Ambiguity and Corporate Bond Prices

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Abstract

This paper explores the relations between credit information uncertainty and corporate bond prices. Theory suggests that ambiguous quality of credit information makes bond prices respond more to bad news than to good news, and noisy and obscure information about default likelihood increases premiums for holding corporate bonds. Empirical results strongly support the hypotheses using our measures of credit information uncertainty based on both time-series and cross-sectional fluctuations in credit rating distributions. The findings are robust to the inclusion of a battery of controls such as issue-specific characteristics, risk and alternative uncertainty factors as well as macroeconomic variables.

Keywords: Ambiguity, Asymmetric Price Reaction, Corporate Bond Uncertainty Premiums, Return Predictability, Credit Rating Uncertainty

JEL Classification: G12, G14, G24

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1 Introduction

Is more information always better to assess the likelihood of a major credit event and to predict corporate bond prices? Conventional wisdom prompts us to answer yes, but this may be partly true only when the quality of information is guaranteed. An illustrative example is the Dodd-Frank Act,[1] which aimed at overhauling the financial regulatory system in the aftermath of the financial crisis. Regarding credit rating agencies (CRAs), one main measure requires improvements in the quantity and timeliness of the information provided. Despite the intention to make credit ratings more informative and accurate, Dimitrov et al. (2015) find that their quality actually deteriorates after the enactment. In a similar vein, Becker and Milbourn (2011) posit that the material addition of Fitch into the ratings industry relates to a lower quality of information provided by the agencies.

Heterogeneity and ambiguity in signals complicate the information processing and decision making of investors, which can explain the mentioned phenomena. We explore such uncertainty channels in the corporate bond space, which is a very large and important financial market.[2] Of the large amount of information available for corporate bonds, credit rating news particularly influence decisions made by market participants and affect bond prices. However, if the quality of information is uncertain, it can cause difficulty in assessing the likelihoods of default and financial distress. Of course, investors keep learning from the influx of credit news and update their views on credit risks, accounting for the obscurity as they see fit.

This paper theoretically and empirically studies corporate bond prices in this con-

[1]The Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) was signed on July 21, 2010. In regard to CRAs, the Act increases CRAs' liability for issuing inaccurate ratings, encourages strengthening of internal controls and corporate governance, and requires more disclosures concerning their rating procedures.

[2]According to the Securities Industry and Financial Markets Association (SIFMA), over \$1.6 trillion of U.S. corporate debt was issued in 2017, and the outstanding amount for the corporate bond sector at the end of 2017 is over \$9 trillion.

text, assuming bondholders dislike ambiguity *à la* Gilboa and Schmeidler (1989). Key contributions in the literature regarding the link between ambiguity aversion and asset prices include Epstein and Wang (1994), Hansen et al. (1999), Hansen and Sargent (2001), Chen and Epstein (2002), Epstein and Schneider (2003), Epstein and Schneider (2008), Drechsler (2013), Jeong et al. (2015), and Kim (2016). However, no existing work focuses on the corporate bond market despite its importance, and this paper contributes in filling the void.

Incorporating ambiguity aversion and uncertainty about credit information into a corporate bond pricing model, we derive testable implications and document supportive empirical evidence. Following Epstein and Schneider (2008) and Kim (2016), the preference of the representative bond investor is assumed to be recursive multiple-priors utility, and she receives an ambiguous signal about credit events. The setup of multiple-priors preferences axiomatized by Epstein and Schneider (2003) assumes that ambiguity-averse agents maximize expected utility in each period under the worst-case scenario, chosen from a set of one-step-ahead conditional probabilities. That is, the uncertain quality of new information affects the set of subjective conditional probabilities.

How well does this assumption fit reality? Credit rating agencies produce a large amount of news for corporate bonds, but their integrity is not without question. A common view is that they do not always provide timely and correct information on the credit conditions of assets, and discordant opinions among them can increase the difficulty of learning for the investor.[3] Other related concerns are the 'issuer-pays' model of the ratings industry, and their black-box nature of decision-making which further

[3]While Cheng and Neamtiu (2009) report that rating agencies improved rating timeliness and accuracy after the major bankruptcy scandals in the early 2000s, Oxley (2005) and Hughes (2006) attribute lack of timeliness of credit rating agencies to the inefficient market structure of the credit rating industry. On the other hand, Beaver et al. (2006) show that non-certified rating agencies' ratings are timelier and lead Moody's ratings, and are symmetrical in incorporating good news and bad news, whereas Moody's Investors Service tends to do a better job of reflecting negative news than positive news.

clouds the clean transmission of information to corporate bond market participants. Skreta and Veldkamp (2009), Jiang et al. (2012), Cornaggia et al. (2015), and Cornaggia et al. (2017) are recent studies reflecting this view. Based on these factualities and related studies, we postulate that credit news contains useful information, yet investors cannot be fully confident about its reliability in a Knightian sense.

Our model delineates how the investor reacts more to bad than to good credit news, regardless of risk aversion. Whereas the pattern of significant price responses only in cases of downgrades has been extensively documented in prior literature, theory explaining the phenomenon is still wanting. In particular, we show that asymmetric price reactions can depend on key bond characteristics. For bonds with higher (lower) priority of claims or seniority, hence higher (lower) recovery values, prices will be less (more) affected by credit news, and therefore its information quality is less (more) likely to affect them. Since uncertainty is distinct from risk, a relevant hypothesis is that bonds with lower priority should exhibit larger price responses, even after controlling for typical sources of risk for corporate bonds. We also show that with higher credit risk or its uncertainty, the asymmetric price reaction becomes stronger. Plus, the theory states that a positive uncertainty premium exists in that expected excess returns from holding corporate bonds is increasing in credit news ambiguity. Due to the nature of uncertainty, this premium distinguishes itself from conventional sources of corporate bond risk premiums.

In addition to the obscure information quality of news, how investors react to multiple news sources is another key theme of this paper. Whereas more news may strengthen the signal and facilitate learning, processing different news sources with heterogeneous levels of information quality is more strenuous for bond market participants. The multiple credit news setting of our model is a close resemblance of reality in which several credit rating agencies exist. The extended model states that first, multiple news sources can augment ambiguity and lead to more pronounced asymmetric price reactions, contrary to common perceptions. Second, mixed signals (in terms of signs) tend to have adverse effects on bond prices. This is because the ambiguity-averse investor will select the worst case scenario, picking the lowest accuracy for good news and the highest accuracy for bad news. Since she assigns low weights to good news and high weights to bad news, prices will react negatively even if the average of credit signals is close to neutral.

Note that the above theory paves the way for gauging the degree of uncertainty in credit news.[4] In particular, the model suggests that researchers can use cross-sectional dispersions among credit rating agencies as an empirical measure of ambiguity in credit news. In the stock market, forecast dispersion has been used to measure uncertainty, yet alternative interpretations are available. Diether et al. (2002) use the measure as a degree of information asymmetry or differential degree of issuer-specific risks, whereas Johnson (2004), Anderson et al. (2009), and Carlin et al. (2014) use forecast dispersions as measures of uncertainty. In addition, forecast dispersion may capture higher-order risks such as return volatility, volatility of return volatility, or skewness. Although it is difficult to fully disentangle the channels associated with forecast dispersions, Barron et al. (2009) empirically show that analyst forecast dispersions are closely related to uncertainty instead of other characteristics and risks. In treasury markets, Kim (2016) computes a residual level of forecast dispersions netting out various risk and uncertainty measures, to find that the remaining term is associated with economic uncertainty. We also perform extensive robustness checks controlling for a long list of variables related to the alternative channels, to report results that are consistent with uncertainty-based models.

To verify if theoretical derivations match actual data, we construct our main measure of credit news ambiguity using Mergent's Fixed Income Securities Database (FISD),

[4] Ambiguity and uncertainty are interchangeably used throughout the paper, following the related literature.

and test its effects on returns obtained from Trade Reporting and Compliance Engine (TRACE) data for a sample period of July 2002 to June 2017. We find empirical results that are strongly supportive. Corporate bond prices react asymmetrically to good and bad credit news, reactions are larger for bad news than for good news and more pronounced for bonds with lower priority, more credit risk, and higher ambiguity.

Our credit news ambiguity measure significantly and positively predicts the cross section of corporate bond returns, robust to controlling for various risk and uncertainty factors as well as bond characteristics.[5] Our ambiguity proxy retains significance in explaining the corporate bond cross section in the presence of macroeconomic uncertainty measures including but not limited to the VIX, forecast dispersions in inflation, the real gross domestic product, and the short-term interest rate.

The results are robust to excluding the financial crisis period of 2007 to 2008, suggesting that credit news uncertainty matters in normal times as well. In other tests using an economic milestone (the Dodd-Frank Act), we find that availability of more information renders the ambiguity premium more potent, in line with the model. We also include an aggregated variable of our ambiguity measure to find that the main uncertainty measure is still significant. This further corroborates the theory stating that idiosyncratic uncertainty is positively priced, unlike idiosyncratic risks.

The remainder of the paper proceeds as follows. Section 2 outlines the relevant literature. We develop the model and set out its implications in Section 3. Section 4 describes the data and explains the empirical results. Section 5 concludes.

[5]This is a stark contrast to the equity market literature which generally shows a negative premium for uncertainty (often proxied by analyst forecast dispersions), frequently attributed to stock investor irrationality or resource constraints in trading. We posit that this difference can partly result from the nature of corporate bond market participants, who are mostly large institutions and therefore are highly sophisticated and less constrained in liquidity. Plus, our result suggests that the ambiguity channel outweighs other additional channels in corporate bond markets.

2 Literature Review

This paper extends the setting of Epstein and Schneider (2008) and Kim (2016) to the corporate bond market. Epstein and Schneider (2008) show that ambiguity aversion can produce asymmetric asset price reactions to information and cause ambiguity premiums. Kim (2016) develops a model of default-free debt prices based on Epstein and Schneider (2008) to show that bond uncertainty premiums exist robustly even after controlling for various known risk factors. However, prior work has not studied the importance of ambiguity aversion in understanding corporate bond prices, which we address. In particular, we explore whether ambiguous credit news predicts the cross section of corporate bond returns.

Motivated by the Ellsberg (1961) paradox and related work on decision theories, a line of literature links asset prices to ambiguity or uncertainty in the economy.[6] Gilboa and Schmeidler (1989) incorporate ambiguity aversion in an atemporal setting, arguing that decision makers have a class of probability distributions and act following a max-min rule, i.e., maximization of utility in the worst-case scenario. Epstein and Wang (1994) propose a dynamic version of Gilboa and Schmeidler (1989) in a discrete-time framework, and Epstein and Schneider (2003) provide axiomatic foundations for recursive multiple-priors utility. Hansen et al. (1999), Hansen and Sargent (2001), and relevant works use a robust control setup to study the problems with ambiguity, while Chen and Epstein (2002) focus on the formulation of utility in continuous time. Jeong et al. (2015) estimate a multiple-priors continuous-time model to show that ambiguity aversion plays a significant role in explaining the market equity premium. Ulrich (2013) studies the term premium in a model with Knightian uncertainty to show that a positive inflation ambiguity premium exists.

Recently, a growing literature empirically studies how various proxies for ambiguity

[6] See Epstein and Schneider (2010) for a comprehensive survey of models on ambiguity aversion and asset prices.

aversion can impact asset prices, but with mixed results. Anderson et al. (2009) use the degree of disagreement among professional forecasters as an aggregate uncertainty proxy, and show that the uncertainty-return tradeoff is stronger than the traditional risk-return tradeoff in the equity market. Kim (2016) uses forecast dispersions regarding the short-term interest rate to report a significantly positive ambiguity premium in treasury bonds. Dimmock et al. (2016) measure ambiguity preferences of individual investors through Ellsberg-urn type questions, and link ambiguity aversion to representative household portfolio choice puzzles. Brenner and Izhakian (2018) construct their market-wide ambiguity measure based on high frequency data (ETF SPDR), and find a positive ambiguity premium. On the other hand, Diether et al. (2002) report that higher analyst forecast dispersions lower future stock returns, reflecting the view of optimistic investors only due to short-sale constraints. Baltussen et al. (2018) use the variance of a stock's implied volatility as a measure of ambiguity and find that stocks with high ambiguity underperform stocks with low ambiguity. Hollstein and Prokopczuk (2018) employ a measure of the option implied volatility of the volatility index and show a significantly negative risk premium in the cross-section of stock returns. To the best of our knowledge, no existing paper yet studies the link between credit news uncertainty and the cross section of corporate bond returns, both theoretically and empirically. Our paper contributes to this literature by providing evidence that the novel credit news uncertainty measure, CR_amb, significantly and positively predicts corporate bond returns, controlling for various bond characteristics and risks.

Our work also joins an area of study that explores the relation between credit news and asset prices. The empirical evidence supports an asymmetric price reaction to negative and positive news, which is documented in earlier literature by Pinches and Singleton (1978). Using 180 rating changes data from Moody's and Standard and Poor's, they find the existence of negative stock price changes following downgrades. Goh and Ederington (1993) observe similar phenomena for equity price reactions around

Moody's credit events, and Dichev and Piotroski (2001) for long-run stock returns. Hand et al. (1992) note that both stock and bond markets show significantly negative abnormal returns for downgrades, but no significant reaction for upgrades. The asymmetry in price reactions has been a long-standing puzzle in the literature, for which this paper provides a theoretical explanation. Our model suggests that ambiguity about credit news can produce non-linear sensitivities of corporate bond price movements to ratings news, resulting from ambiguity aversion.

There do exist questions regarding the informativeness or integrity of credit ratings, which are essentially paid for by the entities that are being rated. Our concern is not just the quality of ratings *per se*, but more importantly, how issuer-specific idiosyncratic noise of each credit rating can augment the overall size of ambiguity for investors in the presence of multiple news sources. There are papers that deal with the topic of split credit ratings, with differing implications. Morgan (2002) argues that split credit ratings result from the asset opacity of issuing firms, Livingston et al. (2008) find that split rated bonds are more likely to have subsequent rating changes, and Livingston and Zhou (2010) note that split rated bonds have higher yields compared to those with similar credit risk but no split. Bongaerts et al. (2012) explore existing theories about multiple credit ratings, finding support only for the regulatory certification theory and conclude that there is no additional information about credit quality provided.

Despite the documentation of the empirical link between split credit ratings and the opacity or uncertainty of credit information, limited theoretical underpinnings exist on whether ambiguous credit news is related to corporate bond prices. Further, no work empirically studies its implications in the cross section of future bond returns. We add to the literature with a model offering novel interpretations about the effects of multiple credit news sources. If bond investors dislike uncertainty and ambiguous idiosyncratic information exists, additional news may not always be beneficial, and corporate bond returns will reflect the preference. Consistent with this hypothesis, our empirical results show that positive credit news uncertainty premiums increase with the number of credit ratings available.

Apart from the nature of credit news (good or bad), debt priority structure can also create non-linearity in price reactions. Our model suggests that the bond recovery value is related to ambiguity and credit risk - the higher the recovery value, the lower the weight allocated to news ambiguity. Thus, the redemption priority of claims causes differential effects of credit news ambiguity on bond prices, which is a subtle but important result in better understanding the nature of uncertainty premiums in corporate bonds.

Last but not least, our work expands the literature explaining the cross section of corporate bond returns. In addition to the long-established aggregate factors affecting bond markets (Fama and French (1993), and Elton et al. (1995)), a number of research has found evidence of bond-level factors that are priced in the cross section, including liquidity (Lin et al. (2011), and Acharya et al. (2013)), default and term betas (Gebhardt et al. (2005)), and credit qualilty (Greenwood and Hanson (2013)), among many others. Bai et al. (2018) posit that downside risk predicts future bond returns better than traditional risk factors, and Chung et al. (2018) show high volatility betas are negatively related to expected returns while high idiosyncratic bond betas are positively related. Given that our credit news uncertainty measure, CR_amb, theoretically and empirically predicts the cross section of corporate bond returns, our paper provides a direct link between the ambiguity of credit markets and the cross-sectional predictability of corporate bond returns, controlling for the variables mentioned.

3 Theory and Hypotheses

In this section, we develop a model of corporate bond pricing with ambiguity aversion. This extends the theories by Epstein and Schneider (2008) on equity pricing, and Kim

(2016) on default-free bonds. The model features arrival of uncertain credit news about future default likelihoods, ambiguity aversion, and learning by the investor.

3.1 Basic Model

Suppose that Ω is a state space of which an element $w_t \in \Omega$ prevails every period. At each time t, the representative investor has information of the history $w^t \equiv \{w_0, \cdots, w_t\}$. Consumption plans are sequences $c = (c_t)$. Given a history vector, w^t, a conditional utility function U_t represents preferences over c and is recursively constructed as

$$U_t(c; w^t) = \max_{c} \min_{p_t \in \mathcal{P}_t(w^t)} E_t^{p_t} \left[u(c_t) + \delta U_{t+1} \left(c; w^t, w_{t+1} \right) \right], \tag{1}$$

where δ refers to time discount with the value being between zero and one, and u is a periodic utility function. $\mathcal{P}_t(w^t)$ on Ω denotes the set of one-step-ahead probability measures, representing conditional beliefs about the next observation w_{t+1}. Epstein and Schneider (2003, 2007) propose a specific functional form for $\{\mathcal{P}_t(w^t)\}$ to capture learning from a sequence of conditionally independent signals. Under the assumption, solutions to equation (1) satisfy dynamic consistency as well as the Gilboa-Schmeidler axioms. For simplicity and tractability, we assume that there are three dates, $T = 0, 1,$ and 2. Following Epstein and Schneider (2008), there exists a representative investor who is risk-neutral, yet averse to ambiguity. This assumption can be easily relaxed to incorporate risk aversion, but we adopt it to highlight the role of ambiguity aversion. The representative investor holds the total market issuance of corporate debt and therefore prefers higher values of corporate bonds.

To price corporate securities in this setting, we extend a simple reduced-form model from Duffie and Singleton (1999, 2003), based on the risk-neutral pricing method. Suppose that v is the total value of the firm, and D is the face value of its debt. If default occurs in the sense that $v \leq D$, the recovery value is assumed to be X. Define V, the value of debt in the next period to be

$$V = \begin{bmatrix} D & \text{if } v \geq D \\ X & \text{otherwise} \end{bmatrix}.$$

We denote $\phi = \Pr(v > D)$, the risk-neutral conditional probability of survival in the next period. In addition, the representative investor is assumed to receive credit news about the risk-neutral probability of conditional default in the next period, $1-\phi$, where $\phi \in (0,1)$ holds. To model ambiguity in credit news, we assume that the investor does not know the distribution of information quality. In particular, the risk-neutral probability ϕ is assumed to be

$$\begin{aligned} \phi_t &= \bar{\phi} + \varepsilon_t, \\ \varepsilon_t &\sim N(0, \sigma_\phi^2), \end{aligned} \tag{2}$$

where $\bar{\phi}$ is the mean probability of survival in the next period. The signal (z) is ambiguous in that

$$\begin{aligned} z_t &= \varepsilon_{t+1} + u_t + \eta_{t-1} v_t, \\ u_t &\sim N(0, \sigma_z^2), v_t \sim N(0,1), \sigma_z^2 \in \left[\underline{\sigma}_z^2, \bar{\sigma}_z^2\right], \end{aligned} \tag{3}$$

where η_t is a Markov process, and ε_t, u_t, η_t, v_t are independent of each other. That is, the investor knows only the interval of σ_z^2. For a zero-coupon, defaultable corporate bond, its price at t is denoted as $Q_t^{(n)}$, where n refers to its maturity. Without loss of generality, the face value of the bond is set to be 1 from now on. Thus, if default occurs, the investor can recoup a value of $X < 1$. The short-term risk-free rate is assumed to be constant at r.

3.2 Bond Prices Around Credit News

Using the above setup, we explore how credit news affects bond prices immediately after its release. To this end, we compute corporate bond prices before and after credit news releases. We first investigate a baseline case, followed by cases with differing priority of claims, credit risks, and ambiguity.

3.2.1 Benchmark Case

For a one-period corporate bond, today's bond price immediately after receiving the signal in period 0 (z_0) can be stated as

$$\begin{aligned} Q_0^{(1)} &= \min_{\sigma_z^2 \in [\underline{\sigma}_z^2, \bar{\sigma}_z^2]} \frac{E\left[\phi_1 + (1-\phi_1)X|z_0\right]}{1+r} \\ &= \frac{X + (1-X)\left(\bar{\phi} + \beta_0^* z_0\right)}{1+r}, \end{aligned} \tag{4}$$

$$\begin{aligned} \beta(\sigma_z^2) &= \frac{Cov\left(\phi_1, z_0\right)}{Var\left(z_0\right)} = \frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_z^2}, \\ \beta_0^* &= \begin{cases} \beta(\bar{\sigma}_z^2) & \text{if } z_0 > 0 \\ \beta(\underline{\sigma}_z^2) & \text{otherwise} \end{cases}, \end{aligned} \tag{5}$$

where η_{-1}, the value of η_{t-1} at $t = 0$, is assumed to be zero, and $E\left[\cdot|z_0\right]$ is the conditional expectation operator based on the signal z_0. We denote $\underline{\beta} = \beta(\bar{\sigma}_z^2)$ and $\beta(\underline{\sigma}_z^2) = \bar{\beta}$, and it is clear that $\underline{\beta} < \bar{\beta}$ holds. Equation (4) states that the price of a credit-risky bond is affected by credit news (z_0) that includes information regarding next period's shock to its survival likelihood. The impact depends on the ambiguity of information quality, as dictated by equation (5).

To study bond price reactions around credit news announcements, we compute the price right before the signal, denoted as $Q_{0-}^{(1)}$ as follows:

$$Q_{0-}^{(1)} = \frac{X + (1-X)\bar{\phi} - \frac{\left(\bar{\beta}_0 - \underline{\beta}_0\right)}{\sqrt{\underline{\beta}_0}}\sqrt{\frac{\sigma_\phi^2}{2\pi}}}{1+r}, \tag{6}$$

where $Q_{0-}^{(1)}$ refers to the expectation where the investor integrates out the information z in computing the price at this point, because she has yet to observe the signal.[7] Equation (6) states that ambiguity affects the bond price, because the signal's precision cannot be determined. The term $\left(\bar{\beta}_0 - \underline{\beta}_0\right)$ reflects the size of ambiguity in credit news, and the bond price is lower than in the case with no ambiguity ($\bar{\beta}_0 = \underline{\beta}_0$), because the investor dislikes it. Comparing equation (6) with (4), we arrive at the following interpretation. When credit news is good ($z_0 > 0$), prices react to news by $\underline{\beta}$, whereas $\bar{\beta}$ is the sensitivity of corporate bond prices when news is bad ($z_0 \leq 0$). That is, corporate bond prices respond *more* to bad news, and *less* to good news in terms of the size of the responses. This asymmetry in price reactions is an important testable implication of our model.

Albeit simple, the result of overreaction (underreaction) to bad (good) news has been a puzzle in related empirical literature (e.g., Pinches and Singleton (1978), Goh and Ederington (1993), Hand, Holthausen, and Leftwich (1992), Hite and Warga (1997)). We show that uncertainty about credit news quality in conjunction with investors' concerns about ambiguity can account for this phenomenon. The following hypothesis summarizes the first result of our model.

Hypothesis 1 *If there exists uncertainty in credit news and corporate bond investors are averse to ambiguity, price reactions to good and bad news are asymmetric. The size of bond price decreases to bad credit news is greater than that of price increases to good news.*

[7] In deriving the result, we use the properties of truncated normal distribution and the fact that $Var(z) = \beta^* \sigma_\phi^2$. For more details, readers are referred to Epstein and Schneider (2008) and Kim (2016).

3.2.2 Priority, Risk and Uncertainty of Credit Information

Equation (4) dictates that recovery value X works as a weight of credit-news-driven ambiguity ($\beta_0^* z_0$) and credit risk ($\bar{\phi}$ and σ_ϕ^2). That is, a higher value of X implies a lower weight assigned to news ambiguity, and holding $\beta_0^* z_0$ constant, bonds with higher recovery values are safer and less susceptible to credit news shocks. This result also suggests that the priority of a bond matters in understanding the size of the cross-sectional differences in bond price dynamics with credit news ambiguity. Suppose that the total recovery value of a bond issuer is X^{Total}, and the face value of senior/secured bond is D^S. Then the scrap value of senior bond X^S becomes $\min(D^S, X^{Total})$. Similarly, for a junior/unsecured debt with a face value of D^J, the scrap value of junior bond, denoted as X^J, becomes $\min(X^{Total} - X^S, D^J)$. From equation (4), the price of a one-period senior bond ($Q_0^{(1,S)}$), and that of a corresponding junior bond ($Q_0^{(1,J)}$) are as follows:

$$Q_0^{(1,J)} = \frac{X^J + (1 - X^J)\left(\bar{\phi} + \beta_0^* z_0\right)}{1 + r}, \tag{7}$$

$$Q_0^{(1,S)} = \frac{X^S + (1 - X^S)\left(\bar{\phi} + \beta_0^* z_0\right)}{1 + r}, \tag{8}$$

$$X^J = \min(X^{Total} - X^S, D^J), \tag{9}$$

$$X^S = \min(X^{Total}, D^S). \tag{10}$$

Equations (7) to (10) state that redemption priority is an important determinant in accounting for the differential effects of ambiguity on credit news. If the value of total recovery is high (low), then the degree of cross-sectional differences in price reaction to news becomes smaller (larger).

Next, we observe that certain characteristics of credit risk can also affect the size of asymmetric and heterogenous reactions to credit news arrivals. Suppose that we have two different bonds with high credit risk ($risky$) and low credit risk ($safe$). We view that $\bar{\phi}_{safe} > \bar{\phi}_{risky}$ and $\sigma^2_{\phi,safe} < \sigma^2_{\phi,risky}$ appropriately capture the cross section of credit risk profiles in our model. The following equations describe corporate bond price responses to a news shock.

$$Q_0^{(1,risky)} = \frac{X + (1-X)\left(\bar{\phi}_{risky} + \beta^*_{0,risky} z_0\right)}{1+r}, \tag{11}$$

$$Q_0^{(1,safe)} = \frac{X + (1-X)\left(\bar{\phi}_{safe} + \beta^*_{0,safe} z_0\right)}{1+r}. \tag{12}$$

Note that $\sigma^2_{\phi,safe} < \sigma^2_{\phi,risky}$ implies $\beta^*_{0,risky} > \beta^*_{0,safe}$ from equation (5). Importantly enough, if σ^2_ϕ is close to zero, there exists virtually no price reaction to credit news, regardless of the ambiguity in news quality. Thus, equations (11) and (12) state that the impact of credit news (z_0) does not directly depend on the size of mean survival probability $\bar{\phi}$, but the news sensitivity in equation (5) indicates that a credit-riskier bond in the sense of a higher σ^2_ϕ can have a larger price reaction than a bond with a lower σ^2_ϕ, and for safe bonds such as investment-grade bonds, little price reaction to ambiguous credit news is expected. Related, the size of β^*_0 depends on the distance of the interval for credit news ambiguity, $[\underline{\sigma}^2_z, \bar{\sigma}^2_z]$. Simply put, the longer the distance of this interval, the larger the credit news ambiguity, which renders bond price reactions asymmetric. Summing up, we have the following hypothesis.

Hypothesis 2 *Credit news ambiguity interacts with credit risk and the priority of debt claims. The degree of asymmetry in price reaction is greater (smaller) if bonds are junior (senior), credit-riskier (less credit-risky), or more (less) ambiguous in credit news.*

3.3 Ambiguous Information and Credit Uncertainty Premium

Does uncertainty about credit-related information create a premium for holding corporate bonds? We tackle this question by computing the price of a two-period bond (i.e., a long-term debt in this model). At the beginning of period 0, denoting the price of the bond as $Q_0^{(2)}$, the basic formula is

$$Q_0^{(2)} = \min_{\sigma_{z,1}^2, \sigma_{z,2}^2} \frac{E\left[\phi_0 Q_1^{(1)} + (1-\phi_0)X | z_0\right]}{1+r}, \tag{13}$$

where $\sigma_{z,1}^2 \in [\underline{\sigma}_z^2, \bar{\sigma}_z^2]$ and $\sigma_{z,2}^2 \in [\underline{\sigma}_z^2, \bar{\sigma}_z^2]$ are the volatilities of ambiguous signals in period 0 and 1 respectively, and $Q_1^{(1)}$ is the price of one-period maturity bond in period 1. From equation (4), we write this as

$$Q_1^{(1)} = \frac{X + (1-X)\left(\bar{\phi} + \beta_1^* z_1\right)}{1+r}. \tag{14}$$

$\beta_1^* z_1$ is the posterior mean, conditional upon the signal available in period 1 regarding the survival probability in period 2 (ϕ_2), or $E(\phi_2 | z_1)$. Then, the econometrician's unconditional expectation for one-period excess bond returns is computed as:[8]

$$E^\kappa \left[Q_1^{(1)} - Q_0^{(2)}(1+r)\right] = \alpha_0 + \gamma \cdot \left(\frac{\bar{\beta}_0 - \underline{\beta}_0}{\sqrt{\beta_0^\kappa}}\right), \tag{15}$$
$$\alpha_0 = 1 + \frac{\bar{\phi}\left(1 - X\left(r + \bar{\phi}\right)\right) + X + (1-X)\left(\bar{\phi} - \mu_\beta\right)}{1+r},$$
$$\gamma = \left(\frac{1}{1+r}\right)\left((1-X)\left[\bar{\phi} - \mu_\beta\right]\sqrt{\frac{\sigma_\phi^2}{2\pi}} - rX\right)\sqrt{\frac{\beta_0^\kappa}{\underline{\beta}_0}}\sqrt{\frac{\sigma_\phi^2}{2\pi}},$$

where $\mu_\beta \equiv E\left[(\bar{\beta}_1 - \underline{\beta}_1)/\sqrt{\beta_1^*}\right]$ denotes the unconditional mean of period-1 ambiguity and β_0^κ is the estimate of β_0 by an econometrician. Equation (15) describes how ambiguous credit news today (z_0) plays an instrumental role in generating positive expected excess returns of credit-risky bonds as long as the risk-free interest rate is not too high. Without ambiguity, $\bar{\beta}_0 = \underline{\beta}_0$ holds, and the expected excess return becomes smaller. The sensitivity to ambiguity term γ implies that a lower recovery

[8] The derivation is available in the Appendix.

value (smaller X), a higher level of credit risk (higher σ_ϕ^2), or a higher ambiguity-adjusted and risk-adjusted survival probability (higher $(\bar{\phi} - \mu_\beta)$) can increase the size of credit news uncertainty premium, given the size of ambiguity in credit news. The first two components can be viewed as channels of risk and uncertainty trade-off. The last part simply tells us that, controlling for risk and uncertainty, bonds with higher survival likelihoods have higher returns. Equation (15) provides us with a testable implication stated as follows.

Hypothesis 3 *Under the existence of uncertainty in credit news and ambiguity aversion by bond market investors, a positive credit news uncertainty premium prevails. The size of the credit news uncertainty premium can depend on issuer characteristics.*

3.4 Measuring Uncertainty in Credit Information

The theoretical results obtained thus far provide us with clues on how to measure uncertainty in credit information. In this section, we utilize the model to refine this intuition and propose an empirical proxy of credit news ambiguity, letting multiple providers of credit news enter the scene. This is a valid extension in that a number of key credit rating agencies, most notably the 'Big Three', independently feed new information to market participants on the credit conditions of corporate debts. More information is generally considered to be better in making decisions, but if different news sources are available with heterogeneous levels of *ambiguous* information quality, this may further complicate information processing by bond market participants, and the ambiguity effect on bond prices can still prevail.

In this line of reasoning, equation (3) is extended as follows:

$$
\begin{aligned}
& z_t^i = \varphi_i \varepsilon_{t+1} + u_t^i, \\
& u_t^i \sim N(0, \sigma_{z,i}^2), \sigma_{z,i}^2 \in \left[\underline{\sigma}_{z,i}^2, \bar{\sigma}_{z,i}^2\right],
\end{aligned} \tag{16}
$$

where $i = 1, ..., n$ denotes sources of credit news, and φ_i refers to the relative strength of signs for i. For tractability, we analyze the case where $n = 2$. Then, the investor updates the conditional likelihood of new information using z^1 and z^2 to compute the posterior mean as follows.[9]

$$
E\left[\phi | z_0^1, z_0^2\right] = \bar{\phi} + \beta_1 z_1 + \beta_2 z_2, \tag{17}
$$

where

$$
\begin{aligned}
\beta_1 &= \frac{\varphi_1 \sigma_\phi^2}{\varphi_1^2 \sigma_\phi^2 + \sigma_{z,1}^2 + \varphi_2^2 \sigma_\phi^2 \frac{\sigma_{z,1}^2}{\sigma_{z,2}^2}}, \\
\beta_2 &= \frac{\varphi_2 \sigma_\phi^2}{\varphi_2^2 \sigma_\phi^2 + \sigma_{z,2}^2 + \varphi_1^2 \sigma_\phi^2 \frac{\sigma_{z,2}^2}{\sigma_{z,1}^2}}.
\end{aligned} \tag{18}
$$

Equation (18) states that the less noisy signal contributes more to the posterior mean of ϕ. For instance, if $\sigma_{z,1}^2$ is much larger than $\sigma_{z,2}^2$, β_1 can be a small number close to zero, and most of the update comes from z_2.

The one-period bond price then becomes

$$
Q_0^{(1)} = \frac{X + (1 - X)\left(\bar{\phi} + \min\limits_{\sigma_{z,1}^2, \sigma_{z,2}^2} (\beta_1 z_1 + \beta_2 z_2)\right)}{1 + r}. \tag{19}
$$

Inferring from equations (16), (19) and (18), choosing $\sigma_{z,1}^2$ and $\sigma_{z,2}^2$ is not trivial because

[9] The derivation is available in the Appendix.

of the terms of ratios between $\sigma^2_{z,1}$ and $\sigma^2_{z,2}$ in β_1 and β_2, as well as the signs and relative magnitudes of z_1 and z_2.

Suppose that different sources provide mixed news in terms of signs - that is, there is dispersion in credit news. Then assume that $z_1 > 0$ and $z_2 < 0$ hold. In this case, from equations (17) and (18), it is easy to show that the investor will select the highest noise variance $\bar{\sigma}^2_{z,1}$ for z_1 (good news), and the smallest variance $\underline{\sigma}^2_{z,2}$ for bad news, z_2. Therefore, when dispersions in credit news arise, it is likely to affect bond prices negatively or increase credit news uncertainty premiums, because both ambiguity and aversion to it lead to asymmetric responses. Thus, corporate bond prices can react negatively to news even if the averages of credit signals do not vary, as long as dispersions exist.[10]

This observation is quintessential because it provides a rationale for using dispersions in information providers' credit news as an empirical proxy for ambiguity. Because ambiguity-averse investors will react asymmetrically to good and bad news, dispersions in news, especially with opposite directions can help identify ambiguity bounds. In the following section, based on this intuition and result, we propose an empirical measure that proxies for the degree of credit news ambiguity, by quantifying the cross-sectional dispersion of credit ratings among major rating agencies for each bond issue at each given point in time.

If both z_1 and z_2 are good news, i.e., $z_1 > 0$ and $z_2 > 0$, the ambiguity-averse agent makes β_1 and β_2 as small as possible. With only a single source of ambiguous information, this is achieved simply by choosing the highest possible variance. Now, depending on the relative strength of signal z_1 and z_2 (the ambiguity bounds of $\sigma^2_{z,1}$ and $\sigma^2_{z,2}$), the investor does not necessarily choose the highest variance of information noise for both news sources. If the sizes of z_1 and z_2 are comparable and ambiguity

[10]If there were no ambiguity and ambiguity aversion, dispersions in news with the opposite signs can neutralize the effect, provided that both news sources have a similar level of noise.

bounds are similar, it is expected that the investor selects the noisier case as the worst-case belief, and the impact of bond prices on credit news is a weighted average of the sensitivity of news to actual credit risk. The case of bad news is a mirror image in that the investor tries to choose the most accurate signal, amplifying the importance of bad forecasts. In the case of news with the same sign but of much difference in strength (if one news is much more informative than the other), it may be optimal for the investor to select the highest noise variance for the stronger signal and the lowest noise variance for the weaker signal to boost the effect from the stronger signal. Thus, even with the same sign, dispersions in credit news due to different degrees of informativeness can help measure credit news ambiguity. Finally, note that our theory shows that ambiguity can still affect asset prices with only one information provider. Because dispersion-based measures cannot identify this specific channel, we believe that our empirical measure is conservative, hence the actual effects from credit news ambiguity can be larger.

4 Empirical Analysis

4.1 Data and Variables

This section describes our measure of credit news ambiguity, corporate bond returns, and other variables used in empirical tests. Descriptive statistics of corporate bond returns and their predictive variables are reported as well.

4.1.1 Corporate Bond Returns

We construct corporate bond returns using the Enhanced Trade Reporting and Compliance Engine (TRACE) data from July 2002 to June 2017. Following Bessembinder et al. (2009), we compute daily prices as trade-quantity weighted averages of all intra-day transactions, adjusting for cancellations and revisions. In addition, we follow the data filtering procedure in Bai et al. (2018) and remove trades that are when-issued, locked in, have special sales conditions, have more than a two-day settlement, or have a trading value of less than $10,000. Equity-linked trades and transaction records with a reported price of less than $5 or greater than $1,000 are also eliminated. We exclude any floating-rate coupon bonds, convertibles, asset-backed or mortgage-backed securities, foreign-currency denominated bonds, private placements, bonds under rule 144A, perpetual bonds, and bonds with less than one year to maturity.

If a bond has a valid price observation for any of the last 5 trading days in a month, the latest one is considered as the 'month-end' price, and the first valid price observation in the earliest 5 trading days of the month is considered as the 'month-start' price. For monthly return computations, the month-end to month-end price pairs are used when available, and if not, the 'month-start' to 'month-end' pairs are considered.

The monthly price data are merged with bond issue specific information from Mergent's Fixed Income Securities Database (FISD) by CUSIP number. We obtain the coupon rate, coupon payment frequency, issue and maturity dates, first interest date, par value, and principal amount of each bond to calculate coupon dates and accrued interest. The monthly return for bond i at time t is computed as:

$$R_{i,t} = \frac{(P_{i,t} + AI_{i,t} + C_{i,t})}{(P_{i,t-1} + AI_{i,t-1})} - 1, \tag{20}$$

where P is the price, AI the accrued interest, and C the coupon payment (if any). Excess monthly bond return ($ExRet$) is the raw monthly return (Equation (20)) minus the one-month treasury bill rate from Kenneth French's website. Bond market returns (r_{MKT}) are calculated as the amount-outstanding weighted average excess returns of all bonds in our sample.

4.1.2 Dispersion in Credit Ratings

Our measure of credit news ambiguity employs credit ratings of individual bonds from the FISD database. We take each available rating from Moodys, Standard & Poors, and Fitch, assign a value of 1 to the highest rating (Aaa for Moodys, AAA for S&P and Fitch), and add 1 point for each notch moving down. The lowest grade in our sample has a score of 25, which is the equivalent of a 'D' rating from S&P. We denote as *Ratings* the average of all available credit scores at each calculation date.

In line with our model and the related literature, we consider multiple signals, or dispersion among rating agencies' opinions, as a source of ambiguity. Our measure of credit news ambiguity, CR_amb, is motivated by our model and constructed in the spirit of the uncertainty measures proposed by Diether et al. (2002), Epstein and Schneider (2008), Ilut and Schneider (2014) and Kim (2016) as:

$$CR\_amb_{i,t} = \frac{STDDEV_{Ratings_{i,t}}}{\sqrt{Ratings_{i,t}}}, \tag{21}$$

where $STDDEV_{Ratings_{i,t}}$ is the standard deviation of credit scores available for bond i at time t. Recall that equation (15) suggests that credit-rating ambiguity is expressed by a normalized distance of ambiguity bound measured by β, where β can be interpreted as the extent to which issuer credit information covaries with its default likelihood. Thus, if credit rating provides a good proxy for the size of covariation, and the disagreement among credit rating agencies can span the distance of this boundary, we believe that CR_amb is consistent with our theory. In addition, note that higher rating scores mean lower credit quality of issuers. Thus, the normalization lowers the size of CR_amb for low credit-quality issuers, and CR_amb can be viewed as an ambiguity measure controlling for the credit risk or quality. To make sure that our empirical results do not depend on the normalization, we also use the raw measure of dispersion, $STDDEV_{Ratings_{i,t}}$ to show that the results are highly robust.

Around a third of our sample bonds have zero CR_amb, of which only 32,816 observations have one available rating, indicating that concurrent ratings are quite common. We aggregate individual CR_amb numbers by each month to gauge the level of market-wide credit news ambiguity and name the variable $TotalCR\_amb$. $TotalCR\_amb$ is value-weighted using bond amounts outstanding.

4.1.3 Alternative Ambiguity Measures

We test volatility of return volatility ($VolofVol$) as an alternative ambiguity proxy for corporate bond markets. The specification of $VolofVol$ is based on realized bond return volatility ($Volatility$)[11], calculated from daily return premiums in excess of the risk-free rate (1-month T-bill, adjusted for daycount). This method follows Barndorff-Nielsen and Shephard (2002), Barndorff-Nielsen and Shephard (2004), Chang et al. (2016), and others. They show that using high-frequency observations is desirable in measuring return volatilities and the higher-order moments. For each bond, the monthly realized volatility is the volatility of daily return premiums within the respective month[12], and $VolofVol$ is the volatility of 36 monthly volatilities leading up to, but not including, the calculation month (a minimum of 24 data observations within the estimation period are required). $Skewness$ and $Kurtosis$ of monthly bond returns are also estimated from the same window with similar requirements. To remove the effect of outliers and possible errors in trade reporting, we exclude daily returns greater than 100 percent from our calculations. For a robustness check, we also construct an equivalent measure of the volatility of return volatility in stock markets, $VolofVol_{stock}$. Data on daily stock returns are collected from the Center for Research in Security Prices

[11] As an ambiguity measure of stock markets, Baltussen et al. (2018) use the variance of a stock's implied volatility and Hollstein and Prokopczuk (2018) employ a measure of the option implied volatility of the volatility index.

[12] We construct and test an alternative measure of volatility with monthly returns, using a 36-month rolling estimation window, similar to estimating $VolofVol$, $Skewness$, and $Kurtosis$. Our Fama-MacBeth and panel regression results remain qualitatively similar.

(CRSP). The S&P 500 Volatility Index (VIX) is also added in empirical specifications, from the Chicago Board Options Exchange (CBOE).

We include dispersion in analysts' earnings forecasts ($Disp_{EPS}$) for robustness. Following Diether et al. (2002), $Disp_{EPS}$ is the standard deviation of EPS forecasts scaled by the absolute value of its mean. The forecasts are obtained from the Institutional Brokers Estimate System (I/B/E/S). We account for the level of macroeconomic uncertainty, with ambiguity measures for the short-term interest rate (r_amb), inflation ($infla\_amb$), and the real GDP growth ($rgdp\_amb$). The dispersion for each item is defined as the difference between the 25th and 75th percentiles of quarterly forecasts, scaled by the square root of its absolute mean. Forecast data are from the Survey of Professional Forecasters (SPF) by the Philadelphia Federal Reserve Bank, and have been shown to predict Treasury bond returns (Kim (2016)).

4.1.4 Other Variables Used

An important factor in our corporate bond pricing model is the priority of claims. The FISD database specifies the security/seniority level of each issue as Junior, Junior Subordinate, Senior, Senior Subordinate, Senior Secured, Subordinate, or None. We classify Junior, Junior Subordinate, Senior Subordinate, and Subordinate bonds into the subordinated bond category (SUB), Senior Secured bonds into the secured bonds group (SEC), and 'None' as regular bonds. We search bond names in the Senior category indicative of their priority status ('sub' for subordinated bonds, 'senior', 'secd', 'sr' for senior/secured bonds) and assign accordingly the SUB and SEC dummies. In our sample, there are 395,918 observations for secured bonds, 84,089 observations for subordinated, and 519,192 for regular bonds.

Following Bai et al. (2018), we control for downside risk (VaR) and illiquidity ($Illiquidity$) in the model specification of corporate bond pricing. VaR is based on the second lowest return (premium) observation from prior 36 months, multiplied by

-1. We calculate this variable for observations that have 24 or more valid returns in the 36-month window. Monthly *Illiquidity* is estimated from the covariance of consecutive two daily log price changes within the month. In the methodology of Bao et al. (2011), we let 'consecutive' days be up to one week in case a bond does not trade daily. Specifically,

$$Illiquidity_{i,t} = -cov_t(\Delta p_{i,t,d}, \Delta p_{i,t,d+1}), \tag{22}$$

where $\Delta p_{i,t,d}$ is the log price change for bond i on day d of month t.[13] At least 10 pairs of price change correlations are required in calculating this illiquidity measure.

We regress individual bond returns on our constructed market return measure (r_{MKT}) over a rolling 36-month estimation period to obtain bond market betas ($\beta_{r_{MKT}}$). In a similar way, we estimate term spread betas and default spread betas (β_{TERM} and β_{DEF}) in individual regressions including market returns. Term spread ($TERM$) is the difference in yields of 10-year and 1-year constant maturity treasuries, and default spread (DEF) is the difference between Moody's Baa and Aaa corporate bond yields, both from the Federal Reserve Economic Data (FRED) of St. Louis Federal Reserve Bank. We perform 3 by 3 independent sorts on our sample by *Ratings* and VaR, and the VaR_{HL} factor is calculated as the average return differences between the 3 highest and 3 lowest VaR portfolios. We estimate loadings of VaR_{HL} on monthly excess returns as $\beta_{VaR_{HL}}$, again controlling for market excess returns and with the 24-month minimum data requirement.

For additional tests, we create a bond momentum factor and beta (MOM and β_{MOM}), and a systematic liquidity factor and beta ($ILLIQ_{PS}$ and $\beta_{ILLIQ_{PS}}$). To create the MOM factor, we start by doing 5x5 double sorts on credit rating (*Ratings*) and bond momentum (cumulative returns from month t-6 to t-1) for our sample bonds.

[13] The more illiquid an asset, the larger the magnitude of the transitory component in its price movements. This transitory component shows up in negative serial correlations in price changes, thus this negative of the autocovariance can measure illiquidity (Bao et al. (2011))

Then we calculate the bond momentum factor as the difference between average returns of the 5 highest and 5 lowest momentum portfolios at each month t. Following Lin et al. (2011), Pástor and Stambaugh (2003) liquidity is measured for each month t. Liquidity betas are then estimated with this liquidity proxy and market returns using 5-year rolling windows. Bonds are placed into deciles by liquidity beta, and the $ILLIQ_{PS}$ factor is the difference between average returns of the highest β_{LIQ} decile and the lowest β_{LIQ} decile. In estimating β_{MOM} and $\beta_{ILLIQ_{PS}}$, we control for bond market returns. Controls for basic bond characteristics are $Size$ (the log of amount outstanding), $Coupon$ (coupon rate), and $Maturity$ (time to maturity in years).

4.1.5 Descriptive Statistics

Panel A of Table 1 shows descriptive statistics for the main variables of interest. We obtain a total of 999,233 monthly corporate bond returns during our sample period of July 2002 to June 2017. The summary statistics for corporate bond returns and their predictive variables are generally consistent with the results in previous literature (*e.g.*, Bai et al. (2018)). The mean excess return during this period is 0.796 percentage points, and the median is 0.523. On average, our sample bonds have a rating of Moody's Baa1 or equivalent (BBB+ for S&P and Fitch). *Credit Rating Ambiguity* (or CR_amb), our measure of credit news uncertainty, has a mean value of 0.232 and a median of 0.209. Our illiquidity estimates are about half of the number of returns, since we lose some observations due to the minimum requirement of 10 price change pairs within a month, and has skewness in its distribution. The number of VaR estimations are further reduced, as they require at least 24 months of return observations during the 36 month estimation period. The mean VaR is 5.771, while its median is 3.941.

Panel B shows correlations between the variables in Panel A, and conveys a clear message. Our empirical proxy of credit news ambiguity, CR_amb, has very little correlation with variables shown to predict bond returns in the extant literature. In particular, it is not highly correlated with VaR, which is a downside risk measure, or $\beta_{r_{MKT}}$, the traditional risk proxy. It also has a low correlation with $VolofVol$, which is an alternative ambiguity proxy suggested by prior studies.

[Insert Table 1 around here.]

4.2 Empirical Results

In this section, we analyze price reactions to credit rating announcements. Then, we study the cross-sectional predictability of corporate bonds using Fama and MacBeth (1973) and panel regressions under various empirical specifications.

4.2.1 Asymmetric Reactions to Good and Bad News

Price Reactions to Upgrades and Downgrades To analyze the model prediction of asymmetric price responses to good and bad news, we graph the daily log excess returns and CARs of individual bonds around the rating change announcement date (t).[14] We check a period of $[t-30, t+30]$ days and display the one-week window results in Figure 1. Panel A illustrates the clear asymmetry, with the amplitude of the negative reaction to downgrades being much larger than that for its positive upgrades counterpart.

[Insert Figure 1 around here.]

Table 2 expresses the pattern in numbers, with Panel A showing that the absolute value of average CARs over a $[t-3, t+3]$ day window[15] for downgrades is almost quadruple that of upgrades. Both graphically and numerically, we document the existence of larger reactions to bad news and smaller reactions to good news, finding

[14]Daily excess returns are computed against the market average return (amount-outstanding weighted). Cumulative abnormal returns (CARs) are the cumulative log excess returns during the specified time window.

[15]Results with different windows are nearly identical to those of $[t-3, t+3]$.

strong support for Hypothesis 1.

[Insert Table 2 around here.]

Bond Priority, Credit Risk, and Credit News Uncertainty Our model implies that debt priority structure is an important feature in corporate bond prices, suggesting an inverse relationship between priority of claims and susceptibility to credit news ambiguity. Panel B of Figure 1 graphs this feature, showing that downgraded subordinated bonds have more negative CARs than downgraded secured bonds. We confirm this phenomenon numerically in Panel B of Table 2, where both secured and subordinated bonds respond to good news on a similar scale, but the negative $[t-3,t+3]$ CARs for downgrades is almost double for subordinated bonds compared to secured bonds.

Credit risk also plays a role in explaining the asymmetric price responses in our model. We divide our sample into Investment (Moody's Baa equivalent or better) and Non-investment grade bonds to show that negative CARs for downgrades are much larger for noninvestment than for investment grade bonds (Panel C of Table 2). A distinguishing feature of our model stipulates that credit news ambiguity is a bond characteristic that accentuates the asymmetry of price reactions. We empirically test our uncertainty proxy CR_amb in this context, and show in Panels D of Figure 1 and Table 2 that indeed, bonds with higher ambiguity respond much more negatively to downgrades. Taken together, results strongly support our model conjecture of greater asymmetry in price reactions for junior, riskier, and more uncertain bonds to good and bad news (Hypothesis 2).

4.2.2 Credit News Uncertainty Premiums

Is CR_amb **Priced?** In this section, we describe how CR_amb predicts the cross section of corporate bond returns. We begin with univariate sorts of corporate bonds on CR_amb, reporting bond characteristics by its portfolio in Table 3. In each month, we form tercile portfolios on CR_amb, which allows us to match the number of observations quite evenly - around a third of our sample have zero dispersion (all agency ratings are concurrent, or the observation has only one available rating). The portfolios are weighted using bond amounts outstanding.

The differences in excess returns between the High CR_amb and Zero CR_amb terciles are statistically and economically significant, at approximately 9 basis points per month. Additionally, we find that the estimated alpha ($\alpha_{6factor}$) of the Zero CR_amb portfolio is significantly higher than that of the High CR_amb portfolio, controlling for well-known bond return factors - excess market returns, term spread, default spread, momentum factor, the Pastor-Stambaugh illiquidity factor, and the VaR factor. Bonds with higher CR_amb tend to have longer maturities, larger amounts outstanding, and higher market betas.

[Insert Table 3 around here.]

Our dataset contains a large cross section of corporate bonds, which we fully exploit in testing our hypotheses. First, we run Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns with CR_amb as our ambiguity proxy.

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{CR\_amb,t} \cdot CR\_amb_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{i,k,t} + \epsilon_{i,t+1}, \tag{23}$$

where $r_{i,t}$ is the excess return of corporate bonds and CR_amb is dispersion in credit ratings. To control for bond issue characteristics, we include credit rating scores, time to maturity, amount outstanding, and illiquidity. Lagged returns, volatility, skewness, kurtosis, and VaR control for return characteristics. For sensitivity to systematic risks, we employ return loadings of excess market returns, term spread, default spread, momentum factor, Pastor-Stambaugh illiquidity factor, and the VaR factor.

Table 4 shows results of Fama and MacBeth (1973) cross-sectional regressions with CR_amb. t-statistics with Newey and West (1987) standard errors that correct for serial correlation and heteroscedasticity (adjusted for 4 lags) are reported beneath the coefficient estimates. In all specifications, including those with controls for bond characteristics (columns 2 to 5), higher moments of bond returns (columns 3 and 5), and sensitivities to various price factors (columns 4 and 5), CR_amb has a significant and positive relation with the cross section of one-month-ahead excess bond returns. The significant and positive sign is consistent with hypothesis 3.

[Insert Table 4 around here.]

Next, we construct and test a return-based factor based on credit news ambiguity, CR_amb, and examine whether the proposed factor can help explain the cross section of corporate bond returns. First, to construct the CR_amb portfolio factor, we form bivariate portfolios by independently sorting bonds into three portfolios with their credit rating, and three portfolios with their CR_amb values. The factor of CR_amb is the value-weighted average return difference between the high CR_amb portfolio and the zero CR_amb portfolio across the rating portfolios. To verify if this factor is priced, we estimate the factor beta (denoted β_{CR_amb}) for each bond at each month, from monthly rolling regressions of excess bond returns on the CR_amb factor over a 36-month window. Finally, we run the following cross-sectional regressions with

β_{CR_amb} as well as bond characteristics and sensitivities to various price factors.

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{\beta_{CR\_amb,t}} \cdot \beta_{CR\_amb_{i,t}} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{i,k,t} + \epsilon_{i,t+1}. \tag{24}$$

According to Table 5, a positive and statistically significant ambiguity premium via credit news prevails. Note that the magnitudes of the coefficients for β_{CR_amb} are stable across all regressions, which supports our prediction of a credit news uncertainty premium. Adequate controls for risk factors are critical for our empirical analysis. Our results are robust to the inclusion of conventional bond risk factors and other variables that can capture the cross section of return distribution such as $Skewness$ and $Kurtosis$. Higher moments of bond returns do not drive out credit news ambiguity.

[Insert Table 5 around here.]

Robustness Checks and Discussions A number of prior studies explore how return volatility or volatility of volatility can be linked to ambiguity. In addition, the existing work finds that uncertainty in macroeconomic variables plays an instrumental role in explaining asset returns. Uncertainty measures related to the stock market can affect the corporate bond market as well. We scrutinize these alternative empirical specifications by incorporating variables that proxy for the uncertainties mentioned. Tables 6 and 7 tabulate the results.

[Insert Table 6 around here.]

In Table 6, we again use Model (23) to extend the empirical models. We add volatilities of return volatility from both corporate bond and stock markets, analyst forecast dispersions for each issuer, and sensitivities (betas) to interest rate, inflation, and the real GDP ambiguities. The results strongly suggest that credit news ambiguity

(CR_amb) is a significant predictor of corporate bond returns, while most alternative uncertainty measures are statistically and economically insignificant. Whereas volatility of stock volatility ($VolofVol_{stock}$) tends to have negative effects on returns, the volatility of bond return volatility ($VolofVol$) is significant with a positive sign.

[Insert Table 7 around here.]

As an extension, we address our research question by incorporating both individual and aggregate variables in the following panel regression setting.

$$r_{i,t+1} = \beta_0 + \beta_{0,i} + \Sigma\beta_{0,Year} \cdot Year + \beta_{CR\_amb} \cdot CR\_amb_{i,t} + \sum_{k=1}^{K} \beta_k \cdot Control_{i,k,t} + \epsilon_{i,t+1}, \quad (25)$$

where $\beta_{0,i}$ captures the issuer-fixed effect, and $\beta_{0,Year}$, the year-fixed effect.

Table 7 reports estimates of panel regressions of one-month-ahead corporate bond excess returns on predictive variables with year and issuer fixed effects. 2-way clustered t-statistics (issuer, year) appear in parentheses. Consistent with previous results, CR_amb significantly and positively predicts corporate bond returns. One major difference compared to Table 6 is that $VolofVol$ does not have statistical significance in any model. $Volatility$ loses its power once all the macro ambiguity proxies (r_amb, $infla\_amb$, $rgdp\_amb$, and VIX) have been added into the regression model.[16]

In sum, both Fama and MacBeth (1973) (Table 6) and panel regressions (Table 7) show that in various specifications with volatility, volatility of volatility, and other uncertainty measures, CR_amb continues to maintain significant predictive power on one-month-ahead excess returns. As mentioned earlier, the measure of credit rating ambiguity is normalized by the square root of the average credit rating. To verify the sensitivity of our results to the choice of dispersion measures, we adopt the raw

[16] Some stock market variables, such as $VolofVol_{stock}$, are also added in the regression model. CR_amb is statistically significant with a positive coefficient in all specifications, while stock market variables are insignificant. These results are available from the authors.

dispersion measure ($STDDEV_{Ratings_{i,t}}$) to repeat our panel analysis, and Table 8 shows that the results are highly significant.

[Insert Table 8 around here.]

We consider two historical events in accounting for the ambiguity premium. The financial crisis is an important period in which uncertainty in credit news culminated, and the Dodd-Frank Act aimed at enhancing the transparency of credit ratings. The period of financial turmoil is naturally accompanied by extreme observations in key explanatory variables, especially return volatility and downside risk, and to confirm that our results are not driven by this specific time period, we run panel regressions with observations in years 2007 and 2008 excluded in Table 9 (columns 1 to 3). In all subsamples we test, CR_amb continues to predict future returns, suggesting that ambiguity in credit news matters, even if the economy does not experience financial distress.

In addition, we regard the Dodd-Frank Act as a major economic event requiring CRAs to disclose more information in an expedient manner. Regressions by subperiods before and after the enactment on July 21st 2010 (columns 4 and 5 respectively) tie well with the theory that more news is not necessarily better, as the size of the credit news ambiguity premium is larger and statistically significant in the period following the Act.

[Insert Table 9 around here.]

We document clear evidence of differences in bond price reaction asymmetry according to bond priority and bond risk in Table 2. We explore the possibility that these characteristics may also affect credit news ambiguity premiums in Table 10. As in the case of price reactions, the effect of credit news ambiguity differs greatly by bond subsample with its priority and credit risk. First, comparing investment grade (column

1) and non-investment grade bonds (column 2), we see that CR_amb produces a much larger premium in riskier bonds. Related, one interesting and important observation is that for investment-grade bonds, the interest rate ambiguity (r_{amb}) term becomes highly significant both economically and statistically. Kim (2016) shows that the interest rate ambiguity strongly predicts future returns of treasury bonds, which are arguably the safest assets in terms of credit risk. The results from bond subsamples connote that market participants focus more on credit news uncertainty for credit-riskier bonds, whereas they appear to pay more attention to the uncertainty in interest rate news for credit-safer bonds. Thus, our results shed additional light on sources of uncertainties priced in the cross section of bond prices. Similarly, the effect is much more significant for subordinated bonds (column 4) than for secured bonds (column 3). The empirical evidence again supports our hypothesis of credit news ambiguity having greater impact on bonds with more risk or lower priority.

Does the aggregate level of credit news ambiguity matter? Our main measure is issue-specific, so it is natural to investigate if macro-level effects explain our result. To this end, we repeat panel regressions in Table 11 with aggregate credit rating ambiguity ($TotalCR\_amb$) included, and find results that are qualitatively similar to previous specifications. Our aggregate measure is marginally significant, suggesting that there does exist an aggregate channel of credit news ambiguity, but our main result is still intact for the whole sample and all subsamples with different priority and credit risk structures, stating that individual-level uncertainty does matter.

[Insert Table 10 around here.]

[Insert Table 11 around here.]

Whereas the credit rating literature often argues that more news is better for investors, our model states that this is not necessarily the case, and more news can mean more ambiguity if the quality of news is uncertain and bond investors are ambiguity-averse. We show this briefly in Table 9, and elaborate here as it is a key theme of this paper. In fact, this is an important economic mechanism that allows us to use dispersions among credit rating agencies as a credit news ambiguity measure. This line of reasoning allows us to derive another testable implication from the theory - additional credit ratings do not mean a decrease the size of the uncertainty premium, provided that the additional credit rating is sufficiently informative.

Table 12 documents evidence to support our view, by showing the price of ambiguity according to the number of ratings available. Excluding issues with a single rating (for which CR_amb is zero by definition), we test for the effect of credit news ambiguity in subsamples with 2 available ratings (column 1) and 3 available ratings (column 2). The results show that the effect of ambiguity is both positive and significant in both samples, and larger in the sample with more ratings. We repeat the analysis for those issues with non-zero CR_amb (column 3 for 2 ratings and column 4 for 3 ratings), and find similar results. It is worth noting here that our empirical credit news ambiguity measure assigns zero values to those observations with only one rating. With this observation, we do not argue that there is no ambiguity in these cases, but simply that this downward bias should work *against* our case. Preferring to err on the side of conservatism, we still find economically and statistically meaningful results.

[Insert Table 12 around here.]

Finally, we investigate asymmetric price responses and credit news uncertainty premiums in an integrated setting. The results are coherent when taken together, and consistent with the theory. This specification incorporates *changes* in ambiguity, ratings and their interactions. Since theory dictates that responses to good and bad news are asymmetric, we differentiate between increases and decreases in ambiguity

(CR_amb+ and CR_amb-) as well as deteriorations and improvements in credit quality ($\Delta Downgrade$ and $\Delta Upgrade$). Table 13 shows that credit news ambiguity (CR_amb) significantly predicts future returns in all specifications, even with changes and their interactions present. Increases in credit news ambiguity (CR_amb+) is positively related to increases in return premium (columns 1, 3, and 5), which is only subsumed by the interaction of ambiguity increase and rating downgrade ($\Delta CR\_amb+ \times \Delta Downgrade$) in columns 2, 4, and 6. The strong reaction to deteriorations in both aspects is a natural implication of the model.

[Insert Table 13 around here.]

5 Conclusion

This paper develops and tests a corporate bond pricing model that incorporates the investor's concern about the quality of credit news and learning in an ambiguous information environment. The model proposes an empirical measure of credit news ambiguity that is intuitive and easy to quantify. Despite its simple structure, the model generates a rich set of testable implications. First, the model can explain one of the long-standing puzzles in the corporate bond price literature - the asymmetric reaction to good and bad news. Many studies find that on the arrival of credit news, corporate bond prices show significantly negative reactions to bad news, yet insignificantly positive reactions to good news. Existing theories based on risk have difficulty in explaining the aforesaid results, whereas our model produces the feature. Second, the theory also suggests economic links between debt priority structure, risk, the size of ambiguity, and premiums for taking uncertainty. Third, and perhaps most interestingly, multiplicity in sources of credit news does not guarantee the reduction of ambiguity. In fact, ambiguity may increase under these circumstances due to mixed signals.

We document empirical findings that strongly support our model. Our measure of credit news ambiguity performs well after controlling for variables known to affect corporate bond returns in the literature. This measure outperforms or even renders insignificant, many other possible proxies for risk and uncertainty.

Appendix

This appendix derives some theoretical results in section 3.

A.1. Proof: Credit News Uncertainty Premium

We repeat the equation for a two-period corporate bond price from section 3.3.

$$
\begin{aligned}
Q_0^{(2)} &= \min \frac{E\left[\phi_0 Q_1^{(1)} + (1-\phi_0)X\right]}{1+r} \\
&= \min \frac{E\left[\left(\bar{\phi} + \beta_0^* z_0\right)\left(\frac{X+(1-X)\left(\bar{\phi}+E[\beta_1^* z_1]\right)}{1+r}\right) + \left(1-\left(\bar{\phi}+\beta_0^* z_0\right)\right)X\right]}{1+r}.
\end{aligned}
$$

To derive the result involving the term $E[\beta_1^* z_1]$, we use the properties of a truncated normal distribution. Specifically, in case of the standard normal random variable x, the following theorem holds.

$$
\begin{aligned}
E(x|x > a) &= \lambda(a), \\
E(x|x < a) &= -\lambda(-a),
\end{aligned} \tag{26}
$$

where a is a threshold, $\lambda(\cdot)$ is the hazard function, or the ratio of the normal probability density function to 1−cumulative distribution function. Similarly, the conditional variance of the standard normal distribution can be computed as follows:

$$
\begin{aligned}
Var(x|x > a) &= 1 - \lambda(a)\left(\lambda(a) - a\right), \\
Var(x|x < a) &= 1 - \lambda(-a)\left(a + \lambda(-a)\right).
\end{aligned} \tag{27}
$$

Then, we compute the following result.

$$
\begin{aligned}
(1+r)Q_0^{(2)} &= \min E\left[\left(\bar{\phi} + \beta_0^* z_0\right)\left(\frac{X + (1-X)\bar{\phi} + (1-X)E[\beta_1^* z_1]}{1+r}\right) + \left(1 - \bar{\phi}X - \beta_0^* z_0 X\right)\right] \\
&= \bar{\phi}\left(\frac{X + (1-X)\bar{\phi}}{1+r}\right) + 1 - \bar{\phi}X \\
&\quad - \left(\frac{1}{1+r}\right)\left(\frac{\bar{\beta}_0 - \underline{\beta}_0}{\sqrt{\beta_0^*}}\right)\sqrt{\frac{\sigma_\phi^2}{2\pi}}\left((1-X)\left[\bar{\phi} - E\left(\frac{\bar{\beta}_1 - \underline{\beta}_1}{\sqrt{\beta_1^*}}\right)\right]\sqrt{\frac{\sigma_\phi^2}{2\pi}} - rX\right)
\end{aligned}
$$

Using the above result, we can derive the credit news uncertainty premium.

A.2. Proof: Cross-sectional Dispersions of Credit News

When there exist two sources of credit news as in section 3.4, the investor updates the conditional likelihood of new information using z^1 and z^2 to compute the posterior mean as follows. Similar to the univariate case, the investor projects ϕ onto information sources z_0^1 and z_0^2, expressed as follows,

$$E\left[\phi|z_0^1, z_0^2\right] = \bar{\phi} + E\left[\varepsilon_1|z_0^1, z_0^2\right].$$

Then, $E\left[\varepsilon_1|z_0^1, z_0^2\right] = \beta_1 z_0^1 + \beta_2 z_0^2$ can be computed by the following formula.

$$\left[\begin{array}{c} \beta_1 \\ \beta_2 \end{array}\right] = \left(\left[\begin{array}{cc} E\left(z_0^1\right)^2 & E z_0^1 z_0^2 \\ E z_0^1 z_0^2 & E\left(z_0^2\right)^2 \end{array}\right]\right)^{-1} E\left[\begin{array}{c} z_0^1 \varepsilon_1 \\ z_0^2 \varepsilon_1 \end{array}\right].$$

From the setup, it is easy to show $E\left(z_0^1\right)^2 = \varphi_1^2\sigma_\phi^2 + \sigma_{z,1}^2$, $E\left(z_0^2\right)^2 = \varphi_2^2\sigma_\phi^2 + \sigma_{z,2}^2$, $E z_0^1 z_0^2 = \varphi_1\varphi_2\sigma_\phi^2$, $E z_0^1\varepsilon_1 = \varphi_1\sigma_\phi^2$, and $E z_0^2\varepsilon_1 = \varphi_2\sigma_\phi^2$. Then, we have

$$\left(\left[\begin{array}{cc} E\left(z_0^1\right)^2 & E z_0^1 z_0^2 \\ E z_0^1 z_0^2 & E\left(z_0^2\right)^2 \end{array}\right]\right)^{-1} = \frac{\left[\begin{array}{cc} \varphi_2^2\sigma_\phi^2 + \sigma_{z,2}^2 & -\varphi_1\varphi_2\sigma_\phi^2 \\ -\varphi_1\varphi_2\sigma_\phi^2 & \varphi_1^2\sigma_\phi^2 + \sigma_{z,1}^2 \end{array}\right]}{\varphi_1^2\sigma_\phi^2\sigma_{z,2}^2 + \sigma_{z,1}^2\varphi_2^2\sigma_\phi^2 + \sigma_{z,1}^2\sigma_{z,2}^2}.$$

Then, putting the terms together, we have

$$\left[\begin{array}{c} \beta_1 \\ \beta_2 \end{array}\right] = \frac{\left[\begin{array}{cc} \varphi_2^2\sigma_\phi^2 + \sigma_{z,2}^2 & -\varphi_1\varphi_2\sigma_\phi^2 \\ -\varphi_1\varphi_2\sigma_\phi^2 & \varphi_1^2\sigma_\phi^2 + \sigma_{z,1}^2 \end{array}\right]\left[\begin{array}{c} \varphi_1\sigma_\phi^2 \\ \varphi_2\sigma_\phi^2 \end{array}\right]}{\varphi_1^2\sigma_\phi^2\sigma_{z,2}^2 + \sigma_{z,1}^2\varphi_2^2\sigma_\phi^2 + \sigma_{z,1}^2\sigma_{z,2}^2},$$

or

$$\begin{aligned} \beta_1 &= \frac{\varphi_1\sigma_\phi^2}{\varphi_1^2\sigma_\phi^2 + \sigma_{z,1}^2 + \varphi_2^2\sigma_\phi^2\frac{\sigma_{z,1}^2}{\sigma_{z,2}^2}}, \\ \beta_2 &= \frac{\varphi_2\sigma_\phi^2}{\varphi_2^2\sigma_\phi^2 + \sigma_{z,2}^2 + \varphi_1^2\sigma_\phi^2\frac{\sigma_{z,2}^2}{\sigma_{z,1}^2}}. \end{aligned}$$

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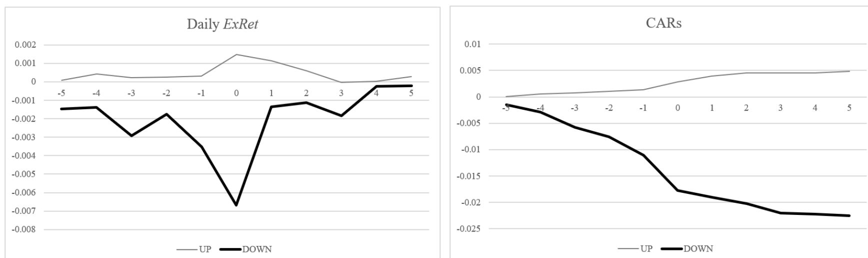
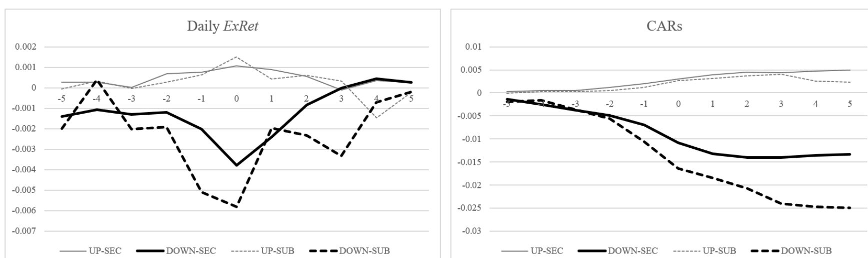
Figure 1: **Daily returns and CARs around credit news announcements - Upgrades and downgrades**

This figure shows daily excess returns (*ExRet*) and cumulative abnormal returns (CARs) around credit rating upgrades and downgrades. Panel A shows results for the entire sample, Panel B for Secured/Subordinated, Panel C for Investment/Non-investment grade, and Panel D for Low/High ambiguity (*CR_amb*) subsamples. The solid or dashed lines plot return responses to good news, while the bold solid or bold dashed lines represent return reactions to bad news. All returns are log returns, and the sample period is July 2002 to June 2017.

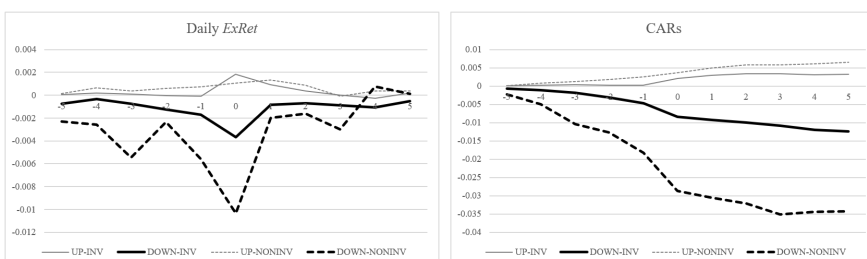
(a) Panel A - Total Sample



(b) Panel B - Secured/Subordinated Bonds



(c) Panel C - Investment/Non-investment Grade



(d) Panel D - Low/High Ambiguity (*CR_amb*)

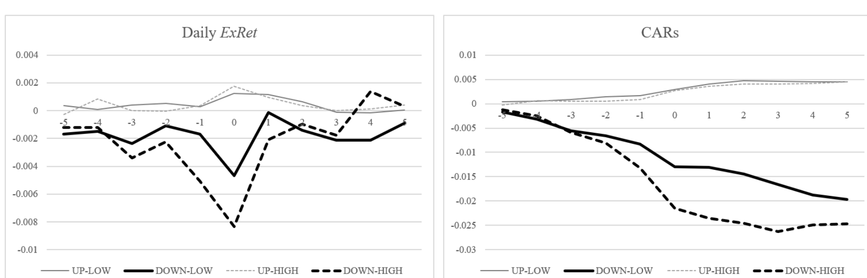


Table 1: **Summary Statistics**

This table reports descriptive statistics and correlations for predictive variables of corporate bond returns. $ExRet$ is monthly bond returns in excess of the risk-free rate in percentage points, CR_amb is the credit news ambiguity measure (STDDEV_score/sqrt($Ratings$)), $Ratings$ is the average credit rating score, $Maturity$ is the time to maturity of the bond in years, $Size$ is the log of bond amount outstanding, $VolofVol$ is bond-specific volatility of realized volatility measured using 36 prior monthly volatilities, $Illiquidity$ is the covariance of daily log price changes within a month multiplied by -1 (after Bao, Pan, and Wang (2011)), VaR is based on the second-lowest observation from 36 prior monthly returns multiplied by -1, and $\beta_{r_{MKT}}$ is bond market beta estimated using a 36-month rolling window. The sample period is July 2002 to June 2017.

Panel A: Descriptive Statistics of Predictive Variables						
$Variable$	Obs	$Mean$	$Median$	$StdDev$	$25th$	$75th$
$ExRet$	999,233	0.796	0.523	4.136	-0.289	1.830
CR_amb	999,233	0.232	0.209	0.240	0	0.343
$Ratings$	999,233	8.584	8	3.999	6	10.333
$Maturity$	999,233	9.340	6.400	8.577	3.589	11.104
$Size$	998,556	12.418	12.766	1.619	11.984	13.458
$VolofVol$	573,426	0.786	0.502	0.948	0.291	0.894
$Illiquidity$	545,659	1.096	0.098	11.198	0.017	0.443
VaR	459,416	5.771	3.941	6.132	2.290	6.698
$\beta_{r_{MKT}}$	423,405	1.124	0.939	0.914	0.542	1.483

Panel B: Correlations of Corporate Bond Return Predictive Variables								
	CR_amb	$Ratings$	Mat	$Size$	VoV	$Illiq$	VaR	$\beta_{r_{MKT}}$
CR_amb	1.000							
$Ratings$	-0.128	1.000						
$Maturity$	0.007	-0.118	1.000					
$Size$	-0.018	-0.105	-0.014	1.000				
$VolofVol$	0.059	0.243	0.095	-0.246	1.000			
$Illiquidity$	0.024	0.096	0.019	-0.053	0.133	1.000		
VaR	0.073	0.427	0.164	-0.073	0.601	0.155	1.000	
$\beta_{r_{MKT}}$	0.034	0.265	0.311	0.044	0.364	0.073	0.602	1.000

Table 2: **Price Response to Upgrades and Downgrades**

This table reports average cumulative abnormal returns (CARs) for announcements of credit rating upgrades and downgrades (day t), and the results of t-tests for *absolute* differences between them. The announcement windows are from 3 days before the announcement ($t-3$) to 3 days following the announcement date ($t+3$). Panel A shows CARs for the total sample, Panel B for Secured/Subordinated, Panel C for Investment/Non-investment grade, and Panel D for Low/High ambiguity (CR_amb) subsamples. t-stats for tests of differences are reported in parentheses. The sample period is July 2002 to June 2017.

Panel A:	UP		DOWN			
	0.0025		-0.0094			
$\mid DOWN \mid - \mid UP \mid$	$Diff$	0.0069	$t-stat$	(14.17)		
Panel B:	Secured		Subordinate		SEC-SUB	
	UP	DOWN	UP	DOWN	UP	DOWN
	0.0019	-0.0062	0.0023	-0.0105	-0.0004	0.0042
$\mid DOWN \mid - \mid UP \mid$	0.0043	(8.42)	0.0082	(4.75)	(-0.66)	(4.11)
Panel C:	Investment		Non-Investment		INV-NONINV	
	UP	DOWN	UP	DOWN	UP	DOWN
	0.0025	-0.0052	0.0025	-0.0149	0.0000	0.0092
$\mid DOWN \mid - \mid UP \mid$	0.0026	(5.89)	0.0124	(12.99)	(0.07)	(12.73)
Panel D:	Low CR_amb		High CR_amb		LOW-HIGH	
	UP	DOWN	UP	DOWN	UP	DOWN
	0.0024	-0.0072	0.0027	-0.0116	-0.0003	0.0044
$\mid DOWN \mid - \mid UP \mid$	0.0048	(9.38)	0.0089	(10.31)	(-0.92)	(6.14)

Table 3: **Tercile Portfolios Sorted by Credit Rating Ambiguity (**CR_amb**)**

This table reports bond characteristics for tercile portfolios sorted by CR_amb. Tercile 1 has zero CR_amb values and Tercile 3 has highest CR_amb values. Each portfolio is value-weighted using bond amounts outstanding as weights. *ExRet* is excess returns and α_6 is the 6-factor alpha, which includes excess bond market returns, term spread, default spread, momentum factor, the Pastor-Stambaugh illiquidity factor, and VaR factor. *Ratings* is the average credit rating score, $Maturity$ is the time to maturity of the bond in years, $Size$ is the log of bond amount outstanding, *Illiquidity* is the covariance of daily log price changes within a month, multiplied by -1 (after Bao, Pan, and Wang (2011)), and $\beta_{r_{MKT}}$ is bond market beta, estimated using a 36-month rolling window. Newey-West corrected t-statistics (adjusted for 4 lags) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

Panel A: Bond Characteristics for Portfolios by CR_amb									
Tercile	Obs	CR_amb	*ExRet*	$\alpha_{6factor}$	*Ratings*	$Maturity$	$Size$	*Illiquidity*	$\beta_{r_{MKT}}$
Zero CR_amb	292,789	0.00	0.74	-0.06	7.62	9.49	13.62	0.51	0.49
Mid CR_amb	300,281	0.21	0.78	-0.05	9.23	9.38	13.53	0.53	0.59
High CR_amb	300,542	0.46	0.84	0.15	7.42	8.44	13.80	0.75	0.60
High - Zero		0.46	0.09	0.21	-0.20	-1.05	0.17	0.24	0.11
			(2.18)	(1.83)	(-1.70)	(-12.96)	(7.12)	(1.71)	(9.01)

Table 4: **Fama-MacBeth Cross-Sectional Regressions with Credit Rating Ambiguity (CR_amb)**

This table reports estimates of Fama and MacBeth (1973) cross-sectional regressions of one-month ahead corporate bond excess returns on predictive variables: $r_{i,t+1} = \lambda_{0,t} + \lambda_{CR\_amb,t} \cdot CR\_amb_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{i,k,t} + \epsilon_{i,t+1}$, where $r_{i,t}$ is the excess return ($ExRet$) of corporate bonds. CR_amb is the credit rating ambiguity measure. $Ratings$ is the average credit rating score, $Maturity$ is the time to maturity of the bond in years, $Size$ is the log of bond amount outstanding, and $Illiquidity$ is the covariance of daily log price changes within a month, multiplied by -1 (after Bao, Pan, and Wang (2011)). $Volatility$, $Skewness$, and $Kurtosis$ are measured using prior 36 monthly returns, β_x are loadings on x, which are excess market return (r_{MKT}), term spread ($TERM$), default spread (DEF), momentum factor (MOM), PS illiquidity factor ($ILLIQ_{PS}$), and the VaR factor (VaR_{HL}), estimated over 36-month rolling windows. Newey-West corrected t-statistics (adjusted for 4 lags) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds				
CR_amb	0.44	0.37	0.17	0.22	0.14
	(2.68)	(3.25)	(2.12)	(2.67)	(2.39)
$Ratings$	0.07	0.07	0.03	0.03	0.03
	(3.34)	(3.32)	(1.74)	(2.17)	(1.65)
$Maturity$		0.01	0.01	0.00	0.00
		(2.60)	(1.69)	(1.08)	(1.01)
$Size$		0.06	0.05	0.04	0.04
		(2.66)	(2.35)	(3.15)	(1.96)
$Illiquidity$		0.01	0.00	0.01	0.01
		(1.02)	(0.20)	(0.75)	(0.72)
$ExRet_{lagged}$			-0.10		-0.09
			(-5.31)		(-5.12)
$Volatility$			0.03		-0.02
			(0.32)		(-0.23)
$Skewness$			-0.02		-0.02
			(-0.93)		(-0.83)
$Kurtosis$			0.01		0.01
			(1.11)		(0.89)
VaR			0.03		0.03
			(1.98)		(2.53)
$\beta_{r_{MKT}}$				0.15	0.07
				(2.38)	(1.27)
β_{TERM}				0.19	0.16
				(1.54)	(1.93)
β_{DEF}				-0.16	-0.10
				(-2.01)	(-1.80)
β_{MOM}				0.09	0.13
				(0.75)	(1.25)
$\beta_{ILLIQ_{PS}}$				0.00	0.01
				(0.60)	(0.79)
$\beta_{VaR_{HL}}$				0.04	0.03
				(0.74)	(0.57)
Constant	0.10	-0.88	-0.58	-0.47	-0.44
	(0.71)	(-2.73)	(-1.74)	(-2.64)	(-1.31)
Obs	893,612	526,728	285,626	245,036	244,975

Table 5: **Fama-MacBeth Cross-Sectional Regressions with β_{CR_amb}**

This table reports estimates of Fama and MacBeth (1973) cross-sectional regressions of one-month ahead corporate bond excess returns on betas: $r_{i,t+1} = \lambda_{0,t} + \lambda_{\beta_{CR\_amb,t}} \cdot \beta_{CR\_amb_{i,t}} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{i,k,t} + \epsilon_{i,t+1}$, where $r_{i,t}$ is the excess return on corporate bonds. Betas are estimated from time-series regressions. To obtain $\beta_{CR\_amb,t}$, we first construct the CR_amb variable, then form 3x3 bivariate portfolios by independent sorts on credit ratings and CR_amb values. The CR_amb factor is the value-weighted average return difference between the high CR_amb portfolio and the zero CR_amb portfolio across the rating portfolios. Then, for each bond at each month, we estimate β_{CR_amb} from rolling regressions of excess bond returns on the CR_amb factor over a 36-month window. The other regressors are defined in Table 4. Newey-West corrected t-statistics (adjusted for 4 lags) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds				
β_{CR_amb}	0.08	0.08	0.06	0.07	0.06
	(2.51)	(2.49)	(2.46)	(2.55)	(2.33)
$Maturity$	0.01	0.01	0.00	0.01	0.01
	(1.97)	(2.33)	(0.94)	(1.15)	(1.46)
$Size$	0.02	0.02	0.02	0.02	0.04
	(0.64)	(0.76)	(1.14)	(1.15)	(2.87)
$Illiquidity$	0.01	0.01	0.01	0.01	0.01
	(0.50)	(0.51)	(0.71)	(0.72)	(0.57)
$ExRet_{lagged}$		-0.06		-0.07	-0.08
		(-2.98)		(-3.48)	(-3.96)
$Ratings$					0.03
					(1.59)
$\beta_{r_{MKT}}$			0.18	0.21	0.18
			(2.35)	(2.61)	(2.65)
β_{TERM}			0.19	0.21	0.22
			(1.31)	(1.62)	(1.83)
β_{DEF}			-0.17	-0.14	-0.15
			(-2.11)	(-2.04)	(-2.02)
β_{MOM}			0.14	0.21	0.19
			(1.26)	(1.64)	(1.57)
$\beta_{ILLIQ_{PS}}$			0.01	0.01	0.00
			(1.61)	(1.56)	(0.48)
$\beta_{VaR_{HL}}$			0.03	0.01	0.02
			(0.48)	(0.21)	(0.25)
Constant	0.35	0.34	0.19	0.21	-0.29
	(0.88)	(0.92)	(0.73)	(0.85)	(-1.57)
Obs	275,683	275,613	245,036	244,975	244,975

Table 6: **Fama-MacBeth Cross-Sectional Regressions with Alternative Ambiguity Measures**

This table reports estimates of Fama and MacBeth (1973) cross-sectional regressions of one-month ahead corporate bond excess returns on predictive variables: $r_{i,t+1} = \lambda_{0,t} + \lambda_{CR\_amb,t} \cdot CR\_amb_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Control_{i,k,t} + \epsilon_{i,t+1}$, where $r_{i,t}$ is the excess return ($ExRet$) of corporate bonds. $VolofVol_{stock}$ is stock-specific volatility of realized volatility of the bond issuer, using 36 prior monthly volatilities. $Disp_{EPS}$ is the dispersion of analyst EPS forecasts from I/B/E/S measured as STDDEV_feps/sqrt(abs(mean_FEPS)). β_x are loadings on x, which are interest rate ambiguity (r_amb), inflation ambiguity ($infla\_amb$), and real GDP growth ambiguity ($rgdp\_amb$) in the macro-economy, constructed from the Survey of Professional Forecasters (SPF). Other regressors are as defined in Table 4. Newey-West corrected t-statistics (adjusted for 4 lags) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds					
CR_amb	0.13	0.14	0.20	0.19	0.13	0.14
	(2.55)	(2.27)	(2.78)	(2.72)	(2.59)	(2.32)
$Ratings$	0.03	0.03	0.03	0.03	0.03	0.04
	(2.47)	(2.62)	(2.39)	(1.91)	(2.74)	(2.93)
$Maturity$	0.00	0.00	0.00	0.01	0.00	0.00
	(0.49)	(0.47)	(1.01)	(1.23)	(0.26)	(0.27)
$Size$	0.06	0.06	0.04	0.04	0.05	0.05
	(2.96)	(2.85)	(2.88)	(2.85)	(2.91)	(2.77)
$Illiquidity$	-0.01	-0.01	0.01	0.01	-0.01	-0.01
	(-0.73)	(-0.68)	(1.01)	(0.78)	(-0.51)	(-0.49)
$ExRet_{lagged}$		-0.15		-0.08		-0.16
		(-9.88)		(-4.68)		(-9.97)
$\beta_{r_{MKT}}$	0.18	0.21	0.14	0.18	0.17	0.21
	(2.79)	(2.96)	(2.19)	(2.62)	(2.58)	(2.84)
β_{TERM}	0.10	0.12	0.18	0.22	0.08	0.10
	(0.72)	(0.85)	(1.36)	(1.59)	(0.77)	(0.97)
β_{DEF}	-0.10	-0.11	-0.08	-0.09	-0.04	-0.05
	(-1.56)	(-1.47)	(-1.14)	(-1.25)	(-1.05)	(-1.21)
β_{MOM}	0.09	0.07	0.04	0.05	0.11	0.09
	(0.81)	(0.64)	(0.35)	(0.52)	(1.09)	(0.89)
$\beta_{ILLIQ_{PS}}$	0.01	0.01	0.01	0.01	0.00	0.00
	(0.43)	(0.45)	(0.72)	(0.53)	(0.37)	(0.39)
$\beta_{VaR_{HL}}$	-0.03	-0.03	0.08	0.08	-0.02	-0.01
	(-0.95)	(-0.95)	(1.17)	(1.09)	(-0.53)	(-0.41)
$VolofVol$	0.21	0.23			0.22	0.24
	(2.58)	(2.70)			(3.08)	(3.18)
$VolofVol_{stock}$	-0.22	-0.26			-0.21	-0.26
	(-2.85)	(-3.12)			(-2.74)	(-2.98)
$Disp_{EPS}$	0.00	-0.01			-0.00	-0.01
	(0.08)	(-0.20)			(-0.08)	(-0.34)
β_{r_amb}			-0.01	-0.02	0.01	0.02
			(-0.46)	(-0.68)	(0.52)	(0.70)
β_{infla_amb}			-0.00	-0.00	-0.01	-0.01
			(-0.03)	(-0.14)	(-0.63)	(-0.56)
β_{rgdp_amb}			-0.00	0.00	-0.00	-0.00
			(-0.07)	(0.22)	(-0.35)	(-0.09)
Constant	-0.45	-0.37	-0.38	-0.34	-0.41	-0.31
	(-1.95)	(-1.53)	(-2.40)	(-2.14)	(-2.03)	(-1.47)
Obs	144,377	144,342	245,036	244,975	144,377	144,342

Table 7: **Panel Regressions with Credit Rating Ambiguity (CR_amb)**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables of various specifications, with year and issuer fixed effects. VIX is the S&P 500 VIX index from CBOE. Other regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds				
CR_amb	0.64	0.46	0.46	0.47	0.46
	(2.17)	(2.06)	(2.06)	(2.05)	(2.04)
$Ratings$	0.24	0.14	0.14	0.14	0.14
	(3.42)	(3.27)	(3.28)	(3.30)	(3.22)
$Coupon$	-0.01	0.04	0.04	0.04	0.04
	(-0.49)	(2.14)	(2.18)	(2.21)	(2.04)
$Maturity$	0.02	-0.01	-0.01	-0.00	-0.00
	(2.35)	(-0.51)	(-0.49)	(-0.48)	(-0.48)
$Size$	0.00	0.00	0.00	0.00	0.00
	(1.27)	(2.08)	(2.10)	(1.76)	(1.76)
$ExRet_{lagged}$	-0.15	-0.08	-0.08	-0.08	-0.08
	(-2.80)	(-1.19)	(-1.17)	(-1.10)	(-1.03)
$Illiquidity$		0.01	0.01	0.01	0.01
		(1.11)	(1.08)	(1.02)	(1.17)
$Volatility$		0.33	0.33	0.33	0.31
		(1.86)	(1.82)	(1.82)	(1.55)
$Skewness$		-0.05	-0.05	-0.05	-0.05
		(-0.98)	(-1.06)	(-0.95)	(-0.95)
$Kurtosis$		0.02	0.02	0.02	0.02
		(1.20)	(1.31)	(1.16)	(1.18)
VaR		5.33	5.19	5.18	5.23
		(1.84)	(1.93)	(1.91)	(1.93)
$\beta_{r_{MKT}}$		-0.05	-0.06	-0.06	-0.05
		(-0.48)	(-0.48)	(-0.47)	(-0.46)
$VolofVol$			0.03	0.03	0.03
			(0.26)	(0.26)	(0.30)
r_{MKT}	0.31	0.20	0.20	0. 20	0.24
	(3.48)	(2.33)	(2.36)	(2.22)	(2.02)
$TERM$	0.75	0.53	0.52	0.47	0.49
	(2.62)	(2.96)	(3.00)	(2.30)	(2.80)
DEF	1.42	0.99	0.99	0.99	0.62
	(2.95)	(2.44)	(2.45)	(2.29)	(1.36)
r_amb				0.68	0.53
				(1.42)	(1.00)
$infla\_amb$				-0.05	0.02
				(-0.11)	(0.03)
$rgdp\_amb$				-0.57	-0.95
				(-0.69)	(-1.12)
VIX					0.03
					(1.44)
Constant	-4.57	-3.58	-3.58	-3.52	-3.57
	(-4.14)	(-4.97)	(-4.96)	(-7.22)	(-7.76)
$Adj.R^2$	0.074	0.083	0.083	0.084	0.085
Obs	829,291	275,522	275,522	275,522	275,481

Table 8: **Panel Regressions with an Alternative Credit Rating Ambiguity ($STDDEV\_Ratings$)**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables of various specifications, with year and issuer fixed effects. For credit rating ambiguity, the standard deviation of credit ratings for each issuer, denoted as $STDDEV\_Ratings$, is used. VIX is the S&P 500 VIX index from CBOE. Other regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds				
$STDDEV\_Ratings$	0.330	0.255	0.255	0.256	0.255
	(2.43)	(2.85)	(2.82)	(2.86)	(2.64)
$Ratings$	0.216	0.117	0.117	0.118	0.118
	(3.07)	(2.63)	(2.62)	(2.62)	(2.48)
$Coupon$	-0.012	0.045	0.045	0.046	0.044
	(-0.48)	(2.06)	(2.07)	(2.08)	(2.01)
$Maturity$	0.016	-0.005	-0.005	-0.005	-0.004
	(2.31)	(-0.49)	(-0.47)	(-0.44)	(-0.44)
$Size$	0.000	0.000	0.000	0.000	0.000
	(1.31)	(2.06)	(2.08)	(1.92)	(1.84)
$ExRet_{lagged}$	-0.155	-0.089	-0.089	-0.089	-0.088
	(-2.89)	(-1.39)	(-1.35)	(-1.19)	(-1.06)
$Illiquidity$	0.313	0.205	0.205	0.198	0.243
	(3.50)	(2.40)	(2.43)	(2.28)	(2.06)
$Volatility$		0.336	0.335	0.334	0.315
		(1.90)	(1.87)	(1.87)	(1.59)
$Skewness$		-0.040	-0.041	-0.040	-0.040
		(-0.74)	(-0.82)	(-0.73)	(-0.74)
$Kurtosis$		0.022	0.022	0.022	0.021
		(1.20)	(1.32)	(1.19)	(1.27)
VaR		5.475	5.404	5.392	5.438
		(1.80)	(1.93)	(1.90)	(1.92)
$\beta_{r_{MKT}}$		-0.070	-0.070	-0.071	-0.070
		(-0.57)	(-0.56)	(-0.55)	(-0.53)
$VolofVol$			0.014	0.015	0.018
			(0.13)	(0.14)	(0.17)
r_{MKT}	0.313	0.205	0.205	0.198	0.243
	(3.50)	(2.40)	(2.43)	(2.28)	(2.06)
$TERM$	0.762	0.533	0.532	0.479	0.492
	(2.66)	(3.11)	(3.15)	(2.34)	(2.86)
DEF	1.436	0.997	0.997	1.001	0.624
	(3.01)	(2.48)	(2.49)	(2.32)	(1.38)
r_amb				0.695	0.543
				(1.45)	(1.04)
$infla\_amb$				0.013	0.082
				(0.03)	(0.16)
$rgdp\_amb$				-0.605	-0.992
				(-0.72)	(-1.14)
VIX					0.034
					(1.45)
Constant	-4.467	-3.437	-3.440	-3.394	-3.442
	(-4.31)	(-5.22)	(-5.21)	(-8.21)	(-8.70)
$Adj.R^2$	0.076	0.084	0.084	0.084	0.086
Obs	811,622	272,810	272,810	272,810	272,769

Table 9: **Panel Regressions by Subperiods**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables, with year and issuer fixed effects. Regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017, excluding 2007 in column 1, 2008 in column 2, and excluding both 2007 and 2008 in column 3. Column 4 shows results for the period preceding the Dodd-Frank Act (DF), and column 5 for the period after.

	Excess Returns on Corporate Bonds				
	Ex 2007	Ex 2008	Ex 2007-08	Pre DF	Post DF
CR_amb	0.485	0.489	0.535	0.657	0.705
	(1.99)	(2.02)	(1.96)	(1.44)	(2.02)
$Ratings$	0.159	0.134	0.151	0.186	0.185
	(3.65)	(3.37)	(3.78)	(2.40)	(2.21)
$Coupon$	0.042	0.035	0.034	0.038	0.051
	(2.17)	(1.97)	(1.96)	(0.96)	(3.42)
$Maturity$	-0.003	-0.006	-0.004	-0.010	-0.002
	(-0.33)	(-0.57)	(-0.42)	(-0.53)	(-0.19)
$Size$	0.000	0.000	0.000	0.160	0.025
	(1.85)	(1.49)	(1.59)	(2.55)	(0.37)
$ExRet_{lagged}$	-0.087	-0.012	-0.017	-0.139	0.000
	(-1.08)	(-0.47)	(-0.71)	(-1.16)	(0.00)
$Illiquidity$	0.007	0.012	0.011	0.007	0.002
	(1.04)	(1.32)	(1.24)	(1.09)	(0.17)
$Volatility$	0.328	0.381	0.412	0.320	0.191
	(1.64)	(1.65)	(1.74)	(1.37)	(0.45)
$Skewness$	-0.076	-0.037	-0.063	-0.042	-0.089
	(-1.52)	(-0.64)	(-1.11)	(-0.36)	(-1.06)
$Kurtosis$	0.026	0.006	0.008	0.036	0.013
	(1.32)	(0.64)	(0.84)	(0.73)	(0.77)
VaR	5.231	4.127	4.099	10.066	1.522
	(1.87)	(1.75)	(1.71)	(2.65)	(0.67)
$\beta_{r_{MKT}}$	-0.063	0.024	0.016	-0.423	0.154
	(-0.49)	(0.29)	(0.17)	(-1.90)	(1.25)
$VolofVol$	0.030	-0.055	-0.066	0.185	-0.111
	(0.27)	(-0.76)	(-0.90)	(1.23)	(-1.17)
r_{MKT}	0.254	0.114	0.119	0.412	0.016
	(2.03)	(1.42)	(1.42)	(2.44)	(0.18)
$TERM$	0.566	0.317	0.350	0.382	0.468
	(3.04)	(1.68)	(1.53)	(0.93)	(1.58)
DEF	0.562	0.524	0.458	0.153	1.114
	(1.24)	(1.19)	(1.05)	(0.35)	(1.30)
r_amb	0.409	0.719	0.644	0.577	0.516
	(0.77)	(1.62)	(1.34)	(0.43)	(0.80)
$infla\_amb$	0.316	0.167	0.371	-1.267	1.169
	(0.62)	(0.33)	(0.67)	(-1.45)	(0.95)
$rgdp\_amb$	-1.271	-1.220	-1.723	-0.613	-1.030
	(-1.61)	(-1.06)	(-1.50)	(-0.20)	(-0.87)
VIX	0.039	0.015	0.018	0.051	0.031
	(1.59)	(0.75)	(0.78)	(0.96)	(0.93)
Constant	-3.902	-2.609	-2.657	-5.438	-4.910
	(-7.89)	(-4.77)	(-3.28)	(-4.15)	(-2.58)
$Adj.R^2$	0.088	0.086	0.090	0.112	0.070
Obs	261,278	261,649	247,447	95,161	178,355

Table 10: **Panel Regressions with Credit Rating Ambiguity (CR_amb) - By Subsample**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables, with year and issuer fixed effects. The first to fourth columns report statistics for Investment grade (INV), Non-investment grade (NONINV), Secured bond (SEC), and Subordinated bond (SUB) subsamples respectively. Regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds			
	INV	NONINV	SEC	SUB
CR_amb	0.162	1.344	0.695	1.274
	(0.92)	(2.54)	(1.78)	(2.35)
$Ratings$	0.066	0.235	0.131	0.146
	(2.03)	(3.22)	(2.92)	(1.82)
$Coupon$	0.051	0.025	0.054	0.154
	(3.39)	(0.73)	(2.43)	(1.83)
$Maturity$	-0.006	0.005	-0.010	-0.026
	(-0.72)	(0.72)	(-0.90)	(-1.57)
$Size$	0.000	0.000	0.000	0.000
	(1.73)	(1.96)	(0.69)	(1.42)
$ExRet_{lagged}$	-0.121	-0.107	0.013	-0.111
	(-3.10)	(-1.05)	(0.53)	(-0.89)
$Illiquidity$	0.008	0.007	0.003	-0.049
	(1.11)	(0.96)	(0.31)	(-2.26)
$Volatility$	0.331	0.250	0.344	0.965
	(2.39)	(0.89)	(1.17)	(2.50)
$Skewness$	-0.060	-0.123	-0.141	-0.056
	(-1.03)	(-1.03)	(-1.89)	(-0.64)
$Kurtosis$	0.020	0.024	0.015	0.021
	(1.03)	(1.55)	(1.01)	(1.01)
VaR	3.488	5.262	5.458	6.793
	(1.66)	(2.09)	(1.57)	(2.10)
$\beta_{r_{MKT}}$	0.061	-0.173	0.018	-0.112
	(0.65)	(-1.08)	(0.12)	(-0.55)
$VolofVol$	-0.043	0.184	0.037	-0.044
	(-0.66)	(1.27)	(0.52)	(-0.44)
r_{MKT}	0.131	0.603	0.248	0.231
	(2.03)	(2.35)	(1.99)	(1.64)
$TERM$	0.751	-0.115	0.393	0.424
	(5.03)	(-0.36)	(2.07)	(1.57)
DEF	0.601	0.616	0.357	0.265
	(1.40)	(0.79)	(0.74)	(0.45)
r_amb	0.860	-0.439	0.361	0.527
	(2.36)	(-0.32)	(0.57)	(0.55)
$infla\_amb$	-0.129	0.449	0.579	0.146
	(-0.31)	(0.42)	(0.83)	(0.24)
$rgdp\_amb$	-0.129	-2.858	-1.247	-0.459
	(-0.18)	(-1.57)	(-1.16)	(-0.41)
VIX	0.034	0.035	0.040	0.007
	(1.56)	(1.17)	(1.45)	(0.26)
Constant	-3.503	-3.846	-3.514	-4.308
	(-14.87)	(-4.58)	(-5.06)	(-5.23)
$Adj.R^2$	0.091	0.113	0.091	0.090
Obs	194,659	80,799	111,030	21,025

Table 11: **Panel Regressions Controlling for Aggregate Credit Rating Ambiguity ($TotalCR\_amb$)**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables with aggregate credit news ambiguity ($TotalCR\_amb$), with year and issuer fixed effects. The first to fourth columns report statistics for Investment grade (INV), Non-investment grade (NONINV), Secured bond (SEC), and Subordinated bond (SUB) subsamples respectively, and the last column for the whole sample (ALL). The aggregate credit news ambiguity ($TotalCR\_amb$) is value-weighted using bond amounts outstanding. Regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds				
	INV	NONINV	SEC	SUB	ALL
CR_amb	0.146	1.314	0.688	1.250	0.445
	(0.87)	(2.60)	(1.77)	(2.43)	(2.04)
$Ratings$	0.066	0.236	0.133	0.145	0.144
	(2.08)	(3.24)	(2.85)	(1.69)	(3.24)
$Coupon$	0.048	0.020	0.048	0.148	0.038
	(3.49)	(0.66)	(2.21)	(1.91)	(2.10)
$Maturity$	-0.006	0.006	-0.010	-0.026	-0.004
	(-0.75)	(0.80)	(-0.88)	(-1.54)	(-0.44)
$Size$	0.000	0.000	0.000	0.000	0.000
	(1.76)	(2.18)	(0.68)	(1.49)	(1.79)
$ExRet_{lagged}$	-0.121	-0.107	0.013	-0.111	-0.082
	(-3.09)	(-1.05)	(0.53)	(-0.90)	(-1.01)
$Illiquidity$	0.008	0.007	0.003	-0.049	0.008
	(1.13)	(0.96)	(0.33)	(-2.36)	(1.21)
$Volatility$	0.329	0.248	0.343	0.959	0.308
	(2.41)	(0.84)	(1.17)	(2.53)	(1.46)
$Skewness$	-0.054	-0.120	-0.134	-0.054	-0.046
	(-0.98)	(-1.04)	(-1.85)	(-0.63)	(-0.89)
$Kurtosis$	0.019	0.025	0.016	0.022	0.024
	(1.01)	(1.62)	(1.07)	(1.11)	(1.21)
VaR	3.415	5.270	5.398	6.730	5.192
	(1.66)	(2.09)	(1.56)	(2.12)	(1.93)
$\beta_{r_{MKT}}$	0.063	-0.172	0.017	-0.109	-0.054
	(0.68)	(-1.09)	(0.11)	(-0.55)	(-0.45)
$VolofVol$	-0.044	0.179	0.031	-0.045	0.029
	(-0.66)	(1.23)	(0.43)	(-0.49)	(0.27)
r_{MKT}	0.109	0.576	0.216	0.201	0.218
	(1.94)	(2.19)	(1.68)	(1.49)	(1.82)
$TERM$	0.726	-0.167	0.373	0.350	0.454
	(4.53)	(-0.51)	(1.79)	(1.45)	(2.49)
DEF	0.739	0.791	0.531	0.512	0.765
	(2.16)	(1.14)	(1.39)	(1.20)	(2.17)
$TotalCR\_amb$	0.001	0.001	0.001	0.002	0.001
	(1.42)	(1.56)	(2.33)	(1.41)	(1.67)
r_amb	0.814	-0.497	0.295	0.461	0.478
	(2.42)	(-0.38)	(0.54)	(0.51)	(0.99)
$infla\_amb$	-0.188	0.393	0.440	0.149	-0.039
	(-0.49)	(0.38)	(0.65)	(0.23)	(-0.07)
$rgdp\_amb$	-0.229	-2.993	-1.362	-0.690	-1.062
	(-0.33)	(-1.60)	(-1.39)	(-0.53)	(-1.28)
VIX	0.031	0.032	0.036	0.002	0.030
	(1.46)	(1.12)	(1.39)	(0.08)	(1.38)
Constant	-4.869	-5.573	-5.325	-6.512	-5.011
	(-4.26)	(-4.66)	(-4.83)	(-3.45)	(-4.61)
$Adj.R^2$	0.093	0.114	0.093	0.093	0.086
Obs	194,659	80,799	111,030	21,025	275,481

Table 12: **Panel Regressions by Number of Credit Ratings**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables with CR_amb, with year and issuer fixed effects. The first column reports statistics for sample issues with 2 credit ratings (2R), and the second for those with 3 ratings (3R). The third column reports estimates for the subsample with 2 credit ratings and non-zero CR_amb (2R_NZ), and the last (3R_NZ) for those with 3 credit ratings and non-zero CR_amb. Regressors are as defined in Tables 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds			
	2R	3R	2R_NZ	3R_NZ
CR_amb	0.474	0.564	0.903	1.040
	(2.30)	(2.26)	(3.29)	(2.93)
$Ratings$	0.129	0.151	0.173	0.180
	(1.44)	(2.34)	(1.20)	(2.58)
$Coupon$	0.058	0.039	0.083	0.044
	(2.78)	(1.93)	(3.92)	(2.15)
$Maturity$	-0.010	-0.003	-0.013	-0.003
	(-0.73)	(-0.33)	(-1.00)	(-0.28)
$Size$	0.063	0.110	0.079	0.112
	(1.00)	(2.01)	(1.04)	(2.19)
$ExRet_{lagged}$	0.038	-0.142	0.025	-0.156
	(2.36)	(-1.40)	(1.06)	(-1.53)
$Illiquidity$	-0.005	0.010	-0.005	0.009
	(-0.83)	(1.24)	(-0.85)	(1.36)
$Volatility$	0.314	0.370	0.473	0.411
	(1.20)	(1.92)	(1.52)	(1.93)
$Skewness$	-0.110	-0.024	-0.228	-0.023
	(-1.01)	(-0.46)	(-1.23)	(-0.44)
$Kurtosis$	0.022	0.025	0.022	0.030
	(1.69)	(1.23)	(1.16)	(1.30)
VaR	7.234	4.784	6.148	4.871
	(1.65)	(1.88)	(1.60)	(1.87)
$\beta_{r_{MKT}}$	-0.036	-0.077	-0.018	-0.107
	(-0.16)	(-0.63)	(-0.07)	(-0.80)
$VolofVol$	0.078	0.033	0.181	0.033
	(0.86)	(0.32)	(1.42)	(0.33)
r_{MKT}	0.243	0.234	0.304	0.267
	(1.89)	(1.89)	(1.81)	(2.09)
$TERM$	0.212	0.529	0.075	0.508
	(0.86)	(2.97)	(0.30)	(2.66)
DEF	0.279	0.856	0.220	0.935
	(0.56)	(2.30)	(0.42)	(2.39)
$TotalCR\_amb$	0.001	0.001	0.001	0.001
	(2.38)	(1.28)	(1.93)	(1.29)
r_amb	0.357	0.505	0.243	0.345
	(0.51)	(1.08)	(0.33)	(0.63)
$infla\_amb$	0.802	-0.205	1.083	-0.117
	(1.08)	(-0.43)	(1.29)	(-0.25)
$rgdp\_amb$	-1.932	-0.966	-2.566	-1.296
	(-1.48)	(-1.16)	(-1.57)	(-1.39)
VIX	0.039	0.027	0.037	0.026
	(1.33)	(1.19)	(1.15)	(1.05)
Constant	-5.567	-6.404	-6.271	-6.889
	(-3.04)	(-3.59)	(-2.40)	(-3.72)
$Adj.R^2$	0.102	0.095	0.128	0.104
Obs	57,868	214,845	34,549	158,089

Table 13: **Panel Regressions with Changes in** CR_amb**,** $Ratings$**, and Interactions**

This table reports estimates of panel regressions of one-month ahead corporate bond excess returns on predictive variables with CR_amb, with year and issuer fixed effects. ΔCR_amb+ is the size of increase in ambiguity, and ΔCR_amb- is the size of its decrease. $\Delta Downgrade$ is the size of increase in $Ratings$ or deterioration in credit quality, and $\Delta Upgrade$ is the size of its improvement. The other regressors are defined in Table 4 and 6. 2-way clustered t-statistics (issuer, year) appear in parentheses below the coefficient estimates. The sample period is July 2002 to June 2017.

	Excess Returns on Corporate Bonds					
CR_amb	0.363	0.312	0.348	0.320	0.340	0.313
	(2.11)	(1.80)	(2.13)	(1.97)	(2.12)	(1.88)
$Ratings$	0.216	0.215	0.190	0.190	0.191	0.191
	(3.07)	(2.93)	(3.33)	(3.42)	(3.19)	(3.46)
ΔCR_amb+	3.764	-1.711	3.087	0.376	3.038	0.331
	(1.83)	(-1.26)	(2.52)	(0.31)	(2.52)	(0.28)
ΔCR_amb-	-2.490	-1.740	-0.020	-0.229	0.012	-0.177
	(-1.13)	(-0.95)	(-0.02)	(-0.17)	(0.01)	(-0.13)
$\Delta Downgrade$	0.693	-0.143	0.203	-0.188	0.208	-0.181
	(3.37)	(-0.25)	(0.78)	(-0.44)	(0.84)	(-0.43)
$\Delta Upgrade$	-0.013	0.354	-0.302	0.015	-0.312	0.005
	(-0.09)	(1.65)	(-2.65)	(0.10)	(-2.79)	(0.03)
$\Delta CR\_amb+\times\Delta Downg$		6.751		3.420		3.412
		(2.37)		(1.92)		(1.91)
$\Delta CR\_amb+\times\Delta Upg$		-0.011		-0.502		-0.498
		(-0.02)		(-0.82)		(-0.82)
$\Delta CR\_amb-\times\Delta Downg$		-0.146		0.418		0.400
		(-0.09)		(0.51)		(0.49)
$\Delta CR\_amb-\times\Delta Upg$		0.586		0.386		0.373
		(1.02)		(0.79)		(0.77)
$Coupon$	-0.001	-0.002	0.021	0.020	0.018	0.017
	(-0.04)	(-0.10)	(1.21)	(1.04)	(0.97)	(0.94)
$Maturity$	0.015	0.015	0.006	0.006	0.006	0.007
	(2.04)	(2.03)	(0.70)	(0.66)	(0.91)	(0.79)
$Size$	0.005	0.005	0.076	0.071	0.073	0.068
	(0.31)	(0.33)	(3.06)	(2.70)	(2.62)	(2.24)
$ExRet_{lagged}$	-0.129	-0.125	-0.091	-0.090	-0.091	-0.090
	(-2.08)	(-2.42)	(-1.76)	(-1.63)	(-1.83)	(-1.93)
$Illiquidity$			0.005	0.006	0.005	0.006
			(0.70)	(0.61)	(0.68)	(0.73)
$Volatility$			0.331	0.312	0.314	0.295
			(2.38)	(2.22)	(2.23)	(2.00)
Macro Vars	Yes	Yes	Yes	Yes	Yes	Yes
Macro Amb	No	No	No	No	Yes	Yes
Constant	-4.385	-4.335	-4.944	-4.849	-5.958	-5.882
	(-4.34)	(-4.39)	(-4.77)	(-4.87)	(-3.23)	(-3.21)
$Adj.R^2$	0.077	0.090	0.078	0.081	0.081	0.084
Obs	764,068	764,068	510,539	510,539	510,455	510,455