

The Corporate Supply of (Quasi) Safe Assets

Lira Mota*

Columbia University, Graduate School of Business

Job Market Paper

[Click here for the latest version.](#)

January 10, 2021

Abstract

Investors value safety services in financial assets, such as the ability to serve as a store of value, to serve as collateral, or to meet mandatory capital and liquidity requirements. I present a model in which investors value safety services not only in traditional safe assets such as US Treasuries, but also in corporate debt. Shareholders thus maximize the value of the firm by complementing standard business operations with safe asset creation. Based on this theoretical framework, I use the CDS-bond basis to derive a measurement of the safety premium of corporate bonds. I document substantial cross sectional variation in the safety premium of corporate bonds, which allows me to test the model's predictions. I show that a high safety premium leads to a marked increase in debt issuance by relatively safer firms. These debt proceeds have a small impact on real investment and are largely used instead for equity payouts. This mechanism can explain why, in the aftermath of the financial crisis, non-financial investment grade companies significantly increased their debt issuance and equity payout while investment remained weak.

Keywords: Safe assets, CDS-bond basis, Capital structure.

*Corresponding author: Lira Mota, lmota20@gsb.columbia.edu

*I am grateful to my advisors Kent Daniel, Olivier Darmouni, Tano Santos, and Jesse Schreger for their invaluable guidance and continuous support, and to Simona Abis, Patrick Bolton, Douglas Diamond, Jason Donaldson, Amanda Dos Santos, Polina Dovman, Philip Dybvig, Yifeng Guo, Harrison Hong, Jeremias Huber, Philip Kalikman, Yiming Ma, Harry Mamaysky, Daniel Mertens, Luca Mertens, Vrinda Mittal, Melina Papoutsis, Giorgia Piacentino, Simon Rottke, Kerry Siani, Suresh Sundaresan, Cristina Tessari, Tuomas Tomunen, Stijn Van Nieuwerburgh, Neng Wang, seminar participants at Macro and Finance at Columbia Business School and the Finance Colloquium at Columbia University Economics Department, and conference participants at the Diamond-Dybvig 36th Anniversary Conference, the 2020 AFA PhD Poster Session, and the Macro Finance Research Program of the Becker Friedman Institute Summer Session for their helpful discussions and suggestions. I acknowledge the support of the Chazen Institute for Global Business at Columbia Business School. I welcome comments, including references to related papers that I have inadvertently overlooked. All errors are my own.

1. Introduction

There is a particular class of financial assets that can serve as a store of value, be used as collateral, and be used to meet mandatory capital and liquidity requirements. The stability and safety of their cash flows are what makes these assets ideal vehicles for the provision of these *safety services*, and as a result, some refer to these securities as *safe assets*. When these assets are in limited supply, they might command a *safety premium*, i.e., a value investors are willing to pay above the discounted cash flows because of the aforementioned services they provide. Some have argued that, since the global financial crisis, the demand for safety services has increased above the supply of assets that can meet this demand, leading to an increase in the safety premium.¹ The literature has traditionally relied on a pragmatic and narrow definition of safe assets, which include liabilities issued by developed countries or by the financial sector.² In this paper, I argue that non-financial corporations can act as a class of safety service suppliers, and I study their supply responses to changes in the safety premium.

The starting point of this paper is the observation that safety is not a binary characteristic of an asset. Different assets can provide different amounts of safety services, depending on the underlying characteristics of their cash flows. I first show that US corporate bonds have earned a safety premium in recent years, with safer firms earning a higher premium. Corporate bonds are not entirely insulated from credit risk, but they can still function as a store of value, as collateral, or as regulatory capital, thereby providing an imperfect substitute for traditional safe securities. Thus, in the presence of a positive safety premium, corporate managers may create shareholder value by issuing debt. I show that firms do indeed respond to an increase in their relative safety premia by issuing more debt. In my sample, rather than using the new funds to invest, they pay out the borrowed money to shareholders. The demand for safe assets therefore has direct implications for corporate borrowing behavior and capital structure.

I begin by presenting a model that fleshes out the safety-creation mechanism in non-financial firms. The model fulfills two purposes. First, it defines the safety premium compo-

¹See *inter alia* Krishnamurthy and Vissing-Jørgensen [2012a], Gorton, Lewellen, and Metrick [2012], Caballero, Farhi, and Gourinchas [2017], Caballero and Farhi [2018].

²See *inter alia* Caballero, Farhi, and Gourinchas [2016], Gorton [2017], Caballero et al. [2017], Caballero and Farhi [2018], Farhi and Maggiori [2018], or more broadly, works that study the non-pecuniary value of US Treasuries or money-like securities such as Sunderam [2015], Nagel [2016], Du, Im, and Schreger [2018a], Binsbergen, Diamond, and Grotteria [2019], He, Krishnamurthy, and Milbradt [2019], Jiang, Krishnamurthy, and Lustig [2020], Diamond [2020].

ment in corporate debt prices. The safety premium varies across both time and firms, and maps to an empirically observable measure that I call the *cross-basis*. Second, it generates predictions about firms' responses to shocks in the safety premium. I then use data on US non-financial corporations to test the model's predictions.

Following [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#), I take a reduced-form approach and model the demand for safety services as a primitive. The model innovates in assuming that *all* debt securities can potentially provide *some* safety services.³ In equilibrium, two securities with the same cash flows can have different prices simply because they provide different safety services. The difference in prices between two such assets measures the *relative* safety premium between them. This conceptual innovation allows me to use cross sectional data to bypass the traditional difficulty faced by the literature of estimating the *aggregate safety premium*, the market price of one unit of safety services. As a result, I can use the cross section of bond prices to identify the effect of fluctuations of the relative safety premium on corporate debt issuance, as well as on other firm policies such as capital and intangible investment and payout policy.

In my model, the firm-specific safety premium depends on both the aggregate safety premium, which I assume to be exogenous, and on firms' decisions, which are endogenous. In particular, as firms issue more debt, the firm-specific safety premium goes down. Three main empirical predictions emerge from the model. First, firms respond to an increase in the safety premium by issuing more debt. Second, for financially constrained firms, an increase in the relative safety premium relaxes this constraint and leads to more investment. Third, for financially unconstrained firms, variation in debt issuance due to fluctuations in the safety premium mostly results in equity payout.

To test the model predictions, the first empirical challenge is to measure the safety premium of corporate bonds. The safety premium of a particular bond is the difference in the prices of the bond and of a benchmark asset with the same cash flows but no safety services. This benchmark is not readily available. I overcome this issue by constructing, for each bond in the sample, a synthetic asset, which is a portfolio that combines the corporate bond and the maturity-matched credit default swap (CDS). I call this synthetic asset the *hedged bond*. Under the assumption that the CDS perfectly hedges the credit risk, for all bonds the hedged bond's cash flows are the same. Then, by comparing the yields of the

³For the micro-foundations for investor's demand for securities with stable cash-flows, such as debt, the reader should refer to [Gorton and Pennacchi \[1990\]](#), [Dang, Gorton, and Holmström \[2015\]](#), [Dang, Gorton, and Holmström \[2019\]](#).

hedged bonds, I am able to quantify the *relative* safety premia among those assets.

Specifically, I introduce the cross-basis as a measure of *relative* safety premium in corporate bonds. Theoretically, the cross-basis measures the safety premium of a specific firm relative to the average firm. Empirically, I construct the cross-basis by first calculating the CDS-bond basis for each bond, which is the difference in yields between the hedged bond and the maturity- and coupon-matched US Treasury, and then define the cross-basis as the firm-specific CDS-bond basis minus the *basis index*, which is the face-value weighted average CDS-bond basis in the sample. There is a direct connection between the investors' Euler equation from the model and the cross-basis, which yields three predictions. First, in the cross section, cross-basis is monotonic in *perceived safety*, i.e., the amount of safety services an asset provides. Second, one factor, the aggregate safety premium (normalized to be the US Treasury safety premium), fully explains the time series variation of cross-basis. Third, loadings on the aggregate safety premium are monotonic in perceived safety. I find strong support for all three predictions in the data, which validates the connection between the cross-basis and firm-specific safety premium.

Equipped with an empirical measurement of the safety premium in corporate bonds, I test how firms react to variations in the safety premium. I find that in the cross section, firms with higher cross-basis in a given quarter issue more debt in the following quarter. A one percentage point increase in the cross-basis forecasts an increase of net debt issuance of 10 basis points as a share of total assets, which translates to an increase of \$27.4 million in debt issuance for the average firm or a 31% increase relative to their quarterly average debt issuance. On the other hand, the cross-basis has a small impact on real investment, measured by capital investment, intangible investment, or acquisitions. Instead, the safety premium strongly forecasts equity payouts in the form of dividends and equity repurchases. A one percentage point increase in the cross-basis forecasts a 8 basis points increase in firms' net payout as a share of total assets, or in dollars, \$23.2 million, a number very close to the effect of the cross-basis on net debt issuance. In light of the corporate bond supply model I introduced, this is evidence that companies with relatively high safety premium are not financially constrained, consequently almost all debt issued in response to the safety premium is converted into equity payouts.

I conduct a battery of additional tests to confirm these findings. A possible worry with the cross-basis as a measure of the relative safety premium is that it may be capturing frictions not related to safety, such as counterparty risk, mis-measurement due to bond illiquidity, restructuring uncertainty, or mismatch in the payoff structure of bonds. However, one important feature of the cross-basis is that any friction that affects all bonds or CDS

equally does not affect the cross-basis. Moreover, only frictions that are systematically correlated with firms' fundamentals are of concern when assessing the impact of the cross-basis on firms' choices, such as debt issuance. I show that none of these confounders are large enough to explain the cross sectional variation of the cross-basis⁴ or to be of concern regarding the interpretation of the results.

The results presented here give a new perspective on the impact of the demand for safety on the overall economy. By using a narrow definition of safe assets, [Caballero et al. \[2017\]](#) predicted that the high demand for safety would decrease risk-free interest rates, but would have the opposite effect on risk premia. This is at odds with the observed historical low credit-spreads in corporate bonds in recent years, since corporate bonds are intrinsically not risk-free. The fact that the safety premium can affect yields of imperfect substitutes to traditional safe assets is one likely explanation for the recent low yields, and it opens the possibility for a broader impact of the demand for safety, one that affects firms' cost of capital, capital structure, and business operation.

Most importantly, my paper sheds light on the determinants of the supply of safety services. Historically, the government and the financial sector have been the main producers of safe assets. The common feature of the public sector is that their debt issuance does not seem to respond to demand pressures, even if this could be associated with economic gains ([Jiang et al. \[2020\]](#)). Furthermore, given the high public indebtedness and the sluggish growth of most developed countries, many have argued that the public sector has exhausted its ability to expand the production of safe assets ([Caballero et al. \[2017\]](#)). Likewise, in the aftermath of the financial crisis, the financial sector's ability to engineer safe substitutes for Treasuries has been diminished by regulation and constrained capital. In a landscape of limited alternative safe assets, non-financial firms with ratings comparable to a sovereign are viable alternatives.

The findings in this paper also shed light on recent macroeconomic trends. In the aftermath of the financial crisis, the aggregate amount outstanding of non-financial corporate bonds almost doubled, while aggregate investment remained weak ([Gutiérrez and Philippon \[2017\]](#) and [Crouzet and Eberly \[2019\]](#)). Although investment grade (IG)⁵ firms are the largest bond issuers, their average investment in capex and R&D together represents only 60% of their total net profits, suggesting that all investment in the last ten years could have

⁴For instance [Arora, Gandhi, and Longstaff \[2012\]](#) show that counterparty risk in CDS contracts is “vanishingly small,” and [Bai and Collin-Dufresne \[2019\]](#) show that only bonds' collateral value is persistently important in explaining the cross sectional variation of the CDS-bond basis.

⁵Bonds rated BBB or more.

been financed with retained earnings alone. Another important empirical observation is that payouts have been largely financed by debt issuance ([Farre-Mensa, Michaely, and Schmalz \[2018\]](#)). In the last ten years, 90% of IG firms that issued debt in a given quarter also engaged in positive distribution to shareholders in that same quarter. For every dollar issued in IG bonds, 0.80 cents were paid back to shareholders within the same quarter by the median firm.⁶ In summary, evidence suggests that IG firms are changing their capital structure by issuing debt to repurchase their own equity and pay dividends, but not necessarily to invest more. The theory of corporate safety creation presented in this paper provides a coherent explanation for these facts.

2. Related Literature

This paper relates to and draws from several strands of literature. I build on the safe-assets literature that shows that investors value safe assets with stable cash-flows and that there is a shortage in supply of asset with this characteristic.⁷ The contribution of my paper is to study a new class of safe-asset supplier, non-financial corporations, and to show that the response to the safety premium is not concentrated on the safest firms in the US, as discussed in [Krishnamurthy and Vissing-Jørgensen \[2012b\]](#), but rather is pervasive across the corporate sector.

Much like banks, I show that non-financial corporations respond to the discount in their liabilities by issuing debt, even if this tends to be a purely financial operation unrelated to the firms' business operations. The elasticity of the supply of corporate bonds to changes in safety premium is akin to the creation of money-like short-term claims by the financial sector in response to shocks in the safety and liquidity premia (see, e.g., [Sunderam \[2015\]](#), [Nagel \[2016\]](#), [Krishnamurthy and Vissing-Jørgensen \[2015\]](#) and [Kacperczyk, Pérignon, and Vuillemeay \[2020\]](#)). The difference is that, instead of providing substitutes to money claims, highly rated corporate bonds can be good substitutes for the safety properties of long-term Treasuries. Hence, my paper shows evidence that the private sector elasticity of supply of safe assets is not concentrated in highly liquid short-term liabilities.

This paper relates to the literature that investigates the interconnection between Treasury bond issuance and corporate decisions. I show that corporate bonds are imperfect substitutes

⁶All summary statistics were calculated using the sample of Compustat firms described in Section 4.

⁷A non-exhaustive list of related paper is [Gorton et al. \[2012\]](#), [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#), [Caballero et al. \[2016\]](#), [Caballero et al. \[2017\]](#), [Caballero and Farhi \[2018\]](#), [Lenel \[2020\]](#), [Diamond \[2020\]](#).

to Treasury bonds not only with respect to maturity, like in [Greenwood, Hanson, and Stein \[2010\]](#) and [Badoer and James \[2016\]](#), but also in providing safety services. Furthermore, an innovation with respect to this literature is to measure the firm-level safety premium, which allows me to find variation in firms' behavior that is not captured by the variation in the supply of US Treasury bonds, as is explored in the aforementioned papers and in [Graham, Leary, and Roberts \[2014\]](#), [Liu, Schmid, and Yaron \[2020\]](#) and [Giambona, Matta, Peydro, and Wang \[2020\]](#). This also allows for leveraging the cross section of firms to alleviate endogeneity concerns related to the time series of the supply of Treasury bonds.

[Kacperczyk et al. \[2020\]](#) also look at the cross section to identify how fluctuations in the safety premium affect issuance. Their focus is on short-term liabilities, certificate of deposits issued by commercial banks and commercial paper issued by non-financial firms. They find that the financial sector issues certificate of deposits in response to an increase in the safety premium, but that non-financial corporations do not issue more commercial paper in response to this increase. By focusing on longer maturity debt,⁸ I find that non-financial corporations actively respond to an increase in the own safety premium by issuing more debt. I interpret these results as evidence that while banks and other intermediaries are probably the marginal producers of short-term safe assets, non-financial corporates have a role in producing safe assets in longer maturities.

Also related to this paper are the works by [Lenel \[2020\]](#) and [Diamond \[2020\]](#) who consider the collateral value of corporate bonds for financial intermediaries and its interaction with the demand for safe assets. [Lenel \[2020\]](#) studies how the variation in the supply of US Treasury bonds affects asset prices and lending volumes in the financial sector, and [Diamond \[2020\]](#) presents a theory on how the financial sector is organized to engineer safe assets backed by bonds, and how this mechanism affects firms' capital structure. I contribute to these works by using market prices to construct a firm-level measure of the corporate safety premium, and provide empirical evidence that variation in the safety premium, which include compensation to the collateral value corporate debt, has a direct impact on firms' cost of borrowing and therefore leverage decisions.

Finally, this paper also connects to the literature on the market timing of firms' capital structure. One explanation for the existence of market timing is information asymmetry, i.e., managers have better information than the market about firm fundamentals ([Baker and Wurgler \[2002\]](#), [Baker, Greenwood, and Wurgler \[2003\]](#), [Warusawitharana and Whited \[2016\]](#)

⁸The empirical part of this paper looks at non-financial corporate debt with 1-year or more time to maturity.

and Ma [2019]). Another reason for corporate market timing is precautionary savings, firms raise external finance when it is cheap, guaranteeing liquidity for periods when external finance is expensive (Bolton, Chen, and Wang [2013] and Eisfeldt and Muir [2016]). My model does not rely on information asymmetry, as the safety premium is observable to all agents. Furthermore, I do not find that fluctuations in the relative safety premium are associated with corporate savings, but instead, they are associated with equity payouts. Thus, my paper presents a new channel explaining why we might observe corporate debt issuance when corporate debt yields are depressed. That is, if the safety premium is positive, some firms are able to create value to shareholders by issuing debt because in doing so, they increase the amount of safety services in the economy.

3. Model

In this section, I present a model of safety creation by non-financial corporations. Section 3.1 presents the model, and the results are found in Section 3.2. Section 3.3 summarizes the testable predictions derived from the model, and section 3.4 discusses how to empirically test them. The empirical tests are performed in Section 6.

3.1. Setup

There are three sets of agents in the model: representative investors, a set of heterogeneous firms, and an exogenous supplier of safe assets, like US Treasury bonds.

3.1.1. Investors

The key innovation of this paper is to allow for the possibility that different assets provide different degrees of safety services. More formally, I normalize to one the amount of safety services provided by one dollar of face value of US Treasuries (henceforth UST). Let $\alpha_{i,t+1}$ be the safety services by unit of face value provided by any other bond i . Thus, if $q_{T,t+1}$ and $q_{i,t+1}$ are the total face value of UST and bond i respectively, the total supply of safety services in the economy, S_t , is given by

$$S_t = q_{T,t+1} + \sum_{i=1}^N \alpha_{i,t+1} q_{i,t+1}. \quad (1)$$

I refer to $\alpha_{i,t+1}$ as *perceived safety* throughout.

I follow [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#) and take the demand for safety services as a primitive. I assume investors derive utility from safety services in a way that is separable from standard utility from consumption. Specifically, the problem of the representative investor is

$$\begin{aligned} \max_{\{c_t, \mathbf{Q}_{t+1}\}_{t=0}^{\infty}} \mathbb{E}_t \left[\sum_t \beta^t u(c_t) + \Theta_t v(S_t) \right] \\ \text{s.t.} \quad c_t + \mathbf{Q}_{t+1} \mathbf{P}_t \leq \omega_t + \mathbf{Q}_t \mathbf{X}_t, \end{aligned} \quad (2)$$

where \mathbf{P}_t is a column vector of asset prices, \mathbf{X}_t are realizations of the corresponding payoffs at time t , \mathbf{Q}_t is a row vector of portfolio positions, c_t is consumption, ω_t is an exogenous wealth flow, and β is the standard discount rate. The assumptions on the functions u and v are standard: $u' > 0$, $u'' < 0$, $v' > 0$ and $v'' < 0$. Finally, given the normalization of the safety services provided by UST, Θ_t is a demand shifter that allows us to identify the impact of an aggregate shock in the demand for safety services supplied by UST.

From the consumers' Euler equation, the price for each asset i is

$$P_{i,t} = \mathbb{E}_t [M_{t+1} X_{i,t+1}] + \alpha_{i,t+1} \varphi_t, \quad (3)$$

where $M_{t+1} := \beta \frac{u'(c_{t+1})}{u'(c_t)}$, $\theta_t := \frac{\Theta_t}{\beta u'(c_t)}$ and $\varphi_t := \theta_t v'(S_t)$.

Prices consist of the standard discounted cash flows component and the *safety premium* component, measured by $\alpha_{i,t+1} \varphi_t$. I refer to φ_t as the aggregate safety premium; it is the market price of one unit of safety services. Given that I have normalized to one the safety services associated with one dollar of face value of UST, φ_t is also the safety premium of UST. In what follows, I refer to φ_t as the aggregate safety premium or the UST safety premium interchangeably.

In this model, the law of one price does not hold: two assets can have the same cash flows X , but have different prices precisely because they provide different safety services. The difference is measured by the perceived safety, $\alpha_{i,t+1}$. Perceived safety can be correlated with X_i , to allow for the possibility that the amount of safety services an asset provides relates to its cash flow characteristics, but in a way that is not fully captured by the correlation between M and X_i .

3.1.2. Environment

Firms' production is subject to aggregate productivity shocks x_t and idiosyncratic productivity shocks $z_{i,t}$. The two stochastic processes are described by

$$x_{t+1} = \rho_X x_t + \sigma_X \eta_{t+1}^x, \quad (4)$$

$$z_{i,t+1} = \rho_Z z_{i,t} + \sigma_Z \eta_{i,t+1}^z. \quad (5)$$

where η_t^x and $\eta_{i,t}^z$ are IID standard normal random variables. The parameters ρ_X and ρ_Z represent the persistence of the aggregate and the idiosyncratic shocks, and σ_X and σ_Z the respective volatilities.

The aggregate safety premium, φ_t , depends on preference shock θ_t , and the exogenous supply of UST bonds and of other assets that provide safety services. I assume that the total amount of safety services provided by the non-financial corporate sector is small, therefore φ_t is exogenous in my model. The stochastic process that drives φ_t is described by

$$\log \varphi_{t+1} = \log \bar{\varphi} + \rho_\varphi \log \varphi_t + \sigma_\varphi \eta_{t+1}^\varphi, \quad (6)$$

where η^φ is an IID standard normal random variable; $\bar{\varphi}$, σ_φ , and ρ_φ represent respectively the median, volatility, and persistence of the aggregate safety premium.

I assume that the stochastic discount factor is given by

$$\log M_{t,t+1} = \log \beta - \gamma(x_{t+1} - x_t), \quad (7)$$

where β is the rate time of preference, γ is the relative risk aversion, and x_t is the economy's aggregate productivity shock. Equation (7) follows from the reduced-form assumption that the aggregate consumption c_t is an affine function of the aggregate productivity $c_t = a + bx_t$ with $b > 0$. Notice then that this model is not a general equilibrium one, because there are sources of consumption other than the dividends paid by the non-financial corporations.

3.1.3. Firms

There is a set of heterogeneous firms, indexed by $i \in \mathcal{I}$. The operating profits of a firm are determined by

$$\Pi_{i,t}(k_{i,t}; x_t, z_{i,t}) = \exp(x_t + z_{i,t}) k_{i,t}^\zeta, \quad (8)$$

where x_t and $z_{i,t}$ are the aggregate and idiosyncratic productivity shocks defined in (4) and (5), $k_{i,t}$ is the capital of the firm, and $0 < \zeta < 1$ is the capital share of production. $\zeta < 1$ implies firms' technology exhibits decreasing return-to-scale.

Firms may need external funds to finance dividends or investment. To allow for a firm to be financially constrained, equity issuance must be costly. Thus, for simplicity, I assume all external finance is in the form of one-period debt. Let $b_{i,t+1} \geq 0$ be the face value of debt issued at time t , which is due at time $t + 1$. $P_{i,t}$ is the market price for one dollar of face value of debt. At time t , a solvent firm pays $b_{i,t}$ and receives $b_{i,t+1}P_{i,t}$ from bondholders. Shareholders are protected by limited liability, and distributions to shareholders are denoted by $d_{i,t}$. Investment, equity payout, and financing decisions must satisfy the budget constraint

$$d_{i,t} = \Pi_{i,t} + (1 - \delta)k_{i,t} - b_{i,t} - k_{i,t+1} + P_{i,t}b_{i,t+1} \geq 0 \quad (9)$$

where $\delta > 0$ is the *depreciation rate of capital*.

Let time t net worth be $w_{i,t} := \Pi_{i,t} + lv(1 - \delta)k_{i,t} - b_{i,t}$ and $lv \in (0, 1)$ be the *liquidation value of capital*. I assume that debt is protected by a positive net worth covenant, as in [Brennan and Schwartz \[1984\]](#). Thus, default occurs whenever $w_{i,t}$ first becomes negative,^{9,10} and the default region can be written as

$$\Delta\{x_t, z_{i,t}\} = \{x_t + z_{i,t} < \ln(\tilde{w}_{i,t})\} \quad \text{where} \quad \tilde{w}_{i,t} = \frac{b_{i,t} - lv(1 - \delta)k_{i,t}}{k_{i,t}^\zeta}.$$

In a default scenario, the bondholders receive a *default payoff* equal to

$$L(b_{i,t}, k_{i,t}; x_t, z_{i,t}) = (1 - \xi) \frac{\Pi_{i,t} + lv(1 - \delta)k_{i,t}}{b_{i,t}},$$

where $\xi \in (0, 1)$ is the *bankruptcy cost*.

Let $\mathbb{I}_{\Delta_{i,t+1}}$ be an indicator variable for the default region of firm i , at time $t + 1$. The market price of debt $P_{i,t}$ is given by¹¹

$$P_{i,t} = \mathbb{E}_t \left[M_{t+1} \left((1 - \mathbb{I}_{\Delta_{i,t+1}}) + \mathbb{I}_{\Delta_{i,t+1}} L(b_{i,t+1}, k_{i,t+1}; x_{t+1}, z_{i,t+1}) \right) \right] + \alpha_{i,t+1} \varphi_t. \quad (10)$$

⁹For examples of other work that uses a solvency default definition see [Crouzet \[2018\]](#) [Elenev, Landvoigt, and Van Nieuwerburgh \[2020\]](#).

¹⁰The advantage of this approach, compared to the traditional strategic default, is that it allows, for each action and state, a closed form solution for debt prices, as shown in [Appendix C.1](#). This avoids the computational cost of solving jointly the value of the firm and the default threshold. As discussed in [Strebulaev and Whited \[2012\]](#), the “loop-within-a-loop” algorithms to solve dynamic models with strategic defaults can be very computationally costly, in particular when we have many state variables, as my model does.

¹¹I calculate the debt price in closed form for each $(k_{t+1}, b_{t+1}; s_t)$. This calculation can be found in [Appendix C.1](#).

A key ingredient of the model is that, while the aggregate safety premium φ_t is exogenous, firm’s decisions regarding debt issuance, payout, and investment affect the firm’s perceived safety, $\alpha_{i,t+1}$. For most of the empirical results of the paper, the specific functional form and even the determinants of $\alpha_{i,t+1}$ do not need to be specified. The reason is that, as shown later, my approach allows for an estimate of $\alpha_{i,t+1}$ (up to a scalar) directly. However, the theoretical characterization of this problem requires a functional form of $\alpha_{i,t+1}$. For this reason, I assume that

$$\alpha_{i,t+1} = \alpha_{i,t}^\mu \exp\left(-\psi \frac{b_{i,t+1}}{\mathbb{E}_t \Pi_{i,t+1}}\right), \quad (11)$$

where the parameter μ represents the memory of investors and ψ is a positive scalar.

Expression (11) links the perceived safety to the inverse of the interest coverage ratio ($\frac{b_{i,t+1}}{\mathbb{E}_t \Pi_{i,t+1}}$), one of the key determinants of bond ratings.¹² In addition, perceived safety is persistent, as measured by the parameter μ . These choices are made to match the empirical observations discussed in Section 5, that perceived safety is monotonic in ratings and ratings are persistent in time.

Furthermore, equation (11) captures in a tractable way an important feature about safe assets: “When it comes to forming beliefs about which assets are safe, reputation and history matter” (Caballero et al. [2017]). Moreover, there is an additional benefit of specifying the functional $\alpha_{i,t+1}$, which is that it allows for the structural estimation of the UST safety premium, φ_t , as discussed in Section 5.2.

Finally, a firm’s value is defined as the discounted value of all future distributions to shareholders and can be written recursively as:

$$V(\mathcal{J}_{i,t}) = \max_{k_{i,t+1}, b_{i,t+1}} d(k_{i,t+1}, b_{i,t+1}; \mathcal{J}_{i,t}) + \mathbb{E}_t [M_{t,t+1} V_{i,t+1}(\mathcal{J}_{i,t+1})] \quad (12)$$

where $M_{t,t+1}$ is the one-period stochastic discount factor in (7), the dividends d_t satisfy the budget constraint (9) and $\mathcal{J}_{i,t} = \{w_{i,t}, \alpha_{i,t}, x_t, z_{i,t}, \varphi_t\}$ are the state variables. The expectation is taken over the joint conditional distribution of aggregate, idiosyncratic, and aggregate safety premium shocks. Note that the limited liability assumption is naturally met by the positive dividend constraint.

The firm’s model deviates from the Modigliani-Miller benchmark in two dimensions: (1) there are financial constraints related to the solvency default and bankruptcy cost ξ , and (2)

¹²A common practice is to measure the interest coverage ratio is the ratio between company’s earnings before interest and taxes (EBIT) during a given period divided and the company’s interest payments due within the same period. To see its importance for ratings, see Moody’s credit rating methodology [here](#).

bonds carry a safety premium $\alpha_{i,t+1}\varphi_t$. The underlying assumption is that firm managers can create value to shareholders by changing their firm’s capital structure to produce safety services that are valuable to investors.

3.2. Model Results

To allow for a sharp characterization of the results of the model, I restrict myself to a two-period version of the model, and leave a complete treatment of the fully dynamic model for the appendix. Qualitatively, both versions of the model deliver similar results; though obviously, quantitative statements rely on the fully dynamic model.

3.2.1. Bond Prices

A firm’s safety premium depends on the aggregate safety premium, φ_t , and the firm-specific perceived safety, $\alpha_{i,t+1}$. A positive safety premium acts as a discount in a firm’s cost of borrowing by increasing the price of their debt. Furthermore, since perceived safety depends on the debt coverage ratio, as $b_{i,t+1}$ increases, the safety premium converges to zero.

Figure 1 illustrates how a firm’s safety premium and debt prices depend on the level of debt issued for different levels of the aggregate safety premium for a fixed set of state variables. *Ceteris paribus*, the larger the amount of debt issued, the smaller the debt price. There are two reasons for this. First, there is the traditional risk mechanism in which an increase in debt issuance increases the probability of default and lowers debt prices. Second, if the aggregate safety premium is positive, larger issuance decreases the firm’s perceived safety and thereby decreases its safety premium and price.

3.2.2. Model Mechanics

To illustrate the mechanics of the model, Figure 2 shows how the total value varies with the amount of bonds issued for different levels of the aggregate safety premium. Consider first the case in which $\xi = 0$, i.e., there is no bankruptcy cost. If the aggregate safety premium is also zero, $\varphi_t = 0$, corporate debt does not carry a safety premium either, and the value of the firm would be invariant to debt issuance. This is the Modigliani-Miller benchmark.

If safety services are valuable in this economy, $\varphi_t > 0$, the total value of the firm has two components: the value of the normal business operation and the value due to safe-asset creation. In Figure 2a, the green area shows the value of a firm’s business operation, which

is the firm’s value if the aggregate safety premium is zero. The blue areas represent that additional value created by issuing debt that carries a safety premium for different levels of aggregate safety premium φ_t . The maximum value is achieved when the marginal safety premium received by issuing debt is equal to the marginal decrease in safety value for making the firm more leveraged.

The second step is to introduce a bankruptcy cost greater than zero. In this case, the firm faces an additional trade-off for issuing bonds: On one hand, issuing bonds creates value for the firm due to the extra creation of safety services; on the other hand, it increases the probability of bankruptcy, which increases expected bankruptcy cost. Again, for each level of φ_t , there is a unique investment- and debt-level pair that maximizes the value of the firm. Figure 2b shows how the total value of the firm varies with issuance for different levels of aggregate safety premium. The dotted lines represent the optimal debt level $b_{i,t+1}^*$ that maximizes the value of the firm for each φ_t .

3.3. Comparative Statics and Empirical Predictions

I want to understand how firms react to variations in the safety premium, both in the time series and in the cross section. In the cross section, the objective is to understand how cross sectional differences in initial perceived safety, $\{\alpha_{i,t}\}_{i \in \mathcal{I}}$, affect the optimal policy. In the time series, instead, the objective is to understand how a single firm optimally adjusts its policy in response to fluctuations in the aggregate safety premium, φ_t .

Armed with the main intuition of the model, I turn next to illustrate the numerical solutions the model. Parameter choices are described in Table 1. Parameters, such as the decreasing returns to scale, depreciation, the idiosyncratic and aggregate shock parameters, and the stochastic discount factor parameters are standard and follow the literature closely in selecting them.

The model predictions depend on whether the firm is financially constrained or not. I define a firm to be unconstrained at time t whenever the dividend constraint is slack, i.e., $d_{i,t}^* > 0$.¹³ Notice that I use the word dividends, but the reader should understand “payouts,” since it is immaterial whether the firm distributes these payouts in the form of dividends, equity repurchases, or some combination of both. As an illustration, Figure C.11 plots the

¹³Strictly speaking, there could be firms that have $d_{i,t}^* = 0$ and are not financially constrained, because they achieved their optimal scale exactly at the boundary. A small perturbation in the parameters, of course, places this firm at one side or the other of the constraint.

valuation as function of the actions $\{k_{i,t+1}, b_{i,t+1}\}$ and the optimal policy for an unconstrained and a constrained firm.

Consider first the implications of the model for the cross section. Figure 3 shows optimal bond issuance, investment, and payouts as a function of the initial perceived safety, $\alpha_{i,t}$, for two different firms, one constrained and another unconstrained, for three different levels of the aggregate safety premium, φ_t . As shown in panels (a) and (b), for both the unconstrained and the constrained firms, as long as $\varphi_t > 0$, the higher the initial perceived safety, the higher the bond issuance. The difference between these two firms lies on how they use the proceeds from debt issuance. Unconstrained firms, even if the aggregate safety premium is zero, can always achieve their optimal capital scale. Therefore, the money borrowed mostly translates into higher payouts. Instead, constrained firms with higher perceived safety are less financially constrained than otherwise identical companies with lower perceived safety, thus the higher investment of the former relative to the later. Intuitively, payouts are equal to zero in this case. I summarize these results in the following prediction.

Prediction 1. (Cross Section) *In the cross section, if the aggregate safety premium is positive ($\varphi_t > 0$), ceteris paribus, optimal bond issuance, $b_{i,t+1}^*$, is increasing in the firm's initial perceived safety, $\alpha_{i,t}$. Furthermore, if a firm is financially unconstrained, investment increases by less than the proceeds from bond issuance, with the remainder being distributed to equity holders.*

The predictions are similar for the time series. Figure 4 shows the effect of the aggregate safety premium on bond issuance, investment, and payouts for two different firms, one constrained and another unconstrained, for three different levels of the firm-specific perceived safety, $\alpha_{i,t}$. I summarize these predictions next.

Prediction 2. (Time Series) *In the time series, for a firm with positive perceived safety, $\alpha_{i,t} > 0$, ceteris paribus, optimal bond issuance, $b_{i,t+1}^*$, is increasing in the aggregate safety premium, φ_t . Furthermore, if the firm is financially unconstrained, investment increases by less than the proceeds from bond issuance, the remainder being distributed to equity holders.*

There are obviously interaction effects between the two components of the safety premium. For instance, debt issuance of firms with higher initial level of perceived safety will respond more to variation in the aggregate safety premium than otherwise equal firms with lower initial level of perceived safety. In Figure 5, I plot the first derivative of optimal bond issuance with respect to φ_t as a function of initial perceived safety. An equivalent effect exists for variation of the first derivative of optimal bond issuance with respect to $\alpha_{i,t}$ as a function of aggregate safety premium. This result thus generates the next prediction.

Prediction 3. (Heterogeneous Effects A) *Firms with higher perceived safety respond to an increase in the aggregate safety premium by increasing bond issuance more than firms with lower perceived safety. Furthermore, the difference in bond issuance among firms with different levels of initial perceived safety is larger when the aggregate safety premium is higher.*

Finally, there are also interactions between the two components of the safety premium and firms' initial net worth, $w_{i,t}$. Consider two firms that are financially constrained, one with higher net worth than the other. Then, the marginal cost of issuing an additional dollar of debt in response to an increase in, say, the aggregate safety premium is lower for the company with higher net worth. The reason is that the expected bankruptcy cost is lower for this company than for the company with lower net worth. Clearly this effect disappears when the net worth is sufficiently high and the firms are no longer financially constrained. This phenomenon is illustrated in Figure 6 and generates the following empirical prediction.

Prediction 4. (Heterogeneous Effects B) *Firms that are financially unconstrained respond to a higher perceived safety or the aggregate safety premium by increasing bond issuance more than financially constrained firms.*

There are implications of this model regarding the interaction between safety premium and bankruptcy cost. Testing these implications requires proper time or cross sectional varying measures of the bankruptcy cost, which are notably hard to estimate, and is therefore out of the scope of this paper.

3.4. Bringing the Model to the Data

The model yields several predictions regarding firms' responses to variations in the safety premium. The rest of the paper is dedicated to testing them using data on US non-financial corporations. With the goal of mapping the predictions described in the previous subsection to reduced-form linear regressions, I calculate a policy function linearization.

Let the state space be $\mathcal{S} := \{w_{i,t}, \alpha_{i,t}, x_t, z_{i,t}, \varphi_t \in \mathbb{R}^+ \times (0, 1) \times \mathbb{R} \times \mathbb{R} \times \mathbb{R}^+\}$ and the action space be $\mathcal{A} := \{b_{i,t+1}, k_{i,t+1} \in \mathbb{R}^+ \times \mathbb{R}^+\}$. Note that in order to be feasible, an action must satisfy the budget constraint. Let π^* be the optimal policy function, $\pi^* : \mathcal{S} \rightarrow \mathcal{A}$.

Consider the Taylor expansion of the policy function around the point $s_0 = \{\bar{w}_t, \bar{\alpha}_t, \bar{x}, \bar{z}_t, \bar{\varphi}\}$, where \bar{w}_t , $\bar{\alpha}_t$, and \bar{z}_t are the time t cross sectional averages of firms' net worth, perceived safety, and idiosyncratic productivity shock, respectively; and \bar{x} and $\bar{\varphi}$ are time series averages of the aggregate productivity shock and the aggregate safety premium.

As will be discussed in the next section, it is difficult to observe $\alpha_{i,t}$ or φ_t directly in the data. A quantity that turns out to be empirically important is the cross-basis, defined as

$$CrossBasis_{i,t} := (\alpha_{i,t} - \bar{\alpha}_t) \varphi_t. \quad (13)$$

Hence, the optimal policy around \mathcal{s}_0 is approximately

$$\Delta b_{i,t+1} \approx \beta_{1,t} \frac{1}{\varphi_{t-1}} CrossBasis_{i,t-1} + \beta_{2,t} z_{i,t} + \beta_{3,t} w_{i,t} + \delta_t + \delta_i, \quad (14)$$

where β s are the partial derivatives evaluated in \mathcal{s}_0 , and δ_t and δ_i collect variables that are constant in the cross section and in the time series. An equivalent specification can be written for investment $i_{i,t}$ and payout $d_{i,t}$.

Empirically estimating how bond issuance, investment, and payouts vary as a function of the cross section allows me to identify how a firm’s decision changes as a function of perceived safety, conditional to a constant aggregate safety premium, φ_t .

4. Data

I study the impact of variation in the safety premium on the behavior of non-financial firms in the United States. To this end, I use four main data sets: (i) bond characteristics, from the Mergent Fixed Income Securities Database (FISD) for academia, (ii) Treasury yields and corporate bond yields, respectively from the CRSP US Treasury Fixed-Term Indexes and WRDS Bond Returns databases (iii) CDS spreads for single-name CDS composites from Markit, and (iv) firm balance sheet data from Compustat quarterly data. The empirical tests focus on the period from January 2003 to September 2020. The starting date coincides with Markit’s CDS data starting date and the end data with the last updated of WRDS Bond Returns database.

The bond-level data set is created by merging corporate bond characteristics, bond prices data, and single-name CDS data. For bonds, I apply standard filters and exclude bonds not listed or traded in the US public market, not traded in US dollars, whose issuers are not in the jurisdiction of the United States, with convertible or floating rates, with non senior-unsecured claims, with issuance size of less than 100 thousand dollars, or with time to maturity less than 1 year. For CDS spreads, I select only CDS spreads for US dollar contracts that refer to senior unsecured debt and with the documentation clause type “No Restructuring” (XR).¹⁴

¹⁴This option excludes restructuring altogether from the CDS contract, eliminating the possibility that

The final data set contains information about corporate yields, duration, bid and ask spreads, volume traded, bond characteristics, and CDS spreads quoted in basis points per annum for a notional value of \$10 million.

The original Markit data set provides a CDS-spread term structure incorporating maturities of 1y, 2y, 3y, 4y, 5y, 7y, 10y, 15y, 20y, and 30y. I use a locally constant hazard rate interpolation of CDS spreads to match the bonds' duration. To mitigate the concern that the 5y maturity is the most liquid, I only consider CDS spreads that have valid quote rating; this guarantees that the CDS spread has passed several tests ran by Markit to assure the quality of the quote.¹⁵

The firm-level data set is formed by merging the bond-level data set with firms' balance sheet data from Compustat quarterly data. The sample includes all Compustat firms that have publicly traded equity in one of the three main stock exchanges (NYSE, NASDAQ, and Amex), except regulated utilities (SIC codes 4900-4999), financial firms (SIC codes 6000-6999), and firms categorized as public service, international affairs, or non-operating establishments (SIC codes 9000+). Finally, following standard data-cleaning methodology applied in the literature, I also exclude firms with missing or non-positive book value of equity or sales and firms with less than \$1 million in total assets. For firm-level analyses, I aggregate yields, CDS spreads, and bases at the firm level by calculating the face-value weighted averages.

All the empirical results use the universe of US firms in the Compustat sample with successful merges with non-missing CDS spread, yields, and bonds outstanding. I winsorize all yields, CDS spreads, CDS-bond bases, and financial ratios at 1% and 99% to remove outliers. The final data set for bond prices is monthly, the same frequency as the corporate bond prices data set. The firm-level data is quarterly, the same frequency as Compustat.

The coverage per year is reported in Table 2. The final sample covers on average 2793 bonds and 395 firms per year. It is worth noting that coverage is not concentrated in a few rating buckets and is rather representative of the credit-risk spectrum. Table 3 reports the

the Protection Seller suffers a "soft" Credit Event that does not necessarily result in losses to the Protection Buyer. Since the implementation of SNAC in 2009, CDS with this clause are the most traded in North America. For more detail see, e.g., [Boyarchenko, Costello, and Shachar \[2019\]](#)

¹⁵The documentation on Markit quote ratings can be found at Markit.com Guide Version 14.4 ([here](#)). The manual says: "Ratings are assigned based on both quantitative criteria - of which the most important is the number of distinct passing contributions - and qualitative measures: how competitive, liquid, and transparent the market is; and whether the trades are time stamped, frequently updated tradable quotes. To achieve a rating at all, our composites must have passed stringent standards on these criteria."

quarterly data summary statistics.

5. Measuring the Corporate Safety Premium

The first empirical challenge to test the model of corporate safety creation is to measure the safety premium in corporate liabilities. So far I have been speaking of corporate liabilities or debt, but for measuring non-financial corporate safety premia, I focus on corporate bonds. This is due to data availability. Data on corporate bond instruments is more readily available and comprehensive than other forms of corporate debt. Moreover, for simplicity in notation, while explaining the safety premium measurement construction, I assume that each firm in the sample has only one bond outstanding. I discuss the empirical implementation of multiple bonds per firm in the next subsection.

From equation (3), the safety premium of a particular bond is the difference in prices of this bond and of a benchmark asset with the same cash flows, but no safety services. This benchmark is not readily available. I overcome this issue by constructing, for each bond in the sample, a synthetic asset which is a portfolio that combines the corporate bond and the maturity-matched credit default swap (CDS). I call this synthetic asset the *hedged bond*. Under certain assumptions, which are discussed below, the cash flows of the hedged bonds are the same among all bonds. Then, by comparing the yields of the hedged bonds, I am able to quantify the relative safety premium between different bonds.

The building blocks of the hedged-bond construction are the CDS contracts. A CDS contract is a derivative instrument that can be used to hedge against default risk of the reference entity. If there exists a CDS contract that perfectly hedges the default risk of a corporate bond, investors can create a hedged bond that closely replicates the cash flow of a risk-free bond by buying a corporate bond and the maturity-matched CDS.

To formally see how one can use the difference in yields of hedged bonds to measure the relative safety premium, let $y_{i,t} = -\ln(P_{i,t}) \approx 1 - P_{i,t}$ be the yield of bond i at time t . From (3), yields are approximately

$$\begin{aligned} y_{T,t} &= 1 - \mathbb{E}_t [M_{t+1} X_{T,t+1}] - \varphi_t && \text{for Treasuries,} \\ y_{i,t} &= 1 - \mathbb{E}_t [M_{t+1} X_{j,i,t+1}] - \alpha_{i,t} \varphi_t && \text{for bond } i. \end{aligned}$$

I make three assumptions, which are discussed further below. First, the CDS perfectly hedges against credit risk; second, the CDS does not provide any safety services; and third,

the US Treasury bond is risk-free. Consider a hedged bond constructed by buying a bond j and a corresponding CDS_j . Under the three assumptions, the hedged bond has exactly the same payoff as the Treasury.

I define the CDS-bond basis as the difference in yields between the UST bond and the hedged bond. Hence, the CDS-bond basis is

$$Basis_{i,t} = y_{T,t} - (y_{i,t} - CDS_{i,t}) = (\alpha_{i,t+1} - 1) \varphi_t \quad \forall i, \quad (15)$$

where the bond i and UST bond T are of equal maturity and coupons. The basis is thus a measure of the safety premium differential between the UST bond and the bond i . If the bond offers safety services similar to UST, then $\alpha_{i,t+1}$ is close to one and the basis will be close to zero.

As discussed in Section 3, the variables of interest for testing the model of corporate safety creation are $\alpha_{i,t+1}$ and φ_t , which are not observable directly in the data. Therefore, I define cross-basis, which is the dependent variable of interest in equation (13). The cross-basis of bond i is the difference in the yields of this hedged bond and of the average hedged bond in the sample, which I denote by \overline{Basis}_t .

$$CrossBasis_{i,t} = Basis_{i,t} - \overline{Basis}_t = (\alpha_{i,t+1} - \bar{\alpha}_{t+1}) \varphi_t \quad (16)$$

Equation (16) yields three testable predictions for the cross-basis and its connection with the safety premium. First in the cross section, the cross-basis is monotonic in perceived safety ($\alpha_{i,t+1}$); second, one factor, the US Treasury safety premium (φ_t), fully explains the time series variation of the cross-basis; third, loadings on the US Treasury safety premium are monotonic in bonds' perceived safety. I test these predictions below and find considerable support for them, which validates my interpretation of the cross-basis as a measure of *relative* safety premium.

5.1. Empirical construction of the CDS-bond basis

I now map the theoretically defined CDS-bond basis, cross-basis and basis index to the non-financial US corporate bond data. I begin by following the standard methodology (Oehmke and Zawadowski [2017], Kim, Li, and Zhang [2016], among others), and for each bond j with maturity τ of firm i , I calculate the CDS-bond basis at time t as

$$Basis_{j,\tau,i,t} = CDS_{\tau,i,t} - CreditSpread_{j,\tau,i,t} \quad (17)$$

where $CDS_{i,\tau,t}$ is the CDS spread for company i , interpolated to have the same maturity τ as the bond. $CreditSpread_{j,\tau,i,t}$ is the difference in yields between the bond j and the duration-matched Treasury yield. The firm-level CDS-bond basis at each time t is the face-value weighted average $Basis_{j,i,\tau,t}$ across all bonds j outstanding of firm i in the sample.

The cross-basis calculation follows directly from equation (16), and it is defined as

$$CrossBasis_{i,t} = Basis_{i,t} - Basis_{index,t}, \quad (18)$$

where $Basis_{i,t}$ is firm i CDS-bond basis and $Basis_{index,t}$ is the face-value weighted bases for all companies in the sample. Considering the value weighted average instead of simple averages reduces the influence of small issuers with extreme basis values.

Table 4 reports summary statistics for cross-basis, CDS-bond basis, yields, and CDS spreads in my sample; and Figure 7 shows the face-value weighted average CDS-bond basis by rating category for corporate bonds of US non-financial firms. The CDS-bond basis is on average negative, reaching points as low as -10% during the peak of the financial crisis. This indicates that investors are willing to forgo yields to hold a US Treasury rather than a hedged bond. In light of the model of demand for safety, I interpret this result as evidence that US Treasuries provide more safety services than corporate bonds.

In the absence of frictions, the CDS-bond basis and the cross-basis should be zero. The prevalence of negative CDS-bond bases in the market is a well-known empirical regularity in the corporate bond literature (e.g. Longstaff, Mithal, and Neis [2005], Oehmke and Zawadowski [2017], Bai and Collin-Dufresne [2019]). The cross-basis captures the cross sectional dispersion in the CDS-bond basis.

I interpret the cross-basis as capturing the premium attached to the services associated with the ownership of high-quality bonds, such as collateral value, regulatory relief, or simply psychological relief. All these interpretations are consistent with the model in Section 3. But it also may be capturing frictions not associated with safety such as counterparty risk (Giglio [2014]), illiquidity (Longstaff et al. [2005], Oehmke and Zawadowski [2015, 2017]), restructuring uncertainty (Berndt, Jarrow, and Kang [2007]), or mismatch in the payoff structure of bonds (Duffie [1999]). In Section 7.1, I argue that none of these confounders are large enough to explain the cross sectional variation of the cross-basis.

The innovation of this paper is, first, to show that cross sectional variation in the cross-basis captures cross sectional variation in the safety premium of different corporate bonds, and, second, that firms respond to variation in the cross-basis by issuing bonds. I turn next to the first contribution and leave the second to Section 6.

5.2. The Validity of Cross-Basis as the Relative Safety Premium Measure

To validate the connection between the CDS-bond basis and the safety premium, I test the three predictions from the model. First, I run the following Fama-MacBeth regressions to test whether the cross-basis is monotonic in firms' perceived safety

$$CrossBasis_{i,t} = \beta_0 + \beta_1 \hat{\alpha}_{i,t} + \varepsilon_{i,t}, \quad (19)$$

where $\hat{\alpha}_{i,t}$ are proxies for the perceived safety of firm i at time t . I measure safety in several ways: rating category buckets (AA and above, A, BBB, BB, B and below); rating rank (1 for AAA, 2 for AA+, 3 for AA, etc.); interest coverage ratio ($ICR_{i,t}$), measured as interest expenses over $EBITA$; and the structurally estimated $\alpha_{i,t}$.¹⁶

Column (1) and (2) of Table 5 shows that, on average, the basis is monotonic on ratings. Moreover, ratings alone are able to explain 25% of the cross sectional variation of cross-basis. I also test the explanatory power of ICR and the structurally estimated $\hat{\alpha}_{i,t}$. The results are reported in columns (3) and (4). The highly statistically significant coefficient for ICR means that the cross-basis is monotonically increasing in the inverse of the ICR. The highly significantly significant coefficient for $\hat{\alpha}_{i,t}$ is yet another evidence that the cross-basis is monotonically increasing in perceived safety. I interpret these results as supporting evidence for the predictions that the cross-basis is monotonic in firms' perceived safety and that perceived safety explains a lot of the cross sectional variation in of the cross-bases.

Next, I turn to time series analyses to test the two remaining predictions. I run the following regression

$$CrossBasis_{r,t} = \beta_{0,r} + \beta_{1,r} UST SP_t + \varepsilon_{r,t}, \quad (20)$$

where $CrossBasis_{r,t}$ is the value-weighted average of the basis for the rating category r and $UST SP_t$ is a proxy for the safety premium of Treasury.

There is no consensus in the literature about how to measure the US Treasury safety premium. I use four distinct measures: two measures inspired by [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#) (henceforth KV-J): (i) AAA–Treasury and (ii) BBB–(AAA and AA) basis spread;¹⁷ (iii) the box-trade spread as in [Binsbergen et al. \[2019\]](#); and (iv) the structurally

¹⁶Details of this estimation are in [Appendix B](#).

¹⁷[Krishnamurthy and Vissing-Jørgensen \[2012a\]](#) make the simplifying assumption that the AAA–Treasury spread reflects liquidity premium whereas the BBB–AAA spread reflects safety premium. Their assumption is that, AAA-rated securities and UST have the same safety but different liquidity, whereas AAA- and BBB-rated securities have different safety but roughly the same liquidity. In my paper, I do not focus on

estimated safety premium based on the model in this paper. A more detailed discussion about each of the measures is presented in [Appendix B](#).

Figure 8 shows the time series of each one of the safety premium measures, and Table 6 shows the summary statistics and correlation matrix between all these measures. They are all closely related. All of the measures of the US Treasury safety premium, except the one estimated from the model, are a *relative* premium of Treasuries with respect to a benchmark. The only measure that attempts to properly capture the correct level is $\hat{\varphi}_t$, and this is the reason why it is relatively higher than the others.

Table 7 shows the estimation results for equation (20). Results are qualitatively similar across all measures. The loading on the safety premium should capture $(\alpha_i - \bar{\alpha})$, therefore we expect it to be monotonically decreasing in how safe the bonds are. The loadings are indeed monotonic in ratings for all four proxies of the US Treasury safety premium. Furthermore, the UST safety premium should explain a large fraction of the time series variation of the cross-basis. As shown in Panel A, for $\hat{\varphi}_t$, the r -squared of the regressions range between 43% and 90%, for a mean of 60%. This means that one factor explains a large portion of the time series variation of the cross-basis. Results are similar for the two K-VJ safety premium measures. The lowest r -squared is reported for the box-trade spread. This is expected at least for one reason: the box-trade is calculated from the put-call parity relationship for European-style option contracts and the longest maturity available is 18 months, whereas the average maturity of the corporate bond is 7 years in my sample. It could be that the drivers of short-term UST convenience yield are different than the long-term safety premium. In summary, these are evidences in support for the close connection between the basis and corporate bonds safety premium.

6. Firms' Response to Safety Premium

This section studies how firms' decisions relate to the safety premium in corporate bonds. I present evidence that supports the predictions of the model of corporate safety creation presented in Section 3. In the cross section of US non-financial firms, high perceived safety,

differentiating liquidity and safety premium. Nevertheless, to get the best possible measures of the Treasury safety premium, I also construct the two measures. There are two issues in using the BBB–AAA spread: (i) In recent years, there are only two US corporations that are rated AAA, Johnson & Johnson and Microsoft; (ii) a large component of the BBB–AAA spread is due to credit risk. In order to minimize the influence of company-specific shocks, I use the face-value weighted CDS-bond basis spread between “BBB” and “AAA and AA.” The difference in credit risk is controlled by the CDS correction.

measured by high cross-basis, forecasts high net debt issuance. Net debt issuance is not reverted into real investment but is instead used for net payouts, measured as the sum of dividends and equity repurchases. These results suggest that companies that can create safety services are, on average, not financially constrained, and that bond issuance can be a financial maneuver that benefits equity holders.

6.1. Impact of Safety Premium on Net Debt Issuance

The first set of empirical tests aims to identify how variation in a firm’s safety premium affects net debt issuance. Since $\alpha_{i,t}$ is not directly observed in the data, the first empirical specification includes the cross-basis, which is a proxy of a firm’s relative safety premium with respect to the market and the dependent variable of interest after the linearization described in (14). For each time t , the cross-basis captures cross section variation in perceived safety across companies.

Prediction 1 from the model says that firms with higher perceived safety issue more debt than otherwise similar firms with low perceived safety. I test this prediction by running the following regression

$$NDI_{i,t+1} = \beta_1 CrossBasis_{i,t} + \beta_2 X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}, \quad (R1)$$

where $NDI_{i,t+1}$ is long-term net debt issuance as a share of lagged total assets, $CrossBasis_{i,t}$ is the CDS-bond basis minus the basis index, the basis index is the corporate bond market value-weighted average of $Basis$, $X_{i,t}$ are controls, and δ_i and δ_t are firm and time fixed effects, respectively.

Based on equation (14), it is clear that controls should capture firm net worth ($w_{i,t}$) and investment opportunities ($z_{i,t}$). In the baseline specification, the controls are $\log(\text{TotalAssets})$ and cash normalized by assets, to account for firms’ net worth, and Tobin’s Q to control for firms’ investment opportunities. Due to the limitations of those control variables, I also include the CDS spread as a control. The CDS price captures any factor that affects a firm’s credit risk in a way that is not related to the safety provision of the firm’s bonds. Net debt issuance is measured in quarter $t + 1$, and all independent variables are measured in quarter t in order to avoid the “bad controls problem” (Angrist and Pischke [2009]).

The identification assumption to correctly estimate the impact of firms’ safety premium on debt issuance is that the error term in (R1), $\varepsilon_{i,t}$, is orthogonal to the measure of relative safety premium, $CrossBasis_{i,t}$. This assumption is violated if there are factors correlated to the cross-basis that affect a firm’s net debt issuance and are not fully captured by the controls.

The most salient confounder is the possibility that the controls are not good enough to fully account for investment opportunities. If investment opportunities are the main confounder, cross-basis should then be a strong predictor of investment. As will become clear in the next subsection, on average, firms do not use the funds raised from issuing safe debt for investment. The results are robust to different measures of investment: capital investments, intangible investments, and acquisitions. Therefore, not properly controlling for investment opportunities should not be the major concern. Still, the lack of a natural experiment or a valid instrument leaves space for possible confounders that can threaten the identification. I alleviate this concern by showing that the regression results are robust to the inclusion of several extra controls, and in Section 7, I develop a myriad of tests to rule out other possible alternative hypotheses.

Table 8 shows the regression estimated for model R1. Column (1) shows that the cross-basis forecasts a positive net debt issuance for the average firm. The effect of cross-basis on debt issuance is statistically and economically significant. The point estimate means that a 1 percentage point increase in the cross-basis forecast an increase of net debt issuance by 10 basis points as a percentage of total assets. This represents an increase of \$27.4 million ($= \beta_2 \times \text{mean}(\text{atq})$) in debt issuance, which is a 31% ($= \frac{\beta_2}{\text{mean}(\text{NDI})} \times 100$) increase relative to the quarterly average debt issuance.

To assess the magnitude of the results, it is useful to compare the elasticity of leverage to the cross-basis with capital structure literature. Heider and Ljungqvist [2015] estimate that a 1 percentage point increase in taxes leads to a 40 basis points increase in the long-term leverage ratio. The semi-elasticity coefficient estimated in Column (1) of Table 8, suggests that 1 percentage point increase in the cross-basis forecasts a 35 basis points ($= \frac{\beta_2}{\text{mean}(\text{long-term leverage})} \times 10^4$) increase in long-term leverage ratio. The two estimates are in the same order of magnitude, but it is worth noting that the quarterly standard deviation in the cross-basis is 0.96%, whereas tax changes are relatively infrequent. The magnitude of the point estimates is evidence that the safety premium is an important economic force in determining firms' leverage ratios.

To ensure results are robust, I consider three extra controls: ratings fixed effects, leverage ratios, and return on assets (ROA). Credit ratings are intrinsically related to firm default probability and expected cost of bankruptcy, forces that impact firm leverage decisions in many traditional corporate theories, such as the trade-off theory. Although the CDS spread should largely capture this effect, there could be time-varying frictions, systematically correlated with ratings, that affect a firm's access to credit and are not related to the firm's perceived safety. Since credit rating is one of the main drivers of cross sectional variations

in the cross-basis, those omitted factors could be of concern. I control for credit ratings by re-estimating (R1) including rating buckets fixed effects.¹⁸ The results are reported in column (2) of Table 8. The cross-basis has a significant impact on net debt issuance even within a rating bucket. The point estimate is 8 basis points. As expected, the point estimate is slightly smaller than the baseline specification, reflecting the fact that ratings are intrinsically related to perceived safety, as shown in Section 5.2, and the rating fixed effects subsume this variation. Nevertheless, the results are qualitatively unchanged.

In dynamic models of firm capital structure, leverage can be path dependent (see, *e.g.*, [Hennessy and Whited \[2005\]](#) and [Admati, Demarzo, Hellwig, and Pfleiderer \[2018\]](#)). One concern is that the cross-basis is capturing variation in the leverage ratio in the cross section. To alleviate this concern, in column (3) of Table 8, I include leverage ratio as one of the control variables. After controlling for the leverage ratio, the impact of cross-basis on net debt issuance remains significant. The point estimate is 8 basis points, which means that a 1 percentage point increase in the cross-basis forecasts a 24% increase in debt relative to the average quarterly net issuance. The slightly smaller point estimate is expected because, like ratings, leverage ratio is one of the drivers of the cross sectional variation in the cross-basis; consequently, it subsumes part of the firms' safety premium variation.

One interesting difference between the baseline specification and the one that includes leverage ratio as a control is the impact of the CDS spread on net debt issuance. Whereas a decrease in the CDS spread forecasts larger issuance in the main specification, this is not robust to including leverage ratio as a control. The credit premium measured by the CDS spread has a small impact on debt issuance after controlling for leverage ratios. This result is probably related to the strong correlation between the leverage ratio and the CDS spread.

Previous literature has documented the impact of profitability on leverage. Theoretically, how profitability should impact net debt issuance is not straightforward. Under the trade-off theory, profitable firms face lower expected costs of financial distress and find interest tax shields more valuable, therefore high profitability should be related to higher debt issuance ([Myers \[1984\]](#)). Under the pecking order theory of capital structure, firms should rely on external finance only if the internal funds are not enough to meet the financing needs ([Myers and Majluf \[1984\]](#)). In this case, everything else constant, firms with high profitability should issue less debt. In any case, the source of concern for identifying the impact of the cross-basis on net debt issuance is that the cross-basis is systematically correlated with firms'

¹⁸I consider 5 rating buckets: AAA and AA, A, BBB, BB, and B and below. All notches are included in the associated bucket.

profitability in a way that is not captured by the controls and is not related to firms' safety premium. To alleviate this concern, I control for return on assets as a measure of profitability. Column (4) reports the results. The effect issuance response to cross-basis variation remains almost unaltered. The ROA regression coefficient is not statistically significant. Due to the relatively recent period that my sample covers compared to other studies of firms' capital structure, this result is consistent with [Goyal and Frank \[2009\]](#), who show that the impact of profitability on leverage has been diminishing over time.

All together, the results reported in Columns (1) to (4) of [Table 8](#) provide strong support for the response in net debt issuance due to cross sectional variation in perceived safety, as described in Prediction 1.

I now turn to explore the direct effect of the aggregate safety premium on issuance. Prediction 2 says that net debt issuance should respond to variation in the the aggregate safety premium. Moreover, Prediction 3 says that this response should be stronger for firms with higher perceived safety. I test these predictions by running the following regression

$$NDI_{i,t+1} = \beta_1 \text{UST SP}_t \times \alpha_{i,t}^H + \beta_2 \alpha_{i,t}^H + \beta_3 X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}, \quad (\text{R2})$$

where USTSP_t is the UST safety premium and $\alpha_{i,t}^H$ is a dummy variable equal to 1 if the firm has high $\alpha_{i,t}$ and 0 otherwise. I construct $\alpha_{i,t}^H$ in two ways. First, I set $\alpha_{i,t}^H$ to one if the firm belongs to the highest quintile of the quarterly cross-basis distribution. Second, I set $\alpha_{i,t}^H$ to one if the firm is rated A- and above in the quarter. "UST SP" is a proxy for the US Treasury safety premium. The baseline estimation uses the structurally estimated US Treasury safety premium.¹⁹ The controls are the same as in [\(R1\)](#).

The results are reported in columns (5)-(8) of [Table 8](#). In all specifications, firms with high safety premium respond to an increase in the aggregate safety premium by issuing relatively more debt. This result is robust to including rating buckets fixed effects and/or extra controls as shown in columns (6) and (8). It is noteworthy that estimating the aggregate safety premium coefficient is not possible in this specification, since it is subsumed by the time fixed effects. Nevertheless, the interaction coefficient provides evidence in support to Prediction 2 and 3.

This specification also alleviates concerns that noise in the cross-basis measure is systematically correlated with firm decisions and could be biasing the results from regression [R1](#). The results in columns (5)-(8) of [Table 8](#) provide strong evidence for the cross sectional effects of safety premium variation on the net debt issuance, that they are not driven by

¹⁹Results considering other proxies for the aggregated safety premium are reported in the appendix.

idiosyncratic noise in the firm-level cross-basis measure.

In summary, I find strong evidence that firms respond to higher safety premia by issuing more debt than their comparable peers with lower safety premia. This result is robust to the inclusion of ratings fixed effects and extra controls. The impact of the cross-basis on net debt issuance is statistically and economically significant.

6.2. Impact of Safety Premium on Firms' Real Decisions

The second set of empirical tests aim to identify how firms use the proceeds from issuing safe debt. Let *DebtIssuance* be an indicator variable equal to 1 if the firm has strictly positive net debt issuance value and 0 otherwise. I run the following empirical model

$$y_{i,t+1} = \beta_1 \text{CrossBasis}_{i,t} \times \text{DebtIssuance}_{i,t+1} + \beta_2 \text{CrossBasis}_{i,t} + \beta_3 \text{DebtIssuance}_{i,t+1} + \beta_4 X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}, \quad (\text{R3})$$

The cross-basis and controls are the same as in regression (R1). The main y -variables of interest are net payouts and investment. I measure payouts as the sum of dividends and equity repurchases. The proper measure of investment must consider the increasing share of intangible investment among corporate investment (Crouzet and Eberly [2020]) and also acquisitions. To this end, I measure investment in three different ways: (1) the traditional capital investment, defined as CAPEX plus net PPE bought; (2) intangible investment, measured as the sum of R&D and 30% of SG&A expenses, as in Peters and Taylor [2017]; and (3) acquisitions.

Although the model presented in Section 3 does not cover the impact of safety premium variation on liquid assets accumulation, this is an important margin to be empirically tested. To this end, I include ΔCash and financial investment in the set of y -variables. Using financial investments instead of Compustat CHE changes is important. It captures the increasing relevance of the financial assets portfolio in non-financial firms, which is often not properly accounted for in the Compustat CHE variable. Those issues are described in Darmouni and Mota [2020].

Table 9 shows the regression results. Interestingly, only payouts respond to the cross-basis conditional on positive debt net issuance. The impact on payouts is statically and economically significant. The point estimate signifies that 1 percentage point increase in the cross-basis forecasts 8 basis points ($= \beta_1 + \beta_2$) increase in total net payouts as a percentage of total assets. This is an increase of 8% $\left(= \frac{\beta_1 + \beta_2}{\text{mean}(\text{payouts} \mid \text{DebtIssuance})} \right)$ to firms' average quarterly net payout conditional on positive net debt issuance. In dollar amounts, 1 percentage point

increase in the cross-basis forecasts \$23.2 million, a number very close to the effect of the cross-basis on net debt issuance, \$27.4 million.

Investment and liquid assets accumulation do not respond to the cross-basis conditional on positive issuance. The proceeds from issuing safe debt are largely transformed into equity payouts rather than investment. This result is consistent with the hypothesis that firms that benefit from a safety premium are not likely to be financially constrained. It is also consistent with [Stein \[1996\]](#), who says that firms with decreasing returns to scale will not respond to cheap financing by investing more as long as they are already at their optimal scale.

The lack of response in cash accumulation or financial investment differentiates the safety premium mechanism from the market timing described in [Bolton et al. \[2013\]](#) and [Eisfeldt and Muir \[2016\]](#). In case of a stochastic cost of external finance, firms should raise external finance when it is cheap, guaranteeing liquidity if future adverse shocks happen in periods when external finance is expensive. Under this theory, firms should issue debt in times of high safety premium and accumulate liquid assets. The results in this paper suggest instead that firms that benefit from a high safety premium are not likely to face financial constraints in raising funds, thus the liquidity accumulation response is not observed.

In summary, the results of this subsection show that the proceeds from issuing debt in response to variation in the safety premium are most converted into equity payout, rather than real investments. Based on Predictions 1 and 2, this is strong evidence that companies most affected by the safety premium are not likely to be financially constrained. Furthermore, the results described in this subsection are robust to including rating fixed effects, leverage ratio, and past profitability as controls. The results are reported in Table [E.15](#) in [Appendix E](#).

6.3. Heterogeneity across Firms' Characteristics

According to the model's predictions, responses to variation in the safety premium vary across firms' initial conditions. First, according to Prediction 4 the extent to which a firm can increase its leverage in response to an increase in the safety premium depends on its debt capacity and its expected bankruptcy cost. Effectively, its default risk acts as a constraint on its ability to take advantage of the discount in debt financing provided by the safety premium. Second, according to Predictions 1 and 2, the impact on investment or payouts is related to the firm's financial constraints. Unconstrained firms are more likely to operate at their optimal scale. Therefore, an increase in the safety premium should have a stronger payout response than in real investment. The opposite should be true for constrained firms.

I examine the heterogeneity across different firms by running the following regression

$$Y_{i,t+1} = \beta_1 CrossBasis_{i,t} \times UNC_{i,t} + \beta_2 CrossBasis_{i,t} + \beta_3 UNC_{i,t} + \beta_4 X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}, \quad (R4)$$

where UNC is a dummy variable equal to one if the firm is likely to be unconstrained and 0 otherwise. I group firms by five relevant characteristics: ratings, profitability, cash, payouts, and size. For each characteristic and quarter, I set $UNC_{i,t} = 1$ for firms that are in the largest 20% quantile. For ratings, I consider investment grade ratings (BBB– and above) to be unconstrained. To study a firm’s response conditional on issuing, I select the sample for which net debt issuance is strictly positive.²⁰

Table 10 reports the results for each one of the five characteristics. Column (1) shows that the issuance response of investment grade and large firms to the cross-basis is stronger than other firms, suggesting that they have a smaller marginal cost of increasing leverage. Investment grade firms also engage in higher payouts in response to the cross-basis, as shown in column (2) of Panel A. As predicted by the model, in all specifications, the impact on capital investment is smaller for unconstrained firms, as shown in column (3). The differential impact in intangible investment for investment grade, profitable, and high-payout firms is solely driven by SG&A expenses. Columns (8) and (9) show that there are no differential effects in liquidity accumulation. Finally, one intriguing result emerges from the heterogeneous analysis, reported in column (7). Investment grade and large firms engage in acquisitions in response to an increase in the cross-basis. Although speculative, this last result suggests that the safety premium can act as a financial advantage for firms that can benefit from it, potentially having consequences for product market competition.

In summary, the results presented in this subsection are largely consistent with the corporate safety-creation model. Firms that are likely to be financially unconstrained, in the sense that they could achieve their optimal investment and scale even in the absence of a safety premium, respond to the cross-basis by issuing debt and engaging in payouts. The impact of the cross-basis on capital investment is smaller than for the contained group. These are in accordance with Predictions 1 and 2. Furthermore, in accordance with Prediction 4, unconstrained firms respond to higher cross-basis by issuing more debt than constrained firms.

²⁰Ideally, the triple interaction of $CrossBasis \times UNC \times DebtIssuance$ should be considered. Due to sample size restrictions, I consider instead the selected sample in which net debt issuance is strictly positive.

6.4. Summary

The results in this section show two notable patterns governing firms' activities. First, the cross-basis, a measure of relative safety premium in corporate bonds, strongly forecasts net bond issuance. The results are robust to adding rating fixed effects and several extra controls. Second, the proceeds from issuing safe debt are not converted into investment measured either as capital investment or intangible investment. Instead, the proceeds from issuing debt in response to the cross-basis are used to finance payouts in the form of equity repurchases or dividends. The results suggest that firms that benefit from a safety premium embedded in the price of their liabilities are likely to be financially unconstrained.

7. Robustness and Additional Tests

7.1. *Is the Cross-basis Really Capturing Variation in the Safety Premium?*

To validate the cross-basis as measure of the relative safety premium in corporate bonds, it is important to consider factors that could influence the cross-basis that are not related to the aggregate safety premium or the firm specific perceived safety. The first point worth noting is that any frictions that affect all bonds or CDSs equally affect the CDS-bond basis, but they do not affect the cross-basis. Second, frictions that are not systematically correlated with firms' fundamentals would make the cross-basis measurement noisy, but would not jeopardize the validity of the analyses on how firms respond to safety premium variation. The frictions of concern are then those likely to exhibit strong cross sectional correlation with the reference firm's fundamentals, such as credit quality.

[Bai and Collin-Dufresne \[2019\]](#) present a list of factors that could explain the cross sectional variation of CDS-bond basis. From this list, the factors of concern for my study are counterparty risk and bond liquidity. I add to that the restructuring uncertainty and mismatch in the payoff structure of bonds. In this section, I discuss in detail why each one of these factors is unlikely to be a first-order concern in validating cross-basis as a measure of the safety premium.

Before I start, it is worth noting that, after a thorough study of the cross section of the CDS-bond basis, [Bai and Collin-Dufresne \[2019\]](#) conclude that only credit rating is consistently significant in explaining the cross sectional variations of the basis, indicating that collateral quality is always relevant in explaining the cross sectional variation in the CDS-bond basis. Since collateral value is one of the safety services of interest, this result is reassuring of the interpretation of the cross-basis as a relative safety premium measure.

7.1.1. Can it be counterparty risk?

In case of a credit event, the protection seller of the CDS contract must deliver the face value of the bond in exchange for, typically, a bond from an eligible pool. Though, if the protection seller counterparty defaults (or has defaulted) when the underlying firm defaults, then the CDS protection expires worthless. This is called counterparty risk.

The evidence is that counterparty risk is small in CDS contracts. [Arora et al. \[2012\]](#) use the Lehman default to assess the premium associated with counterparty risk. In the authors' own words, they find that counterparty effects on CDS prices are "vanishingly small." The modest size of counterparty risk is also documented by [Du, Gadgil, Gordy, and Vega \[2017\]](#). There are some reasons that rationalize why the counterparty risk is likely to be small. First, CDS are highly collateralized; second, derivative contracts are senior liabilities in case of counterparty default; third, the typical counterparty is a large bank, or more recently, very often a central counterparty,²¹ all of which have a low probability of default. The combination of a high concentration of counterparty entities for single-name CDS, together with the small counterparty risk, makes it unlikely that the counterparty risk is the main driver of the cross sectional variation in the CDS-bond basis.

7.1.2. Can it be restructuring risk?

Bond investors might incur losses due to credit restructuring events that do not trigger the CDS payment under the "No Restructuring" (XR) CDS contract. This friction would make the hedged bond carry a credit risk. The evidence though is that restructuring risk is also small. I am able to measure the premium that investors are willing to pay for restructuring risk by comparing the prices for different restructuring clauses. By comparing the difference in prices to buy protection for the same entity at the same time, I find that the difference in prices accounts for less than few basis points of the CDS spread, and moreover it has small explanatory power for cross sectional regressions. The small premium paid for restructuring risk is consistent with the magnitude found by [Berndt et al. \[2007\]](#).

7.1.3. Can it be mismatch between the payoff structure of the bond and that of the CDS?

Another issue that potentially affects the CDS-bond basis is the mismatch between the payoff structure of the bond and that of the CDS. For instance, the typical corporate bond

²¹Following the great financial crisis, regulatory changes moved the market to become more centrally cleared through a CCP, as recommended by the Dodd-Frank Act in 2009.

has a fixed coupon with semiannual coupon payments, whereas a CDS has fixed spreads paid quarterly. It is also typical that in case of default, the CDS protection buyer has to pay the accrued interest from the last coupon payment to the CDS protection seller, whereas the holder of the bond would not necessarily receive the last coupon. Furthermore, the credit spread might not be the ideal comparison to the CDS spread, since the typical bond is fixed rate rather than floating.²²

The CDS-spread Par Equivalent CDS (PECS) method to calculate the CDS-bond basis is a well-known methodology that accommodates the differences in payoff structure of the bond and the CDS.²³ In the appendix, I recalculate the basis using the PECS methodology and I show the assumptions necessary to achieve the equivalence between equation (15) and the PECS basis. The result is that the CDS-bond basis calculated with the PECS methodology is very similar to the simplified method described in equation (15). The disadvantage of the PECS methodology is that it is more vulnerable to outliers. For this reason, I use the CDS-bond basis introduced in equation (17) as my benchmark measure. As shown in [Appendix F](#), results are qualitatively unchanged when using PECS.

7.1.4. *Can it be liquidity?*

Finally, differences in the cross-basis could be driven by differences in market liquidity of the underlying bond. One could think that bond yields are noisy proxies for the true price because of lack of trading or high bid-ask spreads, and that this noise is correlated with bond characteristics such as ratings. I deal with this concern by testing how much of the cross sectional variation of the CDS-bond basis is explained by bid-ask spread or turnover. As shown by the r -squares of regressions in columns (5)–(7) of [Table 5](#), the two variables together add very little explanatory power. These results alleviate concerns related to the mis-measurement in the cross-basis due to bond illiquidity.

Clearly, the notion of liquidity goes beyond measures of bid-ask spreads and turnover. For example, in [Holmstrom and Tirole \[2001\]](#), assets earn a liquidity premium whenever they are good “reserve assets,” simply because they offer better insurance than others against income shortfalls and other liquidity needs. Liquidity is also related to assets’ exposure to adverse selection, and information-insensitive assets are likely to be more liquid (see, *e.g.* [Dang et al.](#)

²²[Duffie \[1999\]](#), the ideal corporate spread to compute the CDS-bond basis would be that of a floating rate bond. This issue is also studied by [Longstaff et al. \[2005\]](#).

²³PECS was developed by JP Morgan. For further details see [Elizalde, Doctor, and Saltuk \(2009\)](#). PECS is also the methodology used in [Bai and Collin-Dufresne \[2019\]](#).

[2015]). In both cases, assets with stable cash flows are more likely to be liquid.

Indeed the regulatory development of Dodd-Frank has induced a demand for safety directly linked to liquidity considerations. Banking institutions are now required to hold in their balance sheet a particular fraction of assets deemed to be liquid (the liquidity coverage ratio or LCR). Amongst the assets that can meet the LCR is high quality corporate debt as level 2B assets.²⁴ In my terminology this is akin to an increase in the demand for safety, which translates into an increase in demand for corporate debt. Liquidity and safety are thus fundamentally intertwined.

7.2. Delayed Reactions: Effect of Safety Premium in Different Time Horizons

There is large evidence that firms' financial and investment decisions can be lumpy and delayed. In Section 6, I found that the cross-basis forecasts higher debt issuance and does not forecast investment in the span of one quarter. It is interesting to check whether these results are robust when considering longer response periods. To this end, I re-estimate regressions in Model (R1) and Model (R3) considering different horizons of the y -variable.

Figure 9 shows regression coefficients and 5% confidence intervals for dependent variables 1 to 8 quarters ahead. Panel (a) plots β_1 coefficient of Model (R1). This picture shows that the effect of cross-basis on net issuance is concentrated in the first quarter, and there is no evidence of lagged responses.

Panels (b)–(g) of Figure 9 show β_1 coefficients for Model (R3). The dependent variables are the same as in Table 9. In this case, coefficients are interpreted as firms' future response to a variation on the cross-basis conditional on positive net debt issuance at t . I do not find evidence that firms that issue debt in response to a high cross-basis respond by investing more in any period ahead. The response is concentrated in net payouts in the one quarter ahead.

In summary, by looking at different horizons, I do not find evidence of pronounced delay in firms' behavior that contradicts the previous section's conclusions.

²⁴For details see the Federal Register Vol.79 No.197., [Department of the Treasury \[2014\]](#). The directive allows for corporate debt of non-financial firms that meet the definition of "investment grade" under 12 CFR to be part of Level 2B high-quality liquid assets (HQLA). According to the agencies, "meeting this standard is indicative of lower overall risk and, therefore, higher liquidity for a corporate debt security." (pg. 61459)

7.3. Limits to Arbitrage and the Demand for Safety

If we depart from the representative investor economy, there could be investors that value safety services and investors that do not. Investors that do not value safety services are natural arbitrageurs that can supply safety services by shorting safe assets. In this economy a positive safety premium will only exist in equilibrium if there are arbitrage costs related with supplying safe assets. Furthermore, the equilibrium aggregate safety premium must be both the marginal utility of consuming one extra unit on safety services and the marginal cost of arbitrageurs of supplying this unit.

Clearly violations of the law of one price cannot be too high. In [Appendix G](#), I develop an alternative model that explicitly incorporates arbitrageur along the lines of [Gârleanu and Pedersen \[2011\]](#). I also develop an example on how an arbitrageurs can exploit the negative CDS-bond basis trade, and specifically link it to the implicit cost of capital of the arbitrageur (see also [Boyarchenko, Gupta, Steele, and Yen \[2018\]](#) and [Bai and Collin-Dufresne \[2019\]](#)).²⁵ As it is intuitive, this cost of capital places a upper bound on the CDS-bond basis, and thus how much prices can deviate from the discounted cash flows on account of the demand for safety.

More broadly, the higher regulatory cost imposed on intermediaries since the Great Financial Crisis have forced many of them on the side of the demand for safety rather than on the supply. Intermediaries now have to hold particular securities in order to meet liquidity or capital requirements, for example. When these constraints bind, their activities as arbitrageurs are curtailed.²⁶ Thus the high correlation in the different measures of violations of arbitrage relations that have been observed since the passage of the new, more stringent regulatory framework for financial institutions around the world. For instance, in my case the average cross-basis for IG bonds is highly correlated with the magnitude of violations of other apparent arbitrage trades such as the dollar CIP-deviation described in [Du et al. \[2018b\]](#).

²⁵I would like to thank Aref Bolandnazar for helpful discussions about the CDS contract margins requirements, which are necessary to properly calculate the cost of arbitrage of the negative CDS-bond basis trade.

²⁶A rapidly growing literature explores how the balance sheet cost of financial intermediaries can address violations of the law of one price in a variety of markets, as well as the effect on market liquidity and volume. Some examples are [Du, Tepper, and Verdelhan \[2018b\]](#), [Duffie \[2018\]](#), [Andersen, Duffie, and Song \[2019\]](#), [Fleckenstein and Longstaff \[2020\]](#), [Bolandnazar \[2020\]](#), among others.

8. Conclusion

In this paper, I study the role of non-financial corporations in the supply of safe assets. I argue that corporate debt of highly rated firms, while not completely insulated from credit risk, has some of the safety features needed to function as a store of value, as collateral, or as regulatory capital. Thus, corporate debt can serve as imperfect substitutes for traditional safe securities such as US Treasuries, other developed countries' sovereign debt, and highly rated asset-backed securities. In this case, by issuing debt, corporate managers may capture the premium investors are willing to pay for safe assets.

The paper introduces a model of the supply of safety services by non-financial corporates. The model generates testable predictions regarding the safety premium component in corporate debt prices and about the firm's response to variation in the safety premium. The paper innovates in modeling corporate debt as supplying safety services to varying degrees; that is, safety is not binary, as has been traditionally assumed in the literature, but rather it varies smoothly between the safety provided by US Treasuries and that of an asset that provides no safety services whatsoever. This innovation allows me to exploit cross sectional differences in bond prices to identify firm specific components of the safety premium without the need to estimate the aggregate safety premium, an estimation which is often contentious.

I introduce a novel measure of this relative safety premium, the cross-basis, and I show that firms with a higher cross-basis issue more debt. I argue that this is because firm managers create additional shareholder value, above the value associated with standard business operations, by engaging in the supply of safety services. The supply of safety services by non-financial corporates, through corporate debt issuance, only occurs when the supply of safety services is in limited supply relative to the demand for safety. This paper is the first to offer a model of the supply of safety services and to show the existence of an upward sloping supply curve among non-financial corporates.

Much remains to be done to understand the market for safety services, in particular what determines the time series variation in the demand and supply of safety. First, as already mentioned, a key building block of my framework is the observation that different securities provide different degrees of safety services. US Treasury officials are on record as stating that they do not take into account the level of the demand for safety in their decisions regarding the supply of Treasuries. Thus one can safely assume that the sources of variation in the supply of safety services is exogenously driven by the funding needs of the US government, as has been traditionally assumed in the literature. Moreover, informal accounts of the years leading up to the global financial crisis suggest that the financial services sector was in the

business of providing safety services. However, regulation after the financial crisis seems to have greatly impaired the ability of the financial sector to increase the supply of safety services. Is this in fact the case? And, is this the reason non-financial corporations are in the business of supplying safety services? The image that my model suggests is that there are multiple suppliers of safety services with different marginal costs of supplying these services, and that the non-financial corporate sector is one such supplier.

In addition, progress needs to be made on the determinants of the demand for safety. The literature, and this paper is no exception, takes the demand for safety services as a primitive, and models it in reduced form. But these safety services are tangible. For example, the ability of a particular asset to relieve liquidity or regulatory constraints, while challenging to measure, in principle could be observed and measured. Thus, it would be helpful to link exogenous sources of variation in liquidity or capital requirements to changes in asset premia in a way that establishes the presence of a particular channel in the demand for safety. Moreover, it might be that agents experience a particular form of psychological relief when holding certain assets that is not captured by the cash flow characteristics of the asset in question. This consideration may suggest the need for further development of a behavioral theory of taste for safety.

This paper shows that the safety premium affects the yields of a much broader class of financial assets than has been recognized. Additionally, safety may explain part or all of a puzzling present phenomenon. Yields on financial assets, across classes and jurisdictions, have been extraordinarily low for years. Why should this be so? The safety premium may contribute to such consistently and extraordinarily low yields, as investors who would otherwise have demanded higher risk premia have instead been constrained in holding assets that offer some safety services. As markets and contracts develop greater complexity in collateral requirements, insurance considerations, and regulation, we can expect the safety premium to be even more central in explaining the cross section of asset prices.

Figures

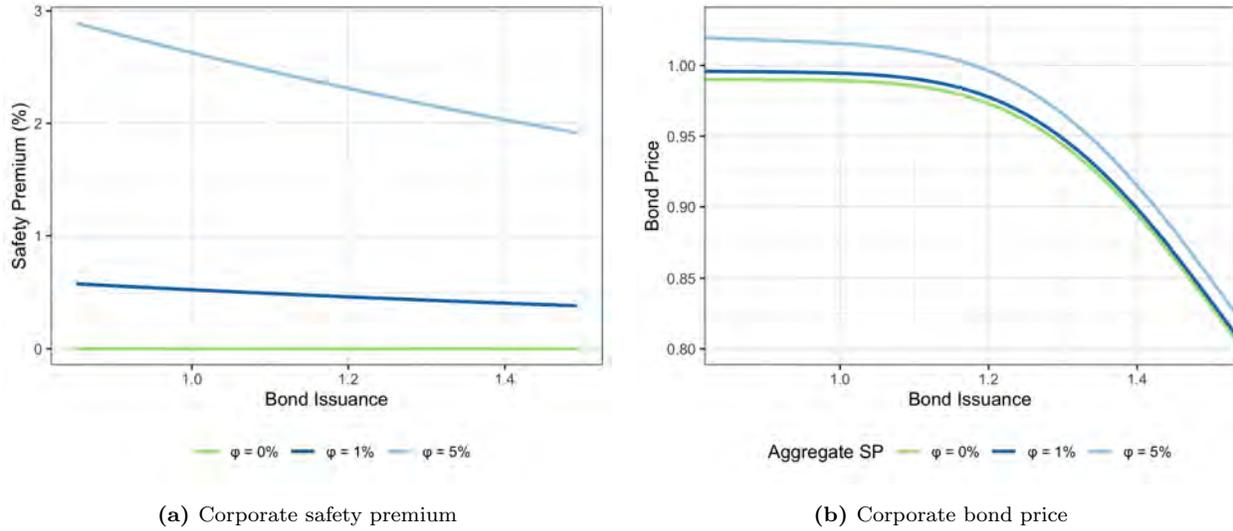


Figure 1: Corporate Safety Premium and Bond Price. This figure shows how, for a fixed level of investment, the corporate safety premium and corporate bond price vary with the amount of bonds issued. Each line shows the value for different levels of aggregate safety premium denoted by φ .

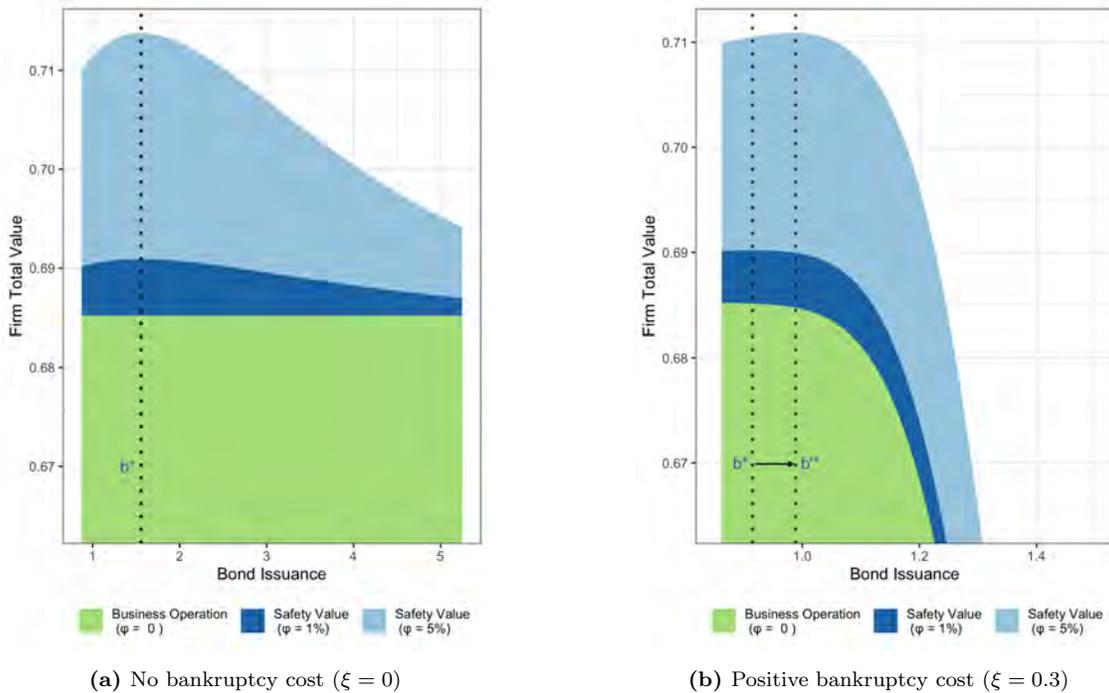
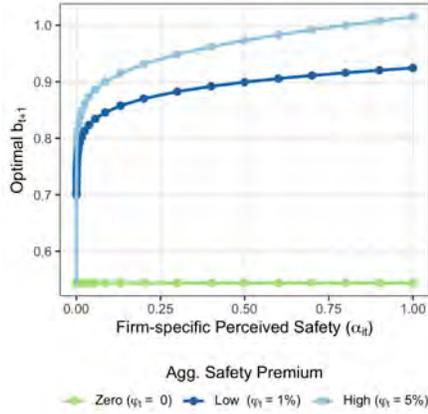
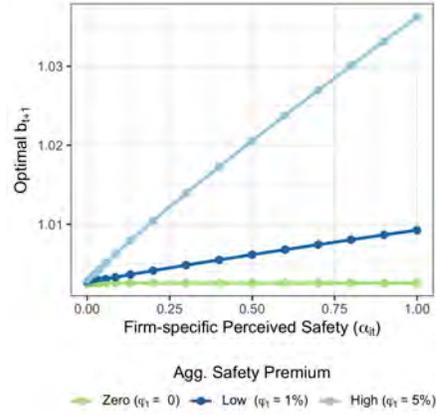


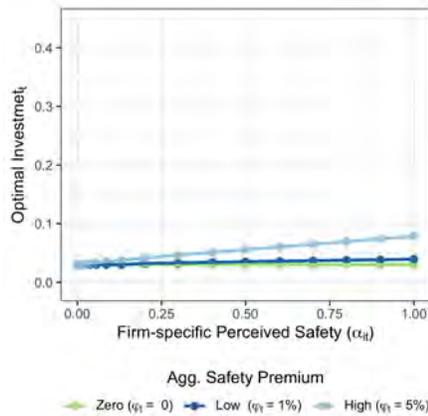
Figure 2: Firm's Total Value as a Function of Debt Issuance. This figure shows how, for a fixed level of investment, the total value of the firm varies with the amount of bonds issued. Each area shows the value for different levels of UST safety premium denoted by φ_t . The dashed line is the value of b that maximizes the value of the firm for each value of φ_t .



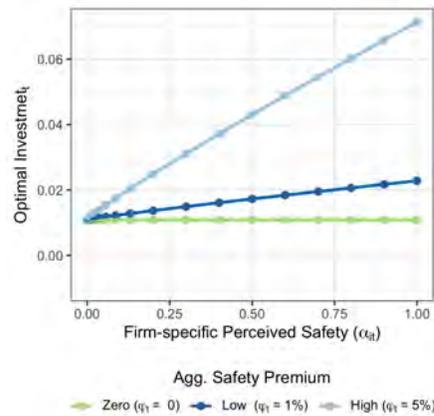
(a) Unconstrained optimal debt issuance



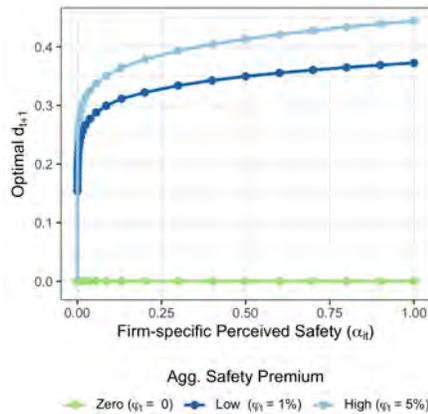
(b) Constrained optimal debt issuance



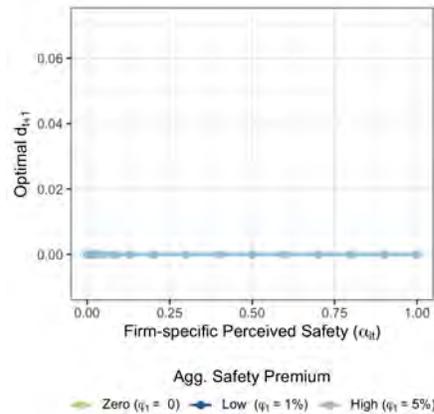
(c) Unconstrained optimal investment



(d) Constrained optimal investment

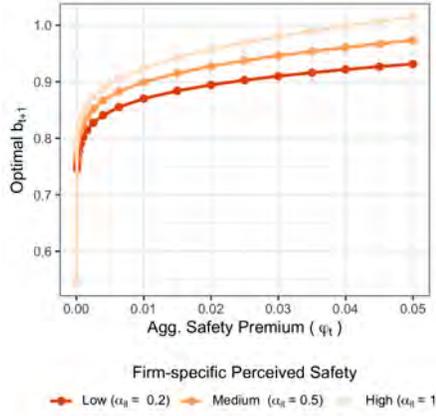


(e) Unconstrained optimal dividends

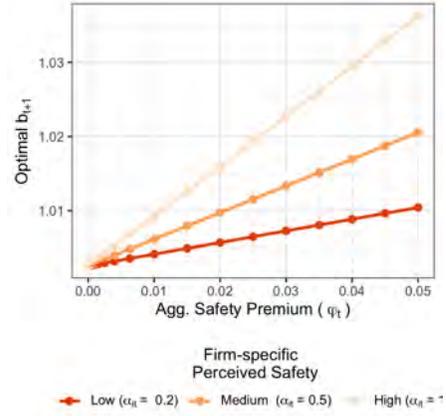


(f) Constrained optimal dividends

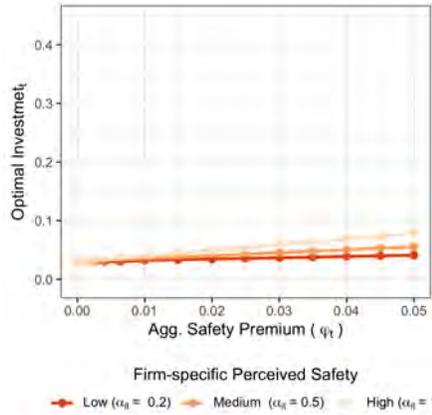
Figure 3: Response to Perceived Safety This figure shows optimal debt issuance, optimal investment, and optimal dividends as a function of the firm-specific perceived safety, $\alpha_{i,t}$, for different levels of the aggregate safety premium, φ_t . The plots on the left are for a firm that is financially unconstrained, and the plots on the right are for a firm that is financially constrained.



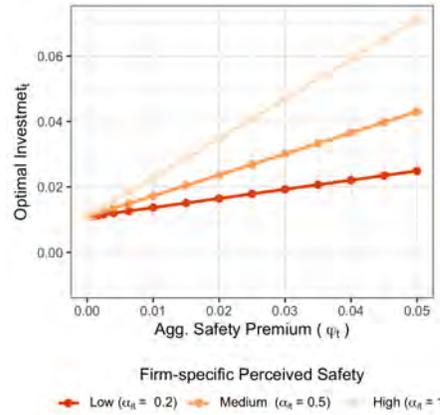
(a) Unconstrained optimal debt issuance



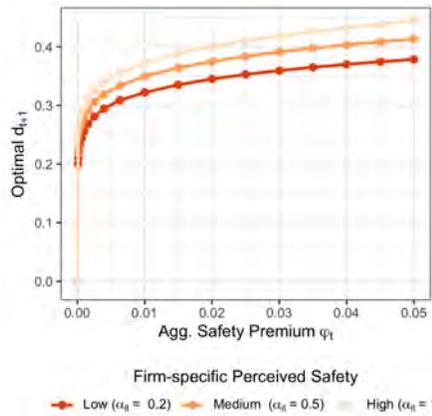
(b) Constrained optimal debt issuance



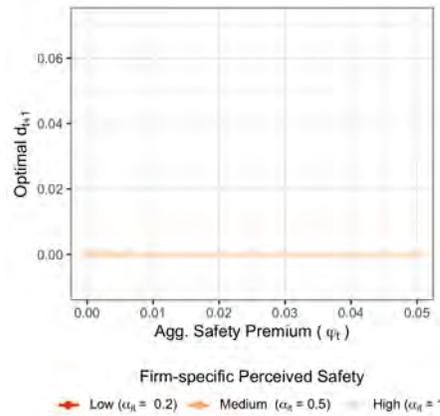
(c) Unconstrained optimal investment



(d) Constrained optimal investment



(e) Unconstrained optimal dividends



(f) Constrained optimal dividends

Figure 4: Response to Aggregate Safety Premium This figure shows optimal debt issuance, optimal investment, and optimal dividends as a function of the aggregate safety premium, φ_t , for different levels of perceived safety, $\alpha_{i,t}$. The plots on the left are for a firm that is financially unconstrained, and the plots on the right are for a firm that is financially constrained.

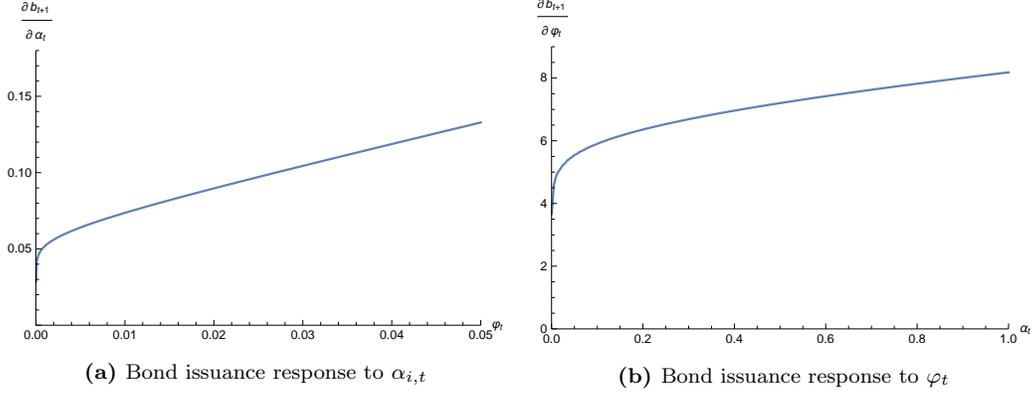


Figure 5: Interaction Effects of Bond Issuance Response to Safety Premium. This figure shows how optimal bond issuance responds to perceived safety $\alpha_{i,t}$ as function of φ_t , and how optimal bond issuance responds to perceived safety φ_t as function of $\alpha_{i,t}$.

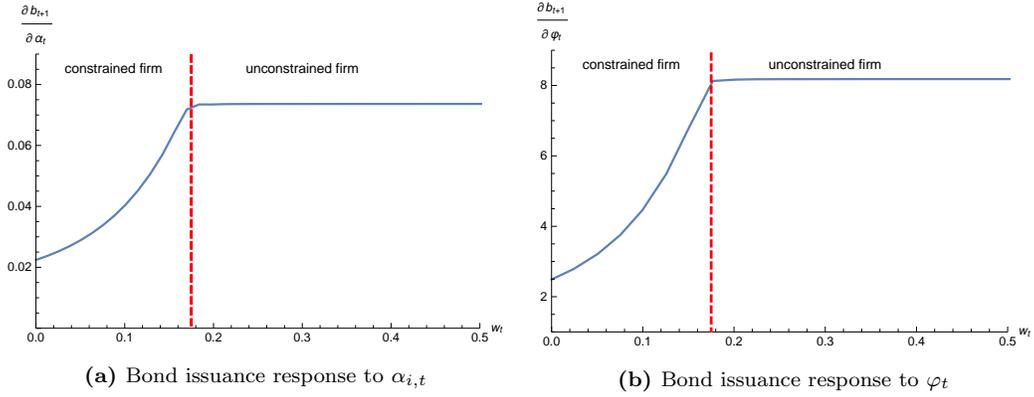


Figure 6: Heterogeneous Effects on Bond Issuance Due to Initial Net Worth. This figure shows how the optimal bond issuance responds to perceived safety $\alpha_{i,t}$ and φ_t as a function of the initial net worth $w_{i,t}$. Firms with low net worth are financially constrained, and firms with high net worth are not financially constrained. These curves are calculated from applying the implicit function theorem to firms' first-order conditions.

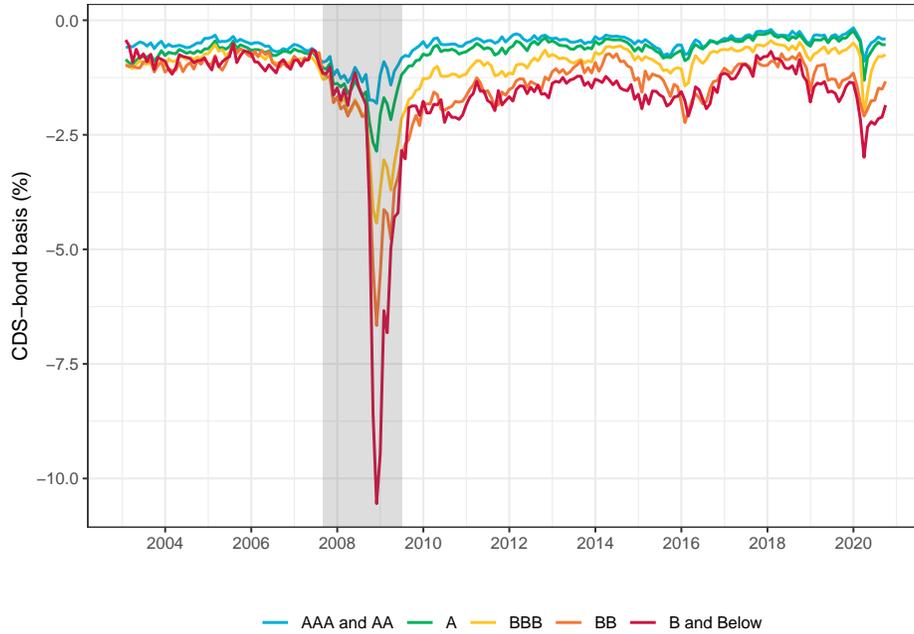


Figure 7: The CDS-bond Basis. This figure shows the times series of the CDS-bond basis across ratings. The CDS-bond basis is the difference between the CDS spread and the bond’s implied credit spread. For each rating class, the CDS-bond basis is the face-value weighted average.

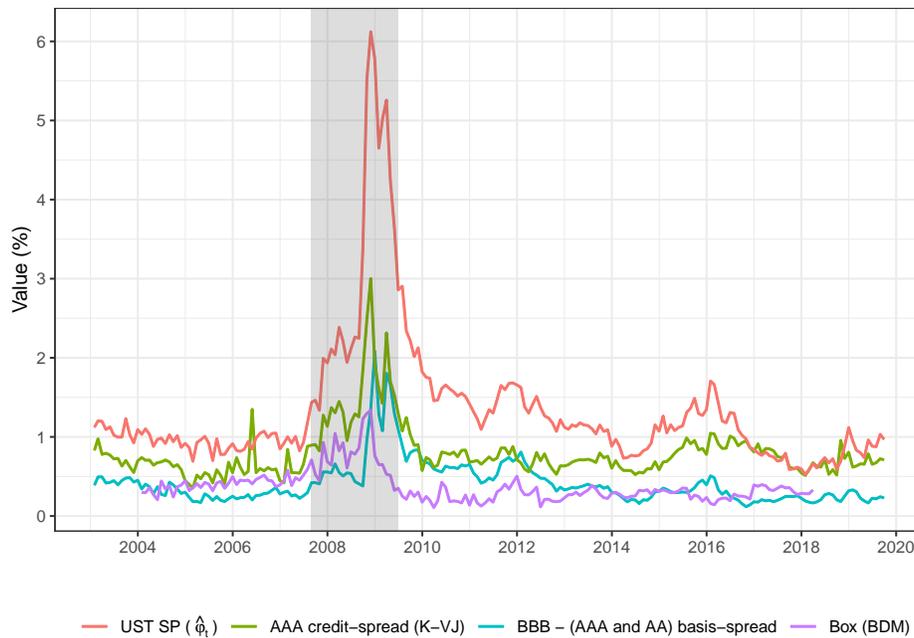


Figure 8: US Treasury Safety Premium. This picture shows the time series of different measures of the US Treasury safety premium. All measure definitions are described in detail in [Appendix B](#).

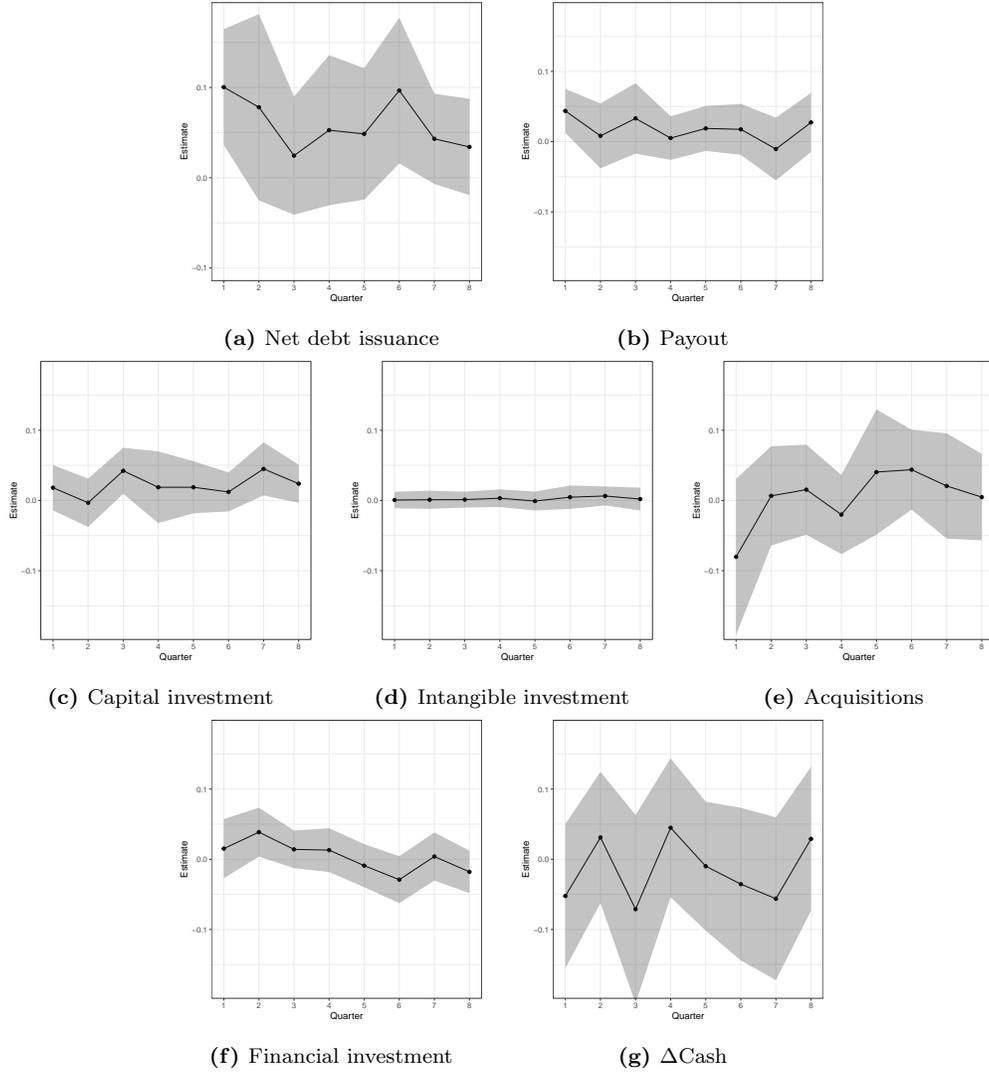


Figure 9: Effect of Cross-Basis on Firms' Decisions for Different Time Horizons. This picture shows regression coefficients in the y -axis and 1 to 8 quarters ahead in the x -axis. Panel (a) plots the cross-basis regression coefficients, β_1 , of Model (R1). Panels (b) - (g) plots the interaction cross-basis and debt issuance dummy coefficient, β_1 , of Model (R3) for different dependent variables. The shaded area is the estimated coefficient 95% confidence interval. Standard errors are clustered by both firm and time. Data is quarterly from 2003Q1 to 2019Q3.

Tables

Table 1: Calibration

| Parameter | Description | Value | Target |
|------------|-----------------------------|--------|----------------------------|
| ζ | Decreasing returns to scale | 0.65 | Kuehn and Schmid [2014] |
| δ | Depreciation rate | 0.03 | Kuehn and Schmid [2014] |
| ξ | Bankruptcy costs | 0.30 | Crouzet [2018] |
| ρ_z | Idiosy. shock persistence | 0.85 | Kuehn and Schmid [2014] |
| σ_z | Idiosy. shock volatility | 0.15 | Kuehn and Schmid [2014] |
| ρ_x | Agg. shock persistence | 0.89 | Begenau and Salomao [2019] |
| σ_x | Agg. shock volatility | 0.0093 | Begenau and Salomao [2019] |
| β | Rate of time preference | 0.996 | Kuehn and Schmid [2014] |
| γ | Relative risk aversion | 7.5 | Kuehn and Schmid [2014] |

Table 2: Number of Bonds and Firms with Valid CDS-Bond Basis

| Year | Number of Bonds | | | | | | Number of Firms | | | | | |
|------|-----------------|------|------|-----|-------------|-------|-----------------|-----|-----|-----|-------------|-------|
| | AAA and AA | A | BBB | BB | B and Below | Total | AAA and AA | A | BBB | BB | B and Below | Total |
| 2003 | 114 | 676 | 1054 | 301 | 197 | 2342 | 18 | 85 | 128 | 64 | 37 | 332 |
| 2004 | 103 | 634 | 1023 | 376 | 272 | 2408 | 16 | 92 | 146 | 79 | 60 | 393 |
| 2005 | 106 | 653 | 1006 | 485 | 317 | 2567 | 16 | 100 | 166 | 106 | 79 | 467 |
| 2006 | 117 | 641 | 900 | 413 | 361 | 2432 | 19 | 105 | 174 | 95 | 82 | 475 |
| 2007 | 144 | 620 | 896 | 363 | 408 | 2431 | 19 | 91 | 168 | 95 | 103 | 476 |
| 2008 | 130 | 609 | 886 | 348 | 352 | 2325 | 19 | 78 | 159 | 102 | 94 | 452 |
| 2009 | 128 | 637 | 979 | 324 | 335 | 2403 | 17 | 79 | 171 | 82 | 75 | 424 |
| 2010 | 166 | 648 | 1038 | 317 | 341 | 2510 | 18 | 79 | 171 | 79 | 75 | 422 |
| 2011 | 180 | 789 | 1078 | 362 | 311 | 2720 | 17 | 84 | 174 | 89 | 59 | 423 |
| 2012 | 253 | 922 | 1106 | 364 | 297 | 2942 | 21 | 90 | 167 | 87 | 63 | 428 |
| 2013 | 273 | 944 | 1213 | 347 | 267 | 3044 | 21 | 89 | 162 | 76 | 54 | 402 |
| 2014 | 288 | 931 | 1263 | 332 | 227 | 3041 | 21 | 85 | 159 | 71 | 40 | 376 |
| 2015 | 326 | 987 | 1435 | 360 | 212 | 3320 | 22 | 82 | 164 | 78 | 41 | 387 |
| 2016 | 365 | 936 | 1514 | 319 | 219 | 3353 | 23 | 73 | 166 | 71 | 46 | 379 |
| 2017 | 380 | 927 | 1550 | 275 | 203 | 3335 | 23 | 68 | 159 | 59 | 39 | 348 |
| 2018 | 339 | 951 | 1628 | 248 | 179 | 3345 | 22 | 69 | 153 | 52 | 34 | 330 |
| 2019 | 286 | 1010 | 1572 | 255 | 148 | 3271 | 19 | 73 | 138 | 50 | 32 | 312 |
| 2020 | 279 | 1076 | 1566 | 341 | 125 | 3387 | 15 | 70 | 131 | 47 | 26 | 289 |
| avg | 221 | 811 | 1206 | 341 | 265 | 2843 | 19 | 83 | 159 | 77 | 58 | 395 |

This table shows the number of distinct bonds and distinct firms in the sample per year and rating bucket. The last row shows the average annual numbers during the sample. Data is from January 2003 to September 2020.

Table 3: Firm-Level Summary Statistics

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---|--------|--------|----------|----------|--------|----------|
| Basis (%) | 19,227 | -1.149 | 1.168 | -1.393 | -0.850 | -0.536 |
| Cross basis (%) | 19,227 | -0.228 | 0.942 | -0.418 | -0.052 | 0.220 |
| Credit-spread (%) | 19,227 | 2.590 | 2.391 | 1.191 | 1.839 | 3.251 |
| CDS-spread (%) | 19,227 | 1.461 | 1.792 | 0.482 | 0.874 | 1.724 |
| Net Debt Issuance (% lag assets) | 19,227 | 0.324 | 3.329 | -0.555 | -0.009 | 0.232 |
| $\mathbb{I}\{\text{DebtIssuance}\}$ | 19,227 | 0.307 | 0.461 | 0 | 0 | 1 |
| Net Payout (% lag assets) | 19,227 | 0.012 | 1.362 | 0 | 0 | 0 |
| ST Debt Net Issuance (% lag assets) | 19,227 | 1.090 | 1.644 | 0.102 | 0.595 | 1.601 |
| CAPEX (% lag assets) | 19,227 | 1.287 | 1.321 | 0.496 | 0.899 | 1.576 |
| Capital Investment (% lag assets) | 19,227 | 1.224 | 1.255 | 0.464 | 0.864 | 1.529 |
| R&D (% lag assets) | 19,227 | 0.387 | 0.791 | 0.000 | 0.000 | 0.452 |
| $.3 \times \text{SGA}$ (% lag assets) | 19,227 | 1.057 | 1.046 | 0.362 | 0.733 | 1.362 |
| Intangible Investment | 19,227 | 1.444 | 1.300 | 0.463 | 1.026 | 2.187 |
| Acquisitions (% lag assets) | 19,227 | 0.515 | 2.289 | 0 | 0 | 0.1 |
| Financial Investment (% lag assets) | 19,227 | 0.016 | 1.145 | -0.003 | 0.000 | 0.012 |
| Δ Cash (% lag assets) | 19,227 | 0.152 | 2.991 | -0.869 | 0.044 | 1.094 |
| Net Operating Cash Flows (% lag assets) | 19,227 | 4.051 | 3.095 | 2.173 | 3.674 | 5.578 |
| Other Cash Flows (% lag assets) | 19,227 | 0.068 | 2.431 | -0.174 | 0.004 | 0.214 |
| Total Assets (\$ Bi) | 19,227 | 27.339 | 46.642 | 5.810 | 12.107 | 27.952 |
| CHE (% assets) | 19,227 | 8.718 | 8.807 | 2.547 | 5.782 | 11.986 |
| ROA (%) | 19,227 | 3.449 | 2.023 | 2.381 | 3.314 | 4.377 |
| Leverage Ratio (%) | 19,227 | 30.997 | 13.776 | 20.878 | 29.177 | 39.575 |
| Long-term Leverage Ratio (%) | 19,227 | 27.574 | 13.492 | 17.678 | 25.648 | 35.545 |

This table shows the firm-level quarterly data summary statistics. Mean, median, standard deviation, and selected percentiles are presented. For comparability, the statistics for the Compustat sample are presented based on the same time period. Data is quarterly from 2003Q1 to 2019Q3. See [Appendix A.1](#) for the details on the construction of each variable.

Table 4: CDS-bond Basis Summary Statistics

Panel A: Full Sample

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---------------|--------|--------|----------|----------|--------|----------|
| Cross-basis | 68,463 | -0.256 | 1.183 | -0.453 | -0.052 | 0.239 |
| Basis | 68,463 | -1.179 | 1.404 | -1.417 | -0.851 | -0.513 |
| Yield | 68,463 | 5.231 | 3.130 | 3.395 | 4.806 | 6.267 |
| Credit-spread | 68,463 | 2.815 | 3.101 | 1.212 | 1.921 | 3.477 |
| CDS-spread | 68,463 | 1.666 | 2.416 | 0.491 | 0.914 | 1.924 |

Panel B: Pre-GFC (January 2003 – November 2007)

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---------------|--------|--------|----------|----------|--------|----------|
| Cross-basis | 19,026 | -0.114 | 0.468 | -0.295 | -0.054 | 0.143 |
| Basis | 19,026 | -0.887 | 0.501 | -1.095 | -0.810 | -0.587 |
| Yield | 19,026 | 6.036 | 1.583 | 5.084 | 5.798 | 6.749 |
| Credit-spread | 19,026 | 2.055 | 1.526 | 1.055 | 1.562 | 2.599 |
| CDS-spread | 19,026 | 1.201 | 1.571 | 0.292 | 0.572 | 1.543 |

Panel C: During GFC (December 2007 – June 2009)

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---------------|-------|--------|----------|----------|--------|----------|
| Cross-basis | 6,535 | -0.783 | 3.013 | -1.085 | -0.245 | 0.398 |
| Basis | 6,535 | -3.067 | 3.255 | -3.555 | -2.191 | -1.563 |
| Yield | 6,535 | 9.117 | 6.654 | 5.827 | 7.319 | 9.620 |
| Credit-spread | 6,535 | 6.544 | 7.018 | 2.859 | 4.546 | 7.250 |
| CDS-spread | 6,535 | 3.492 | 5.474 | 0.741 | 1.639 | 3.943 |

Panel D: Post-GFC (July 2009 – September 2020)

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---------------|--------|--------|----------|----------|--------|----------|
| Cross-basis | 42,902 | -0.239 | 0.837 | -0.504 | -0.034 | 0.277 |
| Basis | 42,902 | -1.021 | 0.904 | -1.330 | -0.775 | -0.428 |
| Yield | 42,902 | 4.282 | 2.071 | 2.950 | 3.780 | 5.132 |
| Credit-spread | 42,902 | 2.585 | 2.094 | 1.213 | 1.868 | 3.373 |
| CDS-spread | 42,902 | 1.594 | 1.745 | 0.581 | 0.976 | 1.867 |

This table shows the summary statistics for the cross-basis, defined as the basis minus the basis index, where the basis index is the face-value weighted average of all basis in the sample; the basis, defined as the difference between credit spread and maturity-matched CDS spread; corporate bond yield; credit spread (over US Treasury); and the CDS spreads. Data is monthly and the full sample is from January 2003 to September 2020. Panels B, C, and D shows the same summary statistics for different sample windows.

Table 5: CDS-Bond cross section Analyses

| | <i>Dependent variable:</i> | | | | | | |
|------------------|----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | Cross-basis | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| A | -0.169*** (0.011) | | | | -0.165*** (0.011) | -0.167*** (0.011) | -0.162*** (0.010) |
| BBB | -0.573*** (0.032) | | | | -0.538*** (0.031) | -0.582*** (0.032) | -0.547*** (0.031) |
| BB | -0.947*** (0.045) | | | | -0.907*** (0.044) | -0.977*** (0.047) | -0.935*** (0.045) |
| B and Below | -1.132*** (0.084) | | | | -1.060*** (0.080) | -1.187*** (0.086) | -1.114*** (0.082) |
| Rating rank | | -0.102*** (0.007) | | | | | |
| ICR | | | -0.671*** (0.056) | | | | |
| $\hat{\alpha}_i$ | | | | 1.159*** (0.073) | | | |
| Bid-ask spread | | | | | -0.219*** (0.018) | | -0.213*** (0.019) |
| Turnover | | | | | | 0.008*** (0.001) | 0.008*** (0.001) |
| Constant | 0.349*** (0.020) | 0.718*** (0.055) | -0.113*** (0.011) | -0.418*** (0.023) | 0.451*** (0.025) | 0.297*** (0.018) | 0.397*** (0.023) |
| Observations | 66,549 | 66,549 | 62,964 | 62,964 | 66,549 | 66,549 | 66,549 |
| R ² | 0.255 | 0.249 | 0.119 | 0.105 | 0.269 | 0.264 | 0.278 |

Note: *p<0.1; **p<0.05; ***p<0.01

This table presents Fama-MacBeth regression results of cross-basis on bond characteristics, as specified in equation (19). In Column (1), the proxy for safety is the rating buckets categorical variables: AAA and AA, A, BBB, BB, and B and below, the first category is omitted due to multicollinearity. In Column (2), the proxy for safety is rating rank, which is equal to 1 if the bond is rated AAA, 2 if the bond is rated AA+, 3 if the bond is rated AA, etc. In Column (3), the proxy for safety is the interest coverage ratio (ICR) at the firm level, which is the total long-term debt divided by EBITA; both variables are quarterly and extracted from Compustat. In column (4), the proxy for safety is the structurally estimated perceived safety $\hat{\alpha}_{i,t}$ as described in Appendix B. Data is monthly from January 2003 to September 2020. Standard errors are shown in parenthesis.

Table 6: Treasury Safety Premium Proxies**(a) Summary Statistics**

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|-------------------------------|-----|-------|----------|----------|--------|----------|
| UST SP | 213 | 1.299 | 0.845 | 0.859 | 1.060 | 1.394 |
| AAA credit-spread (K-VJ) | 213 | 0.800 | 0.331 | 0.617 | 0.718 | 0.857 |
| AAA and AA - BBB basis-spread | 213 | 0.440 | 0.324 | 0.255 | 0.338 | 0.506 |
| Box (BDG) | 171 | 0.371 | 0.204 | 0.250 | 0.325 | 0.420 |

(b) Correlation Matrix

| | UST SP | AAA credit-spread (K-VJ) | BBB - (AAA and AA) basis-spread | Box (BDG) |
|---------------------------------|--------|--------------------------|---------------------------------|-----------|
| UST SP | 1 | | | |
| AAA credit-spread (K-VJ) | 0.887 | 1 | | |
| BBB - (AAA and AA) basis-spread | 0.900 | 0.697 | 1 | |
| Box (BDG) | 0.573 | 0.650 | 0.286 | 1 |

This table shows the summary statistics and correlation matrix of different proxies for US Treasury safety premium. [Appendix B](#) describes the details of the estimation of each of those proxies. Data is monthly from January 2003 to September 2020 if available.

Table 7: CDS-Bond Time Series AnalysesPanel A: UST SP ($\hat{\varphi}_T$)

| rating | β_0 | β_r | t-stat(β_0) | t-stat(β_r) | R^2 |
|-------------|-----------|-----------|---------------------|---------------------|-------|
| AAA and AA | -0.146 | 0.393 | -10.329 | 43.112 | 0.898 |
| A | -0.094 | 0.227 | -7.045 | 26.397 | 0.768 |
| BBB | -0.028 | -0.073 | -3.355 | -13.253 | 0.454 |
| BB | -0.092 | -0.285 | -2.842 | -13.581 | 0.466 |
| B and Below | 0.131 | -0.551 | 1.946 | -12.689 | 0.433 |

Panel B: AAA–Treasury Spread

| rating | β_0 | β_r | t-stat(β_0) | t-stat(β_r) | R^2 |
|-------------|-----------|-----------|---------------------|---------------------|-------|
| AAA and AA | -0.294 | 0.823 | -7.429 | 17.998 | 0.606 |
| A | -0.171 | 0.465 | -6.080 | 14.332 | 0.493 |
| BBB | 0.020 | -0.178 | 1.585 | -12.362 | 0.420 |
| BB | 0.077 | -0.674 | 1.560 | -11.873 | 0.400 |
| B and Below | 0.384 | -1.212 | 3.661 | -9.989 | 0.321 |

Panel C: BBB–(AAA and AA) CDS-Bond Basis Spread

| rating | β_0 | β_r | t-stat(β_0) | t-stat(β_r) | R^2 |
|-------------|-----------|-----------|---------------------|---------------------|-------|
| AAA and AA | -0.070 | 0.989 | -4.249 | 32.680 | 0.835 |
| A | -0.056 | 0.585 | -4.410 | 25.058 | 0.748 |
| BBB | -0.039 | -0.191 | -5.025 | -13.380 | 0.459 |
| BB | -0.154 | -0.702 | -4.929 | -12.222 | 0.415 |
| B and Below | -0.029 | -1.265 | -0.432 | -10.300 | 0.335 |

Panel D: Box-Trade Spread

| rating | β_0 | β_r | t-stat(β_0) | t-stat(β_r) | R^2 |
|-------------|-----------|-----------|---------------------|---------------------|-------|
| AAA and AA | 0.100 | 0.765 | 1.780 | 5.779 | 0.165 |
| A | 0.106 | 0.299 | 2.889 | 3.460 | 0.066 |
| BBB | -0.050 | -0.206 | -3.585 | -6.282 | 0.189 |
| BB | -0.384 | -0.212 | -6.644 | -1.556 | 0.014 |
| B and Below | -0.290 | -0.776 | -2.504 | -2.837 | 0.045 |

This table shows the results of the time series regressions specified in equation (20). The dependent variable is the face-value weighted average cross-basis for each rating bucket. Each panel corresponds to a different proxy for the US Treasury safety premium. [Appendix B](#) describes the details of the construction of each of those proxies. Data is monthly from January 2003 to September 2020 if available.

Table 8: Impact of Safety Premium on Net Debt Issuance

| <i>Dependent variable:</i> | | | | | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Net Debt Issuance(% of Lag Assets) at $t + 1$ | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cross-basis | 0.100*** (0.032) | 0.090** (0.035) | 0.079** (0.034) | 0.077** (0.034) | | | | |
| USTreas SP \times HighCBB | | | | | 0.120** (0.051) | 0.115** (0.050) | | |
| USTreas SP \times A and Above | | | | | | | 0.134** (0.055) | 0.155*** (0.055) |
| HighCBB | | | | | 0.041 (0.102) | -0.021 (0.100) | | |
| A and Above | | | | | | | 0.383*** (0.134) | 0.156 (0.133) |
| CDS-spread | -0.106*** (0.025) | -0.095*** (0.029) | -0.043* (0.026) | -0.039 (0.026) | -0.112*** (0.024) | -0.042 (0.026) | -0.084*** (0.021) | -0.011 (0.022) |
| log(Total Assets) | -0.905*** (0.154) | -0.936*** (0.148) | -0.829*** (0.138) | -0.815*** (0.138) | -0.892*** (0.151) | -0.806*** (0.136) | -0.887*** (0.151) | -0.800*** (0.144) |
| CHE (% assets) | -0.024*** (0.008) | -0.025*** (0.008) | -0.027*** (0.008) | -0.027*** (0.008) | -0.025*** (0.008) | -0.027*** (0.008) | -0.025*** (0.007) | -0.027*** (0.008) |
| Tobin's Q | 0.005 (0.005) | 0.006 (0.005) | 0.028*** (0.007) | 0.027*** (0.007) | 0.006 (0.005) | 0.027*** (0.007) | 0.006 (0.005) | 0.026*** (0.007) |
| Leverage Ratio (%) | | | -0.059*** (0.008) | -0.058*** (0.008) | | -0.058*** (0.008) | | -0.056*** (0.007) |
| ROA (%) | | | | 0.020 (0.014) | | 0.021 (0.014) | | 0.020 (0.014) |
| Firm FE | Yes |
| Time FE | Yes |
| Rating FE | No | Yes | Yes | Yes | No | Yes | No | No |
| Observations | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 |
| R ² | 0.065 | 0.066 | 0.077 | 0.077 | 0.065 | 0.077 | 0.066 | 0.077 |
| Adjusted R ² | 0.031 | 0.031 | 0.043 | 0.043 | 0.031 | 0.043 | 0.031 | 0.043 |

Note:

*p<0.1; **p<0.05; ***p<0.01

This table presents regression results of net debt issuance on different measures of the safety premium in corporate debt, as described in (R1) and (R2). The y -variable is net debt issuance normalized by lag total assets in quarter $t + 1$. The x -variables of interest are the cross-basis, defined as the CDS-bond basis minus the basis index; HighCBB, an indicator variable equal to 1 if the firm belongs to the highest quintile of cross-basis and 0 otherwise; “A and Above”, an indicator variable equal to 1 if the firm is rated A- and above and 0 otherwise; and the US Treasury safety premium (UST SP). All independent variables are measured in quarter t . Standard errors are reported in parenthesis and are clustered by time. Data is quarterly from 2003Q1 to 2019Q3. See Appendix A.1 for the details on the construction of variables and controls.

Table 9: Impact of Safety Premium on Firms' Decisions

| | <i>Dependent variable:</i> | | | | | | | |
|-----------------------------------|----------------------------|----------------------|----------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cross-basis \times DebtIssuance | 0.044*** (0.016) | 0.018 (0.016) | -0.002 (0.005) | 0.003 (0.004) | 0.001 (0.006) | -0.080 (0.056) | 0.015 (0.021) | -0.052 (0.051) |
| Cross-basis | 0.041** (0.018) | 0.035** (0.015) | 0.002 (0.003) | 0.005* (0.002) | 0.007* (0.004) | 0.035 (0.023) | 0.008 (0.008) | -0.016 (0.022) |
| DebtIssuance | 0.301*** (0.031) | 0.193*** (0.013) | 0.003 (0.007) | 0.011** (0.005) | 0.014* (0.008) | 0.885*** (0.081) | 0.114*** (0.024) | 0.891*** (0.089) |
| CDS-spread | -0.085*** (0.019) | -0.085*** (0.018) | -0.005** (0.002) | -0.002 (0.002) | -0.007** (0.003) | -0.033** (0.014) | -0.010* (0.005) | -0.007 (0.018) |
| log(Total Assets) | -0.229*** (0.041) | -0.124*** (0.023) | -0.109*** (0.010) | -0.341*** (0.008) | -0.450*** (0.012) | -0.274*** (0.077) | -0.024 (0.033) | -0.651*** (0.095) |
| CHE (% assets) | 0.024*** (0.003) | 0.001 (0.001) | -0.0003 (0.001) | -0.004*** (0.0005) | -0.005*** (0.001) | 0.083*** (0.009) | -0.004 (0.003) | -0.180*** (0.009) |
| Tobin's Q | 0.017*** (0.004) | 0.008*** (0.002) | 0.001 (0.001) | 0.002*** (0.001) | 0.002** (0.001) | 0.002 (0.004) | -0.002 (0.002) | 0.009 (0.007) |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 |
| R ² | 0.397 | 0.680 | 0.765 | 0.939 | 0.901 | 0.116 | 0.058 | 0.137 |
| Adjusted R ² | 0.375 | 0.668 | 0.757 | 0.937 | 0.897 | 0.083 | 0.023 | 0.105 |

Note:

*p<0.1; **p<0.05; ***p<0.01

This table presents regression results of firms' decisions on the safety premium in corporate debt, measured by the cross-basis, as described in equation (R3). The y -variables are (1) net payout, defined as dividends plus net equity repurchase, (2) capital investment, defined as CAPEX plus net PPE bought, (3) R&D expenses, (4) 30% of SG&A expenses, (5) intangible investment, defined as R&D plus 30% of SG&A expenses, (6) acquisitions, (7) financial investments, and (8) change in cash from the cash flow statement. All independent variables are measured in quarter $t + 1$ and normalized by lag total assets. The x -variables of interest are the cross-basis, defined as the CDS-bond basis minus the basis index; and DebtIssuance, an indicator variable equal to 1 if net debt issuance is strictly positive and 0 otherwise. All independent variables are measured in quarter t . Standard errors are reported in parenthesis and are clustered by time. Data is quarterly from 2003Q1 to 2019Q3. See Appendix A.1 for the details on the construction of variables and controls.

Table 10: Heterogeneous Impact of Cross-Basis on Firms' Decisions

Panel A: Investment Grade

| <i>Dependent variable:</i> | | | | | | | | | |
|----------------------------|---------------------|---------------------|----------------------|--------------------|--------------------|-----------------------|-------------------|----------------------|-------------------|
| | Net Debt Issuance | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Cross-basis × IG | 0.145** (0.057) | 0.114* (0.058) | -0.104*** (0.030) | 0.011 (0.009) | 0.025** (0.012) | 0.036** (0.015) | 0.224* (0.115) | 0.021 (0.047) | -0.104 (0.152) |
| Cross-basis | 0.048 (0.036) | 0.046* (0.023) | 0.104*** (0.025) | -0.008* (0.004) | -0.001 (0.004) | -0.009 (0.006) | -0.021 (0.045) | 0.007 (0.022) | -0.067 (0.052) |
| IG | 0.511*** (0.102) | 0.483*** (0.123) | 0.198** (0.075) | 0.021 (0.025) | 0.051** (0.024) | 0.072** (0.036) | 0.396 (0.281) | 0.072 (0.081) | 0.293 (0.235) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 |
| R ² | 0.066 | 0.450 | 0.765 | 0.772 | 0.947 | 0.907 | 0.244 | 0.192 | 0.233 |
| Adjusted R ² | 0.032 | 0.384 | 0.737 | 0.744 | 0.940 | 0.896 | 0.153 | 0.095 | 0.141 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Panel B: Cash Rich

| <i>Dependent variable:</i> | | | | | | | | | |
|----------------------------|---------------------|---------------------|----------------------|-------------------|---------------------|-----------------------|-------------------|----------------------|-------------------|
| | Net Debt Issuance | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Cross-basis × CashRich | -0.021 (0.077) | 0.020 (0.066) | -0.073*** (0.026) | 0.001 (0.010) | -0.007 (0.012) | -0.006 (0.016) | 0.065 (0.194) | -0.088 (0.056) | -0.137 (0.156) |
| Cross-basis | 0.104*** (0.038) | 0.090*** (0.023) | 0.095*** (0.021) | -0.005 (0.005) | 0.009** (0.004) | 0.004 (0.007) | 0.041 (0.059) | 0.031 (0.021) | -0.062 (0.053) |
| CashRich | -0.296** (0.140) | 0.095 (0.113) | -0.071 (0.048) | 0.005 (0.034) | -0.040** (0.018) | -0.035 (0.035) | -0.003 (0.315) | -0.123 (0.111) | -0.291 (0.299) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 |
| R ² | 0.066 | 0.448 | 0.764 | 0.772 | 0.947 | 0.907 | 0.243 | 0.192 | 0.233 |
| Adjusted R ² | 0.031 | 0.381 | 0.736 | 0.744 | 0.940 | 0.896 | 0.152 | 0.095 | 0.141 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Panel C: High Profitability

| <i>Dependent variable:</i> | | | | | | | | | |
|----------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|-----------------------|-------------------|----------------------|---------------------|
| | Net Debt Issuance | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Cross-basis × Profitable | 0.087 (0.094) | -0.024 (0.073) | -0.149** (0.067) | 0.009 (0.020) | 0.030* (0.016) | 0.039* (0.022) | -0.032 (0.150) | 0.098 (0.081) | 0.135 (0.160) |
| Cross-basis | 0.087** (0.033) | 0.083*** (0.020) | 0.085*** (0.020) | -0.007* (0.004) | 0.003 (0.004) | -0.004 (0.006) | 0.052 (0.049) | 0.007 (0.024) | -0.106** (0.048) |
| Profitable | 0.282*** (0.086) | 0.465*** (0.070) | 0.285*** (0.062) | 0.054*** (0.017) | 0.099*** (0.013) | 0.153*** (0.019) | 0.156 (0.162) | 0.011 (0.052) | 0.341** (0.144) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 |
| R ² | 0.066 | 0.453 | 0.767 | 0.772 | 0.948 | 0.908 | 0.243 | 0.192 | 0.233 |
| Adjusted R ² | 0.031 | 0.387 | 0.739 | 0.745 | 0.941 | 0.897 | 0.152 | 0.095 | 0.141 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Panel D: High Payout

| <i>Dependent variable:</i> | | | | | | | | | |
|----------------------------|---------------------|---------------------|---------------------|-------------------|---------------------|-----------------------|----------------------|----------------------|-------------------|
| | Net Debt Issuance | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Cross-basis × HighPayout | 0.112 (0.087) | -0.070 (0.066) | -0.014 (0.034) | 0.016 (0.017) | 0.031** (0.014) | 0.048*** (0.018) | 0.255* (0.145) | -0.029 (0.056) | -0.009 (0.204) |
| Cross-basis | 0.087** (0.034) | 0.085*** (0.019) | 0.082*** (0.021) | -0.006 (0.004) | 0.004 (0.004) | -0.002 (0.006) | 0.037 (0.049) | 0.019 (0.025) | -0.082 (0.053) |
| HighPayout | 0.220*** (0.074) | 0.720*** (0.062) | 0.021 (0.027) | -0.006 (0.014) | 0.028*** (0.010) | 0.022 (0.016) | -0.420*** (0.117) | -0.051 (0.047) | -0.200 (0.131) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 |
| R ² | 0.066 | 0.463 | 0.764 | 0.772 | 0.947 | 0.907 | 0.245 | 0.192 | 0.233 |
| Adjusted R ² | 0.031 | 0.399 | 0.736 | 0.744 | 0.940 | 0.896 | 0.154 | 0.095 | 0.141 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Panel E: Large

| <i>Dependent variable:</i> | | | | | | | | | |
|----------------------------|---------------------|---------------------|---------------------|-------------------|-------------------|-----------------------|-------------------|----------------------|-------------------|
| | Net Debt Issuance | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Cross-basis \times Large | 0.165 (0.115) | -0.073 (0.100) | -0.184** (0.074) | 0.008 (0.025) | -0.002 (0.014) | 0.006 (0.030) | 0.431* (0.242) | 0.007 (0.085) | -0.054 (0.194) |
| Cross-basis | 0.091*** (0.033) | 0.099*** (0.023) | 0.095*** (0.020) | -0.005 (0.004) | 0.008* (0.004) | 0.003 (0.006) | 0.022 (0.049) | 0.014 (0.022) | -0.083 (0.053) |
| Large | -0.118 (0.106) | -0.136 (0.100) | -0.138* (0.074) | -0.011 (0.020) | -0.014 (0.018) | -0.025 (0.028) | 0.128 (0.203) | 0.037 (0.087) | -0.213 (0.271) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 | 5,905 |
| R ² | 0.065 | 0.448 | 0.765 | 0.772 | 0.947 | 0.907 | 0.244 | 0.192 | 0.233 |
| Adjusted R ² | 0.031 | 0.382 | 0.737 | 0.744 | 0.940 | 0.896 | 0.153 | 0.094 | 0.140 |

Note:

*p<0.1; **p<0.05; ***p<0.01

This table presents regression results of firms' heterogeneous response to the safety premium, measured by the cross-basis, as described in equation (R4). The y -variables are (1) net debt issuance, (2) net payout, defined as dividends plus net equity repurchase, (3) capital investment, defined as CAPEX plus net PPE bought, (4) R&D expenses, (5) 30% of SG&A expenses, (6) intangible investment, defined as R&D plus 30% of SG&A expenses, (7) acquisitions, (8) financial investments, and (9) change in cash from the cash flow statement. All independent variables are measured in time $t + 1$ and normalized by lag total assets. The x -variable of interest is the cross-basis, defined as the CDS-bond basis minus the basis index. UNC is an indicator variable equal to one if the firm belongs the 20% highest quantile of each one of the firm characteristics: CHE, profits, payout (all three as share of the total assets), and size. IG is a dummy variable equal to 1 if the firm is rated BBB- or above, 0 otherwise. Standard errors are reported in parenthesis and are clustered by time. Data is quarterly from 2003Q1 to 2019Q3. See [Appendix A.1](#) for the details on the construction of variables and controls.

References

- Admati, Anat R., Peter M. Demarzo, Martin F. Hellwig, and Paul Pfleiderer, 2018, The Leverage Ratchet Effect, *Journal of Finance* 73, 145–198.
- Andersen, Leif, Darrell Duffie, and Yang Song, 2019, Funding Value Adjustments, *Journal of Finance* 74, 145–192.
- Angrist, Joshua D, and Jorn-Steffen Pischke, 2009, *Mostly harmless econometrics: An empiricist's companion* (Princeton University Press).
- Arora, Navneet, Priyank Gandhi, and Francis A. Longstaff, 2012, Counterparty credit risk and the credit default swap market, *Journal of Financial Economics* 103, 280–293.
- Badoer, Dominique C., and Christopher M. James, 2016, The Determinants of Long-Term Corporate Debt Issuances, *Journal of Finance* 71, 457–492.
- Bai, Jennie, and Pierre Collin-Dufresne, 2019, The CDS-bond basis, *Financial Management* 48, 417–439.
- Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2003, The maturity of debt issues and predictable variation in bond returns, *Journal of Financial Economics* 70, 261–291.
- Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–32.
- Begenau, Juliane, and Juliana Salomao, 2019, Firm financing over the business cycle, *Review of Financial Studies* 32, 1235–1274.
- Berndt, Antje, Robert A. Jarrow, and Choong Oh Kang, 2007, Restructuring risk in credit default swaps: An empirical analysis, *Stochastic Processes and their Applications* 117, 1724–1749.
- Binsbergen, Jules H Van, William F Diamond, and Marco Grotteria, 2019, Risk-Free Interest Rates, *SSRN Electronic Journal* .
- Bolandnazar, Mohammadreza, 2020, The Market Structure of Dealer-to-Client Interest Rate Swaps 1–47.
- Bolton, Patrick, Hui Chen, and Neng Wang, 2013, Market timing, investment, and risk management, *Journal of Financial Economics* 109, 40–62.

- Boyarchenko, Nina, Anna M. Costello, and Or Shachar, 2019, The Long and Short of It: The Post-Crisis Corporate CDS Market, *SSRN Electronic Journal* .
- Boyarchenko, Nina, Pooja Gupta, Nick Steele, and Jacqueline Yen, 2018, Trends in Credit Basis Spreads, *Federal Reserve Bank of New York Economic Policy Review* 24, 15.
- Brennan, Michael J, and Eduardo S Schwartz, 1984, Optimal Financial Policy and Firm Valuation, *Journal of Finance* 39, 593–607.
- Caballero, Ricardo J., and Emmanuel Farhi, 2018, The safety trap, *Review of Economic Studies* 85, 223–274.
- Caballero, Ricardo J., Emmanuel Farhi, and Pierre Olivier Gourinchas, 2016, Safe asset scarcity and aggregate demand, *American Economic Review* 106, 513–518.
- Caballero, Ricardo J., Emmanuel Farhi, and Pierre Olivier Gourinchas, 2017, The safe assets shortage conundrum, *Journal of Economic Perspectives* 31, 29–46.
- Crouzet, Nicolas, 2018, Aggregate implications of corporate debt choices, *Review of Economic Studies* 85, 1635–1682.
- Crouzet, Nicolas, and Janice Eberly, 2020, Rents and Intangible Capital: A Q+ Framework, *Working Paper* .
- Crouzet, Nicolas, and Janice C. Eberly, 2019, Understanding Weak Capital Investment: the Role of Market Concentration and Intangibles, *NBER Working Paper Series* 53, 1–10.
- Dang, Tri Vi, Gary B. Gorton, and Bengt R. Holmström, 2019, The Information View of Financial Crises, *SSRN Electronic Journal* .
- Dang, Tv, Gary Gorton, and Bengt Holmström, 2015, Ignorance, Debt and Financial Crises, *Working Paper* 1–40.
- Daniel, Kent, Lira Mota, Simon Rottke, and Tano Santos, 2020, The Cross-Section of Risk and Returns, *Review of Financial Studies* 33, 1927–1979.
- Darmouni, Olivier, and Lira Mota, 2020, The Financial Assets of Non-Financial Firms, *SSRN Electronic Journal* .
- Department of the Treasury, 2014, Liquidity Coverage Ratio: Liquidity Risk Measurement Standards; Final Rule.
- Diamond, William, 2020, Safety Transformation and the Structure of the Financial System, *Journal of Finance* 1–40.

- Du, Wenxin, Salil Gadgil, Michael B. Gordy, and Clara Vega, 2017, Counterparty Risk and Counterparty Choice in the Credit Default Swap Market, *SSRN Electronic Journal* .
- Du, Wenxin, Joanne Im, and Jesse Schreger, 2018a, The U.S. Treasury Premium, *Journal of International Economics* 112, 167–181.
- Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018b, Deviations from Covered Interest Rate Parity, *Journal of Finance* 73, 915–957.
- Duffie, Darrell, 1999, Credit Default Swap Valuation, *Financial Analysts Journal* .
- Duffie, Darrell, 2018, Post-Crisis Bank Regulations and Financial Market Liquidity, *Baffi Lecture* .
- Eisfeldt, Andrea L., and Tyler Muir, 2016, Aggregate external financing and savings waves, *Journal of Monetary Economics* 84, 116–133.
- Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, 2020, A Macroeconomic Model with Financially Constrained Producers and Intermediaries, *SSRN Electronic Journal* .
- Elizalde, Abel, Saul Doctor, and Yasemin Saltuk, 2009, Bond-CDS Basis Handbook Measuring, Technical report.
- Farhi, Emmanuel, and Matteo Maggiori, 2018, A model of the international monetary system, *Quarterly Journal of Economics* 133, 295–355.
- Farre-Mensa, Joan, Roni Michaely, and Martin C. Schmalz, 2018, *Financing Payouts*.
- Fleckenstein, Matthias, and Francis A Longstaff, 2020, Renting Balance Sheet Space: Intermediary Balance Sheet Rental Costs and the Valuation of Derivatives, *The Review of Financial Studies* 33, 5051–5091.
- Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.
- Giambona, Erasmo, Rafael Matta, Jose-Luis Peydro, and Ye Wang, 2020, *Quantitative Easing, Investment, and Safe Assets: The Corporate-Bond Lending Channel*, volume 00.
- Giglio, Stefano, 2014, Credit default swap spreads and systemic financial risk, *SSRN Electronic Journal* .
- Gorton, By Gary, Stefan Lewellen, and Andrew Metrick, 2012, The Safe-Asset Share, *American Economic Review: Papers & Proceedings* 102, 101–106.

- Gorton, Gary, 2017, The history and economics of safe assets, *Annual Review of Economics* 9, 547–586.
- Gorton, Gary, and George Pennacchi, 1990, Financial Intermediaries and Liquidity Creation, *The Journal of Finance* 45, 49–71.
- Goyal, Vidhan K., and Murray Z. Frank, 2009, Capital Structure Decisions: Which Factors Are Reliably Important?, *Financial Management* 1–37.
- Graham, John R., Mark T. Leary, and Michael R. Roberts, 2014, How Does Government Borrowing Affect Corporate Financing and Investment?, *SSRN Electronic Journal* .
- Greenwood, Robin, Samuel Hanson, and Jeremy C. Stein, 2010, A gap-filling theory of corporate debt maturity choice, *Journal of Finance* 65, 993–1028.
- Gutiérrez, Germán, and Thomas Philippon, 2017, Declining Competition and Investment in the U.S., *Mimeo* 1–77.
- He, Zhiguo, Arvind Krishnamurthy, and Konstantin Milbradt, 2019, A model of safe asset determination, *American Economic Review* 109, 1230–1262.
- Heider, Florian, and Alexander Ljungqvist, 2015, As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes, *Journal of Financial Economics* 118, 684–712.
- Hennessy, Christopher A., and Toni M. Whited, 2005, Debt dynamics, *Journal of Finance* 60, 1129–1165.
- Holmstrom, Bengt, and Jean Tirole, 2001, LAPM : A Liquidity-Based Asset Pricing Model, *The Journal of Finance* LVI, 1837–1867.
- Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig, 2020, Foreign Safe Asset Demand and the Dollar Exchange Rate, *SSRN Electronic Journal* .
- Kacperczyk, Marcin, Christophe Pérignon, and Guillaume Vuillemeys, 2020, The Private Production of Safe Assets, *Journal of Finance* .
- Kim, Gi H., Haitao Li, and Weina Zhang, 2016, CDS-bond basis and bond return predictability, *Journal of Empirical Finance* 38, 307–337.
- Kopecky, Karen A, and Richard M H Suen, 2010, Finite state Markov-chain approximations to highly persistent processes, *Review of Economic Dynamics* 13, 701–714.

- Krishnamurthy, Arvind, and Annette Vissing-Jørgensen, 2012a, The aggregate demand for Treasury debt, *Journal of Political Economy* 120, 233–267.
- Krishnamurthy, Arvind, and Annette Vissing-Jørgensen, 2012b, Why an MBS-Treasury swap is better policy than the Treasury twist, *Working Paper* 1–5.
- Krishnamurthy, Arvind, and Annette Vissing-Jørgensen, 2015, The impact of Treasury supply on financial sector lending and stability, *Journal of Financial Economics* 118, 571–600.
- Kuehn, Lars Alexander, and Lukas Schmid, 2014, Investment-Based Corporate Bond Pricing, *Journal of Finance* 69, 2741–2776.
- Lenel, Moritz, 2020, Safe Assets, Collateralized Lending and Monetary Policy, *SSRN Electronic Journal* .
- Liu, Yang, Lukas Schmid, and Amir Yaron, 2020, The Risks of Safe Assets, *Working Paper* 1–39.
- Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* 60, 2213–2253.
- Ma, Yueran, 2019, Nonfinancial Firms as Cross-Market Arbitrageurs, *Journal of Finance* 74, 3041–3087.
- Myers, Stewart C., 1984, The Capital Structure Puzzle, *The Journal of Finance* 39, 574–592.
- Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.
- Nagel, Stefan, 2016, The Liquidity Premium of Near-Money Assets, *The Quarterly Journal of Economics* 131, 1927–1971.
- Oehmke, Martin, and Adam Zawadowski, 2015, Synthetic or Real? the Equilibrium Effects of Credit Default Swaps on Bond Markets, *Review of Financial Studies* 28, 3303–3337.
- Oehmke, Martin, and Adam Zawadowski, 2017, The anatomy of the CDS market, *Review of Financial Studies* 30, 80–119.
- Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.
- Rouwenhorst, Geert, 1995, Asset Pricing Implications of Equilibrium Business Cycle Models.

- Stein, Jeremy C., 1996, Rational capital budgeting in an irrational world, *Journal of Business* 69, 429–455.
- Stokey, Nancy L, 1989, *Recursive methods in economic dynamics* (Harvard University Press).
- Strebulaev, Ilya A., and Toni M. Whited, 2012, Dynamic models and structural estimation in corporate finance, *Foundations and Trends in Finance* 6, 1–163.
- Sunderam, Adi, 2015, Money creation and the shadow banking system, *Review of Financial Studies* 28, 939–977.
- Tauchen, George, 1986, Finite state markov-chain approximations to univariate and vector autoregressions, *Economics letters* 20, 177–181.
- Tauchen, George, and Robert Hussey, 1991, Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models, *Econometrica: Journal of the Econometric Society* 371–396.
- Warusawitharana, Missaka, and Toni M. Whited, 2016, Equity market misvaluation, financing, and investment, *Review of Financial Studies* 29, 603–654.

Appendix

Appendix A. Data Appendix

Appendix A.1. Variable definitions

For corporate bond pricing data, I use WRDS bond returns which is based on TRACE and FISD. For CDS-spreads data, I use Markit single name CDS-spread composites. All data is downloaded directly from the WRDS data service. The data set is bond returns centered. Details on the merging algorithm can be found in [Appendix A.4](#).

| | |
|-----------------|--|
| $Basis_{index}$ | Face value weighted CDS-bond basis average. |
| CDS-bond basis | For each bond, the CDS-bond basis is the difference between the end of month maturity-matched CDS spread and the credit spread. The firm level CDS-bond basis is the face-value weighted bond level CDS-bond basis. Original data is monthly. For quarterly regressions, I consider the average firm level CDS-bond basis within the quarter. |
| CDS-spread | For each bond, the CDS curve is interpolated to match the same maturity as the bond, I call this the <i>bond level CDS-spread</i> . The <i>firm level CDS-spread</i> is the face-value weighted bond level CDS-spread. The original CDS-spread data is daily. To match the bond data, I consider end of month CDS-spreads. For quarterly regressions, I consider the average firm level CDS-spread within the quarter. |
| Credit spread | Difference in bond yield and the duration matched US Treasury yield fixed key rates curve. The firm level credit spread is the face-value weighted bond level credit spread. The original is US Treasury yield curve daily. To match the bond data, I consider end of month US Treasury yields. For quarterly regressions, I consider the average firm level CDS-spread within the quarter. |
| Cross-basis | Difference between firm level CDS-bond basis and $Basis_{index}$. |
| Ratings | For bond level, rating is the first rating available in the order Standard and Poor's, Moody's and Fitch. The large majority of Compustat firms (GVKEY level) have only one long term rating. In the few cases there are more than one rating available for one GVKEY, the firm level rating is the lowest available rating. |

For quarterly firm level variables, I use data from Compustat and CRSP, both downloaded directly from the WRDS data service.

| | |
|--------------|--|
| Acquisitions | Cash outflow of funds used for and/or the costs relating to acquisition (AQC). Normalized by lag of total assets (AT). |
|--------------|--|

| | |
|----------------------------------|---|
| Book Equity (BE) | Same as in Daniel, Mota, Rottke, and Santos [2020] , which is, stockholders book equity, minus the book value of preferred stock, plus balance sheet deferred taxes if available and fiscal year is < 1993, minus investment tax credit if available, minus post-retirement benefit assets (PRBA) if available. Stockholders book equity is shareholder equity (SEQ), common equity (CEQ) plus preferred stock (PSTK) or total assets (AT) minus liabilities (LT) plus minority interest (MIB), if available (depending on availability, in that order). Book value of preferred stock is redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK) (depending on availability, in that order). Deferred taxes is deferred taxes and investment tax credit (TXDITC) or deferred taxes and investment tax credit (TXDB) plus investment tax credit (ITCB) (depending on availability, in that order). To be valid, BE must be greater than zero. |
| Capital investment | Capital expenditure (CAPX) minus sale of property, plant, and equipment (SPPE) if available. Normalized by lag of total assets (AT). |
| Δ Cash | Cash and cash equivalents increase (CHECH). Normalized by lag of total assets (AT). |
| CHE | Cash and short-term investments (CHE). Normalized by lag of total assets (AT). |
| Intangible investment | Sum of research and development expenditure, R&D (XRD) and 30% of selling, general and administrative expenses (SG&A). See Appendix A.2 for details on the SG&A calculation. Normalized by lag of total assets (AT). |
| Financial Investment | Increase in investments, minus change in short-term investments if available (IVSTCH), minus sale of investments (SIV) if available. All variables from the statement of cash-flows. Normalized by lag of total assets (AT). |
| Leverage Ratio | Total debt, which is long-term debt (DLTT) plus debt in current liabilities (DLC), normalized by total assets AT. |
| Long-term Leverage Ratio | Long-term debt (DLTT), which is debt with one or more year before maturity, normalized by total assets AT. |
| Market Equity (ME) | Total firm market value ($ PRC * SHROUT$) summed over all securities belonging to a firm, identified by GVKEY, and if missing, by PERMCO, as of June. To be valid, ME must be greater than zero. |
| Net debt issuance (<i>NDI</i>) | The total long term debt issuance (DLTIS) minus total long term debt reduction (DLTR). This variable captures the total net debt issuance of debt maturing in one year or more, and it is not limited to bonds. Normalized by lag of total assets (AT). |
| Net Operating Cash-Flows | Operating activities net cash-flow (OANCF) plus intangible investment. |
| Net payouts | Net equity repurchase is the purchase minus sale of common and preferred stock (PRSTKC - SSTK). Normalized by lag of total assets (AT). Net payouts is net equity repurchases plus total dividends (DV). Normalized by lag of total assets (AT). |
| ROA | Operating income before depreciation (OIBDP) divided by total assets (AT). |

| | |
|----------------------------------|--|
| Current Debt Net Issuance (CNDI) | Net change in short-term borrowings and/or current maturities of long-term debt. It captures debt change in debt of less than one year maturity. Normalized by lag of total assets (AT). |
| Tobin's Q | Market equity as end of quarter divided by book equity ($\frac{ME}{BE}$). |

Appendix A.2. Measuring SG&A

I follow [Peters and Taylor \[2017\]](#) in measuring SG&A. Specifically, SG&A is the Compustat variable XSGA minus XRD minus RDIP. There are two exceptions to this rule: (1) When XRD exceeds XSGA but is less than cogs, SG&A is measured as XSGA with no further adjustments or (2) When XSGA is missing, SG&A is set to zero. I also set XRD and RDIP to zero when missing.

As explained by [Peters and Taylor \[2017\]](#), the logic behind this formula is as follows:

According to the Compustat manual, XSGA includes R&D expense unless the company allocates R&D expense to cost of goods sold (COGS). For example, XSGA often equals the sum of Selling, General and Administrative and Research and Development on the Statement of Operations from firms' 10-K filings. To isolate (non-R&D) SG&A, we must subtract R&D from XSGA when Compustat adds R&D to XSGA. There is a catch: When a firm externally purchases R&D on products not yet being sold, this R&D is expensed as In-Process R&D and does not appear on the balance sheet. Compustat adds to XSGA only the part of R&D not representing acquired In-Process R&D, so our formula subtracts RDIP (In-Process R&D Expense), which Compustat codes as negative. We find that Compustat almost always adds R&D to XSGA, which motivates our formula above. Standard & Poor's explained in private communication that, "in most cases, when there is a separately reported XRD, this is included in XSGA." As a further check, we compare the Compustat records and 10-K filings for a random sample of one hundred firm-year observations with non-missing XRD. We find that Compustat includes R&D in XSGA in 90 out of one hundred cases, partially includes it in XSGA in one case, and includes it in COGS in seven cases. Two cases remain unclear even after asking the Compustat support team. The screen above lets us identify obvious cases in which xrd is part of COGS. This screen catches six of the seven cases in which XRD is part of COGS. Unfortunately, identifying the remaining cases is impossible without reading SEC filings. We thank the Compustat support team from Standard & Poors for their help in this exercise. **(Appendix B.2)**

Appendix A.3. FISD Cleaning

FISD provides 4 databases of interest: “fisd_issue” that gives information at bond issue level, “fisd_mergedissuer” that gives information about the bond issuer , “fisd_ratings_hist” to access the historical rating at each moment in time, and finally “fisd_amt_out_hist” to be able to access each bonds amount outstanding.

To calculate amount outstanding by firm, we consider the following bond types: US Corporate Convertible (CCOV), US Corporate Inflation Indexed (CCPI), US Corporate Debentures (CDEB), US Corporate LOC Backed (CLOC), US Corporate MTN (CMTN), US Corporate MTN Zero (CMTZ), US Corporate Paper (CP), US Corporate Pass Thru Trust (CPAS), US Corporate PIK Bond (CPIK), US Corporate Strip (CS), US Corporate UIT (CUIT), US Corporate Zero (CZ), US Corporate Bank Note (USBN), US Corporate Insured Debenture (UCID).

To calculate firms bond net issuance we use variation in amount outstanding from Merget FIDS.

Appendix A.4. Merge FISD to Compustat

We use Merget FISD data set to retrieve bond characteristics. The bond identifier in FISD is ISSUE ID, that maps one to one to CUSIP 9-digits. We use Compustat data set to retrieve firm-level characteristics. Firm identifier in Compustat is GVKEY. The goal is to merge firm with the bonds they issued.

CUSIP 6-digit is a firm identifier. The main challenge is though is that firms can issue bonds through their subsidiaries and the CUSIP 6-digit does not reflect the parent company identity.

Our first task is to go from CUSIP 9-digit to a parent 6-digit CUSIP. I do this in two steps. First, I merge FISD-issue data with FISD-issuer to the PARENT ID. I then get PARENT CUSIP, the CUSIP 6-digit to the PARENT ID from FISD-issue. Second, I use SDC to get the UPARENT CUSIP, the Ultimate Parent CUSIP 6-digit.

The figure below shows for all corporate bonds in FISD the successful merges with Compustat (Panel a) and the successful merge with Compustat and Markit CDS data (Panel b).

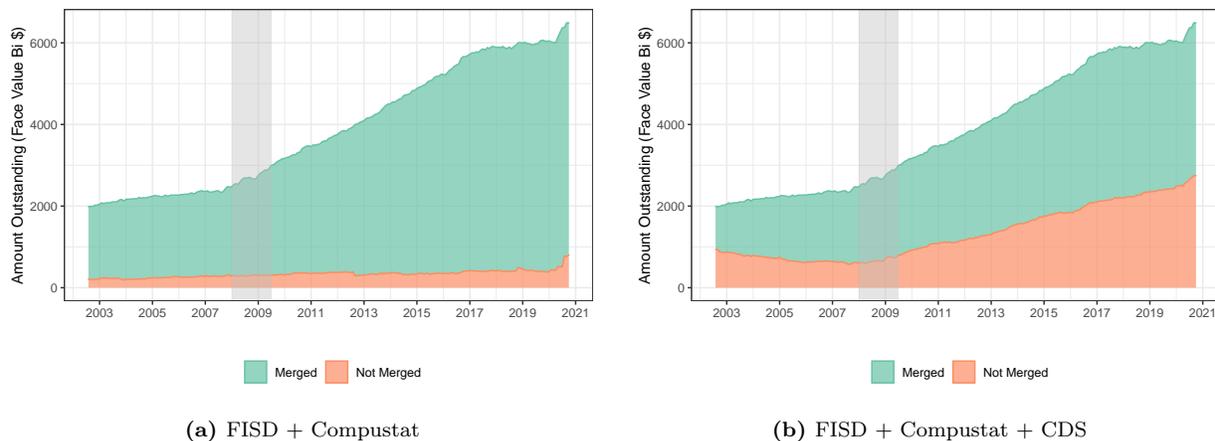


Figure A.10: Successful Mergers. This figure shows the amount outstanding of all corporate bonds in FISD dataset. In green it is the amount outstanding with successful merge with Compustat (Panel a) or Compustat and CDS data from Markit (Panel b). In red is the amount outstanding not merged.

Appendix B. Measures of Aggregate Safety Premium

AAA credit spread: It is the face-value weighted credit spread of AAA rated firms. I consider all bonds in the sample. This measure was first introduced by [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#).

BBB – (AAA and AA) basis spread: It is the face-value weighted CDS-bond basis spread between “BBB” and “AAA and AA.” The difference in credit risk is controlled by the CDS correction in the basis calculation. This measure is inspired by [Krishnamurthy and Vissing-Jørgensen \[2012a\]](#) safety premium, who suggest to use the credit spread between BBB and AAA, but control for differences in credit risk. The reason I use “AAA and AA” instead only “AAA” is because, in recent years, there are only two US corporations that are rated AAA, Johnson & Johnson and Microsoft. In order to minimize the influence of company-specific shocks I use the set of AAA and AA bonds. Note that a large component of the BBB–AAA spread is due to credit risk, this is the reason I use the basis spread instead of credit spread.

Box trade: Difference between a benchmark rates from the put-call parity relationship for European-style options and UST yields. I used the 18-months maturity. Data is downloaded from Binsbergen’ personal website ([here](#)).

Structurally estimated: Based on the the model presented in Section 3, we can write the

basis as

$$basis_{i,t} = (\alpha_{i,t+1} - 1)\varphi_t \quad (\text{B.1})$$

$$= \left[\alpha_{i,t}^\mu \exp\left(-\psi \frac{b_{i,t+1}}{E_t(\Pi_{t+1})}\right) - 1 \right] \varphi_t. \quad (\text{B.2})$$

Substituting all $\alpha_{i,t}$, we can re-write this relation as

$$basis_{i,t+1} = \left[\exp\left(-\psi \sum_{k \geq 0} \mu^k I_{t-k}\right) - 1 \right] \varphi_t \quad \text{where} \quad I_t = \frac{b_{t+1}}{\mathbb{E}_t \Pi_{t+1}} \quad (\text{B.3})$$

From this relationship we would like to estimate ψ , μ and $\boldsymbol{\varphi} = [\varphi_1, \dots, \varphi_T]$. I use a non-linear least square estimation.

Consider the following estimation equation

$$basis_{i,t} = (\alpha_{i,t+1} - 1)\varphi_t + \varepsilon_{i,t} \quad (\text{B.4})$$

Let

$$\{\widehat{\psi}, \widehat{\mu}, \widehat{\boldsymbol{\varphi}}\} = \operatorname{argmin}_{\psi, \mu, \boldsymbol{\varphi}} \sum_t \sum_i \varepsilon_{i,t}^2 \quad (\text{B.5})$$

be the unbiased estimator of interest.

Notice that given $\widehat{\psi}$ and $\widehat{\mu}$, each $\widehat{\varphi}_t$ necessary is

$$\widehat{\varphi}_t = (\mathbf{x}_t^T \mathbf{x}_t)^{-1} \mathbf{x}_t^T \mathbf{b}_t, \quad (\text{B.6})$$

where $\mathbf{b}_t = [basis_{1,t}, \dots, basis_{N,t}]$, $\mathbf{x}_t = [x_{1,t}, \dots, x_{N,t}]$ and

$$x_{i,t}(\widehat{\psi}, \widehat{\mu}) := (\alpha_{i,t+1} - 1) \quad (\text{B.7})$$

Hence, we can replace (B.7) in (B.8) and get that

$$\{\widehat{\psi}, \widehat{\mu}\} = \operatorname{argmin}_{\psi, \mu} \sum_t \left[\mathbf{b}_t^T \mathbf{b}_t - \frac{\mathbf{x}_t^T \mathbf{b}_t}{\mathbf{x}_t^T \mathbf{x}_t} \right]. \quad (\text{B.8})$$

Once we have $\{\widehat{\psi}, \widehat{\mu}\}$, we can simply replace it in (B.6) to have an estimation of the UST safety premium, φ_t .

Appendix C. Model

Appendix C.1. Price of the Bond

The main advantage of considering a model with liquidity default is that we can calculate the price of the debt for each (K_{t+1}, B_{t+1}) in closed form. The price of the debt is given by

$$P_{t+1} = a_1(1 + rc_0p_1) + a_2rc_1p_2 + \varphi(K_{t+1}, B_{t+1}; x_t, z_t) \quad (\text{C.1})$$

$$\text{where } rc_0 = (1 - \xi) \frac{(1 - \delta)K_{t+1} - fK_{t+1} - B_{t+1}}{B_{t+1}} \quad (\text{C.2})$$

$$rc_1 = (1 - \xi) \frac{K_{t+1}^\zeta}{B_{t+1}} \quad (\text{C.3})$$

$$\bar{m}_t = \frac{\beta}{\exp(x_t)^\gamma} \quad (\text{C.4})$$

$$\mu = \mu_x + \mu_z + \sigma_x^2 \gamma \quad (\text{C.5})$$

$$\sigma = \sqrt{\sigma_x^2 + \sigma_z^2} \quad (\text{C.6})$$

$$a_1 = \bar{m}_t \exp\left(\mu_x \gamma + \frac{1}{2} \sigma_x^2 \gamma^2\right) \quad (\text{C.7})$$

$$a_2 = a_1 \exp\left(\mu + \frac{1}{2} \sigma^2\right) \quad (\text{C.8})$$

$$p_1 = \Phi\left(\frac{\ln d - \mu}{\sigma}\right) \quad (\text{C.9})$$

$$p_2 = \Phi\left(\frac{\ln d - \mu - \sigma^2}{\sigma}\right) \quad (\text{C.10})$$

$$\Phi(\cdot) \text{ is the normal distribution cdf.} \quad (\text{C.11})$$

To see that, start with the bond price equation:

$$P(K_{t+1}, B_{t+1}; x_t, z_t) = \mathbb{E} \left[M_{t+1} \left((1 - \mathbb{I}_{\{V_{t+1} < 0\}}) + \mathbb{I}_{\{V_{t+1} < 0\}} \frac{L_{t+1}}{B_{t+1}} \right) \right] + s(K_{t+1}, B_{t+1}; x_t, z_t) \quad (\text{C.12})$$

Or we can rewrite it as

$$P(K_{t+1}, B_{t+1}; x_t, z_t) = \left[\mathbb{E}[M_{t+1}] - \mathbb{E} \left[M_{t+1} \mathbb{I}_{\{V_{t+1} < 0\}} \frac{B_{t+1} - L_{t+1}}{B_{t+1}} \right] \right] + s(K_{t+1}, B_{t+1}; x_t, z_t) \quad (\text{C.13})$$

where $s(K_{t+1}, B_{t+1}; x_t, z_t)$ is the safety premium for the bond.

But,

$$\frac{B_{t+1} - L_{t+1}}{B_{t+1}} = \frac{B_{t+1} + (1 - \xi)(f - (1 - \delta))K_{t+1}}{B_{t+1}} - \frac{(1 - \xi)X_{t+1}Z_{t+1}K^\zeta}{B_{t+1}} \quad (\text{C.14})$$

$$= rc_t - rc_{t+1}X_{t+1}Z_{t+1} \quad (\text{C.15})$$

We can find a close form solution to P_t , by solving the expectation in equation (C.13).

Lemma 5. *Let $X = \exp(x)$ and $Z = \exp(z)$, such that $x \sim N(\mu_x, \sigma_x)$ and $z \sim N(\mu_z, \sigma_z)$. Then,*

$$\mathbb{E} [X^\alpha Z^\beta \mathbb{I}_{\{XZ < d\}}] = \exp(\mu_x \alpha + \mu_y \beta + \frac{1}{2}(\sigma_x^2 \alpha^2 + \sigma_z^2 \beta^2)) \Phi \left(\frac{\ln d - \mu_x - \mu_y - \alpha \sigma_x^2 - \beta \sigma_z^2}{\sqrt{\sigma_x^2 + \sigma_z^2}} \right) \quad (\text{C.16})$$

Hence, the price of the bond is:

$$P_{t+1} = \bar{m}_t \mathbb{E} [X_{t+1}^\gamma + rc_t X_{t+1}^\gamma \mathbb{I}_{\{XZ < d\}} + rc_{t+1} X^{\gamma+1} Z \mathbb{I}_{\{XZ < d\}}] + s(K_{t+1}, B_{t+1}; x_t, z_t) \quad (\text{C.17})$$

$$= [a_{t+1}(1 + rc_t p_{t+1}) + a_2 rc_{t+1} p_2] + s(K_{t+1}, B_{t+1}; x_t, z_t) \quad (\text{C.18})$$

$$(\text{C.19})$$

where $a_{t+1} = \exp \left(\mu_x \gamma + \frac{1}{2} \sigma_x^2 \gamma^2 \right), \quad (\text{C.20})$

$$p_{t+1} = \Phi \left(\frac{\ln d - \mu_x - \mu_z - \gamma \sigma_z^2}{\sqrt{\sigma_x^2 + \sigma_z^2}} \right) \quad (\text{C.21})$$

$$a_2 = \bar{m}_t \exp \left(\mu_x (\gamma + 1) + \mu_z + \frac{1}{2} (\sigma_x^2 (\gamma + 1)^2 + \sigma_z^2) \right) \quad (\text{C.22})$$

$$p_2 = \Phi \left(\frac{\ln d - \mu_x - \mu_z - (\gamma + 1) \sigma_z^2 - \sigma_z^2}{\sqrt{\sigma_x^2 + \sigma_z^2}} \right) \quad (\text{C.23})$$

Appendix C.2. Optimization

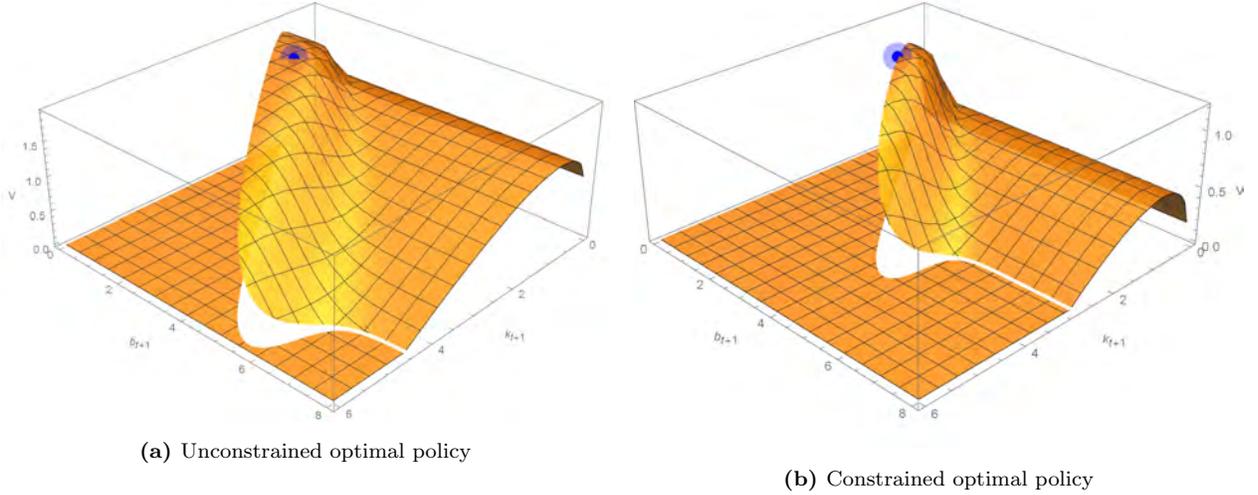


Figure C.11: Firm's Total Value as Function of Capital and Debt Issuance. This figure shows how, the total value of the firm varies with the amount capital invested and bond issued. The blue dot is the optimal policy $\{k_{t+1}^*, b_{t+1}^*\}$ that maximizes the value of the firm. In Panel (a) the firm's investment is unconstrained and Panel (b) firm's investment is constrained. The parameter choices are: $\varphi_t = 1\%$.

Appendix D. Infinite Horizon Dynamic Model

In this section, I present a numerical implementation of the infinite horizon version of the model introduced in Section 3. The results are qualitatively equivalent to those obtained in the two period model.

Appendix D.1. Simulation Strategy

For easiness of notation, in this section I omit the i subscript. Let

$$s_t = (k_t, b_t, \alpha_t, x_t, z_t, \varphi_t) \quad (\text{D.1})$$

be the vector state space representation of the firm at time t , where k_t and b_t are respectively the level of capital and the debt issuance of the firm, i.e. the *action*, taken by the firm at time $t - 1$, α_t is the firm's perceived safety, while x_t , z_t and φ_t are respectively the aggregate and idiosyncratic productivity shocks and the aggregate safety premium. Note that the description of the state space given here is slightly different than the one given in Section 3, as I replaced the net worth w_t with the action variables k_t and b_t . Recall that the net worth of the company is determined by the formula

$$w_t := \exp(x_t + z_t)k_t^\zeta + lv(1 - \delta)k_t - b_t, \quad (\text{D.2})$$

hence, given the action and the realization of productivity shocks, the net worth is determined. The advantage of the parametrization proposed here is that it allows for a joint discretization of the state space and the action space where each possible level of net worth generated by the choice of an action and a realization of productivity shocks is faithfully represented.

As observed in Section 3, the value of the firm is given by the solution of the Bellman equation

$$V(\mathcal{J}_t) = \max_{k_{t+1}, b_{t+1}} d(k_{t+1}, b_{t+1}; \mathcal{J}_t) + \mathbb{E}_t [M_{t,t+1} V_{t+1}(\mathcal{J}_{t+1})]. \quad (\text{D.3})$$

To find the optimal policy, first I discretize the state space, and then I apply the standard value function iteration method (see for e.g. [Stokey \[1989\]](#)).

Appendix D.2. State Space Discretization

I discretize the state space by defining discrete spaces S_k , S_b , S_α , S_x , S_z and S_φ for each component of the state space vector and taking the Cartesian product of these sets. For S_k , S_b and S_α I take a uniformly spaced grid of 41 points ranging from 1 and 1200 for S_k , 0 and 90 for S_b , and 0 and 1 for S_α . For S_x , S_z and S_φ , I follow a technique for approximating AR(1) models with Markov chains originally introduced by [Rouwenhorst \[1995\]](#), generating three points for each space. As noted in [Kopecky and Suen \[2010\]](#), when simulating highly persistent processes, this approximation scheme is more reliable than alternative approaches commonly used in the literature such as [Tauchen \[1986\]](#) or [Tauchen and Hussey \[1991\]](#).

Appendix D.3. Main Results

This paper is mainly interested in the sensitivity of optimal bond issuance as a function of perceived safety. In Figure [D.12](#) I plot the numerical simulation of this function for the set of approximation scheme described above. As one can see, the full dynamic model preserves the qualitative behavior observed in the two period model.

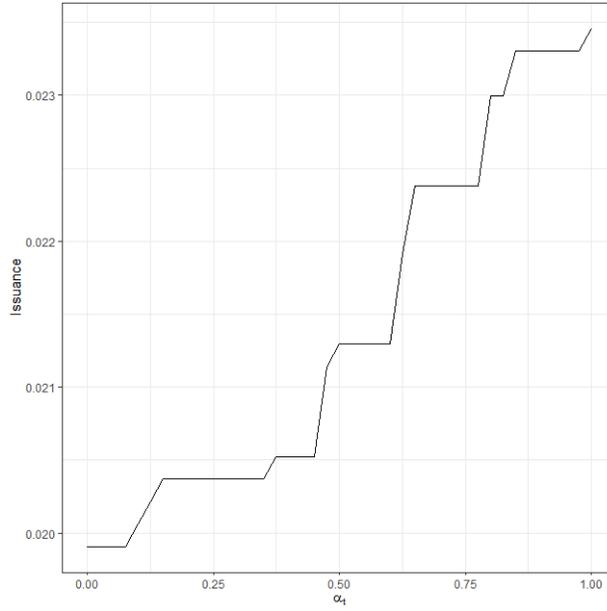


Figure D.12: Issuance Response to Perceived Safety: This figure shows the optimal debt issuance as a share of k_t as function of perceived safety, α_t .

Appendix E. Additional Empirical Results

Table E.15: Impact of Cross-basis on Firm’s Decisions Conditional on Positive Debt Issuance Including Ratings FE. This table shows regression results from estimating R3. The y -variable are (2) net payout, which is dividends plus net equity repurchase, (2) capital investment, which is CAPEX plus net PPE bought, (3) R&D expenses, (4) 30% of SG&A expenses, (5) intangible investment, which is R&D plus 30% of SG&A expenses, (6) acquisitions. All independent variables are measured in time $t + 1$ and normalized by lag total assets. For the x -variables, cross-basis is the firm-level CDS-bond basis minus the basis index, basis index is the face-value weighted average of CDS-bond basis in the corporate bond market and DebtIssuance is an indicator variable equal to 1 if net debt issuance is strictly positive and 0 otherwise. The controls are CDS spread at the firms level, log of total assets, Tobin’s Q, CHE as percentage of total assets, book leverage ratio and return on assets (ROA). All columns include time, firm and rating buckets fixed effects. All independent variables are measured in quarter t . Standard errors are reported in parenthesis and are clustered by time. Data is quarterly from 2003Q1 to 2019Q3.

| <i>Dependent variable:</i> | | | | | | | | |
|-----------------------------------|----------------------|----------------------|-----------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cross-basis \times DebtIssuance | 0.041** (0.016) | 0.017 (0.016) | -0.002 (0.004) | 0.003 (0.004) | 0.001 (0.006) | -0.082 (0.056) | 0.014 (0.021) | -0.051 (0.052) |
| Cross-basis | 0.003 (0.011) | 0.017 (0.011) | 0.0004 (0.003) | 0.001 (0.002) | 0.001 (0.003) | 0.030 (0.023) | 0.005 (0.008) | -0.019 (0.023) |
| DebtIssuance | 0.278*** (0.028) | 0.183*** (0.012) | 0.001 (0.007) | 0.007 (0.005) | 0.008 (0.008) | 0.887*** (0.082) | 0.115*** (0.024) | 0.879*** (0.091) |
| CDS-spread | -0.005 (0.012) | -0.050*** (0.013) | -0.0002 (0.002) | 0.006*** (0.002) | 0.005** (0.002) | -0.024* (0.013) | -0.005 (0.006) | 0.009 (0.017) |
| log(Total Assets) | -0.183*** (0.042) | -0.099*** (0.026) | -0.102*** (0.010) | -0.330*** (0.007) | -0.432*** (0.013) | -0.272*** (0.075) | -0.015 (0.033) | -0.604*** (0.096) |
| CHE (% assets) | 0.023*** (0.003) | -0.0001 (0.001) | -0.0005 (0.001) | -0.005*** (0.0005) | -0.005*** (0.001) | 0.083*** (0.010) | -0.004 (0.003) | -0.181*** (0.009) |
| Tobin’s Q | 0.023*** (0.005) | 0.010*** (0.002) | 0.001 (0.001) | 0.003*** (0.001) | 0.004*** (0.001) | -0.001 (0.004) | -0.003* (0.002) | 0.017** (0.007) |
| Leverage Ratio (%) | -0.021*** (0.002) | -0.010*** (0.001) | -0.001*** (0.0003) | -0.005*** (0.0005) | -0.006*** (0.001) | 0.002 (0.004) | 0.001 (0.002) | -0.019*** (0.004) |
| ROA (%) | 0.087*** (0.014) | 0.044*** (0.013) | 0.008*** (0.002) | 0.008*** (0.002) | 0.015*** (0.004) | 0.026*** (0.008) | 0.019*** (0.007) | 0.013 (0.020) |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Ratings FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 |
| R ² | 0.418 | 0.688 | 0.766 | 0.940 | 0.902 | 0.116 | 0.059 | 0.139 |
| Adjusted R ² | 0.396 | 0.676 | 0.757 | 0.938 | 0.898 | 0.083 | 0.024 | 0.106 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Table E.16: Impact of Cross-basis on Firm’s Decisions Conditional on Positive Debt Issuance Including Ratings FE. This table shows regression results from estimating R3. The y -variable are (2) net payout, which is dividends plus net equity repurchase, (2) capital investment, which is CAPEX plus net PPE bought, (3) R&D expenses, (4) 30% of SG&A expenses, (5) intangible investment, which is R&D plus 30% of SG&A expenses, (6) acquisitions. All independent variables are measured in time $t + 1$ and normalized by lag total assets. For the x -variables, cross-basis is the firm-level CDS-bond basis minus the basis index, basis index is the face-value weighted average of CDS-bond basis in the corporate bond market and DebtIssuance is an indicator variable equal to 1 if net debt issuance is strictly positive and 0 otherwise. The controls are CDS spread at the firms level, log of total assets, Tobin’s Q, CHE as percentage of total assets, book leverage ratio and return on assets (ROA). All columns include time, firm and rating buckets fixed effects. All independent variables are measured in quarter t . Standard errors are reported in parenthesis and are clustered by time. Data is quarterly from 2003Q1 to 2019Q3.

| <i>Dependent variable:</i> | | | | | | | | |
|----------------------------|----------------------|----------------------|----------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| | Net Payout | Capital Investment | R & D | SG & A | Intangible Investment | Acquisitions | Financial Investment | Δ Cash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cross-basis | 0.055*** (0.018) | 0.040*** (0.013) | 0.002 (0.003) | 0.005** (0.002) | 0.007* (0.004) | 0.019 (0.016) | 0.013 (0.010) | -0.025 (0.022) |
| CDS-spread | -0.087*** (0.019) | -0.086*** (0.019) | -0.005** (0.002) | -0.002 (0.002) | -0.007** (0.003) | -0.038** (0.015) | -0.010** (0.005) | -0.012 (0.019) |
| log(Total Assets) | -0.231*** (0.041) | -0.125*** (0.024) | -0.109*** (0.010) | -0.341*** (0.008) | -0.450*** (0.012) | -0.281*** (0.080) | -0.024 (0.033) | -0.658*** (0.097) |
| CHE (% assets) | 0.023*** (0.003) | -0.0004 (0.001) | -0.0004 (0.001) | -0.005*** (0.0005) | -0.005*** (0.001) | 0.078*** (0.009) | -0.005 (0.003) | -0.186*** (0.009) |
| Tobin’s Q | 0.018*** (0.005) | 0.008*** (0.002) | 0.001 (0.001) | 0.002*** (0.001) | 0.002** (0.001) | 0.004 (0.004) | -0.002 (0.002) | 0.012 (0.007) |
| Firms FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 | 19,227 |
| R ² | 0.391 | 0.675 | 0.765 | 0.939 | 0.901 | 0.087 | 0.056 | 0.120 |
| Adjusted R ² | 0.369 | 0.663 | 0.757 | 0.937 | 0.897 | 0.053 | 0.021 | 0.088 |

Note:

*p<0.1; **p<0.05; ***p<0.01

Appendix E.1. Cash Flow Identity

It is useful to do a complete study of how firms use the proceeds from debt issuance in response to the cross-basis. We can use the cash-flow statement to do a “follow the money” approach and how does the firm use the funds from issuance. This identity also justifies my measures of real investment (capital, intangible and acquisitions) and financial investment. I also estimated Equation (R3) for all variables in (E.1), I did not find any patterns that alters the results and interpretation in the body of the paper.

To follow the money, for every firm and quarter, consider the augmented budget equation

$$F - (i + l' - (1 + r_l)l) = (d - e) - (Pb' - b),$$

the prime notation denotes one period ahead values, F as before is the net cash flow from operations, i is total investment, $l - (1 + r_l)l$ is change in cash (or liquid assets), d is total payouts to shareholders, e is equity issuance, therefore $d - e$ is net payout to equity holders and $Pb' - b$ net debt issuance.

I map the budget equation to the cash-flow identity in Compustat data by calculating the following:

$$\begin{aligned} \text{Total Net Debt Issuance} = & \text{Net Payouts} + \text{Real Investment} + \\ & \text{Financial Investment} + \Delta\text{Cash} - \text{Net Operating Profits} + \text{Others} \end{aligned} \quad (\text{E.1})$$

I consider further breakdowns for total net debt issuance and real investments. In Compustat one can disentangle total debt issuance in current debt (less than one year maturity), and long-term debt (less than one year maturity). This differentiation is interesting because the basis calculations only captures bond liabilities for time to maturity longer than one year. Therefore long-term debt issuance is the main dependent variable of interest. Real investment can be broken down in three categories: capital investment, intangible investment and acquisitions. This is interesting because forms of investment that are not purely capital expenditure is becoming increasingly important among the largest US firms.

- Net Operating Profits (F): net operating cash flow net minus intangible investment.
- Total Debt Issuance (TDI): the total net debt issuance, $\text{TDI} = \text{NDI} + \text{NCDI}$, where NDI is the non-current net debt issuance and NCDI is the current debt issuance.
- Real investment (RINV): $\text{RINV} = \text{KINV} + \text{ACQ} + \text{IINV}$, where $\text{KINV} = \text{CAPX} - \text{SPPE}$, ACQ is acquisitions and IINV is in intangible investment, $\text{IINV} = \text{R\&D} + \text{SG\&A}$.
- ΔCash is the cash variation, $\Delta \text{Cash} = \text{CHECH}$.
- Financial Investment (FINV): $\text{FINV} = \text{IVCH} - \text{SINV} - \text{IVSTCH}$.
- Other: the residual, $\text{Others} = - \text{IVACO} - \text{FIAO} - \text{TXBCOF}$

Appendix F. CDS-bond Basis

We follow [Elizalde, Doctor, and Saltuk \[2009\]](#) and apply the par equivalent CDS spread methodology, or PECS, to compute the CDS bond basis.

To fix notation, let $r(s)$ be the instantaneous short interest rate, and $\lambda_i(s)$ the instantaneous hazard rate for issuer i . We define the discount curve $Z(t)$ and the survival probability curve $S_i(t)$ for issuer i as

$$Z(t) := e^{-\int_0^t r(s)ds}, \quad (\text{F.1})$$

$$S_i(t) := e^{-\int_0^t \lambda_i(s)ds}. \quad (\text{F.2})$$

$$(\text{F.3})$$

Given a bond issued by issuer i with N interest payments CF_1, CF_2, \dots, CF_N at times t_1, t_2, \dots, t_N , principal value V and maturity t_N , its dirty price²⁷ is given by the formula

$$P = \sum_{n=1}^N Z(t_n)S_i(t_n)CF_n + Z(t_N)S_i(t_N)V. \quad (\text{F.4})$$

Given a CDS contract with M remaining payments, with payment times t_1, t_2, \dots, t_M and year fractions $\Delta_1, \Delta_2, \dots, \Delta_M$ the present value of the contract for the *protection buyer* is given by

$$\pi^{pb} = NC \sum_{m=1}^M \Delta_m Z(t_m)S_i(t_m) + \frac{NC}{2} \sum_{m=1}^M \Delta_m Z(t_m) [S(t_{m-1}) - S(t_m)] \quad (\text{F.5})$$

while for the counter-party of the contract, the *protection seller*, the net present value is given by

$$\pi^{ps} = N(1 - RR) \sum_{m=1}^M Z(t_m) [S(t_{m-1}) - S(t_m)]. \quad (\text{F.6})$$

where N is the notional value, RR is the recovery rate, and C is the CDS spread. In particular, the CDS par spread C_{par} is the one for which

$$\pi^{pb}(C_{par}) = \pi^{ps} \quad (\text{F.7})$$

The PECS methodology consists in three steps. First, one bootstraps a survival probability curve $S_i^{CDS}(t)$ from CDS prices. Second, one defines the bond-implied survival probability

²⁷Inclusive of accrued interest.

curve $S_i^{Bond}(t) = S_i^{CDS}(t) + \beta_i$ by choosing the β that minimizes the difference between market prices P_j^{Mkt} and prices $P_j(S_i^{Bond})$ implied by Formula (F.4), averaging over all issued bonds j for issuer i

$$\beta_i := \operatorname{argmin} \sum_j (P_j^{Mkt} - P_j(S_i^{Bond}))^2. \quad (\text{F.8})$$

In this phase, one needs to recall that bonds in the US market are quoted using the clean price, hence one must re-add the accrued interest before taking the difference. Finally, one can define the par equivalent CDS spread C_{pecs} for a given tenor t_M by solving Equation (F.7) with the survival probability given by $S_i^{Bond}(t)$. The CDS-bond basis $B(t)$ is given by the difference $C_{pecs} - C_{par}$.

Appendix G. Alternative Model with Limits to Arbitrage

Appendix G.1. Explicit Model of Arbitrageurs

At each time t , the arbitrageur must choose his consumption C_t^a , his investment in risky assets $Q_{i,t+1}^a$, in the uncollateralized loans $B_{u,t+1}^a$ and in the collateralized loans $B_{c,t+1}^a$.

Let W_t^a be the wealth of the arbitrageur in time t .

$$W_t^a = \mathbf{Q}_t^a \mathbf{X}_t + B_{u,t}^a + B_{c,t}^a - C_t^a \quad (\text{G.1})$$

As in [Gârleanu and Pedersen \[2011\]](#), I assume that arbitrageurs must post margins to finance their positions. Margins are paid both in long and short positions.

The arbitrageur solves the problem²⁸

$$\max_{\{c_t, \mathbf{Q}_{t+1}, B_{u,t+1}, B_{c,t+1}\}_{t=0}^{\infty}} \mathbb{E}_t \left[\sum_t \beta^t U(C_t) \right] \quad (\text{G.2})$$

$$s.t. \quad \mathbf{Q}_{t+1} \mathbf{P}_t + B_{u,t+1} P_{u,t} + B_{c,t+1} P_{c,t} \leq W_t \quad (\text{G.3})$$

$$\sum_i m_{i,t} |Q_{i,t+1}| P_{i,t} + B_{u,t+1} P_{u,t} \leq W_t, \quad (\text{G.4})$$

where $m_{i,t}$ is the margin requirement of asset i and time t . All other terms are standard.

Suppose that $u(c) = \frac{c^{(1-\gamma)}}{1-\gamma}$ and $\Delta c_{t+1} = \ln \left(\frac{C_{t+1}}{C_t} \right) = \mu_c + \rho_c \Delta c_t + \sigma_c^2 \eta_{c,t+1}$, where $\eta_{c,t+1} \sim N(0, 1)$

²⁸We drop the subscript a to ease the notation.

From the agent's a first-order conditions we have:

$$\mathbb{E}(r_{u,t+1} - r_{c,t+1}) = \psi_t \quad (\text{G.5})$$

$$\mathbb{E}(r_{i,t+1} - r_{c,t+1}) + \frac{1}{2}\sigma_i^2 = \text{cov}_t(m_{t+1}^a, r_{i,t+1}) - \tilde{m}_{i,t} \quad (\text{G.6})$$

where $\psi_t = \ln\left(\frac{\lambda_t + \kappa_t}{\lambda_t}\right)$ and $\tilde{m}_{i,t} = \ln\left(\frac{\lambda_t + \kappa_t m_{i,t} \text{sign}(Q_{i,t+1})}{\lambda_t}\right)$

To see this, I solve the Lagrangian,

$$\begin{aligned} \mathcal{L} = \mathbb{E}_t \left[\sum_t \beta^t U(C_t) + \lambda_t (W_t - \mathbf{Q}_{t+1} \mathbf{P}_t - B_{u,t+1} P_{u,t} - B_{c,t+1} P_{c,t}) + \right. \\ \left. \kappa_t \left(W_t - \sum_i m_{i,t} |Q_{i,t+1}| P_{i,t} - B_{u,t+1} P_{u,t} \right) \right] \quad (\text{G.7}) \end{aligned}$$

$$\left[\frac{\partial \mathcal{L}}{\partial Q_{i,t+1}} \right] : \quad \mathbb{E}_t [-(\lambda_t + \kappa_t m_{i,t} \text{sign}(Q_{i,t+1})) P_{i,t} + (\lambda_{t+1} + \kappa_{t+1}) X_{i,t+1}] = 0 \quad (\text{G.8})$$

$$\implies P_{i,t} = \mathbb{E}_t \left[\frac{\lambda_{t+1} + \kappa_{t+1}}{\lambda_t + \kappa_t} \frac{\lambda_t + \kappa_t}{\lambda_t + \kappa_t m_{i,t} \text{sign}(Q_{i,t+1})} X_{i,t+1} \right] \quad (\text{G.9})$$

$$\left[\frac{\partial \mathcal{L}}{\partial B_{u,t+1}} \right] : \quad \mathbb{E}_t [-(\lambda_t + \kappa_t) P_{u,t} + (\lambda_{t+1} + \kappa_{t+1})] = 0 \quad (\text{G.10})$$

$$\implies P_{u,t} = \mathbb{E}_t \left[\frac{\lambda_{t+1} + \kappa_{t+1}}{\lambda_t + \kappa_t} \right] \quad (\text{G.11})$$

$$\left[\frac{\partial \mathcal{L}}{\partial B_{c,t+1}} \right] : \quad \mathbb{E}_t [-\lambda_t P_{c,t} + \lambda_{t+1} + \kappa_{t+1}] = 0 \quad (\text{G.12})$$

$$\implies P_{c,t} = \mathbb{E}_t \left[\frac{\lambda_{t+1} + \kappa_{t+1}}{\lambda_t} \right] \quad (\text{G.13})$$

$$\left[\frac{\partial \mathcal{L}}{\partial C_t} \right] : \quad \mathbb{E}_t [u'(C_t) - \lambda_t - \kappa_t] = 0 \quad (\text{G.14})$$

$$\implies u'(C_t) = \lambda_t + \kappa_t \quad (\text{G.15})$$

Hence, the price of each asset i must be equal evolves two Lagrange multipliers from the arbitrageur problem. The first λ_t is the traditional budget constraint. The second is the κ_t

is the margin constraint. In world in which there is a second set of agents that value safety services, the arbitrageurs is short in in assets that provide safety services. In this case, the safety premium is higher, higher the margin of requirement of the asset.

Appendix G.2. An Example of a Negative CDS-bond Trade

In this subsection I present an example for the negative CDS-bond basis for a Marriot (MAR 3 3/4 10/01/25, rated BBB-), 5-year maturity bought in end of September 2020. The example builds on negative CDS-basis trade presented in [Boyarchenko et al. \[2018\]](#) and [Bai and Collin-Dufresne \[2019\]](#). At the time, the CDS-bond basis of MAR was -1.3% . If investors were able to finance themselves at the UST rate, this would represent an arbitrage trade with profits of 1.3% per year. The key idea of this example is to flesh out the true funding costs a financial intermediary would incur if she enters this trade. By looking at the net payouts, one can then calculate the implicit funding cost that would make this trade unattractive.

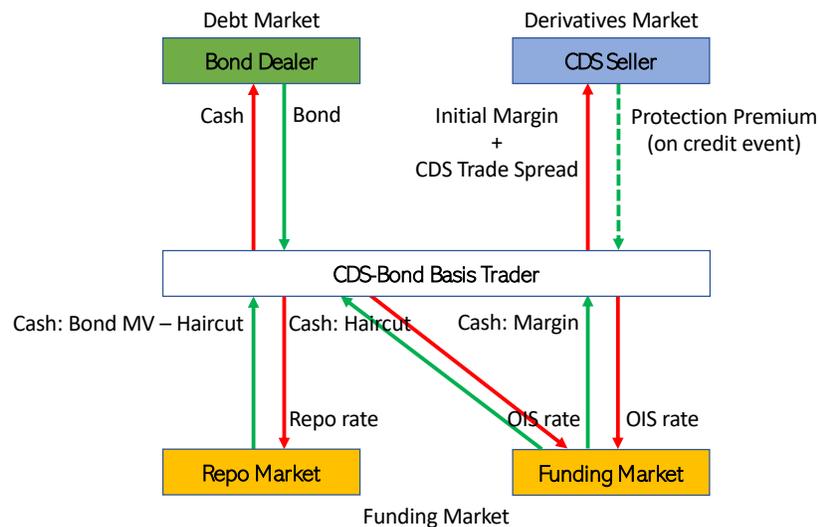


Table G.17: Negative CDS-bond Basis Cash Flow Diagram

Figure G.17 shows a cash-flow diagram for a generic negative trade transaction. In this example, the investor is a generic intermediary that buys the bond in the bond market, buys

CDS protection in the derivatives market and funds the position in the funding market. Funding markets are of two types: secured lending and unsecured lending. I assume the bond transacts at par and the investor enters in \$10 Million position. All the cash flows are summarized in Table [G.18](#).

The first transaction is to buy the cash bond. The investor uses the bond as collateral in the repo market and pays the repo rate. I follow [Gârleanu and Pedersen \[2011\]](#) and assume that haircuts for IG bonds is 25%. She need to finance the haircut on the unsecured funding market.

The second transaction is to buy the CDS protection for the total notional value. The investor pays the upfront payment and the CDS fixed premium of 1%. She also needs to post margin for the CDS position. I follow the FINRA guidelines and set the margin to 12.5% of the notional.²⁹ Both CDS payments and margins are funded in the unsecured funding market.

Finally, the investor needs to fund the total of repo haircut, and CDS upfront payment, fixed premium and margin. The unsecured borrowing cost is investor-specific and it is not easily observable. In general, the funding cost is a base rate, like OIS, plus a spread. As a benchmark, as shown in Table [G.18](#), I assume this spread is zero and calculate what would be net payoff of this trade. For the notional of \$10 Million, the net payoff of this trade would be \$116 Thousand per year, or 1.16%. This number is smaller than the negative CDS-bond basis, but it is still large.

Finally, what would be the minimal funding cost that would make this transaction unattractive to the investor? This rate is simply the calculation net payoff as a ratio of total unsecured funding needed. As shown in Table [G.19](#), this number is 3.06%, which means that an unsecured funding cost of OIS plus a spread of 3.06% would make this trade unprofitable. When compared to the 5-year credit spread of large banks in the US, this number looks high.³⁰ If the credit spread is the proper cost of funding of large financial institutions, they should have been engaging in the negative CDS-bond basis trade. Though, the credit spreads do not take into consideration the regulation burden in taking this trade. This investment, although theoretically risk free, adds to the risk based capital and liquidity requirements of financial institutions. 3.06% thus represent the shadow cost of funding of the intermediary, which includes, among others, “balance sheet rental cost” due to regulation

²⁹For more details see [FINRA website](#).

³⁰For comparison, 5-years yield for unsecured senior debt on September 30, 2020 for JP Morgan was 0.86%, Bank of America was 0.9% and Citi Bank was 1.15%.

constraints.

The balance sheet rental cost include costs related stringent regulation such as liquidity coverage ratios. For details on how this trade affects the balance sheet of the intermediary, the reader can consult [Boyarchenko et al. \[2018\]](#). More broadly, a recent literature explores how these balance sheet costs are linked to prices and liquidity in a variety of markets ([Du et al. \[2018a\]](#), [Duffie \[2018\]](#), [Andersen et al. \[2019\]](#), [Fleckenstein and Longstaff \[2020\]](#), [Bolandnazar \[2020\]](#)).

Table G.18: A Negative CDS-bond Basis Example

| Variable | Rate | Dollar Value |
|--|--------|-------------------|
| Corporate Yield | 3.10% | |
| Treasury Yield | 0.30% | |
| CDS spread | 1.50% | |
| CDS-bond basis | -1.30% | |
| Cash position | | |
| Bond Market Value | | 10,000,000.00 |
| Secured Funding | 75.00% | 7,500,000.00 |
| Repo Haircut | 25.00% | 2,500,000.00 |
| CDS position | | |
| Notional Value | | 10,000,000.00 |
| Upfront Payment | | (52,020.00) |
| Initial margin | 12.50% | (1,250,000.00) |
| Funding cost of the cash position | | |
| Repo Rate on 75% notional | 0.38% | (28,500.00) |
| OIS Rate on Haircut | 0.40% | (10,000.00) |
| OIS Upfront Payment | 0.40% | (208.08) |
| OIS rate on CDS initial margin | 0.40% | (5,000.00) |
| Trade Cashflow | | |
| Bond Coupon | | 310,000.00 |
| CDS fixed premium | 1.00% | (100,000.00) |
| CDS trade spread (effective) | | (150,000.00) |
| Total | | 160,000.00 |
| Totals | | |
| Total Payoff | | 160,000.00 |
| Total Funding Cost | | (43,708.08) |
| Net Payoff | | 116,291.92 |

This table shows the annual cash flows for negative CDS-bond trade on bond MAR 3 3/4 10/01/25 (Marriott bond, rated BBB-) bought on Sep 2020. Bond and UST yields are from Bloomberg. Repo rate is from Bloomberg repo rate calculation. CDS spread and OIS is from Markit. Upfront payment is from Market calculator, which can be found [here](#).

Table G.19: Implicit Funding Cost

| Variable | Rate | Dollar Value |
|-------------------------|-------------|---------------------|
| Net Payoff | | 116,291.92 |
| Total Unsecured Funding | | 3,802,020.00 |
| Implicit funding rate | 3.06% | |

This table shows the implicit funding cost that would make the negative CDS-bond trade not profitable. The example considers Marriot bond (MAR 3 3/4 10/01/25, BBB– bond) bought on Sep 2020.