Contagion and risk premia in the amplification of crisis:

Evidence from Asian names in the global CDS market*

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Abstract. In the turmoil of 2007–2009, troubles in a small corner of the US mortgage market escalated into a crisis of global proportions. A striking feature of the crisis is the contagion that hit Asia. In a region where exposures to problem mortgages were minimal, credit spreads for major borrowers widened as much as they did in Europe and the United States. We argue that the contagion was part of an amplification mechanism driven by valuation losses caused by the bursting of a global credit bubble. The valuation losses stemmed not so much from a reassessment of credit risks as from a global repricing of these risks. It was this repricing that was the main channel for contagion into Asian credit markets. For empirical evidence, we analyze fluctuations in credit default swap (CDS) spreads and expected default frequencies (EDFs) for major Asian borrowers. Because EDFs reflect forward-looking information in stock prices, they would account for the knock-on effects of a slowing economy on default risk. We find that valuation losses on CDS contracts for these Asian borrowers arose in large part from movements in global and region-specific risk pricing factors and

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only to a smaller degree because of revisions in individual expected losses from default.

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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 US mortgage market. Had the losses of U.S. financial institutions been limited to those caused by defaults on sub-prime mortgages, the losses would have been easily manageable and there would be no global crisis. These institutions, however, suffered losses on most other credit instruments, and so heavy were these losses that many of the institutions had to be rescued by the government and so did a number of their counterparts in Europe. Even Asia was not spared. In a region, where exposures to U.S. sub-prime mortgages were much smaller, credit spreads rose in tandem with those in Europe and the United States. The question of amplification is then how did a small problem get to be so big? In this paper, we focus on a particular aspect of that question: Can one explain how the problem spread to the credit markets in Asia?

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) propose such a deleveraging mechanism. Given that financial institutions on average have a target leverage of ten-to-one, estimated 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 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 that arises from a 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 *de facto* 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. A possible aspect of this run was a sudden aversion to complex credit instruments, such as collateralized debt obligations.

In this paper, we propose that valuation losses played a large role in the amplification process and, importantly, that these losses had more to do with a rise in the price of risk than the in risk itself. It was because the repricing of risk was a global phenomenon that contagion arose. We analyse valuation losses as something distinct from actual default losses and do so by analyzing credit spreads on major Asian borrowers. The default risk of these borrowers, as we show below, did not rise very much during the crisis. However, with mark-to-market accounting, sharp increases in risk premia resulted in losses that have devastated financial institutions even without any defaults occurring.[1] 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 we characterize as a credit bubble. Several events between August 2007 and September 2008 then caused the price of risk to soar, serving to prick the bubble. Valuation losses have been so large precisely because the underlying bubble had become so large.

We provide empirical evidence that shows that when valuations of credit instruments rose before the crisis and then fell during the crisis, it was not so much because of a reassessment of default risks as because of movements in credit risk premia. In the case of Asian borrowers, credit spreads rose because default risk premia were driven by a global risk factor, which acted as the source of contagion. To measure credit spreads, we rely on credit default swap (CDS) contracts, which have continued to trade actively. Since these are rather simple derivative instruments, the issue of a sudden aversion to complex instruments does not arise in matters of pricing. To measure "pure" default risk, we rely on estimates by Moody's KMV of expected default frequencies (EDFs), which take into account information contained in the balance sheets of borrowers, the values of their assets and liabilities, and the volatility of their asset values. As such, EDFs are a forward-looking estimate of risk that takes into account possible knock-on effects of a slowing economy. To consider additional risk pricing factors, we use principal components derived from the major CDS indices for Europe, the United States and Asia. Our results suggest that credit spreads even for Asian borrowers were

[1] A large Dutch bank 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."

driven by movements in global risk aversion.[2] Our results appear to be robust to whether financial institutions are included in the sample or not.

The remainder of this paper is organized as follows. Section 2 poses the question of amplification and contagion and offers as an hypothesis the bursting of a global credit bubble. Section 3 specifies our analytical framework and presents stylized facts about our data on CDS spreads and EDFs for Asian names and CDS indices. Section 4 performs a preliminary analysis of the panel-dataset properties of the relationships between CDS spreads and EDFs for the Asian names. Section 5 provides our examination of what drives changes in credit spreads for major Asian borrowers. Section 6 concludes.

2. Amplification, contagion and the credit bubble

2.1 Amplification and contagion

The global financial meltdown of 2007–2009 started out in the floating-rate segment of the US sub-prime mortgage market. Total issuance in this market during 2005–2007 amounted to $1 trillion. This is relatively small compared to the total stock of U.S. mortgage debt on 1- to 4-family homes of about $11 trillion. By analyzing different vintages of the sub-prime mortgages, Goldman Sachs (2007) estimates that default losses would total around $250 billion. By including knock-on effects from a decline in housing prices, Greenlaw et al (2008) estimate that such default losses could reach $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% of their assets. These direct losses, however, have somehow led to losses on other credit instruments that have been far more serious. In total, these valuation losses have been so heavy that governments in the United States and in Europe have had to step in a massive way to save their financial systems from collapse. 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 Greenlaw et al (2008) estimate of losses on U.S. sub-prime mortgages. Government rescue packages in the Eurozone, the United

[2] It is a common assumption in macroeconomic models that risk aversion is a deep parameter that is fixed. However, there is strong empirical evidence that risk aversion varies over time and indeed can be quite volatile. See, for example, Ait-Sahalia et al (2001), Bliss and Panigirtzoglou (2004) and Bekaert et al (2009).

Kingdom, and the United States now amount to about \$6 trillion.[3] The question of amplification is then, how did a small problem get to be so big?

An interesting aspect of the meltdown is how it has affected Asia. In a region where exposures to U.S. sub-prime mortgages have been minimal, credit spreads for major borrowers have risen at least as much as they have for major borrowers in the United States and Europe. From the start of the crisis in August 2007 to its peak in November 2008, credit spreads for the 125 U.S. investment-grade borrowers included in the DJ CDX Index rose by an average of over 170 basis points, while spreads for the 125 European borrowers in the iTraxx Europe Index rose by over 120 basis points. The credit markets seemed not to make a distinction for Asian borrowers. During the same period of the turmoil, the spreads for borrowers included in the iTraxx Asia ex-Japan Index rose by over 320 basis points.

What is behind these global co-movements in credit spreads since the onset of the crisis? Is it because liquidity in credit markets had been priced in the spreads and liquidity for all credit instruments on these borrowers vanished at the same time? Is it because the crisis was a wake-up call for a global reassessment of risks, in which investors decided that they had previously badly underestimated risks and were now just correcting their mistakes? While not wishing to dismiss the potential explanatory power of these hypotheses, in this paper we propose a third possibility, namely that the events that marked the crisis affected the risk aversion of global investors and that it was largely the resulting increase in risk aversion that led to the widening of credit spreads.

2.2 The rise and fall of the credit bubble

We propose that the contagion in Asia as reflected in credit spreads has been part of a larger phenomenon, namely that of a global credit bubble that inflated over time and that burst during the crisis. Such a bubble would be a simple answer to the amplification question: the crisis got so big because the underlying bubble was so big. The sub-prime mortgage disaster was merely the pin that pricked the bubble.

We study valuation in credit markets by analyzing data on credit default swaps (CDSs). One advantage of relying on CDS spreads is that they do not raise the issue of complexity,

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[3] 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.

since these are rather simple derivative contracts. Since the early 2000s, these CDSs have been among the most liquid credit instruments available and seem to have maintained a modest degree of liquidity even during the crisis.[4] By far the most actively traded of 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 have been those that are included in the indices.[5] The DJ CDX NA IG Index contains 125 investment-grade U.S. corporate names, the iTraxx Europe Index consists of 125 investment-grade European corporate names, and the iTraxx Asia ex-Japan Index is composed of 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 average credit spreads, as measured by CDS indices, depicts the evolution of a global credit bubble since 2002. As shown in Figure 1, CDS indices started to decline in late 2002.[6] 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 levels. Calculations show that 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 valuation 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, which had experienced large losses due to their exposure to U.S. sub-prime mortgages. This event triggered a widespread and prolonged decline in the amount of outstanding asset-backed commercial paper, not just in real-estate backed short-term instruments. 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

[4] Remolona and Shim (2008) analyse the market for these instruments with regard to major Asian borrowers.

[5] A primary criterion for inclusion of a corporate name in a CDS index is the liquidity of its credit instruments. Membership in CDS indices is generally reviewed every six months, and names that have become less liquid are replaced by those that are more liquid.

[6] Credit spreads were elevated during the period from mid-2001 to late 2002 which was marked by several large-scale corporate accounting scandals and resulting valuation losses in stock markets.

and most devastating lancing of the bubble occurred after the collapse of Lehman Brothers on September 15, 2008 and of Washington Mutual a few days later. By November 2008, the US IG index had risen to 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 investment-grade 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 default risk declined, i.e., because investors were willing to accept a lower compensation for bearing default risk? And, when the bubble burst, was it because perceived default risks rose suddenly, or was it mainly because the price of default risk jumped up?

3. Analytical framework and data

3.1 Risk-neutral and physical probabilities

We now specify a framework of analysis that allows us to distinguish between risk and the price of that risk in the valuation of credit instruments. We apply the framework particularly to credit default swaps (CDSs) and expected default frequencies (EDFs), the former representing "risk-neutral" expected losses from default and the latter "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* (or 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.[7] It is important to keep in mind that this expression can

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

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) reports that λ^Q, on average, exceeds λ^P by a factor of about two; for BBB/Baa bonds, Amato and Remolona (2005) report a factor of four. Berndt et al (2008) find 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.

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). As explained below, the EDFs are calculated based on a Merton-type structural model of credit risk using data on a firm's balance sheet, asset values and equity volatility. 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

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

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

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, and we shall include other regressors to capture the effects of variations in the price of default risk. As we explain below, the EDFs are a forward-looking measure of default risk that incorporate the near term prospects of the economy as perceived by investors.

3.2 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, EDFs are available for corporate names, while they are not for sovereign names. Among the 41 corporate names in our sample are eight financial institutions, seven telecommunication firms and four semiconductor firms. Ten of the names are from Korea, six from Singapore, five from Hong Kong, five from India, four from China, four from Malaysia, three from Thailand and one each from Indonesia, the Philippines and Taiwan.

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). In general, the EDFs are calculated based on a Merton-type structural model of credit risk using data on a firm's balance sheet, asset values and equity volatility. A wide class of Merton-type models have been described and their empirical performance assessed by Huang and Huang (2002) and Eom et al (2004). 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 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 in Figure 1, spreads on the DJ CDX IG and iTraxx Europe indices rose abruptly around each of these three events. For the 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.

The crisis seems to have driven a wider and wider wedge between time series of the average CDS spreads of the names in our sample and the time series of the average expected losses. Figure 2 shows the evolution of these time series over the sample period. Expected losses are calculated based on the EDFs and assuming a loss given default (LGD) of 0.5. Over the whole period, CDS spreads remain much wider than expected loss rates, with the risk premium accounting for the differential. Based on the summary statistics provided in Table 2, on average the risk premium accounted for 85% of the spread and the expected loss for 15%. CDS spreads began to rise from a very low level in July and August 2007, rose rapidly in the first quarter of 2008, retraced some of that run-up during the second quarter, soared dramatically to about 750 basis points in October 2008, and remained very high over the remainder of the sample period. In contrast, expected losses did not begin to move up noticeably until September 2008, and even then they rose much less than did CDS rates spreads. The challenge we face is how to explain the sharp widening of the differential between CDS rates and expected loss rates, i.e., the risk-premium component of CDS rates.

The major CDS indices exhibit a high degree of co-movement. Figure 3 shows the time series of the first three principal components computed from the log-levels of the five CDS indices. The first principal component (PC) explains about 98% of the total variation of the five series. As shown in the figure, this PC exhibits a time trend over the entire sample period: it first declines steadily, until mid-2007, and then 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 clearly stationary and thus describe only deviations from the dominant trend.[8] The factor loadings of the logs of the individual CDS indices on the second through fifth PC do not lend themselves to any clear-cut economic interpretations.

Summary statistics for CDS spreads, EDFs, and CDS indices for the full sample period, the pre-crisis period, and the crisis period are given in Table 2. As elsewhere in this paper, the crisis period is defined as the period from August 2007 to January 2009. Assuming an LGD of 0.5, the CDS spreads of the Asian investment-grade names exceed expected losses by a factor of almost 8, while spreads of the high-yield names exceed expected losses by a factor of almost 7. This shows that by far the larger part of the spread is a risk premium. In terms of first differences, the volatility of CDS spreads is about 60% higher than that of EDFs.

4. Modeling the relationship between the levels of 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 spreads (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 the presence of heteroskedasticity in the regression errors; second, a scatterplot of pairs of CDS spreads and EDFs revealed that the bivariate relationship between the levels of 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 spreads) and the regressor (the EDF rates).

We attempted to replicate the pooled double-log specification of Berndt et al (2008) for our full dataset, which consists of 41 Asia-ex-Japan corporate names during the period from January 2005 until January 2009:

$$\log CDS_{it} = a + b \log EDF_{it} + u_{it}$$

The OLS regression results are reported in column (1) of Table 3. The estimated intercept and slope coefficients are both positive and strongly significant by ordinary statistical conventions. However, the Durbin-Watson statistic of this regression is only 0.07.[9] As was

[8] The fact that only one PC has a trend also implies that the 5 CDS index series, which are individually nonstationary, have a single cointegrating vector.

[9] The DW statistics of the individual, i.e., non-pooled regressions were also uniformly very low, indicating that the result for the pooled regression is not an artifact of an invalid pooling assumption. 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 (usually unobserved) global stochastic trends, the least squares estimator is in general inconsistent owing to spuriousness induced by the I(1) trends. Bai et al (2009) suggest an iterative estimator to address this issue. Additional references to the panel unit root testing and cointegration literature are Gengenbach et al (2005), Levin et al (2002), and Pedroni (2004).

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 the variables in the regression may not be related to each other. Indeed, further tests showed that the EDFs and CDS rates of individual names, though clearly nonstationary, are not cointegrated with each other.[10]

Given the known presence of strong trend components in the CDS spread indices and the EDFs, the rejection of the null that the simple model is specified correctly is not unexpected. We next considered the following, expanded model:

$$\log CDS_{it} = a + b \log EDF_{it} + c_1 \log PC_{1t} + c_2 \log PC_{2t} + u_{it,}$$

where $\log PC_{kt}$ denotes, with some abuse of notation, the *k*th principal component of the logarithms of the CDS indices. The results of this regression are reported in column (2) of Table 3. Adding these two additional variables does not ameliorate the specification problem. We next considered the possibility that a structural break in the relationship between (log) CDS spreads and EDFs around the time of the onset of the crisis may give rise to this problem. However, letting each of the three slope coefficients vary across the pre-crisis and crisis periods – see column (3) – did not solve the mis-specification problem either.

Rather than apply a direct "correction" of the serial correlation issue, such as the Cochrane-Orcutt procedure, we chose to add the lagged endogenous variable to the basic bivariate regression; see column (4) of Table 3. With this modification, the regression model no longer appears to be statistically mis-specified, and the R^2 statistic jumps to 95%. However, the numerical influences of the constant term and the log EDFs on log CDS rates drop to nearly zero. Put differently, the inference that the intercept and slope coefficient of the simple bivariate model are both nonzero is not warranted once a better-specified model is obtained. Column (5) of Table 3 reports the results of augmenting this model by letting the slope coefficients vary across the two subsamples, but doing so does not alter our conclusions regarding the potential insignificance of the EDFs in the pooled time-series cross-section model.

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[10] Because EDFs are estimated quantities, they contain measurement error. Unless there are significant methodological shifts in the calculation methods of EDFs – which was not the case in our sample – it may be assumed that these measurement errors are stationary. Granger (1986, p, 217) notes that if two time series are cointegrated but are only observed with measurement error, the two observed series will also be cointegrated if all measurement errors are I(0). Therefore, (stationary) measurement errors in EDFs cannot explain our finding that EDFs and CDS rates are not cointegrated. Inference issues arising in models in which observed variables contain I(1) measurement error components are examined in Gyntelberg et al (2009).

We also considered the possibility that the lack of statistical evidence for a relationship between the variables could be driven by the fact that the full sample contains both financial and nonfinancial firms; if the relationship is not homogeneous across these subsets of firms, spurious regression results might be generated. We re-estimated regression models (1) through (5) on the subset of nonfinancial firms but the results were qualitatively very similar to those obtained for the full sample. Hence, they are not caused by heterogeneity in the composition of the sample.

These results are admittedly negative, in the sense that the statistical model using log levels of the variables does not let us draw meaningful conclusions regarding the relationship between CDS spreads and EDFs (and hence the difference between these two series). Nevertheless, these findings suggest that any known cross-sectional results between the two series are simply swamped by the time trends in the series. This is useful knowledge, however, as it motivates us to study the relationship between the variables in a first-differenced model. First differencing is well known to remove both stochastic and deterministic trends. This model is the subject of the next section.

5. What drives changes in credit spreads?

5.1 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 names in the iTraxx Asia ex-Japan Index for which we have good data. We also analyse a sample of 33 names that excludes financial firms. 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.

5.2 Principal components

Before we run our regressions, it is useful to discuss the principal components (PCs) that we have extracted from the first differences in the various CDS indices. As shown in Table 4, the first PC explains 72% of the movements of the five CDS indices. An analysis of its loadings and its time series properties suggests that it is a global risk pricing factor. The second PC 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 PC explains 9% of the movements in the indices, and it appears to be a Europe-specific risk pricing factor. The fourth and fifth PCs contribute negligible proportions to the total variance.[11] We do not have a good interpretation of the fourth and fifth principal components.

5.3 Estimates

Our basic estimating equations are

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

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

where Δ denotes first differences, the subscript *i* the *i*th name in the panel, the subscript *t* the observation month, and (again with some abuse of notation) ΔPC_{kt} the *k*-th principal component of the first-differenced CDS indices. 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 columns 2 and 3 of Table 5, the EDF variable as well as 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 indeed succeeded in eliminating the trend components noted in Section 4 that could give rise to spurious regressions. The onset of crisis seems not to change the relationships.[12]

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[11] 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.

[12] 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

The coefficients of some of the explanatory variables are estimated rather tightly, and it is interesting to interpret their economic significance. In the more comprehensive model, the coefficients of the EDF variable and of the first two principal components are estimated with very small standard errors. In the case of the EDF variable, a 100 basis-point move, ceteris paribus, 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 CDS spreads. Put another way, a one standard-deviation move in the physical probability of default on average leads to a change in the risk-neutral probability of only three tenths of a standard deviation.

The estimated coefficients of the first two principal components are even smaller in absolute value. 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, ceteris paribus, to a change in the CDS spread of an Asian name by 0.46 of its standard deviation. This is a much stronger economic effect than that of changes in EDFs. Similarly, 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, roughly the same economic effect as that of the EDF variable.

Note that because these results are based on the economic significance of the coefficients, they do not hinge on us having access to the precise measures of default risk that were on the minds of investors. Our inference requires only that we have an unbiased measure of default risk.[13]

Our results appear to be robust to a number of specification choices. For instance, because EDF estimates are likely to be less reliable for financial institutions, which tend to have very high leverage, we ran the same regressions for only the subsample of 33 Asian names that are non-financial firms. As shown in columns 3 and 4 of Table 5, we do get a slightly better goodness of fit when financial firms are excluded. However, the qualitative results do not change. We also interacted our explanatory variables with dummy variables that represent various phases of the crisis. The interaction terms do not result in statistically

changes in the explanatory variables, and the resulting regression model was characterized by severe multicollinearity among some of the regressors.

[13] Because default probabilities are not observable, one cannot test this unbiasedness hypothesis directly. However, KMV aims to have EDFs equal actual default frequencies over suitably chosen longer time intervals.

significant coefficients, suggesting that the crisis did not change the relationships among the variables. If the liquidity of CDS contracts did change because of the crisis, this did not seem to discernibly affect the price determination process.

Summing up, our analysis shows that valuations in credit markets do react consistently to reassessments of default risk. However, this reaction is rather small. Instead, changes in valuations appear to be driven largely by changes in the price of default risk, and this price seems to be affected by both global and region-specific fluctuation in investors' risk aversion.

6. Conclusion

A striking feature of the 2007–2009 global financial 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 losses from actual defaults. We propose that these valuation losses played an important role in the amplification of the crisis. While it could be argued that the decline in valuations simply reflected the knock-on effects on default risk of an anticipated economic slowdown, our results do not bear this out. 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 risk aversion, both of global investors and investors with a regional focus.

To analyse valuation, we rely on spreads on CDS contracts, which are rather simple derivative instruments that continued to trade even during the crisis. 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 as well as 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 do not just apply 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. We find no change in the price determination relationships between the pre-crisis and crisis periods. 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. 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: Sample of Asian names, countries and industries

Company	Country	Industry
Aromatic Thailand Public Co. Ltd.	Thailand	Petrochemicals
Bank of China Ltd.	China	Banking
Bank of India	India	Banking
Capitaland Ltd.	Singapore	Real Estate
Cathay Financial Holdings Co. Ltd.	Taiwan	Insurance
Chartered Semiconductor Manufacturing Ltd.	Singapore	Semiconductor
China Fishery Group Ltd.	Singapore	Fishery
CITIC Resources Holdings Ltd.	China	Diversified
CNOOC Ltd.	China	Oil and Gas
Chartered Semiconductor Manufacturing Ltd.	Singapore	Semiconductor
Genting Bhd.	Malaysia	Casino / Hotel
Hana Bank	Korea	Banking
Hutchison Whampoa Ltd.	Hong Kong	Diversified
Hynix Semiconductor Incorp.	Korea	Semiconductor
Hyundai Motor Co.	Korea	Automobile
ICICI Bank	India	Banking
Industrial Bank Korea	Korea	Banking
IOI Corp. Bhd.	Malaysia	Agriculture
KT Corp.	Korea	Telecommunication
Korea Electric Power Corp.	Korea	Electricity
MTR Corp.	Hong Kong	Transportation
Noble Group Ltd.	Singapore	Diversified
PCCW HKT TEL Ltd.	Hong Kong	Telecommunication
Philippines Long Distance Telephone	Philippines	Telecommunication
POSCO	Korea	Steel
PT Indosat Terbuka	Indonesia	Telecommunication
PTT Aromatics and Refining Pub. Co. Ltd.	Thailand	Oil Refining
PTT Public Co. Ltd.	Thailand	Oil and Gas
Reliance Communications Ltd.	India	Telecommunication
Reliance Industries Ltd.	India	Oil Refining
Road King Infrastructure Ltd.	Hong Kong	Infrastructure
Samsung Electronics Co. Ltd.	Korea	Electronics
SK Energy Co. Ltd.	Korea	Oil Refining
SK Telecom Co. Ltd.	Korea	Telecommunication
Stats Chippac Ltd.	Singapore	Semiconductor
Swire Pacific Ltd.	Hong Kong	Diversified
Tata Motors Ltd.	India	Automobile
Telekom Malaysia Bhd.	Malaysia	Telecommunication
Tenaga Nasional Bhd.	Malaysia	Electricity
United Overseas Bank	Singapore	Banking
Xinao Gas Holdings Ltd.	China	Energy

Source: Bloomberg.

Table 2: Summary statistics for CDS spreads and EDFs

	Full sample[1]		Pre-crisis period[2]		Crisis period[3]	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Levels						
CDS spreads						
Asia ex Japan	169.0	280.4	66.2	64.8	317.4	387.8
Investment grade	97.9	132.9	40.0	26.4	189.0	175.5
High yield	376.1	444.1	157.8	75.3	608.2	547.8
EDF						
Asia ex Japan	41.3	150.7	19.1	36.0	72.8	228.5
Investment grade	22.1	81.1	15.2	29.9	33.1	123.9
High yield	95.8	255.6	32.8	49.8	162.8	352.8
CDS indices						
DJ CDX NA IG	76.4	54.3	44.3	10.5	131.5	55.3
DJ CDX NA HY	483.2	275.9	335.7	62.2	737.3	316.2
iTraxx Europe	56.3	42.7	32.0	7.4	98.2	45.9
iTraxx Asia ex Japan IG	85.0	98.2	34.4	6.9	172.0	120.3
iTraxx Asia ex Japan HY	372.2	344.3	199.9	42.7	668.8	429.2
First differences						
CDS spreads						
Asia ex Japan	13.7	99.8	0.1	14.5	32.8	151.8
Investment grade	7.8	53.6	0.2	8.0	19.8	84.1
High yield	30.6	173.3	-0.3	26.9	62.2	241.1
EDF						
Asia ex Japan	4.4	61.1	-0.9	9.8	11.9	93.5
Investment grade	1.4	30.3	-0.8	8.0	4.8	47.4
High yield	13.1	108.5	-1.5	14.6	27.9	152.2
CDS indices						
DJ CDX NA IG	3.2	18.5	1.2	8.4	6.5	28.4
DJ CDX NA HY	22.9	95.4	6.6	49.0	50.0	140.7
iTraxx Europe	2.6	14.2	0.6	5.9	6.0	21.8
iTraxx Asia ex Japan IG	6.4	31.6	0.1	5.0	16.9	50.3
iTraxx Asia ex Japan HY	22.4	124.9	-1.3	25.1	61.9	198.6

[1] Full sample period is from January 2005 to January 2009. [2] January 2005 to July 2007. [3] August 2007 to January 2009

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

Table 3: Regression results for log-log model

Dependent variable: log CDS_{it} . Full sample (41 names).

	(1)	(2)	(3)	(4)	(5)
Intercept	3.2866***	3.6163***	3.5449***	0.0401	0.3367***
	(0.0456)	(0.0349)	(0.0480)	(0.0256)	(0.0324)
Log EDF	0.4763***	0.3186***	0.3025***	0.0118**	0.0106
	(0.0167)	(0.0131)	(0.0163)	(0.0056)	(0.0076)
Log PC1	-	0.3010***	0.2494***	-	0.0619***
	-	(0.0079)	(0.0281)	-	(0.0111)
Log PC2	-	–0.0613	0.3178*	-	-0.0271
	-	(0.0806)	(0.1650)	-	(0.0576)
Crisis*Log EDF	-	-	0.0375*	-	0.0276***
	-	-	(0.0210)	-	(0.0101)
Crisis*Log PC1	-	-	0.0585	-	0.0202
	-	-	(0.0369)	-	(0.0127)
Crisis*Log PC2	-	-	-0.5819***	-	-0.3752***
	-	-	(0.1979)	-	(0.0688)
Log CDS (-1)	-	-	-	0.9957***	0.9277***
	-	-	-	(0.0069)	(0.0092)
Crisis*Log CDS(-1)	-	-	-	-	-0.0318***
	-	-	-	-	(0.0081)
R-squared	0.3327	0.6471	0.6503	0.9528	0.9629
Adjusted R-squared	0.3323	0.6464	0.6490	0.9527	0.9627
S.E. of regression	0.9538	0.6941	0.6916	0.2550	0.2264
Log likelihood	–2251.3130	–1728.3430	-1720.9040	-82.7683	111.1608
Durbin-Watson statistic	0.0710	0.0722	0.0804	1.9352	2.1115

Sample period is from January 2005 to January 2009. Standard errors are shown in parentheses.

*** indicates significance at the 1% level. ** indicates significance at the 5% level. * indicates significance at the 10% level

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

Table 4: Principal components of the 5 first-differenced CDS indices

	ΔPC1	ΔPC2	ΔPC3	ΔPC4	ΔPC5
Factor Loadings					
iTraxx Asia ex Japan IG	0.4703	–0.4469	0.0050	–0.5752	–0.4983
iTraxx Asia ex Japan HY	0.4244	–0.5932	0.2558	0.3542	0.5264
iTraxx Europe	0.4669	0.1208	–0.6494	0.5199	–0.2745
DJ CDX NA IG	0.4631	0.4648	–0.1923	–0.4688	0.5593
DJ CDX NA HY	0.4078	0.4666	0.6898	0.2317	–0.2941
Cumul. fraction of variance explained	0.7156	0.8905	0.9777	0.9931	1.0000

Sources: JPMorgan Chase; authors' estimation.

Table 5: Regression results for first-differences model

Dependent variable: ΔCDS (= $CDS_t - CDS_{t-1}$)

	Full sample (41 names)		Non-financials only (33 names)	
	(1)	(2)	(3)	(4)
Intercept	10.2552***	9.8759***	11.0370***	10.7865***
	(2.1965)	(1.6859)	(2.5497)	(1.9442)
ΔEDF	0.7807***	0.4763***	0.7728***	0.4588***
	(0.0359)	(0.0292)	(0.0377)	(0.0307)
ΔPC1	-	0.2398***	-	0.2573***
	-	(0.0880)	-	(0.0102)
ΔPC2	-	–0.3382***	-	–0.3493***
	-	(0.0171)	-	(0.0196)
ΔPC3	-	0.0476*	-	0.0645**
	-	(0.0249)	-	(0.0278)
ΔPC4	-	0.0632	-	0.1426**
	-	(0.0581)	-	(0.0670)
R-squared	0.2285	0.5467	0.2441	0.5619
Adjusted R-squared	0.2280	0.5453	0.2435	0.5603
S.E. of regression	87.6618	67.2438	91.7754	69.9728
Log likelihood	–9432.7710	–9006.9570	–7736.5820	–7381.1530
Durbin-Watson	2.1298	2.1599	2.0800	2.1108

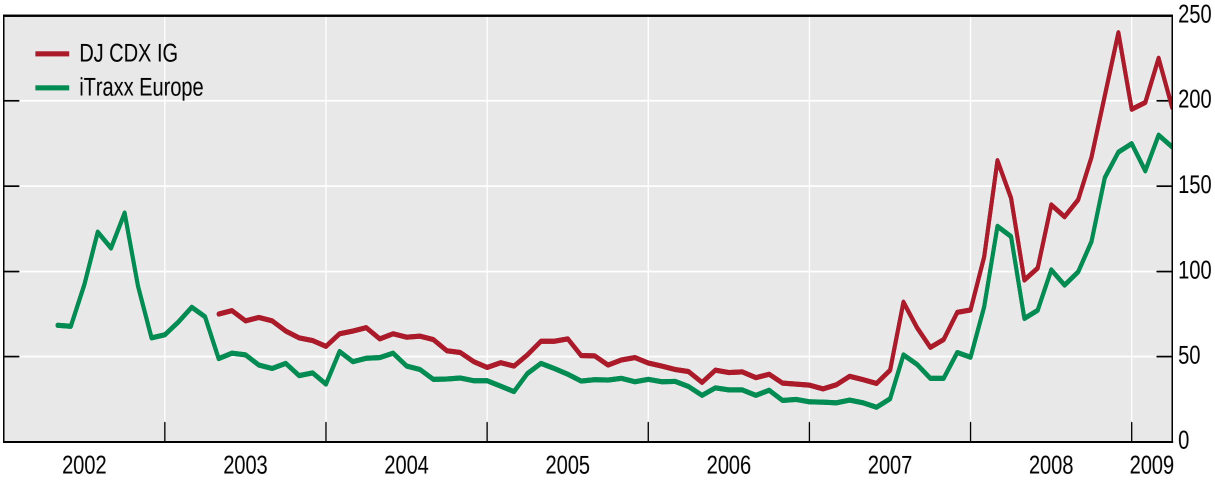
Sample period is from February 2005 to January 2009. Standard errors are shown in parenthesis. PC*x* variables are the principal components

*** significant at the 1% level. ** significant at the 5% level. * significant at the 10% level.

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

Figure 1: CDS index spreads

In basis points

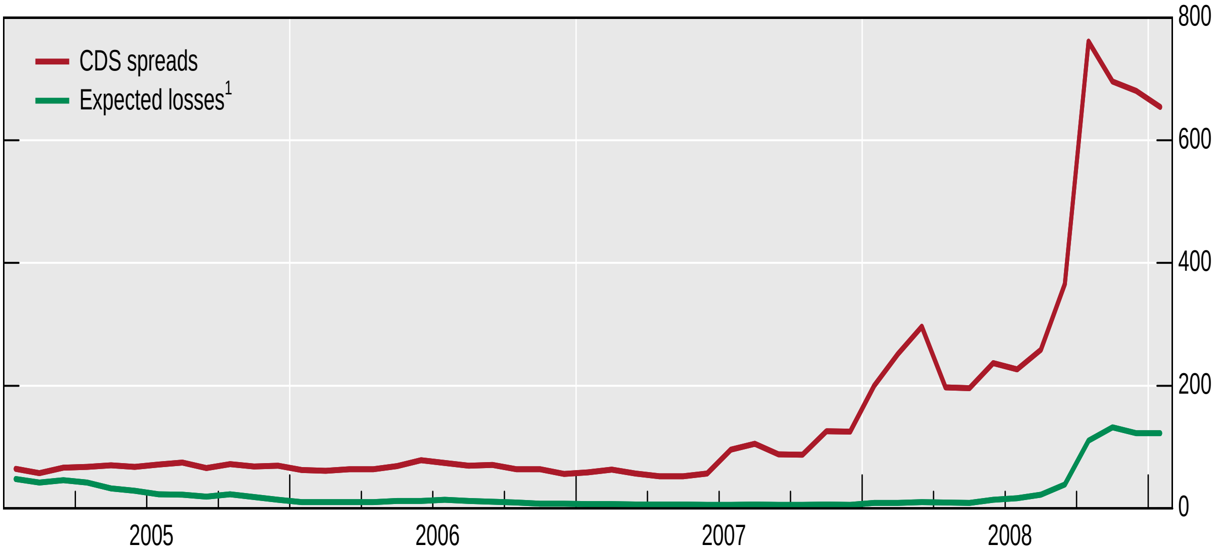


Five-year on-the-run CDS spreads.

Source: JPMorgan Chase.

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

41 names; in basis points

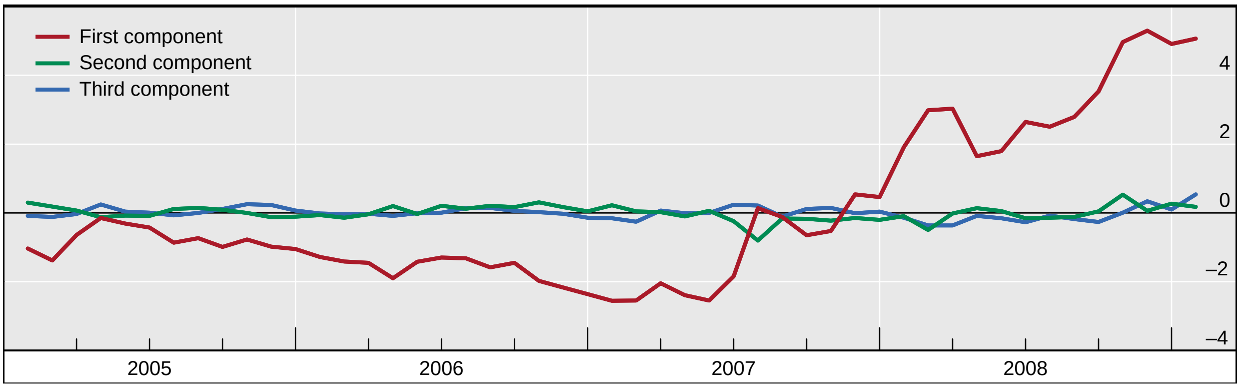


[1] Average EDF multiplied by 0.5, which is the historical loss given default.

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

Figure 3: First three principal components of logs of five CDS indices

Sample period: Feb 2005 to Jan 2009



Sources: JPMorgan Chase; authors' calculations.