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CONTAGION AND RISK IN THE AMPLIFICATION OF CRISIS: EVIDENCE FROM ASIAN NAMES IN THE CDS MARKET

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Contagion and risk premia in the amplification of crisis: evidence from Asian names in the CDS market

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Abstract

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Keywords: sub-prime, mortgage crisis, turmoil, meltdown, amplification, valuation, credit default swap, expected default frequency, risk premia, credit bubble

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1. Introduction

The overriding analytical question of the global turmoil of 2007–2009 is that of amplification. The turmoil started out in the floating-rate segment of the US sub-prime mortgage market, a relatively small part of the entire US mortgage market.[1] Greenlaw et al (2008) estimated, in early 2008, that default losses on the outstanding stock of mortgages could total $500 billion. Because U.S. financial institutions hold less than half of the sub-prime mortgages, their exposure to these losses would amount to an easily manageable 1 percent of their assets. Yet the most recent estimates by the IMF (2009, p. xi) of potential write-downs for assets originated in mature markets total $4 trillion, eight times the initial estimate of losses on U.S. mortgages. Our own estimate of valuation losses in the credit markets during the crisis is $4.1 trillion. Government rescue packages in the Eurozone, the United Kingdom, and the United States now amount to about $6 trillion.[2] The question of amplification is, how did a small problem get to be so big?

There has been no shortage of proposed amplification mechanisms. One mechanism is a positive feedback loop between conditions in the nonfinancial and financial systems of economies. Here, losses on mortgages led to a contraction in credit, which in turn caused the economic slowdown. The slowdown, in turn, led to further credit losses. Greenlaw et al (2008) themselves propose a deleveraging mechanism. Given that financial institutions on average have a target leverage of ten-to-one, losses of $500 billion would imply that their balance sheets need to shrink by $5 trillion, unless the institutions in question could raise new capital to cover these

[1] In 2005–2007, total issuance of floating-rate sub-prime mortgages amounted to $1 trillion, compared to a total stock of US mortgage debt on 1- to 4-family homes of $11 trillion.

[2] In terms of the amounts already spent, the rescue packages include $1.8 trillion from the U.S. Treasury, $1.7 trillion from the U.S. Federal Reserve, $680 billion from the U.K. government and $1.4 trillion from Eurozone governments.

losses. During the crisis, the efforts to shrink balance sheets took the form of both asset sales and cut-backs in lending, both of which exacerbated the situation. Brunnermeier (2009) proposes a liquidity spiral, which arises from the maturity mismatch in leveraged financing. When asset prices and liquidity fell during the crisis, the collateral values of assets held by financial institutions deteriorated. This made it difficult for them to raise funds and forced them to reduce leverage, leading to further asset price declines. Gorton (2009) focuses on a panic in the "shadow banking system," in which financial firms ran on other financial firms by withdrawing from participation in the repo market. This led to massive deleveraging and resulted in an insolvent banking system.

In this paper, we focus on the role of valuation losses, another important part of the amplification process. It is important to distinguish between such valuation losses and expected losses from default. The former include losses induced by a rise in risk premia. With mark-to-market accounting, valuation losses could inflict serious damage on financial institutions even without any defaults.[3] In our story of the amplification process, the price of risk in global credit markets had declined over several years earlier this decade, thus helping to inflate what may be described as a credit bubble. Several events between August 2007 and September 2008 then caused the price of risk to jump back up, helping to prick the bubble. Valuation losses have been so large precisely because the underlying bubble had become so large. Here, we provide empirical evidence showing that when valuations of credit instruments rose before the crisis and fell during the crisis, it was not so much because of a reassessment of default risks as because of movements in credit risk premia, and more specifically, movements in the price of default risk.

The remainder of this paper is organized as follows. Section 2 presents stylized facts about CDS spreads and EDFs and other features of the data. Section 3 performs a preliminary analysis of the panel dataset properties of the relationships between CDS spreads and EDFs for the Asian names in our dataset. Section 4 provides a further examination of what drives changes in credit spreads. Section 5 concludes.

[3] A large Dutch bank, ING, was rescued by the Netherlands government in October 2008 because valuation losses had rendered it insolvent even though, according to a senior supervisor, there was "not a single penny of default."

2. Stylized facts of credit spreads and expected losses from default

2.1 The rise and fall of the credit bubble

We study valuation in credit markets by analyzing data on credit default swaps. Since the early 2000s, these default swaps have been among the most liquid credit instruments available. By far the most actively traded such instruments are the CDS index contracts, such as the DJ CDX NA IG Index for U.S. names, the iTraxx Europe Index for European names and the iTraxx Asia ex-Japan Index for Asian names outside Japan. Among the single-name CDS contracts, the most liquid ones are those that are included in the indices. The DJ CDX NA IG Index contains 125 investment-grade U.S. corporate names, the iTraxx Europe Index 125 investment-grade European corporate names and the iTraxx Asia ex-Japan Index 64 corporate and 6 sovereign names, 50 of which are investment grade and 20 high-yield. The indices are constructed as simple averages of the spreads on the constituent names.

The behavior of the CDS indices since 2002 depicts the evolution of a global credit bubble. As shown in Figure 1, credit spreads as measured by CDS indices started to decline in late 2002. At the end of May 2003, the US index stood at 77 basis points and the European index at 52 basis points. Both spread series declined further over the next four years. By May 2007, the US index had fallen to 31 basis points and the European index to 20 basis points, about two-fifths of their former level. This narrowing of spreads implies that the corporate bonds underlying the US index had risen in value by an average of about 2.3 percent and those underlying the European index by an average of about 1.6 percent. These are very large gains as investment-grade corporate bonds go, and they constitute a sign of the inflation of the global credit bubble.

The deflation of the credit bubble is generally dated to have started on August 9, 2007, when BNP Paribas announced that it was suspending valuation of three of its funds that had experienced losses due to their exposure to U.S. sub-prime mortgages. The bubble was pricked for a second time following the weekend of March 15 and 16, 2008, when liquidity problems forced Bear Stearns to allow itself to be taken over by JP Morgan Chase. The third and most devastating pricking of the bubble occurred after the collapse of Lehman Brothers on September 15, 2008. By November 2008, the US IG index had risen 240 basis points and the European index to 180 basis points. The valuation losses implied by the widening of these spreads averaged about 10.4 percent for US corporate bonds and about 8.0 percent for European bonds. At the end of July 2007, just before the start of the crisis, the size of the global corporate bond market as a whole stood at \$48 trillion. Assuming that the names in the CDS indices constitute a representative sample of the whole market, the implied valuation losses during the crisis would total \$4.1 trillion.

The slow growth and swift collapse of the credit bubble raise the question of what elements of valuation were involved. In this paper, we pose this question in terms of two elements that enter credit spreads, *default risks* and the *risk premia* associated with these risks. When the bubble was growing between 2002 and 2007, was it primarily because investors believed that default risks were declining, or was it because the price of these risks was falling? When the bubble burst, was it because perceived default risks suddenly rose, or was it mainly because the price of default risk jumped up?

2.2 Risk-neutral and physical default probabilities

The CDS spread can be decomposed as:

CDS spread = (Actual) expected loss + Default risk premium.

Technically speaking, we can represent CDS spread as a *risk-adjusted* (risk-neutral) expected loss rate: $CDS_t = E_t^Q(\lambda^Q L)$, where λ^Q is the risk-neutral default intensity and L is loss-given-default.[4] It is important to keep in mind that this expression can differ from the *actual expected loss* rate $E_t^P(\lambda^P L)$, both because λ^Q can be different from the physical default intensity λ^P, and also because the uncertainty associated with the movement of λ^Q can command a risk premium. These effects can lead to a nontrivial default risk premium. Indeed, Driessen (2005) and Berndt et al (2008) report that λ^Q, on average, exceeds λ^P by a factor of about 2 and that the ratio λ^Q / λ^P varies over time. Thus, a substantial part of the CDS spread variations may be due to fluctuations in a time-varying default risk premium.

[4] More precisely, the CDS spread is a present-value-weighted risk-neutral expectation of $\lambda^Q L$.

In order to quantify the part of the CDS spread variation that is attributable to variations in the default risk premium, one needs to have information on the physical default probability, with which to calculate the actual expected loss. For this purpose, we take the EDF measure calculated by Moody's-KMV as a proxy for the actual default probability, following the approach taken by Berndt et al (2008). A firm's τ -year EDF at time t is defined as

$$EDF_{t,\tau} = 1 - P(t, t+\tau),$$

where $P(t,t+\tau)$ is the actual (physical) probability that a surviving firm at time t will also survive τ periods later. The physical default intensity λ^P can be inferred from $P(t,t+\tau)$, as they are related via

$$P(t,t+\tau) = E_t^P[\exp(-\int_t^{t+\tau} \lambda^P(s)ds)].$$

For relatively short horizons τ, such as one year, $EDF_{t,\tau} \approx E_t^P(\int_t^{t+\tau} \lambda^P(s)ds)$. Thus, the actual expected loss rate can be approximated as the one-year EDF times the mean loss rate (assuming that the default intensity and loss-given-default are uncorrelated).

In view of the close relationship between the EDF and the physical default intensity, in our regressions of the CDS spread (or monthly change in CDS spread) we shall use the EDF (or monthly change in EDF) as a proxy for the variation of in the amount of the default risk, while other regressors may be also included to capture the effect of the variation in the price of default risk.

2.3 The Data

Our main dataset consists of monthly-frequency values, for the period from January 2005 until January 2009, for CDS spreads and EDFs for 41 corporate names from the Asia-ex-Japan region. The CDS data were obtained from MarkIt, and the EDF data from Moody's-KMV. The names are listed in Table 1. This set is the subset of all names that were listed in one or more of the iTraxx Asia-ex-Japan CDS indices (either IG or HY) for which we were able to construct complete monthly CDS and EDF series. We focus on these 41 names because they would seem to be among the ones for which default risks would be unlikely to be affected by troubles in the

U.S. sub-prime mortgage market. Moreover, unlike for sovereign names, EDFs are available for corporate names.

The monthly-frequency CDS data were constructed from daily CDS values, using quotes from the last-available day in each month; in most cases, this was the last trading day of the month. CDS spreads are quoted in over-the-counter markets; the world's largest financial institutions are usually the main market makers in these products.

The EDF data are also for the end of each calendar month. Aspects of the design of the models that underlie the proprietary calculation methods for EDFs by Moody's-KMV are discussed in Agrawal et al (2004) and Levy (2008). Basically, EDFs are calculated based on a Merton-type model using a firm's balanced sheet and equity price data. According to Moody's-KMV, their EDF data are used by a clear majority of major financial institutions as well as by many investment houses.

In addition, we use monthly-frequency data on the values of the iTraxx Asia ex Japan CDS indices (both IG and HY), as well as data for the DJ CDX NA (both IG and HY) CDS indices and the iTraxx Europe CDS index. We also use the CDS spreads for the constituent names of the latter three indices.

We treat the following three dates as crucial markers for the global financial crisis: (i) August 7, 2007, when BNP Paribas' decision to cease valuation of three of its mutual funds; (ii) March 17, 2008, the day after the weekend when Bear Stearns was taken over by JP Morgan Chase; and (iii) September 15, 2008, the day that Lehman Brothers declared bankruptcy. As may be readily seen from the time series shown Figure 1, spreads on the DJ CDX IG and iTraxx Europe indices rose abruptly around each of these three events. For sake of brevity, we will refer to the period from August 2007 to the end of the sample in January 2009 as the crisis period, noting of course that the crisis did not consist of a single defining event.

Figure 2 shows the time series of CDS spreads and EDFs of the 41 Asian names over our sample period. CDS spreads began to rise from a very low level in July and August 2007, rose rapidly in the first quarter of 2008 and retraced some of that run-up during the second quarter, and soared dramatically to about 750 basis points in October 2008, and remained very high over the remainder of the sample period. Strikingly, EDFs did not begin to move up noticeably until September 2008, and even then rose much less than CDS rates did. The challenge we face is how to explain the widening differential between CDS rates and EDFs, i.e., the risk premium component of CDS rates.

Figures 3 and 4 show the first three principal components computed from the set of five CDS indices; Figure 3 is based on the levels of the indices, and Figure 4 is based on the log-levels of the indices. In both cases, the first principal component, or PC, explains about 98% of the total variation of the five series. As may be seen from both figures, the first PC exhibits a time trend during the sample period: it declines until mid-2007 and rises sharply on balance over the remaining 18 to 20 months. In contrast, the second and third PCs (as well as the fourth and fifth, which are not shown to reduce clutter), are stationary time series and thus describe deviations from the overall trend. The presence of only one trending PC also implies that the 5 CDS index series, which are individually nonstationary, have a single cointegrating vector.

Summary statistics for CDS spreads, EDFs, and CDS indices for the pre-crisis and crisis periods are given in Tables 2 and 3.

3. A direct test of the relationship between CDS spreads and EDFs

A natural starting point for our empirical analysis is to specify and estimate a bivariate relationship between EDFs (the independent variable) and CDS rates (the dependent variable). Berndt et al (2008) found that a linear specification for the relationship between levels of CDS spreads and EDFs, over their sample period from 2000 to 2004, was unsatisfactory for two reasons: First, they noted heteroskedasticity in the regression errors; second, a scatterplot of pairs of CDS spreads and EDFs revealed that the functional relationship between the two variables tended to be concave rather than linear. To address these two issues, they took logarithms of both the dependent variable (the CDS rates) and the regressor (the EDF rates).

We attempted to replicate the double-log specification of Berndt et al (2008) for our dataset of 41 Asia-ex-Japan corporate names during the period from January 2005 until January 2009. However, we found that this specification was not well suited for our dataset, mainly because both the CDS and the EDF data exhibit strong time trends.[5] For instance, the Durbin-

[5] Values for both time series started out and remained low in 2005 and 2006, began to ratchet up in the second half of 2007, rose some more beginning in February 2008, and jumped up abruptly in September 2008. By the end of our sample, in January 2009, CDS and EDF rates remained high, as did the differences between the paired series.

Watson statistics of both the individual log-log regressions and the pooled log-log regression of CDS spreads on a constant and EDFs (see Table 4) were all very close to zero. As was noted first by Granger and Newbold (1974) and was explained rigorously by Phillips (1986), very low values of the Durbin-Watson statistics are generally strong warning signals that the regression relationship may be spurious and need not be related directly to each other. Indeed, further tests showed that the EDFs and CDS rates do not appear to be directly cointegrated with each other, despite the fact that they are individually nonstationary.

From the principal components analysis reported in the preceding section, we deduce that both the dependent variables and the regressors are characterized by dominant stochastic trends that generate strong cross-sectional dependence in the series. As has been noted recently by Bai et al (2009) and Breitung and Das (2008), in panel cointegration models with cross-sectional dependence generated by (generally unobserved) global stochastic trends, the least squares estimator is in general inconsistent owing to spuriousness induced by the I(1) trends.[6] Bai et al (2008) suggest an iterative estimator to address this issue. For our setup, since we may guess that the (unobserved) global stochastic trend is well proxied by the first PC, we may simplify the estimation procedure to obtain a consistent estimator.

Indeed, adding the variable $\log PC_{1t}$, the first principal component of the set of 5 log CDS indices (which captures 98% of the total variation of the five series), to the pooled regression of individual log CDS rates on log EDFs led to a more satisfactory regression model:

$$\log CDS_{it} = a_i + b_i \log EDF_{it} + c_i \log PC_{1t} + u_{it}$$

The results are shown in Table 5.[7] The residuals from this pooled regression appear to be stationary, and the fraction of the total variation of the 41 series that is explained by the model jumps from 33.2% in the simple bivariate model to 64.7% in the model that includes the first PC as an extra regressor. Interestingly, the pooled estimate of the coefficient b declines from 0.476 to 0.319 if the first PC is included. This suggests that the omission of that regressor introduces an omitted-variable bias in the bivariate relationship. Either way, however, the coefficient estimates

[6] Additional references to the panel unit root testing and cointegration literature are Gengenbach et al (2005), Levin et al (2002), and Pedroni (2004).

[7] We also included the second PC in the regression to verify that its influence is both numerically small and statistically insignificant.

are far below 1, which would be the value one would expect to find if there were no fluctuations in risk premia. We now turn to an examination of what drives the credit spreads.

4. What drives changes in credit spreads?

4.1 Variables

To explain how credit spreads narrowed between 2002 and 2007 and how they widened afterwards, we analyze first differences in CDS spreads. For these spreads, we focus on the 41 corporate names in the iTraxx Asia ex-Japan Index for which we have good data. Our explanatory variables consist of a measure of default risk and of variables representing risk pricing factors. For changes in default risk, we use first differences in EDFs for each of our 41 Asian names. For risk pricing factors, we extract four principal components from the first differences of the five CDS indices. Changes in correlations among default probabilities should also be important risk factors and should be priced.[8] As is shown in Figure 5, the cross-sectional correlation of EDFs for Asian names, the green line, is quite volatile, whereas the cross-sectional correlation of EDFs for U.S. names, the red line, is much less volatile.[9] Over the entire sample period, both average cross-sectional correlation is close to zero for both series. Our proxy for the relevant correlation parameter is the cross-sectional correlation of changes in EDFs for all names in the five CDS indices, which moves very similarly to that for just the U.S. names.

4.2 Principal components

Before we run our regressions, it is useful to discuss the principal components that we have extracted from the first differences in the various CDS indices. The first principal component explains 72% of the movements of the five CDS indices, and an analysis of its loadings and its time series properties suggests that it is a global risk pricing factor. The second principal component explains an additional 17% of the variance of the movements in the indices, and its loadings suggest that it is an Asia-specific risk pricing factor. The third principal component

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[8] Zhang et al (2008) provide an overview of the issues that arise in the process of estimating the correlation factor.

[9] We conjecture that the higher volatility of the cross-sectional correlations of Asian EDF returns owes importantly to the smaller sample size of the set of Asia-ex-Japan names.

explains 9% of the movements in the indices, while the fourth and fifth PCs contribute negligible proportions to the total variance.[10]

4.3 Estimates

Our basic estimating equations are

(1) $\Delta CDS_{it} = b_0 + b_1 \Delta EDF_{it} + u_{it}$

(2) $\Delta CDS_{it} = b_0 + b_1 \Delta EDF_{it} + b_2 PC_{1t} + b_3 PC_{2t} + b_4 PC_{3t} + b_5 PC_{4t} + u_{it}$,

where Δ denotes first differences, the subscript *i* the *i*th name in the panel, the subscript *t* the observation month and PC_{kt} the *k*th principal component. The first equation includes only the EDF variable as an explanatory variable. The second includes the four principal components. As before, we fit the equations to data involving a cross-section of 41 names and a time series of 48 months, running from February 2005 to January 2009.

The panel regression results show that risk pricing factors as well as reassessments of default risk have been important drivers of changes in CDS spreads. As reported in Table 6 and Table 7, the EDF variable and the first three principal components are statistically significant at conventional confidence levels. Notably, the fitted model that only has the EDFs as explanatory variables has an adjusted R^2 of 22.8%. Once the principal components are included, the adjusted R^2 more than doubles to 54.5%. The Durbin-Watson statistics are close to 2, suggesting that taking first differences has eliminated the trend components that could lead to spurious regressions. The onset of crisis seems not to change the relationships.[11]

The coefficients on some of the explanatory variables are estimated rather tightly, and it is interesting to interpret their economic significance. In the more comprehensive model, the

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[10] Goyal et al (2008) discuss methods for estimating principal components that are common to variables across groups of variables, as well as specific to individual groups of variables. In future work, we plan to employ their methodology to test for commonalities among the principal components of each of the three groups.

[11] When we added dummy variables for the crisis periods, both as intercept terms and as interactive variables, the adjusted R^2 did not improve. Instead, the crisis dummy variables seem to act merely as proxies for large changes in the explanatory variables, and the resulting regression model was characterized by severe multicollinearity among some of the regressors.

coefficients on the EDF variable and the first two principal components are estimated with very small standard errors. In the case of the EDF variable, a 100 basis-point move on average results in a 48 basis-point change in the spread in the same direction. This is a strikingly weak effect, given that EDFs are always much smaller and less volatile than the corresponding spreads. Put another way, a one standard-deviation move in the physical probability of default leads to a change in the risk-neutral probability by only three tenths of a standard deviation. It is the case that the estimated coefficients on the first two principal components are even smaller in absolute values. However, these variables are also larger and more volatile than the EDF variable. Indeed, a one standard-deviation move in the first principal component leads on average to a change in the CDS spread of an Asian name by 0.46 of its standard deviation. This is a much stronger effect than that of EDFs. Similary, a one standard-deviation move in the second principal component leads on average to a change in the CDS spread by 0.32 of its standard deviation, still a stronger effect than that of the EDF regressor.

Our analysis shows that valuations in credit markets do react consistently to reassessments of default risk. However, this reaction is surprisingly small. Instead, much of the changes in valuations appear to be driven by changes in the price of default risk, a price that seems to be affected by both global risk aversion and regional risk aversion.

5. Conclusion

A striking feature of the 2007–2009 global meltdown is the fact that credit spreads widened sharply for everyone, even for large borrowers in Asia who were far removed from the problems of the U.S. sub-prime mortgage market. As a consequence, valuation losses on credit instruments were massive, dwarfing the losses from actual defaults. Hence, these valuation losses played an important role in the amplification of the crisis. It could be argued that the decline in valuations simply reflected the knock-on effects on default risk of an anticipated economic slowdown. In this paper, we take account of such knock-on effects on large Asian borrowers and still find strong effects on spreads that seem to stem from shifts in the risk aversion of global investors and in the risk aversion of investors with a regional focus.

To account for the knock-on effects on default risk, we rely on EDFs, which are estimates of default probabilities that exploit the forward-looking nature of stock prices. To account for global and regional risk aversion, we extract principal components from the movements of various CDS indices comprising U.S., European and Asian names. We then regress monthly first differences in CDS spreads for a cross-section of Asian names on monthly first differences in their respective EDFs and on the principal components. We find significant but economically weak effects of EDFs on spreads and significant and strong effects of the principal components. The results suggest that shifts in risk aversion rather than reassessments of risk are what drive valuations of credit instruments. Moreover, there is an important global component to risk aversion, and a rise in such risk aversion would naturally be a source of contagion.

These results are not special just to the period of the crisis of 2007–2009. They account for the narrowing of credit spreads before the onset of the crisis as well as the widening of spreads around the various events that marked the crisis. Our results are consistent with the notion that the global turmoil was an accident waiting to happen. Between 2002 and 2007, as risk appetites in credit markets grew, a large credit bubble developed. The troubles in the U.S. sub-prime mortgage market were merely the trigger for the crisis. If not for these mortgages, something else would inevitably have pricked the bubble. And the crisis became so large because the underlying bubble was so large. We conclude that periods of rising credit bubbles are essentially periods of declining risk aversion. When a bubble bursts, it bursts because risk aversion suddenly jumps up. To better understand the formation of bubbles and their destruction would require a better understanding of the behaviour of investor risk aversion.

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Table 1: List of 41 names included in Asia ex Japan group

[to be completed]

Table 2: Summary statistics for CDS spreads and EDF during pre-crisis period[1]

	Mean	Standard Deviation	Maximum	Minimum
Levels				
CDS spreads				
Asia ex Japan	66.2	64.8	406.6	4.9
Investment grade	40.0	26.4	139.0	4.9
High yield	157.8	75.3	406.6	39.1
EDF				
Asia ex Japan	19.1	36.0	303.0	1.0
Investment grade	15.2	29.9	303.0	1.0
High yield	32.8	49.8	303.0	3.0
CDS indices				
DJ CDX NA IG	44.3	10.5	82.0	31.1
DJ CDX NA HY	335.7	62.2	521.6	236.9
iTraxx Europe	32.0	7.4	51.0	20.4
iTraxx Asia ex Japan IG	34.4	6.9	46.1	22.5
iTraxx Asia ex Japan HY	199.9	42.7	283.4	130.9
First differences				
CDS spreads				
Asia ex Japan	0.1	14.5	103.4	-115.2
Investment grade	0.2	8.0	54.6	-42.1
High yield	-0.3	26.9	103.4	-115.2
EDF				
Asia ex Japan	-0.9	9.8	70.0	-109.0
Investment grade	-0.8	8.0	70.0	-109.0
High yield	-1.5	14.6	70.0	-109.0
CDS indices				
DJ CDX NA IG	1.2	8.4	40.0	-9.9
DJ CDX NA HY	6.6	49.0	184.8	-51.4
iTraxx Europe	0.6	5.9	25.8	-6.0
iTraxx Asia ex Japan IG	0.1	5.0	16.2	-7.1
iTraxx Asia ex Japan HY	-1.3	25.1	67.0	-45.4

[1] Sample period is from January 2005 to July 2007. All numbers are expressed in basis points.

Sources: Markit; Moody's Investors Service; JPMorgan Chase; authors' calculations.

Table 3: Summary statistics for CDS spreads and EDF during the crisis[1]				
	Mean	Standard Deviation	Maximum	Minimum
Levels				
CDS spreads				
Asia ex Japan	317.4	387.8	2850.0	15.4
Investment grade	189.0	175.5	1280.2	15.4
High yield	608.2	547.8	2850.0	80.0
EDF				
Asia ex Japan	72.8	228.5	2131.0	1.0
Investment grade	33.1	123.9	1567.0	1.0
High yield	162.8	352.8	2131.0	1.0
CDS indices				
DJ CDX NA IG	131.5	55.3	240.0	55.5
DJ CDX NA HY	737.3	316.2	1421.4	405.2
iTraxx Europe	98.2	45.9	175.0	37.3
iTraxx Asia ex Japan IG	172.0	120.3	404.0	42.4
iTraxx Asia ex Japan HY	668.8	429.2	1529.0	217.9
First differences				
CDS spreads				
Asia ex Japan	32.8	151.8	1598.2	-659.6
Investment grade	19.8	84.1	750.2	-551.2
High yield	62.2	241.1	1598.2	-659.6
EDF				
Asia ex Japan	11.9	93.5	1238.0	-659.0
Investment grade	4.8	47.4	606.0	-545.0
High yield	27.9	152.2	1238.0	-659.0
CDS indices				
DJ CDX NA IG	6.5	28.4	56.5	-48.0
DJ CDX NA HY	50.0	140.7	304.4	-236.5
iTraxx Europe	6.0	21.8	47.3	-48.0
iTraxx Asia ex Japan IG	16.9	50.3	161.1	-74.9
iTraxx Asia ex Japan HY	61.9	198.6	771.5	-166.8

[1] Sample period is from August 2007 to January 2009.

Sources: Markit; Moody's Investors Service; JPMorgan Chase; authors' calculations.

Table 4

Dependent Variable: Log CDS

Method: Pooled Least Squares

Sample: 2005M01 2009M01

Included observations: 49

Cross-sections included: 41

Total pool (unbalanced) observations: 1642

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.286565	0.045570	72.12188	0.0000
Log EDF	**0.476275**	**0.016657**	**28.59389**	**0.0000**

R-squared	0.332685	Mean dependent var	4.402273
Adjusted R-squared	0.332278	S.D. dependent var	1.167299
S.E. of regression	0.953849	Akaike info criterion	2.744595
Sum squared resid	1492.119	Schwarz criterion	2.751177
Log likelihood	-2251.313	Hannan-Quinn criter.	2.747036
F-statistic	817.6107	Durbin-Watson stat	0.071027
Prob(F-statistic)	0.000000		

Table 5

Dependent Variable: Log CDS

Method: Pooled Least Squares

Sample: 2005M01 2009M01

Included observations: 49

Cross-sections included: 41

Total pool (unbalanced) observations: 1642

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.616281	0.034884	103.6657	0.0000
Log EDF	**0.318600**	**0.013084**	**24.35057**	**0.0000**
PC_LOG1	**0.301046**	**0.007897**	**38.12141**	**0.0000**
PC_LOG2	-0.061329	0.080610	-0.760809	0.4469

R-squared	0.647070	Mean dependent var	4.402273
Adjusted R-squared	0.646423	S.D. dependent var	1.167299
S.E. of regression	0.694103	Akaike info criterion	2.110040
Sum squared resid	789.1537	Schwarz criterion	2.123204
Log likelihood	-1728.343	Hannan-Quinn criter.	2.114922
F-statistic	1001.048	Durbin-Watson stat	0.072175
Prob(F-statistic)	0.000000		

Table 6

$$\Delta CDS_{it} = b_0 + b_1 \Delta EDF_{it} + u_{it}$$

Dependent Variable: First-differenced CDS spreads

Method: Pooled Least Squares

Sample (adjusted): 2005M02 2009M01

Included observations: 48 after adjustments

Cross-sections included: 41

Total pool (unbalanced) observations: 1601

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	**10.25515**	**2.196513**	**4.668831**	**0.0000**
D_EDF	**0.780734**	**0.035880**	**21.75934**	**0.0000**

R-squared	0.228456	Mean dependent var	13.68189
Adjusted R-squared	0.227974	S.D. dependent var	99.76870
Sum squared resid	12287657	Schwarz criterion	11.79282
F-statistic	473.4689	Durbin-Watson stat	2.129783
Prob(F-statistic)	0.000000		

Table 7

$$\Delta CDS_{it} = b_0 + b_1 \Delta EDF_{it} + b_2 PC_{1t} + b_3 PC_{2t} + b_4 PC_{3t} + b_5 PC_{4t} + u_{it}$$

Dependent Variable: First-differenced CDS spreads

Method: Pooled Least Squares

Sample (adjusted): 2005M02 2009M01

Included observations: 48 after adjustments

Cross-sections included: 41

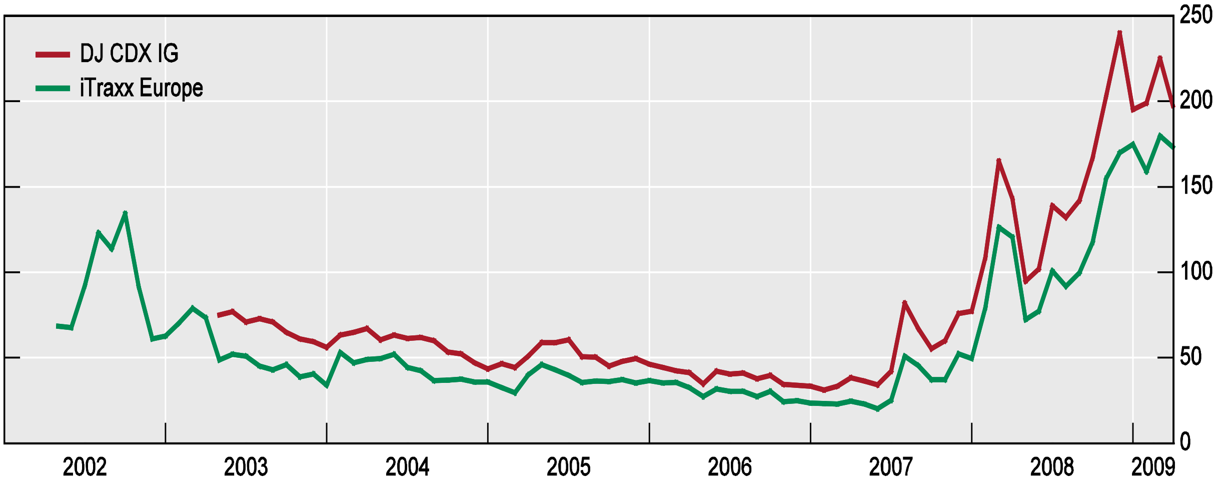
Total pool (unbalanced) observations: 1601

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.875948	1.685875	5.858054	0.0000
D_EDF	**0.476329**	**0.029218**	**16.30275**	**0.0000**
PC1	**0.239791**	**0.087972**	**27.25773**	**0.0000**
PC2	**-0.338200**	**0.017091**	**-19.78819**	**0.0000**
PC3	0.047568	0.024880	1.911849	0.0561
PC4	0.063222	0.058056	1.088970	0.2763

R-squared	0.546744	Mean dependent var	13.68189
Adjusted R-squared	0.545323	S.D. dependent var	99.76870
S.E. of regression	67.27379	Akaike info criterion	11.25916
Sum squared resid	7218591.	Schwarz criterion	11.27932
Log likelihood	-9006.957	Hannan-Quinn criter.	11.26664
F-statistic	384.7961	Durbin-Watson stat	2.159854
Prob(F-statistic)	0.000000		

Figure 1: CDS index spreads

In basis points

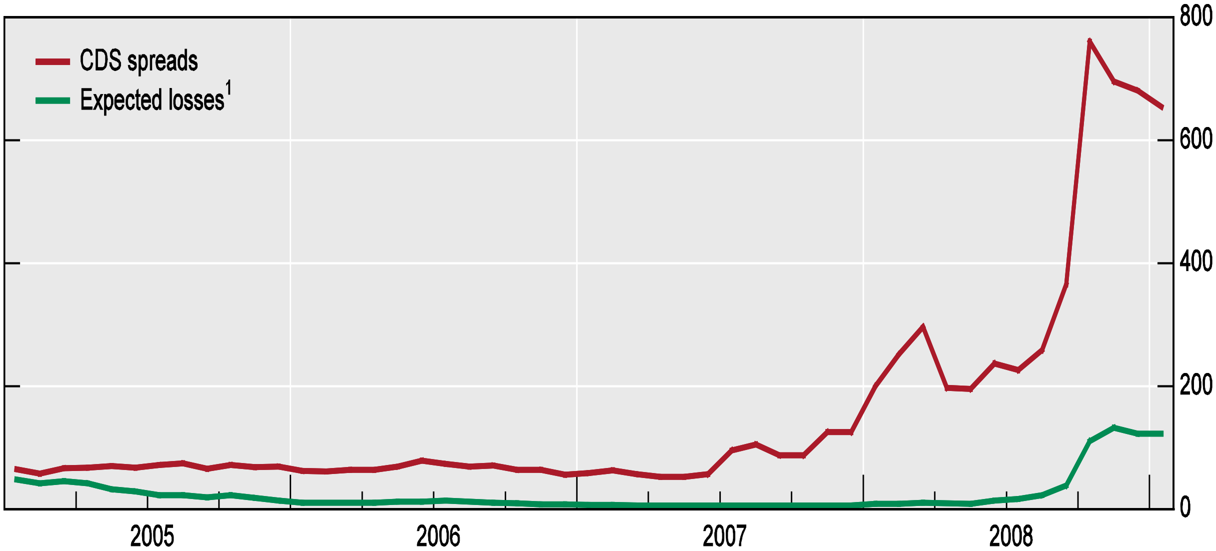


Five-year on-the-run CDS spreads.

Source: JPMorgan Chase.

Figure 2: Average CDS spreads and expected losses for Asian companies

41 names; in basis points

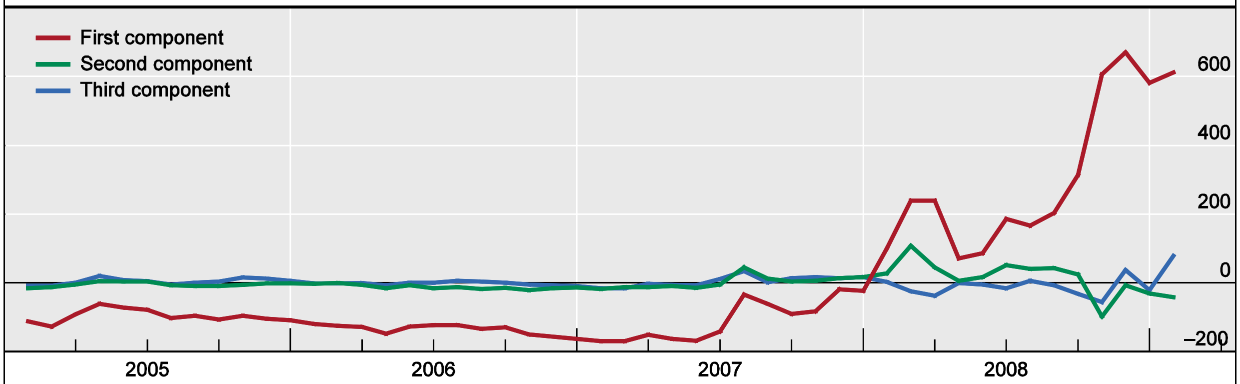


[1] Average EDF multiplied by 0.5, which is the historical loss given default.

Sources: Markit; Moody's Investors Services; authors' calculations.

Figure 3: First 3 principal components of the set of 5 CDS indices

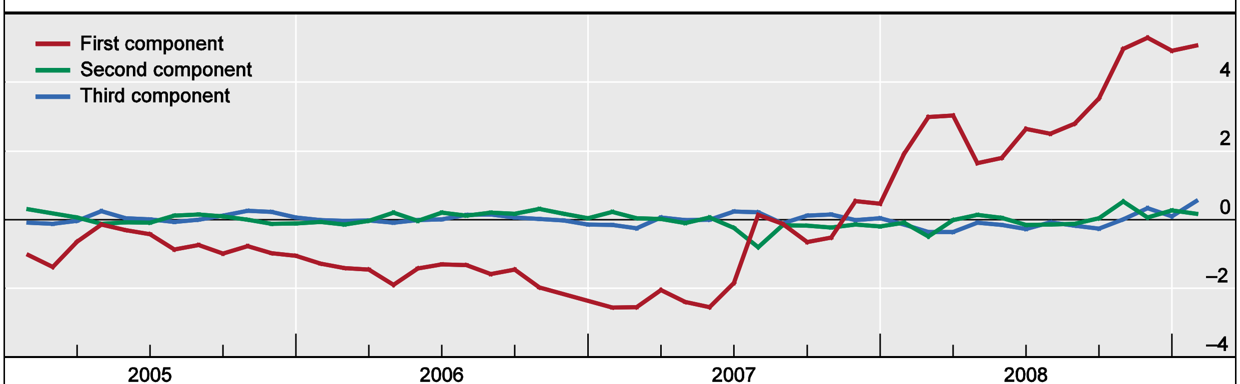
Sample period: Feb 2005 to Jan 2009



Sources: JPMorgan Chase; authors' calculations.

Figure 4: First 3 principal components of the set of logs of the 5 CDS indices

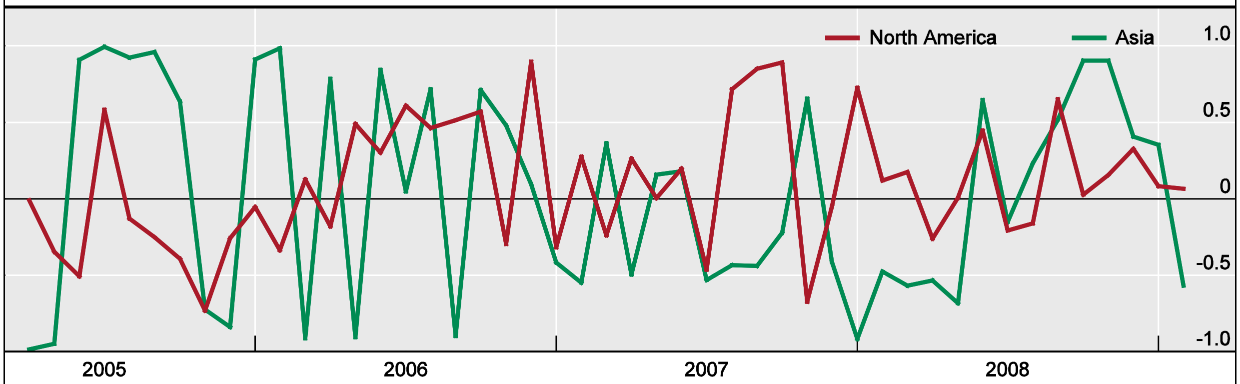
Sample period: Feb 2005 to Jan 2009



Sources: JPMorgan Chase; authors' calculations.

Figure 5: Correlations of monthly changes in EDFs

Names in DJ CDS North America and iTraxx Asia ex-Japan indices



Sources: Moody's Investors Services; authors' calculation.