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Chang-Chih Chen, Kung-Cheng Ho, Cheng Yan, Chung-Ying Yeh, Min-Teh Yu

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Does Ambiguity Matter for Corporate Debt Financing? Theory and Evidence [1*]

Chang-Chih Chen, Kung-Cheng Ho, Cheng Yan, Chung-Ying Yeh, Min-Teh Yu

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[*] We are indebted to John Cochrane, Jianjun Miao, Jaccob Thijssen, Yanzhi Wang, and K.C. John Wei for valuable comments. We especially thank Nengjiu Ju and Jinqiang Yang for endless patience in answering our questions. Chen is an Assistant Professor of Finance at Providence University, E-mail: cjchen3@pu.edu.tw. Ho is an Associate Professor of Finance at Zhongnan University of Economics & Law, E-mail: kcho731101@163.com. Yeh is a Professor of Finance at National Chung Hsing University, E-mail: cyyeh1@dragon.nchu.edu.tw. Yan is an Associate Professor of Finance at University of Essex, E-mail: cheng.yan@essex.ac.uk. Yu is a Professor of Finance at Providence University and National Tsing Hua University, E-mail: mtyu@nycu.edu.tw. Corresponding: Yu.

Abstract

Traditional tradeoff theories puzzlingly predict that firms use high leverage, issue debt carrying a high duration and low yield spread, and have optimal debt policies highly affected by managerial risk-shifting behavior. We offer an ambiguity-based explanation for these corporate debt puzzles. The key intuition is that ambiguity-averse managers hold the worst-case belief about EBIT growth, resulting in upward (downward) distortion of bankruptcy (restructuring) probability. While firms under ambiguity aversion take less leverage, optimal leverage increases with ambiguity (if holding information constraints fixed). Our theoretical predictions about the impact of ambiguity aversion on corporate debt financing are supported by empirical evidence. Moreover, we document that the tradeoff models allowing for ambiguity aversion achieve a better performance in fitting real data, and information-constraint heterogeneities can be a distinctive determinant of leverage variations.

Keywords: ambiguity; information constraints; corporate debt; SMM estimation; pricing kernel;

JEL *classification codes*: G32; D81;

1. Introduction

Various puzzles about corporate debt emerge from the fact that traditional tradeoff theories are hard to reconcile with capital structure empirical patterns. Theories puzzlingly predict that (i) firms choose high leverage and enjoy large tax benefits on debt use; (ii) corporate bonds carry a low yield spread and a high duration; and (iii) managerial risk-shifting incentives (e.g., hedging benefits, asset substitution effects, etc.) deliver a critical impact on firm value and debt policies.[2] Standard determinants extracted from traditional theories struggle to explain leverage variations. Their explanatory power declines over time, especially for within-firm and within-industry cross-sectional leverage variations (see Graham and Leary, 2011). Traditional tradeoff theories relying on rational expectations ignore the influence of ambiguity preference on decision behavior. However, the relevance of ambiguity in decision-making has been widely documented (e.g., Dimmock et al., 2016). This motivates us to introduce ambiguity into corporate debt financing research.

We examine how ambiguity aversion affects corporate debt financing decisions theoretically and empirically. Mukerji and Tallon (2001) argue that agents' ambiguity aversion endogenously shapes market incompleteness. Hence, we follow prior studies (Cont, 2006; Boyle et al., 2008; and Thijssen, 2011) and consider a natural type of ambiguity accompanying market incompleteness — pricing kernel ambiguity. We propose a novel good-deal-free multiple-prior approach to measure this ambiguity, and embed our ambiguity model into the tradeoff theory. We show that ambiguity aversion goes a long way toward explaining various corporate debt puzzles. Empirical results help justify the significance of ambiguity aversion in improving the tradeoff model's goodness of fit, predicting debt-financing decision behavior, and shaping leverage variations.

We develop the ambiguity model under market incompleteness due to financial frictions that firms' cash flows (or EBIT) are non-tradable and their dynamics cannot be fully replicated from a tradable diversified market portfolio (i.e., basis asset). Public market information is insufficient to create financial hedges against EBIT idiosyncratic risk involving trading in corporate securities

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[2] Evidence on corporate debt puzzles and theoretical overstatement of managerial risk-shifting has been documented in Miller (1977), Graham and Harvey (2001), Schaefer and Strebulaev (2008), Huang and Huang (2012), and others.

(e.g., corporate bonds). Information constraints cause the exact fair price of bearing idiosyncratic risk to be unavailable, and make agents feel ambiguous about the choice of the idiosyncratic-risk price when specifying stochastic discount factors (SDFs). Ambiguity over the idiosyncratic-risk price is converted into the agent's ambiguous belief about the risk-adjusted expected EBIT growth rate (via probability measure changes), which further shapes EBIT model misspecification. As in the robust control theory of Hansen and Sargent (2001), the deviations of the misspecified EBIT models from the reference EBIT model are quantified using relative entropy.

Agents apply the misspecified EBIT models when making the decisions on trading financial securities backed by firms. All trading prices are within good-deal bounds that preclude arbitrage opportunities delivering too high Sharpe ratios.[3] Good-deal bounds help agents identify the upper bound on Sharpe ratios in markets as well as the upper constraint on SDF variance (SDF variance is an increasing quadratic function of the idiosyncratic-risk price). This upper constraint not only determines the quasi arbitrage-free interval of the idiosyncratic-risk price, but also fixes the upper constraint on model-misspecification entropy. The good-deal-free condition enables us to derive the structural form of the entropy constraint, which provides an alternative formula for measuring ambiguity.[4] Preference toward ambiguity affects decision behavior if and only if the EBIT-market correlation is lower than 100% (financial markets are incomplete). This correlation, employed as an inverse indicator of information constraints, reflects how much information about EBIT can be learned from diversified market portfolios. Information constraints take the form of the proportion of idiosyncratic risk to EBIT total risk, and thus, offer a proxy for measuring the firm's exposure to ambiguity on the idiosyncratic-risk price. Changes in ambiguity and in information constraints separately affect how ambiguity aversion alters decision behavior.

The proposed ambiguity model is applied to the tradeoff theory. Preference for ambiguity is characterized by using the max-min utility theory of Gilboa and Schmeidler (1989). In our model,

[3] There is a long tradition in finance that regards the trading with high Sharpe ratios as an arbitrage opportunity (e.g., Ross, 1976; Shanken, 1992; Cochrane and Saa-Requejo, 2000).

[4] In our model, the upper constraint on the entropy of EBIT model misspecification implies a dispersion of the space of multiple priors, equivalent to the ambiguity parameter in the multi-prior literature (e.g., Chen and Epstein, 2002).

ambiguity-averse managers require the highest compensation for bearing EBIT idiosyncratic risk, which implies not only the most pessimistic belief about the prospect of risk-adjusted EBIT growth but also the worst-case pricing kernel choice or highest discount rate (Jagannathan et al., 2016).[5] Such pessimism causes downward (upward) distortion of restructuring (default) probability and further affects debt financing decision-making through probabilistic distortion. On the one hand, decrements in restructuring probability decrease the expected value of options to upwardly adjust leverage in the future. Such an effect, increasing in ambiguity, motivates firms to reserve less debt capacity for future capital restructurings, thereby increasing current leverage. On the other hand, increments in default probability make firms earn less tax-bankruptcy tradeoff benefit from debt use, and are less willing to take leverage. The latter effect, increasing in information constraints (because this accompanies EBIT idiosyncratic volatility), always outweighs the former effect. As a result, under ambiguity aversion, firms execute a more conservative debt policy and pay higher interest for debt carrying a shorter duration. Optimal leverage reduces as information constraints tighten (ambiguity lowers), holding ambiguity (information constraints) fixed. Raising ambiguity and tightening information constraints both amplify bond yield spread and shorten duration. Also, we find that managerial risk-shifting incentive under ambiguity aversion is relatively weak, since managers are only able to adjust their systematic-risk-bearing level via trading market portfolios. In the presence of ambiguity, firms' total risk is less sensitive to managerial risk-shifting, causing a weaker effect of asset-substitution agency conflicts and of corporate hedging on debt financing.

Extracting the proxies for ambiguity and information constraints from our model, we explore related empirical implications in three dimensions. First, we test the over-identifying restrictions on the model specifications, which show that either the static or dynamic tradeoff model allowing for ambiguity aversion performs better than that ignoring ambiguity in fitting capital structure data. Second, we find empirical regularities that justify our theoretical predictions about the impact of ambiguity aversion on corporate debt financing. In regressions, we document that ambiguity and

[5] Using a field survey, Jagannathan et al. (2016) document puzzling evidence that firms choose high discount rates to evaluate project investment opportunities. Firms' discount rates, on average, are twice the cost of financial capital.

information constraints respectively have a positive and negative association with leverage, and both are positively (negatively) associated with bond yield spread (duration). Third, information-constraint heterogeneities can be a distinctive determinant of leverage variations. Heterogeneities among firms' information constraints produce across-firm differences in the impact of ambiguity aversion on leverage, and hence, are positively associated with leverage variations.

Our paper is closely related to the literature on the implications of ambiguity for corporate debt and capital structure. This literature focuses narrowly on leverage use (Lee, 2017; Attaoui et al., 2021; and Izhakian et al., 2022) or bond valuation (Korteweg and Polson, 2010), adopt a static capital structure tradeoff framework, and examine the implications of ambiguity for corporate debt by analyzing comparative statics or accessing the effect of ambiguity in the tradeoff models. We focus, in contrast, on a variety of corporate debt issues, including leverage use, bond pricing, bond duration, agency conflicts, and hedging demand. In addition to comparative statics, we conduct an in-depth examination of the implications of ambiguity by (i) empirically verifying our theoretical predictions for corporate debt financing, (ii) testing the effectiveness of preferences to ambiguity in shaping leverage variations, and (iii) drawing a goodness-of-fit comparison between traditional tradeoff models and our modified models. Our model, based on a dynamic tradeoff framework, enables us to examine the restructuring-based mechanism through which ambiguity preferences influence firms' leverage choices. This delivers an interesting finding on the positive ambiguity-leverage relation (while firms under ambiguity aversion take less leverage), which is supported by our empirical evidence but cannot be replicated from prior studies applying outcome-dependent preferences (e.g., a smooth preference or a max-min preference).

Moreover, we propose a new no-good-deal multi-prior approach to modelling pricing kernel ambiguity that makes a methodological contribution to the related literature. Our ambiguity model departs from the existing ambiguity models by distinguishing between information constraints and ambiguity. It uses the no-good-deal condition to solve the structural form of the entropy constraint, manifesting an alternative formula of ambiguity. Information constraints are measured from the correlation between the non-tradable state variables and tradable basis assets. These unique model features deliver twofold advantages over the existing models. First, our model offers an empirical guide to extracting the proxy variables for information constraints and ambiguity separately from the structural formulae of the EBIT-market correlation and entropy constraint. These two proxies can be constructed using conventional data on macroeconomic factors (e.g., market Sharpe ratios), financial statements, and stock markets. They are thus tractable for various empirical applications, including regression analyses, structural estimation, etc. Second, our model captures the difference between the implication of ambiguity and that of information constraints for observed variations in firms' capital structures. Information constraints refer to a firm-specific factor manifesting the individual firm's exposure to ambiguity. In contrast, ambiguity refers to a common factor for all firms, since it is measured from macroeconomic variables involved in the no-good-deal condition. Hence, shifts in ambiguity systematically affect firms' capital structure decision-making through ambiguity preference, while heterogeneities among individuals' information constraints generate across-firm variations in the impact of ambiguity aversion on capital structure decision-making.

Also, our research is related to the literature on SDF misspecification and model uncertainty. Hansen and Jagannathan (1997) find evidence on SDF misspecification. Cogley (2001) analyzes the decomposition structure of SDF specification errors. Cont (2006) defines SDF multiplicity due to market incompleteness as one type of model uncertainty, and examines its impact on financial derivative valuation. Boyle et al. (2008) study how an agent's fear of SDF misspecification shapes the robustness of decision rules. Thijssen (2011) and Chen and Chang (2019) respectively apply the SDF ambiguity model to issues on irreversible investment and mortgage insurance valuation. We extend this line of research to corporate debt financing. We reconcile the tradeoff theories with capital structure empirical patterns from arguments concerning aversion to SDF ambiguity.

This paper proceeds as follows. Section 2 builds a good-deal-free multi-prior model of SDF ambiguity. Section 3 introduces SDF ambiguity into the tradeoff theory. Sections 4-7 do structural estimations, comparative statics, empirical tests, and robustness checks. Section 8 concludes.

2. Pricing Kernel Ambiguity: A Good-Deal-Free Multi-Prior Approach

We consider a continuous-trading economy characterized by a complete filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$, where Ω denotes the state space, $\mathcal{F}_t$ the set of information generated by two-dimensional standard Brownian motions $[z(t), w(t)]'$, and $\mathbb{P}$ the reference belief (prior). Time continuously varies over $[0,\infty)$. To fix the term structure of interest rates, we assume that default-free bonds trade continuously and pay interest at a constant rate $r > 0$.

2.1. Preliminaries and a Brief Review of the Good-Deal Bound Theory

We consider a standard incomplete-market setting, as in Cochrane and Saa-Requejo (2000). The representative firm is un-levered at initial time and holds a set of capital assets that generate non-tradable EBIT flows. These flows are governed by a diffusion process:[6]

$$df(t)/f(t) = \mu_f\, dt + \sigma_{fz}\, dz^{\mathbb{P}}(t) + \sigma_{fw}\, dw^{\mathbb{P}}(t), \quad f(0) = \boldsymbol{f} \tag{1}$$

with the drift rate μ_f, idiosyncratic volatility σ_{fw}, and systematic volatility σ_{fz}. Denote by S the tradable basis asset (e.g., a diversified market portfolio) used for hedging financial securities backed by the firm's EBIT flows (as in Miao and Wang, 2007). Its value evolves according to

$$dS(t)/S(t) = \mu_S\, dt + \sigma_S\, dz^{\mathbb{P}}(t), \quad S(0) \equiv \boldsymbol{S} \tag{2}$$

with the drift rate μ_S and nonnegative volatility σ_S. All parameters are observable constants.

Using Proposition 5 in Cochrane and Saa-Requejo (2000), SDF Λ is specified as

$$d\Lambda(t)/\Lambda(t) = -r\, dt - h_S\, dz^{\mathbb{P}}(t) + \gamma\sqrt{A^2 - h_S^2}\, dw^{\mathbb{P}}(t) \tag{3}$$

In (3), A^2 is the upper limit of volatility, and $\gamma \in [-1,1]$ controls the range of SDF variation to

[6] The firm's asset value can be an effective alternative state variable. Switching the state variable from the firm's cash flow to asset value does not alter our main research results or the source of ambiguity.

ensure the satisfaction of volatility constraint $\mathrm{E}_t^{\mathbb{P}}[(d\Lambda(t)/\Lambda(t))^2] \le A^2$. The diffusion terms h_S and $-\gamma\sqrt{A^2 - h_S^2}$ denote the price of bearing systematic risk and idiosyncratic risk, respectively.

Notably, the correlation between the firm's EBIT flows and basis assets' return, symbolized by $\rho \equiv \mathrm{corr}(dS/S, df/f) = \sigma_{fz} \Big/ \sqrt{\sigma_{fz}^2 + \sigma_{fw}^2}$, is less than 100% as long as $\sigma_{fw} > 0$. This means that the dynamics of non-traded EBIT flows cannot be perfectly replicated from basis-asset trading. Given imperfect replication, perfect hedge is unachievable, so the single-price law relying on the standard arbitrage-free condition is not applicable for valuing financial securities on firms' EBIT (e.g., corporate bonds). This is because the fair price or compensation for bearing non-hedgeable idiosyncratic risk on EBIT is unknown, SDF is non-unique, and the trading prices of all financial securities depend on traders' SDF choices (price and SDF have a 1-to-1 relation). In this case, only the price bounds for financial securities can be determined. Hence:

Theorem. *Let* x^c *be the payoff of a focus perpetual claim on the firm's EBIT. Given EBIT, SDF, and basis assets as shown by* (1)-(3), *the lower good-deal pricing bound of the focus claim solves*

$$\underline{C}(0) = \min_{\Lambda} \mathrm{E}_0^{\mathbb{P}}\left[\Lambda(0)^{-1} \int_0^{\infty} \Lambda(s)\, x^c(s)\, ds\right] \tag{4}$$

$$\textbf{s.t.} \quad \boldsymbol{S} = \Lambda(0)^{-1}\,\mathrm{E}_0^{\mathbb{P}}[\Lambda(t)S(t)];\;\; \Lambda(t) \ge 0;\;\; \mathrm{E}_t^{\mathbb{P}}[(d\Lambda(t)/\Lambda(t))^2] \le A^2;\;\; 0 \le t \le \infty.$$

The upper good-deal pricing bound solves the corresponding maximum.

Hansen and Jagannathan (1991) regard the restriction on SDF volatility as the upper limit of Sharpe ratios in a public market. Cochrane and Saa-Requejo (2000) argue that investors will chase good deals delivering a Sharpe ratio exceeding twice the market index. Investors' behavior shapes the no-good-deal (quasi no-arbitrage) condition that determines the good-deal pricing bounds for all financial trading. These bounds enable us to identify whether the focus trading is a good deal or approximate arbitrage opportunity, because any trading outside good-deal bounds always delivers an abnormally high Sharpe ratio to buyers or sellers.

2.2. From Pricing Kernel Ambiguity to EBIT Misspecification

We now specify how ambiguity emerges from the SDF model (3), and how to convert pricing kernel ambiguity into EBIT model misspecification. We first rewrite the SDF model (3) as

$$d\Lambda(t)/\Lambda(t) = -r\,dt - h_S\,dz^{\mathbb{P}}(t) - h\,dw^{\mathbb{P}}(t);\quad -\sqrt{A^2 - h_S^2} \le h \le \sqrt{A^2 - h_S^2}\,.$$

While the exact price of systematic risk h_S is known, that of idiosyncratic risk h is not and must be inferred from the good-deal-free bounds $\{h \in \mathbb{R} : h^2 \le A^2 - h_S^2\}$. This is because in an incomplete market, non-tradable EBIT's idiosyncratic risk is non-hedgeable. Such an SDF feature enables us to treat uncertainty on the choice of the idiosyncratic-risk price as parameter uncertainty embedded into the SDF specification, which implies pricing kernel ambiguity (or model uncertainty).

For proceeding, let $\hat{h}$ and h' respectively denote the reference price of idiosyncratic risk and the deviation of the distorted risk price from the reference risk price. Then using the reference risk price $\hat{h}$ and the unique transformation from the physical measure to the reference martingale measure $\mathbb{Q}$ with discounter $\tilde{\Lambda}(t) \equiv \mathrm{e}^{-rt}$ yield the reference risk-adjusted EBIT model:

$$df(t)/f(t) = (\mu_f - \sigma_{fz} h_S - \sigma_{wf}\hat{h})\,dt + \sigma_{fz}\,dz^{\mathbb{Q}}(t) + \sigma_{wf}\,dw^{\mathbb{Q}}(t)\,. \tag{5}$$

Note that the risk prices enter the risk-adjusted drift of EBIT through measure change. This drift term reduces to r only if agents detect the fair price for bearing associated risks.

Uncertainty over the idiosyncratic risk price causes information insufficiency about the risk-adjusted expected EBIT growth rate. As a result, when specifying the risk-adjusted EBIT process and assessing the prices of financial securities contingent on the firm's EBIT, agents in fact use an approximate (or misspecified) risk-adjusted EBIT model featuring a subjective idiosyncratic risk price $h = \hat{h} - h'$, chosen from the good-deal-free set of risk prices $\{h \in \mathbb{R} : h^2 \le A^2 - h_S^2\}$. That is,

$$df(t)/f(t) = [\mu_f - \sigma_{fz} h_S - \sigma_{fw}(\hat{h} - h')]dt + \sigma_{fz}\,dz^{\mathbb{Q}h}(t) + \sigma_{fw}\,dw^{\mathbb{Q}h}(t)\,. \tag{6}$$

where $\mathbb{Q}h$ is an absolutely continuous contamination with respect to reference risk-neutral belief $\mathbb{Q}$; $w^{\mathbb{Q}h}$ follows the form of probability-scenario transformations mentioned in the multi-prior literature (e.g., Gilboa and Schmeidler, 1989): $w^{\mathbb{Q}h}(t) = w^{\mathbb{Q}}(t) - \int_0^t h' ds$; $z^{\mathbb{Q}h} = z^{\mathbb{Q}}$ is a Brownian motion under $\mathbb{Q}h$; and the contaminating drift h' is governed by the *good-deal-free* condition

$$(\hat{h} - h')^2 \le A^2 - h_S^2 \Leftrightarrow \mathrm{E}_t^{\mathbb{P}}\left[\left(d\Lambda(t)/\Lambda(t)\right)^2\right] \le A^2 . \tag{7}$$

2.3. Solving the Structural Formula for Ambiguity

The multi-prior literature mostly uses the upper constraint on state-variable misspecification as an ambiguity measure. Following suit, we derive the upper constraint on EBIT misspecification from the no-good-deal condition. We quantify the deviation of the misspecified EBIT model (6) from the true model (1) using the standard measure — entropy. We thus calculate the discounted relative entropy $\mathcal{R}(\mathbb{Q}h)$ (proposed by Hansen and Sargent, 2001) under subjective prior $\mathbb{Q}h$:

$$\mathcal{R}(\mathbb{Q}h) \equiv \int_0^\infty -\mathrm{E}_0^h(\log m(t))\, d\Lambda(t), \quad m(t) = \exp\left[\int_0^t -h\, dw^{\mathbb{Q}h}(s) + 0.5\int_0^t h^2\, ds\right]$$

where *m* denotes the Radon-Nikodym derivative of $\mathbb{P}$ with respect to $\mathbb{Q}h$, and $\mathrm{E}_0^h(\cdot)$ denotes the expectation operator at initial time under $\mathbb{Q}h$. Using the good-deal-free condition (7) yields the implied upper constraint on EBIT misspecification:

$$\mathcal{R}(\mathbb{Q}h) \le \phi \equiv \int_0^\infty -0.5(\eta - h_S) h_S\, t\, d\tilde{\Lambda}(t) = \frac{(\eta - h_S) h_S}{2r} .$$

This constraint fixes the set of multiple priors $\mathcal{H}(\phi) = \{\mathbb{Q}h \in \mathcal{H} : \mathcal{R}(\mathbb{Q}h) \le \phi\}$ used for guiding decision-making under SDF ambiguity, and also shows the explicit formula for ambiguity ϕ. Its structural formula consists of macroeconomic variables, including the riskless interest rate r, the basis-asset Sharpe ratio h_S, and the upper bound on Sharpe ratios in an open market $A^2 = h_S \eta$.

2.4. Max-Min Corporate Decision Problem under Ambiguity Aversion

Consider now the managerial decision making of the representative firm under ambiguity. We assume managers display ambiguity aversion.[7] According to the Ellsberg Paradox, an ambiguity-averse agent behaves as if she maximizes her expected utility under the worst-case belief chosen from a set of conditional priors. Following this notion, we express the firm's decision problem as

$$\max_{x\in\mathbb{R}_+}\min_{\mathbb{Q}h\in\mathcal{H}(\phi)} TFV(h,x;\boldsymbol{f},\rho)^{8} \tag{8}$$

It suggests that managers make an optimal business strategy *x* (expressed by a vector of decision variables) that maximizes total firm value *TFV* under the worst case belief about EBIT growth chosen from the set of multiple priors $\mathcal{H}(\phi)$.

When the EBIT-market correlation, ρ, reaches 100%, the max-min problem (8) reduces to a rationally-expected case. As ρ decreases (increases), agents gather less (more) information on the firm's EBIT dynamics from market portfolios. The tightness of information constraints (i.e., the value of $(1-\rho^2)^{0.5}$) essentially determines how large the influence of ambiguity on decision-making and on EBIT specification is. This insight can be clarified using the following:

$$df(t)/f(t)=[\mu_f-(h_S\rho+h\sqrt{1-\rho^2})\sigma_f]dt+\sigma_f(\rho dz^{\mathbb{Q}h}(t)+\sqrt{1-\rho^2}\,dw^{\mathbb{Q}h}(t)). \tag{9}$$

Note that, if $\rho\to100\%$, information constraints are removed, the effect of ambiguity on the risk -adjusted expected EBIT growth rate $h\sqrt{1-\rho^2}$ disappears, and control problem (8) reduces to the corresponding rationally-expected (ambiguity-free) case: $\max_{x\in\mathbb{R}_+} TFV(0,x;\boldsymbol{f},1)$.

3. Revisiting the Tradeoff Theory of Capital Structure

This section applies our pricing kernel ambiguity model to the dynamic capital structure trade -off framework of Goldstein et al. (2001). For model goodness-of-fit comparisons, we additionally

[7] We justify this assumption in Online Appendix G.
[8] Problem (8) is equivalent to the constrained robust control problem shown in Hansen and Sargent (2001), and also fits the max-min expected utility theory of Gilboa and Schmeidler (1989).

consider Leland's (1994) static framework (technical details are given in Online Appendix A.).

We will modify the dynamic tradeoff model of Goldstein et al. (2001) by applying the mis-specified risk-adjusted EBIT dynamics (expression (9)). The price for bearing EBIT idiosyncratic risk *h*, equivalent to the choice of conditional prior $\mathbb{Q}h$, is treated as an arbitrary constant during model development.[9] We also follow Goldstein et al. (2001) and switch the central state variable from EBIT to asset value, because these two economic quantities have a linear monotonic relation $V(t;h)=f(t)(r-\mu_f+\sigma_{fz}h_S+\sigma_{fw}h)^{-1}$.[10] We resort to a numerical algorithm to search for optimal capital structure and optimal prior choices. As the drift and diffusion terms of the EBIT dynamics are stationary, the technique for deriving our model is identical to that in Goldstein et al. (2001). Hence, we do not repeat the derivations and related proofs.

3.1. Debt Structure Settings and Debt Value

Consider a circumstance where the representative un-levered firm intends to sell a long-term debt and maintain a perpetual debt structure. As long as the firm remains solvent, firm managers do upward capital restructurings cyclically by replacing the debt in place with a new larger debt. Each debt continuously pays a fixed interest payment until either the firm goes into bankruptcy or the firm restructures its capital. Each debt is issued and callable at par. Each restructuring incurs a proportional transaction cost. The net proceeds from the debt issue are distributed on a pro rata basis to shareholders at the time of issuance.

Given the above specifications, we can express the value of the initial debt issue as

$$D(\boldsymbol{V};h,I,\varpi,\rho)=\underbrace{d(\boldsymbol{V};h,I,\varpi,\rho)}_{\substack{PV\ of\ debt\ over\ the\\ first\ financing\ cycle}}+\underbrace{D(\boldsymbol{V};h,I,\varpi,\rho)\xi_{res}(\boldsymbol{V};h,I,\varpi,\rho)}_{PV\ of\ cash\ flows\ from\ debt\ repurchase}. \tag{10}$$

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[9] Our undisclosed numerical tests show that the values of all corporate securities display a monotonic sensitivity to changes in the idiosyncratic-risk price (risk price has a 1-to-1 relation with conditional prior). Moreover, the property that all ambiguity components are constants implies a stationary level of ambiguity. So, given the max-min decision problem subject to a finite range of prior choices, our model always delivers a corner solution to the optimal prior (i.e., $h^*=(\eta h_S-h_S^2)^{0.5}$), meaning that the conditional prior chosen by an ambiguity-averse agent is stationary as well. Hence, we treat the idiosyncratic-risk price as an arbitrary constant when deriving the modified tradeoff model.

[10] For brevity, we occasionally simplify asset-value expressions by using V or $V(h)$.

The first right-hand-side term in (10) is solved from

$$d(\boldsymbol{V};h,I,\varpi,\rho)=\underbrace{\mathrm{E}_0^h\int_0^T\tilde{\Lambda}(s)I(1-\tau_i)ds}_{PV\ of\ interest\ payments}+\underbrace{\mathrm{E}_0^h\tilde{\Lambda}(T_D)(1-\tau_{eff})(1-\beta)Vb1_{(T_D<T_U)}}_{PV\ of\ recovered\ payments\ at\ default} \tag{11}$$

where I is the interest payment, $\varpi=Vu/\boldsymbol{V}$ is the scaling factor, Vu denotes the restructuring threshold, Vb denotes the bankruptcy threshold, β is the bankruptcy cost rate, τ_i is the rate of personal tax on interest, $\tau_{eff}=1-(1-\tau)(1-\tau_d)$ is the effective rate of tax on firm owners' equity holding, τ is the nominal rate of tax on firm EBIT, τ_d is the rate of personal tax on dividends, $T=T_D\wedge T_U$ is the first time that the firm changes its debt policy, $T_D:=\inf(t>0:V(t)\le Vb)$ is the random default time for the first financing cycle, and $T_U:=\inf(t>0:V(t)\ge Vu)$ is the random restructuring time for the first financing cycle.

Note that debt's recovered value is taxed at the rate of τ_{eff}, rather than τ_i. This is because, once bankruptcy occurs, debt holders will take over the firm and become shareholders. The value of the remaining assets received by them is equivalent to the sum of all discounted dividends in the future. A straightforward implication behind (11) is that the value of debt over the first financing cycle equals the sum of a contribution from interest if neither bankruptcy nor restructuring occurs and a contribution from the recovered payment if bankruptcy occurs.

The second right-hand-side term in (10) embodies the expected value of call, equivalent to the sum of all claims to intertemporal interest and recovered payment over future financing cycles. For a single debt issue, all claims over future financing cycles share the same coupon level, and so the discounting factor should be ξ_{res}, rather than $\varpi\xi_{res}$. This factor represents the present value of a financial claim that pays \$1 contingent on the firm's first capital restructuring. We solve for discounting factor from the following pricing equation:

$$\xi_{res}(\boldsymbol{V};h,I,\varpi,\rho)=\mathrm{E}_0^h\tilde{\Lambda}(T_U)1_{(T_U<T_D)}.$$

The formula for ξ_{res} has the restructuring-invariant property, which enables it to be applicable to all restructurings. The reason is that at all restructuring time points, the factors by which managers scale up the restructuring threshold of asset value are identical.[11] The explicit formulae for ξ_{res} and d are given in Online Appendix B.

3.2. Equity Value

Consider next the valuation of equity. We start by calculating the aggregate value of all equity claims to intertemporal dividends over all future financing cycles. Let $e(\cdot)$ be the present value of the equity claim over the first financing cycle and $e_i(\cdot)$ the *initial* value of equity claim over the *i*+1th financing cycle at the *i*th restructuring time. We know from the scaling property that the prerequisite of launching restructuring is to increase asset value by the factor ϖ. Furthermore, after restructuring, the firm instantly increases the level of interest, the restructuring threshold, and the default threshold by the same factor. Doing so scales up dividend payments and the one-cycle equity value by this factor as well, because (i) asset value and dividends, respectively, have a linear relationship with EBIT and equity value; (ii) after-tax net profits (equaling EBIT less the sum of interest and proportional tax payments) increase by the same factor; and (iii) the firm distributes all after-tax net profits as dividends to shareholders. Hence, the recursive expression of the initial value of the equity claim over the *i*+1th financing cycle is given by

$$e_i(\boldsymbol{V};h,I,\varpi,\rho)=e_{i-1}(\boldsymbol{V};h,I,\varpi,\rho)\varpi=e_{i-2}(\boldsymbol{V};h,I,\varpi,\rho)\varpi^2=\cdots=e(\boldsymbol{V};h,I,\varpi,\rho)\varpi^i \quad (12)$$

where $e(\cdot)$ is calculated using the sum of all after-tax discounted dividend payments over the first financing cycle (shareholders receive dividends until either restructuring or default occurs):

$$e(\boldsymbol{V};h,I,\varpi,\rho)=\mathrm{E}_0^h\int_0^T\tilde{\Lambda}(s)div(s)(1-\tau_d)ds,\ \ div(s)\equiv\underbrace{f(s)-I}_{Before-tax\ \ profits}-\underbrace{(f(s)-I)\tau}_{Proportional\ \ tax}. \quad (13)$$

[11] All restructurings motivate the firm to raise debt par, interest payments, the restructuring threshold, and the default threshold by the same factor (the so-called scaling property). For a detailed proof, see Goldstein et al. (2001).

Note that $e_i(\cdot)$ will be received at the *i*th restructuring, rather than the present time. To get the present value, we multiply it by the *i*-cycle discounting factor $(\xi_{res}(\cdot))^i$.

We are ready to show the total present value of equity claims to intertemporal dividends over all future financing cycles. Using expression (12) yields

$$\mathbb{E}(\boldsymbol{V};h,I,\varpi,\rho) = \underbrace{e(\boldsymbol{V};h,I,\varpi,\rho)}_{\substack{PV\ of\ equity\ over\ the \\ first\ financing\ cycle}} + \underbrace{e_1(\boldsymbol{V};h,I,\varpi,\rho)\xi_{res}(\cdot)}_{\substack{PV\ of\ equity\ over\ the \\ second\ financing\ cycle}} + \cdots = e(\cdot)\sum_{i=0}^{\infty}(\varpi\,\xi_{res}(\cdot))^i. \tag{14}$$

We can then show the total present value of debt claims over all financing cycles. Restructuring also scales up the one-cycle debt value by the factor ϖ, so that the present value becomes

$$\mathbb{D}(\boldsymbol{V};h,I,\varpi,\rho) = d(\boldsymbol{V};h,I,\varpi,\rho)\sum_{i=0}^{\infty}(\varpi\,\xi_{res}(\boldsymbol{V};h,I,\varpi,\rho))^i. \tag{15}$$

Finally, we consider the total present value of debt transaction costs over all financing cycles. Debt transaction costs and debt claims share the same patterns because these costs are proportional π to debt principal. The total present value of debt transaction costs thus can be given by

$$\mathbb{RC}(\boldsymbol{V};h,I,\varpi,\rho) = \pi D(\boldsymbol{V};h,I,\varpi,\rho)\sum_{i=0}^{\infty}(\varpi\,\xi_{res}(\boldsymbol{V};h,I,\varpi,\rho))^i. \tag{16}$$

Using expressions (14)-(16), the total value of equity just *before* the initial debt issuance is

$$E_{before}(\boldsymbol{V};h,I,\varpi,\rho) = \underbrace{d(\cdot)+e(\cdot)-\pi D(\cdot)}_{\substack{Net\ cash\ inflows\ over\ the \\ first\ financing\ cycle}} + \underbrace{E_{before}(\cdot)\varpi\,\xi_{res}(\cdot)}_{\substack{Equity\ value\ appreciation \\ received\ at\ restructuring}}, \tag{17}$$

which equals the sum of the total present values of debt and equity claims to intertemporal interest and dividends over all financing cycles less the total present value of debt transaction costs; i.e., $\mathbb{D}(\cdot)+\mathbb{E}(\cdot)-\mathbb{RC}(\cdot)$. An important role of E_{before} is to help us fix managers' objective in decision making, because it is equivalent to the firm's total levered value at present.

The right side of expression (17) illustrates the composition of equity value. The first term refers to shareholders' cash inflows in terms of interest and dividends over the first financing cycle minus transaction costs on the first debt issuance. The inclusion of interest reflects the manner of capital structure adjustments — the firm adjusts its capital structure by replacing a part of equity capital with new capital raised from debt holders, and thus, the proceeds from debt issues will be distributed to shareholders. The second term refers to shareholders' benefits from appreciation in the value of equity contingent on restructuring. As noted, restructuring scales up the values of all financial claims by the factor ϖ, so that the total value of equity shares the same scaling feature.

Besides, (17) offers a benchmark for measuring the value of equity just *after* the initial debt issuance, denoted by E_{after}. The difference between E_{before} and E_{after} arises from the fact that the firm executes a stock repurchase with the net proceeds obtained from the initial debt issuance. This implies $E_{before} = E_{after} + (1-\pi)D$ (their formulae are given in Online Appendix B).

3.3. Decision Problem

Recall from Section 3.2 that the total value of equity just before the initial debt issuance is equivalent to the firm's total levered value, which can be used as the managers' objective function. We thus define the capital structure decision problem as

$$\max_{I,\varpi} \min_{\mathbb{Q}h\in\mathcal{H}(\phi)} E_{before}(V;h,I,\varpi,\rho) \quad \textbf{s.t.} \quad \frac{\partial}{\partial V}E_{after}(V;h,I,\varpi,\rho)\bigg|_{V\downarrow Vb}=0\,. \tag{18}$$

Problem (18) means that the managers' objective is to select an interest I^* and a scaling factor ϖ^* that jointly maximize the firm's total levered value under the most pessimistic prior about risk -adjusted EBIT growth h^*, chosen from the set of multiple priors $\mathcal{H}(\phi)$. As usual, the choice of the bankruptcy threshold should satisfy the smooth-pasting condition (i.e., the constraint imposed on (18)). A closed-form solution to the optimization problem (18) does not exist, so we solve I^*, ϖ^*, and h^* by using standard numerical procedures.

4. Structural Estimation and Goodness-of-Fit Comparisons

Section 4 estimates our modified tradeoff model by using the simulated methods of moments (SMM) and tests the over-identifying restriction on model specifications using the ***J*** statistic. To save space, we describe the data in Online Appendix C.

4.1. SMM Procedure

When implementing the SMM, we estimate the vector of firm-specific model parameters $\boldsymbol{\theta}=(\sigma_f,\rho,\beta,\mu_f)$ and fix the rest of parameters at their baseline levels. The strategies to calibrate non-firm-specific parameters are as follows. We choose the corporate tax rate at 35%, a standard level in the literature (e.g., Goldstein et al., 2001). We choose the tax rate for interest at 30%, close to the estimation results in Graham (2000), about 29.6%. We choose a 15% dividend tax rate by following Glover and Levine (2017). We calculate the average Sharpe ratio of market portfolios using the market-return data from Kenneth French's website and take the calculation result to set the market's Sharpe ratio at 0.425.[12] The riskless interest rate is set at 4.5%, matching the mean of one-month Treasury bill rates. The transaction cost rate is chosen at 1%, which is in the range of empirical estimates from Altinkilic and Hansen (2000) and Edwards et al. (2007). We calibrate the Sharpe-ratio upper bound to be $2\times h_S$, consistent with Cochrane and Saa-Requejo (2000).

Moreover, in the SMM implementation, we select six data moments (i.e., the target moments) to match, including the first three moments of the return on firm total value and market leverage. The variances (the second moments) of the return on firm total value and of market leverage help identify EBIT volatility σ_f. This is because a higher value of σ_f generates larger variations in returns on firm total values and market leverage. The skewness (the third moment) helps identify the EBIT-market correlation ρ. The returns on firm values and market leverage are skewed when the correlation ρ is low. β and μ_f both are associated with the first moments of the returns on firm values and market leverages. For example, a higher EBIT growth rate μ_f causes lower

[12] Market return refers to the value-weighted return of all CRSP firms listed on the NYSE, AMEX, or NASDAQ.

market leverages. Overall, six moment conditions and four unknown parameters constitute an over -identified SMM framework. For more details about the SMM procedure, see Online Appendix D.

4.2. Parameter Estimates, Simulated Moments, and Over-Identifying Restrictions

Table 1 presents the results of the SMM estimation and the ***J*** statistics for the dynamic and static tradeoff models. Panel A reports the actual moments, the simulated-data moments, and the corresponding ***t***-statistics of the differences between these moments. The ***J*** statistics for the model specifications and the estimators for the firm-specific parameters are presented in Panel B. Table 1 also reports the ***J*** statistics for our two benchmark models (i.e. Leland, 1994; Goldstein et al., 2001). Comparisons of the ***J*** tests highlight the importance of our incomplete-market assumption that enables us to introduce ambiguity over the idiosyncratic-risk price into the SDF. Note that a large ***J***-statistic implies rejection of the model specification — the simulated-data moments from the model fail to match the real ones.

[Insert Table 1 here]

The results in Panel A show that the simulated data moments match the corresponding real data moments quite well. All ***t*** values are statistically insignificant at the 1% level. Our two base-line models thus explain the market data quite well. Take our dynamic model as an example. The SMM results deliver an estimate of 0.563 for the EBIT-market correlation, which helps justify our incomplete-market assumption. The estimated EBIT growth rate is 13.7%, slightly higher than the estimate (11.5%) in Strebulaev (2007). The estimate for EBIT volatility reaches 45.20%, which implies a 25.4% EBIT systematic volatility. This systematic volatility conceptually corresponds to EBIT total volatility in the case of complete markets considered by traditional tradeoff theories (no idiosyncratic volatility exists in complete markets). The implied EBIT systematic volatility is close to the estimated EBIT volatility (25.5%) in Strebulaev (2007). The estimate for bankruptcy costs is 36.5% of firm value, which is in the range of estimates (roughly 30%-40%) reported by

Korteweg (2010), Davydenko et al. (2012), and Glover (2016). All estimates above are statistically significant at the 1% level. The ***J*** statistic is 2.584 and statistically insignificant. These outcomes show that our model fits the real data on capital structures fairly well.

We proceed to the dynamic benchmark model. We fix the EBIT-market correlation at 100% according to the complete-market setting. The results show that the estimate of bankruptcy costs is 40.4%. Estimated EBIT volatility is 37.7%, statistically significant at the 1% level. This lower EBIT volatility estimate causes the benchmark model to generate a smaller simulated variance of the return on firm values (0.149) and of market leverages (0.011), which match the corresponding data moments poorly (about 0.240 and 0.057). The estimate of the EBIT growth rate (equivalent to the risk-adjusted EBIT growth rate in a complete market) is 0.5% and statistically insignificant. This value is close to the calibration results in Goldstein et al. (2001). The ***J*** statistic is quite large, significantly rejecting the benchmark model at 1%. The specification of the benchmark model is sharply at odds with the real sample. Similar results can be found in the static case. The ***J*** statistic in our static baseline model is 2.819, statistically insignificant, while that in the static benchmark model (Leland, 1994) is significant at 1%. In short, the SMM results present that the inclusion of SDF ambiguity is crucial and our two baseline models both explain the real sample very well.

5. Impacts of Ambiguity Aversion on Corporate Debt Financing

We conduct numerical analysis to examine the qualitative implications of ambiguity aversion for issues on corporate debt financing, including leverage usage, debt valuation, and hedging. For isolating the ambiguity aversion effect from corporate-debt financial variables, we use the models of Leland (1994) and Goldstein et al. (2001) as benchmarks (given $\rho = 1$ or $\sigma_{fw} = 0$). Also, we employ the parameter values reported in Section 4 as the baseline levels.

5.1. Optimal Leverage

We first examine the influence of ambiguity aversion on corporate leverage usage, measured by using $D(\boldsymbol{V};h^*,I^*,\varpi^*,\rho)\big/E_{before}(\boldsymbol{V};h^*,I^*,\varpi^*,\rho)$. Table 2 reports optimal leverage and the impact of ambiguity aversion on leverage use under various parameter combinations. Observe that, in either the dynamic or static model, ambiguity aversion delivers a significant negative effect on leverage. While leverage displays a positive sensitivity to the corporate tax rate (Panel D) and to the riskless interest rate (Panel B) and displays a negative sensitivity to EBIT systematic volatility (Panel A) and bankruptcy cost (Panel C), the sign of this effect remains unchanged given various reasonable parameter ranges. In the dynamic (static) model, ambiguity aversion reduces leverage by about 579 bps (1942 bps), or 14.59% (29.93%) of leverage use. Even if dynamic restructurings considerably dilute the ambiguity-aversion effect on leverage, this effect is sufficient to improve the tradeoff model's goodness of fit (see the ***J*** statistic in Table 1).

[Insert Table 2 and Figure 1 here]

Preference for ambiguity in fact affects the leverage choice through two channels: the risk-adjusted EBIT growth rate and EBIT idiosyncratic volatility. On the one hand, it makes managers require the largest compensation for bearing EBIT idiosyncratic risk h^*, which results in a most pessimistic belief about the prospect of risk-adjusted EBIT growth. Such an effect, increasing in ambiguity (because $h^*=(2\phi r)^2$), means that the possibility of executing upward restructurings in the future (see the solid line in Panel A of Figure 1) as well as the expected value of options to do capital restructurings becomes lower. Hence, managers tend to reserve less debt capacity for future capital restructurings, thereby increasing current leverage use. The inverse leverage-growth relation is consistent with empirical findings in Lang et al. (1996) and Billett et al. (2007).

On the other hand, ambiguity is accompanied by market incompleteness that generates non-replicable idiosyncratic volatility on firm EBIT. Such an effect, positively related to the tightness of information constraints (because $\sqrt{1-\rho^2}=\sigma_{fw}\sigma_f^{-1}$), lowers leverage usage through amplifying subjective default probability (check the dotted lines in Figure 1). Given the reasonable ranges of ambiguity and information-constraint tightness, the latter negative effect always outweighs the former positive effect (numerical analyses on the sensitivity of leverage to information constraints and ambiguity are discussed in Section 5.4). As a result, firms under ambiguity aversion display a weaker willingness to use leverage, consistent with Lee (2017) and Attaoui et al. (2021).

Ambiguity-averse managers might, of course, adopt a more conservative debt policy. Thus, we examine how well the ambiguity-based implications for leverage explain the so-called under-leveraged puzzle. This puzzle, found by Miller (1977), refers to the stylized fact that, on average, firms have low leverage ratios relative to what we may predict from the tradeoff theories. Unlike the literature, we seek to explain this puzzle by using preference for ambiguity in two steps. First, ambiguity aversion makes managers pessimistically assign higher probabilities to worse states of EBIT growth. Second, through increasing subjective default probability, preference for ambiguity lowers the expected bankruptcy-tax tradeoff value, causing a more conservative debt choice. That is, we use an ambiguity-driven co-movement among tax benefits, bankruptcy costs, and default rates to decrease the puzzling gap between observed leverage and theoretical predictions.

5.2. Yield Spread

Consider next the yield spread on corporate bonds, measured using $I/D - r(1-\tau_i)^{-1}$. Huang and Huang (2012) show that, especially for investment-grade bonds, traditional structural pricing models predict credit spreads well below Moody's historical averages. This is the so-called credit spread puzzle. Hence, the main challenge to this puzzle is to explain the spreads between treasury bonds and investment-grade bonds. To study the implication of ambiguity aversion for the credit spread puzzle, we plot yield spread as a joint function of coupon and the restructuring threshold in Figure 2 (using the dynamic model) and plot yield spread against leverage in Figure 3 (using the static model). Also, the impacts of ambiguity aversion on yield spreads under various parameter combinations are plotted in Figures 4 and 5.

[Insert Figures 2-5 here]

We observe that yield spreads generated by our models (see the surface in Panel A of Figure 2 and the solid lines in Figure 3) are larger than those by the benchmark models (see the surface in Panel B of Figure 2 and the dashed lines in Figure 3). Preference toward ambiguity marginally generates a large premium on yield spreads, no matter whether bonds have investment grades and whether dynamic restructurings are taken into account. This premium remains conspicuous even if the level of coupon is low or leverage is small (i.e., high-rating bonds). Moreover, as the patterns in Figures 4-5 show, the existence of the ambiguity-based premium is robust to various parameter combinations. The ambiguity-based premium, in effect, arises for two reasons. First, ambiguity aversion motivates firms to choose a lower default threshold that implies a lower bond recovery rate. Second, ambiguity aversion amplifies subjective default probability. As a result, if ambiguity preference is ignored, corporate bonds will be overpriced and carry too low a yield spread.

Two additional findings emerge from Figures 4 and 5. First, the ambiguity-based premium displays a strong positive sensitivity to EBIT volatility changes (see Panels A and B of Figure 5). This is because, when holding the EBIT-market correlation fixed, raising EBIT volatility makes firms bear a higher idiosyncratic risk, which causes managers' pessimistic belief about the price of idiosyncratic risk to generate a stronger negative effect on the risk-adjusted EBIT growth rate $\mu_f - \sigma_{fz} h_S - \sigma_{fw} h^*$. This reinforces the impact of ambiguity aversion on yield spread by increasing subjective default probability. Second, the ambiguity premium is decreasing in the riskless interest rate (see Panel D in Figure 4 or Panel F in Figure 5). Increasing the riskless interest rate boosts the yield rate and yield spread by decreasing bond value (holding the coupon fixed). The sensitivity of yield spread to interest rate changes under ambiguity aversion is weaker than that under rational expectations, since duration under ambiguity aversion is shorter (for a detailed discussion of the impact of ambiguity aversion on duration, see Section 5.3). Hence, the differences in yield spread under ambiguity aversion versus rational expectations diminish as the riskless interest rate rises.

In order to further highlight the effectiveness of ambiguity aversion in explaining the credit spread puzzle, we compare model-implied yield spreads with Moody's historical data reported by Huang and Huang (2012). Before proceeding, it is noteworthy that all corporate bonds covered by Moody dataset have an explicit maturity date. Such a data feature is inconsistent with the feature of our models considering a perpetual debt without an explicit maturity date. Through generating the effect of term premium, the inconsistency in bond maturity between the data and models will cause models' performance in explaining the credit spread puzzle to be overstated. To tackle these problems, we modify our models by replacing the infinite-maturity setting with the conventional finite-maturity setting of Leland and Toft (1996) and Ju et al. (2005). Model-implied yield spreads and the related results of comparisons are presented in Table 3.

[Insert Table 3 here]

The numbers in this table embody the effectiveness of ambiguity aversion in explaining the credit spread puzzle. In most circumstances, yield spreads obtained from our models are close to market data. Taking ambiguity aversion into account decreases pricing errors in 10-year (4-year) Baa bonds, A bonds, Aa bonds, and Aaa bonds by 59.9%-62.1% (75.8%-79.4%), 87.2%-88.6% (24.8%-26.3%), 88.7% (6.8%-7.1%), and 23.9%-24.5% (0.05%-0.07%), respectively. Except for the cases of short-term Aaa bonds and Aa bonds, the sizes of the ambiguity-based decrements in bond pricing errors are generally large, offering an effective ambiguity-based explanation for the credit spread puzzle. Our main results are also robust to alternative structural bond pricing models.

5.3. Duration

Schaefer and Strebulaev (2008) point out that the traditional structural models of credit risk fail in capturing the interest rate sensitivity of corporate bonds, which is far lower than would be expected from conventional duration measures. Similarly, Leland (2019) holds that the traditional

Macaulay duration measure overstates effective duration, which for speculative-grade bonds may even be negative. We now examine how the implication of ambiguity aversion for duration helps us explain the low-duration puzzle. According to the definition of duration proposed by Macaulay (1938), we calculate duration using $-(\partial D/\partial r)D^{-1}$. Then we plot durations from the dynamic and static models given various parameter combinations in Figures 6-10.

[Insert Figures 6-10 here]

We observe that corporate bond duration under ambiguity aversion (see Panel A of Figure 6 or the solid lines in Figure 9) is lower than that under rational expectations (see Panel B of Figure 6 or the dashed lines in Figure 9). Given various combinations of parameter choices, the negative influence of ambiguity aversion on duration remains valid (Figures 7, 8 and 10). These results are not beyond our expectations. As discussed earlier, ambiguity aversion generates a large premium on corporate bond yield spread through increasing subjective default probability. This implies that bonds under ambiguity aversion are relatively riskier. Usually, riskier bonds have a market value lower than safer bonds, and thus, riskier bonds' value displays a weaker sensitivity to interest rate changes, leading to a shorter duration. In traditional structural models, therefore, underestimating the default rates of corporate bonds causes too low a yield spread and too high a duration.

Three additional findings emerge from Figures 7, 8 and 10. First, the influence of ambiguity aversion on duration has a U relation with coupon (see Panel A in Figure 7) or leverage usage (see Figure 10). This suggests that as leverage or coupon increases, the impact on high-leverage (junk bond) duration falls whereas that on low-leverage (investment-grade bond) duration rises. Raising leverage use or coupon payment lowers bond value as well as the interest rate sensitivity of bond value through increasing default rates. In comparison with rational expectations, bond value under ambiguity aversion has a stronger negative reaction to default rate increases, and also converges to zero more quickly when default rates rise to a very high level (given a high level of coupon or leverage use). Because of the duration-value synchronicity, the differentials of duration between the benchmark models and ours first widen and then narrow with leverage use or coupon increases.

Second, raising EBIT volatility weakens the impact of ambiguity aversion on high-leverage (junk bond) duration but strengthens that on low-leverage (investment-grade bond) duration (see Panels A and B of Figure 7 and Panel A of Figure 10). EBIT volatility, which has a strict positive -convex relation with default probability, affects bond value as well as duration via default rates, and its increment accelerates the convergence of bond value as well. Hence, the reactions of the ambiguity aversion impact to EBIT volatility changes parallel those to leverage/coupon changes.

Third, the impact of ambiguity aversion on duration reduces as the riskless interest rate rises (compare Panel D in Figures 7, 8, and 10). As bond value is convex in the interest rate, duration and its decrement due to ambiguity aversion synchronically fall when the interest rate increases.

We next draw a preliminary comparison between model-implied and observed durations. The phenomenon of theoretical overpredictions of duration is documented using an investment-grade-bond-dominated sample.[13] In view of this fact, our comparison puts the focus on high-rating bond duration. We borrow summary statistics on duration (data source: Merrill Lynch Corporate Master index), asset volatility, and leverage from Schaefer and Strebulaev (2008). Note that the contracts of corporate bonds included in Merrill Lynch's index all specify an explicit maturity date. Such a data feature may downplay our perpetual-bond model's performance in the comparisons with data, as duration has a strong positive sensitivity to bond maturity. To tackle this problem, we consider the finite-maturity bond models of Leland and Toft (1996) and Ju et al. (2005). We incorporate ambiguity aversion into these two alternative models, and calculate duration by matching leverage, maturity, and asset volatility with empirical counterparts. The related results are shown in Table 4.

[Insert Table 4 here]

[13] In the final sample constructed by Schaefer and Strebulaev (2008), over 90% of observations on bond duration are matched with investment-grade credit ratings. Because evidence on theoretical overpredictions of duration primarily exists in investment-grade bonds, our comparison only includes bonds rated above Baa.

Observe that either in the case where the mean of observed duration is used as the target or in the case where the median is used as the target, prediction errors generated by our models broadly seem smaller than those by the benchmark models. Except for the case of Aaa bonds, prediction errors under ambiguity aversion range between 0.19-2.57, while those under rational expectations range between 1.37-3.16. Preference for ambiguity accounts for 1.47% (0.71%), 27.70%-28.64% (18.67%-19.30%), 92.96%-93.33% (62.62%-62.66%), and 28.47%-29.93% (89.38%-91.20%) of prediction errors in Aaa-rated, Aa-rated, A-rated, and Baa-rated duration, when the mean (median) of observed duration is the target. Overall, taking ambiguity aversion into account lowers duration prediction errors by 71.59%-84.96%. This highlights the effectiveness of ambiguity preference in explaining the low-duration puzzle.

5.4. Comparative Statics: Information Constraints versus Ambiguity

One of the attractive features of our model is to permit the distinction between ambiguity and information constraints. The influence of ambiguity aversion on corporate debt financing is highly sensitive to changes in these two economic factors. We now analyze the comparative statics of the ambiguity aversion impact with respect to these two factors and examine related implications. For convenience in subsequent discussions, we plot the ambiguity aversion impact on leverage, yield spread, and duration under different levels of information-constraint tightness $(1-\rho^2)^{0.5}$ and of ambiguity ϕ in Figures 11-15.

[Insert Figures 11-15 here]

The impacts of ambiguity aversion on model outputs are positively related to the tightness of information constraints (see Panel B of Figure 11, and Panels A-C of Figures 13 and 15). An increase in tightness lowers risk-adjusted EBIT growth, makes EBIT more volatile, and causes a larger upward default-probability distortion through EBIT idiosyncratic volatility. As a result, the ambiguity premium on yield spread and the reduction in duration due to ambiguity aversion both increase, and firms decrease leverage usage. Hence, information constraints provide a proxy for measuring the firm's exposure to ambiguity over the idiosyncratic-risk price, because information constraints reflect the proportion of idiosyncratic risk to EBIT aggregate risk. A lower proportion enables firms to learn more information about the risk-adjusted EBIT dynamics from open markets. When firms suffering tighter information constraints bear a higher idiosyncratic risk, pessimistic belief about the idiosyncratic-risk price arising from ambiguity aversion h^* generates a greater marginal impact on the risk-adjusted EBIT growth rate $\mu_f - \sigma_{fz} h_z - \sigma_{fw} h^*$ as well as on capital structure decision-making, which implies a larger ambiguity exposure. While the ambiguity level cannot be altered by individuals, firms are able to manage the influence of ambiguity and adjust their ambiguity exposure by varying the structure of EBIT volatility (via market-portfolio trading). Such a concept of *ambiguity management* is similar to risk management.

Information constraints also help explain, using ambiguity aversion, variations in corporate capital structures. The features of ambiguity exposure captured by information constraints are firm-specific, so heterogeneities among the individual's information constraints (ambiguity exposure) form across-firm differences in the impact of ambiguity preferences on corporate debt financing. This implies that higher information constraint heterogeneities are associated with larger capital structure variations. We will empirically verify this inference in Subsection 6.3.

We next consider the comparative statics regarding ambiguity. Except for the case of optimal leverage, the impact of ambiguity aversion on corporate debt financing consistently increases with ambiguity (please find Panels A-C of Figures 12 and 14). The exception for leverage occurs since optimal leverage has a positive association with ambiguity (see Panel C of Figure 11). As noted in Subsection 5.1, via downward restructuring-probability distortion and risk-adjusted EBIT growth, raising ambiguity lowers firms' incentives to reserve debt capacity for future capital restructurings, and thus, makes firms increase current leverage. Given a reasonable range of ambiguity (varying the market-portfolio Sharpe ratio from 0.2 to 0.5), the positive effect of ambiguity on leverage is always weaker than the corresponding negative effect of information constraints, so that changing ambiguity does not reverse the direction of the impact of ambiguity aversion on leverage. Because duration and yield spread respectively display a negative and positive monotonic relationship with leverage, the negative ambiguity aversion impact on duration and the ambiguity premium on yield spread both increase with ambiguity.

Ambiguity and information constraints differentially affect the effects of ambiguity aversion. Ambiguity, measured from macroeconomic variables involved in the good-deal-free condition, is common to all firms. In contrast, the ambiguity exposure implied by informational constraints is firm-specific. Hence, heterogeneous information constraints generate across-firm differences in the impact of ambiguity aversion, while ambiguity shifts influence this impact systematically.

Note that, in our model, a higher Sharpe ratio of market portfolios leads to a larger degree of ambiguity. This implies that ambiguity, as well as the impact of ambiguity aversion on corporate debt financing (in terms of default rate, leverage, bond pricing, etc.), is inversely related to macro-economic state. Such an inference is supported by related empirical findings. For example, Perez-Quiros and Timmermann (2000), Brennan et al. (2004), and Savor and Wilson (2013) find that a growing market-portfolio Sharpe ratio or a higher Sharpe-ratio upper bound usually accompanies economic deterioration. Driessen (2005) discovers that, when an economy enters recession, credit contagion effects will systematically increase the likelihood of individual default, and firms in a common market default simultaneously. Chen (2010) has a similar simulation of high default rates under a worse economy state. Hackbarth et al. (2006) and Chen (2010) both find counter-cyclical credit spread on corporate bonds. Halling et al. (2016) find that firms' target leverage ratios evolve counter-cyclically. Korteweg and Polson (2010) and Boyarchenko (2012) document increases in uncertainty in bond pricing during times of financial crises or market stress. Our outcomes agree well with the above empirical arguments.

6. Empirical Tests

The proposed ambiguity model offers the alternative formulae of information constraints and ambiguity, which enable us to develop corresponding empirical measures. With the application of such measures, Section 6 empirically verifies theoretical predictions about the ambiguity aversion impact on corporate debt financing and the inference on the association between capital structure variations and information-constraint heterogeneities.

6.1. Empirical Measures of Ambiguity and Information Constraints

According to the structural formulae of the entropy constraint and EBIT-market correlation from our ambiguity model, we empirically measure ambiguity and information constraints as

$$\phi = \frac{(\eta - h_S)h_S}{2r} \text{ and } \varsigma = \sqrt{1-\rho^2}.$$

Specifically, we calculate *r* using the one-month U.S. Treasury bill rate, h_S using the ratio of average monthly CRSP market-index excess return to its standard deviation, and η using the maximum Sharpe ratio for each industry in the stock market divided by the market-index Sharpe ratio.[14] We calculate the EBIT-market correlation from its alternative formula implied by Ito's lemma $\rho = \rho_E = \beta_E \sigma_S \sigma_E^{-1}$. In this alternative formula, σ_S is the standard deviation of market index returns, σ_E is the standard deviation of the individual firm's stock returns, and β_E is the CAPM beta for the individual firm.

To examine which types of firms face higher ambiguity *AMBIG* or suffer tighter information constraints *IC*, we further consider several conventional firm characteristics, including firm size *SIZE*, age *AGE*, ROA *ROA*, PPE *PPE*, Market-to-Book ratio *MB*, R&D expenditure *RD*, capital expenditure *CFV*, HHI of sales *HHI*, squared HHI of sales *HHI2*, and litigation risk *LITIGATION*. Details about the definitions and calculation of these variables are shown in Online Appendix C.

[14] Theoretically, ambiguity is a market-level variable. Without loss of generality, here we calculate an industry-level proxy to facilitate empirical implementation. Furthermore, we force η to equal 2 if it exceeds 2. This helps ease the influence of outliers.

Table 5 reports the overall summary statistics (i.e., mean and standard deviation values) for our empirical measures of information constraints and ambiguity as well as other common firm characteristics. The summary statistics for the common firm characteristics are largely compatible with the literature. Moreover, the correlation coefficients between the two new empirical measures and the other firm characteristics are smaller than 0.22. These suggest that our empirical *AMBIG* and *IC* measures are at most weakly correlated with common firm characteristics in the literature, and hence, capture aspects other than the common firm characteristics.

To be specific, *AMBIG* is correlated to a few common firm characteristics only (i.e., *AGE*, *RD*, and *CFV*), while *IC* is correlated to all firm-characteristic variables. This might be attributed to the fact that *AMBIG* is measured at the industry level but *IC* is measured at the firm level. Since the latter is a firm-specific factor manifesting the individual firm's ambiguity exposure, it is more likely to be correlated with common firm characteristics than the former.

[Insert Tables 5 and 6 here]

Table 6 presents the mean values of firm characteristics when we sort firms into groups by either *AMBIG* (2 groups in Panel A) or *IC* (3 groups in Panel B). For comparisons only, we report ***t*** statistics in parentheses, while ***, **, and * represent the statistical significance at 1%, 5%, and 10%, respectively. Observe from Panel A that, in the high-*AMBIG* group, mean leverage (36.27%) is far higher than in the low-*AMBIG* group (28.24%), and the difference is statistically significant with a ***t*** statistic of 7.06. This pattern is consistent with Izhakian et al. (2022). Panel B shows that mean leverage in the high-*IC* group (37.55%) is lower than that in the low-*IC* group (38.48%), and the difference is statistically significant with a ***t*** statistic of -3.0. Moreover, firms suffering tighter *IC* are likely to operate in less competitive industries featuring a higher *HHI*, receive lower market valuation (lower *MB*), and invest more in *PPE* but less in *RD*.

6.2. Results on Corporate Debt Financing

According to the comparative statics in Subsection 5.4 (see Figures 11-15), we propose the following three testable hypotheses.

H1: *Corporate leverage increases with ambiguity but decreases with information constraints.*

H2: *Corporate bond yield increases with ambiguity and information constraints.*

H3: *Corporate bond duration decreases with ambiguity and information constraints.*

To test these hypotheses, we regress corporate-bond financial variables (i.e., leverage *LEV*, yield spread *YIELD*, and duration *DUR*) on information constraints and ambiguity:

$$LEV_{ijt} = \gamma_0 + \gamma_1 \phi_{jt} + \gamma_2 \varsigma_{ijt} + \gamma_3 \sum Control + Year + Industry + \varepsilon_{ijt}$$

$$YIELD_{ijt} = \gamma_0 + \gamma_1 \phi_{jt} + \gamma_2 \varsigma_{ijt} + \gamma_3 \sum Control + Year + Industry + \varepsilon_{ijt}$$

$$DUR_{ijt} = \gamma_0 + \gamma_1 \phi_{jt} + \gamma_2 \varsigma_{ijt} + \gamma_3 \sum Control + Year + Industry + \varepsilon_{ijt}$$

We control for several accounting variables (i.e., firm size, age, ROA, PPE, Market-to-Book ratio, HHI of sales, squared HHI of sales, R&D expenditure, capital expenditure, and litigation risk), as well as year and industry fixed effects. We calculate leverage, duration, and yield spread using data collected from COMPUSTAT, CRSP, and the TRACE Enhanced database. Details about the data description and the calculation of these three financial variables are shown in Online Appendix C. Table 7 reports the regression results.

[Insert Table 7 here]

In terms of results, we document that ambiguity and information constraints have a positive and negative association with firm leverage at 1%, with ***t*** statistics of 2.58 and -3.73, respectively.

Moreover, they are positively associated with corporate bond yields at 1%, with ***t*** statistics of 3.73 and 8.47, and negatively associated with bond duration at 5%, with ***t*** statistics of -2.24 and -2.62. These empirical patterns indicate a first-order impact of ambiguity preferences on corporate debt financing, which justifies our theoretical predictions.

6.3. Results on Capital Structure Variations

Recall from our inference in Subsection 5.4 that heterogeneities among firms' information constraints may generate across-firm differences in the impact of ambiguity preferences on capital structure decision-making. Hence, we propose the fourth hypothesis.

H4: *Higher information-constraint heterogeneities lead to larger capital structure variations.*

To test this hypothesis, we follow Graham and Leary (2011) and consider two standard types of leverage variations — (i) industry-level (within-industry across-firm) leverage variations $\bar{\mathcal{L}}_{.jt}$ and (ii) between-industry leverage variations $\bar{\bar{\mathcal{L}}}_{..t}$. These are defined as

$$\bar{\mathcal{L}}_{.jt} = \sum_i (LEV_{ijt} - \bar{\bar{L}}_{.jt})^2 \quad \text{and} \quad \bar{\bar{\mathcal{L}}}_{..t} = \sum_j (\bar{\bar{L}}_{.jt} - \bar{\bar{\bar{L}}}_{..t})^2$$

where $\bar{\bar{L}}_{.jt}$ is the industry mean of leverage for industry *j* at year *t* and $\bar{\bar{\bar{L}}}_{..t}$ is the grand mean of leverage at year *t*. Also, we use one minus the HHI of individuals' information constraints as our proxies for information-constraint heterogeneities; i.e., $\bar{\mathcal{V}}_{.jt}$ and $\bar{\bar{\mathcal{V}}}_{..t}$. Details about calculations are shown in Online Appendix C.

[Insert Table 8 here]

We then run the following two regressions, controlling for various accounting variables (as in the first three hypotheses), as well as year and industry fixed effects:

$$\bar{\mathcal{L}}_{.jt} = \gamma_0 + \gamma_1 \bar{\mathcal{V}}_{.jt} + \gamma_2 \sum Control + Year + Industry + \varepsilon_{.jt},$$

$$\bar{\bar{\mathcal{L}}}_{..t} = \gamma_0 + \gamma_1 \bar{\bar{\mathcal{V}}}_{..t} + \gamma_2 \sum Control + Year + \varepsilon_{..t}.$$

The results justify our inference of a positive association between capital structure variations and information-constraint heterogeneities. Between-industry and within-industry leverage variations are both positively associated with information-constraint heterogeneities at 1%, with ***t*** statistics of 6.93 and 5.34 (see Table 8). Overall, we find a new determinant of capital structure variations: information-constraint heterogeneities. An immediate implication is that, because the features of ambiguity exposure implied by information constraints (like a channel through which ambiguity influences firms' decision-making) are firm-specific and firms differ in the ambiguity exposure, heterogeneities among individuals' information constraints may generate across-firm differences in the influence of ambiguity on leverage use.

7. Robustness and Additional Results

Section 7 examines the robustness of our main results along three directions. We first merge managerial risk-shifting incentives (proposed by Leland, 1998) into the model, then replace the max-min ambiguity preference with the smooth ambiguity preference of Klibanoff et al. (2005), and finally measure ambiguity from the exogenous dispersion of the subjective idiosyncratic-risk prices by following Thijssen (2011).

The numerical tests show that our main results remain unchanged under the aforementioned alternative specifications. Moreover, we find the significance of ambiguity aversion in explaining theoretical overstatements of asset substitution agency conflicts and corporate hedging incentives, documented by Graham and Harvey (2001), Jin and Jorion (2006), and others. Agency costs and hedging benefits generated by our calibrated model both are much lower than those by the model under rational expectations, and are closer to corresponding empirical estimates in the literature (see Graham and Rogers, 2002; and Morellec et al., 2012). The detailed discussions on our results of robustness checks and related technical details are given in Online Appendices E-F.

8. Conclusion

This paper can be viewed as a first step toward understanding the quantitative and empirical implications of ambiguity aversion for corporate debt financing. We propose a novel good-deal-free multi-prior approach to model ambiguity about pricing kernel specification. The model (i) is appropriate for firm-based decision analyses; (ii) provides a useful guide to empirical research for constructing proxies for Knightian uncertainty and informational constraints separately by using conventional economic variables; and (iii) allows us to analyze comparative statics with respect to informational constraints (ambiguity) holding ambiguity (informational constraints) fixed. These form the theoretical and empirical advantages of our model over traditional ambiguity models.

We merge the proposed ambiguity model into a standard dynamic tradeoff framework, which shows that ambiguity aversion goes a long way toward explaining many corporate debt puzzles, including the under-leveraged puzzle, the credit spread puzzle, and the low-duration puzzle. An ambiguity-based explanation for theoretical overstatements of managerial risk-shifting incentives, as well as their impact on capital structure, is also provided. Our theoretical predictions about the impact of ambiguity aversion on corporate debt financing are supported by empirical evidence and robust to various specifications. Using a large U.S. corporate cross section, we also document that ambiguity aversion significantly improves the goodness of fit of tradeoff models and information -constraint heterogeneities can be a distinctive determinant of corporate leverage variations.

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Table 1. SMM Estimations and Assessment of Model Specifications

This table reports the results of the SMM estimation and J tests for both dynamic and static tradeoff models. We use a sample that includes nonfinancial unregulated firms between 1966 and 2021. Regulated, financial, and quasi-public firms are excluded. Observations with missing data or ones that fail to obey accounting identity are omitted. The base sample consists of 133,739 firm-year observations. Panel A shows the data moments, the simulated moments, and the corresponding t-statistic values of the differences between these two types of moments. Panel B reports the parameter estimators (the corresponding standard errors are given in parentheses) and the J-statistic (corresponding p-values are given in parentheses). Estimated parameters include (from left to right) EBIT/asset volatility, the EBIT/asset-market correlation, the bankruptcy cost rate, and the EBIT growth rate.

Panel A: Moment Tests

Moment Items:	Data	Simu. (dynamic)	Simu. (static)	*t*-stat. (dynamic)	*t*-stat. (static)

Variance of the return on *TV*	0.240	0.237	0.241	0.004	0.001
Mean of the return on *TV*	0.060	0.046	0.068	-0.014	-0.010
Skewness of the return on *TV*	-0.010	-0.027	-0.021	0.050	0.015
Variance of market leverage	0.056	0.030	0.061	0.044	-0.004
Mean of market leverage	0.245	0.255	0.255	-0.014	-0.038
Skewness of market leverage	0.012	0.010	0.018	0.018	-0.006
Panel B: Parameter estimates					
Model Type:	σ_f	ρ	β	μ_f	*J*-stat.
Dynamic baseline model	0.452	0.563	0.365	0.136	2.584
	(0.046)	(0.002)	(0.016)	(0.069)	(0.125)
Dynamic benchmark model	0.377	1.000	0.404	0.005	27.908
	(0.022)	-------	(0.001)	(0.023)	(0.001)
Static baseline model	0.421	0.625	0.016	------	2.819
	(0.055)	(0.011)	(0.093)		(0.115)
Static benchmark model	0.427	1.000	0.175	------	36.956
	(0.063)	-------	(0.663)		(0.001)

Table 2: Impacts of Ambiguity Aversion on Optimal Leverage

This table reports optimal leverage for various parameter combinations as well as the impacts of ambiguity aversion on optimal leverage by the quintiles of model parameters. "AA" ("RE") refers to the model under ambiguity aversion (rational expectations).

Model type	Parameter level					
	1st Quintile (very low)	2nd Quintile (low)	3rd Quintile (moderate)	4th Quintile (high)	5th Quintile (very high)	Average
Panel A: EBIT/asset systematic volatility (from 23% to 27%; step size: 1%)						
AA (dynamic)	34.06	33.98	33.89	33.80	33.70	33.89
RE (dynamic)	42.29	41.28	40.11	39.23	38.22	40.23
Effect (dynamic)	-8.23	-7.30	-6.22	-5.43	-4.52	-6.34
AA (static)	45.56	45.48	45.40	45.32	45.24	45.40
RE (static)	66.24	65.20	64.21	63.26	62.36	64.25
Effect (static)	-20.68	-19.72	-18.81	-17.94	-17.12	-18.85
Panel B: Riskless interest rate (from 4% to 6%; step size: 0.5%)						
AA (dynamic)	33.24	33.89	34.09	34.48	34.85	34.11
RE (dynamic)	38.55	39.68	40.83	41.81	42.76	40.73
Effect (dynamic)	-5.31	-5.79	-6.74	-7.33	-7.91	-6.62
AA (static)	44.85	45.46	46.05	46.64	47.22	46.04
RE (static)	63.45	64.88	66.17	67.34	68.41	66.05
Effect (static)	-18.60	-19.42	-20.12	-20.70	-21.19	-20.01
Panel C: Bankruptcy cost rate (from 33% to 37%; step size: 1%)						
AA (dynamic)	36.56	35.77	35.01	34.24	33.52	35.02
RE (dynamic)	40.72	40.46	40.07	39.81	39.56	40.12
Effect (dynamic)	-4.16	-4.69	-5.06	-5.57	-6.04	-5.10
AA (static)	59.76	59.24	58.72	58.20	57.69	58.72

RE (static)	71.70	71.45	71.20	70.95	70.70	71.20
Effect (static)	-11.94	-12.21	-12.48	-12.75	-13.01	-12.48
Panel D: Corporate tax rate (from 34% to 36%; step size: 0.5%)						
AA (dynamic)	31.46	32.58	33.89	34.76	35.83	33.70
RE (dynamic)	38.67	39.26	39.68	40.10	40.64	39.67
Effect (dynamic)	-7.21	-6.68	-5.79	-5.34	-4.81	-5.97
AA (static)	44.08	44.77	45.46	46.13	46.80	45.45
RE (static)	64.05	64.47	64.88	65.29	65.69	64.88
Effect (static)	-19.97	-19.70	-19.42	-19.16	-18.89	-19.43
Panel E: Debt transaction cost rate (from 0.5% to 1.5%; step size: 0.25%)						
AA (dynamic)	33.82	34.04	33.89	33.81	33.40	33.79
RE (dynamic)	38.14	38.66	39.68	39.48	39.85	39.16
Effect (dynamic)	-4.32	-4.62	-5.79	-5.67	-6.45	-5.37
AA (static)	-----	-----	-----	-----	-----	-----
RE (static)	-----	-----	-----	-----	-----	-----
Effect (static)	-----	-----	-----	-----	-----	-----

Table 3: Comparisons of Pricing Errors in Investment-Grade Corporate Bonds

This table draws the comparisons of investment-grade bond pricing errors between the modified benchmark models and our modified models. Columns (from left to right) report credit rating, target leverage (observed), calibrated asset volatility, observed average yield spreads, model-implied yield spreads under rational expectations, model-implied yield spreads under ambiguity aversion, absolute pricing errors under rational expectations, absolute pricing errors under ambiguity aversion, and decreases in pricing errors due to ambiguity aversion. Debt's par value is calibrated to make model-generated leverage match target leverage. Coupon payments are endogenously determined using the sell -at-par condition. Asset volatility is calibrated from estimates for asset volatility reported by Table 7 in Schaefer and Strebulaev (2008). In Panels C and D, we set the exponent of bankruptcy boundary function g at 3.69% by following Ju et al. (2005), and the payout rate at 0 for parameterization consistency. The rest of parameters are set at the baseline levels. The numbers of observed yield spread and target leverage are acquired from Huang and Huang (2012).

Credit rating	LEV (%)	VOL (%)	Observed YS (bps)	RE model YS (bps)	AA model YS (bps)	RE absolute PE (bps)	AA absolute PE (bps)	AA effect on PE (%)
Panel A: Leland and Toft (1996), Maturity = 4 years								
Aaa	13.08	21	55	0.00	0.04	55.00	54.96	0.07
Aa	21.18	22	65	0.20	4.81	64.80	60.19	7.11
A	31.98	20	96	2.10	26.76	93.90	69.24	26.26
Baa	43.28	20	158	21.47	129.93	136.53	28.07	79.44
Panel B: Leland and Toft (1996), Maturity = 10 years								
Aaa	13.08	21	63	0.25	15.63	62.75	47.37	24.51
Aa	21.18	22	91	4.58	81.21	86.42	9.79	88.67
A	31.98	20	123	13.01	137.11	109.99	14.11	87.17
Baa	43.28	20	194	44.41	253.94	149.59	59.94	59.93

Panel C: Ju et al. (2005), Maturity = 4 years								
Aaa	13.08	21	55	0.00	0.03	55.00	54.97	0.05
Aa	21.18	22	65	0.19	4.59	64.81	60.41	6.79
A	31.98	20	96	1.88	25.25	94.12	70.75	24.83
Baa	43.28	20	158	18.84	124.38	139.16	33.62	75.84
Panel D: Ju et al. (2005), Maturity = 10 years								
Aaa	13.08	21	63	0.22	15.25	62.78	47.75	23.94
Aa	21.18	22	91	3.97	81.16	87.03	9.84	88.69
A	31.98	20	123	10.57	135.82	112.43	12.82	88.60
Baa	43.28	20	194	34.65	254.45	159.35	60.45	62.06

Table 4: Comparisons of Duration Prediction Errors in Investment-Grade Bonds

In this table, the columns (from left to right) report bond credit rating, target leverage (median), the average remaining time to maturity date, calibrated asset volatility, observed duration, model-implied duration under ambiguity aversion, model-implied duration under rational expectations, prediction errors (the gap between observed and model-implied duration) under ambiguity aversion, prediction errors under rational expectations, and prediction-error reduction due to ambiguity aversion. Debt's par value is calibrated to make model-implied leverage match target leverage. Coupon payments are endogenously determined using the sell-at-par condition. Asset volatility is calibrated from estimates for asset volatility reported by Schaefer and Strebulaev (2008). In Panels B and D, we set the exponent of the bankruptcy boundary function *g* at 3.69% by following Ju et al. (2005), and the firm's payout rate to be zero for parameterization consistency. The rest of parameters are set at their baseline levels. The numbers of observed duration, bond maturity, and target leverage are acquired from Schaefer and Strebulaev (2008).

Credit rating	LEV (%)	MAT (year)	VOL (%)	Observed DUR (year)	DUR under AA (year)	DUR under RE (year)	AA-PE (year)	RE-PE (year)	Reduction in PE (%)
Panel A: Median Observed DUR, Benchmark based on Leland and Toft (1996)									
Aaa	6	10.16	21	3.93	8.12	8.15	4.19	4.22	0.71
Aa	14	9.45	22	4.52	7.07	7.68	2.55	3.16	19.30
A	27	10.13	20	4.78	5.95	7.91	1.17	3.13	62.62
Baa	36	9.14	20	4.76	4.57	6.92	0.19	2.16	91.20
Overall	30	9.50	21	4.73	5.16	7.33	0.43	2.60	83.46
Panel B: Median Observed DUR, Benchmark based on Ju et al. (2005)									
Aaa	6	10.16	21	3.93	8.12	8.15	4.19	4.22	0.71
Aa	14	9.45	22	4.52	7.09	7.68	2.57	3.16	18.67
A	27	10.13	20	4.78	5.96	7.94	1.18	3.16	62.66
Baa	36	9.14	20	4.76	4.52	7.02	0.24	2.26	89.38
Overall	30	9.50	21	4.73	5.13	7.39	0.40	2.66	84.96
Panel C: Mean Observed DUR, Benchmark based on Leland and Toft (1996)									
Aaa	6	10.16	21	6.11	8.12	8.15	2.01	2.04	1.47

Aa	14	9.45	22	5.55	7.07	7.68	1.52	2.13	28.64
A	27	10.13	20	5.81	5.95	7.91	0.14	2.10	93.33
Baa	36	9.14	20	5.55	4.57	6.92	0.98	1.37	28.47
Overall	30	9.50	21	5.63	5.16	7.33	0.47	1.70	72.35

Panel D: Mean Observed DUR, Benchmark based on Ju et al. (2005)

Aaa	6	10.16	21	6.11	8.12	8.15	2.01	2.04	1.47
Aa	14	9.45	22	5.55	7.09	7.68	1.54	2.13	27.70
A	27	10.13	20	5.81	5.96	7.94	0.15	2.13	92.96
Baa	36	9.14	20	5.55	4.52	7.07	1.03	1.47	29.93
Overall	30	9.50	21	5.63	5.13	7.39	0.50	1.76	71.59

Table 5: Empirical Measures of Ambiguity and Information Constraints

This table reports the summary statistics (i.e., mean values and standard deviations) for the empirical information-constraint and ambiguity measures as well as the pairwise correlation coefficients between the empirical information-constraint and ambiguity measures and other firm characteristics. *LEV* refers to leverage. *AMBIG* refers to ambiguity. *IC* refers to information constraints. *SIZE* refers to firm size. *AGE* refers to firm age. *ROA* refers to returns on book assets. *PPE* refers to property, plant, and equipment. *MB* refers to the Market-to-Book ratio. *RD* refers to R&D expenditure. *HHI* refers to the Herfindahl-Hirschman index (HHI) of sales. *HHI2* refers to squared HHI of sales. *CFV* refers to capital expenditure. *LITIGATION* refers to litigation risk.

	Mean	STD	*LEV*	*AMBIG*	*IC*	*SIZE*	*AGE*	*ROA*	*PPE*	*MB*	*RD*	*CFV*	*HHI*	*HHI2*
LEV	0.362	0.122												
AMBIG	3.105	0.002	0.023											
IC	0.684	0.121	**-0.030**	**0.065**										
SIZE	139.401	292.049	**-0.200**	-0.013	**0.031**									
AGE	36.158	9.396	**-0.120**	**0.033**	**-0.21[illegible]**	**0.034**								
ROA	0.054	0.087	**0.149**	-0.017	**-0.196**	**0.349**	**0.164**							
PPE	0.327	0.252	**0.15[illegible]**	0.[illegible]00	**-0.088**	**-0.172**	**-0.029**	**-0.198**						
MB	7.452	6.529	**0.441**	-0.014	**-0.144**	**0.334**	0.018	**0.542**	**-0.256**					
RD	0.043	0.075	**-0.133**	**-0.044**	**0.076**	**0.223**	**-0.046**	**0.222**	**-0.416**	**0.125**				
CFV	0.036	0.027	-0.013	**-0.070**	**0.080**	**0.104**	**-0.106**	**-0.136**	**0.572**	**-0.120**	**-0.132**			
HHI	0.025	0.022	**0.208**	0.001	**0.034**	**0.041**	**-0.026**	**-0.065**	**0.332**	**0.126**	**-0.317**	**0.177**		
HHI2	0.001	0.002	**0.164**	-0.003	**0.094**	**0.020**	0.010	**-0.047**	**0.205**	**0.177**	**-0.265**	**0.103**	**0.356**	
LITIGATION	0.314	0.464	**-0.044**	-0.013	**0.128**	**0.438**	**-0.101**	**0.346**	**-0.251**	**0.299**	**0.582**	**-0.060**	**0.254**	**0.283**

Table 6: Firm Characteristics, Ambiguity, and Information Constraints

This table presents the comparisons of firm characteristics between the cases of high and low ambiguity (information constraints) in Panel A (Panel B). *AMBIG* refers to ambiguity. *IC* refers to information constraints. *LEV* refers to market leverage. *SIZE* refers to firm size. *AGE* refers to firm age. *ROA* refers to returns on book assets. *PPE* refers to property, plant, and equipment. *MB* refers to the Market-to-Book ratio. *RD* refers to R&D expenditure. *CFV* refers to capital expenditure. *HHI* refers to the Herfindahl-Hirschman index (HHI) of sales. *HHI2* refers to squared HHI of sales. *LITIGATION* refers to litigation risk. Robust *t* statistics are given in parentheses, while ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Sorting Firms by *AMBIG*

Firm Characteristics	*AMBIG* group Low	*AMBIG* group High	High-Low Differences
LEV	0.2824	0.3627	0.0803 *** (7.06)
SIZE	39.1115	140.3000	101.1885 *** (3.72)
AGE	37.7586	36.1428	-1.6158 * (-1.84)
ROA	-0.0017	0.0544	0.0561 *** (6.9[illegible])
PPE	0.3885	0.3261	-0.0624 *** (-2.65)
MB	1.0752	7.5114	6.4362 *** (6.44)
RD	0.0454	0.0429	-0.0025 (-0.36)
CFV	0.0822	0.0354	-0.0468 *** (-19.00)
HHI	0.0109	0.0255	0.0146 *** (7.04)
HHI2	0.0002	0.0012	0.0010 *** (5.69)
LITIGATION	0.0001	0.3169	0.3168 *** (7.33)

Panel B: Sorting Firms by *IC*

Firm Characteristics	*IC* group Low	*IC* group Middle	*IC* group High	Hig Diffe
LEV	0.3848	0.3437	0.3755	-0 (-3
SIZE	184.7000	92.4954	188.0000	3. (-1
AGE	37.8056	36.9731	32.8807	-4 (-2
ROA	0.0896	0.0484	0.0291	-0 (-2
PPE	0.3641	0.2705	0.4017	0. (5
MB	10.0205	6.4844	6.8206	-3 (-1
RD	0.0448	0.0431	0.0405	-0 (-2
CFV	0.0319	0.0341	0.0434	0. (1
HHI	0.0280	0.0199	0.0336	0. (9
HHI2	0.0012	0.0008	0.0018	0. (1
LITIGATION	0.4169	0.2146	0.4098	-0 (-0

Table 7: Ambiguity, Information Constraints, and Corporate Debt Financing

This table shows the regression results of corporate debt financing on ambiguity and information constraints. Columns (from left to right) report the regression results of corporate leverage, corporate bond yield, and bond duration. The regressions control for a variety of macroeconomic and accounting variables, as well as year and industry fixed effects. Robust *t*-statistics are reported in parenthesis, while ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	*LEV*		*YIELD*		*DUR*	
AMBIG	0.908	***	0.555	***	-93.591	**
	(2.58)		(3.73)		(-2.24)	
IC	-0.040	***	0.030	***	-2.577	***
	(-3.73)		(8.47)		(-2.62)	
Control Variables	YES		YES		YES	
Year fixed effect	YES		YES		YES	
Industry fixed effect	YES		YES		YES	
ADJ-RSQ	0.847		0.714		0.365	

Table 8: Information-Constraint Heterogeneities and Leverage Variations

This table shows the regression results of leverage variations on information-constraint heterogeneities. *Bet-Industry LEV* refers to between-industry leverage variations. *Within-Industry LEV* refers to within-industry across-firm leverage variations. Columns (from left to right) report the regression results of between-industry and within-industry leverage variations. The regressions control for a large battery of macro and accounting variables, as well as year and industry fixed effects. Robust *t*-statistics are reported in parenthesis, while ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	*Bet-Industry LEV*		*Within-Industry LEV*	
IC heterogeneities	0.0633	***	0.045	***
	(6.93)		(5.34)	
Control Variables	YES		YES	
Year fixed effect	YES		YES	
Industry fixed effect	NO		YES	
ADJ-RSQ	0.214		0.237	

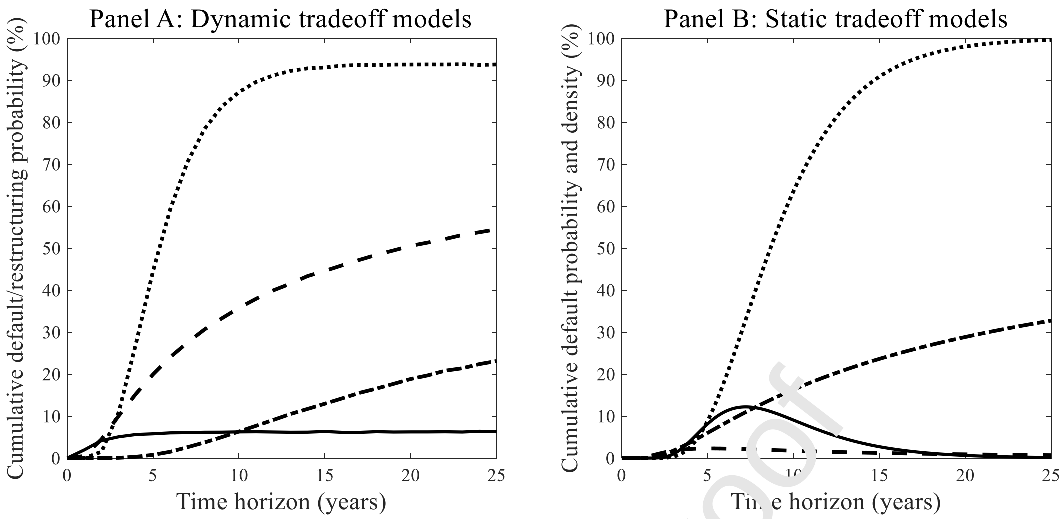

Figure 1. Term structure of cumulative default/restructuring probability. In Panels A and B, the solid (dashed) lines respectively plot cumulative restructuring probability and default density under ambiguity aversion (rational expectations). The dotted and dash-dotted lines respectively plot cumulative default probability under ambiguity aversion and that under rational expectations. Model parameters are chosen at their baseline levels. The restructuring and default thresholds are solved from the corresponding max-min capital structure decision problems.

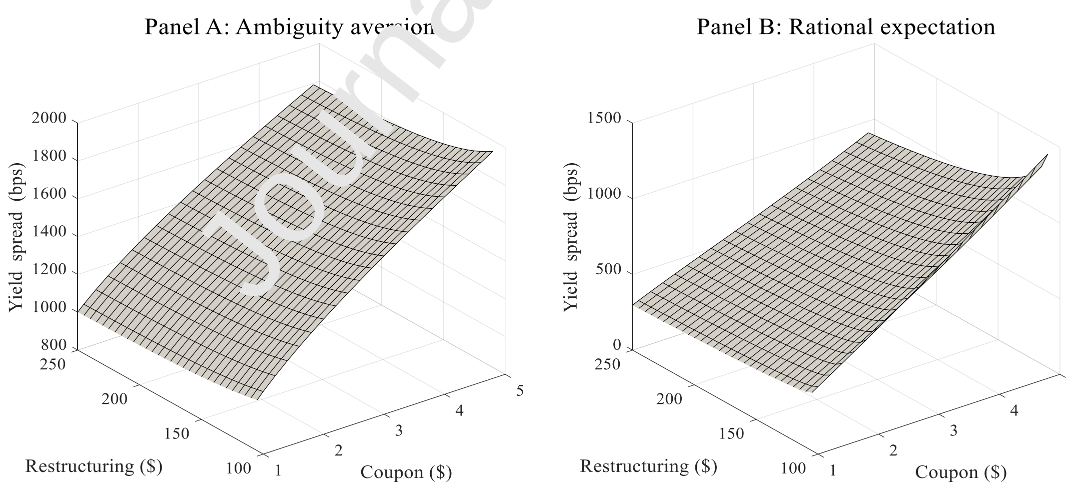

Figure 2. Yield spread, coupon, and dynamic restructuring choice. All parameters are chosen at their baseline levels. Yield spreads are calculated from the dynamic tradeoff models.

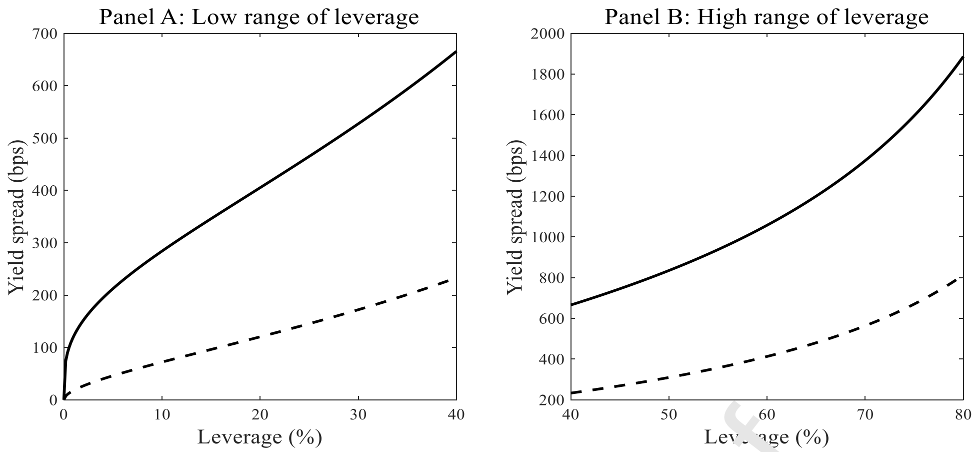

Figure 3. Yield spread against leverage. All parameters are chosen at their baseline levels. Yield spreads under ambiguity aversion (rational expectations) are plotted using the solid (dashed) lines.

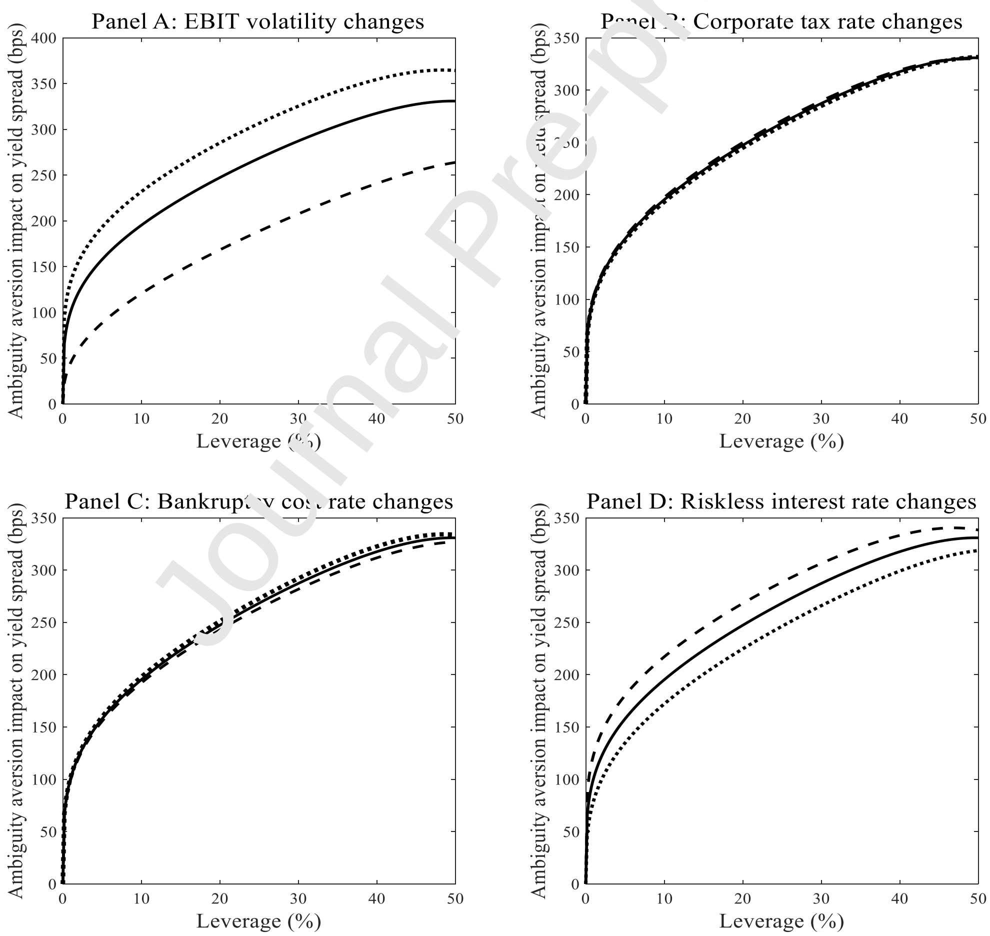

Figure 4. Ambiguity premium on yield spreads against leverage. Yield spreads are calculated from static tradeoff models. In Panels A-D, the dashed (dotted) lines are plotted using 30% (50%) EBIT volatility, 32% (38%) corporate tax rate, 55% (70%) bankruptcy cost rate, and 3.5% (5.5%) riskless interest rate, respectively. The solid lines are plotted using baseline parameters.

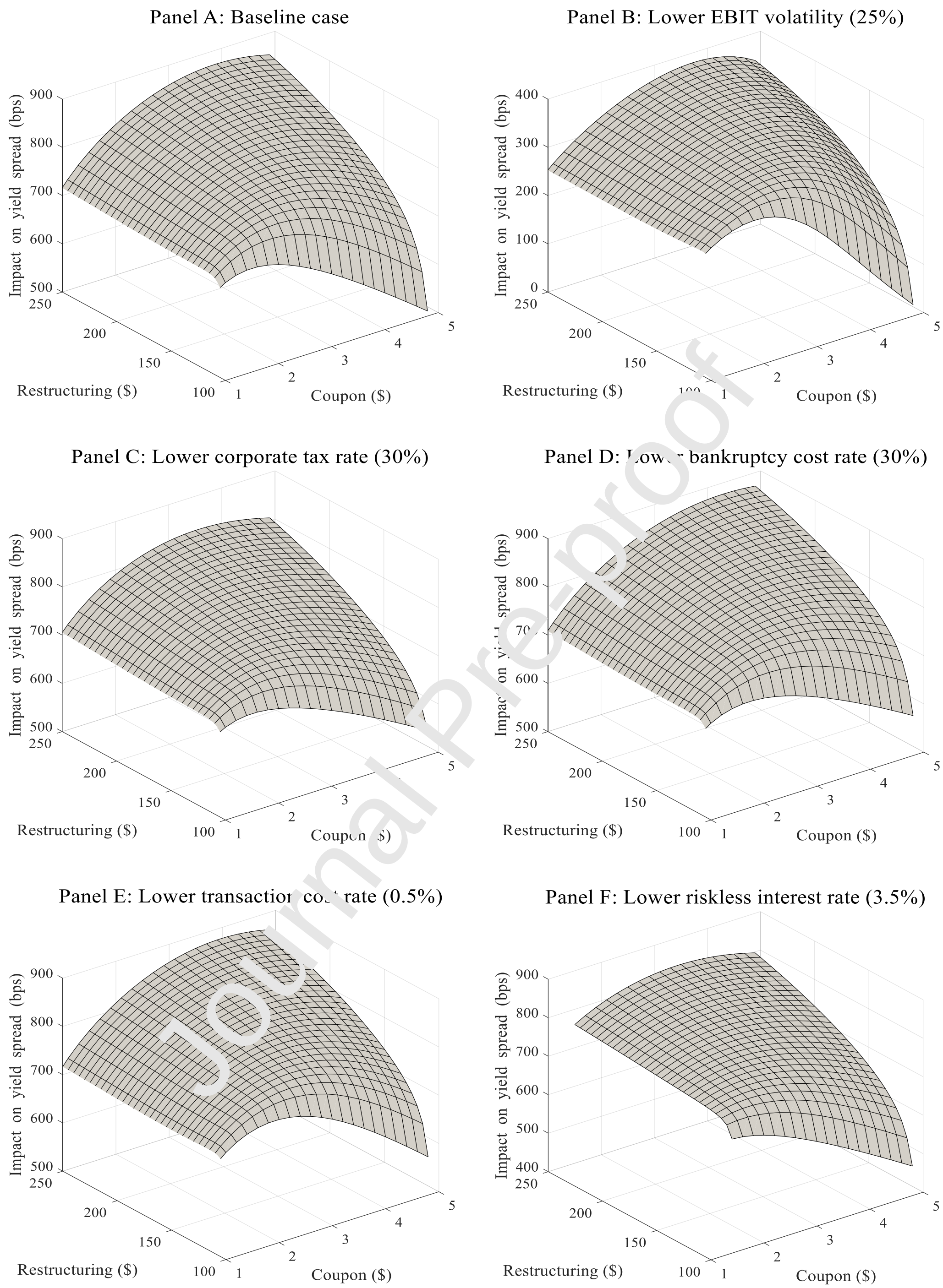

Figure 5. Ambiguity premium on yield spread, coupon, and dynamic restructuring choice. Yield spreads are calculated from the dynamic tradeoff models. Except for indicated parameters, all parameters are chosen at their baseline levels.

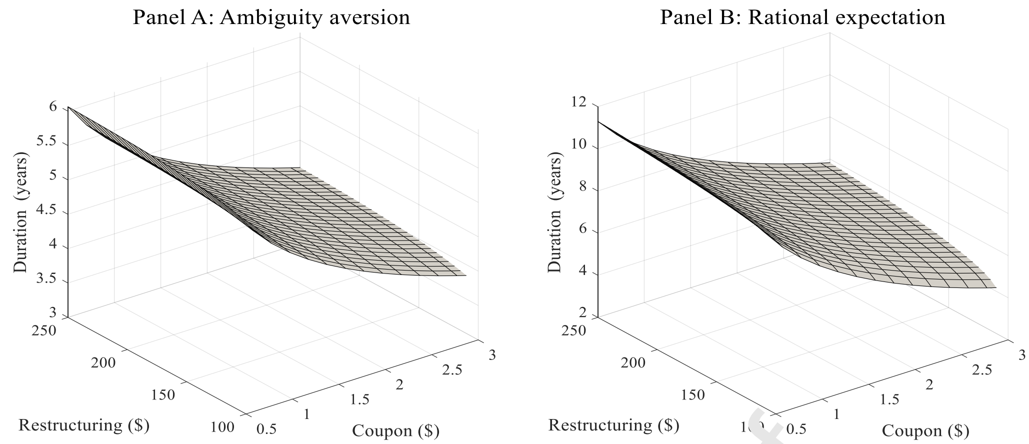

Figure 6. Duration, coupon, and dynamic restructuring choice. All parameters are chosen at their baseline levels. Duration is calculated from the dynamic tradeoff models.

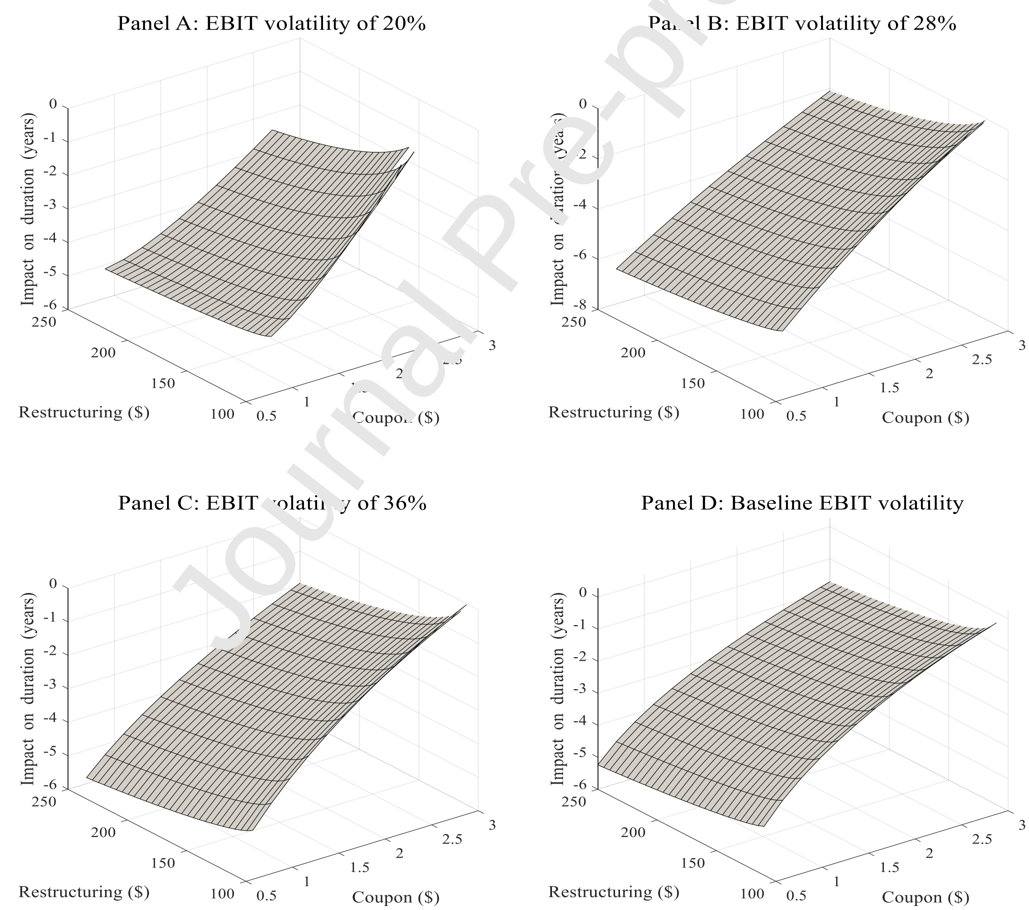

Figure 7. Ambiguity aversion impact on duration under dynamic restructuring along EBIT volatility changes. Except for EBIT volatility, all parameters are chosen at their baseline levels. Duration is calculated from the dynamic tradeoff models.

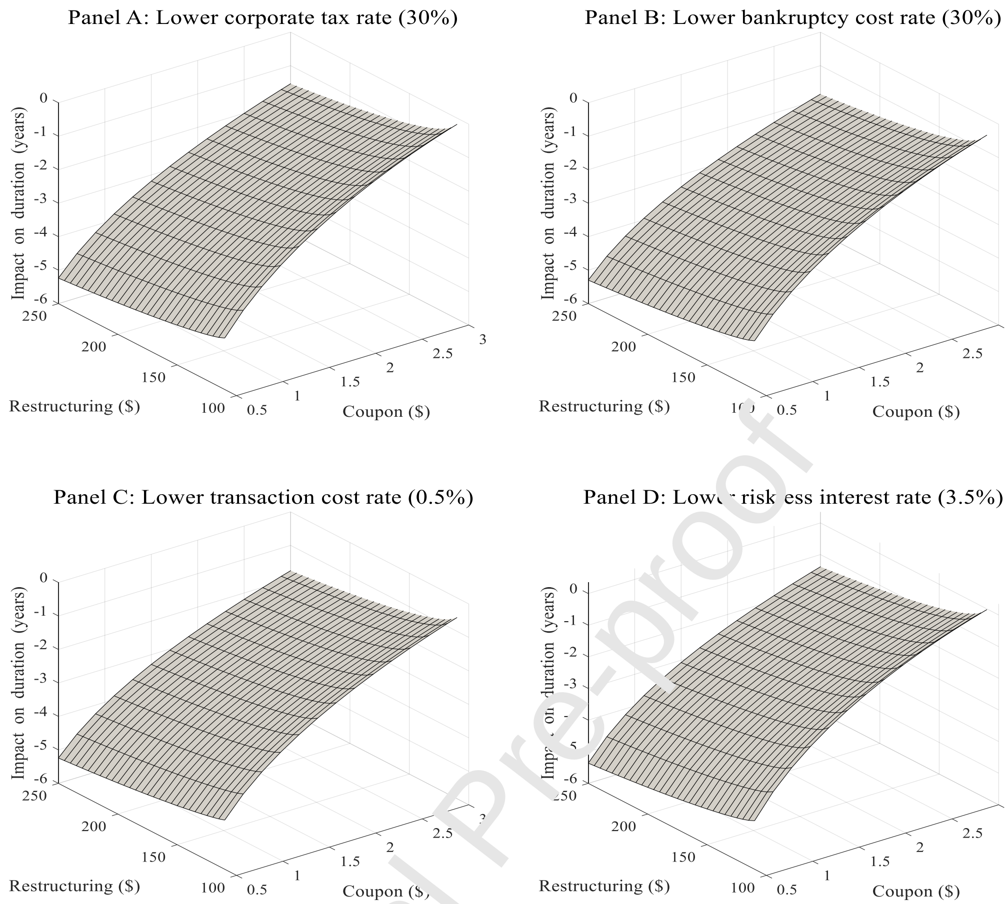

Figure 8. Ambiguity aversion impact on duration under dynamic restructuring with various parameter combinations. Except for indicated parameters, all parameters are set at their baseline levels. Duration is calculated from the dynamic tradeoff models.

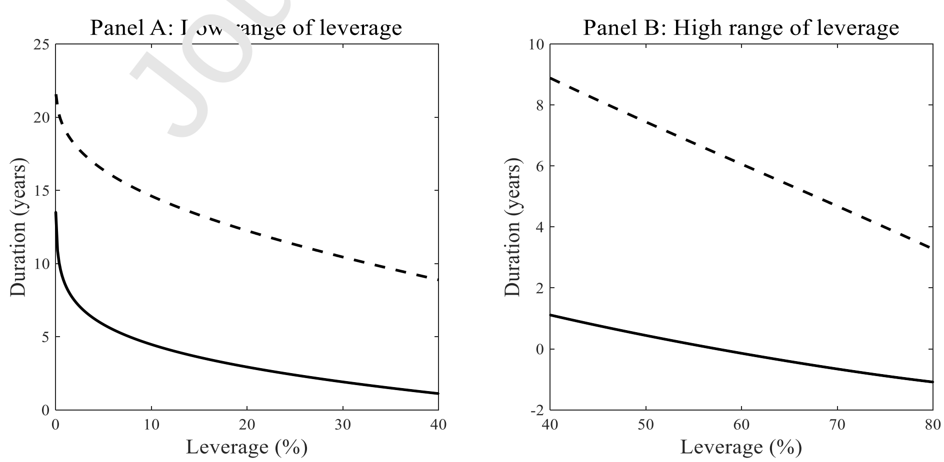

Figure 9. Duration against leverage. All parameters are chosen at their baseline levels. Duration is calculated from the static tradeoff models. The solid and dashed lines respectively plot duration under ambiguity aversion and under rational expectations.

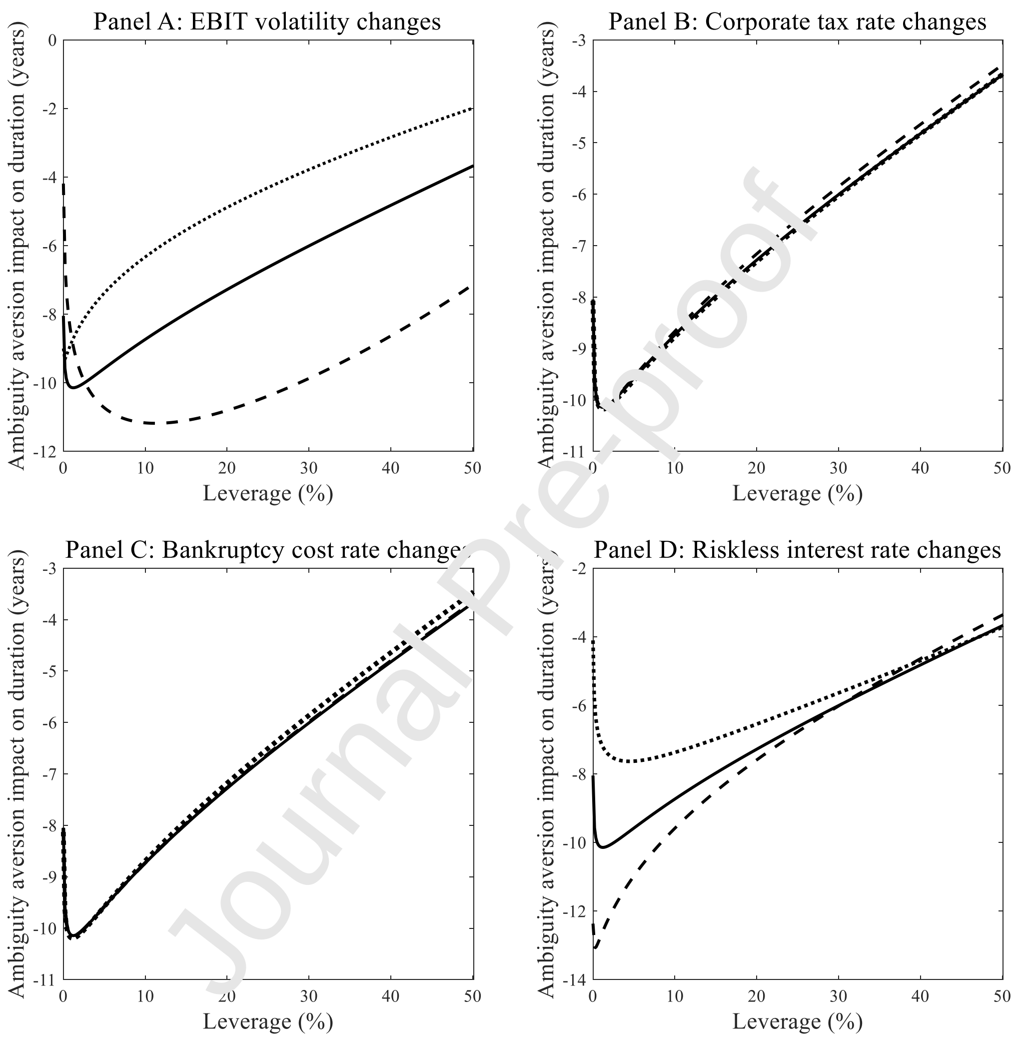

Figure 10. Ambiguity aversion impact on duration against leverage. In Panels A-D, the dashed (dotted) lines are plotted using 30% (50%) EBIT volatility, 32% (38%) corporate tax rate, 55% (70%) bankruptcy cost rate, and 3.5% (5.5%) risk-free interest rate, respectively. The solid lines are plotted using baseline parameters. Duration is calculated from the static tradeoff models.

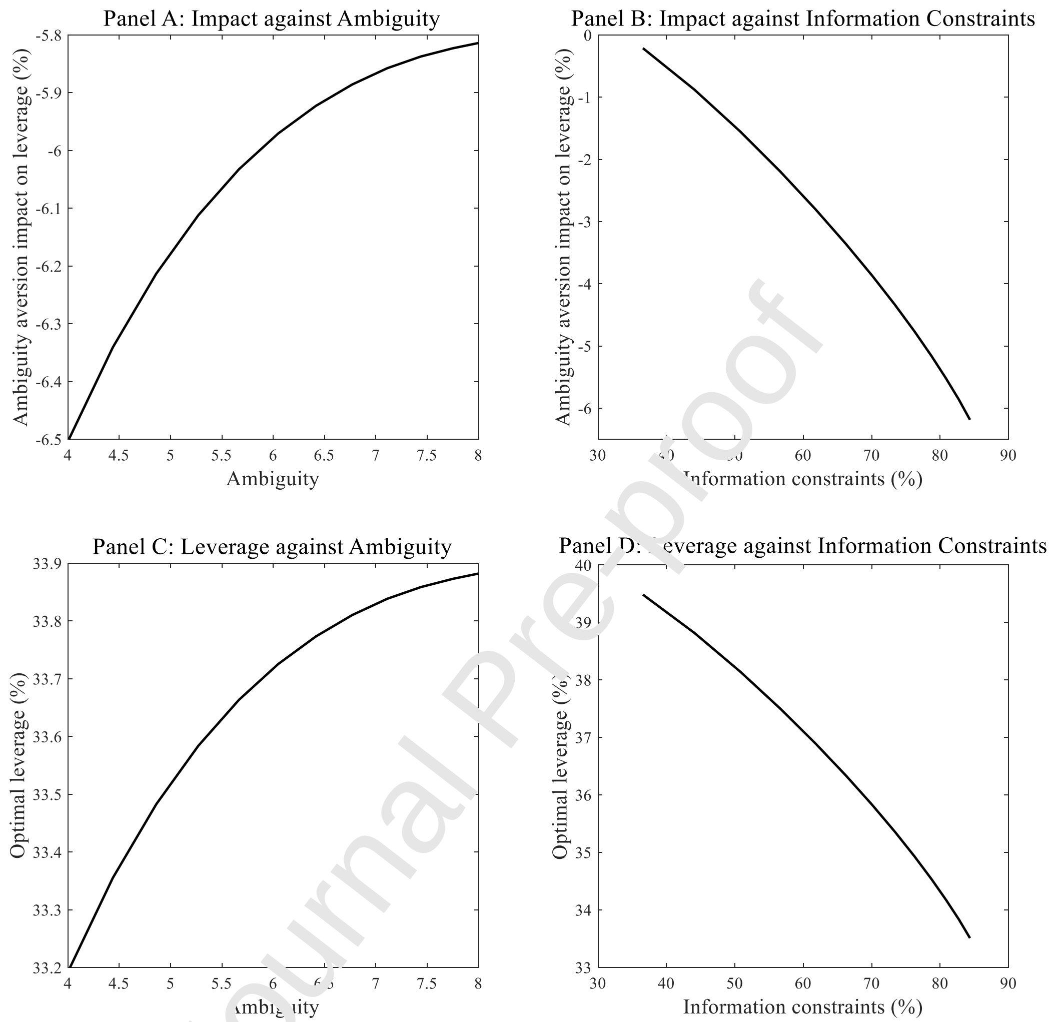

Figure 11. Optimal leverage and the ambiguity aversion impact on optimal leverage against ambiguity/information constraints. Panels A and C respectively depict the impact of ambiguity aversion and optimal leverage against ambiguity by varying the Sharpe ratio of market portfolios h_S from 0.2 to 0.5. Panels B and D respectively plot the ambiguity-aversion impact and optimal leverage against information constraints by varying idiosyncratic EBIT volatility σ_{fw} from 10% to 40% (holding systematic EBIT volatility fixed at its implied baseline level). The rest of model parameters are set at their baseline levels. All lines are plotted using the dynamic tradeoff models.

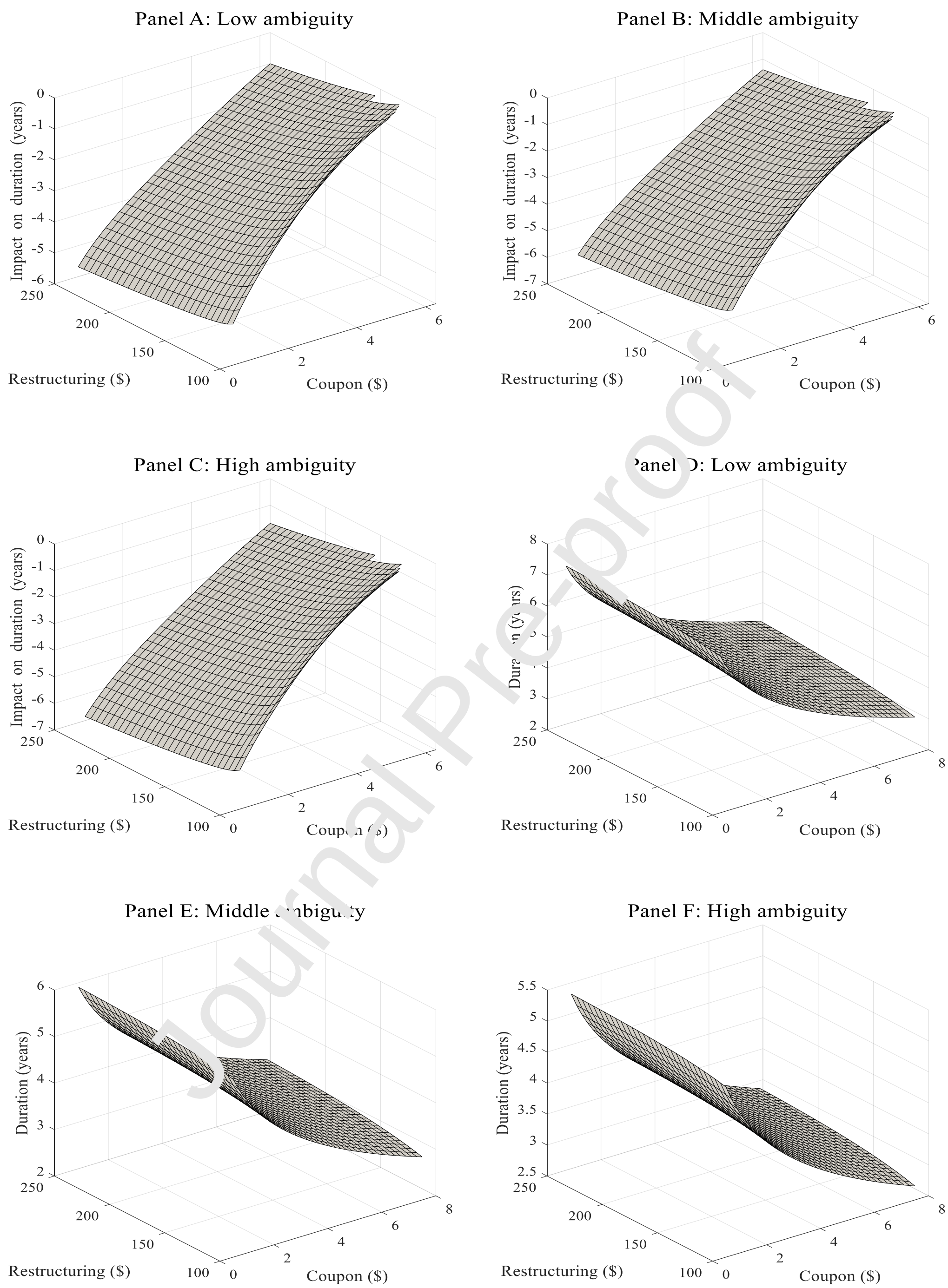

Figure 12. Duration and the ambiguity-aversion impact on duration under different levels of ambiguity. In all panels, "Coupon" and "Restructuring" respectively refer to the coupon level and restructuring threshold of asset value. The surfaces in the cases of low, middle, and high ambiguity are plotted with the market's Sharpe ratio of 0.25, 0.35, and 0.45, respectively.

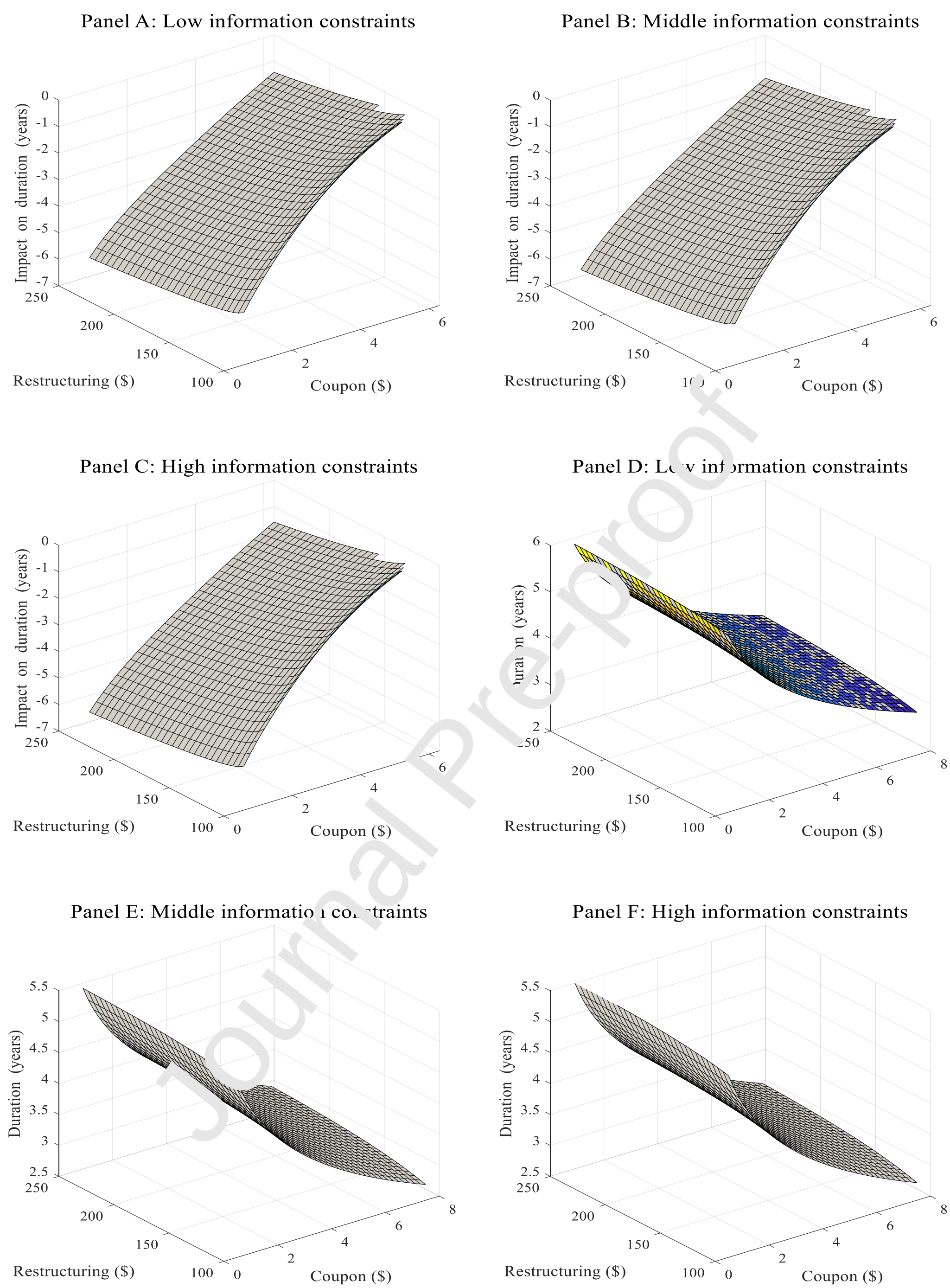

Figure 13. Duration and the impact of ambiguity aversion on duration under different levels of information constraints. In all panels, "Restructuring" and "Coupon" refer to the restructuring threshold of asset value and coupon choice, respectively. The surfaces in the cases of low, middle, and high information constraints are plotted with the market-EBIT correlation of 80%, 50%, and 20%, respectively.

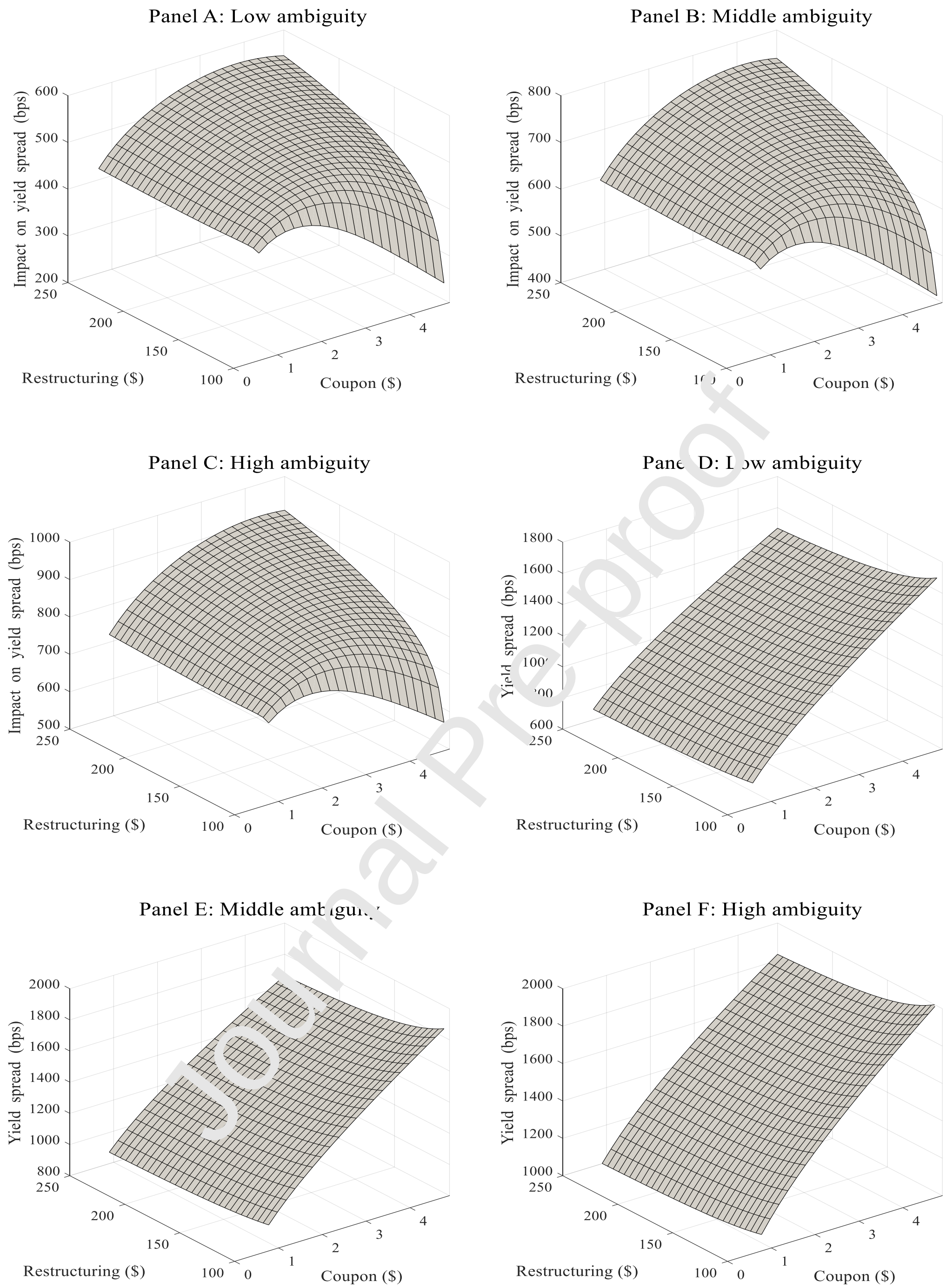

Figure 14. Yield spread and the ambiguity-aversion impact on yield spread under different levels of ambiguity. In all panels, "Coupon" and "Restructuring" respectively refer to the coupon level and the restructuring threshold of asset value. The surfaces in the cases of low, middle, and high ambiguity are plotted with the market's Sharpe ratio of 0.25, 0.35, and 0.45, respectively.

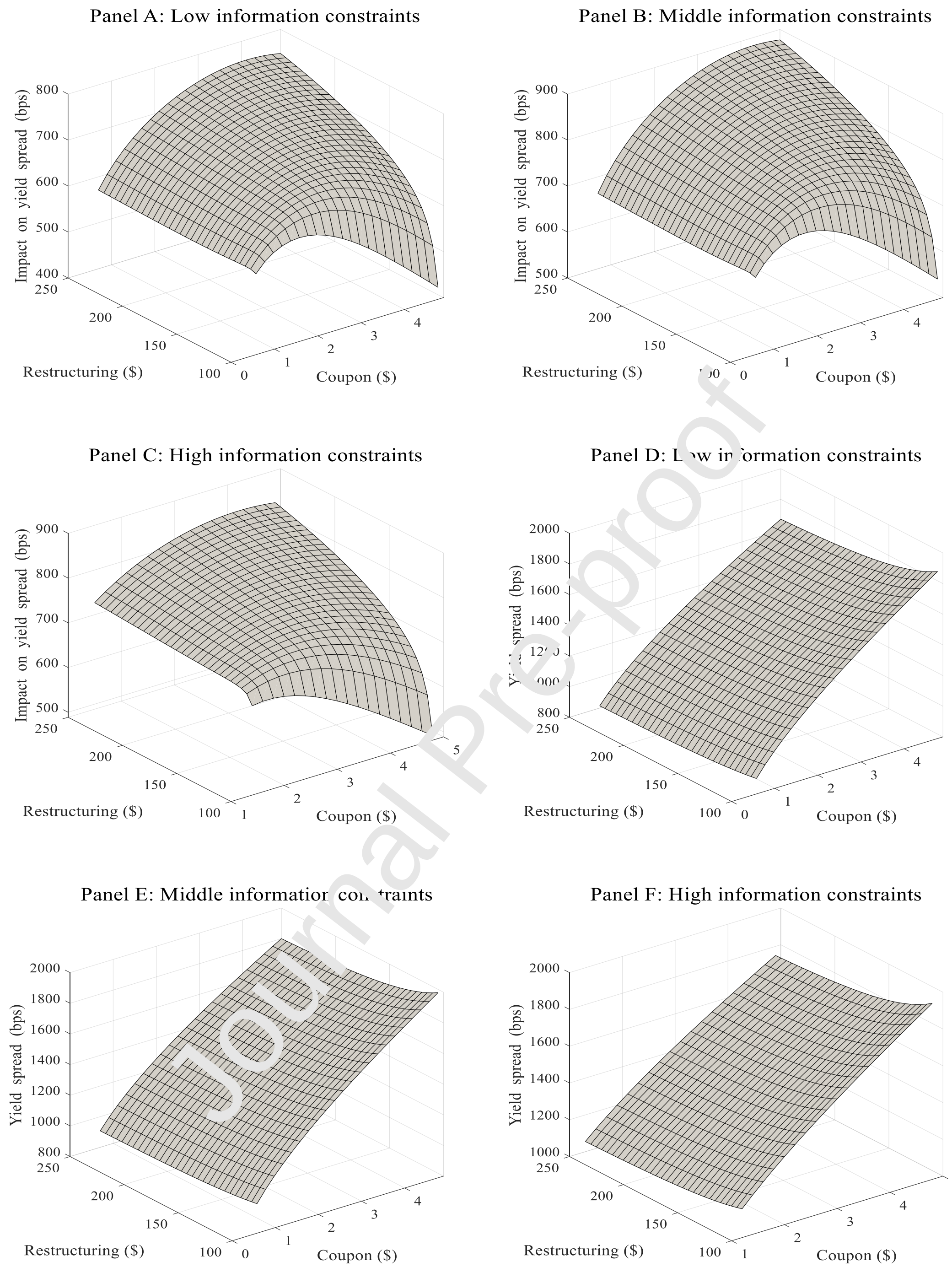

Figure 15. Yield spread and the ambiguity-aversion impact on yield spread under different levels of information constraints. In all panels, "Coupon" and "Restructuring" respectively refer to the coupon choice and restructuring threshold of asset value. The surfaces in the cases of low, middle, and high information constraints are depicted with the market-EBIT correlation of 80%, 50%, and 20%, respectively.