Good and Bad Credit Contagion: Evidence from Credit Default Swaps

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Abstract

This study examines the information transfer effect of credit events across the industry, as captured in the Credit Default Swaps (CDS) and stock markets. Positive correlations across CDS spreads imply dominant contagion effects, whereas negative correlations indicate competition effects. We find strong evidence of dominant contagion effects for Chapter 11 bankruptcies and competition effect for Chapter 7 bankruptcies. We also introduce a purely unanticipated event, which is a large jump in a company's CDS spread, and find that this leads to the strongest evidence of credit contagion across the industry. These results have important implications for the construction of portfolios with credit-sensitive instruments.

JEL Classifications: G14 (Market Efficiency), G18 (Policy and Regulation), G33 (Bankruptcy)

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1. Introduction

In recent years, the financial industry has made tremendous progress in credit risk modeling. Building on advances in market risk models, financial institutions are now developing quantitative tools to manage the credit risk of their overall portfolio. The key insight of these models is that risk needs to be measured in the context of a portfolio, instead of on a stand-alone basis. Their main difficulty, however, is the measurement of correlations for extreme credit events, which are by definition relatively rare but nevertheless drive the tails of the credit loss distributions.

Oftentimes, credit events seem to cluster.[1] Such positive correlations can be defined as "credit contagion," but surely must depend on the characteristics of the credit event, as well as of the company and industry. Credit contagion has important consequences for the construction of credit-sensitive portfolios for the banking and investment management industry. For example, the pricing and risk measurement of Collateralized Debt Obligations (CDOs) requires quantifying correlations among underlying credits, and in particular, accounting for the heavy tails possibly induced by contagion dynamics. Indeed, investors in CDOs incurred large losses in May 2005 when Standard and Poor's, a credit rating agency, downgraded General Motors and Ford to speculative grade. These unexpected losses were due to deficient assumptions about credit risk correlations.

Once portfolio risk is measured, it can be managed. The heightened interest in credit risk explains the phenomenal growth of credit derivatives market, which by now exceeds

[1] For example, Moody's reports that default rates reached 3.7% in 2001, which is a "statistical extreme." In the previous 30 years, the average default rate was 1.2% only. There is also industry clustering: In 2002, the telecommunication sector accounted for 56% of all corporate bankruptcies in terms of dollar debt defaulted, or 31% of all issuers.

$12,400 billion in notional amount, up from $40 billion only in 1996.[2] These new instruments, such as Credit Default Swaps (CDSs), allow institutions to exchange their credit risks and are essential tools for the management of credit risk.

At the same time, the CDS market provides a high-quality data source for the measurement of credit risk, heretofore not available. Previous studies on contagion have exclusively used stock prices, which are useful for some purposes but have only limited applications to the risk measurement of corporate debt portfolios. This study uses the recently developed and increasingly liquid CDS market to assess intra-industry credit contagion.

A better understanding of credit contagion is crucial to the proper specification of default correlations in second-generation credit risk models.[3] In current portfolio credit risk models, default correlations across obligors are introduced through dependences on common risk factors only. Financial distress across companies is driven by *common economic factors*, such as negative shocks to cash flows across the industry. In particular, reduced-form models can incorporate correlations between defaults by allowing hazard rates to be stochastic and correlated with macroeconomic variables.

One issue, however, is whether such models can generate sufficient dependencies across obligors to fit the observed default patterns.[4] Das, Duffie, and Kapadia (2005) find evidence of excess clustering of credit events conditional on their set of common factors. More recent models try to account for this clustering. Some models add *counterparty risk*,

[2] From the June 2005 survey by the International Swaps and Derivatives Association (ISDA). Single-name credit default swaps are the most popular credit derivatives product, capturing 51% of the market share.
[3] A partial list of recent papers includes Duffie and Singleton (1999), Zhou (2001), Giesecke and Weber (2003), and Yu (2005). Crouhy et al. (2000) and Gordy (2000) provide a useful survey of the credit risk literature.
[4] Schonbucher and Schubert (2001) doubt whether default correlations reached within a restrictive common factor structure will be sufficient to fit the empirical data. Hull and White (2001) have similar concerns. Das, Duffie, and Kapadia (2005) test whether a doubly-stochastic model, which assumes the hazard rates are independent except through dependence on macroeconomic variables, can fit empirical default correlations. Their results generally rejected this assumption. Yu (2005), on the other hand, argues that a sufficiently rich factor structure could match the empirical level of default correlations.

which occurs when the default of one firm causes financial distress on other firms with which the first firm has close business ties.[5] Yet another class of models focuses on the *updating of beliefs*, which arises when investors learn from other defaults. For example, the failure of Enron led investors to reassess their views of the quality of accounting information from other firms. Collin-Dufresne, Goldstein and Helwege (2003) show that this can lead to a contagion risk premium.[6] Generally, a "contagion effect" implies positive default correlations.

There may be cases, however, of negative default correlations. As an example, Bethlehem Steel benefited from the demise of its major rival, LTV Corporation. This "competitive effect" arises because, with a fixed demand for the product, remaining firms can capture new clients from the displaced firms, or generally have more market power. Even before liquidation occurs, financial distress can generate competitive effects if customers become reluctant to do business with the affected firms, perhaps because of a loss of reputation for supplying high-quality products (Maksimovic and Titman (1991)).

These two effects, contagion and competition, may coexist with each other and the observed effect will be the net result of the two. The paper provides cross-sectional evidence on these two effects, using CDS and stock price data.

A unique feature of this study is the use of the CDS data. We use a comprehensive CDS daily spread dataset spanning the period from 2001 to 2004. A CDS seller provides insurance against default risk of a reference entity. In return, the protection buyer makes periodic payments. The annual payment that is expressed as a percentage of the notional value of a contract is called the CDS spread. This provides a direct measure of credit risk for the underlying reference entity from a very liquid market.

[5] See Davis and Lo (2001), Jarrow and Yu (2001).
[6] See also Giesecke (2004).

Moreover, CDS spreads are superior to corporate-Treasury bond yield spreads, which are sensitive to the choice of benchmark risk-free rate and may reflect other factors that are not related to default risk, such as tax differences between Treasury and corporate bonds.[7] Chen et al. (2006), for example, find that the cross-section of yield spreads is strongly related to liquidity indicators such as bond bid-ask spreads, which suggests that liquidity is an important component of bond yield spreads. Recent research by Blanco et al. (2005) and Zhu (2004) also provides empirical evidence that the CDS market leads the bond market in terms of price discovery. The CDS market is also complementary to the stock market because some credit events imply differing movements across these markets. An increase in leverage, for example, leads to higher credit risk or wider CDS spreads but can create a wealth transfer to shareholders, in which case the stock price appreciates. In this situation, stock prices cannot be good measures of credit risk, unlike the CDS market.

The previous literature has used bankruptcy filings as credit events.[8] In the United States, bankruptcies include Chapter 11 reorganization and Chapter 7 liquidation. Chapter 11 protects a firm from its creditors while it works out a formal plan of reorganization. It is designed to save supposedly economic viable firms that are in temporary distress. In contrast, Chapter 7 forces the liquidation of the distressed firm. Under Chapter 11, the bankrupt firm might reemerge with lower costs, e.g. from debt forgiveness and concessions from unions, which is unfavorable to competitors. As a result, we would expect stronger competitive effects under Chapter 7 than Chapter 11.

[7] See Elton et al (2001) for a structural explanation of the factors driving corporate bond yield spreads.
[8] Credit rating agencies include various events in their definition of default. Moody's, for example, includes (1) bankruptcy, (2) failure to pay interest and/or principal, and (3) a distressed exchange, which lowers the financial obligation or helps the borrower avoid default.

Our study significantly extends the work of Lang and Stulz (1992), who examine the intra-industry effect of Chapter 11 bankruptcies in the stock market. They report significant contagion effects from Chapter 11 bankruptcies based on 59 filings over the period 1970 to 1989. Chapter 7 bankruptcies seem to lead to competitive effects, but the sample size of 6 filings is too small to draw strong conclusions. Our sample is much larger, with 272 Chapter 11 bankruptcies and 22 Chapter 7 bankruptcies. This gives more precise estimates of bankruptcy effects. In addition, the observed effects are much stronger with CDS data than the usual equity data.

Another major advantage of CDS markets is that we can directly identify major credit events as jumps in CDS spreads.[9] In practice, bankruptcy filings are often anticipated by markets. This mutes the reaction of market prices to the final event. In this study, we also consider extreme upward jumps in CDS spreads, which we call "*jump events*." By definition, these must be largely unanticipated credit events and as a result, may give rise to stronger effects across industry competitors. We examine the effect of bankruptcies and jump events on the stock prices and CDS spreads of industry competitors. This is the first paper to examine credit events using jumps in the CDS market.

This paper makes a number of contributions to the literature. We find widely different patterns of industry CDS spread and stock price responses to these three credit events (Chapter 11 bankruptcies, Chapter 7 bankruptcies, and jump events). Our cross-sectional analysis also reveals that contagion and competition effects are reliably associated with industry characteristics. Such results can be used to further our understanding of credit correlations. In addition, we provide evidence that contagion effects are better captured in the

[9] This paper defines credit events more generally than those that trigger payments on credit derivatives (using the formal ISDA definition, this includes bankruptcy, failure to pay, and restructuring.) Here, jumps in the CDS spread are also defined as "credit events" even though they would not trigger payment on CDSs.

CDS market than the stock market. Finally, our work adds to the growing empirical research on credit default swaps, an interesting market in its own right.[10]

The remainder of this paper is structured as follows. Section 2 presents the research framework and hypotheses. Section 3 describes the data and explains research methods. Section 4 then presents the empirical findings. The conclusions are summarized in Section 5.

[10] Hull et al. (2004) examine whether the CDS market anticipates bond rating changes. Norden and Weber (2004) investigate the CDS and stock market reactions to credit rating announcements. Other recent empirical work on CDS includes Blanco et al (2005), Houweling and Vorst (2005), Longstaff et al. (2005), and Zhu (2004).

2. Research Hypotheses

The major concern of our study is whether a marked deterioration in the underlying creditworthiness of an issuer will negatively or positively affect the credit risk of its industry peers. Presumably, the effect will depend on the type of credit event, company, and industry. Because we want to focus on the tail of the credit risk distribution, we identify extreme credit events, selected as bankruptcies and large jump in CDS spreads.

Bankruptcies are indeed severe credit events but may be anticipated by the market. In contrast, jumps in CDS spreads, which we call "jump events," must be largely unanticipated. As an illustration, Figure 1 compares CDS spreads and equity prices for WorldCom before its bankruptcy on July 21, 2002. This represented the largest corporate default ever, measured in terms of assets. The CDS spread, however, had been moving up in anticipation of this event. It started at 120 basis points (bp) in January 2001, then moved up to 480bp in February 2002. On April 29, 2002, the spread jumped to 2050bp and continued to increase thereafter. Many of these movements are also reflected in the stock price. This example illustrates that much of the bad news had been incorporated in market prices before the bankruptcy. In this case, earlier jumps precede the bankruptcy and provide valuable indication that new information is reaching markets. As a starting point, we first examine the effect of bankruptcies.

[Insert Figure 1]

Chapter 11 Bankruptcies

A bankruptcy filing is an extreme credit event, leading to default on obligations. The U.S. bankruptcy code recognizes two forms of bankruptcy filings: Chapter 11 reorganization and Chapter 7 liquidation. We expect contagion effects to be stronger under Chapter 11 bankruptcies than under Chapter 7 as the firm may reemerge as a stronger competitor under Chapter 11.

This is due to the substantial rights bestowed by Chapter 11 to the distressed firm, so-called debt-in-possession (DIP).[11] Firms operating under Chapter 11 can enjoy important subsidies including additional financing resources from DIP creditors, lower debt costs, tax loss carry-forwards, concessions from unions and other stakeholders.[12] As a result, industry competitors will be hurt if reorganized firms emerge from Chapter 11 with lower costs.[13]

This leads to the first hypothesis:

H1: Chapter 11 bankruptcy filings should lead to a dominant contagion effect, or for industry rivals, wider CDS spreads and lower stock prices.

Chapter 7 Bankruptcies

In contrast, liquidation leads to termination of operations and complete exit from the industry. The forced exit should reduce industry overcapacity problem, allowing other firms to gain ground in a newly reshaped competitive landscape. Additionally, a Chapter 7 resolution of financial distress due to problematic capital structure or poor management will have a disciplinary effect for surviving firms in the industry. As a result, we conjecture stronger competitive effects for Chapter 7 than Chapter 11.

This leads to:

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[11] Debtor-in-Possession includes rights to retain control of the business, to propose a plan of reorganization in the first 120 days, to obtain extensions, to secure DIP financing, and non-unanimity requirements.

[12] Bronars and Deere (1991) and Dasgupta and Sengupta (1993) claim that financial distress can improve a firm's bargaining power with its unions and other stakeholders earning economic rents. White (1989) summarizes important subsidies to reorganizing firms coming from the government or creditors, which give them advantages over both liquidated firms and surviving firms. Chapter 11 firms can even launch a price war with surviving firms. For example, United Airlines has used Chapter 11 to cut worker wages and benefits significantly, to outsource more work and to dump underfunded pensions on a federal pension insurer.

[13] One recent example is the emergence of retailer giant Kmart. It secured abundant financing, shuffled its management team, and reduced its debt burden in the process of Chapter 11 reorganization. Its takeover of Sears indicates the rebirth of a strong competitor in the industry.

H2: Chapter 7 bankruptcy filings should lead to a dominant competition effect, or for industry rivals, narrower CDS spreads and higher stock prices. More generally, the contagion effects should be weaker than under Chapter 11.

Jump Events

A jump event represents a purely unanticipated credit shock. The question is how this shock is transmitted to other firms in the industry. We expect a stronger contagion effect for jump events than for Chapter 11 bankruptcy filings, for a number of reasons.

A jump event is a signal of credit deterioration. This could evolve in several ways. First, as argued by Collin-Dufresne et al. (2003), "many corporate bonds experience a large jump in their yield spreads without ever defaulting (e.g., the RJR LBO)." In this situation where the firm is not yet driven out of the market, industry rivals do not necessarily benefit from its difficulties.[14] This suggests weaker competitive effects.

Another possibility is bankruptcy, either in the form of Chapter 11 or Chapter 7. As we will see later, Chapter 11 bankruptcies are 12 times more frequent than Chapter 7 cases. Even when assuming identical unanticipated contagion and competition effects, the net effect would still be contagion because of the higher frequency of Chapter 11 bankruptcies. In addition, the industry-wide effect should be very strong because it is truly unanticipated. Later, when bankruptcy actually happens, markets are generally less surprised.

Collectively, these arguments lead to the following hypothesis:

H3: Jump events should lead to contagion effect, or for industry rivals, wider CDS spreads and lower stock prices. The effect should be stronger than for Chapter 11 bankruptcies.

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[14] Brander and Lewis (1988) explain that the economic rent gained by rivals should increase with the extent of financial distress of the affected firm

3. Data and Research Design

A. The Credit Default Swap Dataset

A credit default swap contract is the simplest type of credit derivative. The buyer of the contract makes periodic payments over the life of the contract, in exchange for protection against default or other credit events specified in the contract. The seller agrees to compensate the buyer for the difference between the par value and the market value of the reference bond if the reference entity experiences a credit event. Essentially, the CDS market allows the exchange of credit risk between financial institutions. As explained earlier, the rapid growth of this market has led to increased liquidity and large trading volume, which creates an opportunity to use meaningful transaction prices.

This paper uses CDS spreads taken from a comprehensive dataset from the Markit Group Limited. The original dataset provides daily quotes on CDS spreads for over 1,000 North American obligors from January 2001 to December 2004. Quotes are collected from a large sample of banks and aggregated into a composite number, ensuring reasonably continuous and accurate prices quotations.[15]

We use only the five-year spreads because these contracts are the most liquid and constitute over 85 percent of the entire CDS market. To maintain uniformity in contracts, we only keep CDS quotations for senior unsecured debt with a modified restructuring (MR) clause and denominated in U.S. dollars.[16] A firm is kept in the sample only if it has sufficient

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[15] The Markit Group collects more than a million CDS quotes contributed by more than 30 banks on a daily basis. The quotes are subject to filtering that removes outliers and stale observations. Markit then computes a daily composite spread only if it has more than three contributors. Once Markit starts pricing a credit, it will have pricing data generally on a continuous basis, although there may be missing observations in the data. Because of these features, the database is ideal for time-series analysis. These data have also been used by Zhu (2004) and Micu et al. (2004).

[16] The Modified Restructuring clause was introduced in the ISDA standard contract in 2001. This limits the scope of opportunistic behavior by sellers in the event of restructuring agreement to deliverable obligations with a maturity of 30 months or less. This clause applies to the majority of quoted CDS for North American entities.

pricing information once started, but not necessarily to the end as some firms exited the database, e.g. when a credit event triggers payment on the CDS.[17] This sample has 820 credits and 512,292 daily observations on CDS spreads.

Summary statistics on the CDS data are provided in Table I. The top panel describes the distribution of reference credits by year and credit rating. The number of quoted reference entities steadily increases over time, reflecting the growth of this market. The sample includes a wide range of credit ratings, from AAA to B or below. BBB-rated firms, using Standard and Poor's definitions, constitute the largest credit ratings group.

[Insert Table I]

The lower panel shows that on average a firm has 624 CDS daily data points. Even with daily trading, however, the CDS spread does not necessarily change from one day to the next, perhaps because there is no sufficiently new information to justify changing quotes. As the table shows, 37% of observations display no change from the previous day, on average.

Next, Table II describes summary statistics for CDS spreads and daily spread changes in Panels A and B. The average CDS spread is 185bp for this sample. There are variations across years, however, reflecting changing credit conditions. Spreads were higher in 2002 and lower in 2004. Some spreads can be quite high. The 99.9th percentile for spread levels is 5,480bp.[18] The average spread change is -0.46bp. The 99.9th percentile for spread increases is 97.5bp.

[Insert Table II]

[17] We discard companies with more than 50% missing observations between their first and final dates because this would create too many holes in the series.

[18] Such high numbers would indeed be justified by a high probability of a credit event in the near future. Suppose that a default was certain in 1 year, with zero recovery. It would then be necessary to charge a spread of 10,000 bp to cover the loss. If default would occur in 1 month, then the required annualized spread would be 120,000 bp, which would be collected for one month only. In practice, the CDS market becomes illiquid just before bankruptcy. When this is the case, however, the time series collected by Markit would stop.

B. Identification of Credit Events

The sample of credit events includes Chapter 11 bankruptcies, Chapter 7 bankruptcies, and jump events over the period 2001 to 2004. Chapter 11 bankruptcies are collected from the website www.bankruptcydata.com. Some tests involve an 11-day trading window, which could lead to some event clustering. To avoid this, we identify all consecutive events in the same three-digit industry and only keep the first observation within this window. Because we require pricing data in the CDS and CRSP, and COMPUSTAT dataset, the final Chapter 11 sample includes 272 public firms traded on the NYSE, AMEX, or NASDAQ. These cover 86 industries in terms of 3-digit SIC code. Table I in the Appendix describes the distribution of events for each industry, which ranges from 1 to 42 per industry.

Chapter 7 bankruptcies are hand collected.[19] This leads to a final sample of 22 filings by public firms covering 12 industries. This sample of 22 events is much smaller than for Chapter 11 bankruptcies. Of these, 10 are for the computer storage devices industry. So, there is much less dispersion for this sample, which will lead to less precise results.

To identify jump events, we consider all changes in daily CDS spreads above the 99.9th percentile value of 97.5bp. Large changes in CDS spreads, however, are more likely for firms that already have a low credit rating, or large spread. To include a broader spectrum of credit ratings, we only keep the top third of this group in terms of the relative change in spread. Finally, to minimize data overlap effects, we identify all consecutive events in the same three-digit industry and only keep the first observation within the 11-day window. This leads to a sample size of 170, covering 55 industries. The distribution of the CDS spread

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[19] This was done by searching keywords 'chapter 7 bankruptcy', 'chapter 7 liquidation', 'liquidation', 'cease operation', 'shutdown' in ABI/Inform for the sample period. The bankruptcy type and the filing date were confirmed in the EDGAR archives of the SEC.

changes for this sample is described in Panel D of Table II. These changes are only recorded over two consecutive days with non-missing observations.

Table III describes the distribution of credit events by year. Generally, the credit events are fairly spread out over all four years. About half of the jump events, however, occur during 2002. Also, Chapter 11 bankruptcies have occurred at a frequency that is more than ten times that of Chapter 7 bankruptcies.

[Insert Table III]

C. Construction of Industry Portfolios

The purpose of this study is to study the market reaction of industry competitors surrounding credit events. For each event, we construct an industry portfolio as an equally-weighted portfolio of firms satisfying the following conditions. Each firm must have (1) the same 3-digit SIC code of COMPUSTAT as the 'event' firm; (2) continuous daily CDS spread data around the event window, and (3) stock return data in the CRSP Daily database.

Table I in the Appendix describes the distribution of peer firms in the industry portfolio. On average, there are 5.6, 5.5, and 10.3 firms in the industry portfolio for Chapter 11, Chapter 7, and jump events respectively. For the whole sample, the industry portfolio contains about 7 firms on average. The distribution of CDS spreads for this industry sample is described in the Panel C of Table II. This sample only uses firms with continuous data over the 11-day event window.

D. Measures of Industry Responses

To test for changes in credit risk of industry rivals around credit events, we apply the standard event study method to the CDS spread of industry portfolios. We calculate industry *Cumulated CDS Spread Changes* (CSCs) for a time interval [t_1, t_2] as the CDS spread of the industry portfolio for day t_2 minus that for day t_1, where t_1 and t_2 are the number of days relative to the event date. We calculate the cross-sectional mean and standard deviation for CSCs for the full sample, e.g. of 272 industries for Chapter 11 bankruptcies. T-statistics are computed in the standard way. In addition, we report the percentage of positive values.

We also report measures that are adjusted for general market conditions, as proxied by the same credit rating, to obtain the rating-adjusted CDS spread (*AS*). For firm *j* with rating *r* at time *t*, AS_{jt} is defined as: $AS_{jt} = S_{jt} - I_{rt}$, where S_{jt} denotes the CDS spread of reference entity *j* at day *t*, and I_{rt} denotes that of the equally-weighted CDS index of rating *r* at day *t*. The index *r* refers to the broad rating category AAA and AA, A, BBB, BB, and B or below B, with *r* = 1,2,3,4, 5, respectively. For each event, CASCs are calculated as $CASC_j(t_1, t_2) = AS_{jt_2} - AS_{jt_1}$, and then processed as before.

This adjustment is similar to measuring equity returns in excess of the market. It will, however, understate contagion effects because these feed into the CDS spreads of the ratings index. In addition, the number of components of the ratings index is considerably less than the number of stocks in a typical equity index, which can bias the CASC toward zero, because the same entities may appear in the industry portfolio and ratings index. For instance, Table I shows there are only 32 entities in the index rated B or below in 2001. The average industry portfolio contains about 7 firms. Assuming that they are all B-rated, the overlap is more than 20% (7 out of 32). This overlap between the industry portfolio and ratings index will bias the CASC toward zero.

Finally, we also report results using conventional stock prices. For each industry portfolio, we replace the CDS data by equity price data. Abnormal returns are computed from a market model estimated over the period [-252,-21], prior to the event. We then aggregate the time series across our various credit events, following MacKinlay (1997).

4. Empirical Results

A. CDS Market Reactions of Industry Rivals to Credit Events

The main contribution of this paper is a detailed comparison of industry reactions to credit events conditional on event types. The principal results are presented in Table IV. Panel A, B and C report industry rivals CDS spread reactions around Chapter 11 bankruptcies, Chapter 7 bankruptcies, and jump events, respectively. The left panels report the distribution of spread changes, CSCs; the right panels report the distribution of abnormal spread changes, CASCs. For each case, the table reports cumulative effects over 3-day and 11-day windows.

[Insert Table IV]

Chapter 11 Bankruptcies

Panel A reports the effect of Chapter 11 bankruptcies. Overall, contagion effects are dominant. The average CSC for industry portfolios is positive, at 1.84bp for the 3-day event window and 4.82bp for the 11-day event window. Both numbers are significantly different from zero at the 5% level.[20] Similar results are observed with CASCs, but the numbers are closer to zero, as expected. Thus, the credit risk of industry competitors increases when a company files for Chapter 11 bankruptcy. This confirms the results in Lang and Stulz (1992) that contagion effects dominate Chapter 11 bankruptcies, based on 59 filings. Our results, however, focus on effects on credit default swap spreads rather than equity prices.

Chapter 7 Bankruptcies

Panel B reports the effect of Chapter 7 liquidation bankruptcies. As predicted, competition effects are dominant. The average CSCs for industry portfolios is negative, at –1.61bp (–3.21bp) for the three (eleven) day event window, with the first one statistically significant. Similarly, average CASCs are also negative. Thus, the credit risk of industry competitors decreases when a company files for Chapter 7 bankruptcy. These results confirm our hypothesis that industry rivals benefit from the liquidation of their competitors.

Jump Events

Panel C reports the effect of jump events on industry competitors. The table shows a very strong positive effect, which means that the credit spread of competitors increases significantly. The average CSCs is 5.25bp (13.03bp) for the three (eleven) day window, respectively. The magnitude is several times that for Chapter 11 bankruptcies. Thus, the credit risk of industry competitors increases when a company experiences a jump event. As hypothesized, the contagion effect is even stronger than with Chapter 11. This is because the firm affected is still far from default, on average, which rules out competitive effects. In addition, the event is truly unanticipated, unlike the actual bankruptcy which is generally not a surprise by the time it happens.

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[20] For the CSCs, the fraction of changes that is positive is greater than 50 percent over the event day. Over longer intervals, the fraction of positive changes is slightly less than 50 percent. This difference with the significant average reflects data skewness.

Overall Comparison

Taken together, we find that the impact of credit events on default risk of industry rivals depends heavily on the type of triggering credit event. Contagion effects are strongest for jump events, then Chapter 11 bankruptcies. On the other hand, competition effects dominate Chapter 7 bankruptcies. These results are in accord with the hypotheses.

Panel D in Table IV provides tests of statistical significance in differences of industry responses. The tests involving Chapter 7 are significant for CSCs.

B. Stock Market Reactions of Industry Rivals to Credit Events

The existing empirical contagion literature exclusively focuses on the stock market.[21] This was primarily for data considerations. As corporate bond markets are rather illiquid, it is difficult to find good quality daily bond data across a wide spectrum of issuers. This problem is largely solved, however, with the CDS market.

For equities, a negative (positive) change in abnormal for industry portfolio is indicative of contagion effects (competitive effects). Table V compares the mean of the equity CARs to those of the CDSs.

[Insert Table V]

As shown in the table, the direction of industry responses in the stock market has systematically the opposite sign to the CDS market. This is as expected. On average, the industry equity 3-day CAR is -0.08% for Chapter 11 bankruptcies, +0.44% for Chapter 7 bankruptcies, and -0.56% around jump events. For Chapter 11 bankruptcies and jump events,

[21] See, for example, Aharony and Swary (1983, 1996), Lang and Stulz (1992), Slovin et al. (1999), Polonchek and Miller (1999).

the negative sign indicates a net contagion effect, which is consistent with the observed increase in CDS spreads. For Chapter 7 bankruptcies, the positive sign indicates a net competition effect, which is consistent with the observed reduction in CDS spreads.

It is interesting to note, however, that reactions in equity markets are barely statistically significant. The 11-day return of -0.41% for Chapter 11 bankruptcies is similar in magnitude to the -1.07% number reported by Lang and Stulz (1992) over the same 11-day period, but has a t-statistic of only -0.92. The t-statistic for the CDS market and same events is 2.42, which is much higher. Likewise, for jump events, the 11-day equity effect is barely negative, while the CDS effect is extremely strong. This indicates that CDS spreads are more sensitive to downside risk than equity prices. Another interpretation is that stock prices are much more volatile and "noisy" than CDS spreads, thus leading to less powerful tests.

C. Cross-Sectional Reactions

This section examines to what extent contagion and competitive effects are related to industry and firm characteristics. To this end, we estimate cross-sectional regressions where the dependent variable is the 3-day CSC around the event date, for our three event types. The model is:

$$CSC_j = \alpha_0 + \beta_1 CORR_j + \beta_2 HERF_j + \beta_3 LEV_j + \beta_4 SIZE_j + \varepsilon_j \qquad (1)$$

where

- CORR is the correlation of equity returns between the portfolio of industry rivals and the event firm for twelve months preceding the credit event,
- HERF is the average industry Herfindahl index over previous four quarters, computed as the sum of the squared fractions of each individual firm sales over total sales of the

industry (higher values mean more concentrated industries),

- LEV is the average leverage ratio of the industry portfolio during the previous 12 months,
- SIZE is the natural log of the total liabilities of the distressed firm.

The three industry variables were also used by Lang and Stulz (1992). Contagion effects are expected to be greater among industries with greater similarities of cash flows. This is proxied by equity correlations. As a result, the coefficient on CORR is hypothesized to be positive. Next, competition effects are expected to be stronger for industries that are more concentrated, or with a high Herfindahl index. Companies are more likely to benefit from the exit of a competitor that dominates the industry. As a result, the coefficient on HERF should be negative. Next, LEV is the leverage of the industry portfolio. We expect more highly levered industries to be more affected by contagion effects, so the coefficient on LEV should be positive.

Finally, SIZE is a company specific-factor, which is the size of the distressed firm. A Chapter 11 bankruptcy for a large firm will convey more information about commonalities in cash flows, leading to greater contagion effects. In contrast, a Chapter 7 bankruptcy of a large firm will allow other firms to grab a large market share, leading to greater competition effects. So, the sign should be positive for the Chapter 11 and jump events, but negative for Chapter 7 events. Results are presented in Table VI.

[Insert Table VI]

As predicted, the coefficients on CORR are all positive and generally significant, indicating contagion effects. The HERF coefficient is negative for Chapter 11 bankruptcy as expected, and significant. For other events, the coefficient is positive but not significant. For jump events, the coefficient on LEV is positive, as predicted, and significant. For Chapter 11 bankruptcy, the coefficient on SIZE is positive, as expected, and significant. Overall, significant effects are in the predicted direction. So, even though we observe substantial heterogeneity in unconditional effects across the three types of credit events, the cross-sectional analysis confirms the importance of these variables. It is interesting to note that the combination of greater sample size and CDS data leads to much greater precision than in previous studies.[22]

D. Implications for Diversification

Overall, this evidence should improve our understanding of intra-industry contagion and competition effects substantially. This should help risk managers build credit portfolios that are less affected by contagion dynamics, or experience less extreme losses, using the predetermined variables used in the cross-sectional regression. For instance, a portfolio of firms with low equity correlations and high Herfindahl index should experience weaker contagion effects and stronger competition effects than otherwise. This should lead to lower portfolio risk when extreme events occur.

We now explore how these results can be used to control the risk of portfolios of CDS contracts. To keep the experiment simple, we only examine portfolios including the distressed firm and the peer industry portfolio. Because bankrupt firms do not have CDS data, we restrict the analysis to jump events. Returns are measured in terms of relative changes in the CDS spreads. The variance of a CDS portfolio during a jump event can be derived from the cross-section of events. Assigning equal weight on each observation and defining N as the number of observations, the average daily variance is

[22] In the Lang and Stulz (1992) study, the highest t-statistic for these variables had a value of 1.85.

$$\sigma^2 = \frac{1}{3}\frac{1}{(N-1)}\sum_{i=1}^{N}(R_i - \bar{R})^2 \qquad (2)$$

where R_i is the raw 3-day return around event window i, and σ has been normalized to a 1-day risk measure. This can be computed across the 170 jump events, with resulting volatility given by σ_F for a distressed firm F. Similarly, define σ_I as the volatility of the industry portfolio I, σ_P as the volatility of a portfolio P equally invested in the firm and the industry portfolio, and $\sigma_{F,I}$ as the covariance between F and I. Using the information in this paper, we seek to construct portfolios with lower credit risk.

The "ex post," or out-of-sample, diversification benefits across the distressed firm and its industry peers can be measured by the coefficient

$$\rho = \frac{\sigma_{F,I}}{\sigma_F \times \sigma_I} \qquad (3)$$

Table VII presents the average cross-sectional volatility of distressed firms, peer industry indices, combined portfolios, and the correlation. The top panel includes the full sample of 170 observations. We sort the sample into events conditioned by characteristics above and below the median, using prior-year equity correlation (CORR), Herfindahl index (HERF), firm size (SIZE), and industry leverage (LEV). Focusing first on the column with the correlation ρ, we see that high HERF, low SIZE, and low LEV produce lower ex post correlations, as expected. In fact, sorting by these variables produces greater dispersion in ρ than sorting by equity correlations (CORR). For instance, high HERF portfolios, representing more concentrated industries, have average correlation between firms and industries of 0.14 only, versus 0.28 for low HERF portfolios. This greater diversification effect, however, is offset by a higher firm volatility for the high HERF, low SIZE, and low

LEV groups, so that we end up with greater portfolio risk, as indicated in the column with portfolio volatility.

In the second panel, we attempt to control for this firm volatility by sorting firms according to their prior-year CDS volatility and keeping only a subsample with a narrow range of historical CDS volatility, falling between the 25^{th} and 75^{th} percentile of the sample. This procedure should help reduce the distortions created by observations with extreme volatility and is still based on prior information. Now, the portfolio volatility effects are all in line with expectations. Consider, for instance, the sorting based on HERF index. The high HERF portfolio has volatility of 8.2%, against volatility of 9.9% for the low HERF portfolio. This lower volatility reflects stronger competition effects in the first portfolio, thus confirming the usefulness of our analysis. Similarly, sorting by low SIZE and low LEV produces less risky portfolios. Hence, these empirical results should help risk managers build better credit portfolios.

[Insert Table VII]

5. Conclusions and Implications

Das, Duffie, and Kapadia (2005) indicate that it is particularly important to check whether current credit risk models are consistent with observed contagion dynamics. To provide a solid empirical foundation for such models, this paper examines information transfer effects within industries around different types of credit events.

Using a novel database of CDS spreads, the paper shows that intra-industry effects depend on the type of credit event. Chapter 11 bankruptcies create contagion effects, as indicated by increases in spreads of industry competitors. On the other hand, Chapter 7 bankruptcies are associated with significant competitive effects. Similar patterns are also observed from equity prices, albeit more muted and less precisely estimated.

We also extend the literature by investigating industry responses around jump events. These are measured from jumps in spreads and are more relevant for portfolios that are marked to market, rather than simply dependent on default events. We find the strongest contagion effects yet for jump events. Cross-sectional analysis reveals that contagion and competition effects can be reliably predicted from industry variables.

The empirical findings of this study can be used to improve the specification of default correlations. Theoretical models should be developed and calibrated so that they can replicate the information transfer effects observed here. For the financial industry, these results can be used to construct better diversified credit portfolios. This is of particular interest to bank risk managers and bank regulators. For example, the level of economic capital required to support levered credit-sensitive portfolios is driven by the shape of the loss distribution, which reflects credit contagion dynamics.

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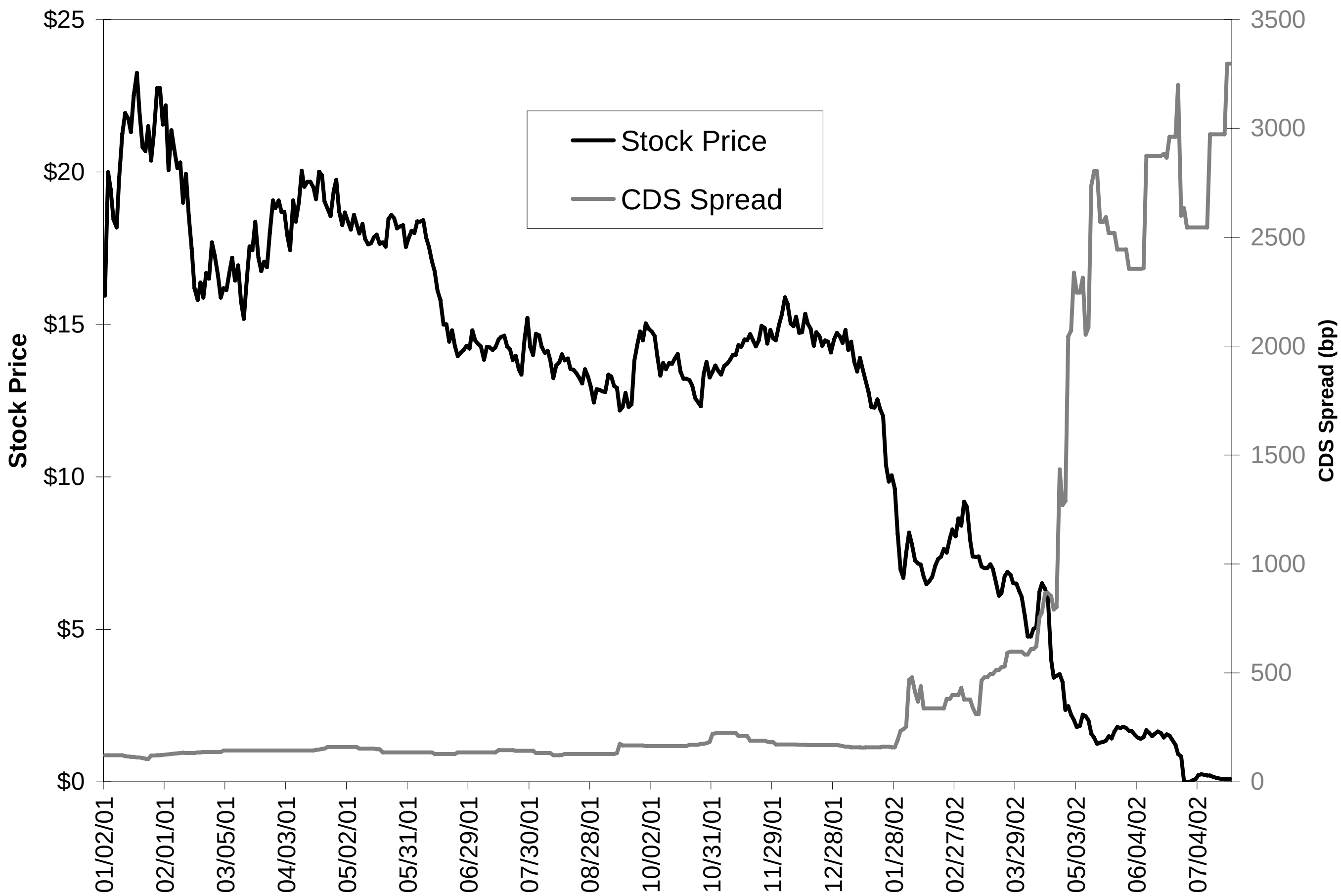

Figure 1: CDS Spread and Stock Price of WorldCom Inc.

Table I
Summary Statistics of the CDS Dataset

The CDS dataset spans the period from January 2001 through December 2004. The top panel reports the number of underlying credits by year and by Standard & Poor's rating for our sample. The bottom panel describes the distribution of the number of CDS observations for a firm, as well as that of the percentage of daily observations with no change. All contracts have a 5-year maturity.

Panel A: Rating Distribution of Number of Underlying Reference Entities

Year	AAA, AA	A	BBB	BB	B or below	Total
2001	19	71	128	39	32	289
2002	41	148	229	61	46	525
2003	55	181	312	96	72	716
2004	59	193	342	124	85	803
Number of firms	60	195	344	126	95	820

Panel B: Summary Statistics for the Number of CDS Observations for a Firm

	Mean	Std Dev	Median	Max	Min
All Firms	624	281	665	1044	99
Percentage of observations with no change	37%	14%	36%	85%	1%

Table II

Summary Statistics for CDS Spreads and Spread Changes (Basis Points)

This table reports summary statistics for the CDS spreads and spread changes in basis points, by year and for the total sample. Each panel reports the mean, standard deviation, median, maximum, minimum, and selected percentiles. The third panel reports the distribution of observations that are used for the industry portfolio over the event windows. The last panel reports the distribution of observations in the top 99.9th percentile used for jump events.

Panel A: Summary Statistics of CDS Spreads by Year (bp)

Year	N	Mean	Std Dev	Median	Max	Min	p99	p99.9
2001	47,764	178	266	104	4,105	12	1,042	3,425
2002	109,556	304	787	118	19,967	12	3,227	9,500
2003	153,480	181	384	65	19,082	5	1,560	4,050
2004	201,492	126	246	50	6,899	5	1,195	2,649
Total	512,292	185	460	71	19,967	5	1,764	5,480

Panel B: Summary Statistics for CDS Spread Changes by Year (bp)

Year	N	Mean	Std Dev	Median	Max	Min	p99	p99.9
2001	47,519	0.19	8.5	0.0	473	-330	21.7	79.2
2002	109,289	-0.34	39.9	0.0	4350	-5950	44.2	188.1
2003	153,297	-0.93	19.9	0.0	1540	-1761	13.8	72.8
2004	201,367	-0.32	15.5	0.0	1267	-2135	19.7	88.7
Total	511,472	-0.46	23.7	0.0	4350	-5950	24.9	97.5

Panel C: Summary Statistics for CDS Spreads in the Industry Sample (bp)

Year	N	Mean	Std Dev	Median	Max	Min	p99	p99.9
2001	3,132	179	203	115	2,839	17	964	1,138
2002	13,305	346	488	163	3,706	14	2,761	3,689
2003	10,450	189	341	76	3,700	9	1,626	3,600
2004	13,721	130	190	59	2,338	5	951	2,184
Total	40,608	219	362	93	3,706	5	1,800	3,625

Panel D: Summary Statistics for Daily CDS Spread Changes for Jump Events (bp)

	N	Mean	Std Dev	Median	Max	Min
Total	170	326.0	426.4	194.0	4350	98

Table III
Description of Credit Events

This table reports the number of credit events per year. Chapter 11 bankruptcies are obtained from the website www.bankruptcydata.com. Chapter 7 bankruptcies are hand collected from ABI/Inform. A "jump event" is defined as a daily increase in the CDS spread that is greater than the 99.9th percentile of the distribution for the whole sample (97.5 bp) and, within this group, in the top third of the relative change in spread.

Frequency of Credit Events by Year

Type	2001	2002	2003	2004	Total
Chapter 11 Bankruptcy	67	80	85	40	272
Chapter 7 Bankruptcy	6	6	5	5	22
Jump Event	9	82	23	56	170
Total	82	168	113	101	464

Table IV
Effect of Credit Events on Industry CDS Spreads

The table compares the industry effects of Chapter 11 bankruptcies, Chapter 7 bankruptcies, and jump events over the period 2001 to 2004. An industry portfolio is an equally-weighted portfolio of firms with the same 3-digit SIC code ('Header SIC Industry Group' in CRSP) as the distressed firm and for which CDS data are available. CSC is the cumulative change in the CDS spread for the industry index over a day or time interval. CASC is adjusted for movements in the average spread for the same credit rating.
The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. The "% (>0)" entry indicates the percentage of observations with positive or zero values. Panel D reports tests of equal effects across credit events.

Panel A: Chapter 11 Bankruptcy (N=272)

	CSC			CASC		
Day	**Mean**	**t-stat.**	**% (>0)**	**Mean**	**t-stat.**	**% (>0)**
-5	0.18	0.55	52.2	0.24	0.65	47.1
-4	0.08	0.45	56.6	0.16	0.53	52.2
-3	-0.06	-0.27	55.9	-0.08	-0.33	47.1
-2	0.25	1.67	56.6	0.11	0.50	52.9
-1	0.29	1.28	51.8	0.09	0.36	52.2
0	0.28	1.07	54.4	0.25	0.76	52.9
1	1.26	2.54**	54.8	1.20	2.62***	50.0
2	0.55	1.32	56.6	0.56	1.34	53.3
3	0.53	1.99**	57.4	0.70	2.17**	56.6
4	0.41	1.36	57.4	0.40	1.26	55.5
5	1.02	2.76***	58.8	1.10	2.88***	55.5
-1,1	1.84	2.44**	47.8	1.53	2.13**	50.4
-5,5	4.82	2.42**	45.6	4.72	2.62***	54.4

Panel B: Chapter 7 Bankruptcy (N=22)

	CSC			CASC		
Day	**Mean**	**t-stat.**	**% (>0)**	**Mean**	**t-stat.**	**% (>0)**
-5	-0.71	-1.09	40.0	-3.79	-1.33	54.5
-4	-0.62	-0.61	27.8	0.24	0.18	61.9
-3	0.51	0.72	58.8	-0.65	-0.82	50.0
-2	1.47	1.29	41.2	3.02	0.98	40.9
-1	-0.44	-1.00	35.7	-1.34	-1.15	54.5
0	-0.47	-1.43	42.9	0.46	0.84	61.9
1	-0.69	-1.73	18.8	-0.44	-0.53	47.6
2	-1.30	-1.31	35.3	-0.79	-0.70	40.9
3	-0.12	-0.17	28.6	0.58	0.74	54.5
4	-0.53	-0.98	33.3	-4.53	-1.53	40.9
5	-0.30	-0.42	13.3	1.55	1.45	68.2
-1,1	-1.61	-2.43**	33.3	-1.32	-0.94	45.5
-5,5	-3.21	-1.29	36.4	-5.71	-1.42	63.6

Table IV (Continued)

Panel C: Jump Event (N=170)						
		CSC			**CASC**	
Day	**Mean**	**t-stat.**	**% (>0)**	**Mean**	**t-stat.**	**% (>0)**
-5	-1.32	-1.00	53.5	-1.55	-1.17	46.5
-4	0.62	1.12	61.2	0.17	0.32	41.8
-3	-0.13	-0.33	55.3	-0.16	-0.42	48.8
-2	0.83	1.73	58.8	0.55	1.18	51.2
-1	0.49	1.29	58.2	-0.16	-0.41	48.2
0	2.85	2.93***	64.1	1.70	1.81	49.4
1	1.90	2.45**	57.1	1.24	1.66	47.1
2	4.44	1.79	53.5	4.26	1.76	54.7
3	0.86	0.99	58.2	0.92	1.08	52.9
4	1.62	1.49	61.8	1.39	1.37	57.1
5	0.76	0.81	53.5	0.42	0.45	52.4
-1,1	5.25	3.08***	56.5	2.78	1.73	48.2
-5,5	13.03	2.30**	54.1	8.85	1.66	51.8

Panel D: Comparisons of Industry Effects						
	Chapter 11 Chapter 7		Chapter 11 Jump Event		 Chapter 7 Jump Event	
3-Day Difference	CSC	CASC	CSC	CASC	CSC	CASC
Average	3.44	2.85				
(t-statistic)	(3.44)***	(1.80)				
Average			-3.41	-1.25		
(t-statistic)			(-1.83)	(-0.71)		
Average					-6.86	-4.09
(t-statistic)					(-3.76)***	(-1.92)

Table V
Comparisons of Contagion Effects between the CDS Market and the Stock Market

CAR is the cumulative abnormal equity return, defined using a market model residual and in percent. CSC is the cumulative daily change in the CDS spread, in basis points. The t-statistic is computed following MacKinlay (1997) and is between parentheses; ***, ** and * indicates significance at 1%, 5% and 10% two-tailed levels, respectively. An industry competitor portfolio is an equally-weighted portfolio of firms with the same primary 3-digit SIC code as the distressed firm and for which CDS data are available. The sample consists of 272 Chapter 11 bankruptcies, 22 Chapter 7 bankruptcies, and 170 jump events between 2001 and 2004.

Event	Chapter 11 Bankruptcy		Chapter 7 Bankruptcy		Jump Event	
Day /Window	Equity CAR	CDS CSC	Equity CAR	CDS CSC	Equity CAR	CDS CSC
-5	0.10	0.18	0.50	-0.71	-0.04	-1.32
	(0.73)	(0.55)	(1.08)	(-1.09)	(-0.34)	(-1.00)
-4	-0.12	0.08	-0.31	-0.62	-0.11	0.62
	(-0.88)	(0.45)	(-0.67)	(-0.61)	(-0.92)	(1.12)
-3	-0.10	-0.06	-0.24	0.51	-0.16	-0.13
	(-0.75)	(-0.27)	(-0.52)	(0.72)	(-1.26)	(-0.33)
-2	0.00	0.25	-0.35	1.47	-0.02	0.83
	(-0.14)	(1.67)*	(-0.76)	(1.29)	(-0.14)	(1.73)*
-1	0.04	0.29	0.75	-0.44	-0.22	0.49
	(0.29)	(1.28)	(1.63)	(-1.00)	(-1.84)*	(1.29)
0	-0.03	0.28	0.13	-0.47	-0.21	2.85
	(-0.22)	(1.07)	(0.27)	(-1.43)	(-1.68)*	(2.93)***
1	-0.09	1.26	-0.43	-0.69	-0.13	1.90
	(-0.69)	(2.54)**	(-0.90)	(-1.73)*	(-1.02)	(2.45)**
2	0.17	0.55	-0.15	-1.30	0.44	4.44
	(1.25)	(1.32)	(-0.32)	(-1.31)	(3.62)***	(1.79)*
3	-0.06	0.53	-0.56	-0.12	0.29	0.86
	(-0.41)	(1.99)**	(-1.06)	(-0.17)	(2.36)**	(0.99)
4	-0.19	0.41	-0.38	-0.53	0.04	1.62
	(-1.38)	(1.36)	(-0.82)	(-0.98)	(0.30)	(1.49)
5	-0.13	1.02	-0.77	-0.30	0.09	0.76
	(-0.92)	(2.76)***	(-1.69)	(-0.42)	(0.73)	(0.81)
[-1,1]	-0.08	1.84	0.44	-1.61	-0.56	5.25
	(-0.35)	(2.44)**	(0.55)	(-2.43)**	(-2.62)**	(3.08)***
[-5,5]	-0.41	4.82	-1.83	-3.21	-0.02	13.03
	(-0.92)	(2.42)**	(-1.17)	(-1.29)	(-0.06)	(2.30)**

Table VI
The Impact of Industry and Firm Characteristics on Industry Rivals' CDS Spread Reactions

This table presents the coefficient estimates of cross-sectional regressions for each type of credit event:

$$CSC_j = \alpha_0 + \beta_1 CORR_j + \beta_2 HERF_j + \beta_3 LEV_j + \beta_4 SIZE_j + \varepsilon_j$$

The estimates are from an OLS regression. Heteroskedasticity robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Independent Variables	Expected Sign	Chapter 11 Bankruptcy	Chapter 7 Bankruptcy	Jump Event
		Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Constant		-1.92	-5.00	-27.40
		(-0.90)	(-2.98)***	(-1.80)*
CORR	+	24.46	2.39	19.86
		(3.51)***	(0.31)	(2.35)**
HERF	–	-12.94	11.31	13.40
		(-2.08)**	(1.16)	(0.63)
LEV	+	-0.39	0.82	23.36
		(-0.08)	(0.16)	(1.93)*
SIZE	+/–/+	0.77	0.60	1.57
		(2.20)**	(1.54)	(0.96)
R-square (%)		11.10	22.42	7.49
R-square adj. (%)		9.77	4.16	5.24
p-value for F-stat		(<0.0001)***	(0.3359)	(0.0117)**
# of Obs.		272	22	170

Variable definitions:

CSC is the dependent variable, defined as the cumulated CDS spread change of the industry portfolio for the [-1,1] daily interval around the event; CORR is the correlation of equity returns between the portfolio of industry rivals and the ‘event’ firm for twelve months preceding the credit event; HERF is the industry Herfindahl index, computed as the sum of the squared fractions of each individual firm sales over total sales of the industry (higher values mean more concentrated industries); LEV is the average leverage ratio of the industry portfolio during the preceding year; SIZE is the natural log of the total liabilities of the distressed firm.

Table VII

Comparisons of Portfolio Risk across Jump Event Windows

This table reports the cross-sectional average of the volatility for firms with jump events, peer industry indices, and equally-weighted portfolios invested in both. The average correlation coefficient between the firm and industry index is also displayed. These measures are "ex post," or over the event window. Returns are measured as CDS spread relative changes over a 3-day period around the jump event; volatility is adjusted to a daily measure. The sample is then sorted into observations with measures above and below the median: prior-year equity correlation (CORR), Herfindahl index (HERF), distressed firm size (SIZE), and industry leverage (LEV). Higher HERF means more concentrated industries.

The second panel uses a subsample with a narrow range of historical CDS volatility for distressed firms, falling between the 25th and 75th percentile of the sample. The historical volatility is calculated as the time series volatility of the CDS spread relative changes over an annual period prior to the jump event.

	Volatility (%)		Correlation	Volatility (%)	# of
	Firm	Industry	ρ	Portfolio	Obs.
Full Sample	21.4	3.8	0.19	11.2	170
High CORR	20.4	4.0	0.19	10.8	85
Low CORR	22.5	3.5	0.20	11.7	85
High HERF	23.9	4.1	0.14	12.4	85
Low HERF	18.4	3.5	0.28	9.8	85
High SIZE	19.7	3.5	0.33	10.6	85
Low SIZE	22.9	4.0	0.10	11.8	85
High LEV	18.2	3.7	0.22	9.7	85
Low LEV	23.8	3.9	0.18	12.4	85
Subsample with Narrow Range of Historical CDS Volatility	16.6	3.7	0.34	9.1	86
High CORR	17.5	3.4	0.39	9.5	43
Low CORR	15.8	4.0	0.29	8.7	43
High HERF	15.0	4.1	0.25	8.2	43
Low HERF	18.2	3.2	0.45	9.9	43
High SIZE	18.6	3.5	0.40	10.1	43
Low SIZE	14.5	3.9	0.27	8.0	43
High LEV	17.5	3.4	0.38	9.6	43
Low LEV	15.5	3.9	0.28	8.5	43

Appendix -Table I
List of Industries and Distribution of Firms in the Industry Portfolio

			Number of Peer Firms within Industry Portfolio				
Event Type	N of Industries	N of Events	Mean	Std Dev	Median	Max	Min
CHAPTER 11	86	272	5.6	5.7	4	33	1
CHAPTER 7	12	22	5.5	5.4	4	22	1
JUMP	55	170	10.3	10.0	7	42	1

		Chapter 11		**Chapter 7**		**Jump**	
Name	SIC	N of Events	Mean Nb of Firms	N of Events	Mean Nb of Firms	N of Events	Mean Nb of Firms
Gold and Silver Ores	104	3	2				
Crude Petroleum & Natural Gas	131	4	8			3	15
Oil, Gas Field Services	138	7	8			3	5
Operative Builders	153					1	4
Meat Packing Plants	201					1	1
Special Industry Machinery	202			1	1		
Can, Frozen Preserve Fruit & Vegetable	203	1	1				
Food and Kindred Products	205	1	1				
Men, Youth, Boys, Work Clothing	232	2	2				
Women’s, Misses, Juniors Outerwear	233	1	1				
Wood Household Furniture	251	1	1				
Public Building Furniture	253					1	1
Paper Mills	262					2	7
Paperboard Mills	263	2	4				
Plastic, Foil, Coated Paper Bags	267	1	1			1	1
Periodical: Publishing & Print	272					1	1
Books: Publishing & Printing	273					2	1
Records, Audio Tape, Disk	274	1	1				
Industrial Inorganic Chemicals	281	3	4			3	3
Industrial Organic Chemicals	282					1	3
Pharmaceutical Preparations	283	8	10	1	13		
Drugs and Proprietary	284	1	6				
Plastic Material, Industrial Organic Chemicals	286					7	4
Natural Gas Transmission	287	1	4			3	2
Petroleum Refining	291			1	9	1	11
Misc. Chemical Products	308	3	2				
Electronic Components	322	1	1			1	1
Steel Works & Blast Furnaces	331	10	2			2	3
Iron and Steel Foundries	332	2	2			1	2
Rolling & Draw Nonfer Metal	333	1	3			1	1
Heating Equipment, ex Electronic, Air	343	1	1				
Fabricated Plate Work	344	1	1				
General Industrial Machinery & Equipment	349	2	3			2	2
Heavy Construction	351					2	2
Farm Machinery and Equipment	352					1	2
Construction Machinery & Equipment	353					2	7
Metalworking Machinery & Equipment	354	2	1				
Special Industry Machinery	355	1	1	1	1		
Industrial Process Furnaces, Ovens	356	2	2				
Computer Communication Equipment	357	10	7			4	7
Refrigerator & Service Industrial Machine	358	1	1			1	1
Electrical Industrial Apparatus	362	1	1				
Industry Machinery	363	1	2				
Electric Lighting, Wiring Equipment	364	1	3				
Household Audio & Video Equipment	365	1	1				
Tele & Telegraph Apparatus	366	7	1			4	6
Semiconductor, Related Device	367	12	5	1	9	3	8

Misc. Transportation Equipment	371	5	8			5	8
Machinery and Equipment	372	1	4			1	6
Guided Missiles & Space Vehicle	376	1	1				
Electric Measures & Test Instruments	382	2	3				
Ortho, Prosth, Surgery Appliances, Supply	384	6	4	2	5		
Computer Peripheral Equipment	386	2	2				
Plastics Products	399	1	2				
Trucking	421	2	2				
Air Transport, Scheduled	451	4	5	1	3	5	4
Phone Communications Ex Radiotelephone	481	29	14	1	22	13	18
Radio Broadcasting Stations	483	2	2			1	1
Business Services	484	6	6			7	9
Communications Services	489	4	1			2	3
Electric Services	491	3	29			16	25
Natural Gas Transmission	492	1	3			6	6
Electric & Other Service Comb	493	4	14			12	18
Refuse Systems	495	2	2				
Computer Programming	504	1	1				
Non-Operating Establishments	506	1	1				
Computers & Software	511	1	1				
Security Brokers & Dealers	512	3	2				
Agriculture Production-Crops	514	1	1				
Misc. Shopping Goods Stores	521	2	2			1	1
Variety Stores	531	2	7			4	7
Lumber & Other Building Material	533	3	2				
Grocery Stores, Convenience Stores	541	4	4			4	3
Family Clothing Stores	565					1	2
Catalog, Mail-Order, Record&Tape Stores	573	3	2				
Eating Places	581	10	5				
Misc. Shopping Goods Stores	594	2	2			1	1
Apparel and Accessory Stores	596	4	1				
Commercial Banks	602	1	15			5	14
Savings Institutions, Fed Chartered	603	1	2				
Personal Credit Institutions	614	1	3			3	2
Misc. Business Credit Institutions	615	2	5	1	12	2	9
Mortgage Bankers & Loan Brokers	616	2	1				
Accident & Health Insurance	631	1	5			4	4
Hospital & Medical Service Plans	632	2	5			3	7
Fire, Marine, Casualty Insurance	633	1	10			2	11
Surety Insurance	635	1	1				
Fire, Marine, Casualty Insurance	641	1	1				
Textile Mill Products	671	2	9			5	9
Real Estate Investment Trust	679					6	37
Misc. Amusement & Recreation Service	701					1	3
Advertising Agencies	731					2	2
Misc. Equip Rental & Leasing	735	2	2			1	4
Help Supply Services	736	1	1				
Computer Storage Devices	737	29	6	10	4	1	2
Data Process	738	5	1	1	1		
Auto Rent & Lease	751	1	2				
Misc. Amusement & Recreation Service	799	4	3				
Skilled Nursing Care Facilities	805					1	1
Gen Med & Surgical Hospitals	806	1	2			1	1
Medical Laboratories	807	1	2				
Biological Products	809	2	1				
Coml Physical, Biologcl Resh	873	1	1	1	1		
Hazardous Waste Management	874	1	1				
N of Events		272		22		170	
N of Industries		86		12		55	