Did CDS Trading Improve the Market for Corporate Bonds?[1]

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Abstract

Did CDS Trading Improve the Market for Corporate Bonds?

Financial innovation through the creation of new markets and securities impacts related markets as well, changing their efficiency, quality (pricing error) and liquidity. The credit default swap (CDS) market was undoubtedly one of the salient new markets of the past decade. In this paper we examine whether the advent of CDS trading was beneficial to the underlying secondary market for corporate bonds. We employ econometric specifications that account for information across CDS, bond, equity, and volatility markets. We also develop a novel methodology to utilize all observations in our data set even when continuous daily trading is not evidenced, because bonds trade much less frequently than equities. Using an exhaustive sample of CDS and bond trades over 2002–2008, we find that the advent of CDS was largely detrimental – bond markets became less efficient, evidenced greater pricing errors and experienced lower liquidity. These findings are robust to various slices of the data set and specification of our tests.

Key words: CDS, bond market efficiency.
JEL classification: G10, G14

“...We need broad regulatory reform of over-the-counter derivatives to best lower risk and promote transparency in the marketplace...”
CFTC Chairman Gary Gensler,
OTC Derivatives Reform Conference (Mar 9, 2010)

1 Introduction

Innovation is a double-edged sword and can have positive and negative outcomes. The creation of new securities completes markets, and modifies information generation and liquidity. A major innovation in the fixed-income and credit markets since the turn of the century is the introduction of the credit default swap (CDS), a credit insurance contract with a payoff linked to that of the default or change in credit characteristics of an underlying reference bond or issuer. It is only to be expected that the advent of the CDS bond market would have resulted in a change in the information environment, likely favorable, for the underlying bonds. In this paper we examine whether the introduction of CDS improved the secondary corporate bond market in terms of underlying efficiency, market quality and liquidity.[1] Taking a time-series perspective we ask: did an issuer’s bonds become more efficient and liquid after CDS trading was instituted on the reference instruments of the issuer? From a cross-sectional perspective we query: are bonds of firms with traded CDS contracts more efficient and liquid than bonds of firms without any CDS contracts?

Did corporate bond trading decline after the introduction of CDS, because traders were able to implement a credit view better and more cheaply in the CDS markets? Figure 1 shows the mean size of trades in our data sample relative to the date of inception of CDS trading: the mean size of a trade falls to less than a million dollars – an evident decline in secondary bond market activity. Similarly, Figure 2 depicts a sharp drop in turnover of bonds once CDS trading begins.

Figure 1: here.

Figure 2: here.

Figures 1 and 2 indicate that bond trading may have declined, but it is likely that bond market efficiency may have improved if the CDS market generated useful information that

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[1] Most equity options are exchange traded, and hence the introduction of an equity option is decided by the corresponding options exchange depending upon factors such as trading volume, market capitalization and turnover of the underlying stock. In contrast, the CDS market is OTC over the period of this study and hence decentralized; CDS introduction is initiated by the dealer banks depending on factors such as size of outstanding debt on an issuer, underlying credit risk of the issuer, and demand for credit protection. More recently, CDS are being moved to a centralized clearing system, and are also exchange traded.

was quickly reflected in bond prices. As our empirics will show, the informational efficiency of corporate bonds is poor both before and after the advent of CDS trading, and interestingly, bonds become more inefficient after CDS trading commences. This suggests that the CDS markets did have detrimental effect on bond market efficiency. Market quality too showed no signs of improvement after CDS introduction. Also, using various measures of liquidity we find that post-CDS bond liquidity is lower than pre-CDS liquidity.

The prior literature on bond market efficiency has examined lead-lag relationships between corporate bonds and equity markets as a way of assessing the relative efficiency of bonds to equity (e.g., Kwan (1996), Hotchkiss and Ronen (2002), Downing, Underwood and Xing (2009), Ronen and Zhou (2009)), and Ismailescu and Phillips (2011); the findings, as we discuss in the next section, are mixed. Our goal in this paper is different from that of the prior literature. Whereas we do revisit the issue of bond market efficiency, our goal is to assess what role the CDS markets played vis-a-vis the bond markets, and to determine whether CDS trading was beneficial or detrimental to the bond markets on criteria such as efficiency, quality, and liquidity.

Our econometric specifications extend earlier work, necessitated by the increasing complexity of the fixed-income markets. Corporate bonds contain call and amortization features, various default triggers, and conversion and put options. Therefore, in this paper we consider multivariate lead-lag relationships of corporate bond returns to returns on various other securities that would also be incorporating issuer-specific information. These issuer-specific securities and information include (a) the equity of the issuer, (b) the implied volatility embedded in options traded on equity (to capture information about business and credit risk), (c) the CDS spreads of the issuer, and (d) the return on Treasury securities. Hence, a wide range of factors are used to assess the efficiency of bonds. In addition, (e) lagged corporate bond returns may explain current returns if bonds are weak-form inefficient. We run relative efficiency tests for periods prior to the commencement of CDS trading for a firm, and compare these results to the period after CDS trading commences. In this way we judge whether or not the introduction of CDS was beneficial in enhancing bond market efficiency.

In structural models, pioneered by Merton (1974), equity value and implied equity volatility are inputs to deriving firm value and volatility that in turn drive a firm's credit spreads. In addition, an important non-issuer specific explanatory variable is the return on an index of risk-free bonds, such as a government bond index. Further, credit risk may be measured as the spread on CDS contracts. By regressing bond returns on contemporaneous and lagged values of these variables, and testing for the joint significance of the lagged variables, we determine whether bonds were relatively inefficient compared to other securities that were also impounding information about the firm. Using this approach, we find that corporate bonds became increasingly inefficient as CDS markets matured.

Did CDS trading improve the accuracy of bond prices? Following Hotchkiss and Ronen (2002) we implement the market quality measure (q) of Hasbrouck (1993). Hasbrouck's measure examines the discrepancy between efficient prices and transaction prices to assess the extent of pricing error. The inverse of the variance of pricing error is a metric of market quality. Whereas this metric is related to market efficiency, its focus is on whether prices accurately impound information. We compute q for bonds before and after the advent of CDS trading. The measure does not improve after CDS trading begins, suggesting that CDS markets did not enhance bond market quality.

Did bond market liquidity respond favorably to the inception of CDS? We compute several proxies for liquidity before and after the introduction of CDS trading. Our metrics include the number of daily trades, the dollar volume of trades per day, turnover, the LOT illiquidity measure of Lesmond, Ogden and Trzcinka (1999), the covariance illiquidity measure of Bao, Pan and Wang (2008), and the well-known illiquidity metric of Amihud (2002). Whereas the mean number of daily trades increased with the growth of bond markets over time, the mean size of the trades declined after CDS markets opened. All other measures – daily turnover, LOT, covariance illiquidity, and Amihud's metric – indicate significant declines in liquidity post-CDS.

Unlike equity markets that have much higher trading frequencies, examining these properties of bond markets is complicated by the fact that bonds are thinly traded, and consecutive days of trading may not always exist in order to compute returns for our tests. In order to ensure that available data is used to the best extent possible, we develop alternative approaches to augmenting the data thereby resulting in larger data sets. The procedures are described in Appendix B. Re-running our analysis on the augmented data set confirms the robustness of our empirical analyses. Taken together, the results suggest that CDS introduction did not improve secondary bond market efficiency, quality or liquidity.

What explains our results? One possible explanation is that price discovery mainly occurs in the CDS market because of micro-structure factors that make it the most convenient location for the trading of credit risk; second, there are different participants in the cash and derivative markets who trade for different reasons (e g., Blanco, Brennan and Marsh (2005)). The CDS market involves very active trading and is mostly dominated by institutional players, and hence constitutes a highly likely venue for all informed trading.[2] At the same

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[2] BIS indicates that more than 95% of CDS transactions occur between financial institutions.

time, corporate bond markets are significantly less liquid; bonds are traditionally held by buy-and-hold investors. Further, with the proliferation of the CDO securitization market, corporate bonds were increasingly parked inside pools and were not actively traded. For these reasons, as institutional investors migrated to the CDS markets over time, corporate bond markets became less liquid and active (though TRACE mandates did improve bond market liquidity somewhat; e.g., Edwards, Harris and Piwowar (2007), Bessembinder, Maxwell and Venkataraman (2006)).

Our findings echo earlier results found in option markets, where the price discovery role of options is more pronounced when the liquidity of the option market is higher compared to that of the stock market, when options provide higher leverage, and when the probability of informed trading is high (Easley, O'Hara, and Srivinas (1998)).

Our findings have a bearing on revealing where informed trading – and hence price discovery – might take place in credit markets, thereby indicating that excessive regulations in CDS markets may be punitive. Our findings provide insights into how the bond markets may have been impacted following CDS introduction, and also have bearings on the recent global OTC derivative market reform, in particular the regulatory efforts in US spearheaded by CFTC and SEC.[3]

The paper proceeds as follows. In Section 2 we review related work and distinguish our goals and methodology from earlier research. Section 3 describes the data set we employ. This section is complemented by Appendix B that explains our new approach to creating non-overlapping returns with a view to utilizing the entire data set for analysis, particularly for robustness tests. Section 4 presents tests of bond market efficiency, and the finding that CDS markets may have been detrimental to bond market efficiency. We explore alternative cuts of the data set as robustness tests and show that the main findings about efficiency are preserved. Section 5 explores the impact of CDS trading on bonds through the lens of Hasbrouck (1993)'s q-measure, and finds no improvement in market quality. Section 6 examines how CDS trading impacted the liquidity of bonds using several metrics—liquidity in fact worsens. In Section 7 we consider various alternate specifications and variations of our tests in order to assess the robustness of the results and find that the results are well-supported. Conclusions and discussion are offered in Section 8.

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[3] For example, CDS markets were blamed for naked shorting and excessive speculation, lowering capital requirements for FIs, lowering underwriting standards in ABS market, and lowering monitoring incentives for banks, among others (Source: ISDA). The Dodd-Frank Act in the US introduces regulatory measures such as dealer collateral requirements, promoting transparency, setting up centralized clearing houses, regulating naked CDS positions, and imposing position limits.

2 Background and Related Literature

Early work on bond market efficiency focused on whether bond prices rapidly and accurately incorporated relevant information about issuer firms. A simple way to examine this proposition is to look at whether information that is incorporated into equity prices is incorporated fully into bond prices in a timely manner. Such an analysis does not presuppose that the equity markets are efficient, yet tests whether the bond market is less efficient than the equity market.

For example, Kwan (1996) finds that, although there exists a positive contemporaneous relationship between changes in bond yields and stock returns, stocks lead bonds in incorporating firm-specific information, suggesting that bonds are less efficient than stocks of issuing firms. In contrast, Hotchkiss and Ronen (2002) find individual bonds to be as informationally efficient as equity in rapidly responding to event-driven news, and market quality is no different for bonds than for the corresponding underlying stocks.[4]

Downing, Underwood and Xing (2009) report that stock returns lead non-convertible bond returns at the hourly level for bonds of *low* credit quality. They also find convertible bonds to be less efficient than stocks for all credit qualities. Thus they conclude that bonds that are of lesser quality and have complex features are more likely to be inefficient. However, Ronen and Zhou (2009) argue that the corporate bond market is not necessarily slower than the equity market in processing information and that it serves as an important venue for information-based trading, particularly when stock market liquidity is low. In these instances, bond trades are found to fully incorporate all information content in earnings surprises before significant stock market reactions occur.

Previous work has also examined the source of linkages between bond and equity markets. For example, Gebhardt, Hvidkjaer and Swaminathan (2005) document momentum spillovers from equities to investment grade corporate bonds of the same firm. In addition, corporate news events such as mergers, takeovers, new debt issues, and/or stock repurchases involving wealth transfer to equity holders can further induce linkages between bonds and underlying stocks (Alexander, Edwards and Ferri (2000) and Maxwell and Stephens (2003)).

There is growing evidence of the linkage between bond and CDS markets too. For instance, Hull, Predescu and White (2004) study the information impact of CDS spreads on bond

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[4] The authors suggest that the introduction of the fixed-income pricing system (FIPS) by the National Association of Securities Dealers (NASD) in 1994 might have enhanced bond market transparency, thereby leading to improved informational efficiency. Beginning July 2002, coinciding roughly with the start of our data, transparency has been enhanced with FIPS being rolled into a larger NASD system, the Trade Reporting and Compliance Engine (TRACE).

market ratings, and find that credit spreads provide helpful information in estimating the probability of negative credit rating changes (downgrades, reviews for downgrade and negative outlooks). Blanco, Brennan and Marsh (2005) find that the CDS market leads the bond market in determining the price of credit risk. For 27 of the firms they examined, the CDS market contributes on average around 80% of price discovery. In four of the remaining six cases, CDS prices Granger-cause credit spreads, suggesting price leadership.

Baba and Inada (2009) find that subordinated bond and CDS spreads for Japanese banks are largely cointegrated, and the CDS spread plays a bigger role in price discovery than the bond spread as evidenced by stronger reactions of the CDS spread to financial market variables and bank-specific accounting variables than the bond spread. Norden and Wagner (2008) find that CDS spreads explain syndicated loan rates much better than spreads of similar-rated bonds.

Forte and Pena (2009) study the long run equilibrium relationships between bond, CDS and stock market implied spreads, and find that stocks lead CDS and bonds more frequently than the reverse, and the CDS market leads the bond market. Ashcraft and Santos (2009) find that CDS introduction has not lowered the cost of debt financing or loan funding for the average borrower. They further report that risky and informationally opaque firms appear to have been more adversely affected by the CDS market. However, they look at bonds at the time of issue whereas our analysis spans the life cycle of bonds pre- and post-CDS. Norden and Weber (2009) study the intertemporal relationships between CDS, stock and bond markets. They find that stock returns lead CDS and bond spread changes, and the CDS market contributes more to price discovery than the bond market; the latter effect is stronger for US than for European firms.

Recently, Boehmer, Chava and Tookes (2010) examine the implications of derivatives and corporate debt markets on equity market quality. They find that listed options have more liquid equity and more efficient stock prices. By contrast, firms with traded CDS contracts have less liquid equity and less efficient stock prices. Overall, they find that the impact of CDS markets is generally negative.

These recent findings raise the question as to whether the introduction of CDS markets may have impaired the informational efficiency of bond markets, and we empirically assess this question in this paper.[5] Unlike earlier work, our focus lies in assessing whether the inception

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[5] There is a long history of articles examining the impact of new derivatives markets on the market for the underlying security. Studies such as Conrad (1989) and Skinner (1989) show that equity option listing results in volatility reduction for the underlying. Long, Schinski, and Officer (1994) found a marked increase in trading in the underlying, but no change in price volatility. Sorescu (2000) finds positive (negative) abnormal returns for options listed during 1973–1980 (post-1980). Most recently, in sovereign bond markets, Ismailescu

of CDS trading was beneficial to bond markets in terms of efficiency, pricing error, and liquidity. We also use an extensive data set, running from 2002–2008, a period that spans the introduction of CDS on many reference names. Our findings are mostly consistent with much of the literature in that we find corporate bonds to be relatively inefficient. In addition, we show that corporate bonds did not become more efficient after the introduction of CDS trading; efficiency, in fact, appears to have deteriorated. We find no evidence of increases in market quality, as defined by Hasbrouck's measure. We also document a decline in bond liquidity, using several different metrics, after the emergence of CDS markets.

3 Data

We construct a comprehensive data set of bonds and CDS trades for the period spanning the third quarter of 2001 to the third quarter of 2009. The sample period spans the years in which the CDS markets experienced rapid growth. We undertake an extensive sample construction and data-filtering process to arrive at our final data set. We first obtain corporate bond trading data from TRACE; our initial sample consists of trades in 34,900 bonds issued by 4,869 firms, resulting in 5,768,201 daily time series observations. Next we collect daily trade data on 5-year maturity CDS from Bloomberg; our preliminary sample consists of CDS trades of 620 issuing firms, amounting to 598,221 daily CDS spread observations.

We merge the data for trades on bonds and CDS with bond issue-specific data from the Fixed Income Securities Database (FISD) and with equity data from CRSP. We filter out bonds with incomplete data, and retain bonds issued between 1994 and 2007. We keep only those bonds that are US-domestic, dollar-denominated, non-convertible issues. Our final sample includes straight bonds, and bonds with call, and put features. After eliminating bonds that do not belong to publicly-traded firms, and merging and matching FISD, CRSP, TRACE and CDS data sets, we end up with 1,545 bonds issued by 350 firms in our data set, comprising 1,365,381 transactions. The data spans, on average, 884 trading days per bond issue, and runs from 2002 to 2008. Appendix A provides the details of sample construction and data-filtering process. The data summary is provided in Table 1.

Table 1: here.

After filtering the data for days on which concurrent observations are available on returns in the different markets under consideration, we are left with fewer observations when our

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and Phillips (2011) provide evidence that the introduction of credit default swaps improved efficiency in the underlying bonds.

empirical test requires the joint use of data from equity, bond, CDS and volatility markets. Details on all these breakdowns as well as the breakdowns based on pre-CDS and post-CDS partitions are provided in Panel A of Table 1. While equity and CDS markets are highly liquid and have daily returns for most of the relevant time spans (95% and 69% of the sample for equity and CDS respectively), bond markets are far less liquid. We find that valid daily bond returns (namely, two consecutive trading days with valid bond prices) exist for only 24% of the bond transaction data of 1.36 million bond trading days, implying that more than three-fourth of the bond transaction data is sparse (that is, bond prices exist for non-consecutive trading days only), making it harder to construct daily bond returns. Overall, only 18% of the total time-series data sample has valid (daily) returns jointly for bonds, CDS as well as stocks. Of the total of 1.36 million bond price observations, the vast majority (i.e., 1.25 million transactions or 92% of bond trading prices) occur after the introduction of the corresponding CDS, and only about 21% of such post-CDS trading days have valid returns jointly for bonds, CDS as well as stocks. The fact that the coverage period of TRACE database almost exactly coincides with the emergence of the CDS market explains why the vast majority of bond transaction observations correspond to the post-CDS period (and not before).

In Panel B of Table 1 we present definitions of the five empirical daily return variables used in our tests. These include the return on corporate bonds (computed as changes in daily yields), return on stocks, changes in CDS spreads, changes in matching maturity swap rates, and changes in the volatility index. All results reported in this paper are based on bond returns computed using mean daily yields. Our findings and conclusions remain unaltered if we compute bond returns using median or end-of-day (last) daily yields.

Table 2 presents the classification of time-series observations on bond trading by year and by relation to CDS trading, and also the descriptive statistics and correlations of different return variables. Table 2, Panel A reports the number of bond trades with valid returns each year (classified based on whether these trades correspond to the period before or after the introduction of CDS on the underlying bond). From 2002 to 2008, the number of bond transactions rises at first, peaks in 2005, and declines thereafter. Panel A also reports the number of new CDS introduced by year. The vast majority of CDS are introduced in the first three years of our sample, 2002–2004 (the table excludes the 18 CDS introduced in 2001).

Table 2: here.

Given the disparate types of securities involved in our analysis, i.e., stocks, bonds, and

CDS, consecutive days on which all these securities are traded may not always be available, but are nevertheless required for the econometric tests we conduct. Of the 1,365,381 daily transactions observations, only 249,605 have valid daily returns jointly for bonds, stocks and CDS. However, our requirement is more stringent in the empirical analysis of efficiency which involve concurrent as well as *lagged* daily return variables. This results in additional attrition of the sample, biasing it towards bonds that are more actively traded and have more information available (this will also bias the sample towards comprising more efficient bonds, and thus bias the tests *against* a finding of inefficiency in the bond markets). We apply two alternative sample selection criteria to parse the data for our empirical tests. The default approach, which we call "sample selection criteria 1", invokes three successive trading days requirement: transaction observations for any day t are included only if all return variables exist for day t as well as lagged trading day $t-1$. We also use an alternate data sampling procedure which we denote as "sample selection criteria 2"; this approach is based on a novel parsing of the data and results in more observations than criteria 1. Criteria 2 allows us to include more data for our analysis, and constitutes both an innovation in data construction for efficiency tests as well as robustness test for our main results. Appendix B provides details of the data construction procedure under criteria 2.

Table 2, Panel B shows that available data doubles when this alternate data construction approach is used. For example, from the initial total sample of 1,365,381 observations, only 198,131 observations (15%) meet the requirement of valid contemporaneous as well as one-day lagged values of all five return variables under sample selection criteria 1. The size of the screened sub-sample increases to 411,148 observations (30%) under sample selection criteria 2.

Table 2, Panel C presents the daily returns on bonds, CDS, stocks, Treasuries, and the VIX for the data used. The number of observations for bonds is indeed lower than that for the other securities, confirming that bonds trade less frequently than stocks, Treasuries and volatility. Panels D and E show the correlations of various return variables, and almost all the pairwise correlations are significant at the 1% level. As expected bond returns are positively correlated to stock and Treasury returns, and negatively correlated to volatility and CDS spreads, both contemporaneously and lagged. Bond returns are negatively correlated to lagged bond returns, suggesting that there may be frequent return reversals in the bond markets. The correlations have the expected sign for all securities – this sets the stage for more formal empirical analysis, undertaken in the next section.

4 Empirical Analysis of Bond Efficiency

In order to ascertain whether there are delays in relevant information being incorporated into bond prices, we regress contemporaneous bond returns on contemporaneous and lagged values of the following: stock returns, Treasury returns, changes in equity volatility (VIX), changes in CDS spreads (for the post-CDS-commencement period), as well as lagged bond returns. If the lagged data in these regressions is *jointly* significant, it is evidence that information has been incorporated in other traded securities of an issuer, but not in its bonds, thereby implying that the bonds are relatively inefficient in comparison to the other traded securities.

We run partitioned (i.e., pre-CDS period versus the post-CDS period) panel regressions. The regression model is as follows:

$$\begin{aligned} bndret_{it} &= a_{i0} + a_{i1} stkret_{it} + a_{i2} tryret_{it} + a_{i3} vixchng_{it} + a_{i4} cdsret_{it} \\ &\quad + b_{i0} bndret_{i,t-1} + b_{i1} stkret_{i,t-1} + b_{i2} tryret_{i,t-1} + b_{i3} vixchng_{i,t-1} + b_{i4} cdsret_{i,t-1} \end{aligned}$$

Of course, in the pre-CDS period, the variable relating to changes in CDS spreads is non-existent. In the post-CDS period, we may choose to exclude this variable in order to be consistent with the regression in the pre-CDS period, or include it to better reflect the entire information set available to the bond market. In order to be agnostic on this choice, we do both, with consistent results.

In all regressions we compute the F–statistic for the joint significance of the lagged variables. If the lagged variables are jointly significant, it implies that the bonds are relatively inefficient. For corroboration, we create a second measure to compare the fit of the model that only has contemporaneous data on the right-hand-side of the regression (i.e., giving the "constrained" R^2), and the fit of a model with both contemporaneous and lagged data ("unconstrained" R^2, see the model in the regression above). This measure is denoted

$$D_1 = 1 \; - \; \left(\frac{\text{Constrained } R^2}{\text{Unconstrained } R^2} \right) \in (0,1)$$

The higher D_1 is, the greater the extent to which current bond returns are explained by lagged information, i.e., D_1 is a measure of bond inefficiency (Hou and Moskowitz (2005)). We run this test for each bond separately.

4.1 Analysis of individual bonds

For each bond we use returns based on mean daily yields if there was more than one observed transaction during the day. The results for the D_1 measure are presented in Table 3. There are two data sets based on two different sample-selection criteria as described in Appendix B. The results from both samples are consistent with each other.

Table 3: here.

Table 3 presents analysis of bond inefficiency pre-CDS and post-CDS by individual bond. The D_1 metric is shown for the pre-CDS period and post-CDS period using the mean and median of daily observations. The analysis is done with and without lagged bond returns. For both analysis, across both sample selection criteria, the D_1 metric becomes *larger* in magnitude in the post-CDS period. Furthermore, in all four cases, more individual bonds experience an *increase* in value of $D1$ measure after the introduction of CDS than those that experience a decrease in value. These findings indicate that bonds appear to have become relatively more inefficient after CDS trading commenced.

4.2 Period-partitioned panel data analysis

Next we conduct partitioned panel regressions and the results are shown in Table 4. These results complement the results of Table 3 by taking all bonds together in a panel. The empirical implications of the panel regressions are as follows. First, the information model is validated because bond returns are explained by returns in equity markets, Treasury markets, and volatility markets, as seen in the highly significant coefficients on contemporaneous variables in Table 4. This implies that different securities issued by the same firm are responding together to common information (we do not include contemporaneous or lagged changes in CDS spreads in order to keep the information sets common across the pre- and post-CDS periods; however, as a robustness check, we redo the regressions with the CDS variables as well for the post-CDS period, and find similar results). Second, bonds are informationally inefficient relative to other securities in both pre-CDS and post-CDS periods – the lagged variables in the regression are highly significant on a joint basis. Third, the F-statistic for joint significance of the lagged variables becomes much higher in the post-CDS period in comparison to the pre-CDS period, suggesting that bond markets likely became more inefficient *after* the introduction of CDS markets. For the regression without lagged bond returns, using sample criteria 1, the F-statistic increases from 4.21 to 60.15 (pre- to post-CDS), and when lagged bond returns are included, the same statistic increases from

115.10 to 1646.84. When we include the data on contemporaneous and lagged changes in CDS spreads, both coefficients are negative and significant. Again, the F-statistic for the joint significance of lagged variables is much higher in the post-CDS period than in the pre-CDS period. The results for sample criteria 2, also shown in Table 4, are similar as with sample criteria 1.

Table 4: here.

Table 4 also presents the D_1 score from the panel regressions (versus that computed for individual bonds in Table 3). As in Table 3, the D_1 score increases in the post-CDS period, indicating an increase in relative inefficiency of bonds. This is consistent across both sample selection criteria 1 and 2.

As a robustness check (not reported), we redo the regressions using bond returns computed based on median and end-of-the-day (last) daily yields instead of mean daily yields. Qualitatively similar results obtain for all three measures of bond returns.

4.3 Joint panel data analysis

In order to combine the period-partitioned data and use it completely, we also undertake joint panel regressions using a CDS dummy, where $CDS_{it} = 1$ if CDS was trading for a particular bond i on a given day t, and 0 otherwise. The specification effectively keeps two series of independent variables in the panel regression, one for the pre-CDS period and one for the post-CDS period, though both are combined into one regression. Results are shown in Table 5 for both sample criteria 1 and 2.

Table 5: here.

Table 5 shows the following results both, with and without lagged bond returns in the regression. First, the contemporaneous variables are all significant with only one exception, volatility, that appears to be subsumed by lagged bond returns. The signs of all variables are exactly as expected. Second, in the pre-CDS period, for sample criteria 1, not all lagged variables are significant, even though they are jointly significant. the F-statistic for the joint significance of lagged variables is 4.44 (highly significant) when lagged bond returns are excluded, and 115.05 when lagged bond returns are included. But, in the post-CDS period, all lagged variables are significant, individually and jointly. The F-statistic for the joint significance of lagged variables increases sharply to 36.18 when lagged bond returns are excluded, and 1350.25 when lagged bond returns are included. Thus, we find no evidence of improvement in bond market efficiency with the advent of CDS trading; in fact, our results, on the contrary, suggest that bond market efficiency likely dropped significantly following the introduction of CDS. The results in Table 5 complement those in Tables 3 and 4. Panel *B* of Table 5 uses sample selection criteria 2 and confirms the results of Panel *A* that is based on sample criteria 1. The *F*-statistic for joint significance of lagged variables is significant both pre- and post-CDS, and when lagged bond returns are not used, is six times in size post-CDS versus pre-CDS. When lagged bond returns are used in the regression, the *F*-statistic post-CDS is more than 11 times its pre-CDS value.

Table 6: here.

As another robustness test, the results in Tables 4 and 5 are re-examined by running a joint panel regression with a CDS dummy interaction. In Table 6, the post-CDS period data is interacted with a dummy variable. Specifically, the explanatory return variables (lagged and contemporaneous) are included twice: stand-alone and multiplied by the CDS dummy, CDS_{it}. The interaction variables reflect the *incremental* explanatory power of the return variables in the post-CDS period *relative to* the pre-CDS period. The significance of the lagged dummy interaction variables is of particular interest because these variables highlight the incremental dependence on past information in the post-CDS period. As before, for robustness, the results for sample criterion 1, shown in Panel *A* of the Table 6, are complemented with results for sample criterion 2, shown in Panel *B*. We find that interaction variables corresponding to contemporaneous and lagged stock and CDS returns are always significant, indicating that these returns demonstrate relatively greater incremental explanatory power after the introduction of CDS (this is confirmed by the large and significant *F*-statistics for all interaction variables taken jointly). Further, *F*-statistics corresponding to lagged interaction variables always show very strong significance (*F*-values of 10.61, 51.67, 12.50 and 35.94, all with *p*-values less than 0.001). These reveal that lagged return variables have significantly greater information content for bond returns after CDS introduction as compared to the pre-CDS period; thus, we find that bond market efficiency deteriorated. These results once again confirm the earlier finding that bond market efficiency did not improve after the introduction of CDS for both sample selection criteria.

5 Market Quality

In this section we assess the quality of the bond market before and after the introduction of CDS trading using the measure proposed in Hasbrouck (1993). Hasbrouck defines pricing error s_t of a security as the difference in its log transaction price (p_t) and its efficient log price (m_t). The return of a security is equal to $r_t = m_t - m_{t-1} + s_t - s_{t-1}$. The variance of pricing error divided by the variance of return (i.e., σ_s^2/σ_r^2) is a metric of normalized pricing error. Market quality q is defined as one minus this ratio, i.e.,

$$q = 1 - \frac{\sigma_s^2}{\sigma_r^2}$$

Higher q denotes better market quality, i.e., lower risk of deviation of prices from their efficient levels. The formula is implemented by estimating an MA(1) process (without intercept) for security returns, i.e.,

$$r_t = e_t - a \cdot e_{t-1}$$

where the values $\{a, \sigma_e^2\}$ are obtained from the MA(1) estimation and then used in the equation for q above. The resulting expression for q is

$$q = \frac{\sigma_e^2 - 2a \cdot Cov(e_t, e_{t-1})}{\sigma_e^2 + a\sigma_e^2 - 2a \cdot Cov(e_t, e_{t-1})} \in (0, 1)$$

Details of this derivation are provided in Appendix C that provides more information about Hasbrouck's model.

The q measure is applied to individual bonds with at least 30 trading days with return observations in both pre- and post-CDS periods. This measure accesses more data than the efficiency regressions because it does not require concurrent stock returns, CDS spreads, Treasury returns, or volatility data. The total number of bonds meeting our sampling criteria is 82, more than the 45 bonds that are available using sample selection criteria 1, but less than the 130 bonds used in sample selection criteria 2.

Table 7: here.

The values of q are presented in Table 7. The q measure based on mean bond returns has a value of 0.86 in the pre-CDS period and 0.82 in the post-CDS period. Therefore market quality drops in the post-CDS period in comparison to the pre-CDS period, though the decline is statistically not significant. In results not reported, we find similar drops in the value of q when we use median or last returns instead of mean returns.

For comparison to the bond markets, we also compute the market quality measure, both before and after CDS introduction, for equities corresponding to the bonds in our data set.

The sample comprises 107 stocks with at least 30 trading days of data pre- and post-CDS. Across stocks, on average, measure q is 0.98 pre-CDS and 0.99 post-CDS (the difference is not statistically significant). The quality of equity markets is thus much higher than that of bonds. For the post-CDS period, we also examine the quality of the CDS market itself. We use 325 individual CDS with at least 30 trading days data to compute q. The average value of q is 0.92. Hence, CDS markets are of higher quality than bond markets, though not as high quality as equities.

In summary, based on market quality tests we find no evidence to show that bond market quality has improved after the introduction of CDS markets.

6 Bond Liquidity

A likely consequence of CDS trading is that fixed-income traders no longer need to use bond markets to speculate on or hedge credit risk. The evidence in Figures 1 and 2 clearly shows how drastically bond trading patterns changed after the introduction of CDS trading. There is a clear drop-off in both trading volume and turnover. The question is: did liquidity in the bond market also suffer?

To assess this, we compute multiple measures that are either proxies for liquidity or may be highly correlated to liquidity. First, the analysis of these measures is undertaken as a panel – all observations, irrespective of identity of the bond, are lined up as a panel with respect to the CDS introduction date. These results are shown in Table 8, Panel A. The analysis of liquidity for individual bonds is shown in Table 8, Panel B. A bond issue needs to have at least 30 observations of returns in pre- as well as post-CDS periods to qualify into the sample; 82 bonds meet this criteria. This is larger than the number of individual bonds (45) under sampling criteria 1 because the current criteria does not require lagged bond returns or concurrent stock or CDS returns. However, the current sample is smaller than the number of individual bonds (130) under sampling criteria 2 because the latter criteria generates many additional observations.

Using this data, we compute the following measures:

1. A simple count of the number of trades per day, where we report the total and mean values for the day. Figure 1 plots the trend of total number of daily trades.
2. The dollar volume of trading, both total and mean, for each day.

3. Turnover, defined as the percentage of the outstanding issue of the bond that trades on a given day; again, we report the total and mean values. Figure 2 plots the trend of mean turnover.

4. The LOT measure of Lesmond, Ogden and Trzcinka (1999). We use the Das and Hanouna (2010) adaptation of the LOT measure and compute three types of LOT measures separately for pre- and post-CDS periods: (i) fraction of zero return trading days, (ii) fraction of zero volume (i.e., no trade) trading days, and (iii) fraction of zero return plus zero volume trading days. The total number of trading days in the entire pre- or post-CDS period constitute the denominator of these fractions. The number of observations for the LOT measure is lower than that for the other measures (e.g., number of trades or turnover) because the entire pre- or post-CDS time-period span is counted as just one observation instead of counting individual trading days.

5. The covariance illiquidity measure proposed by Bao, Pan and Wang (2008) based on covariances of price changes. We compute the covariance measure of illiquidity as $\gamma_i = -Cov(bndret_{it}, bndret_{i,t-1})$, where $bndret_{it}$ is the return of bond i on day t. The covariances are computed on a trading day basis, and not on a calendar time basis (i.e., day $t-1$ is the previous *trading* day). Since bond return covariances are typically negative, measure γ is mostly positive and a higher value of γ denotes a higher level of illiquidity. The covariance measure of illiquidity is not meaningful for the panel data sample, and is hence applied only to the sample of individual bonds (Table 8, Panel B). The number of observations is 82 – the covariance measure of illiquidity is computed twice (once pre-CDS and once post-CDS) for each bond.

6. The Amihud (2002) illiquidity measure, computed as follows:

$$ILLIQ_i = \frac{1}{DAYS_i} \sum_{t=1}^{DAYS_i} \frac{|bndret_{it}|}{VOL_{it}} \times 10^6$$

   where $bndret_{it}$ is the ith bond's return on day t, VOL_{it} is the total daily trading volume in dollars, and $DAYS_i$ is the total number of trading days in the entire pre- or post-CDS period. Here too the number of observations is 82 because the Amihud illiquidity measure is computed twice (once pre-CDS and once post-CDS) for each bond.

Table 8: here.

The computed liquidity measures are shown in Table 8. In Panel A, we see that the mean number of daily trades doubles as we go from the pre-CDS period to the post-CDS period, as is expected given the growth in the capital markets. However, the mean daily trade size becomes smaller, dropping to \$0.31 million in the post-CDS period versus \$0.50 million in the pre-CDS period. These differences are statistically significant. A more suitable indicator of the clear decline in bond trading may be gleaned by looking at turnover – mean daily turnover declines from 0.22% (pre-CDS) to 0.11% (post-CDS), a statistically significant 50% drop. The three LOT measures indicate that there are probably fewer zero return and no trade days post-CDS. The Amihud illiquidity measure reveals that liquidity drops in the post-CDS period; however, the difference is not significant.

Panel B of Table 8 examines pre- and post-CDS liquidity at the individual bond level for 82 bonds. Post-CDS, mean number of daily trades goes up, but the mean daily trade size declines substantially. Mean daily turnover declines from 0.11% (pre-CDS) to 0.06% (post-CDS), and the drop is significant. The LOT measures and the covariance based measure increase from the pre-CDS period to post-CDS period, indicating a reduction in liquidity; however the differences are not significant. The Amihud illiquidity measure shows a statistically significant increase in illiquidity in the post-CDS period in comparison to the pre-CDS period – illiquidity more than doubles. Taken together, the evidence suggests that the introduction of the CDS markets damaged liquidity in the bond markets.

7 Additional Robustness Tests

We conduct two sets of additional tests to check the robustness of our finding that dependence on lagged information content (and hence inefficiency) increased after the introduction of CDS markets. First we replicate the joint panel regressions for different sub-samples of CDS issuers. Then we conduct difference-in-differences tests after augmenting our CDS data sample with a control sample of CDS non-issuers.

7.1 Partitioned tests over sub-samples

We implement the regression in Table 6 (joint panel regression with a CDS dummy interaction) for different sub-samples of CDS issuers. For brevity, in Table 9 we report only the values of different F-statistics for various sub-samples and different test specifications. Of particular interest is the F-statistic corresponding to the lagged interaction variables which captures the incremental significance of lagged information in the post-CDS period relative to that in the pre-CDS period.

Table 9: here.

Effect of the financial crisis:

If the 2007–2008 financial crisis resulted in unexpected credit and liquidity shocks to financial markets, we would expect a drying up of liquidity in equity and credit markets, and even possible deterioration in the efficiency of corporate bond markets during this period. Is it possible that the results in Table 6, which find increased inefficiency in the post-CDS period, are really driven by the crisis sub-period? We test this proposition by dropping the crisis years 2007 and 2008, and repeating the Table 6 regressions. The values of the F-statistics corresponding to lagged interaction variables are smaller but remain strongly significant. The results of Table 6 are robust and the conclusion of increased dependence on lagged information post-CDS persists even for non-crisis periods.

Effect of nascency of the CDS market:

The initial years of any financial innovation are likely to be characterized by gradual evolution and limited informational impact. If the CDS market was not very liquid in the nascent phase, does the slow initial trading and price discovery in the CDS market (at the beginning of our sample) affect our tests for efficiency of underlying bond market? We examine this question by applying Table 6 regressions for two separate sub-samples − the initial nascent three-year sub-period 2002–2004, and the post-nascent sub-period after eliminating the initial years 2002 and 2003. We find that the values of the F-statistics corresponding to lagged interaction variables are strongly significant for both sub-samples; in fact, the lagged information set has greater impact in the later 2004–2009 sub-period. Thus, the results reported in Table 6 are not driven by the infancy of CDS market in the initial years of our sample.

Effect over time after introduction of CDS:

Is there is a difference between the short-term versus long-term effects of CDS introduction on underlying bonds? How does the inefficiency of the bond market (dependence on lagged information) in the short-term post-CDS window compare to that in the long-term period following the introduction of the corresponding CDS? To explore the effects over time, we form sub-samples by including only those bond transactions that occur within 1-, 2- and 3-years after the introduction of the corresponding CDS, and repeat the joint panel regressions of Table 6. We find that the lagged interaction variables become more significant over time (that is, F-statistics increase in value when the post-CDS horizon considered gets longer), suggesting that bond markets are likely relatively more efficient in the short-term following the onset of CDS trading, and get less efficient (depict greater dependence on lagged information) in subsequent years.

Effect of underlying bond liquidity:

Does CDS introduction favorably impact bonds that are more liquid and hence are widely traded? Is it likely that the emergent CDS market improved the informational efficiency of more liquid bonds while adversely affecting that of less liquid issues? To address these questions using the median values of total bond amount outstanding (a commonly accepted bond liquidity attribute) in the year of CDS introduction, we classify all transaction observations into low and high amount outstanding (liquidity) portfolios and repeat the joint panel regressions of Table 6. We find that the F-statistics corresponding to lagged interaction variables are large and significant for both liquidity portfolios; in fact, F-statistics are larger for the more liquid portfolio. This implies that CDS introduction had an adverse impact on the efficiency of bonds irrespective of the liquidity of the underlying bonds.

Effect of firm size:

Smaller firms are inherently more risky, are less likely to be covered by informed institutional market participants, and are more likely to issue lower rated and less liquid bonds. Hence it may be expected that returns on bonds of smaller firms rely on past information to a greater extent. To explore the impact of firm size on the post-CDS bond market efficiency, based on the median values of equity market capitalization in the year of CDS introduction we classify our sample into small and large firm size portfolios and replicate the joint panel tests of Table 6 for the two sub-samples. We find that the F-statistics corresponding to lagged interaction variables, though larger for smaller firms, are significant for both firm size portfolios. The dependence on lagged information set increased after the introduction of CDS for bonds of smaller as well as larger firms.

Effect of bond ratings and maturity:

Since default risk and duration are the key determinants of bond returns, it is likely that bond ratings and maturity bear impact on the evolution of relative efficiency of the bonds. Focusing on the subset of bonds outstanding on the CDS introduction date (that is, we drop bonds that *mature before* or *are offered after* CDS introduction date), we classify bonds based on S&P (or Moody's) ratings (investment grade: BBB−/Baa3 and above; junk grade: BB+/Ba1 and below) and time to maturity (short-term: <7 years; medium-term: 7-15 years; long-term: >15 years), and repeat the joint panel tests of Table 6 for each sub-sample. A vast majority of the bonds in the above subset are investment grade (90%) and short-term (49%). In results not reported for brevity, we again find that the F-statistics corresponding to lagged interaction variables are always significant; moreover, these F-statistics are larger for the high-rated and long-term maturity bond sub-samples. Thus, all our findings are robust to controls for credit and duration risk.

7.2 Difference-in-differences tests

The preceding results reveal that bond returns demonstrate greater dependence on the lagged information set following the introduction of CDS. However, such inferences of deteriorating bond market efficiency are likely to be unconvincing if there are permanent differences between firms with and without CDS introduction or if there exist trends (such as systematic evolution in the type of firms issuing bonds, or fundamental shifts in market or economic conditions) over the time-period of study. Empirical inferences of market inefficiency can be disentangled from such contaminating effects through the use of difference-in-differences (DiD) tests that entail the comparison of CDS introduction firms with a control group of firms that have no underlying CDS.

To implement DiD tests, we augment our sample of pre- and post-CDS bond transactions for CDS issuers with a control sample of bond transactions by CDS non-issuers (firms with no CDS introduction). The control sample consists of all bond transactions by firms which meet the selection criteria outlined in Appendix A, but did not issue any CDS until the end of 2008. For the combined sample of all observations, we run the following regression[6]:

$$\begin{aligned} bndret_{it} &= \alpha_i + \beta_{i1} CV_i + \beta_{i2} LV_i + \beta_{i3} CDS_{it} * CV_i + \beta_{i4} CDS_{it} * LV_i \\ &\quad + \beta_{i5} E_i * CV_i + \beta_{i6} E_i * LV_i \\ &\quad + \beta_{i7} E_i * CDS_{it} * CV_i + \beta_{i8} E_i * CDS_{it} * LV_i \end{aligned}$$

where

$CV_i \equiv \{stkret_{it}, tryret_{it}, vixchng_{it}, cdsret_{it}\}$

$LV_i \equiv \{bndret_{i,t-1}, stkret_{i,t-1}, tryret_{i,t-1}, vixchng_{i,t-1}, cdsret_{i,t-1}\}$

$CDS_{it} = 1$ if post-CDS period and 0 if pre-CDS period

$E_i = 1$ for event sample of CDS-issuers and 0 for control sample of non-issuers

CV_i denotes contemporaneous return variables and LV_i encompass one-day lagged return variables. For the sample of CDS issuers (E_i=1), based on the actual CDS introduction date, transactions are classified into pre- and post-CDS periods ($CDS_{it} = 0$ vs. 1). For each bond in the control sample of CDS non-issuers (E_i=0), a date is arbitrarily selected

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[6] The first line of the regression (i.e., coefficients α and β_1 through β_4) denotes the joint panel test with CDS dummy interaction underlying Table 6.

(with uniform probability) within the range of the first and last trading dates of the bond, and pre- and post-event transactions are categorized relative to this random "non-event" date.[7] In Table 10, we report the F-statistics (and associated p-values) corresponding to the joint significance of various explanatory variables in the above DiD regression framework. Of particular interest are the F-statistics corresponding to regression coefficients $\beta_3 + \beta_4$, $\beta_5 + \beta_6$, and β_8. In terms of relative explanatory power of contemporaneous and lagged variables, the coefficients $\beta_3 + \beta_4$ reveal time trends within the control sample, and $\beta_5 + \beta_6$ jointly capture the differences between the CDS and the control samples. Crucial to our analysis, β_8 reflects the incremental effect of the lagged variables in the post-CDS period relative to the pre-CDS period *over and above* similar time-trend effects within the control group.

Table 10: here.

Table 10 reveals that $\beta_3 + \beta_4$ or just β_4 are either not significant or marginally significant, which implies that the explanatory power of various contemporaneous and lagged return variables did not change substantially over time within the control group of CDS non-issuers. On the other hand, $\beta_5 + \beta_6$ are always significant, indicating fundamental differences between the CDS and control firms in terms of the dependence of bond returns on various contemporaneous and lagged return variables. Most importantly, the F-statistics corresponding to β_8 always show very strong significance (F-values of 10.81, 49.60, 13.67 and 34.84, all with p-values less than 0.001). These imply that the lagged return variables retain incrementally greater explanatory power for bond returns of CDS-issuing firms in the post-CDS period compared to the pre-CDS period even after controlling for time-trends and differences between CDS issuers and non-issuers. These results confirm the robustness of our findings that bond market efficiency did not improve after the introduction of CDS.

8 Conclusions and Discussion

The credit default swap (CDS) market was one of the salient new markets of the past decade. Trading in CDS has been blamed for the speculative frenzy leading to the beginning of the financial crisis in 2008 though Stulz (2010) concludes that credit default swaps were not responsible for causing or worsening the crisis. Nobelist Joseph Stiglitz went so far

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[7] Instead of the random date approach to select the non-event date for the control sample, we also explore two alternatives: midpoint date approach (where the non-event date is the midpoint of the first and last trading dates) and the fixed date approach (where the date 30 June 2005, the midpoint of our data sample, is the chosen non-event date). All results, not reported for brevity, and consequent conclusions are identical to those reported here.

as to suggest that CDS trading by large banks should be banned.[8] Still, the creation of new markets may have beneficial information and liquidity effects on underlying markets – Conrad (1989), Skinner (1989) showed that options trading reduced volatility in underlying equity markets. In sovereign bond markets, Ismailescu and Phillips (2011) provide evidence that the introduction of credit default swaps improved efficiency in the underlying sovereign bonds. We examine whether CDS trading was beneficial to bonds in reference names by looking at whether informational efficiency, market quality and liquidity improved once CDS trading commenced. Our econometric specification accounts for information across CDS, bond, equity, and volatility markets. We also develop a novel methodology to utilize all observations in our data set even when continuous daily trading is not evidenced, because bonds trade much less frequently than equities. The empirical evidence suggests that the advent of CDS was largely detrimental to secondary bond markets – bond markets became less efficient, evidenced greater pricing errors, and lower liquidity. These findings are robust to various slices of the data set and specifications of our tests. Our findings have bearings on the recent CDS market regulatory reform proposals and the debate surrounding the impact and usefulness of CDS markets.

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[8] Reported by Bloomberg, Octover 12, 2009.

Appendix

A Bond sample construction

The project data comes from four sources: corporate bonds (TRACE and FISD), stocks (CRSP in WRDS), CDS (Bloomberg), and swap rates and VIX (Datastream).

Step 1: TRACE data

We start with the Trade Reporting and Compliance Engine (TRACE) bond transaction database which lists all over-the-counter secondary market bond transactions since July 2002 by all brokers or dealers who are member firms of Financial Industry Regulatory Authority (FINRA). We collect transaction information such as trade date, trade price, trade size, and underlying yield corresponding to all bond transactions between July 1st, 2002 and September 30th, 2009. Since TRACE reports multiple intra-day bond transactions, for each bond we aggregate all intra-day transactions into a single summary transaction observation each day. For each bond transaction date, the aggregated observation consists of number of trades; mean and total trading size; and mean, median and closing (last) daily yields and prices.

We impose certain screening criteria on the bond transaction sample. We exclude: (a) transactions identified as trade cancelations or corrections, (b) when-issued trades, (c) trades with commissions, (d) as-of-trades, (e) special price trades, and (f) trades with sale conditions. The screened sample consists of 5,768,201 transaction date observations for 34,900 bond issues by 4,869 firms.

Step 2: FISD data

Separately, from Mergent's Fixed Investment Securities Database (FISD) issuance database which includes in depth issue- and issuer-related information on all U.S. debt securities maturing in 1990 or later, we collect issuance related information such as issuance date, maturity date, offer amount, etc for all bonds issued between 1994 and 2007. From dynamic FISD tables, we extract bond ratings and amount outstanding on the transaction date of each bond trade. For bond ratings, we use the Standard & Poor's rating if it exists; otherwise we use Moody's rating.

Based on FISD variables, we further exclude the following bond issues: bonds with redeemable, exchangeable, convertible, sinking fund, enhancement, or asset-backed features; perpetual and variable rate bonds; medium-term notes; Yankee, Canadian, and foreign currency issues; Rule 144a issues; TIPS, Treasuries, Munis, Treasury coupon- and principal-strips; and agency-type bonds. We retain bonds with call and put features. The FISD sample yields 11,950 U.S. domestic corporate bond issues.

Step 3: Intersection of FISD and CRSP data

Using the 6-digit CUSIP identifiers, the screened sub-sample of FISD bond issues is then merged with the Center for Research in Security Prices (CRSP) database. We eliminate bond issues that do not belong to firms with public equity, that is, do not have any matching stocks in the CRSP database. The merged FISD-CRSP sample consists of 8,291 U.S. domestic corporate bond issues.

Step 4: Intersection of TRACE and FISD-CRSP data

Based on the 6-digit CUSIP identifiers, we merge the TRACE bond transaction sample with the FISD-CRSP bond issue- and issuer-attributes sample. The merged sample consists of 843,442 trading date observations for 2,806 bond issues by 967 issuers.

Step 5: Bloomberg data

We obtain trades data on 5-year CDS from Bloomberg. Bloomberg consists of two sources of CDS data: CBGN and CMAN. CBGN is Bloomberg's own composite data, and reports the generic price data for each CDS as an average of the contributed spreads from multiple data vendors. CMAN is an external data provider that offers its pricing data on the Bloomberg terminal. We assume that the starting date of CDS spreads in Bloomberg is also the date of introduction of the CDS; the assumption is reasonable given that Bloomberg has an extensive coverage of CDS data and is recognized as a benchmark pricing source.

We use the Bloomberg default CBGN source as the primary data; for 314 CDS issues, CBGN data is complete and is used as is. For 293 CDS, CBGN data is incomplete (largely before 2008) and is augmented with data from CMAN. For another 13 CDS, CBGN has no data and CMAN becomes the primary source of CDS spreads. Altogether, we obtain daily CDS spreads on 620 CDS issues by 620 U.S. firms for a total of 598,221 daily observations between August 3rd, 2001 and September 30th, 2009.

Step 6: Intersection of TRACE, FISD, CRSP and Bloomberg data

We merge the data obtained from TRACE, FISD, CRSP and Bloomberg to yield a composite sample of 2,806 bond issues by 967 issuers and 1,987,410 time-series observations.[9] Of the

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[9] 1,987,410 = (number of bonds) * (days with a valid return on at least one of the three securities: bonds, CDS or stocks); hence, this number is larger than the separate trading date observations reported in Steps

composite sample, 355 issuing firms (37%) or, equivalently, 1,559 bond issues (56%) have corresponding CDS issues.

We impose a few additional filters: (a) we eliminate 2009 data because it is incomplete; (b) we exclude 612 bond issuing firms which do not introduce any CDS till the end of 2008; (c) we remove 8,208 bond trades reported in TRACE for 28 bonds that occur after the maturity date reported in FISD; and (d) we discard 645 bond issues which have valid stock returns before July 2002 but the stock is delisted prior to the bond transaction data being available on TRACE.

Our final screened sample consists of 1,365,381 time-series observations on 1,545 bond issues by 350 issuing firms (which also had CDS introduced between 2001 and 2008).

Step 7: Augmentation with Datastream data

From Datastream, we collect daily values for the VIX index and daily swap rates for 15 different maturities (ranging between 1 and 30 years) from August 2001 through December 2008. Each bond trading date is matched to a corresponding swap rate based on linear interpolation of the two closest neighboring maturity swap yields; this yields a time-series of swap rates matching in maturity to the corresponding bond issue. The swap rates and VIX index values are augmented to our screened data sample.

B Alternate approaches to data construction

In this Appendix we describe an alternate approach to the primary approach used in the paper. The primary filter of the data is explained in Section 3 and is denoted “sample selection criteria 1” whereas “sample selection criteria 2” is based on the alternate approach described below.

The main objective of extending the data construction methodology of sample criteria 1 is to include more data for analysis, and to offer a robustness test of the main results of the paper. Recall that in our main approach we retain those days on which we have three consecutive observations of all traded securities in our sample. Hence, we will be focusing on periods of active trading, which are more likely when information is being released – these are exactly the periods when we want to test for market efficiency.

The key idea of this extended data construction approach is to expand the calculation of re-

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1, 4 and 5.

turns to windows of time that are greater than one day between observations of transactions. In periods when information about the bond issuer is high, the inter-arrival time between transactions will be small, and in periods of low information, inter-arrival times will be large. So the extended data approaches allow for efficiency tests on non-standard inter-transaction times. The alternate data construction approach (denoted as sample selection criteria 2) is briefly explained as follows.

Stock data is available every day. The gaps in the data occur because of the absence of consecutive days when both CDS and bonds trade, precluding return calculations. Therefore, in this approach we use all dates on which both bonds and CDS were traded (and had observations) – these dates need not be consecutive. An example will make this clear. Suppose we have observations of both bonds and CDS only on days $\{1, 2, 5, 7, 8, 9, 12, 15, 16\}$. We compute a return series (i.e., yield changes) as $R(t, t + k) = [y(t + k) - y(t)]/k$, where k is the number of days between observations (the sign of the numerator would depend on whether we are looking at bonds or CDS – $y(t)$ is the yield on the bond or cds spread as the case may be). Note that by dividing by k we are still getting an average daily return, thereby constructing a non-overlapping time series of "average daily returns" and consequently, all the tests applied to daily returns remain the same, and may be applied just as in the main set of tests. It is important for the test of bond efficiency that the information sets for contemporaneous returns and lagged returns do not overlap and this is still maintained when we construct our return series using this approach. This approach has the advantage of focusing more on days when there was trading, i.e., days when information was more likely to be released.

C Market quality measure (q)

This Appendix present a brief summary of the Hasbrouck (1993) model of market quality for a security. We retain the same notation, though our final measure is not the same albeit in the same spirit.

Hasbrouck defines market quality as the inverse of the variance of the pricing error after accounting for the efficient component of returns. The log transaction price of the security is given as

$$p_t = m_t + s_t \tag{1}$$

where m_t is the efficient component (i.e., a random walk) and s_t is the pricing error. The smaller that $Var(s_t)$ is, the higher is market quality q. The security's continuous return may be written as the difference of log transaction prices:

$$r_t = m_t - m_{t-1} + s_t - s_{t-1} \tag{2}$$

and it remains to specify the processes for m_t and s_t. The process for the former is a simple random walk, i.e.,

$$m_t = m_{t-1} + w_t \tag{3}$$

and the process for the pricing error may be information-related, i.e., related to innovation w_t, or it may be non-information related, i.e., independent of w_t with separate innovation term η_t. To cover both cases, Hasbrouck posits that

$$s_t = \alpha \; w_t + \eta_t \tag{4}$$

where the information related pricing error is the case where $\alpha \neq 0$ and $\eta = 0$. In the case of a non-information related pricing error, we will have $\alpha = 0$ and $\eta \neq 0$ instead.

Take the first case, i.e., information related pricing errors. Using equations (3) and (4) in (2) and setting $w_t = (1-a)e_t$ and $\alpha = \frac{1}{1-a}$, we get after simplification

$$r_t = e_t - ae_{t-1} \tag{5}$$

which is an MA(1) process. Estimating this process on return data gives the parameters $\{a, \sigma_e^2\}$. We can easily see that $\sigma_s = a\sigma_e$.

Now take the second case, i.e., non-information related pricing errors. Setting $w_t = (1-a)e_t$ and $s_t = \eta_t = ae_t$, and substituting these values into equation (2) results in the same MA(1) process as before, i.e., $r_t = e_t - ae_{t-1}$. Again, we see that $\sigma_s = a\sigma_e$.

We do not need to ascertain whether we are in the first or second case, because the pricing error equation is the same in both cases. Of course, the value of a will turn out to vary empirically depending on the structure of the pricing error, i.e., related to information or not. Once we compute the total return error, $\sigma_r^2 = Var(r_t)$, we can compute the measure of market quality, i.e.,

$$q = 1 - \frac{\sigma_s^2}{\sigma_r^2} = \frac{\sigma_e^2 - 2aCov(e_t, e_{t-1})}{\sigma_e^2 + a^2\sigma_e^2 - 2aCov(e_t, e_{t-1})} \tag{6}$$

It is clear that when $a = 0$, the market quality is $q = 1$.

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FIGURE 1: Mean Size of Corporate Bond Trades (in $ Million) Before and After Introduction of CDS

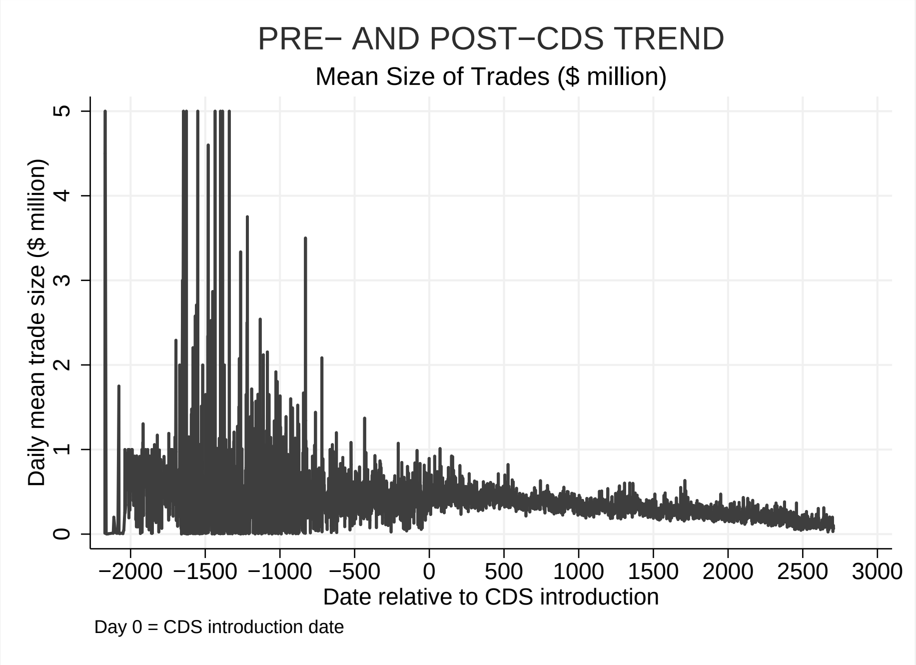

FIGURE 2: Mean Bond Turnover (as % of Total Amount Outstanding) Before and After Introduction of CDS

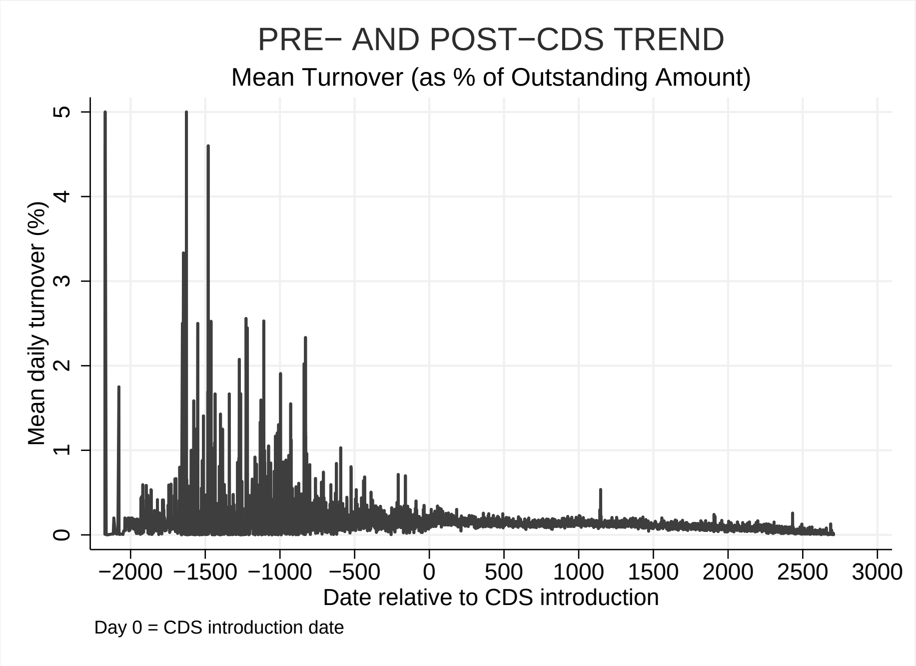

TABLE 1: Data Summary Statistics and Definition of Variables

Panel A: Final merged data summary statistics

- Sample period: 2002-2008
- 1,545 bond issues by 350 issuing firms with CDS issues
- 1,365,381 time-series observations (bond issues × trading days)
- 883.74 trading days per bond issue

- 1,545 bond issues:
  - 1,352 senior issues, remaining some form of junior issues
  - 1,520 fixed coupon issues, 25 zero coupon issues
  - all issues non-convertible
  - 662 callable, remaining non-callable
  - 63 putable, remaining non-putable
  - 983 Industrials, 355 Financials, 207 Utilities

- 1,365,381 time-series observations:
  - # with valid bond returns = 328,130 (24.03%)
  - # with valid CDS spread changes = 938,944 (68.77%)
  - # with valid stock returns = 1,294,161 (94.78%)
  - # with valid bond returns + CDS spread changes = 258,945 (18.97%)
  - # with valid bond returns + CDS spread changes + stock returns = 249,605 (18.28%)

  - # of observations prior to the introduction of CDS = 110,934 (8.13%)
  - # of observations subsequent to the introduction of CDS = 1,254,447 (91.88%)

- 110,934 pre-CDS time-series observations:
  - # with valid bond returns = 17,159 (15.47%)
  - # with valid stock returns = 105,517 (95.12%)
  - # with valid bond returns + stock returns = 16,236 (14.64%)

- 1,254,447 post-CDS time-series observations:
  - # with valid bond returns = 310,971 (24.79%)
  - # with valid CDS spread changes = 938,944 (74.85%)
  - # with valid stock returns = 1,188,644 (94.75%)
  - # with valid bond returns + CDS spread changes = 258,945 (20.64%)
  - # with valid bond returns + CDS spread changes + stock returns = 249,605 (19.90%)

Panel B: Definitions of variables

- *bndret*: refers to bond returns (in %) obtained as the difference of consecutive mean daily yields, i.e., as $-(y_t - y_{t-1})$, where y_t and y_{t-1} are mean bond yields (in %) on days t and $t-1$ respectively.

- *cdsret*: refers to CDS returns (in basis points, bp) based on CDS spread changes and computed as the difference of consecutive daily yields, i.e., as $(y_t - y_{t-1})$, where y_t and y_{t-1} are CDS spreads (in bp) on days t and $t-1$ respectively.

- *stkret*: refers to daily stock return (in %).

- *tryret*: refers to swap return (in %) defined as change in (matching maturity) consecutive swap yields, i.e., as $-(y_t - y_{t-1})$, where y_t and y_{t-1} are swap yields (in %) on days t and $t-1$ respectively.

- *vixchng*: refers to change in VIX measure (index value) over consecutive days.

All five variables are winsorized at the 1% level.

TABLE 2: Bond Transactions by Year and Relationship to CDS Trading Status

The table presents the number of observations by year and by CDS-status of the firm at the time of the observation. Bond trades of issuers of CDS are classified into two types: (a) bond trades that occurred before CDS introduction (pre-CDS sample), and (b) bond trades that occurred after CDS introduction (post-CDS sample). Panel A shows the breakdown by year. Panel B lists the breakdown for data sample selection criteria 1 and 2 (both criteria are described in Section 3 and Appendix B). Panel C reports the descriptive statistics of various returns (defined in Table 1, Panel B), winsorized at the 1% level. Panels D and E present the correlation coefficients between different return variables.

Panel A: Bond transactions and new CDS issues by year

Year	Pre-CDS Sample	Post-CDS Sample	All Issues	Number of new CDS introductions
2002	2,022	5,637	7,659	104
2003	40,860	105,209	146,069	83
2004	33,472	155,798	189,270	107
2005	15,477	271,305	286,782	14
2006	9,558	257,474	267,032	4
2007	7,096	241,738	248,834	4
2008	2,449	217,286	219,735	16
Total	110,934	1,254,447	1,365,381	332

Panel B: Bond transactions by sample selection criteria

	Pre-CDS Sample	Post-CDS Sample	All Issues
Total	110,934	1,254,447	1,365,381
Sample selection criteria 1	11,128	187,003	198,131
%	10.03%	14.91%	14.51%
Sample selection criteria 2	27,771	383,377	411,148
%	25.03%	30.56%	30.11%

Panel C: Descriptive statistics of daily return variables

	NOBS	Mean	Std. dev.	Min	Max
bndret	328,130	0.0122	0.5170	−2.2404	2.3245
cdsret	938,944	0.2001	4.4810	−19.0559	24.3352
stkret	1,294,161	0.0284	1.8567	−6.4143	6.4693
tryret	1,365,381	0.0008	0.0557	−0.1643	0.1683
vixchng	1,365,381	0.0041	1.3436	−5.5600	5.4500

Panel D: Correlations between contemporaneous and lagged return variables based on sample selection criteria 1 (NOBS: 187,003)

	$bndret_t$	$bndret_{t-1}$	$cdsret_t$	$cdsret_{t-1}$	$stkret_t$	$stkret_{t-1}$	$tryret_t$	$tryret_{t-1}$	$vixchng_t$	$vixchng_{t-1}$
$bndret_t$	1.000^*									
$bndret_{t-1}$	-0.428^*	1.000^*								
$cdsret_t$	-0.071^*	-0.051^*	1.000^*							
$cdsret_{t-1}$	-0.035^*	-0.072^*	0.195^*	1.000^*						
$stkret_t$	0.031^*	0.003	-0.161^*	-0.016^*	1.000^*					
$stkret_{t-1}$	0.036^*	0.029^*	-0.202^*	-0.156^*	0.002	1.000^*				
$tryret_t$	0.047^*	0.011^*	0.072^*	0.007^*	-0.095^*	-0.058^*	1.000^*			
$tryret_{t-1}$	0.009^*	0.047^*	0.050^*	0.069^*	-0.006^*	-0.092^*	0.019^*	1.000^*		
$vixchng_t$	-0.015^*	-0.005	0.096^*	-0.006	-0.485^*	0.072	0.112^*	0.009^*	1.000^*	
$vixchng_{t-1}$	-0.025^*	-0.012^*	0.135^*	0.084^*	0.015^*	-0.496^*	0.083^*	0.104^*	-0.112^*	1.000^*

* correlation values significant at 1% level

Panel E: Correlations between contemporaneous and lagged return variables based on sample selection criteria 2 (NOBS: 383,377)

	$bndret_t$	$bndret_{t-1}$	$cdsret_t$	$cdsret_{t-1}$	$stkret_t$	$stkret_{t-1}$	$tryret_t$	$tryret_{t-1}$	$vixchng_t$	$vixchng_{t-1}$
$bndret_t$	1.000^*									
$bndret_{t-1}$	-0.398^*	1.000^*								
$cdsret_t$	-0.052^*	-0.029^*	1.000^*							
$cdsret_{t-1}$	-0.019^*	-0.050^*	-0.009^*	1.000^*						
$stkret_t$	0.027^*	-0.001^*	-0.117^*	-0.002^*	1.000^*					
$stkret_{t-1}$	0.022^*	0.027^*	-0.131^*	-0.109^*	-0.007^*	1.000^*				
$tryret_t$	0.034^*	0.006^*	0.047^*	0.003	-0.093^*	-0.045^*	1.000^*			
$tryret_{t-1}$	0.006^*	0.035^*	0.036^*	0.043^*	-0.010^*	-0.094^*	0.019^*	1.000^*		
$vixchng_t$	-0.014^*	0.000	0.066^*	-0.011^*	-0.490^*	0.059^*	0.111^*	0.012^*	1.000^*	
$vixchng_{t-1}$	-0.017^*	-0.014^*	0.092^*	0.062^*	0.026^*	-0.490^*	0.058^*	0.112^*	-0.103^*	1.000^*

* correlation values significant at 1% level

TABLE 3: Individual Bond Regressions

For individual bonds, we run regressions of contemporaneous bond returns on contemporaneous and lagged values of the following: stock returns, Treasury returns, changes in equity volatility (VIX), as well as with and without lagged bond returns. Panel A presents the results for sample selection criteria 1, and Panel B for sample selection criteria 2 (both criteria are described in Section 3 and Appendix B).

Panel A: Sample selection criteria 1

	$D1$ Measure		# of bonds for which lagged variables are jointly significant at		
	Mean $D1$	Median $D1$	1% level	5% level	10% level
without lagged bond returns					
Pre-CDS period	0.33	0.27	3	4	6
Post-CDS period	0.37	0.35	4	9	10
with lagged bond returns					
Pre-CDS period	0.71	0.79	33	38	38
Post-CDS period	0.82	0.84	40	44	44
Number of bond issues	45				
NOBS: Pre-CDS period	6,163				
NOBS: Post-CDS period	10,588				

Number of individual bonds with at least 30 observations in pre- and post-CDS periods is 45. Overall, 21 bonds experience decrease in value of $D1$ measure after the introduction of CDS, and 24 bonds experience increase in value. When lagged bond returns are included, 15 bonds experience decrease in value of $D1$ measure after the introduction of CDS, and 30 bonds experience increase in value.

Panel B: Sample selection criteria 2

	$D1$ Measure		# of bonds for which lagged variables are jointly significant at		
	Mean $D1$	Median $D1$	1% level	5% level	10% level
without lagged bond returns					
Pre-CDS period	0.31	0.25	4	12	19
Post-CDS period	0.34	0.30	12	22	29
with lagged bond returns					
Pre-CDS period	0.67	0.72	83	95	98
Post-CDS period	0.69	0.77	88	96	102
Number of bond issues	130				
NOBS: Pre-CDS period	18,290				
NOBS: Post-CDS period	34,164				

Number of individual bonds with at least 30 observations in pre- and post-CDS periods is 130. Overall, 61 bonds experience decrease in value of $D1$ measure after the introduction of CDS, and 69 bonds experience increase in value. When lagged bond returns are included, 59 bonds experience decrease in value of $D1$ measure after the introduction of CDS, and 61 bonds experience increase in value.

TABLE 4: Partitioned Panel Regressions

We run panel regressions of contemporaneous bond returns on contemporaneous and lagged stock returns, Treasury returns, changes in equity volatility (VIX), as well as with and without lagged bond returns, separately for pre- and post-CDS periods. Panel A presents the results for sample selection criteria 1, and Panel B for sample selection criteria 2 (both criteria are described in the Appendix B). Table 1, Panel B describes all the variables used. Each regression implements Newey and West (1987) adjustment for heteroscedasticity and autocorrelation, and we report the coefficients (and p-values), the number of observations (NOBS), adjusted R^2 values (Adj R^2) and different F-statistics (and corresponding p-values).

Panel A: Sample selection criteria 1												
	Without lagged bond returns						With lagged bond returns					
	Pre-CDS panel		Post-CDS panel				Pre-CDS panel		Post-CDS panel			
	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value
$stkret_t$	0.014	0.00	0.008	0.00	0.006	0.00	0.018	0.00	0.008	0.00	0.005	0.00
$tryret_t$	0.484	0.00	0.478	0.00	0.499	0.00	0.535	0.00	0.530	0.00	0.556	0.00
$vixchng_t$	−0.011	0.08	−0.004	0.01	−0.003	0.05	−0.008	0.18	−0.006	0.00	−0.004	0.00
$cdsret_t$					−0.005	0.00					−0.007	0.00
$bndret_{t-1}$							−0.413	0.00	−0.432	0.00	−0.439	0.00
$stkret_{t-1}$	0.010	0.00	0.008	0.00	0.005	0.00	0.017	0.00	0.012	0.00	0.007	0.00
$tryret_{t-1}$	0.081	0.28	0.119	0.00	0.144	0.00	0.254	0.00	0.313	0.00	0.359	0.00
$vixchng_{t-1}$	−0.002	0.79	−0.007	0.00	−0.005	0.00	−0.005	0.39	−0.007	0.00	−0.005	0.00
$cdsret_{t-1}$					−0.002	0.00					−0.004	0.00
intercept	0.011	0.01	0.002	0.03	0.004	0.00	0.015	0.00	0.003	0.00	0.006	0.00
NOBS	11,128		187,003		187,003		11,128		187,003		187,003	
Adj R^2	0.008		0.005		0.010		0.178		0.191		0.201	
F-stat, overall	14.42		126.96		156.74		75.13		1046.29		930.70	
p-value	0.00		0.00		0.00		0.00		0.00		0.00	
F-stat, lagged	4.21		60.15		36.19		115.10		1646.84		1350.01	
p-value	0.00		0.00		0.00		0.00		0.00		0.00	
$D1$	0.20		0.35		0.24		0.96		0.98		0.96	

Panel B: Sample selection criteria 2

	Without lagged bond returns						With lagged bond returns					
	Pre-CDS panel		Post-CDS panel				Pre-CDS panel		Post-CDS panel			
	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value
$stkret_t$	0.013	0.00	0.010	0.00	0.008	0.00	0.015	0.00	0.009	0.00	0.007	0.00
$tryret_t$	0.535	0.00	0.468	0.00	0.483	0.00	0.556	0.00	0.503	0.00	0.522	0.00
$vixchng_t$	−0.012	0.03	−0.004	0.02	−0.003	0.03	−0.008	0.11	−0.005	0.00	−0.004	0.01
$cdsret_t$					−0.003	0.00					−0.004	0.00
$bndret_{t-1}$							−0.378	0.00	−0.407	0.00	−0.410	0.00
$stkret_{t-1}$	0.010	0.00	0.007	0.00	0.004	0.00	0.014	0.00	0.011	0.00	0.007	0.00
$tryret_{t-1}$	0.056	0.35	0.109	0.00	0.128	0.00	0.252	0.00	0.292	0.00	0.323	0.00
$vixchng_{t-1}$	0.005	0.28	−0.006	0.00	−0.005	0.00	0.001	0.75	−0.007	0.00	−0.006	0.00
$cdsret_{t-1}$					−0.001	0.00					−0.002	0.00
intercept	0.012	0.00	0.002	0.00	0.003	0.00	0.016	0.00	0.003	0.00	0.005	0.00
NOBS	27,771		383,377		383,377		27,771		383,377		383,377	
Adj R^2	0.004		0.003		0.005		0.141		0.162		0.167	
F-stat, overall	18.87		110.61		107.38		63.12		777.65		644.80	
p-value	0.00		0.00		0.00		0.00		0.00		0.00	
F-stat, lagged	4.68		46.21		33.75		85.70		1194.49		982.99	
p-value	0.00		0.00		0.00		0.00		0.00		0.00	
$D1$	0.14		0.27		0.25		0.97		0.99		0.97	

TABLE 5: Joint Panel Regressions

We run joint panel regressions of contemporaneous bond returns on contemporaneous and lagged values of the following variables: stock returns, Treasury returns, changes in equity volatility (VIX), changes in CDS spreads (for the post-CDS period), as well as with and without lagged bond returns, using both pre- and post-CDS samples simultaneously. CDS is a dummy variable that has a value of 1 for the post-CDS period, and 0 for the pre-CDS period. Panel A presents the results for sample selection criteria 1, and Panel B for sample selection criteria 2 (both criteria are described in Section 3 and Appendix B). Table 1, Panel B describes all the variables used. Each regression implements Newey and West (1987) adjustment for heteroscedasticity and autocorrelation, and we report the coefficients (and p-values), the number of observations (NOBS), adjusted R^2 values (Adj R^2) and different F-statistics (and corresponding p-values).

Panel A: Sample selection criteria 1				
	Without lagged bond returns		With lagged bond returns	
	coefficient	p-value	coefficient	p-value
$stkret_t \times (1 - CDS)$	0.015	0.00	0.018	0.00
$tryret_t \times (1 - CDS)$	0.490	0.00	0.542	0.00
$vixchng_t \times (1 - CDS)$	−0.012	0.07	−0.008	0.15
$stkret_t \times CDS$	0.006	0.00	0.005	0.00
$tryret_t \times CDS$	0.499	0.00	0.556	0.00
$vixchng_t \times CDS$	−0.003	0.05	−0.004	0.00
$cdsret_t \times CDS$	−0.005	0.00	−0.007	0.00
$bndret_{t-1} \times (1 - CDS)$			−0.412	0.00
$stkret_{t-1} \times (1 - CDS)$	0.010	0.00	0.018	0.00
$tryret_{t-1} \times (1 - CDS)$	0.086	0.25	0.260	0.00
$vixchng_{t-1} \times (1 - CDS)$	−0.002	0.76	−0.005	0.35
$bndret_{t-1} \times CDS$			−0.439	0.00
$stkret_{t-1} \times CDS$	0.005	0.00	0.007	0.00
$tryret_{t-1} \times CDS$	0.144	0.00	0.359	0.00
$vixchng_{t-1} \times CDS$	−0.005	0.00	−0.005	0.00
$cdsret_{t-1} \times CDS$	−0.002	0.00	−0.004	0.00
intercept	0.004	0.00	0.006	0.00
NOBS	198,131		198,131	
Adj R^2	0.010		0.199	
F-stat, overall (p-value)	96.05 (0.00)		556.68 (0.00)	
When $CDS = 0$				
F-stat, contemp. (p-value)	22.74 (0.00)		30.42 (0.00)	
F-stat, lagged (p-value)	4.44 (0.00)		115.05 (0.00)	
When $CDS = 1$				
F-stat, contemp. (p-value)	246.82 (0.00)		361.24 (0.00)	
F-stat, lagged (p-value)	36.18 (0.00)		1350.25 (0.00)	

Panel B: Sample selection criteria 2

	Without lagged bond returns		With lagged bond returns	
	coefficient	p-value	coefficient	p-value
$stkret_t \times (1 - CDS)$	0.013	0.00	0.016	0.00
$tryret_t \times (1 - CDS)$	0.540	0.00	0.562	0.00
$vixchng_t \times (1 - CDS)$	−0.012	0.03	−0.009	0.09
$stkret_t \times CDS$	0.008	0.00	0.007	0.00
$tryret_t \times CDS$	0.483	0.00	0.522	0.00
$vixchng_t \times CDS$	−0.003	0.03	−0.004	0.01
$cdsret_t \times CDS$	−0.003	0.00	−0.004	0.00
$bndret_{t-1} \times (1 - CDS)$			−0.378	0.00
$stkret_{t-1} \times (1 - CDS)$	0.010	0.00	0.015	0.00
$tryret_{t-1} \times (1 - CDS)$	0.061	0.31	0.258	0.00
$vixchng_{t-1} \times (1 - CDS)$	0.005	0.31	0.001	0.84
$bndret_{t-1} \times CDS$			−0.410	0.00
$stkret_{t-1} \times CDS$	0.004	0.00	0.007	0.00
$tryret_{t-1} \times CDS$	0.128	0.00	0.323	0.00
$vixchng_{t-1} \times CDS$	−0.005	0.00	−0.006	0.00
$cdsret_{t-1} \times CDS$	−0.001	0.00	−0.002	0.00
intercept	0.004	0.00	0.005	0.00
NOBS	411,148		411,148	
Adj R^2	0.005		0.165	
F-stat, overall (p-value)	69.81 (0.00)		390.60 (0.00)	
When $CDS = 0$				
F-stat, contemp. (p-value)	32.33 (0.00)		41.59 (0.00)	
F-stat, lagged (p-value)	5.03 (0.00)		85.63 (0.00)	
When $CDS = 1$				
F-stat, contemp. (p-value)	177.57 (0.00)		225.91 (0.00)	
F-stat, lagged (p-value)	33.74 (0.00)		983.17 (0.00)	

TABLE 6: Joint Panel Regressions with CDS Dummy Interaction

We run joint panel regressions of contemporaneous bond returns on contemporaneous and lagged values of the following variables: stock returns, Treasury returns, changes in equity volatility (VIX), changes in CDS spreads (for the post-CDS period), as well as with and without lagged bond returns, using both pre- and post-CDS samples simultaneously. CDS is a dummy variable that has a value of 1 for the post-CDS period, and 0 for the pre-CDS period. Panel A presents the results for sample selection criteria 1, and Panel B for sample selection criteria 2 (both criteria are described in Section 3 and Appendix B). Table 1, Panel B describes all the variables used. Each regression implements Newey and West (1987) adjustment for heteroscedasticity and autocorrelation, and we report the coefficients (and p-values), the number of observations (NOBS), adjusted R^2 values (Adj R^2) and different F-statistics (and corresponding p-values).

Panel A: Sample selection criteria 1				
	Without lagged bond returns		With lagged bond returns	
	coefficient	p-value	coefficient	p-value
$stkret_t$	0.015	0.00	0.018	0.00
$tryret_t$	0.490	0.00	0.542	0.00
$vixchng_t$	−0.012	0.07	−0.008	0.15
$bndret_{t-1}$			−0.412	0.00
$stkret_{t-1}$	0.010	0.00	0.018	0.00
$tryret_{t-1}$	0.086	0.25	0.260	0.00
$vixchng_{t-1}$	−0.002	0.76	−0.005	0.35
$stkret_t \times CDS$	−0.009	0.02	−0.013	0.00
$tryret_t \times CDS$	0.009	0.91	0.014	0.85
$vixchng_t \times CDS$	0.009	0.18	0.004	0.50
$cdsret_t \times CDS$	−0.005	0.00	−0.007	0.00
$bndret_{t-1} \times CDS$			−0.027	0.20
$stkret_{t-1} \times CDS$	−0.006	0.09	-0.011	0.00
$tryret_{t-1} \times CDS$	0.057	0.46	0.099	0.17
$vixchng_{t-1} \times CDS$	−0.004	0.55	0.000	0.96
$cdsret_{t-1} \times CDS$	−0.002	0.00	−0.004	0.00
intercept	0.004	0.00	0.006	0.00
NOBS	198,131		198,131	
Adj R^2	0.010		0.199	
F-stat, overall (p-value)	96.05 (0.00)		556.68 (0.00)	
F-stat, all interaction variables (p-value)	62.51 (0.00)		106.32 (0.00)	
F-stat, only lagged interaction variables (p-value)	10.61 (0.00)		51.67 (0.00)	

Panel B: Sample selection criteria 2				
	Without lagged bond returns		With lagged bond returns	
	coefficient	p-value	coefficient	p-value
$stkret_t$	0.013	0.00	0.016	0.00
$tryret_t$	0.540	0.00	0.562	0.00
$vixchng_t$	−0.012	0.03	−0.009	0.09
$bndret_{t-1}$			−0.378	0.00
$stkret_{t-1}$	0.010	0.00	0.015	0.00
$tryret_{t-1}$	0.061	0.31	0.258	0.00
$vixchng_{t-1}$	0.005	0.31	0.001	0.84
$stkret_t \times CDS$	−0.005	0.09	−0.009	0.00
$tryret_t \times CDS$	−0.057	0.42	−0.040	0.54
$vixchng_t \times CDS$	0.009	0.11	0.005	0.39
$cdsret_t \times CDS$	−0.003	0.00	−0.004	0.00
$bndret_{t-1} \times CDS$			−0.032	0.14
$stkret_{t-1} \times CDS$	−0.005	0.05	-0.007	0.01
$tryret_{t-1} \times CDS$	0.067	0.30	0.064	0.30
$vixchng_{t-1} \times CDS$	−0.010	0.04	−0.007	0.13
$cdsret_{t-1} \times CDS$	−0.001	0.00	−0.002	0.00
intercept	0.004	0.00	0.005	0.00
NOBS	411,148		411,148	
Adj R^2	0.005		0.165	
F-stat, overall (p-value)	69.81 (0.00)		390.60 (0.00)	
F-stat, all interaction variables (p-value)	32.40 (0.00)		42.69 (0.00)	
F-stat, only lagged interaction variables (p-value)	12.50 (0.00)		35.94 (0.00)	

TABLE 7: Market Quality Before and After Introduction of CDS

We report market quality of the bond market before and after the introduction of CDS. We employ all individual bonds with at least 30 valid trading days in both pre- as well as post-CDS periods (82 bonds meet this criteria) and, for each sub-period, compute the Hasbrouck q measure of market quality,

$$q = \frac{\sigma_e^2 - 2a \cdot Cov(e_t, e_{t-1})}{\sigma_e^2 + a^2\sigma_e^2 - 2a \cdot Cov(e_t, e_{t-1})}$$

where a is the coefficient on a MA(1) process without intercept for bond returns, σ_e^2 is the variance of MA(1) residuals, and $Cov(e_t, e_{t-1})$ is the covariance of lagged MA(1) residuals.

	Sub-period		t-statistic
	Pre-CDS	Post-CDS	of difference
Parameter a	0.20	0.29	−0.51
Residual variance σ_e^2	0.55	2.87	−2.11
Covariance $Cov(e_t, e_{t-1})$	−0.00	−0.02	0.65
q measure	0.86	0.82	1.32

Out of 82 bonds overall, 45 bonds experience decrease in value of q measure after the introduction of CDS, and 37 bonds experience increase in value.

TABLE 8: Bond Liquidity Attributes Before and After Introduction of CDS

We report the values of various liquidity metrics for the bond market before and after the introduction of CDS. Panel A employs the full sample of all observations. Panel B is based on individual bonds with at least 30 valid trading days in both pre- as well as post-CDS periods; 82 bonds meet this criteria (257 bonds for the relaxed LOT measure criteria). LOT measure is based on Das and Hanouna (2010) adaptation of Lesmond et al. (1999) measure and computes the frequency of zero return and zero volume (no trade) trading days as a fraction of total number of trading days in the sample period. Covariance measure of illiquidity is based on Bao et al. (2010) and is computed as $\gamma_i = -Cov(bndret_{it}, bndret_{i,t-1})$. Following Amihud (2002), Amihud illiquidity measure is computed as:

$$ILLIQ_i = \frac{1}{DAYS_i} \sum_{t=1}^{DAYS_i} \frac{|bndret_{it}|}{\$VOL_{it}} \times 10^6$$

where $bndret_{it}$ is the ith bond's return on day t, $\$VOL_{it}$ is the total daily trading volume in dollars, and $DAYS_i$ is the total number of trading days for bond i in the sample period.

Panel A: Based on all observations as a panel					
Liquidity	Pre-CDS period		Post-CDS period		t-statistic
measure	NOBS	Value	NOBS	Value	of difference
Average of					
total # of daily trades	30,932	54.08	476,673	910.36	−91.37
mean # of daily trades	30,932	3.03	476,673	6.05	−28.29
Average (in $ million) of					
total daily trade size	30,932	23.35	476,673	282.18	−71.26
mean daily trade size	30,932	0.50	476,673	0.31	18.08
Average (as % of outstanding) of					
total daily turnover	30,932	0.51	476,673	0.33	12.70
mean daily turnover	30,932	0.22	476,673	0.11	15.62
LOT measure (as fraction)					
zero return days	383	0.12	1,470	0.10	1.93
zero volume days	383	0.75	1,470	0.73	1.99
zero return + zero volume days	383	0.87	1,470	0.83	3.30
Covariance illiquidity measure	na	na	na	na	na
Amihud illiquidity measure	345	39.38	1,392	44.00	−0.29

Panel B: Based on 82 individual bonds					
Liquidity	Pre-CDS period		Post-CDS period		*t*-statistic
measure	NOBS	Value	NOBS	Value	of difference
Average of					
total # of daily trades	11,335	53.98	25,601	64.44	−4.89
mean # of daily trades	11,335	4.60	25,601	5.21	−3.37
Average (in $ million) of					
total daily trade size	11,335	20.78	25,601	19.58	1.26
mean daily trade size	11,335	0.40	25,601	0.27	9.75
Average (as % of outstanding) of					
total daily turnover	11,335	0.40	25,601	0.26	10.15
mean daily turnover	11,335	0.11	25,601	0.06	14.62
LOT measure (as fraction)					
zero return days	257	0.10	257	0.09	1.71
zero volume days	257	0.77	257	0.79	−1.35
zero return + zero volume days	257	0.87	257	0.88	−0.97
Covariance illiquidity measure	82	0.43	82	0.56	−0.28
Amihud illiquidity measure	82	9.57	82	23.89	−2.82

TABLE 9: Joint Panel Regressions with CDS Dummy Interaction for Different Sub-Samples

For different sub-samples of data, we repeat Table 6 tests: we run joint panel regressions of contemporaneous bond returns on contemporaneous and lagged values of stock returns, Treasury returns, changes in equity volatility (VIX), changes in CDS spreads (for the post-CDS period), as well as with and without lagged bond returns, using both pre- and post-CDS samples simultaneously. The explanatory return variables are included without and with interaction with CDS, a dummy variable that has a value of 1 for the post-CDS period, and 0 for the pre-CDS period. Panel A presents the results for sample selection criteria 1, and Panel B for sample selection criteria 2 (both criteria are described in Section 3 and Appendix B). We form sub-samples (a) after excluding 2007–2008 (the liquidity crisis years) observations, (b) after excluding 2002-2003 (the first two years of emergence of CDS market) observations, (c) including only 1-, 2-, and 3-years of post-CDS observations, and (d) based on median values of amount outstanding in the year of CDS introduction. We report the F-statistics (and associated p-values) for the overall model and those corresponding to the CDS dummy interaction variables.

Panel A: Sample selection criteria 1							
		Without lagged bond returns			With lagged bond returns		
		F-statistics (p-value)			F-statistics (p-value)		
Sub-sample	NOBS	Overall model	All interaction variables	Lagged interaction variables	Overall model	All interaction variables	Lagged interaction variables
Full 2002–2009 period	198,131	96.05 (0.00)	62.51 (0.00)	10.61 (0.00)	556.68 (0.00)	106.32 (0.00)	51.67 (0.00)
Excluding 2007–2008	154,126	103.41 (0.00)	46.89 (0.00)	3.58 (0.01)	526.09 (0.00)	93.46 (0.00)	32.35 (0.00)
Only 2002–2004	73,762	53.91 (0.00)	10.42 (0.00)	3.21 (0.01)	287.17 (0.00)	20.04 (0.00)	13.55 (0.00)
Excluding 2002–2003	159,110	69.15 (0.00)	51.55 (0.00)	10.13 (0.00)	414.14 (0.00)	88.39 (0.00)	42.52 (0.00)
Only 1-year post-CDS	23,703	14.75 (0.00)	3.70 (0.00)	0.38 (0.83)	81.98 (0.00)	6.96 (0.00)	3.34 (0.01)
Only 2-years post-CDS	58,462	38.86 (0.00)	13.03 (0.00)	3.78 (0.00)	212.13 (0.00)	23.57 (0.00)	16.95 (0.00)
Only 3-years post-CDS	98,981	60.60 (0.00)	19.39 (0.00)	2.53 (0.04)	357.90 (0.00)	37.02 (0.00)	18.33 (0.00)
Low amount outstanding	55,499	18.62 (0.00)	12.49 (0.00)	6.12 (0.00)	236.41 (0.00)	21.62 (0.00)	15.58 (0.00)
High amount outstanding	142,632	83.50 (0.00)	53.12 (0.00)	6.49 (0.00)	329.09 (0.00)	87.18 (0.00)	36.55 (0.00)
Small sized firms	91,671	44.13 (0.00)	37.82 (0.00)	9.03 (0.00)	264.49 (0.00)	62.26 (0.00)	33.12 (0.00)
Large sized firms	106,213	58.40 (0.00)	27.87 (0.00)	3.36 (0.01)	298.05 (0.00)	46.59 (0.00)	18.20 (0.00)

Panel B: Sample selection criteria 2

		Without lagged bond returns			With lagged bond returns		
		F-statistics (p-value)			F-statistics (p-value)		
Sub-sample	NOBS	Overall model	All interaction variables	Lagged interaction variables	Overall model	All interaction variables	Lagged interaction variables
Full 2002–2009 period	411,148	69.81 (0.00)	32.40 (0.00)	12.50 (0.00)	390.60 (0.00)	42.69 (0.00)	35.94 (0.00)
Excluding 2007–2008	307,128	92.30 (0.00)	21.36 (0.00)	5.30 (0.00)	347.77 (0.00)	41.02 (0.00)	28.08 (0.00)
Only 2002–2004	137,953	53.36 (0.00)	6.67 (0.00)	2.88 (0.02)	196.47 (0.00)	11.91 (0.00)	10.69 (0.00)
Excluding 2002–2003	341,486	47.77 (0.00)	25.89 (0.00)	11.32 (0.00)	299.14 (0.00)	33.53 (0.00)	29.84 (0.00)
Only 1-year post-CDS	60,290	17.71 (0.00)	2.53 (0.01)	0.69 (0.60)	64.71 (0.00)	3.91 (0.00)	1.98 (0.08)
Only 2-years post-CDS	130,526	42.90 (0.00)	7.95 (0.00)	4.64 (0.00)	159.45 (0.00)	13.78 (0.00)	13.34 (0.00)
Only 3-years post-CDS	213,016	62.55 (0.00)	10.91 (0.00)	4.41 (0.00)	256.66 (0.00)	19.69 (0.00)	17.10 (0.00)
Low amount outstanding	157,374	15.17 (0.00)	5.69 (0.00)	2.51 (0.04)	180.63 (0.00)	7.76 (0.00)	6.74 (0.00)
High amount outstanding	253,774	60.84 (0.00)	29.44 (0.00)	10.87 (0.00)	216.40 (0.00)	37.55 (0.00)	30.75 (0.00)
Small sized firms	187,490	31.53 (0.00)	19.86 (0.00)	8.61 (0.00)	181.68 (0.00)	27.43 (0.00)	23.23 (0.00)
Large sized firms	223,153	44.03 (0.00)	14.39 (0.00)	3.85 (0.00)	218.00 (0.00)	16.78 (0.00)	12.24 (0.00)

TABLE 10: Difference-in-Differences Tests: Full Panel Regressions based on CDS and non-CDS Samples

We augment our sample of pre- and post-CDS bond transactions for CDS issuers with a control sample of bond transactions by CDS non-issuers (firms with no CDS introduction). The control sample consists of all bond transactions by firms which meet the selection criteria outlined in Appendix A but did not issue any CDS until the end of 2008. For the combined sample of all observations, we run the following regression with Newey and West (1987) adjustment for heteroscedasticity and autocorrelation:

$$\begin{aligned} bndret_{it} &= \alpha_i + \beta_1 CV_i + \beta_2 LV_i + \beta_3 CDS_{it} * CV_i + \beta_4 CDS_{it} * LV_i \\ &\quad + \beta_5 E_i * CV_i + \beta_6 E_i * LV_i + \beta_7 E_i * CDS_{it} * CV_i + \beta_8 E_i * CDS_{it} * LV_i \end{aligned}$$

where

$CV_i \equiv \{stkret_{it}, tryret_{it}, vixchng_{it}, cdsret_{it}\}$
$LV_i \equiv \{bndret_{i,t-1}, stkret_{i,t-1}, tryret_{i,t-1}, vixchng_{i,t-1}, cdsret_{i,t-1}\}$
$CDS_{it} = 1$ if post-CDS period and 0 if pre-CDS period
$E_i = 1$ for event sample of CDS-issuers and 0 for control sample of non-issuers

CV_i and LV_i denote contemporaneous and lagged (explanatory) variables respectively. Classification of transactions into pre- and post-CDS periods ($CDS_{it} = 0$ vs. 1) is based on the actual CDS introduction date for CDS issuers (E_i=1) and an arbitrarily selected date (based on uniform random distribution) for CDS non-issuers (E_i=0). We report the F-statistics (and associated p-values) for the overall model and those corresponding to the joint significance of various explanatory variables.

	F-statistics (p-value)			
	Sample selection criteria 1		Sample selection criteria 2	
Regression coefficients	Without lagged bond returns	With lagged bond returns	Without lagged bond returns	With lagged bond returns
[Full model]	67.89 (0.00)	342.01 (0.00)	49.42 (0.00)	258.61 (0.00)
$\beta_1 + \beta_2$	49.43 (0.00)	113.49 (0.00)	39.74 (0.00)	116.83 (0.00)
β_2	46.78 (0.00)	146.87 (0.00)	42.39 (0.00)	153.83 (0.00)
$\beta_3 + \beta_4$	1.35 (0.23)	1.43 (0.19)	2.70 (0.01)	3.23 (0.00)
β_4	2.34 (0.07)	1.69 (0.15)	3.24 (0.02)	2.97 (0.02)
$\beta_5 + \beta_6$	9.43 (0.00)	11.29 (0.00)	5.94 (0.00)	5.96 (0.00)
β_6	8.64 (0.00)	14.96 (0.00)	6.24 (0.00)	6.59 (0.00)
$\beta_7 + \beta_8$	62.33 (0.00)	104.98 (0.00)	32.91 (0.00)	41.97 (0.00)
β_8	10.81 (0.00)	49.60 (0.00)	13.67 (0.00)	34.84 (0.00)