The Dynamics of Credit Rating Disagreement

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Abstract

If all credit rating agencies (CRAs) perform the same task, why do multiple CRAs exist and why do firms purchase multiple credit ratings? The latter evidence suggests that CRAs have to disagree at least in certain instances, otherwise multiple agencies and ratings would be redundant. We shed light on this question by measuring and explaining the rating disagreement for multi-rated firms over time. Our principal findings are that higher firm-specific uncertainty and more private information increase rating disagreement. In addition, there is some evidence that more systematic risk lowers rating disagreement and more firm-specific credit risk increases rating disagreement. Our results highlight time-varying costs and benefits of CRAs' monitoring role: weak disagreement implies little potential for rating error diversification and duplicated monitoring, while strong disagreement combined with highly correlated private information implies inconsistencies due to discretion, heterogeneous policies, incentive problems, and strategic use of information.

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1. Introduction

The function of a credit rating agency (CRA) is to facilitate debt contracting in capital markets by reducing informational asymmetries through screening and monitoring. During the past two decades the number of CRAs has grown and there has been a clear trend towards multiple ratings per firm. However, if all CRAs perform the same task then multi-rated firms should display identical ratings, implying neither a need for multiple rating agencies nor for multiple ratings per firm. Hence, there must be instances in which CRAs disagree. Such disagreement between CRAs could impact the pricing, the issue volume, and financial regulations related to corporate debt. In a recent study Bongaerts, Cremers and Goetzman (2012) show that the way in which financial regulations such as investment restrictions, collateral and margin rules and bank capital requirements take into account multiple credit ratings explains why firms have incentives to obtain a third rating. This tiebreaker role of the third rating is only needed when the first two ratings of the firm (or bond) differ. Hence, the question is what causes CRAs to disagree and assign different ratings to the same firm. Disagreement can result from different rating levels at a given point in time or rating changes at different times and/or of different magnitudes. We note that rating actions might create, increase, decrease or eliminate disagreement.

In this paper, we document and explain the dynamics of rating disagreement for firms with multiple ratings. We measure rating disagreement with firm-specific and time-varying rating disagreement index based on the ratings assigned by Moody's, Standard & Poor's and Fitch Ratings. Our study extends and complements the earlier literature on the existence, determinants, and consequences of split ratings by conducting a dynamic analysis of the consistency of CRAs' monitoring role. The dynamic aspect of disagreement between CRAs has a substantial impact on continuously changing capital market outcomes, such as trading volume, credit spread levels and stock return volatilities, but it has largely been ignored in earlier studies that focus on rating level disagreement across agencies at the moment of bond issues. Our empirical analysis of rating disagreement considers timing differences in rating actions, highlights important costs and benefits of CRAs' monitoring role, and explains their variation across firms and over time.

The early theoretical research on information production has examined the delegation of monitoring and its potential gains (e.g., Ramakrishnan and Thakor, 1984; Millon and Thakor, 1986). Subsequent studies provided rationales for the existence, functions, and problems of credit rating agencies (e.g., Boot, Milbourn and Schmeits, 2006; Bolton, Freixas and Shapiro, 2012; Manso, 2012; Mariano, 2012). However, these studies do not explain why monitoring by multiple agencies occurs, and how the actions of different rating agencies that cover the same firm are spread over time.

There are different arguments why weak or strong disagreement in the context of multi-rated firms can be beneficial. On the one hand, weak (or no) disagreement among CRAs indicates that they perform their monitoring of firms in a similar way, making multiple ratings redundant and implying welfare costs due to duplicated monitoring. Moreover, weak disagreement excludes rating error diversification as motive for purchasing multiple ratings. On the other hand, strong disagreement among CRAs in combination with a low correlation of private information is likely beneficial because it helps reduce aggregate and firm-specific informational asymmetries and improves price discovery in capital markets. It might also strengthen the functioning of credit ratings as coordination mechanism in debt contracting by providing focal points (e.g., Boot, Milbourn and Schmeits, 2006). But, strong rating disagreement in combination with a high correlation of private information would hint at inconsistencies such as discretionary policies, incentive problems, and strategic use of information. These inconsistencies might arise from competition between CRAs, reputational concerns, payment models, and organizational procedures within CRAs. Such situation would impede the coordination function of credit ratings for firms and their investors. The model by Mariano (2012) predicts that with credit rating competition, agencies have incentives to contradict public information pretending that they hold precise private information. These incentives include the possibility to inflate ratings to protect market power (e.g., Griffin and Tang, 2012; He, Qian and Strahan, 2012). Furthermore, rating error diversification as motive for having multiple ratings is only reasonable if rating errors are not highly correlated and if the rating error diversification benefits exceed the increased costs due to multiple rating fees.

In this study, we develop a time-varying firm-specific index of disagreement among CRAs for multi-rated firms. The index is defined as the average of the pairwise Euclidian distances between credit rating levels from all CRAs that cover the firm. The index captures rating level differences and rating changes over time. Based on this index we examine whether and how *information* (uncertainty and private information) and *risk* (systematic risk and credit risk) affects the way in which CRAs perform their monitoring role. Our sample comprises 228 large firms from the United States and Europe that are frequently traded in the credit default swap (CDS) market. We focus on CDS market-traded firms because empirical research has documented the CDS market is particularly efficient in reflecting credit risk-related information, (e.g., Hull, Predescu and White, 2004; Norden and Weber, 2004; Blanco, Brennan and Marsh, 2005; Acharya and Johnson, 2007). Because of our focus we likely underestimate the rating disagreement in the market (as asymmetric information about firms with traded CDS should be lower than for those without traded CDS), which makes it harder to find significant explanatory factors. Moreover, credit rating actions are of key importance for the trading activities in the CDS market (e.g., Norden, 2011), and we can benchmark credit rating-implied information with market-implied information about firms' credit risk by examining their CDS spreads. The analysis spans the period from 2000 to 2010, including several credit market up- and downturns as well as the global financial crisis of 2007-2009. In all analyses we control for the number of rating actions per time window, the financial crisis, firm-fixed effects, and time-varying industry effects. The latter is important to capture methodological rating differences between CRAs (probability of default vs. expected loss ratings) as the loss-given-default estimates that are part of the expected loss ratings are largely industry driven. Our principal findings are that higher firm-specific uncertainty, measured by firms' stock return volatility, and more private information increase rating disagreement. Both results are statistically strong, economically meaningful, and robust in various empirical models. But, we also show that CRAs' private information about the same firm exhibits a large overlap, as reflected by an average pairwise correlation across agencies of 72%. We further find some evidence that more systematic risk leads to less rating disagreement and more firm-specific credit risk to more rating disagreement. Our findings suggest that factors related to the *information*, and to a lesser extent factor related to *risk*, help explain credit rating disagreement. Moreover, they hint at discretionary policies, incentive problems, and strategic use of information in the rating industry.

Our study contributes to the literature on information production by financial intermediaries, especially the monitoring by CRAs, in several ways. First, the structure and standards of the credit rating industry has substantially changed over the past 20 years (e.g., Blume, Lim, MacKinlay, 1988; Cantor and Packer, 1995; Jorion et al., 2005; White, 2010; Alp, 2012). The rating business has been dominated by the two large players Moody's and S&P for a long time but in the recent past Fitch and other smaller, specialized and domestic rating agencies entered the industry, gradually increasing competition. As a result firms are increasingly covered by multiple rating agencies. Empirical research further documents that more competition in the credit rating industry affects the aggregate pricing of corporate bonds and therefore firms' cost of capital and the overall allocation in credit in markets (e.g., Kisgen and Strahan, 2010; Becker and

Milbourn, 2011). These studies do not investigate whether and how strategic use of information by CRAs as a response to competition affects the rating disagreement over time.

Second, a significant fraction of multi-rated firms exhibit split ratings from the start or in later periods. Also, combinations of differences in credit rating levels at the start and differences in the timing of subsequent rating actions can be frequently observed. The earlier literature has investigated why (and which) firms prefer to have multiple ratings and what the implications of split ratings are (e.g., Ederington, 1986; Jewell and Livingston, 2000; Morgan, 2002; Livingston and Naranjo, 2007; Livingston, Wei and Zhou, 2010). But, none of these studies has examined the extent and determinants of rating disagreement over time. Our study is the first attempt to help fill this void. Analyzing the clustering of rating actions is an important issue since credit risk can change continuously. To track these changes in credit risk and translate them into discrete rating actions is the core of CRAs' monitoring function. Considering the level of credit risk at firms' financing events, which are relatively rare, is clearly not sufficient (e.g., Goh and Ederington, 1993; Kisgen, 2006). Stated differently, the monitoring of firms after the issuance of a bond is as important as the initial screening of the firms before a financing event.

Third, credit ratings have gained in importance in financial regulation. Examples are investment rules and restrictions for certain institutional investors, capital requirements for banks (Basel II and Basel III), monetary policy, and bankruptcy and restructuring procedures including bail-outs and interventions by governments. Interestingly, different agencies, once nationally recognized as statistical rating organization (NRSRO) by financial supervisors, are treated equally in rules and regulations although empirical research hints at substantial differences in their accuracy, timeliness, stability, and impact on bond, stock and CDS markets (e.g., Holthausen and Leftwich, 1986; Hand, Holthausen and Leftwich, 1992; Dichev and Piotroski, 2001; Hull, Predescu and White, 2004; Norden and Weber, 2004; Löffler 2004; Löffler, 2005; Güttler and Wahrenburg, 2007; Galil and Soffer, 2011).

Fourth, the role of credit rating agencies has increasingly come under scrutiny during the recent financial crisis (e.g., White, 2010; Bolton, Freixas and Shapiro, 2012; Griffin and Tang, 2012; He, Qian and Strahan, 2012; Chava, Ganduri and Ornthanalai, 2012; Hilscher and Wilson, 2013). CRAs have been criticized for assigning *too high* credit ratings for structured products such as subprime mortgage backed securities (and a variety of other securitized items) and, recently, for assigning *too low* credit ratings and political pressure during the sovereign debt crisis, especially for certain countries from the Euro area such as Greece, Portugal, Spain and Italy. Also, the speed and timing of rating downgrades differs substantially between agencies. Hence, understanding the consistency of CRAs' monitoring behavior over time is important of issuers, investors and policy makers.

The remainder of the paper is organized as follows. In Section 2, we propose a set of hypotheses about factors that help explain the dynamics of rating disagreement. In Section 3, we describe how we measure rating disagreement. In Section 4, we present the data and summary statistics. In Section 5, we report the main results of the empirical analysis. Section 6 concludes.

2. Measuring rating disagreement

We derive a firm-specific and time-varying index of rating disagreement for firms with multiple ratings. The rating disagreement index (DIS) is defined as the average Euclidian distance between all rating vectors that summarize rating levels by the three major credit rating agencies (Moody's, S&P, and Fitch). The Euclidian distance between points p and q is the length of the line segment connecting them. In Cartesian coordinates, if $p = (p_1, p_2, \dots, p_n)$ and $q =$

$(q_1, q_2, \dots, q_n)$ are two points in Euclidian $n-$ space, then the distance from p to q is given by $d(p,q) = \sqrt{\sum_{m=1}^{n}(p_m - q_m)^2}$.

We apply this mathematical transform to our rating level vectors and average it across all rating agency pairs. Let $RAT_{ij,t}$ denote the credit rating level assigned by credit rating agency j to firm i at time t and $RAT_{ij,t}^{\tau}$ be the corresponding time series vector of size τ, namely,

$$RAT_i^{\tau} = \left(RAT_{ij,t}, RAT_{ij,t+1}, \dots, RAT_{ij,t+\tau}\right)', \text{ where } RAT_{ij,t} \in [1,25]. \quad (1)$$

For every pair of credit ratings for the same firm from different agencies we calculate the Euclidian distance, $d\left(RAT_{ij,t}^{\tau}, RAT_{ik,t}^{\tau}\right)$. We fix τ and calculate these distance rolling over time. We then average each of these pairwise distances at every time point, i.e.,

$$\bar{d}_{i,t} = \frac{1}{J_i} \times \sum_{j \neq k} d\left(RAT_{ij,t}^{\tau}, RAT_{ik,t}^{\tau}\right), \quad (2)$$

where J_i is the number of credit rating agencies following firm i.

To measure disagreement in rating levels, we first calculate all pairwise distance measures between these vectors for all rating agency pairs and average them for each firm over time. Again, we fix τ and roll these windows over time. We then normalize the average distance by their theoretical maxima in the cross section. We have

$$DIS_{it} = \bar{d}_{i,t}/d_{max}. \quad (3)$$

For expositional reasons we transform the measure to a scale from 0 to 100. Intuitively, a greater value indicates more disagreement among CRAs. As such, the rating disagreement index DIS reflects differences in rating levels as well as rating changes over time. The index is comprehensive, model-free, and easy to interpret. We avoid choosing a model or benchmark-based disagreement index since the latter requires assumptions, and different modeling approaches and/or choices that might result in conflicting results.

Let us provide some intuition for the rating disagreement measure DIS. Consider two CRAs that assign ratings (on a scale from 1 to 25) to the same firm and do not change their ratings during a predefined time interval of one week, i.e., the rating level vector is defined over five trading days. In this situation, there is no disagreement because of identical ratings on each day and no rating changes by any CRA. After normalization, the rating disagreement index DIS equals 0%. Alternatively, consider that the difference in rating assessments by any two CRAs is always at 24 notches within the specified time interval. In this situation, our rating disagreement index equals 100% because we observe the maximum distance in all pairwise rating level comparisons. A similar reasoning can be applied to firms with three ratings. More generally, rating disagreement between the three CRAs increases whenever the assigned ratings *diverge*, and it decreases whenever the assigned ratings *converge* within the predefined time interval. We define the rating disagreement index DIS only for firms with two or three ratings and calculate the index as a daily average for predefined quarterly rolling intervals.

3. Hypotheses

We propose two sets of hypotheses about market-wide and firm-specific factors that influence disagreement among CRAs over time. The factors relate to *information* about and *risk* of the rated firms. In our context, information might lead to disagreement through the variation in the extent and reliability of information, while risk might lead to disagreement through systematic risk and credit risk. The hypotheses refer to the effect of each factor ceteris paribus. In the empirical analysis we conduct univariate and multivariate tests.

Our first set of hypotheses relates to *information* about the firm. We argue that asymmetric information (similarly: opaqueness, transparence, uncertainty) affects the consistency of credit rating assessments made by different CRAs. We expect that higher uncertainty in the capital market as well as higher uncertainty about individual firms increases rating disagreement. In times of high uncertainty, the private information of agencies becomes more valuable than in times of low uncertainty. Hence, better informed CRAs change the ratings (earlier), while less informed CRAs do not change the ratings (or lag behind; e.g., Güttler and Wahrenburg, 2007). We use the VIX index for US firms (and the VDAX for European firms), and the firm-specific stock volatility as measures of uncertainty.

Hypothesis H1: Higher uncertainty increases rating disagreement.

Second, we investigate the impact of CRAs' private information on rating disagreement over time. To do so, we extract the non-public component from the three rating agencies' ratings. We first analyze how this component overlaps between agencies and then study its impact on the rating disagreement index. We use the firm's average CDS spread per time window and the Altman (1968) Z-Score as public information-based measures of credit risk. Research has shown that firms' CDS spreads have a high sensitivity to credit risk-related information and therefore have become a widely used market-based measure of corporate credit risk (e.g., Blanco, Brennan and Marsh, 2005; Acharya and Johnson, 2007; Norden and Wagner, 2008). For comparison, the Altman (1968) Z-Score is an accounting-based measure of credit risk that is free rating policies and market (microstructure) effects but it might be distorted by accounting discretion. We assume that private information differs across CRAs and hypothesize:

Hypothesis H2: More private information increases rating disagreement.

Our second set of hypotheses relates to the risk of the rated firm. Rating disagreement is expected to become lower when systematic risk in the economy increases. Systematic risk has macro-economic causes, affects by definition a large fraction of the economy, and is reflected by capital market outcomes. For instance, the recent study by Hilscher and Wilson (2012) shows that credit ratings are inaccurate measures of firm's raw default probability but largely driven by systematic risk. If different CRAs measure systematic risk in the same way, rating disagreement should decrease when systematic risk increases. Also, an increase of individual firms' sensitivity to systematic risk should be reflected in a lower rating disagreement. This reasoning is consistent with increased correlations between CDS spreads in times of crisis (e.g., Berndt and Obreja, 2010).

Hypothesis H3: Higher systematic risk decreases rating disagreement.

We further test whether rating disagreement relates to credit risk. Given the function of CRAs their ratings should be more consistent when the overall credit risk and/or firm-specific credit risk increases. This reasoning is in line with CRAs' incentives to be conservative when credit risk increases. Overstating an increase in credit risk by assigning a too bad rating level and/or more announcing rating downgrades than actually warranted protects the reputation of CRAs, while the opposite does not (i.e., overstating a decrease in credit risk by assigning a too good rating level and/or announcing more rating upgrades than warranted). Based on this reasoning we hypothesize:

Hypothesis 4: Higher credit risk decreases rating disagreement.

4. Data

We collect data on firms that are frequently traded in the CDS market from Markit and CreditTrade and merge this data with daily information on credit ratings and rating actions from the three major CRAs Moody's, S&P and Fitch from Bloomberg (e.g., Norden and Weber, 2004; Blanco, Brennan and Marsh, 2005). We consider firms from the US and Europe that are rated by at least two of the three major rating agencies. We match the resulting sample with firm data from CRSP (US firms' stock prices), DATASTREAM (European firms' stock prices), and COMPUSTAT GLOBAL (items from financial statements). In addition, we collect a set of aggregate market variables related to information (uncertainty) and risk (systematic risk and credit risk), such as the volatility index (VIX), a measure of aggregate systematic risk (SYSRISK), its standard deviation (STDSYSRISK), and the spread on a credit default swap index (CDS_INDEX). The variable SYSRISK is defined as the average of all firms' individual sensitivities to systematic risk (SYSRISK_{it}), which are calculated as follows

$$\text{SYSRISK}_{it} = 1 - \sigma_{e_{i,t}} / \sigma_{R_{i,t}}, \tag{4}$$

where $\sigma_{e_{i,t}}$ is the standard deviation of the error term from a market model regression, and $\sigma_{R_{i,t}}$ is the standard deviation of firm's stock return within a particular quarter. The market-wide variables come from DATASTREAM. Our final sample comprises data on 228 US and European firms for the period from 2000 to 2010. The names, descriptions and summary statistics of the main variables are shown in Table 1.

(Insert Table 1 here)

The VIX displays a mean of 24.23, ranging from 9.89 and 83.23. The CDS_INDEX has a mean of 124.20 bps and a maximum of 662.47 bps. Considering the firm-specific variables, the mean CDS spread level of the firms in our sample is 129 basis points, the average stock return of 0.00% per day and the standard deviation of stock returns is 3%. The mean ZSCORE (following Altman (1968)) is 3.09. The average firm in our sample has a rating of 7.08 on a scale from 1 to 25 where 1 corresponds to the highest rating (AAA or Aaa) and 25 to the lowest rating level (D). In our sample, the S&P rating exhibits a mean of 7.12, Moody's of 6.73, and Fitch of 6.87. Figure 1 shows the distribution of credit rating levels by agency.

(Insert Figure 1 here)

Daily credit rating levels for the pooled data across firms and over time are similar but not identical. For instance, in rating classes 4 (AA-) and 5 (A+) there are substantial differences, also in class 10 (BBB-), which is the investment grade boundary. We will control for industry effects in rating disagreement, which may arise due to technical differences in the rating methodology, in all empirical analyses.

Figure 1 does not indicate how much of the differences in ratings is due to persistence in split ratings or due to asynchronous rating changes across agencies (that may lead to split ratings or increase the gap between existing split ratings). As described in Section 3, the rating disagreement index DIS allows us to measure and explain the time variation of rating differences within firm. Summary statistics for DIS are shown in the bottom panel of Table 1. DIS exhibits a mean of 2.13% and ranges between 0% and 25% (on a scale from 0% to 100%). Much of the time-variation within in firms disappears in summary statistics based on data pooled across firms and over time. This is because rating actions for different firms do not happen at the same time and rating actions and split ratings occur at a relatively low frequency.

Figure 2 shows the rating disagreement index for Ford Motor Company as an example. The daily average rating disagreement (per quarterly rolling windows) among Moody's, S&P and Fitch ranges between 0% and 9%. Interestingly, there is substantial time variation in rating disagreement for this firm – for instance, a stark increase in quarter 3 of 2008 when Lehman Brothers failed. Measuring and explaining this within-firm time variation in rating disagreement is the main purpose of our paper.

(Insert Figure 2 here)

5. Empirical results

We conduct three sets of empirical tests to study whether the dynamics of rating disagreement can be explained with time series of market-wide and firm-specific variables that relate to information (hypothesis H1 on uncertainty and hypothesis H2 on private information), risk (hypothesis H3 on systematic risk and hypothesis H4 on credit risk) or both (joint test of hypotheses H1-H4). In all stages of the analysis, we estimate panel data regression models with quarterly data, in which we control for effects due to the financial crisis, firm fixed effects, and, alternatively, firm fixed effects and a full set of interacted industry*year-quarter fixed effects. It is particularly important to control for industry fixed effects because rating methods differ with regard to one important technicality. S&P derive ratings from ordinal rankings based on an estimate of the borrower's probability of default (PD), while Moody's ratings are based on an estimate of the borrower's expected loss (EL= PD x LGD). Thus, the PD is a common (quasi identical) component that does not help explain rating disagreement. But, the LGD estimate by Moody's, which is largely driven by industry effects, can explain some of the differences. That is the reason why we control for (time-varying) industry fixed effects in all of our analyses.

5.1. The influence of uncertainty and private information on rating disagreement (H1 and H2)

We investigate hypothesis H1, which states a positive relation between uncertainty and rating disagreement, by regressing the rating disagreement index $DIS_{i,t}$ on the market-wide volatility index (VIX_t) and, alternatively, on firms' stock return volatility and comprehensive set of control variables. We also control for the number of rating actions per quarter and firm (ACTIONS). Table 2 reports the results. Models 1-3 show the influence of market-wide uncertainty measured by the quarterly average of the VIX and models 4-6 the influence of firm-specific uncertainty measured by firms' quarterly stock return volatility. Model 3 and 6 are particularly careful as the comprehensive set of control variables allows us to deal with various forms of unobserved heterogeneity.

(Insert Table 2 here)

We find that an increase in market-wide uncertainty is associated with less rating disagreement, as indicated by the significantly negative coefficient of VIX in models 1-3. The result implies that when aggregate uncertainty increases credit ratings tend to converge. This could happen when those CRAs that lag behind others announce rating actions that move their ratings closer towards the "rating average" expected by the market (e.g., Norden and Weber, 2004). Also, moving away from the "rating average" becomes less likely when market-wide uncertainty rises. Interestingly, in models 4 and 6 we find the opposite result for firm-specific uncertainty. An increase in firms' quarterly stock return volatility (STDRET) leads to more rating disagreement, as stated in hypothesis H1. We note that this result might be explained with differences across CRAs in private information about individual firms, while the result on aggregate uncertainty is likely unrelated to private information about individual firms.

The mixed evidence on the effect of uncertainty leads us to the test of hypothesis H2. We now investigate the effect of each rating agency's private information on rating disagreement. If private information is identical across all agencies (and/or interpreted and used in identical ways) we should find a significantly negative impact on rating disagreement. However, if it differs across agencies it is likely that it increases rating disagreement.

We have to obtain a proxy for CRAs' private information in the first step, which we can use as explanatory variable for the rating disagreement index in the second step. For this purpose, we follow Agarwal and Hauswald (2010), who extract private information of banks from the residual of a regression of bank-internal borrower ratings on public information about the borrower, and adapt their approach to the context of our study. We regress the quarterly average credit rating from each CRA per firm, respectively, on the same firm's quarterly CDS spread that reflects public information about that firm (e.g., Norden and Weber, 2004; Blanco, Brennan and Marsh, 2005; Acharya and Johnson, 2007). In an alternative specification, we use Altman's Z-Score (1968) (ZSCORE) as explanatory variable. The ZSCORE, calculated as a linear combination of five financial ratios, is an indicator of corporate default risk and various studies have demonstrated its predictive power for US and European firms. It is plausible to assume that the ZSCORE is highly correlated with the financial statement information used by CRAs to assign credit ratings. Our approach allows us to benchmark CRAs' credit ratings with a market-based and an accounting-based indicator for public information. Most important, the residual of these firm-specific time series regressions can be used as a proxy of either average private information of all CRAs (when we use the average of all three credit ratings per quarter and firm as dependent variable) or a particular CRA's private information (when we use the quarterly average of one particular rating per firm). One additional remark is in order at this point. In a strict sense, the residual captures all non-public information, such as private information, rating errors, and rating policies, etc. (see Löffler, 2005). We are aware that the residual is neither a perfect nor an absolute measure of private information. But, we believe it is reasonable to assume that this proxy is positively correlated with true unobservable extent of private information and therefore can serve as a relative proxy. Table 3 reports the results.

(Insert Table 3 here)

Panel A of Table 3 shows that the average R^2 for the CDS and ZSCORE regressions are relatively similar. The R^2 levels for the regressions with the ZSCORE as explanatory variable range between 31% and 34%, while those for the CDS regressions range between 24% and 26%. It is plausible that the market-based indicator exhibits a lower R^2 than the accounting based indicator because CRAs' policies aiming at rating stability make ratings more similar to accounting numbers than market prices (e.g., Altman and Rijken, 2004; Löffler, 2005). Overall, these results indicate that CRAs make as expected use of public information.

Furthermore, Panel B of Table 3 indicates that the pairwise correlations of private information range between 0.67 (Moody's, Fitch) and 0.76 (S&P, Fitch), with a pairwise average of 0.72. This is a relatively high overlap, which potentially limits the role of private information as a candidate to explain rating disagreement. It also limits potential benefits from rating error diversification. Such high overlap makes it unlikely that the benefits of mitigating rating errors exceed the costs of paying a rating fee to three (instead of one) agency. Furthermore, it might be that the high overlap in the residuals stems from CRAs' slow response to new information compared to the fast response of market prices. Given that we obtain similar findings for the regressions with the ZSCORE, which is based on quarterly financial statements, it is unlikely that the response time to market prices can explain the high overlap in private information of rating agencies.

To explore the effect of CRA's private information we estimate a model with the rating disagreement index $DIS_{i,t}$ as dependent variable and CRA's private information (i.e., the residual from the firms-specific time-series regression models with the CDS spread or ZSCORE, as described above). Table 4 reports the findings.

(Insert Table 4 here)

The results are clear and consistent. In all specifications we find that CRAs' private information increases rating disagreement. The coefficients of the variable "average private information" and the private information of Moody's, S&P and Fitch, respectively, are all significantly positive and large. The coefficient is biggest for Moody's and smallest for Fitch. The evidence supports hypothesis H2.

Our findings on the influence of private information on rating disagreement are paradoxical. On the one hand, the high overlap in private information suggests CRAs are likely to make similar decisions (Table 3). On the other hand, the strong and very consistent result that more private information leads to more rating disagreement points in the opposite direction (Table 4). In this context, it is important to note that the proxy of private information exhibits substantial within-firm time variation. This is the reason why it helps explain the dynamics of the rating disagreement index. We reported the means of firm-specific correlations over the whole sample period in Panel B of Table 3. These correlations indicate a high overlap for the entire sample period, but they do not inform us about the time variation in private information. Hence, rating disagreement combined with on average highly correlated private information implies inconsistencies in the rating industry due to discretion, heterogeneous policies, incentive problems, and strategic use of information.

5.2. The influence of systematic risk and credit risk on rating disagreement (H3 and H4)

We continue the analysis by examining whether systematic risk and credit risk are related to the dynamics of rating disagreement. We estimate a model similar to the one shown in Table 2 and 4 but now use SYSRISK, which reflects the systematic risk in the financial market, and alternatively SYSRISK_FIRM, as key explanatory variables to test our hypothesis H3. We control for effects due to the financial crisis, firm fixed effects, and, alternatively, firm fixed effects and a full set of interacted industry*year-quarter fixed effects. Table 5 presents the results.

(Insert Table 5 here)

We find some indication that more market-wide systematic risk leads to less rating disagreement, as reflected by the negative coefficients of SYSRISK in models 1-3. However, the effect is weak and only statistically significant at the 10% level (model 2). The sensitivity of individual firms to systematic risk, SYSRISK_FIRM, has no significant effect. Our findings complement the study of Hilscher and Wilson (2013), who find that individual ratings are largely driven by systematic risk but not by raw firm-specific default risk. Their result implies that it should not be possible to explain differences between ratings from different CRAs for the same firm with measures of systematic risk as the latter should cancel out. That is exactly what we find.

In a next step, we investigate whether market-wide and firm-specific measures of credit risk affect rating disagreement, as suggested by our hypothesis H4. For this purpose, we estimate a regression model with the rating disagreement index as dependent variable and the CDS_INDEX or the firm-specific CDS spread as explanatory variable. Several studies document that CDS indices and individual firms' CDS spreads have become a benchmark to measure and price credit risk (e.g., Chava, Ganduri, Ornthalai, 2012; Knaup and Wagner, 2012). We again use the same control variables as beforehand. Table 6 shows the regression results.

(Insert Table 6 here)

We find some evidence that higher aggregate credit risk (CDS_INDEX) tends to reduce rating disagreement (model 3). The effect of firm-specific credit risk (CDS) on rating disagreement is positive (model 4) but disappears if we add the control variables to the regression model. Both findings are rather weak but they mimic the evidence on market-wide and firm-specific uncertainty in our test of hypothesis H1, which we carried out with volatility variables (VIX, STDRET). It is well known that stock return volatility measures are significantly related to measures of credit risk (e.g., Blanco, Brennan and Marsh, 2005; Zhang, Zhou and Zhu, 2009). We note that the result on firm-specific credit risk goes against the interests of users of ratings (and regulators that have delegated the safety judgments to CRAs) when disagreement between CRAs increases when credit risk increases. This is exactly the situation in which accurate and consistent credit risk assessments are needed.

5.3. Joint test of the determinants of rating disagreements

We now conduct a joint test of the hypotheses H1-H4 to examine whether information, risk or both help explain the dynamics of rating disagreement. We estimate a regression model with the firm-specific and time-varying rating disagreement index $DIS_{i,t}$ as dependent variable and market-wide and firm-specific measures of information and risk as explanatory variables. As before, we control for effects due to the financial crisis, firm fixed effects and, alternatively, time-varying industry fixed effects. The results are reported in Table 7.

(Insert Table 7 here)

We obtain two main results. First, the higher the firm-specific uncertainty, as measured by the individual firm stock return volatility the higher is the rating disagreement over time. The coefficient of STDRET is significantly positive and large. The result is consistent with the main finding from Table 2. Second, the more private information rating agencies have about a firm the larger the disagreement, as indicated by the significantly positive coefficient of "Average private information". This result fully confirms the earlier findings reported in Table 4.

In addition, and less strong than the two results above, the higher the aggregate systematic risk the lower the rating disagreement. The coefficient of SYSRISK is significantly negative but it becomes less significant the more control variables we add, which we also observed in Table 5. Furthermore, the coefficient of the firm-specific CDS spread is significantly positive and the significance increases the more controls we add. This result is only partly consistent with the findings from Table 6.

We also conduct a number of robustness tests to examine how sensitive our results are to specific variable definitions, measurement approaches, and sample splits. For instance, we revisit the raw data and recalculate the rating disagreement index on daily and yearly frequencies. We also vary the time interval over which we calculate the rating disagreement from a quarter, 6 months, 9 months, and one year. We further employ alternative definitions of the variable CRISIS (e.g., equal to one for the period from August 2007 to June 2009 and shorter sub-periods). For each of these scenarios, we re-run all models to test hypotheses H1-H4 and obtain similar results, which are available from the authors upon request. Moreover, we consider alternative measures of rating disagreement, based on changes in rating levels, and the magnitude of rating upgrades and downgrades, respectively. For most of these models, results are consistent with our previous analysis.

In sum, the main and most consistent findings of the joint test of hypotheses H1-H4 are that higher firm-specific uncertainty (H1) and more private information of CRAs (H2) are associated with more rating disagreement. These findings suggest that variables related to the *information* environment have major influence on rating disagreement.

6. Conclusion

The vast majority of firms that issue bonds are covered by multiple credit rating agencies (CRAs) and the number of rating agencies has increased in the last 20 years. The goal of this paper is to document and explain the dynamics of credit rating disagreement for multi-rated firms with market-wide and firm-specific factors related to information and risk. Disagreement among CRAs can result from different rating levels at a given point in time or rating changes at different times and/or of different magnitudes. We note that rating actions might create, increase, decrease or eliminate disagreement.

Our principal findings are that higher uncertainty, measured by a firm's stock return volatility, and more private information of CRAs increase rating disagreement. In addition, we find some evidence that more systematic risk leads to less rating disagreement and more firm-specific credit risk to more rating disagreement. Our results highlight time-varying costs and benefits of CRAs' monitoring role: No or little disagreement implies little potential for rating error diversification and duplicated monitoring, while strong disagreement combined with highly correlated private information implies inconsistencies due to discretion, heterogeneous policies, incentive problems, and strategic use of information.

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Figure 1: Distribution of credit rating levels

The figure displays the distribution of the credit rating levels assigned by Moody's (MD25), S&P (SP25) and Fitch (FI25) for the pooled sample of daily data (2000-2010, 228 firms, and 662,124 firm-day observations).

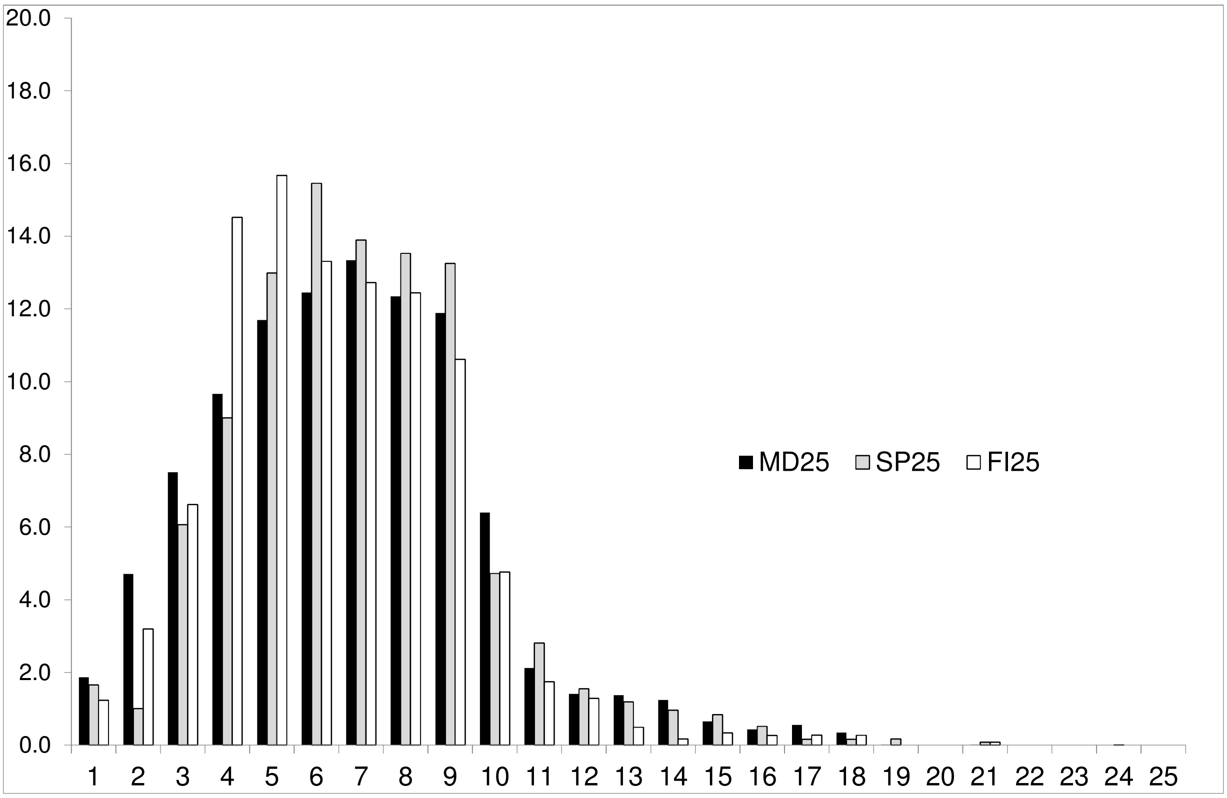

Figure 2: The rating disagreement index for Ford Motor Company

The figure shows the quarterly rating disagreement index for Ford Motor Company on the y-axis (scale from 0% to 100%) over the period from January 2000 to October 2010. The shaded area indicates the financial crisis.

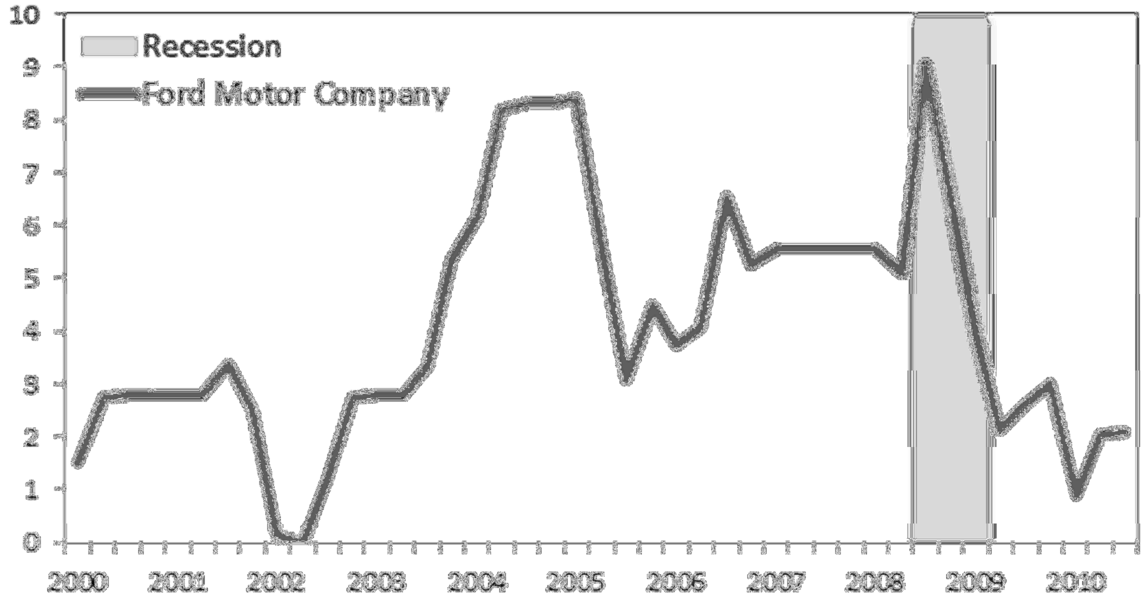

Table 1: Variables and summary statistics

The table presents the variable names, descriptions, and summary statistics for the main variables. The primary sources for our dataset are Bloomberg for credit ratings data, Markit and CreditTrade for CDS spreads, CRSP and Datastream for US and European firm stock returns, respectively, COMPUSTAT US and Global for other firm-specific variables, and Datastream for market variables.

Variable name	Description	Frequency	Obs.	Mean	Std. dev.	Min	Max
Market variables							
VIX	Volatility index	Dynamic	659,192	24.23	10.48	9.89	83.23
SYSRISK	Measure of aggregate systematic risk	Dynamic	644,728	0.03	0.03	-0.17	0.11
STDSYSRISK	Standard deviation of aggregate systematic risk	Dynamic	644,728	0.05	0.06	0.01	2.13
CDS_INDEX	CDS index	Dynamic	659,576	124.20	103.11	24.20	662.47
CRISIS	Dummy (1 from Sept 1, 2008 to June 1, 2009, 0 otherwise)	Daily	659,576	0.07	0.25	0.00	1.00
Firm-specific variables							
CDS	CDS spread (in bps)	Daily	484,621	129.10	420.98	0.00	24896.79
RET	Stock return (in %)	Daily	410,354	0.00	0.03	-0.82	1.24
STDRET	Standard deviation of stock return	Dynamic	406,544	0.02	0.01	0.00	0.51
SYSRISK_FIRM	Firm's sensitivity to systematic risk	Dynamic	406,521	0.03	0.08	-25.99	0.61
ZSCORE	ZSCORE	Quarterly	310,481	3.09	4.30	-7.91	87.65
AVGRAT25	Average rating	Daily	620,021	7.08	2.94	1.00	24.00
MD25	Moody's rating	Daily	523,179	6.73	2.93	1.00	18.00
SP25	Standard & Poor's rating	Daily	590,062	7.12	2.79	1.00	21.00
FI25	Fitch's rating	Daily	464,913	6.87	3.12	1.00	24.00
Rating clustering							
DIS	Rating disagreement index	Dynamic	558,690	2.13	2.05	0	25.00
ACTIONS	Sum of rating actions	dynamic	558,690	1.84	11.01	0	127

Table 2: The effect of uncertainty on rating disagreement over time

The table presents regression regressions results for DIS for firm i at time t as dependent variable. Independent variables are the volatility index (VIX) or the standard deviation of the firm's stock return STDRET, the number of rating ACTIONS per firm and quarter, and the CRISIS dummy. All models employ panel data fixed effects estimation with robust standard errors clustered at the firm level. The corresponding standard errors are in parentheses. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Dep. Var.:			$DIS_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	-0.017***	-0.017***	-0.010**			
	(0.005)	(0.004)	(0.004)			
STDRET				16.120***	5.436	8.247**
				(4.556)	(4.183)	(3.665)
ACTIONS	-0.000	0.010	0.010	-0.003	0.014**	0.016**
	(0.003)	(0.006)	(0.007)	(0.005)	(0.007)	(0.006)
CRISIS	0.671***	0.691***	0.253**	-0.0371	0.241*	-0.169
	(0.130)	(0.122)	(0.098)	(0.152)	(0.140)	(0.116)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	No	Yes	Yes
Industry*time fixed effects	No	No	Yes	No	No	Yes
Observations	8,636	8,636	8,636	5,662	5,662	5,662
R^2	0.008	0.014	0.085	0.014	0.009	0.107
Number of firms	228	228	228	147	147	147

Table 3: Private information in credit ratings

Panel A shows the average R^2 from regressing the average rating level (AVGRAT25), Moody's rating level, S&P's rating level, and Fitch's rating level on either the CDS spread or the ZSCORE for each firm in our sample. The CDS regressions are quarterly, while the ZSCORE regressions are yearly. ***, **, * denote significance at 1%, 5%, and 10% level, respectively. Panel B reports the Pearson's correlation coefficients between the average and each CRA's private information over time. The private information component is the error term from regressing a CRA's credit rating on the firm's CDS spread.

Panel A: Average R^2 from firm-specific time series regressions

	CDS			ZSCORE		
	Average R^2	*t*-stat	Obs.	Average R^2	*t*-stat	Obs.
Average rating	0.25***	15.54	219	0.33***	12.97	109
MD rating	0.24***	14.18	191	0.34***	11.86	99
SP rating	0.26***	14.79	204	0.31***	11.45	106
FI rating	0.26***	13.68	175	0.33***	11.41	89

Panel B: Pairwise correlations between CRA's private information

	Average	MD	SP	FI
Average private information	1.00	-	-	-
MD private information	0.85	1.00	-	-
SP private information	0.92	0.74	1.00	-
FI private information	0.97	0.67	0.76	1.00

Table 4: The effect of private information on rating disagreement over time

The table presents regression regressions results for DIS for firm i at time t as dependent variable. Independent variables are the average of CRAs' private information, Moody's, S&P's and Fitch's private information, respectively, and the number of rating ACTIONS per firm and quarter, and the CRISIS dummy. All models employ panel data fixed effects estimation with robust standard errors clustered at the firm level. The corresponding standard errors are in parentheses. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Dep. Var.:	$DIS_{i,t}$			
	(1)	(2)	(3)	(4)
Average private information	0.256***	-	-	-
	(0.0799)	-	-	-
MD private information	-	0.343***	-	-
	-	(0.0585)	-	-
SP private information	-	-	0.278***	-
	-	-	(0.0910)	-
FI private information	-	-	-	0.194**
	-	-	-	(0.0900)
ACTIONS	-0.001	-0.003	-0.002	0.001
	(0.009)	(0.012)	(0.009)	(0.009)
CRISIS	-0.144	-0.070	-0.161	-0.095
	(0.105)	(0.113)	(0.103)	(0.104)
Constant	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	1,295	1,160	1,257	1,018
R^2	0.138	0.176	0.141	0.100
Number of firms	142	133	139	129

Table 5: The effect of systematic risk on rating disagreement over time

The table presents regression regressions results for DIS for firm i at time t as dependent variable. Independent variables are the measure of aggregate systematic risk (SYSRISK), its standard deviation (STDSYSRISK), the firm's sensitivity to systematic risk (SYSRISK_FIRM), the number of rating ACTIONS per firm and quarter, and the CRISIS dummy. All models employ panel data fixed effects estimation with robust standard errors clustered at the firm level. The corresponding standard errors are in parentheses. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Dep. Var.:				$DIS_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
SYSRISK	-3.609*	-3.476*	-1.259			
	(1.931)	(1.935)	(1.737)			
STDSYSRISK	-2.307	-2.872*	-1.364			
	(1.570)	(1.564)	(1.641)			
SYSRISK_FIRM				0.398	-0.888	0.270
				(1.000)	(0.790)	(0.705)
ACTIONS	0.000	0.011*	0.011	-0.002	0.016**	0.016**
	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
CRISIS	0.245**	0.248**	0.0745	0.320**	0.347***	0.033
	(0.010)	(0.010)	(0.086)	(0.124)	(0.124)	(0.103)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	No	Yes	Yes
Industry*time fixed effects	No	No	Yes	No	No	Yes
Observations	8,636	8,636	8,636	5,662	5,662	5,662
R^2	0.012	0.024	0.085	0.003	0.008	0.104
Number of firms	228	228	228	147	147	147

Table 6: The effect of credit risk on rating disagreement over time

The table presents regression regressions results for DIS for firm i at time t as dependent variable. Independent variables are the CDS Index, the firm's CDS spread, the number of rating ACTIONS per firm and quarter, and the CRISIS dummy. All models employ panel data fixed effects estimation with robust standard errors clustered at the firm level. The corresponding standard errors are in parentheses. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Dep. Var.:	$DIS_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
CDS_INDEX	0.000	-0.000	-0.001**			
	(0.001)	(0.001)	(0.001)			
CDS				0.001***	0.000	0.000
				(0.000)	(0.000)	(0.000)
ACTIONS	0.000	0.010*	0.010	-0.002	0.013***	0.010
	(0.003)	(0.006)	(0.007)	(0.004)	(0.010)	(0.006)
CRISIS	0.352**	0.411**	0.420**	0.161	0.353***	0.150
	(0.165)	(0.165)	(0.164)	(0.142)	(0.119)	(0.102)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	No	Yes	Yes
Industry*time fixed effects	No	No	Yes	No	No	Yes
Observations	8,636	8,636	8,636	6,911	6,911	6,911
R^2	0.003	0.006	0.086	0.027	0.009	0.069
Number of firms	228	228	228	224	224	224

Table 7: Multivariate analysis of rating disagreement over time

The table presents regression regressions results for DIS for firm i at time t as dependent variable. Independent variables relate to information and risk: the volatility index (VIX), the standard deviation of the firm's stock return (STDRET), the CDS index, the firm's CDS spread (CDS), the measure of aggregate systematic risk (SYSRISK), firm's sensitivity to systematic risk (SYSRISK_FIRM), the average measure of CRAs' private information, the number of rating ACTIONS per firm and quarter, and the CRISIS dummy. All models employ panel data fixed effects estimation with robust standard errors clustered at the firm level. The corresponding standard errors are in parentheses. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Dep. Var.:	$DIS_{i,t}$		
	(1)	(2)	(3)
Information			
VIX	-0.003	-0.003	-0.001
	(0.009)	(0.006)	(0.006)
STDRET	21.690***	12.620***	10.170***
	(5.228)	(4.180)	(3.860)
Average private information	0.376***	0.407***	0.450***
	(0.096)	(0.094)	(0.093)
Risk			
SYSRISK	-6.667***	-4.810**	-2.982*
	(2.196)	(1.970)	(1.662)
SYSRISK_FIRM	1.764	0.846	0.684
	(1.094)	(0.778)	(0.753)
CDS_INDEX	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
CDS	0.001*	0.001**	0.000**
	(0.000)	(0.000)	(0.000)
ACTIONS	-0.005	0.010*	0.006
	(0.005)	(0.005)	(0.006)
CRISIS	0.038	0.106	0.193
	(0.207)	(0.201)	(0.188)
Constant	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
Industry*time fixed effects	No	No	Yes
Observations	4,914	4,914	4,914
R^2	0.061	0.085	0.159
Number of firms	146	146	146