Volatility Transmission among the CDS, Equity, and Bond Markets

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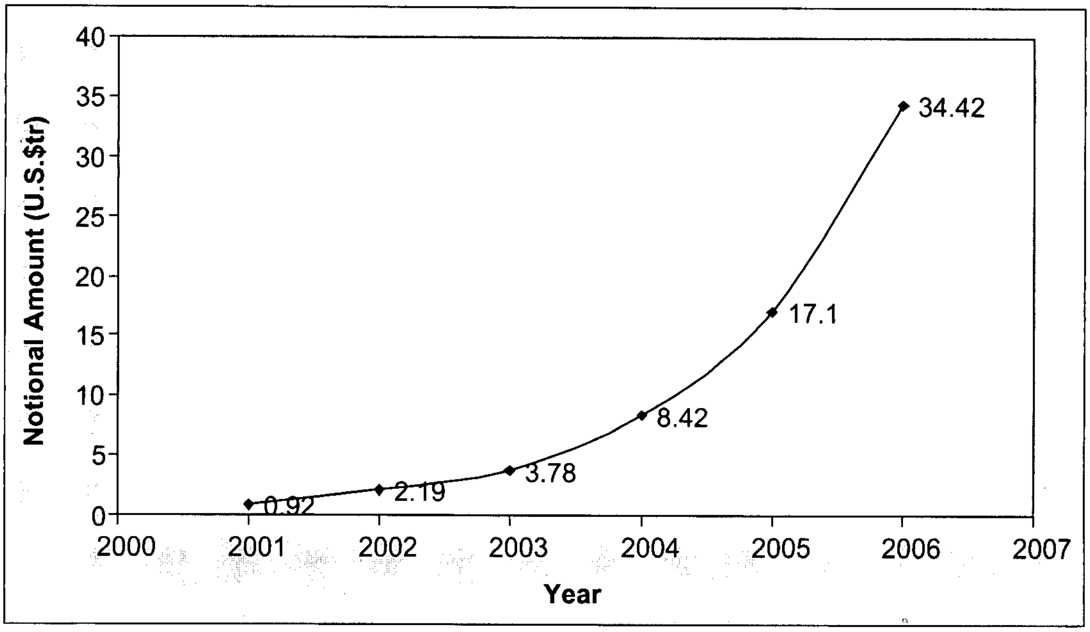
Credit derivatives have become one of the most important financial innovations of the last 25 years (see Greenspan [2004]) due to users' ability to manage credit risk. The credit derivatives market has been one of the fastest growing over-the-counter (OTC) derivatives markets in the past 10 years or so. The notional amount of credit default swaps (CDS), the most important credit derivative product, grew from US$0.92 trillion in 2001 to US$34.42 trillion in 2006, a 3,741% increase (see Exhibit 1). Although the market is still small in absolute terms compared to interest rate and currency swap markets, its relative importance is surging. In 2001, the outstanding amount of interest rate and currency swaps was US$69.21 trillion, around 75 times the outstanding notional amount of CDS. This multiple had fallen to 8 in 2006 when the outstanding amount of interest rate and currency swaps was US$285.73 trillion.

In recent years, CDS have been widely used to construct alternative investment assets, for credit risk portfolio management, and regulatory arbitrage.[1] Above all, they have been used primarily as a trading instrument as an increasing number of investment banks set up proprietary CDS trading units to reap the benefit of a fast-growing credit derivatives market (see FitchRatings [2004, 2005] for an extended discussion of trading credit risk). Adding to the importance of the CDS market is that CDS reference entities, whose outstanding debt issues are quoted for protection against credit events in CDS transactions, are also paying increasing attention to the CDS market. Sometimes they take CDS on their debt issues into consideration when making financial decisions, such as a debt exchange. Some companies even become the CDS protection seller of their own debt issues.

The question addressed in this article is whether such an active CDS market has a significant impact on the equity and bond markets in terms of volatility transmission. Structural-form credit risk models (based on Merton [1974])—one of the two mainstream credit risk modeling approaches used to price CDS[2]—use equity price as a very important model input. Meanwhile, bonds are the prevailing debt assets underlying CDS. Therefore, the choice of these three markets is based on their potential inter-linkage. In addition, according to market participants, the increasing use of derivatives in searching for higher yield across major asset classes is bringing the relationships between various markets closer, and the tighter interrelationships between asset classes have fueled volatility (see Mackenzie, Gangahar, and Scholtes [2007]). A strong interrelationship between different assets prompts the expectation of the transmission of volatility. The IMF [2007] suggested that a potential volatility shock in the financial system could

EXHIBIT 1

Outstanding Notional Amount of Credit Default Swaps



Source: International Swaps and Derivatives Association market survey; historical data from 2001 to 2006.

precipitate drastic portfolio adjustments and disorderly unwinding of positions. An example of the impact of such events is the collapse of Long-Term Capital Management, which led to the Federal Reserve's intervention (see Furfine [2002]). Events during the global credit crunch provide added impetus to our research question.

Previous literature regarding the implications of credit derivatives on financial stability generally focuses on the ability of credit derivatives to reduce credit risk concentration in the financial system. While simulation has been used to assess the implications of collateralized debt obligations (CDOs) on financial stability (e.g., Krahnen and Wilde [2006]), little empirical evidence exists on how CDS could affect financial stability. Jorion and Zhang [2007] investigated the intra-industry information transfer following credit events and found strong evidence of intra-industry contagious effects after Chapter 7 and Chapter 11 bankruptcies and large jumps in the event firms' CDS spreads. The only empirical study on the CDS market with respect to financial stability was that of Acharya and Johnson [2007] who concluded that the shocks experienced by the equity market due to negative credit news from the CDS market indicate the presence of insider trading in the CDS market. While Acharya and Johnson focused on the impact of innovations from the CDS market on stock returns, we investigate the dynamic relationships between the volatility of each market.

Volatility spillover from the CDS market to the equity and/or bond markets would cause concern for regulators and may stand to partly question the raison d'être of the CDS market (i.e., whether it is reducing credit risk concentration in the financial system or transferring volatility risk to other markets). Although volatility transmission has been widely investigated in equity and foreign exchange markets, there has been no empirical study on the volatility transmission among the CDS market, the equity market, and the bond market. This study's findings, which are presented in this article, fill a gap in this domain. In addition, understanding the influence of the joint movements of asset returns also has implications for financial risk management and derivatives pricing (see Calvet, Fischer, and Thompson [2006]).

The study of volatility transmission among CDS, equity, and bond markets will shed light on the efficiency of these markets. Trading counterparties with heterogeneous access to information may take some time and trading to resolve differences in expectations. Market dynamics may lead to a continuation of volatility between markets. In this case, evidence on volatility spillover will shed light on the relative informational efficiency among the three markets.

The remainder of this article is organized as follows. The next section reviews previous literature on volatility transmission and the section following that presents the data and methodology. The fourth section interprets the results, and the last section concludes.

LITERATURE REVIEW

The concepts of *comovement* and *spillover*, also referred to as *interdependency* and *contagion* (e.g., Soriano and Climent [2005]), should be differentiated. Volatility comovement is defined as contemporaneous shocks transmitted between assets, and volatility spillover is defined as the lagged shocks transmitted between assets. In the studies of volatility transmission between financial markets, one or more of three main methodologies have been commonly employed: generalized autoregressive heteroscedasticity (GARCH) models, regime switch models (e.g., Lamoureux and Lastrapes [1990] and Edwards and Susmel [2003]), and stochastic volatility models (e.g., Taylor [1994]). The vast empirical literature using GARCH modeling is indicative of the usefulness of this approach in modeling volatility transmission. This article will hence focus on GARCH models.

After the introduction of the concept of conditional heteroscedasticity (Engle [1982]) and the later extension to the generalized autoregressive conditional heteroscedasticity (GARCH) model by Bollerslev [1986], the literature on volatility transmission can be broadly divided into two groups according to different modeling approaches.

Two-Stage Univariate GARCH

The first group of studies uses two-stage univariate GARCH models. This approach involves estimating univariate GARCH models for each individual market, and then the squared residuals of the previously estimated models are used as explanatory variables in the conditional variance equations of the other markets. Hamao, Masulis, and Ng [1990] used maximum likelihood estimation and found volatility spillovers from the New York Stock Exchange (NYSE) to the London and Tokyo stock markets, and from the London Stock Exchange (LSE) to the Tokyo stock market during the period 1985–1988. However, Susmel and Engle [1994] used quasi-maximum likelihood estimation and found no strong evidence of spillovers between the NYSE and LSE over the period 1987–1989.

Other studies using two-stage univariate GARCH modeling include Wang, Rui, and Firth [2002], who investigated volatility transmission among stocks that were dually listed on the Hong Kong Stock Exchange and the LSE. They found evidence of return volatility spillover in both directions. Hsin [2004] investigated volatility transmission among 10 major stock markets and found that returns on a global index and the dollar exchange rates had explanatory power for the conditional variance.

Soriano and Climent [2005] argued that univariate estimation ignores the possible bi-directional causality in volatility and does not consider the covariance between the two series. As a result, a multivariate GARCH model can be more efficient to estimate the interactions among volatility for several different time series. However, establishing the existence of bi-directional causality in volatility a priori is a prerequisite for estimating a multivariate GARCH model.

Multivariate GARCH

Bollerslev, Engle, and Wooldridge [1988] estimated a trivariate CAPM using a VECH representation of the multivariate GARCH process for the NYSE. They concluded that the expected returns for the assets are influenced by the conditional second moments of returns.

De Santis and Gerard [1997] estimated the conditional CAPM using a diagonal representation of the multivariate GARCH process for the world's eight largest equity markets (i.e., U.K., U.S., France, Germany, Italy, Switzerland, Canada, and Japan). They found that severe U.S. market declines are contagious at the international level. Ledoit, Santa-Clara, and Wolf [2003] developed a flexible multivariate GARCH model with diagonal representation that is numerically more feasible for large samples.

Kearney and Patton [2000] used a BEKK representation of the multivariate GARCH model developed by Baba, Engle, Kraft, and Kroner [1990] to investigate volatility transmission in exchange rates within the European Monetary System. They found that the Deutsche mark played a dominant role in volatility transmission.

Bollerslev [1990] developed a constant conditional correlation (CCC) representation of multivariate GARCH to model short-term nominal exchange rates. This model proved to be very popular in empirical studies due to the reduction in computational complexity. Karolyi [1995] used this framework to investigate volatility transmission between the NYSE and the Toronto Stock Exchange (TSE). He found that the pattern of volatility transmission between the two markets had changed over time, and that shocks originating in the NYSE had a diminishing impact on the TSE since the late 1980s. Steeley [2006] also used this framework to examine volatility transmission between stock and bond markets in the U.K. He found volatility spillover from long-term bond yields to short-term bond yields and stock returns, and from short-term bond yields to stock returns. Koutmos and Booth [1995] tested volatility transmission across the London, New York, and Tokyo stock markets. They found significant asymmetric volatility spillover from New York to London and Tokyo, from London to New York and Tokyo, and from Tokyo to London and New York (i.e., negative innovations in one market caused an increase in volatility in other markets more than positive innovations). Koutmos [1996] investigated the asymmetric volatility transmission between European stock markets, including the U.K., France, Italy, and Germany. He found that the conditional variance in each market was also affected by past innovations generated in the other markets with few exceptions, and a negative innovation in a given market increased volatility across other markets more than a positive innovation. Chulia and Torro [2008] examined volatility transmission between stock and bond markets in Europe by using DJ Euro Stoxx 50 index futures and Euro Bund futures. They found that volatility spillovers between stocks and bonds are reciprocal.

Some extensions to GARCH also control for intra-day seasonality. Kofman and Martens [1997] investigated the intra-day pattern of volatility transmission between S&P 500 futures and FTSE 100 futures. They found spillover from the U.S. to the U.K. during the first 30 minutes after the opening of the Chicago Mercantile Exchange and significant spillover from the U.K. to the U.S. afterwards. Engle, Ito, and Lin [1990] found spillover of yen/dollar exchange rate volatility from Tokyo to New York.

DATA AND METHODOLOGY

Data

The CDS prices are daily benchmark prices from Markit, a leading service provider in the credit derivatives market. The sample period is from March 3, 2003, to March 31, 2005. The dataset initially contained 15 corporate reference entities.[3] All the CDS prices on these reference entities are five-year, U.S.$-denominated, with a senior-ranked underlying asset, and with a modified restructuring or with no restructuring clause. The share prices and bond prices of these reference entities for the corresponding sample period are obtained from Datastream. Share prices for 3 reference entities were not available in Datastream, so the sample was reduced to 12 reference entities. To avoid measurement errors caused by various options in corporate bonds, we only chose bond issues that satisfied the following restrictions: 1) bonds must not be putable, callable, convertible, or reverse convertible; 2) bonds must be denominated in U.S.$; 3) bonds must not be subordinated, structured, or company guaranteed; 4) bonds must have at least five years to maturity during the CDS sample period; 5) the coupon payments must be a fixed rate; and 6) if there is more than one bond qualifying under criteria 1) to 5), the largest senior issue with maturity closest to five years (to align bond maturity with CDS maturity) is used. After applying these criteria, the sample was further reduced to 10 reference entities.[4] Three reference entities have CDS data that became available after March 3, 2003,[5] while the other 7 reference entities have CDS data on all the trading days during the sample period.

Exhibit 2 presents the details of the 10 companies' equity listing and debt issuance. The majority (60%) are in the S&P 100 Index. All of these companies had an investment-grade credit rating by Standard and Poor's in March 2003, and all outstanding bond issues ranged from about U.S.$2 billion to U.S.$30 billion. Given the frequency of trading for these reference entities in the CDS market and the market capitalization of S&P 100 companies at the NYSE, this data sample is fairly representative of the CDS and equity markets.

Vector Autoregressive Model

After Engle and Granger [1987] and Johansen and Juselius [1990] demonstrated the capacity of vector autoregressive (VAR) models to offer insights to the dynamic relationship of a number of variables, they have been widely incorporated as part of the estimation methodologies for investigating volatility transmission (e.g., Karolyi [1995] and In [2007]).

A VAR model presented by Verbeek [2004, p. 322] was firstly used to investigate the dynamic relationships

EXHIBIT 2
Company Information

Company	Equity List	Equity Market Capitalization ($ million)	Stock Index	Outstanding Bond Issues ($ million)	Credit Rating
Altria Group Inc.	NYSE	101049.6	S&P100	5,100.0	A–
AT&T Corp	NYSE	80882.3	S&P100	30,161.6	BBB+
Baxter International	NYSE	18089.0	S&P100	4,748.0	A
Bristol Myers Squibb	NYSE	49012.7	S&P100	6,500.0	AA
Cardinal Health	NYSE	25438.3	S&P500	1,950.0	A
Comcast Communication	NASDAQ	41483.3		10,875.0	BBB
HCA	NYSE	18614.6	S&P100	8,659.7	BBB–
Liberty Media	NYSE	27319.6		5,357.0	BBB–
Time Warner	NYSE	71844.6	S&P100	3,800.0	BBB+
Wyeth	NYSE	54002.1	S&P500	11,250.0	A

Note: Outstanding bond issues and credit ratings are per Standard and Poor's Global Ratings Handbook (April 2003). Market capitalization is the mean daily market capitalization between March 3, 2003, and March 31, 2005.

among CDS, bond, and equity returns. The presence of an interaction among CDS, equity, and bond returns would provide preliminary evidence for potential returns volatility transmission,

$$X_t = \beta_0 + \beta_1 X_{t-1} + \cdots + \beta_n X_{t-n} + \varepsilon_t \qquad (1)$$

where X_t is a 3×1 column vector containing CDS, bond, and equity returns at time t; β_0 is a 3×1 column vector representing the intercepts; β_i $(1 \leq i \leq n)$ are matrices of coefficients of dimensions 3×3; and ε_t is a 3×1 column vector of error terms. The number of lags included in each equation is estimated by using a test of system reduction (i.e., reducing the lag length one at a time until the reduction of an additional lag is rejected).

An impulse response analysis is also conducted to examine the magnitude and persistence of the impact of innovations from a selected market (i.e., bond, CDS, and equity markets) to the others. For volatility to persist, one would expect a fairly long period of time for a stable condition to be restored.

Multivariate GARCH

After confirmation of the existence of interaction among the bond, CDS, and equity returns by using VAR analysis, a multivariate GARCH model is employed to test the following two hypotheses with respect to volatility spillover.

A null hypothesis is proposed as follows. When market participants with extensive research ability and potential access to private information, such as large investment banks, perceive a weakening in a company's financial strength, they start taking positions in the company's CDS since CDS are unfunded, thus making it easy to obtain a leveraged position; the OTC nature of the market also provides extra flexibility. Increased trading causes the CDS premium on the target company to fluctuate. Additionally, CDS are a fundamental credit derivative product used in constructing complex credit derivative products, such as synthetic CDOs and CDS index-related products. Hence, increased CDS return volatility for a specific constituent entity may cause investors in these more complex alternative investment assets to adjust their portfolios such that the volatility continues or/and is magnified.

There are two reasons why CDS market volatility may cause concern to investors in the bond and equity markets. First, CDS premiums are playing an increasingly important role as an indicator of default risk (e.g., Di Cesare [2005]). Bond and equity investors may use CDS as a complement to credit ratings. Second, due to the search for high yield across different asset classes, bonds, equities, and CDS may all be present in one portfolio so that changes in CDS volatility may cause rebalancing of other asset classes in a portfolio. Therefore, increased CDS market volatility may lead to increased bond and equity market volatility as well. In other words, there is volatility spillover from the CDS market to the bond and equity markets. However, the perceived deterioration in the company's financial strength could be invalid, in which case the existence of the CDS market facilitates the unnecessary introduction of volatility risk into the bond and equity markets.

An alternative hypothesis is also proposed. Low yield and high market liquidity encourage financial institutions to expand their business activities (Bank of England [2007]). Their search for high yield across the CDS, bond, and equity markets leads to a strong relationship among these markets (MacKenzie, Gangahar, and Scholtes [2007]). Many institutional investors have all three asset classes in their portfolio; therefore, as the IMF [2007] suggested, innovation from one market causes increased trading activity in the other two markets due to portfolio rebalancing. As a result, instead of unilateral volatility spillover from the CDS market to the equity and bond markets, volatility spillover from the other two markets to the CDS market is also commonly observed. This implies that volatility transmission among these three markets is due to the changing features of investment strategies in the financial system.

We use BEKK parameterization in the analysis of volatility transmission among the three markets, because this type of multivariate GARCH representation ensures a positive definite H_t. The following is a three-variable BEKK model:

$$\begin{aligned} R_t &= \alpha + \varepsilon_t \\ H_t &= C'C + B'\varepsilon_{t-1}\varepsilon'_{t-1}B + A'H_{t-1}A \end{aligned} \qquad (2)$$

where R is a 3×1 vector containing returns on bonds, CDS and equities; A and B are 3×3 parameter matrices; and C is restricted to the upper triangle.

The expansion of such a model is[6]

$$\begin{aligned}
h_{11,t} = {} & C_{11}^2 + C_{12}^2 + C_{13}^2 + B_{11}^2\varepsilon_{1,t-1}^2 + B_{11}B_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
& + B_{11}B_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{11}B_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
& + B_{21}^2\varepsilon_{2,t-1}^2 + B_{21}B_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{11}B_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{21}B_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{31}^2\varepsilon_{3,t-1}^2 + A_{11}^2 h_{11,t-1} + A_{11}A_{21}h_{21,t-1} \\
& + A_{11}A_{31}h_{31,t-1} + A_{11}A_{21}h_{12,t-1} + A_{21}^2 h_{22,t-1} \\
& + A_{21}A_{31}h_{32,t-1} + A_{11}A_{31}h_{13,t-1} \\
& + A_{21}A_{31}h_{23,t-1} + A_{31}^2 h_{33,t-1} \\
h_{22,t} = {} & C_{22}^2 + C_{23}^2 + B_{12}^2\varepsilon_{1,t-1}^2 + B_{12}B_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
& + B_{12}B_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{12}B_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
& + B_{22}^2\varepsilon_{2,t-1}^2 + B_{22}B_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{12}B_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{22}B_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{32}^2\varepsilon_{3,t-1}^2 + A_{12}^2 h_{11,t-1} + A_{12}A_{22}h_{21,t-1} \\
& + A_{12}A_{32}h_{31,t-1} + A_{12}A_{22}h_{12,t-1} + A_{22}^2 h_{22,t-1} \\
& + A_{22}A_{32}h_{32,t-1} + A_{12}A_{32}h_{13,t-1} \\
& + A_{22}A_{32}h_{23,t-1} + A_{32}^2 h_{33,t-1} \\
h_{33,t} = {} & C_{33}^2 + B_{13}^2\varepsilon_{1,t-1}^2 + B_{13}B_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
& + B_{13}B_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{12}B_{23}\varepsilon_{1,t-1}\varepsilon_{12,t-1} \\
& + B_{23}^2\varepsilon_{2,t-1}^2 + B_{23}B_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{13}B_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + B_{23}B_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
& + B_{33}^2\varepsilon_{3,t-1}^2 + A_{13}^2 h_{11,t-1} + A_{12}A_{23}h_{21,t-1} \\
& + A_{13}A_{33}h_{31,t-1} + A_{13}A_{23}h_{12,t-1} + A_{23}^2 h_{22,t-1} \\
& + A_{23}A_{33}h_{33,t-1} + A_{13}A_{33}h_{13,t-1} + A_{23}A_{33}h_{23,t-1} \\
& + A_{33}^2 h_{33,t-1}
\end{aligned}$$

B_{11} and A_{11} measure the dependence of conditional bond return volatility on its own lagged volatility. B_{21} and A_{21} measure the dependence of conditional bond return volatility on the lagged volatility of CDS return, and B_{31} and A_{31} measure the dependence of conditional bond return volatility on the lagged volatility of equity return. B_{22} and A_{22} measure the dependence of conditional CDS return volatility on its own lagged volatility. B_{12} and A_{12} measure the dependence of conditional CDS return volatility on the lagged volatility of bond return, and B_{32} and A_{32} measure the dependence of conditional CDS return volatility on the lagged volatility of equity return. B_{33} and A_{33} measure the dependence of conditional equity return volatility on its own lagged volatility. B_{13} and A_{13} measure the dependence of conditional equity return volatility on the lagged volatility of bond return, and B_{23} and A_{23} measure the dependence of conditional equity return volatility on the lagged volatility of CDS return.

The most supportive evidence for the null hypothesis would be that B_{21}, A_{21}, B_{23}, and A_{23} are significant, while B_{31}, A_{31}, B_{12}, A_{12}, B_{32}, A_{32}, B_{13}, and A_{13} are all insignificant (i.e., the CDS market only transmits volatility to bond and equity markets, but does not receive volatility, and bond and equity markets do not receive volatility spillover from either of the other two markets).

RESULTS AND INTERPRETATIONS

Exhibit 3 presents the descriptive statistics for daily bond, CDS, and equity returns. In general, CDS returns have higher variance, kurtosis, and skewness in comparison to bond and equity returns. The Jacque-Bera statistics indicate that none of the returns are normally distributed.

Short-Term Dynamic Relationship among the CDS, Bond, and Equity Markets

The following unrestricted VAR equations present only the significant (at the 1% or 5% level) coefficients for each of the 10 companies, with the corresponding t-values included in the parentheses:

Altria:

$$B_t = -0.04105CDS_{t-1} + \varepsilon_t \quad \underset{(-3.481)}{} \tag{3}$$

$$CDS_t = \underset{(2.627)}{0.13807CDS_{t-2}} - \underset{(-3.436)}{0.39952S_{t-1}} + \varepsilon_t \tag{4}$$

AT&T:

$$B_t = \underset{(-6.510)}{-0.27561B_{t-1}} + \varepsilon_t \tag{5}$$

$$\begin{aligned} CDS_t = {} & \underset{(5.455)}{0.23908CDS_{t-1}} + \underset{(5.346)}{0.23493CDS_{t-2}} \\ & - \underset{(-2.138)}{0.09361CDS_{t-3}} + \underset{(2.782)}{0.29785S_{t-3}} + \varepsilon_t \end{aligned} \tag{6}$$

Baxter:

$$S_t = \underset{(2.925)}{0.12894S_{t-1}} + \varepsilon_t \tag{7}$$

$$\begin{aligned} CDS_t = {} & \underset{(3.841)}{0.15754CDS_{t-2}} + \underset{(3.011)}{0.12297CDS_{t-4}} \\ & \underset{(-4.564)}{-0.30289S_{t-1}} \underset{(-7.033)}{-0.47734S_{t-4}} + \varepsilon_t \end{aligned} \tag{8}$$

Bristol:

$$B_t = \underset{(2.095)}{0.00972CDS_{t-1}} + \varepsilon_t \tag{9}$$

EXHIBIT 3
Descriptive Statistics of Daily CDS, Bond and Equity Returns

	Altria	AT&T	Baxter	Bristol	Cardinal	Comcast	HCA	Liberty	Time	Wyeth
Panel A. Daily Bond Returns										
Mean	1.74E-04	1.67E-04	6.29E-05	−6.81E-05	−1.29E-04	−9.02E-05	−2.37E-04	−2.51E-05	9.21E-05	1.50E-06
Standard Deviation	5.09E-03	8.56E-03	6.60E-03	3.65E-03	4.37E-03	3.03E-03	4.43E-03	4.20E-03	4.14E-03	5.07E-03
Kurtosis	2.968	75.434	1.705	2.116	6.573	1.498	1.856	11.658	0.865	1.771
Skewness	−0.087	1.276	0.000	0.180	0.112	0.122	−0.108	1.000	−0.052	0.017
Jacque-Bera p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	354	526	526	526	526	315	268	526	526	526
Panel B. Daily CDS Returns										
Mean	−2.16E-03	−2.33E-03	−1.22E-03	−9.36E-04	2.24E-03	−6.18E-04	7.37E-04	−3.63E-04	1.38E-03	−1.46E-03
Standard Deviation	2.78E-02	3.89E-02	3.02E-02	3.56E-02	4.82E-02	1.86E-02	2.76E-02	2.53E-02	1.42E-01	3.00E-02
Kurtosis	59.745	30.241	23.531	93.005	36.831	16.282	89.992	30.379	406.671	25.761
Skewness	3.629	−3.244	2.763	3.633	1.940	2.087	7.319	-0.203	18.797	2.947
Jacque-Bera p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	354	526	526	526	526	315	268	526	526	526
Panel C. Daily Equity Returns										
Mean	1.05E-03	3.63E-04	5.06E-04	2.57E-04	2.20E-04	1.92E-04	1.02E-03	6.37E-04	9.66E-04	4.95E-04
Standard Deviation	1.35E-02	1.49E-02	1.84E-02	1.35E-02	2.27E-02	1.40E-02	1.36E-02	1.44E-02	1.50E-02	1.69E-02
Kurtosis	12.130	4.028	33.050	1.756	43.144	3.665	14.268	2.395	2.059	6.164
Skewness	−0.128	0.566	−2.953	−0.127	−1.978	−0.411	1.025	0.111	0.155	0.388
Jacque-Bera p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	354	526	526	526	526	315	268	526	526	526

Note: The negative mean bond returns may reflect the fact that when a reference entity is quoted in a CDS transaction, it is close to a credit quality deterioration, such that bond prices may have a downward trend during the life of the CDS contract. Theoretically speaking, CDS spreads should widen (i.e., CDS returns should be positive) when a reference entity's credit quality deteriorates. However, another factor that may determine CDS spread changes is liquidity, which was improving during the sample period.

$$CDS_t = 0.19345CDS_{t-1} + 0.21274CDS_{t-3}$$
$$(4.420) \qquad (4.956)$$
$$-0.49863S_{t-1} + \varepsilon_t$$
$$(-4.378) \tag{10}$$

$$S_t = -0.06208CDS_{t-1} + 0.05074CDS_{t-2} + \varepsilon_t$$
$$(-3.606) \qquad (2.931) \tag{11}$$

***Cardinal*:**

$$B_t = -0.00826CDS_{t-2} + \varepsilon_t$$
$$(-2.049) \tag{12}$$

$$CDS_t = 0.12005CDS_{t-1} + 0.14062CDS_{t-2}$$
$$(2.611) \qquad (3.230)$$
$$-0.11799CDS_{t-5} + 0.10174CDS_{t-7} + \varepsilon_t$$
$$(-2.677) \qquad (2.313) \tag{13}$$

$$S_t = 0.04245CDS_{t-5} - 0.04377CDS_{t-7} + \varepsilon_t$$
$$(2.008) \qquad (-2.075) \tag{14}$$

***Comcast*:**

$$CDS_t = 0.25928CDS_{t-1} + 0.19947CDS_{t-3}$$
$$(4.753) \qquad (3.641)$$
$$-0.2488S_{t-1} - 0.17364S_{t-3}$$
$$(-3.684) \qquad (-2.502)$$
$$+0.20775S_{t-4} + \varepsilon_t$$
$$(3.002) \tag{15}$$

$$S_t = -0.12432S_{t-4} + \varepsilon_t$$
$$(-2.125) \tag{16}$$

***HCA*:**

$$B_t = -0.029063CDS_{t-1} + \varepsilon_t$$
$$(-2.752) \tag{17}$$

$$CDS_t = 0.16088CDS_{t-1} + \varepsilon_t$$
$$(2.465) \tag{18}$$

$$S_t = -0.18142S_{t-6} + \varepsilon_t$$
$$(-2.860) \tag{19}$$

***Liberty*:**

$$B_t = -0.09146B_{t-7} + \varepsilon_t$$
$$(-2.242) \tag{20}$$

$$CDS_t = -0.58880B_{t-6} + 0.36433CDS_{t-1} + \varepsilon_t$$
$$(-2.391) \qquad (8.866) \tag{21}$$

$$S_t = 0.31892B_{t-7} + \varepsilon_t$$
$$(2.144) \tag{22}$$

***Time*:**

$$CDS_t = -0.14598CDS_{t-4} + 0.15323CDS_{t-7} + \varepsilon_t$$
$$(-3.318) \qquad (3.455) \tag{23}$$

$$S_t = 0.3491 + 0.01269CDS_{t-6} + \varepsilon_t$$
$$(-3.318) \quad (2.790) \tag{24}$$

***Wyeth*:**

$$B_t = 0.01909CDS_{t-6} - 0.02664CDS_{t-7}$$
$$(2.358) \qquad (-3.376)$$
$$+0.04831S_{t-6} + \varepsilon_t$$
$$(3.573) \tag{25}$$

$$CDS_t = 0.28895CDS_{t-1} + 0.08847CDS_{t-6}$$
$$(6.745) \qquad (1.961)$$
$$-0.32676S_{t-1} + \varepsilon_t$$
$$(-4.375) \tag{26}$$

$$S_t = 0.05582CDS_{t-3} + 0.10820S_{t-4} + \varepsilon_t$$
$$(6.745) \qquad (2.381) \tag{27}$$

These results suggest that there is a dynamic influence from the CDS market to the bond market for five companies (see Equations (3), (9), (12), (17) and (25)). The influence is negative for three companies (see Equations (3), (12), and (17)) and is positive for one company (see Equation (9)). The influence is mixed for another company (see Equation (25)). For all of these companies except for one (see Equation (25)), such dynamic influence comes from the very recent CDS returns (one or two days before). A dynamic influence from the equity market to the bond market is only found in one company (see Equation (25)) for which the equity return of six days before had a positive influence on the current bond return.

A dynamic influence from the bond market to the CDS market is only found in one company (see Equation (21)) for which the bond return of six days before had a negative influence on current CDS return. A dynamic influence from the equity market to the CDS market is found in the majority of the companies (see Equations (4), (6), (8), (10), (15), and (26)). The influence is negative for four companies (see Equations (4), (8), (10), and (26)) and positive for one company (see Equation (6)). The dynamic influence is mixed for one company (see Equation (15)). Such dynamic influences come from one day, three days, or four days before.

A dynamic influence from the bond market to the equity market is found in one company (see Equation (22)) for which the positive influence came from seven days before. A dynamic influence from CDS returns to equity returns is found in five companies. The influence is positive for two companies (see Equations (24) and (26)) and is mixed for the other two companies (see Equations (11) and (14)). A dynamic influence on equity returns comes from the CDS return of one to seven days previously.

Exhibit 4 summarizes the interaction among bond, CDS, and equity returns. A dynamic relationship between CDS and equity returns is the most frequently observed. However, consistent with Zhu [2003] and Norden and Weber [2004], interactions between bond and CDS returns are also common, with previous CDS returns having more influence on current bond returns than the other way around. A dynamic relationship between bond and equity returns is relatively rare.

EXHIBIT 4
Summary of Lags and Signs in VAR Models

	Bond	CDS	Equity	Bond	CDS	Equity
	Altria			**AT&T**		
Bond(L)	N/A	N/A	N/A	-1	N/A	N/A
CDS(L)	-1	+2	N/A	N/A	+1,+2,-3	N/A
Equity(L)	N/A	-1	N/A	N/A	+3	N/A
	Baxter			**Bristol**		
Bond(L)	N/A	N/A	N/A	N/A	N/A	N/A
CDS(L)	N/A	+2,+4	N/A	+1	+1,+3	-1,+2
Equity(L)	N/A	-1,-4	+1	N/A	-1	N/A
	Cardinal			**Comcast**		
Bond(L)	N/A	N/A	N/A	N/A	N/A	N/A
CDS(L)	-2	+1,+2,-5, +7	+5,-7	N/A	+1,+3	N/A
Equity(L)	N/A	N/A	N/A	N/A	-1,-3,+4	-4
	HCA			**Liberty**		
Bond(L)	N/A	N/A	N/A	-7	-6	+7
CDS(L)	-1	+1	N/A	N/A	+1	N/A
Equity(L)	N/A	N/A	-6	N/A	N/A	N/A
	Time			**Wyeth**		
Bond(L)	N/A	N/A	N/A	N/A	N/A	N/A
CDS(L)	N/A	-4,+7	+6	+6,-7	+1,+6	+3
Equity(L)	N/A	N/A	N/A	+6	-1	+4

Note: The top row denotes the dependent variables (i.e., returns of bond, CDS, and equity); the left-most column denotes the explanatory variables; N/A means the explanatory variable does not have a significant impact on the dependent variable; "+" and "−" indicate if the impact is positive or negative; and the number indicates the length of the lag. For example, −1 means that the previous day's return of the explanatory variable has a negative impact on the dependent variable.

Impulse Response Relationship among the CDS, Bond, and Equity Markets[7]

The impulse response analysis shows that the magnitude of impact the bond market receives from the CDS market varies, lasting from 9 days to more than 20 days. However, for six companies, shocks from the CDS market to the bond market take more than 15 days to return to equilibrium. The impact that the bond market received from the equity market lasted from 6 days to more than 20 days. For half of the companies, shocks from the equity market to the bond market took more than 15 days to return to equilibrium.

The magnitude of impact that the CDS market received from the bond market varied, lasting from 9 days to 18 days. For half of the companies the impulse response took more than 15 days to return to equilibrium. The impact that the CDS market received from the equity market lasted from 9 days to 20 days. For half of the companies, shocks from the equity market to the CDS market took more than 15 days to return to equilibrium.

The magnitude of impact that the bond market had on the equity market varied, lasting from 10 days to more than 20 days. For half of the companies shocks from the bond market to the equity market took more than 20 days to return to equilibrium. The impact that the equity market received from the CDS market lasted from 4 days to more than 20 days, whereas for the majority (70%), shocks from the CDS market to the equity market took less than 15 days to return to equilibrium.

To summarize, shocks from the CDS market to the bond market took relatively longer to return to equilibrium than those from the equity market. Shocks from the bond and equity markets to the CDS market took about the same amount of time to return to equilibrium. Shocks from the CDS market to the equity market took relatively longer to return to equilibrium than those from the bond market. In general, shocks from the CDS market to the other two markets took longer to return to equilibrium than shocks received by the CDS market.

Volatility Spillover among the CDS, Bond, and Equity Markets

Exhibit 5 presents the results from estimating Model (2). Panels A, B and C focus on the conditional volatility of the bond, CDS, and equity markets, respectively. Panel A shows that bond return volatility of all companies depended on its own previous days' volatility.[8] However, only half of the companies (Altria, AT&T, Cardinal, Liberty and Wyeth) were also influenced by the previous day's innovation. Volatility spillover from CDS return to bond return was found in 9 companies, among which 5 companies' (Altria, AT&T, Bristol, Liberty, and Time) bond returns received volatility from CDS returns through both the previous days' volatility (conditional variance) and the previous day's innovation (variance). Three companies (Baxter, Cardinal, and Wyeth) received volatility through the previous days' volatility, but not the previous day's innovation, and 1 company (Comcast) was influenced only by the previous day's innovation. Volatility spillover from equity return to bond return was found in 9 companies, of which 6 companies' (AT&T, Bristol, Cardinal, Comcast, Liberty, and Wyeth) bond returns received volatility from equity returns through both the previous days' volatility and the previous day's innovation, and 3 companies (Altria, HCA, and Time) received volatility through the previous days' volatility.

Panel B of Exhibit 5 shows that CDS return volatility of 5 companies (AT&T, Comcast, HCA, Time, and Wyeth) depended on its own previous days' volatility, and all companies, except HCA, were influenced by the previous day's innovation. Volatility spillover from bond return to CDS return was found in 8 companies, of which 4 companies' (AT&T, Comcast, HCA, and Wyeth) CDS returns received volatility from bond returns through the previous days' volatility, and 4 companies (Altria, Baxter, Liberty, and Time) were influenced by only the previous day's innovation. Volatility spillover from equity return to CDS return was found in 8 companies, of which 2 companies (AT&T and Wyeth) received volatility through both the previous days' volatility and the previous day's innovation, 3 companies (Altria, Baxter, and Cardinal) received volatility through the previous days' volatility, and 3 companies (Bristol, Comcast, and Time) were influenced only by the previous day's innovation.

Panel C of Exhibit 5 shows that equity return volatility of 7 companies (Altria, Baxter, Cardinal, Comcast, Liberty, Time, and Wyeth) depended on its own previous days' volatility, and 8 companies (Altria, Baxter, Cardinal, Comcast, HCA, Liberty, Time, and Wyeth) were influenced by the previous day's innovation. Volatility spillover from bond return to equity return was found in 9 companies, of which 6 companies (Altria, Baxter, Bristol, Comcast, Liberty, and Wyeth) received volatility through both the previous days' volatility and the previous day's innovation, 2 companies

EXHIBIT 5

Volatility Spillover: Estimation Results of the BEKK Model

$$H_t = C'C + B'\varepsilon_{t-1}\varepsilon'_{t-1}B + A'H_{t-1}A$$

where A and B are 3 ×3 matrices and C is a 3 ×3 triangular matrix.

	Altria	AT&T	Baxter	Bristol	Cardinal	Comcast	HCA	Liberty	Time	Wyeth
Panel A. Volatility Spillover to Bond Market										
A_{11}	-0.8656	0.0729a	0.5432a	0.9559a	0.8068a	-0.3547a	-0.3611a	-0.9084a	0.9991a	-0.8352a
	(-20.005)	(3.941)	(3.540)	(51.547)	(20.047)	(-2.678)	(-2.748)	(-22.189)	(546.916)	(-45.353)
A_{21}	-0.0358	-0.0268a	0.1282a	-0.0247a	0.0203a	-0.0201	-0.0346	-0.0390a	0.0038a	0.0388a
	(-2.468)	(-6.669)	(5.045)	(-5.492)	(2.719)	(-1.255)	(-1.514)	(-7.551)	(3.340)	(12.551)
A_{31}	0.1982a	-0.0424a	0.0510	-0.0496a	-0.0754a	-0.1945a	-0.3125a	0.1155a	0.0075a	0.1323a
	(5.281)	(-2.774)	(1.037)	(-3.202)	(-5.281)	(-11.510)	(-8.634)	(4.051)	(4.619)	(22.926)
B_{11}	-0.2232a	2.5237a	0.0927	0.0107	0.1273a	0.0677	-0.1432	0.1785a	-0.0092	0.0517b
	(-3.480)	(14.874)	(1.682)	(0.278)	(2.629)	(1.005)	(-1.437)	(6.581)	(-0.313)	(2.187)
B_{21}	0.1235a	-0.1543a	0.0003	0.0161a	-0.0134	-0.0312a	0.0001	-0.0604a	-0.0188a	0.0044
	(5.428)	(-17.123)	(0.024)	(2.659)	(-1.282)	(-2.851)	(0.009)	(-7.051)	(-3.430)	(1.451)
B_{31}	0.0094	0.5165a	-0.0063	-0.0244a	0.0259b	0.0424b	-0.0265	-0.0250a	-0.0099	0.0353a
	(0.410)	(22.335)	(-0.315)	(-2.559)	(2.147)	(2.301)	(-0.935)	(-4.251)	(-1.479)	(6.101)
C_{11}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.011)	(-0.001)	(0.015)
C_{12}	0.0000	0.0000	0.0000	-0.0003a	0.0000	0.0000	0.0000	0.0005a	0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(-2.989)	(0.000)	(0.000)	(0.000)	(4.706)	(0.000)	(-0.016)
C_{13}	-0.0009	-0.0003	-0.0043a	0.0005a	-0.0019a	-0.0008	0.0012	0.0000	0.0000	0.0003b
	(-1.097)	(-1.495)	(-3.655)	(3.439)	(-5.913)	(-0.843)	(1.901)	(0.056)	(0.223)	(2.486)
Panel B. Volatility Spillover to CDS Market										
A_{12}	0.6708	1.7759a	0.4266	-0.3265	-0.1208	2.6124a	4.8094a	0.1211	-0.4510	-1.3594a
	(1.577)	(7.214)	(1.170)	(-1.182)	(-0.167)	(6.266)	(13.424)	(0.685)	(-1.606)	(-5.943)
A_{22}	0.0499	0.4428a	0.0091	-0.0629	-0.0919	-0.7668a	0.2883a	0.0264	0.0209b	0.2399a
	(0.827)	(5.572)	(0.040)	(-0.9880)	(-1.206)	(-10.260)	(2.664)	(0.786)	(2.461)	(5.538)
A_{32}	0.3075b	-1.4697a	1.3620a	-0.1466	1.1869a	-0.0775	-0.1758	0.0343	-0.0283	-1.2264a
	(2.343)	(-8.314)	(14.703)	(-0.7840)	(9.398)	(-0.371)	(-0.681)	(0.619)	(-0.384)	(-21.347)
B_{12}	3.1554a	1.1560	-0.5456a	-0.1829	-0.1389	0.5471	1.0665	-2.2915a	-3.1430a	-0.0966
	(12.898)	(1.776)	(-2.733)	(-0.376)	(-0.273)	(1.3920)	(1.883)	(-8.099)	(-7.731)	(-0.466)
B_{22}	-1.5321a	0.3904a	0.3596a	1.5942a	1.2891a	0.3538a	0.0460	1.5299a	4.6560a	0.2203a
	(-12.611)	(3.433)	(3.845)	(15.972)	(11.794)	(5.252)	(0.699)	(18.153)	(26.251)	(7.365)
B_{32}	0.1057	0.4051a	-0.2035	-0.7248a	0.0655	-0.1979b	0.0306	0.0667	-1.1911a	-0.5231a
	(0.948)	(2.930)	(-1.681)	(-8.502)	(0.493)	(-2.337)	(0.136)	(0.933)	(-9.178)	(-9.572)
C_{22}	0.0000	0.0000	0.0000	-0.0132a	0.0000	0.0000	0.0000	-0.0115a	-0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(-15.185)	(0.000)	(0.000)	(0.000)	(-13.707)	(-0.001)	(0.042)
C_{23}	0.0079a	-0.0009	0.0067a	-0.0011	-0.0090a	-0.0037	-0.0019	-0.0010	-0.0102a	0.0012
	(8.595)	(-0.274)	(3.674)	(-0.968)	(-4.057)	(-1.783)	(-1.061)	(-0.058)	(-10.415)	(0.433)
Panel C. Volatility Spillover to Equity Market										
A_{13}	-1.4297a	0.0051	-1.6077a	-0.7292a	2.3581a	2.9536a	-0.1587	1.4047a	-0.0678a	1.8122a
	(-10.700)	(0.041)	(-13.347)	(-3.576)	(8.873)	(5.145)	(-0.655)	(4.585)	(-5.037)	(8.496)
A_{23}	-0.2883a	0.0441b	0.1968a	-0.0864a	0.2500a	0.1142	0.1253b	0.0253	-0.0123a	0.5363a
	(-8.671)	(2.331)	(3.156)	(-3.341)	(7.605)	(1.438)	(2.402)	(1.057)	(-2.799)	(21.641)
A_{33}	-0.7145a	0.1102	0.2878b	0.0022	0.3233a	-0.2905b	0.2490	0.8965a	0.9870a	0.4790a
	(-14.672)	(1.938)	(2.206)	(0.018)	(3.847)	(-2.334)	(1.796)	(23.118)	(218.304)	(9.784)
B_{13}	-0.5112a	-0.4290	0.9934a	0.5532b	-0.1102	-0.9944a	-2.4691a	0.4281a	0.0661	0.4782a
	(-3.064)	(-1.519)	(4.630)	(2.131)	(-0.423)	(-3.499)	(-11.162)	(4.186)	(0.586)	(3.769)
B_{23}	0.2748a	-0.2054a	-0.3717a	-0.1726a	-0.5816a	-0.0728	-0.0461	0.0465	0.0545b	0.0263
	(4.229)	(-7.002)	(-4.955)	(-5.276)	(-12.578)	(-1.834)	(-1.668)	(1.632)	(2.533)	(1.421)
B_{33}	-0.1679a	-0.0210	0.2675a	0.0952	-0.2493a	0.2962a	0.2678b	0.1009a	0.1271a	0.0948b
	(-3.418)	(-0.312)	(3.340)	(1.597)	(-3.572)	(4.575)	(2.535)	(2.927)	(6.222)	(2.043)
C_{33}	0.0043a	0.0145a	-0.0036b	0.0119a	0.0107a	0.0076a	0.0092a	-0.0000	-0.0007	0.0042a
	(5.143)	(32.980)	(-2.340)	(26.448)	(8.266)	(3.253)	(10.243)	(-0.032)	(-1.421)	(4.868)
LL	4325.19	5900.38	5967.12	6431.45	5917.11	3993.49	3228.67	6472.77	5932.41	6110.25
Obs	354	526	526	526	526	315	268	526	526	526

Note: B_{11} and A_{11} measure the dependence of conditional bond return volatility on its own lagged volatility. B_{21} and A_{21} measure the dependence of conditional bond return volatility on the lagged volatility of CDS return. B_{31} and A_{31} measure the dependence of conditional bond return volatility on the lagged volatility of equity return. B_{22} and A_{22} measure the dependence of conditional CDS return volatility on its own lagged volatility. B_{12} and A_{12} measure the dependence of conditional CDS return volatility on the lagged volatility of bond return. B_{32} and A_{32} measure the dependence of conditional CDS return volatility on the lagged volatility of equity return. B_{33} and A_{33} measure the dependence of conditional equity return volatility on its own lagged volatility. B_{13} and A_{13} measure the dependence of conditional equity return volatility on the lagged volatility of bond return. B_{23} and A_{23} measure the dependence of conditional equity return volatility on the lagged volatility of CDS return. For some C_{11}, C_{12}, and C_{22}, both coefficients and t-values appear to be zero because they are not significant and the size of the coefficients is very small. a *denotes significance at the 1% level and* b *denotes significance at the 5% level.* t*-values are in parentheses.*

(Cardinal and Time) received volatility through the previous days' volatility, and 1 company (HCA) was influenced only by the previous day's innovation. Volatility spillover from CDS to equity was found in 8 companies, of which 7 companies (Altria, Baxter, Cardinal, Comcast, Liberty, Time, and Wyeth) received volatility through both the previous days' volatility and the previous day's innovation, and 1 company (HCA) was influenced only by the previous day's innovation.

Exhibit 6 summarizes the results that indicate the equity market played a relatively more important role than the CDS market in transmitting volatility to the bond market. The bond market was also marginally more important than the equity market in transmitting volatility to the CDS market. The bond market, compared to the CDS market, played a more important role in transmitting volatility to the equity market. The CDS market transmitted less volatility than it received from the bond and equity markets, while volatility transmission between the bond and equity markets was almost reciprocal.

There is little supportive evidence for the null hypothesis that volatility in the bond and equity markets can originate from the CDS market where there is potential insider trading (see Acharya and Johnson [2007]). There is evidence for the alternative hypothesis that as investors search for high yield across different asset classes the links between the CDS, bond, and equity markets become strong. Innovation in any of the three markets can lead to increased volatility in the other two markets.

CONCLUSION

The research presented in this article investigates volatility transmission among the bond, CDS, and equity markets, as represented by 10 large U.S. companies. First, the dynamic relationship between bond, CDS and equity returns is examined through a VAR model. A dynamic relationship between CDS and equity returns is most frequently observed, however, interaction between bond and CDS returns is also common. A dynamic relationship between bond and equity returns is relatively rare. The impulse response analysis suggests that shocks from the CDS market to the other two markets generally take longer to be absorbed than shocks received by the CDS market from the other two markets.

Volatility transmission is investigated through a multivariate GARCH model. Compared to the CDS market, the equity market plays a relatively more important role in transmitting volatility to the bond market. The bond market is also marginally more important than the equity market in transmitting volatility to the CDS market. The bond market, compared to the CDS market, plays a more important role in transmitting volatility to the equity market. The CDS market transmits less volatility than it receives from the bond and equity markets, while volatility transmission between the bond and equity markets might be viewed as reciprocal.

These findings provide little evidence in support of a hypothesis that the CDS market originates and transmits volatility to the bond and equity markets. The almost reciprocal volatility spillover among these markets, however, supports the notion that as investors search for high yield across different asset classes the link between the CDS, bond, and equity markets strengthens. Innovation in any of the three markets can cause trading activity to increase in the other two markets. The reciprocal volatility transmission also suggests that none of these three markets is relatively more efficient than the other two. The findings indicate that for financial regulators who are eager

EXHIBIT 6

Summary of Volatility Spillover among Bond, CDS and Equity Markets

	From	Bond		CDS		Equity	
To		H(-1)	$\varepsilon(-1)^2$	H(-1)	$\varepsilon(-1)^2$	H(-1)	$\varepsilon(-1)^2$
Bond	1%	-	-	4	4	8	6
	5%	-	-	0	0	0	1
CDS	1%	7	6	-	-	6	5
	5%	1	0	-	-	2	1
Equity	1%	9	4	4	4	-	-
	5%	0	2	1	1	-	-

Note: 1% and 5% indicates whether the coefficients of lagged variance and conditional variance are significant at the 1% level or 5% level. H(−1) denotes lagged conditional variance and $\varepsilon(-1)^2$ denotes lagged variance.

to learn the implications of CDS on the financial system, it is important to understand market participants' investment strategies in terms of the composition of their portfolios. Because the links among the CDS, bond, and equity markets are strong, any regulation of the CDS market should not ignore the interaction of these markets.

ENDNOTES

Any views expressed in this article do not necessarily reflect those of Cabot Financial Limited.

[1]Capital requirements are imposed by regulators to protect investors or clients of financial institutions and to enhance financial stability. In this context, *regulatory arbitrage* refers to the practice in which banks hold highly risky financial assets, hedging away the risk with derivatives in order to take on maximum risk with a given level of regulatory capital.

[2]Another type is reduced-form models. See, for example, Duffie and Singleton [1999].

[3]As an independent verification of the prominence of these 15 reference entities in the CDS market, we use a dataset obtained from CreditTrade. During the sample period, the latter dataset contains 721 reference entities with 184,614 quoted or traded prices. The number of quotes or trades on these 15 reference entities selected from Markit is 51,926 (28.13% of the total).

[4]According to the CreditTrade dataset, the number of quotes or trades on these 10 reference entities is 37,835 (20.49% of total).

[5]The sample CDS data of Altria, Comcast, and HCA commences on November 4 and December 31, 2003, and March 8, 2004, respectively.

[6]There are also conditional covariance equations, but they are not central to the research questions addressed in this article.

[7]In the interests of brevity, the figures for the impulse response analysis are not presented. They are available, however, from the authors on request.

[8]Hereafter, "previous days" refers to the influence of the conditional variance and "previous day" refers to the influence of the variance.

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