Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets

Jens Hilscher*
hilscher@brandeis.edu

Joshua M. Pollet†
pollet@illinois.edu

Mungo Wilson‡
mungo.wilson@sbs.ox.ac.uk

This version: May 2013

Abstract

This paper provides evidence that equity returns lead credit protection returns at daily and weekly frequencies, while credit protection returns do not lead equity returns. Our results indicate that informed traders are primarily active in the equity rather than the CDS market. These findings are consistent with standard theories of market selection by informed traders in which market selection is determined partially by transaction costs. We also find that credit protection returns respond more quickly during salient news events (earnings announcements) compared to days with similar equity returns and turnover. This evidence provides support for explanations related to investor inattention.

JEL Classification: G12

Keywords: CDS, market segmentation, inattention

---

*International Business School, Brandeis University, 415 South Street, Waltham MA 02453, USA. Phone +1-781-736-2261.

†College of Business, University of Illinois, 340 Wohlers Hall, 1206 South Sixth Street, Champaign, IL 61820, USA. Phone +1-217-300-1961.

‡Saïd Business School, Oxford University, and Oxford-Man Institute, Park End Street, Oxford OX1 1HP, UK. Phone +44-1865-288-914.

We thank Markit Group for providing us with data on CDS spreads; an anonymous referee, Robin Greenwood, Denis Gromb, David Hirshleifer, Robert Jarrow, Carol Osler, Neil Pearson, and Mark Seasholes as well as seminar participants at Brandeis University, Aalto University, the Federal Reserve Bank of Boston, the 22nd FDIC Derivatives Securities and Risk Management conference, the First Annual Duisenberg Workshop in Behavioral Finance, and Wilfrid Laurier University for helpful comments; Glen Taksler, former head of CDS strategy at Bank of America, for numerous insightful discussions on the institutional details of the CDS market, and Ly Tran and Eugene Kiselev for research assistance. Wilson acknowledges the support of the Oxford-Man Institute and ESRC grant no. ES/K005561/1.

1 Introduction

Credit default swap (CDS) contracts are derivative contracts that implicitly allow investors to trade credit protection. In the event of a deterioration in credit quality, the buyer of credit protection (default insurance) gains and the seller loses. CDS contracts may represent the most prolific financial innovation of the last two decades. However, CDS contracts are also controversial. Many commentators are concerned about the potential to use CDS contracts to exploit private information for excessive profit or as a tool for destabilizing speculation. The European Union enacted a ban on so-called 'uncovered' long positions in CDS contracts on sovereign bonds which became effective in November 2012. The Commissioner announcing the ban on uncovered sovereign CDS stated that it was "...a key provision of the Short Selling Regulation, to ensure that these instruments are used for legitimate hedging purposes only." The SEC stated that CDS contracts for corporate bonds "...can be used in a downward manipulation whereby a manipulator sells the shares of a company short and then spreads lies about a company's negative prospects."[1]

The key question is whether news in CDS markets drives price changes in other markets. Standard financial theory emphasizes that all derivative securities related to the same underlying asset are exposed to the same fundamental shocks, and consequently, that there is no unique informational feature of CDS contracts. More nuanced theory shows how informed traders (or manipulators) may prefer one security market to another due to price impact, leverage, and transactions costs. Hence, informed trading can occur predominantly in one type of security.

We approach the question of relative information content from the perspective of market selection by informed traders (e.g. Easley, O'Hara, and Srinivas (1998)). If informed traders choose to trade in only one market, we expect that market to reflect the most up-to-date information. Thus, if equity returns lead credit protection returns (and not vice versa), we conclude that information is reflected first in the equity market and, therefore, informed traders are active mainly or only in the equity market.

[1]First quote: European Commission Press Release IP/12/746, July 5, 2012; Second quote: SEC Statement 2008-235, October 1, 2008. We note that our results are related to corporate CDS contracts rather than sovereign CDS contracts.

We use daily and weekly data for CDS contracts for almost 800 firms for the period 2001-2007 to examine cross-market predictability. We regress daily and weekly credit protection returns on contemporaneous and lagged equity returns and run the analogous regressions for equity returns. We find that stock returns predict credit protection returns at horizons of up to several weeks. In contrast, credit protection returns contain no statistically significant information about future equity returns. We interpret these results as evidence for the presence of informed traders in the equity market and the general absence of informed traders in the CDS market. These results are also inconsistent with the possibility that CDS trading amplifies shocks in the equity markets because credit protection returns do not predict equity returns.

Easley at al. analyze a model in which there are both informed traders, who seek to profit from their superior private information, and uninformed or liquidity-based traders, whose presence will allow informed traders to trade without revealing their identities. In this setting the two possible equilibria are that "informed traders choose to 'pool' and trade in both markets, or to 'separate' and trade in only one market." An informed investor chooses a market in order to maximize expected profits and is more likely to trade in a market with (1) high sensitivity of the security to the information that will eventually become public; (2) low transaction costs; and (3) a high proportion of uninformed traders.[2] Without evidence, there is no means of determining the prevailing type of equilibrium.

Since the CDS market includes large banks as participants, information-based trading in the CDS market is a possibility. However, even though many firms and institutions participating in this market are sophisticated, a high level of sophistication does not imply that the participants are informed. For example, an insurance company with a corporate bond portfolio might purchase CDS contracts to reduce exposure to a particular bond issuer rather than sell the underlying bonds. A hedge fund could change its exposure to credit risk as an asset class by trading a portfolio of CDS contracts. In both examples, the reason to participate in the CDS market is unrelated to information about the expected future changes of the specific firm's CDS spread.

[2] In the model of Easley et al. option leverage is constant and the strike price changes option delta. In a more realistic setting, option leverage grows more rapidly than the option delta approaches zero as the option moves out of the money.

Our findings imply that there is a separating equilibrium in which informed traders participate in the equity market and only liquidity traders participate in the CDS market. From a theoretical perspective, such an equilibrium would be supported by bid-ask spreads that are high enough to deter informed traders from switching to the CDS market in spite of the high fraction of uninformed traders in the CDS market and the high sensitivity of credit protection returns to information. Bid-ask spreads could be high for two reasons: (1) market makers optimally choose to set high bid-ask spreads to discourage the participation of informed traders, and (2) the costs incurred by CDS market makers, the equivalent of order processing and inventory costs, require high bid-ask spreads due to the dearth of CDS volume compared to equity volume.

Consistent with both of these reasons, we find that CDS bid-ask spreads are very high, and orders of magnitude higher than the bid-ask spreads of equities. In addition, we find that volume is several times greater for the equity market compared to the CDS market. Furthermore, we expect percentage bid-ask spreads to be higher for securities with better credit ratings. Holding credit protection is analogous to owning a put option on the underlying firm (in Merton (1974) risky debt is economically equivalent to a portfolio of risk-free debt and a short position in a put). For firms with better credit ratings, which tend to be far from default, such puts are more sensitive to information about firm value because they are further out of the money. Thus, to deter informed investors from switching from the equity to the CDS market, percentage bid-ask spreads need to be higher for better-rated firms to counteract the larger information sensitivity of the associated CDS contracts.

At the same time, the value or price of the implicit put option is lower for firms with better credit ratings. Holding the level of the bid-ask spread constant, the percentage bid-ask spread for CDS contracts will be much higher for firms with better credit ratings. Thus, if the bid-ask spread for CDS contracts is primarily due to inventory costs (or order processing), the percentage bid-ask spreads would again be higher for firms with better credit ratings. Indeed, we find that percentage bid-ask spreads on firms' CDS contracts rated A and above are almost three times as high as those rated BB and below. This finding is not a priori obvious and provides additional evidence that is consistent with a separating equilibrium in which informed participants primarily trade equities.

If a pooling equilibrium ever prevails, it is more likely to hold for firms with high-risk credit ratings given their relatively lower CDS bid-ask spreads. We find very limited evidence that the credit protection return predicts the equity return two days later for firms rated BB and below. However, even for these firms, equity returns still predict credit protection returns quite strongly at both short and long horizons. Furthermore, we do not find any evidence that a pooling equilibrium prevails following events that would plausibly be associated with initial information acquisition by participants in the CDS market, such as large credit protection returns or positive credit protection returns.

In summary, we find strong evidence that, given a choice of markets, informed traders participate only in the equity market and are deterred from trading in the corporate CDS market by high spreads. This finding is broadly consistent with the separating equilibrium of market selection models and undermines the case for a ban on uncovered positions in corporate CDS markets.

The length of delay in the adjustment of CDS spreads to publicly available equity return data is puzzling, even in a separating equilibrium, because CDS traders can easily gather information from the equity market. It is possible that using quotes from CDS market makers implies that price data from CDS and equity markets may not be synchronized perfectly on a daily basis. Indeed, it could be the case that, due to lack of trading, some CDS quotes are not updated every day. Nevertheless, we find significant predictability of credit protection returns using equity returns with a time lag of five trading days in daily specifications and analogous predictability with a time lag of four weeks in weekly specifications. Thus, nonsynchronous price data for the two markets does not appear to be a valid explanation for the results.

In the absence of limits to arbitrage, credit protection returns should not be predictable using equity returns at such long horizons. We consider two explanations for the delayed response that are not mutually exclusive. First, transaction costs for CDS contracts could be sufficiently high that the predictability based on the midpoint of the quoted CDS spread is not worth exploiting, and so, what appears to be substantial predictability in our analysis is not actually exploitable. Second, the predictability is evidence of mispricing created by inattentive participants in the CDS market and limits to arbitrage.

We find that transaction costs play an important role. The CDS market responds more slowly to news in the equity market for firms with a low number of quotes in the CDS market (a proxy for high transaction costs). In addition, the CDS market responds more rapidly to equity returns that are larger in absolute value. Thus, either CDS quotes update rapidly to preclude profitable trading strategies or transaction costs deter trading and quotes adjust slowly.

If traders in the CDS market are motivated by liquidity considerations and if investor attention is a scarce resource (Della Vigna and Pollet (2007), Barber and Odean (2008), Cohen and Frazzini (2008)), then CDS traders will be less attentive than equity traders to events of common concern. We show that the response of credit protection returns to stock returns is much faster immediately after regular corporate earnings announcements, when, presumably, equity and CDS traders are more likely to pay attention (Frazzini and Lamont (2006)).

These findings provide a counterpoint to the existing literature regarding the role of derivatives markets in determining how information enters prices. Easley et al. (1998), Pan and Poteshman (2006), and Ni, Pan, and Poteshman (2007) provide evidence that stock and option markets are in a pooling equilibrium, in which informed traders choose to trade in both stock and option markets. In more recent work regarding options markets, Muravyev, Pearson, and Broussard (2013) indicate that option prices do not contain any additional information about future stock prices once the current stock price is taken into account. While the equilibrium type must depend on a host of theoretical factors, identifying the equilibrium for a particular pair of markets remains an open empirical question.

Our results are related to the information flow between equities and bonds as well as between bonds and CDS. Kwan (1996) finds that stock returns predict current bond yield changes, while the opposite is not the case. This evidence is consistent with our findings since the sensitivity of bonds to fundamentals is always much lower than the sensitivity of the associated CDS or stock. Blanco, Brennan, and Marsh (2005) and Zhu (2006) find that CDS spreads predict corporate bond credit spreads, and thus, that CDS spreads improve bond price discovery.

Acharya and Johnson (2007), using data for 79 U.S. firms from 2001 to 2004, "find significant incremental information revelation in the credit default swap market ... only for negative credit news and for entities that subsequently experience adverse shocks." The findings in Table 2 of Acharya and Johnson are confined to a small group of distressed firms classified using ex post, rather than ex ante, measures of rising credit risk or high credit risk.[3] The use of ex post measures of credit conditions implies that the regressors contain information about future realizations of firm value, and therefore, the typical assumptions for tests of predictability do not hold. The analogous results in the same table from Acharya and Johnson are not statistically significant using the firm's credit rating at the time – the only ex ante measure of credit risk they consider. If we revisit these results and use standard errors based on a heteroskedasticity consistent estimator, the statistical relations for the ex post measures of credit risk become insignificant or marginally significant for the same sample of firms. In addition, our results for the full sample indicate that credit protection returns do not predict equity returns after conditioning on large credit protection returns or positive credit protection returns. Indeed, even for junk-rated firms, the only consistent evidence of predictability at both short and long horizons in our analysis is from equity to CDS markets rather than from CDS to equity markets.[4]

The remainder of the paper is organized as follows. Section 2 describes the data on CDS spreads, credit protection returns, and equity returns. Section 3 presents our main results. Section 4 analyzes the impact of high transaction costs. Section 5 considers the potential role of investor inattention in the CDS market and section 6 concludes.

[3] In Table 2 of Acharya and Johnson, a firm is classified as having deteriorating credit risk at time t if the credit spread for the firm increases by more than 50 basis points between adjacent trading days at any time from t to the end of the sample period and a firm is classified as having high credit risk at time t if the credit spread remains above 100 basis points from t until the end of the sample period.

[4] Our results are more consistent with the findings in Norden and Weber (2009) for a much smaller sample of 58 firms during the period from 2000 to 2002. However, their analysis does not relate these patterns to theories of market selection, predictions of the Merton (1974) model for corporate debt, implications of transaction costs, or the potential role of inattention.

2 Data Description

We are interested in the links between the equity market and the credit default swap (CDS) market. For this purpose we assemble data on returns for both of these assets.

2.1 Credit Protection Return

Our discussion in the introduction analyzes the properties of a hypothetical credit protection contract in which the buyer of protection pays an up-front premium in exchange for a cash payment if and only if the reference bond defaults before the expiration of the contract. The structure of this contract mimics the most basic kind of insurance agreement. Our approach is to extract the return to holding credit protection from quoted CDS spreads.

It is important to recognize that this implicit return is economically quite different from the excess return on a corporate bond implied by the identical CDS spread, as considered by Berndt and Obreja (2010). In particular, the holder of credit protection gains money for a given absolute deterioration in credit quality and the credit protection return is more sensitive to changes in credit quality for firms with better credit ratings. By contrast, the implied return to a corporate bond for the same deterioration in credit quality is negative and is less sensitive to changes in credit quality for firms with better credit ratings. This analysis follows from the observation that credit protection is similar to an out of the money put option and such puts are more sensitive to information for firms with better credit ratings because they are further out of the money.[5]

The CDS contract can be recast as a credit protection agreement with an up-front insurance premium equal to the discounted present value of the credit spread at date t. Thus, the return to the buyer of the implicit insurance contract is the profit from a strategy that purchases a CDS contract at date t and sells an offsetting CDS contract at date t' divided by this implicit

[5] Based on the Black-Scholes formula, it is straightforward to show that the magnitude of the sensitivity of the put option return to the return of the underlying asset becomes larger as the put option moves further out of the money. This sensitivity is equal to the hedge ratio (or delta) of the put option multiplied by the ratio of the underlying asset price to the put option price (leverage).

premium. We label this return as the credit protection return and it is approximately equal to the percentage change in the quoted CDS spread adjusted by the ratio of two annuity factors (see section A of the online appendix for details). In practice, this annuity ratio will always be close to one relative to the percentage change in the CDS spread. Thus, the credit protection return is well approximated by the percentage change in the credit spread. We use the percentage change in the credit spread as the credit protection return in the empirical analysis below.

2.2 Credit Default Swap Data

CDS data are from Markit Group Limited (Markit). Markit, founded in 2001, uses a network of large partner banks from which they assemble daily CDS spread quotes. According to the Markit User Guide (2007), "Finance industry professionals who need to view and extract various forms of credit spread data and analytics use the Markit website. ... They typically work for financial institutions such as large commercial banks, insurance companies, asset managers, and credit arbitrage funds."

The time period for our data is from January 2001 to December 2007. The number of firms with available data increases from close to 250 names in 2001 to about 650 names in 2005 before stabilizing at that level in 2006 and 2007. We use data for 5-year contracts because these are the most widely traded and the most liquid for U.S. firms.[6] This source of data is also used by Han and Zhou (2008), Acharya, Schaefer, and Zhang (2008), and Kapadia and Pu (2012).

2.3 Summary Statistics

We collect daily equity market data, quarterly accounting data, and monthly S&P credit ratings from CRSP and COMPUSTAT. We calculate market capitalization and book leverage based on this information. We also collect CDS bid-ask spread data for 2007 from Datastream

[6] We include only observations that use the modified restructuring default definition clause since this is the restructuring convention that is most commonly used for U.S. firms.

since Markit only provides the average quote and the number of quotes.

Table 1 Panel A reports basic summary statistics for the firms in our sample. The data set contains 783 firms for which we have CDS and equity data. The average CDS spread is equal to 159 basis points and the average firm has a credit rating of BBB. The wide variation in credit quality is reflected by the inter-quartile rangeS of 43 to 193 basis points for credit spreads and ratings of A- to BB+. The average firm has 1013 days of available CDS data. CDS contracts are predominantly for large firms. The average firm has a market capitalization of $15 billion and 75% of firms have capitalizations greater than $2.5 billion. Leverage, calculated as book assets minus book equity divided by book assets, has an inter-quartile range of 51% to 76%.

Panel B of Table 1 reports mean CDS bid-ask spreads and other microstructure characteristics for three groups of firms based on credit rating. The percentage spread is defined as the bid-ask spread for the CDS contract divided by the CDS spread (the midpoint of the bid-ask spread). The average CDS percentage bid-ask spread is very high, and significantly higher than the analogous average bid-ask spread for equities. Indeed, according to Hendershott, Jones, and Menkveld (2011), round trip quoted bid-ask spreads for equities as a percentage of the midpoint are approximately 10 basis points (0.1%) for large-cap stocks. For the corresponding credit protection premium, the analogous magnitude for the entire sample is 13.9%. Based on these differences in the bid-ask spreads between equity and CDS markets, it is possible that informed traders are deterred from trading in the CDS market and choose to trade in the equity market instead.

In addition, the statistics reported in Panel B indicate that the percentage bid-ask spreads for CDS contracts are considerably larger for firms with lower-risk credit ratings. The average CDS percentage bid-ask spreads for firms rated A and above (20.4%) is approximately three times as high as the average percentage CDS bid-ask spread for firms rated BB and below (7.5%). This result provides additional support for an equilibrium that deters informed traders from participating in the CDS market, because it is the CDS contracts for high-grade firms that are most sensitive to information.

Panel B and Panel C also present information related to other potential determinants of the CDS bid-ask spread, including credit protection return volatility, CDS notional volume (based on data from DTCC), and the frequency of quote updates. These other variables do not vary dramatically by rating, and therefore, the pattern linking relative CDS bid-ask spreads to rating is not driven by these factors.

3 Cross-predictability

We are interested in the location of informed traders in the CDS and equity markets. In this section we examine the location of informed trading by considering whether or not equity returns predict credit protection returns and vice versa. We first examine daily returns and then consider weekly returns.

3.1 Daily Returns

3.1.1 Vector Autoregression (VAR)

We begin by examining the simplest pooled vector autoregression for equity returns and credit protection returns. We estimate these regressions separately for all firms rated A and above, BBB, and BB or below (non-investment grade). We estimate the following specification:

$$\begin{pmatrix} R_{j,EQ,t+1} \\ R_{j,CP,t+1} \end{pmatrix} = \begin{pmatrix} \beta_{0,j,EQ} \\ \beta_{0,j,CP} \end{pmatrix} + \begin{pmatrix} \beta_{1,EQ,EQ} & \beta_{1,EQ,CP} \\ \beta_{1,CP,EQ} & \beta_{1,CP,CP} \end{pmatrix} \begin{pmatrix} R_{j,EQ,t} \\ R_{j,CP,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{EQ,t+1} \\ \varepsilon_{CP,t+1} \end{pmatrix} \quad (1)$$

where the dependent variables, $R_{j,CP,t+1}$ and $R_{j,EQ,t+1}$, are the credit protection return for firm j for day $t+1$ and the equity return for firm j for day $t+1$, respectively. We estimate the pooled vector autoregression specification separately by rating category to allow for different predictability coefficients by rating classification. We allow the intercept to be different for each firm included in the rating category. The t-statistics are based on standard errors that are clustered by date to adjust for heteroskedasticity and contemporaneous correlation of any form.

The first and fourth columns of Table 2 report estimates for a pooled vector autoregression with only one lag. The estimates in column 1 indicate that the equity return is not predictable using either the lagged equity return or the lagged credit protection return for all three rating categories. The analogous estimates in column 4 indicate that the credit protection return is statistically related to the lagged equity return at the 1% level of significance even after controlling for the lagged credit protection return. For instance, the estimate for $\beta_{1,CP,EQ}$ is -0.158 with a t-statistic of 12.3 in Panel A (A, above) and the analogous coefficient and t-statistic are -0.11 and 14.7 in Panel C (BB, below). This pattern is consistent with the prediction regarding coefficient magnitude by credit rating group.[7] In addition, the evidence of credit protection return predictability using equity returns is much stronger than the credit protection return autocorrelation. These patterns of statistical predictability or lack thereof are retained after augmenting the baseline specification with two or three lags. Equity returns at $t-1$, $t-2$, and $t-3$ are all highly significant predictors of the credit protection return at t even after controlling for the corresponding lagged credit protection returns.

Since the credit protection return is calculated using quoted CDS spreads, it is possible that this measure does not necessarily reflect transaction prices. Essentially, the credit protection return could be based on stale quotes. However, it is these observable quotes that would have to generate any potential information flow from the CDS market to the equity market (Markit is one of the largest data providers of CDS spreads). Therefore, the lack of equity predictability using this measure of the credit protection return is the relevant test of the location of price discovery.

3.1.2 Predictability of Credit Protection Returns Using Equity Returns

We analyze the second equation of the VAR above in greater detail by examining the response of credit protection returns to the equity returns of the same firm at different horizons. We estimate the following specification:

$$R_{j,CP,t+T} = \beta_{0,j,T} + \beta_{T,CP,EQ} R_{j,EQ,t} + \beta_{T,CP,CP} R_{j,CP,t} + \varepsilon_{CP,t+T} \tag{2}$$

[7] We discuss relative coefficient magnitudes in more detail in section shortly.

where the dependent variable, $R_{j,CP,t+T}$, is the credit protection return for firm j over day $t+T$ for T from zero to ten days. The independent variables include $R_{j,EQ,t}$, the equity return for firm j for day t, the corresponding credit protection return as a control (if $T > 0$), and firm fixed effects. Again, we estimate these regressions by broad credit rating category.

Panel A of Table 3 reports estimates of the coefficients of $\beta_{T,CP,EQ}$ with t-statistics in parentheses beneath. Credit protection returns are negatively contemporaneously related to equity returns. Increasing the equity return by 1% is associated with a contemporaneous change in the credit protection return for a typical A-or above-rated issuer of -0.18% or 18 basis points (bps), -14 bps for a BBB and -11 bps for a junk-rated issuer, all highly statistically significant. Differences in coefficient magnitudes across the three rating groups are statistically significant at the 1% level (difference between BBB and A, above) and 5% level (difference between BBB and BB, below).

The greater sensitivities for better-rated issuers are consistent with the insight of Merton's (1974) theory of corporate debt as a portfolio of risk-free debt minus a put option on the underlying firm. The specification in equation (2) regresses credit protection returns on equity returns for the same firm. Therefore, the resulting coefficient estimates are actually ratios of sensitivities to the return on the underlying firm, rather than the sensitivity of the credit protection return to the return on the underlying firm. Given the return for the unlevered firm, the sensitivity of the credit protection return to the equity return is the ratio of the sensitivity of the credit protection return to the underlying asset return, $\beta_{CP,V}$ to the sensitivity of the equity return to the underlying asset return, $\beta_{EQ,V}$. Thus, $\beta_{T,CP,EQ} = \beta_{CP,V,T}/\beta_{EQ,V,T}$ holding all else constant. As a firm moves further from bankruptcy, its credit protection becomes further from the money and the firm's equity more in the money. For such lower-risk firms, $\beta_{CP,V}$ is larger in absolute value (more negative) and $\beta_{EQ,V}$ is smaller (positive, but closer to zero). Thus the ratio, that is $\beta_{CP,V}/\beta_{EQ,V}$, is larger in absolute value (more negative), and credit protection returns should be relatively more sensitive (stronger negative relation) to equity returns. Hence, the Merton model of corporate debt predicts that credit protection returns should be more sensitive (further from zero) to equity returns for better-rated firms and this intuition is consistent with our results.

The columns to the right of column one in Panel A of Table 3 report the sensitivities of credit protection returns to lagged equity returns, moving from lags of 1 to 10 days. For all three groups, credit protection returns respond negatively to lagged equity returns at horizons of up to five trading days with statistical significance above 1%. During these first five days, it is also the case that the sensitivity of credit protection returns to equity returns is greater (further from zero) for firms with better credit ratings.

Panel B of Table 3 analyzes cumulative response coefficients for the columns of Panel A. For firms with good credit ratings (A or better), the credit protection return response to a 1% higher equity return is -60 bps after 5 days compared to -18 bps for the contemporaneous response. Similarly, for firms with a credit rating of BBB the five-day response is -49 bps (contemporaneous -14 bps) and for firms with junk credit ratings (BB or worse) the response is -40 bps (contemporaneous -11 bps). The slope of the cumulative sensitivity is negative and the increase in the absolute magnitude of the response to equity returns over time is similar across the rating groups in percentage terms.

Panel C of Table 3 considers the statistical significance of this differential response. The regressions test whether or not there is a statistically significant response to equity returns following the contemporaneous response. The independent variables of the regression are unchanged, but the dependent variable is the cumulative return from day $t+1$ to day $t+5$ in column 1, $t+2$ to $t+6$ in column 2, $t+1$ to $t+10$ in column 3 and $t+2$ to $t+11$ in column 4. For all three rating groups, the cumulative response from one to five days following the equity return for day t is significant at the 1% level and we find similar statistical evidence results for the cumulative return from $t+2$ to $t+6$. We consider this alternative window to ensure that the results are not caused only by the differential response to equity returns at $t+1$. The results for the cumulative credit protection response ten days following the equity return, that is, from $t+1$ to $t+10$ are statistically weaker, but match the pattern found for the shorter horizon.[8]

The t-statistics used in this context must take into account the autocorrelation induced

[8] The coefficient estimates in Panel C differ from those in Panel B because we are using overlapping observations in Panel C.

by using daily overlapping observations of the cumulative credit protection returns as well as the contemporaneous cross-correlation for different firms. We allow for heteroskedasticity and arbitrary contemporaneous correlation across firms by clustering the standard errors by date. In addition, we correct these standard errors to account for autocorrelation in the error structure (see section B of the online appendix). This method is almost always more conservative than clustering by date or stock.

The results reported in Table 3 document a delayed response of credit protection returns to equity returns, controlling for lagged credit protection returns and firm fixed effects. At all horizons, the response is larger (more negative) for better-rated issuers and it is statistically significant at horizons of up to 10 days.

3.1.3 Predictability of Equity Returns Using Credit Protection Returns

Next, we switch the dependent variable in the regression to the equity return and the credit protection return becomes the independent variable. We include firm fixed effects and control for the lagged equity return when estimating the predictive power of credit protection returns for equity returns. Table 4 reports our results in an identical format to Table 3.

Column 1 of Panel A indicates that the contemporaneous response of the equity return to a 1% increase in the credit protection return is -0.033% or -3.3 bps for an A-or above-rated issuer. The estimates in column 2 and column 3 report similar results. The contemporaneous response to the equity return is -3.9 bps for a BBB-rated issuer and -4.9 bps for a junk-rated issuer. All coefficients are highly statistically significant.

In addition, the pattern and the magnitudes of the coefficients are consistent with the Merton model of corporate debt and the differences in the magnitudes are statistically significant. Following the logic above, the sensitivity of the equity return to the credit protection return is the ratio of the sensitivity of the equity return to the underlying asset return, $\beta_{EQ,V}$ to the sensitivity of the credit protection return to the underlying asset return, $\beta_{CP,V}$. Thus, $\beta_{T,EQ,CP} = \beta_{EQ,V,T}/\beta_{CP,V,T}$ holding all else constant. As a firm moves further from bankruptcy, its credit protection becomes further from the money and the firm's equity more in the money. For such high-grade firms, $\beta_{CP,V}$ is larger in absolute value (more negative) and

$\beta_{EQ,V}$ is smaller (positive, but closer to zero). The net effect is that the ratio $\beta_{EQ,V}/\beta_{CP,V}$ is smaller in absolute value (less negative), and equity returns should be relatively less sensitive (weaker negative relation) to credit protection returns. Thus, the Merton model of corporate debt predicts that equity returns should be less sensitive (closer to zero) to credit protection returns for firms with better credit ratings.

With one possible exception, we find no evidence for a delayed response of equity returns to credit protection returns. Our tests for a delayed response in Panel C fail to reject the null hypothesis of no delay for all window lengths and all rating groups. The one potential exception is the marginal statistical evidence in Panel A indicating that the credit protection return for junk-rated issuers predicts the equity return two days later. The coefficient estimate is only marginally significant at the 10% level. Although this estimate could easily be a statistical accident, it is weakly consistent with the possibility that there may be some informed trading in CDS contracts for junk-rated or distressed firms.

3.1.4 Subsamples and Other Insights

We revisit the specifications predicting the credit protection return using equity returns in Table 3 for large equity returns and negative equity returns (Table 5 Panels A and B). We focus on these two subsamples because the features of CDS contracts may imply that CDS spreads react more quickly to large equity returns and/or negative information about firm value. The analysis of observations with large equity returns indicates that there is a greater contemporaneous relation between the credit protection return and the equity return for these observations. Although, the response of credit protection returns to lagged equity returns is also greater (or similar) for these observations compared to coefficients reported in Table 3.

The results for observations with negative equity returns reflect a similar pattern. The contemporaneous relation between the credit protection return and the equity return is more than twice as large as the estimate for the baseline sample. However, the delayed response of the credit protection return to lagged equity returns is also more than twice as large compared to the baseline sample. Thus, even though the total CDS response is larger in magnitude for negative equity returns, there is no clear result regarding a different speed of adjustment for

CDS spreads due to negative equity returns.[9]

We also investigate the possibility that CDS contracts convey information to equity markets for two plausible subsamples. We analyze the relevant predictive relation following large credit protection returns and positive credit protection returns in Panel C and Panel D of Table 5. We consider these two subsets of observations, because it is possible that these events may be more closely associated with information revelation in the CDS market. However, as the coefficient estimates in column 2 and column 3 indicate, there is no statistical relation between equity returns and lagged credit protection returns at the 5% level of significance for either subset of observations. Indeed, the coefficient magnitudes and patterns of significance closely mimic the analogous estimates in Table 4.

We explore why Acharya and Johnson (2007) reach different conclusions regarding the predictability of equity returns in Table 6. The three measures of poor credit conditions in Acharya and Johnson are: (1) a credit spread increase (credit deterioration) of more than 50 basis points between adjacent trading days at any point from time t to the end of the sample period, (2) a credit spread larger than 100 basis points that remains above this level between date t and the end of the sample period, and (3) the firm has a rating equal to or worse than A-. In columns 1 through 3, we analyze regressions of equity returns on lagged credit protection returns and interaction terms for poor credit conditions and lagged credit protection returns using three different estimators for the standard errors: OLS, White (heteroskedasticity consistent), and clustered by date (heteroskedasticity and contemporaneous correlation consistent). In column 4, we restrict the sample to the observations with poor credit conditions (as defined by Acharya and Johnson) and examine predictability from the lagged credit protection returns.

We confirm Acharya and Johnson's findings that there is a negative coefficient on the interaction of lagged CDS returns and the credit condition indicators for poor or deteriorating credit conditions using OLS standard errors. The results are very similar for our data set (using their time period and sample of firms). The t-statistics for the coefficients of interest are 2.71, 2.87, and 1.56 based on this exercise, while Acharya and Johnson report t-statistics of 2.36,

[9] In unreported results, we confirm that the speed of adjustment is not statistically different following negative equity returns using the fractional response methodology described in Section 4.

2.52, and 1.51. The ranking of the t-statistics by the definition of the credit condition is the same. In addition, the absolute and relative magnitudes of these t-statistics are very similar as well. It is important to note that credit conditions (1) and (2) are ex post measures of credit deterioration, rather than ex ante measures, and that the original results are not statistically significant for credit condition (3), the only ex ante measure. Why is this distinction significant? The fact that credit conditions are going to deteriorate (or remain poor) in the future implies that the interaction term in these specifications reflects shocks to future credit conditions and contains information about future shocks to firm value. Thus, the typical orthogonality conditions necessary for tests of predictability appear to be violated.

In addition, heteroskedasticity consistent standard errors are critically important in this context. The standard errors increase substantially for all three credit conditions. This difference implies that the interaction term for credit condition (1) is no longer significant even at the 10% level. For credit condition (2), the p-value increases more than ten-fold from 0.4% to 6.6%. The results for credit condition (3) remain insignificant. The t-statistics in column 3 based on heteroskedasticity and contemporaneous correlation consistent standard errors follow the same pattern as those in column 2. In column 4, the sample is restricted to observations with the poor credit condition indicator and the evidence of predictability in these specifications is similar to the evidence in columns 2 and 3. Taken together, these results indicate that the findings in Acharya and Johnson (2007) depend on the use of ex post rather than ex ante measures of credit conditions and the statistical approach used to calculate standard errors.

3.2 Weekly Returns

Table 7 replicates the results of Table 3 and Table 4 using weekly, as opposed to daily, returns. All of the patterns documented in the previous subsection are again visible in Table 7.

In Panel A, credit protection returns are statistically significantly negatively related to contemporaneous equity returns, controlling for firm fixed effects. An increase of 1% in the weekly equity return is associated with a -44 bps change to the credit protection return for the same week for firms with good credit ratings. The analogous interpretation indicates an impact of -35 bps for BBB and -29 bps for junk issuers. Again, the pattern of the estimated sensitivities across the ratings groups is consistent with the predictions of the Merton model.

Credit protection returns for all rating groups show a highly statistically significant response to the previous week's equity return (controlling for the previous week's credit protection return). For firms with better credit ratings, the response of the credit protection return to the lagged equity return is significant for each of the previous three weeks. For firms with worse credit ratings, the response of the credit protection return to the lagged equity return is highly significant for each of the previous four weeks. For each of the first three weeks, the sensitivities are larger in absolute magnitude for CDS contracts on firms with better credit ratings. The pattern documents a clear delayed response of credit protection returns to equity returns. In Panel B, the cumulative response of credit protection returns to equity returns after 4 weeks is more than twice the contemporaneous response for all three groups.

Panel C shows virtually no evidence of a delayed response by equity returns to credit protection returns in weekly data. For almost all combinations of rating group and time period, the estimated equity response is not significantly different from zero (the only exception is a marginally significant response at the 10% level for junk-rated issuers using the credit protection return lagged by two weeks). The cumulative responses, reported in Panel D, indicate that there is no cumulative delayed response of equity returns to credit protection returns.

Our conclusion from the daily and weekly evidence is that a firm's equity returns predict its credit protection returns at horizons of one month or less and that the long-run response of credit protection returns to equity returns is several times larger than the contemporaneous response. As predicted, the contemporaneous and cumulative responses of credit protection returns for better-rated issuers are larger (further from zero) than the analogous responses for worse-rated issuers. There is no substantial evidence that credit protection returns predict equity returns on a daily or weekly basis.

4 Transaction Costs

The findings in section 3 indicate that there is a separating equilibrium in which informed investors choose to be active primarily in the equity market. Based on the theory of market selection, this equilibrium is supported by market makers setting bid-ask spreads high enough to deter informed traders from switching to the CDS market, particularly for better-rated issuers. The evidence in Table 1 (discussed earlier) regarding percentage bid-ask spreads for CDS contracts is consistent with this theory because these bid-ask spreads are orders of magnitude larger than the bid-ask spreads for equities and CDS bid-ask spreads are considerably larger for better-rated firms.

Since transaction costs must play a role in sustaining the observed separating equilibrium, it is quite possible that these same costs are also at least partly responsible for the delayed response of credit protection returns to equity returns. Intuitively, if transaction costs are sufficiently large to deter informed trading, they may also be sufficiently large to make it difficult to profit from the predictability of the midpoint of the CDS quotes. Only if the equity return is large relative to the CDS bid-ask spread does it become necessary for CDS market makers to adjust quotes. Hence, high transaction costs will slow the adjustment of CDS spreads to information revealed in equity markets.

There are two testable predictions that follow from this analysis. First, credit protection returns should adjust more slowly to equity returns if there is low depth for a CDS contract (a proxy for high transaction costs), holding all else constant. Second, credit protection returns should adjust more quickly if the equity return is large in absolute value, holding all else constant. This second prediction follows from the intuition that important information revealed in equity markets would lead to profitable trading strategies in CDS markets unless CDS quotes adjust in spite of high transaction costs.[10] We measure the speed of the CDS response using the fractional response: the fraction of the credit protection return from t to $t+11$ that occurs immediately at t due to the equity return at t. If CDS quotes change quickly (slowly), then

[10] This prediction is also consistent with investor inattention as discussed in the next section.

the fractional response will be high (low).[11]

The evidence in Table 8 is consistent with both predictions. The fractional response is regressed on different sets of variables including an indicator for low depth[12] and the absolute value of the equity return at t. The specification in column 1 indicates that low CDS contract depth, i.e. high transaction costs, is associated with a significantly lower fractional response. The coefficient estimate for the absolute value of equity returns in column 2 indicates that larger returns are significantly positively related to the fractional response. Column 3 indicates that neither of these statistical relations is subsumed by the other. In column 4, the specification in column 2 is augmented with an interaction term using the indicator for observations with the absolute value of the equity return on date t in the top 10% of the distribution. The estimates show that the marginal relation between this absolute value and the fractional response is nonlinear. The marginal relation is more than four times greater if the equity return is large in magnitude and this difference is statistically significant. Column 5 indicates that this nonlinear relation is not due to the impact of low depth on the fractional response. Turnover may also play a role (e.g. Chae (2005), Graham, Koski, and Loewenstein (2006)). In fact, column 6 indicates that turnover for the underlying equity has considerable impact on the speed of adjustment for the associated CDS contract. Nevertheless, the impact of turnover is distinct from those due to low depth and the nonlinear relation between the speed of adjustment and the magnitude of the equity return.

Since all of these specifications include firm fixed effects, these results are not due to cross-sectional variation associated with firm-specific characteristics. In addition, the patterns of statistical significance for the coefficients of interest remain unchanged if time fixed effects are also included in the specifications or if each rating group is analyzed separately. Of course, there

[11] The fractional response is the ratio of the credit protection return at t and the return from t to $t+11$. If the response from t to $t+11$ is of the opposite sign compared to the date t response we set the fractional response equal to 0. If the date t response is larger than the response from t to $t+11$ we set the fractional response equal to 1. To verify that the results are not sensitive to this definition, we exclude observations where the return for date t and the return for date t to $t+11$ have opposite signs and find similar results.

[12] Firms in the lowest quartile of the distribution for the number of independent quotes in a calendar quarter are defined to have low depth.

could be behavioral explanations for these results, but transaction costs provide a straightforward explanation for the impact of depth and size of equity return on the fractional response.

5 Inattention and Earnings Announcements

Inattention is another potential explanation for the slow adjustment of CDS spreads to information in equity returns. We analyze this hypothesis by examining responses around earnings announcements. Since CDS traders are predominantly trading for non-fundamentals-based reasons, they may not be paying close attention to developments in equity markets. If attention increases around earnings announcements, as several studies have argued, including Frazzini and Lamont (2006), then we should observe a more rapid response of credit protection returns to equity returns around these times.

Table 9 compares credit protection return and equity return cross-responses during earnings announcements to non-announcement days using specifications analogous to those in Table 3. The contemporaneous response to a 1% equity return on a non-announcement day is -13.6 bps versus -21.0 for an earnings announcement day. The next day responses are about the same, at -12.9 bps and -12.4 bps respectively, and are both statistically significant. The subsequent credit protection response ($t+2$ to $t+6$) is 25.5 bps for non-announcement days versus 16.5 bps for announcement days. This pattern holds at longer horizons: for $t+2$ to $t+11$ the non-announcement day response is -34.8 bps compared to the announcement day response of -21.3 bps. The delayed credit protection response is more than 50% larger (further from zero) for non-announcement days even though the initial response on day t (or t and $t+1$) is larger for announcement days.

In addition, earnings announcement equity returns have greater explanatory power for the contemporaneous and subsequent-day CDS return: the R^2 on a typical non-announcement day is 0.5% for the contemporaneous response and about the same for the next day, whereas the R^2 is 3.2% for day t and 1.6% on day $t+1$ whenever day t is an announcement day. We conclude that credit protection returns are more sensitive to equity returns around earnings announcements and that CDS contracts respond to news affecting equity prices more quickly.

Our evidence is consistent with CDS traders who only pay attention to equity returns at certain times of high salience, and therefore pay less attention at other times.

If CDS participants pay attention to equity markets during earnings announcements, CDS prices should also 'catch up' with recent developments in equity markets more rapidly at these times. Intuitively, CDS traders check their trading screens for equity price developments in the recent past and adjust their prices on earnings announcement days. The last two columns of Panel A show that the response of the credit protection return on day t to cumulative equity returns from $t-5$ to $t-1$ or from $t-6$ to $t-2$ are greater on earnings announcement days (-0.12% and -0.10% respectively) compared to non-announcement days (-0.07% and -0.05% respectively). The differences are statistically significant with t-statistics of 2.7 and 3.4 respectively.

Panel B shows the sensitivity of equity returns to credit protection returns during and outside earnings announcements. The contemporaneous relation is large and significant for both announcement and non-announcement days, but the lagged response is essentially zero in either case. The lagged response is neither statistically significant nor does it explain a meaningful amount of the equity return variance. There is a higher correlation during earnings announcements, but very little evidence of a slow response.

There is also no evidence that credit protection returns lead equity returns ahead of earnings announcements. If some informed investors possessed superior information about an upcoming earnings announcement and chose to exploit it in the CDS market, we would expect to see credit protection returns during the $(t-5, t-1)$ and $(t-6, t-2)$ intervals predict date t equity returns. The lack of such predictability means that there is no support for the hypothesis of informed trading around earnings announcements in CDS markets.

Table 10 reports the results from a more specific test of the inattention explanation. Again, we use the fractional response, the fraction of the credit protection return response from t to $t+11$ that occurs immediately at t due to the equity return at t, to measure the speed of the credit market response to information in the equity market. We compare the fractional response for earnings announcement days to the analogous response for non-announcements days.

The first column of Table 10 shows that the fraction of the response from t to $t+11$ due to the response on day t is 2.5 percentage points higher for announcement days compared to ordinary days and this difference is statistically significant at the 1% level. Based on this estimate and the baseline fractional response of 16.4% for ordinary days, the fractional response is 15.2% larger following earnings announcements than the response for ordinary days. Controlling for the depth and the characteristics of the equity return reduces this difference to 1.8 percentage points. Nevertheless, the result remains statistically significant at the 1% level. Even after controlling for equity turnover in addition to depth and the magnitude of the equity return, the fractional response is 6.8% larger following earnings announcements, and so, the difference remains highly economically significant.

The findings indicate that the fraction of the total response of credit protection returns occurring on the first day is greater on announcement days than on other days. The likely explanation for the results is the fraction of traders paying attention. Credit protection returns respond more strongly and more quickly at times of high salience, when CDS market participants are more likely to be paying attention, than at other times. In consequence, it must also be the case that CDS market participants are not normally particularly attentive to events in the underlying equity markets and investor inattention in CDS markets likely contributes to the delayed response documented in section 3.

6 Conclusion

For a large representative sample of U.S. listed firms, credit protection returns respond sluggishly to equity returns, but equity returns do not respond sluggishly to credit protection returns. As a corollary, it is very doubtful that informed speculators with information about corporate securities have a great impact on prices through trading in the CDS market. Consequently, calls to regulate the CDS market, based on the belief that informed trading in the CDS market is destabilizing, are not well-founded.

Our findings are entirely consistent with the choice-of-market theory of Easley et al. (1998). The evidence is consistent with a separating equilibrium that is supported by high CDS transaction costs. In this equilibrium informed traders primarily participate in the equity market and only liquidity traders participate in the CDS market. Moreover, since proxies for transaction costs associated with CDS contracts increase the delayed response to equity returns, the evidence is consistent with transaction costs explaining why informed traders choose to participate predominantly in equity markets.

This evidence is complementary to the results in Pan and Poteshman (2006) and Ni et al. (2007) for options markets. Geanakoplos (2009) argues that CDS trading has exacerbated economic volatility following a period of deleveraging, since pessimists would have a way of allowing their views to impact equity prices, with, in his model, consequent real effects. However, we doubt that CDS trading on its own can have as much of an impact as short selling of equity, especially given the absence of evidence that informed traders prefer CDS markets to equity markets when trading in the securities of distressed firms.

In contrast to the previous literature, we also show that the delayed response is not as prevalent around earnings announcements. Such a response is consistent with inattention by CDS traders on non-announcement days. This finding is exactly what we would anticipate if CDS transactions are primarily motivated by hedging or liquidity considerations.

References

[1] Acharya, Viral V. and Timothy C. Johnson, 2007, "Insider trading in credit derivatives", *Journal of Financial Economics*, Vol. 84, 110-141.

[2] Acharya, Viral V., Stephen Schaefer, and Yili Zhang, 2008, "Liquidity Risk and Correlation Risk: A Clinical Study of the General Motors and Ford Downgrade of May 2005", working paper, London Business School and NYU Stern School of Business.

[3] Barber, Brad and Terrence Odean, 2008, "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors", *Review of Financial Studies*, Vol. 21, 785-818.

[4] Berndt, Antje, and Iulian Obreja, 2010, "Decomposing European CDS Returns", *Review of Finance*, Vol. 14, 189-233.

[5] Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps", *Journal of Finance*, Vol. 60, 2255-2281.

[6] Chae, Joon, 2005, "Trading Volume, Information Asymmetry, and Timing Information", *Journal of Finance*, Vol. 60, 413-442.

[7] Cohen, Lauren and Andrea Frazzini, 2008, "Economic links and predictable returns", *Journal of Finance*, Vol. 63, 1977-2011.

[8] Collin-Dufresne, Pierre and Robert S. Goldstein, 2001, "Do Credit Spreads Reflect Stationary Leverage Ratios?", *Journal of Finance*, Vol. 56, 1929-1957.

[9] Della Vigna, Stefano and Joshua M. Pollet, 2007, "Demographics and industry returns," *American Economic Review*, 97, 1667-1702.

[10] Easley, David, Maureen O'Hara and P. S. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade", *Journal of Finance*, Vol. 53, 431-465.

[11] Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2009, "The Determinants of Credit Default Swap Premia", *Journal of Financial and Quantitative Analysis*, Vol. 44, 109-132.

[12] Fitch Ratings, 2003, "Credit Products Special Report: Fitch Examines Effect of 2003 Credit Derivatives Definitions", www.fitchratings.com.

[13] Frazzini, Andrea and Owen Lamont, 2006, "The earnings announcement premium and trading volume", NBER working paper no. 13090.

[14] Geanakoplos, John, 2009, "The leverage cycle", Cowles foundation discussion paper, Yale University.

[15] Graham, John R., Jennifer L. Koski, and Uri Loewenstein, 2006, "Information Flow and Liquidity around Anticipated and Unanticipated Dividend Announcements", *Journal of Business*, Vol. 79, 2301-2336.

[16] Han, Song and Hao Zhou, 2008, "Effects of Liquidity on the Nondefault Component of Corporate Yield Spreads: Evidence from Intraday Transactions Data", Finance and Economics Discussion Series, Federal Reserve Board, Washington, D.C.

[17] Hendershott, Terrence, Charles M. Jones, and Albert J. Menkveld, 2011, "Does algorithmic trading improve liquidity?" *Journal of Finance*, Vol. 66, 1-33.

[18] Kapadia, Nikunj and Xiaoling Pu, 2012, "Limited Arbitrage between Equity and Credit Markets," *Journal of Financial Economics*, Vol. 105, 3, 542-564.

[19] Kwan, Simon H., 1996, "Firm-Specific Information and the Correlation Between Individual Stocks and Bonds," *Journal of Financial Economics,* Vol. 40, 63-80.

[20] Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market", *Journal of Finance*, Vol. 60, 2213-2253.

[21] Markit Group Limited, 2007, "Markit.com CDS and ABS User Guide Version 12.1," August 2007, www.markit.com.

[22] Merton, Robert C., 1974, "On the pricing of corporate debt: the risk structure of interest rates" *Journal of Finance*, Vol. 29, 449-470.

[23] Muravyev, Dmitriy, Neil D. Pearson and John Paul Broussard, 2013, "Is There Price Discovery in Equity Options?" *Journal of Financial Economics*, Vol. 107, 2, 259-283.

[24] Ni, Sophie X., Jun Pan and Allen M. Poteshman, 2007, "The information in option volume for future volatility", *Journal of Finance*, Vol. 63, 1059-1091.

[25] Norden, Lars and Martin Weber, 2009, "The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis", *European Financial Management*, Vol. 15, 529-562.

[26] Pan, Jun and Allen M. Poteshman, 2006, "The information in option volume for future stock prices", *Review of Financial Studies*, Vol. 19, 871-908.

[27] Taksler, Glen, Jeffrey A. Rosenberg, Ward Bortz, and Xiaodong Zhu, Bank of America, Credit Strategy Research, 2007, "Credit Default Swap Primer," Third Edition.

[28] Zhu, Haibin, 2006, "An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market", *Journal of Financial Services Research*, Vol. 29, 211-235.

Table 1: Summary statistics

This table reports summary statistics for firm characteristics (Panel A), microstructure characteristics (Panel B), and equity and credit protection returns (Panel C). Panel A reports statistics for firms with available spread data. The sample period is from 2001 to 2007. Statistics are based on averaging first within firm and then across firms, including only days with available spread observations, equity returns and S&P credit rating. CDS spread is average 5 year spread in basis points (from Markit), # days is number of spread observations, market equity capitalization is reported in million USD (from CRSP), leverage is the difference between book assets and book equity divided by book assets (from COMPUSTAT), rating is average S&P credit rating. Panel B reports means for three sets of microstructure measures. First, CDS contract bid-ask spread and percentage spread, which is defined as the bid-ask spread divided by the CDS spread (the midpoint of the bid-ask spread); data is from Datastream for 2007; numbers of observation are equal to 86,175 (A, above: 27,898, BBB: 37,437, BB, below: 20,840). Second, statistics on spread update frequency; the fraction of observations with a high update count is the fraction of observations for which the credit protection return is nonzero at date t and for each of the five previous trading days; the fraction of observations with a spread change is the number of observations for which the credit protection return is nonzero at date t; statistics are for the regression sample in Table 3; numbers of observations are reported in Panel C. Third, CDS daily volume is weekly notional volume (in million USD) divided by 5; statistics are based on DTCC data from from July 2010 to December 2011; daily equity volume is from CRSP and is reported for the sample of weeks and firms for which DTCC data is available; numbers of observations are equal to 103,875 (A, above: 31,625, BBB: 44,062, BB, below: 28,188). Panel C reports summary statistics for daily equity returns and credit protection returns (in percent). To control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Statistics are reported for the regression sample in Table 3.

Panel A: Firm level statistics

	CDS spread	# days	market equity	leverage	rating
Mean	159	1,013	14,956	0.63	BBB
Std. dev.	240	535	32,574	0.17	-
25th percentile	43	538	2,489	0.51	A-
75th percentile	193	1,486	13,870	0.76	BB+
Number of firms: 783					

Panel B: CDS bid-ask spreads and other microstructure characteristics (means)

	overall	A, above	BBB	BB, below
Level bid-ask spread (bps)	8.8	4.6	5.7	20.1
Percentage bid-ask spread	13.9%	20.4%	12.6%	7.5%
Fraction of obs with high update count	50.1%	49.4%	51.7%	47.8%
Fraction of obs with a spread change	72.4%	71.8%	73.1%	72.0%
CDS daily volume (notional)	29.1	32.0	25.6	31.2
Equity daily volume	210.2	420.2	147.4	72.7

Panel C: Equity and credit protection return statistics

		overall	A, above	BBB	BB, below
Equity return	Mean	0.055%	0.046%	0.055%	0.069%
	Std. dev.	2.00%	1.71%	1.90%	2.56%
Credit protection return	Mean	0.050%	0.067%	0.039%	0.048%
	Std. dev.	3.78%	3.99%	3.54%	3.88%
Observations		748,598	261,252	325,028	162,318

Table 2: Vector autoregression for equity returns and credit protection returns

This table reports results from a vector autoregression (VAR) daily equity returns and daily credit protection returns across three ratings categories. We group observations into three categories using the monthly S&P credit rating. Regressions include firm fixed effects; to control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Standard errors are adjusted for heteroskedasticity and clustered by date. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%.

Panel A: A, above		equity return (t)			credit protection return (t)		
equity return	t-1	-0.022	-0.022	-0.023	-0.158	-0.161	-0.162
		(1.85)	(1.84)	(1.87)	(12.29)**	(12.60)**	(12.78)**
	t-2		-0.013	-0.013		-0.101	-0.105
			(0.98)	(0.95)		(7.81)**	(8.09)**
	t-3			-0.007			-0.077
				(0.45)			(6.19)**
credit protection ret	t-1	0.001	0.001	0.000	-0.016	-0.019	-0.02
		(0.44)	(0.31)	(0.20)	(2.34)*	(2.77)**	(3.00)**
	t-2		0.000	0.000		0.022	0.019
			(0.19)	(0.20)		(3.91)**	(3.49)**
	t-3			0.002			0.001
				(0.88)			(0.25)
Observations		261,750	261,750	261,750	261,252	261,252	261,252
Panel B: BBB		equity return (t)			credit protection return (t)		
equity return	t-1	-0.010	-0.011	-0.010	-0.125	-0.125	-0.127
		(1.10)	(1.14)	(1.07)	(14.78)**	(15.27)**	(15.64)**
	t-2		-0.014	-0.013		-0.081	-0.083
			(1.38)	(1.32)		(9.90)**	(10.24)**
	t-3			0.002			-0.068
				(0.20)			(7.68)**
credit protection ret	t-1	-0.001	-0.001	-0.001	0.017	0.013	0.011
		(0.20)	(0.44)	(0.47)	(2.40)*	(1.92)	(1.53)
	t-2		0.000	0.000		0.03	0.027
			(0.16)	(0.12)		(5.85)**	(5.44)**
	t-3			0.002			0.016
				(0.78)			(2.94)**
Observations		325,722	325,722	325,722	325,028	325,028	325,028
Panel C: BB, below		equity return (t)			credit protection return (t)		
equity return	t-1	0.010	0.010	0.009	-0.11	-0.109	-0.109
		(1.22)	(1.19)	(1.04)	(14.67)**	(14.65)**	(14.66)**
	t-2		-0.007	-0.008		-0.068	-0.067
			(0.79)	(0.91)		(10.41)**	(10.44)**
	t-3			-0.004			-0.046
				(0.48)			(6.33)**
credit protection ret	t-1	-0.003	-0.004	-0.004	-0.049	-0.055	-0.056
		(1.08)	(1.11)	(1.16)	(5.75)**	(6.29)**	(6.46)**
	t-2		-0.005	-0.005		0.009	0.006
			(1.67)	(1.72)		(1.46)	(0.88)
	t-3			-0.002			-0.003
				(0.67)			(0.44)
Observations		162,911	162,911	162,911	162,318	162,318	162,318

Table 3: Response of the credit protection return to the equity return (daily)

This table reports results from regressions of daily credit protection returns on contemporaneous (lag=0) and lagged (lag=1 to lag=10) daily equity returns. We group observations into three categories using monthly S&P credit rating. Regressions include firm fixed effects; to control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Panel A reports direct effects. We control for autocorrelation in the credit protection return by including the lagged credit protection return. Panel B reports cumulative effects which are calculated as the sum of the direct effects in Panel A. Panel C reports regressions of cumulative 5-day and 10-day credit protection returns on current equity returns, controlling for current credit protection returns. Standard errors are adjusted for heteroskedasticity and clustered by date. To control for overlapping observations in Panel C, standard errors are also adjusted for autocorrelation. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%. Numbers of observations are equal to: 261,252 (A, above), 325,028 (BBB), and 162,318 (BB, below).

Panel A: Regression of the credit protection return on the contemporaneous and lagged equity return

time period	0	1	2	3	4	5	6	7	8	9	10
A, above	-0.18	-0.16	-0.09	-0.07	-0.05	-0.04	-0.02	-0.02	-0.01	-0.01	-0.03
	(9.04)**	(12.29)**	(7.09)**	(5.73)**	(4.45)**	(3.41)**	(1.49)	(1.64)	(0.90)	(1.29)	(2.40)*
BBB	-0.14	-0.12	-0.08	-0.07	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01
	(10.36)**	(14.78)**	(9.48)**	(7.36)**	(5.26)**	(4.19)**	(2.11)*	(2.62)**	(0.74)	(1.42)	(1.70)
BB, below	-0.11	-0.11	-0.06	-0.04	-0.05	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01
	(12.45)**	(14.67)**	(9.54)**	(5.88)**	(7.36)**	(4.67)**	(3.32)**	(1.93)	(2.09)*	(2.05)*	(2.27)*

Panel B: Cumulative coefficient on the equity return

A, above	-0.18	-0.34	-0.43	-0.51	-0.56	-0.60	-0.62	-0.63	-0.64	-0.66	-0.68
BBB	-0.14	-0.26	-0.34	-0.41	-0.45	-0.49	-0.50	-0.52	-0.53	-0.54	-0.55
BB, below	-0.11	-0.22	-0.29	-0.33	-0.37	-0.40	-0.42	-0.44	-0.45	-0.46	-0.48

Panel C: Cumulative credit protection return response

time period	(t+1,t+5)	(t+2,t+6)	(t+1,t+10)	(t+2,t+11)
A, above	-0.44	-0.29	-0.55	-0.39
	(3.65)**	(2.42)**	(2.02)*	(1.45)
BBB	-0.37	-0.25	-0.45	-0.33
	(4.46)**	(2.90)**	(2.32)*	(1.66)
BB, below	-0.30	-0.21	-0.39	-0.29
	(5.33)**	(3.88)**	(3.40)**	(2.63)**

Table 4: Response of the equity return to the credit protection return (daily)

This table reports results from regressions of daily equity returns on contemporaneous (lag=0) and lagged (lag=1 to lag=10) daily credit protection returns. We group observations into three categories using monthly S&P credit rating. Regressions include firm fixed effects; to control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Panel A reports direct effects. We control for autocorrelation in the equity return by including the lagged equity return. Panel B reports cumulative effects which are calculated as the sum of the direct effects in Panel A. Panel C reports regressions of cumulative 5-day and 10-day equity returns on current credit protection returns, controlling for current equity returns. Standard errors are adjusted for heteroskedasticity and clustered by date. To control for overlapping observations in Panel C, standard errors are also adjusted for autocorrelation. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%. Numbers of observations are equal to: 261,750 (A, above), 325,722 (BBB), and 162,911 (BB, below).

Panel A: Regression of the equity return on the contemporaneous and lagged credit protection return

time period	0	1	2	3	4	5	6	7	8	9	10
A, above	-0.033	0.001	0.000	0.002	0.001	0.006	0.001	0.001	0.002	-0.001	-0.004
	(9.45)**	(0.44)	(0.18)	(0.88)	(0.41)	(2.01)*	(0.25)	(0.26)	(1.05)	(0.47)	(1.46)
BBB	-0.039	-0.001	0.000	0.002	0.001	0.003	-0.001	-0.001	0.001	-0.003	-0.002
	(10.77)**	(0.20)	(0.16)	(0.76)	(0.56)	(1.27)	(0.21)	(0.24)	(0.57)	(1.23)	(0.90)
BB, below	-0.049	-0.003	-0.004	-0.002	0.001	0.002	0.002	0.003	-0.004	-0.005	-0.005
	(12.48)**	(1.08)	(1.66)	(0.62)	(0.47)	(0.60)	(0.61)	(0.87)	(1.24)	(1.54)	(1.78)

Panel B: Cumulative coefficient on the credit protection return

A, above	-0.033	-0.032	-0.032	-0.029	-0.029	-0.023	-0.022	-0.022	-0.020	-0.021	-0.024
BBB	-0.039	-0.040	-0.040	-0.038	-0.037	-0.034	-0.034	-0.035	-0.034	-0.037	-0.039
BB, below	-0.049	-0.053	-0.057	-0.059	-0.057	-0.055	-0.054	-0.051	-0.055	-0.060	-0.065

Panel C: Cumulative equity return response

time period	(t+1,t+5)	(t+2,t+6)		(t+1,t+10)	(t+2,t+11)
A, above	0.010	0.010		0.009	0.009
	(0.65)	(0.66)		(0.34)	(0.38)
BBB	0.004	0.005		-0.002	0.002
	(0.22)	(0.32)		(0.07)	(0.07)
BB, below	-0.007	-0.002		-0.018	-0.013
	(0.31)	(0.09)		(0.44)	(0.33)

Table 5: Response of credit protection and equity returns to large and negative news in the other market

This table reports results from regressions of daily credit protection returns on contemporaneous (lag=0) and lagged (lag=1, 2) equity returns (Panels A, B) and regressions of daily equity returns on contemporaneous and lagged credit protection returns (Panels C, D). Coefficients are estimated for four subsamples: large equity returns (above 2% in absolute value; close to 21% of observations), negative equity returns, large credit protection returns (above 2% in absolute value; close to 22% of observations), and positive credit protection returns. We group observations into three categories using monthly S&P credit rating. Regressions include firm fixed effects. To control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. We control for autocorrelation in the credit protection and equity returns by including lagged returns. Standard errors are adjusted for heteroskedasticity and clustered by date. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%. Numbers of observations are equal to: Panels A, B: 261,252 (A, above), 325,028 (BBB), 162,318 (BB, below); Panels C, D: 261,750 (A, above), 325,722 (BBB), 162,911 (BB, below).

Panel A: Response of credit protection returns to large equity returns			
lags	0	1	2
A, above	-0.22	-0.17	-0.10
	(9.06)**	(11.97)**	(6.54)**
BBB	-0.16	-0.13	-0.09
	(10.56)**	(14.62)**	(9.34)**
BB, below	-0.12	-0.11	-0.06
	(12.33)**	(14.60)**	(9.22)**
Panel B: Response of credit protection returns to negative equity returns			
lags	0	1	2
A, above	-0.46	-0.31	-0.14
	(8.90)**	(13.20)**	(5.18)**
BBB	-0.37	-0.24	-0.14
	(12.02)**	(13.43)**	(8.27)**
BB, below	-0.20	-0.18	-0.08
	(9.98)**	(10.73)**	(6.03)**
Panel C: Response of equity returns to large credit protection returns			
lags	0	1	2
A, above	-0.033	0.001	0.001
	(9.26)**	(0.52)	(0.23)
BBB	-0.038	0.000	0.000
	(10.40)**	(0.04)	(0.06)
BB, below	-0.046	-0.003	-0.004
	(11.74)**	(0.83)	(1.66)
Panel D: Response of equity returns to positive credit protection returns			
lags	0	1	2
A, above	-0.034	0.000	0.001
	(6.01)**	(0.04)	(0.32)
BBB	-0.038	-0.002	0.003
	(6.62)**	(0.56)	(0.64)
BB, below	-0.026	0.000	-0.002
	(4.37)**	(0.10)	(0.55)

Table 6: Acharya and Johnson (2007) interaction effects for various credit conditions

This table reports results from regressions of current equity returns on lagged (t-1 to t-5) credit protection returns and lagged credit protection returns interacted with Acharya and Johnson's (2007) credit condition indicators, controlling for lagged equity returns (first three columns). The credit condition indicators are, respectively, set equal to 1 if: there is a one-day spread increase of more than 50 bps at some point between date t and the end of the sample; the spread remains above 100 bps between date t and the end of the sample; the credit rating is equal to or poorer than A-. We report sums of coefficients of the interaction of the credit condition indicator and lagged credit protection returns. The sample (time period and cross section of firms) is the same as what is used in Acharya and Johnson. Columns 1 to 3 report results for three specifications: (1) no adjustment to the standard error calculation; (2) adjusting standard errors for heteroskedasticity; (3) using standard errors that are adjusted for heteroskedasticity and clustered by date. Column 4 reports sums of coefficients on lagged credit protection returns when including only those observations for which the credit condition indicator is equal to 1 (standard errors are adjusted for heteroskedasticity and clustered by date). All regressions include firm fixed effects; to control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. We report p-values based on F-statistics testing if sums of coefficients are different from zero. We also report implied t-statistics of these p-values (using the cumulative normal distribution).

		OLS S.E.	White S.E.	S.E. clustered by date	Credit condition subsample
At least one daily spread chg > 50bps between date t and the end of the sample	sum (1 to 5)	-0.03	-0.03	-0.03	-0.01
	p-value	0.007	0.124	0.202	0.841
	t-statistic	2.71	1.54	1.28	0.20
	Observations	59,149	59,149	59,149	11,773
Spread remains above 100bps between date t and the end of the sample	sum (1 to 5)	-0.05	-0.05	-0.05	-0.07
	p-value	0.004	0.066	0.047	0.052
	t-statistic	2.87	1.84	1.98	1.95
	Observations	59,149	59,149	59,149	4,155
Credit rating poorer or equal to A-	sum (1 to 5)	-0.02	-0.02	-0.02	-0.01
	p-value	0.119	0.284	0.302	0.798
	t-statistic	1.56	1.07	1.03	0.26
	Observations	59,149	59,149	59,149	43,949

Table 7: Response of the credit protection return to the equity return and vice versa (weekly)

This table reports results from regressions of weekly credit protection returns on contemporaneous (lag=0) and lagged (lag=1 to lag=5) weekly equity returns (Panels A, B) and regressions of weekly equity returns on contemporaneous and lagged weekly credit protection returns (Panels C, D). We group observations into three groups using monthly S&P credit rating. Regressions include firm fixed effects; to control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Panels A and C report direct effects. We control for autocorrelation in the credit protection return by including the lagged credit protection return and for autocorrelation in the equity return by including the lagged equity return. Panels B and D report cumulative effects which are calculated as the sum of the direct effects. Standard errors are adjusted for heteroskedasticity and clustered by date. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%. Numbers of observations are equal to: Panels A, B: 52,748 (A, above), 65,318 (BBB), 32,033 (BB, below); Panels C, D: 52,748 (A, above), 65,318 (BBB), 32,033 (BB, below).

Panel A: Regression of the credit protection return on the equity return						
time period	0	1	2	3	4	5
A, above	-0.44	-0.27	-0.10	-0.11	-0.06	-0.04
	(5.94)**	(7.55)**	(2.47)*	(2.90)**	(1.90)	(1.12)
BBB	-0.35	-0.21	-0.09	-0.11	-0.07	-0.04
	(7.50)**	(7.75)**	(3.19)**	(4.23)**	(2.65)**	(1.41)
BB, below	-0.29	-0.20	-0.08	-0.04	-0.08	-0.03
	(8.47)**	(10.03)**	(4.01)**	(2.39)*	(3.63)**	(1.68)
Panel B: Cumulative coefficient on the equity return						
A, above	-0.44	-0.72	-0.82	-0.93	-0.99	-1.04
BBB	-0.35	-0.56	-0.65	-0.76	-0.83	-0.87
BB, below	-0.29	-0.49	-0.58	-0.62	-0.70	-0.73
Panel C: Regression of equity return on contemporaneous and lagged credit protection return						
time period	0	1	2	3	4	5
A, above	-0.063	0.008	0.000	0.002	0.006	-0.005
	(7.03)**	(0.98)	(0.06)	(0.31)	(1.15)	(0.95)
BBB	-0.073	0.004	-0.001	0.005	0.002	-0.004
	(8.25)**	(0.68)	(0.18)	(0.85)	(0.32)	(0.60)
BB, below	-0.095	-0.003	-0.012	-0.007	0.001	0.004
	(10.00)**	(0.41)	(1.66)	(0.90)	(0.15)	(0.54)
Panel D: Cumulative coefficient on the credit protection return						
A, above	-0.063	-0.055	-0.055	-0.054	-0.048	-0.053
BBB	-0.073	-0.069	-0.070	-0.065	-0.063	-0.067
BB, below	-0.095	-0.098	-0.110	-0.117	-0.116	-0.112

Table 8: Determinants of CDS fractional response

This table reports results from regressions of the CDS fractional response on explanatory variables. The fractional response is the ratio of the credit protection return at t and the return from t to t+11. If the response from t to t+11 is of the opposite sign compared to the date t response we set the fractional response equal to 0. If the date t response is larger than the response from t to t+11 we set the fractional response equal to 1. Low Depth is an indicator for an issuer in the lowest quartile of the number of independent CDS quotes for a calendar quarter. Abs(equity return) is the absolute value of the equity return on date t. In specifications (4) to (6) the absolute value of the return is interacted with an indicator, Large Return, for an observation with abs(equity return) on date t in the top 10% of the distribution. Turnover is measured on date t. All regressions include firm fixed effects. For specifications including an interaction with the Large Return indicator we control for the direct effect of Large Return (unreported). To control for outliers, returns and turnover are winsorized at the 0.1% and 99.9% levels. Standard errors are adjusted for heteroskedasticity and clustered by date. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%.

Fraction of credit protection return response from t to t+11 that occurs at t						
	(1)	(2)	(3)	(4)	(5)	(6)
Low Depth	-0.0150		-0.0150		-0.0150	-0.0130
	(9.02)**		(9.57)**		(9.50)**	(8.46)**
Abs(equity return)		0.005	0.005	0.002	0.002	0.0005
		(9.42)**	(9.79)**	(2.74)**	(2.99)**	(0.62)
Abs(eq ret)*Large Ret				0.007	0.007	0.003
				(6.35)**	(6.27)**	(3.03)**
Turnover						0.017
						(16.72)**
Observations	723,051	723,051	723,051	723,051	723,051	723,051

Table 9: Equity returns and credit protection returns during and outside earnings annoucements

Panel A reports results from regressions of credit protection returns on equity returns. We report results from regressing contemporaneous (t), next day (t+1) and subsequent cumulative 5-day (t+2,t+6) and 10-day (t+2,t+11) credit protection returns on date t equity returns. Panel B reports results from regressions of equity returns on credit protection returns. We control for the autocorrelation in credit protection returns (or equity returns) by including the lagged dependent variable (at time t) in all but the contemporaneous regressions. We allow for different coefficients when time t is during earnings announcements and report the difference in coefficients. Regressions include firm fixed effects. To control for outliers, returns are winsorized at the 0.1% and the 99.9% levels. Standard errors are adjusted for heteroskedasticity and clustered by date. For regressions with overlapping observations, the standard errors are also adjusted for autocorrelation of the residuals. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%.

Panel A: Credit protection return response to the equity return						
time period	t → t	t → t+1	t → (t+2,t+6)	t → (t+2,t+11)	(t-5,t-1) → t	(t-6,t-2) → t
No earnings announcement at t	-0.136	-0.129	-0.255	-0.348	-0.071	-0.048
	(11.51)**	(16.52)**	(3.27)**	(2.00)*	(20.99)**	(15.15)**
Earnings announcement at t	-0.210	-0.124	-0.165	-0.213	-0.116	-0.100
	(9.59)**	(8.37)**	(4.99)**	(4.64)**	(6.62)**	(6.37)**
Difference	-0.074	0.005	0.090	0.135	-0.046	-0.052
	(3.35)**	(0.32)	(0.84)	(0.62)	(2.70)**	(3.44)**
Observations	748,376	748,376	748,376	748,376	740,627	738,444
R^2 (within)						
Outside earnings announcement	0.50%	0.45%				
During earnings announcement	3.16%	1.56%				

Panel B: Equity return response to the credit protection return						
time period	t → t	t → t+1	t → (t+2,t+6)	t → (t+2,t+11)	(t-5,t-1) → t	(t-6,t-2) → t
No earnings announcement at t	-0.037	0.000	0.005	0.000	0.000	0.000
	(11.96)**	(0.20)	(0.35)	(0.00)	(0.18)	(0.31)
Earnings announcement at t	-0.147	-0.011	-0.020	-0.014	0.003	0.001
	(11.20)**	(1.27)	(1.12)	(0.72)	(0.51)	(0.17)
Difference	-0.111	-0.011	-0.025	-0.013	0.003	0.001
	(8.48)**	(1.27)	(0.50)	(0.17)	(0.50)	(0.12)
Observations	750,221	750,221	750,221	750,221	742,265	740,038
R^2 (within)						
Outside earnings announcement	0.50%	0.00%				
During earnings announcement	3.14%	0.02%				

Table 10: Fractional response and earnings announcements

This table reports results from regressions of the CDS fractional response on an indicator set equal to 1 if there is an earnings announcements, and including the controls from Table 10. Standard errors are adjusted for heteroskedasticity and clustered by date. The t-statistics are reported in parentheses; ** denotes significance at 1% and * denotes significance at 5%.

Fraction of credit protection return response from t to t+11 that occurs at t			
	(1)	(2)	(3)
Earnings announcement	0.025	0.018	0.011
	(6.74)**	(4.94)**	(3.04)**
Low Depth		-0.012	-0.011
		(7.64)**	(6.65)**
Abs(equity return)		0.002	0.0003
		(2.75)**	(0.45)
Abs(equity return) * Large Return		0.007	0.003
		(6.19)**	(3.01)**
Turnover			0.017
			(16.61)**
Observations	723,051	723,051	723,051