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Credit Contagion from Counterparty Risk

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Credit Contagion from Counterparty Risk

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Abstract

Standard credit risk models cannot explain the observed clustering of default, sometimes described as "credit contagion." This paper provides the first empirical analysis of credit contagion via direct counterparty effects. We examine the wealth effects of bankruptcy announcements on creditors using a unique database. On average, creditors experience severe negative abnormal equity returns and increases in CDS spreads. In addition, creditors are more likely to suffer from financial distress later. These effects are stronger for industrial creditors than financials. Simulations calibrated to these results indicate that counterparty risk can potentially explain the observed excess clustering of defaults. This suggests that counterparty risk is an important additional channel of credit contagion and that current portfolio credit risk models understate the likelihood of large losses.

Portfolio credit risk models have vastly improved in recent years, allowing financial institutions to measure their distribution of their potential credit losses at the top level of the institution. Such information can be used to infer economic capital, which is the amount of equity capital the institution should carry to absorb a large loss over a specified horizon with a high confidence level. These new credit models are now in widespread use in the financial industry, for instance when structuring Collateralized Debt Obligations (CDOs).[1] These models are also the basis for the recently-established regulatory capital charges for commercial banks.[2]

There are, however, nagging concerns about the calibration of these models. In particular, estimation of default correlations is difficult because they cannot be directly measured for specific obligors. In addition, current models for default correlations seem to be unable to reproduce the actual pattern of default clustering, sometimes called "credit contagion". This paper provides an empirical analysis of an important channel of credit contagion, which is counterparty credit risk.

Unexplained default clustering is a major issue for traditional credit risk models because it generates greater dispersion in the distribution of credit losses. This implies a greater likelihood of large losses and an understatement of economic capital. This could lead to a greater number of bank failures in periods of stress, or losses on CDOs that exceed worst estimates. Indeed, losses on CDOs backed by subprime debt have been at the heart of the financial crisis that started in 2007.

In traditional credit models default correlations are inferred from a structural model of the value of the firm or by a reduced-form model of default intensity. A typical simplification uses factor models, where correlations are induced by a common factor that can be interpreted as the state of the economy, plus possibly other factors. Das et al. (2007) indicate that the conditionally

[1] The CDO market has experienced exponential growth in recent years, with more than $550 billion in new issues in 2006 alone.
[2] These new rules, called Basel II, impose minimum levels of capital that commercial banks have to hold to guard against credit and other risks. The credit risk charge roughly corresponds to the worst credit loss over a one-year horizon at the 99.9 percent level of confidence.

independent assumption for factor models forms the current basis of credit risk management practice. Indeed, the new Basel II regulatory capital charges are based on such factor models.[3] This common feature largely explains why recent comparative studies of industry portfolio models show remarkable similarities in their outputs, or measures of economic capital.[4] Such models, however, do not fully capture the clustering in default correlations reported, for instance, in Das et al. (2007).[5]

Second-generation models attempt to provide structural explanations for this default clustering. For instance, Duffie et al. (2006) estimate a "frailty" model where defaults are driven by an unobserved time-varying latent variable, which partially explains the observed default clustering. Another extension would be to consider multiple factor effects, or industry factors. When a firms defaults, other firms in the same industry could suffer from contagion effects, reflecting shocks to cash flows that are common to that industry. Examining firms within the same industry, Lang and Stulz (1992) and Jorion and Zhang (2007) present evidence that industry peers are negatively affected by a firm's Chapter 11 bankruptcy, creating higher correlation within the industry. The recent upheaval in securities backed by subprime mortgage debt indicates that the financial industry indeed has missed major common default factors in this segment.

Another, completely different channel of credit contagion is counterparty risk. This arises when the default of one firm causes financial distress for its creditors. In an extreme case, this can push a creditor toward default as well. This in turn can lead to a cascade of other defaults. Such interactions are particularly worrisome for financial institutions, given their intricate web of relationships. Counterparty risk has been analyzed in a theoretical framework by Davis and Lo (2001), Jarrow and Yu (2001), Giesecke and Weber (2004), and Boissay (2006). The empirical measurement of credit contagion created by counterparty risk is the subject of this paper.

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[3] See Vasicek (1991) for an early description of a one-factor model for portfolio credit risk.
[4] The IACPM and ISDA (2006) study reports similar measures of economic capital across models when adjusted for other parameters.
[5] See also De Servigny and Renault (2004) for empirical evidence on default correlations.

This channel is very different from industry or factor effects. It requires detailed information about counterparty exposures. A unique feature of this study is the use of a data source that identifies detailed credit exposures and which has, to our knowledge, not been explored so far in the literature. We collect a sample of bankruptcy filings listing the top unsecured creditors, credit amounts, and credit types for over 250 public bankruptcies over the period of 1999 to 2005. This allows us to investigate the effect of counterparty risk on different types of creditors, industrial firms and financial firms. To our knowledge, this is the first paper that uses direct and identifiable business ties to assess counterparty risk.

For industrial firms, we find that most exposures take the form of trade credit, defined as direct lending in a supplier-customer relationship. Trade credit is important. Indeed, it constitutes the single most important source of external finance for firms and represents about 20% of debtors' assets.[6]

Why do firms use trade credit? Petersen and Rajan (1997) argue that firms prefer to be financed by their suppliers when the latter hold private information about their customers.[7] Such information is not available to financial institutions, which precludes the financing of some valuable projects. This is especially true for smaller firms which have constrained access to capital markets. Cunat (2007) also argues that suppliers have more leverage over borrowers because they can stop the supply of intermediate goods.

On the other hand, trade credit can create severe problems in case of default. Like a bank, the trade creditor will recover only part of the unsecured exposure. However, because the typical trade credit exposure accounts for a large fraction of the creditor's assets, this loss can create financial distress for the creditor. It is indeed not rare for a company to have one large trade credit

[6] See Cunat (2007). Boissay (2006) reports that the average trade debt of S&P 500 firms is around 30% to 40% of quarterly sales.
[7] This is true even though trade credit is more expensive than bank debt. For a partial list of literature on credit trade, see Allen and Gale (2000), Biais and Gollier (1997), Brennan, Maksimovic, and Zechner (1988), Ferris (1981), Lee and Stowe (1993), and Mian and Smith (1992).

with its main client that accounts for the entire profit of the year. Trade credit is generally not well diversified. Moreover, the business of the trade creditor will be impaired by the bankruptcy of its borrower, which is often a major customer. For example, Handleman, a music distributor, was one of Kmart's largest unsecured creditors. Kmart was its second largest customer and had a $64 million trade credit. Handleman lost over 24% in equity value over the month around the bankruptcy of Kmart in January 2002.[8] This represents a loss close to $100 million. Thus, in addition to the loss on the current credit exposure, which represents a balance-sheet measure, a client bankruptcy will affect future earnings, which is a flow, if the client cannot be replaced quickly.

The present study also examines financial firms. Exposures take the form of loans or bonds. Exposures are generally larger in dollar amounts than for industrial creditors, but less so in relative terms, when considering the larger balance sheets of financial creditors. Banks can also impose limits on the amount of lending to one borrower. Secondly, there are other mechanisms that can help mitigate risk. Financial institutions have the luxury to choose whom they lend to, in contrast to trade credit, which is generally involuntary. Thirdly, bank loans are generally secured, leading to higher recovery rates than unsecured debt.[9] Finally, financial institutions can use credit derivatives to protect against client default. In contrast, the bankruptcy of a debtor subjects an industrial firm to a double penalty, loss of trade credit and loss of valuable customer relationship. Therefore, the direct counterparty effects should be stronger for an industrial counterparty than for a financial institution.

This paper makes a number of contributions to the literature. To our knowledge, this is the first paper to present direct empirical evidence of counterparty risk among industrial corporations.

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[8] Source: "The Kmart effect: Many companies feel the pain", CBS MarketWatch, 1/23/02.

[9] A typical bank loan is senior secured debt, and thus has a high recovery rate. The recovery rate for secured debt ranges from 85% to 100%, according to Weiss (1990) and Franks and Torous (1994). Gupton, Gates and Carey (2000) suggest a recovery rate between 50% and 65% for banks

We analyze the effect of bankruptcy announcements on the stock prices and credit default swaps (CDS) spreads of creditors. By now, the CDS market is increasingly liquid, with outstanding notional in excess of $62 trillion as of 2007. It also provides a direct measure of default risk.

As expected, we find negative stock price responses of creditors to their borrower's bankruptcy, and increases in CDS spreads. To control for market-wide factors, movements in stock prices and in CDS spreads are adjusted for industry effects and credit rating effects, respectively. This allows us to focus on direct counterparty effects. The average abnormal equity return for the 11-day window around the bankruptcy filing is −1.9% after accounting for common factors, which is economically and statistically significant. This translates into a loss of $174 million for the median creditor. CDS spreads increase by 5 basis points over the same window. This corresponds to a drop in credit rating from A to A-, or half a notch when starting from BBB+.

In addition, we track creditor firms that experience a credit loss and find that they are also more likely to fail later than other firms, controlling for industry, size, and rating. Furthermore, our cross-sectional analysis reveals that these counterparty effects are reliably associated with a number of variables, including the relative size of the exposure, the recovery rate, and previous stock return correlations. We also present evidence that the counterparty effect is considerably stronger when the debtor is a major customer of the creditor, and when the debtor liquidates rather than when it reorganizes because the creditor incurs a loss not only from its current exposure but also from future business. Finally, we present simulations of portfolio credit losses calibrated to the empirical data, with and without counterparty risk. The results indicate that counterparty risk has a marked effect on the shape of the default distribution, thus providing an explanation for the observed default clustering.

The rest of the paper is organized as follows. Section I describes counterparty and contagion models and discusses research hypotheses. Section II describes the data and descriptive statistics. Section III explains the methodology. Section IV then presents the empirical findings. The effect of counterparty risk is explored in Section V, which provides simulation results for portfolio credit losses. The conclusions are summarized in Section VI.

I. Credit Contagion

Figure 1 describes channels of credit contagion. When Firm A defaults, or files for bankruptcy, we generally expect negative effects for other firms in the same industry. Contagion effects reflect negative common shocks to the prospects of the industry, and may lead to further failures in industry A. On the other hand, the failure of a firm could help its competitors gain market share. Generally, however, the net of these two effects is intra-industry contagion. Contagion effects can also arise across industries. Suppose that Industry A is a major client of Industry B. The default of Firm A could then reveal negative information about sales prospects for firms in Industry B.

Another channel, however, is the direct counterparty effect. Say that Firm B has made a trade credit, or loan to Firm A. Default by Firm A would cause a direct loss to Firm B, possibly leading to financial distress. This could cause cascading effects to creditors of Firm B. This paper focuses on the counterparty effects between Firms A and B, measuring the price impact for Firm B while controlling for price effects for all firms in the same industry.

Generally, cascading or looping effects are too complex to model analytically because firms may hold each other's debt and also because of the sheer number of networked firms.[10] Jarrow and Yu (2001), for example, do provide closed-form solutions but only for a simple case with two firms and no cascading effects.

[10] The case where firms hold each other's debt more properly describes a banking network. Several papers, summarized for instance in Upper (2007) analyze contagion effects via simulations. One problem, however, is that bilateral exposures are generally not available.

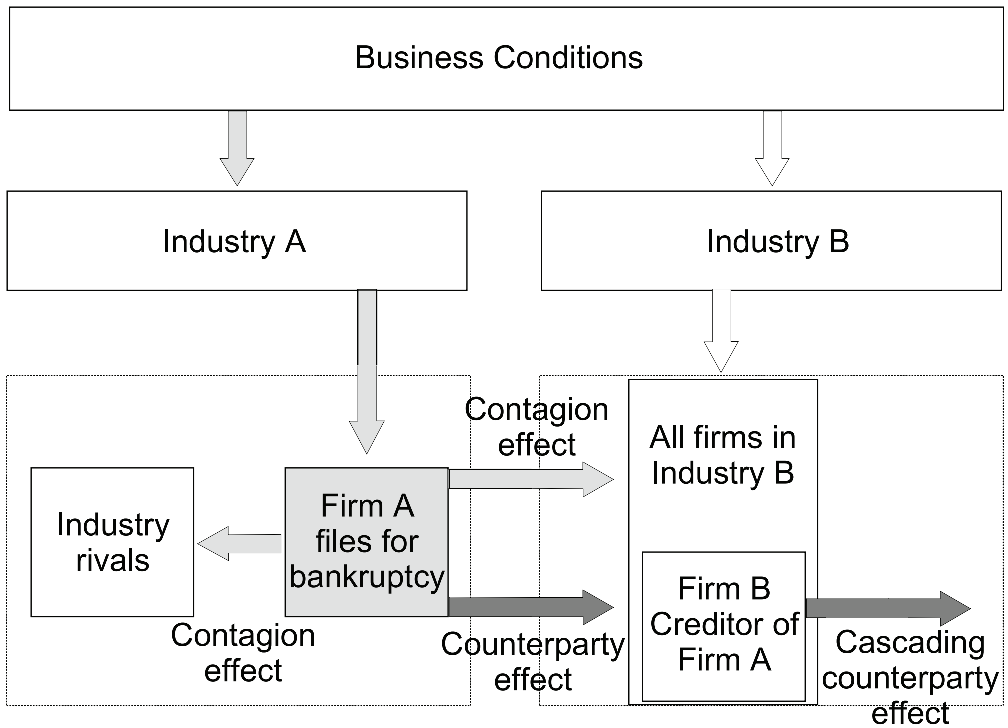

Fig. 1. Channels of Credit Contagion

Empirically, counterparty effects could be analyzed using default data, as in Duffie et al. (2006), from which physical default probabilities could be derived. We provide some evidence that a credit loss due to counterparty risk increases the probability of default for the creditor, relative to others without exposure to the defaulting counterparty. Alternatively, changes in default probabilities could be inferred from changes in stock prices or CDS spreads around the time of the bankruptcy announcement.

Market prices, however, will capture the full effect only if the bankruptcy announcement is entirely unanticipated. In practice, bankruptcy is often preceded by other major public announcements about the debtor, such as some kind of default. We will verify that the bankruptcy announcement is at least partially unanticipated, so that price changes are still informative. In addition, the identity of the creditors in general is not known to market participants. As we will show later, however, even in the cases where the bankrupt firm was previously listed as a major customer in the creditor's annual report, creditors suffer a very large price drop upon the bankruptcy announcement.

We expect that the announcement of bankruptcy by Firm A will lead to lower stock prices and wider CDS spreads for creditor firms. To abstract from more general contagion effects, or perhaps cascading effects in Industry B, the analysis controls for average price effects in Industry B. For example, financial distress in the U.S. automobile industry had negative effects on the parts supplier industry. Among part suppliers, however, those with direct credit relationships have suffered more than others. Adjusting for the industry effect should provide cleaner estimates of the direct counterparty effect.

The analysis can be further enriched by cross-sectional information. The stock price effect for Firm B can be decomposed as follows. Define: AMOUNT as the dollar amount of unsecured credit exposure, MVE as the market value of the creditor's equity prior to the announcement, EXP as the scaled or relative exposure, measured as AMOUNT divided by MVE, REC as the fractional recovery rate, and NPV as the dollar amount of losses of future profits from the customer-lender relationship, also scaled by MVE.

In the simple 2-firm model, the direct wealth effect of a debtor's bankruptcy can be measured by the change in the creditor's stock price, which requires dollar amounts to be scaled by the market value of equity. Thus, the rate of return can be conceptually decomposed into:

$$\text{RATE OF RETURN} = -\text{EXP}(1-\text{REC}) - \text{NPV} \tag{1}$$

which involves an immediate default loss, i.e., the exposure times one minus the recovery rate, plus an effect expressed as the net present value of lost future business. More generally, cascading effects can also arise. Note that Equation (1) does abstract from frailty effects when the rate of return is adjusted for that of other firms in the same industry.

For trade credit, the NPV term could be quite large, reflecting the loss of an on-going business relationship with a major customer. For bond investors, this NPV term should be zero because there is no other business flow between the investor and the debtor. For banks, the NPV term should be small if the value of the banking relationship with the client represents a small fraction of profits. We will verify whether counterparty risk is stronger for industrial creditors than financial creditors, holding exposure constant.

Our paper is related to Dahiya et al. (2003), who examine the costs and benefits of banking relationships over the period from 1987 to 1996.[11] They find a significant negative wealth effect for the shareholders of the lead lending banks on the announcement of bankruptcy and default by borrowers. Ours differ from theirs in several important ways. First, they focus on the leading bank in the case of loans, while we examine all major creditors, including financial institutions such as insurance companies, as well as industrial corporations. Second, the only form of credit in their study consists of loans, which are usually senior and secured. Our study includes unsecured loans, bonds, and trade credit, which is a greater variety of debt types. In addition, unsecured debt is more likely to induce contagion effects due to the lower recovery rates on unsecured debt. We also follow the creditor through time, and assess the effect of the initial bankruptcy on the subsequent default probability.

II. Data and Descriptive Statistics

A. Identification of Creditors

We collected information on 721 Chapter 11 bankruptcies that occurred between January 1999 and December 2005. The information was retrieved from the website

[11] Another paper by Kracaw and Zenner (1996) examine bank share price reactions to nine highly leveraged firms that became financially distressed. They find a negative share price reaction for these banks, but one that was not statistically significant. However these findings were for a very small sample of firms involved in highly leveraged transactions such as LBOs or recapitalizations.

www.bankruptcydata.com and includes information on the top twenty unsecured claimholders, i.e., creditor names, credit types, and credit amounts extended to the bankrupt firm. The identity of the creditors is generally not available from public filings.

For example, Enron filed for bankruptcy on December 2, 2001. With $63.3 billion in assets, this was the second largest bankruptcy in history. In accordance with Federal Regulation bankruptcy 1007(d) for filing under Chapter 11, the petition included the top twenty unsecured creditors. Citibank was the largest unsecured creditor, with $1.75 billion in claims. The following week, the bank announced a write-down of $228 million related to unsecured Enron positions.[12] Citibank had not mentioned its exposures to Enron in annual reports before 2001.

We then excluded all claims by individuals as well as claims from local, state, and federal governments, and other non-profit organizations.[13] Bankruptcies must have at least one remaining creditor. This reduced the sample to 351 bankruptcy events, with 4796 event-creditors. We also eliminated all bond debt reported by a commercial bank, investment bank, broker/dealer, and asset manager, because these institutions generally serve as trustees for the bond investors and do not bear the credit loss.[14]

For the purpose of the subsequent analysis, we require creditors to have equity returns available from CRSP. As we also require firm characteristics, we match identifying codes in CRSP and COMPUSTAT for both bankrupt firms and creditors.[15] To avoid a potential contamination issue, we check the [−5, +5] event window around the bankruptcy filing in the ABI/Inform database to make sure that creditors have no other informative corporate news of their own. This is the longest window centered on the event that is used later in the empirical analysis.

[12] Source: ‘Citigroup Posts 36% Rise in Earnings’, by Paul Beckett. Wall Street Journal, Jan 18, 2002, page, A-3.
[13] Most of individual claims arise from employment contracts, bonuses, compensations, etc. Local or state government claims usually represent taxes.
[14] For instance, the largest single claim in our original sample is listed as a bond claim worth $17.2 billion to WorldCom held by JP Morgan Chase. In its annual report, however, the bank does not even mention direct exposure to WorldCom. Losses were borne by bondholders. So, this observation is discarded from the sample, as are all similar ones.
[15] For firms with a name close to the COMPUSTAT company name, we use an algorithm to look for its 6-digit CNUM code in COMPUSTAT and Permanent number in CRSP. If this method fails, we hand collect the code.

Table I shows the final sample for equity returns. Panel A describes the distribution of bankruptcy filings, industry coverage, number of event-creditors, number of creditors, and credit amounts by year. The sample consists of 251 bankruptcies, 146 industries, 694 event-creditor observations, and 570 creditors. The borrowers and creditors are generally in different industries; only 40 creditors out of 570 are in the same industry as the borrower. The aggregate claims add up to $8 billion for the creditors in this sample.

[Insert Table I]

Panel B shows that the number of public creditors ranges from 1 to 10, with a mean of 2.8 and median of 2. As shown in Panel C, the median creditor has only one exposure to the 251 bankruptcy events. Some companies have much more exposure, however. The largest number of claims is 19, indicating that this creditor, the commercial bank JP Morgan Chase, is involved in 19 bankruptcies where it is in the top creditor group.

This paper also uses CDS spreads taken from a comprehensive dataset from the Markit Group. The original dataset provides daily quotes on CDS spreads for over 1,000 North American obligors from January 2001 to December 2005. Quotes are collected from a large sample of banks and aggregated into a composite number, ensuring reasonably continuous and accurate price quotations.[16] We use the five-year spreads because these contracts are the most liquid and constitute over 85% of the entire CDS market. To maintain uniformity in contracts, we only keep CDS quotations for senior unsecured debt with a modified restructuring clause and denominated in U.S. dollars. Because there are fewer CDS quotes than stock price quotes, the CDS sample is smaller than the equity sample. The CDS final sample consists of 128 bankruptcies, 209 event-creditor observations, 178 creditors, and 91 industries.

[16] 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 Micu et al. (2004) and Zhu (2006).

B. Description of Credit Claims

Table II breaks down credit claims by credit type and creditor type. Panel A partitions claims into three major credit types: trade credit, bond, and loan. The trade credit category accounts for a large fraction of the number of events. There are few cases of unsecured loan claims, due to the fact that most bank loans are secured. The average size of the claim differs widely across credit type. For trade credit, the average claim is $3.2 million, which seems small. For bonds, this is $17.1 million. Loans have the largest average exposure, at $163.6 million.

[Insert Table II]

Next, Panel B partitions the sample by type of creditors. Firms with industry SIC code falling between 6000 and 6999 are classified as financial institutions. These include commercial banks, savings institutions, securities brokers and dealers, insurance companies, credit-card companies, real estate investment trusts, and other financial services. The rest are grouped as industrial firms. We have a total of 583 event-creditors for industrial firms. As expected, trade credit is the main credit type for industrial creditors, accounting for 98% of 583 cases. The single largest trade credit is $79 million due to NEC Corporation and recorded when ICO Global Communications Holdings, a satellite firm, filed for bankruptcy in 1999.

For financials, we have 111 event-creditors. Loans are the most important credit types.[17] The single largest exposure is an unsecured loan of $1.75 billion due to Citibank by Enron in 2001. The average credit amount for financials is $54.9 million, which is much larger than the average exposure of $3.3 million for industrials.

[17] In this sample, all loans are made by commercial banks.

Finally, we obtain recovery rates from Fitch (2005), which reports historical recovery rates of senior unsecured bonds for 24 industries over the period 2000 to 2004.[18] We use average recovery rates by industry. In practice, however, actual recovery rates vary by name, industry, and even over time. So, this is an approximation. In addition, these recovery rates are estimated from a bond sample, and may not fully reflect recovery rates for trade credit or bank loans.[19]

III. Method

This paper investigates the market reaction of creditors around bankruptcies. For each event, we construct a creditor portfolio as an equally-weighted portfolio of firms. On average, there are 2.8 firms in the creditor portfolio. Using equally-weighted portfolio matches the method used for the construction of CDS indices; similar results, however, hold using value-weighted portfolios.

We then apply the standard event study method. First, we calculate abnormal returns (AR_{jt}) for firm j at time t using the market model methodology following MacKinlay (1997), with parameters estimated over a window ranging from 252 days before the event date to 50 days before the event date. Next, these abnormal returns are averaged across bankruptcy events for creditor portfolios. Cumulative abnormal returns (CAR) are then computed from time t_1 to t_2. Finally, t-statistics are computed from the portfolio time-series standard deviation to account for any possible event clustering.

The stock price response of the creditor can be attributed to two types of effects. The first is a direct counterparty effect, due to the immediate loss from default, and is specific to the creditor. The second is a contagion or cascading effect spreading to the rest of the industry. To isolate the first effect, the market model is estimated for each firm relative to two portfolios. The first is the

[18] Recovery values are computed from the price of defaulted securities one month after default and are par-weighted averaged. The mean of average recovery rates is 33% across industries, with a low of 12% for insurance and 66% for gaming, lodging, and restaurants.
[19] Moody's (1999) reports that the average recovery rate on trade claims is 74%, which is higher than the 70% rate for senior unsecured obligations, although the sample size is small.

market index, proxied by CRSP's value-weighted index for NYSE/AMEX/Nasdaq stocks. The second is a portfolio of firms in the same industry as the creditor. This industry index is constructed as a portfolio of value-weighed industry equity returns for all firms with the same three-digit SIC code.

For CDS spreads, we also report measures that are adjusted for general market conditions, as proxied by the same credit rating category, 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 investment-grade or high-yield CDS index at day *t*, depending on whether the rating *r* falls into the investment-grade or the high-yield grade category. We use the actual spread levels for the Investment Grade CDX (CDX.NA.IG) and the High Yield CDX (CDX.NA.HY) to represent these two CDS indices since their inception in April 2004. We extend the indices backwards to January 2001 following the CDX index construction methodology.[20] The Investment Grade CDX is an equal-weighted index made up of 125 firms with the most liquid investment-grade credits. The High Yield CDX is an equal-weighted daily index composed of 100 high-yield entities. Both indices cover companies domiciled in North America. For each event, *cumulative abnormal CDS spread changes* (CASCs) are calculated as $CASC_j(t_1,t_2) = AS_{jt_2} - AS_{jt_1}$, and then processed as in the case of equity returns.

IV. Empirical Results

A. Market Reaction for Bankrupt Firms

Before we examine the effect of financial distress on the creditor's equity returns, we first measure the effect of distress on the borrower itself. To the extent that the bankruptcy announcement is unanticipated, we expect the borrower's stock price should experience significant

[20] The methodology can be found at the website: http://www.markit.com/information/affiliations/cdx.html. The list of component companies as of April 2004 was used to backfill the series.

negative abnormal returns upon the bankruptcy filing. Since many companies had been delisted before the bankruptcy event, the number of borrowers for which these returns are available is considerably smaller than the size of the creditor sample.

We find an average announcement day abnormal return of –16.6% for 66 firms that file for bankruptcy. This is economically and statistically significant. Over a 3-day period, the cumulative abnormal return amounts to -30.0%. These results are comparable to the 2-day loss of -21% reported by Lang and Stulz (1992) and indicate that bankruptcy announcements are not fully anticipated by the market, justifying the use of market data in the analysis.

B. Market Reactions for Creditors

Even if a firm's bankruptcy is not totally unexpected, the announcement also reveals the identity of creditors and the size of their exposures. This brings new information to markets and allows us to quantify the effect of counterparty risk, net of industry effects. The principal results are presented in Table III. Panel A reports abnormal returns for the creditor portfolio using the entire sample of 251 events. The average CAR for the portfolio is negative, at –0.90% (t = –4.09) for the 3-day event window and –1.90% (t = –4.51) for the 11-day event window. The fraction of firms with negative returns is greater than 50 percent, indicating that these averages are not skewed by just a few observations. Thus, there is a significant negative wealth effect on a creditor' equity when a borrower files for Chapter 11 bankruptcy protection, as expected. Note that the magnitude of this effect is greater than the intra-industry contagion observed for industry peers. Jorion and Zhang (2007) report an 11-day return of –0.41% for firms in the same industry as the bankrupt company. The effect here is four times greater. The total effect of -1.90% does not seem very large in absolute terms, but the average exposure is only about 0.30% of the market value of equity, as will be seen later. Thus the wealth effect is much bigger than the immediate credit loss.

[Insert Table III]

We then examine whether this effect differs across industrial or financial creditors, by constructing two creditor portfolios for each event, one containing industrial creditors, and the other containing financial institutional creditors. Results are presented in Panel B of Table III. For industrial creditors, the average CARs is −2.29% for the 11-day window. Furthermore, the negative price impact persists over longer windows.

For financial institutional creditors, the average CARs is −0.34% for the 11-day window. The effect is much less than for industrials and not statistically significant. Dahiya et al. (2003) report slightly stronger effects, with 5-day returns of −0.91% for the lead banks exposed to bankruptcy events, over a different sample period.

As previously noted, Table III reports abnormal returns adjusting for industry effects, which represent pure counterparty risk. We also performed the analysis adjusting for the overall market rather than the creditor's industry. Results are similar and are not presented here.

Panel C reports test statistics of differences across groups, which are statistically significant for the 11-day and 70-day windows. Therefore, financial institutions are less affected by counterparty credit losses than industrials, conditional on being in the list of top creditors. Potentially, this could be explained by a smaller exposure relative to their assets. To further understand the drivers of this effect, we need to turn to cross-sectional regressions.

Next, Table IV reports effects on creditor's CDS spreads.[21] For the entire sample, the average CDS spread, adjusted for the ratings, increases by 2.11 basis points (bp) for the 3-day window and by 5.17 bp for the 11-day window. Both numbers are significant, and confirm the information from equities. This 5bp spread increase can be compared to the level of CDS spreads for different credit ratings. Over the 2001-2006 period, the median spread was 30bp for A credits, 37bp for A−, 46bp for BBB+, 59bp for BBB, and 87bp for BBB−. Thus the 5bp increase in spreads

[21] We also calibrated the Jarrow and Yu (2001) (JY) model to the term structure of CDS spread for creditors before and after the bankruptcy event. Due to its simplifying assumptions, however, the model is unable to reproduce the actual change in CDS spreads.

corresponds roughly to a drop in credit rating from A to A–, or to less than half of the difference between BBB+ and BBB spreads. Further, to the extent that the bankruptcy is anticipated, the increase in default probability should be even higher. Later, we will see that this signal indeed translates into a higher failure rate for the creditor.

[Insert Table IV]

Panel B splits the sample into industrials and financials. For the first group, the 11-day effect is an increase of 5.58bp, versus 2.66bp for the second group. These numbers confirm the findings from equity prices that industrials are much more affected by this credit loss than financials. Here, the difference is statistically significant across the 3-day, 11-day, and 70-day windows.

C. Cross-Sectional Reactions

This section examines to what extent counterparty effects are related to creditor characteristics. This is useful to understand the drivers of counterparty risk. To this end, we estimate cross-sectional regressions where the dependent variable is the 3-day industry-adjusted CAR around the event date. The most general specification is:

$$\mathrm{CAR} = \alpha + \beta_1 \mathrm{EXP} + \beta_2 \mathrm{REC} + \beta_1^* \ \mathrm{EXP(1\text{-}REC)} + \beta_3 \mathrm{CORR} + \beta_4 \mathrm{VOL} + \beta_5 \mathrm{LEV} + \varepsilon \qquad (2)$$

where EXP is the exposure ratio, or ratio of credit amount to the total market value of the creditor's equity, REC is the recovery rate for firms in the same industry as the bankrupt firm, CORR is the correlation of equity returns between the creditor and the borrower for 252 days preceding the event, VOL is the equity return volatility of the creditor for the year preceding the bankruptcy, and LEV is the average of leverage ratio of the creditor over the previous four quarters, defined as the ratio of book value of debt over the market value of assets, taken as the market value of equity plus the book value of debt.

In what follows, we give the predicted sign of the coefficient for the equity regressions. For the CDS spread regressions, all signs should be inverted.

A creditor with greater exposure to the distressed firm is more likely to be hurt from the bankruptcy, so we hypothesize the coefficient on EXP to be negative. For industries with a greater recovery rate, the expected credit loss should be less, and the price impact more muted. We hypothesize a positive coefficient for REC.

In our specifications, we also use the variable EXP(1-REC), which is the expected credit loss upon default. If default was totally unexpected and these variables measured without error, we should find a coefficient of -1 on this variable for the regression on equity returns. In practice, these conditions are not totally satisfied, which should bias the coefficient toward zero. However, Section I argued that a business loss effect may also arise. Assuming this is proportional to the expected credit loss, this should increase the size of the slope coefficient, taken in absolute value. The observed coefficient should reflect the net of these two effects.

We also include CORR as an additional variable, to control for previously observed correlation between the creditor and debtor. Contagion effects are expected to be greater for creditors with higher equity correlation with the borrower, due to commonality in cash flows. As a result, the coefficient on CORR is expected to be negative.

We also add variables that proxy for the creditor's future default probability. Merton-type structural model suggests that companies with higher equity return volatility and higher leverage are associated with a higher default probability. We expect such firms are more vulnerable to negative shock from their borrowers, implying negative coefficients for LEV and VOL. Also included in the regression is a set of year dummies and industry dummies based on the one digit SIC code of the borrower.

We also examined the extent to which credit derivatives use by commercial banks can affect exposure. Only seven banks in our sample have such information, however, and the results were not significant.

Summary statistics for the main variables are presented in Table V. Several points are noteworthy. The average size of bankrupt firms is $1.9 billion in terms of assets. This is much smaller than the average size of creditors, which is $97.9 billion. The average credit amount is $11.5 million only, from Table II. This explains why the average exposure is fairly small, at 0.32% of creditor equity. Average recovery rates are around 0.30. The average rating of creditors is 9.3, which is close to BBB.

There are differences across industrials and financials, however. Table II has shown that the average credit exposure for industrial creditors is $3.3 million, much smaller than the average of $54.9 million for financials. However, taking into account the fact that industrial creditors are much smaller than financial creditors, the average credit exposure is 0.32% for industrial creditors, against 0.16% for financial institutions.

[Insert Table V]

Table VI presents the results of the cross-sectional regressions. OLS regressions are estimated separately for the entire sample, for industrials, and for financials. While the slope estimates are consistent, standard errors should account for the fact than many of these CARs are measured over the same period, for each bankruptcy event. As a result, we report t-statistics based on clustered standard errors, which are adjusted for event clustering.

[Insert Table VI]

As predicted, the coefficients on EXP are negative and statistically significant. We also find that the coefficients on REC are positive, as expected, but barely significant for the overall sample, perhaps because there is not enough meaningful variation within this sample, or because of measurement error.[22]

Model 3 uses the expected credit loss, EXP(1-REC), conditional on default. For the entire sample, the coefficient is −1.01, which is significantly different from zero but not from one. The size of the coefficient is particularly interesting. A coefficient of −1 would indicate that, when a creditor unexpectedly defaults, an exposure of 1% of equity market value is associated with a wealth loss of 1%. This number can differ from −1 for two reasons. First, if the bankruptcy announcement is not totally unexpected or if the variables have measurement errors, the slope should be biased toward zero. Second, if the bankruptcy implies a loss of future business, the slope should be even lower than −1. The actual coefficient should reflect the net of these two effects.

For industrials, the coefficient on EXP(1-REC) is −0.996. For financials, this coefficient is −2.09. Both coefficients are significantly different from zero but not from one. The size of the latter number is somewhat puzzling. This could be due to the use of 3-day equity abnormal returns, which were similar for the industrial and financial subsamples, but much more different over longer intervals and for the CDS data. A possible explanation for this large number is that the loss due to bankruptcy may induce investors to reconsider the risk of the entire bank portfolio, as in the learning hypothesis advanced by Collin-Dufresne et al. (2003). An alternative explanation for the high coefficient for financials is that there could be some additional unrecorded exposure. For example, financial letters of credit or similar off-balance sheet items create bank commitments that are exercised by a third party if the underlying credit fails. Alternatively, the recovery rate could be underestimated for banks either because they choose loans that are more likely to have higher recoveries, or because they take a more active part in the resolution of the bankruptcy process.

[22] Dahiya et al. (2003) find that a recession dummy (July 1990-March 1991) is significant, which can be interpreted as an indicator of lower recovery rates during recessions. If so, assuming fixed recovery rates will induce measurement errors.

Next, the CORR coefficients are negative and significant for the entire sample and the industrial sub-sample, as expected. Including this coefficient does not affect much the coefficients on expected credit loss, however. The latter are slightly lower, but still significant. Consistent with our hypothesis, the coefficients on VOL are negative, and generally significant. The coefficients on the LEV variable are all negative but insignificant.

Table VII repeats the cross-sectional regressions for CDS spread changes. The coefficients have systematically opposite signs to those in Table VII. As predicted, changes in spreads are positively related to exposure, negatively to recovery rates, positively to prior equity correlation, equity volatility, and leverage. The slope coefficient on exposure is around 8, indicating that a credit exposure of 1% is associated with an increase of 8bp in the credit spread over the 3-day interval. Given that the average exposure is only 0.3% in this sample, this explains the small increase of 2bp only reported in Table IV over these 3 days.

Here, industrials are more affected by credit events than financials. The coefficient on the expected credit loss, EXP(1-REC), is 17.08 as compared to 7.65 for financials. The results for this sample conform better to our expectations.

[Insert Table VII]

D. Discussion and Additional Evidence

Counterparty risk should be greater under a number of conditions. Creditors must have a substantial portion of their economic value tied up with the bankrupt firm. In addition, the recovery rate must be low, and the bankrupt firm must shrink sufficiently to affect future business opportunities. For cascading effects to be important, the bankrupt firm must be large as well. We provide additional evidence on these conditions.[23]

Market losses for industrials are generally greater than the direct default losses, which suggests that price changes also account for the net present value of lost future business. Such

[23] This section substantially benefited from the referee's comments.

losses may not always materialize, however, especially when companies continue to operate under the protection of Chapter 11 bankruptcy code. On the other hand, the NPV term is more likely to be substantial when the bankrupt firm liquidates. As an additional check, we construct a subsample of bankrupt firms that were likely to be liquidated.[24] The average 3-day CAR for creditors is -1.32%, with a t-statistic of -2.66, which is greater in absolute value that the CAR in Table III. In addition, the cross-sectional regression coefficient on EXP(1-REC) in Model 3 changes from −1.01 to −2.26. These additional results confirm our hypothesis. The price reaction when the debtor liquidates is stronger than when it reorganizes because the creditor will incur a loss not only on its exposure, but also from its future business.

Overall, however, market losses due to counterparty default on average are small for this sample. This is because the average exposure is small, at 0.32% of equity only. Using Model 3 in Panel A of Table VI, this translates into a fitted loss of −1.01, close to the average loss of −0.90 reported in Table III. This market loss, however, should be much greater for larger exposures. From Table V, the maximum exposure is 37.3%, which translates into a fitted loss of −27.2%. This appears serious enough to cause financial distress for the creditor.

Alternatively, we also examine a subsample of creditor firms for whom the bankrupt firm represents a large fraction of sales. Firms have to disclose in their 10-Ks the identity of any customer representing more than 10% of total sales. For this sample, we find six cases where the creditor lists a firm subsequently filing for bankruptcy as a major customer in the previous two fiscal years. The average exposure ratio is 11.11% for this group. Around the bankruptcy announcement, we find that the average 3-day, 11-day, and 70-day industry-adjusted CARs are −9.23% (t=−2.10), −23.34% (t=−2.99), and −53.17% (t=−2.91), respectively. Around the default

[24]We searched the bankruptcy announcement for terms such as "use Chapter 11 as a vehicle to facilitate its liquidation", "orderly liquidation of the company's assets", "wind down operations", "for a sale of substantially all of the assets", and so on. This gave a subsample of 32 events with 79 creditors.

date, the average 3-day, 11-day, and 70-day industry-adjusted CARs are −12.19% (t=−2.42), −18.71% (t=−2.89), and −51.21% (t=−3.06), respectively. Thus, for firms with large exposures, counterparty default creates substantial market losses, which are a harbinger of subsequent financial distress.

E. Subsequent Financial Distress

We now examine the effect of the bankruptcy on our creditor sample. Counterparty risk arises if a credit loss increases the probability of default of the creditor, compared to others. Table VIII follows the creditors through time, examining the fraction of firms that are delisted or downgraded within one and two years.

[Insert Table VIII]

First, examine the group of 461 industrial creditors with a credit rating. Of these, 9 companies are delisted due to distress within one year, and 12 are delisted within two years.[25] This represents 1.95% and 2.60% of the sample, respectively. To test whether these numbers are abnormally high, we construct a control sample for each creditor that consists of all firms in the same industry, with the same credit rating, and in the same size group, using a partition around the median of total assets. The fraction of firms that are delisted in this control sample within one year and two years is 0.28% and 0.56%, respectively. Therefore, the control sample has a much lower fraction of firms experiencing a delisting. The table reports tests of equal fractions, which show that differences are significant at the 1% level. The difference between the two samples is also economically important. For instance, an increase in the annual default rate from 0.28% to 1.95% is equivalent to pushing a BBB rated borrower into the BB− category.

[25] In this section, the delisting information is obtained from CRSP. We confine our attention to delisting due to financial distress. This corresponds to delisting code starting with 4 and 5.

The table also compares the fraction of firms downgraded within one and two years of the events for the creditor sample and the control sample. The difference is striking. Within one year, the fraction of downgraded firms is 23.64% for industrial creditors and 8.33% for the control sample. The difference is statistically significant at the 1% level. Thus, the probability of a downgrade of a company suffering a credit loss is about three times the unconditional probability.

For the sample of 100 financial creditors with a credit rating, only one company was delisted within the following one or two years. Thus the counterparty effect on financials is minor in this sample. We observe, however, that 14% and 20% of these companies experienced a downgrade in the ensuing one and two years. These fractions are twice those in the control sample, with both differences significant at the 1% level. Financial creditors that suffer a credit loss are more likely to experience downgrades later.

Even so, financial distress is more acute for industrials, where a greater fraction of firms are delisted or downgraded later. This largely confirms the evidence in Table IV that 11-day CDS spreads increase by 5.58bp for industrials, against 2.66bp for financials.

The comparison with the control sample indicates that credit losses are associated with significantly greater financial distress for the creditor. This evidence is indirect, however. We also searched multiple databases for news stories for the 13 delisting and 169 downgrade cases. Among the 13 delisting cases, one news story explicitly linked the delisting to the previous bankruptcy. Among the 169 downgrade cases, there are 8 cases indicating that the creditor was severely affected by the prior bankruptcy, 25 cases where the creditor-debtor relationship was explicitly mentioned, 53 cases where it was pointed out that the creditor and debtor are in the same industry, and 83 cases with no news. We would not expect full coverage of downgrades for small companies, however. Thus, there is some direct evidence of contagion from news reports, but it is limited.

V. Implications for Portfolio Risk

The economic importance of these results is now investigated using simulations calibrated to the empirical findings in this paper. Take a homogeneous sample of N=100 companies, all with unconditional probability of default (PD) of 1% over one year. This number represents the average default rate of BB rated firms. The goal of this analysis is to derive the distribution of number of defaults in this portfolio, using first a conventional factor model and then introducing counterparty risk. The question is whether counterparty risk can explain the greater clustering of defaults observed in practice.

Defaults are simulated by generating normal random variables that represent latent factors such as firm values, and choosing a cutoff point calibrated to the desired default probability. Using the 1% percentile of a normal distribution, the default probability can be translated into a distance to default of 2.326. Asset values start at +2.326, and companies default when asset values fall below a cutoff point of $c = 0$. Correlations are introduced between defaults by assuming equal pairwise correlations of $\rho = 0.20$ between multivariate normal asset values. So, the model generates a vector of joint default state variables d_{it} from asset values V:

$$V_{it} = bI_{it} + \varepsilon_{it}; \quad d_{it} = 1 \text{ when } V_{it} < c \tag{3}$$

where d is a vector of binary variables set to 0 or 1 upon default, I is the single common factor and b is the exposure to this factor, set to $\sqrt{\rho}$. It can be shown that this specification implies a default correlation of 0.0240.

This one-factor model corresponds to the assumption behind the Basel II rules. This model therefore describes the standard methodology for the measurement of portfolio credit risk. We run simulations with 100,000 replications. Results are reported in Table IX.

[Insert Table IX]

The first column describes simulation results for the standard model. Initially, there is no counterparty risk. The replications produces an average default rate d_t across the 100 obligors. In the first column, the average default rate across all replications is 1.00%, which is in line with the underlying PD of 1%. The default correlation is estimated at 0.0237, which is very close to the theoretical value of 0.0240.[26] The table also shows the percentiles of the distribution. For example, the 99.99% quantile, which is often used as a measure of economic capital by commercial banks, has 23 defaults. In other words, there is only a probability of 0.01% or less that 23 firms or more out of 100 will default over the next year based on this model. This type of information is routinely used to create tranches on a portfolio of debt obligations.

The next step is to introduce counterparty default. In Table I, the mean number of creditors was 2.8, so we initially assume that each company has N=3 counterparties only. When the borrower goes into default, the creditor's default probability is increased. Table IV shows an increase in CDS spread of 5bp over a 11-day window. Assuming a recovery rate of 30%, this implies an increase in the risk-neutral default probability of 5/0.30, or 0.17% for the creditor. The actual increase in PD is probably higher because this is the purely unanticipated component. Table VIII show a much higher increase in actual PD for the affected creditors. So, we start with an increase in default probability of 0.50%. This shock is represented by an immediate fall in the asset value. Increasing the unconditional PD from 1.00% to 1.50% changes the normal deviate from 2.326 to 2.170, which represents a fall of $k = -0.156$.

The model for asset values V with counterparty risk is described in Equation (4). The second term now represents counterparty risk, with the vector of defaults d affecting V through a matrix A. Without loss of generality, firms are sorted by counterparty exposure. For example, firms 2, 3, and 4 have exposure to obligor 1, and so on. Thus, the first column in A has zeroes

[26] The default correlation is estimated from the variation in the average default rate across replications, as explained in De Servigny and Renault (2004).

except for the entries two to four, which are set to 1. Upon default by the first company, the asset values for firms 2, 3, and 4 are immediately decreased by *k*, which may cause default for any of these three companies. In turn, this may precipitate other defaults. If so, this process can be iterated up to the point where the number of defaults stabilizes.

$$V_{it} = bI_t + kAd_t + \varepsilon_{it} \tag{4}$$

This framework allows us to model the effect of cascading defaults. Consider, for example, the first column under "Counterparty Risk" in Table IX, with N=3 and conditional PD of 1.50%. Without counterparty risk, the default correlation is 0.0237. With the first counterparty default, this increases from 0.0237 to 0.0278. With multiple defaults, this increases further to 0.0291. This increase in default correlation can be translated back into a higher asset correlation for the baseline model, Equation (3). Here, we would need to have an increase from 0.200 to 0.226, which is substantial. Indeed Das et al. (2007) report that, even after fitting a time-varying intensity model for U.S. corporate defaults, there is still substantial clustering of defaults. They calibrate a normal copula to the residuals and find an excess correlation ranging from 0.01 to 0.04. The increase of 0.226-0.200=0.026 reported here falls within this range. Thus, counterparty risk provides a potential resolution to the observed excess clustering of defaults.

These counterparty effects have important implications for the shape of the default distribution. The table shows that the 99.99% percentile has increased from 23 to 29 defaults when counterparty effects are included and N=3. Relying on the baseline model would underestimate the number of defaults that could occur in a bad scenario.[27] Thus, ignoring this credit contagion effect implies that the likelihood of large losses would be underestimated.

[27] When counterparty effects are added, the average default rate goes up slightly, from 1.00% to 1.05%. So, strictly speaking, the results with counterparty risk should be compared to the standard model with no counterparty risk and PD=1.05%. The second column, however, shows that this increase in the PD has no effect on the tails in the usual factor model.

The rest of the table explores the effect of alternative parameters. The default distribution has longer tails when the conditional probability increases. For instance, going from 1.50% to 2.00% increases the 99.99% percentile from 29 to 35. Similarly, the tails extend when the number of counterparties increases. For instance, going from N=3 to N=10 increases the 99.99% percentile from 29 to 65. This will substantially increase the default probability of the senior tranche. Consider for example a portfolio structured to ensure an AAA rating for the senior tranche. Without counterparty risk, this requires the junior tranche to absorb the first 23 defaults. With counterparty risk and N=10, however, the senior tranche effectively has the default probability of a BBB bond.[28]

All in all, these simulations calibrated to the data in this paper indicate that counterparty credit risk is an important channel of credit contagion. Ignoring credit contagion would understate the amount of economic capital in credit portfolios.

VI. Conclusions

This paper is part of an emerging literature that attempts to build bottom-up models of default correlations that focus on structural interactions between creditors and borrowers. It is motivated by the observation that the usual factor models apparently cannot explain the observed clustering of defaults. Higher default correlations imply greater probabilities of extreme losses on the portfolio. If so, standard models of portfolio credit risk may be seriously misspecified.

Clustering can occur within or across industries via common shocks to cash flows, or via counterparty effects. So far, however, there has been limited empirical evidence of this second channel of credit contagion, which arises from trade credit between industrial partners or from lending by financial institutions.

[28] The default probability increases from 0.01% to 0.27%, which is the annual default rate of BBB-rated bonds, according to Standard and Poor's (2007) transition matrices, Table 23.

This paper attempts to fill this important gap. We examine how a borrower's financial distress affects its creditors in a large sample of bankruptcy announcements listing the top creditors. Creditors experience negative abnormal equity returns and increases in their credit spreads. This loss of value reflects both the direct credit exposure at default and the loss of valuable customer relationships. Even though these losses are small on average, they are very high for firms with larger exposures.

Conditional on having experienced a credit loss, we find that the creditor is more likely to suffer from financial distress as well. The conditional probability of subsequent downgrades is significantly higher than in a control sample. Thus, counterparty risk is an important driver of default correlations.

We also find that the wealth and distress effects are stronger for industrials than for financials. This can be explained by the fact that industrials are less diversified and also suffer a greater loss of on-going business relationship, especially when the bankrupt firm is likely to liquidate and when the bankrupt firm represents a large fraction of sales of creditor firms. Hence, to protect against credit risk, industrials would be well advised to purchase credit protection in the form of credit default swaps.

Finally, we illustrate the economic importance of counterparty credit risk by showing its effect on the distribution of defaults in a portfolio. Using simulations calibrated to the empirical data in this paper, we show that the excess clustering observed in defaults can be explained by counterparty risk. Such results should be useful to develop improved portfolio credit risk models.

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Table I
Distribution of Bankruptcy Events in Sample

This table describes the distribution of final sample of bankruptcies used with equity returns. The sample runs from January 1999 to December 2005 and includes 251 events with complete creditor information including credit amount and credit type, and data on CRSP and COMPUSTAT. Panel A reports the number of bankruptcy events, the industry coverage in terms of 4-digit SIC code, the number of event-creditor observations, the number of creditors, and the credit claims by year for the companies in this sample. Panel B presents summary statistics for the number of creditors associated with a bankruptcy event. Panel C reports summary statistics for the number of credit claims per creditor.

Panel A: Number of Creditors within a Creditor Portfolio

Year	Nb. of Bankruptcy Events	Nb. of Industry	Nb. of Event-Creditors	Nb. of Creditors	Total Credit Amount ($ million)
1999	34	29	99	91	292
2000	35	30	76	73	585
2001	44	37	145	140	4,405
2002	23	20	65	60	852
2003	41	32	128	122	536
2004	35	34	84	77	198
2005	39	35	97	89	1,136
Total	251	146	694	570	8,004

Panel B: Number of Creditors within a Creditor Portfolio

Nb. of Events	Mean	Std Dev	Median	Max	Min
251	2.8	1.8	2.0	10	1

Panel C: Number of Credit Claims per Creditor

Nb. of Creditors	Mean	Std Dev	Median	Max	Min
570	1.2	1.0	1.0	19	1

Table II
Summary Statistics for Credit Amounts

This table provides summary statistics for credit amounts in our final sample. Panel A breaks down the sample into credit types: trade credit, bond, and loan. It describes the number of event-creditor observations and the distribution of credit amounts. Panel B partitions the sample by the type of creditors, i.e., industrials or financials, and by credit type.

Panel A: Credit Amount by Credit Type

	Nb. of Event–	Distribution of Amount ($ million)					
Credit Type	**Creditors**	**Total**	**Mean**	**Std Dev**	**Median**	**Max**	**Min**
Trade credit	635	2,014	3.2	8.8	0.5	79	0
Bond	25	429	17.1	25.4	5.5	91	0
Loan	34	5,561	163.6	338.2	66.4	1,750	2.4
Total	694	8,004	11.5	82.1	0.6	1,750	0

Panel B: Credit Amount by Creditor

		Nb. of Event–	Distribution of Amount ($ million)					
Creditor	**Credit Type**	**Creditors**	**Total**	**Mean**	**Std Dev**	**Median**	**Max**	**Min**
Industrials	Trade credit	570	1,838	3.2	8.8	0.6	79	0
	Bond	13	76	5.9	7.3	1.5	23	0
	Total	583	1,914	3.3	8.7	0.6	79	0
Financials	Trade credit	65	176	2.7	9.2	0.3	66	0
	Bond	12	352	29.4	32.3	16.1	91	0
	Loan	34	5,561	163.6	338.2	66.4	1,750	2.4
	Total	111	6,090	54.9	199.5	1.7	1,750	0

Table III
Contagion Effect of Chapter 11 Bankruptcy on Creditors Stock Prices

The table presents abnormal equity returns (AR) and cumulative abnormal returns (CAR) for major unsecured creditors of the firms filing for Chapter 11 bankruptcy over the period 1999-2005 in our final sample. The creditor portfolio return is constructed in two steps. First, we construct a portfolio of equally-weighted equity returns of publicly-traded creditors for each bankruptcy event. Second, we average these returns across events. AR (CAR) is the industry-adjusted cumulative abnormal returns (in percent) of the creditor, defined from an industry market model estimated over the period (-273, -21). The industry index is constructed from a portfolio of value-weighted industry equity returns for all firms having the same three-digit SIC code as the creditor. t-statistics are computed from the portfolio time-series standard devaition to account for any possible event clustering.
The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. Standard errors are derived from the portfolio time series. The "% (<0)" entry indicates the percentage of observations with negative or
The entire sample (Panel A) contains 251 Chapter 11 bankruptcies. Panel B breaks down the sample across industrials and financial firms. Panel C reports t-test statistics (Wilcoxon statistics) of statistical significance in mean (median) differences of CARs between two portfolios.

Panel A: Abnormal Equity Returns, Entire Sample

	All Creditors (N=251)		
Day	Mean (%)	T-statistic	% (<0)
-5	-0.11	-0.88	45.8
-4	0.00	0.02	51.5
-3	-0.17	-1.32	57.1
-2	-0.15	-1.14	53.6
-1	-0.29	-2.27**	57.0
0	-0.33	-2.59***	52.7
1	-0.30	-2.32**	57.8
2	-0.04	-0.34	47.9
3	-0.26	-2.03**	57.6
4	-0.09	-0.67	55.4
5	-0.19	-1.50	51.7
-1,1	-0.90	-4.09***	57.6
-5,5	-1.90	-4.51***	55.6
-5,65	-7.93	-7.41***	61.7

Table III (Continued)

Panel B: Abnormal Equity Returns by Type of Creditors

Day	Industrial Firms (N=230)			Financial Institutions (N=76)		
	Mean (%)	T-statistic	% (<0)	Mean (%)	T-statistic	% (<0)
-5	-0.22	-1.49	49.1	0.15	0.74	49.2
-4	0.00	0.02	53.1	-0.04	-0.18	50.0
-3	-0.20	-1.37	58.1	0.21	1.05	51.5
-2	-0.27	-1.84*	56.4	0.16	0.80	51.5
-1	-0.30	-2.07**	55.8	-0.14	-0.70	59.4
0	-0.34	-2.30**	52.3	-0.27	-1.31	53.7
1	-0.29	-1.99**	55.1	-0.33	-1.62	59.1
2	0.00	-0.02	48.4	0.05	0.26	42.9
3	-0.28	-1.89*	58.3	-0.06	-0.31	56.3
4	-0.18	-1.24	55.0	0.28	1.38	50.8
5	-0.21	-1.45	51.0	-0.36	-1.77*	54.8
-1,1	-0.93	-3.68***	56.6	-0.74	-2.09**	61.2
-5,5	-2.29	-4.73***	57.0	-0.34	-0.50	53.7
-5,65	-9.56	-7.77***	62.4	-0.65	-0.38	55.2

Panel C: Comparisons of Abnormal Equity Returns across Creditor Types

	CAR (3 days)		CAR (11 days)		CAR (70 days)	
	Mean	Median	Mean	Median	Mean	Median
Industrials	-0.93	-0.38	-2.29	-0.83	-9.56	-3.97
Financials	-0.74	-0.35	-0.34	-0.11	-0.65	-1.5
Difference	-0.19	-0.03	-1.95	-0.72	-8.91	-2.47
T Statistic	(-0.50)		(-2.44)***		(-4.31)***	
Wilcoxon Statistic		(-0.10)		(-1.52)		(-2.26)**

Table IV
Contagion Effect of Chapter 11 Bankruptcy on Creditors' CDS Spreads

The table presents the effects on credit default swap (CDS) spreads of major unsecured creditors of firms filing for Chapter 11 bankruptcy over the period 2001 to 2005. The creditor portfolio is constructed as an equally-weighted average of spread changes for each bankruptcy event. The cumulative adjusted spread change (CASC) is measured in basis points (bp) and is adjusted for movements in the investment-grade (speculative-grade) CDS index level, according to the rating of the creditor. t-statistics are computed from the portfolio time-series standard devaition to account for any possible event clustering.
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.
The entire sample (Panel A) contains 128 Chapter 11 bankruptcies. Panel B breaks down the sample across industrials and financial firms. Panel C reports t-test statistics (Wilcoxon statistics) of statistical significance in mean(median) differences of CASCs between two portfolios.

Panel A: Abnormal CDS Spread Changes (bp), Entire Sample

	All Creditors (N=128)		
Day	**CASC**	**T-statistic**	**% (>0)**
-5	0.25	0.66	56.8
-4	0.31	0.81	61.9
-3	0.50	1.33	54.0
-2	0.12	0.33	59.2
-1	0.54	1.43	65.9
0	0.81	2.16**	65.9
1	0.76	2.03**	67.2
2	0.67	1.77*	63.8
3	0.28	0.73	59.7
4	0.13	0.34	54.5
5	0.81	2.16**	57.6
-1,1	2.11	3.24***	68.0
-5,5	5.17	4.15***	67.2
-5,65	13.33	4.21***	60.5

Table IV (Continued)

Panel B: Abnormal CDS Spread Changes (bp) by Type of Creditors

	Industrial Firms (N=111)			**Financial Institutions (N=30)**		
Day	**CASC**	**T-statistic**	**% (>0)**	**CASC**	**T-statistic**	**% (>0)**
-5	0.31	0.68	55.6	-0.02	-0.03	65.5
-4	0.22	0.49	60.9	0.36	0.63	72.4
-3	0.17	0.38	53.2	1.44	2.51**	58.6
-2	0.26	0.58	55.1	-0.05	-0.09	72.4
-1	0.66	1.46	66.4	-0.14	-0.24	65.5
0	0.93	2.06**	68.8	0.11	0.18	56.7
1	0.88	1.96**	64.9	0.17	0.29	66.7
2	0.73	1.63	62.7	0.25	0.43	63.3
3	0.28	0.62	56.6	0.03	0.06	63.3
4	0.21	0.47	56.6	-0.25	-0.43	50.0
5	0.93	2.07**	55.6	0.77	1.34	63.3
-1,1	2.47	3.17***	70.3	0.13	0.13	56.7
-5,5	5.58	3.74***	66.7	2.66	1.40	70.0
-5,65	15.41	4.06***	58.8	5.34	1.11	66.7

Panel C: Comparisons of Abnormal CDS Spread Changes (bp) across Creditor Types

	CASC (3 days)		CASC (11 days)		CASC (70 days)	
	Mean	Median	Mean	Median	Mean	Median
Industrials	2.47	0.918	5.49	2.08	15.41	3.49
Financials	0.13	0.06	2.61	1.66	5.34	2.67
Difference	2.34	0.858	2.88	0.42	10.06	0.82
T Statistic	(2.90)***		(1.74)*		(1.93)*	
Wilcoxon Statistic		(1.97)*		(0.30)		(0.11)

Table V
Descriptive Cross-Sectional Statistics

	Panel A: All (N=694)				
Variable	Mean	Std Dev	Min	Median	Max
EXP (%)	0.32	1.70	0.00	0.01	37.34
REC	0.30	0.12	0.12	0.28	0.66
CORR	0.08	0.08	-0.23	0.08	0.40
VOL	0.48	0.29	0.11	0.41	2.05
LEV	0.28	0.23	0.00	0.22	0.94
MVE ($ million)	47,201	86,950	3	9,167	521,260
SIZE ($ million)	97,947	195,362	6	17,647	1,199,241
BRSIZE ($ million)	1,889	4,706	1	455	63,577
RATING	9.3	3.9	2.0	9.0	20.0

	Panel B: Creditors: Industrial Firms (N=583)				
Variable	Mean	Std Dev	Min	Median	Max
EXP (%)	0.32	1.84	0.00	0.01	37.34
REC	0.29	0.11	0.12	0.28	0.66
CORR	0.08	0.08	-0.23	0.08	0.40
VOL	0.51	0.30	0.11	0.42	2.05
LEV	0.25	0.22	0.00	0.18	0.91
MVE ($ million)	46,728	90,778	3	7,923	521,260
SIZE ($ million)	55,943	124,174	6	12,323	736,928
BRSIZE ($ million)	1,448	3,551	1	427	33,333
RATING	9.7	4.2	2.0	10.0	20.0

	Panel C: Creditors: Financial Institutions (N=111)				
Variable	Mean	Std Dev	Min	Median	Max
EXP (%)	0.16	0.33	0.00	0.02	2.39
REC	0.32	0.15	0.12	0.29	0.65
CORR	0.08	0.09	-0.15	0.08	0.31
VOL	0.35	0.13	0.13	0.36	0.71
LEV	0.40	0.21	0.00	0.38	0.94
MVE ($ million)	49,684	63,637	130	38,170	257,539
SIZE ($ million)	318,565	316,860	184	189,306	1,199,241
BRSIZE ($ million)	4,204	8,147	1	726	63,577
RATING	7.6	1.9	6.0	7.0	17.0

Variable definitions:
EXP is the exposure ratio, calculated by dividing the credit amount extended to the bankrupt firm by market value of equity of the creditor as reported for the year before the year of bankruptcy; REC is the industry recovery rate obtained from Fitch; CORR is the correlation of equity returns between the creditor and the ‘event’ firm for 252 days preceding the event; VOL is the annual equity return volatility of the creditor for 252 days preceding the event; LEV is the average leverage ratio of the creditor over four quarters during the preceding year, defined as the ratio of book value of debt over the market value of assets, taken as the market value of equity plus the book value of debt; MVE is the market value of equity for the creditors; SIZE is the book value of total assets of the creditors; BRSIZE is the book value of total assets of the 'event' firms; RATING is the creditor's credit rating on a cardinal scale, ranging from 1 for AAA, 2 for AA+, to 21 for C. The number of observations for firms with RATING is 561, 461 and 100 for the full sample, the industrials, and financials respectively.

Table VI
Cross-Sectional Analysis of Creditors' Abnormal Equity Returns

This table presents coefficient estimates of the cross-sectional regression and its variations:

$$\text{CAR} = \alpha + \beta_1 \text{EXP} + \beta_2 \text{REC} + \beta_1^* \text{ EXP(1-REC)} + \beta_3 \text{CORR} + \beta_4 \text{VOL} + \beta_5 \text{LEV} + \varepsilon$$

CAR is defined as the cumulated abnormal stock returns for the creditor for the [-1,1] daily interval around the bankruptcy event from an industry market model; other variables are defined in Table V. The estimates are from an OLS regression. Reported in parentheses are t-statistics based on clustered standard errors, which are robust standard errors adjusted for clustering by events. In addition to the reported variables, yearly dummies and industry dummies based on the one digit of SIC code of the bankrupt firm are also included in the regressions. The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Full Sample (N=694)

Independent Variables	Expected Sign	Model 1	Model 2	Model 3	Model 4
		Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Constant		-0.75	-1.55	-0.78	2.66
		(-3.90) ***	(-2.94) ***	(-4.06) ***	(3.11) ***
EXP	–	-0.84	-0.83		
		(-3.11) ***	(-3.08) ***		
REC	+		2.69		
			(1.83) *		
EXP(1-REC)	–			-1.01	-0.81
				(-2.97) ***	(-2.57) ***
CORR	–				-6.42
					(-3.03) ***
VOL	–				-2.82
					(-2.29) **
LEV	–				-0.61
					(-0.69)
R-square (%)		9.28	9.74	8.86	14.97
R-square adj. (%)		9.14	9.48	8.73	12.70
P-value for F-stat		0.0021	0.0025	0.0032	0.0000
Nb. of Clusters		251	251	251	251

Table VI (Continued)

	Panel B: Industrial Firms (N=583)				Panel C: Financial Isntitutions (N=111)			
Independent Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Constant	-0.85	-1.63	-0.88	2.88	-0.20	-1.01	-0.17	-0.01
	(-3.84) **	(-2.51) ***	(-3.96) ***	(3.19) ***	(-0.94)	(-2.58) ***	(-0.81)	(-0.01)
EXP	-0.84	-0.82			-1.00	-1.39		
	(-3.09) ***	(-3.07) ***			(-2.75) ***	(-3.83) ***		
REC		2.66				2.67		
		(1.41)				(2.40) ***		
EXP(1-REC)			-0.996	-0.81			-2.09	-1.91
			(-2.97) ***	(-2.61) ***			(-4.07) ***	(-1.77) *
CORR				-7.73				-3.89
				(-3.02) ***				(-1.36)
VOL				-2.59				-2.39
				(-1.89) *				(-1.66) *
LEV				-1.05				-0.30
				(-0.89)				(-0.34)
R-square (%)	9.33	9.67	8.88	15.94	3.64	7.95	5.07	22.15
(%)	9.17	9.36	8.73	13.26	2.65	2.64	4.20	6.92
P-value for F-stat	0.0022	0.0039	0.0032	0.0000	0.0075	0.0012	0.0001	0.0000
Nb. of Clusters	230	230	230	230	76	76	76	76

Table VII
Cross-Sectional Analysis of Creditors' Abnormal CDS Spread Changes

This table presents coefficient estimates of the cross-sectional regression and its variations:

$$\text{CASC} = \alpha + \beta_1\text{EXP} + \beta_2\text{REC} + \beta_1^*\ \text{EXP(1-REC)} + \beta_3\text{CORR} + \beta_4\text{VOL} + \beta_5\text{LEV} + \varepsilon$$

CASC is defined as the cumulated abnormal CDS spread change for the creditor for the [-1,1] daily interval around the bankruptcy event, adjusted for the average spread for the same credit rating; other variables are defined in Table V. The estimates are from an OLS regression. Reported in parentheses are t-statistics based on clustered standard errors, which are robust standard errors adjusted for clustering by events. In addition to the reported variables, yearly dummies and industry dummies based on the one digit of SIC code of the bankrupt firm are also included in the regressions. The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Full Sample (N=209)

Independent Variables	Expected Sign	Model 1	Model 2	Model 3	Model 4
		Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Constant		1.82	3.48	1.79	-3.82
		(3.72) ***	(2.59) ***	(3.72) ***	(-2.77) ***
EXP	+	8.01	8.84		
		(3.59) ***	(4.16) ***		
REC	–		-5.44		
			(-1.47)		
EXP(1-REC)	+			14.71	11.01
				(2.52) ***	(2.00) **
CORR	+				10.97
					(2.11) **
VOL	+				11.93
					(1.95) **
LEV	+				2.87
					(0.73)
R-square (%)		2.55	3.27	2.37	11.08
R-square adj. (%)		2.08	2.33	1.90	9.33
P-value for F-stat		0.0005	0.0000	0.0129	0.0007
Nb. of Clusters		128	128	128	128

Table VII (Continued)

Independent Variables	Panel B: Industrial Firms (N=177) Model 1	Model 2	Model 3	Model 4	Panel C: Financial Institutions (N=32) Model 1	Model 2	Model 3	Model 4
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Constant	2.17	3.82	2.13	-4.27	-0.13	0.73	-0.12	-0.87
	(3.87) ***	(2.39) **	(3.86) ***	(-2.88) ***	(-0.33)	(0.73)	(-0.31)	(-0.48)
EXP	9.16	9.85			4.43	5.17		
	(3.36) ***	(3.78) ***			(3.72) ***	(3.43) ***		
REC		-5.44				-2.74		
		(-1.19)				(-0.99)		
EXP(1-REC)			17.08	11.82			7.65	5.09
			(2.45) ***	(1.97) **			(2.48) ***	(1.01)
CORR				11.98				5.15
				(2.06) **				(0.61)
VOL				12.27				-3.05
				(1.81) *				(-0.73)
LEV				5.61				3.28
				(1.10)				(1.16)
R-square (%)	2.85	3.43	2.68	13.32	9.77	12.7	8.78	17.13
R-square adj. (%)	2.30	2.32	2.12	11.30	6.76	6.68	5.74	4.85
P-value for F-stat	0.0011	0.0003	0.0160	0.0003	0.0009	0.0071	0.0192	0.3647
Nb. of Clusters	111	111	111	111	30	30	30	30

Table VIII

Financial Distress of Creditor Firms

This table describes the financial distress of creditors subsequent to having suffered a credit loss, as defined by the bankruptcy filing of the debtor. It reports the number and fraction of firms that were delisted within one and two years, and of firms that were downgraded within one or two years, compared to a control sample over the same period. The firms in the control sample have the same 4-digit SIC code and the same credit rating as the creditor, and fall into the same size cohort (partitioned by the median of total assets) as the creditor. All firms in the creditor sample and control sample have a credit rating, which reduces the original creditor sample.
The superscripts ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively, for the chi-square test that the fractions for the creditor samples are equal to those for the control samples.

	Industrials				Financials			
	Creditor Sample		Control		Creditor Sample		Control	
	Number	Fraction	Sample	Test	Number	Fraction	Sample	Test
Starting sample	461		720		100		427	
Firms delisted:								
within one year	9	1.95%	0.28%	8.77 ***	1	1.00%	0.23%	0.99
within two years	12	2.60%	0.56%	9.10 ***	1	1.00%	0.23%	0.99
Firms downgraded:								
within one year	109	23.64%	8.33%	104.59 ***	14	14.00%	6.79%	12.26 ***
within two years	149	32.32%	12.36%	175.22 ***	20	20.00%	10.07%	22.81 ***

Table IX

Simulations of Portfolio Distributions with Counterparty Risk

This table describes simulations of the distribution of defaults in a portfolio with and without counterparty risk. The portfolio consists of N=100 obligors with identical probability of default (PD). The state of default for each obligor is simulated using a random normal variable, called asset value. When this falls below a cutoff point dictated by the PD, the obligor goes into default. Dependencies across default are introduced by a multivariate normal distribution for asset values with constant correlation of 0.2, which induces a default correlation that depends on the model setup. Counterparty risk is introduced by increasing the PD conditional on a counterparty default. Cascading effects are then modeled by iterating on the portfolio until the number of defaults stabilizes.

The table reports the empirical default correlation for various setups: no counterparty effect, with first counterparty default, and with multiple counterparty defaults. It also shows the distribution of number of defaults, using various percentiles. Simulations are based on 100,000 replications.

	No Counterparty Risk		**Counterparty Risk**						
Number of counterparties	0	0	3	3	3	1	2	5	10
Probability of default (PD)	1.00%	1.05%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%
Conditional PD	1.00%	1.05%	1.50%	1.25%	2.00%	1.50%	1.50%	1.50%	1.50%
Default correlation:									
No counterparty effect	0.0237	0.0244	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237
With first counterp. default			0.0278	0.0258	0.0316	0.0251	0.0264	0.0307	0.0390
With multiple counterp.default			0.0291	0.0262	0.0344	0.0252	0.0267	0.0331	0.0622
Average default rate	1.000%	1.050%	1.051%	1.024%	1.099%	1.016%	1.031%	1.083%	1.226%
Number of defaults:									
99% percentile	9	9	9	9	10	9	9	10	13
99.9% percentile	16	16	19	18	21	16	18	21	36
99.99% percentile	23	23	29	25	35	25	26	33	65