These include Roll (1984), Lesmond, Ogden and Trzinka (1999) and Amihud (2002). Compared with the equity liquidity literature, the literature documenting cross-sectional differences in the credit markets is much smaller and more recent (e.g. Longstaff, Mithal and Neis (2005) and Chen, Lesmond and Wei (2007)). With the notable exception of Das and Hanouna (2007), there is no literature that has studied cross-market liquidity across a firm's equity and credit markets.[9]

Given the finite and possibly short-lived horizon of an arbitrageur, we expect arbitrageurs to be cognizant of the liquidity of both the equity and credit markets. The natural hypothesis that follows is that lower liquidity in either the equity or credit markets will reduce the activities of the arbitrageur, and reduce the level of integration between the two markets.

2.4 Idiosyncratic Risk

Despite having a long and short position, the arbitrageur may not be perfectly hedged. The inability to create a perfectly hedged position results in the arbitrageur being exposed to the idiosyncratic risk of the firm for two reasons. First, there is a fundamental unhedgeable risk that results from the possibility that a firm may unexpectedly change its corporate policies in a manner that results in wealth transfer between shareholders and bondholders. For example, any positive NPV project that also increases the firm's asset volatility would result in a wealth transfer from the bondholders to the stockholders. Because this fundamental risk is firm-specific, it is related to the idiosyncratic risk of a firm. Second, the arbitrageur may not have the correct hedge ratio for the convergence trade. As a result, the arbitrageur will have a net long or short position in the underlying firm, resulting in the arbitrageur bearing an additional exposure to the idiosyncratic risk of the firm.

[9]Chordia, Sarkar and Subrahmanyam (2005) consider cross-market liquidity across the equity and Treasury bond markets, but not across the equity and the corporate bond markets.

Pontiff (2006) argues that idiosyncratic risk is one of the primary source of costs faced by arbitrageurs. There is also significant empirical evidence that 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 into the S&P 500 index. Ali, Hwang and Trombley (2003) and Mashruwala, Rajgopal and Shevlin (2006) relate idiosyncratic risk to the book-to-market anomaly and accural anomaly, respectively.

If arbitrageurs are exposed to idiosyncratic risk, then arbitrageurs will be more active in markets where the firm has less idiosyncratic risk. The level of integration between a firm's equity and credit markets will then be negatively correlated to the magnitude of idiosyncratic risk of the firm.

2.5 Slow-Moving Capital and Horizon

Abreu and Brunnermeier (2002) observe that a capital-constrained arbitrageur may not have sufficient capital to single-handedly eliminate a pricing discrepancy. If so, the elimination of pricing discrepancies will require coordinated action by a number of arbitrageurs. Because arbitrageurs are likely to become aware of a pricing discrepancy slowly over time, arbitrage capital will take time to accumulate and pricing discrepancies will be resistent to being eliminated in the short-run. Mitchell, Pulvino and Stafford (2002) provide evidence that arbitrage capital is slow-moving.

There are two implications of slow-moving capital. First, pricing discrepancies will decline and the markets will be more integrated over longer horizons. Second, as arbitrage activity is more effective over longer horizons, the cross-sectional differences across firms will more closely reflect differences in arbitrage activity. Therefore, arbitrage activity should have a greater explanatory power for explaining cross-sectional variation at long horizons.

3 Data

3.1 Credit Default Swap

Our dataset consists of credit default swap spreads, equity prices, and relevant accounting information for U.S. non-financial firms over the period January 2, 2001 and December 31, 2005.

We obtain daily price data for the five-year credit default swap (CDS) on senior, unsecured debt of non-financial 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 it to remove outliers and stale prices. The obligors that enter our sample are components of the Dow Jones CDX North America Investment Grade (CDX.NA.IG), the Dow Jones CDX North America High Yield (CDX.NA.HY) and the Dow Jones North America Crossover (CDX.NA.XO) indices.[10] We specifically choose firms that form part of the index to ensure continuity in price quotes. The time period of our sample is 2001-2005. We match the data from Markit to CRSP and Compustat manually to construct an initial sample of 223 North American non-financial firms, from which we eliminate 22 firms that were delisted over this period and another 2 firms that had less than a year of data of spread and stock price data. Our final sample set consists of 199 firms of which 95 obligors have an average rating of investment grade (AAA, AA, A, and BBB), and the remaining 104 obligors are below investment grade (BB, B, and CCC).[11]

We obtain daily equity prices, returns, outstanding number of shares, and other equity information from the Center for Research in Security Prices (CRSP). Accounting data is 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 outstanding number of shares. Leverage is computed as the ratio of book debt value to the sum of 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 return over the sample period.

Table 1 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 the firms. The mean CDS spread across the entire sample is 215 basis points (bps). The mean across investment grade firms is 87 bps while that of

[10] The IG index consists of 125 equally weighted investment grade entities, the HY of 100 equally weighted entities of rating below investment grade, and the XO of 35 equally weighted entities with cross-over ratings. Cross-over ratings are defined as a rating of BBB/Baa by one of S&P and Moody's, and in the BB/Ba rating category by the other, or a rating in the BB/Ba category by one or both S&P and Moody's.

[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.

the high yield is much larger at 333 bps. The average size of investment grade firms in our sample is \$22.3 billion versus \$4.9 billion for high yield firms. As might be expected, below investment grade firms have higher equity volatility and leverage than investment grade firms.

Figure 1 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 significantly correlated with the volatility and the leverage. In fact, a linear regression of the mean CDS spread on these variables gives an adjusted R^2 of 61%,

$$\begin{array}{lllllllll} \text{CDS}_i = & \text{-0.0263} & + & 0.0760\ \text{VOL}_i & + & 0.0399\ \text{LEV}_i & + e, & R^2\text{=61\%.} \\ & \text{[-9.1]} & & \text{[12.2]} & & \text{[7.3]} & & \end{array}$$

3.2 Diversity of Opinions, Liquidity and Idiosyncratic Risk

As in Diether, Malloy, and Scherbina (2002) and Anderson, Ghysels and Juergens (2005), we measure diversity of opinions by analysts' forecast dispersion. Analysts' earnings forecasts are obtained from the Institutional Brokers Estimate System (I/B/E/S) detail file. We unadjust the forecasts using the adjustment factor provided by I/B/E/S. The unadjusted analysts forecasts are used to construct the forecast dispersion.[12] For each analyst, we use the most recent 1-year forecast closest to the end of the first calendar quarter (March 31st). The dispersion is then defined as the standard deviation across the earnings forecasts scaled by the year-end stock price. If the stock has a price less than five dollars, then the observation is excluded from the sample. For each firm, the average of the yearly forecast dispersion in the sample period is used in the regressions.

We construct liquidity measures for each firm separately for the equity and credit markets. Equity market liquidity measures are estimated from daily stock price data from CRSP. Our primary measures are (i) the square root of the Amivest measure (*EqLiq*), and (ii) the proportion of zero stock returns (*EqIlliq*). To construct the Amivest measure, we first compute $0.001 * \sqrt{\text{price} * \text{sharevolume}/|\text{return}|}$ from daily data for each firm over our sample period. The time-series mean of the daily estimate is then used as our measure.

[12] Diether,Malloy, and Scherbina (2002) note that I/B/E/S adjusts the forecasts for stock splits and then rounds the estimate to the nearest cent. This rounding off can create a bias. The impact of the bias for our sample is minimal because the vast majority of the firms in our sample did not split during our sample period. Of 199 firms, only 40 firms had a stock split. None had a stock split factor greater than 4, and only four firms had a split factor of 4.

The higher the square root of Amivest measure, the higher is 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 is the stock. Although we do not report the findings, we also used other variables including the Amihud measure (Amihud (2002)) and Roll's covariance measure (Roll (1984)).

We introduce two new credit market liquidity measures. Our first measure is based on the number of contributors that provide quotes to Markit on any given date. As contributors are required by Markit to have firm tradeable quotes, the greater the number of contributors, the greater should be the depth and liquidity of the CDS. Thus, our first measure ($CDSLiq$) is computed as the mean of the daily number of contributors for each firm. Second, analogous to the equity liquidity measure, we use the proportion of zero spread changes, ($CDSIlliq$), defined as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes. As with the equity market measure, a larger proportion of zero spread changes indicates lower liquidity.

We construct the measure of idiosyncratic risk from the the standard market model. We first regress the excess return for stock i,

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \epsilon_{i,t} \tag{2}$$

using daily data over our sample period of 2001 to 2005. Next, following Ferreira and Laux (2007), we compute the ratio of the idiosyncratic volatility to the total volatility for each stock as

$$\begin{aligned} \frac{\sigma^2_{i,\epsilon}}{\sigma^2_i} &= \frac{\sigma^2_i - \frac{\sigma^2_{im}}{\sigma^2_m}}{\sigma^2_i} \\ &= 1 - R^2_i. \end{aligned} \tag{3}$$

The idiosyncratic measure $Idiosyn$ is then defined as the logistic transformation $\ln\left(\frac{1-R^2_i}{R^2_i}\right)$. The corresponding measure computed using the Fama-French three-factor model had a correlation of 0.97 with the measure of idiosyncratic risk from the market model. We only report results from the market model.

Panel A of Table 2 presents the descriptive statistics. Each variable exhibits considerable cross-sectional variation. For example, the number of contributors to the CDS quote ranges from 3 to 18. There is also variation across equity and credit market illiquidity. The mean of the proportion of zero spread changes (0.22) is much larger than the mean of the proportion of zero returns (0.02) consistent with the perception that the equity market is more liquid than the CDS market. Panel B reports the pair-wise correlations amongst the variables. The signs of the correlations are as one would expect. $CDSLiq$ which measures liquidity in the credit market is negatively correlated with $CDSIlliq$ that measures the illiquidity in the credit market. Analogously, the two equity market measures of liquidity and illiquidity, $EqLiq$ and $EqIlliq$, respectively, are negatively correlated with each other. Liquidity in the equity market is positively correlated with liquidity in the credit markets. Riskier firms with higher leverage and equity volatility tend to have higher analysts' dispersion and higher idiosyncratic risk. In terms of the magnitudes, the equity market liquidity measure is highly correlated to both the credit market liquidity and the leverage of the firm (correlation of about 50% to each).

4 Co-movements of CDS Spreads and Stock Prices and Pricing Discrepancies

By the Merton single factor model, a price change is a discrepancy if an increase (decrease) in the stock price is coincident with an increase (decrease) in CDS spread over the same horizon. Define, respectively, the change in CDS and stock prices for a firm i over an interval t and $t+h$ as, $\Delta CDS_{i,t} = (CDS_{i,t+h} - CDS_{i,t})$ and $\Delta P_{i,t} = (P_{i,t+h} - P_{i,t})$. We measure discrepancies for stock i over our sample period of T days as the proportion of total observations for which $\Delta CDS \,\mathrm{x}\, \Delta P$ are positive,

$$\text{posfrac}_i = \frac{1}{M} \sum_{t=1}^{M} \mathrm{I}_{\Delta CDS_{i,t} \Delta P_{i,t} > 0}, \tag{4}$$

where $M = T/h$ and $h \in \{5, 10, 25, 50\}$, corresponding to weekly, bi-weekly, monthly, and bi-monthly horizons. Table 3 reports the proportion of discrepancies averaged over all the firms in our sample. In addition, we also report the average absolute change in CDS spread and stock return.

It is evident that stock prices and CDS spreads do not always co-move in line with the Merton model, and that there are significant pricing discrepancies. Over the entire sample, at a 5 business day frequency, stock prices and spreads co-move as expected only 53.7% of the times. There are significant discrepancies over all horizons. Even over a 50 business day horizon, 31% of co-movements are inconsistent with the Merton model. Moreover, these pricing discrepancies are associated with large and economically significant movements in the underlying markets - the discrepancies over 50 business days occur with an average stock return of 8.4% and an average change in CDS spread of 30 bps in the *wrong* direction.

Two additional observations can be made from Table 3. First, pricing discrepancies decline when we consider longer time intervals. The fraction of discrepancies for 5, 10, 25 and 50 business day intervals are 47%, 42%, 36%, and 31% respectively. This observation is consistent with the implication of Abreu and Brunnermeier (2002) and Mitchell, Pedersen and Pulvino (2007) that arbitrage capital takes time to be deployed, leading to pricing discrepancies declining with time. A large proportion of anomalous observations for the weekly frequency, 5.7% of all observations, are related to cases where CDS spreads or stock prices do not change. Such zero changes reduce as the horizon increases. At a frequency of 50 days, zeros constitute only 0.2% of the observations. As zero changes are likely be associated with limited trading activity, it provides further support for the hypothesis that the level of discrepancies are related to limited arbitrage activity. Moreover, given that changes in firm debt and volatility are more likely to change over longer intervals, the observation that pricing discrepancies decline with horizon is inconsistent with the hypothesis that the discrepancies are a result of wealth transfers.

Second, there are substantial cross-sectional differences. For every time-interval, investment grade firms have more pricing discrepancies. For example, 25 (50) business-day pricing discrepancies for investment grade firms is 39.2% vs. 32.7% (33.8% vs. 28.5%) for below investment grade firms. To illustrate the cross-sectional differences, Figure 2 plots the CDS spread against the stock price over our sample period for three firms: Alcoa, Hilton and General Motors. GM has a below investment grade rating of B and one of the highest average spread of 309 bps in our sample, while Alcoa has a high rating of AA and an average spread of 35 bps. Hilton is rated BB with an average spread of 197 bps. As can be observed, there is a strong relation between GM's stock price and CDS spread, while at the other extreme, Alcoa has almost no relation between its spread and stock price. The relation between Hilton's stock price and CDS spread is clearly discernible unlike Alcoa's, but it is noisier than that of GM's. On a 5-business day frequency, pricing discrepancies are 49%, 34%, and 32% for Alcoa, Hilton, and GM, respectively. These cross-sectional differences will be the primary focus of our tests below.

Finally, Figure 3 plots the fraction of the total number of firms that have pricing discrepancies at a given point in time over our sample period. For horizons of over a week, pricing discrepancies show a downward trend in the first two years of our sample period corresponding to the time period over which the CDS market matured. From about 2003 onwards, the percentage of firms with pricing discrepancies has limited time-variation, which indicates there is not much cross-correlation between pricing discrepancies across firms. If there exists a a systematic time-varying factor causing pricing discrepancies, at best, its impact is muted. That is, the primary puzzle is not that the two markets are not integrated or have a low correlaton but that the level of integration varies significantly in the cross-section.

5 Integration of Equity and Credit Markets and Limits to Arbitrage

In this section, we relate the integration of the equity and credit markets to factors that determine arbitrage activity. We measure the degree of integration by the Kendall tau.[13] We prefer this measure two reasons. First, consistent with our definition of discrepancies, the Kendall correlation measures the concordance of stock returns and changes in CDS spread. It is a robust, model-free measure of correlation of the two markets. Second, the structural relation between CDS spreads and equity returns is non-linear, and therefore the Kendall correlation is more appropriate than other measures such as the Pearson correlation. Table 4 provides a summary of the correlation coefficients measured over intervals of 5 to 50 business days. The mean correlation coefficient, negative for every interval, becomes more negative over longer intervals. The mean correlation is -0.12 for a 5 business day interval and declines to -0.34 for a 50-day interval. These results are consistent with the pricing discrepancies documented in Table 3. As pricing discrepancies decrease, increases in stock prices are more likely to be coincident with decreases in credit spreads, resulting in a more negative correlation. Thus, both Tables 3 and 4 indicate that the equity and CDS markets are more integrated over longer horizons.

In our regressions, we use Fisher's z transformation (David (1949)) of the correlation coefficient, $\frac{1}{2}\ln\frac{(1+\rho)}{(1-\rho)}$, where ρ represents the correlation coefficient. We will focus on inter-

[13]We compute the Kendall's tau-b, where the number of tied values in any group is excluded from the total number of pair observations.

preting the sign of the coefficient for the variables associated with arbitrage activity with a negative (positive) coefficient indicating a more (less) integrated market.

5.1 Diversity of Opinions and Riskiness of Debt

Table 5 report the results of the cross-sectional regression of the correlation against analyst's forecast dispersion and proxies for the riskiness of debt. The riskiness of the firm is measured by equity volatility and firm leverage, and we also include a dummy variable for a below investment grade rating to control for the possibility that equity volatility and debt level may not completely account for the change of riskiness from investment grade to below investment grade. We include the size of the firm as a control variable. We report results for four regressions, corresponding to each horizon.

The forecast dispersion is significant for three of the four horizons, and explains a considerable amount of the cross-sectional variation in market integration. In every regression, the sign of the coefficient associated with analysts' forecast dispersion is negative, indicating that firms' equity and credit market are more integrated when there is greater diversity of opinions. The interesting implication of this result is that it indicates that arbitrage capital is deployed preferentially towards markets with potentially greater mispricing. There are at least two possible explanations why this may be so. As in Merton (1987), information costs may cause arbitrageurs to preferential allocate their capital in markets that are known to have mispricing because of investor disagreement. The finding is also consistent with Abreu and Brunnermeier's (2002) argument that arbitrageur's realize that a critical mass of capital is required to cause convergence, and therefore it is rational to herd and allocate capital in markets where other arbitrageurs are active.

The variables proxying for credit riskiness of the firm are also statistically significant. Equity volatility is significant at all horizons, and the rating dummy is significant in three of the four regressions. Financial leverage is not significant, indicating that its impact is subsumed by equity volatility and rating. The sign of the coefficients for both volatility and rating are negative, indicating that riskier firms have more integrated markets. As convergence trades implemented for firms with riskier debt have lower funding liquidity risk, the results suggest that funding liquidity is an important determinant of arbitrage activity.[14]

[14]The higher integration of equity and credit markets for riskier firms does not appear to be driven by

Analysts' forecast disperson and the credit risk of the firm explain a substantial amount of the cross-sectional variation in the degree of integration. In a univariate regression at the 25 (50) day horizon with only the analysts' forecast dispersion (not reported here), the R^2 of the regression is 19.9% (15.5%). Similarly, in a regression with only the variables measuring credit risk, the R^2 of the regression at the 25 (50) day horizon is 15.5% (36.4%). The size of the firm is also significant, which we shall see below appears to be related to the greater liquidity of these firms' credit market. With both sets of variables in the regression, the adjusted R^2 ranges from 17% for the 5-business day horizon to 36% for the 50-day horizon. Overall, the two measures are both statistically and economically significant in explaining cross-sectional variation in integration.

5.2 Liquidity and Idiosyncratic Risk

Given potential mispricing and the ability to fund a convergence trade, the arbitrageur will next be concerned with costs of undertaking the convergence trade. To understand the marginal impact each cost, we now include each proxy for the cost to the specification of Table (where we omit leverage because of its insignificance).

Table 6 considers the impact of liquidity in the credit market. Panel A reports the results for $CDSLiq$. The coefficient is significant for three of the four horizons. For all four of the regressions, the sign of the coefficient is negative as expected indicating that the greater the liquidity of the CDS market, the more integrated is the credit market with the equity market. Panel B reports the results for the proportion of zero spread changes, $CDSIlliq$. The coefficient is significant for each of our regressions and has the correct positive sign, indicating that the greater the illiquidity of the credit market, the lower is the integration of the two markets. When we include both the two measures, $CDSLiq$ and $CDSIlliq$, the latter retains its explanatory power, and the $CDSLiq$ loses its significance. Finally, when either $CDSLiq$ or $CDSIlliq$ are included in the regression, the significance of size declines,

the fact that riskier firms have debt that is more sensitive to the stock price. First, the Kendall correlation depends on the concordance of changes in stock prices and CDS spreads, and not their relative magnitudes. Therefore, the correlation measure is not biased by the greater sensitivity of the CDS spread to changes in the stock price. Second, the magnitude of "noise" in the data is higher for riskier firms. Noise in the relation between stock prices and CDS spreads can result from wealth transfers between shareholders and bondholders. Wealth transfers can occur because of changes in debt level or volatility. However, in our sample, changes in debt and equity volatility are greater for firms that are below investment grade. Thus, there is greater, and not less, noise in firms with higher credit risk. Finally, the noise may also be related to liquidity. But there is no significant difference between the credit market illiquidity for above investment grade and below investment grade firms.

suggesting that size proxies for liquidity of the CDS market.

Table 7 presents the results equity market liquidity. We provide results for two measures, the square root of the Amivest measure and the proportion of zero stock returns, $EqLiq$ and $EqIlliq$, respectively. Overall, we find almost no evidence of the impact of equity market liquidity. The coefficients are either insignificant or very weakly significant. We also test for other proxies (including the Amihud measure) and also do not find them significant. Overall, the evidence indicates that, at least for our sample, equity liquidity has little impact on the integration of the two markets, and that it is liquidity related costs imposed by trading in the credit markets that impacts the integration of the two markets.

Table 8 presents the results for the impact of idiosyncratic risk. For each of the four intervals, the coefficient on the idiosyncratic risk is significant at the 1% level. The coefficient is positive, consistent with the hypothesis that a higher level of idiosyncratic risk increases arbitrageur's costs and therefore decreases the integration of the two markets. Thus, although an increase in the total volatility of the stock return makes equity and credit markets more integrated, the idiosyncratic component makes it less integrated. For robustness, we also considered the idiosyncratic risk component estimated from the Fama-French three-factor model and found identical results.

Although both liquidity and idiosyncratic risk are significant in explaining the integration between the equity and credit markets, the explanatory power of these variables is lower than that of analysts' forecast dispersion and credit risk of the firm. The adjusted R^2 of the regressions with only $CDSIliq$ and $CDSIlliq$ are lower than the R^2 when only analysts' forecast dispersion is included for three of the four horizons. They are also lower than the adjusted R^2 for all four of the regressions when only credit risk variables are included. For example, the adjusted R^2 for the 30-day horizon is 9.4% for the two credit market liquidity measures compared with 19.9% for forecast dispersion and 15.5% for the credit risk variables. The adjusted R^2 for idiosyncratic risk (1.8% for 30-day horizon) is also lower for all four horizons. This is not entirely surprising. Arbitrageurs will not deploy capital unless there are mispricing and they can fund their trades, and therefore diversity of opinions and funding liquidity should be of primary importance in determining the integration of markets.

5.3 Horizon and Sub-Periods

Table 9 presents the regressions with all of the significant variables from previous tables. Equity liquidity measures and $CDSLiq$ are excluded for their low significance. As in prior tables, the coefficient for analysts' forecast dispersion is significant at the highest level for three of the four horizons, and the coefficients for credit risk, credit market liquidity, and idiosyncratic risk are significant at all horizons. In terms of magnitude, the dummy variable for rating has the largest economic impact. For the 25-day horizon, moving from investment grade to below investment grade increases the absolute value of the correlation by 0.10. For the same horizon, a one standard deviation change in the forecast dispersion, liquidity and idiosyncratic risk impacts the absolute value of the correlation by 0.06, 0.03, and 0.05, respectively. Given that the cross-sectional standard deviation of the correlation coefficient is 0.16 for the 25-day horizon, it is apparent that this relatively small set of variables explains an econonomically significant proportion of cross-sectional differences in integration of equity and credit markets.

Table 9 also demonstrates that the proportion explained increases with horizon. The adjusted R^2 for these regressions ranges from 25% at the 5-day horizon to 42% at the 50-day horizon. The increase in the coefficient of determination with horizon is consistent with the hypothesis that arbitrage activity is more effective at longer horizons.

Table 10 checks robustness of the results in two sub-periods of two and a half years each. Given the shorter time period, we only construct tests upto the monthly horizon. The number of firms in the second sub-period are more than those in the first sub-period reflecting the growth of the CDS market in this time period. Not surprisingly, the results are much stronger in the second sub-period; all of the variables are significant in at least two of the three horizons and with the correct sign. Although weaker, the first sub-period results are also largely consistent with those of the second sub-period and the overall sample in that each variable is significant for at least one horizon, and has the correct sign at all horizons. One interesting observation from Table 10 is that the coefficient for the liquidity of the CDS market is smaller in magnitude, consistent with the growth and increasing liquidity of the CDS market.

6 Alternative Tests

Although our results indicate that a substantial proportion of the cross-sectional variation in the degree of integration is explained by limits to arbitrage, pricing discrepancies may also be related to the two alternative hypothesis that we discussed earlier. First, pricing discrepancies may be related to wealth transfers between equity and bondholders. Second, pricing discrepancies may be related to a market-wide credit liquidity factor or interest rates in the economy.

6.1 Wealth Transfers

In the equity option pricing literature, a fall in the stock price does not necessarily result in a decline in the call price because a stock price decline often coincides with an increase in the implied volatility. Analogously, changes in firm volatility or the face value of debt can explain pricing discrepancies in a Merton (1974) setup by causing wealth transfers between shareholders and bondholders if an increase (decrease) in firm value is coincident with a increase (decrease) in firm volatility or debt.

To do so, we divide pricing discrepancies into groups depending on whether a stock price increase over period coincided with an increase or decrease in volatility (debt) over the horizon. We then compare the frequency of pricing discrepancies in periods when a stock price increase (decrease) coincides with an increase in volatility or debt to periods when it does not. If wealth transfers are a significant cause of pricing discrepancies, then we will observe a significantly greater amount of pricing discrepancies associated with the first set of observations versus the second set.

Panel A of Table 11 reports the result of this exercise for volatility. Given that recent research has shown that implied volatilities can explain changes in credit spread, we use the Black-Scholes implied volatility of the at-the-money near-month option as our proxy for firm volatility. The change in volatility is measured as the change in implied volatility from the first date of the interval to the last date of the interval. The horizon of 1 month allows us to avoid overlapping intervals.

Do wealth transfers from changing volatility explain pricing discrepancies? The evidence in Table 11, in fact, indicates the opposite. A significantly greater proportion of discrepancies - over 59% - are in periods when an increase in stock price coincides with a decrease in volatility and a decrease in stock price coincides with an increase in volatility. That is, any wealth transfers because of non-constant volatility make the pricing discrepancies seem even more anomalous.

Panel B reports pricing discrepancies conditioned on stock price changes and changes in the book value of debt. We compute pricing discrepancies over a quarter so as to match the horizon with that of the financial statements. The proportion of pricing discrepancies when stock price increases (decreases) coincide with increases (decreases) in debt are 51% compared with 49% for the other periods. The two proportions are not significantly different. That there is no significant difference is not entirely suprising as, unlike volatility, firm debt levels do not change much over short horizons - the median quarterly change in the debt ratio is less than 2% in our sample.

6.2 Time-Series Evidence

Next, investigate whether a credit market wide liquidity factor can explain market wide pricing discrepancies. As plotted in Figure 3, we measure market-wide discrepancies at t as the fraction of the N firms in our sample that have a pricing discrepancy at any point in time.

$$\text{posprop}_t = \frac{1}{N}\sum_{i=1}^{N} \mathrm{I}_{\Delta CDS_{i,t}\Delta P_{i,t}>0}. \tag{5}$$

Our measure of market-wide illiquidity, $CDSIlliq_t^M$, is the market-wide analogue of our CDS illiquidity measure for firm i. We compute it as the proportion of the total firms in our sample that have a zero daily change in CDS spread, and then take the average over the h days in the interval.

Both series have very high auto-correlations - over a 5-day interval, the autocorrelation is 0.99 and 0.98, respectively. As observed in Figure 3, the proportion of firms with discrepancies exhibits a time trend. To eliminate the time trend, we first difference the series, and then run our regression,

$$\Delta\text{posprop}_t = \alpha + \beta\Delta\text{CDSIlliq}_t^M + e_t, \tag{6}$$

where Δ is the difference operator. Panel A of Table 12 reports the results for all horizons except the 50 day horizon for which we do not have sufficient observations. The credit illiquidity measure does not explain changes in the aggregate proportion of discrepancies across the equity and CDS market.

Do changes in interest rates in the economy explain discrepancies? It is known that Treasury rates are negatively correlated with credit spreads, and perhaps interest rates movements may impact market-wide disrepancies. To investigate this hypothesis, we regress changes in market-wide discrepancies on changes in the 10-year Treasury rate,

$$\Delta \text{posprop}_t = \alpha + \beta \Delta \text{Treasury}_t + e_t, \tag{7}$$

where $\Delta\text{Treasury}_t = \text{Treasury}_{t+h} - \text{Treasury}_t$. Panel B of Table 12 reports the results. Changes in the 10-year Treasury yield do not explain pricing discrepancies.

The cross-sectional regressions that we reported earlier indicated that a significant proportion of the cross-sectional variation is explained by the rating and the credit riskiness of the firm. We interpreted these results to be consistent with the notion that arbitrageurs are concerned with funding liquidity. If so, we should also find, in the time-series, that the pricing discrepancies are related to time-variation in funding costs. Using the Eurodollar rate as a proxy for the funding cost, we regress changes in market-wide discrepancies on changes in the Eurodollar rate,

$$\Delta \text{posprop}_t = \alpha + \beta \Delta \text{Eurodollar}_t + e_t, \tag{8}$$

where $\Delta\text{Eurodollar}_t = \text{Eurodollar}_{t+h} - \text{Eurodollar}_t$. Panel C of Table 12 reports the results. Except for the shortest time-horizon, 5he sign of the coefficient is significant and positive in two of the three horizons. The positive coefficient is consistent with the hypothesis that an increase in funding costs decreases market-wide arbitrage activity, and therefore increases the proportion of firms with pricing discrepancies.

7 Conclusion

Why are a firm's equity and credit markets not highly correlated? We argue that any theory that seeks to provide an explanation must be consistent with two stylized facts that (i) equity and credit markets are more integrated over longer horizons, and (ii) there are significant cross-sectional variation in the correlation of equity and credit markets. These facts motivate us to examine whether limits to arbitrage explains the cross-sectional variation in integration across firms. We find extensive empirical support in favor of the hypothesis that limited arbitrage activity impacts the integration of a firm's equity and credit market. Moreover, we find no support for alternative hypotheses. The level of pricing discrepancies cannot be explained by wealth transfers caused by changing volatility or debt. Market-wide variation in pricing discrepancies cannot be explained by market-wide changes in credit market liquidity, suggesting that credit market liquidity is not priced. However, changes in the Eurodollar rate, which determines funding costs of arbitrageurs, does impact market-wide variation in pricing discrepancies.

There are several implications of our results. First, our findings suggest that pricing discrepancies across equity and credit markets are anomalies that, in time, should be corrected for markets of firms that attract sufficient arbitrage capital. Second, our empirical analysis can be viewed as a comprehensive test for the implications of the theoretical literature that models arbitrage activity. Given the size and importance of the equity and credit markets, our results provide some of the strongest empirical support for this theoretical literature. Third, our findings suggest that a very small set of factors - investor heterogeneity, funding and market liquidity, and idiosyncratic risk - determines how arbitrage capital is deployed. Overall, our findings indicate the important role of arbitrageurs like hedge funds. We leave, for future research, to delve deeper into the specific role played by hedge funds and hedge fund capital in impacting how equity and credit markets are integrated and priced.

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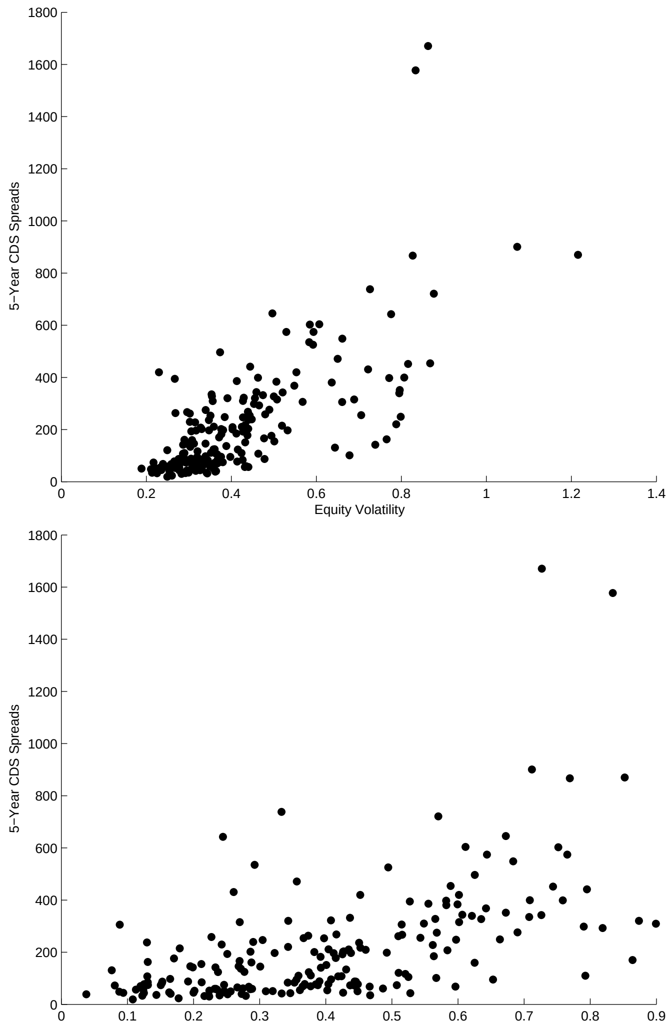

Figure 1: CDS spread vs. volatility and leverage

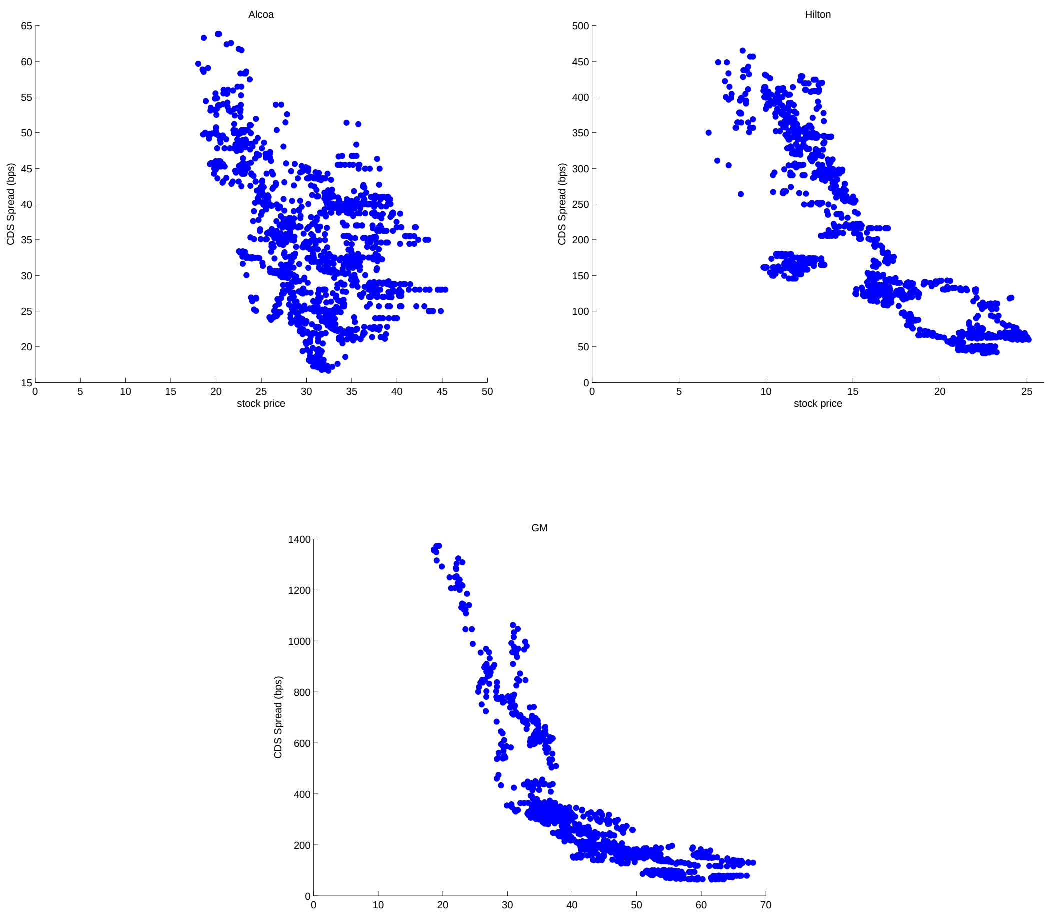

Figure 2: CDS spread vs. Stock Price

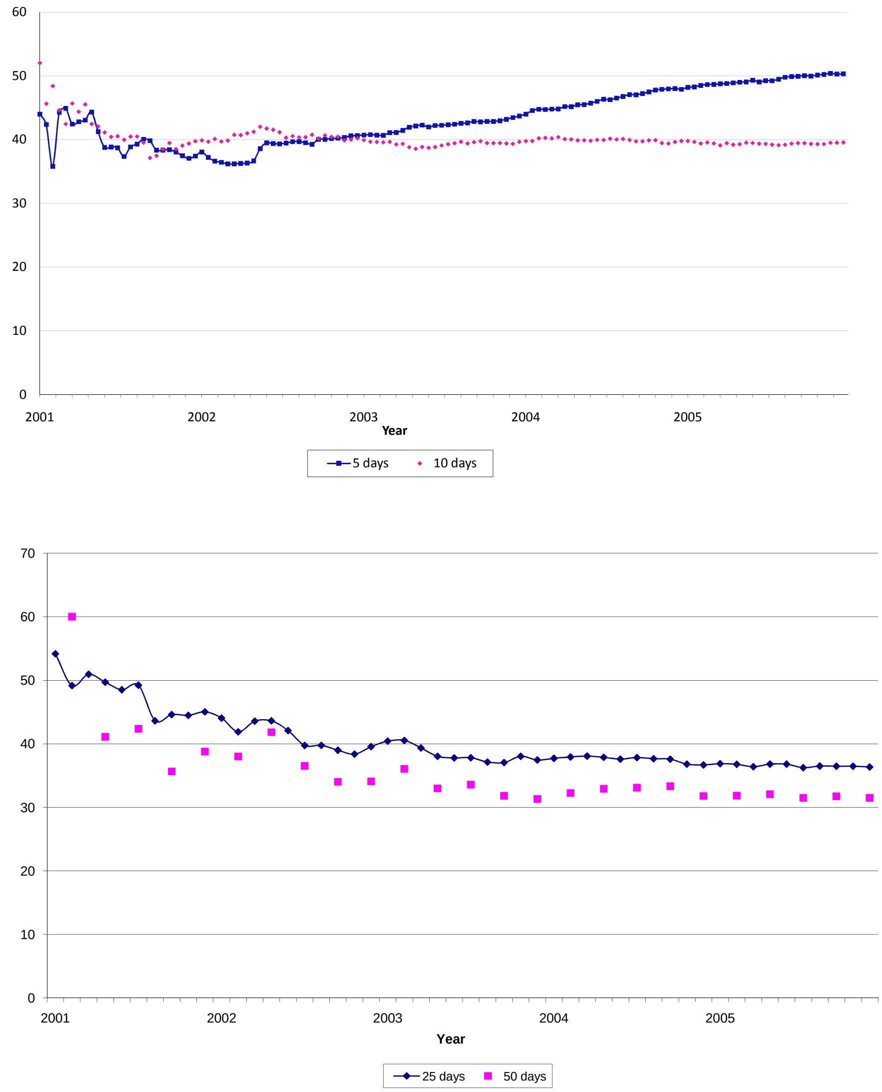

Figure 3: Percentage of Firms with Discrepancies Over Time

Table 1: Descriptive statistics

The sample consists of 199 non-financial N. American firms over the period January 2, 2001 to December 31, 2005, of which there are 95 firms have an average rating above investment grade, and 104 firms have average ratings below investment 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 book debt value to the sum of book debt value and market capitalization. For each obligor, we first compute the time-series mean of its (daily) 5-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 five-year sample period.

	5-year CDS spread (bps)			
	Mean	Median	Min	Max
All	215.20	145.17	19.21	1670.58
Investment Grade	86.57	69.01	19.21	430.98
High Yield	332.69	267.57	44.77	1670.58
	Size ('000,000,000)			
	Mean	Median	Min	Max
All	13.20	6.25	0.40	227.11
Investment Grade	22.30	13.10	1.09	227.11
High Yield	4.90	2.87	0.40	24.66
	Equity Volatility			
	Mean	Median	Min	Max
All	0.42	0.36	0.19	1.22
Investment Grade	0.33	0.32	0.19	0.72
High Yield	0.50	0.45	0.23	1.22
	Leverage			
	Mean	Median	Min	Max
All	0.40	0.38	0.04	0.90
Investment Grade	0.29	0.27	0.04	0.79
High Yield	0.50	0.51	0.08	0.90

Table 2: Summary Statistics

Panel A of the table reports the statistics for analysts' dispersion, equity and credit markets liquidity measures and idiosyncratic risk for our sample of 199 firms over the period January 2001 to December 2005. *ForeDisp* is analysts' forecast dispersion defined as the standard deviation across earnings forecast scaled by the stock price. *CDSLiq* is the number of contributors for the composite quotes of 5-year CDS spreads in daily frequency. The average of daily values is computed as the measure for each firm. *CDSIlliq* is defined as the proportion of zero daily CDS spread changes among all the non-missing daily changes in the sample period. *EqLiq* is constructed as $0.001\sqrt{\text{price} * \text{sharevolume}/|\text{return}|}$ from daily data. The mean of the daily measures is computed as the measure for the firm in the sample period. *EqIlliq* is the ratio of daily zero returns among all the non-missing returns in the sample period. *Idiosyn* is the idiosyncratic risk computed as the logistic transformation of coefficient of determination from a regression of daily excess returns on the market, $\ln\left(\frac{1-R^2}{R^2}\right)$. Panel B of the table reports the cross-sectional correlations between the variables.

Panel A: Descriptive Statistics

	Mean	Median	Min.	Max.	Std
ForeDisp(%)	0.86	0.52	0.04	5.62	0.91
CDSLiq	9	9	3	18	3
CDSIlliq (%)	21.97	21.35	0.00	58.66	9.36
EqLiq	85.49	75.73	7.38	334.99	54.76
EqIlliq (%)	1.60	1.35	0.24	6.29	1.08
Idiosyn	1.46	1.49	0.12	4.42	0.78

Panel B: Correlation Matrix

	ForeDisp	CDSLiq	CDSIlliq	EqLiq	EqIlliq	Idiosyn	Lev	EqVol
ForeDisp	1.00							
CDSLiq	-0.21	1.00						
CDSIlliq	-0.20	-0.45	1.00					
EqLiq	-0.30	0.50	-0.08	1.00				
EqIlliq	0.22	-0.35	-0.004	-0.42	1.00			
Idiosyn	0.17	-0.33	0.03	-0.22	0.44	1.00		
Lev	0.43	-0.25	-0.17	-0.51	0.44	0.28	1.00	
EqVol	0.30	-0.47	-0.03	-0.39	0.48	0.19	0.37	1.00

Table 3: Co-movement of CDS Spreads and Stock Prices

The table reports the direction of co-movement between CDS spreads and stock prices reported as a percentage of total observations over non-overlapping time intervals. $|\Delta CDS|$ is the mean of absolute spread changes. $|\Delta P/P|$ is the mean of absolute stock returns. "Obs" is the total number of non-missing pairs of spread and price changes in the sample.

			$\Delta CDS_i \mathbf{x} \Delta P_i < 0$			$\Delta CDS_i \mathbf{x} \Delta PIi > 0$			$\Delta CDS_i \mathbf{x} \Delta P_i = 0$
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 (%)
All	5	37,643	53.7	14.2	4.0	40.6	10.2	3.1	5.7
	10	18,643	58.0	22.1	5.9	39.6	14.2	4.3	2.4
	25	7,392	63.7	40.2	9.8	35.6	21.3	6.3	0.7
	50	3,661	68.5	65.6	14.9	31.3	30.2	8.4	0.2
Invt. Grade	5	21,098	52.3	6.1	3.4	41.1	4.5	2.7	6.6
	10	10,471	56.0	9.8	4.9	41.3	6.6	3.8	2.7
	25	4,151	60.8	17.9	7.9	38.6	10.9	5.6	0.6
	50	2,059	66.2	29.6	12.0	33.7	15.9	7.4	0.1
High Yield	5	16,545	55.5	23.9	4.8	39.9	17.7	3.6	4.6
	10	8,172	60.6	36.8	7.1	37.4	25.0	4.9	2.0
	25	3,241	67.3	65.9	12.0	31.8	37.3	7.5	0.9
	50	1,602	71.5	108.5	18.4	28.3	52.1	10.1	0.2

Table 4: Correlation Between Stock Returns and Change in CDS Spread

The table reports the descriptive statistics for the Kendall correlation between changes in CDS spreads and stock returns over the period 2001-2005 for the sample of 199 firms. Firms that had less than 15 available observations for computing correlation were excluded.

Interval	No. of Firms	Mean	Median	Max.	Min.	Std.
5	199	-0.12	-0.12	0.08	-0.42	0.08
10	199	-0.17	-0.16	0.16	-0.45	0.10
25	187	-0.25	-0.25	0.24	-0.64	0.16
50	138	-0.34	-0.33	0.13	-0.81	0.18

Table 5: Diversity of Opinion and Riskiness of Firm

The table reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1\text{ForeDisp} + \beta_2\text{EqVol} + \beta_3\text{Lnmcap} + \beta_4\text{Lev} + \beta_5\text{Rating} + \epsilon.$$

tkcorr is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where *kcorr* is the Kendall correlation. $ForeDisp$ is the standard deviation of analysts' forecasts scaled by the period-end stock price. $EqVol$ is the annualized equity volatility in the sample period. *Lnmcap* is the log of the market capitalization. The leverage *Lev* is calculated as the ratio of book debt value to the sum of book debt value and market capitalization. *Rating* is a dummy variable for below investment grade. The t-values are reported in parenthesis. ** and * indicates significance at 5% and 10%, respectively.

Interval	# of Firms	Intercept	ForeDisp	EqVol	Lnmcap	Lev	Rating	Adj. R^2
5	186	0.0954	-2.5794	-0.0844	-0.0177	-0.0549	-0.0228	17%
		(1.57)	$(-3.68)^{**}$	$(-2.06)^{**}$	$(-2.94)^{**}$	(-1.51)	(1.50)	
10	186	0.1182	-3.9716	-0.1359	-0.0233	-0.0385	-0.0447	27%
		$(1.64)^{*}$	$(-4.79)^{**}$	$(-2.81)^{**}$	$(-3.26)^{**}$	(-0.90)	$(2.48)^{**}$	
25	177	0.1294	-6.6331	-0.2505	-0.0285	-0.0752	-0.0718	29%
		(1.06)	$(-4.54)^{**}$	$(-2.95)^{**}$	$(-2.35)^{**}$	(-1.01)	$(2.30)^{**}$	
50	137	-0.1109	-2.9365	-0.5724	-0.0052	-0.1134	-0.1024	36%
		(-0.62)	(-1.51)	$(-4.53)^{**}$	(-0.31)	(-1.09)	$(2.43)^{**}$	

Table 6: Credit Market Liquidity

Panel A reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1\text{CDSLiq} + \beta_2\text{ForeDisp} + \beta_3\text{EqVol} + \beta_4\text{Lnmcap} + \beta_5\text{Rating} + \epsilon.$$

Panel B reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1\text{CDSIlliq} + \beta_2\text{ForeDisp} + \beta_3\text{EqVol} + \beta_4\text{Lnmcap} + \beta_5\text{Rating} + \epsilon.$$

$tkcorr$ is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where $kcorr$ is the Kendall correlation. $CDSLiq$ is average number of contributors to the composite 5-year CDS spread quotes. $CDSIlliq$ is the proportion of zero daily spread changes among all non-missing observations. $ForeDisp$ is the standard deviation of analysts' forecasts scaled by the period-end stock price. $EqVol$ is the annualized equity volatility in the sample period. $Lnmcap$ is log of market capitalization. $Rating$ is a dummy variable for below investment grade. t-values are reported in parenthesis; ** and * indicates significance at 5% and 10%, respectively.

Panel A: CDSLiq

Interval	# of Firms	Intercept	CDSLiq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	0.0724	-0.0103	-2.5914	-0.1199	-0.0063	-0.0412	24%
		(1.40)	$(-4.14)^{**}$	$(-3.95)^{**}$	$(-2.98)^{**}$	(-1.07)	$(2.80)^{**}$	
10	186	0.1090	-0.0106	-3.8982	-0.1724	-0.0124	-0.0622	32%
		$(1.77)^{*}$	$(-3.59)^{**}$	$(-4.99)^{**}$	$(-3.60)^{**}$	$(-1.75)^{*}$	$(3.54)^{**}$	
25	177	0.1000	-0.0144	-6.5509	-0.3098	-0.0122	-0.0942	31%
		(0.94)	$(-2.75)^{**}$	$(-4.69)^{**}$	$(-3.61)^{**}$	(-0.99)	$(3.08)^{**}$	
50	137	-0.1276	-0.0119	-3.4776	-0.6175	0.0061	-0.1177	36%
		(-0.78)	(-1.45)	$(-1.85)^{*}$	$(-4.75)^{**}$	(0.37)	$(2.91)^{**}$	

Panel B: CDSIlliq

Interval	# of Firms	Intercept	CDSIlliq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	-0.0299	0.1865	-2.3357	-0.0818	-0.0110	-0.0252	21%
		(-0.51)	$(3.08)^{**}$	$(-3.40)^{**}$	$(-2.04)^{**}$	$(-1.90)^{*}$	$(1.72)^{*}$	
10	186	-0.0148	0.2345	-3.5208	-0.1324	-0.0163	-0.0452	31%
		(-0.22)	$(3.30)^{**}$	$(-4.37)^{**}$	$(-2.81)^{**}$	$(-2.39)^{**}$	$(2.63)^{**}$	
25	177	-0.0908	0.3634	-6.0793	-0.2491	-0.0166	-0.0725	31%
		(-0.76)	$(2.84)^{**}$	$(-4.27)^{**}$	$(-2.99)^{**}$	(-1.41)	$(2.41)^{**}$	
50	137	-0.4827	0.6461	-1.7462	-0.5484	0.0128	-0.1078	40%
		$(-2.81)^{**}$	$(3.23)^{**}$	(-0.92)	$(-4.48)^{**}$	(0.80)	$(2.75)^{**}$	

Table 7: Equity Market Liquidity

Panel A reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1\text{EqLiq} + \beta_2\text{ForeDisp} + \beta_3\text{EqVol} + \beta_4\text{Lnmcap} + \beta_5\text{Rating} + \epsilon.$$

Panel B reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1\text{EqIlliq} + \beta_2\text{ForeDisp} + \beta_3\text{EqVol} + \beta_4\text{Lnmcap} + \beta_5\text{Rating} + \epsilon.$$

tkcorr is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where *kcorr* is the Kendall correlation. *EqLiq* is $sqrt(abs(return)/(abs(price)*sharevolume))$. The average of the daily values is computed as the measure for the firm in the sample period. *EqIlliq* is the proportion of zero daily stock returns among all the non-missing observations in the sample period. *ForeDisp* is the standard deviation of analysts' forecasts scaled by the period-end stock price. *EqVol* is the annualized equity volatility in the sample period. *Lnmcap* is the log of the market capitalization. *Rating* is a dummy variable for below investment grade. t-values are reported in parenthesis; ** and * indicates significance at 5% and 10%, respectively.

Panel A: EqLiq

Interval	# of Firms	Intercept	EqLiq (10^{-3})	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	0.0525	0.0044	-2.8394	-0.0847	-0.0153	-0.0274	16%
		(0.70)	(0.02)	$(-4.15)^{**}$	$(-2.03)^{*}$	(-1.49)	$(1.82)^{*}$	
10	186	0.0831	-0.0173	-4.1514	-0.1369	-0.0207	-0.0478	27%
		(0.94)	(-0.07)	$(-5.15)^{**}$	$(-2.78)^{**}$	$(-1.72)^{*}$	$(2.70)^{**}$	
25	177	-0.1200	-0.7663	-6.9241	-0.2769	0.0055	-0.0759	30%
		(-0.79)	$(-1.77)^{*}$	$(-4.92)^{**}$	$(-3.24)^{**}$	(0.27)	$(2.50)^{**}$	
50	137	-0.3225	-0.3933	-3.3717	-0.5830	0.0178	-0.1134	35%
		(-1.42)	(-0.68)	$(-1.78)^{*}$	$(-4.55)^{**}$	(0.59)	$(2.79)^{**}$	

Panel B: EqIlliq

Interval	# of Firms	Intercept	EqIlliq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	0.0573	-0.3121	-2.8416	-0.0813	-0.0153	-0.0253	16%
		(1.04)	(-0.47)	$(-4.16)^{**}$	$(-1.94)^{*}$	$(-2.62)^{**}$	(1.62)	
10	186	0.0975	-0.5392	-4.1582	-0.1300	-0.0218	-0.0443	27%
		(1.50)	(-0.68)	$(-5.17)^{**}$	$(-2.64)^{**}$	$(-3.17)^{**}$	$(2.41)^{**}$	
25	177	0.0450	1.5932	-6.9568	-0.2789	-0.0240	-0.0862	29%
		(0.41)	(1.05)	$(-4.92)^{**}$	$(-3.15)^{**}$	$(-2.06)^{**}$	$(2.73)^{**}$	
50	137	-0.2653	3.9318	-3.3191	-0.6236	0.0014	-0.1390	36%
		$(-1.69)^{*}$	$(1.73)^{*}$	$(-1.77)^{*}$	$(-4.83)^{**}$	(0.09)	$(3.26)^{**}$	

Table 8: Idiosyncratic Risk

The table reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1 \text{Idiosyn} + \beta_2 \text{ForeDisp} + \beta_3 \text{EqVol} + \beta_4 \text{Lnmcap} + \beta_5 \text{Rating} + \epsilon.$$

tkcorr is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where *kcorr* is the Kendall correlation. *Idiosyn* is computed as the logistic transformation of the coefficient of determination from a market model regression, $\ln\big((1-R^2)/R^2\big)$. *ForeDisp* is the standard deviation of analysts' forecasts scaled by the period-end stock price. *EqVol* is the annualized equity volatility in the sample period. *Lnmcap* is the log of the market capitalization. The leverage *Lev* is calculated as the ratio of book debt value to the sum of book debt value and market capitalization. *Rating* is a dummy variable for below investment grade. t-values are reported in parenthesis. ** and * indicates significance at 5% and 10%, respectively.

Idiosyncratic Risk

Interval	# of Firm	Intercept	Idiosyn	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	0.0018	0.0268	-2.9533	-0.0700	-0.0152	-0.0429	22%
		(0.03)	$(3.65)^{**}$	$(-4.47)^{**}$	$(-1.75)^{*}$	$(-2.71)^{**}$	$(2.84)^{**}$	
10	186	0.0404	0.0254	-4.2618	-0.1222	-0.0216	-0.0626	30%
		(0.63)	$(2.89)^{**}$	$(-5.40)^{**}$	$(-2.56)^{**}$	$(-3.22)^{**}$	$(3.47)^{**}$	
25	177	-0.0493	0.0714	-6.9819	-0.2459	-0.0247	-0.1096	36%
		(-0.47)	$(4.65)^{**}$	$(-5.22)^{**}$	$(-3.06)^{**}$	$(-2.25)^{**}$	$(3.69)^{**}$	
50	137	-0.2893	0.0660	-3.6711	-0.5527	-0.0022	-0.1373	40%
		(-1.90)*	$(3.15)^{**}$	$(-2.01)^{**}$	$(-4.51)^{**}$	(-0.14)	$(3.44)^{**}$	

Table 9: All Variables

The table reports the results of the regression,

$$\text{tkcorr} = \alpha + \beta_1 \text{idiosyn} + \beta_2 \text{CDSIlliq} + \beta_3 \text{ForeDisp} + \beta_4 \text{EqVol} + \beta_5 \text{Lnmcap} + \beta_6 \text{Rating} + \epsilon.$$

$tkcorr$ is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where $kcorr$ is the Kendall correlation. $Idiosyn$ is computed as the logistic transformation of the coefficient of determination from a market model regression, $\ln\left((1-R^2)/R^2\right)$. $CDSIlliq$ is the proportion of zero daily spread changes among all non-missing observations. $ForeDisp$ is the standard deviation of analysts' forecasts scaled by the period-end stock price. $EqVol$ is the annualized equity volatility in the sample period. $Lnmcap$ is the log of the market capitalization. $Rating$ is a dummy variable for below investment grade. t-values are reported in parenthesis. ** and * indicates significance at 5% and 10%, respectively.

All Variables

Interval	# of Firms	Intercept	Idiosyn	CDSIlliq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	186	-0.0722	0.0256	0.1748	-2.4765	-0.0678	-0.0114	-0.0402	25%
		(-1.24)	(3.56)**	(2.98)**	(−3.72)**	(−1.73)*	(−2.03)**	(2.72)**	
10	186	-0.0542	0.0238	0.2236	-3.6518	-0.1193	-0.0167	-0.0591	33%
		(-0.79)	(2.78)**	(3.20)**	(−4.61)**	(−2.57)**	(−2.49)**	(3.36)**	
25	177	-0.1802	0.0676	0.3097	-6.1977	-0.2435	-0.0176	-0.1033	38%
		(-1.56)	(4.45)**	(2.54)**	(−4.59)**	(−3.08)**	(-1.57)	(3.52)**	
50	137	-0.5073	0.0552	0.5469	-2.2012	-0.5369	0.0086	-0.1279	42%
		(−3.02)**	(2.65)**	(2.75)**	(-1.18)	(−4.49)**	(0.55)	(3.27)**	

Table 10: Sub-Period Results

The table reports the sub-period results of the regression. The first period is from January 2001 to June 2003, and the second period is from July 2003 to December 2005.

$$\text{tkcorr} = \alpha + \beta_1\text{Idiosyn} + \beta_2\text{CDSIlliq} + \beta_3\text{ForeDisp} + \beta_4\text{EqVol} + \beta_5\text{Lnmcap} + \beta_6\text{Rating} + \epsilon.$$

tkcorr is the transformed Kendall correlation, $\frac{1}{2}\ln(\frac{1+kcorr}{1-kcorr})$, where *kcorr* is the Kendall correlation. *Idiosyn* is computed as the logistic transformation of the coefficient of determination from a market model regression, $\ln\left((1-R^2)/R^2\right)$. *CDSIlliq* is the proportion of zero daily spread changes among all non-missing observations. *ForeDisp* is the standard deviation of analysts' forecasts scaled by the period-end stock price. *EqVol* is the annualized equity volatility in the sample period. *Lnmcap* is the log of the market capitalization. *Rating* is a dummy variable for below investment grade. The t-values are reported in parenthesis. ** and * indicates significance at 5% and 10%, respectively.

Period (2001.1-2003.6)

Interval	# of Firms	Intercept	Idiosyn	CDSIlliq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	145	-0.1301	0.0129	0.3864	-1.1976	-0.1037	-0.0177	-0.0266	37%
		(-1.58)	(1.32)	(6.81)**	(-1.30)	(−2.23)**	(−2.24)**	(1.31)	
10	138	-0.2137	0.0062	0.4925	-1.9921	-0.2051	-0.0162	-0.0566	42%
		(−1.98)**	(0.49)	(6.08)**	(−1.66)*	(−3.40)**	(-1.58)	(2.11)**	
25	104	-0.4471	0.0422	0.5386	-2.4659	-0.2583	-0.0111	-0.1241	41%
		(−2.42)**	(2.19)**	(4.00)**	(-1.07)	(−2.35)**	(-0.68)	(2.96)**	

Period (2003.7-2005.12)

Interval	# of Firms	Intercept	Idiosyn	CDSIlliq	ForeDisp	EqVol	Lnmcap	Rating	Adj. R^2
5	177	-0.0018	0.0220	0.2315	-2.2052	-0.2874	-0.0117	-0.0412	22%
		(-0.02)	(2.02)**	(3.39)**	(−2.79)**	(−3.60)**	(−1.68)*	(2.46)**	
10	177	-0.1946	0.0559	0.3529	-1.5204	-0.4485	0.0007	-0.0812	27%
		(−1.80)*	(3.57)**	(3.60)**	(-1.34)	(−3.92)**	(0.07)	(3.38)**	
25	172	0.0220	0.0975	0.2360	-3.1763	-0.7433	-0.0323	-0.1490	28%
		(0.13)	(3.63)**	(1.49)	(−1.75)*	(−4.14)**	(−2.10)**	(4.01)**	

Table 11: Discrepancies Conditioned on Changes in Volatility and Debt

Panel A reports pricing discrepancies conditioned on 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 are 2722. Panel B reports pricing discrepancies between CDS spreads and stock prices conditioned on direction of changes in stock price and 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 are 903.

Panel A: Volatility

Sample	$\Delta P_i >= 0$	$\Delta P_i < 0$
Increase in Vol	0.162	0.313
Decrease in Vol	0.280	0.244

Panel B: Debt

Sample	$\Delta P_i > 0$	$\Delta P_i < 0$
Increase in Debt	0.197	0.219
Decrease in Debt	0.267	0.317

Table 12: Time Series Regression

The table reports the time series regression of market-wide pricing discrepancies defined as the fraction of firms that have a pricing discrepancy at any time t, $\text{posprop}_t = \frac{1}{N}\sum_{i=1}^{N} \mathrm{I}_{\Delta CDS_{i,t}\Delta P_{i,t}>0}$. Panel A reports the results of the regression of Δposprop on changes in market-wide illiquidity, $CDSIlliq_t^M$. Panel B reports the results of the regression of Δposprop on changes in the 10-year Treasury yield. Panel C reports the results of the regression of Δposprop on changes in the Eurodollar rate. ** and * indicates significance at 5% and 10%, respectively.

Panel A: $CDSIlliq^M$

Interval	# of Obs.	Intercept	CDSIlliq(10^{-4})	Adj. R^2
5	250	0.0004	-3.22	0%
		(0.79)	(-0.37)	
10	124	-0.0009	-3.79	-1%
		(-1.02)	(0.09)	
25	49	-0.0041	12.53	-2%
		$(-1.80)^*$	(0.30)	

Panel C: Treasury Yield

Interval	# of Obs.	Intercept	ΔYield	Adj. R^2
5	251	0.0004	-0.0017	0%
		(0.69)	(-0.43)	
10	125	-0.0011	0.0004	0%
		(-1.27)	(0.08)	
25	50	-0.0037	0.0087	2%
		(-1.85)*	(1.35)	

Panel C: Eurodollar

Interval	# of Obs.	Intercept	ΔEurodollar	Adj. R^2
5	251	0.0003	-0.0054	0%
		(0.66)	(-0.81)	
10	125	-0.0009	0.0222	9%
		(-1.06)	(3.58)**	
25	50	-0.0034	0.0203	10%
		(-1.81)*	(2.53)**	