In search of timely credit risk indicators : a view of the current crisis from a market-implied ratings perspective

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Introduction

An important challenge for financial authorities in avoiding a future level of financial distress equal to that experienced in the current crisis will be to identify and assess risks to financial stability in an accurate and timely manner. Such a task requires the collection of a wide range of information, as well as the development of appropriate analytical tools, such as financial stability indicators and early warning signals. Among these should be indicators of banks' default probabilities and credit risk, since monitoring and managing credit risk in the financial system is of crucial importance for financial stability. Such indicators should have the following characteristics. First, they should provide a timely signal of imminent increases in credit risk. The timeliness of the signal is of crucial importance as this determines the ability to maintain financial stability or to limit emerging portfolio losses. Second, changes in credit risk indicators should signal changes in credit risk and not other factors that are unrelated to credit risk. This will help to avoid false alarms or a false sense of confidence. Finally, a third characteristic of credit risk indicators should be a certain degree of stability in times when credit risk is unchanged.

In their search for indicators that possess these characteristics and in order to obtain a broader assessment of banks' credit risk, financial authorities complement confidential supervisory information with publicly available information, such as long-term ratings provided by rating agencies and market prices (e.g. CDS spreads). However, the events in the current crisis have raised questions about risk indicators. In particular, rating agencies are blamed for not having noticed the build-up of risk in the system and for reacting only when it was too late. Similarly, markets are considered to have severely underpriced risk in the run-up to the crisis, raising substantial doubt concerning the efficient markets hypothesis. In addition, market prices (such as CDS spreads) are known to reflect factors other than credit risk, such as market liquidity, investors' risk aversion or general market sentiment.

This raises the question of the usefulness of these signals for macro-prudential supervision. The likely answer is that there is merit in knowing the markets' perception of credit risk, at least under the condition that the credit risk information is accurately filtered out from the other information in market prices. Instruments that are claimed to possess this characteristic are the so-called market-implied ratings (MIRs), which are constructed by combining information from market prices and long-term ratings, and which have recently been introduced by rating agencies as market-based indicators of credit risk. According to the rating agencies, MIRs offer a timely, accurate and easily interpretable representation of market-based information on the credit quality of the issuer of the rated instrument. In particular, MIRs are claimed to isolate changes in risk for individual issuers from the noise of the markets (see e.g. Moody's, 2009). For these reasons, MIRs appear to be actively used by central banks, financial institutions and investors as a complement to long-term ratings and market prices.

In this article, we provide a critical assessment of MIRs. In particular, we investigate whether these indicators offer a more precise measure of credit risk than other credit risk indicators (for instance CDS spreads) and whether information about credit risk is incorporated into one type of MIR more quickly than in the other (CDS-implied ratings versus equity-implied ratings) or than in market prices (CDS spreads).

We use daily data on MIRs from a major rating agency for a sample of 30 large European and US banks covering the period 2005-2009 to compare the behaviour of CDS-implied ratings (CDSIRs) and equity-implied ratings (EIRs) as well as CDS spreads. To our knowledge, we are the first to provide this type of critical assessment of MIRs. As our sample period covers both the run-up to the current crisis and the main events that have occurred during the crisis, we are able to exploit the large variation in the data to provide some basic insights on these market-based indicators of credit risk. As a consequence, we also contribute to the growing literature that studies the events of the current crisis and their consequences.

Our analysis suggests that MIRs are unlikely to fully overcome the deficiencies of their underlying components (long-term ratings and market prices). Instead, the changes in MIRs seem to reflect movements in the underlying market prices which appear to be related to factors other than credit risk, such as market liquidity, investors' risk aversion or general market sentiment. In particular, the behaviour of MIRs obtained from the CDS market and those obtained from the equity market is not always similar. That is, the relationship between CDSIRs and EIRs is time-varying. In addition, the two types of MIRs also seem to differ somewhat in their relationship to CDS spreads. Finally, while we find that during the crisis period, movements in CDS spreads often lead movements in CDSIRs as one would expect, there is no clear leading-lagging relationship between CDSIRs and EIRs.

(1) CDS are credit derivatives that function like a traded insurance contract in which a protection buyer accepts to pay a periodic fee (called "spread" or "premium") in exchange for a payment by the protection seller in the case of a credit event (bankruptcy, failure to pay, ...) on a reference entity.

The remainder of the article is organized as follows. In Section 1, we compare market-implied ratings to more traditional indicators of credit risk (CDS spreads and long-term ratings). In Section 2, we describe our data and examine the general behaviour of the credit risk indicators over time. In Section 3 we consider the contemporaneous relationship between CDSIRs, EIRs and CDS spreads in order to determine to what extent the two types of MIRs appear to be equivalent measures of credit risk. Section 4 presents a preliminary discussion regarding the lead-lag relationship between our market-based metrics of credit risk. Finally, in Section 5 we summarize our main conclusions and outline an agenda for future research on the topic.

1. Market-implied ratings compared with other indicators of credit risk

MIRs are a new type of credit rating that has been recently introduced by rating agencies (see e.g. Fitch Ratings (2007a,b), Moody's (2007) and S&P (2009)). These ratings aim to combine the pure credit risk focus and stable nature of long-term ratings with the timeliness of information provided by market prices (CDS spreads, equity prices, bond prices etc.).[1] For instance, CDS-implied ratings (CDSIRs) are derived by combining credit information obtained from CDS spreads and long-term ratings. Similarly, equity-implied ratings (EIRs) are obtained by first using techniques to extract credit risk information contained in equity prices (such as default probabilities estimated on the basis of a Merton-type

Box 1 – Methodology of market-implied ratings

In this box, we describe in general terms the methodology used by rating agencies to extract credit risk information from market prices and construct equity-implied and CDS-implied ratings.

While the specifics of the methodologies applied by the rating agencies to obtain MIRs show some differences, the general idea is always the same. In particular, the rating agencies consider a reference sample of firms sorted by the firm's long-term rating. Given this sample of firms, the methodologies consist of three steps: (1) obtain credit risk information from market prices for each firm in each long-term rating category, (2) obtain boundaries between adjacent rating categories, and (3) determine each firm's MIR.

STEP 1 : OBTAIN CREDIT RISK INFORMATION FROM MARKET PRICES

For CDS-implied ratings, the relevant credit risk information is simply the (smoothed) CDS spread of the firm. For equity-implied ratings, a proxy for the firm's default probability (PD) is extracted from equity prices using some Merton-type structural model of credit risk.

STEP 2 : OBTAIN BOUNDARIES BETWEEN ADJACENT RATING CATEGORIES

In general, the level of the credit risk implied by market prices is expected to be larger for lower long-term rating categories ; CDS spreads (or Merton-type PDs) of AA firms are generally larger than CDS spreads (or Merton-type PDs) of AAA firms, and so on for lower rating levels. To allow a mapping from the market-based credit risk information to a MIR for each firm in the sample, cut-off points in terms of the credit risk information marking the boundaries between each long-term rating category are calculated. These cut-off points are not fixed in time, i.e. they usually move together with the observations on the credit risk information obtained from market prices within each long-term rating category. For instance, when a substantial number of observations within one or both of two adjacent rating categories see their relevant measure increasing, the boundary separating the two rating categories will increase as well. (1)

STEP 3 : DETERMINE EACH FIRM'S MIR

A firm is assigned a MIR on the basis of where its credit risk observation is situated compared to the boundaries separating the different long-term rating categories. For a firm to have its MIR equal to its long-term rating, the firm's observation on the credit risk information (CDS spread or Merton-type PD) should be situated within the boundaries of the credit risk information for its long-term rating category. A firm outside the boundaries of its long-term rating category is assigned the MIR that is equal to the long-term rating within the boundaries of which the firm's observation of the credit risk information is situated.

To illustrate, consider for instance a two-scale long-term rating system (AAA and AA) and assume that the CDS spread level that is calculated as the boundary between AAA and AA rated firms equals 10 basis points (bp). This implies that firms with a CDS spreads below 10 bp will have a CDSIR of AAA, and those with a CDS spread above 10 bp will have a CDSIR of AA.

(1) Depending on the rating agency and MIR considered, the sample of firms used to determine the boundaries may consist of all firms rated by the agency across sectors and geographic regions, or some segmentation of firms by e.g. sector and geographic location. Also, boundaries may be updated more or less frequently depending on the agency and the type of MIR.

structural credit risk model), then mapping the credit risk information into ratings. Box 1 gives more details on the methodology used by the major rating agencies for constructing CDSIRs and EIRs (due to data availability, this article does not consider another type of MIR, bond-implied ratings).

Two key characteristics of MIRs are the following. First, in contrast to market prices and long-term ratings, MIRs are a relative measure of credit risk (in the cross-sectional dimension). For instance, if all firms' CDS spreads (or Merton-type PDs) were to double *ceteris paribus*, this would have a very limited or even no impact (depending on the credit rating agency considered) on the distribution and the level of MIRs because all the boundaries that separate the different market-implied rating categories would double as well. Therefore, holding long-term ratings constant, changes in a firm's MIR indicate relative under- or outperformance of the firm in terms of CDS spreads (or Merton-type PDs) compared to other firms in the sample.

Second, as MIRs are updated daily following changes in market prices, they may in principle vary on a daily basis. However, in practice, daily changes are not observed. This is due to at least three reasons. First, as just explained, for given long-term ratings, a firm's MIR will likely not change when it performs in a similar way as its peers in terms of the CDS spread or Merton-type PD, even when movements in market prices are large. Second, if a firm does under- or outperform the other firms in the sample, this relative under- or outperformance should be sufficiently large in order to cross the boundaries separating the different rating categories. Third, for given CDS spreads or Merton-type PDs, MIRs may also change due to changes in long-term ratings. However, long-term ratings change very infrequently, and hence, will not result in frequent changes in MIRs. All this implies that MIRs, while reflecting market information, nevertheless offer some stability to their users.

Besides these two key characteristics, MIRs also possess a number of desirable features. First, MIRs are expressed in the familiar ranking ranging from AAA for the most creditworthy firms to C for the firms with the highest credit risk. Consequently, MIRs are based on a scale that facilitates comparison of credit risk for different firms. Second, as MIRs incorporate market information, they may signal changes in credit risk in a more timely manner than long-term ratings do. In addition, because MIRs combine two sources of information (long-term ratings and market prices), they may also provide a more complete view on credit risk than either source of information alone. Finally, and perhaps most important, MIRs may be a more precise and stable measure of credit risk than market prices, since their aim is to isolate changes in credit risk for individual issuers from other information in markets prices. In fact, MIRs were created with the objective of capturing disagreements between long-term ratings and market prices and to give a clean measure of credit risk. Hence, at face value, MIRs seem to possess all the characteristics of a "good" credit risk indicator identified in the introduction (timeliness, accuracy and stability).

A natural question is therefore whether MIRs could potentially be more useful for measuring credit risk than more traditional credit risk indicators, such as long-term ratings or market prices. For example, could MIRs potentially be used as a complement to supervisory information for monitoring emerging risks in the financial sector?

An important argument for such a use is that, in contrast to MIRs, traditional credit risk indicators do not seem to possess all the desirable features identified in the introduction. More precisely, these indicators seem to trade-off between accuracy and stability on the one hand, and timeliness on the other, in identifying emerging credit risk.

In particular, whereas long-term ratings, which represent the rating agencies' views on credit risk, are supposed to have a pure credit risk focus and a through-the-cycle nature that is intended to provide stability to the measure, their major drawback is that, because of this through-the-cycle nature, they adjust more slowly than market prices to changes in risk, as illustrated by the current crisis. Market prices, on the other hand, embody market participants' views on credit risk and may provide more timely signals of financial stress since they quickly react to the available information on changes in credit risk. However, market price movements are likely to also reflect other factors that may be unrelated to credit risk, such as market liquidity, investors' risk aversion or general market sentiment. This is not only true for equity prices, which in general may be expected to depend on all factors that affect the firm's future profitability (both upside and downside), but also for credit default swaps. [1] Therefore, even though CDS in principle closely relate to credit risk and are considered to be a purer measure of credit risk than equity prices, CDS spreads may only be a noisy signal of credit risk.

Given the apparent desirable properties of market-implied ratings and the shortcomings of market prices, it is interesting to investigate in more details whether the former offer a more precise measure of credit risk than the latter, and whether information about credit risk is incorporated into one type of market-implied ratings more quickly than in the other (CDS-implied versus equity-implied ratings) or than in market-prices (CDS spreads). In the remainder of the article, we provide a first attempt to shed light on these issues.

2. General behaviour of MIRs and CDS spreads

In this section, we describe the evolution of average CDSIRs, EIRs and CDS spreads for a sample of European and US banks during the period 2005-2009. We also provide some summary statistics on the variation in these variables for individual banks.

Our data consists of a sample of 30 banks, of which 20 are European and 10 US-based and for which CDSIRs, EIRs, and 5-year senior CDS spreads are available over the period 1 January 2005 to 31 December 2009. This period covers both the run-up to the current crisis as well as several major events during the crisis. The banks in the sample were required to have at least 150 observations per year for each of the three data series. In addition, we dropped banks for which one of the data series is missing for at least 10 consecutive trading days. [2]

(1) See e.g. Collin-Dufresne et al. (2001), Bongaerts et al. (2010) and Annaert et al. (2010).

(2) We impose this criterion to reduce errors caused by the choice to replacing missing observations by moving forward the last observation. If too many observations are missing, by replacing them in this way, the series would no longer be representative. Moreover, for some banks, there were long periods with no observations during the crisis and the series pre- and post-crisis did not longer refer to same legal entity.

The central component of our data is a unique dataset on daily MIRs for financial institutions, which, together with the institutions' long-term credit ratings, were obtained from a major credit rating agency (Moody's). As mentioned in the previous section, MIRs essentially are credit ratings derived from market prices and long term ratings. That is, they are expressed in the familiar ranking ranging from AAA for the most creditworthy firms to C for the firms with the largest credit risk.[1] However, as they incorporate information provided by market prices, they change more frequently than long-term ratings do. In particular, the average number of changes in CDSIRs per year for each individual bank in our sample over the period 2005-2009 amounts to almost 33. The corresponding number for EIRs equals about 23, whereas the long-term rating of the banks in our sample only changes less than 1 time per year on average. These figures confirm that, while being more volatile than long-term ratings, MIRs are much more stable than market prices, which may be a desirable property.

(1) In the analysis, we transform these rating classes into numerical values between 20 for the most creditworthy banks and 1 for the least creditworthy ones: AAA=20, AA+=19, AA=18, AA-=17, A+=16, A=15, A-=14, BBB+=13, BBB=12, BBB-=11, BB+=10, BB=9, BB-=8, B+=7, B=6, B-=5, CCC+=4, CCC=3, CCC-=2, CC and below=1.

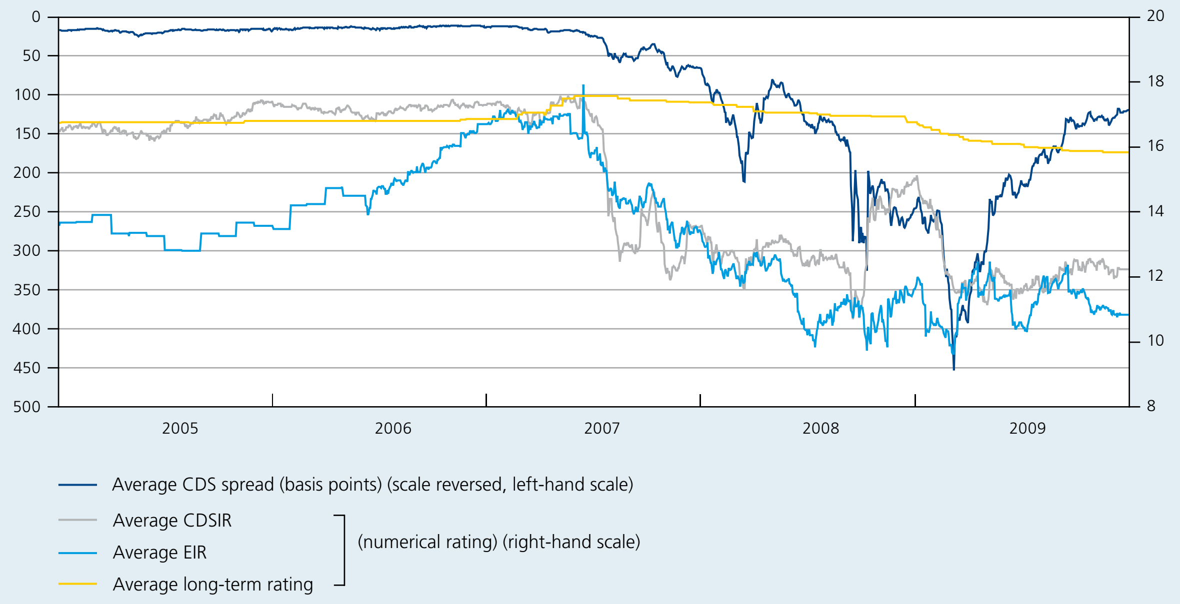
As mentioned above, we examine the relationship between the two types of MIRs and compare their behaviour relative to CDS spreads. We therefore also obtained daily data on 5-year senior CDS spread for our sample banks from Datastream. Note that we do not consider equity prices in our analysis because they are not, from a theoretical point of view, a "pure" measure of credit risk, as they incorporate information on the "upside" of profitability as well as the "downside".

2.1 Initial comparison of the credit risk indicators

Chart 1 compares the historical evolution of average CDSIRs, EIRs and CDS spreads across the banks in our sample. For comparison, we also plot the evolution of the average long-term rating for the banks in our sample.

We can immediately observe significant variation in these series over the sample period. In fact, the average CDS spread across all banks has an overall mean of 89 bp and ranges from a minimum of 10.8 bp to a maximum of 453.2 bp. The overall means of the average CDSIRs and EIRs across the banks in our sample amount to 14.9 and 13.3; these numerical values correspond to ratings between A and A-, and A- and BBB+, respectively.

CHART 1 HISTORICAL EVOLUTION OF AVERAGE CDS SPREAD, CDSIR, EIR, AND LONG-TERM RATING OVER THE PERIOD 1 JANUARY 2005 – 31 DECEMBER 2009



Sources: Own calculations based on data from Moody's and Datastream.
(1) CDS spreads are mid-prices expressed in basis points (bp). The scale for CDS spread is inverted and appears on the left axis. CDSIRs, EIRs and long-term ratings have been transformed to a numeric scale that appears on the right axis: AAA=20, AA+=19, AA=18, AA-=17, A+=16, A=15, A-=14, BBB+=13, BBB=12, BBB-=11, BB+=10, BB=9, BB-=8, B+=7, B=6, B-=5, CCC+=4, CCC=3, CCC-=2, CC and below=1.

Average CDSIRs fluctuated between a minimal value of 10.7 (BBB-) and a maximal value of 17.6 (AA); the corresponding values for the average EIR across the banks in our sample amount to 9.6 (BB+) and 17.9 (AA), respectively. Finally, average long-term ratings showed substantially less variation, ranging from 15.8 (A+) to 17.6 (AA), around a mean value of 16.8 (AA-).

Overall, the market-based metrics in Chart 1 react in a much stronger way to the events occurring during the crisis than long-term ratings do. However, the behaviours of CDSIRs and EIRs do not always seem to coincide. For instance, in the period before July 2007, CDSIRs are quite stable while EIRs increase significantly. In addition, the two series in fact move in opposite directions in October 2008. The different behaviour observed in the two MIRs may be due to specificities in the construction of MIRs. (1) However, it may also be the case that these measures are not necessarily driven by individual credit risk alone, but, like CDS spreads or equity prices, may also reflect non-credit risk related factors such as market liquidity, investors' risk aversion, or general market sentiment. Finally, while showing some differences in the evolution of the three market-based metrics of credit risk, the plotted series in Chart 1 do not allow strong conclusions to be drawn regarding the lead-lag behaviour of the different metrics.

Looking at Chart 1 in more details, three main periods can be distinguished: before the crisis (up to July 2007), the crisis period up to government interventions (from July 2007 up to September 2008), and the crisis period after government interventions (after September 2008).

The credit risk indicators in Chart 1 would seem to indicate that credit risk in the banking sector was stable at a relatively low level (or even decreasing) over the period from 2005 to mid 2007. In particular, average long-term ratings are stable at levels between A+ and AA- and CDS spreads remain fairly constant at levels below 50 bp until June 2007. The same is true for average CDSIRs, which are relatively stable around a level close to AA-. Interestingly, even though they are supposed to measure credit risk in a similar way, average EIRs show a somewhat different behaviour; starting at a level close to A- at the beginning of our sample period, they show a strong but gradual upward trend, closing the gap with CDSIRs towards early 2007.

This observed pattern of EIRs closing the gap with CDSIRs is actually very similar to the behaviour of equity prices of the banks in our sample; while CDS spreads remain fairly constant in this period, equity prices (as shown in Chart A1 in the appendix) show a clear upward trend until June 2007. The behaviour of the CDSIRs and EIRs therefore seems to suggest that these measures pick up movements in the underlying price series that are not necessarily related to individual credit risk but rather reflect factors such as bank profitability or general market sentiment.

During the crisis period (starting in July 2007 with the negative disclosures on subprime credit risk of Bear Stearns' hedge funds), all market-based metrics (CDSIRs, EIRs, CDS spreads) significantly drop (2), probably due to increased investor concern about banks' exposure to subprime mortgages. The plotted series in Chart 1 give the impression that MIRs signal the start of the crisis somewhat earlier than CDS spreads do. (3) Although long-term ratings also gradually decline after the start of the crisis in July 2007, the market-based metrics indicate a much more pronounced increase in the level of credit risk. This is particularly true for the periods when the most important negative events of the crisis took place: e.g. Bear Stearns' hedge fund closures in July 2007, Bear Stearns' takeover in March 2008, Northern Rock in September 2007 and February 2008, the Icelandic banks, Fannie Mae, Freddie Mac, AIG and Lehman Brothers (among others) in September 2008. These episodes would seem to indicate that the market-based metrics signal a large increase in credit risk. However, to the extent that MIRs reflect movements in the underlying price series which are unrelated to changes in credit risk for individual institutions, their significant drops, like CDS spreads, may also reflect factors such as a steep contraction of the risk appetite of market participants.

In October 2008, following various government interventions, CDSIRs show a significant jump upwards (+3 rating notches, from BBB- to A on average). CDS spreads also improve, while EIRs seem to move in an opposite direction. These movements are consistent with similarly opposite movements observed in CDS spreads and equity prices during the same period; however, they are inconsistent with the idea that EIRs and CDSIRs both measure credit risk. Potential explanations for the contrasting movements in CDS spreads and equity prices have been provided by market participants and researchers; i.e., that the government interventions benefited creditors and CDS protection sellers at the expense of shareholders. (4) That is, whereas capital injections increase the loss absorption

(1) Specificities in the mapping of market prices into the traditional rating scale may result in a different behaviour of CDSIRs and EIRs. One example of this may be the use of a different sample of firms used in the construction of CDSIRs than for the construction of EIRs; as MIRs reflect a bank's relative credit risk compared to the other firms in the sample (see Box 1), a different reference sample of firms may result in a different behaviour of the bank's MIRs.

(2) CDS spreads in non-reverse scale increase.

(3) Although MIRs are constructed from the underlying price series, the possibility that MIRs lead the movements in prices cannot be ruled out due to specificities in the construction of MIRs. For a more detailed explanation, we refer to Section 4.

(4) See e.g. Panetta et al. (2009) and King (2009).

buffer before creditors are hit, existing equity holders are worse off, since their share in the capital of the firm is diluted. However, this should not have affected the credit risk signals obtained from EIRs, which, as explained above, are constructed with the purpose of extracting credit risk information from the other drivers of equity prices. The opposite reaction of EIRs compared to CDSIRs provides additional support for the observation that CDSIR and EIR movements do not always coincide and seem to follow similar patterns as the underlying CDS spreads and equity prices. This suggests that the credit risk signals provided by MIRs may be distorted by other determinants of the underlying price series.

Despite the government interventions, the upward jump in CDSIRs was later followed by a strong downward correction, and CDS spreads (inverted scale) and EIRs reached their lowest values in March 2009. The decline in equity prices (Chart A1 in the appendix) and consequent contraction in the risk appetite of market participants, together with the increase in CDS spread volatility, may have caused a contraction in CDS transactions and a consequent increase in CDS spreads from October 2008 to March 2009, despite the government interventions. This movement seems to be followed by the MIRs, which decline during this period. From March 2009 onwards, MIRs and CDS spreads seem to have entered a recovery period, which is more pronounced for the CDS-based measures than for EIRs.[1] The three market-based indicators of credit risk are nevertheless still at substantially worse levels than before the crisis. Long-term ratings seem to be still in a downward movement, which together with their more gradual decline during the crisis, may reflect their through-the-cycle nature. This more gradual and continuing decline in long-term ratings limits the potential for MIRs to quickly revert to higher levels; since MIRs are constructed from long-term ratings, this may be an explanation as to why CDS spreads seem to indicate the recovery after March 2009 earlier than the MIRs.

2.2 Bank-level variation in the credit risk indicators

Table 1 provides a summary of some bank-level statistics on the ranges (i.e. differences between maximum and minimum values) of CDS spreads and MIRs for individual banks over the sample period and the maximal observed daily difference between EIRs and CDSIRs during the period.

The first row of Table 1 indicates that for the median bank, the CDS spread varied over a range of 268.8 bp. The bank with the lowest variation saw its CDS spread cover a range of 55.2 bp, whereas the bank with the highest variation experienced a range of almost 3000 bp. These statistics show that there were significant differences across the banks in the sample with respect to the variation in their CDS spreads during the period.

TABLE 1 BASIC SUMMARY STATISTICS FOR RANGES OF CDS SPREADS, CDSIRS, AND EIRS, AND THE MAXIMAL ABSOLUTE DIFFERENCE BETWEEN EIR AND CDSIR

	Median	Min.	Max.
CDS spread range	268.8	55.2	2,949.2
CDSIR range	8	7	14
EIR range	11	5	19
Max. diff. between EIR and CDSIR	8.5	5	14

Sources: Own calculations based on data obtained from Moody's and Datastream.

Notes: The first three rows of Table 1 present the cross-sectional median, minimum and maximum for the difference between the maximal and minimal value of each variable calculated at bank-level. The fourth row of Table 1 shows the cross-sectional median, minimum and maximum for the maximal absolute difference between the EIR and CDSIR for each bank over the sample period. The summary statistics in the table are based on a cross-section of 30 observations, the total number of observations used to compute the numbers is 39,120. CDS spreads are mid-prices expressed in basis points (bp). CDSIRs and EIRs have been transformed to a numeric scale: AAA = 20, AA+ = 19, AA = 18, AA– = 17, A+ = 16, A = 15, A– = 14, BBB+ = 13, BBB = 12, BBB– = 11, BB+ = 10, BB = 9, BB– = 8, B+ = 7, B = 6, B– = 5, CCC+ = 4, CCC = 3, CCC– = 2, CC and below = 1.
The maximal observed daily difference between EIRs and CDSIRs is expressed in absolute values.

Table 1 also reveals significant variation for banks' CDSIRs and EIRs. For the median bank, the CDSIRs varied by 8 notches over the period and the median range of EIRs was 11 notches. The bank with the largest range for CDSIRs over the period saw a difference of 14 notches, and the bank with the largest range of EIRs experienced a difference of 19 notches.

Finally, we consider the maximum observed daily differences between banks' EIRs and CDSIRs during the period. For the median bank, the maximum daily difference (in absolute value) observed during the period was 8.5 notches. The bank reporting the greatest maximum difference between the two ratings saw a difference of 14 notches. In other words, on some day during the sample period, the EIR and CDSIR for this bank differed by 14 notches.

(1) Equity markets' movements in the second quarter of 2009 (see Chart A1 in the appendix) reflect growing confidence that the worse of the crisis had passed.

3. Contemporaneous relationship between MIRs and CDS spreads

As explained above, MIRs are claimed to filter out changes in credit risk for individual issuers from other information embodied in market prices. If MIRs succeed in doing so, they could potentially offer more precise measures of credit risk than CDS spreads. However, the discussion in the previous section already suggests that this may not be the case. As empirical evidence regarding the factors that affect MIRs does not exist, the existing literature does not provide us with an answer to the question of whether MIRs reflect other factors than credit risk. [1] Whereas such an analysis is beyond the scope of this article, we nevertheless provide a first step. In particular, if MIRs indeed succeed in filtering out credit risk signals from market prices, then MIRs based on different market prices should provide very similar signals regarding the credit risk of an institution and exhibit similar relative behaviour over time. We investigate this more in detail here, using two complementary approaches. First, we analyze the behaviour of the average value of the ratio of banks' EIRs over CDSIRs over the sample period. Second, we examine correlations between changes in banks' EIRs and CDSIRs as well as correlations between EIRs and CDS spreads, and between CDSIRs and CDS spreads.

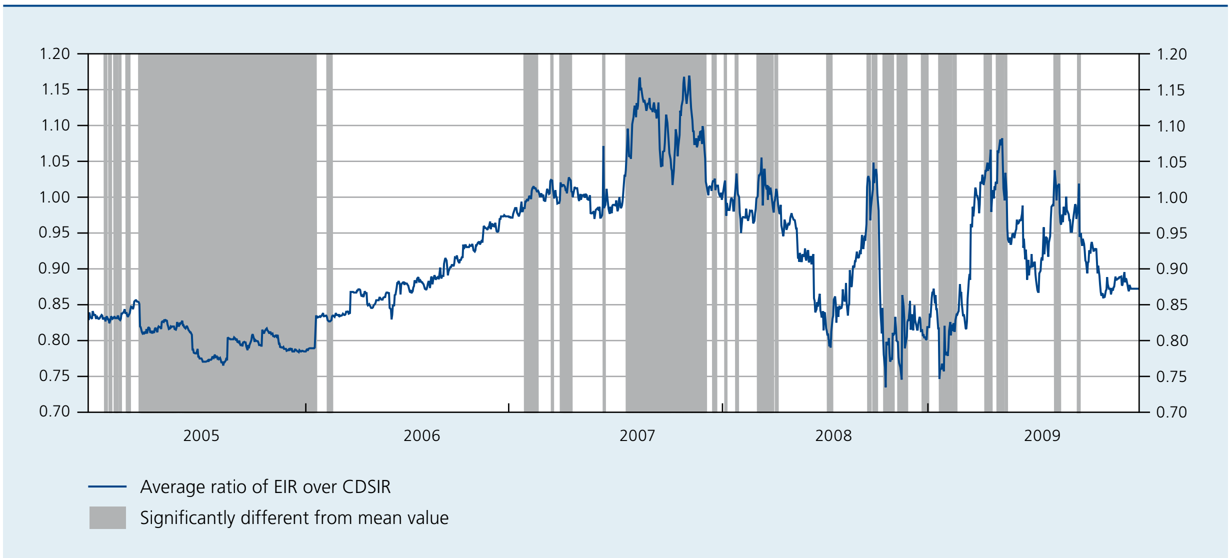
(1) See reports on MIRs from rating agencies, e.g. Fitch Ratings (2007a,b) and Moody's (2007) that show how the difference between MIRs and long-term ratings (rating gaps) relate to default probabilities.

3.1 Ratio of EIR over CDSIR

Chart 2 plots the daily average across banks of the ratio of the EIR over CDSIR for each bank. As suggested above, one might expect that MIRs should provide the same signal regarding the intensity of credit risk at all times. However, this may not necessarily be the case for a number of reasons. First, it may be that, for reasons relating to the computation of MIRs, the default probability associated with a AAA CDSIR may not be the same as the default probability implied by a AAA EIR. However, we would nevertheless expect CDSIRs and EIRs to move in a similar manner over time for each bank, such that their ratio equals some constant. Second, to the extent that different markets (CDS versus equity) incorporate credit risk information at different speeds, we would not expect the ratio of EIRs over CDSIRs to be equal to a constant at all times. However, deviations from this constant should not be persistent, in that the ratio of EIRs over CDSIRs should revert back to its mean as soon as the credit risk information is incorporated in both markets. Persistent deviations from the mean value would suggest that MIRs do not signal potential changes in credit risk in an equivalent manner.

The line in Chart 2 shows the movement of the average across banks of the ratio of EIRs over CDSIRs over the sample period. A first observation is that this ratio is not constant over time; whereas the mean over the entire sample period of the average ratio of EIRs over CDSIRs equals 0.91 (which, with a standard deviation of 0.10, is

CHART 2 AVERAGE RATIO EIR OVER CDSIR FOR SAMPLE OF 30 BANKS



Sources : Own calculations based on data from Moody's.

not significantly different from 1), the daily average ratios fluctuate between about 0.75 and 1.15. Note that these ratios are again daily averages across banks; as shown in Table 1, differences between EIRs and CDSIRs for any given bank may be substantial (up to 14 notches).

To see whether these fluctuations are the result of the different speeds with which different markets incorporate credit risk information, we test whether deviations from the mean value for the ratio over the sample period (0.91) are significant and persistent. We proceed as follows: for each time period, we perform a t-test to see whether the average ratio of EIRs over CDSIRs across the 30 banks in our sample equals 0.91. The grey areas in Chart 2 indicate at which point in time the average ratio of EIRs over CDSIRs is significantly different from 0.91. Although the test indicates that EIRs and CDSIRs were providing similar credit risk signals in the run-up and, to a lesser extent, during the first part of the crisis (January 2008-September 2008), in several periods both before and during the crisis the deviations from 0.91 were significant, indicating that EIRs and CDSIRs were actually providing different (credit risk) signals in these episodes. In addition, these periods of disagreement seem relatively persistent, sometimes covering several weeks or even months.

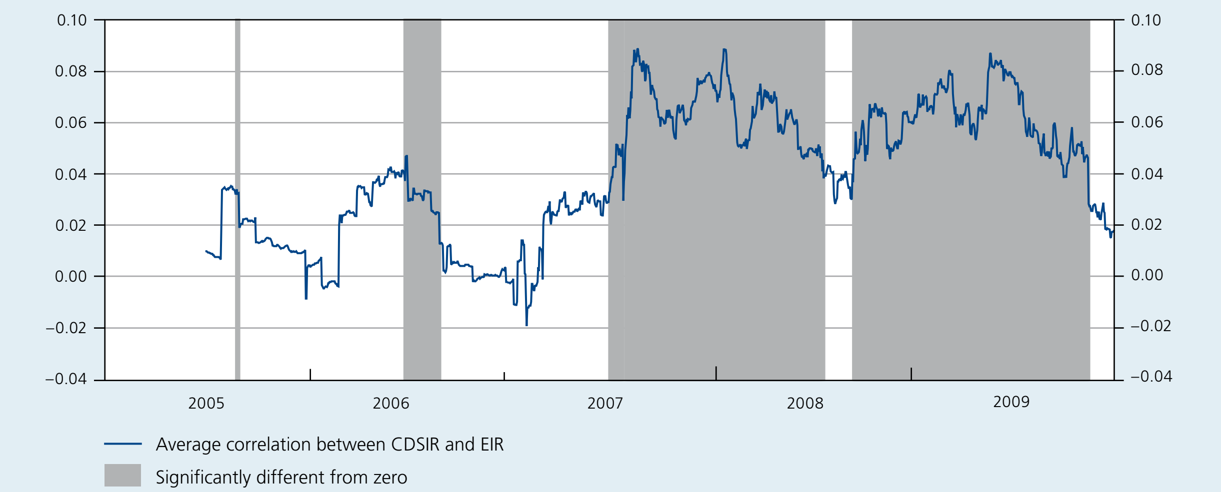
The period before the crisis, up to October 2006, is the period where average EIRs were closing the gap with average CDSIRs, similarly to equity prices versus CDS spreads. Interestingly, as can be observed from Chart A1 in the appendix, the other periods where the different behaviour of EIRs and CDSIRs is statistically significant (August 2008; October 2008-December 2008; early 2009) correspond to periods in which the movements in equity prices and CDS spreads for the banks in our sample diverge the most. For instance, the period after the collapse of Lehman Brothers in September 2008, was characterized by several standalone support actions for large individual institutions, both in Europe and the US. As more and more financial institutions became affected by the crisis, many countries announced comprehensive rescue packages involving some combination of recapitalizations, debt guarantees and asset purchases.

3.2 Rolling correlations between CDSIR and EIR

In this section we provide an analysis of correlations between CDSIRs and EIRs. More specifically, we look at six-month rolling correlations between daily changes in these variables.[1] We analyze correlations in changes in the MIRs rather than in the rating levels since results are qualitatively similar but the graphs and the interpretation of the results for changes are clearer. In particular, we expect the correlation between changes in CDSIRs and changes in EIRs to be positive, as increases (decreases) in both ratings should signal an improvement (a deterioration) in the creditworthiness of issuers.

(1) The six-month rolling correlations are calculated as follows: for each bank the correlation between the changes in the variables is calculated over a window period of six months and the calculation is then repeated by moving ahead the sample period of an increment of one day. This means that for each six-month period after the first one, the earliest observation is dropped from the calculation and the most recent one is added in, again to have a correlation over six months. Rolling analysis is commonly used in time series analysis to assess the stability of a certain relationship over time.

CHART 3 AVERAGE SIX-MONTH ROLLING CORRELATION BETWEEN CDSIR AND EIR FOR SAMPLE OF 30 BANKS



Sources: Own calculations based on data from Moody's.

Chart 3 plots the daily average across banks of the six-month rolling correlations between changes in CDSIR and changes in EIR, calculated for each bank. The grey area indicates periods for which these averages of six-month correlations are significantly different from zero. Given that changes in the CDSIR and the EIR for a given bank should move in the same direction, we would expect the correlation of changes to be positive. A first observation from the chart is that the correlation between the two series is rather low, ranging from about –0.02 to 0.09. A likely reason for this is that we look at correlations between daily changes in CDSIRs and EIRs; as MIRs change with a relatively low frequency (see Section 1.1), the correlation between daily changes cannot be expected to be high. A check of the correlations of weekly changes in CDSIRs and EIRs indeed yields correlations that are somewhat higher, though still far from 1 (ranging between –0.10 and 0.20).

A second observation from the chart is that there is significant time-variation in the correlations between changes in CDSIRs and EIRs.[(1)] In particular, whereas until July 2007 the correlation was not significantly different from zero most of the time, at the beginning of the crisis, in the summer of 2007, the average correlation increased significantly. During almost the entire crisis period, this correlation remains at this higher level (around 0.07). As the grey area indicates, the correlation is significantly different from zero from July 2007 up to August 2008 and in the crisis period following government interventions (from October 2008). Interestingly, the correlation between changes in CDSIRs and EIRs is not significantly different from zero during September 2008; the many crisis events during this month appear to have increased the variation in the signals provided by the two indicators. This correlation then increases and, towards the end of our sample period, seems to revert back to the lower pre-crisis levels.

3.3 Rolling correlations between MIRs and CDS spread

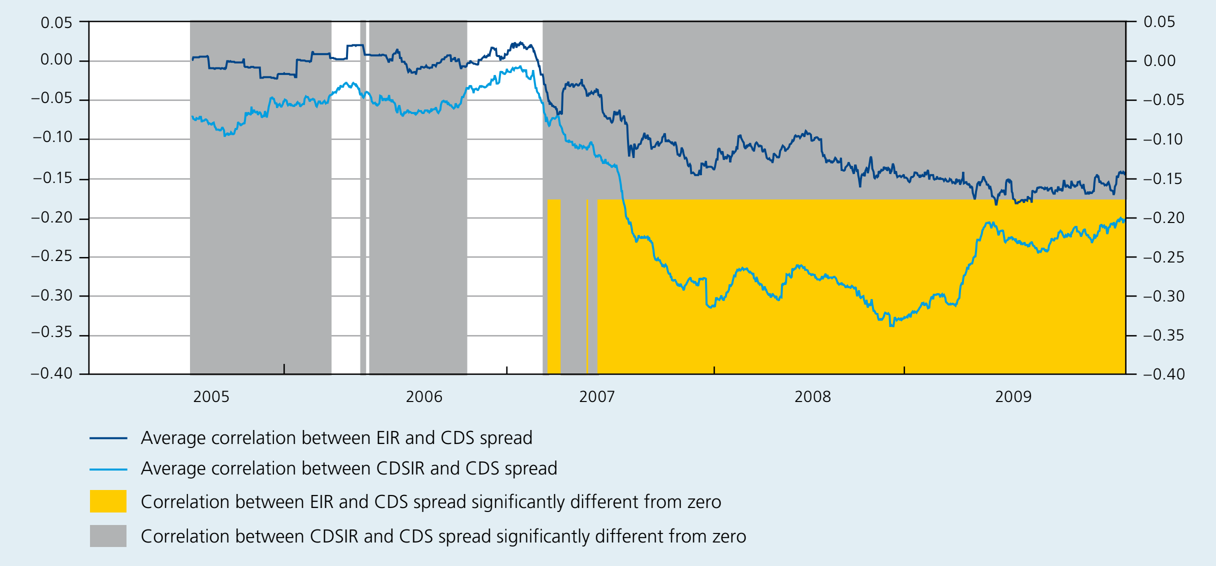
Finally, we also consider the six-month correlations between changes in the two types of MIRs and CDS spreads. We expect a negative correlation between MIRs changes and CDS spread changes, as higher CDS spreads are associated with higher credit risk.

Chart 4 plots the average six-month rolling correlations between daily changes in CDSIRs and changes in CDS spreads, and between changes in EIRs and changes in CDS spreads. The grey and yellow areas indicate periods when the correlations are significantly different from zero.

The chart reveals that prior to the crisis (up until April 2007), the correlations between the changes in the two types of MIRs and the changes in CDS spreads were

(1) This is also true for weekly correlations.

CHART 4 AVERAGE SIX-MONTH ROLLING CORRELATIONS BETWEEN MIRs AND CDS SPREAD FOR SAMPLE OF 30 BANKS



Source: Own calculations based on data from Moody's and Datastream.

substantially lower than during the crisis period. In particular, the correlations between CDSIR changes and CDS spread changes fluctuated between 0 and –0.10 before the crisis. As observed in the discussion of Chart 1 in Section 2.1, CDS spreads and CDSIRs were quite stable from 2005 to April 2007, which may explain the lower correlation in the pre-crisis period. Then, the correlations between changes in CDSIRs and CDS spreads fell to a level around –0.30 during the crisis. From March 2009 onwards, the correlations between changes in CDSIRs and changes in CDS spreads are more or less stable around –0.20.

As for the corresponding correlations between EIR and CDS spreads, Chart 4 shows that the changes in these two credit risk measures were in fact uncorrelated (not significantly different from zero) before the crisis. During the crisis, the correlations dropped to significant levels between –0.10 and –0.20. Overall, the correlations between EIR changes and CDS spread changes were lower (in absolute value) than those between changes in CDSIRs and CDS spreads over the entire sample period.[1]

The low values of the correlations in the contemporaneous changes between MIRs and between the changes in MIRs and CDS spreads suggest that one or more of these series may be leading the others. We investigate this question in the next section.

4. Dynamic lead-lag relationship

In this section we provide a preliminary analysis of dynamic relationships between the MIRs and CDS spreads. We are interested in knowing whether there are strong relationships between lagged changes in the variables and whether one indicator may be leading the others. For example, a finding that one of the indicators systematically moves ahead of the others could be interesting with respect to early detection of financial distress.[2] Since MIRs are constructed in a way that combines the issuers' information from long-term ratings and from the markets, it is likely that CDS spreads lead changes in the implied ratings. However, the possibility of changes in MIRs leading credit spreads cannot be ruled out completely. In particular, as explained above, MIRs are relative measures of credit risk. This implies that a bank's MIR can change before its market underlying market price does for at least two reasons. First, for given long-term ratings of the firms in the reference sample used to construct the MIRs, a strong movement in the (credit risk information obtained from) market prices of (a substantial number of) other firms in

(1) The corresponding correlations in weekly rather than daily changes range between –0.20 and –0.60 for CDS spreads and CDSIRs, and between 0 and –0.30 for CDS spreads and EIRs. Daily changes therefore result in lower correlations, but qualitative results are again similar for weekly changes.

(2) Studies from the academia and rating agencies show that while the CDS market leads the bond market, the evidence on the lead-lag relationships between the CDS and equity markets is inconclusive.

TABLE 2 GRANGER-CAUSALITY TEST RESULTS

(1)	(2)	(1) causes (2)	(2) causes (1)	Bi-lateral causality	No causality link
Whole period: 1 January 2005 – 31 December 2009					
CDS spreads	CDSIR	16	3	9	2
CDS spreads	EIR	6	6	3	15
CDSIR	EIR	0	3	0	27
Pre-crisis period: 1 January 2005 – 31 July 2007					
CDS spreads	CDSIR	5	3	18	4
CDS spreads	EIR	3	3	3	21
CDSIR	EIR	4	4	0	22
Crisis period: 1 August 2007 – 31 December 2009					
CDS spreads	CDSIR	18	2	7	3
CDS spreads	EIR	6	6	0	18
CDSIR	EIR	1	0	1	28

Notes: This table reports the Granger-causality test results of the VAR analysis. The first two columns of the table indicate the number of sample banks for which the hypothesis that one credit risk indicator Granger causes the other cannot be rejected at the 5 p.c. significance level. The third and fourth columns indicate respectively the number of cases in which a bi-lateral causality link and no causality link between the credit risk indicators in question are detected.

the sample may cause a change in the bank's MIR, even if its own market price did not change. Second, for given (credit risk information obtained from) market prices of the firms in the reference sample used to construct the MIRs, a change in the long-term ratings of (a substantial number of) other firms in the reference sample may change the bank's MIR without a change in its underlying market price. Hence, the combination of different information sources (long-term ratings and credit risk information obtained from market prices) into a relative measure of credit risk may explain why the MIRs of our sample banks may move earlier than the underlying market prices do.

To shed light on this issue, we perform a Granger causality tests to check whether lagged values of one variable help to predict the other variables by running a simple vector auto-regression (VAR) for each bank separately. More precisely, a VAR is a linear model of n-equations, n-variables (n=3 in our case). In this system, each variable is explained by its own lagged values, plus the current and past values of the other n-1 variables. The explicit VAR specification used in this analysis expresses each variable as a linear function of its own past values, the past values of all other variables and a serially uncorrelated error term. (1) Hence, this specification allows to capture the lead-lag relationship between CDS spreads, CDSIRs and EIRs. The Granger causality test corresponds to testing whether the relevant sets of coefficients are zero. For example, if EIRs help to predict CDS spreads, then the coefficients on the lags of EIRs will be significantly different from zero in the equation of the VAR system where CDS spreads are the dependent variable.

Table 2 summarizes the Granger-causality test results. In particular, the first two columns report the number of banks in our sample of 30 banks, for which the hypothesis that one indicator Granger-causes the other cannot be rejected at 5 p.c. level of significance. The third column reports the number of banks for which the causality between two indicators is running both ways, i.e. for which a significant non-contemporaneous relationship exists but the direction of causation runs in both ways. (2) The last column reports the number of banks for which there is no Granger-causality link between the indicators considered, i.e. no significant non-contemporaneous relationship can be detected for these banks.

(1) For each bank, we use 5 daily lags for each variable in the equations. The results do not vary significantly if we use a specification where, for each bank, the number of lags is selected using the Bayesian information criterion, which selects the best fitting model, that is the best number of lags to be estimated for each bank.

(2) In this case, the results are hard to interpret and further analysis is required. It could be that the series are driven by a common third process at different lags.

This table reveals that for a majority of the banks in our sample there is a significant non-contemporaneous relationship between changes in CDS spreads and changes in CDSIRs. Given that CDSIRs are derived from CDS spreads and long-term ratings, this may not seem very surprising. In contrast, there is only weak evidence for relationships between CDS spread changes and EIR changes, and no significant relationship between these variables for more than half of the banks in our sample. Finally, there appears to be virtually no non-contemporaneous relationship between CDSIR changes and EIR changes.

Turning to the direction of causality in those relationships found to be significant, we find that CDS spreads are quite often leading CDSIRs, especially during the crisis period. This implies that during the crisis, CDS spreads were signalling credit risk (or other factors, such as increased investors' risk aversion) earlier than CDSIRs did. With respect to changes in CDS spreads and changes in EIRs, Table 2 shows that the number of banks for which the former is leading the latter always equals the number of banks for which the opposite is true. Finally, for the very few banks that have a significant non-contemporaneous relationship between changes in CDSIRs and changes in EIRs, we find no clear direction in which indicator is leading the other.

Overall, these observations suggest that differences in the movement of CDSIRs and EIRs discussed in Sections 2 and 3 cannot be explained by some difference in the timing with which MIRs reflect the market information on individual credit risk.

5. Concluding remarks

In the past decade there has been an increasing focus on financial instability and its early detection as an input to policy decisions. The recent financial crisis, its high costs and the importance of macro-financial factors has revealed the need to strengthen macro-prudential supervision. One of the objectives of macro-prudential supervision is to monitor the cyclical and structural trends in financial markets so as to identify signals and measures of potential vulnerabilities in the financial system in a timely manner. Hence, a related policy question is what instruments or variables might constitute reliable indicators of emerging risks.

Market-implied ratings have been recently introduced by rating agencies as indicators of credit risk that include information on credit risk from the market, but are more stable than prices and are based on a scale (the traditional rating scale) which can be easily understood. For these reasons, market-implied ratings appear to be used by central banks, financial institutions and investors as a complement to long-term ratings and market prices to monitor the financial condition of banks. From a macro-prudential point of view, it is interesting to ask whether such indicators offer a more precise measure of credit risk than e.g. CDS spreads, and whether information about credit risk is incorporated into one of the market-implied ratings (CDS-implied or equity-implied) more quickly than in the other or than in market prices (CDS spreads).

This article addresses these questions by analysing the behaviour of market-implied ratings over a period covering the run-up to the crisis and the crisis period itself. The available evidence seems to suggest that MIRs are unlikely to fully overcome the deficiencies of their underlying components (long-term ratings and market prices). In particular, the behaviour of MIRs obtained from the CDS market and those obtained from the equity market does not always coincide. That is, the relationship between CDSIRs and EIRs is time-varying. In addition, the two types of MIRs also seem to differ somewhat in their relationship to CDS spreads. Correlations between changes in CDSIRs and EIRs are low, and there seems to be no lead-lag relationship between the changes in these variables, suggesting that the low correlations are not due to differences in the speeds at which CDS and equity markets reflect information relating to credit risk.

Instead, the movements in CDSIRs and EIRs seem to reflect movements in the underlying prices in CDS and equity markets, although these movements may not be driven only by factors related to credit risk.

This article represents a first step in analyzing the behaviour of MIRs and suggests several avenues for further research. A natural question which arises from the results is what drives the seemingly unrelated movements sometimes observed in the MIRs. Is the main driver increased credit risk ? Are there methodological reasons suggesting that MIRs should not be expected to offer equivalent measures of credit risk ? To what extent do factors unrelated to credit risk, such as risk premia, liquidity premia, or bank-specific characteristics affect the MIRs ?

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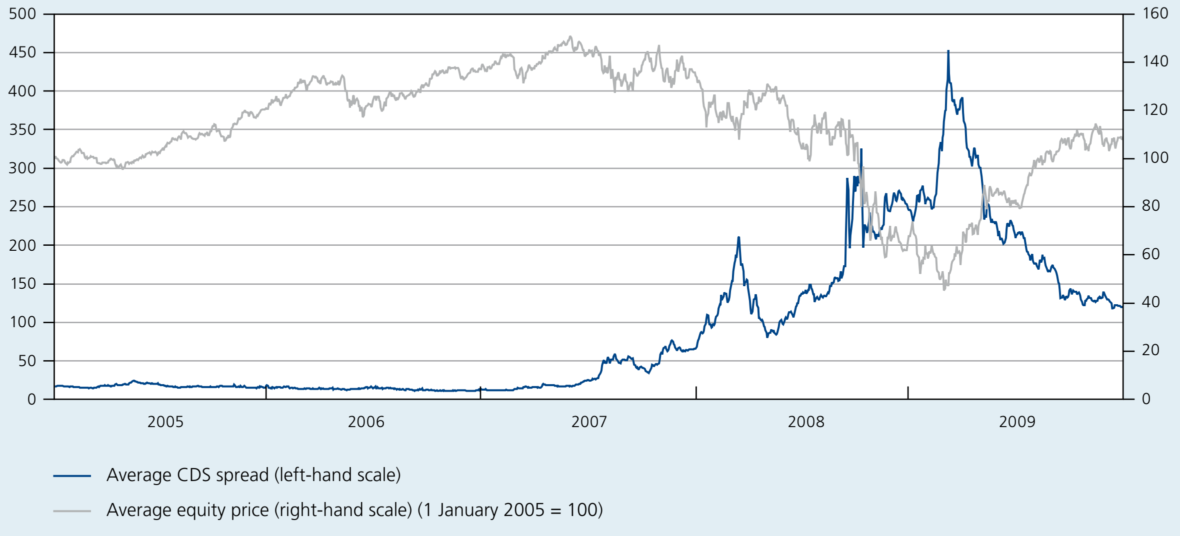
Appendix

CHART A1 HISTORICAL EVOLUTION OF AVERAGE CDS SPREAD AND AVERAGE EQUITY PRICE OVER THE PERIOD 1 JANUARY 2005 – 31 DECEMBER 2009



Source : Own calculations based on data from Datastream.