Related securities and equity market quality: The case of CDS

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ABSTRACT

We document that equity markets become less liquid and equity prices become less efficient when markets for single-name credit default swap (CDS) contracts emerge. This finding is robust across a variety of market quality measures. We analyze the potential mechanisms driving this result and find evidence consistent with negative trader-driven information spillovers that result from the introduction of CDS. These spillovers greatly outweigh the potentially positive effects associated with completing markets (e.g., CDS markets increase hedging opportunities) when firms and their equity markets are in “bad” states. In “good” states, we find some evidence that CDS markets can be beneficial.

I Introduction

Do multiple securities markets, representing different claims on the same underlying asset, impact equity market quality? Although this question is not new, it has re-emerged as a central issue of debate among policymakers, academics, and financial market participants. The growth of credit derivatives markets, hedge funds, and capital structure arbitrage (which involves trading in both equity and credit derivatives), has brought increasing attention to important questions regarding the impact of derivatives on liquidity and market efficiency. Credit default swaps (CDS) have been a particularly controversial financial innovation.[1] For example, investor George Soros has described CDS as "instruments of destruction which ought to be outlawed."[2] Regulators have also questioned their impact: "The SEC has a great interest in the CDS market because of its impact on the debt and cash equity securities markets and the Commission's responsibility to maintain fair, orderly, and efficient securities markets. These markets are directly affected by CDS due to the inter-relationship between the CDS market and the claims that compose the capital structure of the underlying issuers on which the protection is written."[3]

The interest in CDS markets among market participants and regulators highlights the importance of identifying and quantifying the potential effects that CDS might have on the economy. The main goal of this paper is to examine the effect of single-name CDS markets on equity market quality. Using a broad panel of New York Stock Exchange (NYSE) stocks for the 2003-2007 period, we examine the impact of CDS contracts on both liquidity and price efficiency in equity markets.

There are two potentially important benefits of CDS. First, CDS can be valuable hedging tools through which investors can efficiently manage the risk of their positions in other

[1]Credit default swaps are essentially insurance on a firm's risky debt. They are useful tools for hedging and for speculating on credit risk. See, for example, Stulz (2010) for a discussion of the debates regarding CDS markets.

[2]Soros Says Default Swaps Should Be Outlawed, *New York Times Dealbook June 12, 2009.*

[3]See *Testimony Concerning Credit Default Swaps by Erik Sirri, Director, Division of Trading and Markets, U.S. Securities and Exchange Commission, Before the House Committee on Agriculture October 15, 2008.*

securities. Second, they can provide informed traders with incentives to trade, facilitating price discovery. Given that equity can be viewed as a call option on the firm's assets with a strike price equal to the value of the firm's debt (as in Merton (1974)), there is a precise pricing relationship between debt and equity which arbitrageurs can use to identify and correct any mispricings. There may also be costs associated with the introduction of CDS markets. For example, prices may become less informative if the ability to trade CDS increases the complexity of informed traders' strategies, making it difficult for market makers to learn from their trades (as in Biais and Hillion (1994)). Goldstein, Li and Yang (2013), offer another mechanism through which the introduction of CDS can decrease price efficiency: heterogeneity in investors' access to markets. In their model, sophisticated traders speculate in the new market (CDS, in our setting) and hedge in equity, while unsophisticated traders can only speculate in equity. These different trading motives in the same asset (equity) can cause investors to trade in different directions in response to similar information, which can generate a decline in price informativeness. Equity markets can also become less liquid if the ability to hedge in CDS markets increases the willingness of risk-averse informed traders to trade equity, driving out uninformed liquidity traders (as in Dow (1998)). In a more extreme case, Bhattacharya, Reny and Spiegel (1995) describe destructive interference, in which a new securities market causes the collapse of the existing market.[4] Given the theoretical ambiguity of the impact of derivatives markets on equity market quality, the dominant effect of CDS is an empirical question.

Market quality has several dimensions and we examine a range of measures that have been suggested in the market microstructure literature. Specifically, we divide market quality into two categories: liquidity and price efficiency. The liquidity measures that we use are quoted and effective spreads, as well as the Amihud (2002) illiquidity ratio. All three of these measures capture trading costs. The price efficiency measures assume that efficient stock prices follow a random walk and are constructed to capture deviations of price movements

[4] In a general setting, Elul (1995) shows that when there is more than one consumption good, adding a tradable asset to the economy can reduce welfare.

from this benchmark. Our primary objective is to estimate how the introduction of CDS markets affects these dimensions of equity market quality.

In all of our tests, we control for the existence of equity options and bond markets. Doing so is important because we want to ensure that any findings regarding the role of CDS markets are not simply due to the characteristics of markets that trade other related securities. These controls also allow us to draw comparisons between the impact of CDS markets and that of other markets. We also control for equity market trading and volatility, equity market capitalization, and passive liquidity trading since all of these might impact equity market quality directly. The passive trading activity proxy that we use is, to our knowledge, new to the literature. We find that passive, multi-security trading is associated with higher equity market quality. This is useful for two reasons: (1) it suggests that passive trades due to hedging demands are beneficial, rather than destabilizing and (2) it allows us to isolate the impact of speculative/informed trading in the CDS market analysis. We also control for firm characteristics such as distance to default (to control for potential changes in firm risk when CDS markets are introduced), asset tangibility and cash holdings. All of these firm-level control variables help ensure that any observed impact of CDS markets does not stem from changes in credit risk. Finally, we conduct all analyses using firm fixed effects. This forces all variation in the CDS variable to be driven by within-firm changes in whether such a market exists. The interpretation of the results of the regressions is dynamic (it captures the impact of introducing a CDS market), rather than cross-sectional. Our fixed effects specification also helps address concerns about potential endogeneity stemming from a relevant omitted variable, to the extent that the omitted variable is time invariant.

We report three important findings. First, both equity market liquidity and equity price efficiency decline when markets for single-name CDS contracts are introduced. Firms with traded CDS contracts on their debt have less liquid equity and less efficient stock prices following CDS introduction. Second, we analyze the potential mechanisms driving this result and we find evidence consistent with negative trader-driven information spillovers that result from the introduction of CDS. In particular, we observe an increase in informed trading (i.e., trading by instiutions) and an increase in the information-related price impact of equity trades following CDS introduction. Finally, to shed further light on the mechanisms driving our results and on the negative press that CDS markets received during the recent financial crisis, we ask whether the impact of CDS changes in "bad" states of nature: low distance to default (z-score); low concentration of uninformed liquidity trading (our proxy is NYSE program trading); or high market volatility (VIX). We find that the negative trader-driven spillovers associated with CDS markets greatly outweigh the potentially positive effects of CDS when firms and their equity markets are in "bad" states. In "good" states, we find some evidence that CDS markets can actually be beneficial.

The results from analysis of the other related market control variables allow us to compare the impact of CDS with both equity options and corporate bond markets. We find that firms with listed equity options have more liquid equity and more efficient stock prices (this is generally consistent with prior literature).[5] This provides a striking contrast to the CDS findings. The role of publicly traded bonds is more mixed but is generally negative (as one might expect, given the tight links between CDS and bonds).

Interpreting the negative relationship between CDS markets and equity market quality is, of course, complicated by potential endogeneity issues. For example, one might expect firms with CDS markets to be bigger, more visible and more efficiently priced–but that is the opposite of what we find. One might also be concerned that the onset of CDS trading is driven by time varying risk factors that impact equity market quality. To test whether endogeneity and sample selection are driving the main results, we employ propensity score matching, difference-in-difference estimators, and instrumental variables.[6] To control for potential differences between CDS firms and non-CDS firms, we conduct a matched sample

[5]See e.g., DeTemple and Jorion (1990) and Kumar, Sarin, and Shastri (1998) for empirical analyses of the impact of equity options listing on equity market quality. See Easley, O'Hara and Srinivas (1998), Chan, Chung and Fong (2002), Cao, Chen and Griffin (2005), Pan and Poteshman (2006), and Muravyev, Pearson, and Broussard (2013) for the role of options in price discovery.

[6]Roberts and Whited (2013) discuss these standard approaches to addressing endogeneity concerns. Also see Chava and Purnanandam (2011).

analysis using the propensity score methodology in Rosenbaum and Rubin (1983). We match CDS and non-CDS firms according to Ashcraft and Santos (2009) and we repeat the main analysis using only CDS firms and the matched sample. We construct a difference-in-difference estimator by focusing on CDS and matched sample firms around CDS introduction events. In the instrumental variables analysis, we use trading activity in the bonds of the firms in similar industries (based on 2-digit SIC codes) as a proxy for credit market trading demands. The idea behind this instrument is that if investors demand to trade the risk of firms with a particular type of underlying asset (i.e., industry) then the tradability of other firms' bonds will impact CDS market emergence. At the same time, trading activity in similar-industry bonds should not directly impact a given firm's equity market liquidity and efficiency. Regardless of the empirical approach, we observe a striking deterioration in equity market quality following the onset of CDS trading. The results are also remarkably consistent across a wide range of market quality measures.

Our findings of a strong negative role for CDS in equity markets are in line with contemporaneous work on the informational efficiency of corporate bond markets by Das et al. (2012). In that paper, the authors report that bond market informational efficiency deteriorates when CDS are introduced.[7] On one hand, our paper focuses on a more liquid and arguably more important market in terms of trading activity. An empirical challenge in Das et al. (2012) is that there is a paucity of bond market trading before and after CDS introduction due to the fact that many bond market participants are buy-and-hold investors. In fact, Norden and Weber (2009) report that both CDS and equities , rather than bonds, are the relevant markets for price discovery. On the other hand, the theoretical links between bond and CDS markets are stronger, making bond markets a more natural setting for investigation (for example, Hand, Holthausen and Leftwich (1992) report similar sensitivities of bonds and stocks to credit rating downgrades, but no stock sensitivity to upgrades). Thus, our papers

[7]Asquith, Au, Covert and Pathak (2012) examine the market for short selling corporate bonds and report that bonds with CDS tend to have higher borrowing costs and higher borrowing activity, but that these do not change with CDS introduction.

are complementary.

Our results imply a strong negative link between CDS introduction and equity market quality. However, we emphasize that our findings identify *one* effect associated with traded CDS. This does not rule out potential benefits (or other costs) that CDS may have. For example, the ability to hedge may be an important benefit of CDS markets, because it can decrease the cost of supplying capital to firms and increase suppliers' willingness to extend credit. What is important for informed policy-making is that each of the potential costs and benefits associated with CDS be identified and measured. Our analysis takes one step in this direction.

This paper is organized as follows. Section 2 provides motivation and outlines a framework for the analysis. Section 3 describes the data and market quality variable construction. The empirical methodology and results of the baseline analysis of the impact of CDS markets on equity market quality are given in Section 4. The investigation of potential mechanisms driving the main results is presented in Section 5. Section 6 concludes.

II Motivation and Framework

Why might CDS play a role in equity market quality? Does equity market quality depend on the existence of the new CDS market, or does the CDS market bring a change in the structure of equity market trading? In order to clarify the intuition about the potential effects of CDS markets, it is useful to begin with a brief discussion of the basics of CDS contracts and why they are used. A CDS contract provides insurance on a firm's debt. In the event of default, the seller gives the buyer a payment corresponding to the difference between the nominal and the market value of the debt. In exchange, the buyer pays the seller a periodic premium for this protection. CDS can enhance market efficiency for two reasons. First, credit derivatives can improve risk sharing and provide hedging opportunities for risk averse traders (as in Ross (1976)). These hedging opportunities can be valuable, for example, to financial institutions such as banks and insurance companies. These institutions are frequent providers of corporate debt capital. At the same time, such institutions can also face binding regulatory capital requirements or they may simply wish to offload credit risk from loans provided purely for the purpose of maintaining client relationships. Both reasons make CDS attractive because they can reduce portfolio risk.[8] Second, CDS can be used to speculate on credit risk. To the extent that some speculation is informed, it can improve the informativeness of prices in both credit and equity markets. This is because equity can be viewed as a call option on the firm with a strike price equal to the face value of the debt (Merton (1974)). Any mispricing (in equity or credit markets) can generate arbitrage incentives. Given the general paucity of trading in bond markets, and the leverage offered via the structure of the derivative contract, CDS markets may be attractive venues for such arbitrage activities and general trading on credit risk.

A Potential Impact of Risk Sharing

If CDS markets have no informational role and simply allow for risk sharing in credit markets (e.g. if banks and insurance companies use them solely to hedge their loan portfolios), then traders are motivated by hedging needs, not speculation. In that case, we would not expect CDS market emergence to impact directly the informational efficiency of stock prices. This is because equity market trades that may result are based on hedges that are well-understood by all market participants and market makers will take expected hedging activity into account when setting prices. For example, dealers writing CDS contracts might wish to dynamically hedge their positions in equity markets (selling the CDS is equivalent to a short put on the value of the firm). They could do so with a short equity position which they would, under delta hedging strategies, decrease (i.e., buy shares to cover the short) when stock prices rise and increase it (i.e., sell shares) when stock prices decline. While we would not expect these trades to impact price efficiency, it is possible that they could generate a negative liquidity "externality." This is because the hedging strategy generates trades that are in the same

[8] For a more complete discussion of ways in which CDS can alleviate lending frictions, see Saretto and Tookes (2013).

direction of overall order flow and could therefore decrease equity market liquidity.

B Trader-Driven Information Spillovers

CDS markets provide a new venue for traders with private signals about credit risk to trade on their information. Given that bond markets tend to be illiquid, these information-based trades may not occur in the absence of CDS. Consistent with the idea that informed traders trade in CDS, Blanco, Brennan, and Marsh (2005) have found that prices in CDS markets are more informative about the issuing companies' credit quality than the prices of bonds; Berndt and Ostrovnaya (2007) and Acharya and Johnson (2007, 2010) report evidence of insider trading in CDS markets.[9] Given the theoretical links between equity and debt, efficiently priced credit risk in CDS markets, can improve the informational efficiency of equity prices. On the other hand, it is also possible that with the introduction of CDS, informed investors will now trade in both CDS and equity and that their trades will actually make equity prices less efficient (e.g., due to complicated multi-security trading strategies, as in Biais and Hillion (1994) or because of heterogenity in investor access to CDS markets as in Goldstein, Li and Yang (2013)). These two effects are not mutually exclusive; however, the dominant effect is an empirical question.

The theoretical ambiguity regarding the effect of the influx of informed traders on equity price efficiency also applies to equity market liquidity. If CDS markets cause all securities to be more efficiently priced, uninformed agents may be more willing to trade them, thereby increasing equity market liquidity. On the other hand, if informed traders are also risk averse, then their ability to hedge via simultaneous positions in equity and CDS could make them more aggressive and may cause uninformed liquidity traders to exit the market (thereby reducing market liquidity).

To the extent that equity and CDS markets are alternative venues for trading on private

[9]Note that these spillover effects are expected to be most important when the credit markets are most relevant for equity pricing (i.e., the call option on the firm is not very deep in the money). We will examine this later, in the extended analysis (Table 7).

information about firm risk (i.e., they are sufficiently close substitutes), the theoretical ambiguities discussed above have been echoed in the market fragmentation literature. O'Hara (1995) and Madhavan (2001) provide summaries of theoretical approaches to the fragmentation question. Amihud, Lauterbach and Mendelson (2003) report empirical findings that when two identical securities of the same company are traded in the market, the stock's value is depressed due to fragmentation. Recently, O'Hara and Ye (2012), compare stocks with more and less fragmented trading and find that more fragmented stocks are more liquid (faster execution and lower transaction costs), with more price volatility but also greater price efficiency. The mixed theoretical implications in the fragmentation literature motivate further empirical analysis into the effects of fragmenting the flows of orders and, potentially, information.

C Summary

To summarize, if CDS markets only improve risk sharing (i.e., they allow holders of corporate debt to hedge) then we would expect no impact on equity market price efficiency and a possibly negative impact of CDS on equity market liquidity. If CDS markets also allow informed speculators to trade on their private information (the trader-driven information spillover effect), then the theoretical impact on equity market quality is ambiguous (i.e., it is an empirical question); however, we would expect to observe changes in the structure of trading due to CDS (i.e., relative amounts of informed trading and liquidity trading, and in the price impacts of their trades) that are consistent with any observed effects of CDS on quality. The empirical analysis in this paper aims to identify the overall effects of CDS markets on equity market quality. It also aims to uncover the primary mechanisms driving the results.

III Data

A Sample Construction

We use data from six sources. We begin with all NYSE listed firms from the CRSP/Compustat merged database. We focus only on firms with credit ratings so that the market quality comparisons before and after CDS introduction come only from the years that a firm has a credit rating.[10] We then use the NYSE's Trade and Quote (TAQ) database to construct the market quality measures. Because we are, in part, interested in isolating the potential impact of the ability to trade in CDS markets on informed traders' activities, we introduce a proxy for passive multi-security trading using program trading information from NYSE's proprietary Consolidated Equity Audit Trail Data (CAUD).[11]

The CDS data are from the CMA Datavision database ("CMA") and are based on market information from active buy-side credit market investors. We use the CMA data to identify all firms for which we observe CDS quotes on their debt. Given the wide use of CMA among financial market participants (it is the primary source of the CDS data disseminated on Bloomberg[12]), we assume that CDS contracts for which there is quote information in CMA are actually traded.

[10]We do this to ensure that any CDS results are not driven by differences in the credit risk information environment. We thank a referee for suggesting this important filter. When we do not impose this filter, we still observe a significant and negative impact of CDS on equity market quality; however, it becomes more difficult to disentangle the underlying mechanisms since the interpretation can be clouded by potential changes in the existence of credit risk information.

[11]The CAUD data will later help us understand how the structure of trading in equities changes following CDS introduction. The NYSE account types have been used in a handful of other papers. For example, using the same data set, Kaniel, Saar, and Titman (2007) investigate individual investor trading and Boehmer and Kelley (2009) look at the relationship between informational efficiency and institutional trading. Boehmer, Jones, and Zhang (2008) analyze differences in the informativeness of short selling across account types.

[12]Mayordomo, Pena, and Schwartz (2010) compare the six major CDS databases: GFI, Fenics, Reuters EOD, CMA, Markit and JP Morgan and find that the CMA quotes are the best in that they lead the price discovery process. The Bloomberg/CMA historical CDS data have been used in Das, Hanouna and Sarin (2009), Das, Kalimipalli and Nayak (2012), Chava, Ganduri and Orthanalai (2012), and Saretto and Tookes

Given prior findings that option markets impact equity market quality, we need to control for the existence of these markets. Equity option data are from OptionMetrics. We also control for the existence of bonds for which trades are publicly disseminated on the FINRA Trade Reporting and Compliance Engine (TRACE).[13] Since CDS are written on bonds, we include the TRACE data to ensure that any observed impact of CDS is not simply proxying for the impact of the bond market.

The OptionMetrics, TRACE and CDS data are matched with the CRSP/Compustat database based on 6-digit Cusips; TAQ and CAUD data are matched based on Cusips and, where necessary, ticker identifiers from the TAQ Master File. The sample period covers the years 2003-2007 because TRACE reporting did not begin until July 2002 and our NYSE CAUD data end in 2007. For inclusion in the final sample, we require non-missing data on all variables of interest.

B Market Quality Measures: Data

We are interested in two dimensions of market quality: liquidity (trading costs) and price efficiency (deviations of price movements from a random walk). We rely on the TAQ data to construct all equity market quality measures, with the exception of the Amihud (2002) illiquidity ratio, which is based on daily data from CRSP. We use only trades and quotes that occur during regular market hours. For trades, we require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to @, *, B, E, J, or K. We eliminate trades with non-positive prices or sizes. We also exclude a trade if its price is greater than 150% or less than 50% of the price of the previous trade. We include only quotes that have positive

(2013). CMA is also the source for Datastream CDS data.

[13]TRACE collects and distributes transaction information from the over-the-counter corporate bond market for all TRACE-eligible bonds (i.e., publicly traded investment grade, high yield and convertible corporate debt). Dissemination of information for TRACE-eligible bonds was phased in over two years, beginning in July 2002 with just 50 high yield issues as well as all investment grade issues of $1 billion or more. By October 2004, dissemination for all TRACE-eligible bonds was complete.

depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. We require that the difference between bid and ask be less than 25% of the quote midpoint. These filters are the same as those that are applied in Boehmer and Kelley (2009).

For each stock, we aggregate all trades during the same second that execute at the same price and retain only the last quote for every second if multiple quotes are issued. We assume no trade reporting delay and make no time adjustment (Lee and Ready (1991); Bessembinder (2003)).

C Variable Construction

1 Liquidity Measures

To measure liquidity, we compute time-weighted quoted spreads and trade-weighted effective spreads (*QS* and *ES*, respectively) from TAQ. Effective spreads, a measure of execution costs, are twice the absolute difference between the execution price and the quote midpoint prevailing when the trade is reported. Quoted spreads, a measure of displayed liquidity, are the difference between ask and bid prices, weighted by the duration for which a quote is valid. To normalize *QS* and *ES*, we divide by the closing price of the stock and multiply by 100. Lower (percentage) spreads imply greater equity market liquidity.

We also calculate the Amihud (2002) illiquidity ratio, a widely used measure of illiquidity that requires only daily data and performs well in measuring the price impact of trading (see Goyenko, Holden, and Trzcinka (2009)). *Amihud* is defined as $1000000 * \frac{|ret|}{|prc|*vol}$ and can be interpreted as the average price impact of one dollar of trading (times one million). Lower values of this measure are interpreted as greater liquidity.

All liquidity measures are calculated using daily data.

2 Efficiency Measures

Hasbrouck (1993) decomposes the (log) transaction price, p_t, into a random walk component, m_t, and a transitory pricing error, s_t, where t represents transaction time:

$$p_t = m_t + s_t$$

Under the assumption that informationally efficient prices follow a random walk, we measure efficiency based on the distance between actual transaction price movements and a random walk.

The unobservable random walk component m_t represents the expectation of security value. Innovations in m_t reflect both new public information and the information content of order flow. The pricing error, s_t, which captures temporary deviations from the efficient price, may arise from the non-information-related portion of transaction costs, uninformed order imbalances, price discreteness, and dealer inventory effects. It is assumed to follow a zero-mean covariance-stationary process, but may be serially correlated or correlated with the random walk innovation of the efficient price process. Because the pricing error has a mean of zero, its standard deviation, σ_s, is a measure of its magnitude. Intuitively, σ_s describes how closely transaction prices follow the efficient price over time, and can therefore be interpreted as an (inverse) measure of informational efficiency.

We follow Hasbrouck (1993) and estimate a lower bound for σ_s using a VAR system over $\{r_t, x_t\}$, where r_t is the first difference of p_t and x_t is a vector of explanatory variables whose innovations relate to innovations in m_t and s_t. Specifically, we impose the identification restriction that innovations in s_t must be correlated with $\{r_t, x_t\}$, and obtain the estimate of σ_s from the vector moving average representation of the VAR system (Beveridge and Nelson 1981). The VAR has five lags, and x_t is defined as a three-by-one vector of the trade variables: (1) a trade sign indicator; (2) signed trading volume; and (3) the signed square root of trading volume. This structure of x_t allows for a concave relationship between prices and the trade series.

We follow Boehmer and Kelley (2009) and use all trade observations except when reported prices differ by more than 30% from the previous price, which we consider to be erroneous and eliminate from the sample. To sign trades, we assume that a trade is buyer-initiated if the price is above the prevailing quote midpoint (and seller-initiated for the converse). Midpoint trades are not signed, but we include them in the estimation (with $x = 0$). To eliminate overnight price changes, we restart each process at the beginning of each trading day. Due to the relatively large number of transactions required for reliable estimation, we estimate σ_s monthly. To assure meaningful estimates in this case, we only include stock-months with at least 200 stock transactions per month.

We use $V(s)$ or "pricing error" to refer to σ_s. *Hasbrouck* is defined as $V(s)$, normalized by $V(p)$, the standard deviation of (log) transaction prices. *Hasbrouck* is our main stock price efficiency measure.

Similar to Boehmer and Kelly (2009) and Choi, Getmansky and Tookes (2009), we construct an alternative efficiency measure based on return autocorrelations. We estimate quote midpoint return autocorrelations ($|AR|$) using 30-minute quote midpoint return data over one-month horizons. We exclude periods without quote changes to avoid using stale quotes in these computations. For comparability to *Hasbrouck*, we also calculate the |AR| efficiency measure (30-minute return autocorrelations) using data at monthly intervals.

Like the *Hasbrouck* measure, $|AR|$ captures deviations of stock prices from a random walk. Low (absolute) return autocorrelations suggest that prices more closely follow a random walk. Both the *Hasbrouck* and $|AR|$ measures look over short horizons (transaction-to-transaction and 30-minute intervals, respectively), as traders are assumed to move very quickly to eliminate pricing errors in NYSE stocks (see Chordia, Roll, and Subrahmanyam, 2005). Unlike the *Hasbrouck* measure, the $|AR|$ measure is sensitive to price changes due to trade reversals and is calculated at uniform intervals that do not depend on trade intensity. We include the $|AR|$ measure for comparison (while the two are generally consistent, the *Hasbrouck* measure is more powerful in tests), but rely mainly on the *Hasbrouck* measure in interpreting our results.

3 Explanatory Variables

CDS Markets

cds is a dummy variable equal to 1 if the firm has a CDS traded on its debt (there are CDS quotes in the CMA data) during period *t*. Of course, CDS markets can exist without a mechanism for disseminating quote information (i.e., private bilateral trades). However, we are interested in CDS markets in which there is substantial trading activity and about which there is sufficiently broad dissemination of information that equity market participants (especially liquidity providers) can analyze. Because all of the regressions are estimated with firm fixed effects, coefficients on the CDS dummy variable in the regressions are interpreted as the impact of introducing a CDS market on the market quality variables.

Other Related Markets (Controls)

To ensure that *cds* is not picking up the effect of the introduction of other related markets, we include two related-markets dummies: *option* is a dummy variable equal to 1 if the firm has listed options during period *t*, 0 otherwise; *tradedbond* is a dummy variable equal to 1 if the firm's bond information is disseminated on the TRACE system during period *t*.[14] Like the *cds* dummy, coefficients on these dummy variables in the regressions are interpreted as the impact of introducing a related market on the equity market quality variables.

Equity Market Control Variables

We control for overall stock market trading activity using two variables. The first, *lagdvolume*, is the lagged natural log of total daily trading volume as reported on CRSP, times the closing price. The second, *lagprogramtrade*, is the dollar volume of program trading, defined as the (log) sum of buy and sell dollar volume for program trades, based on the daily NYSE CAUD.[15]

[14] The TRACE system provides information regarding transactions in a firm's publicly traded bonds to all market participants. See, e.g., the discussion of the impact of TRACE on transparency in the corporate bond market in Bessembinder and Maxwell (2008).

[15] We obtained NYSE's proprietary Consolidated Audit Trail Data (CAUD) for the January 2000 to August 2007 period. The CAUD cover nearly all trades executed at the NYSE and show, for each trade, the individual

The NYSE defines program trades as the trading of a basket of at least 15 NYSE securities valued at $1 million or more. Many of these trades are part of index arbitrage strategies and probably do not represent trading on firm-specific factors. In the CDS setting, a dealer making markets in a CDS index might dynamically hedge his positions by trading baskets of equities. Other program trades may bundle uninformed order flow, perhaps originating from index funds or a broker's retail clients, where the bundling serves as a way to signal the absence of security-specific information. We are interested in the impact of potentially informed and speculative participants in CDS markets on equity market quality. To differentiate it from uninformed trading we include the *lagprogramtrade* variable as a control for passive transactions. To our knowledge, this proxy is new to the literature.

Outside of the intuition that program traders are unlikely to trade on firm-specific factors, there are theoretical reasons why we would expect program trades to help identify uninformed multi-security trading. Subrahmanyam (1991) shows that because asymmetric information costs are higher in markets for individual securities, uninformed traders choose to trade in baskets. Similarly, Gorton and Pennacchi (1993) show that basket/index securities can reduce the adverse selection costs paid by uninformed traders, making them better off. While neither model implies only uninformed program trades, they both show that trading in such securities will be particularly attractive to uninformed liquidity traders. Indeed, Hasbrouck (1996) finds that while all types of trading have information content, index arbitrage trades (which

buy and sell orders executed against each other (or market maker interest). Each component is identified by an account type variable that gives some information on trader identity. Several different regulatory requirements include obligations to indicate: orders that are part of program trades, index arbitrage program trades, specialist trades, and orders from market makers in the stock who operate at other trading venues. We focus on program trades, taking the sum of buy and sell share volume for each day and security. We exclude trades that are cancelled or later corrected, trades with special settlement conditions, and trades outside regular market hours. Note that because we define program as the sum of buy and share volume, in order to directly compare the magnitude of this measure to the *lagdvolume* variable, we would divide the sum by 2.

comprise the majority of program trades in his sample), have smaller information content than other types of orders.

We also control for equity price volatility (*lagvolatility*, defined as the lagged square of the daily stock return in CRSP) in all regressions. To control for equity market size, we include an equity market capitalization variable, *res_mcap*, defined as the portion of equity market capitalization that is orthogonal to dollar volume. We do not include market capitalization directly because the correlation between market capitalization and dollar volume is high, at 0.86; however, our qualitative results regarding the impact of related markets are not sensitive to the market capitalization transformation. The *lagdvolume*, *res_mcap* and *lagvolatility* variables control for findings in Mayhew and Mihov (2004), who report that firms selected for options listing have high trading volume, market capitalization and volatility.

Firm Level Control Variables

To make sure that any observed impact of CDS markets on equity market quality is not due to changes in credit or firm risk, we include a distance to default measure *zscore*, (following Altman (1968)). Higher *zscore* indicates that the firm is further away from default. We also include: *cash*, defined as total cash and marketable securities, to proxy for the firm's ability to meet its short term obligations; *netppe*, defined as net property, plant and equipment, to capture asset tangibility; and *rd*, total research and development expense, to capture asset complexity. All of these firm-level variables are scaled by the end-of-quarter total assets (based on quarterly data for quarter t-1, from Compustat).

All control variables are winsorized at the 1st and 99th percentiles.

D Descriptive Statistics

Descriptive statistics for all variables are presented in Table 1. There are 1,091 unique firms, with between 858 and 929 firms in the sample each year. There are 781,944 daily observations used in the liquidity analysis and 35,794 monthly observations in the efficiency analysis. CDS markets exist for a significant number of observations during our sample period: 26% have a CDS quoted in the CMA data. The sample of NYSE firms also have other significant related markets: 81% have traded options and 60% have bond information disseminated on the TRACE system. The average (median) debt-to-asset ratio of these firms is 0.31 (0.29), consistent with the high fraction of firms with TRACE bonds.[16] This implies that credit markets and credit risk information will be relevant to our sample of firms.

IV Empirical Analysis

A Methodology

Our goal is to measure the impact of the related markets on equity market quality. The main regression specification is:

$$\text{(1)} \qquad \text{Market Quality}_{it} = \alpha + \beta_1 * cds_{it} + \beta_2 * option_{it} + \beta_3 * bond_{it} + \beta_4 * X_{it} + e_{it}$$

The coefficients β_1, β_2, and β_3, have straightforward interpretations: they capture the impact of having a CDS, listed option, or bond on the TRACE system on the firm's equity market quality. The variables in control vector X are the equity market controls (*lagprogramtrade*; *lagdvolume*; and *lagvolatility*) and firm characteristics (*zscore*; *cash*; *netppe*; *rd*) defined in Section 3.[17] Recall that high values for the market quality measures are associated with low market quality (e.g., large trading costs indicate low liquidity). Therefore, negative estimated coefficients on any of the explanatory variables are interpreted as a positive relationship between the right-hand-side variables and market quality.

In all regressions, we employ multivariate panel regressions with firm fixed effects and standard errors clustered at the time (day or month) level. The fixed effects control for time-invariant firm characteristics, and the *cds* coefficients are therefore interpreted as the change

[16] The *zscore* variable contains the debt-to-assets ratio, so all regressions control for leverage.

[17] *lagdvolume* and *lagprogramtrade* are calculated as ln(dollar trading activity in $000 + .001).

in market quality when CDS are introduced. Identification for the *cds* coefficients comes from firms for which CDS markets are added over the sample period. In the efficiency regressions using monthly data, all independent variables are also calculated at monthly intervals (i.e., we take monthly averages of daily data).

B Main Results

1 The Impact of Related Markets on Equity Market Quality

Table 2 shows results from estimating Equation (1) for each of the five market quality measures. The most important observation is that the results indicate that, all else constant, traded CDS are associated with significant declines in the equity market quality measures. The estimated coefficients on (*cds*) are positive in all regressions and significant in four of five. This indicates that, all else constant, traded CDS are associated with significant declines in equity market quality. For example, the estimated coefficient of 0.0229 on the *cds* dummy variable in the *QS* regression suggests that firms with traded CDS contracts have quoted percentage spreads that are 2.29 basis points higher than they were without CDS (this represents approximately 16.3% of the mean *QS* of 14.1 basis points). Similarly, the onset of CDS trading is associated with an increase in effective spreads of 1.96 basis points (19.4% of the mean *ES* of 10.1 basis points). For firms with traded CDS, the pricing errors (*V(s)*) increase by 0.16% of total price variance (*V(p)*) (approximately 16% of the mean value of 1.02%), suggesting that the prices of these firms begin to deviate from a random walk at the onset of CDS trading. The estimated coefficient of 0.0018 on the $|AR|$ measure is consistent with the *Hasbrouck* findings; however, the coefficient is statistically insignificant. The overall implication is that the dominant impact of CDS markets is negative. This is consistent with the mechanisms in Dow (1998), Biais and Hillion (1994) and Goldstein et al, (2013).

The idea that related markets can generate liquidity and efficiency externalities underlies much of the analysis in this paper. While there is little work on the impact of credit derivatives, there is a substantial theoretical and empirical literature on the impact of the introduction of options (see Mayhew (2000) for an excellent survey). It is therefore useful to compare the *cds* coefficients with the coefficients on the other related markets dummies. The negative and significant estimated coefficients on the option market dummy (*option*) indicate that, all else constant, traded equity options are associated with significantly improved equity market quality. For example, the estimated coefficient of -0.0141 on the *option* dummy variable in the *QS* regression suggests that firms with listed options have quoted percentage spreads that are 1.4 basis points lower than firms without traded options (this represents approximately 10% of the mean *QS* of 14 basis points). For firms with traded options, the pricing errors (*V(s)*) decrease by 0.42% of total price variance (*V(p)*) (approximately 40% of the mean value of 1.02%), suggesting that the prices of these firms more closely follow a random walk. These findings are consistent with the earlier literature (e.g., Easley, O'Hara and Srinivas (1998), Chan, Chung and Fong (2002), Cao, Chen and Griffin (2005) and Pan and Poteshman (2006)).

The *bond* results from Equation (1) in Table 2 are very consistent with the CDS findings and reveal a negative role for bond markets in both liquidity and efficiency. The estimated magnitudes of *bond* are very similar, but slightly lower than the coefficients on *cds*. We find that, all else equal, the overall impact of having bond information disseminated on the TRACE system is associated with greater transaction costs and lower efficiency using the *Hasbrouck* measure (when efficiency is measured according to the $|AR|$ measure, the coefficient is statistically insignificant). It is important to note that we observe *separate* effects of CDS markets and bond markets. Thus, CDS markets may make the learning problem worse.[18]

The estimated coefficients on the program trading volume (*lagprogramtrade*) variable, which we use to proxy for passive multi-security trading in the stock, are worth noting. We

[18]Because debt-linked securities markets might be relatively more relevant to stock prices when they are declining, the difference in signs of the equity options versus CDS and bond market results may be due to their being relevant at different times. In unreported tests, we investigate whether the patterns that we observe are driven by negative stock return days. We find very little difference in the main results on negative versus positive return days.

observe negative and statistically significant estimated coefficients in all of the regressions. It appears that increases in passive trades due to hedging demands have a stabilizing effect on equity markets. This is important, because it helps us isolate the potentially informative component of CDS markets.

The results for the other control variables are as follows. Increases in overall trading activity (*lagdvolume*) are associated with increases in liquidity, but decreases in stock price efficiency. The efficiency finding suggests that trades that are not easily identified as passive make the learning process more difficult. The estimated coefficients on the firm's *zscore* suggest that default risk actually plays a positive role in liquidity, after controlling for the related markets and equity market trading activity. It may be that liquidity traders are attracted to more distressed firms (holding equity price volatility and equity market trading activity constant). There are less consistent patterns for the *res_mcap* and *cash* controls. The estimated coefficients on the *lagvolatility*, *netppe* and *rd* controls are not generally significant.

To summarize, we find an overall decline in equity market quality following the introduction of CDS markets. When we rank the estimated effects of the three related markets for liquidity, we generally find that the impact of CDS markets is the most negative, closely followed by corporate bond markets, and then options (which have an overall positive effect). For efficiency, CDS and bond markets have similar negative effects, and the impact of options is overall positive and larger than the other markets.

C The Impact of CDS Markets: Matched Sample Methodology

Our baseline analysis controls for time-invariant firm specific hetrogeneity. However, given the economic significance of and policy interest in CDS markets, we want to be sure that our CDS results are not driven by time-varying differences between CDS and non-CDS firms. To achieve this, the baseline analysis in Table 2 controls for changes in firm risk (*zscore* and *lagvolatility* controls), the dollar volume of trading in a firm's stock (correlated with size) and whether a firm has a bond listed on the TRACE system (i.e., has publicly traded debt and a credit rating). Still, we want to check that our results are robust to explicitly controlling for potential selection bias. Therefore, we repeat the initial analysis using only CDS firms and a matched sample of non-CDS firms. The matched sample is constructed based on the propensity score methodology in Rosenbaum and Rubin (1983). We first estimate the probability of having a CDS market with a probit model, using the (one-quarter lagged) covariates from Aschcraft and Santos (2009): equity analyst coverage; log stock market volatility; dummy variable equal to one if the firm has a credit rating; log sales; debt-to-assets; book-to-market; and log equity market trading volume. For each CDS firm, we identify a non-CDS firm with the closest propensity score (making sure that the absolute difference in propensity scores is less than 10% of the CDS firm's propensity score). We are able to find a non-CDS match for 293 out of the 314 CDS firms that we observe during our sample period.[19]

Table 3 is analogous to Table 2, but our regressions are based on only CDS firms and the matched sample of non-CDS firms. As in Table 2, all regressions control for time-invariant firm-specific heterogeneity via firm fixed effects. As Table 3 shows, the main findings of a negative role for CDS markets are very robust in the matched sample analysis. The only finding that is inconsistent with the earlier results is that, similar to option markets, the introduction of traded bond markets appears to improve equity market liquidity after we implement the matched sample methodology. It may be that being able to observe trades in a firm's debt makes traders more willing to trade in a firm's equity.

[19]We also check the efficacy of our matching methodology. The probit model on the full sample shows the covariates explain the cross-sectional variation well, with a pseudo R-squared of 34%. This analysis is not meant to draw any causal inferences about CDS introduction, but only to use the resulting likelihood score in the matching exercise. We run the probit model on the matched sample and the results show the CDS and control firms are equally balanced, based on the covariates used in the analysis. The pseudo R-squared drops to 1.4% and none of the variables (except volatility, which is marginally significant at 10% level) are significant in the probit regressions using only the matched sample.

D Equity Market Quality Near the CDS Introduction Event

The results from the regressions so far (Tables 2 and 3) provide strong evidence of a decline in equity market quality near the introduction of CDS markets. However, because these regressions use the entire post-CDS introduction to estimate the impact of CDS markets, the results do not tell us much about the time horizon over which we might expect quality to decline. In this section, we introduce a second empirical approach in which we isolate the CDS introduction event and we examine changes in equity market quality during year t-1 through year t+1 relative to CDS introduction, compared with changes in the matched sample of non CDS firms. That is, we employ fixed-effect regressions using data only during the two-year window centered around the CDS introduction event for the CDS and matched sample firms (similar to Table 3). The results are shown in Table 4. Despite the truncated time series, the CDS results are similar to those shown in Table 3. This suggests a negative role for CDS markets in equity market quality during the year after CDS introduction, and the main tables (2 and 3) reveal that this negative impact is not transient.

E Potential Endogeneity Concerns: IV Regressions

We have presented evidence of a decline in equity market liquidity and price efficiency following the introduction of traded CDS contracts. One remaining concern about the analysis is potential endogeneity. In particular, the concern is that CDS may be capturing time variation in firm risk.[20] It is always a challenging task to conclusively rule out endogeneity concerns but our analyses thus far should have mitigated some of these concerns. First, the inclusion of the *zscore* (distance to default) as an explanatory variable in all regressions helps to control for changes in firm-level risk.[21] Second, we note that none of our independent variables is

[20]Subrahmanyam, Yongjun and Wang (2012) report evidence of risk increases for their sample of firms.

[21]The findings in Chava, Ganduri and Orthanalai (2012) suggest that changes in firm risk should not be a major concern during our sample period. They examine stock price reactions to ratings downgrades when CDS are trading on a firm's debt. They observe significantly less price reaction following introduction of CDS (if firm risk were increasing, we would expect greater price reaction). More importantly, the distributions

contemporaneous-all are lagged with respect to the dependent variables (liquidity and efficiency of the stock prices). Third, CDS contracts are traded on relatively large firms and, unconditionally, firms with CDS contracts have more liquid equity and more efficient stock prices. This is in contrast to the negative effect of the existence of CDS markets on liquidity and efficiency that we find in the paper. Finally, our propensity score matching based results should ameliorate some of the selection bias concerns that may be relevant in this context.

While the discussion above suggests that endogeneity is not likely to be the primary explanation of our findings, in a further step towards addressing endogeneity concerns, we employ instrumental variables regressions. In choosing an instrument, we would like to identify a variable that is related to the emergence of CDS markets, but not directly related to a firm's equity market quality (i.e., it satisfies the exclusion restriction). Oehmke and Zawadowski (2012) examine the determinants of net CDS outstanding and find that CDS are more likely to emerge when bonds are difficult to trade. We therefore use a proxy for bond market trading demands as an instrument for CDS market emergence. Because we want to be sure that the exclusion restriction is satisfied in our regressions, we use trading activity in the bonds in each firm's general industry (based on 2-digit SIC codes) as a proxy for bond trading demands. The idea is that this variable captures the demand of investors to risk of a particular type of underlying asset (i.e., industry). The tradability of bonds of firms within an industry can cause the emergence of CDS markets, but trading activity in other firms' bonds should not directly impact a given firm's equity market liquidity and efficiency.[22] Results are shown in Table 5. When we replace *cds* with *cdsiv*, we find results that are similar to those in the

of ratings upgrades and downgrades that the authors report are very similar prior to and following CDS introduction.

[22]The Durbin-Wu-Haussman (DWH) test using the robust variance estimate is 93.44, indicating that the IV coefficients are different from the OLS estimates. The coefficient estimate on the bond trading activity of the industry is also highly significant in the first stage regression. We also conduct various diagnostics and tests for a weak instrument. The partial (Sheas) R-square and adjusted partial R-square are reasonable, at around 0.13 (0.04). The robust F-statistic is 839, indicating that a weak instrument is not a major concern. Stock-Yogo tests also strongly reject the null hypothesis of weak instruments.

previous tables. Endogeneity is not likely to be driving the results.

V Potential Mechanisms

The results so far suggest that CDS markets cause a decline in equity market quality. Given the fixed effects specification, we can be sure that our findings are not being driven by unobservable time invariant firm characteristics. The matched sample results (using data over the entire sample period in Table 3, as well as the CDS introduction event analysis in Table 4) mitigate concerns that the results are driven by selection issues. Moreover, the IV regression analysis, in which we use the demand for trading credit risk in the bond markets of firms in the same general industry as an instrument for the existence of a CDS market in the firm's debt, leaves our main findings unchanged. Thus, endogeneity is unlikely to drive the results.

Given that we have ruled out the alternative interpretations given above, the finding that CDS markets, on average, reduce market quality leads to several natural questions. What drives the negative role for CDS markets? Do they always lead to a deterioration in equity market quality? Can we use the insights from this analysis to interpret the negative press that CDS received during the recent financial crisis? Our aim is to shed some light on these issues.

A Interpretation of the Role of CDS Markets: Information Environment

The discussion in Section 2 suggests two potential channels through which the emergence of CDS markets might impact equity market quality. The first is via improved risk sharing. If CDS markets improve risk sharing, we would expect no impact on equity market efficiency (since hedging transactions are not likely to have information content), but a potentially negative impact of CDS on equity market liquidity (because the hedging demands of sellers of credit insurance are such that they can become liquidity demanders). Our results are not entirely consistent with the risk sharing channel as the main driver the impact of CDS since we observe a substantial decline in equity market efficiency (this should not occur without a change in the information structure of the market), along with the liquidity decline.

The fact that the informational efficiency of equity prices is reduced suggests that the information environment changes after CDS introduction. This change can be trader-driven or arise internally (i.e., the firm reduces the precision of the information that it reveals to the market). Under the "trader-driven information spillover" hypothesis, there is more informed trading, but it is also more difficult to learn from these trades due to complex trading strategies that now involve multiple markets (as in Biais and Hillion (1994)). Under the "firm-driven information environment change" hypothesis, there is more uncertainty about the firm, but the structure of trading does not change.

In Table 6, we investigate the potential mechanisms through which informational efficiency changes. In particular, we examine the impact of CDS markets on: institutional trading (from the CAUD data); program trading; turnover; the (5-minute) price impact of trading; and analyst forecast dispersion. Institutional trading and program trading are both scaled by all trading activity, so the CDS coefficient is interpreted as the change in the amounts of each type of activity relative to total trading. We control for changes in firm risk in all regressions via the *zscore* and *lagvolatility* controls. Increases in institutional trading activity (after controlling for passive program trading and overall trading activity) are interpreted as an increase in sophisticated, informed trading. Similarly, increases in the 5-minute price impact of trading are indicative of more informed trading. An increase in program trading relative to overall trading activity is interpreted as an increase in liquidity trading. An increase in analyst forecast dispersion is interpreted as an increase in uncertainty about the firm (given public information).

The evidence in Table 6 is most consistent with the trader-driven information spillover hypothesis. We observe striking increases in institutional trading when CDS markets are introduced (Column 1). Importantly, this increase is relative to passive trading activity, which is included as a control variable in the regression. The increase in this informed institutional trading is coupled with an increase in the price impact of trading (column 4), as one would expect if market makers perceive greater adverse selection risk due to a decreased ability to learn from trades following CDS introduction (as in Biais and Hillion (1994)). Of course, more informed trading can enhance price discovery (a positive role for CDS), but in the short run, our analysis reveals that this results in substantially higher transaction costs for all traders. In untabulated analysis, we conducted analysis to further disentangle the transactions cost interpretation from that of improved price discovery. In particular, we analyzed the impact of CDS on realized spreads. Realized spread is calculated as difference between the transaction price and the midpoint of the best bid/offer prices five minutes following trade execution (rather than the prevailing quote midpoint). It removes the information content of the trade and can be viewed as the cost of immediacy. We find that the introduction of CDS is associated with substantial increases in realized spreads. This suggests that CDS introductions affect not only information in trades (as measured by the permanent price impact of trades, as we report in Table 6), but also the underlying cost of liquidity.

It is useful to compare the estimated coefficents on *cds* in the institutional trading and price impact regressions to those on *option* and *bond*. While we observe increases in institutional trading when all related markets are introduced, the price impact of trades decreases following the introduction of options and bonds (i.e., there are *positive* trader-driven spillovers from those markets).

We observe a small increase in the relative amount of program trading when CDS markets are introduced (Table 6, column 2). As discussed above, program trading might increase if writers of CDS contracts (especially on CDS indices) hedge in equity markets. However, because price efficiency also changes when CDS markets are introduced, improved risk sharing/hedging is not likely to be the main driver of our results (hedging transactions are not expected to have information content). Moreover, the results in Column 1 of Table 6 reveal that the increase in other (non-program) institutional trading is larger than the increase in program trading. [23]

[23] We also observe increases in dollar volume when CDS markets are introduced. Program trading and

If the reduced informational efficiency of stock prices comes from an increase in the market's uncertainty about the firm (through a reduction in relevant public information), then the proxy for market uncertainty should increase when CDS markets are introduced. We do not observe this. In fact, the results in Table 6 suggest that analyst forecast dispersion goes down when CDS markets are introduced, implying that there is actually less market uncertainty about the firm's fundamentals, given public information. This is consistent with CDS markets enhancing information production, which can be associated with either increases or decreases in market quality.

B Interpretation of the Role of CDS Markets: The State of the Equity Market

The results in Table 6 are consistent with the idea that CDS markets impact equity market quality via trader-driven information spillovers. If this information channel is, in fact, the mechanism driving our findings, then we would expect the results to be strongest when CDS markets and equity markets have the tightest informational links. To examine this hypothesis, we sort firms by distance to default (*zscore*) and repeat the analysis separately for each *zscore* group. The idea behind this sort is that the view of equity as a call option on the assets of the firm implies that the linkages between debt and equity values become greater when the option is not very deep in the money (i.e., firms are close to default). Results are shown in Table 7. Indeed, we find that the negative role of CDS is strongest when equity and debt markets are closer substitutes. In fact, for most market quality measures, we observe a steep decline in the negative impact of CDS as we move from low-to-high distance to default (from *zcsore* tercile 1 to 3).[24] Interestingly, in the case of liquidity, we actually find some evidence of a *positive* role

dollar volume can both be seen as contributing to higher levels of liquidity but because our main tests hold both effects constant, the overall effect of CDS is still related to a decline in liquidity and efficiency.

[24]From the table, it is obvious that magnitudes of the estimated coefficients decrease in *zscore*. We also note that, while the mean market quality measures vary inversely with *zscore*, the implied percentage decline in market quality measures when CDS markets are introduced are also greater for the low *zscore* sample. For

for CDS in markets where firms are further away from distress. It may be that learning from CDS prices is easier in this case since informed traders may find credit markets a more natural venue for trading on news specific to a firm's credit risk than equity markets when firms are far away from default (i.e., it is easier for market makers to make inferences from informed trading in both CDS and equity markets, so the costs associated with adverse selection risk borne by liquidity traders is lower). By comparison, we do not observe these patterns for equity options. This finding is useful since it suggests that the *zscore* sort captures CDS market relevance, rather than something else. We do observe similar patterns in the estimated coefficients of the impact of bond markets, but this would be expected given the tight links between CDS and bonds.

Asymmetric information models imply that the potential influx of informed traders to markets will have more severe impacts on markets in which there are fewer liquidity traders. In Table 8, we examine this implication of trader-driven information spillovers by sorting stocks by passive trading activity (program trade volume relative to total volume) and re-estimating the regressions for the high (tercile 3), medium (tercile 2) and low (tercile 1) passive trading stocks. The estimated coefficients on CDS generally decline across passive trading portfolios. And, the positive role for CDS on liquidity suggested by the results from the high distance to default firms in Table 7 can also be seen for all but the lowest (tercile 1) passive-trading portfolio. We observe this pattern of an increasingly beneficial role for the other related markets as passive trading in the equity market increases.

As a final check on the mechanisms driving the results, we look at periods of high volatility (i.e., when informed traders can potentially profit most from their information). Results are shown in Table 9. While we observe the significant and negative impact of CDS across all VIX portfolios, it is monotonically increasing as we move from low to high market volatility (for all market quality measures except *Amihud*). Again, it is useful to compare this finding to the results for equity option markets. As markets become more volatile, the equity options

example, the estimated coefficients of 0.0579, 0.00489 and -0.00143 on *cds* in the *ES* regressions correspond to percentage changes of 23.6, 4.1 and -1.8, respectively, relative to the portfolio means of *ES*.

become more helpful in increasing equity market liquidity. In the case of equity price efficiency, the effect of equity options is either relatively constant (based on the *hasbrouck* measure) or increasingly beneficial (based on the *AR* measure) as markets become more volatile. These findings are the opposite of what we observe for CDS markets.

The results in Tables 7 through 9 reveal that the negative role of CDS in equity market quality is driven by *bad* states. This is particularly true in the case of liquidity (the efficiency results are less sensitive to market conditions). When firms are close to default, have lower liquidity trading, and when markets are volatile, the introduction of CDS contracts is more damaging to equity markets. When firms and markets are in *good* states, the negative impact of CDS on price efficiency is far lower and CDS markets can actually improve liquidity when enough uninformed, passive traders are in the market. It is possible that speculative trading demands in CDS markets dominate when market conditions are poor and that speculation subsides during normal times, when hedging and risk management demands of traders become more important.

C CDS Quotes: A Market Activity Proxy

The recent debates regarding the impact of derivatives markets, particularly CDS, make the findings in this paper potentially useful to policy makers. Unfortunately, our CDS market data are also somewhat limited. For example, we would ideally observe daily trading activity in CDS since it is natural to ask whether the CDS findings stem from the existence of CDS markets or from trading activity in CDS. We do not have trading volume data (as we do for equity options and corporate bonds markets); however, we do know on which days CDS are quoted in the CMA data and how many quotes are emitted. We use the number of daily quotes to capture variation in CDS market activity. We introduce *cdsnumquote*, defined as the number of CDS quotes which we observe on day t (or month t, for the regressions using efficiency measures), to capture market activity.

Table 10 is analogous to Table 3, with the *cdsnumquote* variable added to the analysis.

The direct role of having a CDS market remains negative and significant for both spreads and for market efficiency; however, Table 10 also shows that more active CDS markets negatively impact both dimensions of market quality. As in Table 3, all regressions contain firm fixed effects, and the coefficients are interpreted in terms of changes. Thus, we find that increases in CDS market activity have a strong negative effect on liquidity and on price efficiency (captured by the *Hasbrouck* measure), along with a negative direct impact of *cds*, the existence of the CDS market.[25]

To summarize, introducing a CDS market generally negatively impacts equity market liquidity and price efficiency and this effect tends to be even worse when the CDS market is actively quoted. The overall findings support the general interpretation that related markets linked to a firm's debt decrease market quality.

VI Conclusions

We analyze the implications of the introduction of credit default swap markets on the equity market quality. After CDS contracts are introduced, equity markets become less liquid and equity prices become less efficient. Our findings suggest that this result is at least partially driven by the increased presence of informed institutional investors.

Our robustness tests provide sharper interpretation of the mechanisms driving the impact of CDS markets on equity market quality. We find that the impact of CDS markets is more negative when the firm and its equity market are in a "bad" state (i.e., smaller distance to default, fewer liquidity traders, and more market uncertainty). CDS markets play a less negative (and even a positive role) in "good" states. It is possible that there is more speculation in CDS markets when market conditions are poor and that speculation subsides during normal times, when hedging and risk management demands of traders are more relevant. These findings provide some insight into why CDS markets have been the focus of so much negative

[25] We have repeated all regression analysis in the paper to include bond and option market activity (trading volume) as well. All findings regarding the impact of CDS are qualitatively similar.

attention during the recent crisis. We hope that our findings regarding the market-condition-varying role of CDS can help inform policy debates regarding the costs and benefits of CDS.

One factor that may contribute to our overall findings, which we offer to future research, is that the structure of CDS markets may drive the negative impact on equity market quality. CDS markets are opaque and highly decentralized. By contrast, the other related markets controls that we consider are relatively more transparent: equity options are listed on organized exchanges, and corporate bonds, while traded over the counter, are subject to trade dissemination rules.[26] The ranking of the opaqueness of CDS, bond and equity option markets is perfectly correlated with the ranking of the overall negative impact of each of these markets on equity market quality. Recently, CDS markets have moved towards centralized clearing (for example, via the Chicago Mercantile Exchange) and increased standardization. In the wake of the Dodd Frank Act, there have also been policy discussions regarding exchange trading of CDS. These market structure developments have the potential to change the impact of CDS markets going forward.

[26]Bessembinder, Maxwell and Venkataraman (2006), Edwards, Harris and Piwowar (2007), and Goldstein, Hotchkiss and Sirri (2007) all report increases in bond market quality following trade reporting.

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Table 1: **Descriptive Statistics**

The sample includes all NYSE stocks for the years 2003-2007 for which we have debt ratings and non-missing information for the liquidity, efficiency and control variables. The stock market liquidity statistics are based on daily spread data. QS is defined as the time-weighted average of the quoted spread on the primary exchange divided by the quote midpoint. ES is defined as the trade-weighted average of the effective spread divided by the quote midpoint. The stock market efficiency variables are measured using intraday data over monthly intervals. $Amihud$ is the Amihud (2002) illiquidity ratio, defined as $1000000 * \frac{|ret|}{|prc| * vol}$. The stock market efficiency variables are measured using intraday data over monthly intervals. $Hasbrouck$ is defined as the pricing error variance (based on Hasbrouck (1993)), divided by the standard deviation of intraday (log) transaction prices. $|AR|$ is the absolute value of the 30-minute autocorrelation of quote midpoint returns. These efficiency variables measure the extent to which prices deviate from a random walk. The CDS market variable is *cds*, a dummy set equal to 1 if the firm has a CDS quote in the CMA data on day t. *cdsnumquote* is the number of daily CDS quotes, from the CMA data. The other related markets (control) variables are *option* and *bond*. These are set equal to 1 if the firm has a listed option or public bond information on the TRACE system on day t, respectively. Equity market variables are *lagprogramtrade*, *lagdvolume*, *lagvolatility*, and *res_mcap*. *lagprogramtrade* is the dollar volume of program trading, defined as the (log) sum of institutional buy and sell dollar volume for their program trades, based on daily summaries of NYSE CAUD data for each stock. *lagdvolume* is the total daily trading volume as reported on CRSP, times the closing price. The values used to calculate *lagdvolume* and *lagprogramtrade* are both measured at period $t-1$ and are in thousands of dollars. *lagvolatility* is the square of the daily stock return on day $t-1$. *res_mcap* is the portion of equity market capitalization that is orthogonal to dollar volume. Firm level variables are *zscore*, *cash*, *netppe*, and *rd*. *zscore* is Altman's z score computed using Altman's (1968) measure. Higher *zscore* means that the firm is further away from default. *cash* is total cash and marketable securities scaled by total assets; *netppe* is net property, plant and equipment scaled by total assets; *rd* is the firm's research and development expense scaled by total assets. The firm-level variables are scaled by the end-of-quarter total assets (based on quarterly data for quarter t-1, from Compustat). There are 314 unique firms in the full sample with traded CDS contracts.

Table 1: **Descriptive Statistics (Contd.,)**

Descriptive Statistics for Full Sample

	Mean	Median	25^{th} pcntl	75^{th} pcntl	Std. Dev
Stock Market Liquidity Variables (Daily): Trading Costs					
QS	0.1414	0.0796	0.0526	0.1316	0.2801
ES	0.1006	0.0566	0.0375	0.0937	0.2003
$Amihud$	0.0128	0.0004	0.0001	0.0014	0.2873
Stock Market Efficiency Variables (Monthly)					
hasbrouck	0.0102	0.0074	0.0048	0.0117	0.0114
$\|AR\|$	0.0757	0.0623	0.0296	0.1086	0.0598
Credit Default Swaps					
cds	0.2599	0.0000	0.0000	1.0000	0.4386
Other Related Markets					
option	0.8130	1.0000	1.0000	1.0000	0.3899
bond	0.5965	1.0000	0.0000	1.0000	0.4906
Equity Market Controls					
lagprogramtrade	8.8684	9.1122	8.0751	10.0790	1.9785
lagdvolume	9.8160	9.9262	8.8131	11.0142	1.7897
lagvolatility	0.0004	0.0001	0.0000	0.0003	0.0129
Firm Controls					
$\frac{debt}{asset}$	0.3064	0.2888	0.1888	0.4012	0.1726
zscore	1.8465	1.5278	0.8447	2.4769	1.4840
cash	0.0761	0.0419	0.0175	0.1016	0.0906
netppe	0.3076	0.2409	0.1000	0.5027	0.2499
rd	0.0027	0.0000	0.0000	0.0000	0.0083
res_mcap	0	-0.0012	-0.4949	0.4888	0.7813

Table 2: **CDS and Equity Market Quality**

This table presents the results of regressions that estimate the impact of the introduction of CDS markets and equity market quality. The results are based on panel regressions for all NYSE stocks for the years 2003-2007 for which we have credit ratings and non-missing information for the liquidity, efficiency and control variables. The dependent variables are equity market quality measures, which are divided into two groups: liquidity and efficiency. The liquidity measures are quoted and effective spreads (QS and ES, respectively) and the Amihud illiquidity ratio (*Amihud*). Efficiency measures are $Hasbrouck$, defined as the pricing error based on Hasbrouck (1993), divided by the standard deviation of intraday log transaction prices, and $\mid AR \mid$, defined as the 30-minute autocorrelation in quote midpoint returns. The CDS market variable, *cds*, is a dummy variable equal to 1 if there is a CDS quote in the CMA data on day t). Other related market variables are *option* and *bond* (indicator variables set equal to 1 if the firm has a listed option and bond information on the TRACE system on day t, respectively). Equity market control variables are: one period lagged (log) dollar volume of program trades (*lagprogramtrade*) in thousands of dollars; one period lagged (log) total dollar volume (*lagdvolume*) in thousands of dollars; one period lagged volatility *lagvolatility* and the portion of equity market capitalization that is orthogonal to dollar volume (res_mcap). Firm-level control variables are: $zscore$, $cash$, *netppe*, and *rd*. All variables are defined in Table 1. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered at the date level. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 2: **CDS and Equity Market Quality (Contd.,)**

	QS	ES	$Amihud$	$Hasbrouck$	$\mid AR \mid$
cds	0.0229**	0.0196**	0.00927**	0.00160**	0.00183
	(26.69)	(28.69)	(10.84)	(5.31)	(1.21)
option	-0.0141**	-0.00944**	0.00637**	-0.00418**	-0.00906**
	(-10.57)	(-9.44)	(5.24)	(-3.03)	(-3.48)
bond	0.0213**	0.0131**	0.0104**	0.00157**	0.000665
	(22.44)	(19.34)	(10.21)	(5.92)	(0.57)
lagprogramtrade	-0.0788**	-0.0574**	-0.0123**	-0.00660**	-0.00414**
	(-46.44)	(-42.36)	(-4.70)	(-9.52)	(-3.10)
lagdvolume	-0.0566**	-0.0387**	-0.0128**	0.00497**	0.000391
	(-27.10)	(-23.78)	(-5.06)	(7.15)	(0.20)
lagvolatility	0.0980	0.0982	0.0652	-0.0301	-0.0339
	(0.78)	(0.89)	(1.11)	(-1.75)	(-0.72)
res_mcap	-0.114**	-0.0807**	-0.00707**	0.000853*	-0.00331
	(-44.78)	(-43.70)	(-3.42)	(2.01)	(-1.96)
zscore	0.0222**	0.0154**	0.00573**	-0.0000807	-0.0000452
	(29.24)	(27.53)	(8.50)	(-0.74)	(-0.06)
cash	-0.0625**	-0.0397**	0.0215**	-0.000195	0.00687
	(-11.96)	(-10.55)	(2.70)	(-0.17)	(0.82)
netppe	-0.00340	0.0174**	0.00206	0.00165	0.0249**
	(-0.56)	(3.70)	(0.40)	(0.90)	(2.90)
rd	-0.0245	-0.0113	-0.118*	0.0105	0.0124
	(-1.00)	(-0.62)	(-2.45)	(0.87)	(0.18)
N	781944	781923	781322	35794	36748
adj. R^2	0.755	0.735	0.238	0.383	0.050

Table 3: **Matched Sample Analysis**

This table presents matched sample results of regressions that estimate the impact of the introduction of CDS markets on equity market quality. For each firm with a traded CDS contract, we identify a similar non-CDS firm from the sample of all NYSE-listed firms using propensity score methodology in Rosenbaum and Rubin (1983) based on the model in Ashcraft and Santos (2009). Only CDS and matched firms are included in the regression analyses. All regressions contain firm fixed effects. All variables are defined in Table 2. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 3: **Matched Sample Analysis (Contd.,)**

	QS	ES	$Amihud$	$Hasbrouck$	$\mid AR \mid$
cds	0.00627**	0.00771**	0.00313**	0.00156**	0.00140
	(8.55)	(12.77)	(4.85)	(4.44)	(0.85)
option	-0.00383	0.00180	-0.00219**	-0.00191	-0.0134**
	(-1.62)	(0.88)	(-3.59)	(-1.49)	(-3.01)
bond	-0.0105**	-0.00719**	0.00117	0.00181**	0.00267
	(-15.49)	(-14.11)	(1.76)	(6.39)	(1.83)
lagprogramtrade	-0.0629**	-0.0491**	-0.00213	-0.00638**	-0.00808**
	(-27.28)	(-24.64)	(-0.82)	(-8.36)	(-3.98)
lagdvolume	-0.0188**	-0.0103**	-0.00245	0.00440**	0.00409
	(-8.99)	(-5.60)	(-0.88)	(5.96)	(1.42)
lagvolatility	5.251**	3.692**	0.838**	-0.514*	-2.454**
	(15.06)	(10.88)	(3.21)	(-2.07)	(-2.77)
res_mcap	-0.0595**	-0.0417**	-0.000943	0.00102*	-0.00262
	(-28.15)	(-24.61)	(-0.51)	(2.35)	(-0.89)
zscore	0.0164**	0.0110**	0.000344	-0.0000628	-0.00156
	(22.91)	(22.07)	(1.48)	(-0.54)	(-1.33)
cash	-0.0514**	-0.0336**	-0.00296*	-0.00176	0.00531
	(-12.54)	(-12.56)	(-2.07)	(-1.22)	(0.42)
netppe	-0.00567	0.0116**	0.00745*	-0.00158	0.0109
	(-1.31)	(3.67)	(2.58)	(-0.77)	(0.87)
rd	0.0767**	0.0731**	0.00336	0.00911	-0.0153
	(4.82)	(6.02)	(1.03)	(1.31)	(-0.18)
N	369373	369373	368950	17318	17352
adj. R^2	0.663	0.632	0.292	0.433	0.029

Table 4: **Event Analysis: Years t-1 to t+1 Relative to CDS Introduction**

This table presents results of regressions that estimate the impact of the introduction of CDS markets on equity market quality. The analyses use data from 365 days prior to CDS introduction through 365 days following introduction. For each firm with a traded CDS contract, we identify a similar non-CDS firm from the sample of all NYSE-listed firms using propensity score methodology in Rosenbaum and Rubin (1983). Only CDS and matched firms are included in the regressions. All regressions contain firm fixed effects and all variables are defined in Table 2. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 4: **Event Analysis: Years t-1 to t+1 Relative to CDS Introduction (Contd.,)**

	QS	ES	$Amihud$	$Hasbrouck$	$\mid AR \mid$
cds	0.00958**	0.00906**	0.000626	0.00116**	-0.00221
	(6.83)	(7.52)	(0.68)	(2.72)	(-1.21)
option	0.00375	0.0100**	-0.00115*	-0.000265	-0.0144*
	(0.90)	(2.67)	(-2.28)	(-0.31)	(-2.26)
bond	-0.00640**	-0.00457**	0.00155	0.000980**	0.00491
	(-6.18)	(-5.36)	(1.69)	(2.86)	(1.59)
lagprogramtrade	-0.0788**	-0.0657**	0.00229	-0.00517**	-0.0105
	(-10.71)	(-9.74)	(0.41)	(-2.98)	(-1.66)
lagdvolume	-0.0231**	-0.00827	-0.00487	0.00174	0.00772
	(-3.25)	(-1.28)	(-0.70)	(1.04)	(1.05)
lagvolatility	3.667**	2.087**	1.874**	-0.889*	-4.381**
	(13.21)	(12.50)	(3.12)	(-2.49)	(-2.80)
res_mcap	-0.0726**	-0.0459**	-0.00127	-0.00179	-0.00152
	(-11.39)	(-8.23)	(-0.67)	(-1.61)	(-0.23)
zscore	0.0176**	0.0121**	-0.000927	0.000213	-0.00117
	(25.11)	(22.58)	(-1.35)	(1.01)	(-0.42)
cash	-0.0641**	-0.0405**	0.00229	0.00350	0.0203
	(-11.11)	(-9.55)	(1.10)	(1.21)	(0.66)
netppe	-0.0813**	-0.0419**	0.00809	0.00182	0.0362
	(-8.09)	(-5.62)	(0.97)	(0.56)	(0.91)
rd	0.0974**	0.0963**	-0.00242	0.00966	-0.0295
	(5.37)	(6.60)	(-0.96)	(1.05)	(-0.20)
N	127019	127019	126802	6038	6043
adj. R^2	0.652	0.595	0.241	0.471	0.035

Table 5: **Potential Endogeneity: Instrumental Variable Analysis**

This table presents results of regressions that estimate the impact of the introduction of CDS markets on equity market quality. To control for potential endogeneity of CDS markets, we introduce an instrumental variable: the (log) dollar volume of trading in the bonds of all firms in the industry, excluding those of the sample firm. The idea is that CDS markets are more likely to emerge when there is demand to trade a particular type of credit risk (credit of firms with common characteristics). The sample and regression specification is identical to that in Table 2, except that *cds* is replaced with *cds_iv*, the instrument. All regressions contain firm fixed effects. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects (all variables are demeaned in the regressions). $**$ and $*$ denote significance at 1% and 5% respectively.

Table 5: **Potential Endogeneity: Instrumental Variable Analysis (Contd.,)**

	QS	ES	$Amihud$	$Hasbrouck$	$\mid AR \mid$
cds_iv	0.0763**	0.0600**	0.0287**	0.0113**	-0.00248
	(13.14)	(15.00)	(9.00)	(3.71)	(-0.23)
option	-0.0152**	-0.0103**	0.00598**	-0.00381**	-0.00939**
	(-9.78)	(-8.87)	(5.41)	(-3.69)	(-4.11)
bond	0.0139**	0.00750**	0.00777**	0.000354	0.00136
	(15.46)	(12.07)	(8.06)	(1.08)	(0.82)
lagprogramtrade	-0.0791**	-0.0575**	-0.0124**	-0.00681**	-0.00593**
	(-48.62)	(-43.88)	(-5.17)	(-15.00)	(-4.25)
lagdvolume	-0.0611**	-0.0421**	-0.0143**	0.00402**	0.00323
	(-28.68)	(-25.96)	(-5.85)	(7.01)	(1.45)
lagvolatility	0.0982	0.0983	0.0660	-0.0238	-0.0558
	(0.78)	(0.89)	(1.13)	(-1.43)	(-1.22)
res_mcap	-0.121**	-0.0866**	-0.00924**	-0.000216	-0.00165
	(-50.69)	(-49.65)	(-4.44)	(-0.53)	(-0.74)
zscore	0.0229**	0.0160**	0.00594**	0.0000773	-0.000153
	(46.98)	(43.84)	(10.53)	(0.76)	(-0.21)
cash	-0.0736**	-0.0481**	0.0175*	-0.00217	0.00801
	(-15.38)	(-13.85)	(2.31)	(-1.60)	(0.95)
netppe	0.00224	0.0217**	0.00384	0.00282	0.0255**
	(0.33)	(4.36)	(0.75)	(1.60)	(2.76)
rd	-0.00351	0.00566	-0.110*	0.0148	0.00202
	(-0.16)	(0.36)	(-2.35)	(1.37)	(0.03)
N	781301	781301	781301	35794	35794
adj. R^2	0.235	0.221	0.004	0.061	0.003

Table 6: **Interpretation: CDS and the Structure of Equity Market Trading**

This table presents results of regressions that estimate the impact of CDS markets on the structure of equity market trading. All explanatory variables are defined in Tables 1 and 2. Equity market trading variables are: *insttrade_all*, *programtrade_all*, *turnover*, *priceimpact*, and *analystdispersion*. *insttrade_all* is the ratio of one half the sum of institutional buy and sell volume on day t (from the CAUD data) to total volume on day t. *programtrade_all* is the ratio of half of the sum of program trading volume (from the CAUD data) to total volume on day t; *turnover* is daily trading volume divided by shares outstanding; and *priceimpact* is the 5-minute price impact of trades. All regressions contain firm fixed effects and t-statistics are calculated using standard errors that are clustered by day. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 6: **Interpretation: CDS and the Structure of Equity Market Trading (Contd.,)**

	insttrade_all	*programtrade_all*	*turnover*	*priceimpact*	*analystdisp*
cds	0.0254**	0.00273**	0.000293**	0.00161**	-0.0289**
	(21.34)	(4.50)	(5.29)	(7.17)	(-34.92)
option	-0.00302**	0.0179**	0.000295**	-0.00672**	-0.00977**
	(-2.65)	(38.48)	(3.97)	(-12.86)	(-7.65)
bond	0.00870**	0.0128**	0.000652**	-0.00188**	-0.00343**
	(10.25)	(23.76)	(13.51)	(-6.37)	(-5.03)
lagprogramtrade	-0.0283**		0.000359**	-0.0109**	-0.00870**
	(-40.84)		(9.64)	(-21.02)	(-17.04)
lagdvolume	0.0635**	0.00351**	0.00116**	-0.0119**	-0.00474**
	(46.51)	(7.36)	(16.17)	(-21.78)	(-5.82)
lagvolatility	0.0884	-0.0538	0.0675	0.0930	0.383**
	(1.28)	(-1.30)	(1.57)	(1.16)	(3.19)
res_mcap	0.0143**	0.0230**	-0.00457**	-0.0217**	-0.0179**
	(9.80)	(34.28)	(-35.22)	(-34.84)	(-16.06)
zscore	-0.00141**	-0.000306	0.000355**	0.00332**	-0.0111**
	(-5.16)	(-1.85)	(11.09)	(16.15)	(-21.55)
cash	-0.0510**	0.0201**	-0.00117**	-0.00543**	0.0640**
	(-16.10)	(13.86)	(-3.96)	(-3.50)	(10.48)
netppe	-0.0519**	-0.00741**	-0.00613**	0.0122**	0.0551**
	(-14.45)	(-3.65)	(-17.52)	(7.04)	(9.24)
rd	-0.107**	0.0969**	0.00405*	0.00375	-0.107*
	(-3.52)	(7.94)	(2.09)	(0.43)	(-2.33)
N	781944	781944	781944	781913	462135
adj. R^2	0.332	0.369	0.373	0.393	0.365
Firm Fixed Effects	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

Table 7: **Interpretation: CDS, Equity Market Quality and Firm Risk (Altman's *z*score)**

This table presents results of regressions that estimate the impact of CDS markets on equity market quality as we vary the firm-level risk environment. We run separate regressions for stocks with high (Model 1), medium (Model 2) and low (Model 3) levels risk firms (risk is measured by the default risk, based on Altman's (1968) *zscore* measure). Low *zscore* is interpreted as high firm risk. All regressions are identical to those in Table 2 and contain firm fixed effects. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 7: **Interpretation: CDS, Equity Market Quality and Firm Risk (Altman's *z*score) (Contd.,)**

Panel A: Liquidity (Daily)

	QS			*ES*			*Amihud*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.0579**	0.00489**	-0.00143**	0.0484**	0.00450**	-0.0000564	0.0168**	0.00724**	0.00183**
	(33.13)	(8.04)	(-3.18)	(33.08)	(10.59)	(-0.18)	(11.56)	(3.16)	(4.94)
option	-0.0200**	0.00331*	-0.00963**	-0.0122**	0.000763	-0.00774**	0.0137**	0.00151	0.00257**
	(-6.84)	(2.22)	(-7.80)	(-5.66)	(0.79)	(-9.44)	(7.00)	(1.79)	(3.75)
bond	0.0231**	0.00188**	-0.00240**	0.0127**	-0.000968	-0.00161**	0.0175**	0.00283**	0.00269**
	(12.68)	(2.66)	(-4.00)	(8.95)	(-1.94)	(-3.94)	(6.07)	(3.42)	(4.29)
N	260825	260839	260280	260804	260839	260280	260623	260434	260265
adj. R^2	0.769	0.752	0.745	0.744	0.760	0.747	0.235	0.284	0.147
Firm Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: **Interpretation: CDS, Equity Market Quality and Firm Risk (Altman's $z$score) (Contd.,)**

Panel B: Efficiency (Monthly)

	hasbrouck			$\mid AR \mid$		
	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.00320**	0.000684	0.00103**	0.00472	0.000825	0.00175
	(7.33)	(1.94)	(3.64)	(1.77)	(0.28)	(0.67)
option	-0.00237	-0.00560*	-0.00556*	-0.00887*	-0.0107*	-0.0122**
	(-1.88)	(-2.43)	(-2.64)	(-2.06)	(-2.39)	(-3.15)
bond	0.00113**	0.00151**	0.00137**	-0.00317	-0.000522	0.00347
	(2.77)	(3.84)	(5.17)	(-1.74)	(-0.28)	(1.75)
N	11509	12073	12212	12190	12252	12306
adj. R^2	0.437	0.356	0.297	0.066	0.047	0.038
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 8: **Interpretation: CDS, Equity Market Quality and Passive Trading**

This table presents results of regressions that estimate the impact of CDS markets on equity market quality as we vary the equity market trading environment. We run separate regressions for stocks with low (Model 1), medium (Model 2) and high (Model 3) levels of passive trading (the proxy for passive/uninformed trading is *programtrade*, the dollar volume of program trading, defined as the sum of institutional buy and sell dollar volume for their program trades, based on the daily summaries of NYSE CAUD data for each stock). Low *programtrade* is interpreted as a low uninformed trading. All regressions are identical to those in Table 2 and contain firm fixed effects. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 8: **Interpretation: CDS, Equity Market Quality and Passive Trading (Contd.,)**

Panel A: Liquidity (Daily)

	QS			*ES*			*Amihud*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.0351**	-0.0132**	-0.0105**	0.0388**	-0.00804**	-0.00659**	0.0163**	0.0000325	0.000597
	(10.16)	(-22.62)	(-23.79)	(13.40)	(-20.06)	(-22.57)	(10.29)	(0.02)	(1.02)
option	0.0107**	-0.00874**	-0.0120**	0.00727**	-0.00514**	-0.00640**	0.0163**	-0.000166	-0.00111
	(6.04)	(-7.83)	(-9.04)	(5.38)	(-7.86)	(-9.05)	(8.54)	(-0.28)	(-1.29)
bond	0.0334**	-0.00395**	-0.00431**	0.0180**	-0.00297**	-0.00244**	0.0187**	-0.000352	-0.000454
	(20.37)	(-10.62)	(-11.76)	(15.00)	(-12.57)	(-11.03)	(8.25)	(-0.68)	(-1.86)
N	264542	270017	247380	264521	270017	247380	264286	269694	247337
adj. R^2	0.755	0.698	0.571	0.731	0.764	0.694	0.232	0.295	0.306
Firm Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 8: **Interpretation: CDS, Equity Market Quality and Passive Trading (Contd.,)**

Panel B: Efficiency (Monthly)

	hasbrouck			$\mid AR \mid$		
	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.00350**	0.00242**	0.000595**	0.00354	0.00179	0.000365
	(3.38)	(5.19)	(3.12)	(0.80)	(0.80)	(0.18)
option	-0.00460**	-0.00348	-0.00438	-0.00580	-0.0194**	-0.0202*
	(-2.70)	(-1.72)	(-1.08)	(-1.97)	(-3.82)	(-2.07)
bond	0.00257**	0.00134**	0.000644**	-0.00292	0.00411**	0.00303
	(4.70)	(5.46)	(3.47)	(-1.28)	(2.86)	(1.46)
N	11252	12876	11666	12200	12882	11666
adj. R^2	0.291	0.284	0.228	0.058	0.031	0.020
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 9: **Interpretation: CDS, Equity Market Quality and Market-Wide Volatility** This table presents results of regressions that estimate the impact of CDS markets on equity market quality as we vary the equity market trading environment. We run separate regressions for stocks with low (Model 1), medium (Model 2) and high (Model 3) levels of market-wide volatility (captured by VIX). All regressions are identical to those in Table 2 and contain firm fixed effects. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered by day. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 9: **Interpretation: CDS, Equity Market Quality and Market-Wide Volatility (Contd.,)**

Panel A: Liquidity (Daily)

	QS			*ES*			*Amihud*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.00912**	0.0195**	0.0368**	0.00606**	0.0180**	0.0289**	0.0216**	0.00398	0.0162**
	(8.10)	(8.99)	(19.06)	(7.94)	(8.78)	(19.23)	(3.30)	(1.17)	(9.81)
option	0.00566**	-0.00362*	-0.0146**	0.00556**	-0.00384**	-0.00992**	0.00291**	0.00695**	0.00994**
	(4.77)	(-2.34)	(-6.91)	(6.89)	(-3.07)	(-6.34)	(6.75)	(7.21)	(5.76)
bond	0.00622**	0.0193**	0.0402**	0.00322**	0.0119**	0.0266**	0.000762	0.00876**	0.0180**
	(7.78)	(13.17)	(27.71)	(5.72)	(11.71)	(25.11)	(0.78)	(5.91)	(7.78)
N	261389	261614	258941	261389	261608	258926	261180	261356	258786
adj. R^2	0.822	0.767	0.788	0.819	0.749	0.767	0.241	0.279	0.235
Firm Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 9: **Interpretation: CDS, Equity Market Quality and Market-Wide Volatility (Contd.,)**

Panel B: Efficiency (Monthly)

	hasbrouck			$\mid AR \mid$		
	(1)	(2)	(3)	(1)	(2)	(3)
cds	0.00292	0.00141**	0.00116	0.00102	0.000245	0.000839
	(1.78)	(4.40)	(2.02)	(0.12)	(0.07)	(0.36)
option	-0.00343*	-0.00530**	-0.00306	-0.00667	-0.00635	-0.0105*
	(-2.68)	(-3.54)	(-1.29)	(-1.03)	(-1.75)	(-2.31)
bond	-0.000695	0.000689*	0.00157**	-0.00252	0.000968	0.00402
	(-1.70)	(2.10)	(3.87)	(-1.01)	(0.45)	(1.91)
N	12285	12503	11006	12501	12723	11524
adj. R^2	0.501	0.382	0.424	0.046	0.051	0.078
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 10: **CDS Quote Activity and Equity Market Quality**

This table presents the results of regressions that estimate the impact of CDS markets on equity market quality. *num_cds_quote* is the number of CDS quotes in the CMA data on day t in the liquidity regressions and in month t in the efficiency regressions. All other variables are as defined in Table 2. For each firm with a traded CDS contract, we identify a similar non-CDS firm from the sample of all NYSE-listed firms using propensity score methodology in Rosenbaum and Rubin (1983). Only CDS and matched firms are included in the regressions. All regression specifications contain firm fixed effects. Because we control for time-invariant firm characteristics, the *cds* coefficients are interpreted as the change in market quality after the introduction of the CDS market. Liquidity regressions are based on daily data and t-statistics are calculated using standard errors that are clustered at the day level. Because efficiency variables are calculated over monthly horizons, the independent variables are defined as monthly averages and regressions are based on monthly data. Standard errors for the efficiency regressions are clustered at the year-month level. All regressions contain firm fixed effects. $**$ and $*$ denote significance at 1% and 5% respectively.

Table 10: **CDS Quote Activity and Equity Market Quality (Contd.,)**

	QS	ES	$Amihud$	$Hasbrouck$	$\mid AR \mid$
cds	0.0218**	0.0188**	0.00840**	0.00118**	-0.000655
	(22.16)	(24.44)	(10.14)	(3.41)	(-0.37)
option	-0.0140**	-0.00942**	0.00639**	-0.00417**	-0.00899**
	(-10.56)	(-9.43)	(5.26)	(-3.02)	(-3.46)
bond	0.0213**	0.0131**	0.0103**	0.00155**	0.000562
	(22.41)	(19.32)	(10.19)	(5.83)	(0.48)
lagprogramtrade	-0.0788**	-0.0573**	-0.0123**	-0.00657**	-0.00405**
	(-46.43)	(-42.34)	(-4.69)	(-9.46)	(-3.04)
lagdvolume	-0.0567**	-0.0387**	-0.0128**	0.00494**	0.000246
	(-27.09)	(-23.78)	(-5.06)	(7.05)	(0.13)
lagvolatility	0.0980	0.0982	0.0652	-0.0298	-0.0321
	(0.78)	(0.89)	(1.11)	(-1.75)	(-0.69)
res_mcap	-0.114**	-0.0807**	-0.00706**	0.000859*	-0.00326
	(-44.79)	(-43.71)	(-3.41)	(2.03)	(-1.96)
zscore	0.0222**	0.0154**	0.00574**	-0.0000762	-0.0000186
	(29.24)	(27.53)	(8.50)	(-0.70)	(-0.02)
cash	-0.0625**	-0.0397**	0.0215**	-0.000219	0.00673
	(-11.97)	(-10.55)	(2.69)	(-0.19)	(0.81)
netppe	-0.00269	0.0179**	0.00260	0.00192	0.0264**
	(-0.45)	(3.81)	(0.51)	(1.05)	(3.11)
rd	-0.0246	-0.0114	-0.118*	0.0105	0.0125
	(-1.00)	(-0.62)	(-2.45)	(0.87)	(0.18)
cdsnumquote	0.0000416**	0.0000286**	0.0000320*	0.0000116**	0.0000686*
	(3.18)	(3.03)	(2.45)	(2.89)	(2.53)
N	781944	781923	781322	35794	36748
adj. R^2	0.755	0.735	0.238	0.383	0.050