Are the U.S. Stock Market and Credit Default Swap Market Related? Evidence from the CDX Indices

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Abstract

This study examines the market-wide relations between the U.S. stock market and the credit default swap (CDS) market for the period of 2001-2007. Results indicate that the lead-lag relationship between the U.S. stock market and the CDS market depends on the credit quality of the underlying reference entity. Specifically, this study finds significant mutual feedback of information between the stock market and the high-yield CDS market in terms of pricing and volatility, while the stock market leads the investment-grade CDS index in the pricing process. The CDS market seems to play a more significant role in volatility spillover than the stock market. That is, volatilities of both the investment-grade and high-yield CDS indices seem to lead the stock market volatility, while the latter has a feedback effect to that of the high-yield CDS market only. Overall, the implication is that market participants should seek information in both markets when they are about to engage in trading and/or hedging.

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1. Introduction

The credit default swap (CDS) market has grown substantially from $180 billion in notional amount in 1997 to $34.5 trillion in 2006 and $62.2 trillion in 2007 (Figure 1). The phenomenal growth of the CDS market underscores the efficacy of the CDS as a tool for both hedging and speculating on credit risk. In response to the tremendous growth in demand for trading and hedging broad-based credit risk, the Dow Jones CDX indices were launched in 2004, enabling market participants to trade a diversified credit portfolio at low transaction costs in a liquid market. Unlike a credit default swap, a credit default swap index (hereafter, CDS index or CDX) is a highly liquid, standardized credit security that trades at a very small bid-ask spread. It is thus cheaper to hedge a portfolio of bonds or credit default swaps with a CDS index than with several CDS for a similar effect. In addition, the CDS index provides a standard benchmark for evaluating customized pools of exposures. It can also be used as the building blocks for other products.[1] According to a recent Bank for International Settlements report, market participants have attributed the CDS indices and index-related products as one of the two significant innovations in the market since 2004. Market participants believe that the development of broad-based indices was extremely helpful to the growth and liquidity of credit derivatives markets [Bank for International Settlements (2005)]. Likewise, Fitch's *2006 Global Credit Derivatives Survey* also attributes the significant growth of the CDS market to CDS indices and index-related products [Fitch (2006)].

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[1] For example, standardized tranches of the North American investment grade CDS indices are traded in the market.

[Insert Figure 1]

Since the price of a CDS is solely determined by credit/default risk, and given that this market is comprised of a large number of sophisticated participants, information about the CDS should play a leading role in detecting default risk or changes in credit risk.[2] In other words, spreads on the CDS widen when deterioration in credit risk is detected or perceived by the market, and tighten when there is less credit risk perceived. Moreover, changes in CDS spreads are expected to occur before the stock market reacts. A random sampling of recent default events is consistent with the notion that the CDS market anticipates corporate credit deterioration well before other capital markets do.[3]

The financial services industry has already started to take advantage of the possible link between the CDS and stock markets by offering new products that help investors make better investment decisions. For example, the GFI group, an inter-dealer brokerage, designed the MarketHub for cross-asset analytics between the credit and equity markets. The GFI group believes that equity-holders should pay attention to the activities in the CDS market because the CDS market provides the real time assessment of credit risk, acts as an occasional leading indicator, and delivers greater efficiency than the equity market.[4]

Finance theories - the Merton-type structural model and Efficient Market Hypothesis - suggest that the stock market, being efficient, should have already

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[2] This market is essentially dominated by banks, brokerages, investment banks, hedge funds, and insurance companies [Spentzos (2006)].

[3] For example, the CDS market seemingly anticipated the deterioration in the credit condition of GM weeks before the GM's debt was downgraded to a junk bond status on May 5, 2005. More recently, trading in Harrah's CDS contracts surged dramatically before the news of leveraged-buyout was disclosed, while the stock market lagged behind the derivatives markets (*The Wall Street Journal*, "Trading in Harrah's Contracts Surges Before LBO Disclosure," October 4, 2006.)

[4] Source: http://www.gfigroup.com/portal/index.jsp?pageID=def_mdata_markethub

incorporated information pertaining to the default probability of firms.[5] Put it differently, when the financial conditions of a firm deteriorate, the probability of default on the firm's bonds and other obligations increases. Hence, stock prices go down and so will bond prices in efficient markets, while the spreads of the CDS on corporate bonds will go up. But, empirically, does the CDS market provide credit risk information beyond what is available in the stock market? If it does, how does it relate that to the stock market as both the stock and CDS markets try to price the credit risk of firms? Moreover, which market leads and which lags in terms of pricing new information?

To date, evidence on the ability of the CDS market to capture the default information relative to that of the stock market is mixed. Longstaff et al. (2003) are among the first to examine the lead-lag relationship between the stock, bond, and CDS markets based on a sample of 67 single-name CDS for March 2001-October 2002. Their results suggest no definitive relationship between the stock and CDS markets. While the CDS spread was able to forecast the individual stock return with a lag of two for 10 of the firms, the individual stock return was able to forecast its CDS spread for 12 of the 67 firms. Norden and Weber (2004b) investigate the relationship among individual stock returns, bond spreads, and CDS spreads of 58 international firms over a three-year period. Using daily data, they find individual stock returns significantly lead CDS spread changes for 39 firms, while CDS spread changes lead stock returns for five firms. Pena and Forte (2006) find that stock returns lead CDS spread changes in 24 of the 65 cases, while CDS spread changes lead stock returns in five of the 65 cases. As their results are

[5] Since the equity holders are the residual owners of a firm, they are more concerned about the financial conditions of the firm, especially the probability of default or bankruptcy. Thus, they are more likely to monitor the performance of the company more closely than creditors who hold collateral or senior claims on the assets of the firm.

related to international markets, it is not clear if their findings are applicable to the U.S. market.[6] In sum, the firm level evidence in the extant literature shows that CDS spread changes occasionally lead stock returns, but more often, stock returns lead CDS spread changes.[7] It is not clear, however, which segment of the CDS market leads the equity market and when.

This study contributes to the existing literature in three ways. First, in investigating the relationship between the U.S. stock index (S&P 500) and CDS indices, we concentrated on the information flow between the two markets driven by the market-wide, systematic risks.[8] Since movements in the CDS and stock prices can be attributed to changes in the systematic and/or idiosyncratic risk, any lead-lag relationship observed between the stock returns and CDS spread changes based on the firm level data may have been resulted from individual securities' response to changes in the market-wide systematic risks (e.g., wars and economic recessions) and/or the nonsystematic shocks (e.g., corporate events such as corporate restructuring or insider trading).[9] To smooth the disturbances in information flow attributable to firm-specific risks, we used market indices instead of individual stocks and credit default swaps. By using market indices, which have not been used in previous studies, we diversified away the idiosyncrasies of

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[6] Of the 21 companies in their sample, only two are U.S. companies.

[7] Previous empirical work on CDS includes Acharya and Johnson (2007), Benkert (2004), Berndt et al. (2005), Blanco et al. (2005), Cao, Yu, and Zhong (2006), Houweling and Vorst (2005), Hull et al. (2004), Jorion and Zhang (2007), Longstaff et al. (2005), Norden and Weber (2004a), Zhang et al. (2005), and Zhu (2006).

[8] There are two main families of CDS indices: CDX and iTraxx. The CDX indices, marketed by Markit Group Limited, contain North American and Emerging Market companies, whereas the iTraxx index contains companies from the rest of the world. Using the iTraxx index between June 2004 and April 2005, Bystrom (2005) provides evidence that firm-specific information is being embedded into stock prices before into CDS spreads.

[9] The Wall Street Journal has reported suspicious insider trading patterns in several corporate takeovers (Ng, S. and D.K. Berman. "Are deal makers on Wall Street leaking secrets?" *The Wall Street Journal,* July 28, 2006).

individual securities. This is particularly important in light of the evidence of the presence of insider trading in the CDS market documented by Acharya and Johnson (2007). According to Acharya and Johnson, the significant incremental information revealed in the CDS market is conditional on the negative credit news and for entities that have subsequently experienced adverse shocks. Thus, without removing the idiosyncrasies arising from insider trading may bias the overall directional relationship of the information flow between the stock and CDS markets. This is of particular relevance to investors of CDS indices and equity indices as well as investors in general since indices serve as benchmarks for the evaluation of single-name investments.

Second, we studied the information content differential between the investment-grade and high-yield CDS in their relations with the stock market.[10] Since a CDS is essentially an option on corporate default, informed traders who would like to bet on the likelihood of default on a company's bonds or to insure against such default, may prefer to trade CDS in lieu of equity shares for their market opacity and embedded leverage. Moreover, trading in CDS is not limited by the physical size of the market since CDS contracts are based on notional amount and can be created as long as there is a market maker. If informed traders in aggregate have a greater propensity to trade in the CDS market than in the stock market, the CDS spread changes should lead the stock prices. This tends to be the case for the high yield CDS because low credit quality companies tend to be most vulnerable to credit events and rumors. For high credit quality companies, buying insurance against default via CDS is not as widespread as for the low credit

[10] To avoid confusion, we use the term "high-yield" to refer to the speculative-grade or non-investment-grade issues throughout this paper.

quality companies. Hence, the investment-grade CDS spread changes will be less likely to lead the stock prices.

We find that the lead-lag relationship between the stock and CDS markets is indeed contingent upon the credit quality of the underlying reference entity. In particular, the stock market proxied by the S&P 500 appears to embed pricing information before the investment-grade CDS market does, suggesting that the stock market is indeed efficient in reflecting the default risk, whereas the investment-grade CDS market does not predict the price movement of the stock market. In contrast, the high-yield CDS market appears to have the ability to lead the stock market in pricing, a result consistent with the notion that the stock and high-yield CDS markets provide complementary information, which is subsequently incorporated in the other market.

We also examined the volatility of both the stock and CDS markets and find that the CDS market plays a leading role in volatility spillover across markets. Ross (1989) indicates that the rate of transmission of information to a market is related primarily to the volatility of an asset's price changes in a no-arbitrage economy, implying that volatility is more important than mean price changes in the transmission of information. Our results indicate specifically that the volatility of both the investment-grade and high-yield CDS indices leads the stock market volatility, while the latter has a feedback effect to that of the high-yield CDS index only. This finding suggests that the CDS market contains additional information in detecting the default probability beyond what is provided by the stock market. As a result, equity investors may benefit by tracking the volatility of CDS indices. Overall, the implication is that participants of the stock and

CDS markets should seek information in both markets when they are about to engage in trading and/or hedging.

Third, we contribute to the extant literature by ascertaining the general market conditions underlying the credit information flow between the stock and CDS markets. We find that the two-way interaction between the stock and CDS markets is present only when the stock market is on a downturn. Theoretically, a rising stock market infers a lower probability of default of the high-yield firms, resulting in a weaker feedback between the stock and CDS markets.

The rest of the paper is organized as follows. First, we present the data and methodology. Second, we present the empirical results and discuss their implications. We conclude the paper in the final section.

2. Data and Methodology

2.1 The CDS Indices

A credit default swap is a credit derivative that provides protection against losses arising from a credit event. The buyer of a CDS makes periodic payments over the life of the contract in exchange for protection against default or other specified credit events, such as bankruptcy, cross default/cross acceleration, repudiation, and debt restructuring for a specified reference asset. The seller of a CDS agrees to compensate the difference between the par and market value of the reference asset if the underlying reference entity (i.e., the issuer of the reference asset) experiences a particular credit event. Credit default swaps are most often quoted in terms of basis point spread per year. For example, a CDS at 50 basis points (bp) would mean a payment of $50,000 per year to protect $10m notional debt. Essentially, the CDS market facilitates the transfer of credit risk from lenders, banks, and bondholders to those investors, like insurance companies, re-insurers, and hedge funds who are willing to bear the credit risk.

As the importance of the CDS market grows, tradable CDS indices, such as the Dow Jones CDX and iTraxx indices, have been created to allow players to trade a broad spectrum of credit risk in a liquid market at low costs. The CDS index is freely tradable with a low bid-ask spread of ½ to ¼ of a basis point. A consortium of 16 investment banks helps compose and price the indices. Each member bank of the consortium makes a market in the CDS indices. The Investment Grade CDX index (CDX.NA.IG), an equal-weighted index comprised of 125 firms with the most liquid investment-grade credit, is designed for mitigating the trading exposure in the credit risk of North American investment-grade firms. The High Yield CDX index (CDX.NA.HY) an equal-weighted index daily index composed of 100 high-yield entities, is intended to reflect multiple industry sectors and provide a broad exposure to the North American high-yield credits.[11] The benchmark maturity of CDX tends to be five years, though contracts of longer maturity, such as seven and ten years are also traded. [12] We used the 5-year CDX indices in this study.

Because the Dow Jones CDX indices were launched in April 2004, CDX data are not available prior to that date. In order to study the relations between the stock and CDS markets, a longer period is desirable. Therefore, we constructed our own CDS indices with individual CDS names for the period January 2001- April 2004 based on the

[11] These indices were formerly known as the Dow Jones North America Investment Grade and High Yield CDX indices and have been renamed the CDX indices in March 2007. For the rest of the paper, we adopt the new names.
[12] The indices are rolled every six months (March and September) to keep the maturity close to five (seven or ten) years and to maintain liquidity as the index membership changes.

construction methodology of the CDX indices.[13] Mimicking the CDX.NA.IG index, our "IG index" is a daily equal-weighted CDS spread index composed of 125 investment-grade entities domiciled in North America. We constructed the "HY index", which is a daily equal-weighted CDS spread index composed of 100 high-yield entities domiciled in North America, in the same way as the CDX.NA.HY index. The single-name CDS price data used to reconstruct the index level backward were taken from a comprehensive database from Markit, which provides daily quotes on CDS spreads for over 1,000 North American obligors.[14] In this study, we used the spreads based on the constructed indices from January 2001 to March 2004 and the actual spreads on the CDX.NA.IG and CDX.NA.HY indices from April 2004 to December 2007.[15]

[Insert Figure 2]

Figure 2 depicts the price trend of the CDX indices and the S&P 500 index. Both CDX indices appear to be negatively related to the S&P 500 index, and the high-yield CDX index has a much wider spread than the investment-grade CDX index.

We computed the correlation between the CDS indices and the S&P 500 stock index for the entire period between January 2001 and December 2007 (Table 1). We find that the correlation between the IG index and the S&P 500 index as well as between the HY index and the S&P 500 index is about -34%. In contrast, correlations for the period

[13] The CDS spreads for individual firms contained in the indices are obtained from Markit, which provides a large sample of liquid firms with daily continuous trading prices. The CDX index construction methodology can be found at the website: http://www.markit.com/information/affiliations/cdx.html

[14] Markit collects more than a million CDS quotes contributed by more than 30 banks on a daily basis. The quotes are subject to filtering which removes outliers and stale observations. Markit then computes a daily composite spread only if it has more than three contributors. Once the pricing on a credit has started, it will generally have pricing data on a continuous basis. This database has also been used by Cao et al. (2006), Zhang et al. (2005), Zhu (2006), and Jorion and Zhang (2007).

[15] The results are qualitatively the same if we used our estimated index spreads base on the constructed CDX indices for the whole period. We compared the constructed CDX indices with actual index levels for the period from April 2004 to December 2007, and found that daily pricing errors were within 1% of the actual levels. Data were obtained from Markit and JP Morgan.

that ends six month earlier (i.e., January 2001-June 2007) are -28% and -30% for IG and HY, respectively. For July-December 2007, the magnitude of the correlation between IG and the S&P 500 index has strengthened to -69.9%, and to -61.7% between HY and the S&P 500 index. All correlations are statistically significant at the 1% level. The increasing magnitude of the correlation may indicate a tendency for the stock and CDS markets to move together, which appears to have taken place since July 2007 when the subprime loan crisis spread to the CDS market. The spreads of CDS indices widened dramatically with unprecedented volumes of trading in the CDS market, driven by the fear of credit contagion from the subprime market.[16]

[Insert Table 1 here]

Before we examine the lead-lag relationship between the stock and CDS markets, we would ensure that the credit quality of the CDX index and the stock market index is comparable. Given the S&P 500 index is comprised of companies that are generally of high-quality credit, there could easily be a mismatch of credit quality of the index components between the S&P 500 and CDX indices, especially the high-yield CDX index. Hence, we constructed two sets of comparable stock index returns, SIG and SHY, based on the returns of the matching firms of the IG and HY index components, respectively. Since the CDX indices are equally weighted by their underlying single-name CDS contracts, SIG and SHY are also constructed equally weighted. In our investigation of the lead-lag relationship between the stock and CDX indices, we relate the S&P 500 index returns (SPR) and the matching-firm index returns, SIG and SHY, to

[16] S. Boughey, "Subprime storm whips CDS trading to record velocity," Euroweek. London: July 13, 2007, p.1.

the percentage changes of the IG and HY indices in four groups of analysis.[17] Group 1 refers to the analysis between S&P 500 index returns (SPR) and percentage changes of the equal-weighted investment-grade CDX index (IG). Group 2 refers to the analysis between IG and SIG, where SIG represents the matching-firm index returns based on the stock returns of the same investment-grade firms as in the IG index. Group 3 refers to the analysis between SPR and percentage changes of the equal-weighted high-yield CDS index (HY). Group 4, the last group, refers to the analysis between HY and SHY, where SHY represents the returns of the matching-firm index based on the stock returns of the same high-yield firms as in the HY index.

2.2 Methodology

In this study, we use the Vector Autoregression (VAR) model to analyze the lead-lag relationship between the stock and CDS markets.[18] Specifically, we let Y_t denote a ($m \times 1$) vector of stationary processes under investigation, where m is two (stock index returns and CDX index changes) in our case. The dynamic relationship among these processes can be modeled as a VAR of order k,

$$Y_t = \mu + \sum_{i=1}^{k} \Phi_i Y_{t-i} + \varepsilon_t \qquad (t = 1, \ldots, T), \qquad (1)$$

where $Y_t = (Y_{1t}, Y_{2t})'$, μ is a (2×1) vector of intercept terms, Φ_i is a (2×2) coefficient matrix, ε_t is a (2×1) vector of innovations following a multivariate normal distribution

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[17] To test for the stationarity of the first difference of the CDS indices (IG and HY) and the stock indices (SPR, SIG, and SHY), we used the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The lag length was set equal to seven for PP test in order to ensure white noise residuals. Eight lags of ADF test as the maximal value were tested. The non-stationarity can be rejected for all variables at the 1% level.

[18] We did not find the stock and CDS markets to be cointegrated for the entire period 2001-2007, and thus, we used the VAR in our analysis. Cointegration tests are discussed in Appendix A and results are presented in Table A1.

with variance, Σ. Furthermore, ε_t can only be correlated contemporaneously. Equation (1) has an infinite moving average representation:[19]

$$Y_t = \sum_{s=0}^{\infty} \Psi_s \varepsilon_{t-s} \qquad (t = 1, \dots, T). \tag{2}$$

Specifically, a complete set of artificial observations of Y_t based on equation (1) can be obtained by re-sampling the estimated residuals. We then calculate the generalized impulse responses based on the estimated parameters from the simulated data.[20]

The following is the empirical form of the VAR model we used in this study:

$$\begin{aligned} CDS_t &= a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + \varepsilon_1 \\ Stock_t &= a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + \varepsilon_2 \end{aligned} \tag{3}$$

CDS refers to the spread changes of IG in Groups 1 and 2, and HY in Groups 3 and 4. *Stock* refers to the stock market returns for SPR in Groups 1 and 3, SIG in Group 2, and SHY in Group 4. To test for the Granger-causality in Group 1 (SPR~IG), the null hypothesis of the Wald test is that the coefficients on the lagged SPR (IG) are all equal to zero, i.e., $b_{11} = b_{12} = b_{13} = 0$ ($c_{21} = c_{22} = c_{23} = 0$), when the dependent variable is IG (SPR) [Granger (1969)]. It is similarly defined for other groups. To maximize the forecast precision, i.e., to optimize the overall model's ability to fit the observed time series as accurately as possible, and to ensure that there is no serial correlation present in the residuals, we need to choose the optimal number of lagged variables that minimizes the value of the information criteria. We used the Schwarz Bayesian (SBC) and Hannan-

[19] We omit the part corresponding to the intercept term in equation (1), since it is irrelevant in subsequent calculations.

[20] Both bootstrap and normal approximation are asymptotically valid methods to construct confidence intervals. However, in finite samples, they tend to produce wider confidence intervals than those of underlying true distributions, which should be kept in mind in interpreting the results presented later.

Quinn (HQC) information criteria to select the appropriate lag length, which varies according to the stiffness of the penalty term. SBC embodies a stiffer penalty term than HQC. The appropriate lag length for Groups 1, 2 and 3 is two and that for Group 4 is one according to both the SBC and HQC. [21]

3. Empirical Results

Table 2 reports the VAR analysis results for the four groups with the corresponding optimal lag length. For Group 1 (SPR~IG), the F-statistic of the Wald test indicates that the null hypothesis cannot be rejected for the model with SPR as the dependent variable, but it can be rejected for the model with IG as the dependent variable. These results indicate that the lagged S&P 500 index strongly influences IG, but not the other way around. Put in another way, the S&P 500 index leads the IG index in regard to the daily pricing (return) information.

[Insert Table 2 here]

For Group 2 (IG~SIG), test results are similar to those for Group 1. We find a similar pattern of the "Granger-causality" with SIG. That is, the matching-firm index (SIG) strongly influences the IG index spread changes, but there is no significant effect emanating from IG to SIG. Results from Group 1 and Group 2 suggest that market participants reveal their pricing in the stock market before they do the same in the CDS

[21] To conserve space, test results on the selection of the optimal lag length are not reported here but available upon request.

market. This result is consistent with previous results that the stock market leads the CDS market.[22]

More importantly, we find interesting results upon examining the Granger-causality between the high-yield CDS index changes (HY) and S&P 500 index returns, i.e., Group 3 (HY~SPR). First, the lagged S&P 500 returns appear to have affected the high-yield CDX spreads strongly, a result similar to the analysis on the IG index. However, there is a feedback effect emanating from HY to SPR, indicating a potential interaction between the high-yield CDS and stock markets. This stronger link between the stock and CDS markets is in line with the findings of Norden and Weber (2004b) that the CDS market tends to be more responsive to changes in the stock market when there is a flight to quality credit. However, Norden and Weber (2004b) do not find a feedback effect from the high-yield CDS market to the stock market.

For Group 4 (HY~SHY), results are similar to those for Group 3, lending support to the notion that there is indeed interaction between the stock and CDS markets. Moreover, as we expected, the two-way interaction is stronger than that between SPR and HY because SHY is the matching set of the HY index.

One of the shortcomings of the Granger-causality test is that it does not really infer causality. It simply indicates the current value of HY and the past values of SHY are correlated. The correlation may be caused by some intervening factors that influence both the stock and CDS markets. To test the robustness of our results, we included exogenous variables in the VAR analysis to control for possible influences. Following Collin-Dufresne et al. (2001), we included the following exogenous variables in our VAR

[22] Norden and Weber (2004b), using the CDS data from 2000 to 2002, document that individual stock returns lead the CDS and bond spread to change. Bystrom (2005) finds firm specific information has embedded in the stock prices before it is embedded in the CDS spreads in the European markets.

model: changes in the T-bill rate (DTRATE), the slope of the term structure (SLOPE), and the contemporaneous and lagged changes of the implied volatility for the CBOE index (DVIX).[23] The VAR model with exogenous variables (EXO) becomes:

$$CDS_t = a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + X_{1t} EXO_t + \varepsilon_1$$
$$Stock_t = a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + X_{2t} EXO_t + \varepsilon_2 \qquad (4)$$

Table 3 presents the results of the VAR analysis with exogenous variables. Results indicate that the earlier inferences from the observed Granger-causality relationship still hold for the VAR model with exogenous variables. That is, the stock market leads the CDS market and there is interaction between the stock and high-yield CDS markets.

[Insert Table 3 here]

In order to provide further insight into the relationship of the high-yield CDS and stock markets, we computed the impulse response function, which traces out the responsiveness of the dependent variables to shocks to each of the variables in the VAR system. The impulse response function thus gives an indication of the dynamic properties of the system.

[Insert Figure 3-1 here]

Figure 3-1 shows the impulse response function between stock market returns (SPR) and percentage changes in spread of the investment-grade CDX index (IG). The response of

[23] The CBOE Volatility Index (VIX) is a key measure of market expectations of near-term volatility conveyed by the S&P 500 stock index option prices. Since its introduction in 1993, VIX has been considered by many to be a premier barometer of investor sentiment and market volatility. The data was obtained from http://www.cboe.com/micro/vix/historical.aspx. DVIX denotes the changes of the VIX.

SPR to its own shock is found to be significant at the 1% level at lag one, while IG does not appear to affect SPR. In addition, we find that responses of IG to the stock market shock are negative and significant for the first there lags at the 1% level, and responses of IG to its own shock are significant at the 1% level at lag 1 and 3.

[Insert Figure 3-2 here]

The impulse response function between stock index returns (SPR) and percentage changes in spread of the high-yield CDX index (HY) is shown in Figure 3-2. We find that SPR strongly affect HY at lags one to two, while HY affects the stock market returns at lag two. These results further confirm the inferences obtained from the Granger-causality test.

This is, in fact, consistent with the predictions of Merton's structural model that falling stock prices lead to increased leverage, to which the high-yield firms are more sensitive, hence causing an escalation in credit risk, possible downgrades, and substantial widening spreads in the high-yield credit derivatives. Meanwhile, as shown by Avramov et al. (2007), credit rating downgrades and/or deteriorating credit conditions have a strong negative impact on the stock prices of the high-yield companies but almost no impact on those of the investment-grade firms. Our results imply that the reference entities (i.e. constituent firms) of the high-yield CDS index and their securities are subject to greater scrutiny by stock market participants because stockholders, who have the residual claims in the event of default and bankruptcy, and hence the ultimate bearers of the credit risk, would pay more attention to the securities of high-yield firms which are at the verge of default. Likewise, CDS market participants would become more concerned about the increasing risk of default, and would look to the stock market for clues of default. Thus, the information flow between the CDS and stock markets should tend to be stronger for the high-risk groups.

Since the relationship between the stock returns and CDS index changes may not be linear, we investigated further to ascertain whether the second moment of these time series contain additional information. Specifically, we used stock returns squared and absolute values of stock returns to proxy for the stock return volatility. Similarly, percentage changes of the CDS index squared and absolute values of CDS index changes were used to proxy for the volatility of the CDS indices. Table 4 presents the results of the Granger-causality test between the volatility of the CDS market and that of the stock market. Results indicate that, in terms of volatility, the CDS markets lead the stock market strongly for Group 2, 3, and 4. This is probably because the high volatility of the CDS indices had served as a signal of a looming credit event that got fed into the stock return volatility. This is consistent with the findings of Jorion and Zhang (2007) that CDS prices experience dramatic jumps in anticipation of credit deterioration but stay flat during 'calm' (i.e., no news) periods, and that large CDS spread changes are usually followed by large movements in the stock market.

[Insert Table 4 here]

Finally, we examined whether the lead-lag relationship of the stock market with the CDS market depends on the general conditions in the stock market. We hypothesize that there will be minimum feedback to the CDS market when the stock market is doing well. The theory behind this hypothesis is that (1) declining stock prices may push up a firm's leverage to an alarming level [Merton (1974)], and (2) business and financial conditions may be deteriorating as reflected in the declining stock prices. Thus equity investors will typically pay more attention to declining stock prices. Moreover, a high-yield firm at the verge of default is expected to be more sensitive to such a declining stock market condition than an investment-grade firm because any deterioration in the credit condition of the firm may push it over. Since investors in the stock and CDS markets are more readily to take action under deteriorating market conditions than under normal market conditions, we expect the presence (absence) of a two-way feedback between the stock market and the high-yield CDS market under bad (good) stock market conditions. We tested this hypothesis by adding an interaction term conditioned on the stock market performance which is proxied by the S&P 500 stock returns, in the VAR model listed below.

$$
\begin{aligned}
CDS_t &= a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + \sum_{j=1}^{k} d_{1j} Stock_{t-j} \times Sign_t + \varepsilon_1 \\
Stock_t &= a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + \sum_{j=1}^{k} d_{2j} CDS_{t-j} \times Sign_t + \varepsilon_2
\end{aligned}
\qquad (5)
$$

The interaction terms were created by multiplying the variable, *Stock* or *CDS*, with the variable, *Sign,* which was constructed in two steps. First, we sorted the SPR returns into three cohorts: "up market" (positive returns), "flat market", and "down market" (negative returns). Second, we assigned one to *Sign* and zero otherwise, if the SPR of day *t* is in the "down market" cohort. Likewise, we assigned one to *Sign* or zero otherwise, if the SPR of day t is in the "up market" cohort. We then ran separate tests for the "down" and "up" markets.

Results are presented in Table 5, where Panel A reports the results for the "down" stock market and Panel B for the "up" stock market.[24] The null hypothesis of the F-test is

[24] To conserve space, only F-test statistics and p-value are reported in Table 5. Full sets of test results are available upon request.

that the joint coefficients of the interaction term, *d*, are equal to zero. Empirical results generally support our expectations. First, we reject the null hypothesis that the coefficients of the interaction term in Group 3 (HY~SPR) and 4 (HY~SHY) are jointly zero in a "down" stock market (i.e., deteriorating market conditions) (Table 5, Panel A), but generally not in an "up" stock market (or improving market conditions) (Table 5, Panel B).[25] These results imply that the two-way lead-lag relationship between the stock and high-yield CDS markets is more likely to be associated with deteriorating stock market conditions but not with improving stock market conditions.

Second, we cannot reject that the coefficients of the interaction term in Group 1 (IG~SPR) and 2 (IG~SIG) are jointly zero in either type of the stock market conditions, suggesting stock market conditions, deteriorating or improving, have no impact on the lead-lag relationship for the investment-grade firms.

[Insert Table 5 here]

4. Further Analysis of the CDS Behavior during the Credit Crunch of 2007

The above analysis covers a period in which a nascent CDS market has gradually developed into a vibrant market whose recent growth has been stalled by the subprime mortgages implosion and the resulting credit crunch in 2007. As shown in Figure 2, the actual spreads in the CDS index markets since their inception in 2004 had been trending downward, displaying a characteristic of a maturing market. Unfortunately, the collapse of subprime mortgages in mid-February 2007 caused a tremor in credit markets. CDS spreads on U.S. corporate bonds and loans, which represent the cost of protection against

[25] One exception is Group 3 in Panel B. It implies that, in an "up" market, the interaction between SPR and Sign can "Granger-cause" the high-yield CDX spread changes.

default, started to climb sharply as the perceived risk of owning corporate debts jumped. By mid-June 2007, corporate bond prices had gone down, while CDS prices kept climbing. Rating agencies slashed rating on bonds backed by pools of speculative subprime loans because of unusually high rates of defaults and delinquencies among the underlying mortgages, affecting around $3 billion worth of bonds which were issued recently.[26] While corporate default rates remained close to historic lows according to Moody's, the IG index market began to move sharply, climbing to its record high in the second half of 2007.[27] Since the beginning of the year, the IG index had surged more than 145% in basis point spread, whereas the HY index went up by almost 100% by the end of July 2007.

During the second half of 2007, credit market conditions had continued to deteriorate further, signaling a sudden rise in implied risk and volatility for corporate debts. Spreads started widening and volatility kept increasing in the CDS market. An increase in the CDS spread may indicate a perceived deterioration of a company's creditworthiness, possibly because of speculation that a private equity firm might load up a company with the debt that it used to finance the buyout, or because the company itself may be believed to be planning to take on additional debt to make an acquisition or buy back its own shares.[28]

[26] Moody's slashed rating on 131 bonds backed by pools of speculative subprime loans because of unusually high rates of defaults and delinquencies among the underlying mortgages and was reviewing 247 bonds for downgrades, including 111 whose ratings it had just lowered. This lowering of ratings affected around $3 billion worth of bonds, which represented less than 1% of the $400 billion in subprime mortgage-backed bonds that were issued in 2006 (June 15, 2007, Bloomberg.com).

[27] *Moody's Global Corporate Finance*, February 2008, accessed at www.moodys.com.

[28] For example, the CDS on Target bonds soared because investors speculated that an activist investor will pressure management to borrow money to return cash to shareholders. (S.D. Harrington, "Corporate bond risk rises as subprime index falls to record low," July 16, 2007, Bloomberg.com).

It has also been observed that prices for CDS were soaring in tandem with supposedly secret merger talks.[29] Likewise, CDS prices also respond to merger talks that are already known. For instance, CDS tied to Abitibi-Consolidated Inc. rose after its biggest shareholder, Third Avenue Management LLC, said in a regulatory filing that it opposed Abitibi's proposed merger with rival Bowater Inc.[30]

Despite increasing high-yield bond spreads and record-high CDS spreads, the stock market seemed to have ignored the worsening credit conditions during 2007.[31] Since the CDS, stock and bond markets seem to be affected by each other, although evidence from our analysis and previous studies suggests that the CDS market is leading the other two markets, it appears that credit events that had taken place during 2007 may have significantly changed the dynamics of information flow in these capital markets that we have uncovered in our analysis above. Further analysis is warranted.

Lehman (2002) suggests that when closely related assets trade in different markets, it is important to investigate which of the markets contributes the most to the discovery process. To investigate which market, CDS or stock, contributes the most in terms of efficient and timely incorporation of information in the price discovery process, we applied the Hasbrouck-bound test proposed in Hasbrouck (1995) and the Gonzalo and Granger (1995) test as in Blanco et al. (2005). These tests and their results for the second half of 2007 are presented in Appendix B.[32] Results presented in Table A2 indicate that the investment-grade CDS market was dominant in price discovery and stock prices

[29] R. Drummond, July 10, 2007, Bloomberg.com.
[30] S.D. Harrington, "Corporate bond risk falls as subprime spillovers fears ease," Bloomberg.com, July 16, 2007.
[31] The Dow Jones Industrial Average hit the record high at 14,164.53 on October 9, 2007 and closed at 13,264.82 on December 31, 2007, representing a 801.67 point or 6.43% increase from the end of December 2006.
[32] We were able to run the price discovery tests because CDS and stock markets were cointegrated for the second half of 2007.

adjusted to incorporate information coming from the CDS market, while high-yield CDS spreads and stock prices were almost equally important in the price discovery process in the high-yield CDS market.

Overall, we find a closer relationship between the stock and CDS markets and an important role of the investment-grade CDS in the price discovery process during the recent credit crunch period. While the credit crisis is still unfolding, further analysis in the future is warranted as more data become available.

5. Conclusions

We investigated the market-wide relations between the stock and CDS markets, using daily index data from January 2001 to December 2007. Our study differs from prior studies in several ways. First, we examined the market-wide relations instead of the firm level relations since the latter are primarily driven by firm-specific events. By smoothing the firm-specific disturbances, the index/portfolio approach enables us to reveal a clearer relationship between the stock and CDS markets at the aggregate level.

Second, our analysis focused on the potential differences in information content between the investment-grade and high-yield CDS indices. Since the high-yield firms are closer to the default threshold as compared to the investment-grade companies, we expect information flow between the stock and CDS markets is more prominent in the high-yield credit market. Third, we investigated whether information flow between the stock and CDS markets is stronger when the stock market is not doing well. Additionally, we focused on the U.S. stock and CDS markets instead of the European and Asian markets, which are different in many respects, such as regulation, information disclosure, and firm characteristics.

Results from the VAR model indicate that the stock market appears to lead both the investment-grade and high-yield CDS markets. Unlike the investment-grade CDS, there are strong feedback effects emanating from the high-yield CDS market to the stock market, suggesting that the high-yield CDS market may contain certain default risk component of the firms which may not have been embedded in the stock returns. Furthermore, the volatility of both the investment-grade and high-yield CDS indices seems to lead the stock market volatility, while the latter has a feedback effect only to that of the high-yield CDS market. This implies that the stock market plays a more significant role of information transmission in the pricing process, while the CDS market plays a more significant role in volatility spillover. Overall, the high-yield CDS market is more closely related to the stock market than the investment-grade CDS market.

We also find that the feedback effect between the high-yield CDS market and the stock market is associated with deteriorating stock market conditions and absent when stock market conditions are improving. This is consistent with the notion that negative stock price moves and worsening credit conditions are the causes for the observed feedback effect between the stock and high-yield CDS markets.

Results from our study provide evidence in support of the financial theory that the stock market reflects efficiently the default probability of firms in the stock prices. In contrast, the CDS market is empirically found to be the main venue for the price discovery of credit risk.[33] Possible reasons that make the CDS market a better venue than

[33] Blanco et al. (2005) find that the CDS market leads the bond market in price discovery of the credit risk.

the stock market include: (1) participants in the CDS market are typically large financial institutions and hedge funds with information advantages vis-à-vis retail investors in the stock market who have no information advantages, and (2) the CDS market has become very liquid due to the tremendous growth in demand for trading and hedging credit risk.

The significant interaction between high-yield CDS index changes and stock returns suggests that investors should examine more carefully the dynamic information flow between the stock market and the CDS index market, especially the important role of the investment-grade CDX index in the price discovery process when the credit market is in a credit and liquidity crunch like 2007. The extreme volatility in the CDS market in 2007 has provided a good motivation for market participants to monitor both markets more closely. Market participants are advised to seek information in both markets when they are about to engage in trading and/or hedging.

Appendix A

We tested for the presence of an equilibrium price relationship or cointegrating equations using Johansen's cointegration rank tests [Johansen (1991)].[34] For the whole period (2001-2007), we find no evidence of cointegration between the CDS indices and stock prices (Table A1). We, however, find evidence of statistically significant cointegration between the CDS indices and stock prices during the second half of 2007 (July-December). The presence of an equilibrium price relationship between the CDS index market and the stock market in the second half of 2007 provides support for the hypothesis that the CDS and stock markets have become more closely related as the CDS index markets mature. This seems to suggest that CDS indices might have been used in place of equity during that time for various reasons.[35]

Appendix B

Hasbrouck's model of "information shares" assumes that price volatility reflects new information, and so one market that contributes most to the total variance of the innovations is presumed to contribute the most to price discovery. When price change innovations are correlated, Hasbrouck's approach can only provide the upper and lower bounds on the information shares of each market. Gonzalo and Granger's approach decomposes the common factor itself, and by ignoring the correlation between the markets, it attributes superior price discovery to the market that adjusts the least to price

[34] The null hypothesis is no cointegration between the CDS and stock indices. If the null hypothesis is rejected, then the two price series are cointegrated and there exists an equilibrium price relationship between them.

[35] One possible reason that CDS are used in lieu of equities is that CDS are traded over-the-counter and so trades are not as transparent as stocks. Thus, for trades related to possible corporate restructuring, or refinancing, CDS present themselves advantages in reducing the visibility of trading.

movements in the other market. Both approaches rely on the vector error correction model (VECM) of market prices, which we estimate as follows:

$$\begin{aligned}\Delta p_{CDS,t} &= \lambda_1 (p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{SP,t-1}) + \sum_{j=1}^{p} \beta_{1j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \delta_{1j} \Delta p_{SP,t-j} + \varepsilon_{1t} \\ \Delta p_{SP,t} &= \lambda_2 (p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{SP,t-1}) + \sum_{j=1}^{p} \beta_{2j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \delta_{2j} \Delta p_{SP,t-j} + \varepsilon_{2t}\end{aligned} \qquad (6)$$

where *CDS* and *SP* denote CDS index spreads and stock prices. If the stock market is contributing significantly to the price discovery of the credit risk, then λ_1 will be statistically significant as the CDS market adjusts to incorporate this information. Similarly, if the CDS market is an important venue for price discovery, then λ_2 will be statistically significant.

The contributions of the CDS market (denoted as market 1 in the following formulas) to price discovery are defined by the following expressions:

$$HAS_1 = \frac{\lambda_2^{\,2}\left(\sigma_1^{\,2} - \frac{\sigma_{12}^{\,2}}{\sigma_2^{\,2}}\right)}{\lambda_2^{\,2}\sigma_1^{\,2} - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^{\,2}\sigma_2^{\,2}} \quad HAS_2 = \frac{\left(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\lambda_2^{\,2}\sigma_1^{\,2} - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^{\,2}\sigma_2^{\,2}}$$

$$GG = \frac{\lambda_2}{\lambda_2 - \lambda_1}$$

where HAS_1 and HAS_2 give the two bounds of Hasbrouck's measures and *GG* stands for the Gonzalo and Granger measure. If GG is equal to 1, then the CDS market contributes to the price discovery; if GG is equal to 0, then the stock market contributes to price discovery; if GG is equal to 0.5, then both markets do.

The results are reported in Table A2 for July 2007 to December 2007, where cointegration is found to be present between the CDS spreads and stock prices.[36] For the investment-grade CDX, the error-correction coefficient estimate, λ_2 (, -0.5), in the stock equation is significant at the 5% level, suggesting that the CDS market was dominant in price discovery and stock prices adjusted to incorporate information coming from the CDS market. This is supported by the statistics of the Hasbrouck bound (which shows at least 45.5% and at most 99.9% of the price discovery is in CDS market), and the Gonzalo-Granger measure (which shows about 99.5% of the price discovery occurring in the CDS market).

For the high-yield CDX, both the CDS spreads and stock prices are important in the price discovery process, as indicated by the significant coefficients at the 1% level in both equations. The Hasbrouck's lower bound suggests that the stock market is more important in price discovery while the upper bound confirms the important role of the CDS market (i.e., 65.4% of the price discovery in the CDS market). The Gonzalo-Granger statistic shows that both markets contribute to price discovery almost equally.

Overall, we find a closer relationship between the CDS and stock markets during the recent credit crunch period, and an important role of investment-grade CDS in the price discovery process when the credit market is in a tumultuous period.

[36] The Granger Representation Theorem states that the presence of cointegration suggests at least one market is leading the other [Engle and granger (1987)].

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Table 1. Pearson Correlation Coefficients

This table reports the Pearson correlation coefficients and associated significance levels.

Sample Period	IG CDS Index and S&P 500 Index	HY CDS Index and S&P 500 Index
1/2001 -- 6/2007	-0.280***	-0.302***
1/2001 -- 12/2007	-0.339***	-0.337***
7/2007 -- 12/2007	-0.699***	-0.617***

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 2: Vector Autoregression Results

This table summarizes results from the estimation of the Vector Autoregression Model (VAR) for four groups. The VAR model is presented for each group. *CDS* refers to the IG in Groups 1 and 2, and HY in Group 3 and 4. *Stock* refers to SPR in Groups 1 and 3, SIG in Group 2, and SHY in Group 4. t-statistics are reported in parentheses under the coefficient estimates. The Wald test null hypothesis *is* $b_{11}=b_{12}\ldots=b_{1k}=0$ when *CDS* is the dependent variable, and $c_{11}=c_{12}\ldots=c_{1k}=0$ when *Stock* is the dependent variable. The optimal lag is selected by a minimum information criterion. The F-statistic and p-value of the Wald test are reported in the lower panel of the table. The significance of the overall regression is based on a standard F-test. * denotes significance at 10% and *** denotes significance at 1%.

$$CDS_t = a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + \varepsilon_1$$

$$Stock_t = a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + \varepsilon_2$$

Group 1: IG~SPR

Dep.	IGt	SPRt
IGt-1	0.018	0.014
	(0.71)	(1.30)
SPRt-1	-0.154***	-0.035
	(-2.57)	(-1.36)
IGt-2	0.078***	0.0012
	(3.08)	(1.13)
SPRt-2	-0.129**	-0.015
	(-2.17)	(-0.59)
Const.	0.0004	0.0001
Wald test	10.77***	3.12
p-value	0.0046	0.2099
R-Square (%)	1.72	0.45
Overall F Value	7.66***	2.00*

Group 2: IG~SIG

Dep.	IGt	SIGt
IGt-1	0.004	0.019*
	(0.17)	(1.84)
SIGt-1	-0.215***	0.021
	(-3.38)	(0.78)
IGt-2	0.073***	0.008
	(2.83)	(0.73)
SIGt-2	-0.158**	-0.012
	(-2.48)	(-0.47)
Const.	0.0005	0.0001
Wald test	17.44***	4.03
p-value	0.0002	0.1330
R-Square (%)	2.09	0.29
Overall F Value	9.35***	1.26

Group 3: HY~SPR

Dep.	HYt	SPRt
HYt-1	0.052**	-0.013
	(2.10)	(-1.09)
SPRt-1	-0.10*	-0.045*
	(-1.87)	(-1.82)
HYt-2	0.073***	0.025**
	(2.94)	(2.16)
SPRt-2	-0.071	-0.004
	(-1.34)	(-0.18)
Const.	0.0005	0.0001
Wald test	5.03*	5.62*
p-value	0.0808	0.0601
R-Square (%)	1.47	0.50
Overall F Value	6.44***	2.18*

Group 4: HY~SHY

Dep.	HYt	SHYt
HYt-1	0.054**	-0.026*
	(2.15)	(-1.69)
SHYt-1	-0.094**	0.122***
	(-2.28)	(4.88)
Const.	0.0005	0.0001
Wald test	5.20**	2.87*
p-value	0.0226	0.0902
R-Square (%)	0.82	2.00
Overall F Value	7.16***	17.69***

Variable definitions:

SPR	The S&P 500 index returns
IG	Percentage spread changes of the investment-grade CDS index from day t-1 to day t
HY	Percentage spread changes of the high-yield CDS index from day t-1 to day t
SIG	The matching stock portfolio returns for firms included in the IG index
SHY	The matching stock portfolio returns for firms included in the HY index

Table 3: VAR Results After Controlling for Exogenous Variables

This table summarizes results from the estimation of the Vector Autoregression Model (VAR) with exogenous variables (EXO), which include the changes in the 5-year T-bill rate (DTRATE), slope in the term structure (SLOPE), measured by difference in yield to maturities between 10-year and 2-year Treasuries, and contemporaneous and lagged changes of the CBOE's implied volatility index (DVIXt and DVIXt-1). *CDS* refers to the IG in Groups 1 and 2, and HY in Group 3 and 4. *Stock* refers to SPR in Groups 1 and 3, SIG in Group 2, and SHY in Group 4. t-statistics are reported in parentheses under the coefficient estimates. The Wald test null hypothesis *is* $b_{11}=b_{12}\ldots=b_{1k}=0$ when *CDS* is the dependent variable, and $c_{11}=c_{12}\ldots=c_{1k}=0$ when *Stock* is the dependent variable. The optimal lag is selected by a minimum information criterion. F-statistic and p-value of the Wald test are reported in the lower panel of the table. The significance of the overall regression is based on a standard F-test. *** denotes significance at 1% and ** denotes significance at 5%.

$$CDS_t = a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + X_{1t} EXO_t + \varepsilon_1$$

$$Stock_t = a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + X_{2t} EXO_t + \varepsilon_2$$

Group 1: IG~SPR

Dep.	IGt	SPRt
IGt-1	0.048**	-0.001
	(2.03)	(-0.10)
SPRt-1	-0.279***	-0.095***
	(-3.34)	(-4.03)
IGt-2	0.097***	-0.001
	(4.17)	(-1.05)
SPRt-2	-0.169***	0.022
	(-3.13)	(1.46)
DTRATE	-0.033***	0.016***
	(-3.83)	(6.47)
SLOPE	-0.001	-0.001
	(-1.17)	(-1.25)
DVIXt	0.008***	-0.007***
	(17.06)	(-51.57)
DVIXt-1	-0.001	-0.001***
	(-1.50)	(-4.69)
Const.	0.0004	0.0001
Wald test	10.96***	3.23
p-value	0.0042	0.1991
R-Square (%)	19.65	65.03
Overall F Value	175.98***	18.23***

Group 2: IG~SIG

Dep.	IGt	SIGt
IGt-1	0.034	0.005
	(1.43)	(0.71)
SIGt-1	-0.37***	-0.012
	(-4.46)	(-0.49)
IGt-2	0.092***	-0.009
	(3.90)	(-1.28)
SIGt-2	-0.187***	0.026
	(-3.24)	(1.55)
DTRATE	-0.032***	0.014***
	(-3.69)	(5.54)
SLOPE	-0.001	-0.001
	(-1.14)	(-0.58)
DVIXt	0.008***	-0.006***
	(17.21)	(-46.74)
DVIXt-1	-0.001**	-0.001***
	(-2.04)	(-3.39)
Const.	0.0004	0.0001
Wald test	17.73***	4.13
p-value	0.0001	0.1268
R-Square (%)	20.17	60.23
Overall F Value	55.25***	331.11***

Group 3: HY~SPR

Dep.	HYt	SPRt
HYt-1	0.056**	-0.007
	(2.38)	(-1.03)
SPRt-1	-0.215***	-0.077***
	(-2.75)	(-3.30)
HYt-2	0.092***	0.001
	(3.91)	(0.18)
SPRt-2	-0.099**	0.034**
	(-1.97)	(2.45)
DTRATE	-0.029***	0.016***
	(-3.52)	(6.43)
SLOPE	0.001	-0.001
	(0.10)	(-1.12)
DVIXt	0.006***	-0.007***
	(12.64)	(-51.05)
DVIXt-1	-0.001	-0.001***
	(-1.45)	(-3.90)
Const.	0.0004	0.0001
Wald test	5.03*	5.65*
p-value	0.0809	0.0592
R-Square (%)	12.72	64.62
Overall F Value	31.43***	394.14***

Group 4: HY~SHY

Dep.	HYt	SHYt
HYt-1	0.059**	-0.025**
	(2.49)	(-2.28)
SHYt-1	-0.179***	0.158***
	(-3.54)	(6.93)
DTRATE	-0.029***	0.03***
	(-3.49)	(7.99)
SLOPE	0.001	-0.001
	(0.15)	(-0.13)
DVIXt	0.005***	-0.008***
	(12.30)	(-38.01)
DVIXt-1	-0.001*	-0.001
	(-1.78)	(-0.35)
Const.	0.0005	0.0004
Wald test	5.19**	2.87*
p-value	0.0227	0.0904
R-Square (%)	11.66	52.78
Overall F Value	38.04***	322.09***

Variable definitions:

SPR	The S&P 500 index returns
IG	Percentage spread changes of the investment-grade CDS index from day t-1 to day t
HY	Percentage spread changes of the high-yield CDS index from day t-1 to day t
SIG	The matching stock portfolio returns for firms included in the IG index
SHY	The matching stock portfolio returns for firms included in the HY index

Table 4: Testing for the Granger-Causality Relationship between Market Volatilities

This table reports the Granger-Causality test results for four groups of variables. IG_SQ is defined as the IG squared. HY_SQ, SPR_SQ, SIG_SQ, and SHY_SQ are defined in a similar way. IG_ABS is defined as the absolute value of IG. HY_ABS, SPR_ABS, SIG_ABS, and SHY_ABS are defined similarly. The optimal lag is selected by a minimum information criterion. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	Null Hypothesis:	F-Stat.	P-value
Group 1 (IG ~ SPR)	IG_SQ does not Granger-cause SPR_SQ	4.90	0.298
	SPR_SQ does not Granger-cause IG_SQ	7.33	0.120
Group 2 (IG ~ SIG)	IG_SQ does not Granger-cause SIG_SQ	21.65**	0.017
	SIG_SQ does not Granger-cause IG_SQ	20.09**	0.028
Group 3 (HY ~ SPR)	HY_SQ does not Granger-cause SPR_SQ	31.43***	<.0001
	SPR_SQ does not Granger-cause HY_SQ	24.46***	<.0001
Group 4 (HY ~ SHY)	HY_SQ does not Granger-cause SHY_SQ	35.63***	<.0001
	SHY_SQ does not Granger-cause HY_SQ	67.15***	<.0001

	Null Hypothesis:	F-Stat.	P-value
Group 1 (IG ~ SPR)	IG_ABS does not Granger-cause SPR_ABS	3.48	0.480
	SPR_ABS does not Granger-cause IG_ABS	4.61	0.329
Group 2 (IG ~ SIG)	IG_ABS does not Granger-cause SIG_ABS	17.93*	0.056
	SIG_ABS does not Granger-cause IG_ABS	13.76	0.184
Group 3 (HY ~ SPR)	HY_ABS does not Granger-cause SPR_ABS	10.09**	0.038
	SPR_ABS does not Granger-cause HY_ABS	2.38	0.666
Group 4 (HY ~ SHY)	HY_ABS does not Granger-cause SHY_ABS	11.91***	0.008
	SHY_ABS does not Granger-cause HY_ABS	1.36	0.714

Variable definitions:

SPR	The S&P 500 index returns
IG	Percentage spread changes of the investment-grade CDS index from day t-1 to day t
HY	Percentage spread changes of the high-yield CDS index from day t-1 to day t
SIG	The matching stock portfolio returns for firms included in the IG index
SHY	The matching stock portfolio returns for firms included in the HY index

Table 5: A Conditional Test of the Lead-Lag Relationship of the Stock and CDS Markets

This table tests the lead-lag relationship between the stock and CDS markets conditional on the stock market conditions in the following VAR models.

$$CDS_t = a_1 + \sum_{j=1}^{k} b_{1j} Stock_{t-j} + \sum_{j=1}^{k} c_{1j} CDS_{t-j} + \sum_{j=1}^{k} d_{1j} Stock_{t-j} \times Sign_t + \varepsilon_1$$

$$Stock_t = a_2 + \sum_{j=1}^{k} b_{2j} Stock_{t-j} + \sum_{j=1}^{k} c_{2j} CDS_{t-j} + \sum_{j=1}^{k} d_{2j} CDS_{t-j} \times Sign_t + \varepsilon_2$$

CDS refers to the IG in Groups 1 and 2, and HY in Groups 3 and 4. *Stock* refers to SPR in Groups 1 and 3, SIG in Group 2, and SHY in Group 4.

Results in Panel A are based on the model where the interaction term is created with the variable, *Sign*, equal to 1 if the SPR of day t is in the "down market" cohort and 0 otherwise. Results in Panel B are based on the model where the interaction term is created with the variable, *Sign,* equal to 1 if the SPR of day t is in the "up market" cohort and 0 otherwise. The market cohorts are created by sorting the SPR returns into the "up" market cohort (positive returns), flat, and "down" market (negative returns) cohorts. The null hypothesis of the F-test is the joint coefficients of interaction terms, d, are equal to zero. The optimal lag is selected by a minimum information criterion. * and ** denote significance at 10% and 5%, respectively.

Panel A ('Down' Market)

	Dependent Variable	F-Stat.	Probability
Group 1 (IG ~ SPR)	IG	4.56	0.207
	SPR	1.95	0.583
Group 2 (IG ~ SIG)	IG	3.24	0.356
	SIG	2.94	0.402
Group 3 (HY ~ SPR)	HY	9.39**	0.025
	SPR	10.65*	0.059
Group 4 (HY ~ SHY)	HY	8.38**	0.039
	SHY	11.56**	0.041

Panel B ('Up' Market)

	Dependent Variable	F-Stat.	Probability
Group 1 (IG ~ SPR)	IG	3.25	0.355
	SPR	0.95	0.814
Group 2 (IG ~ SIG)	IG	3.50	0.321
	SIG	2.99	0.393
Group 3 (HY ~ SPR)	HY	7.51*	0.057
	SPR	0.35	0.949
Group 4 (HY ~ SHY)	HY	5.41	0.144
	SHY	1.63	0.653

Table A1: Johansen's Cointegration Rank Tests

This table reports Johansen's trace statistics for the null hypothesis of no cointegration.

Sample Period	IG CDS Index and S&P 500 Index	HY CDS Index and S&P 500 Index
1/2001 – 6/2007	4.643	6.746
1/2001 – 12/2007	5.014	3.202
7/2007 – 12/2007	14.125*	16.134**

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2: Price Discovery Measures

This table reports the error-correction coefficients corresponding to the VECM model for the period from July 2007 to December 2007. It also reports the lower and upper Hasbrouck bounds and Gonzalo-Granger statistics showing the price discovery of the CDS market.

					Hasbrouck		
	CDS equation λ_1 coeff.	t-stat	Stock equation λ_2 coeff.	t-stat	Lower bound	Upper bound	Gonzalo-Granger statistics
IG/SPR	0.003	0.047	-0.5**	-2.119	0.455	0.999	0.995
HY/SPR	0.023***	3.487	-0.022***	-2.914	0.063	0.654	0.484

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

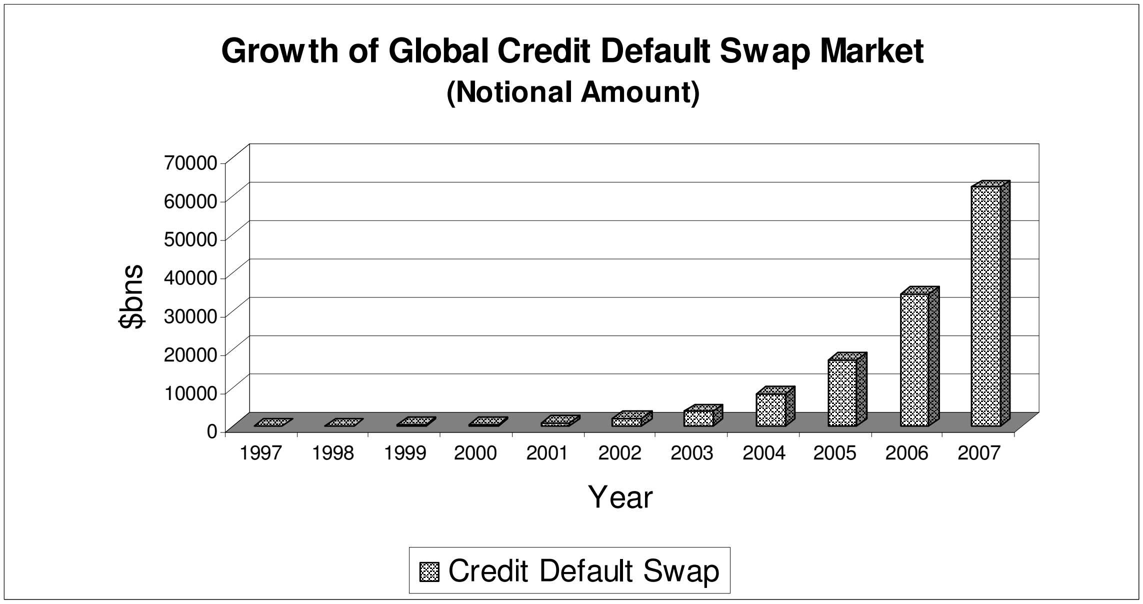


Figure 1: Growth of the Global Credit Default Swap Market
(Source: ISDA Market Survey)

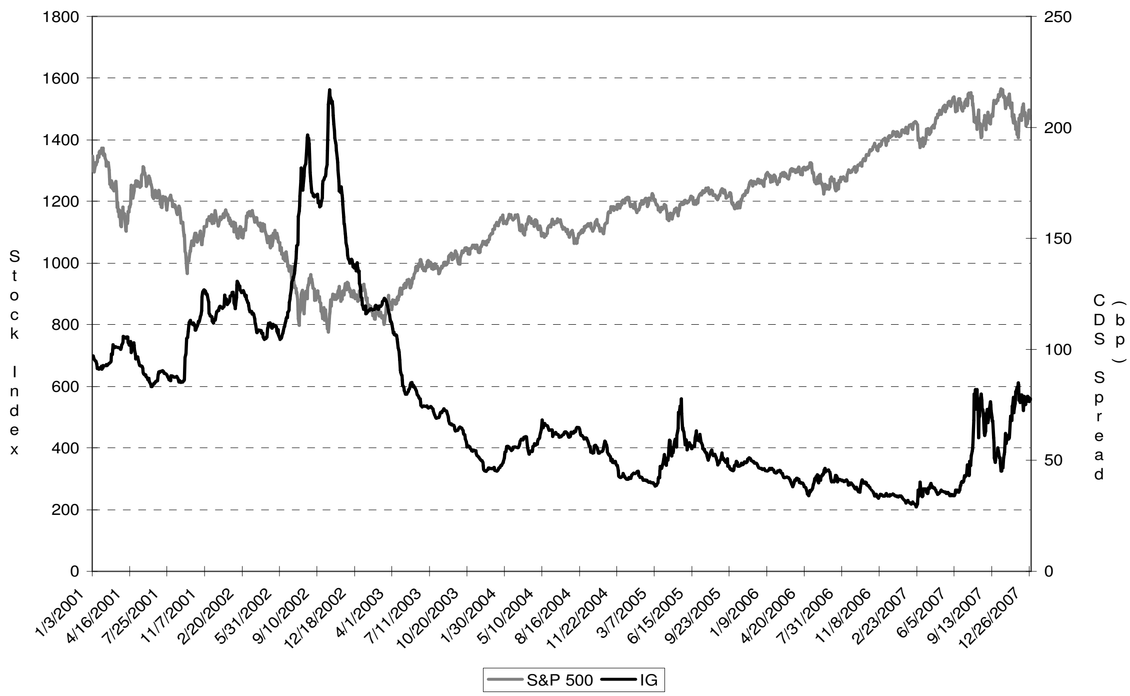


Figure 2-1: Investment-Grade CDS Index vs. S&P 500 Index

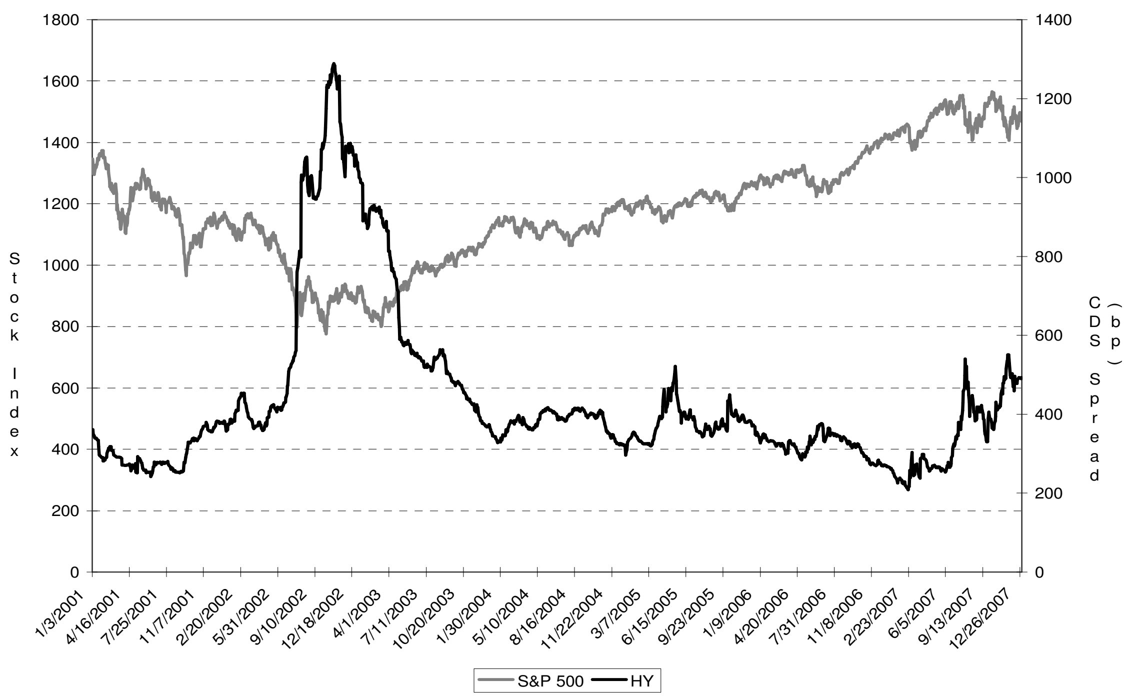


Figure 2-2: High-yield CDS Index vs. S&P 500 Index

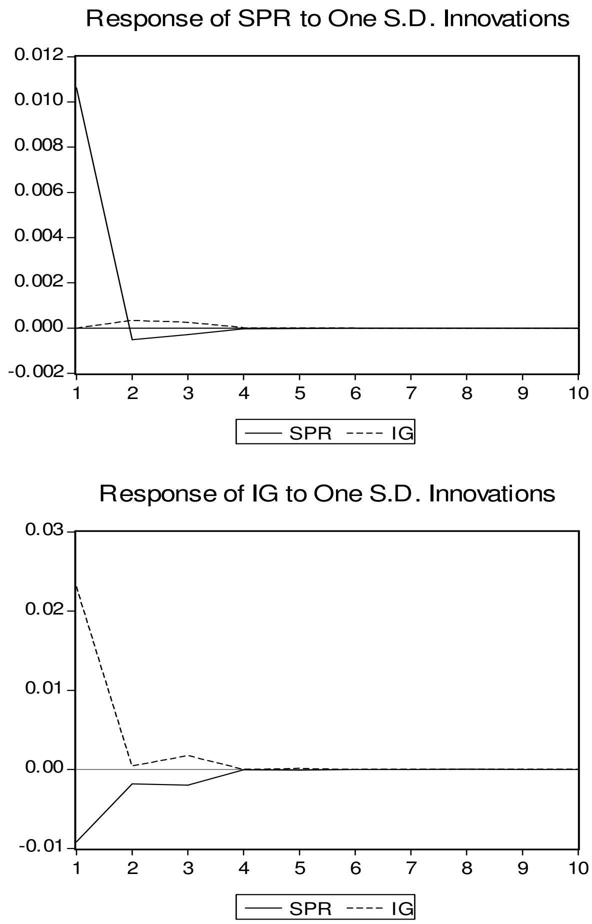
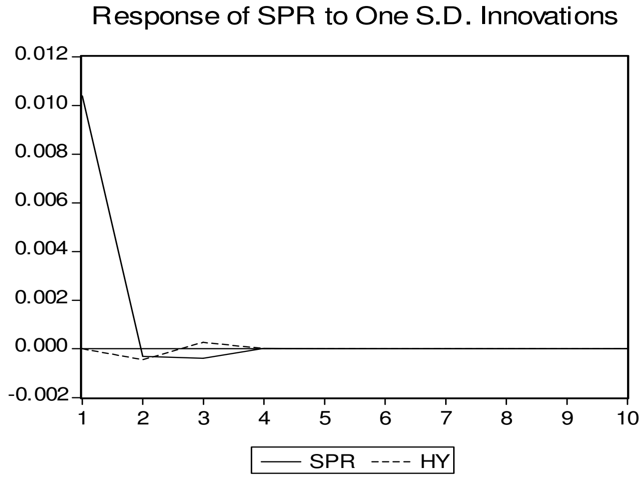


Figure 3-1: Impulse Response:
S&P 500 (SPR) vs. Investment-Grade CDS (IG) Index

The top panel shows the response of SPR to one S.D. innovations from SPR and IG, respectively; the bottom panel shows the response of IG to one S.D. innovations from SPR and IG. The significance levels at different lags are summarized below:
Response of SPR to SPR: significant at the 1% level at lag 1 and at the 10% level at lag 2;
Response of SPR to IG: not significant;
Response of IG to SPR: significant at the 1% level at lag 1-3;
Response of IG to IG: significant at the 1% level at lag 1 and 3.



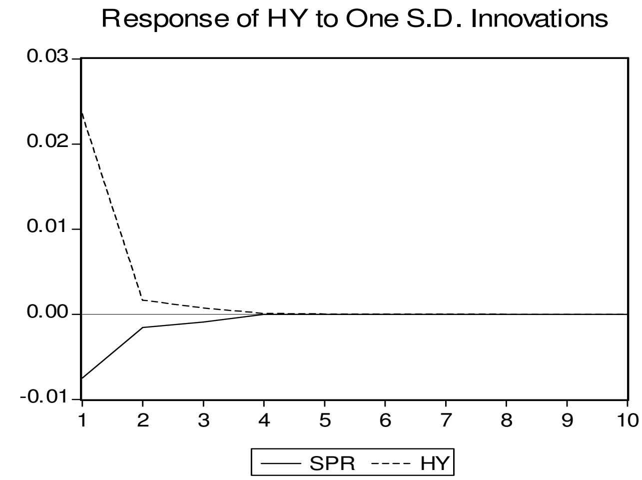


Figure 3-2: Impulse Response:
S&P 500 (SPR) vs. High-Yield CDS (HY) Index

The top panel shows the response of SPR to one S.D. innovations from SPR and HY, respectively; the bottom panel shows the response of HY to one S.D. innovations from SPR and HY. The significance levels at different lags are summarized below:
Response of SPR to SPR: significant at the 1% level at lag 1;
Response of SPR to HY: significant at the 10% level at lag 2;
Response of HY to SPR: significant at the 1% level at lag 1 and 2.
Response of HY to HY: significant at the 1% level at lag 1and 2.