Credit Derivatives and Analyst Behavior

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Abstract

This paper presents a comprehensive analysis of the role of credit default swaps (CDS) in information production surrounding earnings announcements. First, we demonstrate that the strength of CDS price discovery prior to earnings announcements is related to the presence of private information and the illiquidity of the underlying corporate bonds, consistent with the CDS market being a preferred venue for informed trading. Next, we ask how the information revealed through CDS trading influences the output of equity and credit rating analysts. We find that post-CDS trading, the dispersion and error of earnings-per-share forecasts are generally reduced, and downgrades by both types of analysts become more frequent and more timely before large negative earnings surprises, suggesting that the CDS market conveys information valuable to financial analysts.

Keywords: credit default swap; informed trading; earnings announcement; analyst forecast; buy/sell recommendation; rating downgrade.

I. INTRODUCTION

Consider an informed trader who seeks to profit from her information through trading in three related securities: stocks, corporate bonds, and credit default swaps. Transactions in the corporate bond market have been under mandatory reporting through TRACE (the Trade Reporting and Compliance Engine) for well over a decade, making it difficult for informed traders to conceal their trades in that market. Similarly, the stock market is constantly monitored by regulators who are concerned about insider trading. In contrast, the CDS market was largely unregulated during much of its history because of the Commodity Futures Modernization Act of 2000, which exempted over-the-counter derivatives from regulatory oversight.[1] Moreover, because of the synthetic nature of CDS contracts, it is often easier to bet against a company by purchasing credit protection in the CDS market than borrowing its stocks or bonds to sell short (Longstaff, Mithal, and Neis, 2005). These considerations suggest that traders might favor CDS over corporate bonds and stocks as their preferred vehicle for exploiting deteriorating credit conditions at the firm level.

We begin our analysis by presenting empirical evidence regarding price discovery in the CDS market ahead of quarterly earnings announcements. First, we construct an intra-period timeliness (IPT) measure, which uses the area under the cumulative abnormal CDS return function between successive earnings announcements to gauge the speed of price discovery through the quarterly earnings cycle.[2] Second, we follow Acharya and Johnson (2007) to

[1]The 2010 Dodd-Frank Act grants sweeping powers for regulators to determine whether certain OTC derivatives, such as CDS, should be subject to central clearing and exchange trading. Specifically, regulators can request from derivatives clearing facilities full information on individual transactions and counterparty positions, and require that such information be made available to the public in real-time provided that the identities of the participants remain confidential. However, even five years after the passage of the DFA, information about individual transactions in the single-name CDS market is still not publicly disclosed. Therefore, post-trade transparency in the CDS market remains far short of the norm in more standardized markets for stocks and bonds.

[2]Examples of past works that utilize the IPT measure include McNichols (1984), Alford, Leftwich, and Zmijewski

examine the incremental price discovery in the CDS market relative to the stock market using a lead-lag analysis, treating the latter as a benchmark that reflects all publicly available information. Employing a comprehensive sample of 739 firms with CDS trading from 2001 to 2010, we identify faster CDS price discovery and stronger incremental CDS price discovery relative to stocks among firms with greater private information and those with more illiquid corporate bonds. These results are consistent with informed traders exploiting their information advantage in the CDS market, particularly when the alternative—trading corporate bonds—entails large costs.

If the CDS market incorporates information not aggregated into stock prices prior to earnings announcements, it would become an important source of information for equity analysts when they forecast corporate earnings. Exploiting the initiation of CDS trading as an exogenous event, we use a differences-in-differences approach to estimate the effect of CDS trading on analyst forecast characteristics such as forecast dispersion and forecast error, while controlling for common determinants identified in the literature. Furthermore, we use propensity score matching (PSM) to identify firms that did not experience CDS initiation at the same time as the treatment firms, but are otherwise similar in terms of the likelihood of having CDS trading. Our results confirm that forecast dispersion and forecast error experience economically and statistically significant declines after the introduction of CDS trading—relative to their sample mean levels, dispersion and error decrease by 13 percent and 17 percent, respectively, and these estimates are robust to using PSM samples.

Moving beyond earnings forecasts, we are also interested in how CDS trading changes equity analysts' buy/sell recommendations and bond rating analysts' assignment of credit ratings.

(1993), Butler, Kraft, and Weiss (2007), and Bushman, Smith, and Wittenberg-Moerman (2010).

Given the importance of downside risk in the bond and CDS markets, we focus on the behavior of these analyst outputs ahead of large negative earnings surprises. First, we find that downgrades by both types of analysts become more likely after CDS introduction. Second, we show that downgrades by equity analysts happen earlier after CDS introduction. Taken together with the evidence on earnings forecasts, these results suggest that the presence of a CDS market can facilitate the information production of financial analysts.

To our knowledge, this is one of the first studies that examine the effect of CDS trading on firms' information environment. [3] In a related study, Kim, Shroff, Vyas, and Wittenberg-Moerman (2014) posit that greater informed trading in liquid CDS markets (Qiu and Yu, 2012) leads to preemptive disclosures by a firm's management, and they find that management disclosures (management forecasts and press releases) are indeed more likely for firms with more liquid CDS contracts. Our paper differs from Kim et al. (2014) in two main aspects. First, we are analyzing firms' information environment from the broader perspectives of financial analysts rather than what firms' management selectively reveals to the public. Second, we focus on the effect of CDS introduction rather than the difference among CDS firms with varying levels of liquidity (the extensive margin vs. the intensive margin). Since we control for the number of management forecasts in all of our estimations, our results suggest that the effect of CDS trading on analyst behavior goes beyond the influence of preemptive disclosures by management.

While Kim et al. (2014) take for granted that there is informed trading in the CDS market ahead of earnings announcements, we notice that the extant literature (Acharya and Johnson,

[3]These studies, in turn, are part of a burgeoning area of research that focuses on the effect of having an active CDS market on firms' cost of debt, choice of leverage, and likelihood of rating downgrades and bankruptcies, as well as the liquidity of the underlying corporate bonds (Ashcraft and Santos, 2009; Tookes and Saretto, 2013; Subrahmanyam, Tang, and Wang, 2014; Das, Kalimipalli, and Nayak, 2014).

2007; Qiu and Yu, 2012) focuses exclusively on price discovery in the CDS market prior to large jumps in the CDS premium.[4] Events characterized by large jumps in the CDS premium, however, could be fundamentally different from earnings announcements. For instance, while sudden jumps in the CDS premium are by construction unexpected events that might reflect market-wide news, earnings announcements are well-anticipated events that convey mostly firm-specific information. To the extent that various market participants (e.g., institutional investors, analysts, and lenders) constantly analyze and forecast corporate earnings, it might be much harder for insiders to profit from earnings announcements than unexpected credit events. Therefore, our confirmation of the presence of informed trading in the CDS market before earnings announcements is an important step toward understanding why CDS trading affects firms' information environment.

Our paper also contributes to the recent literature on the impact of earnings on credit risk pricing. Easton, Monahan, and Vasvari (2009) document a positive relation between annual corporate bond returns and annual earnings changes that is primarily driven by accounting losses, and Callen, Livnat, and Siegal (2009) and Greatrex (2009) identify a negative relation between CDS premium changes around earnings announcements and the level of the earnings surprise among lower-rated firms. While these results confirm that credit risk pricing indeed reflects accounting information, they are silent on how earnings-related information gets incorporated into credit market prices. Our findings suggest that informed trading likely plays an important role in this process. In particular, our result that the strength of CDS price discovery is positively

[4] Bushman et al. (2010) use the IPT approach to show evidence of informed trading in advance of earnings announcements. However, their study uses market data for bank loans and common stocks, not CDS. A major advantage of using CDS data, besides their novelty and topicality, is that for many firms with CDS trading, we can identify clear dates on which trading first began. Consequently, a more robust differences-in-differences approach can be used to shed light on the various effects of CDS introduction, which are interesting in their own right.

related to the illiquidity of the underlying corporate bonds complements the finding regarding informed trading and CDS liquidity (Qiu and Yu, 2012), in the sense that both results fit nicely into a theoretical framework describing where informed traders might trade (Easley, O'Hara, and Srinivas, 1998). It is also consistent with Oehmke and Zawadowski (2013), who find that CDS net notional amount outstanding is larger for firms with bonds that are fragmented into many separate issues. They argue that such firms' bonds have low liquidity, thus pushing hedgers and speculators towards the alternative trading venue that is the CDS market.

The rest of the paper proceeds as follows. Section II elucidates several hypotheses regarding price discovery in the CDS market and its impact on firms' information environment. Section III outlines the construction of the data and introduces the variables used in our analysis. Section IV presents the methodology and the findings. We summarize and conclude with Section V.

II. HYPOTHESES

Since competition among informed traders will ensure that whatever private information they possess is quickly reflected in market prices (see Holden and Subrahmanyam, 1992, Foster and Viswanathan, 1996, and Back, Cao, and Willard, 2000), the greater is the amount of private information in the market, the more informative CDS pricing should be with respect to future events. Thus, we hypothesize that:

H1a. The speed of CDS price discovery is faster and the strength of incremental CDS price discovery relative to stocks is stronger when there is a greater level of private information in the market.

Although the CDS market appears to be favored by informed traders because of its lack of transparency, where informed traders trade can also be driven by other concerns. Easley et al.

(1998), for example, argue that informed traders might choose to trade derivative securities (options) when the underlying securities (stocks) lack liquidity. In our setting, this argument can be rephrased as saying that a lack of liquidity in the corporate bond market can accentuate informed trading through CDS.[5] Therefore, we conjecture that:

H1b. The speed of CDS price discovery is faster and the strength of incremental CDS price discovery relative to stocks is stronger when the associated corporate bond market is more illiquid.

Turning to the implications of informed trading in the CDS market for financial analysts' information environment, we note the following discussion in Kim and Verrecchia (1994, page 54): "(Disclosing the public signal) creates information asymmetry through the activities of the information processors, and, as a second effect, it reduces information asymmetry by disclosing information that would otherwise be known by only a few participants in the market." Therefore, the implications appear to depend on the nature of CDS market information. If this information is in the form of a clear signal requiring minimal interpretation, then it will improve the accuracy and reduce the dispersion of analyst forecasts. However, it is also possible that this information itself may need to be interpreted. The process of interpreting CDS market information by a diverse set of analysts is likely to produce more divergent forecasts. Hence, focusing on the effect of CDS market information in reducing information asymmetry among equity analysts, we state the following hypothesis:

H2a. The availability of CDS market information improves the accuracy and reduces the dispersion of equity analyst forecasts.

Earnings-per-share forecasts are only one type of output produced by one subset of

[5]The flip side of this argument is that informed trading in the CDS market will be more intense for firms with more liquid CDS contracts. This effect has been empirically confirmed by Qiu and Yu (2012).

analysts, namely, equity analysts. Besides forecasting corporate earnings, equity analysts also make buy/sell recommendations for the stocks that they follow. Furthermore, to the extent that the information revealed through CDS pricing is publicly observable, we expect the behavior of bond analysts to be similarly affected. The information on bond analyst recommendations, however, is notoriously difficult and time-consuming to collect (see details from De Franco, Vasvari, and Wittenberg-Moerman, 2009). Instead, we choose to examine credit rating changes, which reflect the opinions of analysts employed by major bond rating agencies.

Because of the asymmetric nature of its payoff, the CDS market is particularly sensitive to negative news that would increase a firm's credit risk. Therefore, the information revealed through the CDS market ahead of large negative earnings surprises should help analysts revise their recommendations downward. For equity analysts, this means that a previous buy recommendation could be changed to a hold or a sell. For credit rating analysts, this means that a literal downgrade of the firm's bond rating could be called for. We conjecture that the CDS market information allows analysts to issue these downgrades more frequently and in a more timely manner, which yields the following hypothesis:

H2b. The availability of CDS market information increases the frequency and timeliness of equity and rating analyst downgrades ahead of large negative earnings surprises.

One countervailing concern for the credit rating part of the preceding hypothesis has to do with bond rating agencies' blanket exemption from Regulation Fair Disclosure, which was removed only at the end of our sample period (September 2010) due to the Dodd-Frank Act. If the information revealed through CDS trading has previously been disclosed to rating agencies for the purpose of determining a credit rating, then we would not expect the onset of CDS trading to significantly change the information environment of credit rating analysts. For instance, firms regularly disclose debt covenant violations to lenders and rating agencies before making them public. If a lender trades on this information by purchasing credit protection through the CDS market, the subsequent rise in CDS spreads would not tip off rating analysts because they have already been informed of the covenant violations. On the other hand, if trading in the CDS market indeed causes previously undisclosed information to become public, it could serve to pressure rating agencies into making more timely downgrades. In addition, any motives for trading CDS that rating agencies are not privy to can also lead to the effect described in Hypothesis H2b.

III. DATA

Private Information and Bond Illiquidity Measures

The first part of our analysis examines price discovery in the CDS market ahead of quarterly earnings announcements. Therefore, we begin from a sample of firms with CDS trading. Specifically, we obtain from the Markit Group daily composite CDS premiums (resulting from an aggregation of end-of-day dealer quotations) on five-year CDS contracts written on senior unsecured obligations of North American reference entities. We require firms in our sample to have at least 252 daily observations of the CDS premium; this leaves 739 firms with coverage between January 2001 and September 2010.

[Insert Table 1 here]

Next, because of our focus on factors that explain CDS price discovery, we construct several empirical proxies for the level of private information in the CDS market as well as the level of illiquidity in the underlying corporate bond market. Our first proxy for the level of private information is analyst forecast dispersion, which is typically used to measure disagreement among equity analysts. Another interpretation, however, is offered by Barron, Kim, Lim, and Stevens (1998), who construct a theoretical model of analysts' information environment. Assuming that the signals received by analysts are either public (common across all analysts) or private (unique to each analyst), they show that forecast dispersion captures the portion of overall uncertainty among analysts that can be attributed to their private signals. It is important to note that the validity of this variable as a proxy of private information in the CDS market hinges on correlated information environments of equity analysts and CDS investors. Bushman et al. (2010), for example, use equity analysts' forecast dispersion as a proxy for overall firm transparency in evaluating the intra-period timeliness of returns on bank loans.

Operationally, we use the procedure outlined by Gulen and Hwang (2011) to create a sample of quarterly earnings announcements from the Institutional Brokers' Estimate System (I/B/E/S). Using the I/B/E/S Unadjusted Detail History File, we compute the monthly analyst forecast dispersion as the standard deviation of all valid estimates within the month normalized by the share price at the end of the month.[6] While we could have used only estimates submitted in a given month, we find that this often results in too few estimates, which could inject spurious noise into the dispersion measure. Therefore, following Diether, Malloy, and Scherbina (2002), we assume that an earnings-per-share (EPS) estimate remains valid from the time it was submitted until its revision date, i.e., the date on which the estimate was last confirmed by I/B/E/S as accurate. When there are multiple estimates from the same analyst in a given window, we sample only the last estimate in our calculations.

Our second private information proxy is idiosyncratic stock volatility, which is defined as the annualized standard deviation of excess stock returns over the inter-announcement period

[6]Garfinkel (2009) points out that normalizing the standard deviation using the absolute mean of the estimates could result in very large dispersions when the mean estimate is close to zero. Thus, we normalize with respect to the share price. Most of our results are robust to normalizing using the absolute mean of the estimates, as well as leaving the standard deviation unscaled (Cheong and Thomas, 2011).

(roughly 63 trading days). The excess stock returns are based on a market model estimated over the preceding 252 trading days using the CRSP value-weighted index. The validity of idiosyncratic volatility as a proxy of private information has been established in, for example, French and Roll (1986), who find that stock return volatility during trading hours is mostly driven by private information-based trading, and Roll (1988), who demonstrates that idiosyncratic price changes mostly reflect private rather than public information. Again, it is important to highlight the limitation of idiosyncratic volatility—as a measure of private information derived from stock returns, it could very well misidentify private information in the CDS market, unless there is a pooling equilibrium (e.g., Easley et al., 1998) in which the same private information is used for trading in both markets.[7]

Our third proxy is whether the CDS obligor is rated below investment-grade.[8] Easton et al. (2009) find that earnings (especially losses) are more relevant for the pricing of speculative-grade debt, which implies a greater incentive for bond market investors to gather earnings-related information of lower-rated borrowers. Bushman et al. (2010) uncover a greater speed of price discovery in the secondary loan market and the equity market among speculative-grade firms, which they attribute to a stronger demand by lenders for timely information about borrowers' credit risk when the likelihood of default is higher. Presumably, a greater presence of private information about borrowers in the corporate bond and bank loan

[7]In order to more directly measure private information within the CDS market, we use the same procedure to estimate an idiosyncratic CDS volatility. Specifically, following our later analysis of the information flow between CDS and stock markets, we define the daily CDS return as the first difference of the logarithm of the CDS premium, and estimate a CDS market model by regressing individual CDS returns on the return of a CDS market index, which can be either equally-weighted or value-weighted according to the total amount of debt outstanding (total notional amount outstanding for CDS contracts being unavailable until after late 2009). As it turns out, the lack of liquidity in the CDS market, which often results in missing or flat CDS premiums, are likely to cause the CDS volatility to be mis-measured for a significant number of firms. Perhaps that is why we do not find a significant link between idiosyncratic CDS volatility and price discovery in the CDS market.

[8]We convert the Standard and Poor's long-term issuer credit rating, available monthly from Compustat, into a numerical scale from 1 (AAA) to 22 (D).

markets is correlated with the level of private information in the closely related CDS market.

The last private information proxy is related to earnings-based loan covenants. According to Bushman et al. (2010), earnings-based covenants provide a conduit through which private information can flow periodically from borrowers to lenders. This flow of information can, for instance, become especially valuable around covenant violations, which are reported publicly in quarterly or annual reports subject to an extensive delay. Therefore, the existence of earnings-based covenants imparts to lenders a significant information advantage, which could be exploited in the market. Thus, we identify seven earnings-based financial covenants and define a dummy variable to be one if a firm has any outstanding loans with any of the seven covenants.[9]

Our two corporate bond illiquidity measures are based on the Amihud (2002) intuition that less liquid financial securities will experience greater price changes for a given level of trading volume. In the corporate bond market, where bonds are traded over-the-counter with the help of dealers, a greater bond price uncertainty is also likely to increase dealers' cost of maintaining an inventory. Therefore, we follow Helwege, Huang, and Wang (2014) to use a slight modification of the Amihud measure. Specifically, we define bond illiquidity as bond price uncertainty divided by trading volume (in millions of dollars). Since corporate bonds do not trade very often, we measure both price uncertainty and trading volume over monthly intervals. We calculate price uncertainty in two ways, as either the standard deviation or the range (difference between the maximum and the minimum) of the bond price over the average price. When a firm has multiple bonds trading in a month, we compute an equally-weighted average of the bond-level illiquidity measures.[10] Our bond price and trading volume information is

[9]Similar to Bushman et al. (2010), the set of earnings-based covenants include debt to EBITDA, senior debt to EBITDA, cash interest coverage, debt service coverage, EBITDA, fixed charge coverage, and interest coverage.

[10]Using the issue size or the monthly trading volume of the bonds as alternative weighting schemes makes little

obtained from TRACE.

[Insert Table 2 here]

With all variables defined in Table 1, Panel A of Table 2 summarizes the characteristics of CDS firms. It shows that these are mainly large investment-grade companies. The median firm, which is rated BBB, has total assets of $9.2 billion, an idiosyncratic stock volatility of 23 percent, a forecast dispersion equal to 0.1 percent of the stock price, and a five-year CDS premium of 76 basis points. In addition, the median (mean) number of earnings-based covenants is 1 (2.6), with 54 percent of the firm-day observations having at least one earnings-based covenant. For the bond illiquidity measures of the median firm, a one-million-dollar monthly trading volume is associated with a standard deviation (range) of the bond price equal to 0.06 (0.15) percent of the average price.

Characteristics of Analyst Output

The second part of our analysis examines the effect of having an active CDS market on firms' information environment, which we capture using the output of equity and credit rating analysts over the quarterly earnings cycle. Therefore, we begin with a sample of firms that have I/B/E/S coverage. This is a much larger sample with 6,115 firms, the majority of which do not have actively traded CDS contracts.

First, we focus on earnings-per-share forecasts, a key output of equity analysts. Specifically, we measure the difference of opinion among analysts using forecast dispersion, and the accuracy of their forecasts using forecast error. Forecast dispersion is defined in the same way as in the preceding subsection, except that we broaden the monthly construction to include the last EPS estimate made by each analyst within 90 days before the earnings announcement.

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difference to our results.

Forecast error is computed as the absolute value of the difference between the actual EPS and the median of the same set of estimates, normalized by the share price at the end of the quarter. We measure the demand for analyst service using the logarithm of the number of analysts following a firm during a given quarter. We count the number of forecast revisions during a given quarter, which may be related to the amount of private information analysts receive as a result of having access to the CDS market. Finally, we compute the share of revisions occurring within 30 trading days before the EAD, since our subsequent analysis reveals an incremental information flow from CDS to stocks as the EAD is drawing near.

Prior research has identified many firm characteristics that help explain equity analyst behavior. For example, Lehavy, Li, and Merkley (2011) examine analyst following and argue that the demand for analyst service is higher for firms that are larger, more complex, more volatile, experiencing faster growth, and have a larger amount of intangible assets. They also show that these firm characteristics are also likely to affect forecast dispersion and forecast error. Therefore, we include firm size, the number of business segments, stock return volatility, sales growth, and R&D and advertising expenditures as control variables when analyzing the effect of CDS introduction on analyst forecast characteristics. One important control variable that warrants separate mention is the number of management forecasts, which we obtain from I/B/E/S. Kim et al. (2014) argue that informed trading among liquid CDS obligors can pressure management into making preemptive disclosures so as to reduce litigation risk. Therefore, any observed association between the existence of CDS trading and more accurate equity analyst forecasts (our Hypothesis H2a) could be attributed to more frequent management disclosures. By including the number of management forecasts as a control variable in our analysis, we can estimate the effect of CDS trading on analyst forecast characteristics beyond the influence of management disclosures.

The existing literature recognizes that CDS introductions are not exogenous events, but can be predicted based on firms' credit risk and investors' demand for hedging. Following Subrahmanyam et al. (2014), we include additional firm characteristics such as leverage, CAPEX, EBIT, working capital, cash holdings, asset turnover, retained earnings, PP&E, ROA, excess stock return, whether the firm is rated, and whether the rating is investment-grade.[11] These variables will be used later on to construct a propensity score matched control sample that can be compared to the treatment firms, or those that experienced CDS introduction in our sample period.

Besides the EPS forecasts of equity analysts, we also focus on the decision to downgrade as an output of both equity analysts and credit rating analysts. For equity analysts, this occurs when they revise their recommendations downward as recorded in I/B/E/S, for example, from strong buy to buy or from buy to hold. For credit rating analysts, this occurs when any of the three major rating agencies (Moody's, S&P's, and Fitch) downgrades an issuer's credit rating according to the Mergent Fixed Income Securities Database. For equity analyst downgrades, we use the number of days between the actual downgrade and the EAD to measure the timeliness of the downgrade ahead of large negative earnings surprises. For rating downgrades, a similar measure can be constructed, though we do not examine the timeliness of rating downgrades because there are relatively few such events in our sample.

Panel B of Table 2 summarizes the aforementioned variables over two subsets of firm-quarter observations: those with CDS trading and those without. While there is little

[11] For the detailed definitions of these control variables, refer to Table 1. We further include the naive distance-to-default (Bharath and Shumway, 2008) and the Altman Z-score in order to classify the sample firms according to their credit quality in later analysis.

difference between the two groups in terms of forecast dispersion and forecast error, those with CDS trading tend to have higher analyst followings, more frequent forecast revisions, and a greater share of these revisions occurring within 30 days of upcoming earnings announcements. Regarding downgrades, those with CDS trading are more likely to be downgraded by both equity analysts and credit rating agencies. The comparison also reveals that those with CDS trading tend to be larger firms with investment-grade credit ratings, a higher number of management forecasts, more complexity (a larger number of business segments), more debt, and lower and less volatile stock returns. They grow more slowly in terms of sales, have better profitability (higher EBIT and ROA) and greater retained earnings, but hold less cash. They also have more tangible assets (PPE) and spend less on advertising. Overall, these differences are consistent with the CDS firms being substantially more mature than the non-CDS firms, and will need to be adequately controlled for in our regression analysis.

IV. EMPIRICAL RESULTS

Pre-announcement Returns

We begin our analysis by constructing abnormal returns around earnings announcements based on CDS premiums and contrasting them with abnormal stock returns. This comparison provides motivation for our subsequent analysis, such as computing the intra-period timeliness measure for the speed of CDS price discovery and estimating the incremental information flow of the CDS market relative to the stock market.

We define the daily CDS return as the difference in the logarithm of the CDS premium.[12]

[12]This definition is also used in Acharya and Johnson (2007). As our purpose is to examine the information efficiency of the CDS market, it is not crucial that the CDS premium does not itself represent the price of a traded security. In fact, we note that the change in the value of a CDS contract is equal to the change in the CDS premium times the value of a defaultable annuity, whose calculation requires the extraction of survival probabilities from the term structure of CDS premiums, which is a non-trivial exercise. Hence, we refrain from this more complicated definition of the CDS return.

The abnormal CDS return is then computed by subtracting the equally-weighted average CDS return across all CDS obligors in our sample. We also define the daily abnormal stock return as the holding period return minus a value-weighted index return, both available from the Center for Research in Security Prices (CRSP).[13]

[Insert Figure 1 here]

Figure 1 illustrates the average abnormal CDS and stock returns in the 25 trading days before and after earnings announcements. There are a total of 19,822 quarterly earnings announcements in our sample, 12,514 of which with positive or zero earnings surprises (which are lumped together in the positive earnings surprises category) and 5,517 of which with negative earnings surprises.[14] For negative surprises, Panel A shows that the average abnormal stock return on the EAD is about -0.9 percent and the average abnormal CDS return is about 0.3 percent. For positive surprises, they are 0.6 percent and -0.3 percent, respectively, according to Panel B. The lower sensitivity of the CDS premium to the earnings surprise compared to that of the stock price can be attributed to the fact that the majority of our sample firms are rated investment-grade with low credit risk. The slightly stronger stock market response to negative surprises is likely due to the prevalence of earnings management to avoid earnings losses (Burgstahler and Dichev, 1997; Matsumoto, 2002). To the extent that loss-reporting firms are in essence revealing that they do not have enough accounting slack to produce the numbers necessary to get over the earnings loss threshold, investors could rationally infer that these firms

[13]Besides constructing abnormal returns by subtracting appropriately defined benchmark market returns, we also estimate abnormal CDS and stock returns as single-factor model residuals. In particular, we estimate our single-factor CDS return model over a 252 trading day window for CDS obligors with at least 200 non-missing return observations within that window. Although the more stringent CDS data requirement causes some additional sample attrition, the patterns documented in this section of pre-announcement returns and later results on intra-period timeliness measures are largely robust to these alternative constructions.

[14]We have verified that our results are not sensitive to the exclusion of zero earnings surprises. Note that the numbers of positive and negative surprises do not add up to that of all earnings announcements because there are some announcements without a corresponding earnings surprise observation.

must be in a really bad shape.

[Insert Figure 2 here]

Figure 2 then presents the average cumulative abnormal CDS and stock returns around earnings announcements. Consistent with Figure 1, the overall magnitude of the CDS market reaction to the announcements is smaller than that of the stock market. However, a closer inspection reveals a more important distinction. For negative earnings surprises, Panel A shows that the CDS premium begins to rise and the stock price begins to fall as far as 25 trading days before the announcements. However, while the bulk of the reaction in the stock price takes place within the [-1, 0] window, only a small part of the reaction in the CDS premium takes place during the same interval. This suggests that the price discovery in the CDS market is more front-loaded compared to that of the stock market. A similar conclusion is reached when examining positive earnings surprises in Panel B.

These preliminary results suggest that there could be substantial differences in the amount of pre-earnings announcements price discovery between the CDS and equity markets. Furthermore, casual observations about how quickly earnings-based information gets incorporated into market prices should be formalized. We turn to these issues in the next two subsections.

Speed of CDS Price Discovery

First, we formalize the intra-period timeliness (IPT) measure in the CDS market, which provides an estimate of the speed of CDS price discovery through the quarterly earnings cycle. Specifically, given a list of earnings announcements, we compute the cross-sectional averages of the daily abnormal CDS returns in event time, and then the average cumulative abnormal returns (CARs) by summing the average daily abnormal returns. Using the period from 61 trading days before to two days after each earnings announcement and standardizing the average CAR at $t = -61$ to zero and $t = 2$ to one, we define the IPT as the area under the standardized average CAR function from $t = -61$ to $t = 2$ using the trapezoidal approximation:[15]

$$\mathrm{IPT} = \frac{1}{\mathrm{CAR}_2} \sum_{t=-60}^{2} \frac{\mathrm{CAR}_{t-1} + \mathrm{CAR}_t}{2} = \sum_{t=-60}^{1} \frac{\mathrm{CAR}_t}{\mathrm{CAR}_2} + 0.5. \qquad (1)$$

Intuitively, when there is no early release of earnings-related private information before the EAD, the IPT should be close to zero. In contrast, when this information is revealed early through the quarterly earnings cycle, the IPT could become much larger.

Our empirical strategy, then, is to assign CDS abnormal return observations to one of two portfolios that differ in characteristics that proxy for the presence of earnings-related private information or bond market illiquidity. We then compute and compare the IPT across these portfolios. If Hypotheses H1a and H1b are correct, then we should expect to find that the IPT is large when there is an abundance of earnings-related private information or when the underlying corporate bond market is illiquid. As discussed earlier, we will consider four empirical proxies of private information based on the information set of financial analysts (forecast dispersion), the information set of stock market investors (idiosyncratic stock return volatility), the information set of lenders via their relationships with borrowers (presence of earnings-based loan covenants), and the level of credit risk (credit rating), as well as two empirical proxies of corporate bond market illiquidity.

[Insert Figure 3 here]

Figure 3 presents the average CAR function through the quarterly earnings cycle. It

[15] This definition mirrors the one used by Bushman et al. (2010), with the exception that they construct their IPT measure using buy-and-hold abnormal returns, while we use cumulative abnormal returns. As explained by Fama (1998), any potential problems with model misspecification in generating daily excess returns can be exacerbated by the process of compounding when computing buy-and-hold abnormal returns. In equation (1), we loosely refer to the average CAR as CAR.

shows that the average CAR rises more quickly to its post-earnings announcement level for the portfolio of firms that have speculative-grade credit ratings and earnings-based loan covenants, as well as those with above-median forecast dispersion, idiosyncratic stock return volatility, and corporate bond illiquidity measures. To more formally test whether the IPTs are different across any two characteristics portfolios, we randomly scramble the time ordering of the daily average abnormal return pairs (of the two portfolios) 1,000 times and calculate the IPT difference. This allows us to simulate the distribution of the IPT difference under the assumption that the time ordering of the returns is irrelevant (hence the IPT difference has zero mean).[16]

[Insert Table 3 here]

Table 3 shows that the IPT differences are all statistically significant at conventional levels. For example, the portfolio with above-median (below-median) forecast dispersion has an IPT value of 38.25 (24.98). This produces an IPT difference of 13.26 that falls beyond the 91st percentile of the simulated distribution, thus favoring the hypothesis that firms with greater analyst forecast dispersion tend to have faster pre-earnings announcement price discovery in the CDS market. The formal test statistics (the percentiles) of the IPT differences associated with the other five characteristics are higher. Overall, the results of this section offer consistent support of Hypotheses H1a and H1b, namely, that the speed of CDS price discovery is faster when there is a greater presence of private information and when the underlying corporate bonds are less liquid.

Incremental CDS Price Discovery Relative to Stocks

Next, we analyze the incremental price discovery in the CDS market relative to the stock market before earnings announcements. Our methodology follows Acharya and Johnson (2007) in

[16]This procedure follows Bushman et al. (2010, Appendix B).

assuming that the stock price reflects all publicly available information, and the information flow from the CDS market to the stock market reflects private information-based trading in credit derivatives.

All Earnings Announcements

Specifically, we measure the incremental price discovery close to the EAD through the sum of the coefficients $\sum_{k=1}^{5} b_k^D$ in the following panel regression specification:

$$\begin{aligned}\left(\text{Stock return}\right)_{it} &= a + \sum_{k=1}^{5}\left(b_k + b_k^D\left(\text{EA dummy}\right)_{it}\right)\left(\text{CDS innovation}\right)_{i,t-k} \\ &+ \sum_{k=1}^{5}\left(c_k + c_k^D\left(\text{EA dummy}\right)_{it}\right)\left(\text{Stock return}\right)_{i,t-k} + \varepsilon_{it},\end{aligned} \tag{2}$$

where the EA dummy indicates whether there is an EAD within the next five, 30, or 45 trading days, and the CDS innovation captures news specific to the CDS market, estimated as the residual u_{it} of first-stage time-series regressions for each sample firm after filtering out the effect of past shocks to the stock and CDS markets up to five lags, along with the contemporaneous stock return:[17]

$$\begin{aligned}\left(\text{CDS return}\right)_{it} &= \alpha_i + \sum_{k=0}^{5}\left(\beta_{ik} + \gamma_{ik} / \left(\text{CDS premium}\right)_{it}\right)\left(\text{Stock return}\right)_{i,t-k} \\ &+ \sum_{k=1}^{5}\delta_{ik}\left(\text{CDS return}\right)_{i,t-k} + u_{it}.\end{aligned} \tag{3}$$

Panel A of Table 4 presents the results of estimating equation (2) using all earnings announcements. We find that while $\sum_{k=1}^{5} b_k$ is only marginally significant, $\sum_{k=1}^{5} b_k^D$ is negative and significant at the one-percent level (and much larger in size) for the five-, 30-, and 45-day windows, which shows that a positive CDS innovation is typically followed by a sequence of

[17]In equation (3), the dependence of the stock return coefficients on the inverse of the CDS premium is designed to capture the nonlinear relation between credit spreads and stock returns in the classical Merton (1974) model (see Acharya and Johnson, 2007, page 120).

negative reactions in the stock market, i.e., information that uniquely affects the CDS market can subsequently flow into the stock market. The magnitude of $\sum_{k=1}^{5} b_k^D$, around two to five percent, is consistent with the findings of Acharya and Johnson (2007) using adverse credit events defined solely on the basis of a sudden increase of the CDS premium.

[Insert Table 4 here]

Extreme Surprises and Positive vs. Negative Surprises

We also offer a more detailed analysis of the set of earnings announcements by first focusing on extreme earnings surprises, defined as the earnings surprise being more than half a standard deviation above or below its sample mean.[18] Doyle, Lundholm, and Soliman (2006) report that firms with extreme earnings surprises tend to be small with low analyst coverage and high forecast dispersion. To the extent that these characteristics signal a high degree of information asymmetry, we expect there to be a more significant information flow from the CDS market to the stock market ahead of extreme earnings surprises. Second, we analyze positive and negative surprises separately in light of the different market reactions documented earlier. Whether there is informed trading in the CDS market ahead of positive earnings surprises is an interesting question in its own right, because it is commonly believed that the nature of private information in the CDS market is one-sided, i.e., a privately informed bank would purchase CDS protection from an uninformed institution (e.g., insurance companies) to profit from the declining credit quality of its borrowers. Indeed, the empirical studies to date of informed trading in the CDS market are both based on inferring the CDS-to-stock information flow exclusively prior to adverse credit events (Acharya and Johnson, 2007; Qiu and Yu, 2012). Yet, there is little friction

[18] We assume this cutoff in order to preserve a sufficiently large number of observations for the analysis. Restricting to earnings surprises more than one standard deviation above or below the sample mean results in too small a sample and large estimation errors.

in the CDS market that would prevent informed traders from selling credit protection ahead of positive news.

We entertain these additional issues in the remainder of Table 4.[19] First, Panel B shows that the size of $\sum_{k=1}^{5} b_k^D$ for extreme earnings surprises is much larger than the earlier estimate using all earnings announcements. For example, for the five-day window, we find that $\sum_{k=1}^{5} b_k^D$ is equal to -0.119, which is more than twice the size of the estimate in the case of all earnings announcements, -0.048. Therefore, the CDS market does appear more informative ahead of extreme earnings surprises. In Panels C and D, we find that the magnitude of $\sum_{k=1}^{5} b_k^D$ is indeed larger for negative earnings surprises, especially for shorter window lengths such as five days and 30 days. This confirms that CDS trading ahead of negative earnings surprises is more informative. Still, Panel C shows that $\sum_{k=1}^{5} b_k^D$ is significant at the one-percent or five-percent level across all window sizes for positive earnings surprises, which suggests that informed traders also trade in the CDS market before the announcement of good news, possibly by selling CDS contracts and profiting from the subsequent decline in the CDS premium.

Turning now to the length of the pre-announcement window, Table 4 shows generally that the strongest incremental information flow effect corresponds to a window length of five trading days, and the effect is slightly weaker using a 30-day window, eventually turning insignificant with a 45-day window. These findings are consistent with the intuition that private information about an upcoming earnings announcement is unlikely to be available when the

[19] To estimate the incremental CDS price discovery ahead of extreme earnings surprises, we include only observations that belong to firm-quarters associated with an extreme earnings surprise. Similarly, to estimate the incremental information flow prior to positive (negative) announcements, we include only observations during firm-quarters associated with a positive (negative) earnings surprise. This explains the changes in the number of observations across the different panels of Table 4 (in particular, positive announcements are much more prevalent than negative ones).

announcement is still many days ahead.

Conditioning on Firm Characteristics

To see the effect of private information and bond illiquidity on incremental CDS price discovery relative to the stock market, we sort the observations into subgroups using the previously introduced private information and bond illiquidity proxies.[20] We then estimate equation (2) for each of these subgroups separately and compare the estimates of $\sum_{k=1}^{5} b_k^D$ (specializing to a 30-day pre-announcement window).

[Insert Table 5 here]

We first sort the observations into two equal subgroups based on the sample median value of forecast dispersion. Columns (1) and (2) of Table 5 show that $\sum_{k=1}^{5} b_k^D$ is equal to -0.063 (-0.015) for the high (low) dispersion subgroup. While both estimates are significant at the one-percent level, the magnitude of the estimate for the high dispersion group is more than four times that for the low dispersion group. Similarly, Columns (3) and (4) show that the CDS-to-stocks information transmission is much stronger among firms with above-median idiosyncratic stock return volatility—$\sum_{k=1}^{5} b_k^D$ is equal to -0.059 for the above-median subgroup and only -0.019 for the below-median subgroup. To the extent that high forecast dispersion and idiosyncratic stock return volatility capture the presence of private information among equity analysts and stock market investors, respectively, our results suggest that they can also serve as valid proxies of private information among CDS market participants. In contrast, Columns (5)-(8) show a significant CDS-to-stocks information transmission that does not vary with credit rating or the presence of earnings-based loan covenants.

[20]Specifically, we assign an entire firm-quarter to one of two subgroups depending on the average value of the characteristic for the firm-quarter.

We next consider the two bond illiquidity proxies based on bond price variations over the trading volume. Columns (9)-(12) show that firms with highly illiquid corporate bonds have much stronger incremental information flow from CDS to stocks than those with less illiquid corporate bonds ($\sum_{k=1}^{5} b_k^D$ of -0.076 vs. -0.013 in the first case and -0.073 vs. -0.016 in the second). These findings are consistent with informed traders favoring the CDS market when the corporate bond market is plagued by high trading costs.

As a robustness check, we divide our sample period of 2001-10 into the great financial crisis period of August 2007 to March 2009 and the non-crisis period that falls outside that interval.[21] Untabulated results indicate that the information flow from CDS into stocks is much stronger during the financial crisis period and is concentrated among financial institutions, which generated the bulk of market-moving news at the time. During the normal period, the information flow is relatively weaker and is only significant among industrial firms.

In summary, in this subsection we identify a significant incremental CDS price discovery relative to the stock market ahead of quarterly earnings announcements, which is further strengthened among a subsample of extreme earnings surprises. While the effect is present in both positive and negative earnings announcements, it is somewhat stronger among a subsample of negative earnings surprises. Furthermore, the effect is accentuated among firms with higher analyst forecast dispersion and idiosyncratic stock return volatility, and those with more illiquid corporate bonds. These results are broadly consistent with Hypotheses H1a and H1b.

CDS Introduction and Equity Analyst Forecasts

Having demonstrated that the CDS market disseminates private information ahead of earnings

[21] We select the financial crisis period primarily based on the timeline published by the Federal Reserve Bank of St. Louis (http://timeline.stlouisfed.org/index.cfm?p=timeline). Moreover, we follow Ivashina and Scharfstein (2010) in setting the beginning of the financial crisis as August 2007, when the CDS premiums of financial institutions began rising and the subprime mortgage market collapsed.

announcements, we are naturally interested in the effect of having active CDS trading on firms' information environment. In particular, how do equity analysts view the information content of the CDS market? Does it help them make more accurate earnings forecasts? Does the additional information conveyed through the CDS market lead to less demand for analyst services? How does it affect the frequency of forecast revisions? In this subsection, we estimate the effect of CDS introduction on equity analyst forecasts.

Benchmark Regressions

Our main variable of interest is CDSActive, a dummy variable equal to one if a firm has active CDS trading by quarter *t*.[22] The empirical methodology is that of standard differences-in-differences (DID) estimation in a panel data setting with quarterly observations. Specifically, we include CDSActive in a regression specification with one of the analyst forecast characteristics as the dependent variable, controlling for lagged firm characteristics that have been shown to explain analyst behavior (see the discussion in Section III), along with firm and quarterly fixed effects (the *t*-statistics of our estimates are calculated using standard errors clustered at the firm level):

$$y_{i,t} = \alpha_i + \beta_t + \gamma \text{CDSActive}_{i,t} + \theta' X_{i,t-1} + \varepsilon_{i,t}. \qquad (4)$$

By including firm fixed effects to control for unobserved time-invariant heterogeneities at the firm level, this specification relies on within-firm variations of the dependent variable to estimate the effect of CDS introduction. Also, since CDS introduction happens at different times for different firms, both non-CDS firms (those that never had CDS trading during our sample period) and a subset of CDS firms (those that did not experience CDS introduction in quarter *t*) serve as the control in the DID estimation, easing concerns that the treatment and control are

[22]As the Markit historical daily CDS coverage begins on January 2, 2001, we treat firms with CDS pricing data available on January 2, 2001 as having earlier, hence unknown, CDS initiation dates.

systematically different.

One remaining issue with the above specification is that CDS introduction may be endogenous to the left hand side variable. For example, Saretto and Tookes (2013) examine the effect of CDS introduction on firms' leverage and debt maturity choice, and Subrahmanyam et al. (2014) conduct a similar analysis for the likelihood of rating downgrades and bankruptcies. In both cases, it could be argued that hedgers who demand CDS trading are probably anticipating an elevation of credit risk, which is closely correlated with the objects of interest in these papers. As a result, these authors had to try hard to identify instrumental variables that are correlated with CDS introduction but not the CDS obligor's credit risk. Such a concern is less pressing in our case, since it is difficult to imagine a scenario in which CDS hedgers are motivated by their expectation of analyst behavior. Still, we include a set of variables (refer again to Section III) that have been used in Subrahmanyam et al. (2014) to explain the introduction of CDS trading. This fulfills two purposes. First, these variables help to control for cross-sectional differences among firms with and without CDS trading. Second, they also serve as effective controls for the scenario in which CDS introduction anticipates future changes in credit risk, and credit risk variables are correlated with analyst forecast characteristics.

[Insert Table 6 here]

First taking a look at the range and accuracy of analyst forecasts, Table 6 show that both forecast dispersion and forecast error are lower for less risky and better performing firms, which tend to be larger and rated investment-grade, and have higher excess stock returns, lower leverage and stock return volatility, more rapid sales growth, greater EBIT, and spend more on capital expenditures. More importantly, controlling for all of these firm characteristics, we find that both dispersion and forecast error decline after CDS trading begins. The coefficient on

CDSActive is -0.0004 for forecast dispersion, which is around 13 percent of its sample mean (see Table 2) and is significant at the ten-percent level. Similarly, the coefficient on CDSActive is -0.001 for forecast error, which is around 17 percent of its sample mean and is significant at the one-percent level. Importantly, these estimates are obtained while controlling for the number of management forecasts, which, as expected, is negatively related to both forecast dispersion and forecast error. Therefore, the effect of CDS trading on analyst forecasts goes beyond its pressure upon management for preemptive disclosures.

Moving on to analyst following and the frequency of forecast revisions, we find that they are often associated with the same firm characteristics that drive forecast dispersion and forecast error, but in the opposite direction. In other words, less risky and better performing firms tend to have greater analyst coverage and more frequent forecast revisions.[23] When it comes to the effect of CDS introduction, we find that the coefficient on CDSActive for the frequency of forecast revisions is equal to 1.22, which is significant at the one-percent level. This also appears to be an economically significant effect when compared to a sample average of 4.13 revisions for non-CDS firm-quarters and 10.45 for CDS firm-quarters (see Table 2). For analyst following, our estimation does not uncover any significant effect. Finally, the last column of Table 6 shows that the share of revisions within 30 trading days of upcoming EADs increases by 1.9 percentage points after the introduction of CDS trading, and is significant at the five-percent level. It is likely that the additional information revealed through the CDS market is causing analysts to revise their earnings forecasts as the EAD approaches.

Putting these results together and in view of the discussion of Hypotheses H2a in Section

[23]An exception is the coefficient on excess stock return, which suggests that firms with poor recent stock market performance (all of our explanatory variables are lagged by one quarter) tend to be followed by more analysts and have a greater number of forecast revisions. This is, nevertheless, consistent with analysts' attention being drawn disproportionately towards negative news in the stock market.

II, it appears that CDS introduction primarily has the effect of reducing information asymmetry regarding the upcoming earnings announcement, resulting in less forecast dispersion and forecast error. Furthermore, the results of Table 6 show that the additional information accompanying an active CDS market triggers more frequent forecast revisions, especially as the EAD approaches, but does not lead to any significant reduction in analyst coverage.

Propensity Score Matching

To explicitly address any systematic differences between CDS and non-CDS firms, we use propensity score matching to identify control firms. Specifically, we estimate a probit model for predicting the introduction of CDS, by including most of the variables used in a similar analysis by Saretto and Tookes (2013) and Subrahmanyam et al. (2014), along with industry and quarterly fixed effects. For each CDS firm observed during the quarter immediately prior to the start of its CDS trading (treatment), we identify either the five closest matches in terms of propensity scores or all matches within one percent of the propensity score of the treatment. A potential match can include either firms that never experienced CDS trading or firms that started CDS trading in a different quarter. When a matching firm (with replacement) is found, we include its entire time-series of observations in the matched sample.

[Insert Table 7 here]

Table 7 offers an evaluation of the performance of the matching procedure. The pre-matching column of Panel A shows that larger rated firms with investment-grade credit ratings and a greater amount of outstanding debt are more likely to experience CDS trading. This is consistent with the summary statistics of the variables in Table 1 as well as the findings of Saretto and Tookes (2013) and Subrahmanyam et al. (2014). It suggests that CDS introduction is primarily driven by investors' hedging demand, which would be more prominent for large firms with a lot of investment-grade debt (many institutional investors are not allowed to hold speculative-grade debt).

Panel A also compares the estimation of the probit model based on the pre- and post-matching samples. Since firms in the post-matching samples are more uniform in terms of the predicted probability of CDS introduction, many of the same predictors are still significant, albeit with smaller *t*-statistics. For the same reason, the pseudo-R^2 of the estimation is lower for the post-matching samples. In Panel B, we compare the propensity scores of the treatment and control firms during the quarter prior to CDS introduction—this is the quarter in which the matching was made. The scores for the treatment and control firms are apparently quite similar. Finally, Panel C compares the mean value of the predictors across treatment and control firms during the matching quarter. Although some variables are still statistically different across the two groups, the differences are much smaller compared to the pre-matching sample. For example, the logarithm of total assets has a mean value of 9.12 for CDS firm-quarters and 6.48 for non-CDS firm-quarters in Panel B of Table 2. Here, they are 8.96 and 8.70, respectively, for the treatment and control during the matching quarter, using five-nearest-neighbor matching.

[Insert Table 8 here]

Table 8 presents the estimation of equation (4) using the propensity score matched samples. Since the results using five-nearest-neighbor matching is quite similar to those using all-within-one-percent matching, we will focus on the former. For forecast dispersion and forecast error, our results are similar to those in Table 6. For example, forecast dispersion drops by 0.001 after CDS introduction, which is significant at the five-percent level and is 33 percent of the sample mean (see Table 2). Likewise, forecast error drops by 0.001 after CDS introduction, which is significant at the ten-percent level and is 17 percent of the sample mean. On the other hand, results do change somewhat on the frequency of forecast revisions. Previously, we identified a significantly positive effect on the number of forecast revisions and the share of revisions within 30 trading days of the EAD, but now the estimated coefficients are no longer significant. Therefore, combining the benchmark DID estimation and PSM-based results, we conclude that forecast dispersion and forecast error are reduced following CDS introduction, which is consistent with Hypothesis H2a.[24]

Conditioning on Credit Quality

Another way to check the robustness of our analyst forecast related findings is to condition the analysis on the credit quality of the firms. There are several reasons why this might yield additional insights into how CDS trading affects firms' information environment. To the extent that there is a natural tendency for the credit market to reflect negative news, and assuming that negative news are more prevalent among firms with lower credit quality, we expect the preceding results to be stronger among lower credit quality firms. On the other hand, CDS transaction liquidity peaks around the BBB rating and declines dramatically for speculative-grade firms (Qiu and Yu, 2012). The lack of trading activities might make it difficult to interpret information from the CDS market. This difficulty with information processing could produce even more divergent forecasts among equity analysts, rather than reducing their difference of opinion. Bearing in mind these competing possibilities, we condition the main effects (on forecast dispersion and forecast error) of the previous analysis on the credit quality of firms as measured by the naive distance-to-default (Bharath and Shumway, 2008), the Altman Z-score, and the firms' credit ratings. Specifically, we include dummy variables for low naive

[24]As we estimate propensity scores using firm-quarters within CRSP and Compustat (but not necessarily I/B/E/S), some CDS firms are matched to fewer than five neighbors. When we restrict neighbor selection to firms with both I/B/E/S data and analyst characteristic controls, we find no change in coefficient estimate magnitudes, but more precise estimates, especially for forecast error.

distance-to-default, low Altman Z-score (both below the 25th percentile), and speculative-grade credit ratings, as well as their interactions with CDSActive. Firms with these characteristics constitute a small subset (no more than ten percent) of those with CDS trading.

Untabulated results are fairly uniform across all three credit quality measures. First, the coefficients on CDSActive are negative and significant, showing that the main effect of lower forecast dispersion and error after CDS introduction is present after parceling out the lower credit quality firms. Second, the coefficients on the low credit quality dummies are positive and significant, consistent with Table 6 showing that riskier firms have greater forecast dispersion and error. Third, the interaction terms between the low credit quality dummies and CDSActive generally have positive and significant coefficients for dispersion only (with larger magnitude than the coefficients on CDSActive in some cases), indicating that lower credit quality firms could have higher dispersion post-CDS introduction. While these findings are certainly intriguing and suggest that more work is needed to understand how the nature of CDS market information varies across firms, we also repeat this conditional estimation using the PSM procedure, finding the positive coefficients on the interaction terms to be insignificant in nearly all specifications. Therefore, there is no conclusive evidence that the effect of CDS trading on analyst forecast dispersion and error varies systematically across firms' credit quality.

CDS Introduction and Analyst Downgrades

In the last part of our analysis, we look beyond equity analyst forecasts and ask whether CDS trading affects firms' information environment in other ways. We focus on two additional analyst outputs—the recommendations of equity analysts and the credit ratings assigned by major rating agencies. Because of the focus on downside risk for bond and CDS investors, we will examine the decision by equity analysts and credit rating agencies to downgrade firms ahead of large negative earnings surprises. These events serve as anchors that allow us to evaluate the performance of the analysts—specifically, we will check if their downgrades ahead of such events become more frequent and more timely after the start of CDS trading.

We perform two types of analysis. First, we estimate a probit regression for the likelihood of downgrades. Second, conditional on a downgrade, we estimate a regression for the duration (in trading days) between the downgrade and the announcement of the negative earnings surprise, which we use to measure the timeliness of the downgrade. For rating downgrades, the probit analysis uses a sample that is essentially a subset of I/B/E/S firms that have bond ratings. Therefore, it is not surprising that the sample size is much smaller than that of our earlier analysis. If we further restricted the sample to actual rating downgrades, our sample size would have been even smaller, rendering the duration analysis for rating downgrades infeasible.

[Insert Table 9 here]

Column (1) of Table 9 presents the results of our probit analysis of the downgrade decision of rating analysts, which equals one if any of the three major rating agencies decides to downgrade the firm's debt. We first find that downgrades become more frequent across the board after CDS introduction (note the positive and significant coefficient on CDSActive), which is consistent with Subrahmanyam et al. (2014). Focusing on downside risk, we define a large negative earnings surprise as one where the negative surprise exceeds 0.5 percent of the firm's total market capitalization.[25] As expected, the likelihood of rating downgrade is higher for firms about to experience large negative earnings surprises. What is more interesting, however, is that the interaction between CDSActive and the large negative earnings surprise dummy has a positive and significant coefficient. The marginal effect of this estimate corresponds to an

[25]We have also used one percent of the market capitalization as the threshold in this definition. Results are weaker perhaps because there are fewer such large negative earnings surprises.

increase of downgrade probability from eight percent to 14 percent.[26] This confirms that rating downgrades are more likely ahead of negative earnings surprises when there is an actively traded CDS market.

For the probit analysis of equity analyst downgrades in Column (2), we use a much bigger sample (essentially all I/B/E/S firms). One key difference here is that the coefficients on CDSActive and the negative earnings surprise dummy are no longer significantly positive. The reason why equity analysts fail to lower their recommendations before negative earnings surprises could be that they are less informed at such times than rating agencies. For CDSActive, we note that the main driver for CDS introduction is the anticipation of rising credit risk, which clearly explains the positive coefficient in the probit regression for rating downgrades. However, the link between rising credit risk and falling equity prices is not so straightforward. For example, if the rising credit risk is caused by a higher asset volatility, then the equity price can increase according to the Merton model. In any case, we find that the interaction between CDSActive and the negative earnings surprise dummy has a positive and significant coefficient, suggesting that the likelihood of equity analyst downgrades before negative earnings surprises is higher post-CDS introduction. The marginal effect corresponds to an increase of downgrade probability from 35 percent to 42 percent.[27] This is consistent with our findings based on rating downgrades.

We further examine the timeliness of equity analyst downgrades, using the average number of trading days from the downgrade to the EAD across all analysts issuing a downgrade

[26] We obtain the marginal effect by setting continuous variables and time period dummies to their sample means, the large negative earnings surprise dummy to one, and the investment-grade dummy to one because most of the sample firms included in this regression are rated investment-grade.

[27] We use the same procedure for computing the marginal effect in the probit regression for rating downgrades, but with the rated dummy and the investment-grade dummy set to zero because the majority of the sample firms here are not rated.

as the dependent variable. Column (3) shows that the coefficient on the interaction between CDSActive and the negative earnings surprise dummy is positive and significant, indicating that downgrades ahead of large negative EADs are happening sooner in the presence of CDS trading.[28] Although the magnitude of the estimate is small (it indicates that downgrades occur around two days earlier), this is an average effect across all analysts issuing downgrades. To the extent that not all equity analysts are paying attention to the CDS market, the effect from any individual analyst could be much larger. Summarizing the findings in this subsection regarding analyst downgrades, it seems that the information conveyed through CDS trading can help equity and credit rating analysts make more frequent and more timely downgrades ahead of large negative earnings surprises.

V. CONCLUSION

We examine price discovery in the CDS market ahead of earnings announcements and its implications for the output of financial analysts. Previous research has either theorized about the heightened production of private information around public news announcements (e.g., Kim and Verrecchia, 1991) or empirically analyzed its implications for stock market liquidity (e.g., Lee, Mucklow, and Ready, 1993). We focus instead on the CDS market, for which these issues have not been previously explored, and yet allegations of private information-based trading have been pervasive (Acharya and Johnson, 2007).

Using a sample of 739 CDS firms and 19,822 quarterly earnings announcements during 2001-10, we first analyze factors that influence the strength of CDS price discovery through the quarterly earnings cycle. Constructing an intra-period timeliness variable as well as performing a

[28] In results not presented here, we follow the PSM procedure to re-estimate all of these regressions. We find that the probit results are generally weaker, but the result on the timeliness of equity analyst downgrades actually becomes stronger.

lead-lag analysis against the stock market as a source of public information, we show that CDS price discovery is strengthened when there is a greater amount of private information among financial market participants and when it is more costly to trade the underlying corporate bonds.

Having confirmed that the CDS market conveys private information ahead of earnings announcements, we expand our sample to include 6,115 firms with I/B/E/S coverage. Using a differences-in-differences analysis based on CDS introductions as the treatment and propensity score matched observations as the control, we find robust evidence that the accuracy of analyst forecasts improves following the start of CDS trading. Specifically, both forecast dispersion and forecast error decrease by around 13-17 percent of their sample means after CDS introduction. Furthermore, we show that downgrades by both credit rating and equity analysts ahead of large negative earnings shocks become more frequent and more timely in the presence of CDS trading. These findings are consistent with financial analysts exploiting the information content of the CDS market to improve the quality of their output. We believe that these results enhance our understanding of how private information gets impounded into the output of financial analysts.

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Table 1: Definitions of variables

Variable	Definition
CDS Premium	Daily composite five-year CDS premium in basis points. Data are from Markit.
CDSActive	A dummy variable equal to one if a firm has active CDS trading by quarter *t*, and zero otherwise. Data are from Markit.
Assets	Total assets (ATQ) of a firm in billions of dollars. Data are from Compustat.
Credit Rating	S&P's long-term issuer credit rating obtained from Compustat and converted into a numerical scale from 1 (AAA) to 22 (D).
Monthly Dispersion	Standard deviation of all valid EPS estimates within a given month normalized by the share price at the end of the month. Data are from I/B/E/S.
Idiosyncratic Volatility	Standard deviation of excess stock returns (estimated using the CRSP value-weighted index over the preceding 252 trading days and annualized using the square root of time rule) over the inter-announcement period (roughly 63 trading days).
Number of Covenants	The number of earnings-based covenants from outstanding facilities in the LPC DealScan database.
Bond Illiquidity 1	The average, across all bonds outstanding of a firm with trading data in TRACE, of the monthly standard deviation of the bond price (scaled by the monthly average price) divided by the monthly trading volume.
Bond Illiquidity 2	The average, across all bonds outstanding of a firm with trading data in TRACE, of the difference between the monthly maximum and minimum bond price (scaled by the monthly average price) divided by the monthly trading volume.
Dispersion	The standard deviation of the last estimate given by analysts following a firm that were made within 90 calendar days of the earnings announcement, scaled by the price per share as of the end of the fiscal quarter. Data are from I/B/E/S.
Forecast Error	The absolute value of the difference between the actual EPS and the median of the last estimate given by analysts following a firm that were made within 90 calendar days of the earnings announcement, scaled by the price per share as of the end of the fiscal quarter.
Following	The number of analysts issuing estimates within 90 calendar days of the earnings announcement. Data are from I/B/E/S.
Revisions	The number of current quarter forecast revisions made within 90 days of the quarterly earnings announcement. Data are from I/B/E/S.
Revision Share < 30 days	The percentage of earnings forecast revisions that occur within 30 trading days of a quarter's earnings announcement date. Data are from I/B/E/S.
Time to Downgrade	The mean number of trading days to the earnings announcement date from any equity analyst recommendation downgrades made during a quarterly inter-announcement period. Data are from I/B/E/S.
Downgrade (equity analysts)	An indicator variable for whether any equity analyst made a recommendation downgrade during the inter-announcement period. Data are from I/B/E/S.
Downgrade (rating agencies)	An indicator variable for whether any rating agency made a rating downgrade during the inter-announcement period. Ratings are obtained from the Mergent FISD Bond Ratings file.
Management Forecasts	The number of management quarterly EPS forecasts issued within a quarter from the I/B/E/S Guidance database, excluding any forecasts announced after the fiscal quarter end date.
Sales Growth	The compounded twelve to twenty-quarter sales growth rate (depending on data availability). Sales is SALEQ from Compustat.
Volatility	Annualized standard deviation of trailing 252-day stock returns, as of the month before current quarter earnings are announced. Data are from CRSP.
R&D	Research and development expense (XRD), scaled by operating expenses (XOPR) and divided by four. Data are from Compustat Annual and are coded as zero if missing.
Advertising	Advertising expenses (XAD), scaled by operating expenses (XOPR) and divided by four. Data are from Compustat Annual and are coded as zero if missing.
Ln(Segments)	Logarithm of the number of business segments listed in the Compustat Segment file.
Leverage	The book value of debt (DLCQ + 0.5 x DLTTQ) divided by the sum of the book value of

	debt and the market value of equity. Data are from Compustat and CRSP.
Capex	Quarterly net purchases of property, plant, and equipment (computed from CAPEXY), scaled by beginning total assets (ATQ). Data are from Compustat.
EBIT	Earnings before interest and taxes (PIQ+XINTQ), scaled by beginning total assets (ATQ). Data are from Compustat.
Working Capital	Cash and short-term investments (CHEQ), inventory (INVTQ), net receivables (RECTQ), and other current assets (ACOQ), less accounts payable (APQ), debt in current liabilities (DLCQ), taxes payable (TXPQ), and other current liabilities (LCOQ), scaled by beginning total assets (ATQ). Data are from Compustat and are coded as zero if missing.
Cash	Cash and short-term investments (CHEQ), scaled by beginning total assets (ATQ). Data are from Compustat.
Asset Turnover	Sales (SALEQ), scaled by beginning total assets (ATQ). Data are from Compustat.
Retained Earnings	Retained earnings (REQ), scaled by beginning total assets (ATQ). Data are from Compustat.
PPE	Property, plant, and equipment (PPENTQ), scaled by beginning total assets (ATQ) from Compustat.
ROA	Net income before extraordinary items and discontinued operations (IBQ), scaled by beginning total assets (ATQ) from Compustat.
Excess Stock Return	Compounded 12-month stock returns less the compounded 12-month returns from the CRSP value-weighted index.
Rated	A dummy variable equal to one if a firm has an active long-term S&P issuer-level credit rating, and zero otherwise. Data are from Compustat.
Investment-grade	A dummy variable equal to one if a firm has a long-term S&P issuer-level credit rating above BB+, and zero otherwise. Data are from Compustat
Distance-to-default	The naïve distance-to-default measure from Bharath and Shumway (2008).
Altman-Z	Calculated as: (working capital (CHEQ+INVTQ+RECTQ+ACOQ-APQ-DLCQ-TXPQ-LCOQ) /total assets (ATQ)) x 1.2 + (retained earnings (REQ)/total assets) x 1.4 + (Trailing 4-quarter EBIT (PIQ+XINTQ)/total assets) x 3.3 + (market capitalization/total liabilities) x 0.6 + (Trailing 4-quarter sales (SALEQ)/total assets). Financial data are from Compustat. Market capitalization is from CRSP.

Table 2: Summary statistics

This table presents the summary statistics for the variables used in our study. Panel A shows statistics for firms with outstanding CDS contracts. Panel B shows statistics for all firms within I/B/E/S with sufficient data available. The sample period is from 2001 to 2010. The definitions of the variables are provided in Table 1.

Panel A: Firms with outstanding CDS contracts

	mean	stdev	p25	p50	p75
CDS Premium	190.1	465.2	37.9	75.6	189.1
Assets ($B)	38.7	107.1	4.3	9.2	23.4
Credit Rating	8.8	3.1	7.0	9.0	10.0
Monthly Dispersion	0.002	0.006	0.000	0.001	0.002
Idiosyncratic Volatility	0.28	0.22	0.16	0.23	0.32
Number of Covenants	2.6	5.0	0.0	1.0	3.0
Bond Illiquidity 1	0.0017	0.0037	0.0002	0.0006	0.0014
Bond Illiquidity 2	0.0038	0.0071	0.0006	0.0015	0.0036

Panel B: Firms in I/B/E/S

	No CDS Trading					*CDS Trading*				
	mean	stdev	p25	p50	p75	mean	stdev	p25	p50	p75
Dispersion	0.003	0.006	0.000	0.001	0.002	0.003	0.006	0.000	0.001	0.002
Forecast Error	0.006	0.015	0.001	0.002	0.005	0.005	0.014	0.000	0.001	0.004
Ln(Following)	1.16	0.88	0.69	1.10	1.79	1.88	0.85	1.39	1.95	2.48
Revisions	4.13	6.40	0.00	2.00	5.00	10.45	11.36	3.00	7.00	14.00
Revision Share<30 days	0.33	0.36	0.00	0.25	0.57	0.43	0.30	0.20	0.42	0.64
Time to Downgrade	36.11	19.25	21.00	35.50	52.00	34.12	17.81	20.33	33.80	48.00
Downgrade (equity analysts)	0.36	0.48	0.00	0.00	1.00	0.51	0.50	0.00	1.00	1.00
Downgrade (rating agencies)	0.07	0.26	0.00	0.00	0.00	0.09	0.28	0.00	0.00	0.00
Management Forecasts	0.25	0.58	0.00	0.00	0.00	0.32	0.64	0.00	0.00	0.00
Ln(Assets)	6.48	1.64	5.34	6.47	7.51	9.12	1.22	8.22	8.95	9.88
Sales Growth	0.16	0.51	0.01	0.04	0.10	0.05	0.19	0.00	0.02	0.05
Volatility	0.55	0.29	0.34	0.47	0.68	0.39	0.24	0.23	0.32	0.46
R&D	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Advertising	0.02	0.04	0.00	0.00	0.02	0.01	0.02	0.00	0.00	0.00
Ln(Segments)	0.45	0.62	0.00	0.00	1.10	0.81	0.74	0.00	1.10	1.39
Leverage	0.12	0.12	0.01	0.09	0.18	0.17	0.10	0.10	0.16	0.23
Capex	0.02	0.02	0.00	0.01	0.02	0.02	0.02	0.00	0.01	0.02
EBIT	0.01	0.05	0.00	0.01	0.03	0.02	0.03	0.01	0.02	0.03
Working Capital	0.24	0.27	0.04	0.21	0.42	0.12	0.17	0.00	0.09	0.21
Cash	0.20	0.23	0.03	0.09	0.30	0.09	0.11	0.02	0.05	0.12
Asset Turnover	0.23	0.20	0.08	0.19	0.32	0.21	0.17	0.09	0.18	0.29
Retained Earnings	-0.20	1.31	-0.10	0.08	0.30	0.17	0.58	0.04	0.19	0.37
PPE	0.21	0.24	0.03	0.12	0.31	0.29	0.26	0.07	0.23	0.48
ROA	0.00	0.05	0.00	0.01	0.02	0.01	0.02	0.00	0.01	0.02
Excess Stock Return	0.12	0.59	-0.23	0.01	0.31	0.07	0.40	-0.15	0.02	0.20
Rated	0.26	0.44	0.00	0.00	1.00	0.97	0.17	1.00	1.00	1.00

Investment-grade	0.11	0.32	0.00	0.00	0.00	0.73	0.45	0.00	1.00	1.00
Distance-to-default	6.13	4.93	2.84	5.24	8.30	7.41	5.23	3.68	6.75	10.31
Altman-Z	4.33	8.32	0.91	2.77	5.36	2.57	2.82	1.12	2.21	3.63

Table 3: Intra-period timeliness (IPT) values

This table presents intra-period timeliness (IPT) values for CDS portfolios based on portfolio cumulative abnormal CDS returns (CARs) from 61 trading days before to two days after the earnings announcements, normalizing the CAR at $t = -61$ to zero and $t = 2$ to one. The IPT is specifically defined as the area under the standardized CAR function from $t = -61$ to $t = 2$ using the trapezoidal approximation:

$$\text{IPT} = \frac{1}{\text{CAR}_2}\sum_{t=-60}^{2}\frac{\text{CAR}_{t\text{-}1}+\text{CAR}_t}{2} = \sum_{t=-60}^{1}\frac{\text{CAR}_t}{\text{CAR}_2} + 0.5.$$

For analyst forecast dispersion, idiosyncratic volatility, bond illiquidity 1, and bond illiquidity 2, a trading day is assigned to Portfolio 1 if the value of the characteristic for that day is above its sample median. For credit rating, a trading day is assigned to Portfolio 1 if the credit rating for that day is speculative-grade. For earnings-based covenants, a trading day is assigned to Portfolio 1 if the firm has any loans with earnings-based covenants outstanding for that day. All firm characteristics are defined in Table 1. Percentile ΔIPT indicates whether the difference in IPT values across the two portfolios is statistically significant. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The parentheses contain the average daily number of observations in each characteristics portfolio across the 63 trading days used to compute the IPT. It measures, approximately, the number of firm-quarters used in constructing these portfolios.

	Portfolio 1	Portfolio 2	Difference	Percentile ΔIPT
	(1)	(2)	(3)	(4)
Dispersion	38.25	24.98	13.26*	0.915
	(6,891)	(6,955)		
Idiosyncratic Volatility	38.34	15.18	23.15***	0.999
	(6,218)	(6,182)		
Speculative-grade	35.83	24.73	11.10**	0.961
	(3,845)	(12,823)		
Covenants	33.23	19.64	13.60*	0.934
	(9,078)	(7,998)		
Bond Illiquidity 1	25.72	-12.26	37.99***	0.995
	(3,277)	(3,278)		
Bond Illiquidity 2	25.88	-2.50	28.39***	0.992
	(3,407)	(3,405)		

Table 4: Information flow from the CDS market to the stock market

This table presents the results of a pooled regression of daily stock returns on lagged CDS innovations and lagged stock returns as follows:

$$(\text{Stock return})_{it} = a + \sum_{k=1}^{5}\left(b_k + b_k^D (\text{EA dummy})_{it}\right)(\text{CDS innovation})_{i,t-k}$$
$$+\sum_{k=1}^{5}\left(c_k + c_k^D (\text{EA dummy})_{it}\right)(\text{Stock return})_{i,t-k} + \varepsilon_{it},$$

where the EA dummy is a dummy variable indicating whether there is an earnings announcement day within the next 5, 30, or 45 trading days. Panel A includes all earnings announcements. Panel B includes only observations from inter-announcement periods before earnings surprises that are greater than half a standard deviation above or below the sample mean earnings surprise. Panel C (D) includes only observations from inter-announcement periods ahead of positive (negative) earnings surprises. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	A: All announcement dates			B: Extreme surprises		
	within 5	within 30	within 45	within 5	within 30	within 45
a	0.0006***	0.0006***	0.0006***	0.0007***	0.0007***	0.0007***
	(23.61)	(23.90)	(23.67)	(8.24)	(8.27)	(8.25)
$\sum_{k=1}^{5} b_k$	0.003	0.017***	0.013**	0.001	0.022	0.012
	(0.99)	(4.03)	(2.38)	(0.11)	(1.33)	(0.53)
$\sum_{k=1}^{5} b_k^D$	-0.048***	-0.037***	-0.020***	-0.119**	-0.066***	-0.032
	(4.25)	(6.98)	(3.19)	(2.42)	(3.04)	(1.2)
$\sum_{k=1}^{5} c_k$	-0.059***	-0.101***	-0.114***	-0.036**	-0.078***	-0.088***
	(8.94)	(12.72)	(11.1)	(2.52)	(4.42)	(3.75)
$\sum_{k=1}^{5} c_k^D$	0.008	0.09***	0.081***	0.071*	0.1***	0.083***
	(0.45)	(9.83)	(7.41)	(1.67)	(4.56)	(3.22)
N	1,113,971	1,113,971	1,113,971	157,821	157,821	157,821

	C: Positive surprises			D: Negative surprises		
	within 5	within 30	within 45	within 5	within 30	within 45
a	0.0007***	0.0007***	0.0007***	0.0001***	0.0002***	0.0001***
	(25.98)	(26.22)	(26.07)	(2.77)	(3.04)	(2.84)
$\sum_{k=1}^{5} b_k$	0.002	0.017***	0.015***	0.008	0.021**	0.006
	(0.66)	(4.02)	(2.76)	(1.24)	(2.53)	(0.53)
$\sum_{k=1}^{5} b_k^D$	-0.022**	-0.034***	-0.021***	-0.101***	-0.045***	-0.010
	(2.27)	(5.94)	(3.23)	(3.63)	(4.01)	(0.75)
$\sum_{k=1}^{5} c_k$	-0.056***	-0.094***	-0.105***	-0.081***	-0.13***	-0.142***
	(8.39)	(10.89)	(9.42)	(6.88)	(8.85)	(7.75)
$\sum_{k=1}^{5} c_k^D$	-0.005	0.079***	0.07***	0.028	0.105***	0.091***
	(0.23)	(7.98)	(6.07)	(0.78)	(5.65)	(4.49)
N	697,509	697,509	697,509	306,651	306,651	306,651

Table 5: Information flow from the CDS market to the stock market – firm characteristics

This table presents the results of a pooled regression of daily stock returns on lagged CDS innovations and lagged stock returns estimated using samples partitioned by analyst forecast dispersion, idiosyncratic volatility, credit rating, covenant presence, and bond illiquidity. The regression specification is as follows:

$$(\text{Stock return})_{it} = a + \sum_{k=1}^{5}\left(b_k + b_k^D (\text{EA dummy})_{it}\right)(\text{CDS innovation})_{i,t-k} + \sum_{k=1}^{5}\left(c_k + c_k^D (\text{EA dummy})_{it}\right)(\text{Stock return})_{i,t-k} + \varepsilon_{it},$$

where the EA dummy is a dummy variable indicating whether there is an earnings announcement day within the next 30 trading days. All firm characteristics are defined in Table 1. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dispersion		Idiosyncratic Volatility		Rating	
	High	Low	High	Low	INV	SPEC
	(1)	(2)	(3)	(4)	(5)	(6)
a	0.0005***	0.0006***	0.0004***	0.0007***	0.0006***	0.0007***
	(13.97)	(22.50)	(10.08)	(37.19)	(22.83)	(9.49)
$\sum_{k=1}^{5} b_k$	0.027***	0.014***	0.023***	0.016***	0.029***	-0.027**
	(3.63)	(4.16)	(3.00)	(7.05)	(7.64)	(2.04)
$\sum_{k=1}^{5} b_k^D$	-0.063***	-0.015***	-0.059***	-0.019***	-0.04***	-0.031*
	(6.67)	(2.96)	(6.24)	(5.84)	(7.62)	(1.86)
$\sum_{k=1}^{5} c_k$	-0.102***	-0.118***	-0.111***	-0.073***	-0.136***	-0.039***
	(9.85)	(15.60)	(11.46)	(14.8)	(16.70)	(2.86)
$\sum_{k=1}^{5} c_k^D$	0.101***	0.048***	0.101***	0.037***	0.077***	0.098***
	(7.87)	(4.78)	(8.98)	(5.66)	(7.37)	(6.08)
N	468,031	467,905	516,760	516,926	830,157	254,681
	Covenants		Bond Illiquidity 1		Bond Illiquidity 2	
	With	Without	High	Low	High	Low
	(7)	(8)	(9)	(10)	(11)	(12)
a	0.0006***	0.0006***	0.0006***	0.0007***	0.0006***	0.0007***
	(16.89)	(19.62)	(11.84)	(17.65)	(11.78)	(18.53)
$\sum_{k=1}^{5} b_k$	0.013**	0.02***	0.041***	.013***	0.038***	0.017***
	(2.11)	(3.65)	(3.77)	(2.63)	(3.51)	(3.47)
$\sum_{k=1}^{5} b_k^D$	-0.038***	-0.035***	-0.076***	-0.013*	-0.073***	-0.016**
	(4.83)	(5.20)	(5.66)	(1.89)	(5.50)	(2.37)
$\sum_{k=1}^{5} c_k$	-0.086***	-0.124***	-0.12***	-0.096***	-0.119***	-0.098***
	(8.81)	(10.74)	(8.87)	(7.52)	(8.95)	(8.06)
$\sum_{k=1}^{5} c_k^D$	0.091***	0.093***	0.111***	0.055***	0.114***	0.046***
	(8.33)	(6.02)	(6.28)	(3.54)	(6.56)	(3.06)
N	595,848	527,195	239,504	239,428	242,897	242,822

Table 6: CDS introduction and analyst forecast characteristics: differences-in-differences estimations

This table presents the results of regressions of analyst forecast characteristics on a dummy for the quarters in which a firm has active CDS trading and control variables. All variables are defined in Table 1. All independent variables are from the quarter prior to the analyst characteristic quarter. All regressions include quarter and firm fixed effects. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dispersion	Forecast Error	Ln (Following)	Current Q Revisions	Revision Share within 30 Trading Days of EAD
	(1)	(2)	(3)	(4)	(5)
CDSActive	-0.0004*	-0.001***	-0.016	1.224***	0.019**
	(-1.88)	(-2.78)	(-0.74)	(4.82)	(2.44)
Management Forecasts	-0.0002***	-0.0003***	0.039***	0.290***	-0.004*
	(-4.09)	(-3.39)	(7.32)	(4.68)	(-1.65)
Ln(Assets)	-0.001***	-0.003***	0.365***	2.830***	0.034***
	(-6.65)	(-9.24)	(27.38)	(19.09)	(7.11)
Sales Growth	-0.001***	-0.001***	0.030***	0.252***	0.005
	(-4.98)	(-4.88)	(3.13)	(3.30)	(1.20)
Leverage	0.006***	0.014***	-0.293***	-2.093***	0.041
	(7.71)	(7.91)	(-4.38)	(-3.73)	(1.64)
Capex	-0.008***	-0.023***	1.159***	-0.511	0.358***
	(-4.28)	(-5.50)	(7.59)	(-0.32)	(4.30)
EBIT	-0.009***	-0.022***	0.262	2.083	0.171
	(-2.98)	(-3.21)	(1.21)	(1.11)	(1.46)
Working Capital	-0.0003	-0.003**	0.127***	1.522***	0.120***
	(-0.65)	(-2.16)	(3.10)	(4.84)	(6.01)
Cash	-0.001	-0.0004	-0.010	-1.376***	-0.113***
	(-1.24)	(-0.38)	(-0.22)	(-4.04)	(-5.26)
Asset Turnover	0.001	-0.0002	0.184***	1.644***	0.0220
	(1.53)	(-0.14)	(3.49)	(3.98)	(0.97)
Retained Earnings	-0.0002**	-0.0002	0.010	-0.0689	-0.005
	(-2.28)	(-1.06)	(1.18)	(-0.85)	(-1.64)
PPE	0.0005	0.0003	0.165**	2.219***	0.006
	(0.81)	(0.23)	(2.55)	(4.00)	(0.25)
ROA	-0.003	-0.002	-0.109	-3.064	-0.024
	(-1.06)	(-0.34)	(-0.47)	(-1.62)	(-0.20)
Volatility	0.006***	0.014***	-0.055**	0.0837	-0.022**
	(15.90)	(16.43)	(-2.55)	(0.45)	(-2.47)
R&D	-0.004	-0.027	2.507**	9.658	-0.948**
	(-0.47)	(-1.20)	(2.16)	(0.97)	(-2.02)
Advertising	-0.005	-0.012*	-0.024	3.127	-0.231
	(-1.46)	(-1.68)	(-0.07)	(1.12)	(-1.61)
Ln(Segments)	-0.0001	-0.00002	-0.032***	-0.171	0.006

	(-0.83)	(-0.09)	(-2.66)	(-1.45)	(1.33)
Excess Stock Returns	-0.002***	-0.004***	-0.055***	-0.461***	-0.005*
	(-28.03)	(-27.92)	(-12.04)	(-12.92)	(-1.80)
Rated	0.0001	0.0004	0.036	-0.0498	-0.008
	(0.65)	(0.84)	(1.36)	(-0.21)	(-0.89)
Investment-grade	-0.001***	-0.003***	0.056**	1.333***	0.0171**
	(-3.68)	(-4.09)	(2.36)	(4.97)	(2.02)
Constant	0.007***	0.021***	-1.311***	-15.480***	0.007
	(6.28)	(8.58)	(-12.18)	(-13.85)	(0.16)
Observations	78,472	100,414	100,477	112,797	86,935
R-squared	0.450	0.380	0.654	0.669	0.204
Quarter fixed effects?	Yes	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes	Yes

Table 7: Propensity score matching samples

This table summarizes the propensity score matched samples for firms initiating CDS trading. Panel A shows the results of propensity score estimation, using the pre-matching and matched samples. All variables are defined in Table 1. All independent variables are from the quarter prior to the treatment firm-quarter. NN5 uses five-nearest-neighbor matching based on the propensity score, using matching with replacement. All-within-1% includes all matches that lie within 1% of an adopting firm-quarter's propensity score, using matching with replacement. All regressions include quarter and industry (using Fama-French 12-industry categories) fixed effects, and *t*-statistics are calculated using standard errors clustered at the firm level. Panel B shows propensity score summary statistics for both treatment and matching/control firm-quarters, for the quarter in which the match was made. Panel C presents tests of mean differences in lagged predictor variables between treatment and matching/control firm-quarters, for the quarter in which the match was made. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pre- and post-matching propensity score parameters

	Pre-matching	Post-matching	
		NN5	All within 1%
Leverage	0.605***	0.310	0.569**
	(3.57)	(1.34)	(2.27)
Ln(Assets)	0.188***	0.106***	0.183***
	(12.22)	(5.16)	(8.46)
Capex	1.562*	3.379***	3.407***
	(1.78)	(3.10)	(2.94)
EBIT	5.350***	8.417***	7.998***
	(5.04)	(4.55)	(4.21)
Working Capital	0.186*	0.084	0.196
	(1.76)	(0.59)	(1.35)
Cash	-0.116	-0.338	-0.268
	(-0.67)	(-1.27)	(-1.10)
Asset Turnover	0.079	0.091	0.233
	(0.63)	(0.54)	(1.44)
Retained Earnings	-0.041	-0.039	-0.080
	(-1.03)	(-0.84)	(-1.23)
PPE	0.055	-0.199	-0.224
	(0.49)	(-1.38)	(-1.58)
ROA	-5.438***	-9.578***	-9.028***
	(-4.70)	(-4.81)	(-4.23)
Excess Stock Returns	0.009	0.005	0.021
	(0.25)	(0.09)	(0.46)
Volatility	-0.243**	-0.180	-0.240
	(-1.97)	(-1.20)	(-1.58)
Rated	0.960***	0.394***	0.414***
	(12.74)	(4.11)	(4.27)
Investment-grade	0.275***	0.197***	0.256***
	(5.52)	(3.22)	(4.16)
Constant	-5.291***	-3.697***	-4.661***
	(-20.32)	(-10.26)	(-14.29)
Observations	155,645	67,666	86,984
Pseudo R-squared	0.303	0.058	0.075
Quarter fixed effects?	Yes	Yes	Yes
Industry fixed effects?	Yes	Yes	Yes

Panel B: Propensity score summary statistics: treatments and controls

	NN5								
	mean	sd	min	p5	p25	p50	p75	p95	max
Treatments	0.0405	0.0306	0.0000	0.0044	0.0179	0.0321	0.0555	0.0993	0.1751
Controls	0.0403	0.0304	0.0000	0.0044	0.0179	0.0322	0.0554	0.0996	0.1846
Absolute Difference	0.0005	0.0022	0.0000	0.0000	0.0000	0.0001	0.0003	0.0014	0.0453

	All within 1%								
	mean	sd	min	p5	p25	p50	p75	p95	max
Treatments	0.0343	0.0231	0.0000	0.0049	0.0173	0.0281	0.0481	0.0777	0.1751
Controls	0.0343	0.0230	0.0000	0.0049	0.0173	0.0282	0.0482	0.0774	0.1737
Absolute Difference	0.0002	0.0002	0.0000	0.0000	0.0001	0.0001	0.0002	0.0005	0.0017

Panel C: Mean differences in firm characteristics: treatments and controls

	NN5				All within 1%			
	Treatments	Controls	Difference	T-stat	Treatments	Controls	Difference	T-stat
Leverage	0.180	0.187	-0.010	(-1.47)	0.177	0.185	-0.008	(-1.63)
Ln(Assets)	8.959	8.698	0.261***	(3.94)	8.739	8.346	0.393***	(6.94)
Capex	0.019	0.018	0.001	(0.57)	0.018	0.017	0.001	(0.68)
EBIT	0.021	0.021	0.0002	(0.14)	0.021	0.020	0.001	(0.51)
Working Capital	0.106	0.109	-0.003	(-0.29)	0.111	0.112	-0.001	(-0.10)
Cash	0.078	0.080	-0.002	(-0.42)	0.079	0.077	0.002	(0.42)
Asset Turnover	0.217	0.215	0.002	(0.24)	0.218	0.215	0.003	(0.41)
Retained Earnings	0.157	0.125	0.032*	(1.72)	0.150	0.122	0.028*	(1.66)
PPE	0.315	0.320	-0.005	(-0.44)	0.309	0.317	-0.008	(-0.63)
ROA	0.008	0.009	-0.001	(-0.45)	0.008	0.009	0.000	(-0.11)
Excess Stock Returns	0.138	0.181	-0.043**	(-2.16)	0.143	0.194	-0.051**	(-2.45)
Volatility	0.363	0.393	-0.030***	(-3.36)	0.363	0.410	-0.048***	(-5.36)

Table 8: CDS introduction and analyst forecast characteristics - differences-in-differences estimations with propensity score matched samples

This table presents the results of regressions of analyst forecast characteristics on a dummy for the quarters in which a firm has active CDS trading and control variables, using propensity score matched samples for firms initiating CDS trading. All variables are defined in Table 1. All independent variables are from the quarter prior to the analyst characteristic quarter. NN5 uses five-nearest-neighbor matching based on the propensity score, using matching with replacement. All-within-1% includes all matches that lie within 1% of an adopting firm-quarter's propensity score, using matching with replacement. All regressions include quarter and firm fixed effects, and *t*-statistics are calculated using standard errors clustered at the firm level. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	NN5					All within 1% of Propensity Score				
	Dispersion	Forecast Error	Ln (Following)	Current Q Revisions	Revision Share	Dispersion	Forecast Error	Ln (Following)	Current Q Revisions	Revision Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CDSActive	-0.001**	-0.001*	-0.040	0.048	0.001	-0.0004*	-0.001*	-0.040	0.256	0.005
	(-2.01)	(-1.82)	(-1.60)	(0.15)	(0.13)	(-1.69)	(-1.65)	(-1.54)	(0.78)	(0.49)
Management Forecasts	-.0001	-0.0001	0.028***	0.226	-0.002	-0.0001	-0.0002	0.038***	0.269*	-0.001
	(-0.81)	(-0.55)	(2.91)	(1.27)	(-0.40)	(-1.21)	(-0.94)	(3.93)	(1.83)	(-0.13)
Ln(Assets)	-0.001***	-0.002***	0.275***	3.061***	0.021**	-0.0008***	-0.002***	0.289***	3.432***	0.025**
	(-2.66)	(-3.71)	(10.49)	(9.08)	(2.11)	(-2.75)	(-3.69)	(10.83)	(9.77)	(2.49)
Sales Growth	-0.001***	-0.001	0.012	0.434	-0.008	-0.001***	-0.001	0.029	0.570**	-0.012
	(-4.02)	(-1.57)	(0.58)	(1.46)	(-0.94)	(-2.72)	(-1.40)	(1.28)	(2.20)	(-1.08)
Leverage	0.004***	0.008**	-0.207	0.856	0.0302	0.004***	0.009***	-0.261*	-0.489	0.0475
	(2.83)	(2.50)	(-1.30)	(0.50)	(0.58)	(2.71)	(2.69)	(-1.78)	(-0.30)	(0.93)
Capex	-0.010***	-0.028***	1.223***	-2.675	0.242	-0.012***	-0.029***	1.350***	-0.684	0.370**
	(-3.40)	(-4.21)	(3.49)	(-0.54)	(1.39)	(-3.67)	(-4.19)	(3.83)	(-0.13)	(2.34)
EBIT	-0.017*	-0.042**	0.462	0.572	0.405	-0.014	-0.036	0.534	-0.233	0.492
	(-1.75)	(-1.98)	(0.79)	(0.09)	(1.50)	(-1.29)	(-1.53)	(0.85)	(-0.04)	(1.63)
Working Capital	0.001	-0.001	0.102	3.136**	0.074**	0.001	-0.003	0.083	2.576**	0.087**
	(1.06)	(-0.52)	(0.98)	(2.21)	(2.06)	(0.54)	(-1.20)	(0.89)	(2.23)	(2.30)
Cash	0.0002	0.002	0.127	-2.991**	-0.075	-0.0001	0.002	0.109	-2.820**	-0.107**
	(0.14)	(0.91)	(1.17)	(-2.24)	(-1.55)	(-0.06)	(0.93)	(1.05)	(-2.30)	(-2.23)
Asset Turnover	0.001	0.003	0.233*	4.352***	-0.004	0.0001	0.001	0.113	3.184**	-0.049
	(0.72)	(0.99)	(1.91)	(3.13)	(-0.09)	(0.04)	(0.38)	(1.02)	(2.52)	(-0.99)
Retained Earnings	-0.001***	-0.003***	0.070**	1.550***	0.006	-0.002***	-0.003***	0.104***	2.324***	0.009
	(-3.36)	(-3.61)	(2.18)	(3.13)	(0.50)	(-3.27)	(-3.26)	(3.19)	(3.98)	(0.67)
PPE	0.001	0.002	0.326***	4.288***	0.020	0.003**	0.0030	0.387***	5.260***	0.010

	(1.10)	(0.98)	(2.68)	(3.54)	(0.45)	(2.33)	(1.58)	(3.19)	(3.67)	(0.21)
ROA	-0.007	-0.003	-0.131	1.462	-0.209	-0.010	-0.012	-0.193	-0.479	-0.288
	(-0.70)	(-0.17)	(-0.19)	(0.22)	(-0.71)	(-0.90)	(-0.50)	(-0.26)	(-0.08)	(-0.85)
Volatility	0.009***	0.019***	-0.054	0.916	-0.065***	0.009***	0.018***	-0.025	0.874	-0.03***
	(8.86)	(8.51)	(-1.08)	(1.26)	(-3.55)	(8.58)	(8.00)	(-0.49)	(1.12)	(-3.65)
R&D	0.014	0.027	3.357	18.900	-0.654	0.013	0.038	4.415*	16.400	-0.930
	(0.77)	(0.90)	(1.37)	(0.59)	(-0.63)	(0.64)	(1.14)	(1.94)	(0.62)	(-0.95)
Advertising	-0.002	-0.006	1.303*	14.040	-0.301	-0.007	-0.011	1.172	3.503	-0.580
	(-0.32)	(-0.48)	(1.75)	(1.17)	(-1.00)	(-0.79)	(-0.86)	(1.44)	(0.28)	(-1.60)
Ln(Segments)	0.0001	0.00003	-0.024	-0.258	-0.001	-0.0001	-0.0001	-0.026	-0.338	-0.003
	(0.32)	(0.09)	(-1.31)	(-1.21)	(-0.14)	(-0.23)	(-0.33)	(-1.44)	(-1.63)	(-0.29)
Excess stock return	-0.002***	-0.004***	-0.095***	-0.987***	-0.010*	-0.002***	-0.004***	-0.087***	-0.947***	-0.010*
	(-13.27)	(-11.50)	(-7.52)	(-6.43)	(-1.77)	(-12.13)	(-10.30)	(-7.31)	(-6.54)	(-1.89)
Rated	0.0001	0.0014*	0.111**	-0.032	0.002	-0.0002	0.001	0.093*	0.514	0.002
	(0.19)	(1.72)	(2.39)	(-0.06)	(0.13)	(-0.59)	(0.86)	(1.94)	(0.83)	(0.10)
Investment-grade	-0.001*	-0.002***	0.060*	1.320***	0.027**	-0.0005	-0.002***	0.063**	0.987***	0.024*
	(-1.80)	(-2.84)	(1.88)	(4.08)	(2.00)	(-1.46)	(-2.79)	(1.97)	(2.95)	(1.91)
Constant	0.005**	0.015***	-0.830***	-21.830***	0.173*	0.007**	0.017***	-0.941***	-24.560***	0.122
	(2.13)	(2.89)	(-3.37)	(-7.02)	(1.85)	(2.39)	(3.14)	(-3.67)	(-7.60)	(1.32)
Observations	70,461	78,447	78,492	82,401	73,231	90,807	101,663	101,720	107,145	94,262
R-squared	0.487	0.405	0.647	0.661	0.191	0.482	0.376	0.632	0.657	0.185
Quarter fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: CDS introduction and analyst downgrade timing and incidence ahead of large negative earnings surprises

This table presents the results of regressions of the mean number of trading days from any equity analyst downgrade to the earnings announcement date on a dummy for the quarters in which a firm has active CDS trading, large negative earnings surprise interaction terms, and control variables. Probit models for whether any equity analyst makes a recommendation downgrade or any rating agency makes a rating downgrade are also presented. Large Negative Surprise is defined as a negative earnings surprise that is greater than 0.5% of a firm's market capitalization at each quarter end. All variables are defined in Table 1. All independent variables, except for Large Negative Surprise, are from the quarter prior to the analyst characteristic quarter. All regressions include quarter fixed effects, and *t*-statistics are calculated using standard errors clustered at the firm level. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Downgrade in quarter		Time to downgrade
	Rating Agencies	Equity Analysts	Equity Analysts
	(1)	(2)	(3)
CDSactive	0.136**	0.012	-0.459
	(2.52)	(0.47)	(-1.36)
Large Negative Surp (>0.5% of Mcap)	0.338***	-0.060***	0.671
	(4.50)	(-3.29)	(1.53)
CDS Active x Large Negative Surp	0.170*	0.150***	1.932**
(>0.5% of Mcap)	(1.68)	(2.84)	(2.04)
Management Forecasts	0.048*	0.101***	-0.500***
	(1.73)	(9.58)	(-3.11)
Ln(Assets)	0.043**	0.207***	-0.556***
	(2.11)	(29.20)	(-5.55)
Sales Growth	-0.399***	0.089***	0.127
	(-3.42)	(6.57)	(0.51)
Leverage	0.799***	-0.487***	-0.612
	(3.46)	(-6.92)	(-0.52)
Capex	-0.490	3.729***	-5.625
	(-0.40)	(11.70)	(-1.01)
EBIT	-11.430***	1.790***	-13.200
	(-4.89)	(3.97)	(-1.49)
Working Capital	-0.337**	0.067	-1.321*
	(-2.45)	(1.63)	(-1.85)
Cash	-0.663**	0.461***	0.339
	(-2.55)	(9.13)	(0.38)
Asset Turnover	0.222*	0.203***	-2.490***
	(1.80)	(4.65)	(-3.62)
Retained Earnings	0.371***	0.0207**	-0.355**
	(4.58)	(2.37)	(-2.04)
PPE	0.122	0.122***	-1.578***
	(1.07)	(3.00)	(-2.62)
ROA	5.360*	-0.406	10.980

	(1.91)	(-0.83)	(1.11)
Volatility	0.919***	0.279***	-1.185**
	(8.08)	(9.28)	(-1.96)
R&D	2.598	3.365***	9.509
	(0.81)	(3.56)	(0.61)
Advertising	0.994	1.644***	-17.560***
	(0.65)	(6.20)	(-4.06)
Ln(Segments)	0.0573*	-0.059***	0.082
	(1.93)	(-5.02)	(0.48)
Excess Stock Returns	-0.731***	-0.120***	-2.206***
	(-8.84)	(-11.83)	(-10.47)
Rated		0.068***	-0.557
		(3.04)	(-1.61)
Investment-grade	-0.066	-0.079***	-0.855**
	(-1.10)	(-2.99)	(-2.32)
Constant	-2.775***	-2.378***	41.490***
	(-5.48)	(-22.58)	(-16.69)
Observations	15,055	85,098	32,914
R-squared			0.031
Pseudo R-squared	0.149	0.072	
Quarter fixed effects?	Yes	Yes	Yes

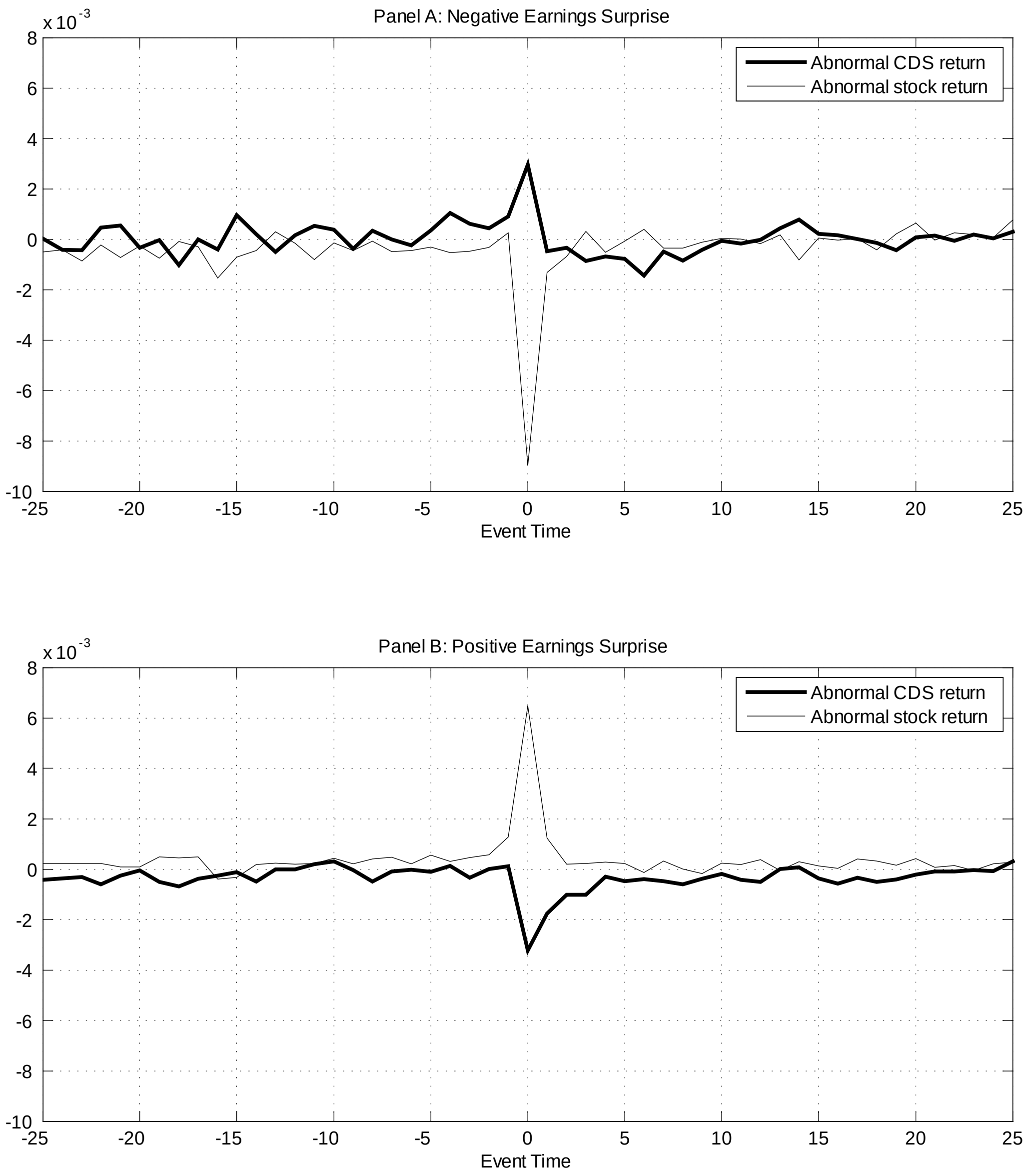
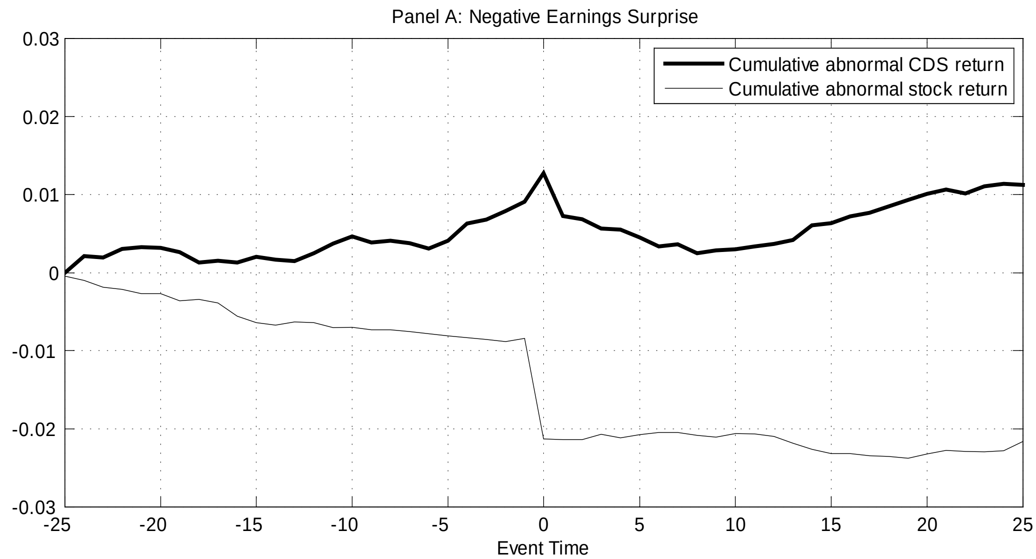


Figure 1: Abnormal CDS and stock returns around earnings announcements.

Figure 1 shows the average daily abnormal CDS and stock returns during the 25 trading days before and after negative (positive) earnings surprises on the earnings announcement day. Earnings surprise is the actual earnings-per-share (EPS) minus the median of all analyst estimates of the EPS submitted within 90 days prior to the earnings announcement date, normalized by the share price at the end of the quarter. Panels A and B show average abnormal returns for negative and positive earnings surprises, respectively. Abnormal CDS returns are raw CDS returns in excess of the equally-weighted average return across all CDS obligors in the sample. Abnormal stock returns are raw stock returns in excess of the value-weighted market return from CRSP.



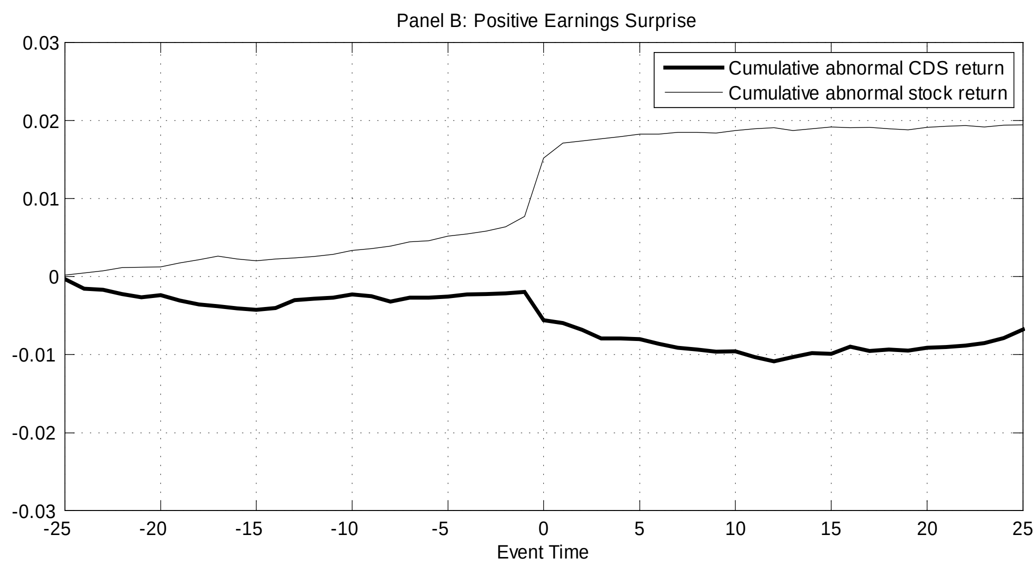


Figure 2: Cumulative abnormal CDS and stock returns around earning announcements.

Figure 2 shows the average cumulative abnormal CDS and stock returns during the 25 trading days before and after negative (positive) earnings surprises on the earnings announcement day. Earnings surprise is the actual earnings-per-share (EPS) minus the median of all analyst estimates of the EPS submitted within 90 days prior to the earnings announcement date, normalized by the share price at the end of the quarter. Panels A and B show average cumulative abnormal returns for negative and positive earnings surprises, respectively. Abnormal CDS returns are raw CDS returns in excess of the equally-weighted average return across all CDS obligors in the sample. Abnormal stock returns are raw stock returns in excess of the value-weighted market return from CRSP.

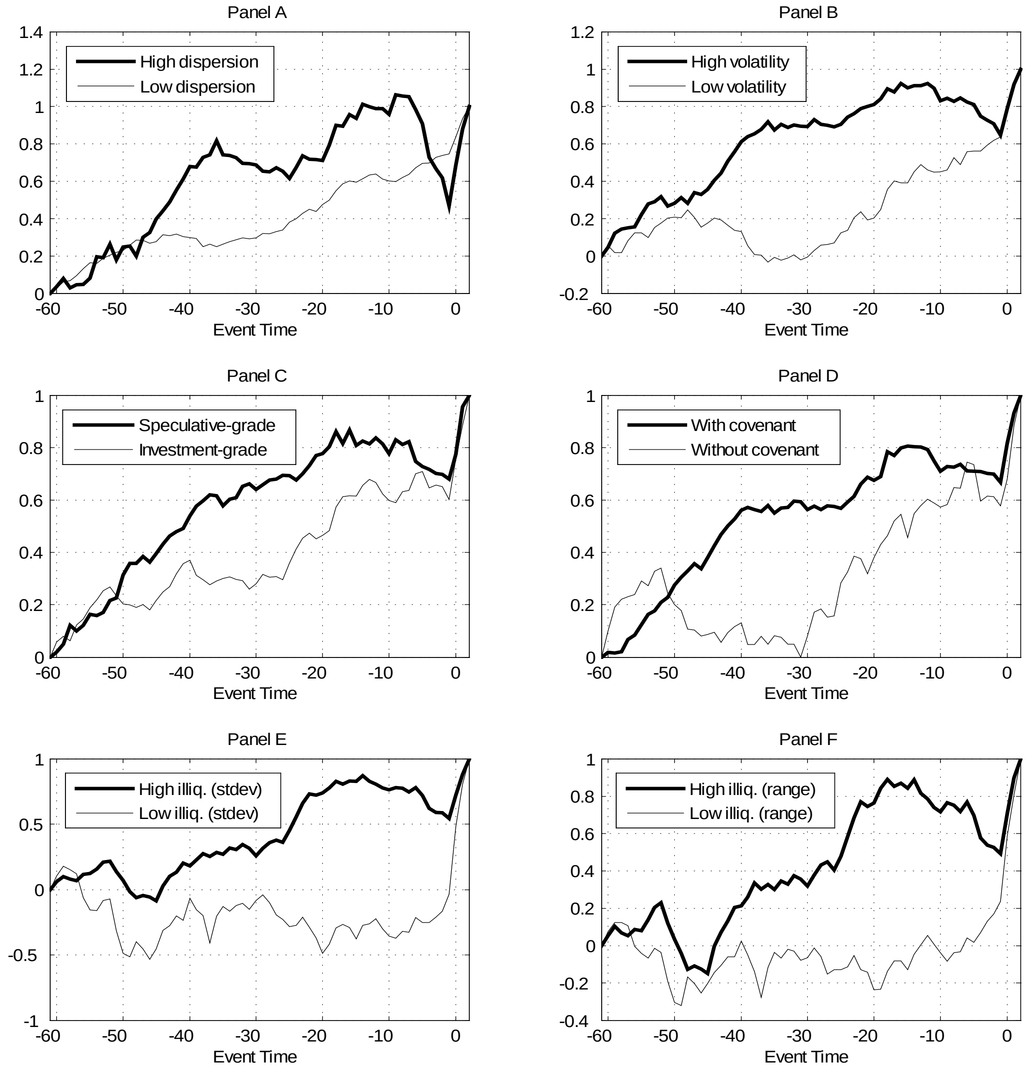


Figure 3: Intra-period timeliness (IPT) returns.

Figure 3 plots portfolio cumulative abnormal CDS returns (CARs) from 61 trading days before to two days after the earnings announcements, normalizing the CAR at $t = -61$ to zero and $t = 2$ to one. The intra-period timeliness (IPT) measure is defined as the area under the standardized CAR function from $t = -61$ to $t = 2$ using the trapezoidal approximation: $\text{IPT} = \frac{1}{\text{CAR}_2}\sum_{t=-60}^{2}\frac{\text{CAR}_{t-1}+\text{CAR}_t}{2} = \sum_{t=-60}^{1}\frac{\text{CAR}_t}{\text{CAR}_2}+0.5$. Panel A shows results for portfolios of firms with above-median and below-median analyst forecast dispersion; Panel B above-median and below-median idiosyncratic stock return volatility; Panel C investment-grade and speculative-grade credit ratings; Panel D with and without earnings-based loan covenants; Panel E above-median and below-median bond illiquidity (using the standard deviation of bond prices within the month); Panel F above-median and below-median bond illiquidity (using the range of bond prices within the month).