MAKING SENSE OF THE MESS: DO CDS'S HELP?

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ABSTRACT

In a firm level matched sample of 499 firms we examine the information flow between stocks and the credit default swap (CDSs) over a period of January 2004 to December 2008. Our study confirms the general findings of previous studies that the information generally flows from equity market to CDS market. However, for a much smaller number of firms we also find that information also flows from the CDS to its stock. A major advantage of our sample period is that it allows us to examine the information flow before and during the crisis. This paper makes two contributions. We document that the firms for which the information flows from the CDS to its stock increases by almost tenfold during the crisis. The current crisis is often referred as a credit crisis, so this finding is consistent with what is expected of CDSs. The major contribution of this paper is that it identifies the firm specific factors that influence the information flow across the two markets. We show that characteristics such as asset size, profitability, and industry, amongst others, play an important role in determining information flow.

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1. INTRODUCTION

In the past few years, credit default swaps (CDS) have become popular instruments for investors to buy and sell the credit risk of an underlying reference entity, allowing them to trade on the risk that a firm will default on its debt. The protection buyer makes periodic payments, where the rate of payments is referred to as the CDS credit spread, and in return, the protection seller agrees to pay an agreed upon amount if the reference entity experiences a credit event.[1] The protection buyer pays a higher spread when there is a greater perceived likelihood of default for the underlying reference entity. As such, CDS credit spreads are a pure measure of credit risk. Furthermore, participants in this market are generally more sophisticated, so information related to default should be incorporated into the CDS credit spread before being incorporated into other markets.[2]

In this study, the main question we explore is whether the CDS market has any informational advantage over the stock market. In particular, we explore whether there is a lead-lag relationship in price discovery between the CDS and equity markets. Several other studies have attempted to examine the relationship between these two markets. These studies include Forte and Pena (2006) and Fung et al. (2008) who find that generally, the stock market leads the CDS market in the price discovery process.

Although in existence since the early 1990's, the CDS market has only recently seen improvements in liquidity that followed contract standardization. Previous studies using CDS data prior to 2004 often have mixed maturities, currencies, and markets. In addition, previous studies that explored the lead-lag relationship do not cover the financial crisis which unfolded in the fall of 2007.[3] Following Forte and Pena (2006) and Fung et al. (2008) we explore the lead-lag relationship of the stock and CDS markets but there are two major distinctions between these studies and our study. Firstly, the sample period of our study starts in January 2004 and ends in December 2008 and uses standardized CDS data.[4] The time period of this study, which includes the

[1] Credit events include bankruptcy, failure to pay, restructuring, repudiation, a moratorium, obligation acceleration, or obligation default (ISDA definition of a credit event http://www.isda.org/).

[2] For example, Pinches and Singleton (1978) and Glascock et al. (1987) find that the stock market anticipates ratings changes, particularly negative rating announcements. Similarly, Hull et al. (2004) find that the CDS market also anticipates negative rating events by agencies.

[3] Fung et al. (2008) include the first few months of the credit crisis: their data ends in December 2007.

[4] All contracts in our study are 5-year maturities denoted in USD and written on U.S. reference entities.

credit crisis period of 2007-08 also provides a unique opportunity to study the effects of a macroeconomic event that directly impacts the ability of a firm to fulfill credit obligations, or its creditworthiness, the very factor that the CDS aims to measure. This gives us the ability to compare the information flow across the markets before and during the crisis. To our knowledge, ours is the first study to do so.

The second distinction is that while almost all of the previous studies examine the lead-lag relationship between an equity market index and a CDS market index such as the CDX or use a small number of firm matched data,[5] in this study we use a sample of 499 firms for which we match each firm's CDS credit spread to its stock return and accounting and financial information. While most previous studies have focused on the overall relationship between the markets, we also focus is on how firm specific characteristics contribute to differences in information flow, which is possible because of our large matched sample.

Following the methodology of previous studies,[6] we use a Granger causality test to examine the dynamic relationship between a firm's stock and its CDS. We first determine the primary direction of information flow for the full sample period, and we find that the first test null hypothesis (GC1), that the stock market does not lead the CDS market, is rejected in 78.23% of the cases (at 5% level) but in only 51.21% of the cases do we reject (at 5% level) the reverse test hypothesis, (GC2), that the CDS market does not lead the stock market. This conforms to the previous literature,[7] which finds that overall the stock market tends to lead the CDS market in price discovery. Interestingly, the rejection increases by almost fivefold from 8.81% in the pre-crisis period compared to 44.70% (at the 5% level of rejection) in the crisis period for the second test hypothesis, suggesting a significant increase in information flow from the CDS to the stock market after the crisis begins.

These findings raise a logical question: Why do we find such a lead-lag relationship for some firms and not for others? To answer this question we group the data using firm specific characteristics. The Granger causality tests based on the grouped data suggest that firm specific characteristics may play a role in how information flows between the markets, particularly from the CDS to the stock market. Our results show that larger, more profitable, and more liquid

[5] Longstaff et al. (2003) use 67 firms, Blanco et al. (2005) use 33, Pena and Forte (2006) use 21, and Norden and Weber (2009) use 58 firms.
[6] See Fung et al. (2008) and Norden and Weber (2009).
[7] See Bystrom (2005), Forte and Pena (2006), Fung et al. (2008), and Norden and Weber (2009).

firms with higher credit ratings tend to have less information flow from the CDS to the stock market. These characteristics do not seem to play as important a role in information flow from the stock to the CDS market which shows a strong information flow overall. The importance of these characteristics also seems to have been intensified by the credit crisis.

We use a logistic regression to explore these issues in a multivariate setting. We find that information flow from the stock to the CDS market is increased for firms with larger asset size, lower profitability, and a lower credit rating. On the other hand, the information flow from the CDS to the stock market is increased for firms in the financial sector and firms with lower profitability. The logistic regression results also indicate that the credit crisis has had a significant impact on information flow even after controlling for these firm specific characteristics.

The rest of the thesis is organized as follows: we provide an introduction to CDSs in Chapter 2, and continue with the background literature and hypothesis development in Chapter 3, research design and data in Chapter 4, analysis in Chapter 5, and finally provide a conclusion in Chapter 6.

2. CREDIT DEFAULT SWAPS

A CDS is a contract where in return for a series of payments from the buyer, the seller will pay a one-time fixed amount if the underlying credit instrument (usually a bond or a loan) goes into default or experiences some other credit event during the term of the contract. In exchange for periodic payments from the protection buyer, where the rate of payments is referred to as the CDS credit spread, which is fixed for the contractual period, the protection seller agrees to pay the face value of the underlying bond or loan if a credit event takes place during the contractual period. The spread, which is determined by the market, is calculated as a percentage of the face value or notional amount of the contract and is expressed in basis points. A higher CDS credit spread indicates a greater market perception of the likelihood that the underlying financial instrument will default. Ford Motor Company is presented as an example in Figure 1 below. As Ford's perceived risk of default increases, so does its spread. On January 1, 2004 Ford Motor Co.'s CDS credit spread was trading at 215 basis points. By December 29, 2008 trading on the CDS credit spread increased to 1,837.9 basis points or $1,837,900/year on a $10,000,000 notional amount.

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CDSs trade primarily on the market perception of the risk of default, although liquidity and counterparty risk (the risk that one of the parties in the CDS contract may default) primia may also affect the credit spread. In spite of these factors, the CDS is considered the cleanest indicator by which to measure credit risk and plays an important role in detecting changes in credit risk. They essentially provide insurance to the holder against a credit event and allow institutions to manage credit risk arising from debt. Thus CDSs for firms with low credit quality are more heavily traded than for firms with high credit quality.[8] The use of CDSs is not limited to hedging, and as the market has matured, their use as a tool for speculation and arbitrage has increased as well.

Although CDSs are still relatively new—they've only become popular in the last decade or so—they are already the most widely traded credit derivative product comprising approxi-

[8] Fung et al. (2008)

mately 33 percent of the global credit derivatives market in 2006.[9] This, along with the ability to either purchase or short sell them also makes them very liquid. The market for CDSs has expanded quite rapidly over the past decade and according to the International Swaps and Derivatives Association (ISDA) market survey results, notional amounts on outstanding CDSs grew from $3.78 trillion in 2003 to $62.2 trillion by the end of 2007. This amount dropped by 38% in 2008 to $38.6 trillion as the market experienced significant turmoil.[10]

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[9] British Bankers' Association,, BBA Credit Derivatives Report 2006.
[10] ISDA Market Survey Results http://www.isda.org/index.html

3. LITERATURE REVIEW

3.1 Related Research on Information Flow between Markets

When analyzing how information is incorporated into the stock and CDS markets, it is important to note that the CDS market trades specifically in credit risk, and as such, only credit related events should impact credit spreads. Since credit quality is an unobservable attribute, credit ratings are often used as proxies for credit quality. There has been an extensive amount of research to analyze the impact of credit ratings announcements on the bond, stock, and CDS markets in an attempt to determine which market reacts to credit related information first. These studies, outlined in the following section, include those by Pinches and Singleton (1978), Holthausen and Leftwich (1986), and Klinger and Sarig (2000) among others. Most of these studies have used a traditional event study methodology to test the window prior to and after a ratings announcement by Standard & Poor's, Moody's, or Fitch to examine price adjustments and thereby deduce the market's price discovery effectiveness. Because the CDS market is still fairly new, the data has been relatively difficult to obtain, and as such, most of the previous studies outlined in this section have looked at the relationships between the stock or bond markets, in reference to ratings announcements.

Numerous studies examine the reaction of the stock market to ratings announcements. For example, while Pinches and Singleton (1978), and Glascock et al. (1987) find that the stock market anticipates ratings changes, Griffin and Sanvicente (1982), Holthausen and Leftwich (1986), Goh and Ederington (1993), Followill and Martell (1997), and Dichev and Piotroski (2001) all find that the stock market reacts negatively to announcements of downgrades. None of them finds a significant reaction to positive rating announcements. Although among these papers, there is general consensus that the market does react to announcements, particularly to negative announcements, indicating that the market does not fully anticipate ratings changes, the results regarding whether or not the stock market (partially) anticipates ratings changes are mixed. Hand et al. (1992) and Klinger and Sarig (2000) look at both the bond and stock markets and find that the two markets react to negative announcements by ratings agencies. Klinger and Sarig (2000) conclude that the evidence supports the importance of agency ratings.

More recently, due in part to the growth in the CDS market and the recent establishment of several CDS indices, a number of studies, such as those by Hull et al. (2004) and Micu et al.

(2004) as well as several others, have looked at the ability of the CDS market to anticipate agency ratings announcements and to do so before either the stock or bond market. Since the CDS market trades primarily on the risk of default, and is not subject to the noise affecting the values of stocks or bonds, it should be able to adjust or correct for any changes in credit value more quickly or efficiently. Hull et al. (2004), use an event study to analyze the reactions of bond and CDS credit spreads to changes in credit rating and then test the ability of their data to predict agency rating changes. They find that CDS credit spreads anticipate rating downgrades, reviews for downgrade, and negative outlooks and that spreads provide some predictive information in estimating the probability of negative ratings changes. The authors find no evidence that positive announcements by agencies have any significant impact on the CDS market. Micu et al. (2004), find that although the CDS market appears to anticipate negative announcements by agencies, the ratings still have a significant impact on CDS credit spreads. Norden and Weber (2004) find that both the CDS and stock markets show anticipation of ratings downgrades. Di Cesare (2006) uses evidence from international banks to analyze the ability of the CDS, bond, and stock markets to anticipate ratings changes. He finds that all three markets anticipate rating announcements, particularly negative announcements, and the CDS market was most efficient in doing so. He also found that stock prices seemed most efficient for predicting positive events and that the bond market was the least reliable indicator of future rating events.

While most previous studies have relied on specific events such as credit rating announcements to determine in what order information flows through the markets, several other studies have attempted to use econometric models to analyse information flow. Longstaff et al. (2003) propose a vector auto-regressive model (VAR) to analyze the lead-lag relationship between the stock, bond, and CDS markets and conclude that the CDS market and the stock market lead the bond market. Norden and Weber (2009) use the VAR model proposed by Longstaff et al. (2003) to analyze the comovement of the stock, bond and CDS markets. For the firms tested, they find that information is discovered first in the stock market, then in the CDS market, and then in the bond market.

Blanco et al. (2005) use Hasbrouck's (1995) and Gonzalo and Granger's (1995) vector error-correction models (VECM) to look at the lead-lag relationship between the CDS and bond markets and consider which of the two markets is more important for price discovery of credit risk. They find that the CDS market leads the bond market, suggesting its primary importance in price discovery. Zhu (2005) tests a VECM on CDS and bond data. He finds that the CDS market is more responsive to new information than the bond market when using a VECM but when testing for Granger causality or cointegration, he finds both markets to be equally important in the discovery of new information.

Bystrom (2005) uses a VAR model with lagged iTraxx CDS index spreads and stock returns and finds that CDS credit spreads tend to widen when stock prices fall and vice versa and that much of the variability in CDS credit spreads can be explained by current and lagged stock returns. He concludes that stock prices lead CDS credit spreads in incorporating firm specific information.

Forte and Pena (2006) use a VAR model to test the lead-lag relationship between bond spreads, CDS credit spreads, and the implied stock spread. They find that for most cases, the stock market leads the credit risk discovery process followed by the bond and CDS markets.

Fung et al. (2008) use a VAR model and examine the lead-lag relationship between the S&P 500 and the CDX index, splitting their data into high yield and investment grade portfolios. They find that the stock market leads in price discovery followed by the CDS market. They also find a feedback effect in the case of the high yield CDSs and the stock market implying information interaction between the two markets. While there are some discrepancies, the general conclusion of these studies is that the stock market leads the CDS market in price discovery or incorporates new information more quickly than the CDS market. Although the goal of our research is to find the reasons why one market leads the other, we hypothesize that in general our results should reflect previous findings that the stock market leads the CDS market.

H1: Overall, stock returns should lead CDS credit spreads.

3.2 The Effects of the Financial Crisis on the CDS and Stock Markets

Between 2004 and 2006, US interest rates increased from 1% to 5.34%.[11] In the beginning of 2006, the US began to see a dramatic nationwide housing price decline as homeowners, many who could barely afford their low interest mortgage payments, began to default on their mortgages.[12] Many of these delinquencies were linked to subprime borrowers with adjustable-

[11] US Federal Funds (effective) rose from 1.01% on 01/02/2004 to 5.17% on 12/29/2006 with a high of 5.34%.
[12] BBC, Timeline: Credit crunch to downturn. http://news.bbc.co.uk/2/hi/business/7521250.stm

rate mortgages who were unable to refinance as housing prices began to decline and mortgage rates began to reset at higher rates. By early 2007, a record number mortgage defaults was causing a significant devaluation in mortgages and their associated derivatives, which resulted in a number of lenders being forced to file for Chapter 11 bankruptcy. In April 2007, New Century Financial, one of the US's largest sub-prime mortgage lenders, filed for Chapter 11 bankruptcy. This was followed by a string of bankruptcy filings, asset devaluations, and postings of huge losses by banks and financial service companies.

The extent of the crisis became apparent on August 9, 2007 when BNP Paribas halted redemption on two of its funds, citing "a complete evaporation of liquidity in certain market segments of the US securitization market" making valuation of their assets impossible.[13] Investors were reluctant to make any further investments and began to demand withdrawals causing a freeze-up of liquidity. Banks and lending institutions, many already concerned with liquidity, refused to lend to one another, either urgently needing the money themselves, or fearful that those borrowing might default as well. This further exacerbated the liquidity issue.

The ripple effects of the financial crisis were felt in the stock and derivative markets as well. Mortgages, along with other loans and assets were repackaged and sold globally as collateralized debt obligations (CDOs), mortgage backed securities (MBSs), or other asset backed derivatives, often with high credit ratings. Stock prices plummeted for companies that had been selling CDS protection without hedging against the possibility that the underlying entities might default. Global stock markets began to experience heavy losses as more companies discovered they had "bad debt." CDSs credit spreads soared as the risk of default increased and the number of credit events on debt formerly considered creditworthy increased.

The credit crisis and consequently the sudden increase in credit events has provided a window of opportunity to examine how increased credit risk in the global markets has impacted the information flow between the stock and CDS market. Because the CDS market is primarily concerned with credit risk, we reason that during times of credit turmoil, investors would increase their participation in the CDS market by insuring against credit events via CDS. This theory is supported by Zhang (2009) who finds that the CDS market is especially efficient at incorporating new credit information and attributes this to special features of the CDS market including large and sophisticated participants with informational advantages.

[13] BNP Press Release, Paris August 9, 2007

H2: Information flow from the CDS market to the stock market should increase during the credit crisis.

3.3 Firm Characteristics That Influence Information Flow

Although the relationship between the equity and the CDS market has received much attention from previous literature, there has been very little research into why in some cases the equity market leads the CDS market in price discovery, and why in other cases, the CDS market leads the equity market. By matching CDS credit spread and stock return data by firm, we are able to look into firm specific characteristics that influence this information flow, building on Norden and Weber's (2009) study that considers the effects of credit rating and firm asset size on the information flows between the stock, CDS and bond markets. Specific characteristics of a company such as industry, liquidity or balance sheet information may also play a role in determining how new credit information is imbedded into the stock and CDS markets. Numerous previous studies have attempted to define various characteristics that impact stock, bond and CDS prices. These same variables that help to value an asset in the market, may also affect price discovery. We attempt to determine what firm specific attributes make price discovery more likely in one market or the other.

Fama and French (1992), find that the book-to-market ratio and company size together can explain much of the cross-sectional variation in stock returns. They find that company size and the book-to-market equity ratio have the most explanatory power in a cross-section of average stock returns. Their motivation behind testing these variables was related to profitability. Larger companies have been found to have higher earnings and companies with a high book-to-market ratio tend to have lower earnings on assets. This study was later extended by Barber and Lyon (1997) who found that the book-to-market ratio and firm size have a similar effect on financial and non-financial firms. While these studies looked only at variation in stock returns, it is possible that their premise can be extended to explain the efficiency of the stock and CDS markets. Since traders tend to purchase insurance against default via CDS for firms with a higher likelihood of default, we hypothesize that CDSs will be relatively less informative for large, highly profitable firms than for small firms with low profitability.

Kwan (1996) finds that bonds and stocks matched by firm are negatively and contemporaneously correlated. He interprets the results as being evidence that firm specific information regarding the mean value of the firm's underlying assets drive individual stock and bond returns. Norden and Weber (2009) examine the affects of asset size on the magnitude of the relationship between CDS, bond spread changes and stock returns. While their results show no significant relationship between size and market sensitivity, they suggest that CDS and bond spreads should be more sensitive to stock returns of small firms than large firms. The basis to their reasoning is that size is negatively related to default risk, and equity, which represents a subordinated claim to the firm's assets, bears the ultimate credit risk. Since profitability is generally also negatively related to default risk, we propose that Norden and Weber's (2009) reasoning of the affects of asset size will also be similar to the affects of a firm's profitability. We infer that information flows for firms with low profitability, as with firms with smaller assets, would receive more attention in the CDS market and large, highly profitable firms would receive more attention in the stock market.

The value of the credit information in the CDS market could also be undermined by government intervention. When studying the effects of the East Asian Crisis, Bongini et al. (2001) find evidence that some institutions are "too big to fail." They find that although large firms experience financial distress, they are less likely to default. There was some evidence of this in the United States in 2009 when government bailout funds were granted to several large firms in financial distress in order to prevent bankruptcy.[14] In situations such as this, we hypothesize that the significance of a widening CDS credit spread caused by a firm's potential failure could be diminished by government intervention thus reducing its informational value.

H3: Stock returns of larger firms (as measured by the book value of assets) should lead their corresponding CDS credit spreads.

H4: Firms with higher profitability (as measured by the market-to-book ratio) should have stock returns that lead their corresponding CDSs.

[14] For example, the Reuters article "Citigroup Gets Massive Government Bailout" (Nov. 24, 2008) reported the government bailout of several large U.S. banks including Citigroup and quotes The Fed, the Treasury Department and the FDIC as saying [the actions were] "necessary to strengthen the financial system and protect U.S. taxpayers and the U.S. economy."

Market efficiency, or a market's ability to rapidly adjust to new information, is strongly linked to liquidity. In this sense, liquidity may play an important role in which market incorporates new credit information first, i.e. which market leads or lags. Several studies have looked at how trading volume, a proxy for a stock's liquidity, affects the speed or efficiency with which a stock will adjust to new information. Karpoff (1987) finds that the price-volume relation is strongest in volatile markets or during times of high information flow volatility. His conclusion is based on the findings of Tauschen and Pitts (1983) who find a positive relationship between volume and the changes in price variability, and Harris (1983) who finds a positive correlation between volume and the square of price change. These findings are consistent with Clark (1973), Epps and Epps (1976), Morgan (1976), Rutledge (1984), Jain and Joh (1986) and many others who also find a positive correlation between volume and absolute price change. Our data, which is grouped by firm stock trading volume rather than CDS trading volume (due to the unavailability of CDS trading volume data) will reflect the effects that a firm's stock trading volume will have on overall information flows. Given the results of previous literature which suggest that a high trading volume increases price variability, we hypothesize that this would also result in more efficient price discovery and thus firms with higher stock trading volume will also have stronger information flows from the stock market to the CDS market.

H5: Firms with high liquidity (as measured by stock trading volume) should have stock returns that lead their corresponding CDS credit spreads.

It is often said that "in a recession, cash is king." During a financial crisis, firms with low cash holdings are hit particularly hard by the lack of liquidity in the credit markets. On the other hand, firms with larger cash holdings are better able to ride out the lack of liquidity in the market place. A large cash holding may be one of the reasons why Ford Motor Co. survived without U.S. federal aid while its competitors General Motors Corp. and Chrysler LLC, both without sufficient liquidity, filed for Chapter 11 bankruptcy protection in 2009 and received government bailout assistance.[15] Baum et al. (2004) argue that during times of information asymmetry such as economic uncertainty, managers may accumulate cash and other liquid assets in order to offset negative cash flow shocks. Bates (2009) finds an upward trend in cash holdings since the

[15] Bloomberg.com, "Ford May Avoid Bailout Even After First-Quarter Loss" April 23, 2009

1980's, and that US firms, on average, have begun to accumulate more cash as a percentage of their assets. We hypothesize that firms with larger cash reserves should be better able to weather recession conditions and are less likely to experience a credit event. We hypothesize that if traders have a greater propensity to buy insurance on low credit quality (or in this case, firms with low cash holdings) companies via CDSs, then CDS credit spread changes for firms with low cash holdings should lead stock returns.

H6: Firms with low cash holdings (as measured by the cash-to-book value of assets ratio) should have CDS credit spreads that lead their corresponding stock returns.

The financial sector makes up a large portion of the CDS market participants. According to the British Bankers Association's (BBA) 2006 report, banks constitute the majority of market participation. Time magazine reported that,

> commercial banks are among the most active in this market, with the top 25 banks holding more than $13 trillion in credit default swaps — where they acted as either the insured or insurer — at the end of the third quarter of 2007, according to the Comptroller of the Currency, a federal banking regulator.[16]

Banks and financial institutions were also among the hardest hit by the credit crisis. AIG, for example, like many other financial institutions, had massive write-downs due to devaluation of reference entities on which they sold CDSs.[17] Ivashina and Scharfstein (2009) consider the fall of 2008 to be a period of "banking panic" after the fall of numerous financial institutions and a run by short-term bank creditors. Because the financial sector is the largest participant in the CDS market (both as a buyer and a seller), and thus one of the hardest hit by the credit crisis, we choose to separate it from the remaining industries. We also hypothesize that since the financial sector had a sudden increase in credit events, information about these firms will also be embedded in the CDS market first.

H7: Firms in the financial sector (as measured by firms with two-digit SIC codes between 60 and 67) should have CDS credit spreads that lead their corresponding stock returns.

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[16] Time.com "Credit Default Swaps, the Next Crisis?" (March 17, 2008)

[17] Moneymorning.com "The Credit Crisis and the Real Story Behind the Collapse of AIG" (September 22, 2008)

Although both the stock and the CDS markets should be affected by a company's creditworthiness, the nature of the CDS market, suggests it will be more sensitive to a change in creditworthiness than a stock. This is because the CDS credit spread is based primarily on the firm's creditworthiness. While firms with a high credit rating are generally considered to be more financially stable, the instability associated with a low rating may cause investors who want protection against default to increase trading in the CDS market more than in the stock market and thus incorporate new changes in a firm's credit standing in the CDS market before the stock market. This is supported by Fung et al. (2008) who find that the credit quality of the underlying reference entity influences the lead-lag relationship between the stock and CDS markets. They find that the high-yield CDS market leads the equity market in price discovery, but that there is a strong feedback affect between the two. They also find that the stock market leads the investment grade index in the price discovery process. Norden and Weber (2009) also find that the CDS market sensitivity increases as credit quality becomes worse.

H8: Firm's with lower credit ratings (as measured by the S&P annual long-term debt ratings) should have CDS credit spreads that lead their corresponding stock returns.

While Hypotheses 3 to 8 will provide valuable information regarding how firm characteristics play a role in information flow and how they affect price discovery in the equity and CDS markets, we also use them as control variables to determine the effects of the credit crisis on overall information flow as well as the directionality of overall information flow (Hypothesis 1 and 2).

4. DATA AND METHODOLOGY

4.1 Data

We extract daily CDS credit spread data from Datastream Advance. CDS data in Datastream is generally only available for dates after January 2004. For this reason our study will cover the period from January 1, 2004 until December 31, 2008. The mid rate spread data is used and is expressed in basis points and denominated in USD.[18] Although several standard maturity contracts are available, we use 5-year maturities because these are the most liquid.[19] We use all available CDS contracts in Datastream with 5-year maturities in US markets, yielding a total of 637 contracts. These CDSs were then matched by hand to individual stocks using ticker symbols and names imbedded in the CDS identifiers. If the search in Datastream yielded multiple common stock issues traded within a United States market, we chose the USD currency traded stock, and recorded their CUSIPs.

We obtained daily stock return data from CRSP matched using CUSIPs. The matched results yielded 499 firms. Firm accounting, industry and credit information were obtained from COMPUSTAT. A summary of all firm specific characteristics is provided in Table 1. The correlations between the characteristics are provided in Table 2. Tables 3 and 4 depict the summary statistics of the firm data split into pre-crisis (2004-2006) and crisis (2007-2008) periods.

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We collect yearly size proxies as well as yearly market-to-book ratios from 2003 to 2007

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[18] The mid rate spread between the entity and the relevant benchmark curve. It is essentially the average between the bid and offer rates.

[19] According to Hull et al. (2004) the 5-year maturity CDS is the most popularly traded of all CDS maturities.

from COMPUSTAT for all available firms.[20] From Table 2, we can see that firm asset size, market value, and sales are highly correlated with several other variables including trading volume and credit rating. In an attempt to reduce the correlation, we created the variable (ASD) and grouped the asset size into terciles coded 0 for firms in the smallest asset size group, 1 for firms in the medium size group, and 2 for firms in the largest size group, where size is measured by the book value of assets and each group has roughly an equal number of observations. Although this does not eliminate the correlation between the variables it reduces the overall correlation from x to y.

Daily stock trading volume is obtained from COMPUSTAT as well. Since CDS trading volume was not available, we test only the effects of stock trading volume on the information flow between the markets. Each firm's daily stock trading volume is converted into yearly averages to match other characteristics of other variables which are also yearly.

The level of cash held by a firm is measured as a percentage of total book value of assets as per Bates (2009) and Zhou (2009) and is referred to as the cash-to-assets ratio. Total yearly asset values as well as yearly cash and equivalents for each firm come from COMPUSTAT.

SIC (Standard Industrial Classification) codes are also retrieved for the list of firms. Firms with two-digit SIC codes 60-67 are categorised as financial firms and denoted as (0) and all others are identified as non-financial denoted as (1).

Generally a company receives an overall credit rating and it is unusual for a company's liabilities to receive different ratings from one another. We use Standard & Poor's yearly long-term debt ratings from COMPUSTAT. All Standard & Poor's ratings are ranked from a highest rating of 1 (denoting AAA) to a lowest grade of 27 (denoting D). These ratings are then split into two groups: investment grade (from AAA to BBB-) and given a dummy of 1, or non-investment grade (from BB+ to D) from and given a dummy of 0. Using a dummy variable rather than the actual numeric rating reduces the correlation between the firm's rating and the firm's size and trading volume.

4.2 Methodology

Following Fung et al. (2008), we employ the Granger causality methodology, an exten-

[20] The book value of assets, market-to-book ratio, and cash-to-assets ratio are retrieved for 2003-2007 to correct for the look-ahead bias. These are then matched to 2004-2008 stock returns and CDS spreads.

sion of Vector Autoregression (VAR), to test the lead-lag relationship between the equity and CDS markets. This allows us to examine the dynamic relationship between the equity and CDS markets and evaluate the information flow between them. Studies such as those by Longstaff et al. (2003) and Norden and Weber (2009) use Vector Autoregression (VAR) or Vector Autoregression Error Correction Models (VECM) to determine whether one market causes change in another market through measuring the lead-lag relationship between the stock and CDS markets. The VAR model tests the evolution of a variable as a linear evolution of itself over some specific time period. More specifically, we consider a bivariate system where both y_t and z_t are stationary and e_{1t} and e_{2t} are uncorrelated white noise disturbances:

$$y_t = a_{10} + a_{11} y_{t-1} + a_{12} z_{t-1} + e_{1t} \tag{4.1}$$

$$z_t = a_{20} + a_{21} y_{t-1} + a_{22} z_{t-1} + e_{2t} \tag{4.2}$$

As per Fung et al. (2008), we can re-write this equation in terms of the two markets being investigated. In this case y_t and z_t correspond to our CDS credit spreads and stock returns respectively and may be written as follows:

$$CDS_t = a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j}\, CDS_{t-j} + e_1 \tag{4.3}$$

$$Stock_t = a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j}\, CDS_{t-j} + e_2 \tag{4.4}$$

To test for Granger causality, we can simply use a Wald test to check whether the lagged coefficients are equal to zero, i.e. $b_{11} = b_{12} = b_{13} = 0$ ($c_{11} = c_{12} = c_{13} = 0$). For Granger causality, the test hypotheses are as follows:

GC1: CDS credit spreads are not Granger caused by stock returns.

GC2: Stock returns are not Granger caused by CDS credit spreads.

For the cross-sectional testing on firm specific variables, we use a logistic regression model where the previous full lag-5 Granger causality probabilities, which are labelled with a 1 if they are significant or a 0 if the results are insignificant at five percent, are used as the dependant variables. A dummy variable indicating the financial crisis period (2004-2006 is the pre-crisis period and 2007-2008 is the crisis period) is the main independent variable, with firm characteristics as control variables. The logistic regression is used as an alternative to Ordinary Least Squares (OLS) regression because it makes the interpretation of the results more straightforward.[21] Using a binary dependent variable based on acceptance or rejection of the earlier null hypotheses (GC1 and GC2) allows the regression coefficients to be interpreted by their effect on the odds ratio. To capture the effects of the credit crisis, a dummy variable of 0 is used for the pre-crisis period (2004-2006) and a dummy variable of 1 is used for the crisis period (2007-2008). To scale firm trading volume, it is divided by 100,000. The regression with all the variables is shown below. Univariate regressions are also run for each variable.

$$Pr(Y_i = 1) = logit[\alpha_0 + D + \beta_{ASD}(ASD_i) + \beta_{\frac{m}{b}}\left(\frac{M}{B}\right)_i + \beta_V(V_i) + \beta_{CR}(CR)_i + \beta_I(I_i) + \beta_R(R_i) + \varepsilon_i] \quad (4.5)$$

Where:

D = the dummy variable indicating the crisis (0 for pre-crisis period, 1 for crisis period)

ASD = Asset Size Dummy

M/B = Firm's market-to-book ratio

V = Firm's stock trading volume divided by 100,000

CR = Firm's cash-to-asset ratio

I = Firm's industry (0 for financial, 1 for non-financial)

R = Firm's credit rating (0 for non-investment grade, 1 for investment grade)

Y = 1 if Granger causality null hypothesis is rejected or 0 if the null hypothesis is accepted at the 5% level

4.3 Testing

In order to comply with the VAR stationarity assumption, we test all stock and CDS data for stationarity using the augmented Dickey-Fuller (ADF) test. These ADF test results are not

[21] We used OLS with the dependent variable being the logistically transformed p-values of the null hypotheses GC1 and GC2. The results were quite different and the levels of significance and signs change for several of the variables both for GC1 and GC2 tests. Ultimately, results from the logit tests were chosen since using a binary dependent variable provides better definition between the acceptance or rejection of the initial Granger causality tests and because the p-values are not normally distributed.

reported due to the vast number of firms used; (499) resulting in 998 ADF tests, but the results clearly show that stock returns are stationary; while, the CDS credit spreads are not. We test the once-differenced CDS credit spreads and find them to be stationary. Granger causality tests are run by firm on the full matched sample of CDS credit spread differences and stock returns. To see the effects of the financial crisis on the information flow between the markets, we split the data into two groups: pre-crisis period (2004-2006) and crisis period (2007-2008). Granger causality tests are run on each of the two groups and compared to the full sample.

Grouping firms in order of characteristics such as size, market-to-book ratios, volume, cash-to-asset ratio, industry, and credit rating allows us to determine whether any of these factors play a role in how information is incorporated into the CDS or stock markets. All firms are sorted from smallest to largest in terms of each of the characteristics for each year. They are then split into three groups: small, medium and large. For the credit rating and industry, we divide the sample firms in to two groups. The firms data is also split by industry SIC codes into financial and non-financial groups. Firms with two digit SIC codes 60-67 are categorised as financial firms and all others are identified as non-financial. Since the firms are not expected to change between industries, the firms are only categorized once and not yearly. Credit ratings from Standard & Poor's are split between investment grade (AAA to BBB-) and non-investment grade (BB+ to D).

After all of the groupings are complete, we create two equally weighted portfolios for each year using the returns and spreads of the firms within each of the groups: one of daily stock returns and one of daily CDS credit spreads. In order to eliminate the look-ahead bias, accounting information such as asset size, market-to-book ratio, and cash holdings which would not be available during the time period being analyzed are matched from year t-1 to year t stock returns and CDS credit spreads. Data available in to the market within the analysis period (trading volume, credit rating, and industry) are matched from year t to year t stock returns and CDS spreads.

We combine the yearly portfolios into full period (2004-2008) roughly equal groups of small, medium, and large for asset size, market-to-book ratio, volume, and cash-to-assets ratio essentially creating an equally-weighted, yearly-rebalanced portfolio for both daily stock returns and daily CDS credit spreads. The same is done for firm credit ratings, but only two portfolios are made – investment and non-investment grade. Since SIC codes are split into financial and non-financial, and firms are assumed not to move between the categories, the portfolios for these are not rebalanced yearly. Rather, we create two-equally weighted portfolios of daily stock return and daily CDS credit spreads for the whole 2004-2008 period. Granger causality tests are then run for the three groups using the CDS and stock indices. We then split these indices into pre-crisis and crisis period groups and re-test. We run Granger causality tests for a lag of 5 trading days.[22] Although most previous studies using a similar methodology have used 2 lags, our study has a much larger sample size where there are occasionally missing data points.

For the cross-sectional test, Granger causality test results from the lag-5 pre-crisis and crisis periods are gathered and are used in a logistic regression as the dependent variable. These are then given a dummy of 1 if the test null hypothesis (GC1 or GC2) is rejected at 5 percent and 0 if the test null hypothesis is not rejected. Firm specific characteristics are used as the independent variables. Characteristics include the firm's total assets (coded by size from 0 for smallest, 1 for medium, and 2 for largest), market-to-book ratio, stock trading volume, cash-to-assets ratio, industry (0 for non-financial and 1 for financial), and rating (0 for investment grade and 1 for non-investment grade). An average of each characteristic is found for the pre-crisis period and the crisis period for each firm.

Dummy variables are used to test the effects of the financial crisis. A dummy variable of 0 is used for data prior to the beginning of the crisis (years 2004-2006) and a dummy variable of 1 is used for data after the crisis begins (years 2007-2008). The tests are run for the Granger causality results from each set of results (GC1 and GC2) and for each set of lags (2, 5, 10, and 22). All logistic regressions are run using robust covariances.

[22] In order to fully capture the interdependencies between the two series', the four different lags are tested but lag-5 will be depicted throughout the results and lag 2, 10, and 22 are used for robustness tests.

5. RESULTS AND ANALYSIS

5.1 Un-Grouped Results

Table 5 shows a summary of the Granger causality results of the full sample (2004-2008) as well as for the pre-crisis period (2004-2006) and the crisis period (2007-2008). The table indicates the percentage of firms for which the test null hypothesis is rejected. GC1 (CDS credit spreads are not Granger caused by stock returns) is rejected for 78.23% of the firms at the 5% level, indicating that there is significant information flow from the stock to the CDS market. When the tests are split between the pre-crisis and crisis periods, the percentage of firms with information flow approximately doubles (from 43.82% to 73.31% at the 5% level). This would seem to indicate that while there was some information flow from the stock to CDS market prior to the beginning of the crisis, the flow increases quite dramatically after the crisis began. T-test results confirm that the difference in the means of the GC1 probabilities is significantly different from zero at the 1% level.

GC2 (stock returns are not Granger caused by CDS credit spreads) is rejected for much fewer companies than that for GC1 for the full period (51.21% of firms at the 5% level) as well as the pre-crisis and crisis periods. This would seem to indicate that overall, there is less information flow from the CDS market to the stock market than from the stock market to the CDS market. Prior to the beginning of the crisis, there is little information flow from the CDS to the stock market (only 8.81% at the 5% level). Despite this, there does seem to be a dramatic increase in the information flow after the crisis begins. The number of firms with information flowing from the CDS to the stock market increases by more than five times at the 5% level after the crisis begins (from 8.81% to 44.70% at the 5% level).

= = = = = Insert Table 5 Here = = = = =

Because there seems to be much more information flow from the stock to the CDS market, than from the CDS to the stock market, (T-test results confirm that the difference in the means of the GC2 probabilities is significantly different from zero at the 1% level) these results seem to support Hypothesis 1. This is consistent with previous findings such as those by Norden and Weber (2009), and Pena and Forte (2006), who conclude that overall the stock market leads the CDS market, but there is a strong feedback effect. The results also show that the credit crisis spurred a substantial increase in information flow from the stock to CDS market and a dramatic increase from the CDS to the stock market, suggesting an increase in feedback between the markets.

5.2 Grouped Results

The tables in this section show the lag-5 Granger causality results for GC1 and GC2 after the data has been grouped into equally-weighted, yearly rebalanced portfolios of stock returns and CDS spreads based on firm specific characteristics. The characteristics asset size, market-to-book ratio, trading volume, and cash-to-asset ratio are grouped into three portfolios and are listed from smallest to largest. Credit rating and industry grouping are grouped into two portfolios: credit rating is split into investment grade and non-investment grade portfolios and industry is grouped into financial and non-financial portfolios. Since each group has a single stock return portfolio and a single CDS credit spread portfolio, the single test results indicates whether or not the test null hypothesis (GC1 or GC2) is accepted or rejected.

5.2.1 Firms Grouped by Asset Size

Table 6 shows the Granger causality results after the data has been grouped by firm asset size. The Small, Medium, and Large groupings represent equally weighted portfolios of the firms with the smallest, medium, and largest asset sizes.

= = = = = Insert Table 6 Here = = = = =

The results from Table 6 indicate that test hypothesis GC1 is strongly rejected for the full-period, pre-crisis period, and the crisis period for all firm asset sizes at the 1% level. This suggests that although neither firm asset size, nor the time periods seem to affect the stock to CDS information flow, there is still an overall information flow from the stock to the CDS market. On the other hand, test hypothesis GC2 results suggest that while there does not seem to be much impact of firm asset size on the full-period results (all groups are rejected at the 1% level), there does seem to be a difference between the effects of asset size before and after the crisis begins. Prior to the beginning of the crisis, GC2 is not rejected for any asset size group suggesting there was little information flow from the CDS market to the stock market before the crisis began. Interestingly, after the crisis begins, GC2 is rejected for small and medium sized firms at the 1% level, but not for large firms. This would suggest that information flow from the CDS market to the stock market since the beginning of the crisis has increased, but only primarily for small and medium sized firms, consistent with Hypothesis 2.

These results are consistent with our Hypothesis 3 that stock returns should lead their corresponding CDS credit spreads for large firms, which is based on the idea that fewer CDSs will be purchased on high quality firms than on speculative firms. This reasoning is also supported by our findings that after the crisis begins, there is a strong feedback effect. These results differ from those of Norden and Weber (2009), who find an insignificant relationship between firm size and CDS credit spread sensitivity.

5.2.2 Firms Grouped by Profitability

Table 7 shows the Granger causality results after the data has been grouped by firm profitability (market-to-book ratio). The Small, Medium, and Large groupings represent equally weighted portfolios of the firms with the smallest, medium, and largest asset sizes.

= = = = = Insert Table 7 Here = = = = =

The results from Table 7 indicate that test hypothesis GC1 is strongly rejected for the full-period, pre-crisis period, and the crisis period for all book-to-market levels at the 1% level. This suggests that although neither firm profitability, nor the time periods seem to affect the stock to CDS information flow, there is still an overall information flow from the stock to the CDS market. On the other hand, test hypothesis GC2 results suggest that book-to-market does not seem to affect CDS to stock market information flow for the full-period results since all profitability portfolios are rejected at the 1% level. However, there does seem to be a difference between the effects of profitability before and after the crisis begins. Prior to the beginning of the crisis, there seems to be little information flow from the CDS market to the stock market since GC2 is not rejected for any book-to-market portfolio. Interestingly, after the crisis begins, GC2 is rejected only for low and medium book-to-market firms at the 1% level. This suggests that the increase in information flow from the CDS market to the stock market during the crisis is due primarily to low and medium book-to-market firms.

These results are consistent with our Hypothesis 4 that stock returns should lead their corresponding CDS credit spreads for more profitable firms, which is based on the idea that fewer CDSs are purchased on highly profitable firms. After the crisis begins, there is a strong feedback effect from the CDS to the stock market for small and medium profitability firms, which supports Norden and Weber's (2009) theory that CDS credit spreads are more sensitive to new information for high risk firms than for low risk firms.

5.2.3 Firms Grouped by Trading Volume

Table 8 shows Granger causality results after the data has been grouped by a firm's stock liquidity (as measured by stock trading volume). The Small, Medium, and Large groupings represent portfolios made of the firms with the smallest, medium, and largest stock trading volume.

= = = = = Insert Table 8 Here = = = = =

As with asset size groupings and profitability groupings, the results from Table 8 indicate that test hypothesis GC1 is strongly rejected for the full, pre-crisis, and crisis periods for all firm liquidity levels at the 1% level. This suggests that although neither firm stock trading volume, nor the time periods seem to cause change in the stock to CDS information flow, there is still an overall information flow from the stock to the CDS market. On the other hand, test hypothesis GC2 results suggest that while there doesn't seem to be much impact of firm liquidity on the full period results (all full period results reject test hypothesis GC2 at the 1% level), there does seem to be a difference between the effects of liquidity before and after the crisis begins. Prior to the crisis, there seems to be little information flow from the CDS market to the stock market since GC2 is not rejected for any level of trading volume. Interestingly, after the crisis begins, GC2 is rejected, but only for the low (at the 1% level) and medium (at the 5% level) trading volume firms. This suggests that the increase in information flow from the CDS market to the stock market during the crisis is due primarily to firms with low and medium levels of liquidity.

These results are consistent with our Hypothesis 5 that stock returns should lead their corresponding CDS credit spreads for more liquid firms. These results are consistent with the results of Tauschen and Pitts (1983) and Harris (1983) who find a positive relationship between trading volume and price change.

5.2.4 Firms Grouped by Cash Holdings

Table 9 shows the Granger causality results after the data has been grouped by a firm's percentage of cash holdings (cash-to-assets ratio). The Small, Medium, and Large groups represent portfolios made of the firms with the smallest, medium, and largest cash holdings as a percentage of total assets.

= = = = = Insert Table 9 Here = = = = =

As with previous groupings, the results from Table 9 indicate that test hypothesis GC1 is strongly rejected at the 1% level for the full-period, pre-crisis period, and the crisis period for all firm cash holding levels. This suggests that although neither firm cash holdings, nor the time periods seem to cause change in the stock to CDS information flow, there is still an overall information flow from the stock to the CDS market. On the other hand, test hypothesis GC2 results suggest that while there does not seem to be much difference between levels of cash holdings on the full-period results (all are rejected at the 1% level), there does seem to be a difference between the effects of the cash-to-asset ratio before and during the crisis. Prior to the beginning of the crisis, there seems to be little information flow from the CDS market to the stock market since GC2 is not rejected for any level of cash holdings. After the crisis begins, GC2 is rejected for all levels of cash holdings, at the 5% level for firms with small and medium cash holdings, and at the 1% level for firms with large cash holdings. This suggests that, consistent with Hypothesis 2, information flow from the CDS market to the stock market since the beginning of the crisis has increased, regardless of a firm's cash holdings.

These results are somewhat contrary to our Hypothesis 6 that firms with low cash holdings should have CDS credit spreads that lead their corresponding stock returns. Rather the results show that prior to the beginning of the credit crisis, the stock market leads the CDS market in price discovery for all levels of firm cash holdings with little to no feedback from the CDS market. After the crisis begins, there is strong feedback between the two markets and this builds some support for the idea that investors increased their purchase of CDSs on firms with decreasing credit quality or lower cash holdings thereby trading more heavily in the CDS market and causing an increase in information flow into the stock market.

5.2.5 Firms Grouped by Industry Sector

Table 10 shows the Granger causality results after the data has been grouped into two industry categories – Financial or Non-Financial.

= = = = = Insert Table 10 Here = = = = =

The results from Table 10 indicate that test hypothesis GC1 is strongly rejected at the 1% level for the full, pre-crisis, and crisis periods for financial and non-financial industry sectors. This suggests that whether or not the firm is in the financial sector, there is still an overall information flow from the stock to the CDS market. Again the results show a strong information flow from the stock to the CDS market before the crisis as well as after it begins.

Although we find a difference in information flow between the full-period or split-period results for test hypothesis GC2, whether or not the firm is in the financial sector does not seem to influence the information flow. The full period results show that GC2 is rejected at the 1% level for both financial and non-financial industries. Prior to the beginning of the crisis, GC2 is not rejected for either sector, but after the crisis begins, GC2 is rejected at the 5% level for firms in the financial sector and at the 1% level for firms in the non-financial sector. Consistent with Hypothesis 2, the results seem to suggest an increase in information flow from the CDS market to the stock market after the crisis begins.

These results are contrary to our Hypothesis 7 that firms in the financial sector is more likely to have CDS credit spreads that lead their corresponding stock returns. Despite the financial sector buying and selling most of the world's CDSs and being among the hardest hit by the credit crisis, this does not seem to influence the information flow more so than the non-financial sector. Whether the firm is part of the financial sector or non-financial sector, prior to the crisis, firms' stock returns lead their corresponding CDS credit spreads. After the crisis begins, there is a strong feedback effect for firms in the financial and non-financial sectors.

5.2.6 Firms Grouped by Creditworthiness

Table 11 shows the Granger causality results after the data has been grouped into two categories of creditworthiness – Investment or Non-Investment grade.

= = = = = Insert Table 11 Here = = = = =

The results from Table 11 indicate that test hypothesis GC1 is strongly rejected at the 1% level for the full, pre-crisis, and crisis periods for Investment-Grade and Non-Investment Grade firms. This suggests that whether or not the firm is creditworthy, there is still an overall information flow from the stock to the CDS market. Again the results show a strong information flow from the stock to the CDS market before the crisis as well as after it begins.

For test hypothesis GC2, we find a difference in information flow between the full-period or split-period results suggesting an increase in information flow from the CDS to the stock market after the crisis begins which is consistent with Hypothesis 2. The full period results show that GC2 is rejected at the 5% level for investment grade firms and at the 1% level for non-investment grade firms. Prior to the beginning of the crisis, GC2 is not rejected for either credit rating group, but after the crisis begins, GC2 is rejected at the 1% level for non-investment grade firms. The results suggest that after the crisis begins, there seems to be more information flow from the CDS to the stock market for firms that are non-investment grade than those that are investment grade,[23] consistent with Hypothesis 8.

These results are consistent with Fung et al. (2008) who find that the stock market leads the CDS market for investment grade index and that there is significant mutual feedback between the equity and the high-yield index. The results also support Norden and Weber's (2009) findings that the magnitude of the CDS market's sensitivity increases as a firm's credit quality deteriorates.

5.3 Cross-Sectional Results

5.3.1 Univariate Results

Table 12 shows the results of the univariate regressions. Firm specific characteristics are the independent variables and probabilities from the full-sample Granger causality lag-5 (also used in Table 5) results are used as the dependent variable. The dependent probabilities are

[23] The probability of rejection for the Non-Investment Grade portfolio is strongly significant at the 1% level but the Investment-Grade portfolio is marginally significant at 10.89% and is thus shown as insignificant in Table 11.

transformed into binary values of 0 if the probability is insignificant at the five percent level or 1 if the probability is significant at the five percent level. The regression is then run as a binary logistic model.

= = = = = Insert Table 12 Here = = = = =

Univariate regressions are run with just a constant, the dummy indicating the crisis period, and the individual variable. Univariate results for the log of asset size are shown but because of the high correlations between the log of asset size and several other variables the size dummy (ASD) is used to control for asset size.

Looking first at the univariate logistic regression results from the test hypothesis GC1 (stock returns do not Granger cause CDS credit spreads) causality probabilities, we see that the crisis timing dummy variable is always positive and significant at the 1% level suggesting that the credit crisis also had an impact on information flow from the stock to the CDS market, something that previous results did not indicate. Results for the coefficients of the univariate tests on the control variables indicate that the log of asset size, and the asset size dummy, are significant at the 1% level, and the market-to-book ratio and volume are significant at the 10% level. While the previous Granger causality results did not indicate that any of these variables significantly changed the information flow from the stock to the CDS market, the regression results seem to indicate that they have at least some cross-sectional effect. Both the log of total assets (0.3) as well as the asset size dummy (0.40) are positive and significant. These results support Hypothesis 3 and suggest that larger firms have higher information flow from the stock to the CDS market. The market-to book ratio (-0.03) is negative and significant and volume (0.001) is positive and significant. The negative sign of the market-to-book ratio seems to contradict Hypotheses 4 which suggests that more profitable firms have higher information flow from the stock to the CDS market. The results for the stock trading volume suggest that larger firms have more information flow from the stock to the CDS market, consistent with Hypothesis 5.

Looking the univariate logistic regression results from the test hypothesis GC2 (CDS credit spreads do not Granger cause stock returns), we again see that the dummy is positive and significant at 1% for all tests. This would indicate an increase in overall information flow from the CDS to the stock market, which is supported by our previous Granger causality tests, is consistent with Hypothesis 2. Results for the coefficients of the univariate tests indicate that the log of asset size, the asset size dummy, the market-to-book ratio and the industry dummy are significant at the 1% level. Volume is significant at the 10% level and the rating dummy is significant at the 5% level.

The univariate results for the log of asset size are positive (0.26) and significant at the 1% level which indicates that a larger firm results in higher information flow from the CDS to the stock market. The asset size dummy also has a positive sign (0.33) and is significant at the 1% level. This conflicts with the Granger causality results from Table 6, which indicates that larger firms have less information flow from the CDS to the stock market than smaller sized firms after the crisis begins. It is important to note that full-period (2004-2008) causality tests point to an overall information flow regardless of firm asset size.

The univariate results for the market-to-book ratio are negative (-0.12) and significant at the 1% level which, as with the previous Granger causality test results from Table 7, suggest that information flow is higher for firms with lower profitability than for firms with high profitability consistent with Hypothesis 4.

The univariate results for stock trading volume is positive (0.002) and significant at the 10% level. This suggests that information flow from the CDS to the stock market is higher for firms with larger stock trading volume. This conflicts with the Granger causality results from Table 8, which indicate that more liquid firms have less information flow from the CDS to the stock market than less liquid firms after the crisis begins. Full-period (2004-2008) causality results show an overall information flow regardless of stock trading volume.

The univariate results for the financial industry dummy and the rating dummy are also significant. The industry dummy is positive (0.93) and significant at the 1% level and the rating dummy is negative (-0.36) and significant at the 5% level. This indicates higher information flow from the CDS to the stock market for financial firms, consistent with Hypothesis 7, and for firms with higher credit ratings, which is inconsistent with Hypothesis 8 and with previous Granger causality results.

5.3.2 Multivariate Results

Table 13 shows the results of the full multivariate regressions. Firm specific characteristics are the independent variables and probabilities from the full-sample Granger causality lag-5 (also used in Table 5) results are again used as the dependent variable. The dependent probabilities are transformed into binary values of 0 if the probability is insignificant at the five percent level or 1 if the probability is significant at the five percent level. The regression is then run as a binary logistic model. In the full multivariate regression, we use an asset size dummy rather than the log of asset size to reduce the correlations between size and the log of volume and the rating dummy.

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Looking first at the multivariate logistic regression results from the test hypothesis GC1 (stock returns do not Granger cause CDS credit spreads) probabilities, we see that the dummy variable is positive and significant at the 1% level again suggesting that the credit crisis also had an impact on information flow from the stock to the CDS market, something that previous Granger causality results did not indicate. The asset size dummy remains significant at the 1% level and positive (0.53) as does the market-to-book ratio (-0.04), which is significant at the 10% level. Although previous Granger causality results do not show that firm asset size has an impact on the overall information flow from the stock to the CDS market, the positive sign for the firm asset size dummy is consistent with Hypothesis 3 and suggests that larger firms have more information flow from the stock to the CDS market than do smaller firms. The negative sign for profitability is surprising and inconsistent with Hypothesis 4, which predicts that more profitable firms should result in higher information flow from the stock to the CDS market. The multivariate results suggest that more profitable firms have lower information flow from the stock to the CDS market. The rating dummy is positive (0.69) and significant at the 1% level. Previous Granger causality results did not indicate that a firm's credit rating impacted the overall information flow from the stock to the CDS market, but the significance of the rating coefficient in the cross-sectional regression seems to indicate otherwise, suggesting that a lower credit rating leads to increased information flow from the stock to the CDS market. These results indicate that larger firms with lower profitability and lower credit ratings tend to have higher information flow from the stock to the CDS market. The test hypothesis GC1 multivariate regression has an R-squared of 11 percent and the calculated likelihood ratio shows that the regression is significant at a one percent level.

The full regression using the test hypothesis GC2, the dummy again remains significant at the 1% level. This is consistent with previous Granger causality results which indicate that information flow from the CDS to the stock market increased after the credit crisis began and these results also support Hypothesis 2. For this regression, only two other coefficients are significant; the market-to-book ratio (-0.09) which is negative and significant at the 5% level, and the financial industry dummy (0.78) which is positive and significant at the 1% level. These results indicate that firms in the financial sector with lower profitability would have higher information flow from the CDS to the stock market. These results are consistent with our Hypotheses 4 and 7 as well as our previous Granger causality results. Our previous causality results show that lower profitability firms are the only firms with information flow after the crisis begins. Causality results also show that after the crisis begins, there is an increase in information flow from the CDS to the stock market regardless of whether the firm is in the financial sector or the non-financial sector. The asset size dummy (ASD) is positive (0.20) and marginally significant. This result contradicts Hypothesis 3 as well as our previous Granger causality results which show that smaller firms have higher information flow from the CDS to the stock market as well. The test hypothesis GC2 multivariate regression has an R-squared of 18 percent and the calculated likelihood ratio shows that the regression is significant at a one percent level.

5.4 Robustness Testing

5.4.1 Granger Causality

All Granger causality tests were run for 2, 5, 10, and 22 lags. When running the tests for individual firms, the results showed that as the lag length increased, so did the number of firms for which the test null hypothesis (GC1 and GC2) was rejected (see appendix Tables 13-15). This would suggest that information flow between the markets may take longer to incorporate into the return or spread than previously thought. Using different lags for the grouped Granger causality tests had little to no affect on the resulting probabilities. The 2 and 22 lag results showed minor discrepancies for several groupings, but overall the 5 lag results reflect those of all other lags.

5.4.2 Cross-Sectional Testing

To measure the impact of the credit crisis on the individual firm characteristics, univariate tests were also run to include the crisis dummy multiplied by each individual characteristic. These results were not found to be significant suggesting that rather than individual characteristics reacting to the credit crisis, there was an overall shift in information flow as demonstrated by a positive and significant crisis dummy in earlier tests.

To ensure robustness of the cross-sectional logistic regression, the dependent variable was tested using several different methods. The dependent variable used the cross-sectional results shown in Table 12 was made up of the lag-5 Granger causality probabilities for each firm. This was then made into a binary variable where the dummy zero represented the failure to reject the test null hypothesis at a 5 percent level and the dummy 1 represented the rejection of the hypothesis at the 5 percent level. The distribution of the lag-5 original probabilities (prior to being made into binary dummies), is depicted in Figure 2 below.

= = = = = Insert Figure 2 Here = = = = =

The distribution shows that the probabilities for both test hypotheses GC1 and GC2 are highly skewed towards zero. Because the binary dummy cuts off at five percent and the probabilities are not normally distributed, a five percent window is cut out of the data to create a more distinct break. In particular, we remove any observations whose p-values fall between five and ten percent.[24] The logistic model is then re-run with the data window removed. Although levels of significance change slightly, both the univariate and multivariate regressions have the same results with only one exception; in A23 the asset size dummy (ASD) for the multivariate regression testing GC2 changes from being marginally significant in the original multivariate regression to significant at the 5% level.

[24] This results in the removal of 48 observations for GC1 and 50 observations for GC2.

6. SUMMARY AND CONCLUSIONS

In this study we analyze whether the CDS market has an informational advantage over the equity market. In particular, we examine the lead-lag relationship between the two markets. We create a data set that contains a large sample of 499 firms, for which we have data from 2004 to 2008. This rich data set allows us to extend research in this area in two dimensions. First, we have enough observations to test whether the nature of the dynamic relationship changes due to the current credit crisis. Second, the firm level matched sample allows us to examine whether firm specific characteristics matter in the information flow across the two markets.

For the entire sample period we find that the stock market leads the CDS market for 78.23% of our firms, but in only 51.21% of the cases do we find the CDS market leading the stock market. This result corroborates that of Forte and Pena (2006) and Fung et al. (2008) as well as several other studies, who find that in general, the stock market leads the CDS market in the price discovery process. Unlike other asset prices, a CDS credit spread only provides information about a firm's likelihood of default, and as such, the current financial crisis gives us an excellent opportunity to test whether the lead-lag relationship between the two markets has changed as its result. We find that during the crisis the dynamic lead-lag relationship between the stock and CDS markets does change. Granger causality test results with the hypothesis that stock returns do not cause CDS credit spreads are rejected in almost twice as many cases when compared to results for the pre-crisis period. On the other hand, the hypothesis that CDS credit spreads do not Granger cause stock returns is rejected in five times as many cases when compared to pre-crisis period results. This change in the dynamic relationship in stock and CDS market is robust for different lag lengths and at different significance levels.

To examine which firm specific characteristics influence the information flow across the market we grouped data by firm size, profitability, cash holding, liquidity, industry and rating. Our results show that larger, more profitable, and very liquid firms with a higher credit rating tend to have less information flow from the CDS to the stock market. These results support the theory of Norden and Weber (2009) who although finding no significant results, suggest that CDSs are more sensitive to stock returns of firms with lower credit ratings. Our results also support their finding that CDS credit spreads become increasingly sensitive to stock returns as a firm's credit rating deteriorates. Our findings also support the results of Fung et al. (2008), who find that the stock market leads the investment-grade CDS index and also find significant feedback between the equity index and high-yield CDS index.

The multivariate logistic regression results confirm that firm specific characteristics have an effect on the information flow. Regression results find that information flow from the stock to the CDS market is increased in firms with larger asset values, lower profitability, and a lower credit rating. The results also show that information flow from the CDS to the stock market is increased in firms in the financial sector with lower profitability. This is further supported by robustness tests.

Limitations of this study include our inability to examine the impact of CDS trading volume on overall information flows due to a lack of data. Using only firm stock trading volume may not fully capture effects the trade liquidity in both markets. Although this study attempts to consider all available characteristics that may impact information flow, it is possible that our list is not comprehensive. Another potential characteristic that was considered was analyst following. Due to our limited access to this data, this characteristic was not included as it would have greatly reduced the sample size of our data.

We believe, that future research could continue this study to include data after the credit crisis has ended to see whether or not the information flow reverts back to its pre-crisis state. While this study uses Granger causality and logistic regressions to determine the impact of firm specific characteristics on information flow, further research could develop more specific methodology to capture the effects of these characteristics particularly with respect to how these characteristics affect the directionality of information flow as well as how they affect price discovery. In particular, further research could extend the VECM model of Eun and Sabherwal (2003) to test for deviations from the equilibrium relationship as a method of testing for price discovery. This study could also be extended to include matching bonds, something that we were unable to include due to a lack of data.

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Table 1
Descriptive Statistics of the Control Variables (Full Sample)

The table below provides the descriptive statistics of the firms used in the logistic regression for the full sample period (2004-2008). Each firm has two observations for each control variable; one observation for the pre-crisis period (2004-2006) and one for the period during the crisis (2007-2008). Log(A) = Log(assets), Log(MV) = Log(market value of equity), Log(S) = Log(sales), ASD = (asset(asset size dummy 0 for small, 1 for medium, 2 for large), M/B = (market-to-book ratio), VOL = firm trading volume/100,000, C/A = cash-to-assets ratio. The firm rating (RD) is given a dummy variable of 0 if the firm is investment grade and 1 if the firm is non-investment grade. Whether or not the firm is in the financial industry (IND) is represented with a 1 if it is, and 0 if is not in the financial sector. The final column (D) represents the dummy variable associated with the pre-crisis (0) and crisis periods (1).

	LOG(A)	LOG(MV)	LOG(S)	ASD	M/B	VOL	C/A	RD	IND	D
Mean	9.39	15.99	8.88	1.01	3.34	43.05	0.08	0.27	0.18	0.50
Median	9.22	15.92	8.92	1.00	2.44	20.08	0.05	0.00	0.00	1.00
Maximum	14.53	19.99	12.80	2.00	44.24	866.24	0.70	1.00	1.00	1.00
Minimum	5.96	12.24	5.25	0.00	0.48	0.00	0.00	0.00	0.00	0.00
Std. Dev.	1.31	1.27	1.29	0.81	3.40	78.28	0.09	0.44	0.38	0.50
Dummy=0	-	-	-	305	-	-	-	686	771	469
Dummy=1	-	-	-	317	-	-	-	253	168	470
Dummy=2				317						
Observations	939	927	878	939	905	938	878	939	939	939

Table 2
Correlation Table of the Control Variables (Full Sample)

The table below provides the correlations between the control variables used in the cross-sectional logistic regression for the full sample period (2004-2008). Log(A) = Log(assets), Log(MV) = Log(market value of equity), Log(S) = Log(sales), ASD = (asset size dummy 0 for small, 1 for medium, 2 for large), M/B = (market-to-book ratio), VOL = firm trading volume/100,000, C/A = cash-to-assets ratio. The firm rating (RD) is given a dummy variable of 0 if the firm is investment grade and 1 if the firm is non-investment grade. Whether or not the firm is in the financial industry (IND) is represented with a 1 if it is, and 0 if is not in the financial sector.

	LOG(A)	**LOG(MV)**	**LOG(S)**	**ASD**	**M/B**	**VOL**	**C/A**	**RD**	**IND**
LOG(A)	1.00	0.79	0.75	0.83	-0.08	0.47	0.04	-0.28	0.26
LOG(MV)	0.79	1.00	0.73	0.71	0.19	0.51	0.22	-0.44	0.03
LOG(S)	0.75	0.73	1.00	0.69	0.03	0.41	0.15	-0.21	-0.19
ASD	0.83	0.71	0.69	1.00	-0.05	0.33	0.03	-0.27	0.10
M/B	-0.08	0.19	0.03	-0.05	1.00	0.10	0.18	0.01	-0.11
VOL	0.47	0.51	0.41	0.33	0.10	1.00	0.30	-0.01	0.00
C/A	0.04	0.22	0.15	0.03	0.18	0.30	1.00	0.03	0.02
RD	-0.28	-0.44	-0.21	-0.27	0.01	-0.01	0.03	1.00	-0.20
IND	0.26	0.03	-0.19	0.10	-0.11	0.00	0.02	-0.20	1.00

Table 3
Descriptive Statistics of the Control Variables (2004-2006)

The table below provides the descriptive statistics for firms used in the cross-sectional logistic regression. Only the firm's (2004-2006) pre-crisis observations are included. Log(A) = Log(assets), Log(MV) = Log(market value of equity), Log(S) = Log(sales), ASD = (asset size dummy 0 for small, 1 for medium, 2 for large), M/B = (market-to-book ratio), VOL = firm trading volume/100,000, C/A = cash-to-assets ratio. The firm rating (RD) is given a dummy variable of 0 if the firm is investment grade and 1 if the firm is non-investment grade. Whether or not the firm is in the financial industry (IND) is represented with a 1 if it is, and 0 if is not in the financial sector.

	LOG(A)	**LOG(MV)**	**LOG(S)**	**ASD**	**M/B**	**VOL**	**C/A**	**RD**	**IND**
Mean	9.29	15.89	8.78	1.02	3.39	28.54	0.08	0.23	0.18
Median	9.14	15.86	8.82	1.00	2.40	14.48	0.05	0.00	0.00
Maximum	14.16	19.57	12.56	2.00	30.26	547.94	0.70	1.00	1.00
Minimum	5.96	12.24	5.25	0.00	0.48	0.00	0.00	0.00	0.00
Std. Dev.	1.31	1.23	1.30	0.81	3.50	53.08	0.09	0.42	0.38
Dummy=0	-	-	-	151	-	-	-	359	385
Dummy=1	-	-	-	159	-	-	-	110	84
Dummy=2				159					
Observations	469	459	432	469	450	468	432	469	469

Table 4
Descriptive Statistics of the Control Variables (2007-2008)

The table below provides the descriptive statistics for firms used in the cross-sectional logistic regression. Only the firms' (2007-2008) crisis period observations are included. Log(A) = Log(assets), Log(MV) = Log(market value of equity), Log(S) = Log(sales), ASD = (asset size dummy 0 for small, 1 for medium, 2 for large), M/B = (market-to-book ratio), VOL = firm trading volume/100,000, C/A = cash-to-assets ratio. The firm rating (RD) is given a dummy variable of 0 if the firm is investment grade and 1 if the firm is non-investment grade. Whether or not the firm is in the financial industry (IND) is represented with a 1 if it is, and 0 if is not in the financial sector.

	LOG(A)	LOG(MV)	LOG(S)	ASD	M/B	VOL	C/A	RD	IND
Mean	9.49	16.09	8.99	1.01	3.29	57.50	0.08	0.30	0.18
Median	9.33	16.03	9.00	1.00	2.45	27.33	0.05	0.00	0.00
Maximum	14.53	19.99	12.80	2.00	44.24	866.24	0.52	1.00	1.00
Minimum	6.63	12.67	5.48	0.00	0.54	0.01	0.00	0.00	0.00
Std. Dev.	1.31	1.30	1.27	0.82	3.31	94.96	0.08	0.46	0.38
Dummy=0	-	-	-	154	-	-	-	327	386
Dummy=1	-	-	-	158	-	-	-	143	84
Dummy=2				158					
Observations	470	468	446	470	455	470	446	470	470

Table 5
Granger Causality as a Percentage of Firms

The table below provides the percentage of firms where we reject the null hypothesis for lag-5 Granger causality tests at the one percent, five percent, and ten percent levels. The total number of firms for the full period lag-5 testing is 496. For the pre-crisis period (2004-2006), there are a total of 477 and for the crisis period (2007-2008) there are a total of 472 firms. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Percent rejected @ 1%	72.98%	30.40%	65.04%	40.32%	3.56%	31.14%
Percent rejected @ 5%	78.23%	43.82%	73.31%	51.21%	8.81%	44.70%
Percent rejected @ 10%	81.25%	51.99%	77.97%	56.85%	14.26%	52.12%

Test of Difference between Means (two-tailed T-test)

Comparison	**T-Statistics**
GC1: Pre-Crisis vs. Crisis	6.557***
GC2: Pre-Crisis vs. Crisis	10.147***

Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 6
Granger Causality Results of Firms Grouped by Asset Size

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped by asset size was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Small, medium and large groupings indicate portfolios made of firms with the smallest, medium, and largest asset sizes respectively. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Small	287.15***	28.73***	141.17***	37.95***	0.82	18.66***
Medium	146.9***	49.01***	64.67***	37.91***	3.97	18.02***
Large	214.04***	32.89***	94.68***	15.41***	5.25	7.81

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 7
Granger Causality Results of Firms Grouped by Profitability

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped by their market-to-book ratio was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Small, medium and large groupings indicate portfolios made of firms with the smallest, medium, and largest market-to-book ratios respectively. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Small	230.48***	36.75***	100.41***	44.49***	5.30	21.07***
Medium	113.45***	51.01***	50.37***	64.58***	3.92	29.67***
Large	165.94***	33.5***	77.38***	11.23**	5.33	5.15

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 8
Granger Causality Results of Firms Grouped by Liquidity

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped by their stock trading volume was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Small, medium and large groupings indicate portfolios made of firms with the smallest, medium, and largest stock trading volume respectively. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Small	111.09***	30.25***	49.46***	73.98***	3.99	33.81***
Medium	183.23***	54.41***	83.54***	24.67***	5.05	12.3**
Large	285.54***	51.68***	127.37***	12.44**	4.53	7.47

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 9
Granger Causality Results of Firms Grouped by Cash Holdings

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped by their cash holdings as a percentage of total assets was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Small, medium and large groupings indicate portfolios made of firms with the smallest, medium, and largest cash-to-assets ratio respectively. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Small	87.20***	26.00***	38.21***	32.51***	2.10	14.88**
Medium	247.02***	45.14***	114.91***	20.49***	2.73	11.50**
Large	291.19***	33.25***	141.69***	34.93**	5.79	21.82***

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 10
Granger Causality Results of Firms Grouped by Industry

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped into either the financial or non-financial sectors was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Financial	306.27***	23.83***	130.32***	25.81***	6.52	11.20**
Non-Financial	198.39***	67.15***	90.39***	31.9***	4.30	18.76***

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 11
Granger Causality Results of Firms Grouped by Credit Rating

An equally-weighted, yearly rebalanced portfolio of stock returns and CDS credit spreads of firms grouped into either the investment-grade or non-investment grade portfolios was used to calculate these Granger causality results. The table below provides the Chi-Squared values of each test. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Lag-5	**GC1: Stock does not cause CDS**			**GC2: CDS does not cause Stock**		
	Full Period	**Pre-Crisis**	**Crisis**	**Full Period**	**Pre-Crisis**	**Crisis**
Investment Grade	199.18***	45.79***	88.19***	15.01**	4.48	9.00
Non-Investment Grade	178.88***	45.91***	82.49***	31.09***	2.41	15.74***

Note: Chi-Squared values shown with 5 degrees of freedom
Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 12
Cross-Sectional Results of Univariate Logistic Regressions

The table below provides the coefficients for the univariate logistic regressions. Each regression includes a constant, the time-period dummy and the listed variable. Their Z-statistics are listed in parenthesis below the coefficients. The dependent variable is the Granger causality probability calculated for each firm: 1 if the null hypothesis is rejected at the 5% level or 0 if it is not rejected. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

	GC1: Stock does not cause CDS				**GC2: CDS does not cause Stock**			
	Crisis Dummy		**Coefficient**		**Crisis Dummy**		**Coefficient**	
Log(Asset Size)	1.24	***	0.30	***	2.12	***	0.26	***
	(8.62)		(5.51)		(11.13)		(4.19)	
Asset Size Dummy	1.29	***	0.40	***	2.15	***	0.33	***
	(9.02)		(4.58)		(11.28)		(3.29)	
M/B Ratio	1.26	***	-0.03	*	2.11	***	-0.12	***
	(8.74)		(-1.71)		(11.04)		(-2.95)	
CA_Ratio	1.40	***	-0.06		2.11	***	-1.00	
	(9.44)		(-0.07)		(10.89)		(-1.02)	
Volume	1.22	***	0.00	*	2.10	***	0.00	*
	(8.58)		(1.83)		(10.89)		(1.66)	
Industry Dummy	1.26	***	0.25		2.17	***	0.93	***
	(8.93)		(1.35)		(11.29)		(4.60)	
Rating Dummy	1.25	***	0.10		2.15	***	-0.36	**
	(8.78)		(0.68)		(11.33)		(-1.98)	

Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Table 13
Cross-Sectional Results of Multivariate Logistic Regressions

The table below provides the coefficients for the multivariate logistic regressions. Z-statistic are listed in parenthesis below the coefficients. The dependent variable is the Granger causality probability calculated for each causality firm: 1 if the null hypothesis is rejected at the 5% level or 0 if it is not rejected. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Coefficient	**GC1: Stock does not cause CDS**		**GC2: CDS does not cause Stock**	
Intercept	-0.82		-2.36	***
	(-4.22)		(-8.56)	
Crisis Dummy	1.46	***	2.18	***
(0=pre-crisis, 1=crisis)	(9.04)		(10.35)	
Asset Size Dummy	0.53	***	0.20	
(0-2 smallest-largest)	(5.07)		(1.62)	
M/B Ratio	-0.04	*	-0.09	**
	(-1.71)		(-2.22)	
CA_Ratio	0.16		-1.24	
	(0.18)		(-1.14)	
Volume	-0.00		0.00	
	(-0.84)		(0.87)	
Industry Dummy	0.10		0.78	***
(0=non-financial, 1=financial)	(0.47)		(3.54)	
Rating Dummy	0.69	***	-0.04	
(0= investment grade, 1=non-investment grade)	(3.58)		(-0.18)	
McFadden R^2	0.11		0.18	
Probability(LR stat)	0.00	***	0.00	***
Obs Dep=0	329		608	
Obs Dep=1	511		232	
Total Obs	840		840	

Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

Figure 1
Diagram of a Credit Default Swap

In the case of a credit default swap (CDS), in exchange for periodic payments from the protection buyer, where the rate of payments is referred to as the credit spread, the protection seller agrees to pay the face value of the underlying bond or loan only in the case of a credit event. Ford Motor is presented as an example in the figure of a CDS below. As Ford's perceived risk of default increases, so does its CDS credit spread. On January 1, 2004 Ford Motor Co.'s spread was 215 basis points. By December 29, 2008 the spread increased to 1,837.9 basis points or $1,837,900/year.

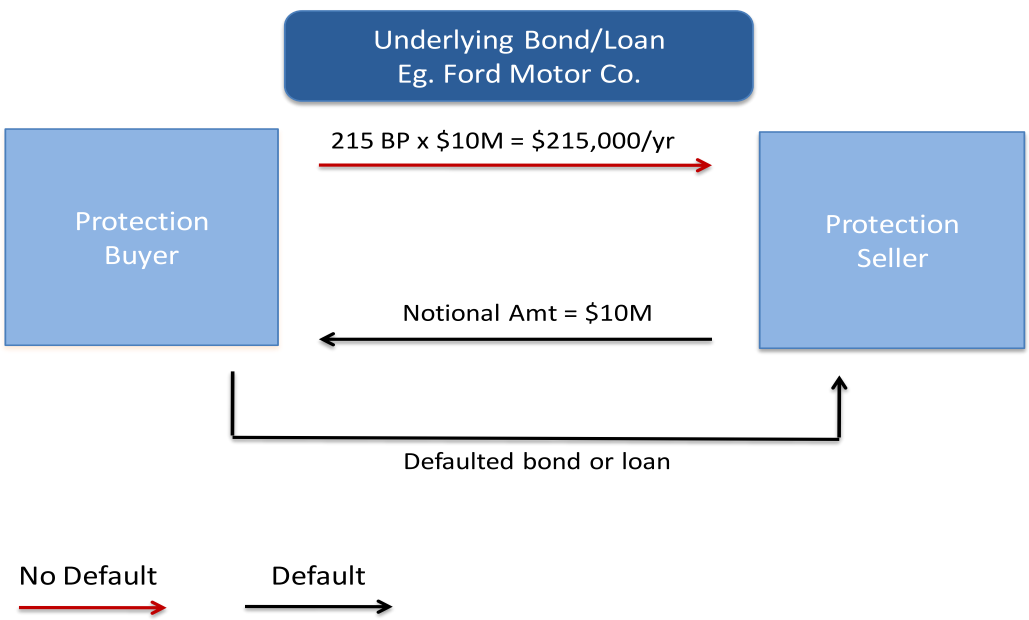
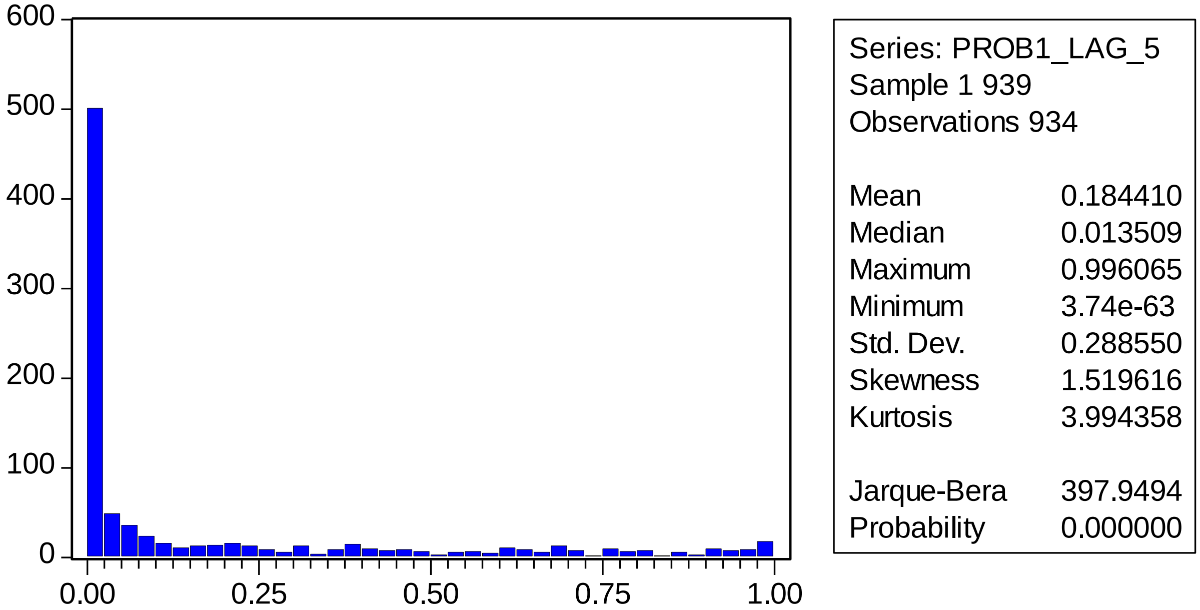
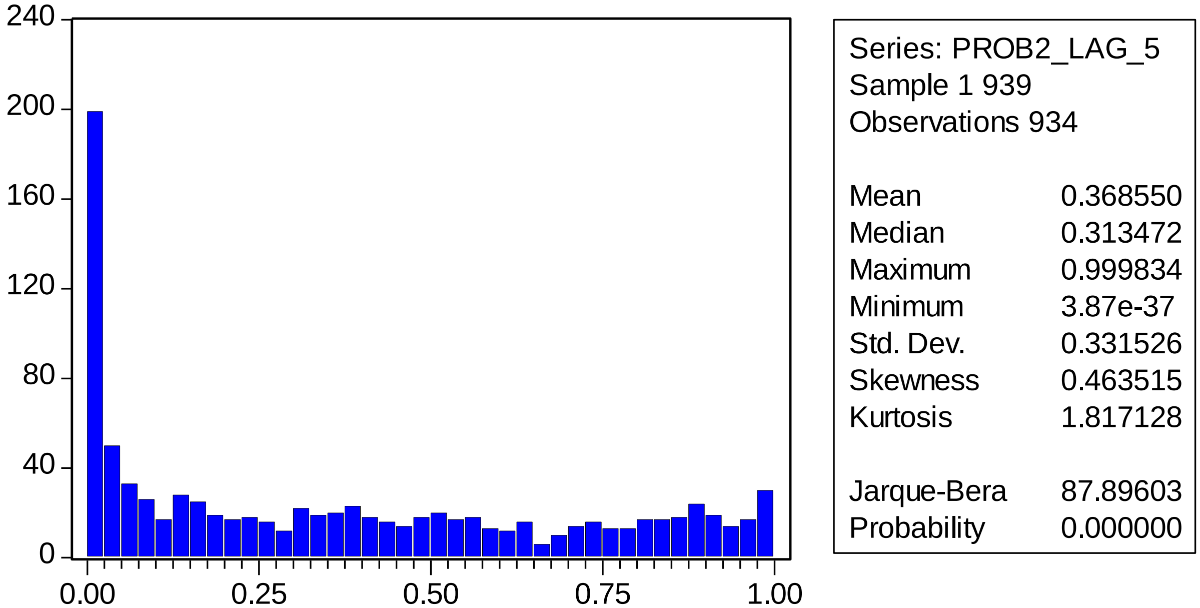


Figure 2
Distribution of the Dependent Variable

Distribution of the Granger causality lag-5 probabilities for Hypothesis GC1.



Distribution of the Granger causality lag-5 probabilities for Hypothesis GC2.



A1
Summary of Full Sample Granger Causality Results

The table below describes the percentage of firms in the full-period (2004-2008) sample in which the hypotheses are rejected for each Granger causality test at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

	GC1: Stock does not cause CDS				**GC2: CDS does not cause Stock**			
	2-lags	5-lags	10-lags	22-lags	2-lags	5-lags	10-lags	22-lags
Percent Rejected @ 1%	71.14%	72.98%	75.35%	77.53%	28.26%	40.32%	53.13%	60.73%
Percent Rejected @ 5%	77.56%	78.23%	80.40%	80.97%	35.87%	51.21%	60.40%	67.61%
Percent Rejected @ 10%	80.16%	81.25%	82.22%	81.98%	42.08%	56.85%	65.25%	71.46%

A2
Summary of Pre-Crisis Granger Causality Results

The table below describes the percentage of firms in the pre-crisis (2004-2006) sample in which the hypotheses are rejected for each Granger causality test at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Pre-Crisis (2004-2006)	**GC1: Stock does not cause CDS**				**GC2: CDS does not cause Stock**			
	2-lags	5-lags	10-lags	22-lags	2-lags	5-lags	10-lags	22-lags
Percent Rejected @ 1%	31.88%	30.40%	28.18%	24.09%	3.13%	3.56%	4.24%	6.18%
Percent Rejected @ 5%	44.38%	43.82%	40.47%	36.25%	9.79%	8.81%	7.84%	10.23%
Percent Rejected @ 10%	53.96%	51.99%	48.94%	42.64%	15.00%	14.26%	14.62%	17.27%

A3
Summary of Crisis-Period Granger Causality Results

The table below describes the percentage of firms in the post-crisis (2007-2008) sample in which the hypotheses are rejected for each Granger causality test at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Post-Crisis (2007-2008)	**GC1: Stock does not cause CDS**				**GC2: CDS does not cause Stock**			
	2-lags	5-lags	10-lags	22-lags	2-lags	5-lags	10-lags	22-lags
Percent Rejected @ 1%	63.37%	65.04%	69.21%	72.10%	18.53%	31.14%	43.95%	55.79%
Percent Rejected @ 5%	73.05%	73.31%	76.22%	78.54%	30.32%	44.70%	53.50%	65.45%
Percent Rejected @ 10%	76.63%	77.97%	78.98%	81.55%	36.84%	52.12%	61.15%	71.67%

A4
Full Sample Granger Causality Results Grouped by Total Assets

The data used in this table is grouped by asset size where group 1 is made up of indices based on firms with the smallest asset sizes and group 3, the largest. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Total Assets Grouped Smallest to Largest

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.0016***
1	5	<.0001***	<.0001***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	<.0001***
2	5	<.0001***	<.0001***
2	10	<.0001***	<.0001***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.0449**
3	5	<.0001***	0.0088***
3	10	<.0001***	0.0025***
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A5
Pre-Crisis Period Granger Causality Results Grouped by Total Assets

The data used in this table is grouped by asset size where group 1 is made up of indices based on firms with the smallest asset sizes and group 3, the largest. The table below describes the Granger causality results for each group for the pre-crisis (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Total Assets Grouped Smallest to Largest 2004-2006

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.8968
1	5	<.0001***	0.9760
1	10	0.0011	0.9422
1	22	0.0096	0.9440
2	2	<.0001***	0.9527
2	5	<.0001***	0.5534
2	10	<.0001***	0.7810
2	22	<.0001***	0.5122
3	2	<.0001***	0.1567
3	5	<.0001***	0.3862
3	10	<.0001***	0.5657
3	22	<.0001***	0.6616

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A6
Crisis-Period Granger Causality Results Grouped by Total Assets

The data used in this table is grouped by asset size where group 1 is made up of indices based on firms with the smallest asset sizes and group 3, the largest. The table below describes the Granger causality results for each group for the post-crisis (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Total Assets Grouped Smallest to Largest 2007-2008

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.0430**
1	5	<.0001***	0.0022***
1	10	<.0001***	0.0002***
1	22	<.0001***	0.0001***
2	2	<.0001***	0.0068***
2	5	<.0001***	0.0029***
2	10	<.0001***	0.0002***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.1959
3	5	<.0001***	0.1672
3	10	<.0001***	0.2943
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A7
Full Sample Granger Causality Results Grouped by Market-to-Book Ratio

The data used in this table is grouped by market-to-book ratios where group 1 is made up of indices based on firms with the smallest ratios and group 3, the largest. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Market-to-Book Ratio Grouped Smallest to Largest			
Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	<.0001***
1	5	<.0001***	<.0001***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	<.0001***
2	5	<.0001***	<.0001***
2	10	<.0001***	<.0001***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.0035***
3	5	<.0001***	0.0470**
3	10	<.0001***	0.0009***
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A8
Pre-Crisis Granger Causality Results Grouped by Market-to-Book Ratio

The data used in this table is grouped by market-to-book ratios where group 1 is made up of indices based on firms with the smallest ratios and group 3, the largest. The table below describes the Granger causality results for each group for the pre-crisis (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Market to Book Ratio Grouped Smallest to Largest 2004-2006

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.3947
1	5	<.0001***	0.3808
1	10	<.0001***	0.5261
1	22	0.0004***	0.3124
2	2	<.0001***	0.5467
2	5	<.0001***	0.5616
2	10	<.0001***	0.8334
2	22	<.0001***	0.9361
3	2	<.0001***	0.3792
3	5	<.0001***	0.3764
3	10	<.0001***	0.9007
3	22	<.0001***	0.7884

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A9
Crisis-Period Granger Causality Results Grouped by Market-to-Book Ratio

The data used in this table is grouped by market-to-book ratios where group 1 is made up of indices based on firms with the smallest ratios and group 3, the largest. The table below describes the Granger causality results for each group for the post-crisis (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Market to Book Ratio Grouped Smallest to Largest 2007-2008

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.0126**
1	5	<.0001***	0.0008***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	0.0002***
2	5	<.0001***	<.0001***
2	10	<.0001***	0.0001***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.0566*
3	5	<.0001***	0.3979
3	10	<.0001***	0.1872
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A10
Full Sample Granger Causality Results Grouped by Volume

The data used in this table is grouped by stock trading volume where group 1 is made up of indices based on firms with the lowest volume and group 3, the highest. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Trading Volume Grouped Smallest to Largest

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	<.0001***
1	5	<.0001***	<.0001***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	0.0029***
2	5	<.0001***	0.0002***
2	10	<.0001***	<.0001***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.123
3	5	<.0001***	0.0292**
3	10	<.0001***	0.0075***
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A11
Pre-Crisis Sample Granger Causality Results Grouped by Volume

The data used in this table is grouped by stock trading volume where group 1 is made up of indices based on firms with the lowest volume and group 3, the highest. The table below describes the Granger causality results for each group for the pre-crisis period (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Trading Volume Grouped Smallest to Largest 2004-2006			
Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.2000
1	5	<.0001***	0.5514
1	10	0.0005***	0.6130
1	22	0.0001***	0.6637
2	2	<.0001***	0.4537
2	5	<.0001***	0.4092
2	10	<.0001***	0.3121
2	22	<.0001***	0.2575
3	2	<.0001***	0.4902
3	5	<.0001***	0.4764
3	10	<.0001***	0.7123
3	22	<.0001***	0.7859

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A12
Crisis-Period Sample Granger Causality Results Grouped by Volume

The data used in this table is grouped by stock trading volume where group 1 is made up of indices based on firms with the lowest volume and group 3, the highest. The table below describes the Granger causality results for each group for the post-crisis period (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Trading Volume Grouped Smallest to Largest 2007-2008			
Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	<.0001***
1	5	<.0001***	<.0001***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	0.0495**
2	5	<.0001***	0.0309**
2	10	<.0001***	0.0016***
2	22	<.0001***	0.0002***
3	2	<.0001***	0.3528
3	5	<.0001***	0.1877
3	10	<.0001***	0.2557
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A13
Full Sample Granger Causality Results Grouped by Cash Holdings

The data used in this table is grouped by firm cash holdings where group 1 is made up of indices based on firms with the lowest cash holdings and group 3, the highest. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Cash Holdings Grouped Smallest to Largest

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.0015***
1	5	<.0001***	<.0001***
1	10	<.0001***	<.0001***
1	22	<.0001***	<.0001***
2	2	<.0001***	0.6311
2	5	<.0001***	0.0010***
2	10	<.0001***	0.0012***
2	22	<.0001***	<.0001***
3	2	<.0001***	0.6603
3	5	<.0001***	<.0001***
3	10	<.0001***	<.0001***
3	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A14
Pre-Crisis Sample Granger Causality Results Grouped by Cash Holdings

The data used in this table is grouped by firm cash holdings where group 1 is made up of indices based on firms with the lowest cash holdings and group 3, the highest. The table below describes the Granger causality results for each group for the pre-crisis period (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Cash Holdings Grouped Smallest to Largest 2004-2006			
Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	<.0001***	0.6640
1	5	<.0001***	0.8351
1	10	0.0002***	0.5624
1	22	0.0005***	0.6113
2	2	<.0001***	0.5443
2	5	<.0001***	0.7417
2	10	<.0001***	0.8949
2	22	<.0001***	0.8595
3	2	<.0001***	0.5794
3	5	<.0001***	0.3275
3	10	<.0001***	0.4606
3	22	<.0001***	0.2350

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A15
Crisis-Period Sample Granger Causality Results Grouped by Cash Holdings

The data used in this table is grouped by firm cash holdings where group 1 is made up of indices based on firms with the lowest cash holdings and group 3, the highest. The table below describes the Granger causality results for each group for the post-crisis period (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Cash Holdings Grouped Smallest to Largest 2007-2008			
Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
1	2	0.0002***	0.0636*
1	5	<.0001***	0.0109**
1	10	<.0001***	0.0197**
1	22	<.0001***	<.0001***
2	2	<.0001***	0.8016
2	5	<.0001***	0.0423**
2	10	<.0001***	0.0761*
2	22	<.0001***	0.0030***
3	2	<.0001***	0.8071
3	5	<.0001***	0.0006***
3	10	<.0001***	0.0006***
3	22	<.0001***	0.0013***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A16
Full Sample Granger Causality Results Grouped by Credit Rating

The data used in this table is grouped into two groups; investment grade and non-investment grade. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into investment grade or non-investment grade ratings. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Investment Grade and Non-Investment Grade

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Investment Grade	2	0.0057***	<.0001***
Investment Grade	5	0.0153**	<.0001***
Investment Grade	10	<.0001***	<.0001***
Investment Grade	22	<.0001***	<.0001***
Non-Investment Grade	2	0.0041***	<.0001***
Non-Investment Grade	5	0.1098	<.0001***
Non-Investment Grade	10	<.0001***	<.0001***
Non-Investment Grade	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A17
Pre-Crisis Sample Granger Causality Results Grouped by Credit Rating

The data used in this table is grouped into two groups; investment grade and non-investment grade. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into investment grade or non-investment grade ratings. The table below describes the Granger causality results for each group for the pre-crisis period (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Investment Grade and Non-Investment Grade 2004-2006

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Investment Grade	2	0.8279	<.0001***
Investment Grade	5	0.6693	<.0001***
Investment Grade	10	0.9076	<.0001***
Investment Grade	22	0.5803	0.0005***
Non-Investment Grade	2	0.0149**	<.0001***
Non-Investment Grade	5	0.0893*	<.0001***
Non-Investment Grade	10	0.0210**	<.0001***
Non-Investment Grade	22	0.0256**	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A18
Crisis-Period Sample Granger Causality Results Grouped by Credit Rating

The data used in this table is grouped into two groups; investment grade and non-investment grade. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into investment grade or non-investment grade ratings. The table below describes the Granger causality results for each group for the post-crisis period (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Investment Grade and Non-Investment Grade 2007-2008

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Investment Grade	2	0.0688*	<.0001***
Investment Grade	5	0.2414	<.0001***
Investment Grade	10	<.0001***	<.0001***
Investment Grade	22	<.0001***	<.0001***
Non-Investment Grade	2	0.0562*	<.0001***
Non-Investment Grade	5	0.4899	<.0001***
Non-Investment Grade	10	<.0001***	<.0001***
Non-Investment Grade	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A19
Full Sample Granger Causality Results Grouped by Industry

The data used in this table is grouped into two industry groups; financial and non-financial. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into financial or non-industries industry SIC codes. The table below describes the Granger causality results for each group for the full-period (2004-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Financial and Non-Financial

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Financial	2	<.0001***	0.0009***
Financial	5	<.0001***	<.0001***
Financial	10	<.0001***	<.0001***
Financial	22	<.0001***	<.0001***
Non-Financial	2	<.0001***	0.0601*
Non-Financial	5	<.0001***	<.0001***
Non-Financial	10	<.0001***	<.0001***
Non-Financial	22	<.0001***	<.0001***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A20
Pre-Crisis Granger Causality Results Grouped by Industry

The data used in this table is grouped into two industry groups; financial and non-financial. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into financial or non-industries industry SIC codes. The table below describes the Granger causality results for each group for the pre-crisis period (2004-2006) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Financial and Non-Financial 2004-2006

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Financial	2	<.0001***	0.6984
Financial	5	0.0002***	0.2586
Financial	10	0.0019***	0.0747*
Financial	22	0.0006***	0.0889
Non-Financial	2	<.0001***	0.5687
Non-Financial	5	<.0001***	0.5070
Non-Financial	10	<.0001***	0.6229
Non-Financial	22	<.0001***	0.6329

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A21
Crisis-Period Granger Causality Results Grouped by Industry

The data used in this table is grouped into two industry groups; financial and non-financial. The indices used for the groups were created from stock returns and CDS credit spreads of firms that fell into financial or non-industries industry SIC codes. The table below describes the Granger causality results for each group for the post-crisis period (2007-2008) sample at the 1 percent, 5 percent, and 10 percent levels. Each test is run for 2, 5, 10, and 22 lags corresponding to 2 days, 1 week, 2 weeks, and one month. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Industry Grouped into Financial and Non-Financial 2007-2008

Group	Lags	GC1: Chi Sq Prob	GC2: Chi Sq Prob
Financial	2	<.0001***	0.0433**
Financial	5	<.0001***	0.0475**
Financial	10	<.0001***	0.0014***
Financial	22	<.0001***	<.0001***
Non-Financial	2	<.0001***	0.3089
Non-Financial	5	<.0001***	0.0021***
Non-Financial	10	<.0001***	0.0027***
Non-Financial	22	<.0001***	0.0002***

Note: Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A22
Windowed Cross-Sectional Results of Univariate Logistic Regressions

The table below provides the coefficients for the univariate logistic regressions. Each regression includes a constant, the time-period dummy and the listed variable. Their Z-statistics are listed in parenthesis below the coefficients. The dependent variable in each case is the Granger causality probability calculated for each firm but with probabilities greater than five percent and less than 10 percent removed. Remaining probabilities are then transformed into binary values: 1 if the null hypothesis is rejected at the 5% level or 0 if it is not rejected. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

	GC1: Stock does not cause CDS				GC2: CDS does not cause Stock			
	Dummy		Coefficient		Dummy		Coefficient	
Log(Asset Size)	1.26	***	0.33	***	2.12	***	0.26	***
	(8.36)		(5.34)		(11.13)		(4.19)	
Asset Size Dummy	1.31	***	0.39	***	2.32	***	0.36	***
	(8.73)		(4.32)		(11.61)		(3.53)	
M/B Ratio	1.29	***	-0.04	**	2.11	***	-0.12	***
	(8.47)		(-1.90)		(11.04)		(-2.95)	
CA_Ratio	1.47	***	0.06		2.11	***	-1.00	
	(9.37)		(0.07)		(10.89)		(-1.02)	
Volume	1.25	***	0.00	*	2.18	***	0.00	*
	(8.31)		(1.80)		(11.62)		(1.66)	
Industry Dummy	1.29	***	0.22		2.26	***	0.92	***
	(8.68)		(1.17)		(11.29)		(4.42)	
Rating Dummy	1.28	***	0.11		2.24	***	-0.38	**
	(8.56)		(0.67)		(11.67)		(-2.02)	

Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level

A23
Windowed Cross-Sectional Results of Multivariate Logistic Regressions

The table below provides the coefficients for the multivariate logistic regressions where the dependent variable has been adjusted to include a five percent break in the probabilities. Z-statistics are listed in parenthesis below the coefficients. The dependent variable is the Granger causality probability calculated for each firm but with probabilities greater than five percent and less than 10 percent removed. Remaining probabilities are then transformed into binary values: 1 if the null hypothesis is rejected at the 5% level or 0 if it is not rejected. Hypothesis GC1: stock returns do not Granger cause CDS credit spreads and Hypothesis GC2: CDS credit spreads do not Granger cause stock returns.

Coefficient	GC1: Stock does not cause CDS		GC2: CDS does not cause Stock	
Intercept	-0.66	***	-2.39	***
	(-3.28)		(-8.48)	
Dummy	1.54	***	2.30	***
	(8.95)		(10.72)	
Asset Size Dummy	0.53	***	0.25	**
	(4.79)		(2.05)	
M/B Ratio	-0.04	**	-0.09	**
	(-2.09)		(-1.99)	
CA_Ratio	0.29		-1.44	
	(0.31)		(-1.31)	
Volume	-0.00		0.00	
	(-0.79)		(0.69)	
Industry Dummy	0.07		0.79	***
	(0.32)		(3.48)	
Rating Dummy	0.70	***	-0.00	
	(3.44)		(-0.00)	
McFadden R^2	0.12		0.20	
Probability(LR stat)	0.00	***	0.00	***
Obs Dep=0	281		558	
Obs Dep=1	511		232	
Total Obs	792		790	

Level of significance: *** denotes 0.01 level, **denotes 0.05 level, and *denotes 0.10 level