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Market-implied ratings and their divergence from credit ratings

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Abstract

In this article, we investigate the divergence between credit ratings (CRs) and Moody's market-implied ratings (MIRs). Our evidence shows that rating gaps provide incremental information to the market regarding issuers' default risk over CRs alone in the short horizon and outperform CRs over extended horizons. The predictive ability of rating gaps is greater for more opaque and volatile issuers. Such predictability was more pronounced during the 2008 financial crisis but weakened in the post–Dodd–Frank Act period. This finding is consistent with credit rating agencies' efforts to improve their performance when facing regulatory pressure. Moreover, our analysis identifies rating-gap signals that do (do not) lead to subsequent Moody's actions to place issuers on negative outlook and watchlists. We find that negative signals from MIR gaps have a real economic impact on issuers' fundamentals such as profitability, leverage, investment, and default risk, thus supporting the recovery-efforts hypothesis.

JEL CLASSIFICATION G14, G20, G24

1 INTRODUCTION

In recent years, and especially during the 2008 global financial crisis and the 2011 European sovereign crisis, credit rating agencies (CRAs) have come under intense scrutiny and have faced strong criticism. The controversy intensified when the US Department of Justice (DOJ) sued Standard & Poor's (S&P) over alleged fraud in its rating of mortgage-backed securities (DOJ, 2013). In January 2015, the US Securities and Exchange Commission (SEC) alleged a series of federal securities law violations by S&P involving fraudulent misconduct in its ratings of certain structured-finance products (SEC, 2015).

Amid these criticisms and the potential problems associated with credit ratings (CRs), regulators have explored the idea of reducing the influence of and even the need for CRAs. However, CRs are still widely embedded in bond deals, bank reserve rules, and financial regulations. Ultimately, the biggest problem has been the lack of a viable substitute (e.g., Flannery et al., 2010).

Using a uniquely matched ratings data set for a sample of 1898 US corporations, we conduct a comprehensive empirical study of the divergence between market-implied ratings (MIRs) derived from bond, equity, and credit default swap (CDS) market prices, and CRs. We seek to answer three research questions: First, do the gaps between CRs and MIRs provide incremental information beyond CRs to predict defaults, and does the predictive power of rating gaps differ across firms and over financial crisis and tranquil periods? Second, do rating gaps induce CRAs to take precautionary actions such as assigning some firms to a credit watch list or a negative outlook? Third, do rating gaps have a real economic effect by alerting issuers to undertake recovery efforts and improve financial fundamentals?

Moody's MIRs, or market-based ratings, refer to CRs or assessments that use *"the prices of traded assets to directly determine the credit ratings for publicly traded firms with a minimal* *amount of subjective input on a firm-by-firm basis"* (Creal et al., 2014).[1] A unique feature of our article is that MIRs are based on Moody's own models, as opposed to other models (e.g., Kou & Varotto 2008).[2] Although both MIRs and CRs are produced by Moody's, the two measures almost always diverge and the differences between them can be attributed to several factors.

Different from CRs that are typically updated slowly, MIRs incorporate subtle and fast-moving changes in borrower conditions and may respond faster to credit risk than do CRs provided by CRAs. A case in point is a comparison between MIRs and CRs around the Lehman Brothers bankruptcy (Figure 1). Before Lehman Brothers filed for bankruptcy on September 15, 2008, its Moody's rating was A1 at the beginning of the year, A2 in early September, and B3 on the day of its bankruptcy. However, Lehman's MIRs provided warning signals before the bankruptcy. Figure 1 shows that the ratings implied from bond spreads, equity prices, and CDS spreads in early 2008 were around Baa2, Baa3, and Ba1, which were much lower than their CRs and indicated a higher chance of default. This example shows that MIRs lead CR changes and defaults by many months. If market participants had tracked Lehman's MIRs and

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[1]CRAs including Fitch and Moody's (Moody's Analytics, 2010a, 2011) use the term "MIR." Moody's shows that MIRs convert prices from bond, equity, and CDS markets into standard Moody's rating grades (Moody's Analytics, 2010a). MIRs are used by Moody's analysts to identify the gaps between their opinions and those derived from market information.

[2]The MIR models used by Moody's have undergone a robust quality-assurance process and out-of-sample validation across the Moody's coverage universe (Moody's Analytics, 2009, 2010b). If any model bias exists, we expect that the Moody's model will bias against finding incremental information of MIRs over CRs because Moody's has an incentive to show that CRs give accurate and timely ratings relative to MIRs.

their divergence from its actual CRs, they may well have made better investment or risk-management decisions.

Why CRAs do not adjust their ratings to converge to MIRs is an interesting question. One explanation is that CRAs endeavor to stabilize ratings to cater to corporate clients, and thus, ratings may be driven by conflicts of interest.[3] Second, information opacity or volatility may make it harder to evaluate a firm's true credit quality. Third, like any market-based measures, MIRs can potentially be affected by market sentiments, leading to higher volatility and more false warnings. CRAs are committed to produce more stable opinions because they can cause harm to firms by downgrading them prematurely and must wait for clearer signals before taking action to downgrade. Because of the tangible costs of lower ratings, a downgrade might lead a firm into a downward spiral. It is not necessarily a bad thing, therefore, that CRAs lag financial markets.

However, gaps between CRs and MIRs may provide information to investors beyond CRs alone in predicting changes in corporate credit quality. In this article, we use CRs as an anchor because of their relative stability and examine the incremental information content of the gaps between CRs and MIRs and their real impact on CRAs' and firms' actions. Specifically, we investigate four issues regarding the gaps between CRs and three MIRs (*BONDGAP, EQUITYGAP,* and *CDSGAP*). First, we explore the predicative ability of rating gaps for actual defaults and default probabilities. Default probabilities are measured in two ways: (1) expected default probabilities (*EDF*), following Bharath and Shumway (2008), and (2) the failure probability (*FAIL*), following Campbell et al. (2008). Our analysis provides strong evidence

[3]Several papers have examined rating quality and conflicts of interest (e.g., Baghai & Becker, 2018; Bolton et al., 2012; Cornaggia & Cornaggia, 2013; Cornaggia et al., 2016; Jiang et al., 2012).

that all three rating gaps are significant in predicting both defaults and default probabilities in a short-term (6-month) horizon after controlling for CRs, and outperform CRs in a longer (3-year) horizon. Addition of the rating gap can improve default prediction over that based solely on CRs.

Second, we explore whether the predictive power of CR–MIR gaps differs across firms and over time. CRAs may be slower to assign ratings to firms with higher information opacity or volatility and their ratings may be less accurate. For example, they may be slow to downgrade firms as they are responsible for their clients and may act only when the rating decision is guaranteed by full information. Moreover, CRAs may be reluctant to revise CRs if a firm has greater volatility, because they adopt a through-the-cycle methodology and strive to maintain ratings stability. Therefore, MIRs are more likely to provide supplemental information. Our multivariate analysis shows that the predictive ability of rating gaps for default probabilities is indeed larger when information opacity is more severe, as measured by fewer analysts making earnings forecasts, and when the issuer's volatility is higher, as measured by the issuer's idiosyncratic risk.[4]

The predictive power of rating gaps may also vary over time. We evaluate how the 2008 financial crisis and the Dodd–Frank Act have affected the predictive ability of rating gaps. Our regression results reveal that each rating gap can better predict default probabilities during a crisis, when default forecasting is vital and in critical demand. This finding supports the criticism that CRAs were slow to adjust CRs during the 2008 financial crisis. After this crisis, however, the Dodd–Frank Act imposed more stringent regulations on CRAs and brought greater discipline and more incentives to provide timelier rating changes (Dimitrov et al., 2015;

[4]Our results are consistent with the finding of Bonsall et al. (2018) that CRs are timelier and more accurate for widely covered firms (with low information opacity).

Goel & Thakor, 2011). Improved rating actions by CRAs can mitigate the predictive power of rating gaps over default risk, which our empirical test confirms as we find lower predictive ability of all three rating gaps after the implementation of the Dodd–Frank Act.

Third, given the predictive ability of the three MIR gaps, we analyze whether CRAs exploit information contained therein and take precautionary action to change their ratings accordingly. Although CRAs are reluctant to change their ratings too frequently because of stability concerns, they can use warning signals such as credit watches and negative rating outlooks to alert issuers to possible downgrade risks. We find that rating gaps between MIRs and CRs can predict credit watches and negative outlooks. Specifically, if rating gaps are larger in magnitude (from one notch to four or more notches), or if two or more MIR gaps give consistent signals, there is a greater likelihood for CRAs to assign a credit watch or negative outlook to an issuer. However, we find that CRAs do not respond to signals from MIR gaps if one MIR shows a negative signal and any other MIR gives a positive signal, or if the signals given by one MIR show reversals over time. Under these circumstances, CRAs are cautious not to incorporate contradictive and noisy information from MIRs into their rating decisions.

Fourth, and perhaps most important, we examine whether issuers pay attention to and act upon CR–MIR gaps. In other words, do rating gaps have a real economic impact on issuers? We test the recovery-effort hypothesis whereby, after observing negative signals from rating gaps, issuers take necessary actions to improve their financial fundamentals (Boot et al., 2006). Recovery efforts are measured by different dimensions of corporate financial performance, such as improvements in profitability, reductions in the use of short-term debt, and cutting back on capital expenditures (Poon & Shen, 2020), which are reflected in lower default risk and lower likelihood of downgrade.

Using a difference-in-differences (DID) analysis, we find that firms in a treatment group that observe negative signals from MIR gaps but receive no subsequent downgrade show significant improvements in their corporate fundamentals in the postsignal period. Firms become more profitable, use less short-term debt, and reduce investment. For example, treatment firms have a return on investment (ROA) that is 0.22% higher than those in the control group, which is economically significant, given that the sample average ROA is 0.9% per quarter. Across the three types of MIR, we find that negative signals from equity-implied ratings have more prominent impacts on all five metrics, consistent with the notion that managers are more responsive to stock market information. Evidence also shows that recovery efforts are more likely to be successfully implemented during a tranquil period than during a financial crisis. Overall, our findings are in line with the theoretical prediction of Boot et al. (2006) that some issuers take recovery action upon receiving negative signals regarding the default risk of their bonds to avoid a subsequent downgrade.

To our knowledge, this is the first comprehensive study to investigate the predictive ability of the discrepancy between actual CRs and MIRs for defaults, and its real economic impact on CRAs' precautionary actions and issuers' recovery efforts. Our study extends the growing literature on ratings quality and behaviors of CRAs.[5] Beyond various concerns and issues with CRAs, the empirical study of complementary sources of credit information that investors and regulators can easily employ is scant (Löffler, 2020). Our study of CR–MIR divergences fills this gap by showing that MIRs provide incremental information to the market beyond CRs alone in the short run and outperform CRs in default prediction for extended horizons. We also uncover rating gap signals that do (do not) lead to Moody's subsequent actions, such as placing issuers on a watchlist and/or negative outlook. Our results have important implications for credit- and equity-market investors, risk managers, and portfolio managers seeking complementary market-based sources of credit information.

[5] See Section 2 for a literature review.

Our article also contributes to the literature on the relation between equity, bond, and CDS markets and CRAs. The equity-implied MIR is based on a firm's expected default frequency (EDF) (Moody's Analytics, 2010a), the performance of which as a measure of default risk has been studied extensively (e.g., Bharath & Shumway, 2008). However, bond- and CDS-implied MIRs have not been widely studied with one notable exception. Kou and Varotto (2008) compare the timeliness of CDS-implied ratings to CRs using implied ratings derived from 4183 Eurobond issues from 1988 to 1998 with their own models. Our study differs from theirs by providing a timely revisit of the predictive ability of three types of MIRs in both short and long terms and demonstrates that the predictive ability of the CR–MIR gaps varies by issuers' information opacity and firm volatility and by crisis and tranquil periods. We also explore the real impact of rating gaps on CRAs' rating actions and issuers' fundamentals.

Although several studies have examined the information effectiveness of CDS prices versus CRs (see, e.g., Acharya & Johnson, 2007; Flannery et al., 2010; Hull et al., 2004; Norden & Weber 2004; Rodríguez et al., 2019), their comparison is not based on the same metrics. In our article, MIRs are expressed on the same rating scale as the Moody's CR scale, making them easier to comprehend and more practical for application. Moreover, raw market prices may contain information unrelated to credit risk. Stock prices incorporate news of both cash flow and credit risk, bond prices are affected by bond features and liquidity risk, and CDS prices include liquidity and counterparty risk (Batta, 2011). In comparison, MIRs isolate idiosyncratic risk–spread movements from changes in the broad market and filter out noncredit risks, making them better measures of credit risk.

Most important, our study finds that firms with greater CR–MIR gaps display improved financial performance. Our empirical results are consistent with the explanation that firms make recovery efforts to reduce their default risk when their credit qualities are deteriorating, as signaled by their market prices. Boot et al. (2006) develop a model showing that firms' recovery efforts are likely to occur when CRAs put them on credit watch. Poon and Shen (2020) confirm that recovery efforts also occur in the negative rating-outlook process. Our article shows that not only are CRAs' coordination mechanisms effective in encouraging firms to undertake greater improvement efforts, but the negative signals sent by more pessimistic MIRs also can trigger firms' recovery efforts, suggesting a real economic impact of the CR–MIR gap. The findings of our study are important and relevant to regulators and market participants who perform monitoring roles and make investment decisions based on forward-looking market prices and CR actions.

2 RESEARCH BACKGROUND

The CR literature examines whether CRAs assign inflated or conservative ratings, whether there are structural shifts in CR standards, and how regulation, business cycles, earnings management, and conflicts of interest affect rating quality (e.g., Alissa et al., 2013; Alp, 2013; Baghai et al., 2014; Bar-Isaac & Shapiro, 2013; Behr et al., 2018; Dimitrov et al., 2015; He et al., 2012; John et al., 2010; Kedia et al., 2014; Liu et al., 2018). Some authors have investigated the impact of competition among rating agencies on credit rating quality (e.g., Bae et al., 2015; Becker & Milbourn, 2011; Bolton et al,. 2012; Flynn & Ghent, 2018; Kedia et al., 2017). Accounting standards and financial-statement comparability can also affect CRs (e.g., Jorion et al., 2009; Kim et al., 2013). Another strand of literature establishes the economic significance of CRs by examining their real effects on firms' cost of capital, leverage, investments, asset growth, cash acquisitions, default probability, and investors' perception of credit risk (e.g., Almeida et al., 2017; Bongaerts et al., 2012; Bonsall & Miller, 2017; Cornaggia et al., 2018; Hilscher & Wilson, 2017; Kisgen, 2009; Kisgen & Strahan, 2010; Manso, 2013; McBrayer, 2019; Sufi, 2009).

Despite its economic significance, the role of CRAs during the 2008 financial crisis has been under debate. White (2009) suggests that CRAs were partially responsible for the mortgage meltdown and the ensuing financial crisis because they gave mortgage issues high ratings due to conflicts of interest. The financial crisis led to the passage of the Dodd–Frank Act in 2010. Besides creating regulation to reduce apparent conflicts of interest among CRAs (because issuers rather than information users pay for ratings), Dodd–Frank requires all federal agencies to review their existing regulations for dependence on CRs issued by nationally recognized statistical rating organizations (NRSROs) and to provide alternative standards of credit risk.[6] Dimitrov et al. (2015) examine the impact of Dodd–Frank on US corporate bond ratings issued by Moody's, S&P, and Fitch from January 2006 to May 2012. However, they find no evidence that Dodd–Frank disciplines CRAs to provide more accurate and informative CRs. On the contrary, deHaan (2017) shows that both the rating accuracy and timeliness of CRAs improved after the financial crisis in response to public criticism and regulatory pressure.

Regulatory dependence on CRAs is not restricted to the United States. The Basel Accords are a set of regulatory recommendations for G-20 countries. The Basel II Accord has been blamed in part for the European financial crisis that began in 2007. Basel II created incentives for European banks to own sovereign debt from other eurozone countries because it reduces capital requirements when banks own highly rated eurozone sovereign bonds. Basel III was introduced to address bank capital adequacy, market liquidity risk, and stress testing, which were perceived as regulatory failures behind the financial crises in Europe and the United States (Bank for International Settlements [BIS], 2010a). Notwithstanding widespread criticism of the role of CRAs in these financial crises, Basel III left intact a role for CRs in capital adequacy measurement (BIS, 2010b).

Although financial regulators have not yet identified better methods for replacing CRs,

[6]See Poon and Firth (2005) and Poon et al. (2009) for a detailed discussion of issuer-paid ratings in terms of solicited compared to unsolicited ratings.

some preliminary studies explore alternative business models for compensating NRSROs. For example, earlier research analyzes the relation (e.g., comovement and lead–lag relation) between CDS and CRs.[7] Several studies find that the CDS market provides helpful information in predicting negative CR changes and review of downgrade and outlook changes by CRAs, especially negative rating changes.[8] In contrast, market participants and regulators are skeptical about the use of CDS spreads to gauge credit, some arguing that the CDS market is not sufficiently liquid and that its coverage is limited. Speculators might create noise, making the movement of CDS spreads erratic, and high volatility can be a serious issue with the CDS market. Relying on market-based information such as swinging CDS spreads is costly for portfolio managers because of the need for frequent portfolio adjustments.

Tsoukas and Spaliara (2014) employ Fitch's MIRs derived from bond and equity prices of traded nonfinancial firms in the United States between 2001 and 2007 to shed light on how financing constraints affect implied CRs. They show that financing constraints are an important determinant of MIRs. Our focus differs from theirs in that we compare the predictive ability and impact on issuers of the gap between CRs and MIRs.

Kou and Varotto (2008) examine market-based measures as alternatives to CRs in

[7] Prior studies examine the CDS market or the role, impact, information content, or determinants of CDS spreads (e.g., Blanco et al., 2005; Bolton & Oehmke, 2011; Bongaerts et al., 2011; Ericsson et al., 2009; Griffin et al., 2016; Hasan et al., 2016; Jorion & Zhang, 2007, 2009; Kanagaretnam et al., 2016; Pan & Singleton, 2008; Saretto & Tookes, 2013; Yang & Zhou, 2013).

[8] A partial list includes Hull et al. (2004), Galil and Soffer (2011), and Finnerty et al. (2013). In addition, Forte and Pena (2009) show that CDS spread leads bond spread. Chava et al. (2019) find that the information content of a CR downgrade is reduced after CDS trading.

assessing creditworthiness. They compare the timeliness of credit-spread-implied ratings to CRs using data from 4183 Eurobond issues from 1988 to 1998. They find that spread-implied ratings often anticipate future agency ratings and, hence, help track credit risk in a timelier manner. Altough they perform tests using implied ratings derived from bond prices with their own models, we base our results on three versions of MIRs directly provided by Moody's that can be easily employed by investors and regulators. Moreover, we examine whether the divergence of MIRs from CRs provides complementary information on defaults over CRs alone, and whether it sends a useful signal to CRAs to take precautionary actions and to issuers to undertake recovery efforts.

3 DATA, HYPOTHESIS DEVELOPMENT, AND EMPIRICAL METHODS

3.1 Sample and data sources

We obtain MIRs on US issuers along with their corresponding CRs and derived differences from Moody's for 2002–2014 (see Appendix A for definitions and rating scales). The sample includes three types of MIRs: bond-implied ratings (*BONDIRs*), CDS-implied ratings (*CDSIRs*), and equity-implied ratings (*EQUITYIRs*).

The MIR platform was introduced to Moody's ratings analysts in 2002 as an internal tool *"to ensure that the analysts have access to all relevant information about the markets' views of an issuer's creditworthiness"* (Moody's Analytics, 2011). Moody's Analytics (2010a) states that

> *Moody's ratings analysts use market-implied ratings to identify material and systematic gaps between Moody's ratings and the ratings implied by market data. They use them to compare their opinions to those held by the broader market or those generated by purely quantitative models, so that they are prepared to clearly articulate the reasons for any*

differences to market participants. Market-implied ratings are not, however, an "input" into their rating decisions. (Fitch Solutions, 2016)[9]

Rating agencies also provide MIRs as a complement to fundamental CR analysis in response to investor needs for greater insight into the dynamic pace and growing complexity of credit markets (Fitch Solutions, 2016).

Daily observations of CRs, MIRs, and the gaps between them are derived from Moody's on its MIR platform (see Appendix B for brief descriptions of MIR; for more detailed discussions, see Moody's Analytics, 2008, 2011, 2013). MIR models have undergone out-of-sample validation across the Moody's coverage universe (see Moody's Analytics, 2009, 2010b). We convert daily MIR observations into monthly observations using the ratings at the end of each month.[10] To construct a firm-quarter sample, we calculate average monthly ratings in a quarter. We restrict our sample to firms with MIR observations that contain financial information from Compustat. Our sample consists of 1898 listed firms, 151,721 firm-month observations, and 44,891 firm-quarter observations. The number of firms in the sample with bond-, equity-, and CDS-implied ratings are 1530, 1590, and 753, respectively.

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[9]Fitch Solutions (2016) also developed its suite of MIRs (CDS-implied ratings and equity-implied ratings). It states: *"Market implied ratings provide timely, market-based indicators of credit quality at short- and medium-term horizons, making them relevant for portfolio management, buy decisions, and early warning of credit events, and ensuring a balanced, timely, and objective assessment for all market participants."*

[10]The rating gaps are the differences between CRs and MIRs at the end of each month. We also conduct a robustness test using the monthly average of daily observations, the results of which are qualitatively similar.

The changes in CRs and MIRs are the differences between ratings for the current month and the previous month. We derive the rating gaps (i.e., differences in rating notch between CRs and MIRs) in the following manner.[11] Using CDS-implied ratings as an example, we assume an issuer has a Moody's rating of Aa3 (rating value = 18). If its 5-year CDS spread is in line with the median CDS spread for all Aaa-rated issuers, giving it a CDS-implied rating of Aaa (rating value = 21), the difference between the issuer's Aaa CDS-implied rating and its Aa3 Moody's rating is three rating notches. Thus, the issuer's CDS-implied rating gap is −3 (CR – MIR = 18 – 21 = −3).

We choose Moody's MIRs because they provide wide coverage of comprehensive daily ratings data in terms of countries, periods, issuers, and types of MIR covered. Moody's MIRs cover all entities with Moody's ratings and traded CDS, bond, and equity prices of corporates, banks, nonbank financial institutions, and sovereigns. Our sample focuses on corporate issuers with CRs and any of the three types of MIR. Brief MIR descriptions are presented in Appendix B. We collect related financial and market information of sample issuers from the Compustat and Center for Research in Security Prices (CRSP) databases. We obtain the number of financial analysts for issuers and their earnings forecasts from Institutional Brokers' Estimate System (IBES). We also compile issuer default information from Moody's and S&P rating reports, including missing interest payments, missing principal payments, distress exchange, Chapter 11, among others.[12] We also calculate EDF from Merton's option-pricing model

[11] Variable definitions are provided in Appendix C.

[12] Moody's categorizes defaults into three broad types of credit events: (1) missed interest and/or principal payments; (2) bankruptcy, administration, legal receivership, or other legal blocks to the timely interest/principal payment; and (3) distressed exchange. Moody's Default & Recovery Database contains issuer defaults observations from global markets for firms rated

(Vassalou & Xing, 2004; Xia, 2014) and failure probability following Campbell et al. (2008), both of which measure the probability of default for an issuer for a given month.

3.2 Hypotheses development and empirical design

3.2.1 Predictability of gaps between MIRs and CRs on default probabilities

We believe that MIRs derived from bond spreads, equity prices, and CDS spreads contain timely information about issuer credit risk from the markets, whereas CRs from CRAs are slower to respond to changes in credit quality because the latter may be reluctant to revise ratings due to considerations of rating stability. Thus, we present the following hypothesis:

H1: *Gaps between CRs and MIRs can predict default risk of issuers beyond the information contained in CRs.*

Rating gaps are the differences between CRs and three MIRs (CRs − MIRs). We use the following regressions to assess the predictive abilities of rating gaps:

$$DEFAULT/EDF/FAIL_{i,t} = \beta_0 + \beta_1 \times MIRGAP_{i,t-m} + \beta_2 \times MOODYCR_{i,t-m} + \beta_3 \times DTC_{i,t-1} + \beta_4 \times PROFIT_{i,t-1} + \beta_5 \times DIV_{i,t-1} + \beta_6 \times ICBT_{i,t-1} + \beta_7 \times LNTA_{i,t-1} + \beta_8 \times Year + \beta_9 \times Industry + \varepsilon_{i,t}. \quad (1)$$

Dependent variables include three measures of default risk. *DEFAULT* is a dummy variable indicating whether firm *i* is in default in month *t*, *EDF* denotes the EDF from Merton's option-pricing model in month *t*, and *FAIL* is the fitted probability of failure in month *t*.[13] The key independent variable is the gap (*MIRGAP*) between CRs and the three MIRs in the lagged 6 months (short horizon) or 3 years (long horizon). We include CRs in the specification to

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and unrated by Moody's.

[13]Following the literature (e.g., Hou et al., 2020; Shen, 2021; Stambaugh et al., 2012), the failure probability is calculated based on the model and parameters from Campbell et al. (2008, column 3 in table 4).

examine whether MIR gaps complement or substitute for CRs.[14] Following Campbell et al. (2008), we construct a logistic regression model in Equation (1) for regressions with the dependent variable *DEFAULT.* We use ordinary least squares (OLS) models for regressions with dependent variables *EDF* and *FAIL*.

A positive rating gap (CR – MIR > 0) indicates that the CR is higher than the MIR, which signals that a firm's creditworthiness deteriorated, as reflected in bond, equity, or CDS prices, but is not fully reflected in CRA ratings. If our hypothesis holds, we expect increased chances of default. Conversely, a negative rating gap (CR – MIR < 0) indicates that the CR is lower than the MIR, which signals that a firm's creditworthiness improves, as reflected in bond, equity, or CDS prices, but is not reflected in CRA ratings. If our hypothesis holds, we expect that the coefficient on *MIRGAP* to be positive in the regression models. The control variables, all lagged by 1 year, include debt-to-capital ratio (*DTC*), profitability ratio (*PROFIT*), dividend payment (*DIV*), interest coverage (*ICBT*), and firm size (*LNTA*), following prior CR studies (e.g., Becker & Milbourn, 2011; Jiang et al., 2012; Tsoukas & Spaliara, 2014; Xia, 2014). We include industry-year dummies in the regressions.

3.2.2 Determinants of predictive power of rating gaps on default probabilities

Second, we examine what affects the predictive power of the MIR–CR gap over the default risk of issuers. Information uncertainty in issuers may influence a CRA's timely decision to downgrade a firm with increasing default probability. First, CRAs feel responsibility toward their clients and can be slow to downgrade if they have insufficient information to warrant the rating decision (Sangiorgi & Spatt, 2017). Morgan (2002) finds that split CRs occur most often for banks and other financial institutions because of their higher information asymmetry.

[14]We thank an anonymous referee for suggesting that we include CRs in the test and extend the analysis to multiple years in the future.

Second, CRAs aim to achieve rating stability by adopting a through-the-cycle methodology, disregarding short-term fluctuations in a firm (Altman & Rijken, 2006). In contrast, MIRs are based on current market conditions and credit risk, providing a point-in-time perspective. Thus, we present the following hypothesis:

H2a: *The predictive power of rating gaps on default probability is larger if the issuer has higher information uncertainty.*

We use the following models to test H2a:

$$EDF/FAIL_{i,t} = \beta_0 + \beta_1 \times MIRGAP_{i,t-6} + \beta_2 \times MIRGAP_{i,t-6} \times VOL/LNANA_{i,t-6} + \beta_3 \times VOL/LNANA_{i,t-6} + \beta_4 \times MOODYCR_{i,t-6} + \beta_5 \times DTC_{i,t-1} + \beta_6 \times PROFIT_{i,t-1} + \beta_7 \times DIV_{i,t-1} + \beta_8 \times ICBT_{i,t-1} + \beta_9 \times LNTA_{i,t-1} + \beta_{10} \times Industry\text{-}Year + \varepsilon_{i,t}. \quad (2)$$

Default probability is measured by expected default frequency (*EDF*) and default probability (*FAIL*) in a month. *MIRGAP* is the gaps between CRs and the three MIRs in the lagged 6 months. The key independent variable is the interaction term of rating gap (*MIRGAP*) and the information-uncertainty variable. Following the literature, we measure information uncertainty via idiosyncratic volatility and analyst coverage. Idiosyncratic volatility (*IVOL*) is the standard deviation of the residuals from a market model via monthly stock returns within the previous 60 months. Analyst coverage (*LNANA*) is the natural log of 1 plus the number of 1-year earnings forecasts by analysts who cover the issuer at the end of each month (Cheng & Subramanyam, 2008).[15] Similar to Equation (1), we include Moody's rating, firm-level control variables, and industry-year dummies in the equations. If the rating gap has stronger power to predict default probability in firms with greater information uncertainty, the coefficient on *MIRGAP × VOL* should be positive and the coefficient on *MIRGAP × LNANA* should be negative.

[15]We also use cash-flow volatility (Zhang, 2006) and analyst forecast dispersion to measure information uncertainty in a firm and find similar results.

We further investigate whether the predictive ability of MIR gaps evolves over time. During the 2008 financial crisis, CRAs were criticized as being slow to adjust their ratings, thereby contributing to the crisis by inflating ratings on structured-finance products. We believe that rating gaps could have better predicted defaults in the crisis period. After the 2008 crisis, the Dodd–Frank Act imposed more stringent regulations on CRAs, and the concomitant increase in litigation costs and reputational risk of CRAs has had two effects. First, CRAs may do more due diligence and provide more informative ratings (Goel & Thakor, 2011). Second, CRAs may be more conservative and assign ratings with a downward bias (Dimitrov et al., 2015). Given that CRAs can improve their rating accuracy and timeliness in response to public criticism and regulatory pressure (deHaan, 2017), we expect that CRs became more informative after the Dodd–Frank Act, which reduced the predictive power of rating gaps on default probability. Thus, we present the following hypothesis:

H2b: *The predictive power of rating gaps on default probability was larger during the 2008 financial crisis but smaller after the Dodd–Frank Act.*

We use the following models to test H2b:

$$EDF/FAIL_{i,t} = \beta_0 + \beta_1 \times MIRGAP_{i,t-6} + \beta_2 \times MIRGAP_{i,t-6} \times CRISIS/DODDFRANK_t + \beta_3 \times CRISIS/DODDFRANK_t + \beta_4 \times MOODYCR_{i,t-6} + \beta_5 \times DTC_{i,t-1} + \beta_6 \times PROFIT_{i,t-1} + \beta_7 \times DIV_{i,t-1} + \beta_8 \times ICBT_{i,t-1} + \beta_9 \times LNTA_{i,t-1} + \beta_{10} \times Industry\text{-}Year + \varepsilon_{i,t}. \quad (3)$$

Key independent variables are the interaction term of rating gap (*MIRGAP*) and the crisis period variable, and the interaction of rating gap and the post–Dodd–Frank Act period. *CRISIS* equals 1 if a month is within the crisis period (July 2007–December 2008), and 0 otherwise. *DODDFRANK* equals 1 if the month is July 2010 or later (after the implementation of Dodd–Frank), and 0 otherwise. We expect the coefficient of *MIRGAP* × *CRISIS* to be positive and the coefficient of *MIRGAP* × *DODDFRANK* to be negative.

3.2.3 MIR signals and CRA actions

Our third hypothesis examines whether the information content of rating gaps affects CRA rating actions or, in other words, whether CRAs can learn from MIRs.[16] We analyze the imposition of negative rating outlooks or credit watches. Both indicate the views of CRAs in relation to the likelihood and direction of future rating changes.[17] Rating decisions in terms of outlooks and credit watchs allows CRAs to show their opinion regarding a firm's credit worthiness without immediately changing its rating (Boot et al., 2006; Kiesel, 2021; Poon & Shen, 2020).

CRAs may be reluctant to change CRs because of their through-the-cycle methodology (Löffler, 2004); however, they can assign outlooks and credit watches to issuers after receiving valuable information from MIRs regarding cyclical components of default risk. We predict that the chance of assigning a negative outlook or credit watch is higher if CRAs observe strong, clear, and consistent signals with respect to a firm's creditworthiness, such as large and persistent negative gaps between MIRs and CRs or affirmative signals from multiple MIRs. In contrast, MIRs can potentially be affected by market sentiments, leading to higher volatility and more false warnings (Type II errors). If signals are volatile or even contradictory among MIRs, CRAs are less likely to assign a negative outlook or credit watch. Thus, we present the following hypothesis:

H3a: *CRAs are more likely to assign a negative outlook or credit watch to issuers if signals from rating gaps are stronger or more consistent.*

H3b: *CRAs are less likely to assign a negative outlook or credit watch to issuers if signals*

[16]We thank the editor for suggesting that we investigate this issue.

[17]S&P uses the term "credit watch" whereas Moody's adopts the term "rating under review" for issuers/ratings that are placed on the watchlist. As both terms essentially mean the same rating procedure, we simply use the term "credit watch" to refer to both.

from rating gaps are contradictory among MIRs or are reversed over time.

H3a is tested by a logistic regression model in following equation:

$$CWOLNEG_{i,t} = \beta_0 + \beta_1 \times BELOW/BELOWSIGNAL_{i,t-6} + \beta_2 \times MOODYCR_{i,t-6} + \beta_3 \times DTC_{i,t-1} + \beta_4 \times PROFIT_{i,t-1} + \beta_5 \times DIV_{i,t-1} + \beta_6 \times ICBT_{i,t-1} + \beta_7 \times LNTA_{i,t-1} + \beta_8 \times Industry\text{-}Year + \varepsilon_{i,t}. \quad (4)$$

The dependent variable, *CWOLNEG*, is a dummy that indicates whether an issuer is placed on a negative credit watch or outlook list in each month. *BELOW* is a series of dummy variables that includes *BELOW1, BELOW2, BELOW3,* and *BELOW4* for each MIR. These dummy variables equal 1 if the MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is one notch and two, three, and four or more notches lower than Moody's rating of an issuer in the previous 6 months. This regression model is run separately for each MIR. The variable *BELOWSIGNAL* is a series of dummy variables that include *BELOWSIGNAL1*, *BELOWSIGNAL2,* and *BELOWSIGNAL3*, which are dummy variables equal to 1 if one MIR, two MIRs, or all three MIRs are below Moody's rating in the lagged 6 months, respectively. The model is run based on the whole MIR sample.

Similar to the previous equations, we include Moody's credit rating, firm-level control variables, and industry-year dummies in the models. If our hypothesis holds, we expect that chances of a subsequent negative credit watch or outlook placement by CRAs will increase if MIRs present stronger and more consistent signals. We expect the coefficients on *MIRBELOW* will be positive and increase monotonically when the rating gaps become larger, that is, from *MIBBRLOW1* to *MIRBELOW4*. Similarly, we expect that the coefficients on *BELOWSIGNAL* will be positive and increase monotonically when more MIRs send out a negative signal, that is, from *BELOWSIGNAL1* to *BELOWSIGNAL3*.

H3b is tested by a logistic regression model in following equation:

$$CWOLNEG_{i,t} = \beta_0 + \beta_1 \times MIRBELOW_{i,t-6} + \beta_2 \times CONTRADICT/REVERSAL_{i,t-6} + \beta_3 \times MOODYCR_{i,t-6} + \beta_4 \times DTC_{i,t-1} + \beta_5 \times PROFIT_{i,t-1} + \beta_6 \times DIV_{i,t-1} + \beta_7 \times ICBT_{i,t-1} + \beta_8 \times LNTA_{i,t-1} + \beta_9 \times Industry\text{-}Year + \varepsilon_{i,t}.$$

(5)

MIRBELOW is a dummy variable equal to 1 if any one MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is lower than Moody's CR in the lagged 6 months, and 0 otherwise. *CONTRADICT* is a dummy variable equal to 1 if one MIR (e.g., *BONDIR*) has a rating that is lower than Moody's, but any other MIR (e.g., *EQUITYIR* or *CDSIR*) has a rating that is higher than Moody's in the lagged 6 months, and 0 otherwise. *REVERSAL* is a dummy variable equal to 1 if one MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is lower than Moody's in the previous 6 months but has a higher rating within any month in the previous 3 months, and 0 otherwise. The models are run separately for *BONDIR, EQUITYIR,* and *CDSIR*. We expect that CRAs are more likely to assign a negative credit watch or outlook if MIRs have lower ratings than CRs; that is, the coefficient on *MIRBELOW* should be positive. However, we expect that the chances of a subsequent negative credit watch or outlook placement by CRAs will decrease if other MIRs give contradictory signals, that is, a negative coefficient on *CONTRADICT* or if one MIR gives reversal signals, a negative coefficient on the variable *REVERSAL*.

3.2.4 MIR signals and issuers' actions

Our last hypothesis examines whether leading signals from MIRs affect a firm's actions in response to potential downgrades.[18] We investigate the scenario whereby MIRs give strong and consistently negative signals. Previous studies have shown that issuers with CRA imposition of a negative credit watch or outlook are induced to exert recovery efforts to avoid downgrades (Boot et al., 2006; Chung et al., 2012; Poon & Shen, 2020). Boot et al. (2006) argue theoretically that by placing issuers on the negative credit watch list, CRAs enter into an implicit contract with issuers, thereby agreeing to discuss remedial actions with management and monitor firms' progress in their recovery efforts. Chung et al. (2012) find that firms tend

[18]We thank an anonymous referee for suggesting that we examine this issue.

to take action in the period between receiving a negative credit watch and subsequent rating revisions. However, given that the time on the credit watch list is short, that is, 90 days, it may be difficult for some firms to exert meaningful recovery efforts to avoid downgrades. Poon and Shen (2020) believe that negative outlooks may induce firms to take remedial actions, however, because negative outlooks also indicate potential downgrades and the outlook period can last up to 2 years, which is considerably longer than a credit watch.

We argue that if MIRs give strong and consistent warning signals of potential ratings downgrades, issuers may undertake remedial action to improve firm fundamentals, such as increasing ROA, reducing leverage, and cutting capital expenditures (Chung et al., 2012; Poon & Shen, 2020) to mitigate possible deterioration of their credit standing.[19] If the efforts are meaningful, a subsequent downgrade by CRAs can be prevented. Therefore, we conjecture that the CR–MIR gap can provide important informational content to corporate issuers and induce them to make recovery efforts. Thus, we present the following hypothesis:

H4: *After receiving strong and consistent negative signals from MIRs, issuers improve financial fundamentals to avoid downgrades from CRAs.*

We employ a DID analysis to test H4. Specifically, we explore differences in changes in corporate fundamentals (i.e., profitability, investment, leverage, and default risk) between treatment and control groups, which allows us to establish the causal link between negative rating gap signals and recovery efforts. Our treatment group comprises issuing firms for which

[19]Chung et al. (2012) show that reasons for negative credit watches by Moody's include merger and acquisition activities, poor financial performance, leverage and financial statement issues, and accounting/litigation problems. Poon and Shen (2020) find that firms can exert recovery efforts by increasing ROA and decreasing expenditures to avoid downgrades.

all three MIRs are at least two notches below CRs in a quarter, there have been no reversal signals in the previous 4 quarters, and no downgrades occur in the subsequent 4 quarters. We match such issuers with a control group of firms in the same industry, with similar CRs, and with similar total assets, but without such signals in the same quarter. The matching procedure guarantees that firms in the treatment and control groups have similar properties except for the signal of a negative ratings gap. If the negative ratings gap do not trigger any recovery efforts, we expect to observe no significant difference in change in corporate fundamentals between treatment and control group firms.

3.3 Summary of descriptive statistics of variables

Table 1 reports the summary statistics of firm-month and firm-quarter observations in the sample. Panel A presents the statistics of variables related to Moody's and MIR ratings. Among MIRs, equity-implied ratings have the most and CDS-implied ratings have the fewest observations. The average Moody's (*MOODYCR*), bond-implied (*BONDIR*), equity-implied (*EQUITYIR*), and CDS-implied (*CDSIR*) ratings are 10.952, 11.422, 11.213, and 12.948, respectively, which correspond roughly to Ba1, Ba1, Ba1, and Baa2. The median ratings are 11 (Ba1), 12 (Baa3), 11 (Ba1), and 13 (Baa2).

The average gap (CRs – MIRs) between a Moody's rating and a bond-implied, equity-implied, or a CDS-implied rating is 0.197, −0.308, and −0.359, respectively. A positive (negative) ratings gap means that the market is more pessimistic (optimistic) about the firm's credit quality than is Moody's. The comparison indicates that Moody's ratings are slightly higher, on average, than bond-implied ratings but slightly lower than equity- and CDS-implied ratings for an average firm. The three MIRs may not necessarily provide consistent signals to the market. The median rating gaps are 0 between CRs and all three MIRs. In all firm-month observations, 15.5% are assigned negative outlooks or credit watches.

Panel B of Table 1 provides the statistics of variables related to MIR signals. For instance, 18.9%, 11.1%, 6.0%, and 5.4% of bond-implied ratings are one notch, and two, three, and more than four notches lower than CRs. In total, 41.3% of bond-implied ratings are lower than CRs. Among all firm-month observations with CRs higher than bond-implied ratings, 11.8% have CRs lower than equity- or CDS-implied ratings, and only 3.8% have a reversal signal in the prior quarter; that is, CRs are lower than bond-implied ratings in the prior quarter. Similar patterns can be found for equity- and CDS-implied ratings. Overall, 36.3%, 13.9%, and 5.3% of firm-month observations have CRs higher than one MIR, two MIRs, and three MIRs.

Panel C of Table 1 reports the statistics of firm variables. We find that only 0.1% are in default within the firm-month observations, or 155 issuer defaults in the sample. Average EDF is 10.2% and average fitted failure probability is 0.1%.[20] Average idiosyncratic volatility is 10.3%. The average log of 1 plus number of analysts in each month is 1.871, corresponding to 9.213 analysts per issuer. We find that 12% of observations are during the 2008 financial crisis period, and 36.7% are in the post–Dodd–Frank Act period. The average debt-to-capital ratio and operating profitability ratio are 33.1% and 12.1%, respectively. We also find that 61.8% of the firms in the firm-month observations pay dividends; the average interest coverage is 14.93, and the average value of the natural log of total assets is 8.47.

Panel D of Table1 presents the statistics of firm and rating variables from firm-quarter observations. Average ROA, average ratio of short-term debt to total debt, and average ratio of capital expenditure per quarter are 0.9%, 12.6%, and 2.9%, respectively. In the firm-quarter sample, 6.2% of firms receive negative MIR signals but are not downgraded in the next 4 quarters, which corresponds to 2770 firm-quarter observations, and 4.3% of firms receive negative MIR signals and then are downgraded by Moody's in the next 4 quarters,

[20] The correlation between EDF and failure probability is 0.45 in our sample. The failure probability has a larger correlation (0.13) with the dummy of actual default than EDF (0.06).

corresponding to 1908 firm-quarter observations.[21] Most issuers downgraded by Moody's receive negative MIR signals in the prior 4 quarters.

In Online Appendix 1, we examine the timeliness and reliability of MIRs relative to CRs for 2002–2014, a period spanning before, during, and after the financial crisis. We calculate changes in CRs and MIRs for each firm in each month and include lagged rating changes up to 12 months in the tests. Using Granger causality tests, we find an overall two-way leadership relation between changes in MIRs and CRs. Changes in bond- and CDS-implied ratings lead Moody's credit rating changes by up to 12 months, and rating changes in equity-implied ratings lead CR changes in 6 of 12 months. The bond and CDS MIRs exhibit better performance in leading CRs than equity-implied ratings, probably because bond and CDS prices are more sensitive to credit risk than are stock prices. In the reverse direction, CRs lead rating changes in bond, equity, and CDS MIRs in 6, 8, and 3 of 12 months, respectively.

4 EMPIRICAL RESULTS

4.1 Predictability of rating gaps on default and default probability

First, we study whether gaps between CRs and MIRs can predict defaults and default probabilities, after controlling for CRs and firm variables related to creditworthiness. Previous studies (Becker & Milbourn, 2011; Cheng & Neamtiu, 2009) show that CRs can predict issuer defaults within 1 to 3 years. However, studies show that bond and CDS spreads react to negative corporate events such as earnings announcements in a timelier manner (e.g., Batta et al., 2016; Defond & Zhang, 2014; Shivakumar et al., 2011).

Figure 2 shows average monthly MIRs and CRs before default. Our sample includes 155 issuer defaults. On average, all three MIRs have much lower ratings than CRs in the 12-month

[21]To identify a negative MIR signal, we require that all three MIRs are at least two notches lower than CRs in a quarter and there are no reversal signals in the prior 4 quarters.

period before default. Among the three MIRs, equity-implied ratings have the largest gaps with CRs (more than two notches), followed by bond-implied ratings (around two notches), and then CDS-implied ratings (around one notch).

We use the models in Equation (1) to test the predictive power of gaps between CRs and MIRs on actual issuer defaults and default probabilities. If rating gaps contain incremental information beyond CRs, we expect positive signs on *BONDGAP, EQUITYGAP,* and *CDSGAP*, after controlling for *MOODYCR*. We use a 6-month rating gap (lagged 6 months) and a 3-year rating gap (lagged 3 years) to assess their predictive abilities.[22]

Panel A of Table 2 presents estimates of how well rating gaps predict issuer defaults using logistic regressions. Columns 1, 2, and 3 report whether rating gaps in the lagged 6-month horizon can predict actual defaults after controlling for Moody's CRs. The coefficients on all three rating gaps are positive and significant at the 1% level. The results indicate that firms are more likely to default in a subsequent 6-month horizon if rating gaps between CRs and MIRs are larger (GAP = CR – MIR > 0) after controlling for CRs and other corporate determinants of defaults. Therefore, MIR rating gaps provide supplemental information to predict an issuer's default.

The coefficients on CRs in the lagged 6-month horizon are negative and significant at the 1% level, confirming a lower likelihood of default for highly rated firms. The coefficients of other control variables are consistent with the findings in previous credit studies (e.g., Kedia et al., 2014; Xia, 2014), although the coefficients are generally insignificant as we incorporate CR level and MIR gaps into the regressions.

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[22]The results are qualitatively similar for 1-, 12-, and 24-month rating gaps. To mitigate the effect from noisy signals in the MIRs, we remove extreme gaps that are larger than 6 or smaller than −6 and find that the results of rating gaps remain robust.

Columns 4–6 in Panel A of Table 2 report the predictive power of rating gaps in the lagged 3 years. The coefficients on *BONDGAP, EQUITYGAP,* and *CDSGAP* are still positive and significant. It is interesting that Moody's CRs are not significant in predicting defaults in the subsequent 3 years. Overall, our results confirm that rating gaps between CRs and MIRs have the ability to predict subsequent issuer default and hence they contain valuable information content that can be used to supplement CRs.

Panels B and C of Table 2 report the estimates of the predictive abilities of rating gaps on subsequent default probabilities measured by EDF and failure probability.[23] Columns 1–3 in Panel B show that issuers with positive rating gaps (CRs > MIRs) have higher EDF in the subsequent 6 months. The coefficients on three types of rating gaps are all positive and significant at the 1% level. The coefficients on Moody's CRs are negative, indicating that issuers with higher CRs have lower default probabilities. Interestingly, the magnitudes of the coefficients on *MOODYCR* are smaller than rating gaps from all three MIRs. Columns 4–6 show that the coefficients on rating gaps are still positive and significant, suggesting that rating gaps can predict default probabilities in a 3-year horizon, whereas Moody's CRs are not significant. Panel C presents similar results for failure probability. Empirical evidence shows that the coefficients of rating gaps in all three default prediction regressions, for all three types of MIRs at 6-month and 3-year horizons, are positive and strongly significant. We also find

[23]Both EDF and failure probability are constructed from stock market and financial statement data, which may lead to measurement error bias in the estimates. The standard errors from OLS regressions may be underestimated. We calculate robust standard error clustered by firms from the regressions. Because EDF and failure probability are derived from different formulas and our results are robust, our main findings are not likely to be driven by the potential measurement error problem. We thank an anonymous referee for raising this point.

evidence that the predictive power of rating gaps is generally stronger than that of CRs in predicting default probabilities.[24] Taken together, our results show that MIR gaps complement but do not substitute for CRs at a shorter horizon but contain more useful information than CRs over extended horizons.

4.2 Determinants of the predictive power of rating gaps on default probabilities

We examine whether gaps between CRs and MIRs predict issuers' default risk equally. As discussed in H2a, we expect that an issuer's information uncertainty could affect the predictive power of rating gaps on default probabilities.[25] That is, if firm value is uncertain and volatile, CRAs are more reluctant to revise CRs because they adopt a through-the-cycle methodology and seek to maintain ratings stability. If a firm's information is more uncertain, CRAs are more likely to be cautious about taking rating actions and take more time to collect information to justify their rating decisions. Thus, the gaps between CRs and MIRs should have more information content to predict the likelihood of default.

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[24] We also conduct an analysis using MIRs and CRs in a horse-race regression for multiple horizons from 6 months to 3 years. The results support our finding that MIRs complement but do not substitute for CRs in a short-term horizon, as claimed by Moody's Analytics (2011). However, MIRs have stronger predictive power over longer horizons than do CRs, which are either insignificant or have the wrong sign. Results are not reported for brevity but are available upon request from the authors.

[25] As the number of actual defaults is small in our sample, we rely on tests of default probabilities to investigate the determinants of the predictive power of rating gaps. We report the results based on rating gaps in the lagged 6 months. The results are similar if other horizons are used.

Table 3 presents the impact of information uncertainty on the predictive power of rating gaps. Panel A displays the results for EDF. As shown in Models 1–3, the coefficients on the interaction terms *MIRGAP* × *IVOL* are all positive and significant at the 1% level, suggesting that the predictive power of rating gaps is stronger for issuers with greater idiosyncratic volatility. Columns 4–6 report the interaction effect of analyst coverage, which is a variable measuring a firm's information transparency. The coefficients on the interaction terms *MIRGAP* × *LNANA* are all negative and highly significant. Our findings indicate that the predictive power of rating gaps on default probabilities is greater when issuers have lower information transparency.

Panel B of Table 3 provides the results for failure probability. The results are similar to those in Panel A: The coefficients on the interaction terms *MIRGAP* × *IVOL* are all positive and significant at the 1% level, and the coefficients on the interaction terms *MIRGAP* × *LNANA* are all negative and significant at the 1% level. These findings suggest that gaps between CRs and MIRs are more likely to predict subsequent failure probabilities when information uncertainty is greater.[26] In sum, the results support H2a that the predictive power of rating gaps on default probabilities is affected by information uncertainty in issuers.

Table 4 presents results that examine whether the predictive power of rating gaps on default probability was stronger or weaker during the 2008 financial crisis and after the Dodd–Frank Act. Panel A reports the estimates for EDF. The coefficients on the interaction terms *MIRGAP* × *CRISIS* are all positive and significant at the 1% level in Columns 1–3, suggesting that rating gaps had greater predictive power on default probability during the financial crisis period. The findings are consistent with the argument that CRAs were too slow to adjust CRs

[26] We also use analyst forecast dispersion and cash-flow volatility to measure information uncertainty. The results are robust.

during the crisis and hence the latter were less informative about credit risk, whereas MIRs provided extra information regarding default probability during this period. Columns 4–6 show that the coefficients on the interaction terms *MIRGAP* × *DODDFRANK* are all negative and significant. These results are consistent with deHaan (2017) and Toscano (2020) that CRs improved their rating performance after the Dodd–Frank Act, which reduced the information content of rating gaps between CRs and MIRs.

Panel B of Table 4 reports the results for failure probability. Similar to the findings in Panel A, the results provide clear evidence that the predictive power of rating gaps on default probabilities was greater during the 2008 financial crisis period but lower in the post–Dodd–Frank Act period. Overall, the findings in Table 4 support H2b that the predictive power of rating gaps is larger (smaller) when CRAs have worse (better) rating performance.

Taken together, our analysis suggests that the predictive power of rating gaps on defaults is driven by information uncertainty and the rating performance of CRAs. Their predictive power is greater when information uncertainty of issuers is greater and when CRAs have worse rating performance. Our analysis suggests that CR–MIR gaps can provide valuable information of credit risk that supplement CRs when the latter cannot reflect the creditworthiness of issuers in a timely or accurate manner.

4.3 Rating gaps between CRs and MIRs and CRAs' actions

Next, we investigate whether rating gaps may prompt CRAs' subsequent rating actions. On one hand, rating gaps can provide leading information about issuers' default risk. On the other hand, MIRs are volatile and may contain noisy information from capital markets. Online Appendix 2 displays the statistics of two types of rating errors: missed defaults and false warnings from CRs and MIRs. The frequencies of missed defaults (Type I error) are significantly lower in two types of MIRs (bond- and equity-implied ratings) than in Moody's CRs, although the frequency of Type I errors in CDS-implied ratings is slightly higher than that in CRs. Conversely, the frequencies of false warnings are much higher in bond-implied ratings (12.71%) and equity-implied ratings (13.94%) than in CRs (8.83%), although the frequency of Type II errors is lower in CDS-implied ratings (4.68%) than in CRs. Statistics show that the predictive ability of MIRs, as measured by Type I and II errors, differs across the three types of MIRs, which do not necessarily provide consistent signals. Another limitation to using MIRs is that capital markets may reveal reversal signals within a short timeframe and provide contradictory signals from different markets. Given the benefits and costs of MIRs, CRs will not necessarily converge to them.

We analyze firms' placement on negative credit watch or outlook lists because these are early warning signals sent by the CRAs without harming their rating stability.[27] First, using logistic regression models in Equations (4) and (5), we examine whether the strengths of MIR signals affect CRAs' decisions to assign a negative credit watch or outlook placement to an issuer. Table 5 presents the results. Columns 1–3 in Panel A includes dummy variables of the different notches of rating gaps between CRs and MIRs, from one notch to four notches and above. The coefficients on these dummy variables, *BELOW1–BELOW4*, are all positive and significant at the 1% level in regressions of the three MIRs, and the magnitudes of the coefficients increase monotonically: The larger the rating gaps between CRs and MIRs, the higher is the probability that CRAs will assign a negative credit watch or outlook to an issuer and the coefficients on *BELOW4* are almost 3 times those of *BELOW1*.

[27]In unreported results, we find that rating gaps can predict subsequent rating changes by CRAs, including downgrades and upgrades. Our analysis suggests that CRs are more likely to downgrade (upgrade) a firm within 6 months if the gap between CRs and MIRs becomes more positive (negative).

Column 4 in Panel A of Table 5 reports the results from a sample of all three MIRs. Results suggest that the probability of a negative credit watch or outlook increases when more MIRs, that is, from one MIR to all three MIRs, give signals in the same direction that these ratings are lower than CRs. The coefficient on *BELOWSIGNAL3* (the signal that MIR–CR gaps are negative from all three MIRs) is almost 3 times that on *BELOWSIGNAL1* (the signal that MIRs are lower than CRs from only one MIR). These results confirm H3a that CRAs are more likely to exploit information from rating gaps and place an issuer on a negative credit watch or outlook when signals from MIRs are strong or consistent, that is, show either large rating gaps in one MIR or multiple affirmative signals from different MIRs.

To examine when CRAs are less likely to follow a rating gap to place firms under negative credit watch or outlook, we examine the impact of inconsistent and "noisy" MIRs. Panel of Table 5 presents the results. In all models, we control for *MIRBELOW* and find positive and significant coefficients, indicating that the likelihood of assigning a negative credit watch or outlook to an issuer increases if MIRs have shown lower ratings than CRs in the prior 6 months. Columns 1–3 demonstrate that the coefficients on *CONTRADICT* are negative and significant at the 1% level, suggesting that CRAs are less likely to rely on MIRs and assign a negative credit watch/outlook to an issuer when one MIR gives a signal that the MIR is lower than the CR whereas any other MIR gives the opposite signal (MIR > CR).

The coefficients on *REVERSAL* are also negative and significant, as shown in Columns 4–6 in Panel B of Table 5. These results imply that CRAs are also less likely to follow the MIR signals and give a negative credit watch/outlook to an issuer when the signals from MIRs are volatile, for example, a signal of MIR < CR in one month and the opposite signal of MIR > CR the following month. Overall, the findings from Panel B of Table 5 confirm H3b that CRAs can be cautious to incorporate information from MIRs into their rating decisions when signals from the latter are contradictory and noisy.

4.4 Rating gaps between CRs and MIRs and issuers' actions

This section examines whether issuers can also use leading information from MIRs and take appropriate actions to avoid possible subsequent downgrades. Boot et al. (2006) argue that CRAs coordinate the behaviors of firms and the beliefs of the market in addition to processing information. Through the credit watch procedure, CRAs form an implicit contract with a firm and induce it to take remedial action to prevent subsequent downgrades. Poon and Shen (2020) find evidence supporting the role of the outlook procedure in the coordination mechanism by inducing firms to undertake recovery efforts. They argue that outlooks indicate possible future downgrades but give firms longer periods to take specific actions.

Positive CR–MIR gaps send early warning signals about issuers' declining credit quality. We investigate whether issuers, upon observing such signals, undertake recovery efforts to improve profitability, reduce short-term debt, and cut investment, thereby leading to reduced default probabilities to avoid downgrades.[28] First, we identify a treatment group of firms for which all three MIRs are at least two notches below CRs in a "signal" quarter, and there were no reversal signals in the prior 4 quarters and no downgrades in the subsequent 4 quarters.[29]

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[28] We conduct a similar analysis when CRs are lower than MIRs; that is, MIRs are more optimistic about the firms. We find no real economic effect on firm financial performance.

[29] We require the treatment firms to have no downgrade in the subsequent 4 quarters because this design helps us separate out firms that are more likely to perform recovery efforts after receiving the MIR signal. Some firms that receive the signals may have no willingness or ability to exert recovery efforts. Including those firms would make it harder to uncover the potential positive impact of MIR signals. Following Poon and Shen (2020), we also compare the changes in the financial ratios and default probabilities in the group of firms that receive MIRs warning signals and are downgraded in the subsequent 4 quarters and in the group of

Second, firms in the treatment group are matched to firms with the same credit rating, in the same industry, and with similar total assets, but without such signals in the same quarter. Next, we calculate the average values of firm financial ratios, that is, *ROA*, *STDTTD* (ratio of short-term debt to total debt), and *CAPEX* (ratio of capital expenditure to total assets), and default probability, measured by *EDF* and *FAIL*, in the 4 quarters before the signal quarter (presignal period) and 4 quarters after (postsignal period) for both the treatment and control groups. Finally, we calculate the differences in pre- and postsignal changes between the treatment and control groups, as well as *t*-statistics for the significance of differences. Panel A of Table 6 reports the results.

We find that issuers in the treatment group have a significant increase in ROA and significant decreases in short-term debt ratios, capital expenditures, and default probabilities during the postsignal period. For matched issuers in the control group, the changes in ROA, short-term debt ratio, and capital expenditures are not significant after the pseudo-signal period. We further find that firms in the treatment group show significantly greater improvement than the control sample in terms of an increase in ROA and reduction in short-term debt, capital expenditures, and default probability. Specifically, ROA is 0.22% higher for the treatment group than for the control group. The magnitude of the improvements in ROA is economically significant, given that the sample average ROA is 0.9%. We also capture greater reductions in

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firms without such signals and with subsequent downgrade. We find that ROA decreases more and default probabilities increase more in firms with negative signal and subsequent downgrade, suggesting that some firms may ignore the warning signals from MIRs or they are not able to exert recovery efforts to improve their financial performance, thereby receiving downgrades afterward. Our results are similar to the findings in Poon and Shen (2020). Results are not reported to save space but are available upon request from the authors.

the short-term debt ratio by 1.07%, in the capital expenditures ratio by 0.15%, and in EDF (failure probability) by 7.08% (0.03%) for the treatment group than for the control sample. Overall, the analysis of financial fundamentals indicates that early warning signals from CR–MIR gaps induce issuers to improve financial performance to avoid subsequent downgrades.[30]

To test whether differences exist among the three types of MIRs in inducing recovery efforts from issuers, we identify the negative MIR signal using bond-, equity-, and CDS-implied ratings separately and run a DID analysis for each MIR. Panels B–D of Table 6 present the results.

We find that each of the three MIRs could send early warning signals to issuers and induce them to improve corporate fundamentals, for example, by increasing ROA, decreasing short-term debt, cutting back capital expenditures, and reducing default risk. However, the outcomes vary across the three types of MIRs. We find evidence that negative signals associated with

[30]We also conduct a DID analysis between firms with negative MIR signals and no subsequent downgrade (treatment group) and the matched firms with negative MIR signals and subsequent downgrades (control group). We find similar results for the treatment group as in Table 6. However, firms in the control group have lower ROA and higher short-term debt and default probability in the postsignal period, indicating that they may not undertake sufficient recovery efforts to prevent subsequent downgrades. The DID test shows that the treatment group has greater ROA and lower short-term debt and default probability during the postsignal period than does the control group. The analysis indicates that even though MIRs can provide leading information, some issuers are not willing or have no ability to conduct sufficient recovery efforts and hence are subsequently downgraded, similar to the findings in Poon and Shen (2020) for their analysis of negative outlook status. Results are not reported to save space but are available upon request from the authors.

equity-implied ratings have the strongest effect on inducing issuers' recovery efforts among the three MIRs. Panel C of Table 6 reports both economically and statistically significant differences between the treatment and control groups in terms of changes in all five measures after the postsignal period, suggesting that managers are most likely to monitor rating signals implied by stock price movements and take remedial action to avoid a downgrade.

Finally, we examine the effectiveness of MIRs in inducing issuers' recovery efforts in different periods. We expect to see more successful recovery efforts during tranquil periods when firms have greater ability to make improvements than during times of financial crisis. Table 7 reports the results. Panel A shows that during the 2008 crisis period, issuers receiving negative MIR signals had lower ROA and greater default probability in the postsignal period, suggesting that issuers cannot significantly improve financial performance and credit worthiness during a crisis even if they are willing to undertake recovery efforts. Although these issuers reduced short-term debt and capital expenditures in the postsignal period, the decreases in default probabilities are not significantly larger than matched issuers without negative MIR signals.

Panel B of Table 7 shows that during tranquil periods, issuers receiving early negative signals from MIRs improve profitability and cut short-term debt and capital expenditures in the postsignal period, leading to a significant decrease in default probability. Negative MIR signals induce issuers to enhance profitability and decrease capital expenditures and default probability. Taken together, the analysis reveals that issuers are more likely to take successful remedial actions after receiving leading information from MIRs during tranquil periods than during times of financial crisis.

5 CONCLUSION

Using a uniquely matched rating data set from Moody's, we conduct the first comprehensive empirical study on the predictive ability of the gaps between CRs and MIRs for the same underlying corporate issuers over defaults, determinants of such predictive ability, and the responses of CRAs and issuers to leading rating gaps. Our sample spans the 2008 financial crisis and the post–Dodd–Frank Act periods.

Our results suggest that rating gaps provide supplemental information to predict default risk beyond CRs alone in a short (6-month) horizon and outperform CRs in a long (3-year) horizon. A positive rating gap (where CRs are higher than MIRs) is associated with a greater probability of default in subsequent periods. We also find that rating gaps can better predict issuers that are more informational opaque or volatile. Evidence shows that the predictive ability of rating gaps was more pronounced during the 2008 financial crisis but was mitigated in the post–Dodd–Frank Act period, supporting the view that CRAs were slow to adjust ratings at the time of the crisis but improved later under regulatory pressure.

Moreover, we show that rating gaps can anticipate CRAs' subsequent assignment of issuers to negative outlook lists and/or credit watches. We find that although larger and more consistent rating gaps offer clear signals for CRAs to take precautionary action, the latter are less likely to follow mixed and noisy signals.

We further investigate the real economic impact on issuers of leading CR–MIR gaps. Consistent with the recovery efforts hypothesis, we find that issuers alerted by large rating gaps display improvement in financial performance to prevent subsequent downgrades, as reflected in higher profitability, lower leverage, reduced investment, and lower chances of default. Equity-implied ratings have a more pronounced effect than do bond- and CDS-implied ratings, indicating that managers are more responsive to signals contained in stock prices. We also find evidence that recovery efforts are more likely to be implemented during periods of financial tranquility than during times of economic crisis.

This article adds to our understanding of MIRs, which are better measures of credit risk than are raw market prices of bonds, stocks, and CDSs. In practice, MIRs are easier and more intuitive to use for application purposes. Our results have important implications regarding the use of CRs and their possible alternatives. Specifically, tracking the gaps between CRs and MIRs can exploit significant incremental information for market participants to predict issuer default probabilities, CRAs to assign precautionary signals, corporate managers to undertake recovery efforts, and regulators to oversee and restructure the CR industry.

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SUPPORTING INFORMATION

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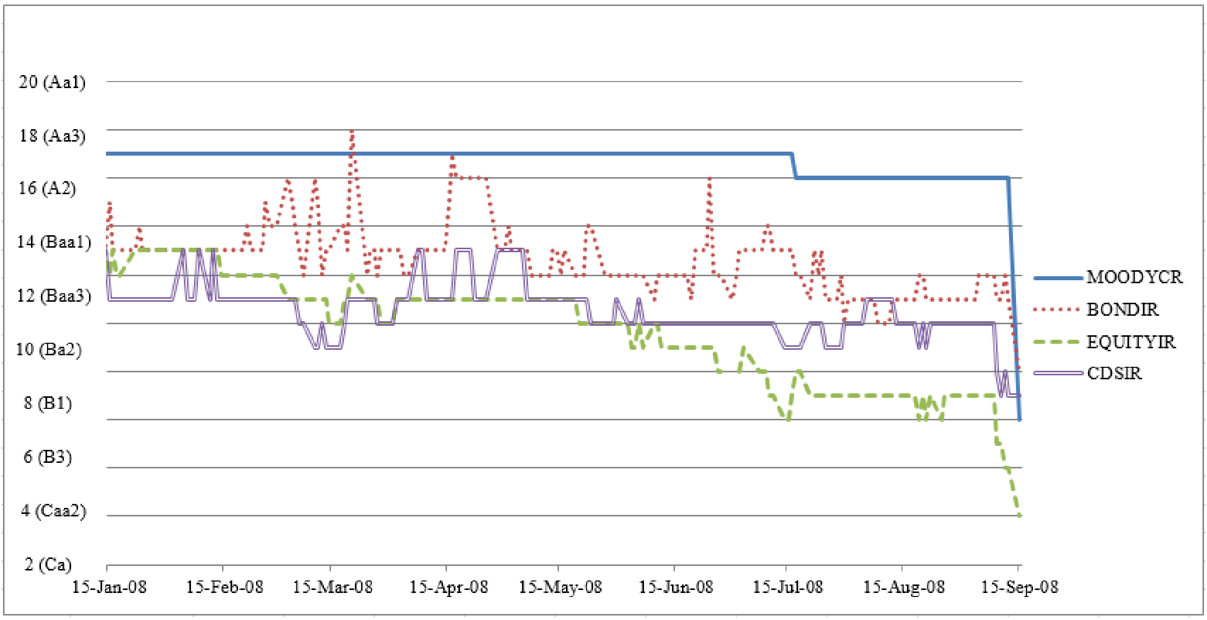

FIGURE 1 Credit ratings (CRs) and market-implied ratings (MIRs) of Lehman Brothers in 2008. This figure shows the daily MIRs and CRs of Lehman Brothers from the first trading day of 2008 to its bankruptcy day, September 15, 2008. Before the bankrucptcy, Moody's downgraded it twice in 2008: (1) from A1 (MOODYCR = 17) to A2 (MOODYCR = 16) on July 17, 2008 and (2) from A2 to B3 (MOODYCR = 6) on September 15, 2008

Abbrevations: MOODYCR, Moody's credit rating; BONDIR, bond-implied rating; EQUITYIR, equity-implied rating; CDSIR, credit-default-swap-implied rating

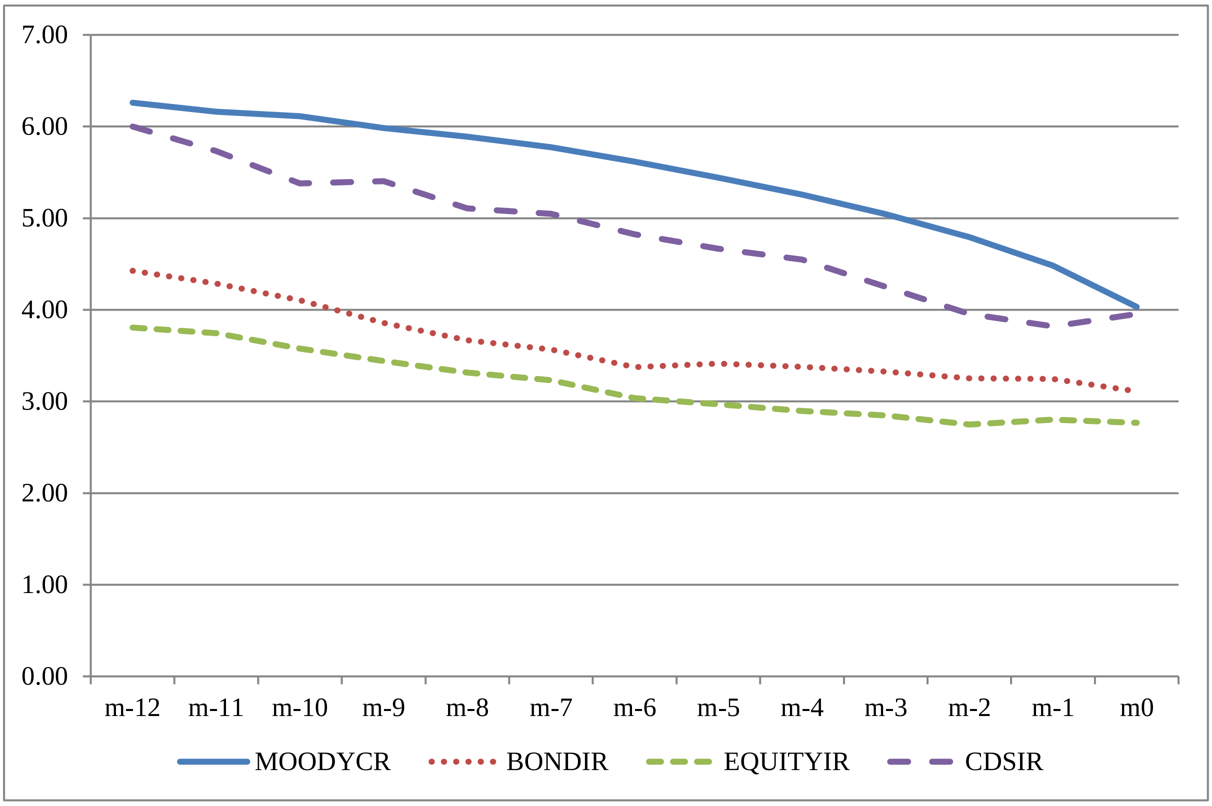

FIGURE 2 Credit ratings (CRs) and market-implied ratings (MIRs) before default. m0 is the month that a firm is in default. We report the average CRs and MIRs from month 12 to 1 month before default. The rating scale 1–7 corresponds to C, Ca, Caa3, Caa2, Caa1, B3, and B2, respectively. For the full rating scale, see Appendix A

Abbrevations: MOODYCR, Moody's credit rating; BONDIR, bond-implied rating; EQUITYIR, equity-implied rating; CDSIR, credit-default-swap-implied rating

TABLE 1 Descriptive statistics

Variable	**Obs.**	**Mean**	**Median**	***SD***	**5th pctl**	**95th pctl**
Panel A: Variables related to Moody's ratings and market-implied ratings (MIRs)						
MOODYCR	151,721	10.952	11	3.860	5	17
BONDIR	105,382	11.422	12	4.130	4	18
EQUITYIR	130,466	11.213	11	5.068	3	21
CDSIR	64,316	12.948	13	4.188	6	20
BONDGAP	105,382	0.197	0	2.039	-3	4
EQUITYGAP	130,466	-0.308	0	3.638	-7	5
CDSGAP	64,316	-0.359	0	2.497	-5	3
CWOLNEG	151,721	0.155	0	0.362	0	1
Panel B: Variables related to MIR signals						
BONDBELOW1	105,382	0.189	0	0.391	0	1
BONDBELOW2	105,382	0.111	0	0.314	0	1
BONDBELOW3	105,382	0.060	0	0.237	0	1
BONDBELOW4	105,382	0.054	0	0.226	0	1
BONDBELOW	105,382	0.413	0	0.492	0	1
BONDCONTRADICT	105,382	0.118	0	0.323	0	1
BONDREVERSAL	105,382	0.038	0	0.192	0	0
EQUITYBELOW1	130,466	0.112	0	0.315	0	1
EQUITYBELOW2	130,466	0.102	0	0.303	0	1
EQUITYBELOW3	130,466	0.082	0	0.274	0	1
EQUITYBELOW4	130,466	0.137	0	0.344	0	1
EQUITYBELOW	130,466	0.433	0	0.495	0	1
EQUITYCONTRADICT	130,466	0.106	0	0.307	0	1
EQUITYREVERSAL	130,466	0.021	0	0.144	0	0
CDSBELOW1	64,316	0.155	0	0.362	0	1
CDSBELOW2	64,316	0.083	0	0.276	0	1
CDSBELOW3	64,316	0.048	0	0.214	0	0
CDSBELOW4	64,316	0.050	0	0.218	0	0
CDSBELOW	64,316	0.336	0	0.472	0	1
CDSCONTRADICT	64,316	0.090	0	0.287	0	1
CDSREVERSAL	64,316	0.036	0	0.186	0	0
BELOWSIGNAL1	151,721	0.363	0	0.481	0	1
BELOWSIGNAL2	151,721	0.139	0	0.346	0	1
BELOWSIGNAL3	151,721	0.053	0	0.225	0	1

Panel C: Variables related to firm characteristics						
DEFAULT	151,721	0.001	0	0.032	0	0
EDF	113,894	0.102	0.000	0.254	0	0.865
FAIL	131,388	0.001	0.000	0.002	0.000	0.002
IVOL	113,122	0.103	0.089	0.055	0.045	0.211
LNANA	151,721	1.871	2.197	1.092	0	3.219
CRISIS	151,721	0.120	0	0.325	0	1
DODDFRANK	151,721	0.367	0	0.482	0	1
DTC	131,821	0.331	0.301	0.204	0.047	0.710
PROFIT	125,377	0.121	0.116	0.075	0.014	0.255
DIV	131,341	0.618	1	0.486	0	1
ICBT	117,249	14.925	8.460	22.381	1.600	47.333
LNTA	132,038	8.470	8.308	1.533	6.179	11.312
Panel D: Variables related to firm actions to MIR signals (firm-quarter sample)						
ROA	44,841	0.009	0.009	0.022	-0.021	0.039
STDTTD	44,307	0.126	0.045	0.192	0	0.565
CAPEX	44,347	0.029	0.014	0.043	0	0.112
NEGSIG (no downgrade)	44,891	0.062	0	0.241	0	1
NEGSIG (downgrade)	44,891	0.043	0	0.202	0	0

Note: This table presents descriptive statistics for the main variables. Variables are defined in Appendix C.

TABLE 2 Predicting issuer default risk by rating gaps between market-implied ratings (MIRs) and credit ratings (CRs)

	Lagged 6 months			Lagged 3 years		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Actual defaults						
$BONDGAP_{m-i}$	0.7295***			0.3636***		
	(0.1161)			(0.1067)		
$EQUITYGAP_{m-i}$		0.6060***			0.1320	
		(0.0925)			(0.1016)	
$CDSGAP_{m-i}$			0.3571**			0.4064**
			(0.1603)			(0.1590)
$MOODYCR_{m-i}$	-0.8522***	-0.8221***	-0.8003***	-0.2422*	-0.1693	-0.3524**
	(0.1465)	(0.0998)	(0.1444)	(0.1282)	(0.1036)	(0.1733)
DTC_{t-1}	1.4425	-0.9124	-0.4847	2.4478**	1.6933*	0.0865
	(0.9915)	(0.6603)	(1.4302)	(0.9732)	(0.8950)	(1.3620)
$PROFIT_{t-1}$	-0.0995	-2.1762	0.5247	-5.0687*	-6.9068***	-4.2362
	(2.9916)	(2.0825)	(5.1922)	(2.9890)	(2.0714)	(5.1931)
DIV_{t-1}	-0.3496	-0.1303	0.1920	-1.7388**	-1.1969*	-0.5903
	(0.4717)	(0.3931)	(0.5787)	(0.8677)	(0.6184)	(0.9741)
$ICBT_{t-1}$	-0.0350	-0.0019	-0.0054	0.0058	-0.0215	-0.0411
	(0.0537)	(0.0190)	(0.0413)	(0.0309)	(0.0273)	(0.0648)
$LNTA_{t-1}$	0.1638	0.0267	-0.2737	0.0294	-0.2025	-0.1723
	(0.1186)	(0.1221)	(0.2400)	(0.1389)	(0.1944)	(0.3232)
Constant	-2.8012*	-1.6576	1.3709	-5.1173*	-2.3154	-1.1122
	(1.5210)	(1.5735)	(2.5047)	(2.7123)	(2.0502)	(3.8497)
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	60,048	81,597	31,698	29,525	47,226	15,325
Pseudo R^2	0.3594	0.2784	0.3377	0.2368	0.2039	0.2548
Panel B: Expected default frequency						
$BONDGAP_{m-i}$	0.0217***			0.0071***		
	(0.0020)			(0.0015)		
$EQUITYGAP_{m-i}$		0.0138***			0.0055***	
		(0.0009)			(0.0008)	
$CDSGAP_{m-i}$			0.0143***			0.0041***
			(0.0018)			(0.0013)
$MOODYCR_{m-i}$	-0.0082***	-0.0096***	-0.0072***	0.0003	-0.0002	0.0014

	(0.0017)	(0.0015)	(0.0021)	(0.0016)	(0.0015)	(0.0020)
DTC_{t-1}	0.3823***	0.3849***	0.3709***	0.3943***	0.3913***	0.3402***
	(0.0339)	(0.0289)	(0.0439)	(0.0376)	(0.0311)	(0.0406)
$PROFIT_{t-1}$	-0.4061***	-0.3994***	-0.4551***	-0.5810***	-0.6191***	-0.5722***
	(0.0552)	(0.0530)	(0.0681)	(0.0661)	(0.0635)	(0.0757)
DIV_{t-1}	-0.0159**	-0.0065	-0.0052	-0.0289***	-0.0194**	-0.0274**
	(0.0075)	(0.0067)	(0.0092)	(0.0099)	(0.0083)	(0.0117)
$ICBT_{t-1}$	0.0012***	0.0011***	0.0011***	0.0012***	0.0010***	0.0008***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$LNTA_{t-1}$	0.0125***	0.0045	0.0040	-0.0024	-0.0077**	-0.0074*
	(0.0033)	(0.0029)	(0.0036)	(0.0032)	(0.0032)	(0.0039)
Constant	-0.0199	0.0685***	0.0630	0.0439	0.1023***	0.1020***
	(0.0299)	(0.0244)	(0.0384)	(0.0300)	(0.0286)	(0.0386)
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	64,436	88,261	41,353	45,105	60,442	31,881
R^2	0.3381	0.3567	0.3905	0.3350	0.3375	0.3625
Panel C: Failure probability						
$BONDGAP_{m-i}$	0.0094***			0.0026***		
	(0.0010)			(0.0008)		
$EQUITYGAP_{m-i}$		0.0054***			0.0025***	
		(0.0004)			(0.0005)	
$CDSGAP_{m-i}$			0.0051***			0.0018**
			(0.0012)			(0.0008)
$MOODYCR_{m-i}$	-0.0046***	-0.0053***	-0.0053***	0.0014	0.0018**	0.0012
	(0.0007)	(0.0007)	(0.0011)	(0.0008)	(0.0009)	(0.0012)
DTC_{t-1}	0.1560***	0.1914***	0.1534***	0.2208***	0.2217***	0.2006***
	(0.0141)	(0.0149)	(0.0207)	(0.0224)	(0.0179)	(0.0233)
$PROFIT_{t-1}$	-0.2528***	-0.2904***	-0.3002***	-0.4309***	-0.4236***	-0.4055***
	(0.0385)	(0.0375)	(0.0568)	(0.0508)	(0.0449)	(0.0658)
DIV_{t-1}	-0.0113***	-0.0121***	-0.0106**	-0.0285***	-0.0277***	-0.0319***
	(0.0029)	(0.0029)	(0.0048)	(0.0052)	(0.0046)	(0.0083)
$ICBT_{t-1}$	0.0007***	0.0007***	0.0007***	0.0009***	0.0007***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$LNTA_{t-1}$	0.0019	-0.0017	-0.0037*	-0.0079***	-0.0100***	-0.0106***
	(0.0014)	(0.0015)	(0.0022)	(0.0020)	(0.0020)	(0.0029)
Constant	0.0618***	0.0990***	0.1371***	0.0975***	0.1137***	0.1388***
	(0.0108)	(0.0121)	(0.0249)	(0.0144)	(0.0150)	(0.0259)

Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	74,599	101,849	49,912	51,417	68,712	37,215
R^2	0.2047	0.2028	0.2025	0.1925	0.1967	0.1938

Note: This table reports the results of predicting issuer defaults and default probabilities using rating gaps. The gaps are measured by the differences between Moody's ratings and market-implied ratings (*BONDGAP*, *EQUITYGAP*, and *CDSGAP*) over the lagged 6 months and the lagged 3 years. The dependent variable in Panel A is *DEFAULT*, equal to 1 if the issuer is in default within a month, and 0 otherwise; the dependent variable *EDF* in Panel B is expected default frequency of an issuer in a month; and the dependent variable *FAIL* in Panel C is the failure probability (× 100) of an issuer in a month. Control variables include *DTC*, *PROFIT*, *DIV*, *ICBT*, *LNTA*, and a series of time and industry (or industry-year) dummy variables. Panel A reports results from logistic regressions. Panels B and C report results from ordinary least squares regressions. Variables are defined in Appendix C. Robust standard errors clustered by firm are presented in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 3 Information uncertainty and predictive power of market-implied rating (MIR) rating gaps on default probabilities

	Sample					
	BONDIR	***EQUITYIR***	***CDSIR***	***BONDIR***	***EQUITYIR***	***CDSIR***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Dependent variable: EDF						
$MIRGAP_{m-i}$	0.0005	0.0015	0.0003	0.0457***	0.0333***	0.0378***
	(0.0039)	(0.0019)	(0.0032)	(0.0054)	(0.0027)	(0.0067)
$MIRGAP \times IVOL$	0.2049***	0.1343***	0.1710***			
	(0.0312)	(0.0201)	(0.0329)			
$IVOL_{m-i}$	0.0114	-0.2763***	-0.0124			
	(0.0888)	(0.0863)	(0.1115)			
$MIRGAP \times LNANA$				-0.0112***	-0.0089***	-0.0096***
				(0.0021)	(0.0010)	(0.0024)
$LNANA_{m-i}$				-0.0175***	-0.0233***	-0.0244***
				(0.0047)	(0.0047)	(0.0063)
$MOODYCR_{m-i}$	-0.0085***	-0.0121***	-0.0076***	-0.0078***	-0.0094***	-0.0069***
	(0.0020)	(0.0020)	(0.0024)	(0.0017)	(0.0015)	(0.0020)
DTC_{t-1}	0.4017***	0.3792***	0.3757***	0.3727***	0.3613***	0.3575***
	(0.0359)	(0.0327)	(0.0456)	(0.0330)	(0.0281)	(0.0419)
$PROFIT_{t-1}$	-0.4370***	-0.4032***	-0.4828***	-0.3783***	-0.3819***	-0.4340***
	(0.0584)	(0.0576)	(0.0694)	(0.0546)	(0.0517)	(0.0666)
DIV_{t-1}	-0.0004	-0.0012	0.0024	-0.0154**	-0.0057	-0.0046
	(0.0074)	(0.0066)	(0.0088)	(0.0074)	(0.0065)	(0.0088)
$ICBT_{t-1}$	0.0012***	0.0012***	0.0011***	0.0012***	0.0011***	0.0011***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
$LNTA_{t-1}$	0.0100***	0.0019	0.0022	0.0166***	0.0105***	0.0069*
	(0.0032)	(0.0029)	(0.0035)	(0.0034)	(0.0032)	(0.0038)
Constant	-0.0046	0.1418***	0.0824*	-0.0235	0.0708***	0.0923**
	(0.0315)	(0.0289)	(0.0439)	(0.0291)	(0.0240)	(0.0371)
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	58,014	79,875	38,977	64,436	88,261	41,353
R^2	0.368	0.3751	0.4052	0.3486	0.3733	0.4025

Panel B: Dependent variable: FAIL

$MIRGAP_{m-i}$	0.0054	0.0024	0.0247***	0.0214***	0.0130***	0.0081
	(0.0109)	(0.0070)	(0.0094)	(0.0032)	(0.0015)	(0.0065)
MIRGAP × *IVOL*	0.6007***	0.4316***	0.3166***			
	(0.0989)	(0.0721)	(0.1044)			
$IVOL_{m-i}$	0.0961**	0.0025	0.1171			
	(0.0411)	(0.0485)	(0.0816)			
MIRGAP × *LNANA*				-0.0054***	-0.0035***	-0.0012
				(0.0012)	(0.0006)	(0.0022)
$LNANA_{m-i}$				0.0026	-0.0032	-0.0028
				(0.0019)	(0.0023)	(0.0028)
$MOODYCR_{m-i}$	-0.0040***	-0.0054***	-0.0043***	-0.0046***	-0.0054***	-0.0053***
	(0.0009)	(0.0008)	(0.0012)	(0.0007)	(0.0007)	(0.0010)
DTC_{t-1}	0.1640***	0.1876***	0.1571***	0.1561***	0.1839***	0.1518***
	(0.0155)	(0.0160)	(0.0224)	(0.0141)	(0.0144)	(0.0209)
$PROFIT_{t-1}$	-0.2647***	-0.3054***	-0.3106***	-0.2633***	-0.2982***	-0.2989***
	(0.0405)	(0.0399)	(0.0572)	(0.0396)	(0.0384)	(0.0546)
DIV_{t-1}	-0.0027	-0.0061**	-0.0073	-0.0105***	-0.0110***	-0.0105**
	(0.0029)	(0.0031)	(0.0048)	(0.0029)	(0.0029)	(0.0048)
$ICBT_{t-1}$	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$LNTA_{t-1}$	0.0007	-0.0025*	-0.0041*	0.0013	-0.0009	-0.0034
	(0.0015)	(0.0015)	(0.0022)	(0.0015)	(0.0016)	(0.0021)
Constant	0.0507***	0.1046***	0.1174***	0.0610***	0.1024***	0.1404***
	(0.0132)	(0.0146)	(0.0233)	(0.0105)	(0.0121)	(0.0239)
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	67,483	91,892	46,994	74,599	101,849	49,912
R^2	0.2220	0.2124	0.2083	0.2113	0.2077	0.2031

Note: This table reports the results of whether information uncertainty affects the predictive power of MIR rating gaps on issuer defaults and default probabilities. The gaps are measured by the differences between Moody's ratings and MIRs (*BONDGAP, EQUITYGAP,* and *CDSGAP*) over the lagged 6 months. The dependent variable *EDF* in Panel A is expected default frequency of an issuer in a month; and the dependent variable *FAIL* in Panel B is the failure probability (× 100) of an issuer in a month. Information uncertainty in a firm is measured by idiosyncratic volatility (*IVOL*) and analyst coverage (*LNANA*) in an issuer in a month. Control variables include *MOODYCR*, *DTC*, *PROFIT*, *DIV*, *ICBT*, *LNTA*, and a series of industry-year dummy variables. Panels A and B report results from ordinary least squares regressions. Variables are defined in Appendix C. Robust standard errors clustered by firm are presented in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 4 Impact of the 2008 financial crisis and the Dodd–Frank Act on the predictive power of market-implied rating (MIR) rating gaps on default probabilities

	Sample					
	BONDIR	***EQUITYIR***	***CDSIR***	***BONDIR***	***EQUITYIR***	***CDSIR***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Dependent variable: EDF						
$MIRGAP_{m-i}$	0.0205***	0.0111***	0.0097***	0.0283***	0.0205***	0.0238***
	(0.0020)	(0.0009)	(0.0016)	(0.0027)	(0.0013)	(0.0027)
MIRGAP ×CRISIS	0.0207***	0.0252***	0.0282***			
	(0.0047)	(0.0021)	(0.0039)			
$CRISIS_{m-i}$	0.0420***	0.0739***	0.0625***			
	(0.0088)	(0.0082)	(0.0099)			
MIRGAP × DODDFRANK				-0.0136***	-0.0145***	-0.0206***
				(0.0031)	(0.0015)	(0.0028)
$DODDFRANK_{m-i}$				-0.0084*	-0.0016	-0.0160**
				(0.0044)	(0.0041)	(0.0067)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	64,479	88,533	41,711	64,479	88,533	41,711
R^2	0.3417	0.3705	0.4103	0.3401	0.3644	0.4064
Panel B: Dependent variable: FAIL						
$MIRGAP_{m-i}$	0.0076***	0.0043***	0.0028***	0.0119***	0.0078***	0.0078***
	(0.0009)	(0.0004)	(0.0008)	(0.0013)	(0.0006)	(0.0016)
MIRGAP × CRISIS	0.0186***	0.0132***	0.0143***			
	(0.0031)	(0.0016)	(0.0028)			
$CRISIS_{m-i}$	0.0227***	0.0278***	0.0304***			
	(0.0043)	(0.0045)	(0.0054)			
MIRGAP × DODDFRANK				-0.0045***	-0.0041***	-0.0056***
				(0.0016)	(0.0007)	(0.0016)
$DODDFRANK_{m-i}$				-0.0107***	-0.0088***	-0.0146***
				(0.0029)	(0.0027)	(0.0048)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

N	74,551	101,994	50,314	74,551	101,994	50,314
R^2	0.1808	0.1770	0.1907	0.1692	0.1678	0.1805

Note: This table reports the impacts of the financial crisis and the Dodd–Frank Act on predicting issuer default probabilities using MIR rating gaps. The gaps are measured by the differences between Moody's ratings and MIRs (*BONDGAP*, *EQUITYGAP*, and *CDSGAP*) over the lagged 6 months. The dependent variable *EDF* in Panel A is expected default frequency of an issuer in a month, and the dependent variable *FAIL* in Panel B is the failure probability of an issuer in a month. Control variables include *MOODYCR, DTC*, *PROFIT*, *DIV*, *ICBT*, *LNTA*, and a series of industry-year dummy variables. Panels A and B report results from ordinary least squares regressions. Variables are defined in Appendix C. Robust standard errors clustered by firm are presented in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 5 Information content of market-implied ratings (MIRs) for Moody's to issue negative outlook and credit watch

Panel A: Strong signals from MIRs

	Sample			
	BONDIR	***EQUITYIR***	***CDSIR***	***MIR***
	(1)	**(2)**	**(3)**	**(4)**
BELOW1	0.6332***	0.3333***	0.5199***	
	(0.0640)	(0.0670)	(0.0886)	
BELOW2	0.9481***	0.5022***	0.9541***	
	(0.0848)	(0.0753)	(0.1019)	
BELOW3	1.1368***	0.7124***	1.3150***	
	(0.1077)	(0.0841)	(0.1264)	
BELOW4	1.5375***	0.9372***	1.4547***	
	(0.1316)	(0.0883)	(0.1817)	
BELOWSIGNAL1				0.5766***
				(0.0633)
BELOWSIGNAL2				1.0300***
				(0.0807)
BELOWSIGNAL3				1.5889***
				(0.1097)
$MOODYCR_{m-i}$	0.0381	0.0235	0.0315	0.0160
	(0.0242)	(0.0206)	(0.0271)	(0.0199)
DTC_{t-1}	1.1281***	1.1299***	0.7153*	1.1164***
	(0.3178)	(0.2404)	(0.3875)	(0.2316)
$PROFIT_{t-1}$	-5.3492***	-5.2973***	-5.9153***	-5.5807***
	(0.8404)	(0.7357)	(0.8811)	(0.7206)
DIV_{t-1}	-0.1565	-0.1676*	-0.0515	-0.1708*
	(0.1070)	(0.0932)	(0.1377)	(0.0897)
$ICBT_{t-1}$	-0.0065*	-0.0055**	-0.0047	-0.0033
	(0.0034)	(0.0027)	(0.0036)	(0.0025)
$LNTA_{t-1}$	0.0977**	0.0304	-0.0539	0.0085
	(0.0445)	(0.0397)	(0.0525)	(0.0371)
Constant	-5.7864***	-5.4523***	-4.0466***	-5.4337***
	(1.0340)	(0.9968)	(1.0211)	(0.9778)
Industry-year fixed effects	Yes	Yes	Yes	Yes
N	75,389	101,707	49,553	106,913
Pseudo R^2	0.1076	0.1071	0.112	0.1197

Panel B: Noisy signals from MIRs

	Sample					
	BONDIR	***EQUITYIR***	***CDSIR***	***BONDIR***	***EQUITYIR***	***CDSIR***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
MIRBELOW	1.0441***	0.7902***	0.9813***	0.9205***	0.6406***	0.8833***
	(0.0774)	(0.0665)	(0.0891)	(0.0719)	(0.0652)	(0.0862)
CONTRADICT	-0.5285***	-0.6750***	-0.4993***			
	(0.0929)	(0.0940)	(0.1242)			

REVERSAL				-0.4147***	-0.3155***	-0.2891***
				(0.0907)	(0.0960)	(0.1070)
$MOODYCR_{m-i}$	0.0459*	0.0366*	0.0437	0.0447*	0.0349*	0.0433
	(0.0239)	(0.0203)	(0.0268)	(0.0238)	(0.0202)	(0.0264)
DTC_{t-1}	1.1113***	1.1505***	0.9139**	1.2376***	1.2136***	0.9477**
	(0.3143)	(0.2388)	(0.3786)	(0.3138)	(0.2380)	(0.3755)
$PROFIT_{t-1}$	-5.4438***	-5.5419***	-6.0407***	-5.6769***	-5.6041***	-6.2577***
	(0.8416)	(0.7393)	(0.8741)	(0.8441)	(0.7339)	(0.8720)
DIV_{t-1}	-0.1491	-0.1540*	-0.0651	-0.1664	-0.1787*	-0.0639
	(0.1069)	(0.0928)	(0.1368)	(0.1067)	(0.0930)	(0.1369)
$ICBT_{t-1}$	-0.0059*	-0.0060**	-0.0043	-0.0058*	-0.0056**	-0.0042
	(0.0034)	(0.0026)	(0.0035)	(0.0034)	(0.0026)	(0.0035)
$LNTA_{t-1}$	0.0795*	0.0546	-0.0553	0.0896**	0.0346	-0.0589
	(0.0442)	(0.0394)	(0.0533)	(0.0441)	(0.0394)	(0.0525)
Constant	-5.7528***	-5.8233***	-4.2990***	-5.7944***	-5.6176***	-4.1993***
	(1.0400)	(0.9943)	(0.9940)	(1.0302)	(0.9867)	(1.0006)
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	75,389	101,707	49,553	75,389	101,707	49,553
Pseudo R^2	0.1053	0.1085	0.1072	0.1025	0.1034	0.1050

Note: Logistic models are used to test whether MIRs can provide leading information to Moody's on placing issuers on the negative credit watch or outlook list. The dependent variable is *CWOLNEG* (i.e., negative credit watch or outlook from Moody's). It is equal to 1 if an issuer is placed on the negative watch or outlook list within a month, and 0 otherwise. Panel A examines the impact of strong signals from MIRs. Panel B examines the impact of noisy signals from MIRS. Control variables include *MOODYSCR, DTC*, *PROFIT*, *DIV*, *ICBT*, *LNTA*, and a series of industry-year dummy variables. Variables are defined in Appendix C. Robust standard errors clustered by firms are presented in parentheses.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

TABLE 6 Recovery efforts induced by market-implied ratings (MIRs) signal: Difference-in-differences analysis

	ROA	***STDTTD***	***CAPEX***	***EDF***	***FAIL***
Panel A: Signal jointly defined by three MIRs					
Treatment group: Firms with negative MIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	-0.0004	0.1781	0.0167	0.2664	0.0011
Postsignal period (4 quarters)	0.0019	0.1694	0.0155	0.1837	0.0008
Post − Pre	0.0023	-0.0087	-0.0012	-0.0827	-0.0003
t-statistics	(5.70)***	(-2.01)**	(-3.88)***	(-9.46)***	(-5.76)***
N	1519	1493	1507	1290	1500
Control group: Firms without negative MIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0076	0.1172	0.0203	0.1226	0.0005
Postsignal period (4 quarters)	0.0077	0.1192	0.0206	0.1108	0.0006
Post − Pre	0.0001	0.0020	0.0003	-0.0119	0.0000
t-statistics	(0.43)	(0.52)	(0.72)	(-1.89)*	(0.97)
N	1559	1524	1548	1278	1556
Difference-in-differences					
Treatment firms − Control firms	0.0022	-0.0107	-0.0015	-0.0708	-0.0003
t-statistics	(4.09)***	(-1.85)*	(-2.76)***	(-6.57)***	(-5.39)***
Panel B: Signal defined by bond-implied ratings (BIRs) only					
Treatment group: Firms with negative BIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0072	0.1262	0.0177	0.1435	0.0005
Postsignal period (4 quarters)	0.0088	0.1219	0.0171	0.0975	0.0004
Post − Pre	0.0016	-0.0043	-0.0007	-0.0460	-0.0001
t-statistics	(3.87)***	(-1.10)	(-1.90)*	(-6.27)***	(-3.73)***
N	1222	1189	1218	994	1213
Control group: Firms without negative BIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0110	0.1099	0.0225	0.0663	0.0004
Postsignal period (4 quarters)	0.0125	0.1157	0.0240	0.0636	0.0003
Post − Pre	0.0015	0.0059	0.0016	-0.0027	-0.0001
t-statistics	(5.20)***	(1.97)**	(3.64)***	(-0.57)	(-5.17)***
N	1246	1210	1238	1012	1244

Difference-in-differences					
Treatment firms − Control firms	0.0002	-0.0102	-0.0022	-0.0433	-0.0000
t-statistics	(0.33)	(-2.08)**	(-4.02)***	(-4.96)***	(-0.94)
Panel C: Signal defined by equity-implied ratings (EIRs)					
Treatment group: Firms with negative EIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0056	0.1438	0.0254	0.1574	0.0008
Postsignal period (4 quarters)	0.0070	0.1367	0.0249	0.1031	0.0005
Post − Pre	0.0014	-0.0071	-0.0005	-0.0543	-0.0002
t-statistics	(5.61)***	(-2.91)***	(-1.91)*	(-12.24)***	(-8.82)***
N	3523	3482	3514	2955	3494
Control group: Firms without negative EIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0135	0.1042	0.0275	0.0396	0.0003
Postsignal period (4 quarters)	0.0140	0.1089	0.0286	0.0310	0.0003
Post − Pre	0.0005	0.0047	0.0011	-0.0087	-0.0001
t-statistics	(2.85)***	(2.34)**	(4.21)***	(-4.14)***	(-6.17)***
N	3562	3507	3536	3098	3562
Difference-in-differences					
Treatment firms − Control firms	0.0009	-0.0118	-0.0016	-0.0456	-0.0002
t-statistics	(2.82)***	(-3.74)***	(-4.36)***	(-9.43)***	(-6.25)***
Panel D: Signal defined credit-default-swap- (CDS) implied ratings (CIRs)					
Treatment group: Firms with negative CIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0088	0.1628	0.0184	0.1433	0.0005
Postsignal period (4 quarters)	0.0093	0.1585	0.0178	0.1129	0.0004
Post − Pre	0.0005	-0.0043	-0.0007	-0.0305	-0.0001
t-statistics	(0.96)	(-1.08)	(-1.95)*	(-3.09)***	(-2.65)***
N	696	679	690	568	696
Control group: Firms without negative CIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0124	0.1343	0.0186	0.0306	0.0003
Postsignal period (4 quarters)	0.0140	0.1290	0.0196	0.0192	0.0002
Post − Pre	0.0016	-0.0053	0.0010	-0.0113	-0.0001
t-statistics	(5.02)***	(-1.12)	(2.78)***	(-2.85)***	(-5.10)***
N	699	684	699	563	699

Difference-in-differences					
Treatment firms − Control firms	-0.0011	0.0010	-0.0016	-0.0191	-0.0000
t-statistics	(-1.75)*	(0.16)	(-3.35)***	(-1.79)*	(-0.59)

Note: This table reports the difference-in-differences analysis of firm fundamentals and default probability between the treatment group of firms receiving negative MIRs signal but without subsequent downgrade from Moody's and the control group of firms without negative MIRs signal or subsequent downgrade, between the presignal period and postsignal period. Firm fundamentals are measured by *ROA*, the ratio of short-term debt to total debt (*STDTTD*), and the ratio of capital expenditure to total assets (*CAPEX*). Default probability is measured by expected default frequency (*EDF*) and failure probability (*FAIL*). Negative MIRs signal is defined if all three MIRs are at least two notches below credit ratins in a "signal" quarter and there are no reversal signals in the prior 4 quarters in Panel A. Signal is defined based on bond-, equity-, and CDS-implied ratings in Panels B, C, and D, respectively. The firms in the treatment group are matched to firms without negative MIRs signals in the same quarter, having the same credit rating, in the same industry, and with similar total assets. The average values of firm fundamentals and default probability in the 4 quarters before the signal quarter (presignal period) and in the 4 quarters after (postsignal period) are calculated. The differences between the presignal period and the postsignal period are calculated for the treatment group and control group. The *t*-statistics for the difference-in-differences measures are reported. Variables are defined in Appendix C. The *t*-statistics are presented in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 7 Recovery efforts induced by market-implied ratings (MIRs) signal: A comparison between the crisis and tranquil periods

	ROA	***STDTTD***	***CAPEX***	***EDF***	***FAIL***
Panel A: Crisis period					
Treatment group: Firms with negative MIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0050	0.1697	0.0221	0.2306	0.0006
Postsignal period (4 quarters)	-0.0005	0.1593	0.0171	0.4418	0.0016
Post − Pre	-0.0056	-0.0104	-0.0049	0.2112	0.0010
t-statistics	(-3.65)***	(-1.38)	(-4.34)***	(7.73)***	(5.82)***
N	161	160	159	133	158
Control group: Firms without negative MIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0073	0.1383	0.0182	0.1552	0.0004
Postsignal period (4 quarters)	-0.0011	0.1588	0.0199	0.3811	0.0016
Post − Pre	-0.0084	0.0206	0.0017	0.2260	0.0012
t-statistics	(-5.78)***	(1.65)	(0.75)	(8.30)***	(6.36)***
N	165	164	165	122	165
Difference-in-differences					
Treatment firms − Control firms	0.0028	-0.0310	-0.0067	-0.0147	-0.0002
t-statistics	(1.33)	(-2.11)**	(-2.57)**	(-0.38)	(-0.64)
Panel B: Tranquil period					
Treatment group: Firms with negative MIRs signal but not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	-0.0011	0.1791	0.0161	0.2705	0.0012
Postsignal period (4 quarters)	0.0022	0.1706	0.0153	0.1540	0.0007
Post − Pre	0.0033	-0.0085	-0.0007	-0.1164	-0.0005
t-statistics	(7.91)***	(-1.78)*	(-2.38)**	(-13.40)***	(-8.59)***
N	1358	1333	1348	1157	1342
Control group: Firms without negative MIRs signal and not downgraded by Moody's in the subsequent 4 quarters					
Presignal period (4 quarters)	0.0076	0.1147	0.0206	0.1192	0.0005
Postsignal period (4 quarters)	0.0087	0.1144	0.0207	0.0823	0.0004
Post − Pre	0.0012	-0.0002	0.0002	-0.0370	-0.0001
t-statistics	(3.46)***	(-0.05)	(0.37)	(-6.32)***	(-3.54)***
N	1394	1360	1383	1156	1391
Difference-in-differences					

Treatment firms − Control firms	0.0021	-0.0083	-0.0009	-0.0795	-0.0003
t-statistics	(3.98)***	(-1.33)	(-1.71)*	(-7.59)***	(-5.88)***

Note: This table reports the difference-in-differences analysis of firm fundamentals and default probability between the treatment group of firms receiving negative MIRs signal but without subsequent downgrade from Moody's and the control group of firms without negative MIRs signal or subsequent downgrade, between the presignal period and the postsignal period. Panels A and B report results for the crisis period (July 2007–December 2008) and tranquil period, respectively. Firm fundamentals are measured by *ROA*, the ratio of short-term debt to total debt (*STDTTD*), and the ratio of capital expenditure to total assets (*CAPEX*). Default probability is measured by expected default frequency (*EDF*) and failure probability (*FAIL*). Negative MIRs signal is defined if all three MIRs are at least two notches below CRs in a "signal" quarter and there are no reversal signals in the prior 4 quarters. The firms in the treatment group are matched to firms without negative MIRs signals in the same quarter, having the same credit rating, in the same industry, and with similar total assets. The average values of firm fundamentals and default probability in the 4 quarters before the signal quarter (presignal period) and in the 4 quarters after (postsignal period) are calculated. The differences between the presignal period and postsignal period are calculated for the treatment group and control group. The *t*-statistics for the difference-in-differences measures are reported. Variables are defined in Appendix C. The *t*-statistics are presented in parentheses.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

APPENDIX A: RATINGS MATRIX FOR MOODY'S ISSUER CREDIT RATINGS AND MARKET-IMPLIED RATINGS

Rating value (ordinal/numeric value assigned to each rating category)	Moody's issuer ratings or Moody's market-implied ratings
21	Aaa
20	Aa1
19	Aa2
18	Aa3
17	A1
16	A2
15	A3
14	Baa1
13	Baa2
12	Baa3
11	Ba1
10	Ba2
9	Ba3
8	B1
7	B2
6	B3
5	Caa1
4	Caa2
3	Caa3
2	Ca
1	C

Note: This ratings matrix (scale) follows Moody's ratings matrix (Moody's Analytics, 2011). The only difference is that we use numeric values 21 and 1 for the highest and lowest ratings, respectively, for ease of illustration; the Moody's scale is the opposite (21 for the lowest and 1 for the highest).

APPENDIX B: BRIEF DESCRIPTIONS OF MARKET-IMPLIED RATINGS

B.1 Descriptions

Moody's issuer ratings represent Moody's opinion on the relative creditworthiness of underlying issuers. According to Moody's Analytics (2010a),

> *Market Implied Ratings [MIR] translate prices from the CDS, bond and equity markets into standard Moody's ratings language. MIRs are available on both issuer-level and security-level basis. An implied rating is calculated by comparing an entity or security's trading price to the trading prices of all other entities of securities in the same Moody's rating category*.

See Moody's Analytics (2010a, 2011) for more detailed descriptions and methodology of MIRs as well as the computation steps of bond-implied ratings, credit-default-swap- (CDS) implied ratings, and equity-implied ratings. MIRs are provided by Moody's Analytics Capital Markets Research Group (CMRC).

B.2 Intended use of MIRs by Moody's

Moody's Analytics (2010a, Point 12) states:

> *Moody's ratings analysts use market implied ratings to identify material and systematic gaps between Moody's ratings and the ratings implied by market data. They use them to compare their opinions to those held by the broader market or those generated by purely quantitative models, so that they are prepared to clearly articulate the reasons for any differences to market participants. Market implied ratings are not, however, an "input" into their rating decisions*.

B.3 Calculations of MIRs

The following steps are described in Moody's Analytics (2010a).

B.3.1 Calculations of bond-implied ratings

1. A daily "pricing grid" is derived from bond market data, relating median spread-over-

treasury to bond duration for every rating category.

2. A market-implied gap (relative to Moody's ratings) is inferred for each bond in the sample from the pricing grid.
3. An issuer's bond-implied rating is the average rating gap across its bonds added to its Moody's senior rating.

B.3.2 Calculations of CDS-implied ratings

1. A daily "pricing grid" is derived from the midpoints of bid/ask spreads on daily 5-year CDS quotes for every rating category.
2. A market-implied gap (relative to Moody's ratings) is inferred for each CDS from the pricing grid.
3. An issuer's CDS-implied rating is the average rating gap across CDS quotes added to its Moody's senior rating.

B.3.3 Calculations of equity-implied ratings

An equity-implied rating is the credit category assigned to a firm based on its expected default frequency (EDF). The equity-implied ratings available through MIRs are based on Moody's Analytics EDF credit measures. The mapping from EDF measures to implied ratings is determined by median EDF measures of firms in rating classes.

B.4 Sources of data for MIR's computations

Referring to Moody's Analytics (2010a, 2011), CMRC sources bond market price and spread data for its bond-implied ratings from industry-leading third-party vendors and market associations including Reuters, Markit Group, MarketAxess (for European bond market data), and TRACE data. It sources CDS price data for its CDS-implied ratings from Markit Group.

APPENDIX C: VARIABLE DEFINITIONS

Variable	Definition
Panel A: Variables related to Moody's ratings and market-implied ratings	
RATING: *MOODYCR* *BONDIR* *EQUITYIR* *CDSIR*	*RATING* represents Moody's issuer credit rating and three market-implied ratings (MIRs) at the end of a month. MIR includes bond-implied rating (*BONDIR*), equity-implied rating (*EQUITYIR*), and credit-default-swap- (CDS) implied rating (*CSDIR*). The MIRs are derived by Moody's through prices from bond, stocks and CDS markets. The letter grades of credit ratings and MIRs are converted into numerical values with Aaa as 21 to C as 1 (see Appendix A)
MIRGAP: *BONDGAP* *EQUITYGAP* *CDSGAP*	*MIRGAP* is the difference between Moody's credit rating and MIR for the issuer at the end of a month. *BONDGAP* = Moody's rating − bond-implied rating; *EQUITYGAP* = Moody's rating − equity-implied rating; *CDSGAP* = Moody's rating − CDS-implied rating
CWOLNEG	Dummy variable equal to 1 if Moody's places the issuer on negative credit watch or outlook list within a month, and 0 otherwise
BELOW: *BONDBELOW1* *BONDBELOW2* *BONDBELOW3* *BONDBELOW4* *EQUITYBELOW1* *EQUITYBELOW2* *EQUITYBELOW3* *EQUITYBELOW4* *CDSBELOW1* *CDSBELOW2* *CDSBELOW3* *CDSBELOW4*	*BELOW1:* dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is one notch lower than Moody's credit rating, and 0 otherwise; *BELOW2:* dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is two notches lower than Moody's credit rating, and 0 otherwise; *BELOW3:* dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is three notches lower than Moody's credit rating, and 0 otherwise; *BELOW4:* dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is four or more notches lower than Moody's credit rating, and 0 otherwise
BELOWSIGNAL: *BELOWSIGNAL1* *BELOWSIGNAL2* *BELOWSIGNAL3*	*BELOWSIGNAL1:* dummy variable equal to 1 if one MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is lower than Moody's credit rating, and 0 otherwise; *BELOWSIGNAL2:* dummy variable equal to 1 if two MIRs (*BONDIR, EQUITYIR,* or *CDSIR*) are lower than Moody's credit rating, and 0 otherwise; *BELOWSIGNAL3:* dummy variable equal to 1 if three MIRs (*BONDIR, EQUITYIR,* or *CDSIR*) are lower than Moody's credit rating, and 0 otherwise
MIRBELOW: *BONDBELOW* *EQUITYBELOW* *CDSBELOW*	Dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is lower than Moody's credit rating, and 0 otherwise
CONTRADICT: *BONDCONTRADICT* *EQUITYCONTRADICT* *CDSCONTRADICT*	Dummy variable equal to 1 if one MIR has lower rating than credit rating (CR) and any other MIRs have higher ratings than CR, and 0 otherwise
REVERSAL: *BONDREVERSAL* *EQUITYREVERSAL* *CDSREVERSAL*	Dummy variable equal to 1 if MIR (*BONDIR, EQUITYIR,* or *CDSIR*) is lower than CR in a month but higher than CR in the prior quarter, and 0 otherwise
NEGSIG: *NEGSIG (no downgrade)* *NEGSIG (downgrade)*	*NEGSIG (no downgrade):* dummy variable equal to 1 if all three MIRs (*BONDIR, EQUITYIR,* or *CDSIRI*) are at least two notches below CRs in a quarter, there are no reversal signals in the prior 4 quarters and no downgrades in the next 4 quarters, and 0 otherwise; *NEGSIG (downgrade):* dummy variable equal to 1 if all three MIRs (*BONDIR, EQUITYIR,* or *CDSIR*) are at least two notches below CRs in a quarter, there are no reversal signals in the prior 4 quarters but there are downgrades in the next 4 quarters, and 0 otherwise

Panel B: Variables related to firm characteristics

DEFAULT	Dummy variable equal to 1 if the issuer is defaulted within a month, and 0 otherwise
EDF	Expected default frequency for the issuer calculated from Merton's option pricing model in a month
FAIL	Failure probability for the issuer from Campbell et al. (2008) in a month

IVOL	Idiosyncratic volatility from market model for the issuer. It is calculated from the regressions of monthly stock returns on monthly market return in the past 60 months' stock returns, with a minimum of 24 months.
LNANA	Log value of one plus the number of analysts making earnings forecasts on the issuer within a month. If there are no earnings forecasts in a month, the value is zero.
CRISIS	Dummy variable equal to one if a month is within the financial crisis periods from July 2007 to December 2008, and zero otherwise
DODDFRANK	Dummy variable equal to one if a month is after the implementation of Dodd-Frank Act from July 2010, and zero otherwise
DTC	Debt-to-capital ratio for a rated corporate issuer (total debt/capital); total debt is the sum of short-term debt and long-term debt; total capital is total debt plus shareholder equity.
PROFIT	Profitability ratio; operating income before depreciation/total assets.
DIV	Dummy variable equal to one if the corporate issuer pays a dividend in the fiscal year, and zero otherwise.
ICBT	Interest coverage before tax for a rated corporate issuer (earnings before interest and tax / (interest expense on debt - interest capitalized))
LNTA	Log value of total assets for a rated corporate issuer.
ROA	Return on total assets for the issuer in a quarter; net income/total assets
STDTTD	Short-term debt to total debt ratio in a quarter; short-term debt/total debt
CAPEX	Corporate investment for the issuer in a quarter; capital expenditure/lagged total assets
Industry-Year	Series of variables for industry-year dummies.